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THE EFFECTS OF THE ANCHORING AND ADJUSTMENT BIAS FOLLOWING A PRICE SHOCK: EVIDENCE FROM THE GERMAN STOCK MARKET

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Abstract

In past studies concerning stock price shocks, there was found evidence of stock return predictability. The most common explanations for this predictability of returns are market microstructure, changing risk and behavioural explanations, this last one usually linked to the investor over/underreaction. Additionally, it has been stated that individuals rely on heuristics when making decisions under uncertainty and that they make estimates by anchoring them into a reference point, and then adjust the estimates from it.

With this dissertation, I aim to study how stock prices react to a large price change, by investigating if investors immediately adjust their estimates of the stock value to the new intrinsic value or if they anchor their estimates to a reference point which will make the adjustment gradual, leading to investor underreaction. The proposed reference points to investigate are the 52 Week High/Low and Investor private information.

To test my hypothesis, I follow a similar methodology to Brady and Premti (2019), when they conducted a study to determine the effects of the above-presented reference points on the post-shock returns in the US stock market, and apply it to the German stock market, for the 1995-2019 period.

The results suggest that investors rely on available reference points when making their price estimations after a large price change. More specifically, investors anchor their price estimations to the 52 Week High/Low in the event of a large negative/positive price change and thus underreact on the event day. Additionally, investors anchor their price estimations to their private information, but only in the presence of large price decreases. The results are also consistent with the ones achieved in the US stock market, although with greater influence in the German market. These results can prove useful for future investor strategies.

JEL codes: G14; G40; G41

Keywords: Anchoring; Reference points; 52 Week High/52 Week Low; Private information; Underreaction; Large price changes

Resumo

Em estudos anteriores relativamente a choques no preço de ações, foi encontrada evidencia de previsibilidade nos retornos de ações. As explicações mais comuns para esta previsibilidade dos retornos são a microestrutura do mercado, alterações do risco e explicações comportamentais, esta última usualmente relacionada com sobre/sub-reação dos investidores. Adicionalmente, foi afirmado que os indivíduos dependem de heurísticas/atalhos quando tomam decisões sob incerteza e que fazem estimativas ancorando-as a um ponto de referência, ajustando as estimativas a partir dele.

Com esta dissertação, pretendo estudar como é que os preços das ações reagem a um choque no preço, investigando se os investidores ajustam imediatamente as suas estimativas do preço das ações para o novo valor intrínseco ou se eles ancoram as suas estimativas a um ponto de referência que irá fazer o ajustamento ser gradual, levando a sub-reação. Os pontos de referência propostos são o 52 Week High/Low e informação privada.

Para testar as minhas hipóteses, seguirei uma metodologia similar com a de Brady e Premti (2019), quando eles conduziram um estudo para determinar os efeitos dos pontos de referência apresentados acima nos retornos após um choque no preço no mercado de ações norte-americano, e aplicá-la ao mercado de ações alemão, para o período 1995-2019.

Os resultados obtidos sugerem que os investidores dependem de pontos de referência quando realizam as estimativas do preço após uma grande variação. Mais concretamente, eles ancoram as estimações de preço ao 52 Week High/Low na ocorrência de um choque negativo/positivo, sub-reagindo no dia do evento. Adicionalmente, os investidores ancoram as suas estimativas à sua informação privada, mas apenas na ocorrência de um choque negativo no preço. Os resultados são consistentes com os alcançados no mercado norte-americano, porém com um maior impacto no mercado alemão, e podem revelar-se uteis para os investidores melhorarem as suas estratégias de investimento.

Códigos JEL: G14; G40; G41

Palavras-chave: Ancoragem; Pontos de referência; 52 Week High/52 Week Low; Informação privada; Sub-reação; Grandes variações de preço

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1. Introduction

The Efficient Market Hypothesis (EMH) states that stock prices reflect all available information and, therefore, investors cannot earn systematic abnormal returns by trying to predict the stock's future returns. Since the EMH was presented, many studies provided some evidence that this claim is not entirely true, by demonstrating that some stocks reported some elements of predictability (Jegadeesh & Titman, 1993, 2001; Rouwenhorst, 1998).

Several researchers started to study the short-term reaction of stock returns, including to large price changes. The general conclusion is that there is evidence of stock return predictability after the occurrence of both positive and negative large price changes, thus contradicting the EMH (Amini *et al.*, 2010; Lobe & Rieks, 2011; Savor, 2012). However, it is not possible to draw any kind of inferences about either the direction of the returns or their magnitude, and it is also proposed more than one possible explanation for the predictability of stock returns after a price shock. The most common explanations are related to market microstructure, with the bid-ask bounce (Campbell *et al.*, 1997) and non-synchronous trading (Lo & MacKinlay, 1990); to changing risk explanations, with the Uncertain Information Hypothesis (Brown *et al.*, 1988) and liquidity issues (Peterson, 1995); and lastly to behavioural explanations, with the Overreaction hypotheses (Larson & Madura, 2003) and the Underreaction hypotheses (Pritamani & Singal, 2001).

Tversky and Kahneman (1974) introduced the theory that, in the absence of information, individuals rely on heuristics when making decisions under uncertainty. In their article, they showed that individuals make estimates by anchoring them into some initial value or reference point and then adjust them from it. Several studies were conducted regarding this heuristic, and it was showed that it can yield strong influence in the process of estimation in individuals, as even a randomly generated number would serve as a reference point, and it would lead the individual's estimation to be biased towards the reference point. One very important characteristic of this heuristic is that it appears to influence very different types of individuals, ranging from the ones with more cognitive capabilities to the ones with less, and also ranging from trivia questions to house appraisals (Northcraft & Neale, 1987).

In this dissertation, I investigate how stock prices react to a large price change, by investigating if investors immediately adjust their estimates of the stock value to the new intrinsic value or if they anchor their estimates to a reference point which will make the adjustment gradual, leading to investor underreaction. At this point, more important than knowing how prices behave after a price shock, is to know the determinants that make prices react in such a way. The proposed reference points to be analysed are the 52 Week High/52 Week Low price and Investor private information.

The 52 Week High/52 Week Low price is an already know anchor from other studies regarding stock return predictability, for example, PEAD and momentum investing (George *et al.*, 2015; George & Hwang, 2004). This reference point could have great importance since it is a type of information that can be easily accessed by every intervenient in the financial markets, including the less-informed investors, more susceptible to behavioural bias. Regarding Investor private information, Daniel *et al.* (1998) showed that overconfidence and biased self-attribution can lead individuals to overreact to signals that confirm their private information but to underreact if the signal contradicts their private information. Again, this reference point was already the subject of some study, more commonly related to M&A deals, but it was also applied to large price changes (Larson & Madura, 2003).

To explore the effects of the reference points, I will use the German stock market. The reason for choosing this market lies in the fact that after the effects of the 52 Week High/52 Week Low and Investor private information reference points have been investigated in the US stock market, there is a gap in the European literature that needs to be closed. So, I decided to choose the stock market of the largest economy in the European Union, which is the sixth-largest market in the world (with 2.6% of total equity market value) and second-largest in the EU, after the French stock market.

To the best of my knowledge, this is the first study to determine the effect of the 52 Week High/52 Week Low and Investor private information reference points on the observable post-event returns after the occurrence of a large price change in the German stock market. The main contribution of this dissertation is the fulfilling of the existing gap in the literature regarding the predictability of returns after a price shock in the German market, by helping to better understand the influence of reference points exert on the investors/returns, and, also, to compare the influence of these effects on the German stock market to the ones achieved US stock market, increasing, therefore, the knowledge of the predictability of returns in the German market and helping investors making better investment strategies.

To test my hypothesis, I follow a similar methodology to the one presented by Brady and Premti (2019), when they conducted a study to determine the effects of the above-presented reference points on the post-shock returns in the US stock market. After identifying all the stocks from the German stock market that experienced a return greater than 10%, in absolute value, in a single trading day over the 1995-2019 period, the total sample consists of 13 137 large price changes, 5 716 regarding price decreases and 7 421 regarding price increases.

The results achieved suggest that during the period of analysis, on average, both positive and negative large price changes are characterized by investor overreaction on the event day, leading to price reversals in the following days. Additionally, I found evidence that investors rely on available reference points when making their price estimations after a large price change. In particular, I found evidence that investors anchor their price estimations to the 52 Week High/52 Week Low in the event of a large negative/positive price change, leading to investor underreaction on the event day. Due to this underreaction, in the following days to the large price change, the stock price continues to drift towards its new perceived intrinsic value. Hence, stocks that are closer to the 52 Week High price are more likely to exhibit lower (negative) returns in the following days after the large negative price change, while stocks that are closer to the 52 Week Low tend to exhibit higher (positive) returns after a large positive price change. Moreover, I found evidence in support of investors anchoring their price estimations to their private information, when the private information is contradicted by the large negative price change. However, regarding large positive price changes, no conclusion was achieved in respect of the anchoring effects of private information. These results are consistent with the ones achieved in the US stock market, revealing the same underreaction features, although the effects of the proposed anchors in the returns appear to be bigger in the German stock market. The results also suggest that during the 2000-2001 years the anchoring effects of the 52 Week Low and Investor private information appear to be stronger when compared to the whole period in analysis. As for the 52 Week High reference point, the results suggest the existence of overreaction in large price decreases.

The remainder of this dissertation is structured as follows. Chapter 2 presents a literature review concerning the main articles about the observable post-event returns after a large price change, as well as a critical literature review of the anchoring heuristic. Chapter 3 introduces the suggested hypotheses regarding the effects of the reference points in the post-event returns. Chapter 4 and Chapter 5 presents the data and methodology applied, respectively. The results achieved are presented in Chapter 6. Lastly, Chapter 7 presents the main conclusions achieved during the dissertation.

2. Literature Review

Eugene Fama first introduced the term "market efficiency" in 1965 and used it to argue that in an efficient market *"on average, competition will cause the full effects of new information on intrinsic values to be reflected instantaneously in actual prices"* (Fama, 1965, p. 57).

Since then, many authors have investigated, and continue to investigate, the short-term reaction of stock market securities, including to large price movements. This effort has been motivated by the fact that these authors have frequently found strong elements of predictability among security return after the release of new information, findings that seem hard to reconcile with the Efficient Markets paradigm proposed by Fama, with some authors arguing that it is due to rational explanations and others appointing to behavioural biases related explanations (less rational).

In this chapter, a literature review will be presented. First, I will focus my attention on the existing literature regarding the observed returns after a large price change, seeking to gather the main conclusions that may be found. Later, I will introduce the main literature evolving the anchoring heuristic, exposing the different types of anchoring we may find and their consequences, and show how it can influence an individual's judgement.

2.1. Return predictability after a large price change

It has been known that price changes are fat-tailed, *i.e.*, there is a higher probability of extreme events than what is considered by the normal distribution (it is actually closer to a T-Student distribution). And this is very important for financial risk since it means that large price changes are more common than one might expect (Lux, 1996). The main reasons why large price changes may occur is due to the release of information, both public and private that will alter the intrinsic value of a stock (Fama, 1965); due to investor sentiment, that could change the price without any fundamental reason but due to "animal spirits" or mass psychology (Shiller, 2003); or, lastly, due to liquidity, as variations in the market capability to absorb new orders, *i.e.*, small liquidity, could lead to extreme price fluctuations (Farmer *et al.*, 2004; Weber & Rosenow, 2006). In a more recent article, Yildiz and Karan (2019) point to new possible causes of large price changes. They concluded that the presence of the momentum effect has a positive effect on the likelihood of large price changes and, also, concluded that through the less volatile and bullish market conditions, the market can provide important signals one day before the large price change that warns investors to rebalance their portfolios.

So, what is the definition of a large price change? As may be expected, there is no exact definition since different authors have determined large price changes in many ways. One commonly used measure is if a security has experienced a return greater than a certain trigger value, in absolute terms, in a single trading day, usually 10% (Brady & Premti, 2019; Larson & Madura, 2003), but other (smaller) trigger values have been also used, for example, 2.5% (Brown *et al.*, 1988). Nevertheless, other types of triggers also appear in the literature, with some articles trying an approach by looking at returns of all sizes from randomly selected stocks (Amini *et al.*, 2010), or even looking for returns that exceed some multiple of past standard deviations of returns (Lasfer *et al.*, 2003). Others, also decide to look at some wider periods, not looking for a specific trigger but for the better or worse performers in that specific period that they believed is worth the analysis (Atkins & Dyl, 1990).

Since this topic has been the subject of study of different authors, several explanations have been pointed out to enlighten the observed post-shock returns, with the main explanations being related to the influence of market microstructure, the response to the investors to the changing risk, and behavioural biases that may affect the individuals. In the remainder of this sub-chapter, I will explore and present the main conclusions achieved by the authors for each explanation. Additionally, I will present some articles that show the main conclusions achieved by other authors that studied the predictability of post-shock returns in other types of financial assets, such as indices, Exchange Trading Funds (ETF), and American Depository Receipts (ADR).

2.1.1. Market microstructure explanations

Market microstructure is the least common explanation found when looking at the observed returns after a large price change, but it is still a valid one. When we look at the microstructure explanations, two effects have been stressed out more commonly: the bid-ask bounce and the non-synchronous trading effect.

According to Campbell *et al.* (1997), the bid-ask bounce effect arises since the reported price for a security is at the ask price if the last trade was buyer initiated, but at a sell price, if the last trade was seller initiated. This bid-ask bounce can induce a spurious negative serial correlation in security returns since the reported prices would "bounce" between the bid and ask prices. The bid-ask bounce is also considered to be the primary driver of observed reversals in stock prices after large price changes (Cox & Peterson, 1994; Park, 1995), and its effect is lower for stocks with small bid-ask spread, thus, it has a higher influence in smaller stocks, since large stocks are known to have a lower bid-ask spread (Stoll, 2000).

The non-synchronous trading effects occur due to the non-trading of stock towards the end of the trading day. This suggests that stock prices recorded at the end of a trading day may reflect transactions that occurred at different points in time for different stocks, and it is pointed as the cause for spurious negative autocorrelation in stock returns (Lo & MacKinlay, 1990).

When we examine the empirical research involving microstructure explanations, we find mixed results. While exploring the US market, using a 10% daily price change as the trigger, Cox and Peterson (1994), Park (1995) and Liang and Mullineaux (1994) found evidence that supports that the bid-ask bounce offers at least a partial explanation for the returns observed post-shock. However, Bharati *et al.* (2009), when exploring the same market and using the same trigger, exclude market microstructure as an explanation, point out instead to an overreaction by investors to positive events, in both short and long term.

Additionally, while analysing the three stocks that exhibit the largest percentage gain and loss in value from 300 randomly selected trading days, Atkins and Dyl (1990) also concluded that price reversals were not a consequence of the bid-ask bounce, whereas Zawadowski *et al.* (2006), when exploring intraday minute-to-minute large price changes, also excluded the bid-ask bounce as an explanation, stating that the price reaction was due to the compensation for liquidity in the financial markets. Furthermore, Michayluk and Neuhauser (2006) using a data set of the aftermath of the October 27, 1997 shock, the "Asian contagion", concluded that the returns were a result of overreaction from the investors and not due to bid-ask bounce.

Lastly, when analysing non-US stocks, Nguyen *et al.* (2007), while covering the Australian, Japanese, and Vietnamese markets, excluded the market microstructure explanation, since they found very common results for these different markets. Instead, the authors found consistent evidence across markets that are supportive of short-term price reversals and the overreaction hypothesis. Additionally, Hamelink (2003), when looking at the French stock market, concluded that after taking into account the bid-ask spread there was the possibility to make profits. However, the overall conclusion achieved was that the profits were too small to reject the EMH. Lastly, Lobe and Rieks (2011), for the Frankfurt stock exchange, concluded that the observed post-shock returns were due to investor overreaction and not due to the existence of bid-ask spreads, or even to lack of liquidity.

2.1.2. Risk related explanations

Another explanation for the returns observed after a large price change is related to risk, one of the most important concepts in finance. It is expected that the returns of an investment should reflect the risk involved. A large negative price change, for example, can be considered as a situation of increased risk, since large price changes translate to increased standard deviations, and as such, increased risk.

One hypothesis that may help better understand how risk may impact the post-shocks returns is the Uncertain Information Hypothesis (UIH), developed by Brown *et al.* (1988). It suggests that the systematic risk of stocks increases temporarily after large price changes, causing rational (and risk-averse) investors to demand a higher return for the increased risk, a concept also supported by Park (1995). The UIH, therefore, predicts high returns after both large positive and negative price changes. The concept is the following, for the arrival of favourable information, it is expected to observe an immediate price increase, which is initially diminished by an increase in risk premium. As uncertainty settles, the risk premium declines, and the price continues to increase even further. In case of a negative event, both the unfavourable information and the increased risk leads to a decrease in the asset price. Later, as uncertainty about the future starts to decline, and so the risk premium, making the price recover to some extent. So, in the case of a large price increase, the UIH predicts an underreaction from the investors, and in the case of a negative large price change, it predicts an overreaction from the investors, leading therefore to a price reversal.

An alternative explanation related to risk explanations is correlated to liquidity issues. Pástor and Stambaugh (2003) state that liquidity can be viewed as a particular type of risk that can be priced in the market and those assets with higher liquidity risk offer higher expected returns. Following this reasoning, it is expected that the presence of excessive price declines will result in price reversals and that this may be viewed as a proper reward for providing liquidity to the market.

When analysing firms from the Fortune 500, Bremer and Sweeney (1991) found support evidence for the UIH, after looking for patterns after large drops, something that is consistent with what Liang and Mullineaux (1994) also concluded, after analysing stocks from the NYSE and AMEX that experienced negative price shocks, with both studies employing the more common trigger of daily price change of 10%.

After presenting their theory in 1988, Brown *et al.* (1993) intended to extend their initial results by exploring the role of changing volatility on the *ex-ante* returns of stocks following a large price change. Their results were still consistent with the UIH. However, the definition of large price movements in Brown *et al.* (1988, 1993) was much smaller than the minimum of 10% usually used, meaning that these type of events would happen more frequently, and as a result, it may not be as comparable to the other results as we expected (Corrado & Jordan, 1997). In order to overcome this obstacle, Corrado and Jordan (1997) reconstructed Brown *et al.* (1988, 1993) studies since they stated that Brown *et al.* (1988, 1993) results were obtained from a potentially miss-specified sampling procedure. By using a modified sampling procedure, Corrado and Jordan (1997) showed that following significant security-specific price shocks, price reversals were typical, finding, therefore, evidence contradicting the UIH.

When we look to the empirical evidence involving the liquidity issues, Peterson (1995), and more recently Choi and Jayaraman (2009), compare the behaviour of stocks with options versus stocks without options. They find that the bid-ask bounce is not responsible for the abnormal returns and that options markets are more liquid and attract more informed investors. In both studies, reversals only happen in stocks without options. Additionally, Mazouz *et al.* (2012), when looking at the FTSE, found that the returns were due to price continuation driven by stock with higher liquidity risk.

2.1.3. Behavioural explanations

Lastly, we have the behaviour explanations, with two contrasting hypotheses being proposed, the Overreaction hypothesis and the Underreaction hypothesis. According to the Overreaction hypothesis, price reversals in stock returns occurs due to an overreaction by the investors to the disclosure of unexpected information (Park, 1995). One possible reason for investors to overreact may be due to the overweight of current information and to underweight past information (De Bondt & Thaler, 1985, 1987), an explanation that derived from Tversky and Kahneman (1974) representativeness heuristic.

As for the Underreaction hypothesis, one of the main reasons for the underreaction may be the slow incorporation of news into prices, leading prices to move in the same of the initial shock (Benou, 2003; Hong & Stein, 1999). Jegadeesh and Titman (1993) showed the momentum effect on stocks, and claimed that it happened due to an underreaction to new information due to the conservatism heuristic, as proposed by Edwards (1968), investors would slowly adapt to the arrival of recent information, gradually incorporating them into their estimations of prices.

Several empirical studies have concluded that behavioural factors provide the best explanations for the observed post-shock returns. While applying a 10% change trigger for the US market, Larson and Madura (2003) find evidence of overreaction, but only if the event is due to unexpected information (unexpected public news announcement), Sturm (2003) found evidence in support of overreaction for large price decreases, but the reaction could be different after controlling for pre-shock returns and firm characteristic, while both studies of Bremer *et al.* (1997) and Claes *et al.* (2010), when looking to Japanese and Dutch stocks respectively, only find strong evidence of overreaction after large price drops. The same conclusion is achieved by Diacogiannis *et al.* (2005) after using an 8% trigger for the Greek stock market, instead.

Even by using other definitions of a large change in prices, overreaction is the most common conclusion achieved, frequently associated/identified by price reversals, for example, Michayluk and Neuhauser (2006), Howe (1986), Otchere and Chan (2003), among others. However, evidence of underreaction was also found. Pritamani and Singal (2001) looked at all the common stocks listed in the AMEX and NYSE, and by applying a daily return larger than three times standard deviations from the mean over the previous 250 trading days trigger, found the existence underreaction conditional to the release of news announcements, *i.e.*, negative returns after a price drop and positive after a price increase, and overreaction, otherwise. Additionally, Gutierrez and Kelley (2007) concluded that a momentum strategy of buying winners and selling losers exhibits short term overreaction and long term underreaction. Also, Parthasarathy (2019) found evidence of reversals after large price changes, which support overreaction, and that were not consistent with risk explanations.

Lastly, there were some interesting conclusions regarding the effects of information release in the observed post-shock returns. Chan (2003), when exploring a random sample from the CRSP stocks, he finds a distinction between events associated with the release of public information where there is evidence of underreaction from the investors, and events that are related to the release of private signals investors tend to overreact. Later, Savor (2012), also conducting a study on the US market, and using recommendation-issuing analyst reports as a proxy for information release, concluded that the post-shock observed returns are characterized by investor underreaction if the large price change was caused by the release of information and that investors overreacted if the cause of the large price change was not initiated by the release of information. Patel and Michayluk (2016) also studied the effects of information release in the Australian market and concluded that when a large price change was caused either by public information or by private information was permanent and that the cause for overreaction in the post-shock returns could be linked to liquidity trading. These findings are consistent with Fama (1965) Efficient Market Hypothesis, and contradicting the results achieved by Pritamani and Singal (2001), Chan (2003) and Savor (2012).

2.1.4. Return predictability in other assets

As mentioned previously, several authors decided to also study the predictability of returns after a large price change in other types of financial assets. In this part of the literature review, I will present some of the main conclusions regarding these assets.

Regarding the return predictability of indices after a large price change, the returns are often characterized by either overreaction or underreaction of the investors, leading to price reversals or price continuation in the following days to the large price change, respectively. When looking for triggers larger than 5% in absolute value, in the US, UK and Japanese markets, Atasanova and Hudson (2008) report the existence of price reversals and attribute those to investor overreaction. Additionally, Atasanova and Hudson (2008), when looking for triggers smaller than 5% in absolute value, report the existence of price continuation, and attribute those to investor underreaction. In this study, the authors discard both bid-ask bounce and non-synchronous trading as an explanation for the observed returns. Similarly, Lasfer *et al.* (2003) found evidence in support of underreaction, when they observed 39 market indices. Lastly, Yu *et al.* (2010) found evidence in support of the UIH in the S&P500 index between 1994 and 2003. A similar conclusion was achieved previously by Ajayi *et al.* (2006) when they studied the US market.

In more recent years, the return predictability of ETFs after a large price change was also studied. Madura and Richie (2004) found the presence of investor overreaction in US ETFs, between 1998 and 2002. Later, and also for the US market, Lobão and Costa (2019, 2020) found evidence in support of investor overreaction in the large price changes in ETFs that occur after hours, causing price reversal in the subsequent period. Additionally, they showed that the magnitude of the reversal tends to be conditional to the previous extreme return. The study points to uninformed investors as the cause of the reversal, instead of changing risk or market microstructure.

Lastly, Lobão and Jerke (2020) studied the short term predictability of ADR returns and found evidence in support of overreaction, showing also that the price reversal tends to be more pronounced when the shock occurred after hours.

2.2. The Anchoring heuristic

Although some may argue that the concept had already been presented previously by other authors, the anchoring and adjustment heuristic is more commonly linked to an article written by Tversky and Kahneman (1974), in which they stated that due to the anchoring bias, individuals tend to make insufficient adjustments to their estimations since their final judgements are assimilated towards the initial estimation made during their deliberations, *i.e.*, the anchor.

In their article, Tversky and Kahneman (1974) present us with a good example of the anchoring and adjustment heuristic. After rotating a wheel of fortune that would generate a "random" number, it was biased, they asked the participants to provide an estimation of the percentage of African countries in the United Nations. Firstly, they asked if the number was higher or lower than the one given by the wheel of fortune, and then participants were asked to provide what they thought was indeed the correct value. The conclusion achieved was that, depending on the reference point, the estimation of the participants was biased towards the number generated by the wheel of fortune.

Before exploring the different types and examples of anchors found, I would like to do a brief presentation of the processes that contribute to the anchoring effect. First, we have the Anchoring and Adjustment perspective, with the articles of Tversky and Kahneman (1974) and Epley and Gilovich (2001, 2005) being the main references. The main point of this is that the anchoring happens as a result of an effortful adjustment process, which is insufficient based on the initial value and/or the anchoring serves as the reference of people to adjust the boundary to the plausible area if people think that the anchor is too extreme (Furnham & Boo, 2011).

Additionally, we have the Selective Accessibility perspective, with the articles of Chapman and Johnson (1994), Strack and Mussweiler (1997) and Mussweiler and Strack (1999) being the main references, and states that individuals test the hypothesis of the anchor being the correct answer, based on the confirmatory hypothesis and by doing so, individuals look for a similar answer that is similar to the anchor and activate aspects of the target that are consistent with the anchor presented to them (Furnham & Boo, 2011).

Lastly, we have the Attitude Change, where anchors serve as a cue or indirectly influence the information processing, with the articles of Wegener *et al.* (2001) and Wegener *et al.* (2010) being the main references. In this perspective, we may have low elaborative anchors, where people do not think about them, meaning that anchors are sometimes treated as a hint to a more reasonable answer, and we have high elaborative anchoring, where people think about the estimations and it involves activation of anchor consistent information that will bias judgement (Furnham & Boo, 2011).

2.2.1. Types of anchors

Over the years, the topic of anchoring has been increasingly explored. Right now, we can identify several varieties of anchors that may influence individuals' decisions. The first one is the self-generated or externally provided anchor. The idea was introduced by Epley and Gilovich (2001, 2005), and they showed that individuals adjust their estimations slightly from values that they know are closer to the correct answer, even if they know that these self-generated anchors are wrong from the start. They also showed that when in a presence of an externally provided anchor, this type of anchor may have more weight and validity, leading individuals to presume that it may be the correct answer. This acts following the confirmatory search and selective accessibility mechanisms of the confirmatory hypothesis testing model, providing, also, an explanation for the findings that the adjustment mechanism accounts for the anchoring effect when the anchor is self-generated but an externally provided anchor is the factor responsible for the activation of the confirmatory hypothesis testing mechanism (Furnham & Boo, 2011).

In a study about factual knowledge, Strack and Mussweiler (1997) showed that the presence of an anchor value that is similar in judgemental dimensions to the estimates produces a significant interaction effect with the anchoring effect. Using the selective accessibility model, Englich *et al.* (2006) were able to demonstrate that the anchoring effect is vulnerable to the relevance of the reference value because when individuals were exposed to high anchor values, they were able to respond much quicker than those who were presented with low anchor values, indicating that anchor-consisting information is activated by relevant anchors.

However, some research demonstrates that anchor values that seem to be uninformative to the estimates can also generate some effect in the individual's judgemental decisions. For example, Tversky and Kahneman (1974) showed that the individuals' anchored their estimations to a random number, with the same conclusion being achieved by Englich *et al.* (2006), where they anchor was based on a random number given by throwing a dice, or with Critcher and Gilovich (2008), who found that the estimate of an athlete performance could be anchored to the number of their jersey. This supports the idea that the assimilation of the anchoring effect is independent of the informational relevance of the anchors, with irrelevant anchors producing similar effects in judgemental decisions in comparison to those of informational relevance (Furnham & Boo, 2011).

Other authors studied implausible or extreme anchors. Strack and Mussweiler (1997) and Wegener *et al.* (2010) claim that implausible or extreme anchors lead to a larger anchoring effect when compared to more plausible anchors. This is related to the mechanism of anchoring and adjustment that states that individuals adjust their estimations according to the initial values presented. This leads to the prediction that increases in anchor extremity should lead to a larger anchoring effect under the condition that the given anchor value is always more extreme than the boundary value for the range of plausible answers (Mussweiler & Strack, 1999; Strack & Mussweiler, 1997). Nevertheless, not all authors agree with these conclusions. Mussweiler and Strack (2001) showed that differences between high and low anchors occurred only with anchor values within the range of plausible answers, but not for the extreme or implausible ones. Additionally, in a study conducted by Wegener *et al.* (2001), the authors found curvilinear effects of extremity for anchoring, which demonstrated that extreme anchors generated smaller anchor effects. These results illustrated that increases in anchor extremity beyond a range of plausible values, do not increase the anchoring effect, with a possible explanation for these contradictory results being the adjustment mechanism, where individuals adjust their estimations until they reach a plausible estimate, independent of the extremity of the anchors since individuals may question the validity of the anchors completely (Wegener *et al.*, 2010; Wegener *et al.*, 2001).

2.2.2. Human factors that may influence the anchor effect

After considering the different types of anchors, authors started to look to potential human factors that may contribute to the susceptibility of the anchor effect. One factor achieved by the researchers is the mood of the individuals, suggesting that the anchor effect is influenced by affective factors since emotions can be used explicitly as information in judgement situations or they can influence decision making by influencing the way people process information (Englich & Soder, 2009). Bodenhausen *et al.* (2000) and Englich and Soder (2009) found that individuals in a sad mood were more susceptible to the anchoring heuristic, in comparison to other participants in a happy or neutral mood. The reasoning is that a thorough process of information should lead to more anchoring because people think more than when they are happy.

Another human factor may be related to the expertise/knowledge of individuals. Once again, Englich and Soder (2009) demonstrated that emotions only affect the magnitude of anchoring with non-expert individuals, with experts being vulnerable to the anchoring effect independent of their mood (emotions). Some authors argue that individuals with higher expertise should have greater knowledge, making them less uncertain when making relevant decisions, and thus, being less influenced by the provided anchors. This idea is supported by Chapman and Johnson (1994), who illustrated that a smaller anchor effect was generated by those with a high certainty about their answer, a conclusion also achieved by Wilson *et al.* (1996). Nevertheless, before these two studies were conducted, Northcraft and Neale (1987) showed that real estate agents, when asked to give estimations about the pricing of a house, were biased towards the anchor values provided. Or the study of Mussweiler *et al.* (2000) showed that car experts, with all information available to evaluate the car, would also make their estimations biased towards the anchor given.

The motivation of the individuals was also explored. Tversky and Kahneman (1974) showed that the anchoring effect is not eliminated by offering payoffs in other to motivate the participants, with the same conclusion being achieved by Wilson *et al.* (1996), where in their study showed that incentives and forewarnings would not eliminate the anchor effect. However, some studies have found the effectiveness of forewarning in diminishing the effects of anchoring when warnings about insufficient adjustment (LeBoeuf & Shafir, 2009), and self-generated anchors are given (Epley & Gilovich, 2005).

Drawing from the theory of cognitive function emphasised by the dual-process model, developed by Stanovich and West (2000) and Kahneman (2003), heuristics, such as anchoring, are characterized as a result of System 1, which is automatic, fast, effortless and often emotionally charged, making it difficult to control or to modify. According to this dual process, anchoring incorporates the descriptions above and the main function of this mechanism serves as universal influence biasing judgements of individuals. However, we are not all equal, and therefore, anchoring does not affect everybody in the same way. This is where System 2 is introduced. This is a slower, serial, and effortful and more likely to be a consciously controlled mechanism. The operations of system 1 can be overridden by system 2, resulting in individual differences in the anchoring effect (Stanovich & West, 2008). However, individuals are subjected to psychological constraints such as the resource-limited nature of the human cognitive system, which leads to computational limitations and further behavioural bias in judgemental decisions.

Finally, we have the cognitive ability or analytic intelligence. It was predicted by Stanovich and West (2008) that there should exist a negative relationship between cognitive ability and biased responding. This prediction is parallel to the findings of Bergman *et al.* (2010), which investigated the relationship between cognitive ability and anchoring effect in economic decisions. As expected, they found that anchoring decreases as the cognitive ability rises. Nevertheless, the anchor values still yield a significant effect in the high cognitive ability group. Oechssler *et al.* (2009) found that the cognitive ability serves as a moderator to biases in decision making but does not play a role in the anchoring effect, it seems that a more reflective decision making does not diminish the effect of anchoring.

In conclusion, the research carried out on the anchoring heuristic appears to be extremely robust, and its influence can be demonstrated in a wide array of decision tasks, with different groups and in different settings, thus making it plausible that the anchoring heuristic can exert its influence even on investors in financial markets during periods of great uncertainty, for example, during a large stock price change. This concludes this chapter of the literature review.

3. Hypotheses development

From the previous chapter, there are some conclusions that we can draw from the several articles presented. The first one is that after the occurrence of a large price change, we may find some predictability of the observed post-event returns, whether in the existence of price reversals or the existence of price drifts, thus contradicting the Efficient Market Hypothesis, suggested by Fama (1965). Several explanations have been provided, such as market microstructure explanations; risk-related explanations; and behavioural explanations.

The second conclusion we can draw is regarding the effect and strength that reference points exert in individuals. As we noticed in the previous chapter, even random generated numbers would yield a strong (and measurable) influence in the process of estimation in individuals. With this being stated, it is feasible to imagine that investors in financial markets can also be affected by the anchoring effects of certain reference points in the market. In traditional finance, investors were treated as rational, and therefore, they are not influenced by possible biases that can undermine their rationality. However, more recently, investors started to being treated as individuals with bounded rationality, susceptible to biases in their judgement. In fact, behavioural explanations are the most common when it comes to the observed returns after large price changes.

In recent times, there has been an increase of literature that seeks to relate the different biases that have been proposed by Psychology over the years with the behaviours that we may observe from investors in the financial markets, some of those behaviours that can lead to the predictability of returns. Tversky and Kahneman (1974)'s Anchoring and Adjustment bias theory suggest that individuals tend to anchor their estimations to salient information when making decisions under uncertainty and that they tend to make insufficient adjustments since they are tied up to the anchor.

The first anchor to take into consideration, in this dissertation, is the 52 Week High/52 Week Low. This is an already known anchor that was employed in different studies. For example, it was applied in George and Hwang (2004), when the authors analysed momentum investing, and concluded that traders appear to use the 52 Week High reference point against which they appear to evaluate the impact of news from it, with investors appearing to be more reluctant to revise their price estimations at price levels closest or farthest from the 52 Week High. Later, George *et al.* (2015) extended their research by examining the Post Earnings Announcement Drift (PEAD), achieving results consistent with the hypothesis that investors anchor their beliefs about securities' values on the 52 Week High price when reacting to extreme earnings surprises. Additionally, the 52 Week High was already been documented as a price barrier that investors would have some difficulty to surpass, leading to underreaction in event of the release of new information (Li & Yu, 2012). Lastly, it is also an already known anchor explored in the M&A deals (see, for example, Baker *et al.* (2012)).

The 52 Week High/52 Week Low could have great importance as a point of reference for the investors since it is a type of information that can be easily accessed by every intervenient in the financial markets. This means that its perverse effects could yield greater effects when compared to other types of information that are only available to a few. The proposal behind this reference point is that if a certain stock is close to its 52 Week High price before a large negative price change, investors will use this reference point as their anchor and adjust their price estimations from it. This suggests that in the days following the large negative price change, we would be able to observe the price slowly adjusting down from the anchor (*i.e.,* in the same direction of the price shock), thus, demonstrating the existence of underreaction from the investors. As time goes by, the stock price will continue to move to the new perceived intrinsic value as investors slowly revise their price estimates. The same reasoning can also be applied to a stock that is close to the 52 Week Low at the time of a large positive price change. If a certain stock is close to its 52 Week Low price the day before the large positive price change, investors will use this reference point as their anchor and adjust their price estimations from it. In the following days, we would see the stock price continue to move up towards the new perceived intrinsic value as investors slowly revise their price estimates. A formalization of these hypotheses presented, for the large negative price change and large positive price change, respectively, are as follows:

$H1_D$: The closer the stock price is to the 52 Week High before a large price negative change, the lower the post-event cumulative abnormal return.

$H1_U$: The closer the stock price is to the 52 Week Low before a large positive price change, the higher the post-event cumulative abnormal return.

The second anchor to consider is Investor private information. According to Daniel *et al.* (1998), overconfident investors overestimate the precision of their private signals and engage in excessive trading when compared if they were rational, thus causing a stock price deviation from their fundamental values and excessive return volatility. Additionally, they also state that investors by overweighting their private signals, trigger stock prices to overreact when the private information is confirmed. It was also stated that the overconfidence bias may have the opposite effect when investor belief is contradicted since overconfident investors are likely to adjust their expectations slowly in the presence of contradictory information to their beliefs, in order to protect their self-esteem, making more evident the existence of post-event drifts (Scott *et al.*, 1999).

So, the proposed hypothesis behind the private information reference point is that since invertors overreact to public information that confirms their private information, it can also be suggested that if a large price change contradicts the prevalent private information, investors would anchor their price estimations to that existent private information, since they overestimate its importance and have a need to protect their self-esteem, and would underreact to the event and be reluctant to contradict their private information. In the following days to the large price change, as the new information persists, it is expected the prices will continue to drift in the same direction of the price shock, as investors continue to revise their price estimations towards the new perceived intrinsic value. To determine the existence of private information, I will adopt a similar approach to Larson and Madura (2003). In their article, the Cumulative Abnormal Returns in the three-day window before a large price change (CAR (-3; -1)) is viewed as a proxy of private information. In this dissertation, I will use a five-day period prior to the event (CAR (-5,-1)). It is expected that in the event of a large negative (positive) price change if a stock had experienced a positive (negative) CAR (-5;-1), investors would anchor their price estimations to that private information, and we would be able to see a price drift in the post-event returns in the same direction as the large price change. The formalization of the hypotheses is as follows:

$H2_D$: A positive CAR (-5, -1) before the one-day large negative price change is associated with lower abnormal returns after the event day.

$H2_U$: A negative CAR (-5, -1) before the one-day large positive price change is associated with higher abnormal returns after the event day.

With these reference points, I intend to expand the European literature, and also to understand how the conclusions obtained in the US market (Brady & Premti, 2019) compare to a substantially smaller market[1], but which has high importance in its European context.

[1] According to Statista (2021), in January 2021 the US stock market represented 55.9% of total world equity market value, while the German stock market represented only 2.6%.

4. Data

To test the hypothesis presented in the previous chapter, it was necessary to obtain security return data from the EIKON/DataStream database, by identifying all the stocks from the German stock market that have experienced a return greater than 10%, in absolute value, in a single trading day between January 1, 1995, and December 31, 2019. Considering this period, we will have a large timeframe of analysis, twenty-five years. Additionally, this data will be free from any COVID-19 possible effects. To compute the stock one-day return, it was used the stock's closing price in each day, including on the day of the event. Furthermore, to reduce the effects of the bid-ask bounce, which could bias the results, other restrictions were imposed on the data. Following Bremer and Sweeney (1991) reasoning, on the event day, the stocks must have a minimum price of 5 EUR, a trading volume on the day of the shock of at least 10 000 shares traded, and in the past year have a price higher than 1 EUR. Lastly, it is necessary that the information for the Control variables, which will be presented in the next chapter, is available, in order to consider a trigger as an event to be analysed.

Considering that both hypotheses to be presented in the following chapter make opposite predictions for one-day large increases and decreases, it is necessary to split the total sample, which includes both positive and negative large price changes, into two subsamples: the Down Sample, which includes all the negative large price changes, and the Up Sample, that includes all the positive large price changes.

Table 1 presents the total number of events for each subsample, as well as the distribution of the events throughout the years that compose each subsample.

As we can see, during the period in analysis, we have a total of 13 137 events, *i.e.*, large price changes, from which 5 716 refer to large negative price changes and 7 421 to large positive price changes.

Additionally, from Table 1, we can observe that the period of 2000 to 2001 is the one with the most events, in either Down and Up Sample, representing 41.86% and 38.27% of the total samples, respectively. A possible explanation for this is that these two years coincide with the end of the Technological Bubble. This type of periods that are usually characterized by higher levels of volatility, with investors sometimes reacting in extreme ways to the release of new information, or even being moved by mass psychology, which leads to a greater occurrence of large price variations.

Furthermore, we can also see the effects of the Subprime Mortgage Crisis in each subsample. that led to an increase in both samples, in the year 2008, although with smaller values, and, therefore, importance when compared to the influence of the Technological Bubble. Such as the Technological Bubble, the Subprime Mortgage Crisis was a period with high volatility and, thus, a lot of uncertainty in the market. This can be observed in one of the control variables that will be used later on, that show us the volatility expected in the following 30 days for the DAX, in which the higher values registered occurred during the 2000, 2001 and 2008 years, with its maximum value being achieved during the year of 2008.

Table 1: Frequency distribution of the events

Year	Num. of down events	Percentage of total	Num. of up events	Percentage of total
1995	5	0.09%	2	0.03%
1996	16	0.28%	6	0.08%
1997	12	0.21%	18	0.24%
1998	7	0.12%	21	0.28%
1999	146	2.55%	378	5.09%
2000	1081	18.91%	1359	18.31%
2001	1312	22.95%	1481	19.96%
2002	510	8.92%	536	7.22%
2003	196	3.43%	446	6.01%
2004	176	3.08%	306	4.12%
2005	143	2.5%	346	4.66%
2006	272	4.76%	379	5.11%
2007	296	5.18%	339	4.57%
2008	516	9.03%	481	6.48%
2009	134	2.34%	242	3.26%
2010	62	1.08%	133	1.79%
2011	172	3.01%	177	2.39%
2012	75	1.31%	123	1.66%
2013	75	1.31%	130	1.75%
2014	86	1.5%	100	1.35%
2015	111	1.94%	93	1.25%
2016	106	1.85%	102	1.37%
2017	91	1.59%	114	1.54%
2018	73	1.28%	63	0.85%
2019	43	0.75%	46	0.62%
Total	**5716**	**100%**	**7421**	**100%**

5. Methodology

To test the two hypotheses presented in chapter 3, I will follow a similar methodology used in the article of Brady and Premti (2019). Following the estimation method of the Ordinary Least Squares, the following regression will be used to test the hypothesis regarding the magnitude of the cumulative abnormal returns (CAR) in the days following the event:

$$\begin{aligned} CAR_{i,t} = \alpha + \beta 1(52\_WK\_HI_{i,t}) + \beta 2(52\_WK\_LO_{i,t}) \\ + \beta 3(CONTRADICITON_{i,t}) + Control\ variables + \varepsilon_{i,t} \end{aligned} \tag{5.1}$$

In this regression, the dependent variable, $CAR_{i,t}$, is the cumulative abnormal return in the days following the large price change. To ensure the robustness of the results achieved, I measure the CAR in the following event windows: (1, 3); (1, 5) and (1, 20), which from now on will be noted as CAR3, CAR5 and CAR20, respectively. To compute the CAR, I employ a conventional event-study methodology. The following one-factor market model, as presented by MacKinlay (1997), is assumed to represent the return generating process:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{5.2}$$

Where $R_{i,t}$ and $R_{m,t}$ are the period *t*, stock *i* and market returns, respectively, regarding the last 250 trading days, before the event. As a proxy for the market return, I used the information regarding the DAX 30. Lastly, the cumulative abnormal returns were computed by applying the following formulas:

$$AR_{i,\tau} = R_{i,\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m,\tau} \tag{5.3}$$

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau} \tag{5.4}$$

Where τ_1 and τ_2 refer to the beginning and the end of the event window, respectively. Additionally, to control for cross-sectional correlation in the residuals, that could lead to biased coefficient estimators, and after applying the Hausman Test, all models were estimated using fixed cross-sectional effects.

Moreover, in order to increase the robustness of the results, I will run a Probit regression, to determine the likelihood of underreaction or overreaction in the days following the event. The regression used is specified as follows:

$$CARPos_{i,t} = \alpha + \beta_1(52\_WK\_HI_{i,t}) + \beta_2(52\_WK\_LO_{i,t}) + \beta_3(CONTRADICTION_{i,t}) + Control\ variables + \varepsilon_{i,t} \quad (5.5)$$

In this regression, the dependent variable used in the OLS regression $CAR_{i,t}$ is replaced by $CARPos_{i,t}$, a dummy variable that assumes the value of 1 if the $CAR_{i,t}$ in the event windows (1, 3), (1, 5) and (1, 20), which from now on will be noted as CARPOS3, CARPOS5 and CARPOS20, is positive and 0 otherwise.

To measure the effect of the 52 Week High reference point on the post-event drift, in both OLS and Probit regressions, I will use the 52_WK_HI variable, which will be measured on the Down Sample. The 52_WK_HI variable is defined as follows:

$$52\_WK\_HI = \frac{Stock's\ price\ on\ the\ day\ before\ the\ large\ price\ change}{Stock's\ 52\ Week\ High\ price} \quad (5.6)$$

As this measure moves closer to 1, it implies that the stock's price has become closer to its 52 Week High on the day previous to the large negative price change. The maximum value it can reach is 1, and it implies that on the previous day to the large negative price change, the stock's price was at its 52 Week High level. As presented previously, if investors anchor their estimations to the 52 Week High before the large negative price change, it is expected that they underreact more to stocks that were trading closer to the 52 Week High. So, as investors slowly revise their price expectations in the following days, the price is expected to move down towards its new perceived intrinsic value. Consequently, it is expected a negative coefficient for the 52_WK_HI variable when applied to the Down Sample.

Additionally, to measure the effect of the 52 Week Low reference point in the post-event drift, in both OLS and Probit regressions, I will use the 52_WK_LO variable, which will be measured on the Up Sample. The 52_WK_LO variable is defined as follows:

$$52\_WK\_LO = \frac{Stock's\ 52\ Week\ Low\ price}{Stock's\ price\ on\ the\ day\ before\ the\ large\ price\ change} \quad (5.7)$$

Just like the 52_WK_HI variable, as this measure moves closer to 1, it implies that the stock's price has become closer to its 52 Week Low on the day previous to the large price change. The maximum value this measure can reach is 1, and it implies that on the previous day to the large price change, the stock's price was at its 52 Week Low level. As predicted previously, if investors anchor their estimations to the 52 Week Low before the large positive price change, it is expected that they will underreact more to stocks that were trading closer to the

52 Week Low. So, as investors slowly revise their estimations in the following days to the event, it is expected that the price continues to move up towards its new perceived intrinsic value. Thus, it is expected a positive coefficient for the 52_WK_LO variable when applied to the Up Sample.

The other main variable is CONTRADICTION. With this variable is intended to capture the private information signals available before the price shock. It consists of a dummy with the value of 1 if the large price change is the opposite to the private signals, and the value of 0 otherwise. Contrary to the two variables present above, CONTRADICTION is measured in both Down Sample and Up Sample. In other words, the CONTRADICTION variable assumes the value of 1 if the CAR(-5, -1) is positive in the Down Sample, or if the CAR(-5, -1) is negative in the Up Sample. As predicted previously, if investors anchor their price estimates to their private information, the overconfidence placed in that information would lead investors to underreact as see their private information is contradicted by the large price change. As investors slowly revise their estimations, the price of the stock continues to move in the same direction of the large price change towards the new perceived intrinsic value. Therefore, it is expected that the CONTRADICTION coefficient assumes a negative value in the Down Sample and assumes a positive value in the Up Sample.

To complement the information provided by the main variables in the regressions, and continuing to follow Brady and Premti (2019) methodology, several Control variables will also be included in the regressions. The list of Control variables, retrieved/computed using information from the EIKON/Datastream database, are as follow:

- RET0: the raw return of the stock on the day of the large price change. Its purpose is to control the impact that the 1-day large price change return may have on the post-event returns.
- LN_MKTVAL: the natural logarithm of the company's market valuation on the day previous to the large price change. It is intended to control the impact of firm size on the post-event returns (see, for example, Fama and French (1993) for the effects of firm size in returns).
- MOMENTUM: the cumulative monthly abnormal returns over the prior six trading months, ending one month before the occurrence of the large price change. It is aimed to control the effect of momentum in stock prices (see, for example, Jegadeesh

and Titman (1993) for the effects of momentum in the returns).

- VDAX: the volatility index of the DAX on the day of the large price change. The VDAX indicates, in percentage points, the volatility to be expected in the next 30 days for the DAX, as anticipated by the derivatives market. It is intended to control the effects of volatility in the post-event returns.

- TOBINQ: the firm's Tobin Q. It controls the effects the firm's investment opportunities have on the stock post-event return. The Tobin Q formula is as follows[2]:

$$Tobin\ Q = \frac{Equity\ market\ value + Liabilities\ market\ value}{Equity\ book\ value + Liabilities\ book\ value} \tag{5.8}$$

- LN_VOL: the natural logarithm of the number of shares traded on the day of the large price change. It intends to control the impact of liquidity on the stock post-event returns. It was shown by Pástor and Stambaugh (2003), stocks that are more sensitive to liquidity experience higher expected returns, even after accounting for exposures to the market return as well as size, value, and momentum factors.

- BETA: the firm's beta as estimated by the one-factor market model. It controls the effect of market risk in the firm post-event returns.

- JANUARY: a dummy that assumes the values of 1 if any of the post drift days happened in January, and 0 otherwise. It is intended to control for the January effect, which states that the returns on common stocks in January are much higher than in other months. To apply this variable to each timeframe, JANUARY was divided into three, being designated JANUARY (1, 3), JANUARY (1, 5) and JANUARY (1, 20).

- MONDAY: a dummy that assumes the value of 1 if any of the days in the post-event drift happened on a Monday, and 0 otherwise. It controls for the Monday effect that refers to the tendency of stocks to exhibit relatively large returns on Fridays compared to Mondays. It is only used in the CAR3 dependent analysis since in CAR5 and CAR20 there is always a presence of a Monday in the post-event returns.

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[2] The formula for Liabilities equity value and Liabilities market value is the same, in the EIKON/Datastream database.

6. Results

In this chapter, the results achieved during my research will be presented. I will start by presenting the results regarding the Down Sample followed by the results for the Up Sample. In addition to the results achieved for the entire period of analysis, I will also present the results concerning a smaller period, between January 1, 1995, and December 31, 2012, the same period as Brady and Premti (2019), in order to have a better comparison with the results achieved in the US stock market.

6.1. Down Sample

Table 2 presents the summary statistics of the variables that were used in the regressions applied to the Down Sample.

Table 2: Summary of statistics of the Down Sample

	Observations	Mean	Std. Dev.	Minimum	Maximum
Dependent variables:					
CAR3	5716	0.008788	0.124198	-0.812472	1.100783
CAR5	5716	0.009015	0.147755	-0.932564	1.251173
CAR20	5716	0.002564	0.241093	-0.972663	1.447144
CARPOS3	5716	0.555458	0.496958	0.000000	1.000000
CARPOS5	5716	0.545836	0.497938	0.000000	1.000000
CARPOS20	5716	0.513821	0.499853	0.000000	1.000000
Independent variables:					
52_WK_HI	5716	0.489137	0.290499	0.007249	1.000000
52_WK_LO	5716	0.653202	0.224973	0.010000	0.904801
CONTRADICTION	5716	0.434045	0.495674	0.000000	1.000000
RET0	5716	-0.150513	0.070195	-0.978379	-0.100012
LN_MKTVAL	5716	18.79887	2.022390	11.77529	26.37485
MOMENTUM	5716	-0.037568	0.111721	-0.648555	0.462663
VDAX	5716	28.60387	12.17680	11.26000	83.23000
TOBINQ	5716	2.501477	7.895592	0.016918	234.0346
LN_VOL	5716	10.66220	1.139397	9.210340	19.53126
BETA	5716	0.963526	0.600361	-0.796673	3.172069
MONDAY	5716	0.573478	0.494615	0.000000	1.000000
JANUARY (1-3)	5716	0.075052	0.263499	0.000000	1.000000
JANUARY (1-5)	5716	0.076102	0.265185	0.000000	1.000000
JANUARY (1-20)	5716	0.142407	0.349498	0.000000	1.000000

Note: CAR3, CAR5 and CAR20 are, respectively, the cumulative abnormal return in the 3, 5 and 20 days following the event. CARPOS3, CARPOS5 and CARPOS20 are dummy variables that take the value of 1 if the CAR in the 3, 5 and 20 days following the event is positive, and 0 otherwise. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. Lastly, JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

Considering the information displayed above, we can realize that the post-event cumulative abnormal return is, on average, positive in the three timeframes in analysis, varying from 0.26%, in the CAR20 measure, to 0.90%, in the CAR5. Additionally, if we consider the mean values of the dummy variables, the CARPOS#, that indicate us if the post-event drift was positive (assuming, in that case, the value of 1) or negative (where it assumes the value of 0), it ranges from 0.5138 to 0.5554, indicating that the majority of the post-event drifts after a large negative price change is positive, although by only a slight margin (between 51.38% and 55.54%). These results, together, suggest that, on average, after experiencing a one-day large negative price change, investors, in the German stock market, between January 1, 1995, and December 31, 2019, overreacted to the large price change on the day of the event, with the stocks experiencing a price drop greater than what it was expected, and that after that initial overreaction there was a correction in the following days, as the stock price moves towards its perceived intrinsic value.

One other very important variable to consider in the Down Sample is the 52_WK_HI, which represents the proximity of the stock to its 52 Week High on the day previous to the large price change. With a mean value of 0.4891, this result suggests that, on the day of the large negative price change, the stocks that experienced the price shock were trading, on average, at 49% of their 52 Week High.

Additionally, another variable to consider is CONTRADICTION, with an average value of 0.4340. This result indicates that, on average, 43% of the cases of a large price drop experienced in a single trading day, that large negative price change was preceded by a positive cumulative abnormal return in the previous five days to the event. Thus, by our proxy, in 43% of the cases, investors have seen their private information contradicted.

Lastly, we can draw some conclusions from the remaining Control variables. The RET0 variable has a mean value of -0.1505, suggesting that the average price shock during the period in analysis was -15% on the event day. Additionally, on average, we may conclude that the Down Sample stocks experienced a -3.76% cumulative monthly abnormal return in the past 6 months before the event. Furthermore, from Table 2, we may also conclude that around 57% of the CAR3 included one Monday trading day, and 7.5% to 14.2% of the cumulative abnormal returns experienced after the price shock included at least one day that was part of January.

6.1.1. Down Sample OLS regression results

Table 3 presents the results regarding regression (5.1), applied to the Down Sample, using the Ordinary Least Squares method. MODEL 1 to MODEL 3 represent the results obtained by applying regression (5.1) to the period from 1995 to 2019. MODEL 4 to MODEL 6 represent the results to a more restricted period, from 1995 to 2012.

Table 3: Down Sample OLS regression results

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CAR3	CAR5	CAR20	CAR3	CAR5	CAR20
Constant	**0.285416*** **	**0.378198*** **	**0.953746*** **	**0.347713*** **	**0.440647*** **	**1.154144*** **
	(5.231014)	(5.841274)	(9.422000)	(5.807060)	(6.209637)	(10.33585)
52_WK_HI	**-0.016416**	**-0.024294***	**-0.079103*** **	**-0.017015**	**-0.025312***	**-0.080587*** **
	(-1.449342)	(-1.808022)	(-3.758929)	(-1.395958)	(-1.752746)	(-3.540514)
52_WK_LO	**-0.028767** **	**-0.028089** **	**0.061814*** **	**-0.033122*** **	**-0.033544** **	**0.033173**
	(-2.562974)	(-2.109870)	(2.971700)	(-2.729944)	(-2.333701)	(1.467091)
CONTRADICTION	**-0.020863*** **	**-0.031340*** **	**-0.029388*** **	**-0.022727*** **	**-0.034419*** **	**-0.034655*** **
	(-5.567619)	(-7.054249)	(-4.233888)	(-5.711377)	(-7.304264)	(-4.676436)
RET0	**0.035553**	**0.007825**	**-0.081623**	**0.039787**	**-0.000907**	**-0.061086**
	(1.301478)	(0.241413)	(-1.611604)	(1.296234)	(-0.024956)	(-1.068171)
LN_MKTVAL	**-0.011431*** **	**-0.015883*** **	**-0.050159*** **	**-0.013565*** **	**-0.018741*** **	**-0.059867*** **
	(-4.636186)	(-5.428034)	(-10.97012)	(-5.062795)	(-5.901619)	(-11.98616)
MOMENTUM	**0.029136**	**0.038862**	**-0.057251**	**0.035259***	**0.052070** **	**-0.064389**
	(1.454100)	(1.633822)	(-1.540864)	(1.672178)	(2.083247)	(-1.637277)
VDAX	**0.000222**	**0.000399***	**0.000717** **	**9.92E-05**	**0.000197**	**0.000669***
	(1.241220)	(1.877170)	(2.150908)	(0.509144)	(0.853328)	(1.838070)
TOBINQ	**0.000168**	**0.000427**	**0.001564*** **	**0.000352**	**0.000605**	**0.001600** **
	(0.562225)	(1.206305)	(2.831241)	(1.055601)	(1.530718)	(2.573360)
LN_VOL	**-0.003024**	**-0.004787***	**-0.007265***	**-0.004478***	**-0.004992***	**-0.007734**
	(-1.293781)	(-1.726315)	(-1.675596)	(-1.771549)	(-1.667231)	(-1.641247)
BETA	**0.007862**	**0.012561** **	**0.033020*** **	**0.010595***	**0.016190** **	**0.040266*** **
	(1.520676)	(2.047073)	(3.442083)	(1.910513)	(2.463117)	(3.892736)
JANUARY	**0.018275*** **	**0.030658*** **	**0.067523*** **	**0.020236*** **	**0.033163*** **	**0.077016*** **
	(2.657690)	(3.781070)	(6.978846)	(2.747355)	(3.821750)	(7.429027)
MONDAY	**-0.005061**			**-0.006945***		
	(-1.423167)			(-1.842487)		
R^2	**0.120055**	**0.124030**	**0.196712**	**0.124330**	**0.128113**	**0.207335**
N	**5716**	**5716**	**5716**	**5131**	**5131**	**5131**

Note: In all models, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event, measured by CAR#. ***, **, and * represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

Starting from the results of the first three models, we may observe that the R^2 ranges from 0.1201 to 0.1967. Since we are analysing the results regarding the Down Sample, the main variables of analysis in these models are the 52_WK_HI and the CONTRADICTION.

The coefficient for the 52_WK_HI variable is negative in all three models. However, it is only statistically significant at the level of 1% in MODEL 3. As for MODEL 1, it is not significant and MODEL 2 is only statistically significant at a level of 10%. These negative coefficients support **H1$_D$** and imply that the closer the stock price before the large price change, in this case negative, is to the 52 Week High, the lower will be the post-event cumulative abnormal return. In this particular case, and taking MODEL 3 as an example, we may conclude that, on average, if a stock is at its 52 Week High the day before it has experienced the large price change, its cumulative abnormal return, in the following twenty days post-event, would have been 7.9 percentage points smaller when compared with a stock with the same characteristics but that it is as far off from its 52 Week High. Similar conclusions could be reached for the other two models.

The other main variable for analysis is CONTRADICTION. In this case, the variable assumes a negative coefficient in all three models, and it is statistically significant at the level of 1% in all three. These results imply that if before the one-day large price negative price change the stock has experienced a positive cumulative abnormal return in the previous five days to the event (the proxy used as private information), the CAR in the following twenty days after the event would have been lower by 2.9 percentage points (conclusion achieved for MODEL 3, but with similar reading for the remaining models) when compared to another stock with similar characteristics except the fact that in the previous five days to the event, its CAR was already negative. These results support **H2$_D$** and indicate that if an investor on the event day sees its private information being contradicted, the investor would underreact in the period after the event, creating, therefore, a post-event drift as these investors revise their expectations on the intrinsic value of the stock and the price of the stock is adjusted towards it.

Additionally, we have several control variables that revealed to be statistically significant at a level of at least 10%, and that yield some influence in the observed post-event returns. The first one worth to be highlighted is the 52_WK_LO, which revealed some contradicting signals when applied to different models. This variable has presented a negative coefficient in MODEL 1 and MODEL 2, being statistically significant at a level of 5%, while if we consider the MODEL 3 coefficient, we obtain a positive coefficient, with a significance level of 1%. This indicates that, if a stock is at its 52 Week Low price the day before the large negative price change, there is the existence of some underreaction from the investors if we look at the first five days (CAR3 and CAR5), but the existence of overreaction if we consider, the longer, twenty-day period following the event. Another variable to take into consideration is the LN_MKTVAL, with a negative coefficient, and statistical significance at the 1% level in all three models. This suggests that, all things equal, the bigger the firm's value the lower the post-event CAR will be, indicating a higher level of underreaction as the firm's value increases. Also, the TOBINQ variable has a positive coefficient, but it is only statistically significant at the 1% level in MODEL 3. This may indicate that the bigger the firm investment opportunities, the greater is the price drift observed after the event. Lastly, we may consider the January variable, with a positive coefficient and statistically significant at 1% in all three models. This also indicates that if the post-event drift happened in January, at least one day of that drift, the CAR would be larger than it would happen in another month.

In order to have a more direct comparison between the results achieved in the German stock market and the results achieved in the US stock market for the time period between 1995 and 2012, the results of MODEL 4 to MODEL6 will now be presented[3]. The models' R^2 ranges from 0.1243 to 0.2073.

The 52_WK_HI coefficient is still negative in all three models and presents the same significance levels as in MODEL 1 to MODEL 3. These results continue to corroborate **$H1_D$**. Additionally, if we compare this smaller period with the wider one, we can observe some slightly stronger effects of underreaction. Moreover, these results are similar to the ones achieved in the US stock market. However, in the US stock market, we have stronger results (with higher significance levels) and the effects of underreaction related to the 52 Week High seem to be smaller since in the US we have smaller coefficients than in the German stock market.

As for CONTRADICTION, the coefficients remain negative and statistically significant at 1% in all models and the results follow the same pattern as the US stock market study, and therefore, support **$H2_D$**. Similar to the conclusions achieved regarding the effect of the 52 Week High, CONTRADICTION reveals stronger effects in the German stock market when compared to the US stock market, although in both cases there is strong evidence of

[3] See the Appendix A1 to check the OLS regression results regarding the US stock market.

underreaction when private information is contradicted.

Lastly, for the Control variables, some highlights must be made. The LN_MKTVAL coefficients achieved for the German stock market are negative, while in the US stock market they are positive, being statistically significant to the 1% level in both markets, thus leading to opposite conclusions regarding the effects of the firm size in the post-event returns. Finally, the MOMENTUM variable uncovers a positive coefficient at a significant level of 10% and 5%, in MODEL 4 and MODEL 5, respectively, and a negative coefficient although not significant at the 10% level by the finest margin in MODEL 6. As for the US stock market, the coefficients are negative in all three models, however, they are only significant in the last one. This indicates that, for the US stock market, stocks that experienced a positive cumulative abnormal return in the past six months would perform worst in the future, while in the German stock market, it indicates that these stocks would continue to perform better than the others.

6.1.2. Down Sample Probit regression results

In order to achieve more robust results, Probit regressions were also conducted, *i.e.*, regression (5.5). The results are summarized in Table 4. Unlike the OLS regressions, where we try to capture the direction and the magnitude of the event through coefficients, in the Probit regressions we are just going to focus on the direction of the post-event drift, *i.e.*, its signal. As it was previously stated, now the dependent variable is CARPOS, which assumes the value 1 if the post-event drift was positive, and 0 otherwise.

As for the OLS regression presented previously, the two main variables of analysis are 52_WK_HI and CONTRADICTION. The models' R^2 values range from 0.0108 to 0.0362.

When examining the 52_WK_HI variable, the only significant result is in MODEL 3, with a level of 1%, and with a negative signal. This suggests that the closer the stock that experienced the price shock is to its 52 Week High, the lower probability of having a positive post-event drift., and thus, the higher the probability of underreaction from the investors supporting **$H1_D$**.

As for the CONTRADICTION coefficient, we achieve much clear results in all three models, presenting negative coefficients and significance levels of 1%. In this case, we have results in line with the ones achieved by OLS regressions. These results are consistent with **$H2_D$** and reveal to us that, considering other things equal, a stock that saw its investor's private information being contradicted, would have a higher likelihood of experiencing a negative post-event drift.

Table 4: Down Sample Probit regression results

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CARPOS3	CARPOS5	CARPOS20	CARPOS3	CARPOS5	CARPOS20
Constant	**0.996756*** **	**0.521274** **	**0.055969**	**0.924732*** **	**0.319058**	**0.093097**
	(4.592349)	(2.420854)	(0.258300)	(3.889632)	(1.353766)	(0.392062)
52_WK_HI	**0.120298**	**0.051869**	**-0.263480*** **	**0.146979**	**0.067828**	**-0.228003** **
	(1.371705)	(0.592393)	(-2.982201)	(1.550468)	(0.716852)	(-2.392521)
52_WK_LO	**-0.032837**	**0.167591* **	**0.813854*** **	**0.019314**	**0.244032** **	**0.796129*** **
	(-0.362816)	(1.853994)	(8.858966)	(0.197925)	(2.504077)	(8.056169)
CONTRADICTION	**-0.181633*** **	**-0.203092*** **	**-0.137973*** **	**-0.194610*** **	**-0.215481*** **	**-0.156855*** **
	(-5.166760)	(-5.792201)	(-3.907520)	(-5.234219)	(-5.810764)	(-4.202705)
RET0	**0.916722*** **	**0.378738**	**-0.169503**	**0.977594*** **	**0.479174* **	**0.023705**
	(3.673003)	(1.526004)	(-0.680574)	(3.471593)	(1.708549)	(0.084126)
LN_MKTVAL	**-0.043287*** **	**-0.029715*** **	**-0.025881** **	**-0.036372*** **	**-0.023075** **	**-0.026338** **
	(-4.084200)	(-2.812115)	(-2.424737)	(-3.183390)	(-2.025097)	(-2.289786)
MOMENTUM	**0.323762* **	**0.459049*** **	**0.600293*** **	**0.406268** **	**0.534551*** **	**0.649665*** **
	(1.849565)	(2.616985)	(3.368396)	(2.192535)	(2.880247)	(3.441169)
VDAX	**0.005479*** **	**0.005462*** **	**0.006414*** **	**0.004731*** **	**0.004910*** **	**0.006862*** **
	(3.632598)	(3.621499)	(4.194225)	(2.961386)	(3.071436)	(4.235462)
TOBINQ	**0.005922** **	**0.008056*** **	**0.008850*** **	**0.008019*** **	**0.010717*** **	**0.008391*** **
	(2.339460)	(3.092518)	(3.312659)	(2.705584)	(3.488053)	(2.999546)
LN_VOL	**-0.003752**	**-0.008266**	**-0.016161**	**-0.010488**	**-0.003410**	**-0.019292**
	(-0.235908)	(-0.520395)	(-1.010060)	(-0.608525)	(-0.198050)	(-1.111780)
BETA	**0.047720**	**0.084734** **	**0.049360**	**0.065280* **	**0.085975** **	**0.068022* **
	(1.344039)	(2.385642)	(1.377540)	(1.709178)	(2.252694)	(1.767980)
JANUARY	**0.151151** **	**0.156439** **	**0.276432*** **	**0.160440** **	**0.189576*** **	**0.295479*** **
	(2.346014)	(2.450294)	(5.587671)	(2.325149)	(2.767214)	(5.601045)
MONDAY	**-0.068042** **			**-0.081936** **		
	(-2.007337)			(-2.289662)		
McFadden R^2	**0.010806**	**0.010988**	**0.036207**	**0.011601**	**0.012769**	**0.036829**
N	**5716**	**5716**	**5716**	**5131**	**5131**	**5131**

Note: In all models, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise. ***, **, and * represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

Looking now to the Control variables, the 52_WK_LO presents a positive coefficient in MODEL 2 and MODEL 3, with a significance level of 10% and 1%, respectively. This suggests that the closer the stock price is to the 52 Week Low, the higher the likelihood of a positive post-event drift, indicating some overreaction from the investors. Additionally, the LN_MKTVAL presents negative and significant coefficients, suggesting that the higher the market capitalization of the company, the more likely is that for the post-event drift to be negative in the occurrence of a negative shock, suggesting that investors tend to underreact more as the size of the firm becomes larger. Another important variable is MOMENTUM. It reveals positive coefficients in all three models, but it is only statistically significant at a level of 5% and 1% in MODEL 2 and MODEL 3, respectively. This suggests that stocks that have been performing well in the past, considering other things equal, will continue to have a better performance in the days following the event. Finally, TOBINQ and JANUARY are positive and significant in all three models. This indicates that the higher the firm investment opportunities, the higher is the likelihood of a positive post-event drift, and also if one of the post-event days occurs in January, the higher the likelihood of experience a positive post-event drift.

Now, looking to the smaller 1995 to 2012 period, MODEL 4 to MODEL 6 present an R^2 that ranges from 0.0116 to 0.0368. In the 52_WK_HI variable, we achieve the same conclusions as for the wider period analysed previously, continuing to support **H1$_D$**. These results are comparable to the ones achieved in the US stock market, where all coefficients were negative and significant[4]. So, in the German stock market, we find some evidence of underreaction, although not very strong, whereas in the US stock market we have a pattern consistent with underreaction.

As for the CONTRADICTION variable, it is negative and significant in all 3 models, with a similar conclusion for the US stock market. This suggests that if the price shock contradicts the private information of the investors, the more likely is to have a negative post-event drift, and therefore the existence of underreaction from the investors. As in the wider period, the results continue to sustain **H2$_D$**.

As for the Control variables, the 52_WK_LO we have a positive coefficient and statistically significant in MODEL 2 and MODEL 3. These results are similar to the US stock market. However, they are not as significant. This suggests that the closer a stock is to its 52 Week Low in the day previous to the event, there is more likely to experience a positive price drift, thus suggesting overreaction to the event from the investors. Other variables such as LN_MKTVAL have negative coefficients, suggesting underreaction to the event, an opposite conclusion to the one achieved in the US stock market, where investors seem more likely to overreact to the event as the firm becomes larger. Lastly, MOMENTUM is positive and

[4] See the Appendix A1 to check the Probit regression results regarding the US stock market.

significant, so if a stock behaved well in the past, it is more likely to continue in the future, an opposite conclusion to the one achieved for the US market.

To sum up, there are some conclusions we may highlight regarding the Down Sample. The first one is that, on average, a large negative price change is followed by positive cumulative abnormal returns. This suggests that, on average, investors overreacted to the large price change on the event day, followed by a correction in the following days. The second conclusion involving the reference points presented that could serve as an anchor to investors during a time of great uncertainty. The obtained results suggest that investors anchor their price estimations to the 52 Week High price, supporting **H1$_D$**, with evidence being found in both OLS and Probit regression models. The results also suggest that investors anchor their price estimations to their private information when they see it being contradicted by the large price change, thus supporting **H2$_D$**. Once again, there was found evidence of underreaction in both OLS and Probit regression models. The results are also compatible with the US stock market study, although the anchoring effects appear to be stronger in the German stock market.

6.2. Up Sample

Table 5 shows the summary statistics of the variables that were used in the regressions applied to the Up Sample.

Considering the information displayed beneath, we can observe that the post-event cumulative abnormal return is, on average, negative in the three timeframes in analysis, ranging from -3.26%, in the CAR20 measure to, -1.33% in the CAR3. Additionally, if we consider the mean value of the dummy variables, CARPOS#, we can realize that they range from 0.4046 to 0.4082. This suggests that around 40% of the post-event drifts were positive, or that the majority of post-event drifts were negative. Compiling these results together, suggest that, on average, a large positive price change, in the German stock market between 1995 and 2019, was characterized by investor overreaction on the event day, and that after that initial overreaction there was a correction in the following days, as the stock price moves towards its perceived intrinsic value.

Table 5: Summary of statistics of the Up Sample

	Observations	Mean	Std. Dev.	Minimum	Maximum
Dependent variables:					
CAR3	7421	-0.013345	0.125686	-0.920382	1.175212
CAR5	7421	-0.016120	0.145058	-0.964717	1.175922
CAR20	7421	-0.032643	0.235549	-0.996202	1.368108
CARPOS3	7421	0.406145	0.491145	0.000000	1.000000
CARPOS5	7421	0.404662	0.490860	0.000000	1.000000
CARPOS20	7421	0.408166	0.491527	0.000000	1.000000
Independent variables:					
52_WK_HI	7421	0.482682	0.273629	0.001942	0.904762
52_WK_LO	7421	0.671372	0.245006	0.024390	1.000000
CONTRADICTION	7421	0.454790	0.497985	0.000000	1.000000
RET0	7421	0.162706	0.087510	0.100009	1.466337
LN_MKTVAL	7421	18.27534	1.943711	11.77529	26.13846
MOMENTUM	7421	-0.031227	0.112537	-0.856549	0.462952
VDAX	7421	27.01150	11.25989	11.21000	83.23000
TOBINQ	7421	2.943607	9.852040	0.016918	234.0346
LN_VOL	7421	10.73250	1.104490	9.210340	18.21445
BETA	7421	0.836681	0.592401	-0.989325	3.083609
MONDAY	7421	0.567174	0.495500	0.000000	1.000000
JANUARY (1-3)	7421	0.140412	0.347438	0.000000	1.000000
JANUARY (1-5)	7421	0.142029	0.349104	0.000000	1.000000
JANUARY (1-20)	7421	0.196739	0.397560	0.000000	1.000000

Note: CAR3, CAR5 and CAR20 are, respectively, the cumulative abnormal return in the 3, 5 and 20 days following the event. CARPOS3, CARPOS5 and CARPOS20 are dummy variables that take the value of 1 if the CAR in the 3, 5 and 20 days following the event is positive, and 0 otherwise. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. Lastly, JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

The main variables of interest in the Up Sample are the 52_WK_LO and CONTRADICTION. The 52_WK_LO assumes a mean value of 0.6714. This result suggests that, on average, in the day previous to the large positive price change, the stocks that suffered the price shock were trading 48.9% above their 52 Week Low price.

As for CONTRADICTION, it assumes a mean value of 0.4547. This result suggests that, on average, around 45% of the large positive price changes were preceded by a negative cumulative abnormal return in the previous five days to the event.

Lastly, we can draw some conclusions from the remaining Control variables. The RET0 variable has a mean value of 0.1627, suggesting that the average price shock during the period in analysis was 16% on the event day. Additionally, on average, we may conclude that the Up

Sample stocks experienced a -3.12% cumulative monthly abnormal return in the past six months prior to the event. Furthermore, from Table 5, we may also conclude that around 57% of the CAR3 included one Monday trading day, and 14% to 19% of the cumulative abnormal returns experienced after the price shock included at least one day that was part of January.

6.2.1. Up Sample OLS regression results

Table 6 presents the results regarding regression (5.1) applied to the Up Sample, using the Ordinary Least Squares method. MODEL 1 to MODEL 3 represent the results obtained by applying regression (5.1) to the period from 1995 to 2019. MODEL 4 to MODEL 6 represent the results to a more restricted period, from 1995 to 2012.

Starting from the results of the first three models, we may observe that the R^2 ranges from 0.1302 to 0.2117. Since we are now analysing the results from the Up Sample, the main variables of analysis in these models are the 52_WK_LO and the CONTRADICTION.

The 52_WK_LO variable presents a positive coefficient in all three models, all of them with a statistically level of significance of 1%. These results corroborate $\mathbf{H1_U}$ and suggest that investors underreact more on the event day as the stock price is closer to the 52 Week Low price the day before the event, revisiting their estimations of the stock's intrinsic value and adjust from that point. In this particular case, and taking MODEL 1 as an example, we may conclude that, on average, if a stock is at its 52 Week Low the day before it has experienced the large positive price change, its cumulative abnormal return, in the following three days post-event, would have been 4.62 percentage points larger when compared with a stock with the same characteristics but that it is as far off from its 52 Week Low. Similar conclusions could be reached for the remaining two models.

As for CONTRADICTION, the variable assumes a positive coefficient in MODEL 1 and MODEL 2, and a negative coefficient in MODEL 3. With these results, we may be guided to conclude, if we look to the first two models, that investors underreact if the shock contradicts their private information, if we analyse a smaller timeframe, and to conclude that they overreact if we consider a longer timeframe. However, none of these models is statistically significant even at a level of 10%, so the conclusions we may draw from these results cannot be very strong. So, in this particular case, we cannot conclude anything about $\mathbf{H2_U}$.

Table 6: Up Sample OLS regression results

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CAR3	CAR5	CAR20	CAR3	CAR5	CAR20
Constant	**0.157115*** **	**0.286168*** **	**0.740748*** **	**0.110706** **	**0.241026*** **	**0.742510*** **
	(3.459279)	(5.498455)	(9.144549)	(2.319032)	(4.359066)	(8.583714)
52_WK_HI	**-0.001699**	**-0.005976**	**-0.013769**	**-0.006871**	**-0.010464**	**-0.021086**
	(-0.164687)	(-0.505637)	(-0.748074)	(-0.639061)	(-0.840411)	(-1.082008)
52_WK_LO	**0.046236*** **	**0.061369*** **	**0.195816*** **	**0.049972*** **	**0.061386*** **	**0.189621*** **
	(5.189579)	(6.010354)	(12.31981)	(5.375957)	(5.699560)	(11.25171)
CONTRADICTION	**0.004452**	**0.005343**	**-0.000151**	**0.006409* **	**0.006770* **	**0.002328**
	(1.376588)	(1.442077)	(-0.026344)	(1.930461)	(1.761192)	(0.388266)
RET0	**-0.159873*** **	**-0.213675*** **	**-0.261624*** **	**-0.209160*** **	**-0.238250*** **	**-0.275033*** **
	(-7.950094)	(-9.270619)	(-7.291906)	(-9.392733)	(-9.234206)	(-6.814733)
LN_MKTVAL	**-0.007329*** **	**-0.013709*** **	**-0.043617*** **	**-0.004900** **	**-0.011204*** **	**-0.043518*** **
	(-3.400082)	(-5.552503)	(-11.34070)	(-2.170873)	(-4.286774)	(-10.63501)
MOMENTUM	**-0.018210**	**-0.020307**	**-0.051627* **	**-0.002037**	**-0.018006**	**-0.049886**
	(-1.100133)	(-1.070839)	(-1.747954)	(-0.119061)	(-0.908596)	(-1.607872)
VDAX	**0.000283* **	**0.000272**	**0.000449**	**0.000296* **	**0.000321**	**0.000370**
	(1.709186)	(1.434287)	(1.519093)	(1.732620)	(1.624682)	(1.195937)
TOBINQ	**0.000340* **	**1.38E-06**	**0.000321**	**0.000170**	**-9.54E-05**	**-0.000191**
	(1.688940)	(0.005987)	(0.896450)	(0.727753)	(-0.352031)	(-0.451448)
LN_VOL	**-0.005926*** **	**-0.006575*** **	**-0.008372** **	**-0.004765** **	**-0.005965*** **	**-0.007354** **
	(-3.104550)	(-3.005521)	(-2.458609)	(-2.399242)	(-2.592559)	(-2.043324)
BETA	**0.001429**	**-0.000852**	**0.006722**	**0.000995**	**-0.002616**	**0.004761**
	(0.313114)	(-0.162965)	(0.825028)	(0.207796)	(-0.471769)	(0.548314)
JANUARY	**0.027780*** **	**0.039241*** **	**0.056339*** **	**0.027200*** **	**0.037752*** **	**0.057101*** **
	(6.165861)	(7.654050)	(7.957079)	(5.852809)	(7.066455)	(7.694719)
MONDAY	**0.011515*** **			**0.008494*** **		
	(3.728823)			(2.673917)		
R^2	**0.130186**	**0.141968**	**0.211652**	**0.121416**	**0.133048**	**0.207702**
N	**7421**	**7421**	**7421**	**6773**	**6773**	**6773**

Note: In all models, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event, measured by CAR#. ***, **, and * represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

Other important Control variables were also included in the regression. The 52_WK_HI variable presents a negative coefficient in all three models, leading us to conclude that as stock gets closer to its 52 Week High, the lower the post-event drift, so investors tend to overreact on the event day and break that price barrier. However, once again, the results are not statistically significant at the appropriate levels, so we cannot conclude anything about the effects of the 52 Week High in the post-event returns, regarding the Up Sample. Furthermore, the RET0 variable presents a negative coefficient in all three models, suggesting that the higher the price shock, the lower will be the post-event drift. Additionally, the LN_MKTVAL also has negative and statistically significant coefficients. This suggests that the larger the firm, the smaller the post-event drift. The MOMENTUM variable presents a negative coefficient, suggesting also that stocks that behaved well in the past will have smaller returns in the future. Finally, the JANUARY variable shows that shocks that happen in January earn higher returns after the shock.

In order to have a more direct comparison between the results achieved in the German stock market and the results achieved in the US stock market, for the time period between 1995 and 2012, the results of MODEL 4 to MODEL6 will now be presented. The models' R^2 values range from 0.1214 to 0.2077.

The conclusions are very similar to the ones applied to the whole period of analysis. The 52_WK_LO variable remains positive and statistically significant at the 1% level, suggesting underreaction on the event day from the investors, thus supporting **$H1_U$**. These are also very similar results to the ones achieved in the US stock market study[5], where the presence of underreaction to the closeness of the 52 Week Low was shown. However, just like the 52_WK_HI in the Down Sample, the effects on the post-event drift appear to be much larger in the German stock market.

The Contradiction variable continues to reveal positive coefficients in all three models. However, this time, both MODEL 1 and MODEL 2 are statistically significant at a level of 10% and thus support **$H2_U$**. The results achieved are must weaker than the ones presented for the US stock market (in terms of statistical significance), but with very similar results in terms of the effects of private information contradiction in the post-event returns.

The remaining Control variables, the 52_WK_HI assumes the same negative coefficients in both German and US stock markets, but it has no significance in the German market while presenting some significance in the US market. The RET0 and LN_MKTVAL both present negative coefficients, the same as for the US stock market. However, once again, the effects seem to be much larger in the German market. Lastly, MOMENTUM has a negative coefficient in both markets. However, these results are not statistically significant in the German stock market, while they are in the US stock market.

[5] See the Appendix A2 to check the OLS regression results regarding the US stock market.

6.2.2. Up Sample Probit regression results

In order to achieve more robust results, Probit regressions were also conducted, regression (5.5). The results are summarized in Table 7. Unlike the OLS regressions, where we try to capture the direction and the magnitude of the event through coefficients, in the Probit regressions we are going to only focus on the direction of the post-event drift, *i.e.*, its signal. As it was previously stated, now the dependent variable is CARPOS, which assumes the value 1 if the post-event drift was positive, and 0 otherwise.

Table 7: Up Sample Probit regression results

	MODEL 1	**MODEL 2**	**MODEL 3**	**MODEL 4**	**MODEL 5**	**MODEL 6**
Dependent variable	CARPOS3	CARPOS5	CARPOS20	CARPOS3	CARPOS5	CARPOS20
Constant	**-0.779766*****	**-0.754183*****	**-0.998054*****	**-0.688348*****	**-0.756619*****	**-1.023495*****
	(-3.761070)	(-3.650895)	(-4.802375)	(-3.129199)	(-3.450803)	(-4.636837)
52_WK_HI	**-0.268304*****	**-0.314587*****	**-0.513091*****	**-0.271197*****	**-0.321020*****	**-0.525808*****
	(-3.160325)	(-3.716679)	(-6.014091)	(-3.001662)	(-3.559023)	(-5.779941)
52_WK_LO	**0.219905*****	**0.240162*****	**0.774823*****	**0.252890*****	**0.291209*****	**0.801590*****
	(2.946063)	(3.219514)	(10.16867)	(3.193755)	(3.675012)	(9.904329)
CONTRADICTION	**0.028606**	**-0.000360**	**-0.021972**	**0.040251**	**0.000594**	**-0.019537**
	(0.922775)	(-0.011623)	(-0.704635)	(1.241436)	(0.018294)	(-0.598070)
RET0	**-0.850043*****	**-1.020966*****	**-1.090205*****	**-1.083767*****	**-1.304951*****	**-1.197771*****
	(-4.334517)	(-5.173431)	(-5.584130)	(-4.818586)	(-5.758326)	(-5.399571)
LN_MKTVAL	**0.045243*****	**0.041410*****	**0.014452**	**0.044830*****	**0.041991*****	**0.012407**
	(4.665539)	(4.270664)	(1.478560)	(4.390684)	(4.109065)	(1.203400)
MOMENTUM	**0.428745*****	**0.340680****	**0.493955*****	**0.500727*****	**0.389643****	**0.556969*****
	(2.831143)	(2.255646)	(3.205146)	(3.158602)	(2.463972)	(3.444042)
VDAX	**0.004727*****	**0.005767*****	**0.006505*****	**0.004207*****	**0.005264*****	**0.007005*****
	(3.267026)	(3.995471)	(4.469751)	(2.772562)	(3.478596)	(4.588293)
TOBINQ	**0.000415**	**0.000559**	**0.000923**	**-0.000988**	**-0.000958**	**0.000334**
	(0.260374)	(0.348546)	(0.581455)	(-0.548976)	(-0.518774)	(0.192353)
LN_VOL	**-0.041361*****	**-0.026792***	**0.020532**	**-0.045372*****	**-0.023419**	**0.025422***
	(-2.876917)	(-1.862702)	(1.420776)	(-2.981617)	(-1.538800)	(1.660520)
BETA	**0.071527****	**0.015258**	**-0.028411**	**0.067410***	**0.007076**	**-0.032777**
	(2.147130)	(0.458253)	(-0.846662)	(1.921252)	(0.201688)	(-0.925944)
JANUARY	**0.200915*****	**0.252904*****	**0.231960*****	**0.217414*****	**0.256128*****	**0.233751*****
	(4.680391)	(5.937184)	(6.151064)	(4.815441)	(5.716058)	(5.900005)
MONDAY	**0.101074*****			**0.094135*****		
	(3.355055)			(2.979811)		
McFadden R^2	**0.020682**	**0.020016**	**0.042236**	**0.022073**	**0.021877**	**0.044691**
N	**7421**	**7421**	**7421**	**6773**	**6773**	**6773**

Note: In all models, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise**.** *******, ******, and ***** represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

As for the OLS regression presented previously, the two main variables of analysis are 52_WK_LO and CONTRADICTION. The model's R^2 values range from 0.02002 to 0.04224.

The 52_WK_LO variable presents a positive signal, and it is statistically significant at a 1% level in all three models. These results suggest that the closer a stock is to its 52 Week Low in the day previous to the event, the higher is the likelihood of experiencing a positive CAR in the post-event drift. These results are, therefore, in line with the OLS results and support **H1**$_U$, that state that as the stock's price becomes closer to the 52 Week Low before the large positive price change, investors will become more allured to underreact on the day of the event.

The CONTRADICTION variable has a positive signal in MODEL 1 and a negative signal in MODEL 2 and MODEL 3. As in the OLS regressions, we may be tempted to conclude that there is investor overreaction by the first two models and underreaction considering the third one. However, the results are not statistically significant, so no conclusion can be taken regarding **H2**$_U$.

As for the Control variables, the 52_WK_HI presents negative signals and is statistically significant at 1% in all three models. These results suggest the closer to the 52 Week High before the event, the lower probability of a positive drift. RET0 is consistent with the OLS regression and has a negative signal, thus suggesting lower post-event drift likelihood as the price shock on the event day becomes larger. However, LN_MKTVAL is not consistent with the OLS regression results and indicate that the higher the company market value, the greater the likelihood of a positive post-event drift, *i.e.*, greater likelihood of underreaction. Finally, MOMENTUM has a positive coefficient and is statistically significant at 1% and 5%, in MODEL 1/MODEL 3 and MODEL 2, respectively. This suggests that stocks that behaved well in the past have a higher likelihood of continuing to behave well in the future.

Now looking to the more restricted 1995 to 2012 period, MODEL 4 to MODEL 6 present an R^2 that ranges from 0.0219 to 0.0447. The 52_WK_LO variable reveals the same conclusions as in the wider period, with positive and statistically significant coefficients in all three models, supporting **H1**$_U$. These results are similar to the ones reached in the US stock market both in signal and statistical significance[6].

[6] See the Appendix A2 to check the Probit regression results regarding the US stock market.

The CONTRADICTION variable presents a positive coefficient in MODEL 4 and MODEL 5, but a negative coefficient in MODEL 6. Just like in the wide period these results are not significant, so no conclusion regarding **H2**$_U$, and are very different from the ones achieved in the US stock market, where the study revealed a higher probability of positive post-event drift, *i.e.*, underreaction, if the investor private information was contradicted by the large positive price change.

Regarding the remaining Control variables, we can observe a negative and statistically significant coefficient of the variable RET0, thus suggesting a lower likelihood of a positive post-event drift, reaching similar conclusions as in the US stock market. Also, MOMENTUM has a positive impact on the likelihood of a positive post-event drift, thus suggesting a higher likelihood of positive abnormal returns in stock that behaved well in the past, and it provides the opposite conclusion to the one achieved in the US stock market.

To sum up, we can highlight some conclusions regarding the Up Sample. The first one is that, on average, a large positive price change is followed by negative cumulative abnormal returns, thus suggesting that, on average, investors overreact to the large price change on the event day and correct that behaviour in the following days as the stock price moves towards the new perceived intrinsic value. The second conclusion involves the reference points presented in the hypothesis that could serve as an anchor to the investor during a large price change. The results obtained regarding the 52 Week Low suggests that investors anchor their price estimations to this reference point, with support for this being found in both OLS and Probit regressions, thus supporting **H1**$_U$. However, the results regarding the anchoring to the investor private information could not be demonstrated for the Up Sample, in both OLS and Probit regressions, either due to the wrong signal coefficient and due to the results not having statistical significance, so no conclusion can be drawn regarding **H2**$_U$. Regarding the comparison to the US stock market, both markets reach the same conclusion regarding the impact of the 52 Week Low reference point in the post-event returns, *i.e.*, investor underreaction. Regarding the influence of private information, no comparison can be made.

6.3. The "2000-2001" years

Moved by curiosity, I decided to perform a "Break Structure" test. The reason for this test is the high frequency of events in the years 2000 and 2001, in both Down Sample (2393 events, with a weight of 41.86% in the total subsample) and Up Sample (2840 events with a weight of 38.27% in the total subsample). This type of periods that contain speculative bubbles, like the Technological Bubble, are periods with high (and sometimes extreme) volatility, where uncertainty reigns among the majority of the investors, and therefore, they become more susceptible to behavioural biases. So, I believe that it could be interesting to see if the conclusions achieved previously still prevail, or if this smaller period led to other types of investor behaviour.

So, after performing a "Break Structure" test in this specific period, I was able to determine that there was in fact a structural break in both samples[7], hence the coefficients achieved for the 52 Week High/52 Week Low and Investor private information reference points are different from the ones obtained in the whole 1995 – 2019 period. Next, I will start by presenting the results regarding the Down Sample[8], followed by the results of the Up Sample[9], for the 2000-2001 years.

6.3.1. Down Sample

Table 8 presents the results regarding the Down Sample. MODEL 1 to MODEL 3 present the OLS results, while MODEL 4 to MODEL 6 present the Probit results.

As in subchapter 6.1, the main variables of analysis are 52_WK_HI and CONTRADICTION. The model's R^2 ranges from 0.1438 to 0.2953 in the OLS regressions and from 0.01580 to 0.0582 in the Probit regressions.

Starting with the CONTRADICTION variable, we achieved negative and statistically significant coefficients, at the level of 1%, in all six models, a similar conclusion to the one achieved in the 1995-2019 period, thus supporting **$H2_D$**. However, now the effects of anchoring to the investor private information, and therefore the underreaction of the investors on the day of the event, appear to be bigger, especially if we consider the results of MODEL 3, which reveals the influence of the private information reference point in the

[7] See appendix A3 for equation used and the results of the Gujarati Break Structure test.

[8] See appendix A4 for data summary statistics regarding the Down Sample.

[9] See appendix A5 for data summary statistics regarding the Up Sample.

cumulative abnormal returns in the twenty days following the event.

Table 8: Down Sample OLS/Probit regression results (2000-2001)

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CAR3	CAR5	CAR20	CARPOS3	CARPOS5	CARPOS20
Constant	**0.683893*** **	**1.131576*** **	**3.302201*** **	**0.774331***	**0.318086**	**0.072927**
	(4.469357)	(6.197317)	(11.14138)	(1.768381)	(0.730340)	(0.164230)
52_WK_HI	**0.030390**	**0.037188**	**0.180501*** **	**-0.069172**	**-0.347084** **	**-0.636072*** **
	(0.962951)	(0.987526)	(2.976550)	(-0.408408)	(-2.048871)	(-3.675308)
52_WK_LO	**-0.029313**	**-0.036727**	**0.069998***	**0.015341**	**0.133756**	**0.685873*** **
	(-1.343240)	(-1.412861)	(1.670883)	(0.100026)	(0.873228)	(4.394600)
CONTRADICTION	**-0.029079*** **	**-0.038790*** **	**-0.058823*** **	**-0.204559*** **	**-0.228601*** **	**-0.192803*** **
	(-4.487509)	(-5.020409)	(-4.725565)	(-3.632371)	(-4.064784)	(-3.376788)
RET0	**0.112963** **	**-0.024786**	**-0.225025** **	**1.390896*** **	**0.482588**	**-0.294315**
	(2.224448)	(-0.410329)	(-2.311107)	(3.043307)	(1.096039)	(-0.666164)
LN_MKTVAL	**-0.036982*** **	**-0.058575*** **	**-0.189098*** **	**-0.061673*** **	**-0.032127**	**-0.063924*** **
	(-4.842684)	(-6.428003)	(-12.82867)	(-2.593972)	(-1.354773)	(-2.639353)
MOMENTUM	**-0.004723**	**0.022282**	**-0.152293** **	**0.261578**	**0.347795**	**0.754508*** **
	(-0.151059)	(0.597323)	(-2.528142)	(1.079543)	(1.433789)	(3.034340)
VDAX	**0.000550**	**-9.06E-05**	**0.002844*** **	**0.015229*** **	**0.011455*** **	**0.022467*** **
	(1.107967)	(-0.153245)	(2.970239)	(4.044418)	(3.064046)	(5.825571)
TOBINQ	**0.006615*** **	**0.007446*** **	**0.022924*** **	**0.030138** **	**0.035606*** **	**0.054655*** **
	(2.847749)	(2.690095)	(5.158655)	(2.372300)	(2.831242)	(4.274471)
LN_VOL	**0.005139**	**0.004307**	**0.007549**	**0.033021**	**0.025608**	**0.025377**
	(1.098121)	(0.774565)	(0.842157)	(1.047911)	(0.814302)	(0.792058)
BETA	**-0.022304***	**-0.041116*** **	**-0.044585** **	**-0.024930**	**-0.053762**	**-0.001045**
	(-1.795089)	(-2.773863)	(-1.854610)	(-0.447382)	(-0.963817)	(-0.018338)
JANUARY	**0.024365*** **	**0.039678*** **	**0.078482*** **	**0.116625**	**0.135797**	**0.285555*** **
	(2.162550)	(2.951555)	(5.084299)	(1.175161)	(1.369289)	(3.961034)
MONDAY	**0.007556**			**0.040818**		
	(1.269026)			(0.771780)		
R^2/McFadden R^2	**0.143757**	**0.157176**	**0.295335**	**0.015801**	**0.016095**	**0.058212**
N	**2393**	**2393**	**2393**	**2393**	**2393**	**2393**

Note: In models 1, 2 and 3, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event. As for models 4, 5 and 6, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise. ***, **, and * represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

The 52_WK_HI variable reveals a rather unexpected result. Here, we accomplish a completely different conclusion to the one in the 1995-2019 period. In this case, all 52_WK_HI coefficients are positive, although only statistically significant in MODEL 3. These results suggest that the closer the stock price one day before the large negative price change is to the 52 Week High price, the larger the post-event returns, suggesting, therefore, the existence of investor overreaction to this reference point on the event day, with the price moving towards its new perceived intrinsic value in the following days, rejecting, therefore, **$H1_D$**. However, when we look to the Probit regression results, MODEL 4 to MODEL 6, we find contradicting results, as the coefficients, with their negative signal, reveal that the closer the stock price is to the 52 Week High price the day before the large negative price change, the lower the probability of experiencing a positive cumulative abnormal return in the following days, thus suggesting the presence of investor underreaction. This contradiction makes it difficult to reach one strong conclusion of the 52 Week High reference point during the 2000-2001 years, but I believe that it is clear that during this period, investors reveal a different behaviour than if with consider the whole period.

6.3.2. Up Sample

Table 9 presents the results regarding the Up Sample. MODEL 1 to MODEL 3 present the OLS results, while MODEL 4 to MODEL 6 present the Probit results.

As in subchapter 6.2, the main variables of analysis are 52_WK_LO and CONTRADICTION. The model's R^2 ranges from 0.1737 to 0.3375 in the OLS regressions and from 0.0210 to 0.0814 in the Probit regressions.

In this case, the situation is different from the one in the Down Sample. Both main variables yield the same conclusions as in the 1995-2019 period regarding the anchoring effects of both proposed reference points, *i.e.*, promote investor underreaction. The reason for the existence of a break structure is due to the magnitude of the coefficients, and therefore the influence they have on the post-event returns. For example, if we consider the 52_WK_LO coefficient regarding MODEL 1, it suggests that if a stock price were at the 52 Week Low price the day before the large positive price change, its cumulative abnormal return would be 14.32 percentage points larger than if it were as far as possible from the reference point. If we consider the whole sample, the influence of this reference point would be only 3.28 percentage points. These results suggest that during this period of higher uncertainty, investors anchor their estimations more than in other periods, thus corroborating **$H1_U$**. Regarding the CONTRADICTION variable, once again no conclusion can be achieved regarding the effect of private information on investor price estimations, i.e., no conclusion regarding **$H2_U$**.

Table 9: Up Sample OLS/Probit regression results (2000-2001)

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CAR3	CAR5	CAR20	CARPOS3	CARPOS5	CARPOS20
Constant	**0.671517*** **	**0.941657*** **	**2.797767*** **	**-1.066411** **	**-1.262482*** **	**-1.886710*** **
	(5.424201)	(6.484921)	(12.43452)	(-2.484153)	(-2.924986)	(-4.278095)
52_WK_HI	**0.102686*** **	**0.133284*** **	**0.426061*** **	**-0.217401**	**-0.272143* **	**-0.469721*** **
	(3.984505)	(4.406676)	(9.091886)	(-1.432270)	(-1.783180)	(-3.001310)
52_WK_LO	**0.142362*** **	**0.162507*** **	**0.395099*** **	**0.516552*** **	**0.603797*** **	**1.421616*** **
	(7.957741)	(7.737467)	(12.14153)	(3.896118)	(4.518004)	(10.14969)
CONTRADICTION	**-0.000378**	**0.005119**	**-0.001052**	**-0.026719**	**-0.005502**	**-0.112021** **
	(-0.064770)	(0.747612)	(-0.099693)	(-0.522715)	(-0.106994)	(-2.132169)
RET0	**-0.236842*** **	**-0.251977*** **	**-0.420288*** **	**-0.971071*** **	**-1.682076*** **	**-1.054927*** **
	(-5.511676)	(-4.998009)	(-5.383328)	(-2.676142)	(-4.452642)	(-2.886905)
LN_MKTVAL	**-0.038679*** **	**-0.054515*** **	**-0.179615*** **	**0.033379**	**0.018179**	**-0.027658**
	(-6.370472)	(-7.648761)	(-16.26775)	(1.547588)	(0.837210)	(-1.246523)
MOMENTUM	**-0.066558** **	**-0.093434**	**-0.289794*** **	**0.316320**	**0.082138**	**0.117830**
	(-2.426893)	(-2.903281)	(-5.816665)	(1.480770)	(0.383700)	(0.530688)
VDAX	**-0.000114**	**0.000724**	**0.003614*** **	**0.009338*** **	**0.018343*** **	**0.029796*** **
	(-0.249036)	(1.345452)	(4.334093)	(2.601263)	(5.070172)	(7.931001)
TOBINQ	**0.004953** **	**0.004452**	**0.024087*** **	**0.030505*** **	**0.043096*** **	**0.095569*** **
	(2.101870)	(1.609030)	(5.618750)	(2.765328)	(3.890780)	(8.197531)
LN_VOL	**-0.001299**	**-0.002602**	**0.007292**	**-0.026013**	**0.005117**	**0.055031* **
	(-0.324544)	(-0.554180)	(1.002203)	(-0.942112)	(0.183402)	(1.933778)
BETA	**-0.052787*** **	**-0.061885*** **	**-0.073751*** **	**0.043991**	**0.016330**	**-0.017915**
	(-4.688384)	(-4.683615)	(-3.586258)	(0.833464)	(0.307577)	(-0.330322)
JANUARY	**0.032884*** **	**0.058893*** **	**0.054239*** **	**0.316597*** **	**0.427123*** **	**0.244571*** **
	(4.460354)	(6.848985)	(4.506083)	(4.855225)	(6.550086)	(4.168187)
MONDAY	**0.007984**			**0.115866** **		
	(1.455324)			(2.346913)		
R^2/McFadden R^2	**0.173741**	**0.199246**	**0.337467**	**0.021029**	**0.033695**	**0.081428**
N	**2840**	**2840**	**2840**	**2840**	**2840**	**2840**

Note: In models 1, 2 and 3, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event. As for models 4, 5 and 6, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise. ***, **, and * represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

To sum up, if we consider the results achieved for both Down and Up Sample during the 2000-2001 years, we find strong evidence in favour of the influence of the anchoring heuristic on investors, presented by Tversky and Kahneman (1974), since these results suggest that during periods of greater uncertainty, the effects of anchoring in the post-shock returns appear to be larger than if we consider the whole 1995 to 2019 period, that as expected presents a smaller level of volatility.

7. Conclusions

After several studies achieving contradicting conclusions to the ones presented by the EMH, and after it has been documented that stock returns are fat-tailed, *i.e.*, the probability of extreme returns is higher than original consider by the normal distribution, many researchers started to study the predictability of stock returns after the occurrence of a large price change. As we would expect, although there is evidence of stock return predictability, there is no consensus among different studies either on the direction or magnitude of the returns after the large price change. There are three possible explanations regarding the predictability of stock returns: market microstructure; changing risk; and behavioural explanations. It was to this last one that I directed my focus. Regarding behavioural explanations, two theories stand out: Overreaction and Underreaction, usually explained by price reversals and price continuation, respectively. However, more important than just concluded if there was over/underreaction to a large price change, it is also important to better understand the underlying reasons that lead investors to react in such a manner.

So, after Brady and Premti (2019) studied the US stock market, I decided to study the influence of the 52 Week High/52 Week Low and Investor private information on the returns after a large price for the German stock market. The proposed hypothesis, following the anchoring and adjustment bias presented by Tversky and Kahneman (1974), was that during a large price change investors would anchor their price estimations to the 52 Week High if the stock experienced a large price drop, and to the 52 Week Low if the stock experienced a large price increase, and that this influence would be larger as the stock price was closer to those reference points. Additionally, it was also proposed that if an investor saw its private information signal being contradicted by the large price change, and since investors usually overweight the importance of their private information, they would anchor their price estimations to their private information. In both hypotheses presented, the reference points are expected to be the determinants of investor underreaction to a large price change, which will oblige investors to revise their price estimations in the following days, forcing the price to move towards its new perceived intrinsic value.

After applying a similar methodology to Brady and Premti (2019), the first conclusion we achieve is that, on average, both positive and negative large price changes are characterized by investor overreaction on the event day, since we can observe, respectively, average negative and positive CAR in the days following the event.

Additionally, I found evidence that investors rely on available reference points when making their price estimations after a large price change. More specifically, I found evidence that investors anchor their price estimations to the 52 Week High in the event of a large negative price change and the 52 Week Low in the event of a large positive price change, and thus underreact on the event day. Due to this underreaction, in the following days, the price continues to drift towards its new perceived intrinsic value. Hence, stocks that are closer to the 52 Week High tend to have lower (negative) returns in the following days after a large negative price change, while stocks that are closer to the 52 Week Low tend to have higher (positive) returns after a large positive price change. Furthermore, I also found evidence in support of investors anchoring their price estimations to their private information. In this case, the evidence is only consistent with the hypotheses presented for the large price decreases, whereas for the large price increases no conclusion was reached regarding the effects of private information contradiction in the post-event returns during the 1995-2019 period. These results hold after controlling for several factors that could also influence the observed post-event returns, such as the impact of the return on the day of the event, the size of the firm, the number of shares traded, the January and Monday effects, etc. Additionally, the results achieved are also consistent with the ones achieved in the US stock market, revealing the same underreaction features, although the influence of the proposed anchors appears to have a greater influence on the post-event returns in the German stock market.

Moreover, due to the high frequency of large price changes in the 2000-2001 years, I also decided to investigate the influence of the proposed reference points during this period. Regarding the 52 Week Low, in the event of a large price increase, and the investor private information, in a presence of a large negative price change, the effects of anchoring appear to be stronger when compared to the whole period in analysis. This period coincides with the end of the Technological Bubble, a period that is usually characterized with higher uncertainty and where it is expected for the anchoring effects to be stronger. As for the 52 Week High, the OLS regressions indicate the existence of overreaction on the day of the event, contradicting the hypothesis presented regarding large price decreases and the results achieved during the 1995-2019 period. Once again, no conclusion was achieved regarding the effects of private information after the occurrence of a large price increase for the years of 2000-2001.

These results suggest that investors can take advantage of the anchoring and adjustment bias in the event of large price changes. They indicate that even if an investor fails to take advantage of the initial price shock, the underreaction effects of the reference points would cause the stock price to drift in the same direction as the initial large price change, exerting its influence for at least the following 20 days after the event. This means that if an investor establishes a strategy where the investor can identify stocks that were close to the proposed reference points before experienced a large price change, and assuming a long position if the stock had experienced a large price increase, or assuming a short position if it experienced a large price decrease, the strategy would lead to systematic positive abnormal returns. However, the results achieved do not consider the transaction costs that investors must support during their financial operations, which may mitigate the returns gained. The results also suggest that during periods of increased market volatility, the anchoring effects appear to be stronger when compared to less volatile periods, suggesting that higher abnormal returns can be achieved during this type of periods.

The present dissertation leaves room for further research. Due to the lack of data, the impact of information release, such as analyst recommendations, dividend announcements, earnings announcements, share issues, etc., was not considered. The incorporation of this data would make the achieved results more robust. Additionally, this research could be applied to emerging markets and small-capitalization markets, so we can establish a comparison of the effects between the different market sizes and, possibly market regulations, although this could prove to be a challenge, due to the lack of data to form an event in those markets. Lastly, there is also the possibility to explore other behavioural biases that could influence the observed returns after a large price change.

Appendix

Appendix A1 – US stock market results from Down Sample

Table 10: US stock market OLS/Probit results from Down Sample[10]

	MODEL 4	MODEL 5	MODEL 6	MODEL 4	MODEL 5	MODEL 6
Dependent variable	CAR3	CAR5	CAR20	CAR3POS	CAR5POS	CAR20POS
Constant	**0.00446**	**-0.000599**	**-0.00139**	**0.0564**	**-0.163**	**-0.268****
	(1.14)	(-0.19)	(-0.84)	(0.50)	(-1.39)	(-2.09)
52_WK_HI	**-0.00510*****	**-0.00412*****	**-0.00334*****	**-0.0813****	**-0.112*****	**-0.246*****
	(-4.08)	(-4.58)	(-8.80)	(-2.13)	(-2.88)	(-6.29)
52_WK_LO	**0.00641*****	**0.00642*****	**0.00452*****	**0.281*****	**0.349*****	**0.604*****
	(5.56)	(7.92)	(11.62)	(8.01)	(10.20)	(16.16)
CONTRADICTION	**-0.00422*****	**-0.00325*****	**-0.00133*****	**-0.137*****	**-0.160*****	**-0.140*****
	(-10.81)	(-11.83)	(-11.11)	(-11.25)	(-12.90)	(-11.28)
RET0	**-0.0260*****	**-0.0162*****	**-0.00678*****	**-0.298*****	**-0.333*****	**0.541*****
	(-5.22)	(-4.80)	(-4.85)	(-2.69)	(-2.97)	(-4.69)
LN_MKTVAL	**0.00135*****	**0.00111*****	**0.000424*****	**0.0562*****	**0.0658*****	**0.0441*****
	(4.53)	(4.68)	(3.62)	(7.09)	(7.83)	(4.97)
MOMENTUM	**-0.000173**	**-0.000345**	**-0.000776*****	**-0.0106**	**-0.0203*****	**-0.0479*****
	(-0.59)	(-1.39)	(-6.38)	(-1.40)	(-2.70)	(-5.72)
VIX	**-0.0000119**	**-0.00000432**	**-0.0000222*****	**0.000654**	**-0.000181**	**-0.00294*****
	(0.49)	(-0.27)	(-2.99)	(-0.86)	(-0.25)	(-3.66)
TOBINQ	**-0.0000415**	**-0.0000192**	**-0.0000224***	**-0.000462**	**-0.000678**	**-0.00112**
	(-1.28)	(-0.83)	(-1.90)	(-0.56)	(-0.85)	(-1.28)
LN_VOL	**-0.00217*****	**-0.00157*****	**-0.000417*****	**-0.0819*****	**-0.0815*****	**-0.0402*****
	(-10.16)	(-9.61)	(-5.40)	(-13.94)	(-13.46)	(-6.26)
BETA	**0.000672***	**0.000423**	**-0.000310****	**0.0115**	**0.00335**	**-0.0339*****
	(1.83)	(1.62)	(-2.23)	(1.19)	(0.36)	(-3.26)
R^2/Pseudo-R^2	**0.016**	**0.021**	**0.051**	**0.011**	**0.015**	**0.029**
N	**69451**	**69437**	**69395**	**69451**	**69437**	**69395**

Source: Brady and Premti (2019)

Note: In models 1, 2 and 3, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event. As for models 4, 5 and 6, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise. *******, ******, and ***** represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

[10] Since I do not consider the impact of information on the regressions used during this dissertation, I can only use MODEL 4 to MODEL 6, from Brady and Premti (2019), as a comparison to my estimations, since they also do not consider the impact of information on returns, in these specific models.

Appendix A2 – US stock market results from Up Sample

Table 11: US stock market OLS/Probit results from Up Sample[11]

Dependent variable	MODEL 4 CAR3	MODEL 5 CAR5	MODEL 6 CAR20	MODEL 4 CAR3POS	MODEL 5 CAR5POS	MODEL 6 CAR20POS
Constant	**0.0116***** (4.40)	**0.00514**** (2.43)	**-0.00106** (-0.82)	**0.118** (1.32)	**-0.0639** (-0.63)	**-0.311**** (-2.42)
52_WK_HI	**-0.00210**** (-2.12)	**-0.000163** (-0.23)	**0.0000603** (0.18)	**-0.206***** (-6.33)	**-0.173***** (-5.08)	**-0.208***** (-5.55)
52_WK_LO	**0.00376***** (4.13)	**0.00488***** (6..67)	**0.00388***** (10.74)	**0.0806**** (2.54)	**0.168***** (4.67)	**0.293***** (8.04)
CONTRADICTION	**0.00348***** (12.60)	**0.00264***** (13.05)	**0.00108***** (10.98)	**0.110***** (10.98)	**0.116***** (11.06)	**0.103***** (9.81)
RET0	**-0.0366***** (-10.03)	**-0.0260***** (-10.71)	**-0.0116***** (-13.07)	**-0.807***** (-13,33)	**-0.866***** (-14.30)	**-1.013***** (-13.75)
LN_MKTVAL	**-0.00156***** (-8.51)	**-0.00118***** (-8.65)	**-0.000347***** (-4.16)	**-0.0436***** (-7.40)	**-0.0397***** (-6.28)	**-0.0218***** (-2.66)
MOMENTUM	**-0.00110***** (-4.73)	**-0.000970***** (-4.65)	**-0.00108***** (-9.73)	**-0.0292***** (-4.88)	**-0.0321***** (-4.97)	**-0.0769***** (-9.21)
VIX	**-0.000142***** (-3.91)	**-0.0000902***** (-3.50)	**-0.0000348***** (-2.88)	**-0.00280**** (-2.55)	**-0.00267**** (2.20)	**-0.00194** (-1.38)
TOBINQ	**0.00000592** (0.27)	**-0.0000254** (-1.57)	**-0.0000415***** (4.31)	**0.00122*** (1.86)	**0.00028** (0.42)	**0.000419** (0.57)
LN_VOL	**0.00176***** (12.59)	**0.00140***** (13.72)	**0.000533***** (10.00)	**0.0570***** (13.13)	**0.0595***** (13.38)	**0.0500***** (9.77)
BETA	**-0.00117***** (-4.40)	**-0.000810***** (3.96)	**-0.000602***** (-5.45)	**-0.0220***** (-2.98)	**-0.0112** (-1.42)	**-0.0202**** (-2.33)
R^2/Pseudo-R^2	**0.018**	**0.021**	**0.045**	**0.007**	**0.009**	**0.017**
N	**128001**	**127979**	**127887**	**128001**	**127979**	**127887**

Source: Brady and Premti (2019)

Note: In models 1, 2 and 3, the dependent variable is the post-event price drift in the 3, 5 and 20 days following the event. As for models 4, 5 and 6, the dependent variable is a dummy variable that takes the value 1 if the post-event is positive and 0 otherwise. *******, ******, and ***** represent the significance at the 1%, 5% and 10% levels, respectively. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

[11] Since I do not consider the impact of information on the regressions used during this dissertation, I can only use MODEL 4 to MODEL 6, from Brady and Premti (2019), as a comparison to my estimations, since they also do not consider the impact of information on returns, in these specific models.

Appendix A3 – Break Structure regression

To determine if there was a break structure in the data, regarding de years 2000-2001, I performed the Gujarati test. The following regression was used:

$$\begin{aligned} CAR_{i,t} = c + {} & \beta 1(52\_WK\_HI_{i,t}) + \beta 2(52\_WK\_LO_{i,t}) + \beta 3(CONTRADICTION_{i,t}) \\ & + \beta 4(RET0_{i,t}) + \beta 5(LN\_MKTVAL_{i,t}) + \beta 6(MOMENTUM_{i,t}) \\ & + \beta 7(VDAX_t) + \beta 8(TOBINQ_{i,t}) + \beta 9(LN\_VOL_{i,t}) \\ & + \beta 10(BETA_{i,t}) + \beta 11(MONDAY_{i,t}) + \beta 12(JAUNUARY_{i,t}) \\ & + \alpha 1(TS_{i,t}) + \alpha 2(TS_{I,T} * 52\_WK\_HI_{i,t}) + \alpha 3(52\_WK\_LO_{i,t}) \\ & + \alpha 4(TS_{i,t} * CONTRADICTION_{i,t}) + \alpha 5(TS_{i,t} * RET0_{i,t}) \\ & + \alpha 6(TS_{i,t} * LN\_MKTVAL_{i,t}) + \alpha 7(TS_{i,t} * MOMENTUM_{i,t}) \\ & + \alpha 8(TS_{i,t} * VDAX_t) + \alpha 9(TS_{i,t} * TOBINQ_{i,t}) \\ & + \alpha 10(TS_{i,t} * LN\_VOL_{i,t}) + \alpha 11(TS_{i,t} * BETA_{i,t}) \\ & + \alpha 12(TS_{i,t} * MONDAY_{i,t}) + \alpha 13(TS_{i,t} * JAUNUARY_{i,t}) + \varepsilon_{i,t} \end{aligned} \tag{A.1}$$

Where $TS_{i,t}$ is a dummy variable that assumes the value of 1, if the period is between 2000 and 2001, and 0 otherwise. The remaining variables have the same significance as present in Chapter 4. After performing the Wal Test, I achieved the following results/conclusions:

Table 12: Down Sample Break Structure results

	F-statistic	Qui-square	Conclusion
MODEL 1	0.0020	0.0020	Structural Break
MODEL 2	0.0023	0.0023	Structural Break
MODEL 3	0.0000	0.0000	Structural Break

Table 13: Up Sample Break Structure results

	F-statistic	Qui-square	Conclusion
MODEL 1	0.0000	0.0000	Structural Break
MODEL 2	0.0000	0.0000	Structural Break
MODEL 3	0.0000	0.0000	Structural Break

Appendix A4 – Summary of statistics for the years 2000-2001 – Down Sample

Table 14: Summary of statistics of the Down Sample (2000-2001 years)

	Observations	Mean	Std. Dev.	Minimum	Maximum
Dependent variables:					
CAR3	2393	0.005979	0.130390	-0.722268	0.698617
CAR5	2393	0.003975	0.156862	-0.802257	0.671781
CAR20	2393	0.002198	0.276513	-0.972663	1.254903
CARPOS3	2393	0.541162	0.498407	0.000000	1.000000
CARPOS5	2393	0.530715	0.499160	0.000000	1.000000
CARPOS20	2393	0.508985	0.500024	0.000000	1.000000
Independent variables:					
52_WK_HI	2393	0.369114	0.271686	0.014898	1.000000
52_WK_LO	2393	0.669917	0.227859	0.037105	0.904801
CONTRADICTION	2393	0.385290	0.486766	0.000000	1.000000
RET0	2393	-0.146142	0.062301	-0.947027	-0.100032
LN_MKTVAL	2393	19.03105	1.528144	14.97866	25.84284
MOMENTUM	2393	-0.080353	0.125383	-0.648555	0.395899
VDAX	2393	27.01094	7.270937	17.06000	54.59000
TOBINQ	2393	2.074656	2.372612	0.016918	20.47842
LN_VOL	2393	10.48715	0.935381	9.210340	14.74064
BETA	2393	1.217863	0.614060	-0.250243	3.172069
MONDAY	2393	0.592562	0.491460	0.000000	1.000000
JANUARY (1-3)	2393	0.076473	0.265809	0.000000	1.000000
JANUARY (1-5)	2393	0.076473	0.265809	0.000000	1.000000
JANUARY (1-20)	2393	0.172169	0.377606	0.000000	1.000000

Note: CAR3, CAR5 and CAR20 are, respectively, the cumulative abnormal return in the 3, 5 and 20 days following the event. CARPOS3, CARPOS5 and CARPOS20 are dummy variables that take the value of 1 if the CAR in the 3, 5 and 20 days following the event is positive, and 0 otherwise. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is positive, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. Lastly, JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

Appendix A5 – Summary of statistics for the years 2000-2001 – Up Sample

Table 15: Summary of statistics of the Up Sample (2000-2001 years)

	Observations	Mean	Std. Dev.	Minimum	Maximum
Dependent variables:					
CAR3	2840	-0.004163	0.132556	-0.605187	1.031335
CAR5	2840	-0.006115	0.158113	-0.672582	1.175922
CAR20	2840	-0.024299	0.269238	-0.974986	1.258486
CARPOS3	2840	0.444014	0.496943	0.000000	1.000000
CARPOS5	2840	0.439789	0.496449	0.000000	1.000000
CARPOS20	2840	0.426761	0.494694	0.000000	1.000000
Independent variables:					
52_WK_HI	2840	0.373325	0.272413	0.016249	0.904762
52_WK_LO	2840	0.690139	0.243776	0.044442	1.000000
CONTRADICTION	2840	0.464085	0.498796	0.000000	1.000000
RET0	2840	0.162294	0.072463	0.100083	1.029619
LN_MKTVAL	2840	18.72274	1.491654	14.47820	26.13846
MOMENTUM	2840	-0.070812	0.127755	-0.856549	0.412298
VDAX	2840	26.81709	6.942195	17.06000	54.59000
TOBINQ	2840	2.163068	2.486677	0.016918	20.47842
LN_VOL	2840	10.62287	0.952162	9.210340	15.06272
BETA	2840	1.109718	0.615528	-0.230501	3.083609
MONDAY	2840	0.609155	0.488026	0.000000	1.000000
JANUARY (1-3)	2840	0.172535	0.377911	0.000000	1.000000
JANUARY (1-5)	2840	0.172535	0.377911	0.000000	1.000000
JANUARY (1-20)	2840	0.232394	0.422433	0.000000	1.000000

Note: CAR3, CAR5 and CAR20 are, respectively, the cumulative abnormal return in the 3, 5 and 20 days following the event. CARPOS3, CARPOS5 and CARPOS20 are dummy variables that take the value of 1 if the CAR in the 3, 5 and 20 days following the event is positive, and 0 otherwise. 52_WK_HI captures the stock proximity to its 52 Week High and is computed as (stock's closing price on the day before the event)/(stock's 52 Week High price). 52_WK_LO captures the stock proximity to its 52 Week Low and is computed as (stock's 52 Week Low)/(stock's closing price on the day before the event). CONTRADICTION is the proxy of private information being contradicted by the price shock and takes the value of 1 if the CAR in the 5 days before the price shock is negative, and 0 otherwise. RET0 is the raw return on the day of the price shock. LN_MKTVAL is the natural logarithm of the firm's market valuation on the day before the price shock. MOMENTUM is the cumulative monthly abnormal return over the prior 6 months ending one month before the event. VDAX is the volatility index on the day of the event. TOBINQ is the firm's Tobin-Q. LN_VOL is the natural logarithm of the number of shares traded on the day of the event. BETA is the firm's beta, as estimated by the market model. MONDAY is a dummy variable that takes the value 1 if any of the days in the post-event drift happen to be on Monday, and 0 otherwise. Lastly, JANUARY is a dummy variable that takes the value 1 if any of the days of the post-event drift happen in January, and 0 otherwise.

References

Ajayi, R. A., Mehdian, S., & Perry, M. J. (2006). A test of US equity market reaction to surprises in an era of high trading volume. *Applied Financial Economics, 16*(6), 461-469. doi:10.1080/09603100500400510

Amini, S., Hudson, R., & Keasey, K. (2010). Stock return predictability despite low autocorrelation. *Economics Letters, 108*(1), 101-103. doi:10.1016/j.econlet.2010.04.031

Atasanova, C., & Hudson, R. (2008). *Short term overreaction, underreaction and price trend continuation in equity markets.* Paper presented at the Proceedings of 2007 Anual Meeting of the Midwest Finance Association.

Atkins, A. B., & Dyl, E. A. (1990). Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis*, 535-547. doi:10.2307/2331015

Baker, M., Pan, X., & Wurgler, J. (2012). The effect of reference point prices on mergers and acquisitions. *Journal of financial economics, 106*(1), 49-71. doi:10.1016/j.jfineco.2012.04.010

Benou, G. (2003). Market underreaction to large stock price declines: The case of ADRs. *The Journal of Behavioral Finance, 4*(1), 21-32. doi:10.1207/S15427579JPFM0401_04

Bergman, O., Ellingsen, T., Johannesson, M., & Svensson, C. (2010). Anchoring and cognitive ability. *Economics Letters, 107*(1), 66-68. doi:10.1016/j.econlet.2009.12.028

Bharati, R., Crain, S. J., & Nanisetty, P. (2009). Evaluating stock price behavior after events: An application of the self-exciting threshold autoregressive model. *Quarterly Journal of Finance and Accounting*, 23-43. doi:10.2307/40473484

Bodenhausen, G. V., Gabriel, S., & Lineberger, M. (2000). Sadness and susceptibility to judgmental bias: The case of anchoring. *Psychological science, 11*(4), 320-323. doi:10.1111/1467-9280.00263

Brady, K., & Premti, A. (2019). How Do Investors Determine Stock Prices after Large Price Shocks? *Journal of Behavioral Finance, 20*(3), 354-368. doi:10.1080/15427560.2018.1511563

Bremer, M., Hiraki, T., & Sweeney, R. J. (1997). Predictable patterns after large stock price changes on the Tokyo Stock Exchange. *Journal of Financial and Quantitative Analysis*, 345-365. doi:10.2307/2331204

Bremer, M., & Sweeney, R. J. (1991). The reversal of large stock - price decreases. *The Journal of Finance, 46*(2), 747-754. doi:10.1111/j.1540-6261.1991.tb02684.x

Brown, K. C., Harlow, W. V., & Tinic, S. M. (1988). Risk aversion, uncertain information, and market efficiency. *Journal of financial economics, 22*(2), 355-385. doi:10.1016/0304-405X(88)90075-X

Brown, K. C., Harlow, W. V., & Tinic, S. M. (1993). The risk and required return of common stock following major price innovations. *Journal of Financial and Quantitative Analysis*, 101-116. doi:10.2307/2331153

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*: princeton University press.

Chan, W. S. (2003). Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of financial economics, 70*(2), 223-260. doi:10.1016/S0304-405X(03)00146-6

Chapman, G. B., & Johnson, E. J. (1994). The limits of anchoring. *Journal of Behavioral Decision Making, 7*(4), 223-242. doi:10.1002/bdm.3960070402

Choi, H. S., & Jayaraman, N. (2009). Is reversal of large stock - price declines caused by overreaction or information asymmetry: Evidence from stock and option markets. *Journal of Futures Markets: Futures, Options, and Other Derivative Products, 29*(4), 348-376. doi:10.1002/fut.20360

Claes, A., De Ceuster, M., & Zhang, H. (2010). How do stocks react after extreme daily returns? The Dutch case. *Dynamics in economics: Essays in honour of Joseph Plasmans*, 11-24.

Corrado, C. J., & Jordan, B. D. (1997). Risk aversion, uncertain information, and market efficiency. *Review of Quantitative Finance and Accounting, 8*(1), 51-68. doi:10.1023/A:1008292620583

Cox, D. R., & Peterson, D. R. (1994). Stock returns following large one - day declines: Evidence on short - term reversals and longer - term performance. *The Journal of Finance, 49*(1), 255-267. doi:10.1111/j.1540-6261.1994.tb04428.x

Critcher, C. R., & Gilovich, T. (2008). Incidental environmental anchors. *Journal of Behavioral Decision Making, 21*(3), 241-251. doi:10.1002/bdm.586

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under - and overreactions. *The Journal of Finance, 53*(6), 1839-1885. doi:10.1515/9781400829125-016

De Bondt, W. F., & Thaler, R. H. (1985). Does the stock market overreact? *The Journal of*

Finance, 40(3), 793-805. doi:10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance, 42*(3), 557-581. doi:10.1111/j.1540-6261.1987.tb04569.x

Diacogiannis, G. P., Patsalis, N., Tsangarakis, N. V., & Tsiritakis, E. D. (2005). Price limits and overreaction in the Athens stock exchange. *Applied Financial Economics, 15*(1), 53-61. doi:10.1080/0960310042000314214

Edwards, W. (1968). Conservatism in human information processing. *Formal representation of human judgment*.

Englich, B., Mussweiler, T., & Strack, F. (2006). Playing dice with criminal sentences: The influence of irrelevant anchors on experts' judicial decision making. *Personality and Social Psychology Bulletin, 32*(2), 188-200. doi:10.1177/0146167205282152

Englich, B., & Soder, K. (2009). Moody experts - How mood and expertise influence judgmental anchoring. *Judgment and Decision making, 4*(1), 41.

Epley, N., & Gilovich, T. (2001). Putting adjustment back in the anchoring and adjustment heuristic: Differential processing of self-generated and experimenter-provided anchors. *Psychological science, 12*(5), 391-396. doi:10.1111/1467-9280.00372

Epley, N., & Gilovich, T. (2005). When effortful thinking influences judgmental anchoring: differential effects of forewarning and incentives on self‐generated and externally provided anchors. *Journal of Behavioral Decision Making, 18*(3), 199-212. doi:10.1002/bdm.495

Fama, E. F. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal, 21*, 55-59. doi:10.2469/faj.v51.n1.1861

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*. doi:10.1016/0304-405X(93)90023-5

Farmer, J. D., Gillemot, L., Lillo, F., Mike, S., & Sen, A. (2004). What really causes large price changes? *Quantitative Finance, 4*(4), 383-397. doi:10.1080/14697680400008627

Furnham, A., & Boo, H. C. (2011). A literature review of the anchoring effect. *The journal of socio-economics, 40*(1), 35-42. doi:10.1016/j.socec.2010.10.008

George, T. J., Hwang, C.-Y., & Li, Y. (2015). Anchoring, the 52-week high and post earnings announcement drift. *Available at SSRN 2391455*. doi:10.2139/ssrn.2391455

George, T. J., & Hwang, C. Y. (2004). The 52‐week high and momentum investing. *The Journal of Finance, 59*(5), 2145-2176. doi:10.1111/j.1540-6261.2004.00695.x

Gutierrez, R. C., & Kelley, E. K. (2007). The long-lasting momentum in weekly returns. *Journal of Finance, forthcoming*. doi:10.1111/j.1540-6261.2008.01320.x

Hamelink, F. (2003). Systematic patterns before and after large price changes: Evidence from high frequency data from the Paris Bourse. *Journal of Forecasting, 22*(6 - 7), 533-549. doi:10.1002/for.874

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*(6), 2143-2184. doi:10.1111/0022-1082.00184

Howe, J. S. (1986). Evidence on stock market overreaction. *Financial Analysts Journal, 42*(4), 74-77. doi:10.2469/faj.v42.n4.74

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65-91. doi:10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance, 56*(2), 699-720. doi:10.1111/0022-1082.00342

Kahneman, D. (2003). A perspective on judgment and choice: mapping bounded rationality. *American psychologist, 58*(9), 697. doi:10.1037/0003-066X.58.9.697

Larson, S. J., & Madura, J. (2003). What drives stock price behavior following extreme one - day returns. *Journal of Financial Research, 26*(1), 113-127. doi:10.1111/1475-6803.00048

Lasfer, M. A., Melnik, A., & Thomas, D. C. (2003). Short-term reaction of stock markets in stressful circumstances. *Journal of Banking & Finance, 27*(10), 1959-1977. doi:10.1016/S0378-4266(02)00313-8

LeBoeuf, R. A., & Shafir, E. (2009). Anchoring on the" here" and" now" in time and distance judgments. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(1), 81. doi:10.1037/a0013665

Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of financial economics, 104*(2), 401-419. doi:10.1016/j.jfineco.2011.04.003

Liang, Y., & Mullineaux, D. J. (1994). Overreaction and reverse anticipation: two related puzzles? *Journal of Financial Research, 17*(1), 31-43. doi:10.1111/j.1475-6803.1994.tb00172.x

Lo, A. W., & MacKinlay, A. C. (1990). An econometric analysis of nonsynchronous trading. *Journal of Econometrics, 45*(1-2), 181-211. doi:10.1016/0304-4076(90)90098-E

Lobão, J., & Costa, A. I. (2019). Short-term overreaction in equity ETFs following extreme one-day returns. *Revista Contabilidade & Finanças, 30*(81), 352-367. doi:10.1590/1808-057x201807630

Lobão, J., & Costa, A. I. (2020). Do Fixed-Income ETFs Overreact? Evidence of Short-term Predictability following Extreme Price Shocks. *Cuadernos de Economía, 43*(122), 131-144. doi:10.32826/cude.v42i122.145

Lobão, J., & Jerke, M. E. (2020). Short-term Overreaction in American Depository Receipts. *Scientific Annals of Economics and Business, 67*(4), 423-435. doi:10.47743/saeb-2020-0023

Lobe, S., & Rieks, J. (2011). Short-term market overreaction on the Frankfurt stock exchange. *The Quarterly Review of Economics and Finance, 51*(2), 113-123. doi:10.1016/j.qref.2010.12.002

Lux, T. (1996). The stable Paretian hypothesis and the frequency of large returns: an examination of major German stocks. *Applied Financial Economics, 6*(6), 463-475. doi:10.1080/096031096333917

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature, 35*(1), 13-39.

Madura, J., & Richie, N. (2004). Overreaction of exchange-traded funds during the bubble of 1998-2002. *The Journal of Behavioral Finance, 5*(2), 91-104. doi:10.1207/s15427579jpfm0502_3

Mazouz, K., Alrabadi, D. W., & Yin, S. (2012). Systematic liquidity risk and stock price reaction to shocks. *Accounting & Finance, 52*(2), 467-493. doi:10.1111/j.1467-629X.2011.00403.x

Michayluk, D., & Neuhauser, K. L. (2006). Investor overreaction during market declines: Evidence from the 1997 Asian financial crisis. *Journal of Financial Research, 29*(2), 217-234. doi:10.1111/j.1475-6803.2006.00175.x

Mussweiler, T., & Strack, F. (1999). Hypothesis-consistent testing and semantic priming in the anchoring paradigm: A selective accessibility model. *Journal of Experimental Social Psychology, 35*(2), 136-164. doi:10.1006/jesp.1998.1364

Mussweiler, T., & Strack, F. (2001). Considering the impossible: Explaining the effects of implausible anchors. *Social Cognition, 19*(2), 145-160.

doi:10.1521/soco.19.2.145.20705

Mussweiler, T., Strack, F., & Pfeiffer, T. (2000). Overcoming the inevitable anchoring effect: Considering the opposite compensates for selective accessibility. *Personality and Social Psychology Bulletin, 26*(9), 1142-1150. doi:10.1177/01461672002611010

Nguyen, T., Pham, V. T. L., & To, T. D. (2007). Abnormal Returns After Large Stock Price Changes: Evidence from Asia-Pacific Markets. *International Financial Review, 8*, 205-227. doi:10.1016/S1569-3767(07)00010-6

Northcraft, G. B., & Neale, M. A. (1987). Experts, amateurs, and real estate: An anchoring-and-adjustment perspective on property pricing decisions. *Organizational behavior and human decision processes, 39*(1), 84-97. doi:10.1016/0749-5978(87)90046-X

Oechssler, J., Roider, A., & Schmitz, P. W. (2009). Cognitive abilities and behavioral biases. *Journal of economic behavior & organization, 72*(1), 147-152. doi:10.1016/j.jebo.2009.04.018

Otchere, I., & Chan, J. (2003). Short-term overreaction in the Hong Kong stock market: can a contrarian trading strategy beat the market? *The Journal of Behavioral Finance, 4*(3), 157-171. doi:10.1207/S15427579JPFM0403_5

Park, J. (1995). A market microstructure explanation for predictable variations in stock returns following large price changes. *Journal of Financial and Quantitative Analysis, 30*(2), 241-256. doi:10.2307/2331119

Parthasarathy, S. (2019). Predictable patterns following large price changes and volume: Evidence from the Indian stock market. *Review of Behavioral Finance*. doi:10.1108/RBF-06-2018-0058

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of political Economy, 111*(3), 642-685. doi:10.1086/374184

Patel, V., & Michayluk, D. (2016). Return predictability following different drivers of large price changes. *International Review of Financial Analysis, 45*, 202-214. doi:10.1016/j.irfa.2016.03.004

Peterson, D. R. (1995). The influence of organized options trading on stock price behavior following large one - day stock price declines. *Journal of Financial Research, 18*(1), 33-44. doi:10.1111/j.1475-6803.1995.tb00209.x

Pritamani, M., & Singal, V. (2001). Return predictability following large price changes and information releases. *Journal of Banking & Finance, 25*(4), 631-656. doi:10.1016/S0378-4266(00)00091-1

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance, 53*(1), 267-284. doi:10.1111/0022-1082.95722

Savor, P. G. (2012). Stock returns after major price shocks: The impact of information. *Journal of financial economics, 106*(3), 635-659. doi:10.1016/j.jfineco.2012.06.011

Scott, J., Stumpp, M., & Xu, P. (1999). Behavioral Bias, Valuation, and Active Management. *Financial Analysts Journal, 55*(4), 49-57. doi:10.2469/faj.v55.n4.2284

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives, 17*(1), 83-104. doi:10.1257/089533003321164967

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and brain sciences, 23*(5), 645-665. doi:10.1017/S0140525X00003435

Stanovich, K. E., & West, R. F. (2008). On the relative independence of thinking biases and cognitive ability. *Journal of personality and social psychology, 94*(4), 672. doi:10.1037/0022-3514.94.4.672

Statista. (2021). Distribution of countries with largest stock markets worldwide as of January 2021, by share of total world equity market value. Retrieved from https://www.statista.com/statistics/710680/global-stock-markets-by-country/ - Accessed on: 27/05/2021

Stoll, H. R. (2000). Presidential address: friction. *The Journal of Finance, 55*(4), 1479-1514. doi:10.1111/0022-1082.00259

Strack, F., & Mussweiler, T. (1997). Explaining the enigmatic anchoring effect: Mechanisms of selective accessibility. *Journal of personality and social psychology, 73*(3), 437. doi:10.1037/0022-3514.73.3.437

Sturm, R. R. (2003). Investor confidence and returns following large one-day price changes. *The Journal of Behavioral Finance, 4*(4), 201-216. doi:10.1207/s15427579jpfm0404_3

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science, 185*(4157), 1124-1131. doi:10.1126/science.185.4157.1124

Weber, P., & Rosenow, B. (2006). Large stock price changes: volume or liquidity? *Quantitative Finance, 6*(1), 7-14. doi:10.1080/14697680500168008

Wegener, D. T., Petty, R. E., Blankenship, K. L., & Detweiler-Bedell, B. (2010). Elaboration and numerical anchoring: Implications of attitude theories for consumer judgment and decision making. *Journal of Consumer Psychology, 20*(1), 5-16. doi:10.1016/j.jcps.2009.12.003

Wegener, D. T., Petty, R. E., Detweiler-Bedell, B. T., & Jarvis, W. B. G. (2001). Implications of attitude change theories for numerical anchoring: Anchor plausibility and the limits of anchor effectiveness. *Journal of Experimental Social Psychology, 37*(1), 62-69. doi:10.1006/jesp.2000.1431

Wilson, T. D., Houston, C. E., Etling, K. M., & Brekke, N. (1996). A new look at anchoring effects: basic anchoring and its antecedents. *Journal of Experimental Psychology: General, 125*(4), 387. doi:10.1037/0096-3445.125.4.387

Yildiz, Y., & Karan, M. B. (2019). Momentum or market? Determinants of large stock price changes in an emerging market. *Applied Economics, 51*(7), 731-742. doi:10.1080/00036846.2018.1524128

Yu, S., Rentzler, J., & Tandon, K. (2010). Reexamining the uncertain information hypothesis on the S&P 500 Index and SPDRs. *Review of Quantitative Finance and Accounting, 34*(1), 1-21. doi:10.1007/s11156-009-0119-x

Zawadowski, Á. G., Andor, G., & Kertész, J. (2006). Short-term market reaction after extreme price changes of liquid stocks. *Quantitative Finance, 6*(4), 283-295. doi:10.1080/14697680600699894