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Bachelor Thesis [Economics & Business Economics]

Is overreaction for technology securities still appropriate with respect to the contemporary economy?

Abstract

In the present study the overreaction phenomenon, according to De Bondt and Thaler (1985) is researched and tested for technology securities. To test overreaction, it is important to know the literature and view behind such theory and this is linked to technology securities. Especially technology securities, because they have different characteristics with respect to the regular securities and especially differ between the dataset from de Bond & Thaler (1985), because there is a significant different economy. Therefor interesting to know if the overreaction for the technology securities in this contemporary economy is still appropriate. Data and methodology is used from CRSP and the methodology is replicated from de Bondt and Thaler (1985) research. Besides, a multiple regression analyses is performed to test if the data gathered and tested was useable. Performing the tests, it shows that the overreaction according to the methodology of De Bondt and Thaler (1985) research still results in an appropriate overreaction in the technology sector.

Key words: Overreaction, Technology sector

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Chapter 1

1.0 Introduction

Many scholars have investigated how stock markets operate and why stock markets behave the way they do. One well-researched theory regarding stock markets is the efficient market hypothesis (EMH; Fama, 1965). Fama (1965) defined an efficient market as a market characterized by an excess supply of rational actors who seek to maximize profits by actively competing against each other while attempting to forecast future market values of the securities of their interest. According to the EMH, share prices mirror all available information for the public concerning the share price of that specific share. The hypothesis states that because stocks always trade at fair values, because the investors know the true value of the stock, it is unlikely for investors to buy undervalued stocks or inflate the selling price of stocks (Kurth, 2011). Consequently, it should be unlikely to outperform the stock market via market timing or skillful stock selection. Therefore, according to the EMH, investors can generate higher returns only by buying investments that are risky. Stocks that are risky in the sense that there is less information available with respect to other stocks in the market.

Following Fama's (1965) definition, in an efficient market, relevant current information is available almost at no financial cost to all investors. Consequently, an efficient stock market should then be close to an ideal market, except for the presence of financial cycles that are typified by price adjustments. Such price adjustments are consistent with fundamentals, like price to earnings ratio and book-to-market ratio. The response of investors to such price adjustments is assumed to be contiguous and error-free. Specifically, as the major assumption of the EMH is that stock prices mirror all available and accessible information, participants in an efficient market are assumed to respond completely and efficiently only after a price adjustment.

Although influential, the EMH remains contentious and has been disputed both theoretically and empirically. In particular, numerous academic studies in the recent past have controverted the hypothesis of stock market efficiency by documenting proof of anomalies in capital markets. Levis (1989) defined capital market anomalies as a combination of circumstances that cause the prices of securities to depart from or be at variance with the norm. Such departures suggest market inefficiency and highlight the imperfect nature of asset-pricing. In particular, De Bondt and Thaler (1985) addressed concerns about one-time events where stocks experience a negative price shock that persists, causing the stocks to underperform in the capital market. This is a concern, because such stocks are then not valued according to their true fundamental value, which results in an incorrect reflection of the intrinsic value of the stock price. De Bondt and Thaler (1985) empirically tested this phenomenon for the period between 1930-1985 and came to the surprising conclusion that stocks that experienced a persistent negative shock indeed underperformed in the first three years. However, interestingly, the performance of such stocks began increasing after three years. De Bondt and Thaler (1985) also reported this effect of a gradual change in stock performance for stocks that experience a persistent positive shock. However, this effect was much less strong.

Importantly, the study of De Bondt and Thaler (1985) was conducted 35 years ago. The contemporary stock market situation and economy are not comparable to the stock market situation and economy in 1985. Particularly, the dotcom-bubble in the late 1990s, terrorist threats, and the financial crisis in 2007-2009 significantly changed the world economy. According to by (Perez, 2013) a new economic era. In fact, after the slow Eurozone recovery from this financial crisis, it was apparent investors were less optimist of good returns in Western capital markets. In addition to this, fast-paced technological developments, for example globally faster internet and not to forget mobile phones, have sped up information processing. More importantly there is an increase in data, because big data is changing the stock markets forever and some investors rely only on algorithms when they trade and big data contributes a lot to this algorithmic design of trading (Seddon & Curry, 2017). These events indicate the vulnerability of the global financial infrastructure to shocks despite the existing regulations and widespread reforms. Consequently, the way the contemporary economy reacts to new information is different from what was described in the study of De Bondt and Thaler (1985). In addition to this, securities in the technology sector often react differently to what was proposed in De Bondt and Thaler (1985), because the production process is still rapidly evolving in the technology sector and chances are that they will improve significantly (Akhigbe, Larson & Madura, 2002). For this to happen they need to invest in research and development (R&D) and in the beginning this will not result in a profitable project in the books at first, but when the R&D project succeed the positive cash-flow comes in and the company becomes more valuable. So the option value can be very high and this is incorporated in the stock price. But when this R&D project fails the stock price can drop sufficiently (Smit, 2010). Future technology stock values are more volatile and therefor have a higher bèta than firms operating not in the technology sector (Akube, Larson & Madura, 2002). This component of the contemporary economic market was not discussed by De Bondt and Thaler (1985). So, it is important that the seminal work of De Bondt and Thaler (1985) is updated to stay relevant to the contemporary economic situation. To address this goal, the following research question was drafted, which was central to the present study:

“Is overreaction on securities in the technology sector appropriate?”

The present study seeks to contribute to the existing literature on market reactions by offering an investigation of abnormal movements in stock prices in the time-being of the new economic era. The goal is to offer new insights into market anomalies within the context of market overreactions in the technology sector that occurred between 1996-2019. To the extent that the present study examines the appropriateness of overreactions, it is essentially controverting the efficient markets premise . Several studies have so far been conducted that investigated essential facets of stock markets, which included investigations of price movements (Muth, 1961), investor behavior (Nagy & Obenberger, 1994), and psychological models of investor decisions that result in underreactions and overreactions (Bondt 1995). The relevance of the present study is that the same methodology from De Bondt and Thaler (1985) is used and tested for the last two decades especially for technology securities. Therefor it is interesting to know if the research fromt De Bondt and Thaler (1985) is still relevant in these days for the technology sector.

The remainder of this paper is organized in the following way. Firstly, Chapter 2 discusses prior literature regarding stock market overreactions. After this literature review, Chapter 3 provides an explanation of the data and methodology used in the present study. Specifically, the present study focused on monthly stock prices of American companies in the tech sector over the period of 1996 until 2019. Furthermore, the methodology section lists the relevant formulas required to calculate cumulative average residual returns. Moreover, this section discusses an Auto Regressive Integrated Moving Average (ARIMA) model, which is a time series-based regression method. Subsequently, Chapter 4 discusses the results from the analysis. Based on these results, Chapter 5 provides conclusions regarding the hypotheses that were drafted in Chapter 2. Lastly, this chapter presents a discussion of the findings and recommendations for further research.

Chapter 2

2.0 Literature Review

The goal is to discuss literature related to the subject of overreaction of stock prices in the technology sector, besides the already discussed research of De Bondt and Thaler (1985). To dive deeper in the understanding in how stock prices react to different types of biases and sentiments some literature is discussed briefly. Also emphasizes if an overreaction is appropriate not only in the technology sector, but in the market as a whole.

2.1 News Sentiment and Stock Market Reaction

First, in the contemporary economy (''new economic era'') that is governed by information and communication technology (ICT), world news spreads quickly through many different platforms, especially social networking sites, which are filled with reactions and opinions and sometimes influenced by bots that are giving false information to influence the stock market and deceive investors opinions. Given such information-centrism, uncovering information about any event that is of relevance to the stock market is particularly important and can make a difference in an investor's stock returns, whether individual or institutional (Dhankar, 2019).

According to Munz (2012), news sentiment affects investment and trading decisions considerably. According to Veld-Merkoulova and Viteva (2016), when significant events occur that may impact trading decisions, investors tend to react to such news by adjusting their views or outlook of the market environment. These adjusted views serve as potential drivers of investor behavior changes within the context of stock trading (Aktan, Sahin, & Kucukkaplan, 2018). This tendency of investors and stock traders is often mirrored in the stock market with a specific stock or collection of stocks showing an opposite-to-expected movement through high volumes that might move against the prevailing trend.

The influence of investor tendencies implies human behavior plays an important role in stock trading. Consequently, scholars in behavioral finance have used human behavior patterns to identify market trends and stock market behavior, such as self-attribution bias (De Bondt, 1987), underreactions (Pleßner, 2017), and even overreactions (Pleßner, 2017), among other regularities. In particular, as argued by many authors, investor sentiment plays an important role in driving such behavior (Ferrer, 2016). Investor sentiment refers to investors' beliefs about future investment risks and cash flow that cannot be explained by the prevailing facts (Ferrer, 2016; Satchell, 2016). From this, it is evident that investors usually have some degree of bias towards a stock or collection of stocks that drives them to defy the prevailing fundamentals of such stocks. Possible reasons for the occurrence of investor sentiment include prior experience with (similar) stocks, the price movement shown by the stock recently, or the influence of news sentiments.

The occurrence of investor sentiment implies that irrationality plays a role in stock markets. Scholars who study behavioral finance therefore contend that standard financial and economic models are imperfect, because these assume the perfect accessibility to information and optimal processing of this information, decision-making alternatives, and ramifications of investor actions (Burghardt, 2011). In fact, humans' processing capabilities are grossly limited, and this makes it challenging to select the optimal decision from a collection of possible decisions. In support of this, insights from behavioral finance have provided some empirical evidence of the significance of irrational behavior demonstrated by some investors and traders. Barber and Odean (2008), for example, came up with a decision-making model in which they established that in cases where investors must make decisions from a collection of alternative decisions, individual investors, unlike their institutional counterparts, will mostly pick the stocks that attract attention. However, this is not the case when selling stocks. Barber and Odean (2008) suggest this is because individual investors often hold relatively few stocks, which gives them limited options.

There are also several behavioral economics models that focus on the influence of investor sentiment on overreaction to news events. Parveen et al. (2020), for example, present an investor sentiment model that suggests cognitive biases and representativeness heuristics often influence investor decisions in the stock market. Consequently, overconfident investors usually depend on such representativeness heuristics to make decisions under conditions of uncertainty. Investors tend to overemphasize and misconstrue their knowledge and assume that past performance is the ideal pointer for measuring a company's future performance (Parveen et al., 2020). Parveen et al. (2020) further note that overconfident investors who employ representativeness heuristics tend to overreact to news sentiments in the market, which impinges on their decision-making capacity. Stock markets are usually underreacted if the average return on a specific stock is higher than the mean return in the aftermath of an announcement of good news. An overreaction, then, usually occurs after unfavorable news.

In short, representativeness heuristics play an important role in explaining stock market overreactions. Investors employing representativeness heuristics examine the likelihood of an uncertain event by the extent to which the event resembles the parent population, and reflect the salient features of the process it generates (Tan, Yeh, & Bhala, 2016; Dhami, 2019). Within the context of investor behavior, representativeness heuristic describes a scenario in which investors take historical events or trends as being representative of future prospects, which overlooks the fact that past high earnings growths seldom repeat themselves. According to Dhami (2019), such investors often overvalue the company, eventually becoming disappointed when their predicted earnings growth does not yield. Empirical evidence suggests that stock markets tend to underreact to news in the short-term (a few months to one year), while in the long-term (between three and five years), the markets overreact to consistent news that suggests a trend. Therefore, a notable phenomenon in stock markets is the short-term nature of under reaction and the long-term nature of overreaction.

Several authors have also attributed investigators' under- or overreaction to news announcements to what they term a 'disposition effect' (Frazzini, 2006; Pleßner, 2017). The disposition effect holds that at the time of receiving favorable news, disposition investors tend to sell their stocks at much faster-than-ideal rates in a quest to benefit from stock gains before the market declines during the period of price recovery (Frazzini, 2006). According to Veronesi (1999), this is attributable to investors becoming overly optimistic after receiving good news, thereby assuming that all announcements in the future will be favorable. Veronesi (1999) notes that successive news announcements controvert this optimism, resulting in lower returns In addition, the disposition effect implies that because disposition investors often ration their stock, the rate at which bad news travels across assets trading is slow, particularly for large capital losses. As a result, the reaction of stock prices to such bad news is delayed and therefore less than what would be rationally expected (Frazzini, 2006). This view is supported by Li et al. (2014), who noted that experienced and professional investors demonstrate a smaller disposition effect compared to amateurs, as that experienced investors tend to deal with the delay of information more subtle.

Economou et al. (2017) argue that the conservative character of disposition investors frequently prevents prices from reaching their actual intrinsic value. Statman (2019) observes that to surmount this difference, experienced and rational investors create momentum with the goal of pushing the price by selling/buying the stock towards the stocks' intrinsic value. .

2.2 The Overreaction Phenomenon

As De Bondt and Thaler (1985) demonstrated, the worst (best) performing stock portfolios in the New York Stock Exchange (NYSE) during a period of three years tended to perform better (poorer) during the subsequent three years. De Bondt and Thaler's (1985) explanation for the overreaction phenomenon was that considerable aberration in the prices of assets from their fundamental value is caused by the irrational behavior of agents who give disproportionately high weight to recent news. An example can be used to illustrate the overreaction phenomenon in more detail. If a stock has been underperforming in comparison with the stock market for a period of three years, followed by a period of three years wherein the same stock is outperforming the market, the stock is likely undervalued. To correct itself to its intrinsic value, the stock price must move in the opposite direction to correct itself from undervalued to his intrinsic value. 'Overreaction', in this sense, follows from investors' expectations that the decline in the stock valuation that occurred during the first three years was permanent, leading such investors to overreact and value the stock accordingly. To prove that the stock was valued appropriately initially, and to highlight the overreaction to negative signals, the stock price then moves into an opposite direction over the next three years. De Bondt and Thaler (1985) also found overreaction to be asymmetrical (that is, it was more pronounced for undervalued stocks), in addition to establishing the presence of the January effect, or clusters of overreactions during that month. The underlying conception is striking because it is not really an economic explanation, but a psychological one, which implies that investors may not always have appropriate reactions to new information (Kahneman & Tyvesky, 1973).

Other studies that have confirmed the presence of overreactions and reached similar conclusions to the seminal work of De Bondt and Thaler (1985). For example, Brown et al. (1988) examined NYSE data for the nearly four decades between 1946 and 1983, and Ferri and Min (1996) used S&P 500 data for the three decades between 1962 and 1991. Another study is one by Larson and Madura (2003) that employed NYSE data for the decade between 1988 and 1998 to establish the presence of overreaction.

2.3 Causes of Stock Market Overreaction

So far, two possible explanations have been suggested in the literature to explain the overreaction phenomenon. The first is the idea that an underreaction causes an overreaction, which is then often succeeded by a long-term reversal. Good news announcements are announcements that fundamentally increase the value of a company and therefor investors are willing to pay more for the same stock, which results in an increase in the stock price (Dhankar, 2019). The opposite happens when investors receive bad news about the company in which they bought stocks (Dhankar 2019). As Dhankar (2019a) observes, stock prices overreact if the mean return after a series of good news announcements is lower compared to the average return in the face of a series of unfavorable or bad news announcements. This implies investor confidence is increased by inherent expectations with regards to stock values due to favorable news reports. Such expectations are then unmet as the announcement changes becomes unfavorable. Moreover, the said overconfidence increases when publicly available information corroborates the information that the investor has but does not decline proportionately when the publicly available information is inconsistent with the private information (Külpmann, 2011). This leads to tendencies of self-attribution. Wärneryd (2002) defines self-attribution as the tendency of people, and investors, to blame external factors for their failure and give credit to themselves for their success. Within the context of stock market overreaction, overconfidence causes an overreaction to drive up stock prices to a level higher than the fundamental value, after which a long reversal ensues. However, some scholars have argued to the contrary, noting that with each announcement of good news, it is only rational for investors to react by buying more of the stock, considering that good news naturally means that the stock price will increase (Greyserman & Kaminski, 2014; Zaremba & Shamer, 2019). At this point, investors are behaving rationally and not overreacting.

2.3.1 ‘’The second idea’’

Overreaction occurs when investors purchase stock as a result of a representative bias (that is, the investor erroneously concludes that the company’s past growth will persist in the future without any objective markers that suggest this would be the case). According to Spellman (2009), stock market overreaction often undergoes a process that is aptly captured by the unified model for over- and under-reaction. This model looks at two categories of agents, namely momentum traders and news-watchers (Ashraf & Jayaraman, 2014). The model also makes three fundamental assumptions. The first is that news-watchers make their predictions according to what they privately observe regarding future fundamentals; they are indifferent to past or present prices. The second is that traders’ forecasts are often based solely on past price changes, while the third assumption is that private information disseminates slowly across the “news-watchers” group (Ashraf & Jayaraman, 2014).

From the abovementioned assumptions, Ashraf and Jayaraman (2014) argue that initially, when news-watchers react to news reports, stock prices adjust gradually to emerging information. However, this adjustment is not adequate, which leads to an under reaction and not an overreaction. Thereafter, momentum traders (basing their predictions or forecasts on the observed gradual price increase) start forcing a higher stock price that leads to a profit. Nevertheless, momentum buyers who entered way later when the price increases beyond the intrinsic value stock price begin to lose money, forcing a reversal (Singal, 2006).

As the work of De Bondt & Thaler (1985) is generally considered a seminal study regarding stock market overreactions, it is interesting to investigate whether its striking results still hold in the contemporary economy. Their main findings were that there is an overreaction on stock prices in the long term and that this effect for stocks that were underperforming and later outperforming the stock market is disproportionate with respect to stocks that were first outperforming and later underperforming the stock market. In short, this effect is bigger for ‘’losers’’ than for ‘’winners’’. Therefore, I have derived the following hypothesis:

Main hypothesis. ''Overreaction on securities in the contemporary technology sector still occurs according to the same model and methods employed by De Bondt and Thaler (1985).''

This hypothesis is related to the research question by examining whether overreactions are appropriate. Overreactions could be viewed as anomalies that produce exploitable opportunities for profit or merely as statistical anomalies. Only the former proves the EMH to be false.

Furthermore, I have derived sub-hypotheses in order to obtain reliable evidence for the main hypothesis. The first sub- hypothesis is:

> ***Sub-hypothesis 1.*** ''Loser portfolios outperform the market three years after the portfolio formation date and winner portfolios underperform with respect to the market returns.''

Because the stocks in the tech-sector are more valuable due to the growth in technological development, the expectations are that the stocks that were prior losers, will be winners in the long term. In this sense, the long term is stated as between three to five years, because according to *The Intelligent Investor* (Graham, 1959), this timeframe is enough for a stock to recover himself from upward or downward price overreactions. In fact, for overreaction to take place, the stock price must move in the opposite direction; losers are going to be winners and winners are going to be losers. Subsequently, I have derived the following sub-hypothesis:

> ***Sub-hypothesis 2.*** ''The difference between the winner and loser portfolio's abnormal returns are significant with respect to market return.''

The cumulative average abnormal returns of the winner and loser portfolios need to be significantly different from each other, otherwise there cannot be an overreaction.

Chapter 3

3.0 Research Design

3.1 Data

For the current study, data was included from the *Center for Research in Security Prices* (*CRSP*), where historical stock market prices from the United States of America are stored for almost a decade. The Standard Industrial Classification codes (SIC-codes), which are recognized by the *CRSP*, were used to select tech-companies to be included in the present study. SIC-Codes were used to collect stock prices for the tech industry, because these codes are simple to identify and easy to interpret. In the United States, The Chamber of Commerce assigns SIC-codes to all its registered companies in order to classify them by industry. To find the relevant codes, information is found on *siccode.com*, which provides a list of every SIC-code that is recognized by the government of the United States. Codes that were used include 3570 to 3580 and 7370 to 7380. These codes are verbally classified as *Office & Computing*, *Machine & Equipment* and *Computer & other data process services,* respectively. Moreover, the date filter from 01-01-1996 until 31-12-2019 was used to select the monthly stock prices for these tech-companies. These dates were selected, because the period of interest for the hypotheses was limited to the contemporary economy. Although this contemporary economy captures the time period 2000 until now, the data used in the present study was selected somewhat before the year 2000 to be able to perform a portfolio selection in the year 2000. Lastly, to estimate excess returns, there needs to be a market index. Therefore, the equal-weighted index returns were selected in *CRSP* for each month in the period from 01-01-1996 until 31-12-2019.

3.2 Methodology

STATA and Microsoft Excel were used for all descriptive and inferential analyses. The empirical procedure to answer the research questions was based on the research design of De Bondt and Thaler (1985). In the present study, it was examined to what extent systematic nonzero residual return behavior post-portfolio formation months ($t > 0$) was associated with systematic residual returns in the pre-portfolio formation months ($t < 0$). The focus was on stocks that have experienced extreme capital gains or losses over periods up to three years.

This means that portfolios were formed based on their past excess returns. These are referred to as Winner portfolios (W) and Loser portfolios (L). Subsequently, both of the analyses were performed based on three types of return residuals. These are the market-adjusted return, market model residuals or excess returns that are measured relative to the Sharpe-Linter version of the Capital Asset Pricing Model (CAPM). De Bondt and Thaler (1985) argued that misspecification problems may still bias the results. However, De Bondt (1985) also reported that the three types of residuals generate similar results and that the choice of residuals does not affect the answers to the research questions. Therefore, in the present study, the results were all based on the market-adjusted excess returns. The following formula defines the market-adjusted excess return mathematically:

$$\widehat{u} = R_{jt} - R_{mt} \qquad (1)$$

Importantly, there are various advantages related to using this formula. First of all, there are no risk adjustments other than for movements in the market, and for every stock this effect is the same. Moreover, it is likely to bias the research against the overreaction hypothesis. Also, there is no systematical difference between the Winner and Loser portfolios, with respect to different company valuation processes.

For every stock j in the dataset with at least 120 months of monthly return data and without missing values in the selected time period, the residual returns u_{jt} were calculated for months 48 to 120. Because of the dotcom-bubble in the late 1990s and the financial crisis in 2008, it is interesting to split up the data into different time-frames. Therefore, 31-12-1998 was marked as the first date for the portfolio formation, which resulted in seven sub-periods. Consequently, every step must be repeated seven times. As time goes on, more stocks are qualified to be included, but also more stocks will be discharged, because they no longer exist. Specifically, for every stock j on the 31st of December in month 85 (t = 0) the portfolio was formed based on the following formula for cumulative excess returns:

$$CU_j = \sum_{t=-35}^{t=0} u_{jt} \qquad (2)$$

This step was repeated seven times. Moreover, on each of the seven portfolio formation dates, the CU_j's were ranked. The ranking process was performed by selecting the upper-class stocks, which are stocks that have a cumulative excess return in the top 50% of the sample, and the bottom-class stocks, which are stocks ranked below 50% of the sample. Respectively, these portfolios, with upper-class and bottom-class stocks, were called Winner and Loser portfolios.

Thereafter, for both portfolio types, it was necessary to compute the cumulative average residual returns for a period of 36 months (t = 1 through t = 36). To do this, the following formula was used:

$$CAR_{wnt} = Average(CU_j) \qquad (3)$$

In Formula (3,) the subscript w indicates a Winner portfolio. This w is replaced by the subscript l when the formula is applied to a Loser portfolio.

Using the *CAR*s from all seven periods, the *average* CAR ($ACAR_{wt}$ and $ACAR_{lt}$) was estimated for every time period in the three years starting from period 1 (01-01-1999 until 31-12-2001) until period 7(01-01-2017 until 31-12-2019. For overreaction to occur, at t > 0, it is necessary that $ACAR_{wt}$ < 0 and $ACAR_{lt}$ > 0, which implies the following:

$$[ACAR_{lt} - ACAR_{wt}] > 0 \qquad (4)$$

Next, a pooled estimation of the population variance in CAR_t was determined to test whether there is a statistically significant difference in the performance of abnormal returns of ''winning'' and ''losing'' stocks. This is defined by the following formula:

$$S_t^2 = \left[\sum_{n=1}^{N}[(CAR_{W,n,t} - ACAR_{W,t})1^2 + \sum_{n=1}^{N}[(CAR_{L,n,t} - ACAR_{L,t})1^2\right]/2(N-1) \qquad (5)$$

where S_t is the standard deviation, N indicates the 36 months or three years, and t is number of months.

Moreover, the unpaired two sample t-test was used to compare the means of the two unrelated groups, $ACAR_{L,t}$ and $ACAR_{W,t}$. When formula (4) holds, this means there is overreaction, to test the significance of formula (4) the formula (5) and (6) are constructed. Because of the two different samples of equal size N, the variance of the difference of the sample means equals $2S_t^2/N$. Hence, the t-statistic was estimated with the following formula:

$$T_t = [ACAR_{L,t} - ACAR_{W,t}]/\sqrt{2S_t^2/N} \qquad (6)$$

where T_t represents the t-statistic.

Although this t-statistic does not generate independent evidence, it is still useful when comparing the Winner and Loser portfolios with respects to performance. The results will be compared to a significance level of 5% at a onesided T-test. Also, performance graphs for the seven sub-periods for both winning and losing stocks were used to indicate important relationships for movements over time. As such, the t-test provides sufficient evidence for the main hypothesis.

To replicate the methodology from Bondt and Thaler (1985) the formulas one to six were used. With these results came Bondt and Thaler (1985) to the conclusions as discussed above. To show some advanced empirical evidence that the data used in this present research is valid, the methodology section continues explaining the last part of the empirical design.

So, the validity of the assumptions of multiple regression analysis on the time series were checked to determine the readiness for data analysis. Because the analysis is performed on stock prices and market returns from the United States, the results are stated and interpreted in US Dollars.

3.2.1 Descriptive statistics

Because in essence we continuously have a dataset divided in two periods: 3 years of monthly stock returns that are followed to estimate a portfolio. This time period is called pre-portfolio formation and after the portfolio is formed, the stock returns are again followed for three years. So for the sake of clarity we divided the descriptive analyses between pre-portfolio formation and post portfolio formation. Also every time period is having its own column as shown in Table 1A and Table 1B. As already mentioned the dotcom bubble and the financial crises in 2008 it is therefore also recommended to explicitly divide the descriptive analyses in different time periods. Interesting to see in Table 1A is that the technology stocks during these crises with respect to other periods have not the worst losses (referred to the minimum numbers provides in Table 1A). -.60 and -0.52 still are smaller than the worst losses in period 2 and 7, respectively -0.63 and -0.90. Meanwhile technology stocks in the Table 1B – stocks that are measured after they have been ranked in pre portfolio formation - show during the dotcom bubble in period 2 the biggest loss with respect to every other period. This lies somewhat in line with the expectations that market specific shocks, as a burst in the dotcom bubble, push technology securities relatively more downward than the market return that applies more to the market as a whole (Fama,1965).

Table 1A.

Descriptive Analyses About Pre-Portfolio Formation

Descriptive	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
	01/01/1996-31/12/1998	01/01/1999-31/12/2001	01/01/2002-31/12/2004	01/01/2005-31/12/2007	01/01/2008-31/12/2010	01/01/2011-31/12/2013	01/01/2014-31/12/2016
N	18	19	21	20	20	18	15
Mean	0.01	-0.01	-0.01	0.01	0.01	-0.00	0.00
SD	0.15	0.20	0.13	0.14	0.15	0.1	0.12
Min	-0.56	-0.63	-0.60	-0.49	-0.52	-0.49	-0.90
Q1	-0.07	-0.11	-0.07	-0.04	-0.05	-0.04	-0.04
Median	0.008	-0.02	-0.01	0.00	-0.00	-0.00	0.01
Q3	0.1	0.1	0.05	0.05	0.05	0.04	0.05
Max	0.43	1.05	0.75	2.72	1.96	0.72	1.24

Note. N is the number of observations that passed the selection criteria. SD stands for standard deviation and min and max stands for the maximum return in that specific period. Q1 and Q3 both stands Quartile one and three, respectively. Where Q2 represents the number between the smallest number and the mean and Q3 stands for the number between the maximum number and the mean. Periods stand for the time-frame in which consistently thru the present papers is referred to. Example given: Period 1 is in the present paper referred as 01-01-1999 – 31-12-2001, but the data destined for this specific period is here gathered 01-01-1996 – 31-12-1998 and therefore the dates that belong to period 1 in this table are not the exact the dates that belong to period 1.

Table 1B.

Descriptive Analyses About Post Portfolio Formation

Descriptive	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
	01/01/1999-31/12/2001	01/01/2002-31/12/2004	01/01/2005-31/12/2007	01/01/2008-31/12/2010	01/01/2011-31/12/2013	01/01/2014-31/12/2016	01/01/2017-31/12/2019
N	18	19	21	20	20	18	15
Mean	-0.01	-0.01	0.01	0.01	-0.00	0.00	0.03
SD	0.19	0.16	0.13	0.15	0.10	0.10	0.37
Min	-0.63	-1.00	-0.49	-0.52	-0.50	-0.90	-0.50
Q1	-0.11	-0.07	-0.03	-0.05	-0.04	-0.03	-0.03
Median	-0.02	-0.011	0.00	-0.00	-0.00	0.01	0.02
Q3	0.09	0.056	0.051	0.54	0.04	0.04	0.05
Max	1.05	1.37	2.72	1.96	0.72	0.66	8.11

Note. N is the number of observations that passed the selection criteria. SD stands for standard deviation and min and max stands for the maximum return in that specific period. Q1 and Q3 both stands Quartile one and three, respectively. Where Q2 represents the number between the smallest number and the mean and Q3 stands for the number between the maximum number and the mean.

3.2.2 Inferential analysis

Lastly, an inferential analysis was performed by means of a time series regression method known as the Auto Regressive Integrated Moving Average (ARIMA) model. This was done because to check for readiness in the data. This was done by utilizing the Box Jenkins (1976) methodology, which applies a combination of first-differenced and lagged levels of co-integrated variables to test the short-run dynamics of the winning and losing stocks. From the Autocorrelation Function (ACF), it can be determined whether there was a gradual decline of the lags up to the third, which would imply lags 1 to 3 were not within the 95% confidence interval. This was done to conclude whether the data were stationary or varying over time.

The following terminologies used in the ARIMA-method are relevant for the current study:

- *Autoregression (AR):* The presently used model employed the dependent relationship between an observed phenomenon and lagged observations.
- *Integrated (I):* The differencing of raw observations, such as the subtraction of an observation at a previous time step, to achieve a stationary time series. Stationary means that it is independent of time through a constant mean and variance.

- *Moving Average (MA):* The presently used model was based on the dependencies between observations and residual errors from a moving average model applied to lagged observations.

These three components were specified explicitly as parameters in the model. Moreover, a standard ARIMA (*p,d,q*) notation was used in which the parameters are replaced with larger integer values to refer to the ARIMA-model being employed. The ARIMA-model parameters were defined as follows:

- *p:* The number of lag observations included in the model, also called the lag order;
- *d:* The number of times that the raw observations were differenced, also called the degree of differencing;
- *q:* The size of the moving average window, also called the order of moving average.

The following equation defines a Loser portfolio in a typical ARIMA-model:

$$ACAR_{L,t\,=}\ \propto + \varphi_1 ACAR_{L,t-1} + \varphi_2 ACAR_{L,t-2} + \ldots + \varphi_p ACAR_{L,t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \ldots \quad (9)$$

where:

- ϕ = the autoregressive model's parameters;
- θ = the moving average model's parameters;
- ∝ = a constant term;
- ε = error terms (white noise).

A similar formula applied to Winner portfolios, indicated by the subscript *W*:

$$ACAR_{W,t\,=}\ \propto + \varphi_1 ACAR_{W,t-1} + \varphi_2 ACAR_{W,t-2} + .. + \varphi_p ACAR_{W,t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + .. + \theta_q \varepsilon_{t-q} \ldots \quad (10)$$

ARIMA model in words:

Predicted Y_t = Constant (∝) + Linear combination of Lags of Loser or Winner portfolios (up to *p* lags) + Linear Combination of Lagged forecast errors (up to *q* lags).

This model was constructed by integrating the itemized numbers and types of terms. Moreover, the data was prepared by a degree of differencing to make it stationary. So, seasonal structures and trends that affect the regression model negatively were eliminated. This is necessary, because the model works on the assumption of stationarity, which means that there must be a constant variance and mean. Subsequently, it was checked whether the *p*-values of the AR and MA were lower than the alpha-threshold of 5%. The estimated coefficient values for both Winner and Loser portfolios demonstrate how positively or negatively the lags of the variables predict the future occurrence. In terms of the most significant coefficient with the lowest volatility and the highest log-likelihood statistics, ARIMA model (1,1,3) would be the most efficient.

For the current study, the first difference I ~ (1) of the series was obtained to make it stationary, as shown in Figures A and B in Appendix A. Using the first difference of the Partial Autocorrelation Function (PACF), a sharp cut-off is shown, while the ACF decays a bit slowly with significant spikes at higher lags. Therefore, it can be concluded that dACAR (first difference if the average cumulative return) is an AR process, which means the autocorrelation pattern is explained more easily by adding AR terms than by adding MA terms.

Chapter 4

4.0 Results

The results based on the in the above explained data and methodology section are presented in the following section. In Table 2, the results are presented of the independent t-tests with overreaction as an outcome variable, referring to formula (6). Table 2 also shows the results for the t-test with two unequal variances. Again For overreaction to occur, at t > 0, it is necessary that $ACAR_{wt}$ < 0 and $ACAR_{lt}$ > 0, which implies that the difference should be greater than zero.

From Table 2, it can be concluded the average cumulative abnormal returns from the Winner and Loser portfolios differed significantly with regards to overreaction occurrence. The Loser portfolios displayed a significant positive degree of deviation from the Winner portfolios. According to formula (4) this concludes an overreaction. This is substantiated by the fact that by an p-value of 0.002 the positive difference between the two portfolio's is stated significant, keeping in mind the 5%-threshold for significance.

The first hypothesis upheld that Loser portfolios should outperform the market three years after the portfolio formation date and the Winner portfolios did not outperform the market three years after the portfolio formation date. When testing formula (4) by using the formula (5) and (6), which is summarized in Table 2, the portfolios do overreact in such a way that it is outperforming the market return post portfolio formation.

Table 2

t-test with two unequal variances

	$ACAR_{L,t}$	$ACAR_{W,t}$
Average	0.33	0.02
Variance	0.35	0.03
Observations	36	36
Degrees of Freedom	35	
T- Stat	3.04	
P(T<=t) one-way	0.00	
Criticial area	1.68	

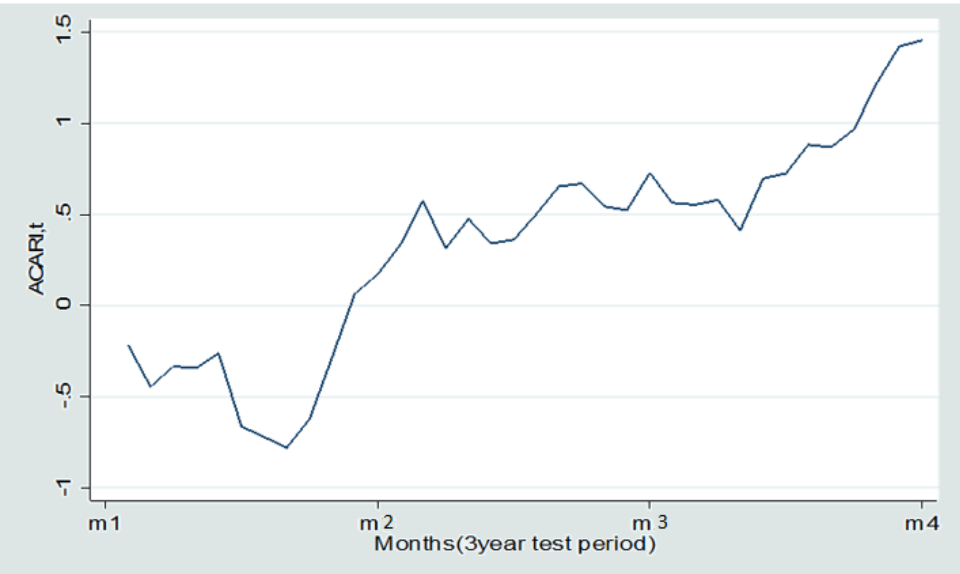
Note. Cumulative Average Returns of seven three-year test periods between January 1999 and December 2019. Length of formation period: Three years. Test whether the positive difference between the loser portfolio and the winner portfolio is significant according to formula (4) for overreaction to occur.

As is evident in Figures 1A and 1B, over the last twenty years, Loser portfolios performed on average approximately 147% above the market returns at the end of the test period (t=36). In the first batch of the first nine months, such portfolios show an accommodating pattern by underperforming the market as a loser stock. Meanwhile, for Winner portfolios, there is a small degree of underperformance with respects to the market returns at the last day of the testing period; this outcome is -1.2%. The difference is therefore $[ACAR_{l36} - ACAR_{w36}]$ 146%, with a *t*-statistic of 3.04 (see Table 2).

As a matter of fact, this also contributes to the answer of the first sub-hypothesis, because it shows that at the end of the testing period the outcome of the average cumulative abnormal returns is for the winner and loser respectively negative and positive. This is also what was expected; the loser portfolio should outperform the market return and the winner portfolio should underperform with respect to the market return

Figure 1A

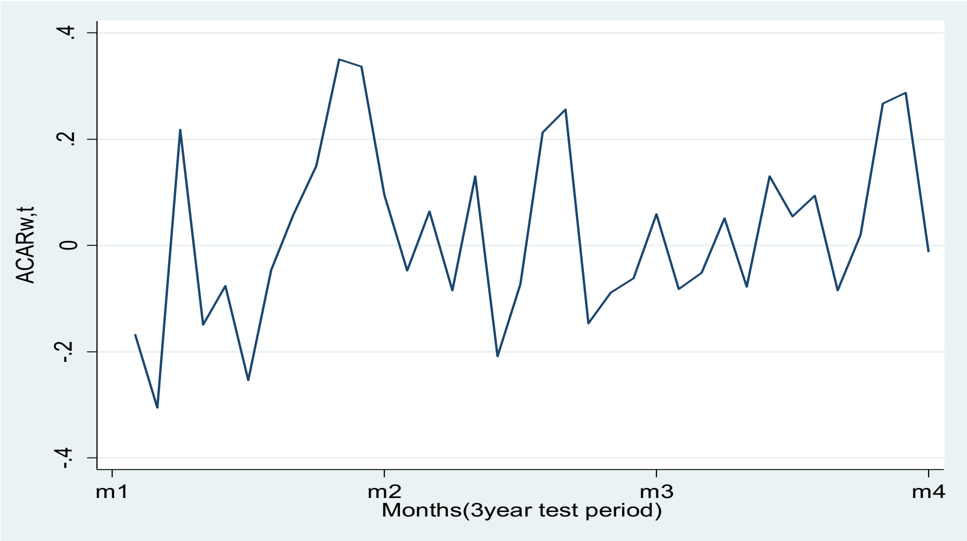
Process of Avarage Cumulative Average Returns for the Loser portfolio in a timeframe of 01-01-1999 until 31-12-2019.



Note: The axis labels in both Figures 1 and 2 represent a cumulative average abnormal returns of a three-year period of nineteen stocks categorized as Loser stocks. M1 denotes the first nine-month period of the 36 months' cumulative average abnormal returns, whereas M2 denotes the second batch of the nine-month period, M3 represents the third batch and M4 represents the last batch of the 36-month period, which are averages for the period spanning from 1999 to 2019.

Figure 1B

Process of Avarage Cumulative Average Returns for the Winner portfolio in a timeframe of 01-01-1999 until 31-12-2019.

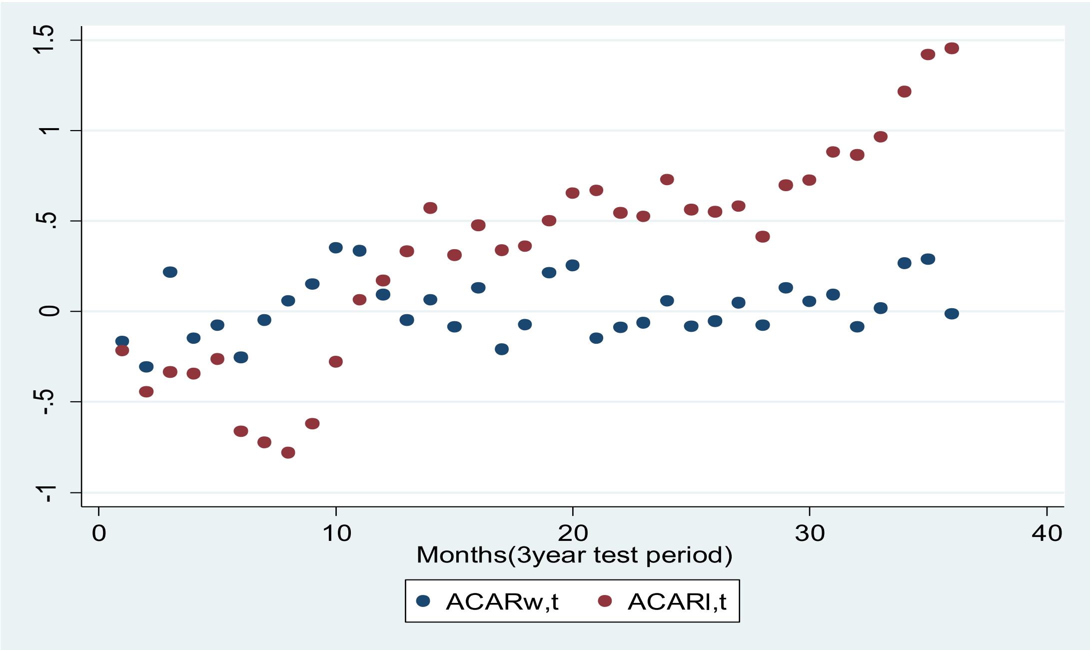


Note: The axis labels in both Figures 1 and 2 represent a cumulative average abnormal returns of a three-year period of nineteen stocks categorized as Winner stocks. M1 denotes the first nine-month period of the 36 months' ACAR, whereas M2 denotes the second batch of the nine-month period, M3 represents the third batch and M4 represents the last batch of the 36-month period, which are averages for the period spanning from 1999 to 2019.

A scatterplot (see Figure 2) was also used to test the association between the portfolios' performance and time for every period of three years (equivalent to 36 months) starting from period one (01-01-1999 until 31-12-2001) until period seven (01-01-2017 until 31-12-2019).

Figure 2

Process Winner- and Loser portfolio



Note. Scatterplot showing a strong association in the pattern suggesting that loser portfolios diverges from the winner portfolio in a positive way, suggesting overreaction and outperforming.

In Figure 2, it can be seen that the Loser portfolio does not necessarily take a linear pattern, but rather a changing trend with a parabola shape or an upward curve at the start of the months. It can also be noted that there is a moderately positive association, where the Loser portfolio converges from the zero bound and the Winner portfolio stays around the zero bound. The pattern suggests that Loser portfolios in the tech-sector outperformed the market in the longer run for this period (at t=30, so basically halfway year three), whereas the Winner portfolio did not., which also contributed to the first sub-hypothesis.

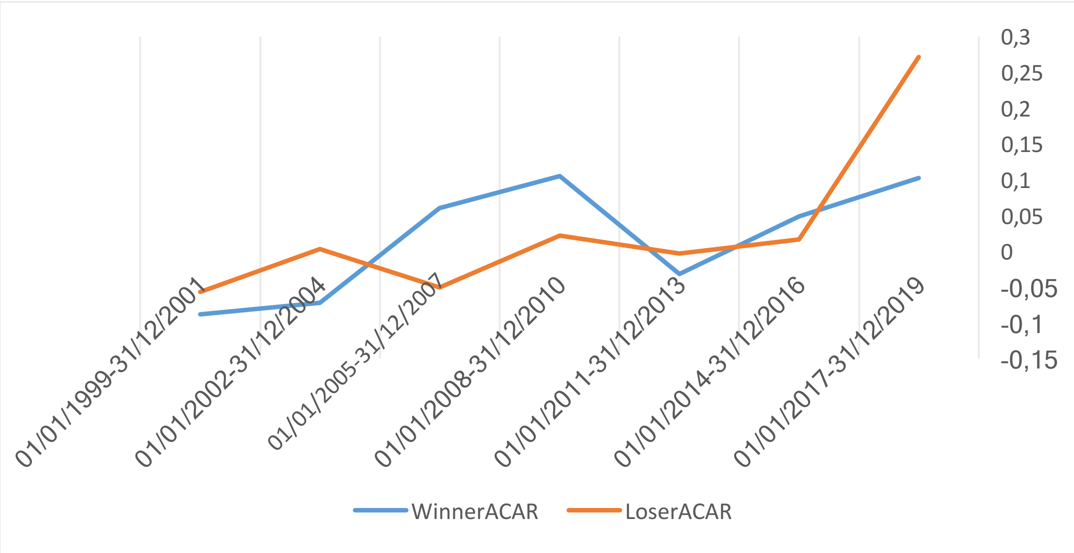
Concerning the crises that were included in the data, Figure 4 indicates there is a relatively bigger difference between the ACARs in the Loser and Winner portfolios in periods three, four and seven. In the periods three and four, the difference is in favor of the Winner portfolio, whereas and in period seven, this is the other way around.

The third and fourth periods encompass the ’08 financial crises. In period three, the returns for the Winner portfolio is on average 6% higher than the market return in this three-year period after portfolio formation. For the Loser portfolio, it was estimated that the returns are

5% under the market returns. The difference is 11% in favor of the Winner portfolio. For the fourth period, the Winner portfolio has a return of approximately 10% on average of all the stocks above the average market return. For the Loser portfolio, this is 2,2% above the average market return. The difference is 8,8% in favor of the Winner portfolio. For the seventh period, the Loser portfolio outperforms not only the market, but also the Winner portfolio in contrast to periods four and seven. The Loser portfolio outperform the average market return with 27,1% and outperforms the Winner portfolio with a solid 10%. The difference is 16,1% in favor of the Loser portfolio.

Figure 3

ACAR starting january 1999 and ending december 2019 and divided into 7 sub-periods for three years



Note. Cumulative average residuals for Winner and Loser portfolios divided into seven periods across three years, with an average of nineteen stocks per portfolio.

Table 3 indicates in which month the difference in the estimated abnormal return between Winner and Loser portfolios is significant. In this table, it can also be seen that the difference between the Winner and Loser portfolios is significant for most months with respects to overreactions for the Loser portfolios and supports therefor the second sub-hypothesis.

Table 3

Month specific difference in Average Cumulative Abnormal Returns between the Winner and Loser portfolio

Months after portfolio formation	Difference in ACAR	T-Stat
1	-0.05	-0.20
12	0.08	0.17
13	0.38	1.87*
18	0.43	2.14*
24	0.67	3.97*
25	0.65	6.32*
36	1.46	3.97*
Average number of stocks		20
ACAR at the end of formation period winner		-0.01
ACAR at the end of formation period loser		1.46

Note. Summarizing statistics and specific month test. *significant at a significance level of 0.05.

From Table 4, it can be seen that the best model to predict overreactions over time is ARIMA (1,1,3), as indicated by the high significant *p*-values for AR(1) (i.e., *p*=0.006) and MA(3) (i.e. *p*=0.021).

Table 4

Regression results from STATA output

Variable	Coefficient	Standard error	*p*-value	95% Confidence interval
Average cumulative return for loser portfolio ($DACAR_{lt}$)- **Constant term**	0.049	(0.012)	<0.001	(0.025, 0.073)
Autoregressive (AR)				
L1. (Lag 1)	0.672	(0.245)	**0.006**	(0.191, 1.152)
Moving average (MA)				
L1. (Lag 1)	-0.825	.	.	.
L2. (Lag 2)	-0.178	(0.320)	0.048	(-0.240, 0.806)
L3. (Lag 3)	-0.353	(0.356)	**0.021**	(-0.550, 0.344)

Note: Results using a ARIMA (1,1,3) model which was deemed significant at a 5% significance-level.

Replacing in the model equation, we get:

ARIMA (1,1,3)

$$\boldsymbol{ACAR_{W,t}} = 0.049 + 0.672\ \boldsymbol{ACAR}_{L,t-1} - 0.825\ \boldsymbol{\varepsilon_{t-1}} - 0.178\ \boldsymbol{\varepsilon_{t-2}} - 0.353\ \boldsymbol{\varepsilon_{t-3}} \ldots\ldots\ldots (12)$$

Where $ACAR_{W,t} =$ the predicted winner's stock**/**portfolio

$ACAR_{L,t-1}$ the lagged loser's stock/portfolio, ε_t is the error term

Both the AR (1) and all three lags of the MA indicate a significant prediction of the future occurrence of the variables. For the AR term, it is evident that the past lag of DACAR can positively predict its future occurrence. Also, the lag of the residual of the MA can negatively predict DACAR at the 1% level. The model equation (13) shows that winner's portfolio can be predicted from loser's portfolio and vice versa by a factor 0.672 within a three-year period (MA (3)). With the significance level less than 0.05 and the ARIMA model at (1,1,3), it is right to state that the winner is preempted to move in the opposite direction from the loser portfolios, and hence this satisfies and supports the Overreaction theory by De Bondt and Thaler (1985).

Chapter 5

5.0 Conclusion and Discussion

Previous studies indicated people tend to overreact to negative news and events. The present study focused on appropriate overreaction in the stock market, especially in the technology sector in the contemporary economy, which is not included in De Bondt and Thaler (1985) research design. For overreaction to initially take place the first hypothesis must hold that Loser portfolios outperformed the stock market in a three-year period following an initial three-year period of lesser performance. Loser portfolios earned 147% more than prior winners in the same industry and time frame. As predicted, the Winner portfolios reversed in returns and eventually show a negative return. As both of the above mentioned results shows that the first hypothesis is confirmed.

The second hypothesis stated that the difference between the Winner and Loser portfolios must be significant to state that there is definitely overreaction and that has to do with reversal behavior of the stock prices. Results show that there was significant difference between the Winner and Loser portfolio's by a T-test resulting in a significant T-stat of 3.03. This implies that overreaction does occur in the contemporary technological economy.

The present study provides evidence in favor of the overreaction hypothesis. This is important, as the dataset used in the analyses included data from stocks in the technology sector after 2000s. This is surprising, as there is evidence increasingly more technological advances are also employed to make market predictions and also plays a part of systematic factor the whole market is exposed at (Akighbe, Larson & Madura, 2002.

As predicted, the losers' portfolios (L) outperformed the stock market in the three-year period following an initial three-year period and this is confirmed by the results of the ARIMA model. Therefore, it can be concluded that reversal behavior is evident and previous winners in the technology sector become outdated and underperform in the future market whereas previous losers outperform in the future market.

The present study had several factors that might limit the interpretation of the results. The extent to which the seasonality's of stock returns are implicated in the results remain unanswered and is beyond the scope of the current study and is therefore a recommendation for further research. The data should be in the same period but tested for seasonality's by using the CAPM beta's like it has been done by De Bond and Thaler (1987) ''*Further Evidence on Investor Overreaction and Stock Market Seasonality*''. Also the methodology should be more month and season specific with respect to the formation of portfolios.

One point of discussion concerns the residual returns; the use of the CAPM might fit better regarding to calculate the abnormal returns. Also, the requirements that every company had to own at least 20.000 outstanding common stocks and have at least 120 months of stock returns is questionable, because it leaves out small companies which have on their behalf also stock returns which can influence the outcomes. Small companies experience higher abnormal returns according to Reinganum (1981) ''*Abnormal returns in small firm portfolios*'' and therefore could bias the dataset.

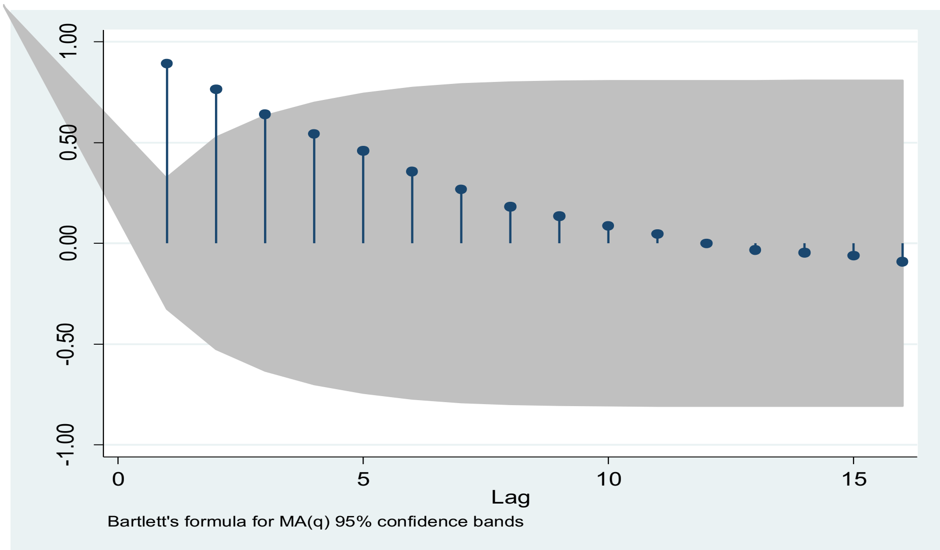
Lastly, the period of 36 months that was employed in the present study may not be optimal. This was done to mimic the methods of De Bondt and Thaler (1985), but as information is processed a lot faster in contemporary markets, it is interesting to investigate briefer time-periods that have more data points.

Overall, it can be concluded that in this contemporary economy and era, due to technological development and even during crises, there is a degree of overreaction present in the markets of the technological sector.

Appendix A

Figure A

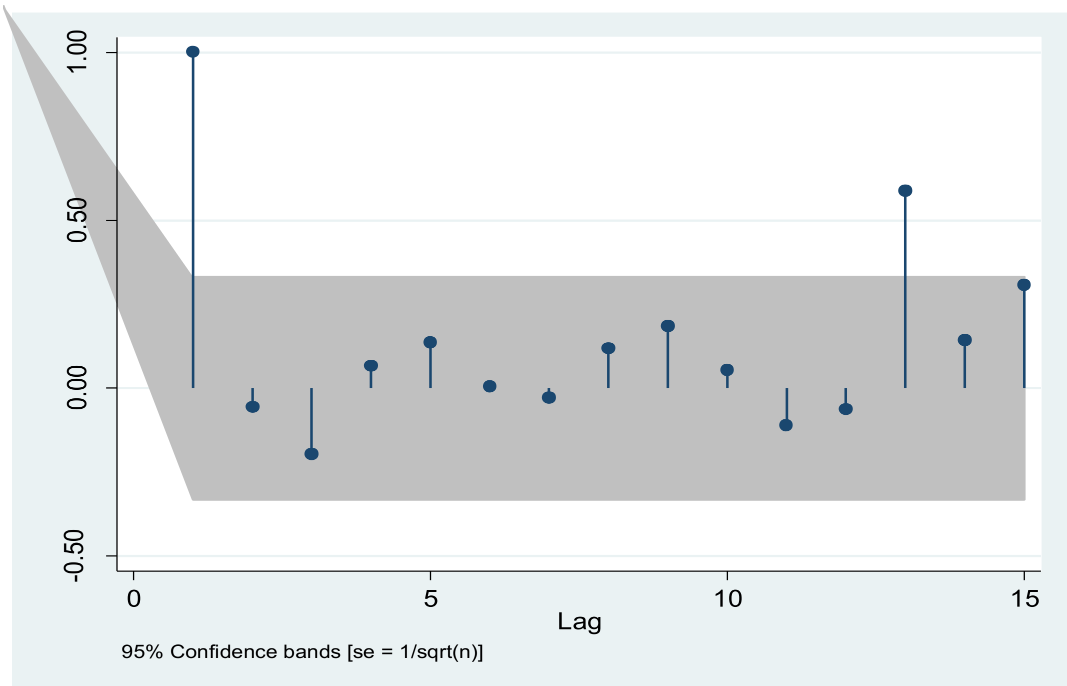
Correlogram of the autocorrelation Function



Note. *Correlogram of the Autocrrelation function (ACF) for loser portfolios in the 7 periods with an average of 19 stocks against the lag length, to help indentify the number of AR and/or MA terms needed.*

Figure B

Partial autocorrelation function



Note. Partial autocorrelation function (PACF) for loser portfolio's dividend into 7 periods of three years each with intermediate lags of 1 each, to measure the marginal impact.

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