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Between the Bull and the Bear: Overreaction and Market Sentiment in the Banking Sector

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PREFACE AND ACKNOWLEDGEMENTS

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ABSTRACT

People tend to overreact when dramatic and unexpected news becomes public. The Banking Sector has been proven to be heavily affected by people "fears and greed": confidence is easily lost, and hard to build up. This study will investigate if this behavior generates opportunities for investors to gain abnormal returns by following a short-term reversal strategy specifically for the banking sector. In particular, it will investigate if overreaction is stronger (and thus more profitable) depending on market sentiment. Results show that there is some level of overreaction in the banking sector as a whole, and Cumulative Average Abnormal Returns are greater for events that happen during High Sentiment periods.

Keywords: Overreaction, Market Sentiment, Short-Term Reversal, Banking Sector, Contrarian Strategy

JEL Classification: G14

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CHAPTER 1 Introduction

In financial markets, understanding the relationship between investor sentiment and stock price movements is crucial for both academics and practitioners. The banking sector, being the backbone of the global economy, often experiences rapid and sometimes exaggerated price changes in response to market news or events. This phenomenon, known as overreaction, and its subsequent short-term reversal, has long intrigued researchers and investors.

The research question at the heart of this thesis is: *Is the overreaction of the banking sector (and thus its following short-term reversal) stronger during low or high market sentiment?*

This study aims to shed light on the underlying psychological and behavioral factors that drive market dynamics. In particular, given the current interest rate environment and the recent news of bank failures, the banking sector is considered a “hot” topic in the financial world. Investor sentiment, whether optimistic or pessimistic, profoundly influences trading decisions, often leading to price distortions.

As bank stocks are by nature difficult to analyze because they behave differently from other sectors’ stocks (among others: high leverage ratio, strong sensitivity to macroeconomic changes, and risk of panic selling), understanding the interplay between market sentiment and the overreaction of the banking sector provides valuable insights. If it can be determined whether overreactions are stronger during low or high market sentiment, it could help investors anticipate short-term price movements and make more informed trading decisions. Various trading strategies could be built to exploit and capitalize on these price inefficiencies.

Additionally, this knowledge can contribute to academic research in behavioural finance and expand the existing literature on the overreaction hypothesis and short-term reversals, which is often focused on the whole market rather than a specific sector.

The literature defines short-term reversal as the phenomenon in which stocks with relatively low returns over the past period (might be day, week, or month) earn positive abnormal returns in the following period. Vice versa, stocks with high returns will subsequently earn negative abnormal returns. This anomaly has been proven both robust and of economic significance for more than 40 years now, even though many of its aspects still remain questionable (Da, Liu, and Schaumburg, 2014).

Among many possible explanations for short-term reversal, this thesis will focus on the overreaction hypothesis. If market prices reflect investor overreaction to information, fads, or cognitive biases, this might lead to the existence of short term reversals (Shiller, 1984; Black, 1986; Summers and Summers, 1989; Subrahmanyam, 2005).

We can call this idea "sentiment-based explanation," as discussed in the study by Da, Liu, and Schaumburg (2014): it suggests that stocks don't behave like random processes over very short time intervals but instead exhibit a noticeable pattern of serial correlation across all time periods. This pattern holds even when there are predictable variations in expected returns.

But how does overreaction relate to market sentiment? Does the stock market always react in the same way, or can it be influenced by investors' "fears and greed"?

John Maynard Keynes in 1936 already asserted the influence of investors' "animal spirits" leads the market to swing wildly, moving prices in a way unrelated to fundamentals. After Keynes, many other authors have considered the possibility that sentiment-driven investors might move prices in an irrational way. Intuitively, in a period of fear, people might reason with their more primitive mental system (System 1 to cite Kahneman's "Thinking Fast and Slow" book), letting emotions overcome rationality. The same might happen in periods of excessive optimism. In these extremely bullish and bearish times, our minds work quickly and automatically, with little or no effort and no sense of voluntary control, and this is then reflected in the market.

Some criticism against sentiment effects argues that they would be eliminated by rational traders seeking to take advantage of the profit opportunities created by mispricing. However, if rational traders cannot fully exploit such opportunities, sentiment effects become more likely. Thus, we can easily say that sentiment plays an important role in asset pricing and can affect the market: *"Nowadays the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects"* (Baker and Wurgler, 2007, p. 1).

A recent example of these periods of sentiment-driven market has been given by the crisis of the banking sector at the beginning of 2023. In fact, between early 2020 and March 2022, banks' deposits had tremendous growth because of the high level of liquidity in the market (see unconventional expansionary monetary policies) and because investing in the money market resulted unattractive. A significant part of this growth was directed towards fixed-income securities (mainly those with fixed coupons), which lost value when interest rates increased again to fight inflation. According to Jiang et al. (2023), the total unrealized losses on securities in US banks amount to around $2.2 trillion.

Banks, more than other types of companies, are built on trust, credibility, and accountability. The functioning of the banking system and society as a whole depends heavily on the trust placed in financial institutions and banks. A changing macroeconomic environment (with the rise of interest rates and inflation), combined with mismanagement issues in a climate of fear, can lead bank stocks' prices to a high volatility scenario, which in some cases might be motivated, but in others, overreaction can play a major role.

A clear case study can be found in Credit Suisse. It hasn't been a great time for Credit Suisse. Its biggest shareholder, Saudi National Bank, was asked if he would buy more stock in the bank by a Bloomberg journalist and he replied: "Absolutely not". The framing of these words caused some "jitters" and the share price fell in the biggest one-day selloff in the stock on record, leaving it down more than 85% over the last year (As of March 21, 2023).

Now, while Credit Suisse's balance sheet was reasonably strong, its reputation was obviously not. The unending list of scandals, most of them coming from the firm's senior management and its investment banking division, have destroyed the once impressive brand. This loss of reputation has driven away top talent and the firm's customers - collapsing profitability. This profitability issue, in a climate of fear, can put a firm like Credit Suisse on the rocks.

This leads to our research question:
Is the overreaction of the banking sector (and thus its following short-term reversal) stronger during low or high market sentiment?

Researchers are still conflicted on this topic. Piccoli and Chaudary (2018), for example, find that overreaction is much stronger when investor sentiment is low. On the other side, Yu and Yuan (2011) and Stambaugh, Yu, and Yuan (2012) find a greater anomaly when investor sentiment is high rather than low. Further analysis of this "conflict" is offered in Chapter 2.

This study finds that while there is some level of overreaction in the banking sector, results are sensible to the type of stock price returns and the trigger used. When using a negative trigger, with closing prices returns, Cumulative Average Abnormal Returns (CAARs) are positive and greater during periods of high market sentiment, but with stock price midpoints returns, high sentiment events lack significance. When using a positive trigger, both with closing and midpoint stock price returns, CAARs are negative and greater during periods of high market sentiment. These findings should thus imply that is it possible to build a Long-Short Strategy in order to exploit the overreaction of the banking sector, where stock prices react too strongly to news and subsequently tend to mean revert, creating the short-term reversal phenomenon. This strategy is much more profitable during bullish periods, but for the timeframe considered (2001 to 2021), there have been many more bearish trading days.

The following paper is structured as follows: Chapter 2 will provide a literature review of the short-term reversal, overreaction, market sentiment, and the banking sector. Chapters 3 and 4 will describe the Data and the Methodology of the research. Results will be analyzed and discussed in Chapter 5. Finally, a summary of the conclusions and main points of the paper is provided in Chapter 6.

CHAPTER 2 Literature Review

The literature in this research area is definitely extensive and still of interest. The studies are similar in general, although it's worth noting the heterogeneity in the specific research designs, "triggers", markets, and the definition of large returns and results: there is not a standard approach and thus many papers might provide very different conclusions and explanations. The following sub-sections will describe and review some of the most influential studies in the field.

2.1 Short-Term Reversal and Contrarian Strategy

De Bondt and Thaler in their popular paper "Does the Stock Market Overreact?" (1985) already had the intuition that if stock prices systematically overshoot, it should be possible to predict their reversal from past data alone. Thus, extreme movements in stock prices will be followed by an opposite direction movement. This represents a clear violation of the weak-form market efficiency.

A contrarian investment strategy aims to exploit this violation of efficiency by buying stocks that have been losers and selling short stocks that have been winners. There can be many strategies to exploit short-term reversals, but the standard one is a zero-investment strategy that in each period sorts stocks into deciles on the basis of prior-period returns, buys stocks in the bottom decile (losers), and short stocks in the first decile (winners) (Da, Liu, and Schaumburg, 2014).

If the premise is that the stock market overreacts to news, winners will tend to be overvalued and losers undervalued (Chan, 1988). Is important to note, as in Chan (1988), that the estimation of the abnormal return to the contrarian investment strategy is sensitive to the model and estimation method. As an example, in his paper, he found that the contrarian strategy earns a very small abnormal return, which is probably economically insignificant.

The way the *Abnormal Return* is calculated is crucial in this type of studies, in particular, the precision in the estimation of *Expected Returns* can completely change the results of research of this type. To avoid this, I will use the Fama-French 3 Factors as main model. A detailed explanation can be found in Chapter 4 (Methodology).

Brown, Harlow, and Tinic (1988) define as an event the one-day residual returns above 2.5 or below -2.5 percent for the largest firms in the SandP500 between July 1963 and December 1985, with a total of 4806 positive and 4319 negative events. On average, over the next 10 trading days after the event, prior winners earn (insignificant) CAPM risk-adjusted excess returns (CAER) of 3 basis points, while prior losers earn about 37 basis points (significant).

Similarly, Bremer and Sweeney (1991) studied all Fortune 500 companies with a one-day return below -10.0 percent and found that, for the period between July 1962 and December 1986, three days after the price "jump", the "Cumulative Excess Return" is an extraordinary 2.643 percent. Also in this case, it is necessary to highlight the fact that Cumulative Excess Returns are calculated by subtracting the sample average returns from the event day's actual returns. Thus, these results might be completely different from a study that uses other models to calculate expected returns.

Lehmann (1990) tests the standard contrarian strategy in order to verify the efficient market hypothesis: it studies the profits of costless (i.e., zero net investment) portfolios which give negative weight to recent winners and positive weight to recent losers. Theoretically, the short-run martingale models predict that these costless portfolios should tend to earn zero profits. In contrast, they will typically profit from return reversals over some horizon if stock prices overreact, and this strongly suggests the rejection of the efficient market hypothesis. Portfolios of securities that had positive returns in one week typically reverted in the next week (-0.35 to -0.55 percent per week on average), while those with negative returns in one week typically had positive returns in the next week (0.86 to 1.24 percent per week on average). The costless portfolio had positive profits in roughly ninety percent of the weeks. It is difficult to account for these results within the efficient market framework. These measured arbitrage profits persist after corrections for the mismeasurement of security returns due to bid-ask spreads and for plausible levels of transaction costs.

Jegadeesh (1990) employed a similar strategy where he created ten portfolios based on returns data and used ex-ante predictions of the regression parameters. Between top and bottom deciles, he found a difference in risk-adjusted returns of 2.49% per month, for the period 1934-1987. He suggested that this consistent pattern might be due to market inefficiencies or systematic changes in expected stock returns.

Another possible explanation for these abnormal returns is the "bid-ask bounce" as in Ball, Kothari, and Wasley (1995). Contrarian strategies' returns are usually estimated from simulated trading using historical data, not from implemented trading. The historical data come almost exclusively from large-scale files such as CRSP which only provide *estimates* of closing prices, and simulated contrarian portfolios tend to buy at the bid and short at the ask, which is not implementable for most investors. This might result in an upward bias when calculating contrarian abnormal returns. To ensure that the results will not be unduly affected by the bid–ask bounce, I will follow Subrahmanyam (2005), among others, and examine returns computed using mid-quotes. The use of mid-quotes returns allays concerns about bid-ask phenomena affecting the results.

Lakonishok et al. (1994) offer an explanation of the outperformance of contrarian strategy using the value factor as an example. Value strategies might produce higher returns because they are contrarian to "naive" strategies followed by other investors. These naive strategies might range from extrapolating past earnings growth too far into the future to assuming a trend in stock prices, overreacting to good or bad news, or simply equating a good investment with a well-run company irrespective of price. Regardless of the reason, some investors tend to overbuy growth stocks because they get overly excited about their recent good performance, so these "glamour" stocks become overpriced. Similarly, they tend to oversell “value” stocks by overreacting to their recent bad performances. These out-of-favor "value" stocks become under-priced. The logic behind Lakonishok’s Growth-Value example is that contrarian investors outperform the market because they bet against such naive investors by investing disproportionately in stocks that are under-priced (value stocks) and underinvest in stocks that are overpriced (growth stocks).

Short-term stock reversals are also often seen as evidence that the market lacks enough liquidity to counteract the impact of sudden buying and selling pressure and that market makers set prices to manage their inventories. For example, Grossman and Miller (1988) and Jegadeesh and Titman (1995) assert that these reversals arise from inventory imbalances experienced by market makers, and that the contrarian profits are a form of compensation for inventory risks.

Madhavan and Smidt (1993), and Hendershott and Seasholes (2007) have found that dealer prices are inversely related to their inventory, lending credence to the idea that dealers proactively manage their inventories. This theory of liquidity suggests that reversals should be decreasing in size over time since market liquidity has considerably increased. Additionally, it predicts that reversals will be more pronounced among small-cap stocks than large-cap stocks, which tend to have lower turnover. On the other hand, De Groot et. al (2012) discovered that the net reversal profits for the largest 500 and 100 US stocks are substantial and positive, and that they did not decrease over the course of the second decade in their sample. This finding refutes the notion that reversals can be explained exclusively by liquidity considerations.

Lo and MacKinlay (1990) provide another possible cause of short-term reversals: nonsynchronous trading (lead-lag effect) contributes to contrarian profits. If the information is diffused gradually in financial markets and large-cap stocks react more quickly to information than small-cap stocks (that are covered by fewer analysts), the returns of large-cap stocks might lead the returns of small-cap stocks. However, always De Groot et al. (2012) find that reversal profits are smaller for the 1500 largest US stocks than for the 500 and 100 largest stocks. This is inconsistent with this explanation since nonsynchronous trading predicts a size-related lead-lag-effect in stock returns and higher reversal profits among small-cap stocks.

Jegadeesh and Titman (1995a, p. 1) further prove the inconsistency of Lo and MacKinlay (1990) nonsynchronous trading explanation: “Most of the contrarian profit is due to stock price overreaction and a very small fraction of the profit can be attributed to the lead-lag effect.”

This behavioural explanation predicts that market prices tend to overreact to information in the short run, as already pointed out in De Bondt and Thaler (1985). Blitz et al. (2013) confirm that the overreaction explanation of short-term reversals is the only one that is “not inconsistent” with their findings.

In conclusion, many authors find different results for short-term reversal, but nowadays, we can affirm that sufficient research and backtests have been made in order to prove that is a profitable and robust strategy. In real-life investments though, many other factors could undermine the actual and concrete applicability of this strategy, such as transaction costs, short-sale constraints, and market sentiment.

In the next sub-section, it will be provided a focus on the “overreaction” literature, given the major importance that it has in financial markets and the fact that it’s one of the most plausible explanations of the short-term reversal anomaly.

2.2 The Overreaction Hypothesis

One of the relatively biggest controversial subjects in the recent financial literature is whether investors rationally price stocks or whether they overreact to market information, generating stock’s overpricing and underpricing (Dreman and Lufkin, 2000).

Brown and Harlow (1988, p. 1) define overreaction as “the general tendency for investors to process event-related news in an overzealous fashion. Market participants can be said to overreact when unexpected favourable (unfavourable) announcements induce trading behaviour that results in price appreciation (depreciation) that is excessive relative to the actual value implied by the nature of the event.”

In their pioneering study, De Bondt and Thaler (1985), formally stated the “Overreaction Hypothesis” (OH), and posed the basis of a new stream of literature with their strong and innovative hypotheses:

OH - 1 Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction (the Directional Effect).

OH - 2 The more extreme the initial price movement, the greater will be the subsequent adjustment (the Magnitude Effect).

To demonstrate these hypotheses, De Bondt and Thaler showed that companies having the largest losses during a three-year estimation period realized returns over the following five years that were 19.6% greater than the market average. On the other side, companies having the largest gains lost 5% relative to the market in that later period. They thus concluded that the stock market tends to overreact to extreme situations and that the long-term overreaction process is apparently asymmetric. It is noticeable that, although it is considered to be a pioneer in the overreaction field, their study strongly differs from this thesis, as it is focused on the long-term reversal phenomenon, and it is a cross-sectional type of research, while this paper will be a time-series analysis related to short term reversals (as further explained in Chapter 4).

The Overreaction Hypothesis predicts that more extreme price changes will cause more extreme responses, so according to Bernstein (1985), Brown and Harlow (1988), it is also conceivable that the size of the subsequent reaction will vary inversely with the amount of time needed for the initial price change to occur. This leads to the third hypothesis:

OH - 3 The shorter the duration of the initial price change, the more extreme the subsequent response (the Intensity Effect).

All three hypotheses imply return forecastability and specific violations of weak form market efficiency (De Bondt, 1987).

Howe (1986) provides further evidence to support the overreaction hypothesis. Specifically, he found that firms with large positive returns because of favourable news, performed poorly in the 50-week period following that event, with returns averaging about 30 percent below the market. The results for the sample of bad news stocks show a large price decline followed by a period of above-average returns.

Given the evidence of the overreaction behaviour, it comes now natural to ask what the underlying explanation for this phenomenon is, and many studies differ in their views.

Daniel et al. (1998) built a model to explain overreaction: if individuals are *overconfident* (e.g., they overestimate the precision of their private information signals and of their predictive skills), they will overweight their private signals relative to the public ones, causing the stock price to overreact.

Zarowin (1990) and Chopra et al. (1992) investigate the impact of the size effect within the overreaction hypothesis using US data and find that adjustment for size does reduce the extra return available from losers. Indeed, Zarowin (1990) believes that all of the extra return can be explained by the size effect, while De Bondt and Thaler (1985) did not believe that their results were due to the size effect.

Dreman and Lufkin (2000) present evidence of overreaction by showing that important fundamentals, upon which securities prices depend, demonstrate little movement in the face of major changes to the returns of favoured and unfavoured stocks, and they find no explanation other than psychological influences to account for this finding.

Griffin and Tversky (1992) argue that, in revising beliefs, people tend to focus on the ‘‘strength” or extremeness of available evidence (e.g., size of an effect) and pay insufficient attention to its ‘‘weight” or credence (e.g., size of the sample). This leads to overconfidence when ‘‘strength” is high and ‘‘weight” is low, and underconfidence when the opposite is the case. In the context of stock prices, this means that investors would tend to have overconfidence in events (news, developments) that are sizable/grave in magnitude but low in frequency, and hence would tend to overreact.

The purpose of this thesis though, is not to provide an explanation for the Overreaction Hypothesis, but rather to study the relationship between OH and Market Sentiment, with an additional focus on the banking sector as shown in the next sections.

2.3 Market Sentiment

“Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than on a mathematical expectation, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of animal spirits—of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities” (Keynes; The General Theory of Employment, Interest, and Money (1936), p. 81).

Investor sentiment, defined broadly, is “a belief about future cash flows and investment risks that is not justified by the facts at hand” (Baker and Wurgler 2007, p. 1).

De Long, Shleifer, Summers, and Waldmann (1990) formalized the role of investor sentiment in financial markets. They demonstrated that sentiment changes will lead to more noise trading, greater mispricing, and excess volatility in the presence of uninformed noise traders (who base their trading decisions on sentiment) and risk-averse arbitrageurs who encounter limits to arbitrage. Based on the idea of Griffin and Tversky (1992) that, in making forecasts, people pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight, Barberis et al. (1998) presented a model of investor sentiment that predicts the underreaction of stock prices to earnings announcements and similar events, and the overreaction to consistent patterns of good or bad news.

According to Shiller (2000), the news media is a significant force in setting the stage for market moves. He affirms that investors often follow the printed word, even though much of it may be pure hype. This suggests that market sentiment is heavily influenced by the content of the news. But how does market sentiment relate to overreaction? As previously stated in the introduction, there are different views.

Yu and Yuan (2011) find that in the mean–variance relation, investor sentiment plays a crucial role. There is a strong positive trade-off between mean and variance when sentiment is low but little (if any) trade-off when sentiment is high. This might happen because sentiment traders are usually reluctant to take short positions in low-sentiment periods, thus they tend to exert greater influence during Bullish markets rather than during Bearish markets (see, for example, Barber and Odean 2008).
Similarly, Stambaugh et al. (2012) combine sentiment and short-sale constraints to investigate the presence of sentiment effects. In particular, the study explores the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns.

With impediments to short-selling, overpricing becomes more difficult to eliminate, so a firm’s stock price can reflect the views of investors who are too optimistic. With market-wide variations in investor sentiment, such overpricing can occur for many stocks during periods of high sentiment.
Karlsson, Loewenstein, and Seppi (2009) build a model that predicts that individuals may add additional information on favourable news and avoid information following neutral or bad news. This Ostrich-like behaviour might lead sentiment-driven investors to participate and trade more aggressively in high-sentiment periods.

So, for some researchers, overreaction is stronger during high market sentiment periods, and this happens mainly because of market frictions (short-sale constraints) and non-rational behaviours (reluctance to take short-positions in low-sentiment periods, Ostrich-like behaviour). On the contrary, another stream of literature predicts the exact opposite: overreaction is stronger during periods of low sentiment.

According to Piccoli and Chaudury (2018), extreme market movements are by construction very unlikely to occur, which makes them surprising and can cause people to overreact. Griffin and Tversky (1992) found that people tend to give more weight to unexpected events, leading to overreaction. However, in times of low sentiment, large market movements stand out more and can be more startling for investors because when people are feeling pessimistic, they may be more uncertain about their beliefs, which can contribute to the overreaction to extreme market events. This view is coherent with Kahneman and Tversky's (1979) prospect theory, in which individuals weigh losses more than gains. Thus, in a “bearish” period where futures expectations are already negative, bad news might provoke a bigger stock sell-off than in a bullish market.

A natural question that comes is if every sector of the market (over)reacts in the same way or if there might be additional factors that influence specific sectors’ stock trends. In the latest months, for example, we have seen how the banking sector’s stock prices have been “nervous” and “noisy”. The collapse of US-based Silicon Valley Bank and Signature Bank followed by the forced takeover of Credit Suisse by UBS sparked widespread worries about a new financial crisis in early March.

The main goal of this thesis is to verify which of the two streams of literature is a more accurate representation of actual market behaviour: *Is the overreaction of the banking sector (and thus its following short-term reversal) stronger during low or high market sentiment?*

From the logical and psychological perspective, I am more inclined to follow Piccoli and Chaudury’s stream of literature: the effects of fears are usually stronger than the effects of greed. As we are behaving under the guidance of “animal spirits”, we usually tend to act more irrationally in moments of panic rather than in moments of excessive optimism: losses are weighted much more than gains (as in the prospect theory). This approach is also supported by episodes of “momentum crashes” (Daniel, Moskowitz, 2016). They found that momentum strategies (which are basically the opposite of contrarian strategies: buy recent winners and short recent losers) tend to perform poorly during panic states, following multi-year market drawdowns, and in periods of high market volatility. In addition, the banking sector has been proven to be particularly affected by irrationality (such as the herding behaviour in the case of bank runs for example), which might be in some cases justified but in others not. Thus, the tentative hypothesis is the following:

Hypothesis*:* *Overreaction of the Banking Sector is stronger during periods of low market sentiment.*

The next subsection will briefly discuss the literature related to the banking sector, sentiment, and overreaction, given the current news and its systemic importance.

2.4 The Banking Sector

Banks, whether commercial or investment, differ a lot from every other type of company. One of the main features of a bank is its complexity: it's an organization with multiple business lines, products, and services. This complexity makes it challenging for new entrants to compete effectively in the sector. In addition, the banking sector is heavily regulated by government authorities to ensure financial stability and consumer protection. Banks are required to meet certain capital requirements, maintain reserves, and comply with a range of other regulations.

By nature, a bank's leverage is much higher than that of nonfinancial corporations. This is also why usually the financial industry is excluded from market and sector-specific research: they follow a completely different framework both in the balance sheet but also in their everyday behaviour, when compared to "traditional" industries. Basel III international regulatory framework specifies a minimum leverage ratio of 3%, which is already much lower when compared to other industries' leverages. The pervasive idea in the sector is that "equity is expensive", and bankers have always asserted that increasing equity requirements would reduce loans supply and thus economic growth. One could then argue that banks and other financial institutions (that hold equity in a very small fraction of their assets) might result fragile from a societal point of view (Admati et al., 2013).

That is why it comes naturally to highlight the importance of "trust". Banks rely on the trust of their customers, which is why reputation and accountability are of major relevance in this sector. The lack of this factor might lead to bank runs and subsequent fall in a bank's stock price (or even bankruptcy, see the Silicon Valley Bank case).

As first modeled in Diamond and Dybvig (1983), during a bank run, depositors rush to withdraw their deposits because they expect the bank to fail. In fact, the sudden withdrawals can force the bank to liquidate many of its assets at a loss and fail.

Banks are clearly fragile to "irrational exuberance" and panic behaviours; thus, they are also highly exposed to market sentiment. Uygur and Tas (2014) analyse the Turkish stock market and find that investor sentiment affects mostly the conditional volatility of the key driving sectors of the Turkish economy and Istanbul Stock Exchange: Industry and Banking sectors.

Gandhi et al. (2019) find convincing evidence that the performance of banks during the period from January 2004 to December 2012 was driven by investors' irrational market-wide crisis sentiment, suggesting that the losses experienced by bank stock investors were amplified both by irrational market-wide and firm-individual crisis sentiment. This can be easily seen in the recent cases of Silicon Valley

Bank, Signature Bank, Credit Suisse, and First Republic Bank. Each of the failures had its characteristics and reasons, but surely the general climate of fear and suspicion in the banking sector has been a common denominator.

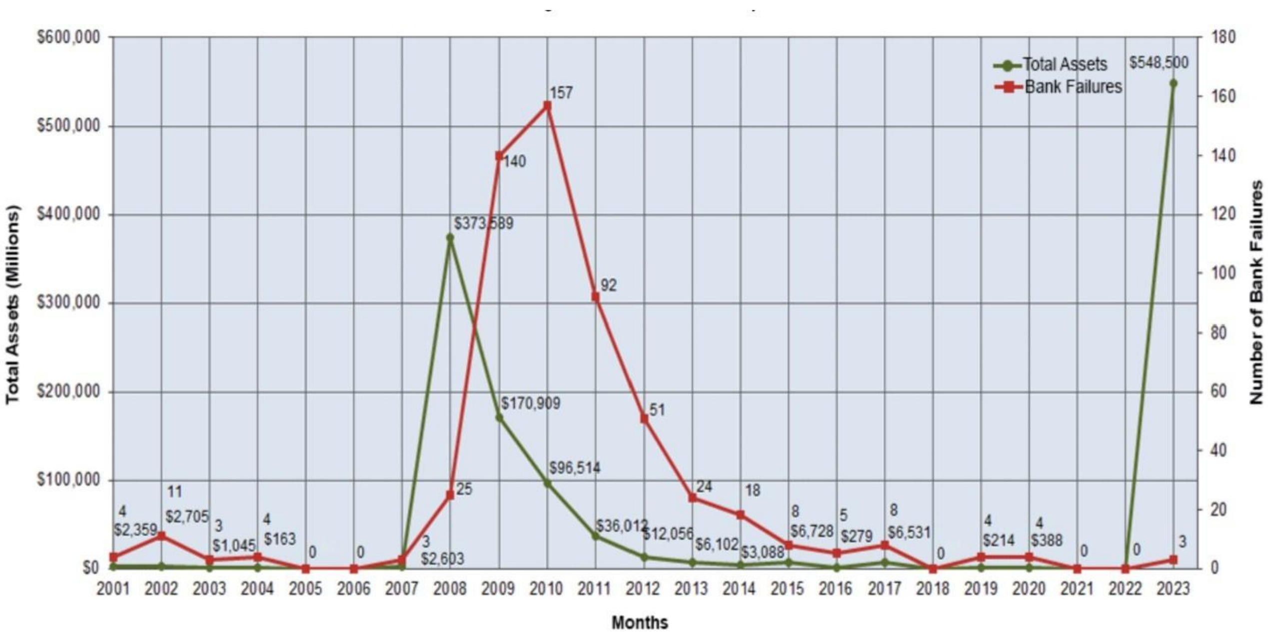

Figure 9 - Bank Failures in Brief from 2001 to May 2023 - FDIC: Bank Failures in Brief

As *Figure 1* shows, bank failures are not as uncommon as expected: on the contrary, since 2001 there have been around 500 bankruptcies. In particular, while the 2008 Great Financial Crisis mainly affected a large number of smaller banks, the 2022-2023 crisis hit three major banks, with a combined value of total assets of more than $500 billion. Is this all due to the interest rates hikes or can there be any other reasons such as market sentiment? The SVB case study offers a clear example of how other external factors can be strongly influential.

2.5 A case study: Silicon Valley Bank

The Silicon Valley Bank (SVB) was one of the main banks that financed start-up projects in Silicon Valley. Just a few weeks before the bank's failure, it was named by Forbes as one of the best American banks based on its impressive growth, credit quality, and profitability, highlighting its success and stability in the industry.

SVB failed on the 10 March 2023, when many of its customers began to withdraw their money due to rumours that the bank might run out of cash. This all began a few years ago when tech and pharmaceutical start-ups were growing at dizzying rates and there was a lot of liquidity in the market. A lot of money was circulating because of the expansionary policy of the FED between March 2020 and April 2022 as a response to the COVID-19 pandemic. Expansionary policies led to a huge increase in investments, and many of these investments went to Silicon Valley start-ups, which were then deposited in banks as SVB.

Banks were incentivized to invest in Government securities because they were considered highly liquid and had low (if any) capital requirements. In addition, SVB were exempted from most of the toughest regulatory measures because they had less than $250 billion in asset under management. This exemption has been said to be the result of lobbying: in 2018 the Dodd-Frank threshold to consider systemically important a bank (and thus incur in higher regulation and supervision) has been raised from 50 to $250bln. Under the Risk-Weighted capital requirements, Treasury Bonds are risk-weighted to zero, meaning that SVB had to hold zero equity against the treasury position. SVB was able to build up a lot of interest rate risk without it being reflected in the capital requirement under the regulatory framework.

In 2022, the global situation worsened with inflation, the war in Ukraine, and an energy crisis. Central Banks then increased interest rates to cool down the economy. The Silicon Valley Bank found itself with two problems: deposits were being withdrawn, and its investments were losing value. So, to provide money to its customers, the bank sold some of its investments at a loss. The market didn't take the situation well, and Moody's downgraded the Silicon Valley Bank to just above junk level. As a result, the SVB also crashed in the stock market, and in the end, it failed in less than 48 hours.

The review of the Federal Reserve’s Supervision and Regulation of Silicon Valley Bank claimed that SVB failed because of a “textbook case of mismanagement by the bank”. Its senior leadership failed to manage basic interest rates and liquidity risk. Its board of directors failed to oversee senior leadership and hold them accountable. And Federal Reserve supervisors failed to take forceful enough action, as detailed in the report (BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM, 2023).

Looking at the broader picture, as also stated by the FED’s report, while the cause of SVB's failure can be mainly attributed to the asset-liability mismatch due to inappropriate risk management, social media and fear-sentiment fuelled and accelerated SVB’s crash (Bales and Burghof, 2023).

The importance of social media in influencing people’s decision-making process has increased notably in recent years, leading to possible contagion of individuals’ moods and fears and to “herding behaviours”. In addition, nowadays bank runs are “virtual”: technology enabled immediate withdrawals of funding. This phenomenon might imply an increased Intensity Effect of the Overreaction Hypothesis:

if news spreads faster and sentiment changes more frequently, we can also hypothesize that there will be shorter durations of the initial price changes, meaning more extreme reversals.

CHAPTER 3 Data

To give our research question an answer, we will need two different types of datasets: bank stocks' daily price returns and a sentiment index.

3.1 Bank Stocks' Daily Price Returns

Each of the many data providers has its own pros and cons, but in general since this study will use daily bank stock price returns, many possible biases must be taken into account when dealing with the data cleaning process. The use of stock price return data instead of total return data is crucial to make sure that the effect of dividends and other distributions does not interfere with the *trigger* measure that is going to be used to find events.

As pointed out in Ball et al. (1995), research on trading rule profitability (as in our case) obtained using CRSP, usually records *estimated* closing prices. The estimated closing price might be the last trade of the day (that could be at the closing bid, or the closing ask, or neither) or the bid-ask average in the absence of a trade. Simulated contrarian portfolios tend to buy at the bid and short at the ask, which generates the "Bid-Ask Bounce". To avoid it, the approach of Subrahmanyam (2005) seems well-suited, since it uses returns calculated from quote mid-points.

Using the Refinitiv Eikon "DataStream" dataset for bank stock will let us obtain *closing prices, bid prices* and *ask prices,* in addition to the banks' *market value.*

This study aims to evaluate the overreaction of bank stocks based on market sentiment. This is why it considers a timeframe that spans from January 1st, 2001, to December 31st, 2021: this period of twenty-one years includes two of the biggest market downturns (The Great Financial Crisis of 2008 and the Coronavirus Crash of 2020), but also many upturns.

The first filter used considers only the banking sector in "The Refinitiv Business Classification" (TRBC), which is a market-based classification system. Other filters applied to the first database selection are the timeframe (daily prices from 2001 to 2021) and the currency (only US dollars-denominated stocks to avoid any currency influence). Following this, I considered only first-class shares (common stocks) and both active and currently inactive banks to avoid survivorship bias.

With the Bid and Ask price, I created a new variable called "Midpoint" which is just the average between bid-ask prices. Unfortunately, Refinitiv does not always provide bids and asks, thus for this research I will first analyze "The Overreaction Hypothesis" using *closing price returns*, then make another study using *midpoint prices returns* when available. It's worth noting that most of the midpoints started in April 2006.

In total, this dataset is composed of 2952 banks, but is also important to note that the data available with price midpoints is smaller (2093 banks). In addition, I will consider 20 years of trading activity from January 1st, 2001 until December 31st, 2021, for a total of 5496 trading days.

3.2 Sentiment Index

Measuring the sentiment might be a difficult task. There are various indicators and studies that assess markets, individual investors, and macroeconomic factors and that try to understand the feelings of specific markets.

Empiricists often proxy for investor sentiment with market-based measures such as trading volume, closed-end fund discount, initial public offering (IPO) first-day returns, IPO volume, option implied volatilities (VIX), or mutual fund flows.

Baker and Wurgler (2007) offer one of the most influential models based on financial markets data:
In particular, they use 6 proxies, such as:

- trading volume as measured by NYSE turnover (TURN)
- dividend premium (PDND)
- closed-end fund discount (CEFD)
- the number of IPOs (NIPO)
- first-day returns on IPOs (RIPO)
- the equity share in new issues (S)

$$SENT = -0.23CEFD + 0.23TURN + 0.24NIPO + 0.29RIPO - 0.32PDND + 0.23S$$

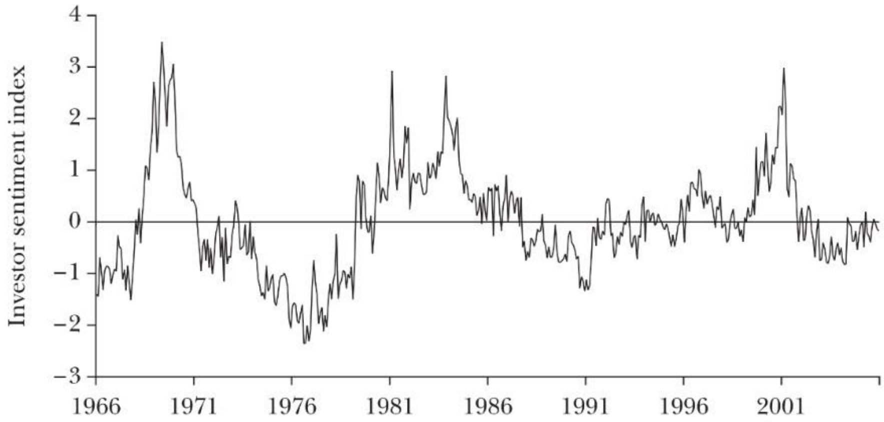

Figure 10 – Baker and Wurgler (2007) Sentiment index

One of the key points is that waves of sentiment have clearly discernible, important, and regular effects on individual firms and the stock market as a whole. When the index is positive (negative), the period corresponds to the high (low) sentiment regime. In naïve terms, a high (low) sentiment period can be considered a proxy for a bullish (bearish) market. Its easy accessibility from the Stern NYU Website and its monthly frequency make it a perfect match for our research purpose. It is useful to observe, as explained in the dataset description, that unlike in Baker and Wurgler (2007), NYSE Turnover has been dropped as one of the six sentiment indicators, thus this sentiment index is going to be based on the other five indicators abovementioned.

Variable	*Mean*	*P50*	*SD*	*Min*	*Max*	*Skewness*	*Kurtosis*
SENT	-0.13	-0.20	0.48	-0.95	2.27	2.04	9.36

***Table 9 – Baker and Wurgler (2007) sentiment index** descriptive table for the period January 2001 to December 2021, with a monthly occurrence.*

In general, this period of twenty-one years has been on average slightly negative in terms of market sentiment, but it is also remarkable that periods of positive market sentiment have been much stronger, and usually present some "peaks", as shown by the underlying *Figure 3*.

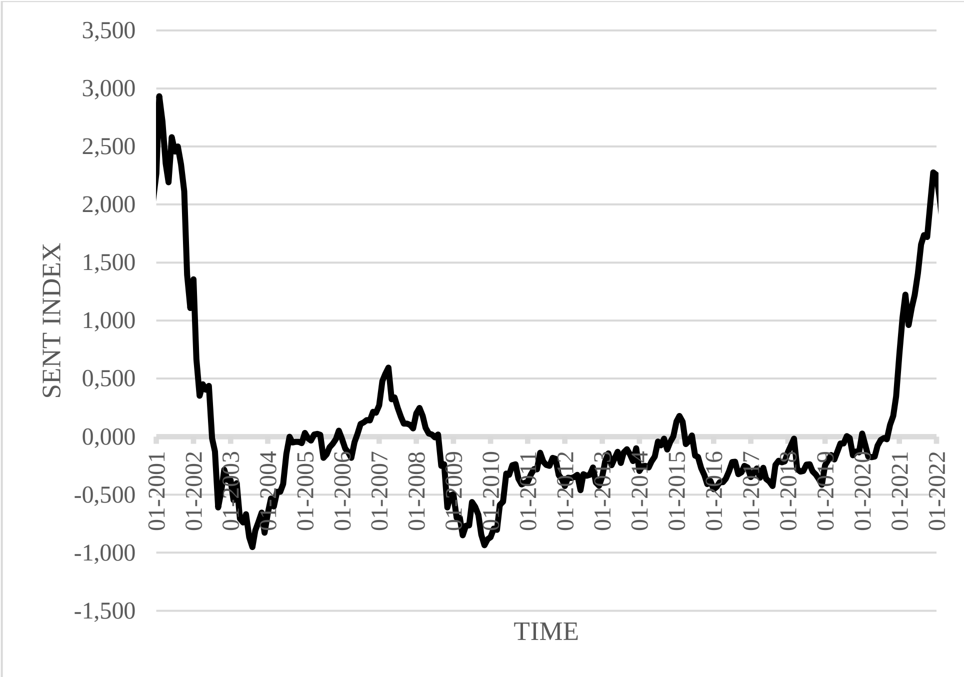

Figure 11 *– Baker and Wurgler (2007) Index from January 2001 until January 2022*

The index shows the drops in sentiment after the 2001 dotcom bubble and after the 2008 GFC, followed by the tremendous increase in 2021, as the 2021 stock market rally confirms.

For this study, is also important to highlight that the vast majority of trading days fell under "low sentiment" periods. As shown in *Figure 4*, the largest part of trading days had a slightly negative sentiment value, mostly ranging between -1 and 0. *Table 2* also shows that while there has not been any day with extremely low sentiment (lower than -1), there have been more than 500 days with extreme excitement in the markets, with sentiment values greater than 1.

B&W Values Range	*N. of Days*
[-2;-1]	0
[-1;0]	3798
[0;+1]	1095
[+1;+2]	294
[+2;+3]	309

Table 10 - Frequency Distribution of Baker and Wurgler index *for the years 2001 to 2021. The table shows that while most of the days were included between -1 and +1 sentiment, there has not been any extreme negative sentiment day but there have been many extremely positive sentiment days with the sentiment index larger than +1 and even +2.*

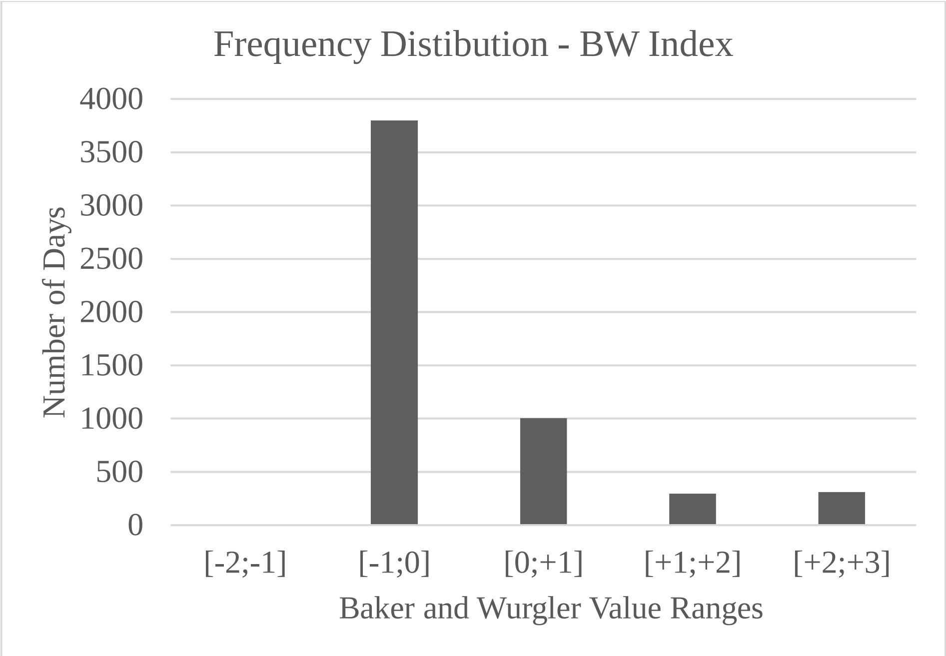

***Figure 12 – Frequency Distribution of Baker and Wurgler index** for the years 2001 to 2021*

The peculiarity of the frequency distribution in this period strongly influenced the features of this study, with the majority of events falling under *negative sentiment trigger,* and thus being defined as negative events.

The following *Method* chapter will better define these characteristics, explaining the “trigger strategy” and the overall design of the study.

CHAPTER 4 Method

Hypothesis: *Overreaction of the Banking Sector is stronger during periods of low market sentiment.*

To test this hypothesis, I will need to combine the (abnormal) returns during the event window and the market sentiment. The following subsections will provide the formal methodology to perform an investigation on whether overreaction is stronger during periods of High or Low sentiment.

4.1 Returns

Consistent with the trigger strategy of Bremer and Sweeney (1991) and Cox and Peterson (1994) I will examine daily stock returns following one-day price changes lower than -10% and greater than +10%. Those one-day extreme returns determine the event day. Thus, an event is identified as a calendar date (t_0) in which an extreme stock price daily movement (-10%; +10%) occurs. In particular, an event is defined "positive event" if the one-day stock price return change is greater than +10%, vice versa a "negative event" happens when the one-day stock price return change is lower than -10%.

In this type of financial studies, the length of the estimation window does not follow a definite rule, rather, it can be adapted based on the specific analysis and event being considered. Following Piccoli and Chaudury (2018), I define an estimation window between the period [t_0 – 136] and [t_0 -10] trading days. This estimation window of 126 trading days in total is well-suited because it represents half of the 252 average trading days in a year. This semi-annual schedule aligns with this research purpose as it is sufficiently balanced between having enough data for the coefficients' estimation and avoiding excessive data that might introduce noise.

The event window, defined as the time period around the event date that we want to analyze, is considered from [t_0 + 1] trading days until [t_0 + 10] trading days, as shown in *Figure 4.* This study will research the short-term reversal for the following event windows: [1,3], [1,5], [1,10]

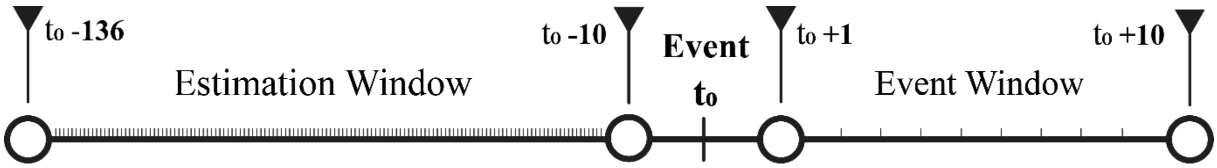

Figure 13 – Timeline of the Event Study*. The Estimation window from 136 trading days before the event until 10 trading days before the event, for a total of 126 trading days (representing half of the 252 available working days in a year). The Total event window is from the day after the "trigger" of [-10%] until 10 trading days after it.*

Abnormal Returns for a stock *i* in a day *t* are defined as the difference between *Actual Returns* and *Expected Returns* in a given event window.

$$Abnormal\ Returns_{(i,t)} = Actual\ Returns_{(i,t)} - Expected\ Returns_{(i,t)} \tag{1}$$

To calculate the conditional expected stock returns component, I use the three-factor model of Fama and French (1993) as a benchmark, following some of the most influential papers in the field (Da, Liu, and Schaumburg, (2014); Piccoli and Chaudury, (2018); Stambaugh, Yu, and Yuan, (2012)).

Fama and French (hereby F-F) model involves regressing daily stocks' returns on three factors: market excess return (MKT, just the Return of the Market minus the Risk-Free rate), the size factor (SMB), and the value factor (HML).

$$Expected\ Returns = R_{i,t} - Rf_t = \alpha + \beta_{(MKT)}MKT_t + \beta_{(SMB)}SMB_t + \beta_{(HML)}HML_t + \varepsilon_t \tag{2}$$

With the daily factors obtained directly from Kenneth French's website, I perform an OLS regression over the estimation windows.

The estimated coefficients, coupled with the mean F-F factor values throughout the event period, yield the expected return for each individual stock. The daily deviation of a stock's return from its expected return is denoted as its Abnormal Return (AR) for that day. Essentially, this represents an approximation of the stock's alpha, based on the F–F three-factor risk adjustment in this context. For a specific event, it's necessary to have a minimum of 30 consecutive data points before applying the resulting coefficients. Otherwise, the observation is excluded from the dataset.
The next step would be to calculate the Average Abnormal Returns (AAR), in order to compare the performances during different sentiments more accurately and with a reduced probability of measurement errors caused by idiosyncratic factors.

$$AAR_t = \frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}} AR_{i,t} \tag{3}$$

Finally, the sum of the AARs during the event windows represents the Cumulative Average Abnormal Returns (CAAR).

$$CAAR = \sum AAR_t \tag{4}$$

Another way to obtain CAAR would be to first calculate the Cumulative Abnormal Returns (CAR) for each event and each specific event window, and then perform an average. Cumulative Abnormal Returns simply represent a sum of abnormal returns in a given event.

$$CAR_{i,[t_1;t_2]} = \sum_{i=1}^{N} AR_{i,[t_1;t_2]} \qquad where \qquad CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,[t_1;t_2]} \tag{5}$$

For simplicity, to obtain CAARs I will use *equation (4)*, but the two methods are perfectly interchangeable. We will use CAR later in the Significance Test chapter (Chapter 4.3). Summing up the AARs will let us compare and evaluate effectively the returns during periods of *High* and *Low* market sentiment.

4.2 Market Sentiment

Firstly, I classify daily returns depending on the sentiment provided by the Baker-Wurgler (BW) index. A trading day is classified as "high sentiment" if its BW Sentiment value is greater than zero. Vice versa, "low-sentiment" days are those with below-zero values. As already mentioned in the data section (Chapter 3), the sample period presents many more low-sentiment (LS) days when compared to high-sentiment (HS) ones (3798 "LS" and 1698 "HS" days), but the bullish periods are usually much stronger.

The following stage consists of calculating the returns separately for the high and low-sentiment days. Equation (5) adds a dummy variable to equation (2) that will let us divide the expected returns during HS and LS event periods.

$$R_{i,t} - Rf_t = d_t^{LS}\alpha^{LS} + \beta_{(MKT)}MKT_t + \beta_{(SMB)}SMB_t + \beta_{(HML)}HML_t + \varepsilon_t \quad (6)$$

$$R_{i,t} - Rf_t = d_t^{HS}\alpha^{HS} + \beta_{(MKT)}MKT_t + \beta_{(SMB)}SMB_t + \beta_{(HML)}HML_t + \varepsilon_t \quad (7)$$

Where d_t^{HS} and d_t^{LS} are dummy variables indicating bullish and bearish periods. With these results in mind, we could finally analyze and compare the CAARs of High and Low periods using the aforementioned triggers of -10% and +10%.

$$CAAR^{HS} = \sum AAR_t^{HS} \quad (8)$$

$$CAAR^{LS} = \sum AAR_t^{LS} \quad (9)$$

In other words, I will investigate if the $CAAR^{LS}$ is larger than the $CAAR^{HS}$, as previously hypothesized.

4.3 Significance Test

For a performance index such as the CAAR, a test statistic is usually measured and compared to its assumed distribution under the null hypothesis the average abnormal returns are equal to zero. The standard procedure for a test statistic for a classic CAAR as in *equation (4)*, is the CAAR divided by an estimate of its standard deviation. For each specific event window [t_1; t_2], the estimated standard deviation used for the CAAR t-test is equivalent to:

$$\hat{\sigma}_{CAAR[t_1;t_2]} = \sqrt{\frac{1}{N(N-d)}\sum_{i=1}^{N}(CAR_{i,[t_1;t_2]} - CAAR_{[t_1;t_2]})^2} \quad (10)$$

Where *N* is the number of observations, *d* is the degree of freedom, and then the squared sum of specific Cumulative Abnormal Returns (CAR) of every event in an event window [t_1; t_2] subtracted by its average for the same event window (CAAR).

It's important to note that to calculate these standard deviations we need the assumption of no overlap of event windows with the estimation windows. This might happen because of "event clustering", a phenomenon that appears when two or more events are too close to each other, creating noise, estimating downwards the standard deviation in *equation (10)* and thus positively skewing the significance test. For simplicity, in this study, I only analysed events that do not overlap to avoid clustering of standard errors, but another possible solution would be to use event-clustered standard errors when performing the t-test[1]. Under the null hypothesis (CAAR = 0) and the assumption that the individual security CARs are independent, the CAAR asymptotical distribution can be approximated as unit normal.

$$CAAR_{[t_1;t_2]} \overset{a}{\sim} N\,(0, \hat{\sigma}_{CAAR[t_1;t_2]}) \tag{11}$$

Finally, the cross-sectional t-test to verify the null hypothesis that CAAR = 0 is given by the division of the CAAR for each event window for its estimated standard deviation:

$$\boldsymbol{J} = \frac{CAAR_{[t_1;t_2]}}{\hat{\sigma}_{CAAR[t_1;t_2]}} \overset{a}{\sim} N\,(0,1) \tag{12}$$

[1] Further details on the potential impact and implications can be found in Chapter 6, Section 6.2 "Limitations and Future Research".

CHAPTER 5 Results

Hypothesis: *Overreaction of the Banking Sector is stronger during periods of low market sentiment.*

In order to verify this hypothesis, I performed separate analysis depending on the trigger used (positive, negative) and the type of prices (Closing and Midpoint), to get a deeper and well-rounded understanding of the short-term reversal phenomenon.

5.1 Negative Trigger Events' Results

Table 3 presents the Cumulative Average Abnormal Returns using *closing prices* for the whole sample of events, but also for the "high sentiment" subsample and the "low sentiment" subsample. Given that this period of twenty years (between 2001 and 2021) mainly presented low sentiment days, and that our trigger is negative, the majority of observations are in the "low sentiment" subsample. The events in total are 1612, with 1507 that happens during bear sentiment, and 105 during bull sentiment.

Table 11 - Cumulative Average Abnormal Returns using Closing Prices, Negative Trigger of -10%
This table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation (12).

	N	*CAAR [1,3]*	*CAAR [1,5]*	*CAAR [1,10]*
All events	1612	0.018	0.025	0.027
(t-stat)		(5.978)***	(6.269)***	(4.594)***
Low Sentiment	1507	0.017	0.024	0.025
(t-stat)		(5.352)***	(5.593)***	(3.926)***
High Sentiment	105	0.034	0.039	0.044
(t-stat)		(5.14)***	(6.287)***	(4.791)***

****Significant at 1% level **Significant at 5% level *Significant at 10% level*

As reported in *Table 3*, all of the samples exhibit economic and statistical significance over each of the three event windows. The most notable result from this table is that, at least by analyzing results using closing prices, Cumulative Average Abnormal Returns are greater during periods of High Sentiment rather than periods of Low Sentiment. This would mean that overreaction is stronger during periods of market optimism, supporting the views of researchers that believe that this happens mainly because of market frictions (short-sale constraints) and non-rational behaviours (reluctance to take short-positions in low-sentiment periods, Ostrich-like behaviour). The statistical significance of the CAARs both in

High and Low Sentiment events would imply that the banking sector does not differentiate when reacting to events.

Figure 6 shows the CAARs in a day-by-day framework rather than the windows as in Table 3. A clear discernible path, in addition to the major difference between "High" and "Low" sentiment events, can be noticed by the fact that until day 6 CAARs seem to monotonically grow, then from day six onwards have a small decrease but generally moving sideways between day 6 and 10. In other words, the larger part of abnormal returns happens until one week after the event.

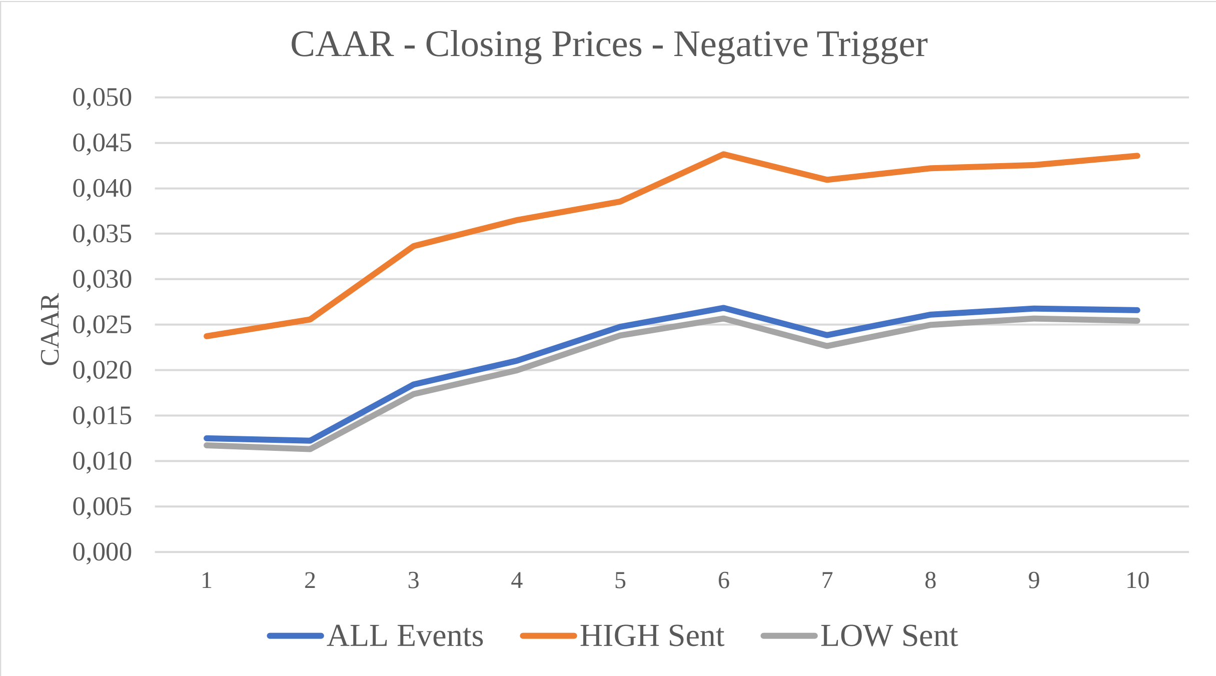

Figure 14 – Cumulative Average Abnormal Return using a Negative Trigger with Closing prices day-by-day. *The figure shows the differences in performances between High Sentiment Events (orange line) and Low Sentiment Events (grey line) and All Events taken together (blue line). Events are considered as every trading day with a daily stock price return of less than -10% (negative trigger).*

It is important to remember that these results are obtained using *closing prices.*

How much the "bid-ask bounce" phenomenon impacts the CAARs calculated with closing prices? I performed the same event study using the price *midpoint*. which represents the average between the bid and the ask price and thus should not be affected by the "bid-ask bounce". *Table 4* presents the results.

Table 12 - Cumulative Average Abnormal Returns using Midpoint Prices, Negative Trigger of -10 %
This table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation (12).

	N	*CAAR [1,3]*	*CAAR [1,5]*	*CAAR [1,10]*
All events	1260	0.023	0.030	0.034
(t-stat)		(6.32)***	(6.506)***	(5.41)***
Low Sentiment	1195	0.022	0.030	0.036
(t-stat)		(7.961)***	(7.837)***	(7.796)***
High Sentiment	65	0.004	0.006	-0.028
(t-stat)		(0.12)	(0.14)	(0.36)

****Significant at 1% level　　**Significant at 5% level　　*Significant at 10% level*

While the sample as a whole and events that happened during periods of Low Sentiment appear statistically significant, by using *midpoints* I obtained statistical and economical insignificant abnormal returns. The fact that using midpoints, the sample *"All events"* shows significant CAARs suggests that there is some level of market overreaction in the banking sector. An interesting finding is the lack of significance of events that happened during periods of High Sentiment, suggesting that during bullish market conditions, the market may be less sensitive to the banking sector's news or events.

These results represent only the negative trigger part of the research, the other side of the coin might add important information to our study.

5.2 Positive Trigger Events' Results

Reminding that positive events are trading days with daily stock price changes of a specific stock greater than +10%, Table 5 shows the CAARs using closing prices.

Table 13 - Cumulative Average Abnormal Returns using Closing Prices, Positive Trigger of + 10%
This table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation (12).

	N	*CAAR [1,3]*	*CAAR [1,5]*	*CAAR [1,10]*
All events	2273	-0.014	-0.015	-0.014
(t-stat)		(5.82)***	(5.328)***	(3.791)***
Low Sentiment	1963	-0.014	-0.015	-0.012
(t-stat)		(5.05)***	(4.433)***	(2.78)***
High Sentiment	310	-0.016	-0.021	-0.031
(t-stat)		(4.59)***	(5.12)***	(5.994)***

****Significant at 1% level　　**Significant at 5% level　　*Significant at 10% level*

A first immediate consideration that we can extrapolate from Table 5 is that there is a short-term reversal in each of the windows, meaning that after a one-day daily stock price return of at least +10%, bank stocks tend to mean-revert and thus have negative abnormal returns. As in Table 3, overreaction seems to be much stronger during periods of High Market sentiment, but in this case, it does not stay stationary between day 5 and day 10, but it rather increases further. Figure 7 shows this fact in a more intuitive manner, with the decline of abnormal returns in High Sentiment between days 5 and 10 but the stationarity (or even small bounce) of Low Sentiment events and more in general, all the events taken together.

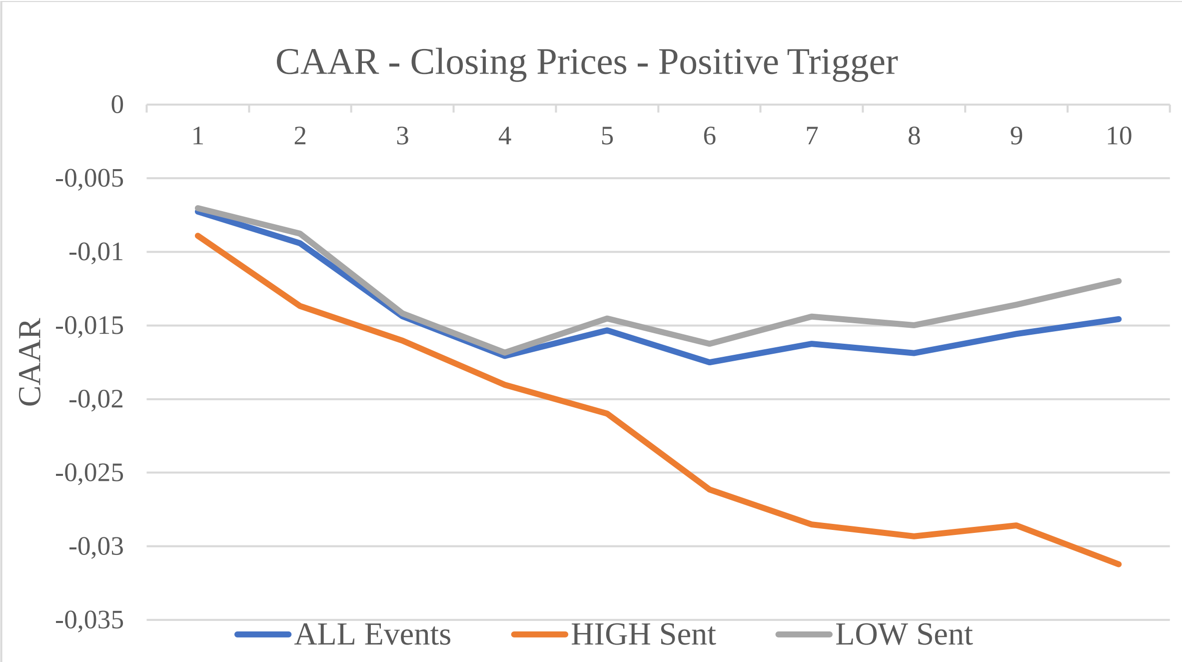

Figure 15 – Cumulative Average Abnormal Return using a Positive Trigger with Closing prices day-by-day. *The figure shows the differences in performances between High Sentiment Events (orange line) and Low Sentiment Events (grey line) and All Events taken together (blue line). Events are considered as every trading day with a daily stock price return of more than +10% (positive trigger).*

Lastly, an analysis of CAARs using Midpoint prices is offered by Table 6, providing this time similar results to Closing Prices CAARs with Positive Trigger: CAARs are always negative, implying some level of overreaction.

Table 14 - Cumulative Average Abnormal Returns using Midpoint Prices, Positive Trigger of +10%. *This table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation (12).*

	N	*CAAR [1,3]*	*CAAR [1,5]*	*CAAR [1,10]*
All events	1666	-0.014	-0.016	-0.011
(t-stat)		(5.25)***	(5.60)***	(3.085)***
Low Sentiment	1501	-0.013	-0.015	-0.09
(t-stat)		(4.60)***	(4.77)***	(2.246)**
High Sentiment	165	-0.020	-0.026	-0.036
(t-stat)		(3.68)***	(4.04)***	(5.38)***

When using both closing and midpoint price returns, an additional key difference between Negative and Positive trigger events can be found in the number of observations: during low market sentiment, there have been around 1500 negative events and 1900 positive events; but it is worth to note that during high sentiment periods, the number of positive events is much smaller (around 100 event for negative events and 300 for positive events).

In general, these results highlight the fact that there might be many moments of irrationality and thus overreaction. Is this irrationality effectively exploitable or not?

5.3 Long-Short Strategy to exploit Short-Term Reversals in Banking Sector

A standard long-short strategy would imply buying a bank stock after it falls more than -10% in a single trading day, and short a bank stock when its daily stock price returns are larger than +10%.

By easily summing the CAARs of positive and negative events, with positive events' CAARs inverted as we are taking a short position, Figure 8 shows in a descriptive manner the possible sum of Cumulative Average Abnormal Returns that could have been gained by following this strategy.

Is important to keep in mind that these are gross returns: they do not consider taxation, which might be relatively high for this short-term trading strategy since it would imply holding the stock for around 10 days. Also, it does not consider trading costs, which are presumably very high because of the large number of operations to carry out, and the fact that short selling, in addition to being not always possible, is also expensive.

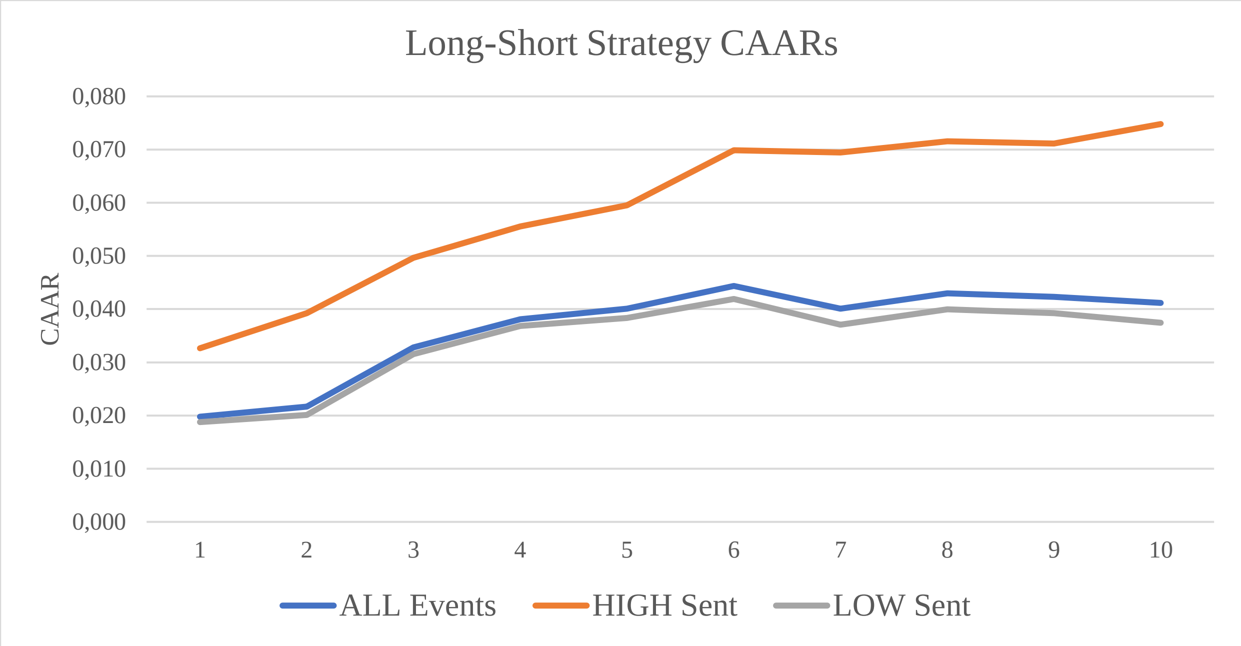

Figure 16 – Sum of Cumulative Average Abnormal Returns of Positive Events and Negative Events using Closing Prices

The key takeaway is that while events that happen in periods of high sentiment are much less, they are much more profitable (almost double returns!) than events during low sentiment.

5.4 *Robustness Checks*

As already mentioned, the choice of the model to estimate expected returns plays a central role in providing the outcomes of this type of study. In this thesis, I used the most popular asset pricing model, the Fama and French 3-factors model, which includes the CAPM beta, the size factor (SMB, small minus big), and the value factor (HML, high minus low). As a robustness check, it is possible to verify whether the results hold even with another model, possibly a more sophisticated one. The Fama and French 5-factor model (Fama and French, 2015) augments their 3-factor model with the incorporation of two additional factors, namely profitability (RMW, robust minus weak) and investment (CMA, conservative minus aggressive).

The regression equation would then become:

$$Expected\ Returns = R_{i,t} - Rf_t = \alpha + \beta_{(MKT)}MKT_t + \beta_{(SMB)}SMB_t + \beta_{(HML)}HML_t + \beta_{(RMW)}RMW_t + \beta_{(CMA)}CMA_t + \varepsilon_t \quad (13)$$

In *equation 13,* RMW adds some explanatory power as it represents the profitability factor: the difference between the returns on diversified portfolios of stocks with Robust and Weak profitability. CMA is the difference between the returns on diversified portfolios of the stocks of Conservative and Aggressive firms, which are companies with low and high investment levels (Fama and French, 2015).

The inclusion of these new factors in the new model, although it raises some concerns, has indeed a significantly improved explanatory power (Blitz, Hanauer, Vidojevic, and Van Vliet, 2018).

The following *Table 7* shows the CAARs of positive events using Closing Prices, as in Table 5, but instead of using the Fama and French 3-factor model, it applies the new Fama and French 5-factor model to estimate Expected Returns.

Table 15 – CAARs of Positive Events using Closing Prices and FF5 model as asset pricing model.
Using equation 13, this table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation 12.

	N	CAAR [1,3]	CAAR [1,5]	CAAR [1,10]
All events	2273	-0.015	-0.017	-0.017
(t-stat)		(7.56)***	(7.19)***	(5.49)***
Low Sentiment	1963	-0.015	-0.017	-0.015
(t-stat)		(6.74)***	(6.27)***	(4.29)**
High Sentiment	310	-0.015	-0.019	-0.029
(t-stat)		(4.21)***	(4.59)***	(5.44)***

****Significant at 1% level   **Significant at 5% level   *Significant at 10% level*

Results are statistically significant and similar to Table 5, the CAARs are even slightly greater than the ones obtained using the 3-factor model, possibly implying that the additional factors are capturing some of the variation in the data that was not considered.

On the other side, *Table 8* has the aim to check whether the results of Table 3 (CAARs of Negative Events) are robust when applying the 5-factor model.

Also in this case, results are similar and significant, suggesting that the factors in both the 3-factor and 5-factor have explanatory power in understanding their influence on abnormal returns.

Table 16 – CAARs of Negative Events using Closing Prices and FF5 model as asset pricing model. *This table reports the CAARs of All events, events that happened during periods of High Sentiment, and events that happened during periods of Low Sentiment. Results are reported for event windows [1,3], [1,5], and [1,10]. T-statistics are in parenthesis and are obtained through equation (12).*

	N	*CAAR [1,3]*	*CAAR [1,5]*	*CAAR [1,10]*
All events	1612	0.02	0.028	0.034
(t-stat)		(7.30)***	(8.62)***	(8.26)***
Low Sentiment	1507	0.019	0.027	0.033
(t-stat)		(6.38)***	(7.69)***	(7.47)**
High Sentiment	105	0.033	0.04	0.042
(t-stat)		(5.75)***	(6.94)***	(5.49)***

****Significant at 1% level   **Significant at 5% level   *Significant at 10% level*

In this analysis, Cumulative Abnormal Returns (CAARs) have been calculated using both closing prices and price midpoints. Closing prices have been widely used in financial research and were included in the primary analysis due to their standard practice and data availability. For simplicity, and to ensure the robustness of the findings, I conducted a robustness check specifically focusing on closing prices. I maintain confidence in the robustness of results also for price midpoint returns, as I do not see any inherent reasons why the use of price midpoints would yield significantly different results in the robustness check.

CHAPTER 6 Conclusion

The main purpose of this thesis was to shed additional light on the overreaction phenomenon of the banking sector, by studying the short-term reversal and its complex relation with market sentiment.

Is the overreaction of the banking sector (and thus its following short-term reversal) stronger during low or high market sentiment? After an extensive study of the existing, relevant, and conflicting literature on whether overreaction is stronger during bullish or bearish markets, I took the side of Piccoli and Chaudury's stream of literature. Thus, the tentative hypothesis is that the *overreaction of the Banking Sector is stronger during periods of low market sentiment*.

This hypothesis has been elaborated mainly because of three reasons. First, the effects of fears are usually stronger than the effects of greed: we are behaving under the guidance of "animal spirits": we tend to act more irrationally in moments of panic rather than in moments of excessive optimism, and losses are weighted much more than gains (as in the prospect theory). Second, the existence of momentum crashes (Daniel, Moskowitz, 2016) affirms that momentum strategies tend to perform poorly during panic states, following multi-year market drawdowns, and in periods of high market volatility. This would imply that "contrarian strategies" should instead overperform during these periods. Third, the banking sector has been proven to be particularly affected by irrationality (such as the herding behaviour in the case of bank runs for example), which might be in some cases justified but in others not.

To test this hypothesis, I have performed an event-study analysis for the period 2001 until 2021, using the time-series approach and the trigger strategy as in Bremer and Sweeney (1991) and Cox and Peterson (1994). To have a complete overview of the phenomenon, two triggers have been used (negative and positive), and to additionally verify for the bid-ask bounce two different types of stock price returns have been used (returns using closing prices and midpoint prices).

Results show that for negative events when using closing prices, we can reject our Hypothesis because overreaction is stronger during periods of high market sentiment. When using price midpoints, we cannot neither reject nor fail to reject it as high sentiment events lack significance. Thus, it is difficult to compare the differences in results between closing prices and midpoints datasets, probably because of the nature of the data, but also of the data quality. In fact, midpoint prices can be less volatile and reflect a different aspect of market sentiment when compared to closing prices. In terms of data quality, observations in midpoints are fewer than observations using closing prices, mainly because as explained in Chapter 3 "Data", the majority of continuously quoted midpoints are available only after April 2006, thus reducing our sample. Because of these differences in the dataset and the observations, we cannot measure the impact of bid-ask bounce in the short-term reversal phenomenon of the banking sector.

On the other hand, for positive events, we can reject the tentative hypothesis both when using closing and midpoint price returns, as the CAARs are greater during high market sentiment periods. It is interesting to note also that while events that happened during high sentiment are more profitable, they appear in a much lower frequency than low-sentiment events in the timeframe considered from 2001 to 2021.

Overall, there is some level of overreaction in the banking sector, as both the closing and the midpoint datasets show abnormal returns because of short-term reversals. This would make possible to build a Long-Short Strategy that buys bank stocks after a negative event and short-sell them after a positive event. Applying this strategy in periods of high market sentiment would be much more profitable, but events falling under bullish sentiment have been much rarer in the last 20 years.

These results contribute to the existing literature on the Overreaction Hypothesis by adding a specific overview of short-term reversals in a “hot” topic such as the banking sector and their relations with market sentiment.

Is overreaction the only plausible explanation for stronger abnormal returns during periods of high market sentiment, or is it possible that there are other factors which might not be considered when explaining abnormal returns due to short-term reversals?

6.1 An alternative explanation: Maverick Risk

A maverick is an independent individual who does not go along with a group or party (courtesy of Merriam-Webster’s definition). The concept of maverick risk is a compelling one. When viewed through the lens of human behavior, our inherent conditioning tends to associate non-conformity with riskiness. This perspective is offered by our evolutionary logic, as our ancestors often lived in circumstances where being part of a collective offered security: there is safety in numbers. Therefore, even though we intellectually recognize the merits of thinking innovatively (“outside the box”) and adopting contrarian approaches, and even though we admire individuals in society who possess the autonomy to chart their own course, our primal instincts often override our rationality when it comes to financial decisions. In such situations, our "lizard brain," the ancient, instinctual part of our minds, takes precedence, compelling us to seek the safety of the crowd.

In general, going against "the herd" usually means stepping out of the comfort zone, thereby putting yourself on the edge. Failing alone while everyone else achieves their results is far more painful than failing when everyone is failing with you.

In the financial markets, losing money during a bull run is much worse than losing money during a recession or a crisis. Similarly, the results of this thesis suggests that abnormal returns are higher during bullish markets rather than negative periods.

Is it thus possible that these stronger abnormal returns during a bullish market are just a premium for the risk of going against the herd? Especially when everyone is making money, taking “naïve” strategies can be seen as a particularly risky move. It is conceivable that the success and profitability of contrarian strategies that bet against market consensus could be a manifestation of investors demanding a “maverick risk premium”, as compensation for the exposure to criticism and deviation from the herd that is not captured by other factors. This field is interesting for future research, further exploring its dynamics and implications.

In conclusion, the overreaction hypothesis remains a prominent explanation for short term reversals and the profitability of contrarian strategies, but the idea of maverick risk introduces a new perspective to our understanding of investor behaviours and market performances.

6.2 Limitations and Future Research

While event studies have become common practice in economics and finance to analyze the impact of specific events on stock prices, this approach presents its own limitations. From a behavioral economics standpoint, the definition of expected returns can be easily criticized, as it is based on the assumption that returns can somehow be predicted in a way. In reality, the market might not always be perfectly efficient, and if we also consider that the model used to estimate these *expected returns* can strongly influence the economic and statistical significance of the whole study, we see how the results and abnormal returns depend on the model used to calculate expected returns. In this thesis, I used the Fama-French 3-factor model to calculate expected returns, and the Fama-French 5-factor model as a robustness check but other instruments such as the Carhart (1997) 4-factors could have influenced the outcomes.

Event clustering is another example of how markets can be inefficient: returns can be correlated, and the clustering of events makes it difficult to attribute stock price movements and returns to a specific event. Also in this case, the approach used in this study is rather simple and might not be the most accurate method to reduce the noise generated by event clustering. The Cross-sectional t-test might result as upwardly skewed as the method to eliminate overlapping of events can still be improved through the use of clustered standard errors for example.

The choice of estimation window is crucial as well: I used the approach of Piccoli and Chaudury (2018), but researchers are still debating on the exact length to minimize the influence of unrelated events while still having enough observation to perform robust regressions,

Lastly, the data offered by Refinitiv Eikon Datastream does not include most of the Bid and Ask prices before April 2006, reducing the observations available and making it difficult to compare CAARs calculated with *midpoints* and CAARs with *closing* prices. The period considered for this study (2001-2021) presents the majority of events falling in Low Sentiment days, thus skewing the research and possibly reducing the accuracy of overall results.

Future research should mitigate all these through careful study design and robust statistical methods while keeping the methodology relatively simple and easy to analyze. The extreme peculiarity of the banking sector offers a unique perspective on the Overreaction Hypothesis, and further studies should investigate how it relates to market and sector sentiment: after all, we still live *"Between the Bull and the Bear".*

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