EXTRAPOLATION BIAS AS A MANIFESTATION OF THE REPRESENTATIVENESS HEURISTIC: EVIDENCE FROM THE CONTENT ANALYSIS OF STOCK MESSAGE BOARD POSTINGS

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ABSTRACT

A large volume of literature identifies that investors are affected by behavioral biases. While most of these biases have been explained by referring to cognitive psychology, the emergence of market anomalies also appears to be due to biased investor behavior. A substantial behavioral bias is extrapolation bias, which constitutes a manifestation of the representativeness heuristic. This study provides a novel examination of extrapolation bias by using the message board postings of a sample of German bank stocks. An innovative methodology that involves qualitative content analysis (QCA) is employed to code the postings and extract private investor sentiment. This thesis tests whether after-hours private investor sentiment is positively predicted by preceding daily stock returns. The impact of extrapolation bias by private investors on the market prices of stocks is examined by testing whether contemporary daily stock returns depend on prior-day daily stock returns; that is, whether daily stock returns are positively autocorrelated. The results reported in this thesis show that daily stock returns are a significant positive factor in explaining after-hours private investor sentiment. This implies that private investors simplistically extrapolate past stock returns for forming expectations with respect to future stock returns. Nevertheless, daily stock returns have not been found to be autocorrelated, which means that extrapolation bias among private investors is not reflected in the market prices of stocks. When prices move sufficiently away from rationality, market participants may enter arbitrage positions which ultimately drive prices back to more rational levels. As the pricing of stocks remains efficient, the random walk hypothesis cannot be rejected. This thesis illuminates the ongoing controversy between neoclassical finance and behavioral finance, demonstrating that private investor behavior is inconsistent with the dominant neoclassical paradigm. Private investor education appears necessary for raising the awareness of extrapolation bias and promoting rational investment behavior. Future research should focus on a different sample and investigate whether the findings in this study are robust to noncrisis periods.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND AND SIGNIFICANCE

The recent financial crisis has led to renewed interest in the efficient market hypothesis (EMH), some arguing that events during the crisis point towards the failure of EMH. In this context, the controversy between neoclassical finance and behavioral finance not only remains unresolved but its topicality is also underlined. The importance of this controversy is confirmed by the most recent award of the Nobel memorial prize in economic sciences. Among the laureates for 2013 were both Eugene Fama, leading proponent of the neoclassical school of thought, and Robert Shiller, leading proponent of the behavioral school of thought (Campbell, 2014).

The neoclassical framework is based on two key assumptions; investor rationality and perfect capital markets which correct any temporary mispricing through arbitrage. However, there is mounting evidence that investors are affected by behavioral biases and limits to arbitrage restrict the effectiveness of markets to correct mispricing that may be induced as a result of those biases (Szyszka, 2011). Taking account of the psychology of market participants with regards to judgment and decision-making is no recent fad or zeitgeist. The importance of the human psyche in the marketplace was first identified by prominent economists Adam Smith and John Maynard Keynes (Abbas, Ayub & Saeed, 2011).

This research study contributes to the continuing controversy between neoclassical finance and behavioral finance by examining stock message board postings to determine whether participants in financial markets are affected by biased behavior or not. Resolving this controversy is important, as behavioral biases by investors have been argued to entail significant deadweight losses in the overall economy (Kent, Hirshleifer & Teoh, 2002).

1.2 THEORETICAL FRAMEWORK

1.2.1 BEHAVIORAL FINANCE

Behavioral finance stresses the importance of the psychological aspects of financial decision-making and involves concepts that are at odds with the assumptions of the neoclassical theory of finance. Following empirical failures of the capital asset pricing model (CAPM), which constitutes a major application of neoclassical finance (Levy, 2010), several market anomalies were identified. These anomalies reflected deviations in the market prices of stocks from their intrinsic values (Fama & French, 1996). Market anomalies can be divided into fundamental anomalies, which relate market prices to accounting measures, technical anomalies, which refer to the predictability of future market prices by referring to past market prices, and calendar anomalies, where returns become predictable for instance during particular months of the year (Latif, Arshad, Fatima & Farooq, 2011).

Behavioral factors have been suggested as an explanation for anomalous pricing (Shiller, 1981). The participants in financial markets appear to be susceptible to behavioral biases, violating one of the key assumptions of CAPM. Of these behavioral biases, cognitive biases are most prevalent, although social biases may also play a role. Behavioral biases may or may not involve emotional aspects.

Cognitive biases can be attributed to either simplistic heuristic thinking or frame dependence (Shefrin, 2002). While heuristics involve rules of thumb for judgment and decision-making (Tversky & Kahneman, 1974), the concept of frame dependence hints at the importance of the particular way an option is presented for whether the option is selected or not (Tversky & Kahneman, 1986). Social biases are assumed to encompass those behavioral biases that emerge due to social influences or the impact of an individual's cultural environment.

A variety of distinct behavioral biases have been suggested with respect to the participants in financial markets. However, empirical tests of these biases have provided only mixed evidence as to the existence of these biases. Private investors, who include individual nonprofessional investors, tend to be more prone to behavioral biases on average than professional investors, who include institutional investors, due to inferior sophistication. It appears that country-specific differences exist in the susceptibility to particular behavioral biases, with the level of development within a country and the cultural environment both likely to play a role. Behavioral biases can have a material impact on market prices, as certain financial anomalies have been shown to result from the biased decision-making of investors (for instance, Miller, 1989).

For behavioral biases to manifest in market prices so that market anomalies emerge, the effects of certain biases must not cancel out against offsetting biases. Furthermore, rational arbitrageurs must be prohibited from eliminating the resulting mispricing completely. Behavioral asset pricing models were contrived for the purpose of determining asset prices while taking account of biased investor behavior (for instance, Barberis, Shleifer & Vishny, 1998).

Recent technological advances have supported the emergence of neurofinance. By way of imaging methods of the human brain, the relevance of the concepts hypothesized by behavioral finance may be confirmed from a biological perspective (for instance, Knutson, Wimmer, Rick, Hollon, Prelec & Loewenstein, 2008).

1.2.2 THE REPRESENTATIVENESS HEURISTIC

The representativeness heuristic has been suggested to be the most important heuristic regarding judgment and decision-making (Nisbett, Krantz, Jepson & Kunda, 2002). In this respect, the decision-making by investors is compromised because they evaluate the likelihood of outcomes according to their ‘representativeness’, as opposed to their actual objective probability (Kahneman & Tversky, 1972). As a consequence, different cognitive biases can arise; namely the representativeness bias, the gambler‘s fallacy, the hot-hand fallacy and extrapolation bias. Interestingly, these biases exhibit attributes that partly oppose each other. Representativeness bias relates to simplifications based on stereotyped thinking. For instance, affected investors assume that the stocks of ‘good’ companies also constitute ‘good’ investments (Shefrin & Statman, 1995).

The gambler‘s fallacy is associated with the biased belief that extreme outcomes which occurred merely by chance necessarily need to be corrected by extreme outcomes in the opposite direction (Tversky & Kahneman, 1974). Financial market participants have been shown to be susceptible to disproportionately predict the reversal of sustained stock price trends (for instance, Loh & Warachka, 2012).

By way of contrast, the hot-hand fallacy entices investors to unjustifiably extrapolate an enduring series of human performance (Gilovich, Vallone & Tversky, 1985). For example, financial market participants have been found to refer to the past performance of investment managers for the purpose of forming expectations with respect to their future performance (for instance, Goyal & Wahal, 2008).

Finally, extrapolation bias is similar to the hot-hand fallacy, except that it addresses inanimate processes instead of human performances (Kahneman & Tversky, 1973; Tversky & Kahneman, 1971). Investors are affected by extrapolation bias if they simplistically extrapolate the prevailing price trend of stocks into the future (Shiller, 1988).

1.3 GAP IN THE LITERATURE

Certain aspects of extrapolation bias appear to be under-researched in the extant literature. Although early research suggested the susceptibility of investors to extrapolation bias (De Bondt, 1993), more recent empirical studies have not been able to provide unambiguous evidence regarding the existence of this bias (for instance, Safdar, 2009). Despite the intuition that private investors should be more susceptible to behavioral biases; empirical evidence has not been able to unambiguously prove that the extrapolation bias affects private investors more than professional investors. A definitive relationship between the extrapolation bias and market prices has also not been established.

Therefore, this research study seeks to answer two distinct research questions. First, does extrapolation bias exist among private investors? Second, does extrapolation bias among private investors have an effect on the market prices of stocks?

Different methodologies and samples have been relied on for the purpose of identifying extrapolation bias in the financial marketplace. However, the author is not aware of any other studies that have used the sentiment implied in stock message board postings to examine extrapolation bias among German private investors. While applying the innovative methodology proposed by Das, Martínez-Jerez and Tufano (2005), which assumes extrapolation bias to prevail if sentiment is positively predicted by prior stock returns, this study also addresses a methodological gap in the literature.

1.4 METHODOLOGY

This study largely relies on deductive positivistic reasoning, including quantitative statistical techniques for the analysis of the collected data. Nonetheless, part of the data collection was conducted by way of a qualitative approach. For the purpose of determining private investor sentiment and constructing a daily sentiment index, the content of stock message board postings was analyzed through qualitative content analysis (QCA) (Schreier, 2012). While preceding studies have tended to rely on computer algorithms for interpreting message board postings, the manual qualitative technique employed in this study is likely to be less affected by errors in the classification of postings, resulting in an increase in the validity of the research undertaken.

This study examines the existence of the extrapolation bias by investigating whether private investors refer to recent stock returns in forming expectations for future stock returns. Specifically, this test is carried out by examining whether short-term private investor sentiment, as extracted from stock message board postings, is positively predicted by preceding stock returns.

This study also investigates whether extrapolation bias by private investors may affect the market prices of stocks by testing whether short-term stock returns are autocorrelated. Positive autocorrelation would indicate that such extrapolation bias impacts on the market prices of stocks, as increased demand for stocks (supply of stocks) by extrapolating investors following positive (negative) sentiment would be reflected in the market prices of stocks.

1.5 CHAPTER OUTLINE

The structure of this research study is as follows. In Chapter 2, existing literature relevant to the study is critically reviewed; following from gaps identified in the literature, specific research questions are derived. Research methodology is described in Chapter 3 and results are reported in Chapter 4. A discussion of the results and an outline of the study's limitations are supplied in Chapter 5. Chapter 6 provides a conclusion.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The behavioral school of finance evolved after the neoclassical school of finance became increasingly criticized. Unrealistic theoretical assumptions that are likely to be violated in practice have been shown to severely affect the validity of the neoclassical school of thought.

In the following, the rationale for behavioral finance is elaborated in detail. Thereafter, empirical evidence of the existence of behavioral biases in the financial marketplace is provided. Finally those behavioral biases that result from reliance on the representativeness heuristic are addressed in particular, as research potential has been identified here.

2.2 RATIONALE FOR BEHAVIORAL FINANCE

The importance of behavioral finance is demonstrated in the following. First, a comprehensive definition of behavioral finance is provided. Then, the development of this area is elaborated, the relevance of market anomalies is explained and the psychological foundations of behavioral finance are outlined. Finally, approaches to behavioral asset pricing and recent discoveries in the area of neurofinance are described.

2.2.1 DEFINITION OF BEHAVIORAL FINANCE

Behavioral finance extends the neoclassical theory of finance by introducing psychological issues into the financial decision-making. The assertion that financial market participants always act in a rational manner, as suggested by stated neoclassical assumptions, is challenged. Within the behavioral finance framework, investors are supposed to be affected by biased behavior and deviate from neoclassical rationality while taking investment decisions (Fromlet, 2001). As a result, market prices can diverge from their fundamental values and market inefficiencies can occur (Shefrin, 2002). However, for market inefficiencies to emerge, there also need to be limits to arbitrage that prevent unbiased traders from instantly arbitraging away mispricing (Shleifer & Vishny, 1997).

The field of behavioral finance is associated with a few main themes. The main themes refer to market anomalies, behavioral biases, heuristic simplification and frame dependence. Market anomalies represent deviations from efficient market prices. They are suggested to arise due to the behavioral biases of investors (Daniel, Hirshleifer & Teoh, 2002; Daniel & Titman, 1999; De Bondt & Thaler, 1985; Lakonishok, Schleifer & Vishny, 1994).

Behavioral biases include a variety of cognitive biases and a couple of social biases. Behavioral biases may or may not imply an emotional component. While social biases emerge as a consequence of environmental impact on investors (for instance, Scharfstein & Stein, 1990), cognitive biases result either from heuristic simplification or from frame dependence (for instance, Singh, 2012).

On the one hand, heuristic simplification relates to rules of thumb that are derived from past experiences and intuitively employed for taking decisions in the present. Heuristic simplification, however, is likely to facilitate biased judgment and decision-making (Tversky & Kahneman, 1974).

On the other hand, frame dependence concerns the importance of the particular context within which a decision problem is presented. Prospect theory describes the way human beings take decisions against the background of frame dependence. Similar to heuristic simplification, frame dependence tends to lead to biased judgment and decision-making (Tversky & Kahneman, 1986).

2.2.2 BACKGROUND AND DEVELOPMENT OF BEHAVIORAL FINANCE

Before neoclassical economics became mainstream in the 1960s (Statman, 2005), the impact of psychology with regards to human economic decision-making was generally accepted in the academia. The incorporation of psychology into decision-making is implied in the work of noted economists, such as Adam Smith and John Maynard Keynes (for instance, Abbas, Ayub & Saeed, 2011).

The neoclassical doctrine, however, intended to position economics as a natural science and incorporated several related assumptions (Bresser-Pereira, 2012). For instance, it was claimed that individuals always act in a rational and wealth-maximizing manner according to their best interests. Such behavior would be consistent with utility theory (von Neumann & Morgenstern, 1947).

A widely cited application of neoclassical finance is CAPM (Sharpe, 1964; Lintner, 1965; Black, 1972), which is based on modern portfolio theory (MPT) (Markowitz, 1952). CAPM was developed for the purpose of calculating the required rate of return of an asset dependent upon its market beta. However, empirical tests of the model failed while anomalous pricing was discovered (Fama & French, 2004). These failures appear to be related to the unrealistic assumptions of CAPM (Vandell & Malernee, 1978). For instance, the model assumes that investors have homogenous preferences and are risk-averse. By way of contrast, real market participants have been shown to exhibit heterogeneous preferences. As some investors have been found to demand socially responsible investments, they deliberately sacrifice part of their investment return and/or deliberately incur higher risk (Glac, 2008).

Against the background of the empirical weaknesses of CAPM, the three-factor model was developed (Fama & French, 1992). This model identified firm size and book-to-market value of equity in addition to market beta as variables for explaining equity returns. Nevertheless, the three-factor model still failed to take account of other significant factors. Return momentum, for instance, has been suggested subsequently to constitute another important variable for predicting equity returns (Fama & French, 1996). By and large, a problem with the three-factor model is that it is empirically driven and no underlying theory exists for the two additional factors that were suggested by Fama and French (1992).

The recent global financial crisis led to a renewed interest in the concepts of behavioral finance. Established models of neoclassical finance have been found to fail during the crisis (Haber, 2011). The concepts of behavioral finance, however, attracted increasing attention as they represented a means of describing the behavior of market participants in a more realistic way (for instance, Grosse, 2012).

2.2.3 MARKET ANOMALIES – DEVIATIONS FROM MARKET EFFICIENCY

One important foundation of behavioral finance has been the occurrence of several market anomalies, which were supposed to emerge due to behavioral biases. Market anomalies are return patterns that deviate systematically from the expected returns according to CAPM (Fama & French, 1996). Following De Bondt (2002), as market anomalies are exploitable, positive abnormal returns can be achieved.

However, a persistent problem in studies that use market anomalies as evidence of behavioral biases is that they are afflicted by the ‘bad model problem’ (Fama, 1998). While empirical evidence shows that the CAPM suffers from empirical problems that may invalidate its use to correctly model required rates of return, one key problem with the implementation of the CAPM is exact determination of the market portfolio (Fama & French, 2004). Thus, the ‘bad model problem’ can result in researchers finding evidence of abnormal returns that can be attributed to a misspecified model of expected returns rather than a true market anomaly.

Even if CAPM is the correct specification for a model of expected returns, the associated estimation of risk may be misspecified. As a result, the computation of the required rate of return would become flawed.

Deviations from required returns might also be explicable in a rational way. Investors might take their decisions on the basis of the availability of only incomplete information, transactions costs might prevent a mispricing from being exploited, or institutional constraints, such as short-sale restrictions, might result in stocks trading permanently above their fundamental value (Nagel, 2005).

Limits of arbitrage refer to the capital restrictions of market participants (Shleifer & Vishny, 1997). As risk-averse investors are likely to be kept from exploiting a mispricing endlessly, arbitrage mechanisms tend to become ineffective during periods of major market disruptions. In contrast with the theoretical assumption of neoclassical finance that arbitrage is performed by a multitude of diversified people investing their own money, arbitrage appears to be carried out in practice by only few undiversified specialists who are dependent upon the willingness of others to provide the required capital for the transactions.

Despite the ‘bad model problem’ (Fama, 1998) and the other alternative explanations for anomalous price behavior, many researchers posit that behavioral biases by investors play an important role for the occurrence of market anomalies (Daniel, Hirshleifer & Teoh, 2002; Daniel & Titman, 1999; De Bondt & Thaler, 1985; Lakonishok, Schleifer & Vishny, 1994). For a mispricing to persist, the underlying behavioral biases need to be correlated among investors so that they do not cancel out against each other, and market participants need to be prevented from exploiting and eliminating mispricing completely, consistent with the limits of arbitrage (Shleifer & Vishny, 1997).

Market anomalies can be classified according to different types: fundamental anomalies, calendar anomalies and technical anomalies (Latif, Arshad, Fatima & Farooq, 2011).

2.2.3.1 FUNDAMENTAL ANOMALIES

Fundamental anomalies occur when market prices deviate from intrinsic values, such as the net present value of expected earnings or book value (Latif, Arshad, Fatima & Farooq, 2011). These anomalies include the closed-end fund puzzle, the dividend puzzle, the equity premium puzzle, the neglected-firm effect, post-earnings announcement drift, the small firm effect and the value effect.

2.2.3.1.1 Closed-End Fund Puzzle

The closed-end fund puzzle has been suggested by Lee, Shleifer and Thaler (1991). This market anomaly grounds on the finding that the market prices of closed-end funds tend to deviate substantially from their net asset value (NAV). The mispricing is attributed to general investor sentiment, since premiums and discounts with respect to NAV have been found to be correlated across funds. Discounts have been suggested to reflect negative sentiment, while premiums have been argued to indicate positive sentiment. The importance of investor sentiment for price deviations from NAV has been underlined by research conducted on the Japanese market (Fujiwara, 2006).

2.2.3.1.2 Dividend Puzzle

The dividend puzzle implies that dividend-paying companies, which tend to be preferred by investors, are demanded to a larger extent than non-dividend-paying companies. As a result, dividend-paying stocks are likely to achieve disproportionately high valuations in the market (Black, 1976). The existence of this anomaly has been acknowledged recently, but it appears to prevail to different degrees in different cultural environments (Shao, Kowk & Guedhami, 2010). The dividend puzzle is based on the concept of mental accounting. This concept is associated with the tendency of individuals to address financial issues by referring to mentally separate accounts (Shefrin & Thaler, 1988). For instance, while investors have been found willing to expend dividend payments for funding purchases, they have been found unwilling to sell stocks of equal value instead (Baker, Nagel & Wurgler, 2006).

2.2.3.1.3 Equity Premium Puzzle

The equity premium puzzle refers to the unusually high return received by equity investors in the past century compared to the return received for holding risk-free securities (Mehra & Prescott, 1985). Fielding and Stracca (2007) scrutinized the stock market in the United States (US) and suggest that aversion to disappointment induces investors to demand fewer stocks on aggregate. This property would result in lower prices and higher associated returns. The tendency by investors to continuously follow the price fluctuations of their investments, which is associated with myopic loss aversion, may also contribute to the equity premium puzzle (Benartzi & Thaler, 1995).

2.2.3.1.4 Neglected-Firm Effect

The neglected-firm effect relates to the phenomenon that less well-known companies, whose stocks tend to be less regularly covered by analysts, are likely to generate above average risk-adjusted returns (Arbel, Carvell & Strebel, 1983). Dowen and Bauman (1986) provided empirical evidence of this anomaly, whereas Beard and Sias (1997) did not find such evidence. Miller (1989) gave a behavioral explanation for the neglected-firm effect, as he found investors to heuristically simplify the investment decision-making process.

2.2.3.1.5 Post-Earnings Announcement Drift

Post-earnings announcement drift is associated with stock prices that adjust only gradually to new price levels after surprising earnings releases. Continuously positive abnormal returns tend to occur after better than expected earnings results and continuously negative abnormal returns tend to occur after worse than expected earnings results (Ball & Brown, 1968). Post-earnings announcement drift has been investigated extensively and appears to be due to investor underreaction (Bernard & Thomas, 1989). According to other researchers (Anderson, Harris & So, 2007; Sadka, 2006), however, the extra return associated with exploiting this anomaly may not be abnormal but merely reflect a compensation for increased risk. It has also been argued that the ostensive extra returns merely account for transactions costs (Ng, Rusticus & Verdi, 2008).

2.2.3.1.6 Small Firm Effect

The small firm effect refers to the finding that positive abnormal stock returns tend to be negatively associated with the total market value of a company. Smaller firms have been shown to provide higher risk-adjusted returns than larger firms (Banz, 1981). Roll (1981), however, challenged the existence of positive abnormal returns, arguing that the risk incurred by investing in smaller firms is understated due to the effects of nonsynchronous trading. According to Levy and Levy (2011), positive abnormal returns associated with small firms dissipate once risk is measured over realistic holding periods. The small firm effect has been confirmed by several empirical studies (for instance, Amel-Zadeh, 2011). By way of contrast, Dimson and Marsh (1999) found evidence of a reverse small firm effect with respect to the stock market in the United Kingdom (UK).

2.2.3.1.7 Value Effect

The value effect implies that stocks characterized by high book value relative to their market price exhibit positive abnormal returns in the future (Rosenberg, Reid & Lanstein, 1985). Lakonishok, Shleifer and Vishny (1994) provided a behavioral explanation of the value effect which is consistent with investor extrapolation. On the other hand, Fama and French (1993) argued that particular risk factors associated with value investing tend to be underestimated. Various studies empirically investigated the existence of the value effect. This market anomaly has been confirmed for several stock markets throughout the world (for instance, Malkiel & Jun, 2009). Following Banko, Conover and Jensen (2006), the degree of the value effect depends upon the particular industry to which a stock belongs, with value industries being more susceptible but growth industries being less susceptible. They argue that although the value effect can be explained at least in part by pricing for risk, irrational pricing cannot be excluded. Investors who identify risk might still misprice it.

2.2.3.2 TECHNICAL ANOMALIES

Technical anomalies refer to particular return or price patterns of stocks that are predictable ex ante by referring to past returns or prices (Latif, Arshad, Fatima & Farooq, 2011). These anomalies include the momentum effect and the phenomena associated with technical analysis.

2.2.3.2.1 Momentum Effect

The momentum effect is related to the general tendency of stocks to show return persistence in the medium term. Stock returns have been found to be autocorrelated, while past outperformers continued to provide positive abnormal returns and past underperformers continued to provide negative abnormal returns (Jegadeesh & Titman, 1993). According to Siganos (2009), this market anomaly actually can be exploited in practice. Momentum does not appear to be explained by risk, as the momentum effect persists after controlling for idiosyncratic factors, industries and the Fama and French factors (Grundy & Martin, 2001). Behavioral interpretations for the occurrence of the momentum effect have been suggested and involve investor underreaction and investor overreaction, respectively (Barberis, Shleifer & Vishny, 1998; Daniel, Hirshleifer & Subrahmanyam, 1998; Hong & Stein, 1999).

2.2.3.2.2 Technical Analysis

Technical analysis posits that the price behavior of stocks is characterized by certain patterns that repeat over time. Against this background, particular trading rules have been suggested for exploiting such predictable price behavior (for instance, Alexander, 1961). The economic value of technical analysis has been demonstrated with respect to the US stock market (Brock, Lakonishok & LeBaron, 1992). However, Bajgrowicz and Scaillet (2012) question the validity of methodologies that suggest the profitability of technical analysis, as they doubt that transactions costs have been accounted for adequately. The patterns of technical analysis can be interpreted as resulting from the behavioral biases of market participants. Certain technical signals have been shown to be explicable by referring to specific biases, such as anchoring and adjustment, herd behavior or biases associated with representativeness (Zielonka, 2004). According to Friesen, Weller and Dunham (2009), confirmation bias leads to the formation of the head and shoulders and double top chart patterns.

2.2.3.3 CALENDAR ANOMALIES

Calendar anomalies relate to the finding that stock returns depend on particular dates or times (Latif, Arshad, Fatima & Farooq, 2011). They include the January effect and the weekday effect.

2.2.3.3.1 January Effect

The January effect is a calendar anomaly associated with the finding that stocks tend to provide positive abnormal returns in the first month of the year (Wachtel, 1942). Recent evidence suggests that this phenomenon is prevalent among small-cap stocks and cannot be explained solely from a rational point of view. While tax-loss selling appears to be partly responsible for the January effect, behavioral biases have also been argued to contribute to an increased propensity to sell stocks in December (Haug & Hirschey, 2006).

2.2.3.3.2 Weekday Effect

The weekday effect suggests that stock returns tend to be lower on Mondays compared to the other days of the week (French, 1980). This market anomaly is likely to be due to psychological reasons, as the mood of individuals has been found to be generally worse at the beginning of the week (Rystrom & Benson, 1989). The weekday effect was specifically acknowledged to exist with respect to technology stocks in the US (Gondhalekar & Mehdian, 2003).

2.2.4 PSYCHOLOGICAL FOUNDATIONS

Behavioral explanations for market anomalies are based on psychological research that is related to economic decision-making. Explanations from cognitive psychology, social psychology as well as references to emotional issues have been provided (Baker & Nofsinger, 2002). Cognitive psychological insights, more specifically the concepts of heuristics and frame dependence, are considered the foundations of behavioral finance while social psychological and emotional aspects provide supplemental explanations (Shefrin, 2002).

2.2.4.1 COGNITIVE PSYCHOLOGICAL EXPLANATIONS – THE FOUNDATIONS OF BEHAVIORAL FINANCE

Cognitive psychology studies the internal mental processes of human beings (Eysenck & Keane, 2010). The cognitive concepts of heuristic simplification and frame dependence provide behavioral explanations for the emergence of market anomalies.

2.2.4.1.1 Heuristic Simplification

In the following, the concept of heuristic simplification is discussed. First, a comprehensive definition is provided. Then, problems that are likely to result from reliance on heuristic simplification are explained. An alternative view that focuses on potential benefits associated with the use of heuristics is outlined, too. Finally, the importance of heuristic simplification among the participants in financial markets is emphasized.

2.2.4.1.1.1 Definition of Heuristics

Heuristics serve as mental shortcuts to facilitate judgment and decision-making. They represent a means for reducing the effort required to solve a particular problem, as they make extensive optimization computations redundant. Increasingly, the concept of heuristics has been broadened to encompass emotional aspects beyond mere cognitive issues. For instance, not only cognitive limitations, such as limited memory capacity, have been suggested to be a driver in the use of heuristics, but also motivational factors, such as avoiding the confrontation with unpleasant feelings, appear to play a role (Pezzo & Pezzo, 2007).

However, a consistent theory with regards to heuristic simplification has not been developed yet, and some heuristics even appear to oppose each other. For instance, the availability heuristic which suggests the subjective likelihood of an event according to the ease with which vivid examples of related events come to mind biases individuals to overestimate the probability of more recent events (Tversky & Kahneman, 1973). By way of contrast, the anchoring and adjustment heuristic, which weighs initial information more heavily, leads to an underestimation of the probability of more recent events (Tversky, & Kahneman, 1974).

2.2.4.1.1.2 Problems Arising due to Heuristic Simplification – Cognitive Biases

As indicated above with regards to the availability heuristic and the anchoring and adjustment heuristic, cognitive biases are likely to occur in a systematic fashion as a result of employing heuristics. So far, a variety of heuristics-based cognitive biases has been identified. These biases will be addressed at length in a separate paragraph. Even the judgment of experts in their area of expertise appears to become impaired by heuristics-based cognitive biases, as psychologists have been found to rely on erroneous intuitions about probabilities (Tversky & Kahneman, 1971).

2.2.4.1.1.3 Alternative View – Benefits Associated with Heuristics

Gigerenzer and Goldstein (1996) criticize a one-sided focus on the behavioral biases that are possibly caused by heuristic simplification. They emphasize that relying on heuristics can be an effective tool for arriving at reasonable judgment and decision-making. Specifically, they assume that individuals make use of a variety of ‘fast and frugal’ heuristics, which facilitates the quick and convenient processing of available information.

For instance, the recognition heuristic implies that a recognized object vis-à-vis an unrecognized object has a higher value with respect to a particular criterion. If provided with a choice between two distinct cities and being asked to judge which one would be bigger, individuals who rely on the recognition heuristic tend to name the city that they recognize as being familiar. Such an approach has been shown to regularly produce correct answers (Goldstein & Gigerenzer, 2002).

In similar vein, the concept of 'bounded rationality' posits that heuristic thinking does not necessarily lead to inferior judgment and decision-making. While this early concept acknowledges that human behavior is restricted by the amount of both information and time available for taking a particular decision as well as by limitations in cognitive abilities, it suggests that deviations from neoclassical rationality can still result in efficient outcomes (Simon, 1955). In the framework of 'bounded rationality', decision-makers are characterized as satisficers, which implies that they tend to seek sufficient satisfaction in economic transactions rather than optimizing results and maximizing expected utility (Simon, 1956).

2.2.4.1.1.4 Heuristic Simplification in Financial Markets

As far as real financial markets are concerned, the reliance of investors on heuristic simplification has been investigated extensively. Empirical evidence suggests that market participants are susceptible to employing particular heuristics, such as representativeness. As a consequence, financial judgment and investment decision-making are likely to become impaired (for instance, Marsden, Veeraraghavan & Ye, 2008). The specific cognitive biases that tend to result from reliance on heuristic simplification will be discussed in detail in a separate paragraph.

2.2.4.1.2 Frame Dependence

The concept of frame dependence is discussed in the following. First, a comprehensive definition is provided. Then, prospect theory is introduced, which constitutes the basis of frame dependence. The concept of mental accounting is also explained, which relates to frame dependence, too. Finally, the importance of frame dependence with respect to financial markets is highlighted.

2.2.4.1.2.1 Definition of Frame Dependence

The concept of frame dependence emphasizes the importance of the particular way an option is presented for whether it is chosen or not (Tversky & Kahneman, 1986). Narrow framing is associated with individuals who assess a decision problem in isolation without taking account of the broader context (Kahneman & Lovallo, 1993). The ‘Asian disease problem’ serves as an example of frame dependence (Tversky & Kahneman, 1981). It has been demonstrated in this case that the preferences of decision makers concerning the losses of human lives shifted merely due to an alteration in the wording of the decision problem. Such preference reversal opposes normative decision theories, for instance subjective expected utility theory. The latter combines the subjective probability of an outcome with the subjective expected utility of the outcome and explains how rational individuals are assumed to take decisions (Savage, 1954).

According to Bordalo, Gennaioli and Shleifer (2012), preference reversal can be caused by altering the salience of an outcome. While outcomes that are framed as more salient tend to receive higher subjective decision weights than justified by their true probability, outcomes that are framed as less salient tend to receive lower subjective decision weights than justified by their true probability. In this respect, frame dependence and the Allais paradox, which provides experimental evidence regarding the violation of the independence axiom of subjective expected utility theory (Allais, 1953), are interrelated.

Interestingly, it was discovered that human judgment becomes less biased when decision problems are described in a frame that employs frequencies instead of probabilities or percentages. Frequencies seem to be more intuitive to human beings than probabilities or percentages (Gigerenzer & Hoffrage, 1995). Descriptions that involve frequencies also tend to highlight the structure of a problem more clearly (Sloman, Over, Slovak & Stibel, 2003).

2.2.4.1.2.2 Prospect Theory

The concept of frame dependence is based on prospect theory, which seeks to describe in a realistic way how human beings take decisions that involve risk, as they choose among alternative options (Kahneman & Tversky, 1979). Prospect theory posits that individuals take decisions against the background of a reference point that represents their current state. With regards to this reference point, individuals are supposed to exhibit loss aversion; that is, they are more sensitive to losses than to gains (Kahneman & Tversky, 1979; Kahneman, Knetsch & Thaler, 1991). As a consequence, individuals prefer a smaller but sure gain over an uncertain gain that has a higher expected value. While some individuals may exhibit an irrational tendency to avoid losses, differences in the degree to which individuals are susceptible to loss aversion have been found to exist (for example Josephs, Larrick, Steele & Nisbett, 1992).

Prospect theory is a landmark theory in psychology and constitutes the foundation for identifying several cognitive biases (McDermott, Fowler & Smirnov, 2008). For instance, the pseudocertainty effect relates to the asymmetrical tendency to take risk-averse decisions when the anticipated outcome is positive but behave in a risk-seeking way when the expected outcome is negative (Tversky & Kahneman, 1986). Zero-risk bias is associated with the human tendency to prefer eliminating a relatively small risk completely over reducing a relatively large risk by an even greater extent (Kahneman & Tversky, 1979).

2.2.4.1.2.3 Mental Accounting

The concept of mental accounting is related to frame dependence. Mental accounting describes the tendency of individuals to approach economic issues by referring to mentally separate accounts (Thaler, 1980). For instance, investors may engage mentally either in ‘individual stock accounting’ or in ‘portfolio stock accounting’. The former implies that investors are loss-averse with respect to movements in each single stock in their portfolio, whereas the latter relates to investors who are loss-averse only to fluctuations in their aggregate portfolio without being affected by movements in individual stocks (Barberis, Huang & Brennan, 2001).

2.2.4.1.2.4 Frame Dependence in Financial Markets

As far as financial markets are concerned, empirical evidence confirms the importance of frame dependence (for instance, Kumar & Lim, 2008). For example, investors have been shown to prefer particular option strategies merely due to the effects of framing. From an objective point of view, however, increases in net cash inflows could not be achieved by following these strategies (Hoffmann & Fischer, 2012). The specific cognitive biases associated with frame dependence will be discussed at length in a separate paragraph.

2.2.4.2 OTHER PSYCHOLOGICAL EXPLANATIONS – ANCILLARY ISSUES

Beyond the cognitive psychological explanations for the concepts of behavioral finance and the emergence of market anomalies, other psychological explanations have been suggested. These refer to social psychological aspects and emotional aspects.

2.2.4.2.1 Social Psychological Aspects

Social psychology studies the ways in which the behavior, thoughts and feelings of an individual can be affected and altered by other people (Allport, 1985). In the financial marketplace, social psychological aspects refer to social issues and cultural impact.

2.2.4.2.1.1 Social Issues

Social issues involve social impact and sociability. Both the degree of social impact and the degree of sociability seem to have an effect on investor behavior.

2.2.4.2.1.1.1 Social Impact

When taking investment decisions, individuals may be influenced by peers, such as neighbors or colleagues. Households have been found to be inclined to purchase those stocks that their neighbors also invest in (Ivkovic & Weisbenner, 2007). Similarly, employees tend to select those mutual funds for retirement saving that their colleagues also prefer (Duflo & Saez, 2002). Social impact may also manifest itself in situations where individuals are required to justify their investment decisions towards others, as anticipated justifications are likely to materially alter investment decisions (Simonson & Staw, 1992).

By way of contrast, Feng and Seasholes (2004) argue that individual investors do not become influenced by their peers with respect to financial decision-making. While investors are supposed to exclusively draw upon the fundamental information available to them, only information asymmetries between investors have the potential to lead to differences in financial decision-making

2.2.4.2.1.1.2 Sociability

Since more sociable investors have been found to be more susceptible to behavioral biases (Knüpfer, 2008), the extent of sociability seems to have an effect on financial judgment and decision-making. More sociable households are in general more likely to invest in stocks (Hong, Kubik & Stein, 2004). The propensity of individuals to purchase stocks is positively related to the degree of stock ownership within their community, while this finding appears to be particularly pronounced for communities where more social interaction takes place (Brown, Ivkovic, Smith & Weisbenner, 2008). According to Guiso, Sapienza and Zingales (2004), the higher the social capital within a community, defined as the links between the inhabitants of the community, the greater the tendency to participate in the stock market.

2.2.4.2.1.2 Cultural Impact

The cultural background of an individual including ethnicity and religion is likely to impact on financial decision-making. Market participants from different cultural backgrounds tend to interpret financial information in different ways. Certain cultures have been found to value risk-taking more than others (Williamson, 2010).

According to Chui, Titman and Wei (2010), the cultural environment has a significant effect on equity investors. The stock markets in more individualistic countries have been associated with higher trading volume and higher price volatility. As these stock markets have been found to provide higher returns on momentum strategies, the relevant investors are likely to weigh their own information more heavily than consensus information.

Market participants have been shown to prefer companies that are related to their own cultural background, while this tendency appears to be more pronounced for unsophisticated investors (Grinblatt & Keloharju, 2001). The degree of risk aversion of an investor seems to be positively related to religiousness (Miller & Hoffmann, 1995).

2.2.4.2.2 Emotional Explanations

In psychology, emotions are related to feelings and motivations that arise as a result of certain stimuli. Emotions have the potential to influence the behavior of individuals (Altarriba, 2012). In the financial marketplace, emotional aspects are associated with the moods and motivations of investors as well as the concept of emotional finance.

2.2.4.2.2.1 Investor Mood

Investor mood refers to the particular psychological state that a market participant is affected by while taking a financial decision (Shu, 2010). In contrast with investor sentiment, which incorporates investment-related variables, such as closed-end fund discounts, investor mood focuses on external variables that are unrelated to financial markets or investments. As stated earlier, the weekday effect appears to be explicable by referring to investor mood (Rystrom & Benson, 1989). Moreover, investor mood has been associated with the extent to which weather, daylight, moon phases or sports events impact on investors and their behavior (Shumway, 2010).

2.2.4.2.2.1.1 Weather

According to Saunders (1993), weather has a significant effect on the stock returns in the US, with returns being lower on rainy days than on sunny days. This weather effect has been supported empirically for various stock markets throughout the world (Hirshleifer & Shumway, 2003; Chang, Nieh, Yang & Yang, 2006). However, as far as the Australian market is concerned, only mixed evidence could be provided (Keef & Roush, 2007). While the weather effect has not been discovered at all for Spain (Pardo & Valor, 2003), with respect to the Korean market the weather effect appears to have diminished over time (Yoon & Kang, 2009). According to Wang, Lin and Lin (2012), the weather in Taiwan is not related to stock market returns but it is related to stock market volatility. Finally, private investors appear to be more susceptible to the weather effect than institutional investors (Shu, 2008).

2.2.4.2.2.1.2 Daylight Length

Studies that incorporate the length of daylight revolve around seasonal affective disorder (SAD), which is associated with the occurrence of depressive moods when the days become shorter during autumn and winter. SAD has been found to cause investors to become more risk-averse (Kamstra, Kramer & Levi, 2003). This phenomenon has been supported by several empirical studies (Lo & Wu, 2010; Stefanescu & Dumitriu, 2011; Wang, Huang & Chen, 2012). The impact of SAD seems to be stronger during winter than during autumn (Wang, Huang & Chen, 2012). On the other hand, for several countries throughout the world, Kelly and Meschke (2010) found no evidence of SAD to occur. Jacobsen and Marquering (2008) provide evidence that casts doubt on the idea that seasonal patterns in stock returns are unambiguously due to weather or daylight.

2.2.4.2.2.1.3 Moon Phases

According to research which relates stock returns to the phases of the moon, returns have been discovered to be higher on new moon days than on full moon days (Dichev & Janes, 2003; Yuan, Zheng & Zhu, 2006). However, with regards to Asian markets, stock returns have been found to behave in the opposite way. This idiosyncrasy is likely to be due to the particular market structures of Asian markets (Liu & Tseng, 2009).

2.2.4.2.2.1.4 Sports Events

Finally, major sports events seem to have an impact on investor mood, as they tend to influence stock market returns. Empirical evidence suggests that domestic stock markets are likely to react negatively after national soccer, basketball, rugby or cricket teams have been defeated by foreign teams. Victories by domestic teams, however, do not appear to have an effect on domestic stock returns (Edmans, García & Norli, 2007). As far as New Zealand is concerned, a relationship between the sporting performance of the national rugby team and the performance of the domestic stock market could not be demonstrated (Boyle & Walker, 2003). According to Boido and Fasano (2006), the stock market performance of listed Italian soccer clubs tends to be positively related to their sporting performance.

2.2.4.2.2.2 Investor Motivation

The motivations of investors behind particular financial decisions can be explained by the concepts of loss aversion and cognitive dissonance. These concepts are introduced below.

2.2.4.2.2.2.1 Loss Aversion

Loss aversion refers to tendency of individuals to weigh losses more heavily than equivalent gains. Loss-averse individuals exhibit risk-averse behavior in the domain of gains but risk-seeking behavior in the domain of losses (Kahneman & Tversky, 1984). On the one hand, loss aversion is explicable by shifting investor preferences, as suggested by prospect theory (Kahneman & Tversky, 1979). On the other hand, loss aversion is also likely to involve motivational aspects, such as the avoidance of regret (Schmidt & Traub, 2002). According to Singh (2012), investors do not only regret the mere existence of a financial loss but also their responsibility for having taken a poor investment decision that led to the loss. As a consequence, investors are motivated to hold losing stocks on the basis of an emotional desire to avoid the confrontation with a bad investment decision. Even more, the motivation to prevent losses is likely to induce risk-seeking behavior (Scholer, Zou, Fujita, Stroessner & Higgins, 2010). In addition to private investors (for instance, Dimmock & Kouwenberg, 2010), professional investors are susceptible to loss aversion, as day traders on the Chicago Board of Trade have been found willing to incur higher risks following losses than following gains (Coval & Shumway, 2005). Interestingly, Schmidt and Traub (2002) report that females exhibit a higher degree of loss aversion than males.

2.2.4.2.2.2.2 Cognitive Dissonance

Investor motivations may also be explained by the concept of cognitive dissonance. This concept acknowledges that individuals feel uncomfortable once their actual behavior becomes incompatible with an attitude. While individuals are motivated to reduce uncomfortableness, that is cognitive dissonance, they are unlikely to effectuate such a reduction by changing their behavior. Rather, they are likely to eliminate cognitive dissonance by altering the attitude that has become inconsistent with actual behavior (Festinger, 1957). Since optimistic investors have been found to discount negative information (Antoniou, Doukas & Subrahmanyam, 2013), the participants in financial markets appear to be susceptible to cognitive dissonance. Smaller investors, presumably private investors, have been demonstrated to be particularly prone to cognitive dissonance (Antoniou, Doukas & Subrahmanyam, 2013).

2.2.4.2.2.3 Concept of Emotional Finance

The concept of emotional finance incorporates psychoanalytic theory into the decision-making of financial market participants (Taffler & Tuckett, 2010). This concept mainly revolves around the notions of integrated states of mind versus divided states of mind as well as phantastic objects. The emotional finance paradigm acknowledges that the future is inherently uncertain, thus risk cannot be seriously quantified ex ante. Investors who are characterized by an integrated state of mind are able to more or less realistically assess the risks and benefits associated with a particular investment. In contrast, investors who are affected by a divided state of mind tend to arrive at one-sided conclusions, as they unconsciously deny or split off the unpleasant aspects of an investment. This may result in wishful thinking and irrational behavior. Particular stocks are supposed to have the potential for becoming phantastic objects. Stocks that have turned phantastic objects are associated with uncritical idealization, while the existence of any risks is entirely denied. Once the investors can no longer suppress acknowledging delusion, however, the formerly loved phantastic objects become hated. Investors are likely to blame others for related financial losses, for instance investment consultants or the company's management (Tuckett & Taffler, 2008).

2.2.5 BEHAVIORAL ASSET PRICING

As outlined earlier, an increasing number of market anomalies emerged over time while financial assets were priced according to neoclassical theory. Against this background, researchers in behavioral finance began to develop alternative asset pricing models that account for the behavioral biases of investors. Quantitative behavioral finance refined behavioral asset pricing by introducing specific statistical techniques.

2.2.5.1 BEHAVIORAL ASSET PRICING MODELS

While some behavioral asset pricing models focus on cognitive biases that result from reliance on heuristic simplification, others address the preferences of investors by incorporating prospect theory. More recently, a more comprehensive generalized behavioral asset pricing model has been suggested (Szyszka, 2009).

2.2.5.1.1 Heuristics-Based Models

A few heuristics-based behavioral asset pricing models have been developed. The major models, which include those by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999), are discussed below.

2.2.5.1.1.1 Barberis, Shleifer and Vishny (1998)

The heuristics-based model by Barberis, Shleifer and Vishny (1998) assumes that investors are affected either by conservatism and react only gradually to new information, or that they are affected by representativeness and extrapolate past returns too far into the future. Although this model has the potential to explain underreaction and overreaction in stock prices, it cannot account for a long-term persistence of abnormal returns (Szyszka, 2010).

2.2.5.1.1.2 Daniel, Hirshleifer and Subrahmanyam (1998)

According to the heuristic-driven model by Daniel, Hirshleifer and Subrahmanyam (1998), investors are prone to overconfidence and biased self-attribution. Following the release of information that is inconsistent with an original opinion, investors will still adhere to the opinion in an overconfident fashion. Only after continuous disconfirming evidence has been provided, an original opinion is changed gradually. This model has the potential to explain both stock price continuations and stock price reversals. However, it cannot account for other phenomena, such as the anomalous long-term abnormal return of initial public offerings (IPOs) (Szyszka, 2010).

2.2.5.1.1.3 Hong and Stein (1999)

The model by Hong and Stein (1999) suggests that two different types of investors dominate the stock market and new information spreads only gradually. This model assumes that neither of the investor types is fully rational, with ‘news watchers’ exclusively focusing on incoming fundamental information and ‘momentum traders’ only considering price information. As new information diffuses only gradually among ‘news watchers’, stock prices tend to underreact and price momentum will develop. Once ‘momentum traders’ recognize a price trend, they will start to extrapolate that trend, which contributes to stock price overreaction. One day, ‘news watchers’ will identify an overpricing and begin to short the stocks. The process of initial underreaction and subsequent overreaction is about to start again, only in the opposite direction. This model provides explanations for short-term trend continuations and long-term trend reversals. However, difficulties arise with regards to long-term momentum as a result of particular events, such as a change in the company’s dividend policy (Szyszka, 2010).

2.2.5.1.2 Prospect Theory-Based Models

Other behavioral asset pricing models are based on prospect theory. The model by Barberis, Huang and Santos (2001) and the probability misperception model (Dacey & Zielonka, 2008) are the main prospect theory-based models. These models are discussed in the following.

2.2.5.1.2.1 Barberis, Huang and Santos (2001)

The behavioral asset pricing model by Barberis, Huang and Santos (2001) is based on prospect theory, as it incorporates related concepts, such as frame dependence and loss aversion. This model assumes that investors are sensitive to changes in the value of their total wealth. Investors are supposed to care more about decreases in wealth than about equivalent increases in wealth, as they become less risk-averse following wealth increases but more risk-averse following wealth decreases. This model provides an explanation for stock price overreaction. Investors who become less risk-averse after stock price increases cause prices to rise even further, and investors who become more risk-averse after stock price decreases, tend to put additional pressure on prices.

2.2.5.1.2.2 Probability Misperception Model

According to the probability misperception model by Dacey and Zielonka (2008), two categories of investors exist. Many quasi-rational investors, who arrive at incorrect probability assessments, face few rational investors, who are capable of determining the correct probabilities. Both investor types are characterized as having the same preferences, which can be described by the value function from prospect theory. As rational and quasi-rational investors attach different probability values to particular price changes, they differ in their assessment as to future stock returns. This model has the potential to explain stock price continuations in the short term. However, it cannot account for the sequence of short-term momentum followed by long-term reversal.

2.2.5.1.3 Generalized Behavioral Asset Pricing Model (GBM)

GBM, which was developed more recently, addresses some of the shortcomings of the earlier behavioral asset pricing models (Szyszka, 2009). This model assumes that investors are either rational in the neoclassical sense or irrational and impaired by behavioral biases. The behavioral biases are supposed to belong to three groups. The first group addresses an erroneous processing of information and includes anchoring and adjustment, availability bias and the overconfidence effect. The second group accounts for biases that result from reliance on the representativeness heuristic; that is, extrapolation bias and the gambler's fallacy. The third group involves biases that are due to changing investor preferences, as explained by prospect theory.

Although the market has the potential to correct mispricing that results from the behavioral biases of investors, rational arbitrageurs are restricted by several limitations that keep them from entirely exploiting every deviation from fundamental value. As irrational investors might dominate the price formation process, rational arbitrageurs are likely to demand a reasonable risk premium as compensation for potential behavioral mispricing.

GBM is able to explain several market anomalies, both price momentum and price reversals, market bubbles as well as excessive price volatility. Still, this behavioral asset pricing model is rather generalizing and cannot be employed ex ante in order to price assets (Szyszka, 2010).

2.2.5.2 QUANTITATIVE BEHAVIORAL FINANCE

Quantitative behavioral finance addresses shortcomings associated with the behavioral asset pricing models. It incorporates mathematical and statistical methods as well as models to quantify behavioral biases for the purpose of valuing financial assets. These methods have the potential to determine the specific impact of a particular bias on the price of an asset. For instance, quantitative behavioral finance relies on regression models that include the fundamental value of the asset as one of the independent variables (Caginalp & DeSantis, 2011a).

By employing nonlinear models, quantitative behavioral finance is able to account for opposing behavioral phenomena, such as underreaction and overreaction. Simple linear methods, which have traditionally been used for explaining stock returns, are unlikely to detect all existing patterns but may erroneously suggest a random (Caginalp & DeSantis, 2011b). Quantitative behavioral finance is also capable of modeling specific behavioral biases, for instance anchoring and adjustment (Caginalp & DeSantis, 2011c). Similarly, chart patterns that bring into question EMH, such as the head and shoulders pattern, can be accounted for in a mathematical sense (Caginalp & Balenovich, 1999).

Furthermore, it has been suggested that quantitative behavioral finance can incorporate models of swarm intelligence. These models are able to determine the proportion of market participants that belongs to a particular behavioral category (Thimmaraya & Masuna, 2012).

Nevertheless, some behavioral biases may be impossible to quantify. For instance, the impact of the affect heuristic, which implies decision-making that is affected by immediate emotional response (Finucane, Alhakami, Slovic & Johnson, 2000), has been found difficult to quantify in a statistical or mathematical model (Caginalp & DeSantis, 2011a).

2.2.6 NEUROFINANCE

Recent advances in neuroscience facilitated the emergence of the field of neurofinance. Neurofinance analyzes the brain processes of individuals while they are engaged in investment decisions. Experimental evidence based on neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), underlines the importance of emotions during financial decision-making (Sahi, 2012). Lo and Repin (2002) provide early empirical evidence, as they demonstrate that emotional reactions associated with financial risk-taking lead to a marked physiological response in market participants. Other studies have confirmed this empirical evidence by examining hormone levels or electrophysiological aspects, for instance the heart rate (Peterson, 2010). The level of testosterone of male traders has been found to be positively related to both financial risk-taking and profitability (Coates & Herbert, 2008). According to Koenigs and Tranel (2007), damage to particular areas of the brain is likely to engender irrational financial decision-making.

Neurofinance has confirmed certain phenomena from a biological perspective that had been suggested earlier by behavioral finance. The existence of irrational investor behavior is supported by neurofinance, as frame dependence and loss aversion have been found to be associated with activation of the amygdala. Rational decision-making, on the other hand, would be associated with activity in the prefrontal cortex and the cingulate cortex (De Martino, Kumaran, Seymour & Dolan, 2006). The importance of emotions and unconscious mental processes, as suggested by the emotional finance paradigm, was also acknowledged by neuroscientific research (Wolozin & Wolozin, 2007).

Moreover, the occurrence of specific behavioral biases can be explained within the neuroscientific framework. Herd behavior by investors has been found to be related to activity in the ventral striatum, an area of the brain that is responsible for reward (Burke, Tobler, Schultz & Baddeley, 2010). Activation of the right anterior insula, which is associated with subjective emotional states and feelings (Critchley, Wiens, Rotshtein, Öhman & Dolan, 2004), tends to cause behavior consistent with the endowment effect (Knutson, Wimmer, Rick, Hollon, Prelec & Loewenstein, 2008). Individual differences in the susceptibility to behavioral biases appear to be due to individual differences in brain activity (De Martino, Kumaran, Seymour & Dolan, 2006).

Nonetheless, the insights gained by research in neurofinance have been criticized for methodological shortcomings. It is doubtful whether the typically experimental and laboratory-like nature of neurofinance research can be generalized toward the decision-making in real financial markets (Peterson, 2010). Reactive effects tend to impair the validity of such study designs, as research participants are likely to exhibit artificial behavior as a result of the presence of a researcher as well as the awareness of taking part in a study (Bryman & Bell, 2011). Neurofinance research tends to employ obtrusive and uncomfortable devices, for instance during the process of fMRI, which is also likely to bias the way research participants behave (Eysenck & Keane, 2010). Finally, since neuroscientific research requires expensive medical equipment, related studies tend to be restricted to relatively small samples (Harrison, 2008).

2.3 EVIDENCE OF BEHAVIORAL BIASES IN FINANCIAL MARKETS

Behavioral biases constitute one major theme in behavioral finance. It has been suggested that market anomalies can be attributed to the occurrence of behavioral biases among investors. Various behavioral biases that had been discovered through early experimental research in psychology were tested empirically with respect to the participants in financial markets. The majority of biases ground on cognitive psychological concepts. Other biases are associated with social psychological concepts. Emotional aspects often play a role when behavioral biases occur.

2.3.1 COGNITIVE BIASES

Cognitive biases are based on insights from cognitive psychology. These biases are likely to emerge when investors rely on heuristic simplification or become susceptible to frame dependence.

2.3.1.1 COGNITIVE BIASES DUE TO HEURISTIC SIMPLIFICATION

Several heuristics-based cognitive biases have been identified. These biases include affect bias, anchoring and adjustment, availability bias, confirmation bias, hindsight bias, optimism bias, overconfidence effect, self-attribution bias as well as the biases that constitute manifestations of the representativeness heuristic.

2.3.1.1.1 Affect Bias

Affect bias is likely to result from reliance on the affect heuristic. This bias refers to individuals whose decision-making becomes compromised by positive or negative feelings that have been triggered by a particular stimulus. Affect bias typically emerges when individuals assess the risks and benefits associated with a particular decision. Arising positive feelings caused by a liked matter tend to bias the perception of risks downward and the perception of benefits upward (Finucane, Alhakami, Slovic & Johnson, 2000). Ex post, individuals are likely to warrant decisions that were impaired by affect bias as having been rational, without becoming aware that their decision-making might have been biased (Zajonc, 1980).

According to experimental evidence in a financial market context, investors have been shown to prefer those industries (MacGregor, Slovic, Dreman & Berry, 2000) and firms (Ackert & Church, 2006) that they have a positive image of. Affect bias can lead to the assessment that high return investments involve low risks while investments providing low returns entail high risks. Such an assessment, however, would entirely contradict neoclassical theory (Markowitz, 1952). Considering experimental research with respect to German blue-chips stocks, more sophisticated investors appear to be less susceptible to affect bias (Kempf, Merkle & Niessen-Ruenzi, in press). Empirical evidence supports the existence of affect bias among financial market participants. Real investors have been shown to be susceptible to this bias, as they tend to purchase the stocks of companies that they fancy. Nevertheless, these stocks have been found to provide lower risk-adjusted returns than the stocks of disliked companies (Barber, Heath & Odean, 2003).

2.3.1.1.2 Anchoring and Adjustment

Anchoring and adjustment is associated with individuals who take decisions on the basis of only particular pieces of information while neglecting others. Decision-makers may be anchored towards the first information that they become aware of, but then only insufficiently incorporate additional information that becomes available subsequently. Anchoring and adjustment has the potential to bias the way people intuitively assess probabilities (Tversky & Kahneman, 1974).

Empirical research suggests that anchoring and adjustment is likely to occur in stock markets. Securities analysts in the US (Amir & Ganzach, 1998) and Australia (Marsden, Veeraraghavan & Ye, 2008) as well as Japanese investors (Nakazono, 2012) have been found susceptible to this bias. According to Amir and Ganzach (1998), anchoring leads to an underreaction in analyst forecasts. Since the most recent financial crisis, anchoring and adjustment appears to have become more prevalent (Nakazono, 2012).

2.3.1.1.3 Availability Bias

Availability bias is also related to incorrect intuitive probability judgments. More specifically, the subjective probability assessments are biased by the ease with which instances of a particular event come to mind (Tversky & Kahneman, 1973). Thus, the likelihood of particularly salient, emotional or recent events tends to be overestimated. According to Shefrin (2002), the intense media coverage of dramatic incidents facilitates the occurrence of availability bias.

Empirical evidence underlines the importance of availability bias in the financial marketplace. Investors into low-capitalization stocks appear to be particularly susceptible (Kliger & Kudryavtsev, 2010). On the other hand, Frieder (2004) found only mixed evidence for the existence of this bias. Obviously, the particular personality traits of an investor play a role for availability bias to emerge. While escalation of commitment has been found to be positively associated with availability bias, investor openness seems to mitigate this bias (Sadi, Asl, Rostami, Gholipour & Gholipour, 2011). According to Semenov (2009), the concept of availability bias can be incorporated into asset pricing models so as to arrive at a more realistic calculation of expected returns.

2.3.1.1.4 Confirmation Bias

Confirmation bias refers to the tendency by individuals to selectively draw upon information that confirms an original belief. Information that may question or refute an initial hypothesis tends to be discarded (Wason, 1960). On the one hand, this bias may be due to wishful thinking and a motivation to avoid or deny discomforting evidence (Szyszka, 2010). On the other hand, confirmation bias may be attributable to memory distortions; that is, cognitive failures that do not involve emotions (Koehler, 1991).

Experimental research demonstrates that the economic decision-making of executives with regards to corporate mergers tends to be impaired by confirmation bias (Bogan & Just, 2009). According to theoretical evidence, this bias seems to be relevant to stock markets, too (Friesen, Weller & Dunham, 2009). The importance of confirmation bias for stock market participants is underpinned by empirical evidence that discovered the susceptibility of securities analysts (Chu, 2006).

2.3.1.1.5 Hindsight Bias

Hindsight bias is associated with individuals who assess events ex post as if they had been predictable ex ante. This bias can adversely affect the ability to evaluate the past and learn from it (Fischoff, 1975). Mazzoni and Vannucci (2007) argue that hindsight bias occurs as a result of memory distortions, while Pezzo and Pezzo (2007) emphasize the importance of motivated forgetting so that a confrontation with uncomfortable feelings can be avoided.

As far as financial market participants are concerned, investment bankers have been found to be prone to hindsight bias irrespective of their professional experience. As a consequence, their performance and risk management tend to be suboptimal (Biais & Weber, 2009). According to survey evidence, investors appear to be affected by hindsight bias dependent upon their personality, with extroverted and open individuals being more susceptible (Sadi, Asl, Rostami, Gholipour & Gholipour, 2011).

2.3.1.1.6 Optimism Bias

Individuals are impaired by excessive optimism if they overestimate the probability of positive outcomes but underestimate the probability of negative outcomes (Weinstein, 1980). Such optimism bias is likely to entail serious misjudgments while risks are not adequately accounted for (Sharot, Riccardi, Raio & Phelps, 2007). Nevertheless, optimism bias has been criticized as being vague and different kinds of optimism bias tend to have different implications for investors (Hynes, 2004).

Empirical evidence suggests that optimism bias is relevant to financial market participants. Stock market investors appear to be susceptible to this bias, as they have been found to overreact after price increases but underreact after price decreases (Ising, Schiereck, Simpson & Thomas, 2006). Furthermore, investors into private stock placements (Marciukaityte, Szewczyk & Varma, 2005), IPO investors (Derrien, 2005; Ljungqvist, Nanda & Singh, 2006) and currency analysts (Rajapakse & Siriwardana, 2007) have been demonstrated to be impaired by optimism bias.

2.3.1.1.7 Overconfidence Effect

The overconfidence effect is associated with an individual's subjective degree of confidence into own judgments that is significantly higher than justified from an objective point of view. This bias involves miscalibration and the better-than-average effect (Glaser & Weber, 2007). Miscalibration relates to decision-makers who overestimate the precision of their information and consequently set confidence intervals too low, for example as to the prediction of future stock prices (Lichtenstein, Fischoff & Phillips, 1982). The better-than-average affect implies the disproportionate belief of an individual to be more sophisticated than others and to be able to generate superior results (Svenson, 1981).

According to survey evidence (Bhandari & Deaves, 2006; Tourani-Rad & Kirkby, 2005) and empirical evidence (Odean, 1998; Chuang & Lee, 2006; Lin, Rahman & Yung, 2010), stock market investors are prone to the overconfidence effect. Private investors seem to be particularly susceptible. While overconfidence tends to increase trading activity (Barber & Odean, 2000) and affected investors fail to diversify their portfolios sufficiently (Odean, 1998), in Taiwan, overconfident investors have been found to prefer small-cap stocks (Ho, 2011). Interestingly, private investors into real estate investment trusts (REITs) do not appear to exhibit overconfidence (Lin, Rahman & Yung, 2010). Investor demographics and personality traits seem to play a role for the overconfidence effect to arise. While males have been found to be particularly susceptible to this bias (Barber & Odean, 2001; Bhandari & Deaves, 2006), this finding is likely to be due to different perceptions of risk between males and females (Mittal & Vyas, 2011). Moreover, the overconfidence effect tends to be positively related to investor income (Mittal & Vyas, 2009) and seems to be facilitated by extroverted investor personalities (Sadi, Asl, Rostami, Gholipour & Gholipour, 2011). Finally, professional investors, such as fund managers, appear to be prone to overconfidence, too (Puetz & Ruenzi, 2011).

2.3.1.1.8 Self-Attribution Bias

Self-attribution bias refers to the tendency by individuals to honor themselves for successes but blame others or external factors for failures. Motivational issues, such as protecting one's self-esteem, appear to play a role for the occurrence of this bias (Miller & Ross, 1975).

The relevance of self-attribution bias in financial markets has been confirmed empirically for online investors (Barber & Odean, 2002) and day traders (Andersson & Tour, 2005). This empirical evidence was recently supplemented by survey research, which discovered that self-attribution bias and investor education tend to be negatively related (Nguyen & Schüßler, 2012). By way of contrast, other research could not find evidence of this bias (Allen & Evans, 2005; Uchida, 2006). Professional proprietary traders do not appear susceptible to self-attribution bias, as they could not be shown to accept higher levels of risk following a streak of profitable trades (Coval & Shumway, 2005).

2.3.1.1.9 Cognitive Biases Resulting from Reliance on the Representativeness Heuristic

As a consequence of making use of the representativeness heuristic, different cognitive biases can emerge. Surprisingly, these biases have partly opposing implications. Although the representativeness heuristic is considered to be the most important judgmental heuristic and a variety of research has been conducted on the related biases (Nisbett, Krantz, Jepson & Kunda, 2002; Bloomfield & Anderson, 2010), not all of biases have been clearly distinguished yet. For these reasons, the cognitive biases associated with the representativeness heuristic will be discussed in detail in a separate paragraph, where arising research potential is also identified.

2.3.1.2 COGNITIVE BIASES DUE TO FRAME DEPENDENCE

Several cognitive biases have been suggested that are based on the concept of frame dependence. These biases include ambiguity aversion, the disposition effect, the endowment effect, hedonic editing, the house money effect and status-quo bias.

2.3.1.2.1 Ambiguity Aversion

Ambiguity aversion relates to the finding that individuals dislike uncertain probabilities (Ellsberg, 1961). This bias implies that investors prefer assets whose riskiness is known in advance, as they dislike situations where risk cannot be determined ex ante. Fear of the unknown seems to be an emotional aspect of ambiguity aversion (Shefrin, 2002).

As a result of investors who are averse to ambiguity, the required rate of return of equity appears to contain an ambiguity premium in addition to the risk premium suggested by CAPM (Chen & Epstein, 2002). In this respect, ambiguity aversion has an effect on the overall economy, as the cost of capital is biased upward (Aloysius, 2005). Ambiguity aversion has been demonstrated to negatively affect the trading volume of stocks, which impairs liquidity and diversification opportunities (Rinaldi, 2009). However, more recent research discovered that the equity premium does not necessarily increase as a consequence of ambiguity aversion, as the demand for uncertain assets may not decrease in some instances (Gollier, 2011). According to experimental evidence, most market participants appear to be unwilling to pay a premium for reducing ambiguity (Grou & Tabak, 2008).

2.3.1.2.2 Disposition Effect

The disposition effect is associated with the tendency by investors to sell stocks that have increased in price but keep stocks that have decreased. This bias can be explained by prospect theory and mental accounting (Shefrin & Statman, 1985). However, an alternative explanation suggests that the disposition effect may be attributable to investors who expect mean reversion in stock prices (Weber & Camerer, 1998). Emotional issues, such as regret avoidance, are also likely to play a role, as investors dislike admitting poor investment decisions (Lehenkari, 2012). According to Roger (2009), awareness of the disposition effect causes market participants to demand an increased risk premium.

Recent empirical evidence underlines the importance of the disposition effect in the financial marketplace. This bias has been shown to emerge both in developed markets (for instance, Lehenkari, 2012; Marciukaityte & Szewczyk, 2012) and emerging markets (for instance, Aftab, Shah & Sheikh, 2012; Chong, 2009; Farag & Cressy, 2010; Lee, Yen & Chan, 2013; Tehrani & Gharehkoolchian, 2012). Professional investors have been examined specifically and appeared susceptible (Ammann, Ising & Kessler, 2012). Interestingly, while domestic stock investors in Estonia have been found prone to the disposition effect, such evidence could not be provided for international investors (Talpsepp, 2011).

2.3.1.2.3 Endowment Effect

The endowment effect refers to the finding that for goods that they own, individuals tend to demand higher prices than they would be willing to pay for the same goods if they did not yet own them. This bias can be explained by referring to prospect theory, whose value function implies that people weigh losses stronger than identical gains. (Thaler, 1980)

According to empirical evidence, the endowment effect is relevant to stock markets. While the liquidity and efficiency of the market tend to become impaired due to this bias, private investors have been found more susceptible than professional investors (Furche & Johnstone, 2006). Risk-averse investors, however, appear to remain rather unaffected compared to risk-seeking investors (Dungore, 2011).

2.3.1.2.4 Hedonic Editing

As hedonic editing is based on the concept of mental accounting, it relates to individuals who integrate and segregate different outcomes in such a way that their subjective perception becomes as positive as possible. For instance, investors have been found to bundle unprofitable trades in one common mental account while they enjoy profitable trades separately. Investors also appear to combine small losses with large gains rather than the other way round. As a result, profits become highlighted whereas losses are de-emphasized (Thaler & Johnson, 1990).

Empirical evidence hints at the importance of hedonic editing in the financial marketplace. Investors have been found to sell several different stocks at the same time when faced with losses instead of gains (Lim, 2006). On the other hand, Lehenkari (2009) did not find convincing evidence of hedonic editing. She reports that investors do not integrate losses more often than gains; neither do they appear to prefer integrating small losses with large gains over integrating large losses with small gains.

2.3.1.2.5 House Money Effect

The house money effect, which is also based on mental accounting, is associated with the tendency by individuals to separate total wealth into initial wealth as well as house money that results from recent gains. As far as the house money is concerned, people tend to be less risk-averse and more willing to engage in speculation (Thaler & Johnson, 1990). The house money effect opposes the disposition effect in that it induces individuals to become less risk-averse following gains rather than more risk-averse (Chiu, Shu & Jian, 2009). Weber and Zuchel (2005) argue that the propensity for the house money effect to occur is likely to depend upon the way a financial decision problem is framed.

According to both experimental evidence (Ackert, Charupat, Church & Deaves, 2006) and empirical evidence (Brown, Chappel, Da Silva Rosa & Walter, 2006; Hsu & Chow, 2010), investors are prone to the house money effect. Professional market participants were specifically examined and have been found susceptible (Frino, Grant & Johnstone, 2008).

2.3.1.2.6 Status-Quo Bias

Status-quo bias refers to the preference of individuals to maintain an original state over accepting alterations to that state although enhancements might be possible. In this respect, decision options are perceived as being more attractive when they suggest reflecting the status quo. The preference for the status quo seems to be positively related to the number of alternative options available (Kahneman, Knetsch & Thaler, 1991). Status-quo bias is explicable both by frame dependence and by referring to heuristics-based cognitive errors. Finally, this bias may involve irrational emotional aspects, such as escalation of commitment (Samuelson & Zeckhauser, 1988).

Empirical research provides evidence for the occurrence of status-quo bias during financial decision-making. Equity fund investors have been found to keep purchasing certain funds although adherence to these funds may no longer represent the optimal choice (Kempf & Ruenzi, 2006). Investors from both Western cultures (Brown & Kagel, 2009) and Asian cultures (Jianbiao, Guangqian, Qiuhua & Lüke, 2009) appear prone to status-quo bias. This bias tends to be more pronounced when the alternatives to keeping the status quo seem rather vague and when investors are impaired by negative emotions (Jianbiao, Guangqian, Qiuhua & Lüke, 2009). Interestingly, status-quo bias has been shown to intensify if equity returns are formulated as ratios, as nominal appreciations or as selling prices instead of percentages (Rubaltelli, Rubichi, Savadori, Tedeschi & Ferretti, 2005).

2.3.2 OTHER BIASES

In addition to the variety of cognitive biases, a few social biases are relevant to financial markets. Besides, behavioral biases in general either include an emotional component or not.

2.3.2.1 SOCIAL BIASES

Two social biases have been identified to impact on investor behavior. These biases may arise as a consequence of social influence or the impact by the cultural environment.

2.3.2.1.1 Social Bias Due to Social Influence

One particular social bias can be attributed to the social influence on investors. This bias refers to herd behavior.

2.3.2.1.1.1 Herd Behavior

Herd behavior is associated with individuals who become influenced by others in their judgment and decision-making, as they imitate the behavior of others (Scharfstein & Stein, 1990). On the one hand, herding can be rational, in instances where decision makers use the information advantage of others (Banerjee, 1992). On the other hand, herding is irrational if decision makers are impaired by unreasonable emotions, such as greed and fear (Shiller, 1995).

With regards to financial markets, herd behavior has been researched extensively. The investors in developed markets (for instance, Belhoula & Naoui, 2011; Khan, Hassairi & Viviani, 2011; Venezia, Nashikkar & Shapira, 2011) as well as emerging markets (Lao & Singh, 2011) have been found susceptible. Foreign investors in emerging markets were specifically addressed and have been shown to be affected by herd behavior in Korea (Jeon & Moffett, 2010) and Taiwan (Chiang, 2008; Chen, Yang & Lin, 2012). While professional investors appear prone to herding (Agudo, Sarto & Vicente, 2008; Sias, 2004; Voronkova & Bohl, 2005; Walter & Weber, 2006; Wylie, 2005), private investors have been demonstrated to be affected to a larger extent (Venezia, Nashikkar & Shapira, 2011). Stocks that are heavily traded (Blasco, Corredor & Ferreruela, 2011) and technology stocks (Hoitash & Krishnan, 2008; Guo & Shih, 2008) seem particularly vulnerable to investor herding. The stocks of large companies (Venezia, Nashikkar & Shapira, 2011) and property stocks (Zhou & Lai, 2008) tend to be less affected. Nevertheless, the existence of herd behavior could not be proven unequivocally. While some studies found only mixed empirical evidence (Agarwal, Chiu, Liu & Rhee, 2011; Al-Shboul, 2012; Chiang & Zheng, 2010; Economou, Kostakis & Philippas, 2011; Gabsia, 2011; Lin & Swanson, 2008), other studies did not find evidence at all (Fu, 2010; Moradi & Abbasi, 2012). According to experimental research, herding tends to be facilitated by uncertainty (Fernández, Garcia-Merino, Mayoral, Santos & Vallelado, 2011).

2.3.2.1.2 Social Bias Due to Cultural Impact

One distinct social bias is associated with the particular cultural environment that an investor belongs to. This bias relates to home bias.

2.3.2.1.2.1 Home bias

Home bias is associated with the tendency by investors to disproportionately prefer domestic stocks while under-investing in foreign stocks. As a result, the benefits from international diversification are not exploited completely (French & Poterba, 1991). On the one hand, this bias is explicable by referring to market imperfections, such as information asymmetries or transaction costs (Sendi & Bellalah, 2010). On the other hand, behavioral issues tend to play a role, most notably overconfidence, regret and social identification (Foad, 2010). The extent of home bias appears to have decreased during recent decades (Sorensen, Wu, Yosha & Zhu, 2007; Hiraki, Ito & Kuroki, 2003), as financial integration has proceeded throughout the world (Mondria & Wu, 2010). Coval and Moskowitz (1999) specify so-called local bias as an extension to home bias. Local bias refers to domestic investors who show preference for companies close to their place of residence.

The importance of home bias has been confirmed by empirical research. Both individual investors (for instance, Nordén, 2010) and professional investors (Ke, Ng & Wang, 2010) appear prone to this bias. While fund managers from industrialized countries have been found to be disproportionately more optimistic for domestic stocks than for foreign stocks

(Strong & Xu, 2003), they seem to be affected by home bias. However, the research results are not unambiguous. For instance, Australian pension fund investors could not be demonstrated to be susceptible to home bias (Gerrans, Gardner, Clark-Murray & Speelman, 2006). According to Antoniou, Olusi and Paudyal (2010), home bias does not necessarily hint at irrational investor behavior, as equity portfolios in the UK could not be shown to become more efficient by including foreign stocks.

2.3.2.2 'EMOTIONAL BIASES'

While it appears difficult to delimit particular behavioral biases as distinct emotional biases, the cognitive and social biases discussed earlier may or may not incorporate emotional elements. While some of the behavioral biases address emotions and feelings directly, other biases involve emotional aspects in a more indirect way and hint at the motivations behind particular decisions.

For instance, affect bias concerns feelings in a straightforward way, as it suggests that decisions are influenced by the particular emotional state of the decision-maker while taking the decision (Finucane, Alhakami, Slovic & Johnson, 2000). Confirmation bias or self-attribution bias, however, may more indirectly involve the motivation of an individual to preserve self-esteem (Park, Konana, Gu, Kumar & Raghunathan, 2013). Similarly, the disposition effect may be explained by referring to the motivation of regret-averse investors who dislike admitting that an original investment decision was wrong (Summers & Duxbury, 2012).

2.3.3 APPRAISAL OF THE FINANCIAL MARKET EVIDENCE

Overall, the evidence concerning the existence of behavioral biases in the financial marketplace is mixed. Different market participants appear to be impaired to different degrees and country-specific factors seem to play a role. Although behavioral biases refer to irrational behavior, deviations from the idealized neoclassical framework do not necessarily constitute irrational behavior. Behavioral biases can materially affect market prices and facilitate the occurrence of market anomalies.

2.3.3.1 MIXED OVERALL EVIDENCE

As outlined earlier, various research studies have underlined the importance of behavioral biases in the financial marketplace. Nonetheless, some studies question the emergence of behavioral biases in financial markets. For instance, Frieder (2004) found only mixed evidence concerning availability bias; Coval and Shumway (2005) could not provide evidence for the existence of self-attribution bias, and Lehenkari (2009) contradicted hedonic editing. While Fu (2010) rebutted herd behavior completely, Al-Shboul (2012) found only ambiguous evidence of investor herding. Finally, Gerrans, Gardner, Clark-Murray and Speelman (2006) cast doubt on the existence of home bias.

2.3.3.2 PRIVATE INVESTORS VS. PROFESSIONAL INVESTORS

According to the financial market evidence of behavioral biases, it appears that the financial decision-making of private investors is somewhat more affected by biased behavior than the financial decision-making of professional investors. This finding has been made with respect to the overconfidence effect (Barber & Odean, 2000), self-attribution bias (Coval & Shumway, 2005), the disposition effect (Hur, Pritamani & Sharma, 2010), the endowment effect (Furche & Johnstone, 2006) and herd behavior (Venezia, Nashikkar & Shapira, 2011).

While it seems reasonable to assume that private investors tend to be less sophisticated on average than professional investors, the degree of investor sophistication has been found to play a role in the susceptibility to behavioral biases. The supposition that more sophisticated investors are less prone to behavioral biases is confirmed by experimental research on affect bias (Kempf, Merkle & Niessen-Ruenzi, in press) as well as survey research on herd behavior, which demonstrated that herd behavior tends to be negatively related to investor experience (Menkhoff, Schmidt & Brozynski, 2006). While stock market participation and the size of risk-adjusted stock returns have been empirically shown to be positively related to IQ, low-IQ investors seem to be susceptible to herd behavior (Grinblatt, Keloharju & Linnainmaa, 2011). Moreover, it has been suggested that self-attribution bias (Nguyen & Schüßler, 2012) and the disposition effect (Goo, Chen, Chang & Yeh, 2010; Tehrani & Gharehkoolchian, 2012) are negatively associated with investor education.

As far as the overconfidence effect is concerned, however, Allen and Evans (2005) found no evidence that experience mitigates this bias. In similar vein, investment bankers have been found susceptible to hindsight bias independent of their level of experience (Biais & Weber, 2009).

2.3.3.3 COUNTRY-SPECIFIC DIFFERENCES

Investors from certain countries have been found to be prone to particular behavioral biases, whereas investors from other countries do not appear to be susceptible to these biases. Relevant differences between countries are likely to relate to the level of development of the economy and the cultural background of a country.

For some countries, it appears difficult to disentangle level of development and cultural background. For instance, China is an East Asian country whose cultural environment can be assumed to differ substantially from that of Western countries. In contrast with most Western countries, China also belongs to the less developed countries (International Monetary Fund, 2014). Against this background, it cannot be determined through cursory assessment if a particular finding is attributable the cultural background or the level of development.

2.3.3.3.1 Level of Development

The disposition effect has been found to emerge both in developed countries (for instance, Lehenkari, 2012; Marciukaityte & Szewczyk, 2012) and in developing countries (for instance, Aftab, Shah & Sheikh, 2012; Chong, 2009; Farag & Cressy, 2010; Lee, Yen & Chan, 2013; Tehrani & Gharehkoolchian, 2012). By way of contrast, while for several developed markets, herd behavior was suggested to occur (for instance, Belhoula & Naoui, 2011; Khan, Hassairi & Viviani, 2011; Venezia, Nashikkar & Shapira, 2011), the existence of investor herding remains controversial with regards to developing countries. On the one hand, Lao and Singh (2011) confirm this bias for China and India. On the other hand, Fu (2010) could not find evidence of herd behavior in the Chinese stock market and Moradi and Abbasi (2012) could not find evidence of herd behavior in the Iranian stock market.

2.3.3.3.2 Cultural Environment

The cultural environment of a country can be specified by drawing upon Hofstede‘s cultural dimensions theory (Hofstede, 1983). For instance, collectivist cultures, which tend to prevail in East Asian countries, have been found to be rather unaffected by self-attribution bias (Chui, Titman & Wei, 2010). This finding is supported by evidence from Japan, which suggests that Japanese online investors are not impaired by self-attribution bias (Uchida, 2006). By way of contrast, online investors from the US, which can be considered an individualistic rather than collectivist country, have been found susceptible to self-attribution bias (Barber & Odean, 2002). While US investors have been suggested to be generally prone to the overconfidence effect (Puetz & Ruenzi, 2011), Taiwanese investors appear to be affected by this bias only after bull markets (Mei-Chen, 2005). Investors from countries that are characterized by high uncertainty avoidance have been shown to be particularly prone to home bias. By way of contrast, investors from countries associated with a high degree of masculinity tend to exhibit a low degree of home bias (Anderson, Fedenia, Hirschey & Skiba, 2011).

2.3.3.4 RATIONAL OR IRRATIONAL BEHAVIOR?

Following the financial market evidence, behavioral biases are likely to involve irrational investor behavior. Several biases appear to entail suboptimal decision-making and financial performance is likely to become impaired. For instance, affect bias has been demonstrated to result in erroneous perceptions of risk and return (Finucane, Alhakami, Slovic & Johnson, 2000). The overconfidence effect has been found to be negatively related to investment returns (Barber & Odean, 2000). The disposition effect seems to be associated with unreasonable investor behavior, as it tends to emerge due to the desire to create positive feelings (Chen, Kim, Nofsinger & Rui, 2007). Since investors who are affected by status-quo bias are likely to engage in inferior decision-making (Kempf & Ruenzi, 2006), rational behavior appears doubtful. According to Uchida and Nakagawa (2007), herd behavior can become irrational during market bubbles. Finally, home bias appears to involve irrational behavior, as investors impaired by this bias have been found to achieve inferior risk-adjusted returns (Nordén, 2010). Nevertheless, according to experimental research, financial market participants have the potential to learn rational behavior (List, 2003).

Certain deviations from behavior consistent with the neoclassical paradigm may yet involve rational investor behavior. Herding does not necessarily have to be unprofitable, as situations have been shown to exist where market participants benefit from deliberately imitating the investment decisions of more sophisticated investors (Tedeschi, Iori & Gallegati, 2012). Furthermore, investors who seem to exhibit home bias do not behave in an irrational way if they can achieve superior portfolio returns by focusing on their domestic stock market (Gorman & Jorgensen, 2002).

2.3.3.5 EFFECT ON MARKET PRICES

Behavioral biases have the potential to significantly affect the market prices of stocks and facilitate the emergence of market anomalies. While different biases tend to have different and in some cases opposing effects on stock prices, certain biases have been found to cause asymmetrical price effects. Nevertheless, in some instances, a material price impact as a result of behavioral biases among investors could not be proven.

2.3.3.5.1 Material Price Effect

Typically, behavioral price effects stem either from biased investor underreaction or from biased investor overreaction. Since anchoring and adjustment has been found to lead to investor underreaction and associated stock price momentum, this bias appears to be responsible for post-earnings announcement drift (Shefrin, 2002). Confirmation bias (Friesen, Weller & Dunham, 2009) and the disposition effect (Grinblatt & Han, 2005) could also be demonstrated to be related to investor underreaction and stock price momentum.

Investor overreaction seems to be attributable to availability bias, as the discounts and premiums of closed-end funds have been found to depend on the saliency of news (Klibanoff, Lamont & Wizman, 1998). While herd behavior appears to facilitate overreaction, too (Hoitash & Krishnan, 2008), investor herding is also likely to increase the volatility of stock prices (Venezia, Nashikkar & Shapira, 2011).

Since investors have been found to exhibit affect bias in a uniform manner (Dowling & Lucey, 2010), this bias has the potential to contribute to the development of market bubbles. The prevalence of home bias, on the other hand, has been discovered to depress market valuations and stocks tend to trade at lower prices than they would otherwise (Chan, Covrig & Ng, 2009). In this regard, home bias entails negative consequences for the overall economy because it increases the cost of capital.

2.3.3.5.2 Asymmetrical Price Effect

The effect of biased investors on market prices does not necessarily have to be symmetrical. Stock prices have been shown to react in an asymmetrical fashion to changes in sentiment, with the announcement of good consumer sentiment having no impact on short-term prices but the announcement of bad consumer sentiment negatively affecting short-term prices (Akhtar, Faff, Oliver & Subrahmanyam, 2011). Such price behavior suggests a negativity effect among market participants. As this effect seemed to be more pronounced for salient stocks, investors also tended to be impaired by availability bias (Akhtar, Faff, Oliver & Subrahmanyam, 2012).

In similar vein, investor mood might have an asymmetric effect on market prices. Domestic stock markets have been found to react negatively to defeats of national sports teams by foreign teams, whereas victories of the former did not influence domestic stock returns (Edmans, García & Norli, 2007).

2.3.3.5.3 No Price Effect

Other research did not find evidence of behavioral biases significantly affecting market prices. According to Wylie (2005), herd behavior by fund managers does not have a material impact on stock prices. As the endowment effect does not appear to impair market participants in a uniform fashion, the associated effect on market prices remains limited (Furche & Johnstone, 2006). Finally, Coval and Shumway (2005) demonstrated that any price impact which arises due to the biased behavior of market participants tends to disappear almost immediately.

2.4 BEHAVIORAL BIASES ASSOCIATED WITH THE REPRESENTATIVENESS HEURISTIC – THE SIGNIFICANCE OF EXTRAPOLATION BIAS

In the following, the representativeness heuristic and its associated behavioral biases are addressed in detail. First, the relevance of the representativeness heuristic is discussed. Then, the features of this heuristic are described. Finally, the distinct cognitive biases that result from making use of the representativeness heuristic are explained.

2.4.1 RELEVANCE OF THE REPRESENTATIVENESS HEURISTIC

While the representativeness heuristic is considered to be the most important of the judgmental heuristics (Nisbett, Krantz, Jepson & Kunda, 2002), several experimental evidence (for instance, Tversky & Kahneman, 1983) and empirical evidence (for instance, Benartzi, 2001) has been provided regarding its existence. As far as financial markets are concerned, the representativeness heuristic has also been incorporated into behavioral asset pricing models (Barberis, Shleifer & Vishny, 1998; Szyszka, 2009). Nevertheless, an unambiguous causal effect on market prices could not be proven.

The label 'representativeness' is regularly attached ex post to market inefficiencies that cannot be explained otherwise in a satisfactory way (Taffler, 2010). Although the specific biases that result from reliance on the representativeness heuristic, such as the gambler's fallacy and the hot-hand fallacy, can have directly opposing impact on market prices (Ayton & Fischer, 2004), past research has not always differentiated between them. For instance, Nguyen and Schüßler (2012) label behavior consistent with the gambler's fallacy as 'representativeness' and Ke and Petroni (2002) regard an irrational earnings extrapolation as 'representativeness bias'. However, the correct designation of the behavioral bias that addresses biased investor extrapolation is 'extrapolation bias' (Bi & Ma, 2012), whereas 'representativeness bias' concerns investor behavior that involves reliance on stereotypes (Agrawal, 2012).

2.4.2 FEATURES OF THE REPRESENTATIVENESS HEURISTIC

The representativeness heuristic relates to individuals who determine the probability of an event according to its similarity to a prototype. These individuals assume that the degree to which an event resembles its parent population in a stereotyped way is proportional to the probability that the event belongs to this population (Kahneman & Tversky, 1972). As a result, judgment and decision-making become flawed to the extent that actual probability and mere representativeness differ from each other. Concepts associated with the representativeness heuristic are base rate neglect, the conjunction fallacy as well as erroneous intuitions about the laws of chance.

2.4.2.1 BASE RATE NEGLECT

Individuals who rely on the representativeness heuristic do not calculate probabilities in a rational way according to Bayes' theorem. Instead, they tend to underweight or even neglect relevant base rates. For instance, considering the 'taxicab problem' (Tversky & Kahneman, 1982), experimental subjects were asked to determine the probability that a blue cab caused a hit-and-run accident. Additional information provided to the subjects was that a witness had identified the color of the involved taxi as being blue, that 15% of all cabs in the city were blue while 85% were green, and that witnesses in general were able to determine the cab's color correctly in 80% of the cases given adverse visibility conditions. The experimental subjects intuitively stated probabilities that were significantly higher than the actual probability consistent with Bayes' theorem. These intuitive probabilities indicated that the subjects did not take account of the base rate in a correct way; that is, the subjects neglected the fact that only 15% of all cabs were blue.

Krynski and Tenenbaum (2007) criticize the use of the classical Bayesian framework by Tversky and Kahneman (1982), however. They show that judgment errors are virtually eliminated where participants are presented with information that includes a clear causal structure and statistics that unambiguously map onto that structure. Following Krynski and Tenenbaum (2007), human perception is far more complex than merely focusing on conditional probabilities. With respect to the 'taxicab problem', understanding the underlying structure of the problem is essential in arriving at correct judgments rather than moronically addressing Bayes' theorem.

2.4.2.2 THE CONJUNCTION FALLACY

According to the conjunction fallacy, individuals tend to evaluate specific but stereotyped scenarios as being more likely than more general scenarios whose true probability is actually higher. This tendency is illustrated by the ‘Linda problem’ (Tversky & Kahneman, 1983). In this experiment, participants were provided with the biographical description of a woman. This description matched the stereotyped picture of a woman that cares about discrimination and social justice. Against this background, the experimental subjects tended to erroneously assess that she was more likely “a bank teller and (is) active in the feminist movement” (Tversky & Kahneman, 1983, p. 299) than that she was merely “a bank teller” (Tversky & Kahneman, 1983, p. 299). Nevertheless, a conjunction, such as ‘bank teller AND active in the feminist movement’, logically cannot be more likely than either constituent; that is, ‘bank teller’ or ‘active in the feminist movement’ (Tversky & Kahneman, 1983).

The importance of the conjunction fallacy has been supported by neuroscientific evidence that refers to dual-process models. As far as human decision-making is concerned, dual-process models assume the existence of an intuitive system and an analytical system. The intuitive system produces reflexive and effortless judgments without necessarily addressing the analytical system which is capable of performing probability calculations (Kahneman & Frederick, 2002). However, the intuitive system can lead to flawed evaluations, as it tends to rely on pattern-matching mechanisms. Considering the ‘Linda problem’ (Tversky & Kahneman, 1983), the experimental subjects intuitively combined all characteristics that they perceived of Linda in order to arrive at a coherent and plausible representation (Lieberman, Gaunt, Gilbert & Trope, 2002).

Hertwig and Gigerenzer (1999) doubt violations of the conjunction rule, as suggested by the ‘Linda problem’ (Tversky & Kahneman, 1983). They question the design of this experiment and posit that the participants behaved according to the conjunction fallacy merely due to framing effects and the particular way the ‘Linda problem’ had been worded. Hertwig and Gigerenzer (1999) argue that individuals tend to focus on a nonmathematical sense of the term ‘probability’ when asked to provide a ‘probability judgment’.

2.4.2.3 ERRONEOUS INTUITIONS ABOUT THE LAWS OF CHANCE

Finally, representativeness is also associated with individuals who violate statistics laws, as they have erroneous intuitions concerning the laws of chance (Kahneman & Tversky, 1973). Belief in the ‘law of small numbers’ (Tversky & Kahneman, 1971) involves the assumption that any sample drawn randomly from a particular population is always representative of the population and matches the features of the underlying probability distribution, irrespective of the size of the drawn sample. In this respect, individuals anticipate that the mean of a sample invariably equals its expected value, as they intuitively assume that the law of large numbers is applicable to small samples, too.

Individuals who believe in the ‘law of small numbers’ (Tversky & Kahneman, 1971) expect that a sequence of random data does not have a pattern; neither with regards to the complete sequence, nor in each single subsection of the sequence. This expectation is related to the concept of local representativeness, which refers to the assumption that even the outcomes of small samples are always representative of the underlying probability distribution. If such local representativeness is not given, individuals are likely to erroneously believe that a particular sequence is nonrandom although it is actually random, or vice versa (Tversky & Kahneman, 1974).

2.4.3 COGNITIVE BIASES RESULTING FROM RELIANCE ON THE REPRESENTATIVENESS HEURISTIC

As a result of making use of the representativeness heuristic in judgment and decision-making, individuals can become prone to different behavioral biases. Representativeness bias, the gambler’s fallacy, extrapolation bias and the hot-hand fallacy represent different manifestations of the representativeness heuristic. While representativeness bias relates to judgments that are based on stereotypes, the other biases are associated with erroneous intuitions about randomness.

2.4.3.1 REPRESENTATIVENESS BIAS

2.4.3.1.1 Definition

Representativeness bias involves stereotyped simplifications by individuals that are based on the conjunction fallacy or base rate neglect. According to experimental evidence by Ganguly, Kagel and Moser (1994), only a minority of market participants tends to incorporate base rates in the appropriate way.

2.4.3.1.2 Financial Market Evidence

Both private and professional investors have been shown empirically to be misled by the assumption that 'good' stocks are the stocks of 'good' companies. This assumption entails the belief that the stocks of companies with reputable management, successful products and valued brands generate above average investment returns (Shefrin & Statman, 1995). It is ignored, however, that fundamental facts that are known to the market, such as superior management, tend to become incorporated into market prices in a timely fashion (Taffler, 2010). According to empirical evidence, the stocks of companies that have been associated with 'good' management even underperformed the stocks of poorly managed companies (Agarwal, Taffler & Brown, 2011; Solt & Statman, 1989).

In similar vein, 'good' industries as a whole seem to be considered as a proxy for identifying stocks that offer positive abnormal returns. For instance, before the Internet bubble burst by the millennium, dot-com stocks were assumed to belong to a particularly 'good' industry and they were supposed to provide extraordinary returns. The mere announcement by a company to change its name and include a '.com' suffix was likely to lead to short-term outperformance in the stock price, even in instances where the business model of the company had not been altered at all (Cooper, Dimitrov & Rau, 2001). This phenomenon implies that investors simplistically assumed that a company involved with the Internet industry generated above average risk-adjusted returns, and that such an involvement would be indicated effectively by the company's name.

After the Internet bubble had burst, dot-com stocks became disdained and considered as ‘bad’ stocks. A removal of the ‘.com’ suffix from the company name on average resulted in positive abnormal returns in the short term (Cooper, Khorana, Osobov, Patel & Rau, 2005). This diametrical attitude towards dot-com stocks before and after the burst of the Internet bubble hints at potential emotional aspects of representativeness bias, as the story of dot-com stocks seems to fit the emotional finance paradigm including phantastic objects that ultimately become hated (Taffler & Tuckett, 2005).

Mutual fund investors tend to be susceptible to representativeness bias, too. They have been suggested to react to advertised changes in a fund’s style, irrespective of whether the investment strategy of the fund had actually been modified. More specifically, the capital inflows into mutual funds have been found to increase for those funds that have replaced an unpopular name by a zeitgeisty label that is appreciated by investors (Cooper, Gulen & Rau, 2005).

2.4.3.2 THE GAMBLER’S FALLACY

2.4.3.2.1 Definition

The gambler‘s fallacy is another cognitive bias in judgment and decision-making that may result from making use of the representativeness heuristic. Individuals can become susceptible to this bias, provided that they know or believe to know the relevant parent population of an event. In this case, they erroneously assume that even small samples are representative of their parent population and closely reflect the properties of that population (Tversky & Kahneman, 1974). For instance, after a series of reds on a roulette wheel, individuals tend to expect that such a sequence inevitably must be corrected by a subsequent run of blacks. The gambler’s fallacy is associated with the erroneous presumption of statistical dependence for a sequence of completely independent events, which involves misconceptions of regression toward the mean. Chance is not a self-correcting process, however, as extreme runs into one direction cannot be anticipated to be corrected by extreme runs into the opposite direction. From a purely statistical point of view, following the occurrence of extreme performances, only more average performances can subsequently be expected (Taffler, 2010). The gambler‘s fallacy is related to chance processes that are inanimate, for instance games of hazard. However, this bias is not associated with the performance of human beings, for instance achievements of athletes (Huber, Kirchler & Stöckl, 2010).

In addition to experimental evidence from the laboratory, the importance of the gambler’s fallacy has been confirmed in the field (for instance, Clotfelter & Cook, 1993). Certain research suggests that individuals tend to be affected by this bias to varying degrees (Sundali & Croson, 2006). Papachristou (2004), however, found no evidence of the gambler’s fallacy to affect lotto players in the UK. According to Suetens and Tyran (2012), while males appear susceptible to the gambler’s fallacy, females do not.

2.4.3.2.2 Financial Market Evidence

As far as the participants in financial markets are concerned, the gambler’s fallacy arises when investors predict the reversal of sustained price trends in an undue fashion (Shefrin, 2002). Both experimental research (Huber, Kirchler & Stöckl, 2010), survey research (Hon-Snir, Kudryavtsev & Cohen, 2012; Nguyen & Schüßler, 2012) and empirical evidence from different stock markets (for instance, Loh & Warachka, 2012) supports the importance of the gambler’s fallacy among investors.

Interestingly, private investors seem to be rather unaffected by the gambler’s fallacy (De Bondt, 1993), whereas professional investors have been found particularly susceptible (De Bondt, 1991). Nonetheless, Nguyen and Schüßler (2012) report that the gambler’s fallacy is negatively related to investor education. According to Johnson and Tellis (2005), the mood of investors constitutes a factor in becoming prone to the gambler’s fallacy.

The gambler‘s fallacy is likely to have an impact on the market prices of stocks. Underreaction (Szyszka, 2010) and post-earnings announcement drift (Loh & Warachka, 2012) appear to be facilitated by the gambler’s fallacy.

2.4.3.3 THE HOT-HAND FALLACY

2.4.3.3.1 Definition

The hot-hand fallacy (Gilovich, Vallone & Tversky, 1985) is a cognitive bias that might also result from relying on the representative heuristic. This bias opposes the gambler‘s fallacy with respect to two distinct features. First, affected individuals assume that the underlying population of a particular event is unknown. While they erroneously believe that even a short random series represents the key features of the unknown population, they tend to unduly extrapolate such a series. Second, the hot-hand fallacy addresses human performances rather than inanimate processes. For instance, this bias suggests that a person that has been successful in the past is likely to continue being successful in the future. The hot-hand fallacy originates in basketball sports and refers to the common assumption that a basketball player who has enjoyed a shooting streak, known as a ‘hot hand’, is likely to maintain superior performance.

2.4.3.3.2 Financial Market Evidence

Considering financial markets, the hot-hand fallacy can be associated with the way mutual fund investors evaluate the performance of investment managers. Similar to the shooting streak in basketball sports, fund investors assume that investment managers who provided positive abnormal returns in the past will continue to do so in the future (Taffler, 2010).

The importance of the hot-hand fallacy has been confirmed by empirical evidence. Private investors in both developed markets (for instance, Barber, Odean & Zheng, 2000) and emerging markets (for instance, Awan & Arshad, 2012) have been found susceptible to this bias while they select mutual funds. Professional investors also appear to be impaired by the hot-hand fallacy, as investment plan sponsors have been found to recruit investment management firms with short-term outperformance while decruiting those with short-term underperformance. Interestingly, previously outperforming investment management firms tend to underperform subsequently, whereas previously underperforming investment managers have been found to outperform in the following (Goyal & Wahal, 2008). Therefore, financial decision-making according to the hot-hand fallacy does not appear to involve rational behavior.

The occurrence of the hot-hand fallacy can have an effect on market prices. Experimental evidence suggests that this behavioral bias is likely to lead to overreaction and resulting price momentum (Offerman & Sonnemans, 2004). The hot-hand fallacy provides an explanation for the fund-flow puzzle, which refers to the tendency of the capital flows into a mutual fund to be positively associated with the fund‘s past performance (Rabin & Vayanos, 2010).

2.4.3.4 EXTRAPOLATION BIAS

Eventually, extrapolation bias also constitutes a manifestation of the representativeness heuristic. Since this bias has been found to be under-researched in certain respects, it is addressed in greater detail. First, a comprehensive definition of extrapolation bias is provided. Then, founding research and financial market evidence including the effects on market prices are discussed. Different methodological approaches in existing studies are also explained. Finally, a crucial gap in the literature is elaborated.

2.4.3.4.1 Definition

Extrapolation bias is associated with individuals who disproportionately extrapolate past trends into the future, as they assume short series to be representative of underlying statistical mechanisms (Kahneman & Tversky, 1973; Tversky & Kahneman, 1971). In this respect, extrapolation bias is similar to the hot-hand fallacy and it underlies the same statistical fallacies. However, extrapolation bias concerns inanimate processes, for instance stock price developments, rather than human performances, such as the shooting streak of a basketball player.

Extrapolation bias has been researched in the past, but often it is simplistically referred to as ‘representativeness heuristic’ or ‘representativeness bias’ (for instance, Finke, 2005). This reference is inappropriate because, as mentioned earlier, the representativeness heuristic encompasses different and partly opposing biases that need to be clearly distinguished.

In some cases, it may be difficult to disentangle whether biased investors have become affected by extrapolation bias, by representativeness bias or by a combination of both. This difficulty becomes obvious with regards to glamour stocks, which are characterized by high earnings growth rates (Lakonishok, Shleifer & Vishny, 1994). On the one hand, investor preference for glamour stocks can be explained as being due to the supposition that high-growth companies are ‘good’ companies that represent ‘good’ investments. On the other hand, it can be argued that investors simplistically extrapolate the past outperformance of glamour stocks into the future. While the first explanation is consistent with representativeness bias, the second explanation appeals to extrapolation bias.

2.4.3.4.2 Founding Research

A general tendency of individuals to rely on extrapolation when forming expectations towards the future has been suggested. According to Andreassen and Kraus (1990), individuals are likely to make predictions by employing cognitive procedures that are similar to models of time series extrapolation.

Such extrapolative behavior is likely to emerge in the financial marketplace, too, as experimental evidence (for instance, De Bondt, 1993) reports that individuals become impaired by extrapolation bias when confronted with investment decisions. Earlier survey evidence by Shiller (1988) detected that investors are prone to simplistically extrapolating past price trends into the future. As their main reason for selling stocks during the stock market crash of 1987, market participants merely stated preceding price declines. Related survey research among participants in the residential estate market also suggests an undue extrapolation of previous price trends (Case & Shiller, 1988).

Subsequent studies examined the financial judgment and decision-making of actors who might be regarded as a proxy for investors. As they have been found to turn optimistic following stock price increases but pessimistic following stock price declines (Clarke & Statman, 1998), the writers of investment newsletters can be assumed to rely on the extrapolation of past returns. In similar vein, stock analysts, who have been shown to become disproportionately optimistic during bull markets but disproportionately pessimistic during bear markets, seem to be affected by excessive extrapolation (Lee, Myers & Swaminathan, 1999).

Although finance experts might reflect more sophisticated investors, they appear prone to biased extrapolation, too. Corporate CFOs have been found to arrive at expectations for future market returns by simplistically referring to past market returns (Graham & Harvey, 2001) and the predictions of finance professors regarding the equity risk premium have been found to be positively associated with prior market developments (Welch, 2000; Welch, 2001).

The propensity to rely on extrapolation when forming expectations towards the future appears to be associated with risk. According to Andreassen and Kraus (1990), individuals are more likely to exhibit extrapolative behavior when the standard deviation of outcomes is low. The degree of extrapolation also tends to be positively related to the forecast horizon, with longer-term predictions becoming more biased (Amir & Ganzach, 1998).

2.4.3.4.3 Empirical Financial Market Evidence

As far as the empirical research in financial markets is concerned, investors have been found to simplistically extrapolate past returns for predicting future returns. Relevant evidence has been provided for various markets throughout the world. Investors in developed markets (for instance, Bauman, Conover & Miller, 1999; He & Shen, 2010; Hibbert, Daigler & Dupoyet, 2008) and developing markets appear to be similarly susceptible (for instance, Bauman, Conover & Miller, 1999; Bi & Ma, 2012; Chen, Kim, Nofsinger & Rui, 2007). The participants in equity derivatives markets (Szymanowska, Horst & Veld, 2009) and bond derivatives markets (Shefrin & Statman, 1993) have been specifically addressed and demonstrated to be prone to extrapolation bias. The susceptibility of securities analysts to this bias has been widely confirmed (Amir & Ganzach, 1998; Cho, Choi, Hwang & Lee, 2014; Marsden, Veeraraghavan & Ye, 2008).

On the other hand, Grinblatt and Keloharju (2000) did not find evidence of extrapolation bias among Finnish investors. Even more, these investors exhibited opposite behavior, as they have been found to follow contrarian strategies. Moreover, research by Brav, Lehavy and Michaely (2005) questions the supposition that security analysts extrapolate past returns. They discovered that analyst predictions tend to be negatively related to previous returns. Safdar (2009) did not find evidence, either, of stock analysts becoming affected by extrapolation bias.

2.4.3.4.3.1 Private Investors vs. Professional Investors

As the proportion of retirement savings that US employees tend to invest into their own company‘s stocks has been found to be positively related to the company‘s prior stock performance (Benartzi, 2001), private investors appear to be prone to extrapolation bias. According to Shefrin (2005), professional investors can also become impaired by extrapolation bias. However, in contrast with the gambler‘s fallacy, private investors tend to be more susceptible to extrapolation bias than professional investors (De Bondt, 1993; Kempf, Merkle & Niessen-Ruenzi, in press).

Interestingly, Grinblatt and Keloharju (2000) found opposing evidence. They report that professional investors are prone to extrapolation bias whereas private investors remain unaffected by this bias.

2.4.3.4.3.2 Rational or Irrational Behavior?

According to He and Shen (2010), investors who exhibit extrapolation bias are likely to commit predictable errors. As market participants neglect base rates, they do not sufficiently account for the mean reversion of stock returns. In this respect, investor extrapolation constitutes irrational behavior.

By way of contrast, Grinblatt and Keloharju (2000) argue that investor extrapolation may be unbiased and involve rational behavior. They report that sophisticated investors rely on momentum strategies. Similarly, Jegadeesh and Titman (1993) suggest that investors can achieve abnormal returns by following momentum strategies over 3 to 12 months.

2.4.3.4.3.3 Effect on Market Prices

Extrapolation bias can have an impact on market prices. As a result of investor extrapolation, stock prices are likely to overreact in the medium term (Jegadeesh & Titman, 1993), which can facilitate the development of price bubbles (Greenwood & Nagel, 2009). However, in the longer term, that is over 3 to 5 years, previously outperforming stocks tend to reverse and begin to underperform while previously underperforming stocks begin to outperform (Chan, Jegadeesh, & Lakonishok, 1996; Chan, Karceski & Lakonishok, 2003; De Bondt & Thaler, 1985; De Bondt & Thaler, 1987).

Market anomalies, such as the momentum effect and the value effect, can be explained by referring to extrapolation bias. According to Choi (2005), this bias also provides an explanation for the equity premium puzzle. Barberis, Shleifer and Vishny (1998) suggest a behavioral asset pricing model that accounts for market participants who overreact to a series of corporate news, relying on excessive extrapolation.

By way of contrast, Chan, Frankel and Kothari (2004) find no evidence of extrapolation bias having a material impact on stock prices. According to Amir and Ganzach (1998), price effects due to this bias tend to be weakened by other behavioral biases that have opposing effects on market prices, for example anchoring and adjustment.

2.4.3.4.4 Methodological Issues

The existence of extrapolation bias in the financial marketplace has been investigated by means of different methodologies and approaches while the focus tended to lie on medium-term and longer-term investor extrapolation. Early survey evidence (Shiller, 1988; Case & Shiller, 1988) has been supplemented by experimental evidence (for instance, De Bondt, 1993), theoretical evidence (Manzan & Westerhoff, 2005) and several empirical studies (for instance, Hibbert, Daigler & Dupoyet, 2008).

As far as the empirical studies are concerned, a number of techniques have been suggested to proxy biased investor extrapolation. For instance, the extent of extrapolation bias has been inferred by regressing the purchase decisions of stocks on prior abnormal stock returns. In case the past outperformance of a stock was a significant predictor of contemporary purchases, investors were considered to be affected by extrapolation bias (Chen, Kim, Nofsinger & Rui, 2007).

Extrapolation bias may also be reflected in the forecasts by stock analysts, who have been suggested a proxy for investors (for instance, Barron, Kim & Stevens, 2002). The degree to which the predictions for a particular stock become positively (negatively) influenced by sustained stock price outperformance (underperformance) has been held to indicate the extent of extrapolation bias. As an alternative to a company's stock performance, the accounting performance of the company may be incorporated for the purpose of specifying extrapolation bias (Safdar, 2009).

He and Shen (2010) inferred biased investor extrapolation by addressing the market prices and book values of stocks as well as the associated earnings predictions by analysts. They employed these variables to determine the expected returns by investors. More specifically, He and Shen (2010) relied on the residual income valuation model for simultaneously calculating expected returns and the expected growth rate of earnings. The extent to which the returns and growth rates anticipated by investors were positively related to past returns and past growth rates was supposed to indicate the degree of extrapolation bias.

According to Hibbert, Daigler and Dupoyet (2008), extrapolation bias can be proxied by analyzing stock prices in conjunction with the implied volatilities of the related stock options. A short-term negative relationship between stock returns and implied volatilities would hint at extrapolation bias, which implies that investors are willing to pay higher prices for option premiums when stock returns are negative. Under this scenario, investors are assumed to increasingly demand portfolio insurance by purchasing put options, as they extrapolate and anticipate negative stock returns to persist.

2.4.3.4.5 Gap in the Literature and Inference of Specific Research Questions

Taking account of the existing research on extrapolation bias, it remains controversial to what degree investors are actually impaired by this bias and whether extrapolation bias has a significant impact on market prices. While a wide variety of stock markets throughout the world have been investigated with respect to extrapolation bias, for instance the US market (He & Shen, 2010; Hibbert, Daigler & Dupoyet, 2008) and the Chinese market (Chen, Kim, Nofsinger & Rui, 2007), other markets appear to be under-researched, for instance the German market. Previous research also seems to have neglected short-term investor extrapolation while the majority of studies focused on a medium or longer-term timeframe (for instance, Benartzi, 2001).

Certain experimental evidence (De Bondt, 1993) and survey evidence (Bange, 2000) has emphasized the importance of extrapolation bias with regards to private investors. However, other research doubts that private investors are particularly impaired (Grinblatt & Keloharju, 2000). Unfortunately, empirical studies tended to employ methodologies that could not account for the behavior specifically of private investors (for instance, He & Shen, 2010; Hibbert, Daigler & Dupoyet, 2008).

Against this background, it is necessary to conduct further research on extrapolation bias while the focus should lie on aspects that have been neglected so far or that remain controversial. Under-researched markets should be investigated for short-term extrapolation bias. It should be examined the susceptibility of private vis-à-vis professional investors, whether extrapolation bias entails irrational investor behavior and whether market prices are affected.

According to their "clinical" (p. 103) study of stock message boards, Das, Martínez-Jerez and Tufano (2005) suggest an alternative methodology to test for short-term extrapolation bias among private investors. They analyze investor sentiment as implied in the postings on stock message boards. Extrapolation bias is assumed to prevail if investor sentiment can be positively predicted by prior stock returns.

Past research that involved stock message board postings tended to focus on boards and stocks from the US (for instance, Antweiler & Frank, 2004; Das, Martínez-Jerez & Tufano, 2005; Sabherwal, Sarkar & Zhang, 2011; Zhang & Swanson, 2010; Zhang, Swanson & Prombutr, 2012). European markets, however, appear to be under-researched while no single study is known to the author that incorporates the postings from a German stock message board for the purpose of analyzing extrapolation bias.

Against the background of the gaps in the extant literature, as elaborated above, a particular research study was designed appropriate to address the gaps. Following the innovative methodology suggested by Das, Martínez-Jerez and Tufano (2005), this study answers two distinct research questions:

> *1. Does Extrapolation Bias Exist among Private Investors?*
> *2. Does Extrapolation Bias among Private Investors have an Effect on the Market Prices of Stocks?*

The sample of this study includes the relatively under-researched German stock market. As the sample period involves a time span during the recent Eurozone crisis, topical data was collected that allowed for the provision of highly relevant research results. In this respect, this study addresses the renewed interest into the concepts of behavioral finance (Grosse, 2012). The research methodology of the study is explained in detail in the next chapter.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 INTRODUCTION

For the purpose of answering the research questions and testing for extrapolation bias among private investors as well as the resulting effects on the market prices of stocks, as indicated in Chapter 2, a particular research study was designed. The design involved a deductive positivistic perspective including statistical hypothesis testing (Hill, 1992). Although the data analysis employed common quantitative techniques, that part of the data collection that referred to the coding of stock message board postings involved a qualitative method.

In the following, first the argument for qualitative manual coding is supplied. Then, the research sample is described and the data collection is explained. The construction of a measure for private investor sentiment is outlined and, finally, the techniques of the data analysis are specified.

3.2 ARGUMENT FOR MANUAL CODING THROUGH QCA

Consistent with previous research (for instance, Antweiler & Frank, 2004; Sabherwal, Sarkar & Zhang, 2011; Tumarkin & Whitelaw, 2001; Zhang & Swanson, 2010; Zhang, Swanson & Prombutr, 2012), private investor sentiment can be inferred effectively from the opinions expressed in stock message boards. Sentiment can be measured and quantified by constructing sentiment indices from aggregated message board postings.

To construct a sentiment index, first, the individual postings need to be coded in order to extract the opinions they contain. Most existing studies do not employ manual coding at all (for instance, Sabherwal, Sarkar & Zhang, 2011), with a small number of studies using manual coding to a slight extent (for instance, Antweiler & Frank, 2004). The main reason for making use of text classifiers instead of manual coding is to be able to manage vast numbers of postings in an efficient and economical way (Das, Martínez-Jerez & Tufano, 2005). However, despite the general preference for text classifiers, this technique of extracting sentiment is subject to several problems.

3.2.1 PROBLEMS IN USING AUTOMATIC TEXT CLASSIFIERS

Given most computer algorithms rely on simplifying heuristics (Das, Martínez-Jerez & Tufano, 2005), they entail the risk of erroneous coding. Some classifiers merely count the number of words in a message that are supposed to indicate positive or negative sentiment and determine the overall sentiment of a message according to the proportion of words in a posting that are identified as having a positive or negative tone (Das & Chen, 2007). There is a substantial risk of postings being misclassified using this approach, as the context surrounding a message is not taken into account. For instance, irony is unlikely to be recognized, which can lead to a message being completely misclassified. Furthermore, uncommented citations of the opinions of persons other than the message board participant, such as analyst recommendations, may not be recognized by a text classifier as such and misinterpreted as representing the opinion of the message board participant.

Text classifiers may also involve unrealistic assumptions that tend to impair coding accuracy. For instance, naïve Bayesian classifiers assume conditional independence in their probability models; that is, they suppose that the occurrence of particular words in a text is completely independent of the other words within the text (Joachims, 1997). However, it is more likely that positive expressions, such as ‘rise’, ‘gain’ or ‘upwards’, occur simultaneously in stock message board postings and negative expressions, such as ‘fall’, ‘lose’ or ‘downwards’, occur simultaneously, too.

Computer algorithms also face certain problems in interpreting spoken language rather than formal text. Stock message boards, however, are typically characterized by postings that are brief and similar to spoken language rather than formal text (Zhang, Swanson & Prombutr, 2012). Message writers frequently disregard the use of appropriate sentence structures and correct grammar, which can lead to flawed interpretations by text classifiers, as these algorithms have difficulty incorporating context. For instance, as a result of an incorrect word order or a lacking question mark, a message may be supposed to constitute a statement instead of a question, which is likely to lead to an erroneous sentiment classification. Moreover, a colloquially accepted but grammatically incorrect use of the tenses by message board participants may induce a computer algorithm to erroneously infer that a particular participant addresses future stock returns although, as a matter of fact, an opinion concerning past returns is expressed. Given the limitations with the use of automatic text classifiers, manual coding seems to be a superior method for measuring sentiment in stock message board postings.

3.2.2 FEASIBILITY OF QUALITATIVE MANUAL CODING

This study improves the existing literature by constructing sentiment measures from manually coded stock message board postings. QCA was used to undertake the manual coding and classifying of the postings according to sentiment. The use of QCA is particularly appropriate, as it facilitates the manual coding of textual data that requires a certain degree of interpretation (Schreier, 2012), such as the postings uploaded in stock message boards.

Manual coding was considered feasible in this study, given the sample, which consists of the DAXsubsector Credit Banks (Deutsche Börse, 2014), is relatively small. These stocks were nevertheless expected to provide sufficient postings on a regular basis for the purpose of constructing a sentiment index. Notwithstanding the fact that a small number of speculative small caps with weak fundamentals tend to be the most heavily discussed in message boards (Sabherwal, Sarkar & Zhang, 2011), there is generally a positive relationship between firm size and message posting volume (Wysocki, 1998).

3.3 SAMPLE – 'DAXSUBSECTOR CREDIT BANKS'

The majority of existing studies that have examined the information content of stock message boards focused on the US stock market. No study is known that analyzed the postings from a German stock message board for testing for extrapolation bias in the German market. Moreover, to date no research appears to have been conducted concerning specifically the DAXsubsector Credit Banks index.

3.3.1 RELATED RESEARCH AND STUDY SAMPLE

Past research that analyzed stock message boards tended to focus on the US market (for instance, Antweiler & Frank, 2004; Das, Martínez-Jerez & Tufano, 2005). In particular, small-cap stocks (Sabherwal, Sarkar & Zhang, 2011) and technology stocks (for instance, Das & Chen, 2007; Tumarkin & Whitelaw, 2001) were examined. Against this background, this study incorporated stock message board postings of German stocks.

Previous studies that analyzed the German stock market tended to incorporate all 30 DAX stocks (for instance, Beltran-Lopez, Grammig & Menkveld, 2012; Webel, 2012; Rossetto & van Bommel, 2009; Jermakowicz, Prather-Kinsey & Wulf, 2007). By way of contrast, this study used a different sample by analyzing the stocks included in the DAXsubsector Credit Banks index. This index relates to domestic blue-chip credit banks and included the stocks of Commerzbank AG and Deutsche Bank AG (Deutsche Börse, 2014).

3.3.2 RATIONALE FOR SAMPLE SPECIFICS

The study sample focused on the DAXsubsector Credit Banks for two reasons. First, the banking sector had become particularly affected during the recent Eurozone crisis and its prospects were discussed rather controversially. Against this background, the year 2012 provides an interesting period of time to examine sentiment and behavioral biases because substantial swings in investor sentiment were supposed to have occurred. Secondly, the sample of the DAXsubsector Credit Banks had not been employed in prior research, thus methodological variety was enhanced.

Considering previous research, the sample period of 1 year seems to constitute an adequate time frame (for instance, Antweiler & Frank, 2004). Periods shorter than 1 year, however, would be likely to introduce bias. After all, incorporating postings from only particular months of the year tends to distort sentiment measures, as investors have been found to be affected by unstable mood during the course of the year (for instance, Lo & Wu, 2010).

3.4 DATA COLLECTION – FOCUS ON STOCK MESSAGE BOARD POSTINGS

In order to carry out the analyses necessary for answering the research questions, data was collected with regards to several different variables. Three different types of data were gathered for this study: stock market data, corporate news data and stock message board postings. The raw postings were coded by means of QCA to capture the investor sentiment they implied.

3.4.1 STOCK MARKET DATA

The stock market data required for conducting this study was retrieved from a Bloomberg terminal. Bloomberg provided data of the opening and closing stock prices on a daily basis including the daily high and low as well as traded turnover. With respect to dividend payments, both the amounts and the payment dates were retrieved from the annual reports of the respective companies.

3.4.2 CORPORATE NEWS

Material corporate news, for instance profit warnings, has the potential to significantly affect stock prices. Therefore, it was identified and taken into account. In Germany, corporate news is provided by the DGAP Deutsche Gesellschaft für Ad-hoc-Publizität. While the associated website could be accessed freely for localizing the news, material corporate news was assumed to include ‘DGAP-Ad-hoc Nachrichten’ and ‘DGAP-News’ (http://www.dgap.de/).

3.4.3 STOCK MESSAGE BOARD POSTING

The stock message board postings were collected from the web-based finance community ‘wallstreet:online’. As this source constituted Germany’s largest web-based finance community (wallstreet:online, n.d.), it was expected that the message board provided a sufficient amount of postings on a regular basis. For merely reading the postings, the related webpage could be accessed freely without having to log in (http://www.wallstreet-online.de/). This website allowed direct searches of a particular company and provided a chronological overview of all message board threads of a company.

3.4.4 QCA OF MESSAGE BOARD POSTINGS

QCA was used to determine the sentiment implied in the individual message board postings. QCA is a research method that incorporates characteristics both of qualitative research and of quantitative research. While QCA evolved from quantitative content analysis, it goes beyond mere quantifications, is capable of incorporating latent content and can take account of context. Nevertheless, this research method can be incorporated into a deductive research design. QCA is particularly appropriate to recorded communication for which a certain degree interpretation is necessary (Mayring, 2000).

However, QCA is not applicable to all kinds of communication. While it is adequate for communication that is characterized by manifest content and can be applied to latent content under certain circumstances, QCA is inappropriate with respect to polysemous content. QCA can be applied effectively to latent content that is merely indirect and/or nonstandardized, for instance textual material that requires only some additional interpretation while taking account of context. By way of contrast, polysemous content, which refers to content implying several different meanings, is not suitable to QCA. As the categories of the coding frame need to be mutually exclusive (Schreier, 2012), QCA yields a clear and unambiguous classification of the material to be analyzed.

The postings in stock message boards are unlikely to exclusively contain manifest content. Latent content that is dependent upon some further interpretation should also be anticipated and the context in which a posting was composed should be incorporated. However, polysemous content does not appear to be associated with stock message board postings, as board participants are assumed to express unequivocal opinions. Therefore, the kind of content that typically occurs in message boards should be appropriate for effectively conducting QCA.

3.4.4.1 CODING FRAME AS RESEARCH INSTRUMENT

In general, research instruments, for instance questionnaires, interview schedules or coding frames are intended to facilitate the collection of data. A researcher may rely on an already existing research instrument or develop one that is tailored to the particular piece of research (Punch, 2006).

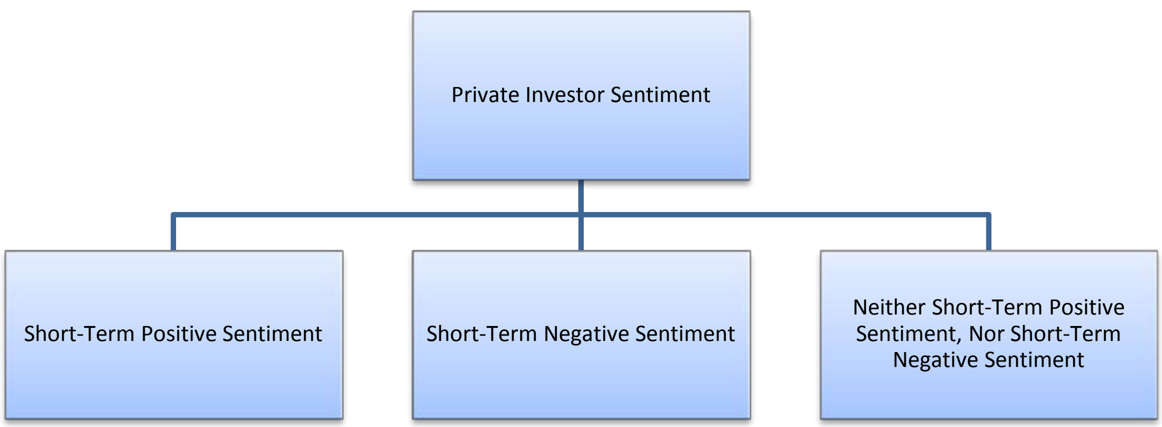
Regarding this study, a coding frame served as the research instrument. This coding frame was specifically developed and tailored to address the research questions.

3.4.4.1.1 Features of Coding Frames

Coding frames usually contain main categories and subcategories and refer to certain research questions. The main categories reflect those aspects of study data that the researcher seeks to investigate. The subcategories that belong to a particular main category indicate the possible characteristics of the aspects under investigation. As a consequence of developing an effective coding frame, the research data is reduced to only those aspects that a particular research question is intended to address. Coding frames can involve different degrees of complexity, depending upon the number of main categories and the number of hierarchical levels of subcategories (Schreier, 2012).

As shown in Figure 1, the coding frame was designed to include one main category and one level of subcategories. The main category relates to the sentiment of the stock message board participants towards the future returns of the discussed stock. Three subcategories follow, which differentiate between short-term positive sentiment, short-term negative sentiment and neither. The emphasis was on short-term sentiment because sentiment concerning the short term can reasonably be related to stock returns that also address the short term. The subcategory of postings that is neither associated with short-term positive sentiment nor with short-term negative sentiment was intended to capture the remainder of postings. The content of these postings was assumed to have no impact on the level of the short-term sentiment measure, which was constructed subsequently. The specifics of this sentiment index are discussed at length in a separate paragraph.

Figure 1: Structure of the Coding Frame



A precise identification of short-term sentiment was only feasible given the use of manual coding in this research. As the conventional use of computer algorithms and text classifiers for coding stock message board postings creates the potential for a greater number of errors, the correct distinction between positive (negative) short-term sentiment and positive (negative) non-short-term sentiment would have been likely to become impaired.

3.4.4.1.2 Requirements of Coding Frames

Coding frames should fulfill certain requirements. They should be unidimensional as well as exhaustive, and their subcategories should be mutually exclusive. Unidimensionality demands that each main category relates to only one particular attribute of the data (Schreier, 2012). As far as this study is concerned, unidimensionality is satisfied because the main category is restricted to the issue of whether the individual stock message board postings imply sentiment or not. Further aspects that the postings might imply, such as the author's happiness with the stock, were not investigated.

Exhaustiveness of a coding frame is given, provided that at least one unit of coding can be allocated to each subcategory (Schreier, 2012). Regarding this study, the criterion of exhaustiveness has been fulfilled, since each of the three predetermined subcategories received at least one posting.

Finally, the mutual exclusiveness of the subcategories of a coding frame is assumed when each unit of coding can be assigned to exclusively one subcategory of a particular main category (Schreier, 2012). This criterion has been achieved in this study, too. For instance, a particular posting cannot be characterized as implying short-term positive sentiment and short-term negative sentiment at the same time. Detailed definitions and illustrations of the subcategories including decision rules are provided in a separate paragraph.

3.4.4.1.3 Concept-Driven versus Data-Driven Coding Frames

Since QCA is able to incorporate elements both from qualitative research and from quantitative research, the associated coding frames can be concept-driven, data-driven or a combination of both. On the one hand, concept-driven coding frames base their categories on existing knowledge and involve deductive reasoning. On the other hand, the categories of data-driven coding frames inductively emerge from the data itself (Schreier, 2012).

Concerning this study, the coding frame was designed to be concept-driven. The categories had been specified in advance and the stock message board postings were subsequently coded as implying short-term positive sentiment, short-term negative sentiment, or as implying neither.

3.4.4.1.4 Category Definitions of Coding Frames

For each category of a coding frame, a definition should be provided, which includes a name, a description, examples and possibly decision rules. The category name is intended to attach a concise label to a category, the category description should indicate the major characteristics of a category and actual and/or hypothetical examples should provide typical instances of and illustrate a category. As subcategories might overlap in some cases, decision rules should be introduced if it is unclear how to code particular content (Schreier, 2012).

3.4.4.1.4.1 Category Names

As indicated earlier, the categories of the coding frame were designed and named against the background of the particular research questions. The single main category was designated as ‘private investor sentiment’. The names of the three subcategories are ‘short-term positive sentiment’, ‘short-term negative sentiment’ and ‘neither short-term positive sentiment, nor short-term negative sentiment’.

3.4.4.1.4.2 Category Descriptions

The main category ‘private investor sentiment’ focuses on whether message board participants express in their postings any opinions concerning the future return of a particular stock under discussion. The subcategory ‘short-term positive sentiment’ refers to all postings that involve a positive view towards the return of the stock in the short term. By way of contrast, the subcategory ‘short-term negative sentiment’ is associated with all postings that imply a negative investor opinion concerning the stock’s short-term return.

Finally, the subcategory ‘neither short-term positive sentiment, nor short-term negative sentiment’ relates to all other postings; that is, postings that imply short-term neutral sentiment, postings that imply longer-term positive, negative or neutral sentiment as well as postings that do not imply any sentiment at all.

3.4.4.1.4.3 Category Examples

As far as examples of the categories of the coding frame are concerned, hypothetical examples were preferred. In contrast with actual examples, which tend to be less obvious and might not be unambiguous, hypothetical examples have the potential to clearly illustrate when a particular category applies (Schreier, 2012).

For example, a posting classified as implying ‘short-term positive sentiment’ may sound like: “Commerzbank stocks will rise tomorrow.”. ‘Short-term negative sentiment’ would be contained in a posting like: “Deutsche Bank stocks will fall tomorrow.”. As described earlier, postings classified as implying ‘neither short-term positive sentiment, nor short-term negative sentiment’ encompass the remainder of postings. Such postings may sound like: “I’m unsure about whether Commerzbank stocks will go up or down.”, “Deutsche Bank stocks will definitely increase (decrease) during the course of the year.”, or “Does anybody know when Q3 results will be released?“.

3.4.4.1.4.4 Decision Rules

After the pilot phase of QCA had been conducted, it became obvious that the original coding frame could be refined further. It appeared that reliability and validity could be enhanced by introducing specific assumptions and decision rules. These assumptions and decision rules were intended to supplement the category descriptions and clearly delimit when each of the subcategories applies in order to avoid inconsistencies and overlaps.

3.4.4.1.4.4.1 General Assumptions

As a basic rule, a posting needed to clearly refer to the future price and/or return of the stock under discussion for being classified as implying sentiment. Those future prices/returns that the author of a posting considered most likely were incorporated. It was assumed that, unless stated otherwise, message board participants meant the closing price of a stock when they referred to a particular price level, price change or return. If the author of a posting expressed to believe that a stock would not increase (decrease), it was supposed that they believed the stock would decrease (increase), if not stated otherwise by the author.

A message board participant might express an opinion concerning the return of other stocks that belong to the same industry like the discussed stock. An opinion might also be expressed with respect to the return of the domestic stock market as a whole. In either case, provided that the stock under discussion was not explicitly excluded, it was assumed that the author of the posting also meant the stock under discussion.

On the other hand, if a message board participant expressed positive (negative) expectations merely with regards to the corporate fundamentals of the stock under discussion without clearly addressing future stock prices or returns, relevant sentiment was not considered to be implied in the posting. For instance, the anticipation of a company to release higher (lower) than expected quarterly earnings does not necessarily involve the expectation of positive (negative) stock returns.

Positive (negative) opinions concerning future stock prices or returns may depend on some condition to be fulfilled. For example, the positive (negative) view contained in the statement “When the dividend is increased (cut) tomorrow, the stock will rise (fall)” is dependent upon an event that has not yet occurred. For the purpose of this study, conditional opinions do not indicate sentiment.

The simple reference by a message board participant to hold a long (short) position in the stock under discussion was not considered as evidence for having a positive (negative) return expectation. It cannot be excluded that investors keep holding stocks although they are not convinced to achieve positive future returns. Furthermore, if a message board participant stated to consider a stock as being “undervalued” (“overvalued”) or that a stock had “potential” (“no potential”), this was not assumed to imply sentiment for the purpose of the study. It might be widely accepted that a particular stock is undervalued, yet an expectation for the undervaluation (overvaluation) to be corrected would not be implied in such a posting.

Certain postings may include citations and contain the opinions of others, for instance the ratings by stock analysts. Unless the authors of such postings unambiguously added their own opinion concerning the future price/return of the stock under discussion, these postings were not supposed to contain any sentiment, whatsoever the opinion held by the cited person.

As a final remark, if a message board participant uploaded more than one posting on a given day, the postings were assumed to be independent of each other. This means that the sentiment exhibited by an individual board participant did not necessarily have to be constant throughout the day. Individual sentiment changed in case the same board participant expressed inconsistent opinions regarding the short term return of the discussed stock in consecutive postings.

3.4.4.1.4.4.2 Specific Decision Rules Concerning Each Subcategory

In addition to the general assumptions outlined above, certain decision rules were specifically devised following the pilot phase of QCA. It was intended to further clarify the appropriate assignment of the stock message board postings to the subcategories of the coding frame.

3.4.4.1.4.4.2.1 'Short-Term Positive Sentiment' ('Short-Term Negative Sentiment')

The subcategory 'short-term positive sentiment' ('short-term negative sentiment') applied to postings that both implied sentiment, as explained earlier, and where a short-term perspective could not be excluded. For instance, a posting implying positive (negative) sentiment that was not explicitly related to a particular timeframe was allocated to this subcategory. It is believed that a message board participant who does not emphasize a particular timeframe involves a short-term view.

More specifically, the 'short term' was defined in this study as referring to the following trading day. This means that postings that implied a positive (negative) expectation concerning the next trading day's stock performance were assigned to this subcategory, whereas postings that hinted at a point in time further into the future were not considered.

In those cases where a message board participant expressed both a relevant short-term opinion and a relevant longer-term opinion, while these opinions diverged from each other, only the short-term opinion was taken into account. The message board posting was coded exclusively according to the short-term opinion, as longer-term private investor sentiment was irrelevant for answering the research questions in this study.

3.4.4.1.4.4.2.2 'Neither Short-Term Positive Sentiment, Nor Short-Term Negative Sentiment'

Following the decision rules, some of the stock message board postings could not be assigned either to the subcategory 'short-term positive sentiment' or to the subcategory 'short-term negative sentiment'. As outlined in the category description, the subcategory 'neither short-term positive sentiment, nor short-term negative sentiment' was deemed to include this remainder of postings. This subcategory constituted kind of a residual category, as neutral sentiment postings, longer-term positive (negative) sentiment postings as well as postings that were unrelated to any sentiment were all allocated here.

Even after the specific decision rules had been applied rigorously to all postings, the definite sentiment, if any, implied by some of the postings remained unclear. Ambiguous postings were also assigned to the subcategory ‘neither short-term positive sentiment, nor short-term negative sentiment’.

3.4.4.2 SEGMENTING THE MATERIAL

In QCA, segmentation refers to dividing the entire textual material that is to be examined into certain units. The primary units are referred to as the units of analysis while the units of coding represent subunits. Units of coding relate to those parts of a unit of analysis that are compatible with and can be assigned to a particular subcategory of the coding frame. Units of coding should be marked directly in the material. Moreover, context units are those surrounding parts of the material that are necessary to correctly understand a particular unit of coding (Schreier, 2012).

As far as this study is concerned, the relevant threads of the stock message board constituted the units of analysis while the relevant postings represented the units of coding. Context units were associated with those postings that preceded a particular posting to be coded so that the content surrounding the posting could be incorporated, if necessary.

Segmentation criteria specify the beginning and ending of a unit of coding. On the one hand, formal criteria go by the structure of the textual material, such as paragraphs or chapters. On the other hand, thematic criteria divide units of coding according to where a particular topic begins and where it ends (Schreier, 2012). While the application of formal criteria leads to an unambiguous segmentation of the material, thematic criteria inevitably involve some discretion. Nevertheless, formal criteria cannot be applied effectively when the material is unstructured. Thematic criteria tend to produce units of coding that are more compatible with the coding frame.

Regarding this study, formal segmentation criteria appeared more adequate. Each separate stock message board posting represented a unit of coding, as the individual postings were assumed to appropriately contain the sentiment of a particular message board participant. As a result of employing a formal segmentation criterion, the process of marking the units of coding and classifying their content could be done simultaneously. Finally, the units of coding were numbered consistently so that tokens could be entered conveniently into a coding sheet. Consistent with Schreier (2012), the first figure of the token identified the associated unit of analysis while the second figure indicated the position of the unit of coding within that unit of analysis.

3.4.4.3 PILOT PHASE

In QCA, a pilot phase involves a trial coding with respect to part of the material that is to be analyzed, as well as an assessment of the quality of the coding frame. Possible weaknesses of the coding frame can be addressed after such a pilot phase (Schreier, 2012).

3.4.4.3.1 Trial Coding

Since this study relied on deductive hypothesis testing for answering the research questions, the trial coding exclusively incorporated stock message board postings that were not used in the main study. To account for a certain degree of variability, an entire month of the year 2011 was involved for conducting the trial coding. September 2011 was randomly selected and all relevant postings of Commerzbank AG and Deutsche Bank AG were coded according to the suggested rules.

For the purpose of performing a consistency check, the coding stability was determined. This was achieved by considering the degree of coding consistency of the researcher over time (Schreier, 2012). In this respect, the postings were coded for a second time 10 to 14 days after the first coding. Those postings that were coded differently during the second round of coding were re-addressed in detail. On the one hand, inconsistent coding may simply be due to erroneous coding. On the other hand, low coding consistency that cannot be attributed to coding errors is likely to be due to weaknesses in the coding frame, such as overlapping subcategories or ambiguous category descriptions.

3.4.4.3.2 Evaluation of the Coding Frame

An assessment of the quality of a coding frame involves determining its reliability and validity (Schreier, 2012). Reliability is associated with the degree to which measures are consistent and research results can be repeated. Validity is related to the degree to which a research instrument actually captures what it seeks to capture (Bryman & Bell, 2011).

The reliability of a coding frame is indicated by its coding consistency, with higher coding consistency being associated with greater reliability. Coefficients of agreement, such as percentage of agreement, quantify the extent of coding consistency. Nevertheless, such measures should be approached with caution because their values are influenced by the degree of interpretation that is necessary for coding particular text data (Schreier, 2012). Since the postings in stock message boards represent relatively homogeneous content that tends to involve only a certain degree of interpretation, coefficients of agreement can be considered adequate measures for determining reliability.

As far as validity is concerned, different concepts of validity are relevant to coding frames, namely construct validity, content validity, criterion validity and face validity (Schreier, 2012). Content validity is used for assessing the validity of a concept-driven coding frame, as employed in this study. Content validity is given to the extent that the concepts under investigation, including all their dimensions, are reflected correctly in the developed categories. In order to determine content validity, expert assessment of a concept-driven coding frame can be sought. Alternatively, coding consistency can be referred to as a proxy for content validity (Schreier, 2012). Since the categories of the coding frame in this study do not relate to complex theoretical concepts but merely to the sentiment of stock message board postings, expert assessment appeared redundant. Instead, a measure of coding consistency was relied on.

Regarding the coding consistency during the trial coding, percentage of agreement was computed. The resulting value of 92.55% means that 92.55% of all postings were assigned the same code during both rounds of coding. A percentage of agreement of this size indicates a certain degree of reliability and validity. Nonetheless, as explained earlier, following the pilot phase, the subcategories of the coding frame were further refined by introducing specific decision rules.

3.4.4.4 MAIN CODING

In QCA, after conducting a pilot phase and possibly revising the coding frame, the main coding is carried out. While the procedure during the main coding is identical to that of the trial coding, the entire material that is intended to be analyzed is coded. If it becomes obvious during the main coding that the coding frame is still inadequate and needs to be revised again, the anticipated main coding can constitute another round of trial coding (Schreier, 2012).

As far as this study is concerned, all relevant postings of the stocks contained in the DAXsubsector Credit Banks index that had been uploaded in the stock message board of ‘wallstreet:online’ throughout the year 2012 were manually coded. Coding consistency was determined by re-coding all postings that had occurred during the randomly selected month of September. Percentage of agreement indicated a value of 94.60%, which implies a reasonable degree of validity and reliability. As percentage of agreement increased by 2.05 percentage points compared to the trial coding, it appears that coding consistency could be enhanced by introducing the suggested methodological refinements.

Those postings that were not allocated to the same category during the second round of coding were first re-examined to check whether they were classified merely erroneously. If this was not the case, secondly, the respective categories of the coding frame were re-assessed for clarity and distinctiveness. If neither was the case but still a final code could not reasonably be determined, to minimize bias turns were taken between the two preceding rounds of coding. The original code and the code from the second round of coding were chosen rotatorily as the final code.

3.5 ‘AFTER-HOURS WEIGHTED OPINION’ – A MEASURE OF PRIVATE INVESTOR SENTIMENT

Several procedures have been suggested to measure the sentiment of stock market participants. On the one hand, investor sentiment can be ascertained directly through surveys (Fisher & Statman, 2000). Alternatively, proxy measures can be developed, for instance by using the size of the discounts of closed-end funds compared to their NAV (Lee, Shleifer & Thaler, 1991) or by the size of monetary flows into mutual funds (Goetzmann, Massa & Rouwenhorst, 2004). According to Antweiler and Frank (2004), private investor sentiment can be determined by analyzing the postings in stock message boards. Small-sized trades, which are related to private investors, have been demonstrated to be particularly associated with the activity in message boards.

Considering this study, first the sentiment implied in the relevant stock message board postings of the stocks that belonged to the DAXsubsector Credit Banks index was quantified in a consistent fashion. Then, an ‘after-hours weighted opinion’ of the individual stocks was determined to represent a measure of daily private investor sentiment suitable for this study. Finally, the individual measures of ‘after-hours weighted opinion’ were equal-weighted in order to obtain an overall index of private investor sentiment towards blue-chip banking stocks.

3.5.1 QUANTIFICATION OF SENTIMENT IMPLIED IN POSTINGS

Each coded stock message board posting was assigned a numerical value consistent with the implied sentiment. While the postings that contained ‘short-term positive sentiment’ were assigned a value of ‘+1’, the postings that contained ‘short-term negative sentiment’ were assigned a value of ‘-1’. Postings that contained ‘neither short-term positive sentiment, nor short-term negative sentiment’ received a value of ‘0’.

Prior studies partly included sentiment as self-reported by the authors of message board postings (Zhang & Swanson, 2010). However, such an approach is likely to introduce subjective biases. For instance, two individuals hold an equal degree of optimism towards the short-term returns of a particular stock. Still, they might self-report a different degree of optimism. Having different personalities, the first individual, who is characterized by a high degree of self-confidence, is likely to report clear optimism while the second, who is more cautious, may not report unambiguous optimism.

This study took precautions to extract sentiment in a more consistent manner. The coding of the stock message board postings was conducted continuously by the same person while a second person that could have biased the results was not involved.

3.5.2 RELATED ASSUMPTIONS

In order to answer the first research question, this study tested whether private investor sentiment was positively predicted by preceding stock returns. For that purpose, a measure of after-hours private investor sentiment was constructed. Only those postings that were uploaded on a trading day after the stock market had closed were included.

For determining the exact time when the German stock market closed for the day, the trading hours of Xetra appeared most relevant, as the majority of trading volume in German blue-chip stocks was processed via this electronic trading system (Deutsche Börse, n.d.). Accordingly, after-hours private investor sentiment was calculated by incorporating the postings that occurred between 5:35:01 p.m. and 11:59:59 p.m. every trading day (Deutsche Börse, 2011). The last trading day of the year, 28 December, was excluded because trading hours were restricted on this day (Deutsche Börse, 2012).

3.5.3 ‘AFTER-HOURS WEIGHTED OPINION’ OF INDIVIDUAL STOCKS

Based on the calculation of “daily weighted opinion” (Tumarkin & Whitelaw, 2001, p. 44), an ‘after-hours weighted opinion’ was determined for either of the stocks that belonged to the DAXsubsector Credit Banks index. The calculation of ‘after-hours weighted opinion’ involved adding up the sentiment values that were assigned to the relevant stock message board postings on a daily basis. In contrast with “daily weighted opinion” (Tumarkin & Whitelaw, 2001, p. 44), only those postings were considered that were uploaded after stock trading had ended for a day. While Tumarkin and Whitelaw (2001) acknowledge that their methodology is only able to account for concurrent associations between stock returns and sentiment, the introduction of ‘after-hours weighted opinion’ in this study allows for drawing conclusions as to effects on sentiment that follow on from stock returns.

In prior related research, Antweiler and Frank (2004) identified the importance of accounting for message board participants who merely repeat their opinions on the same day. They proposed to weight each posting by the inverse of the total number of postings uploaded by a particular participant for a certain stock on the same day. Nevertheless, such an approach was not followed in this study, as it could be argued that individuals who repeat particular opinions tend to hold stronger opinions (Schreier, 2012).

The stock message board of ‘wallstreet:online’ provided a function to rate a posting as being positive. It could be posited that the postings that obtained positive ratings should be weighted more heavily in the sentiment index because such ratings might reflect the opinions of those private investors who only read postings but did not upload postings themselves. However, it was impossible to retrace the very day on which a particular posting received a rating. Furthermore, it was not possible to determine the final rating of a posting because all postings could be rated infinitely. Finally, it was possible to rate postings as being positive but not as being negative, which biased the overall ratings score. Taking account of the extent to which postings received positive ratings was therefore discarded in calculating ‘after-hours weighted opinion’.

The word length of an individual posting has been argued to reflect the importance of the posting, with longer postings being more important than shorter postings. Against this background, longer postings might be weighted more heavily than shorter postings (Antweiler & Frank, 2004). However, the length of a particular posting may depend upon the individual writing characteristics of the author or the time available to produce the text. As the word length of postings was deemed unlikely to provide meaningful insights into sentiment, word length was not accounted for in the calculation of ‘after-hours weighted opinion’.

On certain trading days, relevant postings were not uploaded. For these cases, the value of ‘after-hours weighted opinion’ was supposed to be ‘0’. The alternative assumption of maintaining the previous day’s value was rejected because maintaining the previous day‘s value would have entailed bias into the calculation of the sentiment index (Antweiler & Frank, 2004).

Consistent with Das and Chen (2007), for the purpose of conveniently conducting the subsequent statistical operations, the values of all quantitative variables including ‘after-hours weighted opinion’ were normalized. Normalization was achieved by subtracting the raw arithmetic mean of a particular variable from its daily raw value and dividing the result by the raw standard deviation.

3.5.4 EQUAL-WEIGHTED NORMALIZED AFTER-HOURS WEIGHTED OPINION, *AO*

After ‘after-hours weighted opinion’ had been normalized for both bank stocks, a related equal-weighted index of ‘after-hours weighted opinion’ was constructed. Equal-weighting appeared reasonable because both stocks, which were included in the DAXsubsector Credit Banks index, represented the blue-chip banks in Germany. In order to achieve equal-weighting and arrive at aggregate index values, the individual values of the normalized ‘after-hours weighted opinion’ were weighted by one half. The resulting index, equal-weighted normalized after-hours weighted opinion, *AO*, was intended to reflect the short-term private investor sentiment towards German blue-chip bank stocks. Overall, days that indicate positive index values are associated with positive sentiment and days that indicate negative index values are associated with negative sentiment.

3.6 DATA ANALYSIS – LINEAR STATISTICAL TECHNIQUES

Quantitative data analysis was used to answer the research questions. First of all, it was examined whether private investors are prone to extrapolation bias; that is, whether they simplistically extrapolate past stock returns for forming expectations with respect to future returns (Das, Martínez-Jerez & Tufano, 2005). Then, it was determined whether such extrapolation bias has an impact on stock prices. This quantitative analysis involved Pearson correlation and ordinary least squares regressions.

3.6.1 ASSUMPTIONS

For the purpose of conducting the statistical analyses in a consistent manner, several assumptions were adhered to and the variables used for the quantitative techniques were specified in advance. Similar to the equal-weighted normalized after-hours weighted opinion, *AO*, the normalized values of the other quantitative variables were equal-weighted.

The calculation of daily stock returns, *DR*, was based on the change in the daily closing prices of the stocks. These prices were adjusted for any dividend payments. Daily stock trading volume, *DTV*, was determined by including the turnover of traded stocks as denominated in Euros. Daily stock price volatility, *DV*, was obtained by incorporating intraday volatility, which was computed by dividing the difference between the daily high and the daily low of the stock by the mean of the opening and closing price (Das & Chen, 2007). After-hours posting volume, *APV*, was determined by including the number of postings that had been uploaded after-hours for the discussed stock on a given trading day. The after-hours disagreement among the message board participants regarding the future short-term returns of the discussed stock, *AD*, was calculated using the formula suggested by Das, Martínez-Jerez and Tufano (2005):

$$|(|BUYS-SELLS|)/(BUYS+SELLS)-1|$$

3.6.2 DOES EXTRAPOLATION BIAS EXIST AMONG PRIVATE INVESTORS?

For answering the first research question of whether private investors are prone to extrapolation bias, correlation analysis including simple linear regression analysis was first conducted. Then, multiple linear regression analysis was carried out. Regarding all analytic techniques, robustness checks were performed.

3.6.2.1 PEARSON CORRELATION AND SIMPLE LINEAR REGRESSION

Pearson correlation and simple linear regression analysis were undertaken to determine whether a positive association exists between daily stock returns and after-hours private investor sentiment. A positive association implies that following positive daily stock returns, after-hours private investor sentiment would be positive on average, too, and after-hours private investor sentiment would tend to be negative on days where preceding daily stock returns were also negative.

Pearson correlation is a widely used measure of the linear association between two variables (Rodgers & Nicewander, 1988). The Pearson product-moment correlation coefficient between daily stock returns, *DR*, and after-hours weighted opinion, *AO*, was first calculated.

Simple linear regression is closely related to Pearson correlation. Since the included variables are normalized variables, the slope coefficient equals the correlation coefficient (De Veaux, Velleman & Bock, 2008). Against this background, the related simple linear regression model was readily set up. *AO* represented the dependent variable and was explained by the independent variable *DR*.

$$AO_t=\beta_0+\beta_1(DR_t)+\varepsilon_t \tag{1}$$

where *AO* represents equal-weighted normalized after-hours weighted opinion, β_0 represents the constant term, β_1 represents the slope term, *DR* represents equal-weighted normalized daily stock returns and ε represents the error term.

3.6.2.1.1 Robustness Checks: Correlation and Simple Regression at Individual Stock Levels

DR and *AO* reflect aggregate market values regarding blue-chip bank stocks. For the purpose of performing robustness checks of the Pearson correlation coefficient between *DR* and *AO* as well as of the related simple linear regression model, the underlying individual stocks were analyzed.

3.6.2.1.1.1 Commerzbank

Pearson correlation and simple linear regression analysis was carried out first for the stocks of Commerzbank. Consistent with *AO* and *DR*, the variables *AOcbk* and *DRcbk* were introduced.

$$AOcbk_t=\beta_0+\beta_1(DRcbk_t)+\varepsilon_t \tag{2}$$

where *AOcbk* represents normalized after-hours weighted opinion of Commerzbank stocks and *DRcbk* represents normalized daily stock returns of Commerzbank stocks.

3.6.2.1.1.2 Deutsche Bank

Second, Pearson correlation and simple linear regression analysis was carried out for the stocks of Deutsche Bank. Consistent with *AO* and *DR*, the variables *AOdbk* and *DRdbk* were introduced for Deutsche Bank.

$$AOdbk_t=\beta_0+\beta_1(DRdbk_t)+\varepsilon_t \tag{3}$$

where *AOdbk* represents normalized after-hours weighted opinion of Deutsche Bank stocks and *DRdbk* represents normalized daily stock returns of Deutsche Bank stocks.

3.6.2.2 MULTIPLE LINEAR REGRESSION

In a following step, a multiple linear regression model was developed to be able to substantiate the correlation and simple regression analysis and to find out whether stock market returns are a significant factor in determining private investor sentiment given other predictors. The dependent variable, *AO*, is explained by several independent variables. These variables include *DR* as well as further message board variables, trading variables and indicator variables that were found to be significantly associated with short-term private investor sentiment and/or appeared relevant to short-term private investor sentiment. These independent variables relate to the volume of stock message board postings, *APV*, and disagreement among board participants, *AD*, stock trading volume, *DTV*, and stock price volatility, *DV*, seasonal mood effects, *AW*, weekday mood effects, *M*, and after-hours corporate news, *AN*, as well as lagged values of after-hours weighted opinion, *AO*.

According to previous research, while private investor sentiment seems to be positively associated with posting volume (Antweiler & Frank, 2004; Das, Martínez-Jerez & Tufano, 2005; Das & Chen, 2007), private investor sentiment has been suggested to be negatively related to disagreement (Das & Chen, 2007). Message board sentiment has been shown to be positively related both to the trading volume and the volatility of stock prices (Antweiler & Frank, 2004). In general, while the mood of individuals tends to be lower during autumn and winter due to the impact of seasonal effects (for instance, Lo & Wu, 2010), the 'Monday effect' implies that investor mood is substantially lower on the first day of the week (Gondhalekar & Mehdian, 2003). Message board sentiment was controlled for material after-hours corporate news to account for investors whose true sentiment was distorted merely by the positive or negative content of a corporate announcement after the close of the stock market. Finally, according to different research studies, private investor sentiment tends to be autocorrelated, which indicates persistence in the sentiment level (Tumarkin & Whitelaw, 2001; Das, Martínez-Jerez & Tufano, 2005).

As far as mood and news are concerned, indicator variables were included. The mood of investors was considered by introducing one dummy variable for postings that had been uploaded during autumn or winter, AW, and a second dummy variable for postings that had been uploaded on Mondays, M. Regarding after-hours corporate news, the dummy variable, AN, indicates the days on which material corporate news was released after the close of the stock market by at least one of the banks. The following multiple linear regression model was estimated:

$$AO_t=\beta_0+\beta_1(DR_t)+\beta_2(APV_t)+\beta_3(AD_t)+\beta_4(DTV_t)+\beta_5(DV_t)+\beta_6(AW_t)$$
$$+\beta_7(M_t)+\beta_8(AN_t)+\beta_9(AO_{t-1})+\varepsilon_t \quad (4)$$

where *APV* represents equal-weighted normalized after-hours posting volume, *AD* represents equal-weighted normalized after-hours disagreement, *DTV* represents equal-weighted normalized daily stock trading volume, *DV* represents equal-weighted normalized daily stock price volatility, *AW* represents an indicator variable for autumn or winter, *M* represents an indicator variable for Mondays, and *AN* represents an indicator variable for after-hours corporate news.

3.6.2.2.1 Robustness Checks: Multiple Linear Regression at Individual Stock Levels

Similar to the earlier simple linear regression analysis, robustness checks were carried out with respect to the multiple linear regression model. First, the stocks of Commerzbank were involved. Then, the stocks of Deutsche Bank were involved.

3.6.2.2.1.1 Commerzbank

In the multiple linear regression model of the first robustness check, the after-hours weighted opinion of Commerzbank stocks, *AOcbk*, is explained by related stock market variables and message board variables as well as indicator variables that account for calendar data and corporate news concerning Commerzbank.

$$AOcbk_t = \beta_0 + \beta_1(DRcbk_t) + \beta_2(APVcbk_t) + \beta_3(ADcbk_t) + \beta_4(DTVcbk_t)$$
$$+ \beta_5(DVcbk_t) + \beta_6(AW_t) + \beta_7(M_t) + \beta_8(ANcbk_t) + \beta_9(AOcbk_{t-1}) + \varepsilon_t \qquad (5)$$

where *APVcbk* represents normalized after-hours posting volume of Commerzbank stocks, *ADcbk* represents normalized after-hours disagreement of Commerzbank stocks, *DTVcbk* represents normalized daily stock trading volume of Commerzbank stocks, *DVcbk* represents normalized daily stock price volatility of Commerzbank stocks and *ANcbk* represents an indicator variable for after-hours corporate news of Commerzbank.

3.6.2.2.1.2 Deutsche Bank

Equal to the first robustness check, a second robustness check was conducted. The data of Deutsche Bank stocks was included here.

$$AOdbk_t = \beta_0 + \beta_1(DRdbk_t) + \beta_2(APVdbk_t) + \beta_3(ADdbk_t) + \beta_4(DTVdbk_t)$$
$$+ \beta_5(DVdbk_t) + \beta_6(AW_t) + \beta_7(M_t) + \beta_8(ANdbk_t) + \beta_9(AOdbk_{t-1}) + \varepsilon_t \qquad (6)$$

where *APVdbk* represents normalized after-hours posting volume of Deutsche Bank stocks, *ADdbk* represents normalized after-hours disagreement of Deutsche Bank stocks, *DTVdbk* represents normalized daily stock trading volume of Deutsche Bank stocks, *DVdbk* represents normalized daily stock price volatility of Deutsche Bank stocks and *ANdbk* represents an indicator variable for after-hours corporate news of Deutsche Bank.

3.6.3 DOES EXTRAPOLATION BIAS HAVE AN EFFECT ON MARKET PRICES?

To answer the second research question and determine whether extrapolation bias among private investors has an effect on the market prices of stocks, autocorrelation analysis and autoregression analysis were first conducted. Then, multiple linear regression analysis was carried out.

3.6.3.1 AUTOCORRELATION AND AUTOREGRESSION

The autocorrelation coefficient of daily stock returns was calculated to assess whether stock returns exhibit evidence of autocorrelation. Positive autocorrelation provides evidence of investor extrapolation bias having an impact on stock prices. On the one hand, investors who increase their demand for stocks following most recent positive stock returns are assumed to cause further price rises. On the other hand, investors who decrease their demand for stocks following most recent negative stock returns are assumed to cause further price declines.

However, positive autocorrelation in stock returns does not provide unambiguous evidence concerning the investment behavior specifically of private investors. Theoretically, when stock prices are found to be positively autocorrelated, such a price pattern may be due exclusively to the actions of professional investors. Still, it appears reasonable to assume that private investors are affected by extrapolation bias in instances where equity returns can be shown to exhibit positive autocorrelation, as private investors seem to be particularly susceptible to this bias (For instance, Bange, 2000).

For the purpose of computing the autocorrelation coefficient, a 1-day lag was deliberately chosen, since the focus in this study is on short-term stock returns. In a technical sense, the 1-day autocorrelation coefficient of daily stock returns equals the Pearson correlation coefficient between 1-day lagged daily stock returns, DR_{t-1}, and contemporary daily stock returns, DR.

The related simple linear autoregressive model was also constructed. As a simple linear autoregressive model reflects a simple linear regression model where the independent variable constitutes lagged values of the dependent variable (De Veaux, Velleman & Bock, 2008), daily stock returns, DR, were explained by their own previous values, DR_{t-1}.

$$DR_t = \beta_0 + \beta_1 (DR_{t-1}) + \varepsilon_t \qquad (7)$$

3.6.3.1.1 Robustness Checks: Autocorrelation and Autoregression at Individual Stock Levels

Similar to the earlier analyses, robustness checks were carried out regarding the autocorrelation and autoregression analysis. For that purpose, the stocks of Commerzbank and Deutsche Bank were separately involved.

3.6.3.1.1.1 Commerzbank

First, the 1-day lagged autocorrelation coefficient was computed for the daily returns of Commerzbank stocks. Then, the associated autoregressive model was derived.

$$DRcbk_t = \beta_0 + \beta_1 (DRcbk_{t-1}) + \varepsilon_t \qquad (8)$$

3.6.3.1.1.2 Deutsche Bank

As a second robustness check, the 1-day lagged autocorrelation coefficient of daily stock returns was calculated for Deutsche Bank. The related autoregressive model was also set up.

$$DRdbk_t = \beta_0 + \beta_1 (DRdbk_{t-1}) + \varepsilon_t \qquad (9)$$

3.6.3.2 MULTIPLE LINEAR REGRESSION

In a following step, a multiple linear regression model was developed to find out whether prior stock returns are a significant factor in determining contemporary stock returns. The dependent variable, *DR*, is explained by its own lagged values as well as message board variables, trading variables and indicator variables that were found to be associated with daily stock returns and/or appeared relevant to them. Regarding the daily trading variables and indicator variables, the contemporary values were incorporated. As the message board variables represent after-hours variables, however, the 1-day lagged values of these variables were incorporated. It would be inconsequential to explain daily stock returns by after-hours factors that are not yet known by the time the stock returns are known.

More specifically, the explanatory variables are 1-day lagged after-hours weighted opinion, AO_{t-1}, 1-day lagged after-hours posting volume, APV_{t-1}, 1-day lagged after-hours disagreement, AD_{t-1}, daily stock trading volume, *DTV*, and daily stock price volatility, *DV*, as well as the contemporary indicator variables regarding seasonal mood effects, *AW*, and weekday mood effects, *M*. It was controlled for material daily corporate news, *DN*, to account for contemporary stock returns having become distorted by the release of unexpected corporate news. Daily corporate news were specifically defined to refer to those news releases that had occurred between the stock market’s close on the preceding trading day and the stock market’s close on the current trading day.

According to past research, stock returns are related to private investor sentiment (Das & Chen, 2007), message board posting volume (Wysocki, 1998), disagreement among board participants (Das, Martínez-Jerez & Tufano, 2005), stock trading volume (Chordia, Roll & Subrahmanyam, 2000), stock price volatility (Bekaert & Wu, 2000), seasonal mood effects (Kamstra, Kramer & Levi, 2003), weekday mood effects (Gondhalekar & Mehdian, 2003) and corporate news (Neuhierl, Scherbina & Schlusche, 2013). The following multiple linear regression model was estimated:

$$DR_t = \beta_0 + \beta_1(DR_{t-1}) + \beta_2(AO_{t-1}) + \beta_3(APV_{t-1}) + \beta_4(AD_{t-1}) + \beta_5(DTV_t) + \beta_6(DV_t)$$
$$+ \beta_7(AW_t) + \beta_8(M_t) + \beta_9(DN_t) + \varepsilon_t \qquad (10)$$

where *DN* represents an indicator variable for daily corporate news.

Fundamental variables have traditionally been employed for predicting stock returns, for instance changes in corporate earnings (Ball & Brown, 1968) or book-to-market ratios (Rosenberg, Reid & Lanstein, 1985). Notwithstanding, such variables were discarded for this study because they are unlikely to be relevant to daily stock returns. While companies release accounting numbers only on a quarterly basis, both Ball and Brown (1968) and Rosenberg, Reid and Lanstein (1985) analyze stock returns on a monthly basis.

3.6.3.2.1 Robustness Checks: Multiple Linear Regression at Individual Stock Levels

Consistent with the other analyses, robustness checks of the multiple linear regression model were performed. The stocks of Commerzbank and Deutsche Bank were incorporated on an individual basis.

3.6.3.2.1.1 Commerzbank

In the first robustness check, the multiple linear regression model explains the daily stock returns of Commerzbank by message board variables and stock market variables that are relevant to Commerzbank as well as indicator variables that take account of calendar data and relevant corporate news.

$$DRcbk_t = \beta_0 + \beta_1(DRcbk_{t-1}) + \beta_2(AOcbk_{t-1}) + \beta_3(APVcbk_{t-1}) + \beta_4(ADcbk_{t-1})$$
$$+ \beta_5(DTVcbk_t) + \beta_6(DVcbk_t) + \beta_7(AW_t) + \beta_8(M_t) + \beta_9(DNcbk_t) + \varepsilon_t \qquad (11)$$

where *DNcbk* represents an indicator variable for daily corporate news of Commerzbank.

3.6.3.2.1.2. Deutsche Bank

The multiple linear regression model of the second robustness check explains the daily stock returns of Deutsche Bank by relevant message board variables and stock market variables as well as indicator variables that account for calendar data and relevant corporate news.

$$DRdbk_t=\beta_0+\beta_1(DRdbk_{t-1})+\beta_2(AOdbk_{t-1})+\beta_3(APVdbk_{t-1})+\beta_4(ADdbk_{t-1})$$
$$+\beta_5(DTVdbk_t)+\beta_6(DVdbk_t)+\beta_7(AW_t)+\beta_8(M_t)+\beta_9(DNdbk_t)+\varepsilon_t \qquad (12)$$

where *DNdbk* represents an indicator variable for daily corporate news of Deutsche Bank.

The results of all statistical analyses, as explained in this Chapter, are provided in Chapter 4.

CHAPTER 4: DATA ANALYSIS

4.1 INTRODUCTION

In this Chapter, the data analysis of the study is described at length. First, descriptive statistics of the collected data are provided. Then, the results from the statistical analyses are outlined.

4.2 ATTRIBUTES OF THE COLLECTED DATA

As stated in Chapter 3, stock message board data, stock market data, corporate news data and calendar data was gathered for the trading days in 2012. Since the last trading day of the year, that is 28 December, was excluded, the data set includes 253 days. For summarizing the collected data and highlighting its features, descriptive statistics are provided in the following. Table 1 shows an overview of the descriptive statistics of the quantitative variables; that is, of the variables regarding the stock message board data and the stock market data.

4.2.1 STOCK MESSAGE BOARD DATA

A major part of the data collection revolved around the postings in stock message boards. Measures concerning private investor sentiment, the volume of postings and disagreement among board participants were constructed. As explained in Chapter 3, private investor sentiment was proxied by after-hours weighted opinion.

4.2.1.1 AFTER-HOURS WEIGHTED OPINION (RAW DATA)

The mean value of raw after-hours weighted opinion for Commerzbank, *AOcbk_raw*, is 0.54 and for Deutsche Bank, *AOdbk_raw*, is -0.18. On average, after-hours sentiment among private investors towards short-term stock returns tended to be positive for Commerzbank but negative for Deutsche Bank. The standard deviation of the distribution of raw after-hours weighted opinion is 3.97 and 0.96 for Commerzbank and Deutsche Bank, respectively.

As shown in Figures 2 and 3, the distribution of after-hours weighted opinion is only nearly normal for both stocks. Although the distribution is unimodal and approximately symmetric in shape, it is fairly peaked. The Lilliefors significance level of the Kolmogorov-Smirnov statistic (Lilliefors, 1967) is below 0.05 in both instances.

Figure 2: Distribution of Raw After-hours Weighted Opinion for Commerzbank, *AOcbk_raw*

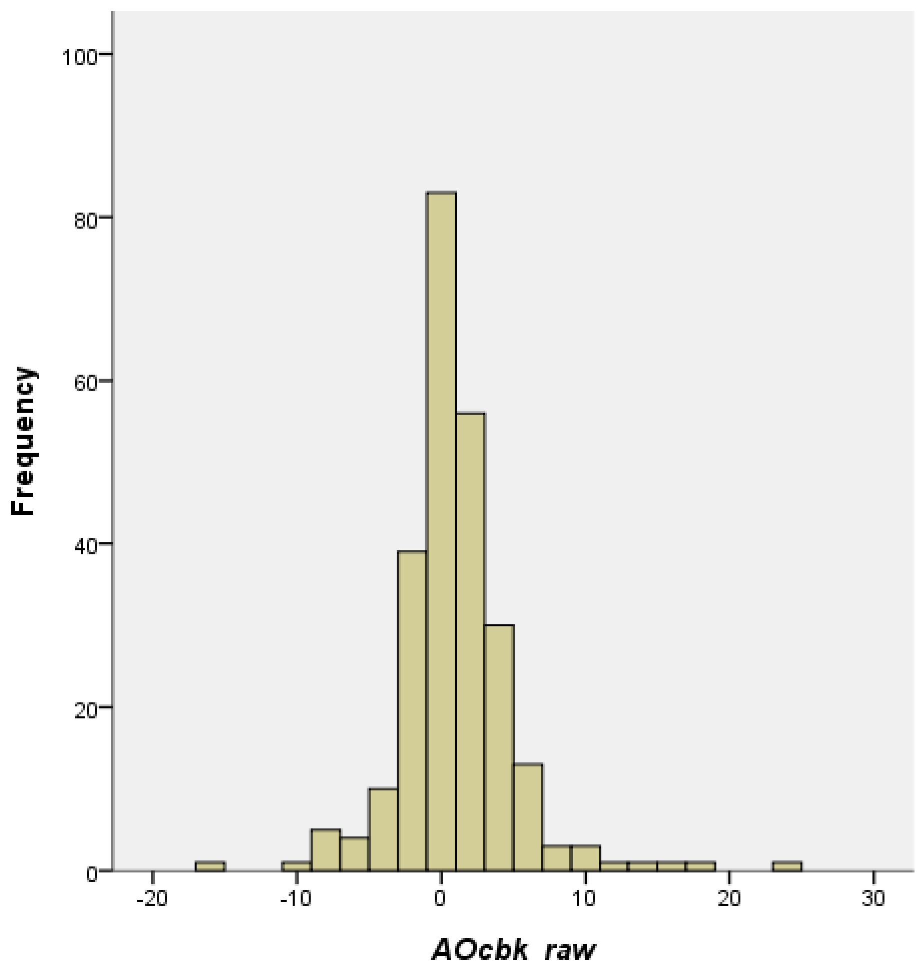
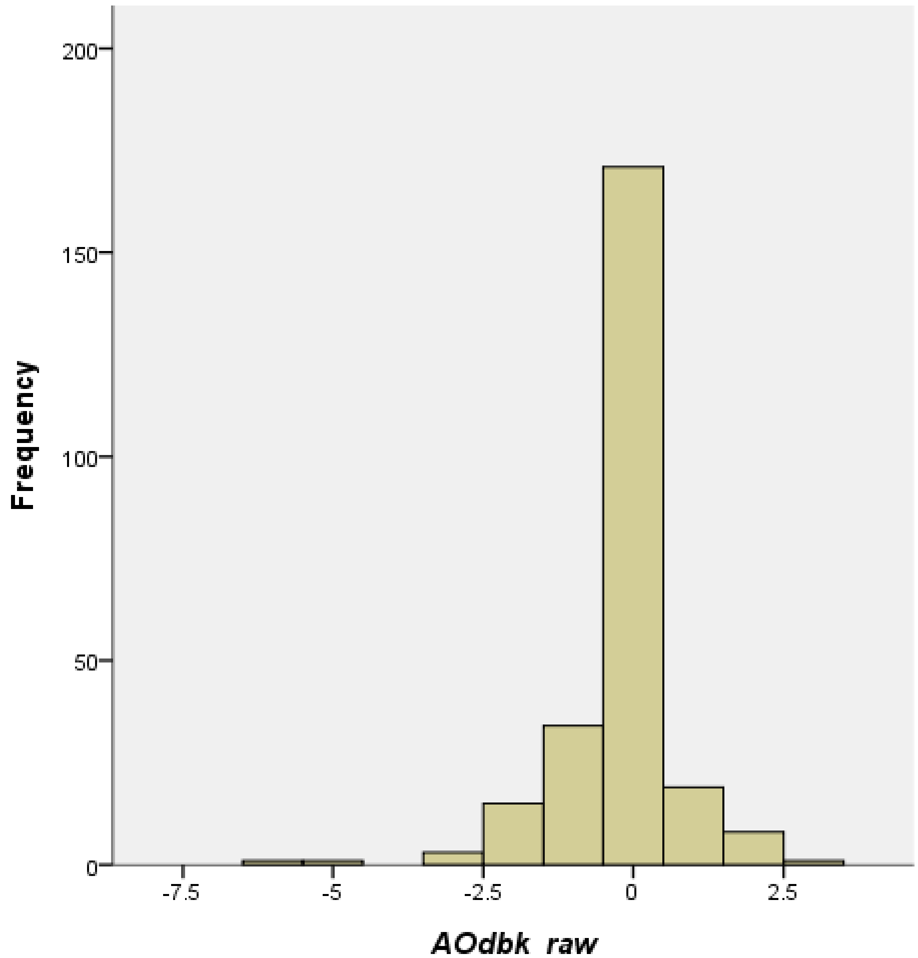


Figure 3: Distribution of Raw After-hours Weighted Opinion for Deutsche Bank, *AOdbk_raw*



4.2.1.2 AFTER-HOURS POSTING VOLUME (RAW DATA)

While the mean after-hours posting volume is 48.5 postings for Commerzbank, it is 8.8 postings for Deutsche Bank. This indicates that substantially more postings occurred for the former. The standard deviation of the distribution of after-hours posting volume equals 35.3 postings for Commerzbank and 11.9 postings for Deutsche Bank.

According to Figures 4 and 5, the distribution of after-hours posting volume is nonnormal and positively skewed for both stocks. The Lilliefors significance level of the Kolmogorov-Smirnov test statistic is below 0.05 in both cases.

Figure 4: Distribution of Raw After-hours Posting Volume for Commerzbank, *APVcbk_raw*

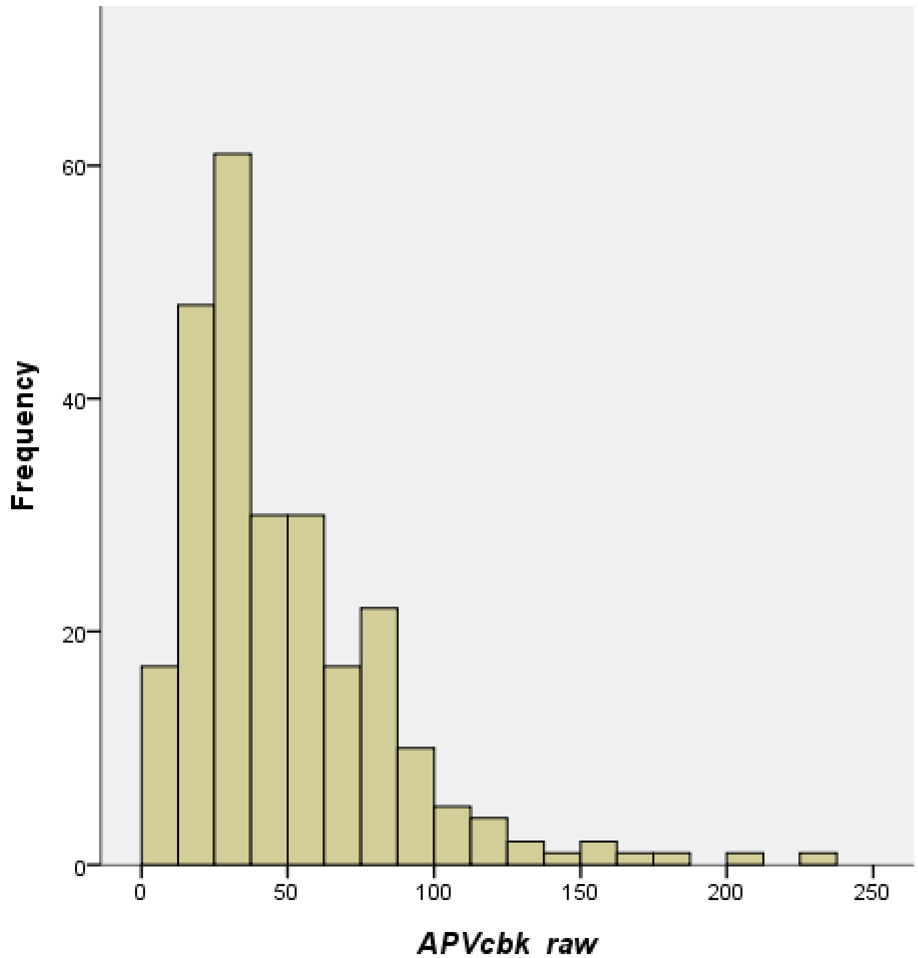
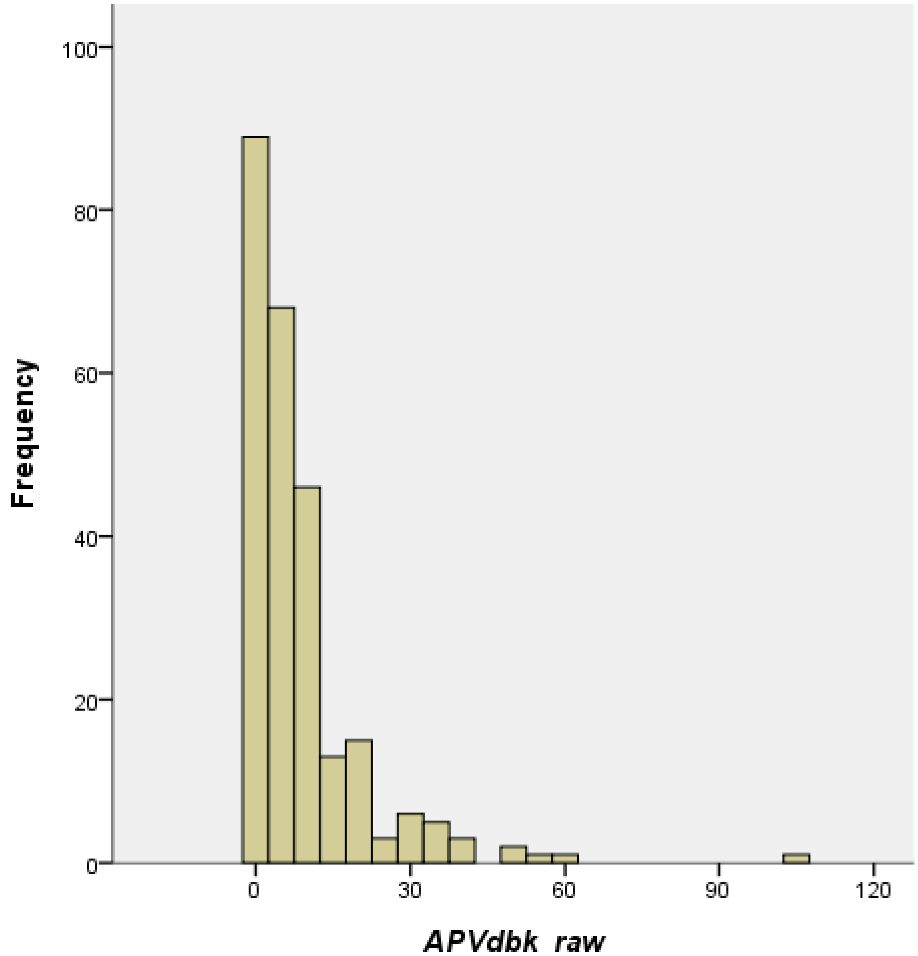


Figure 5: Distribution of Raw After-hours Posting Volume for Deutsche Bank, *APVdbk_raw*



4.2.1.3 AFTER-HOURS DISAGREEMENT (RAW DATA)

In contrast to the values of the other variables, valid values for after-hours disagreement could not be gathered for all 253 trading days. While 32 days are associated with missing values regarding Commerzbank, 170 days show missing values for Deutsche Bank. The mean value of disagreement is 0.3995 and 0.1044 for Commerzbank and Deutsche Bank, respectively. This indicates a clearly lower degree of disagreement in private investor sentiment concerning Deutsche Bank stocks. The standard deviation of the distribution of after-hours disagreement is 0.3694 for Commerzbank and 0.2347 for Deutsche Bank.

As illustrated in Figures 6 and 7, the distribution of after-hours disagreement does not follow the normal distribution; neither for the stocks of Commerzbank, nor for the stocks of Deutsche Bank. The Kolmogorov-Smirnov test statistic shows a Lilliefors significance level below 0.05 in both cases.

Figure 6: Distribution of Raw After-hours Disagreement for Commerzbank, *ADcbk_raw*

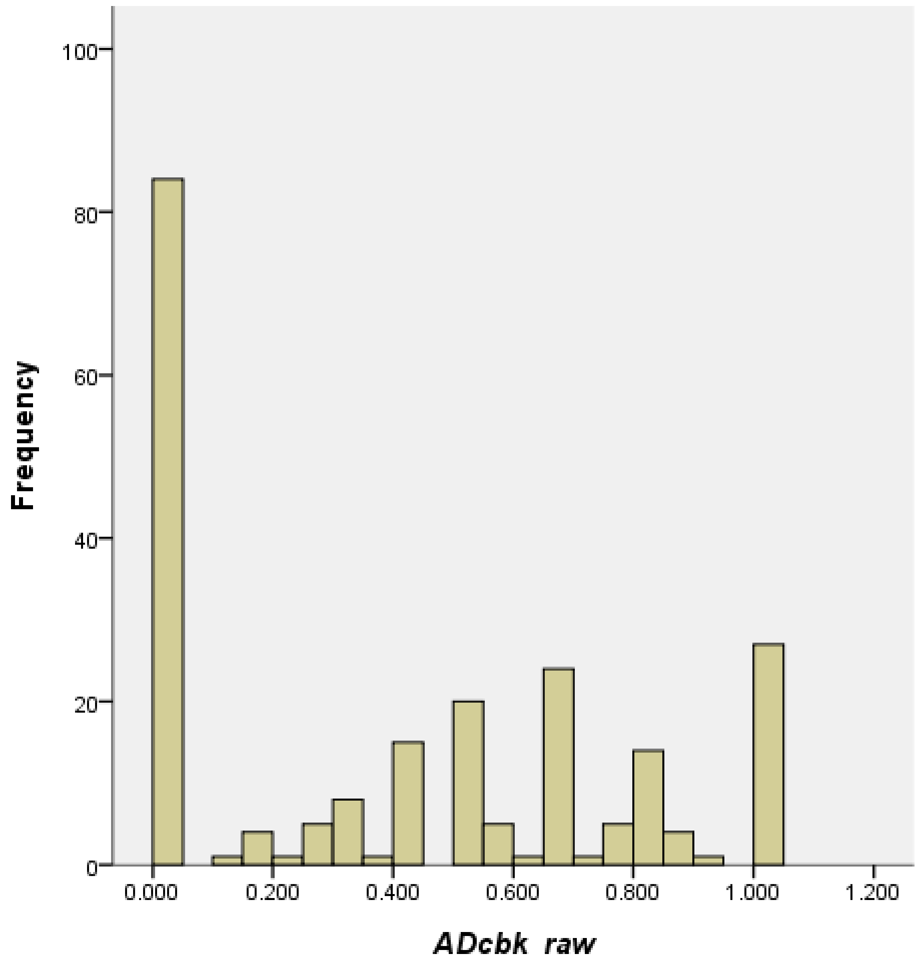
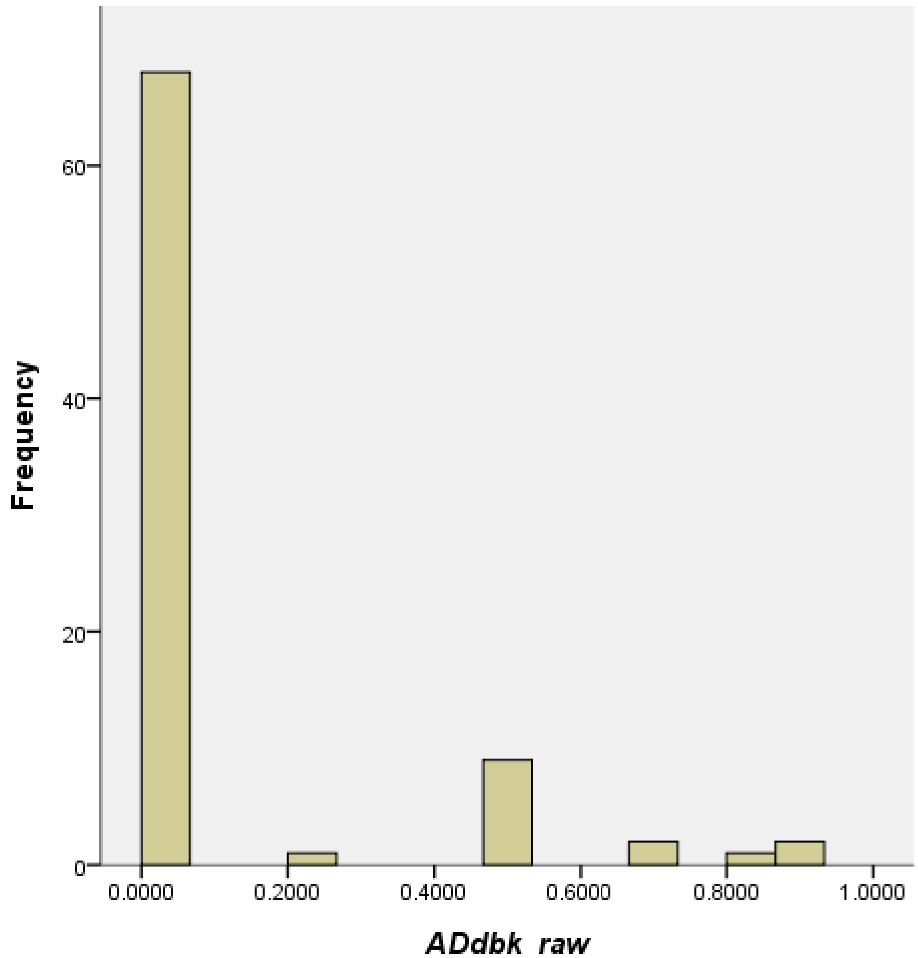


Figure 7: Distribution of Raw After-hours Disagreement for Deutsche Bank, *ADdbk_raw*



4.2.2 STOCK MARKET DATA

In addition to the stock message board data outlined above, particular stock market data was collected for this study. More specifically, daily stock returns, daily stock trading volume and the daily volatility of stock prices were taken account of.

4.2.2.1 DAILY STOCK RETURNS (RAW DATA)

The mean daily stock return amounts to 0.0454% for Commerzbank and 0.0600% for Deutsche Bank, which reveals that daily stock returns were positive for both stocks, on average; however, stock returns tended to be higher for Deutsche Bank. The standard deviation of the distribution of daily stock returns is 3.6381% and 2.5213% for Commerzbank and Deutsche Bank, respectively.

According to Figures 8 and 9, the distribution of daily stock returns more closely follows the normal distribution than the preceding distributions, which related to message board data. While the Lilliefors significance level of the Kolmogorov-Smirnov statistic is somewhat below 0.05 for Commerzbank, it exceeds 0.05 for Deutsche Bank.

Figure 8: Distribution of Raw Daily Stock Returns for Commerzbank, *DRcbk_raw*

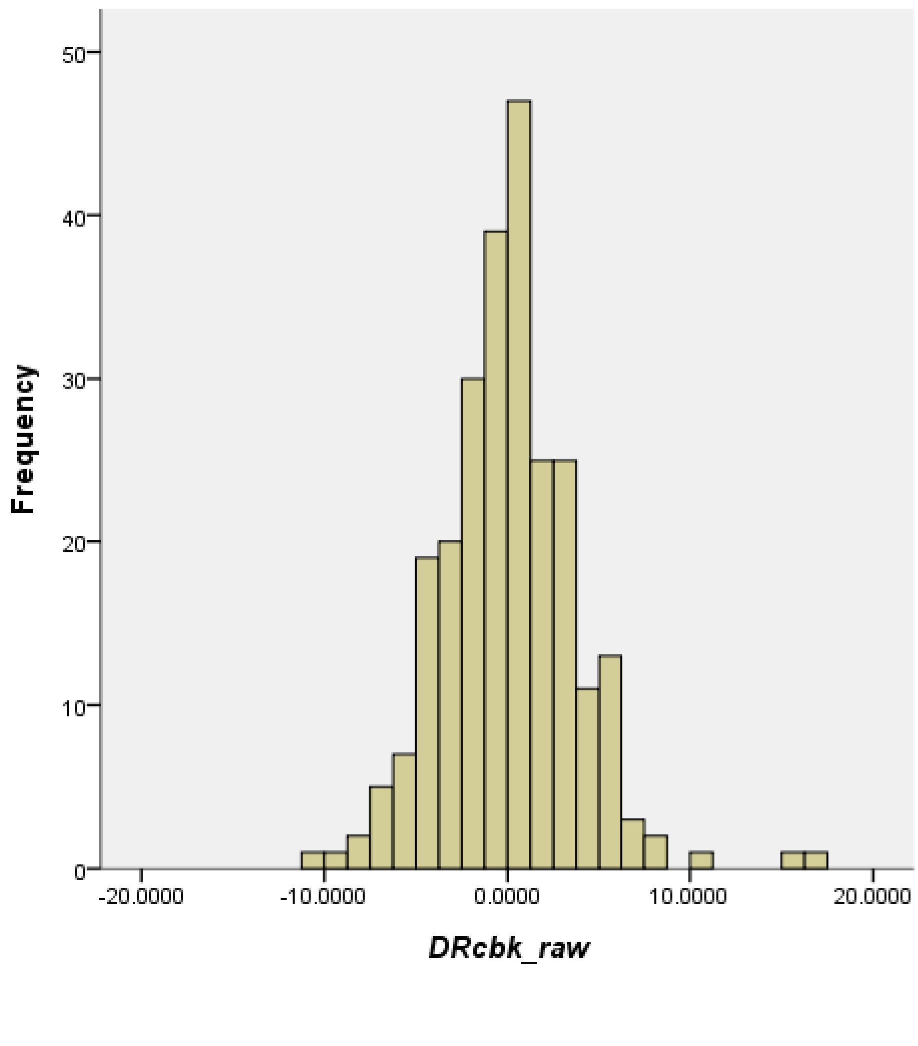
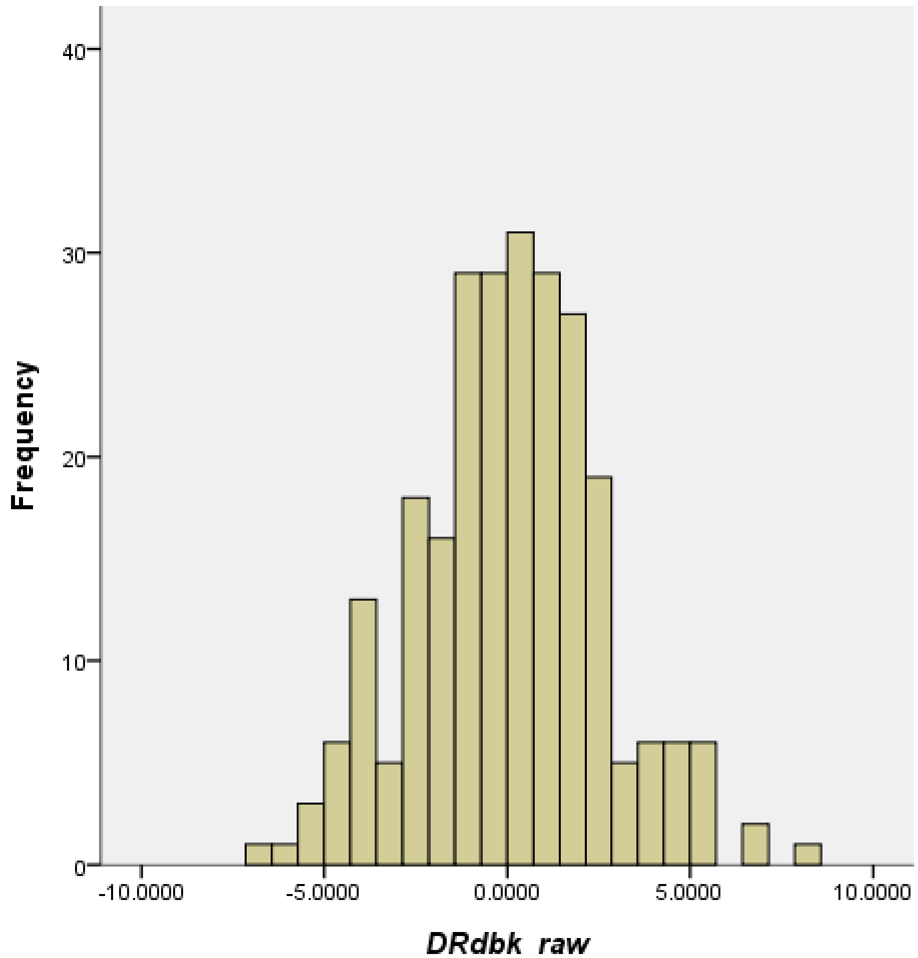


Figure 9: Distribution of Raw Daily Stock Returns for Deutsche Bank, *DRdbk_raw*



4.2.2.2 DAILY STOCK TRADING VOLUME (RAW DATA)

The mean value of daily trading volume equals €93,865,688.85 for Commerzbank stocks and it amounts to €239,407,491.34 for the stocks of Deutsche Bank. This shows that turnover was clearly higher for Deutsche Bank. The standard deviation of the distribution of daily trading volume is €54,450,174.69 and €91,092,578.70 for Commerzbank and Deutsche Bank, respectively.

The figures 10 and 11 illustrate that the distribution of daily trading volume is nonnormal and somewhat positively skewed for both stocks. The Lilliefors significance level of the Kolmogorov-Smirnov statistic is below 0.05 in both instances.

Figure 10: Distribution of Raw Daily Stock Trading Volume for Commerzbank, *DTVcbk_raw*

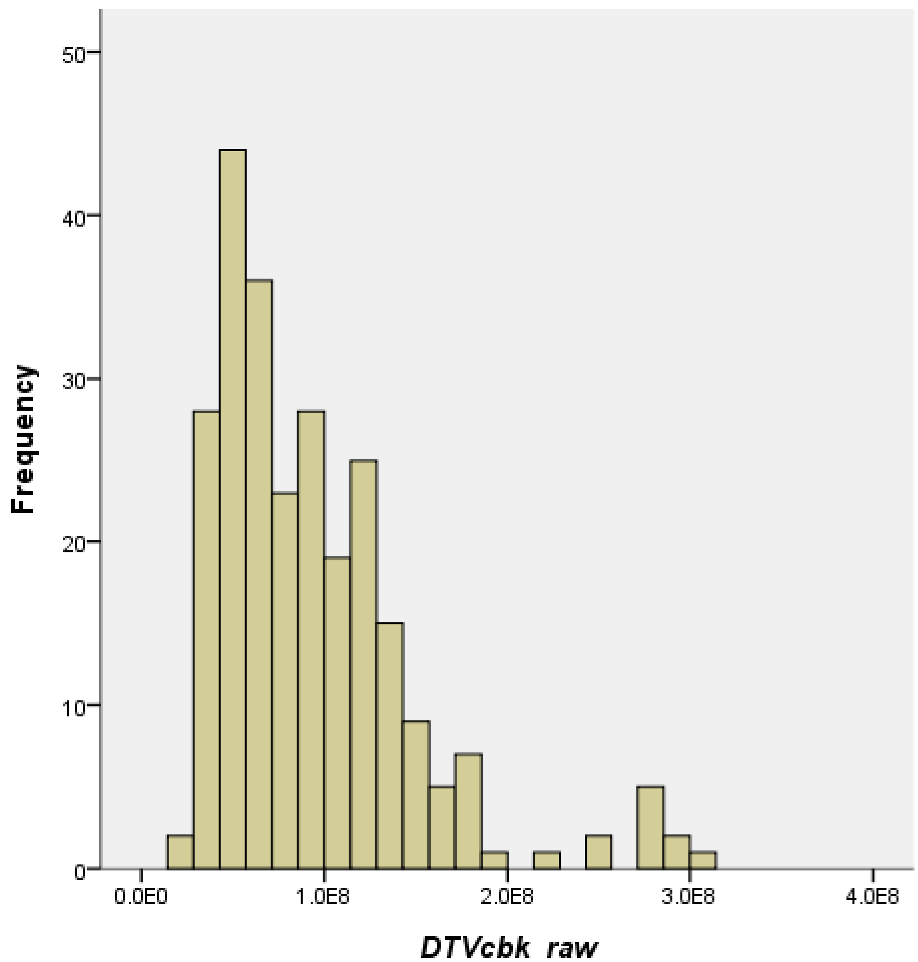
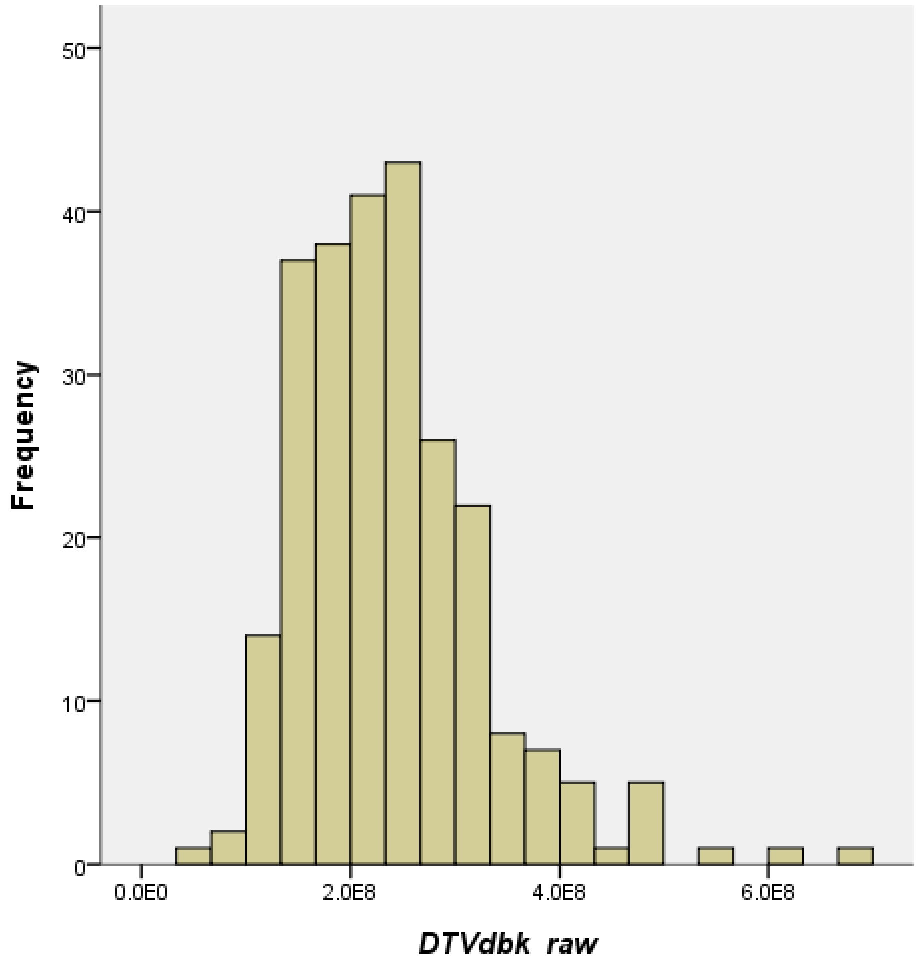


Figure 11: Distribution of Raw Daily Stock Trading Volume for Deutsche Bank, *DTVdbk_raw*



4.2.2.3 DAILY STOCK PRICE VOLATILITY (RAW DATA)

The mean daily stock price volatility was 4.09% for Commerzbank and 3.40% for Deutsche Bank, indicating that the former was more volatile. The standard deviation of the distribution of daily stock price volatility is 1.95% and 1.34% for Commerzbank and Deutsche Bank, respectively.

As shown in Figures 12 and 13, the distribution of daily stock price volatility is nonnormal and slightly skewed to the right for both stocks. The Lilliefors significance level of the Kolmogorov-Smirnov statistic is below 0.05 in both cases.

Figure 12: Distribution of Raw Daily Stock Price Volatility for Commerzbank, *DVcbk_raw*

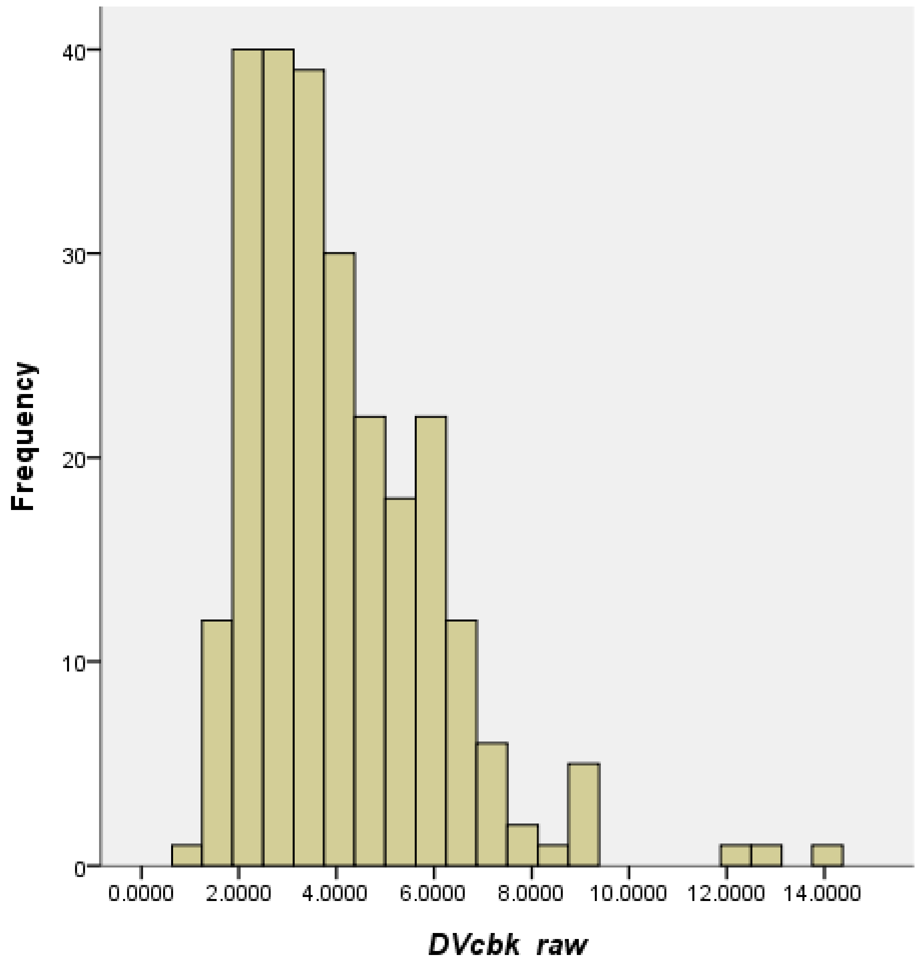
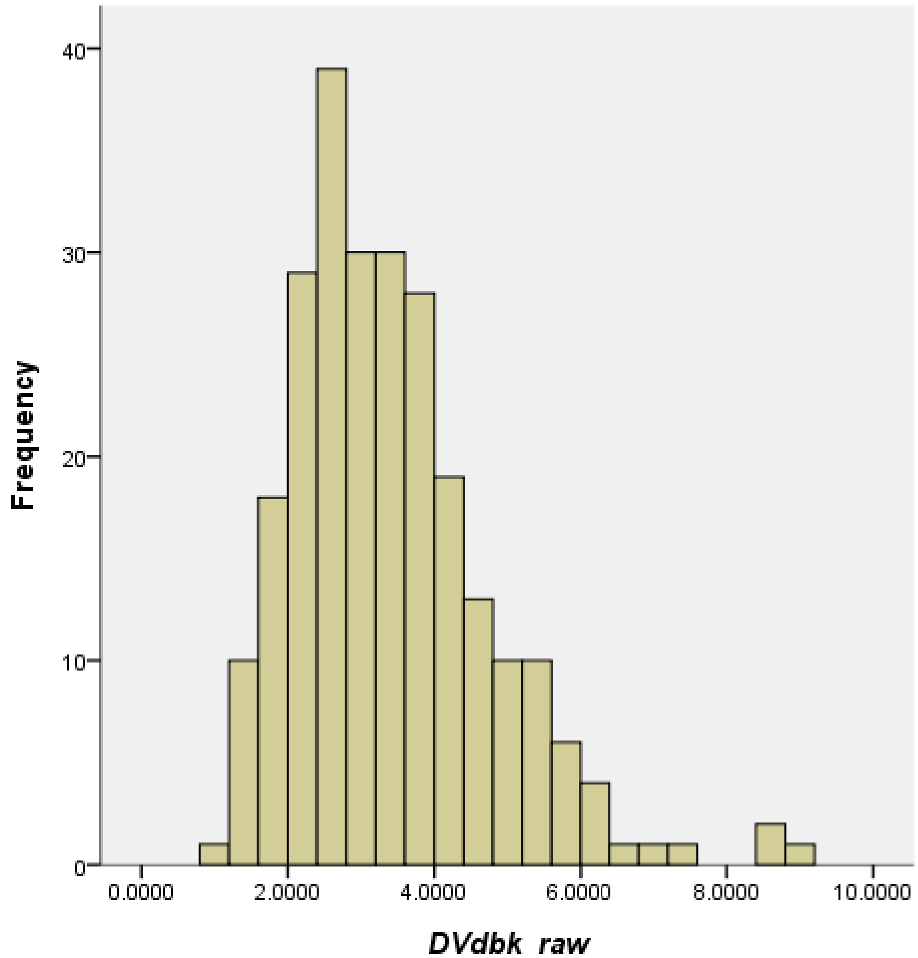


Figure 13: Distribution of Raw Daily Stock Price Volatility for Deutsche Bank, *DVdbk_raw*



4.2.3 CORPORATE NEWS DATA

In addition to the stock message board data and stock market data, material corporate news was collected. As stated in Chapter 3, it was specifically distinguished between after-hours corporate news and daily corporate news. For either kind of news, a particular indicator variable was introduced.

4.2.3.1 AFTER-HOURS CORPORATE NEWS

While five pieces of after-hours corporate news were identified for Commerzbank on trading days throughout the year 2012, after-hours corporate news did not occur for Deutsche Bank. Hence, this kind of news was associated with 1.98% of the trading days for Commerzbank and 0.00% for Deutsche Bank.

4.2.3.2 DAILY CORPORATE NEWS

Daily corporate news occurred on 13 trading days and on 4 trading days for Commerzbank and Deutsche Bank, respectively. This means that in 5.14% of the instances, daily corporate news was released with respect to Commerzbank and in 1.58% of the instances with respect to Deutsche Bank.

Daily corporate news tended to occur more frequently than after-hours corporate news. For both kinds of corporate news, Commerzbank was associated with a higher number of releases than Deutsche Bank.

4.2.4 CALENDAR DATA

Finally, certain calendar data was gathered. Particular seasonal data and weekday data was identified and related indicator variables were constructed.

4.2.4.1 SEASONAL DATA

The dummy variable concerning the seasonal data was intended to indicate those trading days that fell into autumn or winter. In 2012, winter was assumed to last until 19 March (Neue Züricher Zeitung, 2012), and autumn was assumed to begin on 22 September (Zeit Online, 2012).

Of the 253 trading days, 122 were classified as falling into autumn or winter. This represents 48.22% of all trading days.

4.2.4.2 WEEKDAY DATA

The dummy variable regarding the weekday data differentiates between those trading days that are associated with Mondays and trading days that are associated with other days of the week. A particular dummy variable was introduced to indicate all trading days that fell on a Monday.

Considering the entire year 2012, 50 out of the 253 trading days were Mondays. Hence, 19.76% of all trading days constituted Mondays.

Table 1: Descriptive Statistics (Quantitative Variables)

	N	Mean	Standard Deviation	Median	Interquartile Range
AOcbk_raw	253	0.54	3.97	0	3
AOdbk_raw	253	-0.18	0.96	0	0
APVcbk_raw	253	48.5 postings	35.3 postings	38 postings	42 postings
APVdbk_raw	253	8.8 postings	11.9 postings	5 postings	9 postings
ADcbk_raw	221	0.3995	0.3694	0.4000	0.6667
ADdbk_raw	83	0.1044	0.2347	0.0000	0.0000
DRcbk_raw	253	0.0454%	3.6381%	0.0000%	4.0507%
DRdbk_raw	253	0.0600%	2.5213%	0.0988%	3.0473%
DTVcbk_raw	253	€93,865,688.85	€54,450,174.69	€77,234,240	€68,079,890
DTVdbk_raw	253	€239,407,491.34	€91,092,578.70	€225,089,100	€107,528,350
DVcbk_raw	253	4.09%	1.95%	3.63%	2.47%
DVdbk_raw	253	3.40%	1.34%	3.20%	1.62%

4.3 STATISTICAL ANALYSES

After the data required for this study had been gathered and summarized, statistical analysis of the data was undertaken, as explained in Chapter 3. It was first investigated whether extrapolation bias exists among private investors. In a second step, it was analyzed whether extrapolation bias among private investors has an effect on the market prices of stocks.

As suggested earlier, before any statistical analysis of the collected data was carried out, all quantitative raw was normalized and equal-weighted. Equal-weighted normalized quantitative variables and categorical indicator variables served as variables in the statistical analysis.

As far as statistical significance is concerned, p-values smaller than 0.05 were accepted as indicating statistically significant results. The 0.05 confidence level is a common threshold level in hypothesis testing (Dallal, 2001).

4.3.1 DOES EXTRAPOLATION BIAS EXIST AMONG PRIVATE INVESTORS?

For answering the first research question of whether private investors are affected by extrapolation bias, Pearson correlation and ordinary least squares regressions were conducted, as stated in Chapter 3.

4.3.1.1 PEARSON CORRELATION AND SIMPLE LINEAR REGRESSION

Before the Pearson correlation coefficient was calculated between daily stock returns, *DR*, and after-hours weighted opinion, *AO*, and the related simple linear regression model could be set up, the assumptions of Pearson correlation were checked.

4.3.1.1.1 Assumptions of Pearson Correlation

For being able to perform Pearson correlation analysis in the correct manner, the underlying data need to satisfy certain requirements (De Veaux, Velleman & Bock, 2008). Both variables should be quantitative in nature and the relationship between them should be approximately linear while no significant outliers exist. According to Coakes and Ong (2011), the values of the individual variables also should be normally distributed and homoscedasticity should prevail in their relationship; that is, the variance across the distribution of the related pairs should be approximately constant.

However, as far as the normality of the distributions of the individual variables is concerned, other sources posit that this condition is expendable (Nefzger & Drasgow, 1957). The distributions of the individual variables in this study were assumed to suffice Pearson correlation analysis.

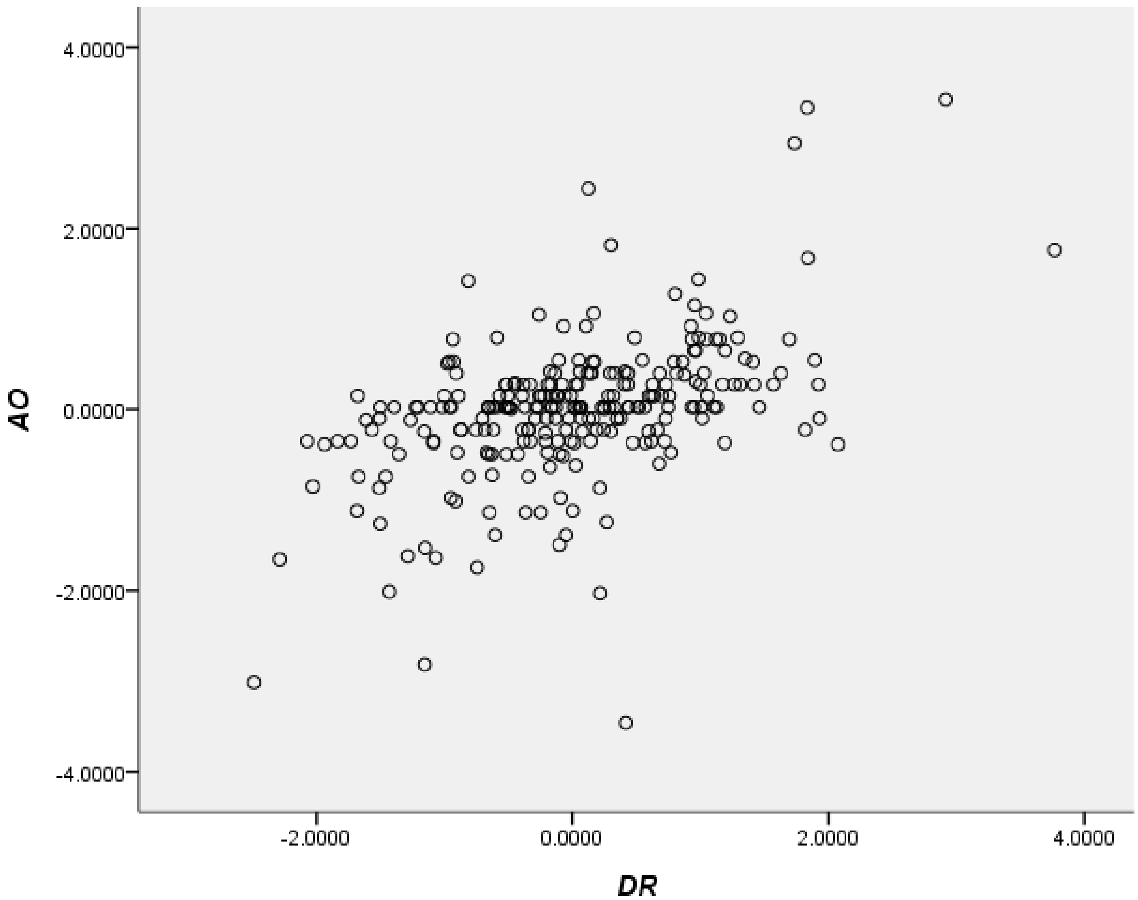
4.3.1.1.1.1 Quantitative Variables Condition

The variables for daily stock returns, *DR*, and after-hours weighted opinion, *AO*, which were involved in the calculation of the correlation coefficient, represent quantitative variables. Both the size of stock returns and the degree of private investor sentiment are measurable in a quantitative fashion.

4.3.1.1.1.2 Linearity, Outliers, Homoscedasticity

In addition to the quantitative variables condition, which concerns the variables in isolation, certain assumptions need to be fulfilled with respect to the relationship between the two variables. Whether the association between *DR* and *AO* is linear, whether material outliers exist in this relationship and whether homoscedasticity is given was determined by inspecting a scatterplot (De Veaux, Velleman & Bock, 2008). According to Figure 14, the relationship between *DR* and *AO* appears to be positive and linear. No significant outliers stick out. Homoscedasticity seems to prevail, as the variability in the values of *AO* is approximately equal across the values of *DR* (Coakes & Ong, 2011).

Figure 14: Scatterplot of *DR* against *AO*



4.3.1.1.2 Correlation Coefficient between *DR* and *AO*

After it had been ensured that the necessary assumptions were fulfilled, the Pearson correlation coefficient between *DR* and *AO* was computed. This correlation coefficient indicates a value of 0.504 and is different from zero to a statistically significant degree (p=0.000). A value of such size implies a moderate degree of positive association between daily stock returns and after-hours private investor sentiment (Dancey & Reidy, 2004; Fitz-Gibbon & Morris, 1987).

4.3.1.1.3 Simple Linear Regression

Following the Pearson correlation analysis, the related simple linear regression model was set up. *AO* constituted the dependent variable while *DR* was employed as the predictor variable.

$$AO_t = 0.427DR_t \tag{13}$$

According to the slope term, after-hours weighted opinion, *AO*, increases by 0.427 per 1-unit increase in daily stock returns, *DR*.

4.3.1.1.4 Evaluation of the Simple Linear Regression Model

The derived simple linear regression model was evaluated for its explanatory power and quality. In this respect, the coefficient of determination, R-squared, the standard deviation of residuals and the scatterplot of residuals were examined.

4.3.1.1.4.1 Coefficient of Determination

The coefficient of determination is an effective measure for assessing a simple linear regression model (De Veaux, Velleman & Bock, 2008). As far as this model is concerned, R-squared shows a value of 0.254. This value indicates that daily stock returns, *DR*, explain 25.4% of the variation in after-hours weighted opinion, *AO*. A value of such size is entirely common for observational studies and provides evidence that the regression is useful (De Veaux, Velleman & Bock, 2008).

4.3.1.1.4.2 Standard Deviation of Residuals

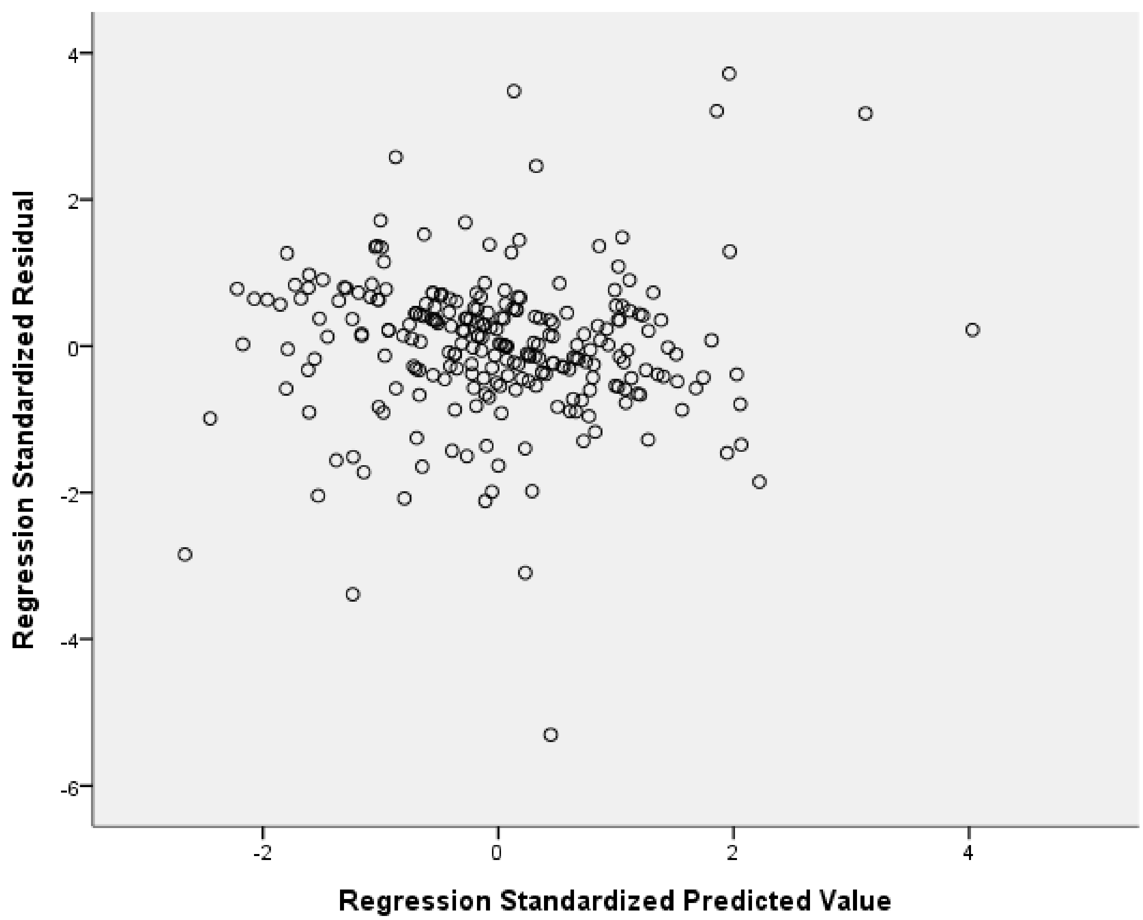
The standard deviation of residuals of a regression model can be compared to the standard deviation of the variable that is explained by the model (De Veaux, Velleman & Bock, 2008). With regards to this model, the standard deviation of residuals equals 0.6845586.

Since this figure is smaller than the standard deviation of after-hours weighted opinion, *AO*, which amounts to 0.7925043, the regression model helps describing the relationship between *DR* and *AO*.

4.3.1.1.4.3 Scatterplot of Residuals

Finally, a scatterplot of residuals was inspected for nonlinearity (De Veaux, Velleman & Bock, 2008). According to Figure 15, a more or less horizontal direction of the data points is observed and approximately equal scatter can be seen for all predicted values. Since the residuals were not found to exhibit a nonlinear shape, the applicability of linear regression analysis to the underlying data set appears to be given.

Figure 15: Scatterplot of Predicted Values against Residuals (Simple Regression)



4.3.1.1.5 Robustness Checks: Correlation and Simple Regression at Individual Stock Levels

As stated in Chapter 3, robustness checks were carried out regarding Pearson correlation and simple linear regression. While the first robustness check involved the stocks of Commerzbank, the second robustness check involved the stocks of Deutsche Bank.

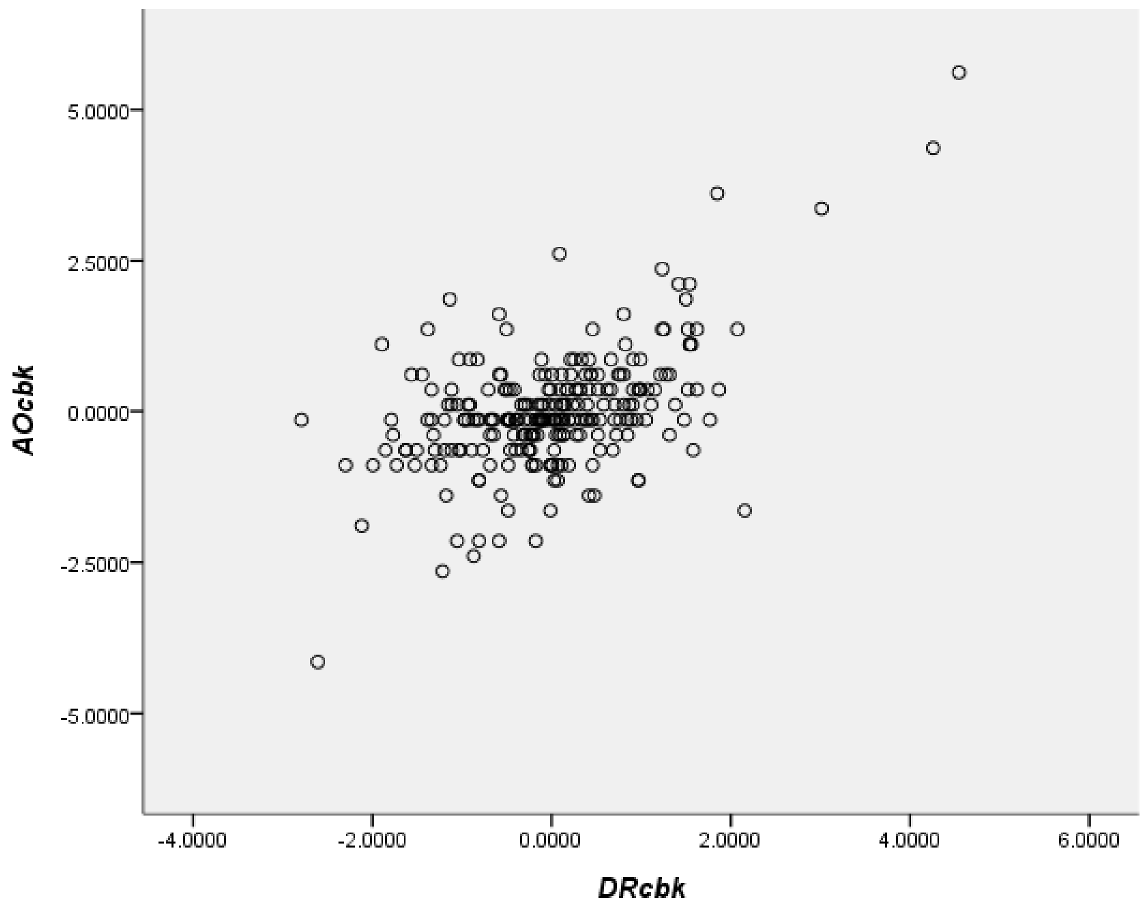
4.3.1.1.5.1 Commerzbank

4.3.1.1.5.1.1 Assumptions of Pearson Correlation

Just as in the case of the primary correlation analysis, the assumptions concerning Pearson correlation were checked for *DRcbk* and *AOcbk*. Equal to *DR* and *AO*, *DRcbk* and *AOcbk* represent quantitative variables, as *DRcbk* and *AOcbk* merely incorporate the values from individual stocks for daily stock returns and after-hours weighted opinion, respectively, while *DR* and *AO* draw upon aggregate index values.

The scatterplot of *DRcbk* against *AOcbk*, as shown in Figure 16, illustrates that a positive linear relationship exists between the two variables. Salient outliers are not suggested and homoscedasticity appears to be given.

Figure 16: Scatterplot of *DRcbk* against *AOcbk*



4.3.1.1.5.1.2 Correlation Coefficient between *DRcbk* and *AOcbk*

The Pearson correlation coefficient computed between *DRcbk* and *AOcbk* shows a value of 0.535 and is significantly different from zero (p=0.000). Consistent with the result from the primary analysis, this value indicates a moderate extent of linear association between daily stock returns and after-hours private investor sentiment.

4.3.1.1.5.1.3 Simple Linear Regression

The associated simple linear regression model was derived, where the dependent variable *AOcbk* is explained by the independent variable *DRcbk*.

$$AOcbk_t = 0.535 DRcbk_t \quad (14)$$

The slope term implies that for Commerzbank stocks, after-hours weighted opinion, *AOcbk*, rises by 0.535 per 1-unit increase in daily stock returns, *DRcbk*.

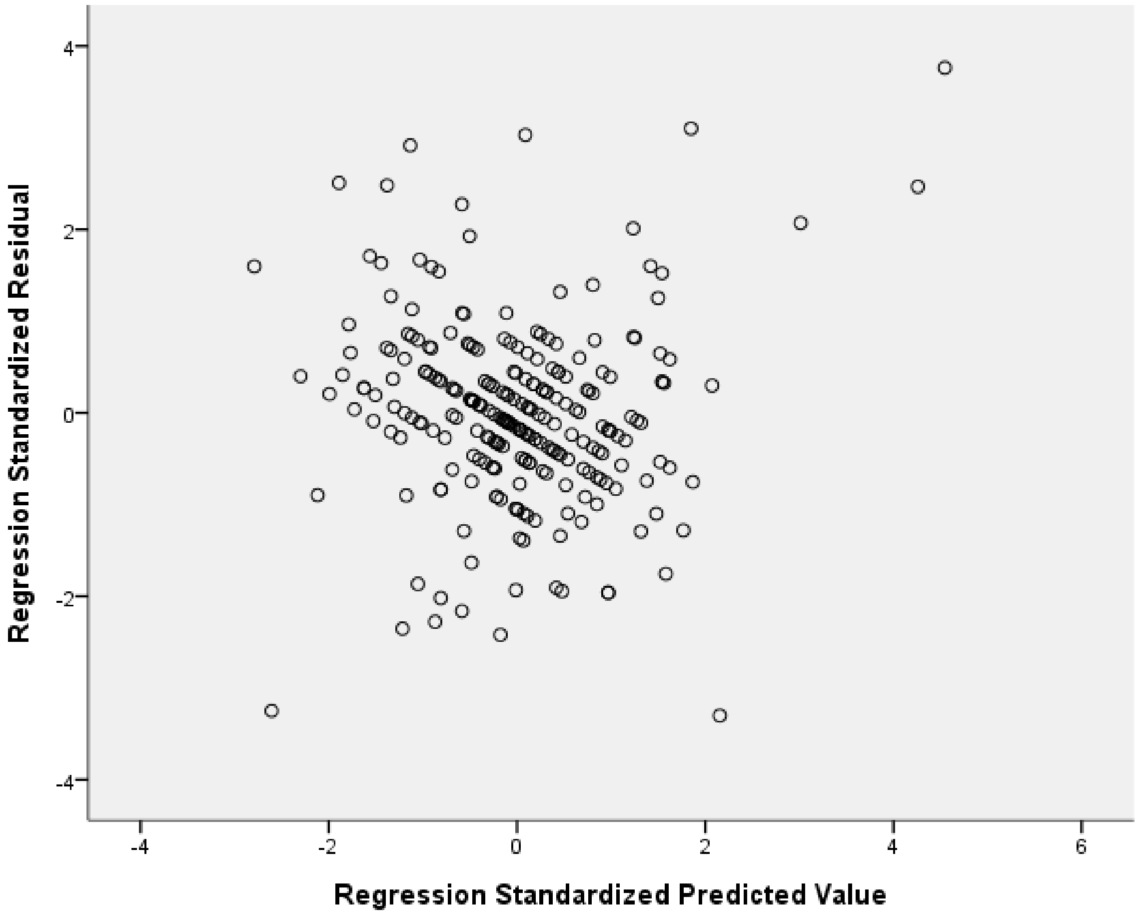
4.3.1.1.5.1.4 Evaluation of the Simple Linear Regression Model

The coefficient of determination, R-squared, related to this simple linear regression model indicates a value of 0.286. This means that daily stock returns of Commerzbank, *DRcbk*, account for 28.6% of the variability in after-hours weighted opinion for Commerzbank, *AOcbk*.

Considering the standard deviation of residuals, which amounts to 0.8449844, this value is lower than the standard deviation of after-hours weighted opinion for Commerzbank, *AOcbk*, which as a normalized variable equals 1. Thus, the regression model seems to be effective in explaining a linear association between *DRcbk* and *AOcbk*.

Finally, the scatterplot of residuals in Figure 17 indicates more or less horizontal shape and equal scatter around the predicted values. Since the residuals do not exhibit a nonlinear pattern, the appropriateness of ordinary least squares regression to the underlying data appears to be given.

Figure 17: Scatterplot of Predicted Values against Residuals (Simple Regression – First Robustness Check)

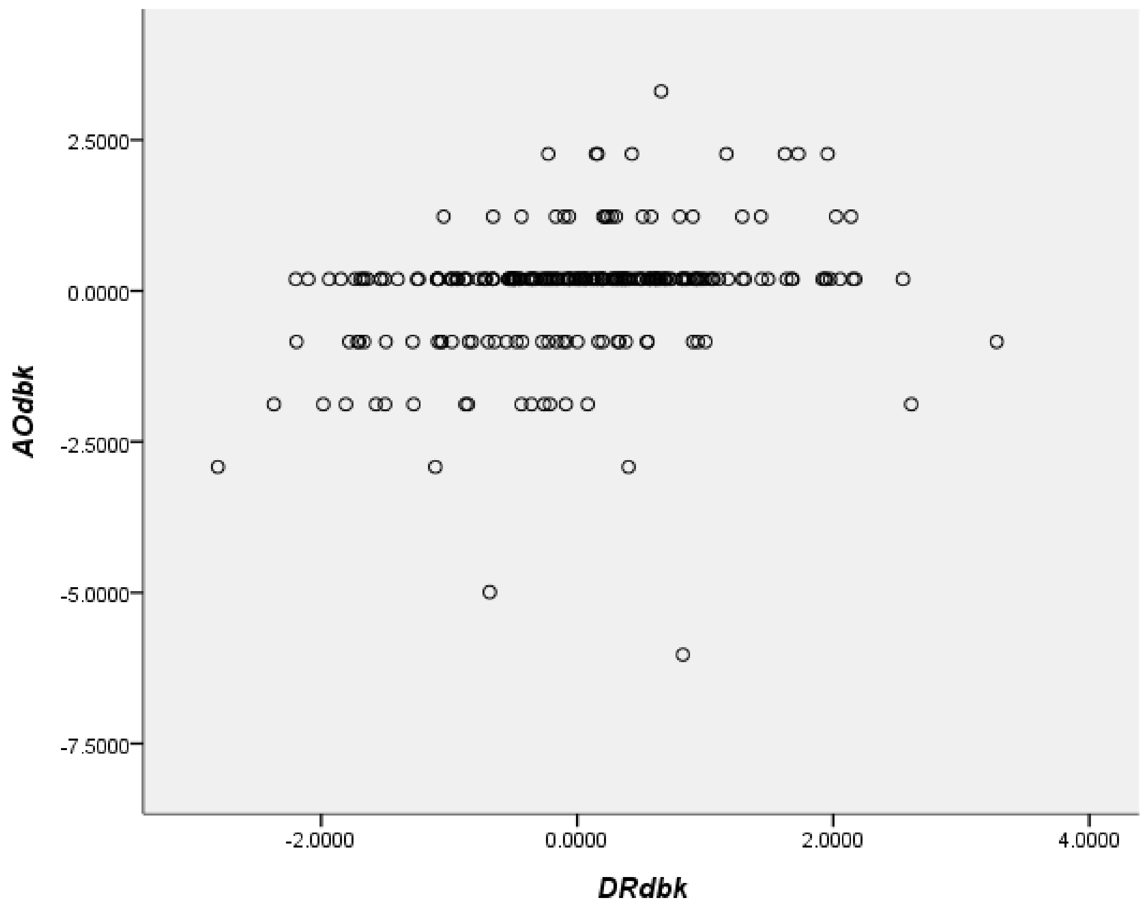


4.3.1.1.5.2 Deutsche Bank

4.3.1.1.5.2.1 Assumptions of Pearson Correlation

Following the argument in the primary correlation analysis and the first robustness check, the variables included into the second robustness check, *DRdbk* and *AOdbk*, also fulfil the characteristics of quantitative variables. According to Figure 18, the scatterplot of *DRdbk* against *AOdbk* shows a somewhat positive linear association between these variables. Moreover, the scatterplot does not indicate striking outliers and the equal variance condition appears to be met.

Figure 18: Scatterplot of *DRdbk* against *AOdbk*



4.3.1.1.5.2.2 Correlation Coefficient between *DRdbk* and *AOdbk*

The Pearson correlation coefficient between *DRdbk* and *AOdbk* indicates a value of 0.279 and is significantly different from zero (p=0.000). Hence, a certain degree of positive association can be assumed to prevail in the relationship between *DRdbk* and *AOdbk*. Following common classification schemes (Dancey & Reidy, 2004; Fitz-Gibbon & Morris, 1987), a correlation coefficient of this size can be regarded as hinting at weak association.

4.3.1.1.5.2.3 Simple Linear Regression

According to the above Pearson correlation analysis, the related simple linear regression model was set up. *AOdbk* constitutes the dependent variable while *DRdbk* serves as the independent variable.

$$AOdbk_t = 0.279 DRdbk_t \tag{15}$$

The slope term indicates that the after-hours weighted opinion of Deutsche Bank stocks, *AOdbk*, increases by 0.279 for a 1-unit increase in the daily stock returns of Deutsche Bank, *DRdbk*.

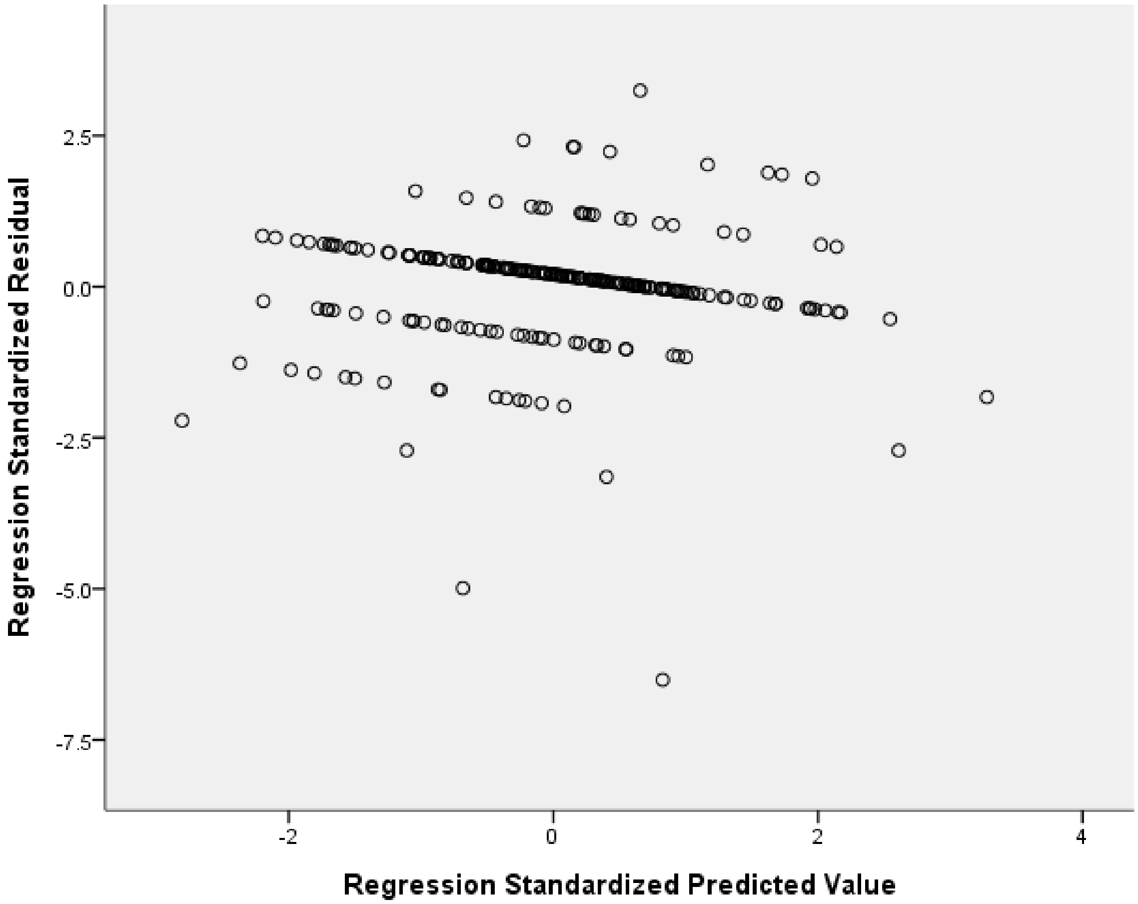
4.3.1.1.5.2.4 Evaluation of the Simple Linear Regression Model

According to the coefficient of determination, R-squared, which shows a value of 0.078, 7.8% of the variation in after-hours weighted opinion for Deutsche Bank, *AOdbk*, is explained by the daily stock returns of Deutsche Bank, *DRdbk*. Obviously, other important factors exist beyond daily stock returns that explain the after-hours private investor sentiment of Deutsche Bank stocks, as 92.2% of the variation in after-hours weighted opinion, *AOdbk*, is not accounted for by this simple linear regression model.

The standard deviation of residuals amounts to 0.9601624. This value is only somewhat lower than the standard deviation of after-hours weighted opinion for the stocks of Deutsche Bank, *AOdbk*, which equals 1.

By inspecting the scatterplot of residuals in Figure 19, deviations from linearity are not observed. By and large, horizontal shape is prevalent and more or less equal scatter fluctuates around the predicted values. Therefore, the applicability of ordinary least squares regression to the underlying data seems to be given.

Figure 19: Scatterplot of Predicted Values against Residuals (Simple Regression – Second Robustness Check)



4.3.1.1.6 Résumé

As consolidated in Table 2, which represents the correlation and simple linear regression results based on equations 13 to 15, the correlation coefficient or slope coefficient, respectively, shows a positive sign both in the primary analysis and in the robustness checks. Against this background, it appears reasonable to assume that short-term private investor sentiment is influenced by prior short-term stock returns. Sentiment seems to be high when most recent returns have been high and it seems to be low when most recent returns have been low.

Table 2: Correlation Coefficients/Slope Coefficients

	AO	*AOcbk*	*AOdbk*
DR	0.504***		
DRcbk		0.535***	
DRdbk			0.279***

*Significant at 10%

**Significant at 5%

***Significant at 1%

4.3.1.2 MULTIPLE LINEAR REGRESSION

According to the primary simple linear regression model, daily stock returns, *DR*, explain 25.4% of the variation in after-hours weighted opinion, *AO*, whereas 74.6% of the variation remains unexplained. Therefore, it appeared also reasonable from a statistical perspective to introduce further independent variables that are likely to account for at least part of the remaining variability. As explained in Chapter 3, a multiple linear regression model was constructed. With regards to after-hours disagreement, a recoded variable needed to be employed, however.

$$AO_t=\beta_0+\beta_1(DR_t)+\beta_2(APV_t)+\beta_3(AD\_recoded_t)+\beta_4(DTV_t)+\beta_5(DV_t)$$
$$+\beta_6(AW_t)+\beta_7(M_t)+\beta_8(AN_t)+\beta_9(AO_{t-1})+\varepsilon_t \qquad (16)$$

where *AD_recoded* represents a recoded variable of equal-weighted normalized after-hours disagreement, *AD*, that takes account of the missing values of *AD* by replacing them through mean substitution.

4.3.1.2.1 Assumptions of Multiple Linear Regression

The assumptions of multiple linear regression analysis entail two categories of assumptions. On the one hand, the assumptions of simple linear regression apply. On the other hand, additional requirements, which are specifically related to multiple linear regression analysis, need to be fulfilled (De Veaux, Velleman & Bock, 2008).

4.3.1.2.1.1 Assumptions of Simple Linear Regression

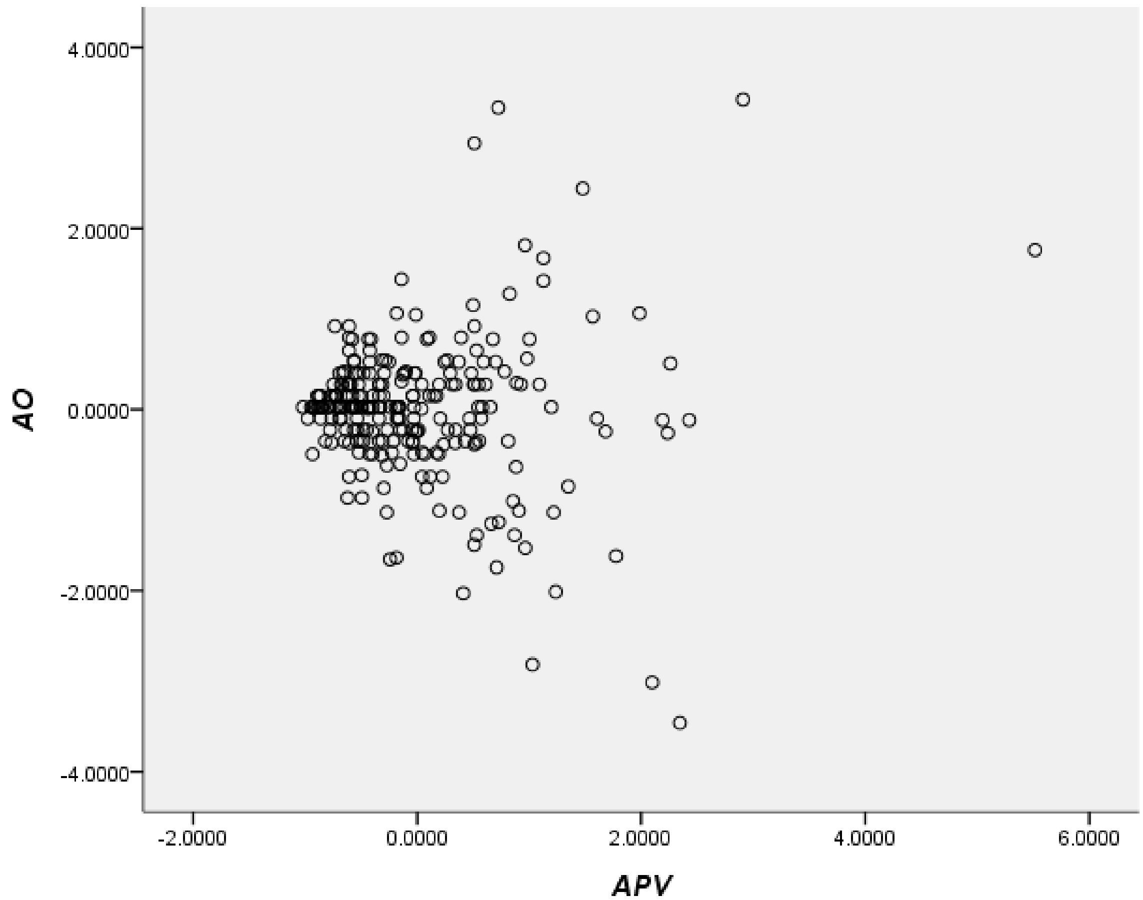
First of all, the assumptions relevant to simple linear regression models should be met. As far as *DR* and *AO* are concerned, the quantitative variables requirement has been adhered to, as outlined earlier in the simple linear regression analysis. Equal to *DR* and *AO*, *APV*, *AD*, *DTV* and *DV* also fulfil the features of measurable quantitative variables. As stated in Chapter 3, *AW*, *M* and *AN* represent categorical variables. Since these categorical variables were coded as indicator variables, they could be integrated into the multiple regression model (De Veaux, Velleman & Bock, 2008).

In contrast to the other variables, valid values were not provided for after-hours disagreement, *AD*, on a daily basis. The missing values were replaced in a consistent way by mean substitution, which entailed replacing the missing values by the mean of the remainder of values. Although this is a popular method of replacing missing values, it needs to be borne in mind that employing mean substitution biases a data set towards lower variability than is actually the case (Olinsky, Chen & Harlow, 2003). All 176 missing values of *AD* were replaced by the mean of the available values, which equals 0.0845, and the resulting recoded variable was labelled *AD_recoded*.

Furthermore, since values for 1-day lagged after-hours weighted opinion, AO_{t-1}, were not available on the first trading day of the year, this day was excluded from the data set. As a consequence, 252 instead of 253 trading days were involved in the multiple regressions.

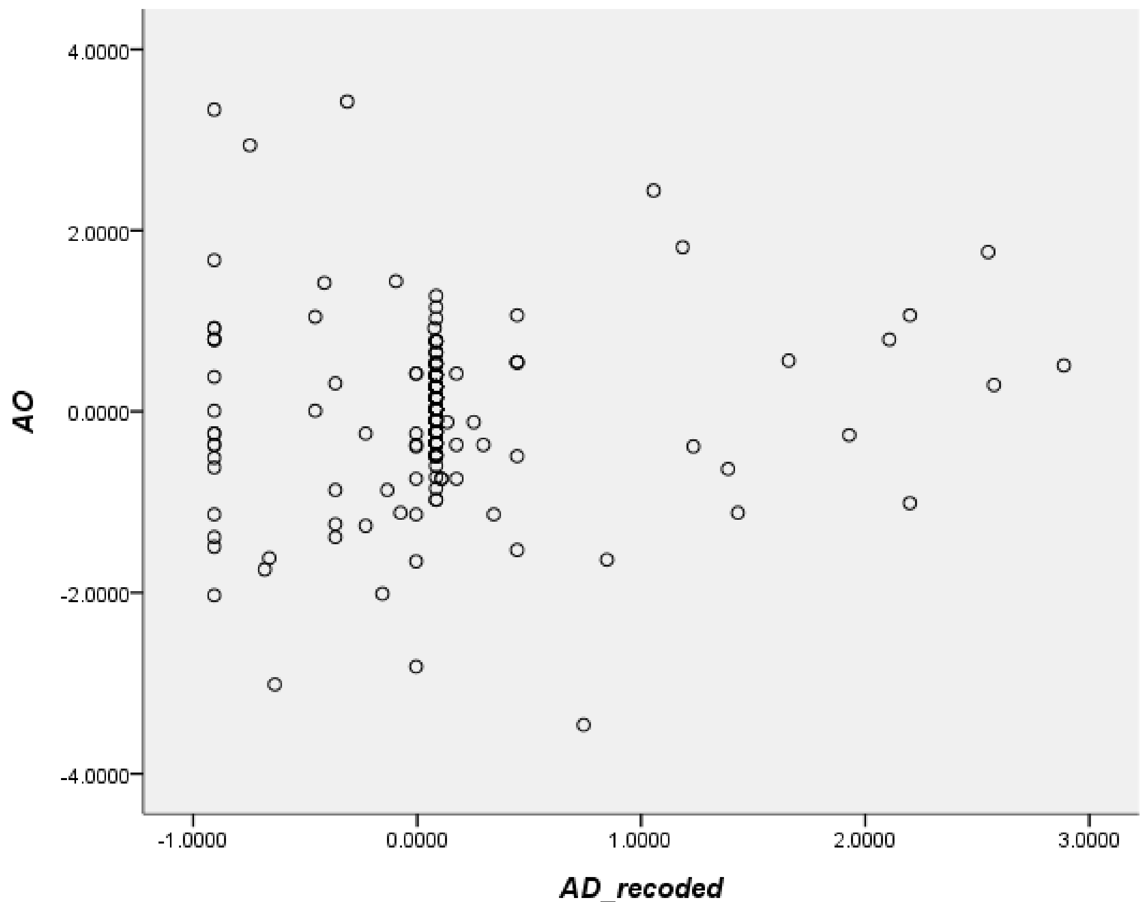
For the purpose of checking those assumptions of simple linear regression that concern the relationship between each of the independent variables with the dependent variable on an individual basis, the respective scatterplots that had not been inspected earlier were addressed. First of all, the scatterplot of *APV* against *AO* was examined. As shown in Figure 20, while a substantial deviation from linearity is not observed, it might be argued that the assumption of homoscedasticity is not strictly adhered to. Furthermore, the rightmost data point might be regarded as an outlier, as it seems to reflect a high leverage point whose x-value lies relatively far from the mean of the other x-values (De Veaux, Velleman & Bock, 2008).

Figure 20: Scatterplot of *APV* against *AO*



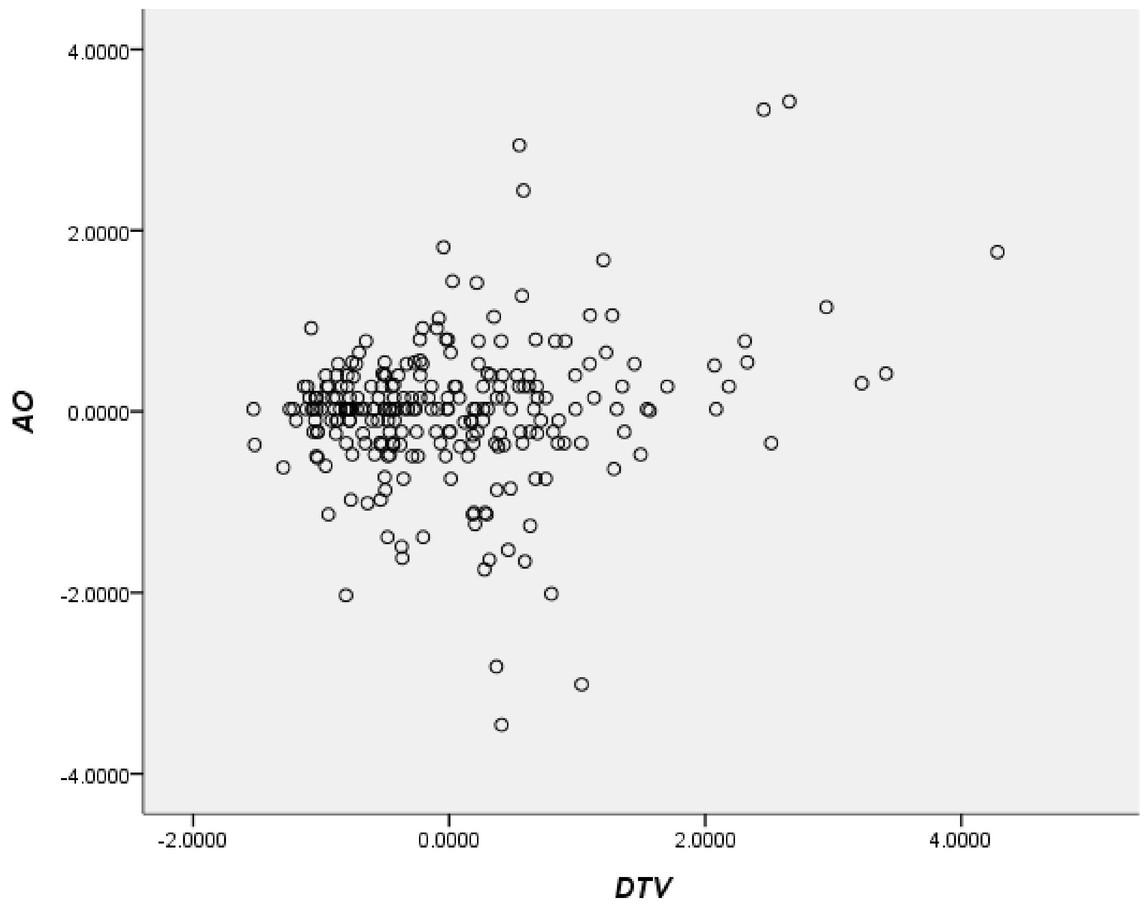
According to Figure 21, the scatterplot of *AD_recoded* against *AO* does not hint at problematic patterns. While the two variables appear to be unrelated to each other, nonlinearity is not suggested. Neither are salient outliers observed, nor seems the condition of homoscedasticity to be violated.

Figure 21: Scatterplot of *AD_recoded* against *AO*



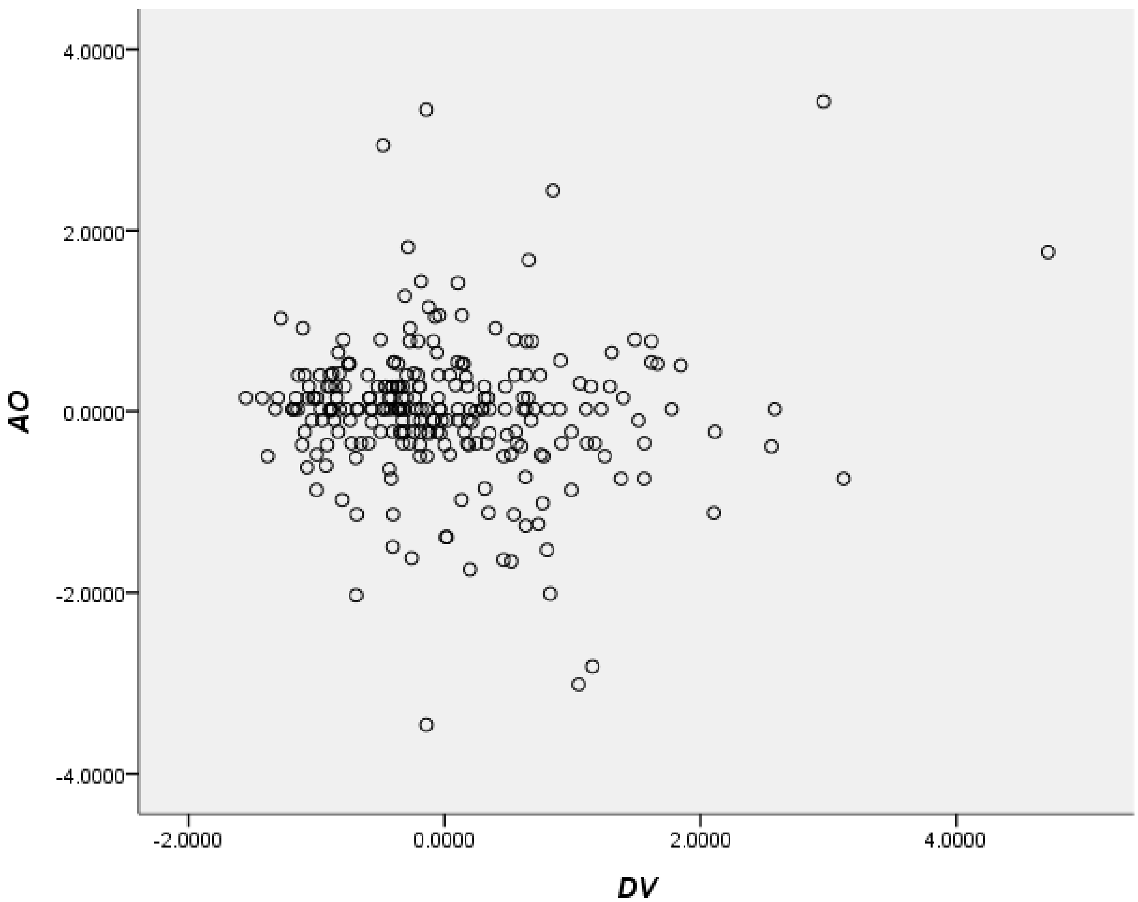
The scatterplot of *DTV* against *AO*, as illustrated in Figure 22, hints at a somewhat positive relationship between the two variables. Nonlinear attributes, such as bends, are not detected. Extraordinary outliers cannot be spotted, either, and the equal variance assumption appears to be adhered to.

Figure 22: Scatterplot of *DTV* against *AO*



Finally, the scatterplot of *DV* against *AO* was inspected. As can be seen in Figure 23, this scatterplot does not suggest a relationship between the two variables. Both the linearity condition and the equal variance condition seem to be met. While two outliers might be argued to lie in the right upper corner of the scatterplot, neither of them is particularly striking.

Figure 23: Scatterplot of *DV* against *AO*



By and large, the assumptions of linearity, outliers and homoscedasticity regarding the relationship of each individual independent variable with the dependent variable can be assumed to be approximately met.

4.3.1.2.1.2 Additional Assumptions Specific to Multiple Linear Regression

Additional assumptions which are specific to multiple linear regression models needed to be fulfilled. These assumptions concern the ratio of cases to independent variables, multicollinearity, multivariate outliers, as well as the linearity, homoscedasticity, independence and normality of the residuals (Coakes & Ong, 2011).

4.3.1.2.1.2.1 Ratio of Cases to Independent Variables

In a multiple linear regression model, the number of cases should be at least 5 times higher than the number of independent variables (Coakes & Ong, 2011). Since the data set in this multiple regression includes 252 trading days while nine independent variables were introduced, the ratio of cases to independent variables amounts to 28 and thus exceeds the minimum requirement. This value is also higher than the ideal ratio of 20, as suggested by Coakes & Ong (2011).

4.3.1.2.1.2.2 Multicollinearity

Multicollinearity is associated with independent variables that are highly correlated with each other. If this phenomenon occurs in a multiple regression model, the conclusions drawn from the model are likely to become biased (De Veaux, Velleman & Bock, 2008). As multicollinearity tends to lead to regression coefficients that exhibit inflated standard errors, the significance of regression coefficients may be understated. Even more, in some cases, the sign of a coefficient changes due to multicollinearity (Greene, 1993). For that reason, independent variables that are affected by excessive multicollinearity should be excluded from a multiple regression model.

For diagnosing the extent of multicollinearity, the variance inflation factor (VIF) of each independent variable was addressed (Chatterjee & Price, 1991). A VIF value exceeding 4 is supposed to indicate substantial multicollinearity (O'Brien, 2007). As the VIF value of daily stock trading volume, *DTV*, which turned out to hold the highest VIF value in this regression, was only 2.003, multicollinearity was not considered to have material impact. The regression coefficients were deemed interpretable.

4.3.1.2.1.2.3 Multivariate Outliers

As opposed to univariate outliers, which refer to the outliers of a single variable, multivariate outliers result from the joint combination of outliers from different variables

(Varmuza & Filzmoser, 2009). Since multivariate outliers have the potential to significantly alter a particular multiple linear regression model, they should be identified and possibly excluded from the model (De Veaux, Velleman & Bock, 2008).

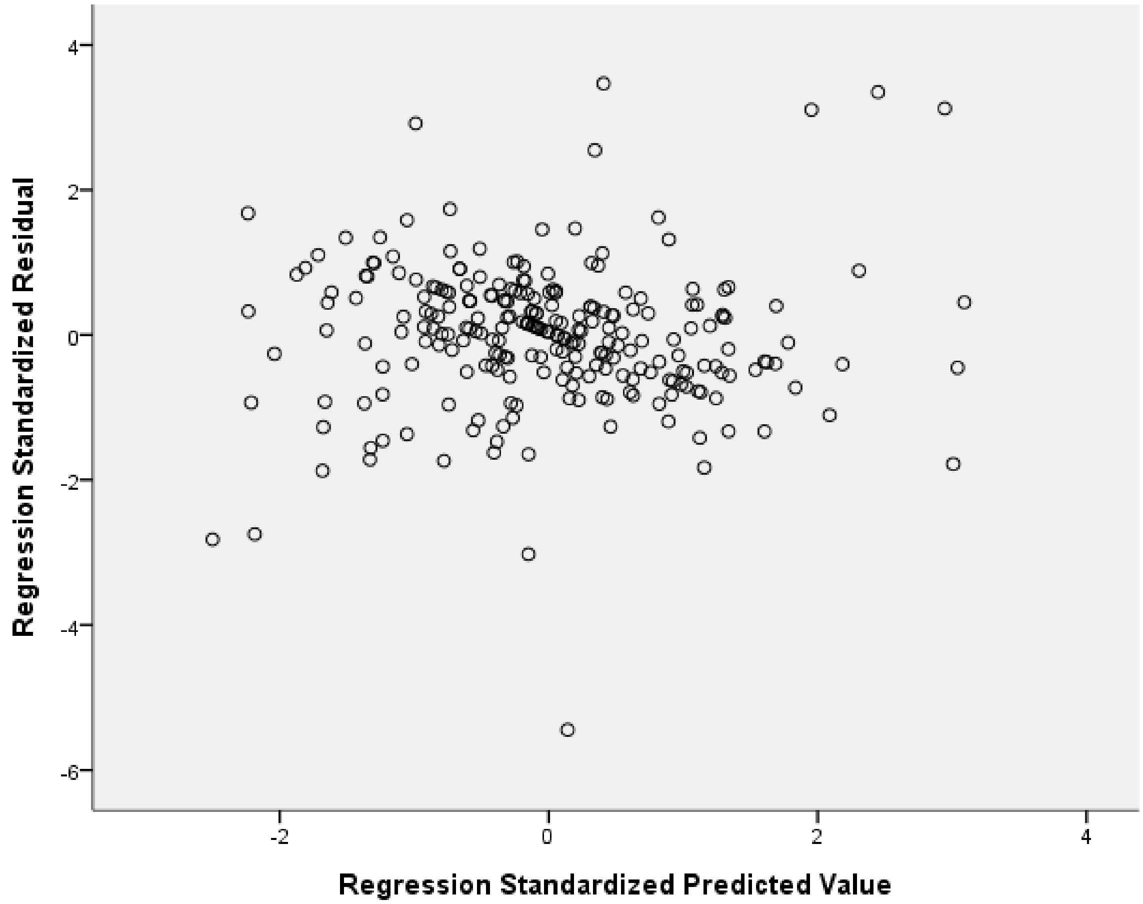
Mahalanobis Distance is a test statistic that uncovers the existence of multivariate outliers (Mahalanobis, 1936). As far as this multiple linear regression model is concerned, where nine degrees of freedom are relevant to Mahalanobis Distance, the critical chi-square value is 27.88 at an alpha level of 0.001 (Tabachnick & Fidell, 2007). According to this value, 10 cases were identified as reflecting multivariate outliers. As 10 outlying cases do not appear to be an unusually high number for a sample size of 252 (Coakes & Ong, 2011), the outliers were maintained in the regression model. As a result of constructing an alternative model that corrects for removed multivariate outliers, unfortunately, new outliers are likely to emerge (De Veaux, Velleman & Bock, 2008).

4.3.1.2.1.2.4 Linearity, Homoscedasticity, Independence and Normality of Residuals

The remainder of conditions relates to the residuals of the multiple linear regression model. First of all, the residuals of a multiple linear regression model should show a linear relationship with the predicted values of the dependent variable (Coakes & Ong, 2011). While looking at the scatterplot of residuals in Figure 24, a pattern that would indicate nonlinearity is not observed.

Another assumption concerning the residuals of a multiple regression is that they should be characterized by homoscedasticity (Defusco, McLeavey, Pinto & Runkle, 2001). According to Figure 24, the scatterplot of residuals does not reveal a pattern that hints at a violation of homoscedasticity.

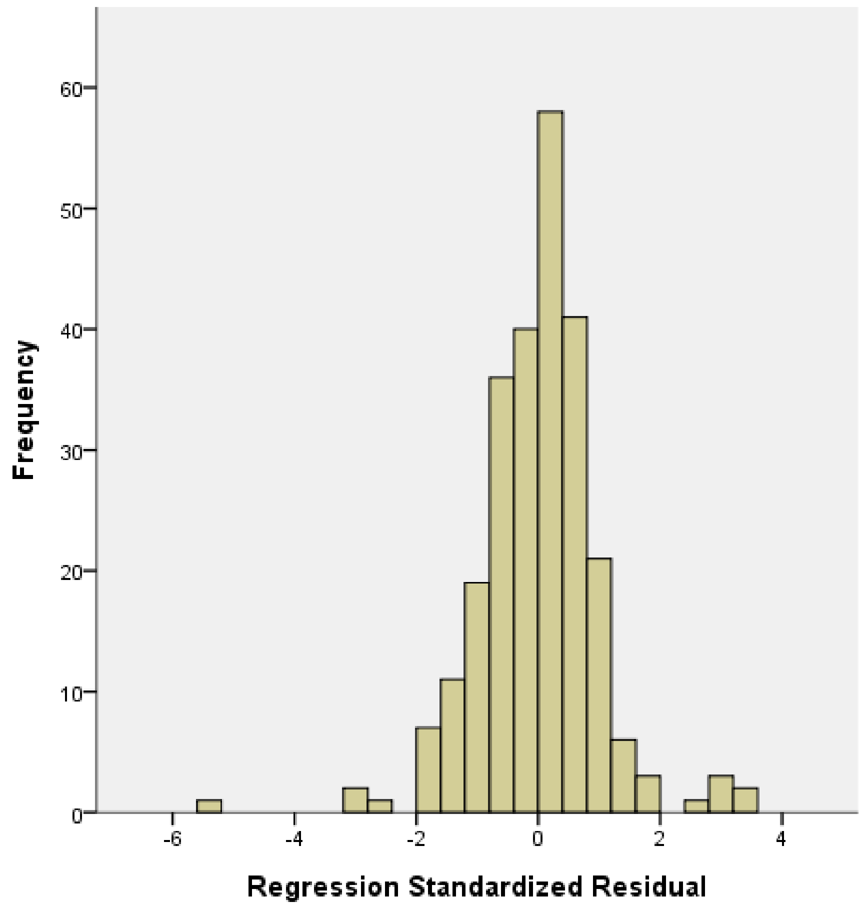
Figure 24: Scatterplot of Predicted Values against Residuals (First Multiple Regression)



Furthermore, the residuals of a regression model are required to be independent of each other. This assumption can be checked by testing whether the residuals are serially correlated (Moran, 1950). The Durbin-Watson test statistic is appropriate for testing serial correlation. This test statistic provides values in a range between 0 and 4. While a value of 2 does not hint at any serial correlation, values clearly below 2 indicate positive serial correlation and values clearly above 2 indicate negative serial correlation (Durbin & Watson, 1950). Regarding this multiple linear regression model, the Durbin-Watson test statistic shows a value of 2.105. As this value lies in the corridor between 1.5 and 2.5, the residuals cannot be assumed to be materially affected by serial correlation. Hence, the residuals were considered to be independent of each other (Vogt & Johnson, 2011).

Finally, whether the residuals in this multiple linear regression model are normally distributed, was checked by inspecting a histogram of their distribution. As shown in Figure 25, this distribution is unimodal and symmetric in shape. It can be assumed that the regression residuals follow the normal distribution at least in an approximate sense.

Figure 25: Histogram of Distribution of Residuals (First Multiple Regression)



4.3.1.2.2 Interpretation of the Regression Coefficients

As the assumptions of multiple linear regression were adhered to, the regression model was set up as originally suggested in equation 16. A summary of the results of this multiple linear regression model is provided in Table 3.

Table 3: Regression Results (First Multiple Regression)

Intercept	-0.106*
DR	0.398***
APV	-0.080
AD_recoded	0.092
DTV	0.099
DV	-0.045
AW	0.136
M	0.163
AN	0.112
AO_{t-1}	0.231***
N	252
R-squared	0.358

*Significant at 10%

**Significant at 5%

***Significant at 1%

4.3.1.2.2.1 Daily Stock Returns, DR

As far as the variable for daily stock returns, *DR*, is concerned, which is directly related to the first research question, the associated coefficient holds a value of 0.398 and is different from zero to a statistically significant degree (p=0.00). This means that daily stock returns, *DR*, are a significant factor in explaining after-hours weighted opinion, *AO*. While the other explanatory variables are held constant, a 1-unit increase in daily stock returns, *DR*, leads to an increase in after-hours weighted opinion, *AO*, by 0.398.

4.3.1.2.2.2 The Remaining Regression Coefficients

With regards to the other variables included in the multiple regression model, that is *APV*, *AD_recoded*, *DTV*, *DV*, *AW*, *M*, *AN* and AO_{t-1}, only one of them is significantly different from zero. AO_{t-1} shows a regression coefficient of 0.231 (p=0.00), which implies that the preceding day's value of after-hours weighted opinion, AO_{t-1}, positively predicts the current day's value of after-hours weighted opinion, *AO*. More specifically, an increase in AO_{t-1} by 1 unit is associated with an increase in *AO* by 0.231 units, ceteris paribus.

While the coefficients that refer to disagreement and trading volume as well as those that indicate autumn or winter, Mondays and corporate news show a positive sign, the coefficients that represent the constant term, posting volume and daily stock price volatility show a negative sign. However, neither the constant term (p=0.090), nor *APV* (p=0.199), nor *AD_recoded* (p=0.274), nor *DTV* (p=0.116), nor *DV* (p=0.457), nor *AW* (p=0.116), nor *M* (p=0.124), nor *AN* (p=0.703) differ from zero to a statistically significant degree.

4.3.1.2.3 Evaluation of the Multiple Linear Regression Model

For the purpose of evaluating the multiple linear regression model, the coefficient of determination and the F-test statistic associated with the model were analyzed (De Veaux, Velleman & Bock, 2008).

4.3.1.2.3.1 Coefficient of Determination

According to the coefficient of determination, R-squared, which equals 0.358, 35.8% of the variation in after-hours weighted opinion, *AO*, is explained by the independent variables. As anticipated earlier, the introduction of further independent variables vis-à-vis the simple regression led to an increase in the proportion of explained variability, namely by 10.4 percentage points.

Adjusted R-squared accounts for the number of predictors in multiple linear regression models, with higher numbers of predictors leading to lower values for adjusted R-squared (De Veaux, Velleman & Bock, 2008). In this model, adjusted R-squared shows a value of 0.334.

4.3.1.2.3.2 F-test Statistic

The F-test Statistic reveals whether the multiple linear regression model represents a significant improvement in explaining after-hours weighted opinion, *AO*, over modeling this dependent variable simply by its mean value (De Veaux, Velleman & Bock, 2008). As the F-test statistic amounts to 15.006 and indicates statistical significance (p=0.00), this model can be considered superior to merely modeling *AO* by its mean value.

4.3.1.2.4 Robustness Checks: Multiple Linear Regression at Individual Stock Levels

Equal to the earlier analyses, robustness checks were carried out with respect to the multiple linear regression model. Again, the stocks of Commerzbank and Deutsche Bank were incorporated.

4.3.1.2.4.1 Commerzbank

The first robustness check involves the stocks of Commerzbank. As far as after-hours disagreement is concerned, the values of the recoded variable needed to be used.

$$
\begin{aligned}
AOcbk_t = & \beta_0+\beta_1(DRcbk_t)+\beta_2(APVcbk_t)+\beta_3(ADcbk\_recoded_t)+\beta_4(DTVcbk_t) \\
& +\beta_5(DVcbk_t)+\beta_6(AW_t)+\beta_7(M_t)+\beta_8(ANcbk_t)+\beta_9(AOcbk_{t-1})+\varepsilon \qquad (17)
\end{aligned}
$$

where *ADcbk_recoded* represents a recoded variable of equal-weighted normalized after-hours disagreement of Commerzbank stocks, *ADcbk*, that takes account of the missing values of *ADcbk* by replacing them through mean substitution.

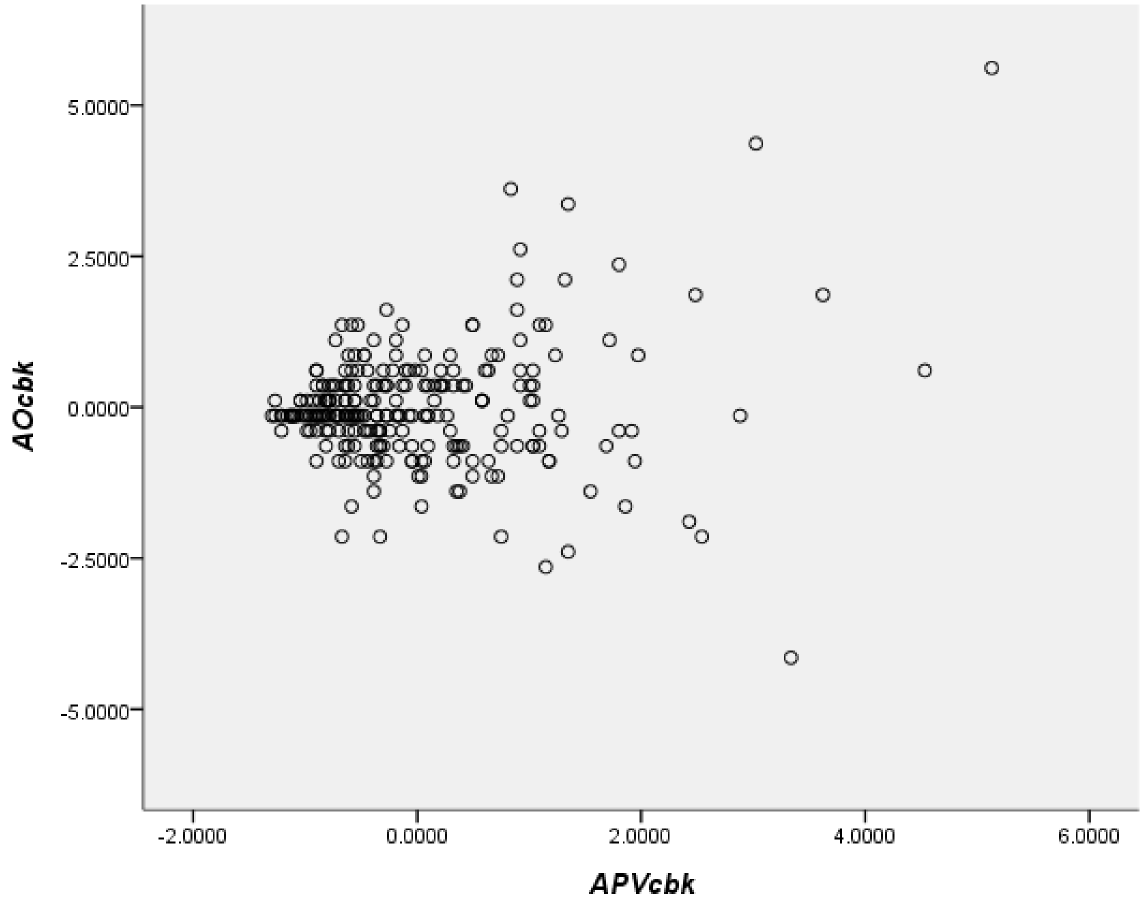
4.3.1.2.4.1.1 Assumptions of Multiple Linear Regression

Equal to the primary model, the robustness checks were required to fulfil the assumptions of multiple linear regression. Following the argument in the primary analysis, the variables included in the multiple regression for the first robustness check also meet the quantitative variables condition. As 32 values of after-hours disagreement were missing for Commerzbank stocks, they were replaced by mean substitution and the variable *ADcbk_recoded* was introduced.

The linearity, outlier and homoscedasticity conditions were examined for those relationships of individual independent variables with the dependent variable that had not been checked earlier. The relevant scatterplots were inspected for striking features, consistent with the primary analysis.

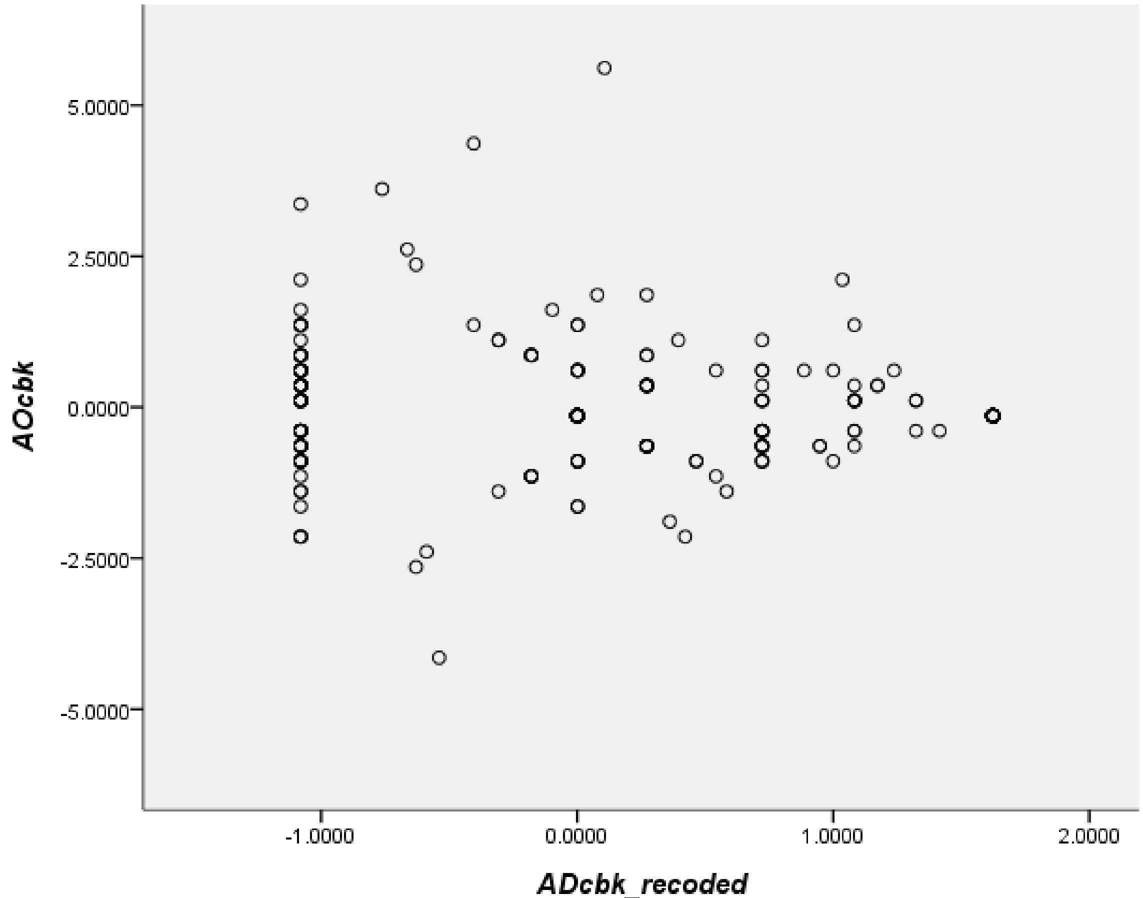
As shown in Figure 26, the scatterplot of *APVcbk* against *AOcbk* indicates a shape similar to that exhibited by the related variables in the primary model. While the homoscedasticity assumption does not seem to be unambiguously met, nonlinear patterns and salient outliers are not observed.

Figure 26: Scatterplot of *APVcbk* against *AOcbk*



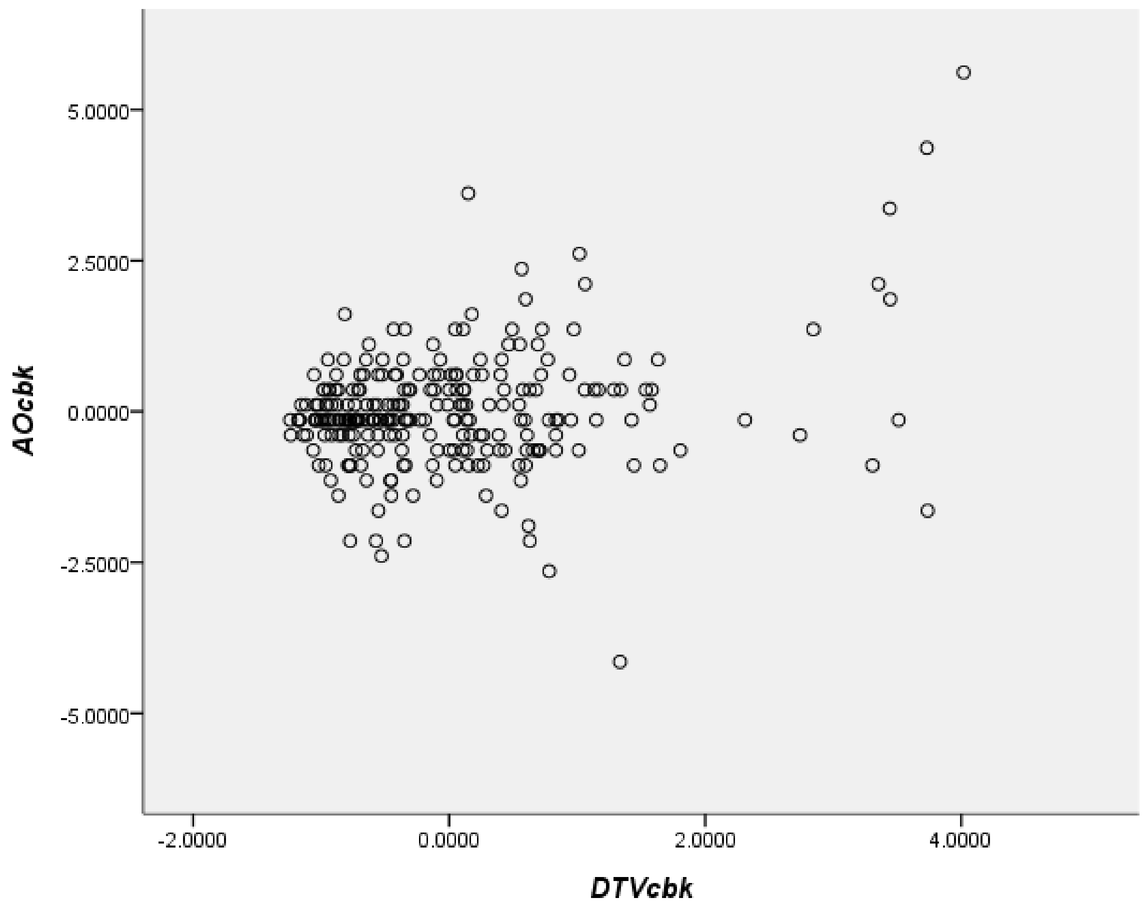
According to the scatterplot of *ADcbk_recoded* against *AOcbk* in Figure 27, problematic patterns are not displayed. There does not appear to be either a linear, or a nonlinear relationship between the two variables. Salient outliers are not present, either, and the assumption of homoscedasticity does not seem to be violated.

Figure 27: Scatterplot of *ADcbk_recoded* against *AOcbk*



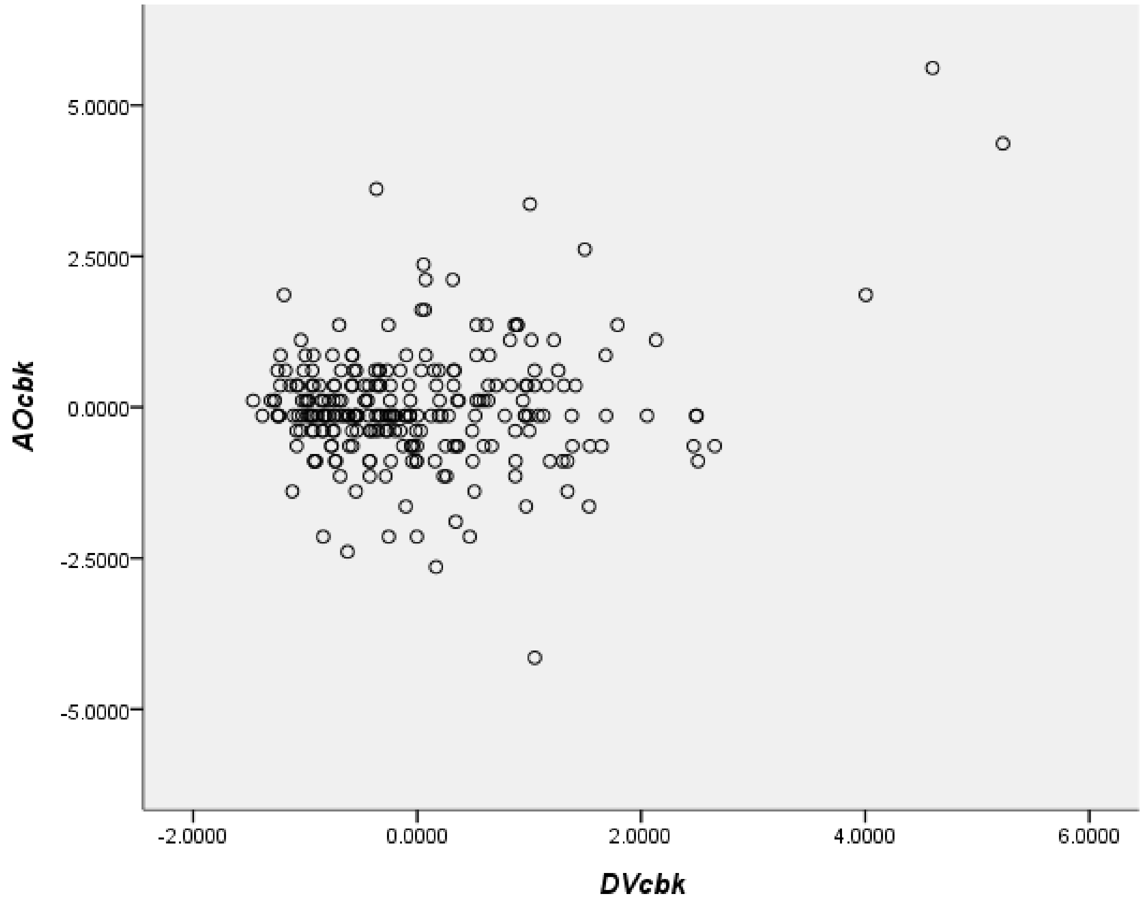
As shown in Figure 28, the scatterplot of *DTVcbk* against *AOcbk* does not hint at a nonlinear relationship between the two variables. Deviations from homoscedasticity are not detected, either. It might be made the point, however, that a couple of outlying cases are located in the right upper corner.

Figure 28: Scatterplot of *DTVcbk* against *AOcbk*



Finally, considering the scatterplot of *DVcbk* against *AOcbk* in Figure 29, a particular relationship does not appear to exist between these variables; neither a linear association, nor a nonlinear association. While homoscedasticity also appears to prevail, two outliers might be argued to be situated in the right upper corner of the scatterplot.

Figure 29: Scatterplot of *DVcbk* against *AOcbk*



By and large, in none of the above relationships between each independent variable with the dependent variable, *AOcbk*, a material violation of the assumptions regarding linearity, outliers and homoscedasticity is assumed to have occurred. The relevant assumptions appear to have been fulfilled at least in an approximate sense.

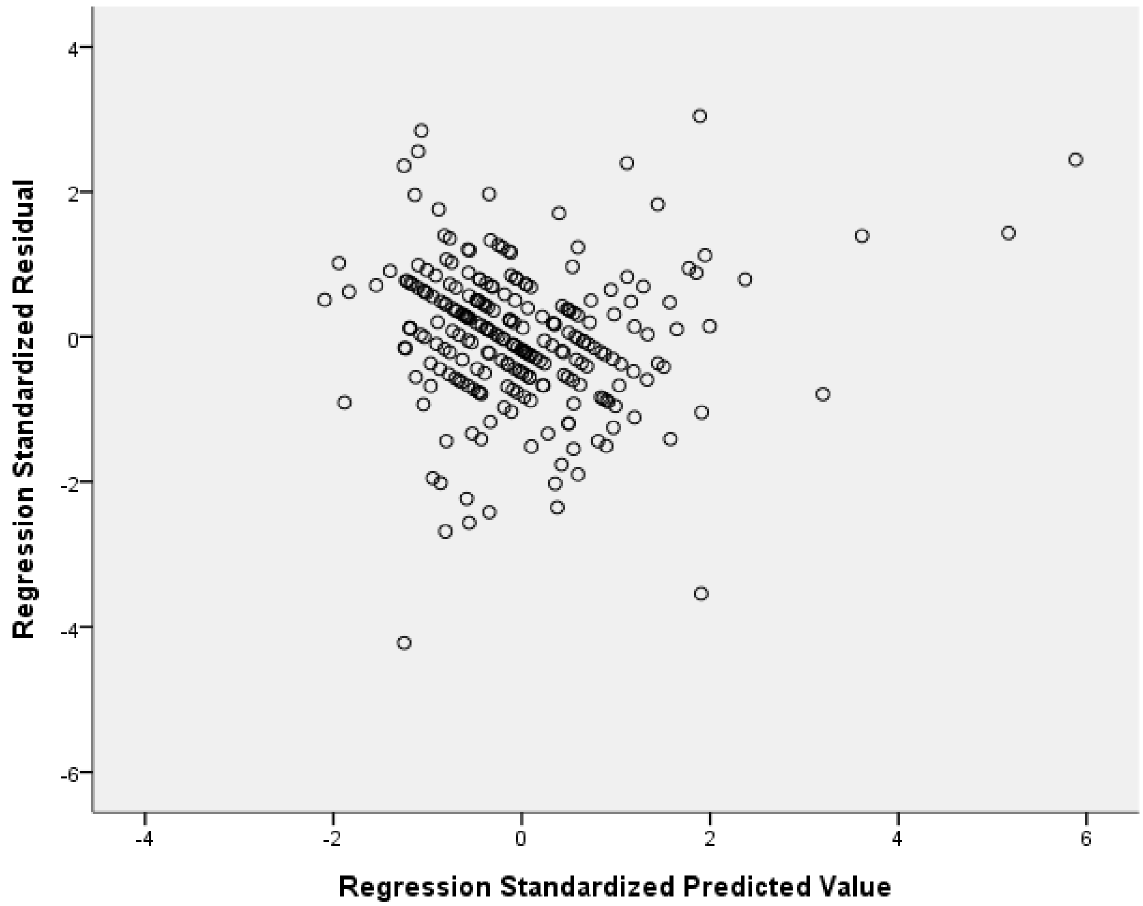
Just as in the case of the primary multiple regression model, the conditions specific to multiple linear regression needed to be fulfilled. The structure of the multiple linear regression model in the first robustness check remained equal vis-à-vis the primary model, as merely the data of individual stocks was used instead of aggregate market data. Therefore, the multiple regression in the first robustness check fulfils the assumption concerning the ratio of cases to independent variables.

As far as multicollinearity is concerned, the variable associated with stock trading volume, *DTVcbk*, again shows the highest VIF value, namely 2.498. Since this value does not exceed 4, multicollinearity cannot be suspected to materially distort this multiple linear regression model (O’Brien, 2007).

Since nine degrees of freedom are again relevant with regards to Mahalanobis Distance, the critical value of chi-square at an alpha level of 0.001 is 27.88 (Tabachnick & Fidell, 2007). Against this background, 12 outlying cases are suggested, which is similar to the number of 10 cases identified in the primary model. The construction of an alternative multiple linear regression model therefore was not considered.

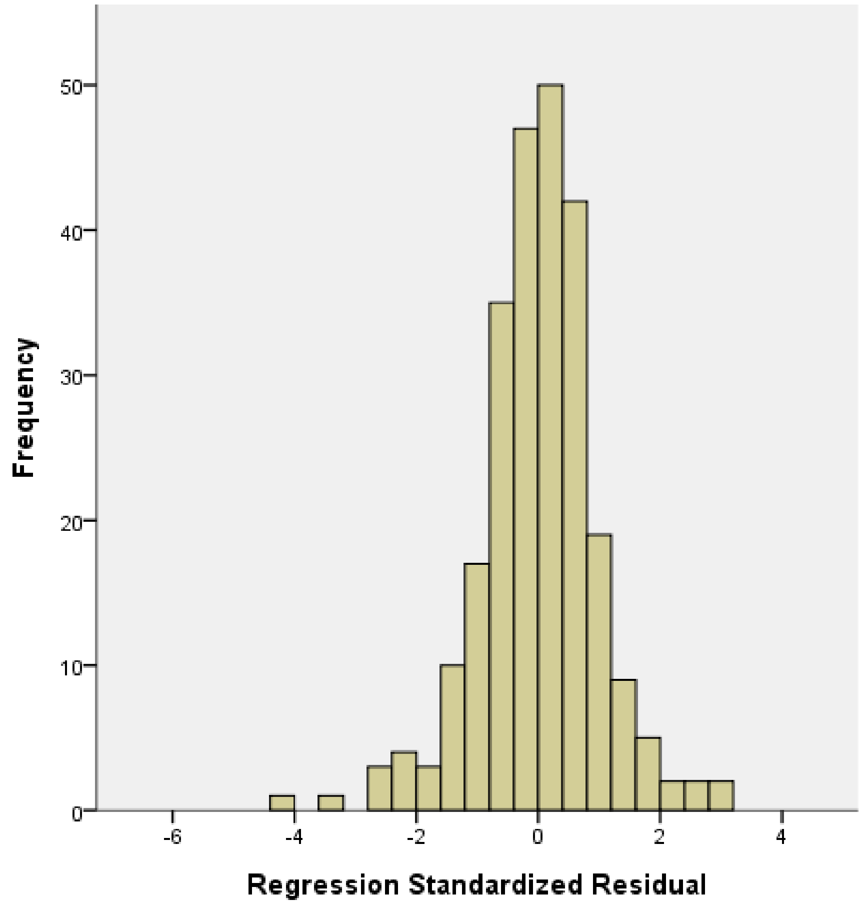
As far as the characteristics of the residual values are concerned, first of all, the scatterplot of residuals was addressed. This scatterplot does not indicate salient patterns, as shown in Figure 30. Neither is a nonlinear association suggested, nor is the assumption of homoscedasticity violated.

Figure 30: Scatterplot of Predicted Values against Residuals (First Multiple Regression – First Robustness Check)



Considering the independence of the residuals, the Durbin-Watson test statistic shows a value of 2.233. As this value does not exceed 2.5, the extent of negative serial correlation remains unobjectionable in this first robustness check (Vogt & Johnson, 2011). A histogram of the residuals, as shown in Figure 31, illustrates that their distribution is both unimodal and symmetric in shape. Hence, the residuals were assumed to be at least approximately normally distributed.

Figure 31: Histogram of Distribution of Residuals (First Multiple Regression – First Robustness Check)



4.3.1.2.4.1.2 Interpretation of the Regression Coefficients

As the necessary assumptions regarding multiple linear regression were at least approximately met in this first robustness check, the model was accepted as originally suggested in equation 17. An overview of the results of the regression is supplied in Table 4.

Table 4: Regression Results (First Multiple Regression – First Robustness Check)

Intercept	-0.166**
DRcbk	0.490***
APVcbk	0.061
ADcbk_recoded	-0.028
DTVcbk	0.020
DVcbk	0.104
AW	0.257**
M	0.248*
ANcbk	-0.136
$AOcbk_{t-1}$	0.168***
N	252
R-squared	0.386

*Significant at 10%

**Significant at 5%

***Significant at 1%

The coefficient for the daily stock returns of Commerzbank, *DRcbk*, exhibits a value of 0.490 and is significantly different from zero (p=0.000). Therefore, *DRcbk* is a significant factor in explaining after-hours weighted opinion of Commerzbank, *AOcbk*. While the remaining regression coefficients are held constant, a 1-unit increase in *DRcbk* is associated with an increase in *AOcbk* by 0.490 units.

As far as the other independent variables in this multiple linear regression model are concerned, significantly different from zero are $AOcbk_{t-1}$ (p=0.003), *AW* (p=0.015) and the coefficient of the constant term (p=0.029). $AOcbk_{t-1}$ and *AW* are associated with a positive sign; that is, 0.168 and 0.257, respectively. The constant term shows a negative sign, namely -0.166. According to the coefficient of $AOcbk_{t-1}$, a 1-unit increase in 1-day lagged after-hours weighted opinion for Commerzbank stocks is associated with an increase in contemporary after-hours weighted opinion, *AOcbk*, by 0.168 units, ceteris paribus. With regards to *AW*, the after-hours weighted opinion of Commerzbank, *AOcbk*, tends to be higher by 0.257 units during autumn or winter, provided that the other independent variables remain unchanged. The coefficient of the constant term implies that *AOcbk* is negative and shows a value of -0.166 if all independent variables hold a value of zero. As the coefficients of *APVcbk* (p=0.339), *ADcbk_recoded* (p=0.629), *DTVcbk* (p=0.803), *DVcbk* (p=0.124), *M* (p=0.054) and *ANcbk* (p=0.713) do not differ from zero to a statistically significant degree, none of the variables is a significant factor in predicting the after-hours weighted opinion of Commerzbank, *AOcbk*.

4.3.1.2.4.1.3 Evaluation of the Multiple Linear Regression Model

Consistent with the primary model, the coefficient of determination and the F-test Statistic were interpreted in this first robustness check. While according to the coefficient of determination, R-squared, 38.6% of the variation in the dependent variable, *AOcbk*, is explained by the regression model, the value for adjusted R-squared amounts to 0.363. The F-test statistic shows a value of 16.904 and is statistically significant (p=0.00); hence, this regression model constitutes an improvement over modeling after-hours weighted opinion of Commerzbank, *AOcbk*, simply by its mean value.

4.3.1.2.4.2 Deutsche Bank

The second robustness check incorporates Deutsche Bank stocks. For after-hours disagreement, the values of the recoded variable were used again.

$$AOdbk_t=\beta_0+\beta_1(DRdbk_t)+\beta_2(APVdbk_t)+\beta_3(ADdbk\_recoded_t)+\beta_4(DTVdbk_t)$$
$$+\beta_5(DVdbk_t)+\beta_6(AW_t)+\beta_7(M_t)+\beta_8(ANdbk_t)+\beta_9(AOdbk_{t-1})+\varepsilon_t \qquad (18)$$

where *ADdbk_recoded* represents a recoded variable of the equal-weighted normalized after-hours disagreement of Deutsche Bank stocks, *ADdbk*, that takes account of the missing values of *ADdbk* by replacing them through mean substitution.

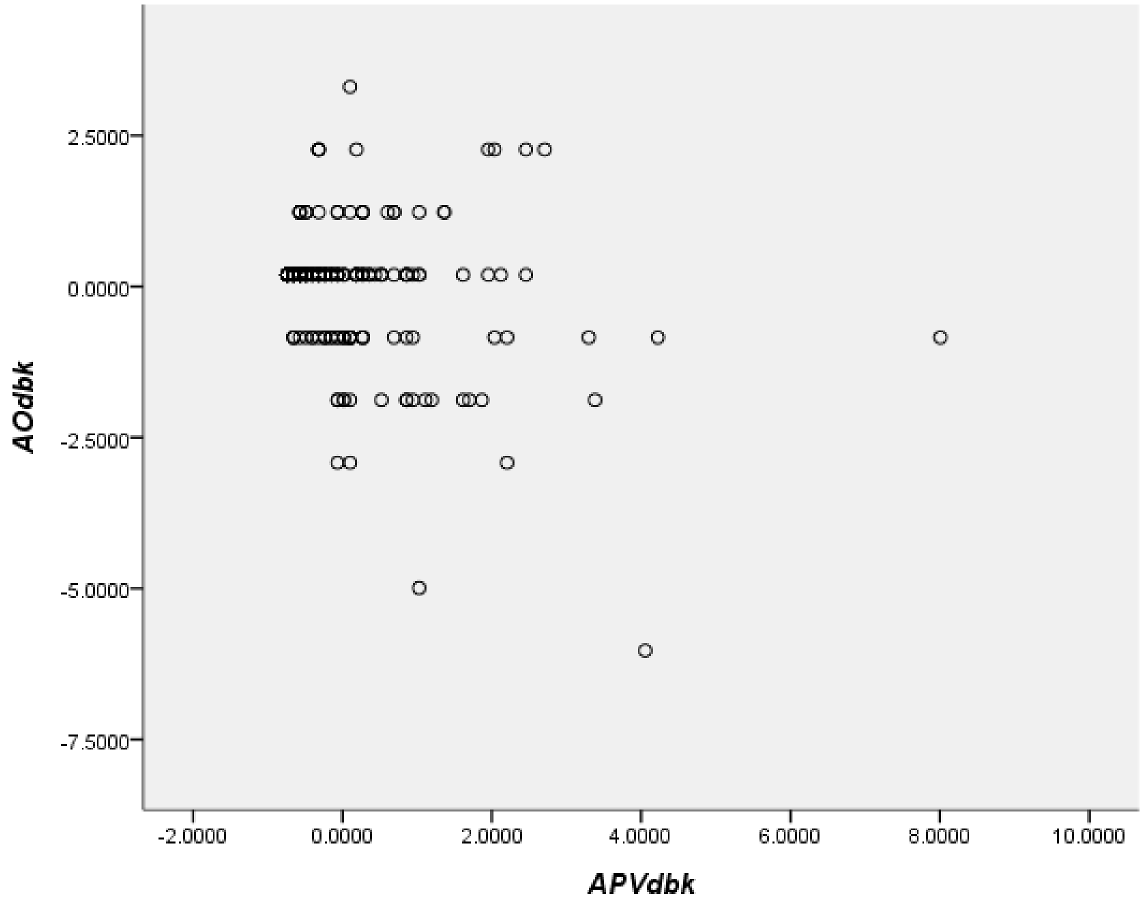
4.3.1.2.4.2.1 Assumptions of Multiple Linear Regression

Various values of after-hours disagreement were missing for Deutsche Bank stocks. All 170 missing values were replaced by mean substitution and the variable *ADdbk_recoded* was introduced.

The linearity, outlier and homoscedasticity conditions were checked for those relationships of individual independent variables with the dependent variable that had not been examined earlier. The relevant scatterplots were again checked for salient features.

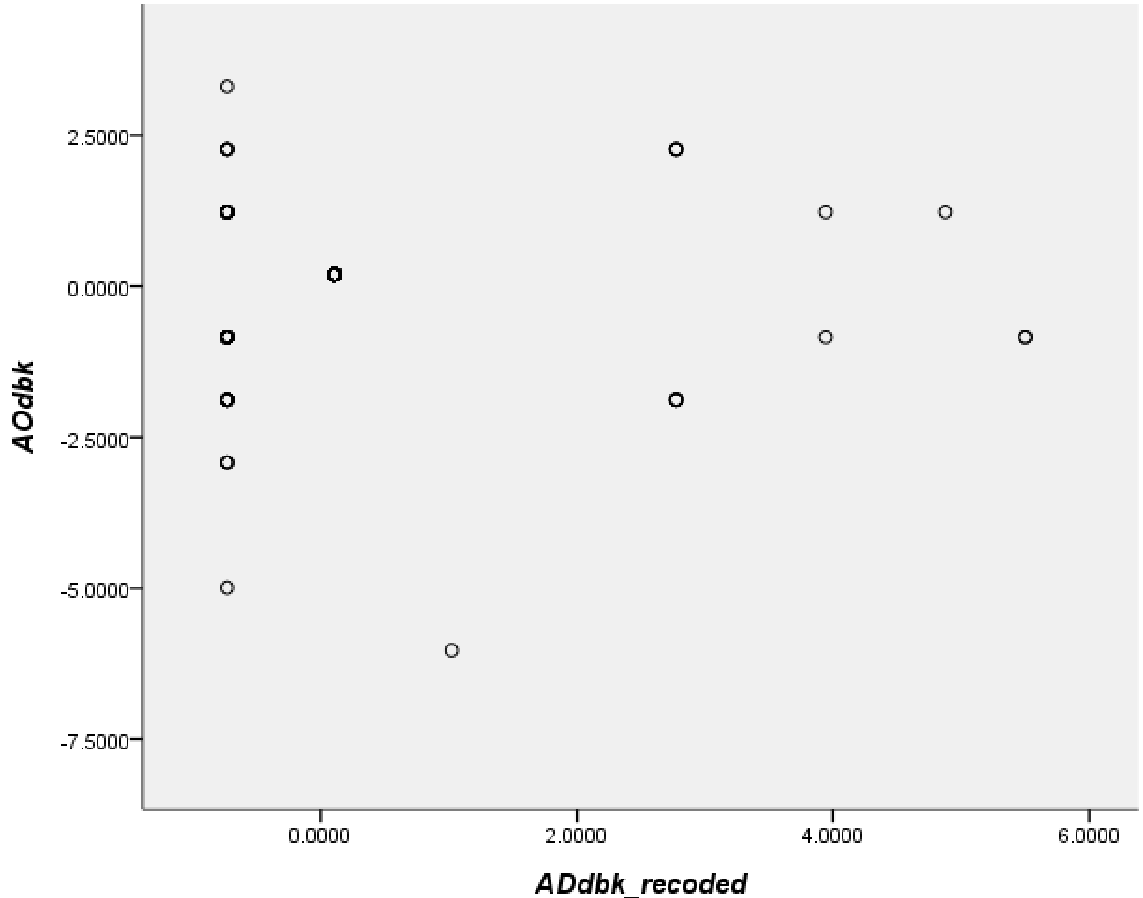
As can be seen in Figure 32, while nonlinearity is not indicated, the scatterplot of *APVdbk* against *AOdbk* does not suggest a particular association between the two variables. A deviation from homoscedasticity is not observed, either. It might be argued that the rightmost data point represents a high leverage point and the bottommost data point might be regarded as an outlier, too; however, neither of them appears particularly salient.

Figure 32: Scatterplot of *APVdbk* against *AOdbk*



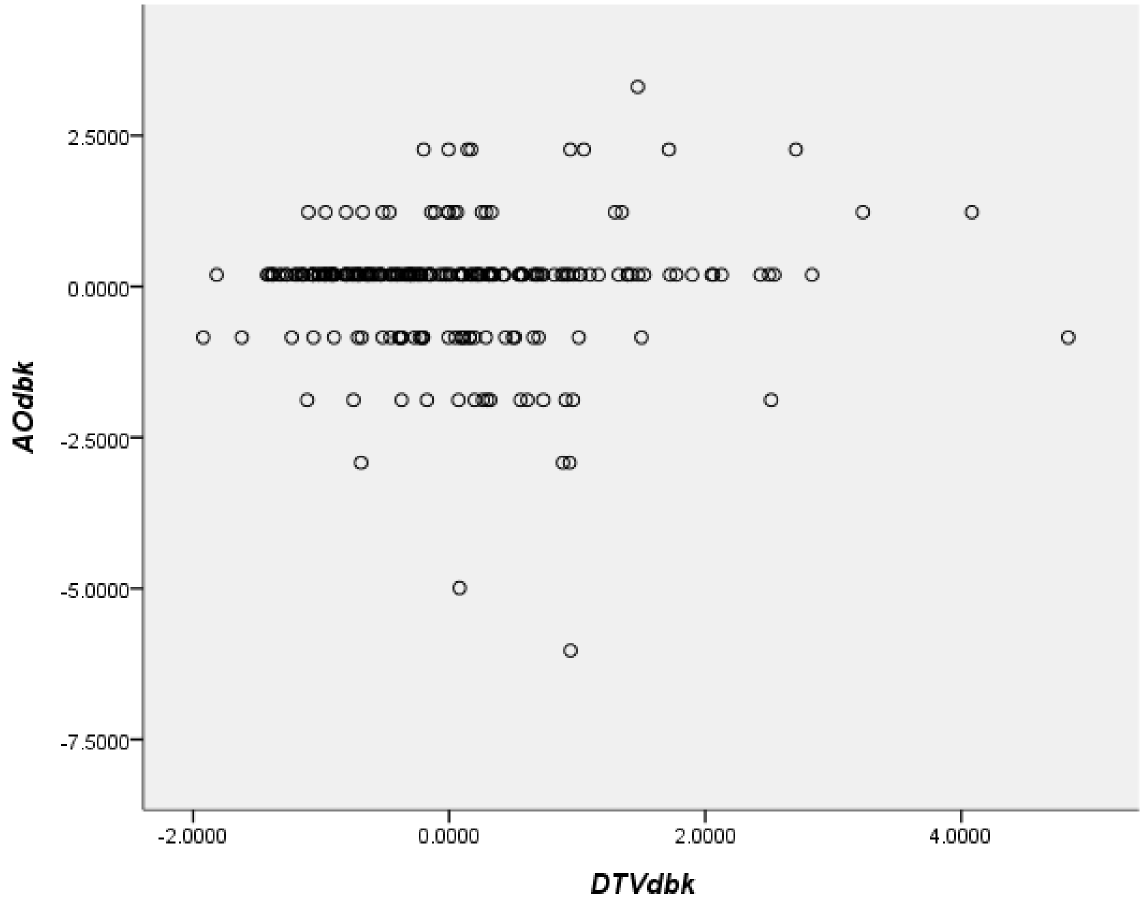
The scatterplot of *ADdbk_recoded* against *AOdbk*, which is shown in Figure 33, illustrates that various cases have common data points. This feature is attributable to the fact that approximately two thirds of the values of after-hours disagreement, *ADdbk*, were replaced by mean substitution. Beyond this idiosyncrasy, the scatterplot does not show problematic features. While an association is not suggested between the two variables, the equal variance condition does not appear to be violated.

Figure 33: Scatterplot of *ADdbk_recoded* against *AOdbk*



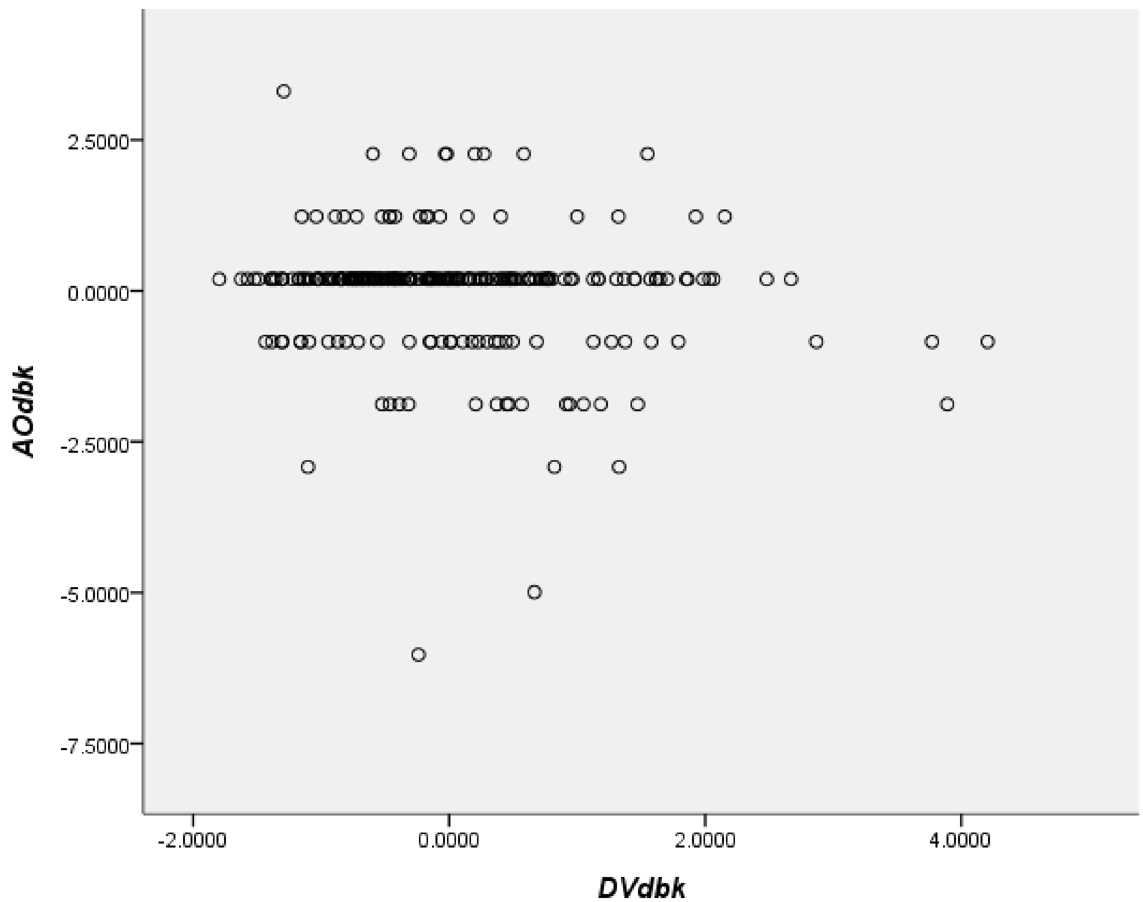
According to Figure 34, the scatterplot of *DTVdbk* against *AOdbk* does not suggest critical features. Neither is a nonlinear relationship indicated, nor is a deviation from homoscedasticity observed, nor are striking outliers present.

Figure 34: Scatterplot of *DTVdbk* against *AOdbk*



Finally, the scatterplot of *DVdbk* against *AOdbk*, as shown in Figure 35, is not characterized by problematic patterns, either. It might be made the point that the two bottommost data points reflect outliers; however, neither is particularly salient.

Figure 35: Scatterplot of *DVdbk* against *AOdbk*



Overall, in none of the above relationships between each of the independent variables with the dependent variable, *AOdbk*, a material violation of the assumptions regarding linearity, outliers and homoscedasticity is assumed to have occurred. The relevant assumptions have been adhered to at least in an approximate manner.

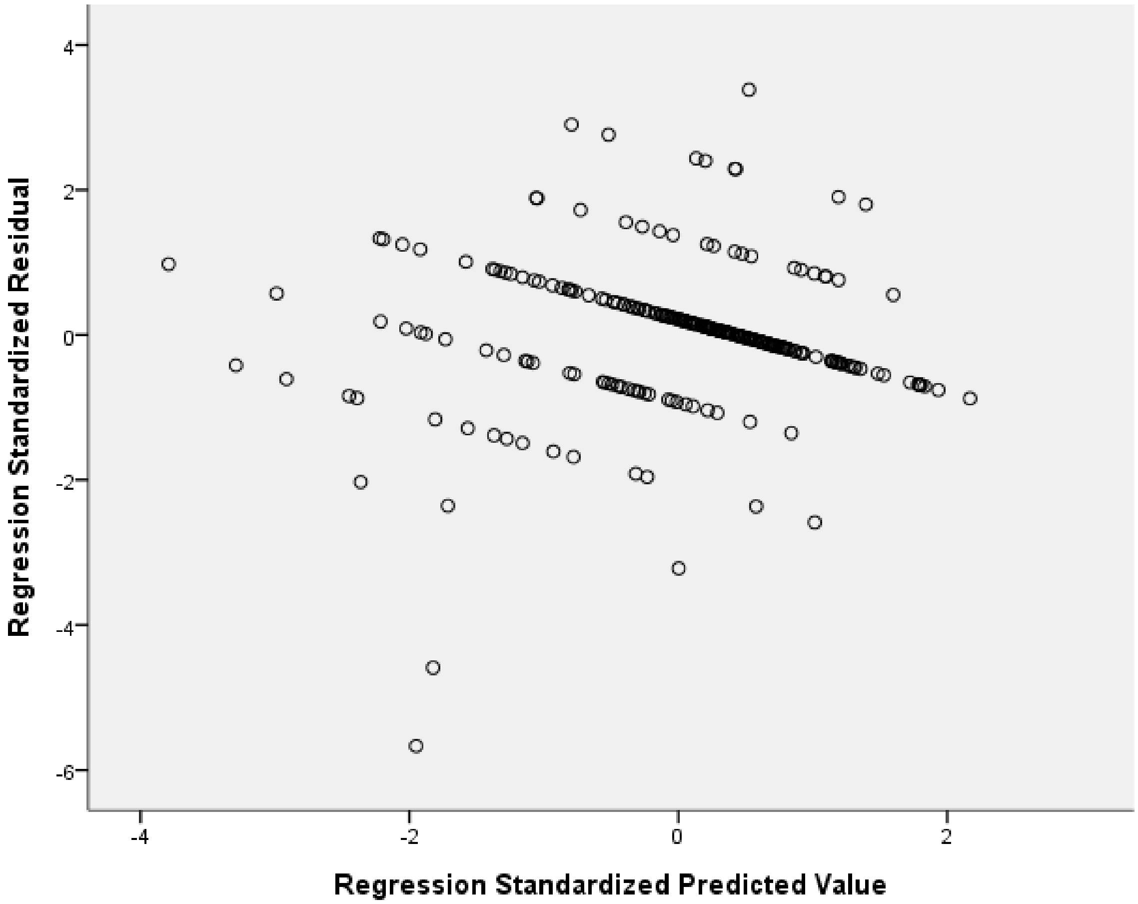
As far as the ratio of cases to independent variables is concerned, compared to the primary model and the first robustness check, this ratio improves to 31.5 in the second robustness check. Since after-hours corporate news did not occur for Deutsche Bank during the study period, the related indicator variable *ANdbk* became redundant and was excluded from the initially suggested multiple regression model.

Considering the VIF values of the individual regression coefficients, the highest VIF value is exhibited by daily stock price volatility, *DVdbk*. As this value amounts to only 1.493, multicollinearity does not materially impact on the multiple regression model in the second robustness check (O'Brien, 2007).

Since the indicator variable *ANdbk* was deleted from this multiple regression model, only eight degrees of freedom are relevant with respect to Mahalanobis Distance and the associated critical chi-square value at an alpha level of 0.001 is 26.13 (Tabachnick & Fidell, 2007). Against this background, 10 multivariate outliers were identified but the construction of an alternative model was again not considered to be useful.

With regards to the characteristics of the residual values, first, the scatterplot of residuals was inspected. This scatterplot does not hint at problematic patterns, as shown in Figure 36. A deviation from linearity is not observed and the assumption of homoscedasticity seems to be met.

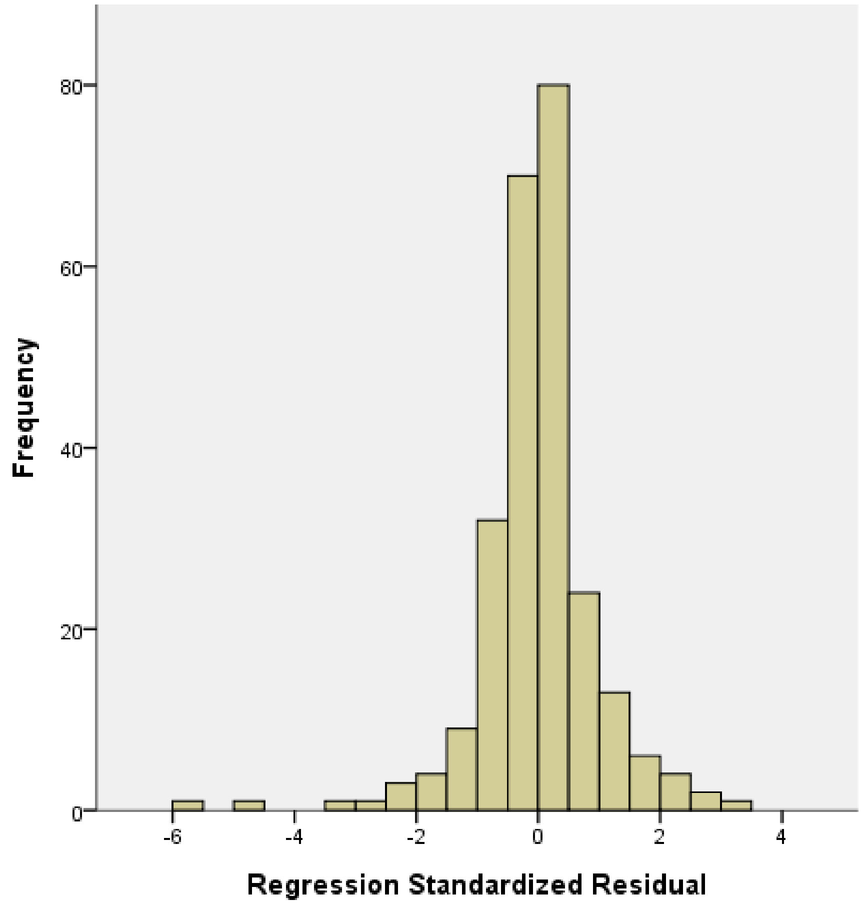
Figure 36: Scatterplot of Predicted Values against Residuals (First Multiple Regression – Second Robustness Check)



Concerning independence of residuals, the Durbin-Watson test statistic indicates a value of 2.079. Since this value lies in the corridor between 1.5 and 2.5, serial correlation was not considered to be an issue (Vogt & Johnson, 2011).

Finally, the histogram of the distribution of residuals, which can be inspected in Figure 37, is unimodal and shows symmetric appearance. Hence, the residuals were deemed to follow the normal distribution at least in an approximate way.

Figure 37: Histogram of Distribution of Residuals (First Multiple Regression – Second Robustness Check)



4.3.1.2.4.2.2 Interpretation of the Regression Coefficients

For this second robustness check, the conditions required for multiple linear regression models are also at least roughly met. As explained earlier, the indicator variable regarding the after-hours corporate news of Deutsche Bank, *ANdbk*, was deleted from the initially devised model in equation 18. A summary of the regression results of this second robustness check is provided in Table 5.

Table 5: Regression Results (First Multiple Regression – Second Robustness Check)

Intercept	-0.056
DRdbk	0.252***
APVdbk	-0.303***
ADdbk_recoded	0.169**
DTVdbk	0.075
DVdbk	-0.061
AW	0.063
M	0.070
$AOdbk_{t-1}$	0.161***
N	252
R-squared	0.207

*Significant at 10%

**Significant at 5%

***Significant at 1%

The coefficient associated with daily stock returns, *DRdbk*, shows a value of 0.252 and is significantly different from zero (p=0.000). Concerning Deutsche Bank, too, daily stock returns positively predict after-hours weighted opinion. Ceteris paribus, per 1-unit increase in daily stock returns, *DRdbk*, after-hours weighted opinion, *AOdbk*, rises by 0.252 units. This coefficient is substantially lower, however, than the related coefficients for daily stock returns in the first robustness check and in the primary model.

Considering the other independent variables in this second robustness check, significantly different from zero are *APVdbk* (p=0.000), $AOdbk_{t-1}$ (p=0.008) and *ADdbk _recoded* (p=0.013). While *APVdbk* shows a negative sign, namely -0.303, *ADdbk_recoded* and $AOdbk_{t-1}$ are associated with positive signs, namely 0.169 and 0.161, respectively. As far as *APVdbk* is concerned, a 1-unit increase in the after-hours posting volume of Deutsche Bank is related to a decrease by 0.303 units in after-hours weighted opinion, *AOdbk*, given the remaining independent variables are held constant. Regarding $AOdbk_{t-1}$, an increase by 1 unit in 1-day lagged after-hours weighted opinion for the stocks of Deutsche Bank is associated with an increase by 0.161 units in contemporary after-hours weighted opinion, *AOdbk*, provided that the other independent variables are held constant. According to *ADdbk_recoded*, a 1-unit increase in the recoded after-hours disagreement of Deutsche Bank is associated with an increase in after-hours weighted opinion, *AOdbk*, by 0.169 units, ceteris paribus. By way of contrast, the positive coefficient of *DTVdbk* (p=0.281), the negative coefficient of *DVdbk* (p=0.387), the positive coefficient of *AW* (p=0.606), the positive coefficient of *M* (p=0.640) and the negative constant term (p=0.518) do not differ from zero to a statistically significant degree. None of the related variables is a significant factor in explaining the after-hours weighted opinion of Deutsche Bank, *AOdbk*.

4.3.1.2.4.2.3 Evaluation of the Multiple Linear Regression Model

The coefficient of determination, R-squared, indicates a value of 0.207, which implies that only 20.7% of the variability in the dependent variable, *AOdbk*, is accounted for by the regression model. Adjusted R-squared shows a value of 0.181. As the related values in the primary model and in the first robustness check are approximately twice as high, these multiple linear regression models tend to explain the relationship between the independent variables and the dependent variable more effectively than the model in the second robustness check. While the F-test statistic exhibits a statistically significant (p=0.000) value of 7.937, this multiple linear regression model is at least superior to predicting *AOdbk* simply by its mean value.

4.3.1.2.5 Résumé

As summarized in Tables 2 to 4, the variables for daily stock returns show statistically significant positive signs. This is true for the primary multiple regression model as well as across the robustness checks. It appears reasonable to presume that stock returns are a significant factor in explaining private investor sentiment. Hence, the results from the earlier correlation and simple linear regression analysis are confirmed.

Beyond stock returns, only the lagged values of private investor sentiment constitute a significant explanatory variable across all three multiple regression models. To subsume, short-term private investor sentiment tends to be predictable, namely by prior short-term stock returns and by its own previous values.

4.3.2 DOES EXTRAPOLATION BIAS AMONG PRIVATE INVESTORS HAVE AN EFFECT ON THE MARKET PRICES OF STOCKS?

In order to answer the second research question of whether extrapolation bias among private investors has an effect on the market prices of stocks, autocorrelation and autoregression as well as multiple linear regression were conducted, as explained in Chapter 3.

4.3.2.1 AUTOCORRELATION AND AUTOREGRESSION

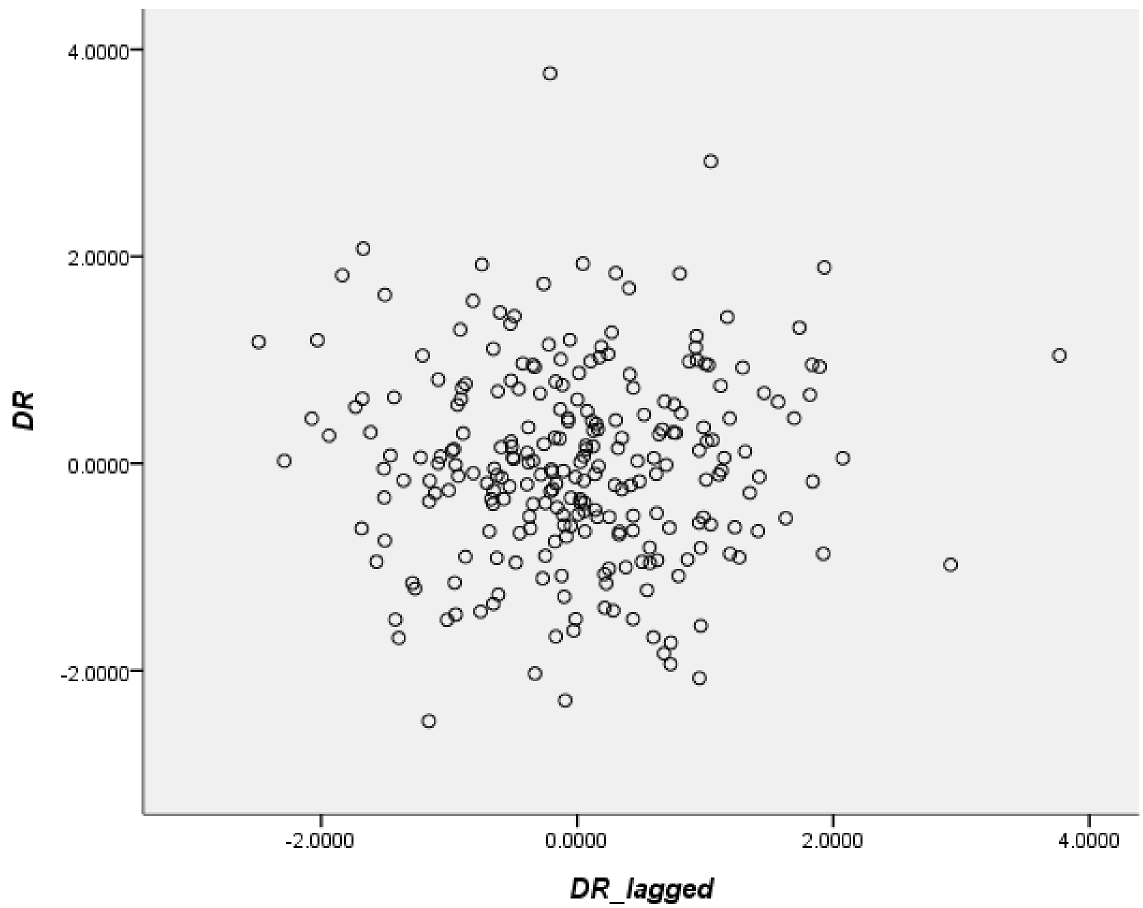
For determining the extent of autocorrelation in stock returns, the 1-day autocorrelation coefficient of daily stock returns, *DR*, was computed. Before any calculations were carried out, it was ensured that the relevant assumptions were adhered to.

4.3.2.1.1 Assumptions of Autocorrelation

As the calculation of the autocorrelation coefficient entailed Pearson correlation, the assumptions of the latter were relevant again. The variable for daily stock returns, *DR*, had been demonstrated already in earlier analysis to represent a measurable quantitative variable.

According to the scatterplot in Figure 38, a particular association between 1-day lagged daily stock returns, DR_{t-1}, and contemporary daily stock returns, *DR*, is not observed. Nonlinearity is not suggested, striking outliers cannot be spotted and the assumption of homoscedasticity is fulfilled.

Figure 38: Scatterplot of DR_{t-1} against DR



4.3.2.1.2 Autocorrelation Coefficient of *DR*

Since it was ascertained that the relevant assumptions are adhered to, the 1-day autocorrelation coefficient for daily stock returns, *DR*, was computed. This coefficient exhibits a value of 0.008 but is not significantly different from zero (p=0.894). Therefore, a linear relationship is not suggested to exist between 1-day lagged daily stock returns, DR_{t-1}, and contemporary daily stock returns, *DR*.

4.3.2.1.3 Simple Linear Autoregression

In the related simple linear autoregressive model, contemporary daily stock returns, *DR*, were explained by lagged daily stock returns, DR_{t-1}.

$$DR_t = 0.008 DR_{t-1} \tag{19}$$

Since the autocorrelation coefficient, which holds a value of 0.008, has not been found to be significantly different from zero (p=0.894), the slope term, being identical to the autocorrelation coefficient, is not different from zero, either. One-day lagged daily stock returns, DR_{t-1}, were not considered to be a significant factor in predicting daily stock returns, *DR*.

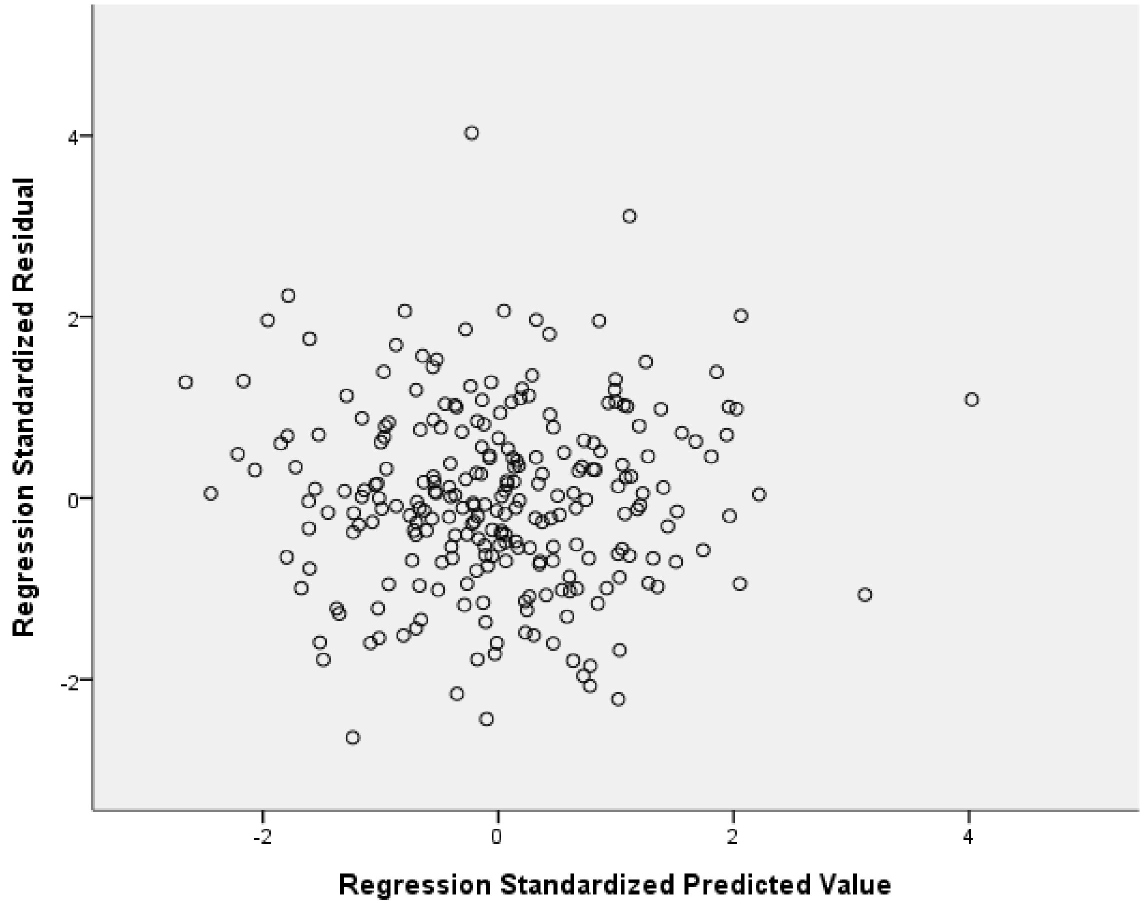
4.3.2.1.4 Evaluation of the Simple Linear Autoregressive Model

The coefficient of determination, R-squared, associated with this linear autoregressive model indicates a value of 0.000. This means that 0.0% of the variability in daily stock returns, *DR*, is accounted for by 1-day lagged daily stock returns, DR_{t-1}. As 100.0% of the variation remains unexplained, this model is ineffective in explaining the variation in daily stock returns.

The regression residuals exhibit a standard deviation of 0.9345643. This value is only slightly lower than the standard deviation of the dependent variable, *DR*, which amounts to 0.9345973, given that the first trading day of the year was excluded. Therefore, the autoregressive model is not useful, either, in identifying a linear relationship between 1-day lagged daily stock returns, DR_{t-1}, and daily stock returns, *DR*.

According to the scatterplot of residuals of this autoregressive model, which can be seen in Figure 39, problematic patterns, such as bends or a changing variance in the data points, are not observed. At least, the appropriateness of ordinary least squares regression to the underlying data set appears to be given.

Figure 39: Scatterplot of Predicted Values against Residuals (Autoregression)



4.3.2.1.5 Robustness Checks: Autocorrelation and Autoregression at Individual Stock Levels

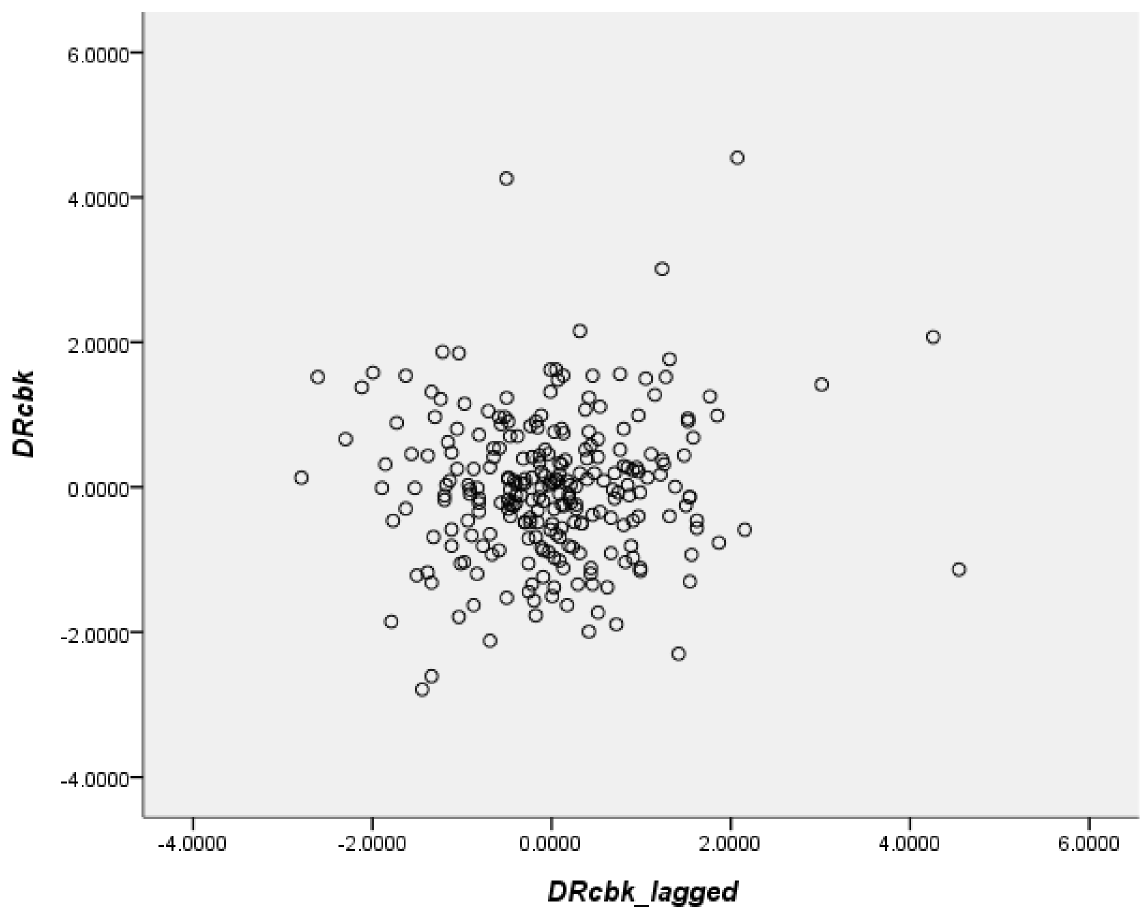
As explained in Chapter 3, robustness checks of the autocorrelation and autoregression analysis were performed. The first robustness check incorporated the stocks of Commerzbank and the second robustness check incorporated the stocks of Deutsche Bank.

4.3.2.1.5.1 Commerzbank

4.3.2.1.5.1.1 Assumptions of Autocorrelation

The variable for the daily stock returns of Commerzbank, *DRcbk*, had been shown already earlier to be a measurable quantitative variable. Considering the scatterplot of $DRcbk_{t-1}$ against *DRcbk* in Figure 40, a particular relationship is not observed. While nonlinearity is not suggested, the homoscedasticity condition appears to be met. It might be argued that a couple of data points to the upper right corner represent outliers; however, they are not particularly striking.

Figure 40: Scatterplot of $DRcbk_{t-1}$ against *DRcbk*



4.3.2.1.5.1.2 Autocorrelation Coefficient of *DRcbk*

Since it was ensured that the relevant assumptions are fulfilled, the 1-day autocorrelation coefficient was calculated for the daily stock returns of Commerzbank, *DRcbk*. This coefficient indicates a value of 0.069 but does not differ from zero to a statistically significant degree (p=0.272). For that reason, a linear association between 1-day lagged daily stock returns and contemporary daily stock returns is not assumed to exist for Commerzbank, either.

4.3.2.1.5.1.3 Simple Linear Autoregression

Consistent with the primary analysis, the associated simple linear autoregressive model was set up.

$$DRcbk_t=0.069DRcbk_{t-1} \tag{20}$$

As the autocorrelation coefficient could not be shown to be significantly different from zero (p=0.272), the slope term, which equals the autocorrelation coefficient here, is not different from zero, either. Daily stock returns of Commerzbank, *DRcbk*, do not appear to be explained by their own 1-day lagged values, $DRcbk_{t-1}$.

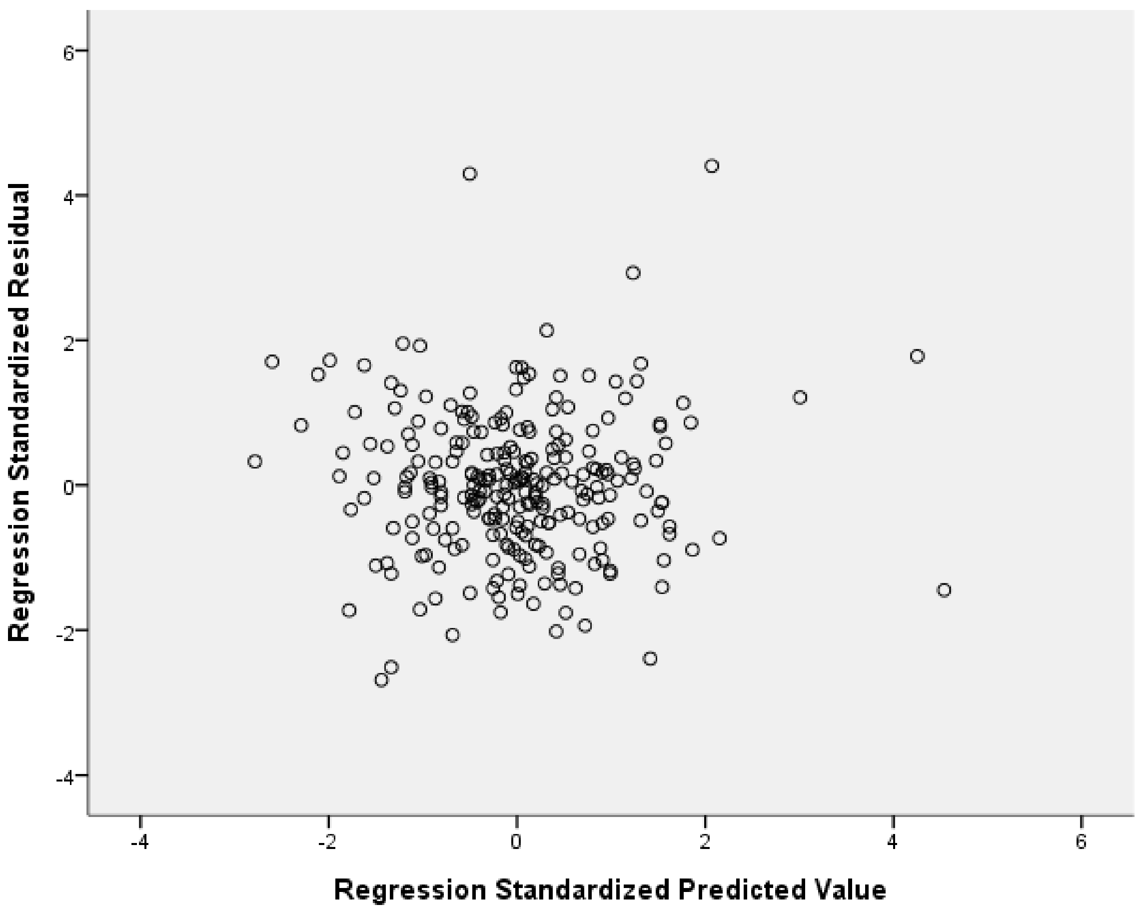
4.3.2.1.5.1.4 Evaluation of the Simple Linear Autoregressive Model

The coefficient of determination, R-squared, indicates a value of 0.005. This means that 0.5% of the variability in the daily stock returns of Commerzbank, *DRcbk*, is accounted for by the variation in the previous day's stock returns, $DRcbk_{t-1}$. Nevertheless, 99.5% of the variation in the dependent variable remains unexplained by the model.

The standard deviation of the regression residuals amounts to 0.9981341. This value is only slightly lower than the standard deviation of the dependent variable, *DRcbk*, which equals 1.0005516, given that the first trading day of the year was excluded. Obviously, this autoregressive model is unable to effectively describe a linear relationship between the 1-day lagged daily stock returns of Commerzbank, $DRcbk_{t-1}$, and the daily stock returns of Commerzbank, *DRcbk*.

As shown in Figure 41, the scatterplot of residuals does not reveal a critical pattern, as more or less horizontal shape and equal scatter around the predicted values is observed. The applicability of ordinary least squares regression to the underlying data at least seems to be given.

Figure 41: Scatterplot of Predicted Values against Residuals (Autoregression – First Robustness Check)

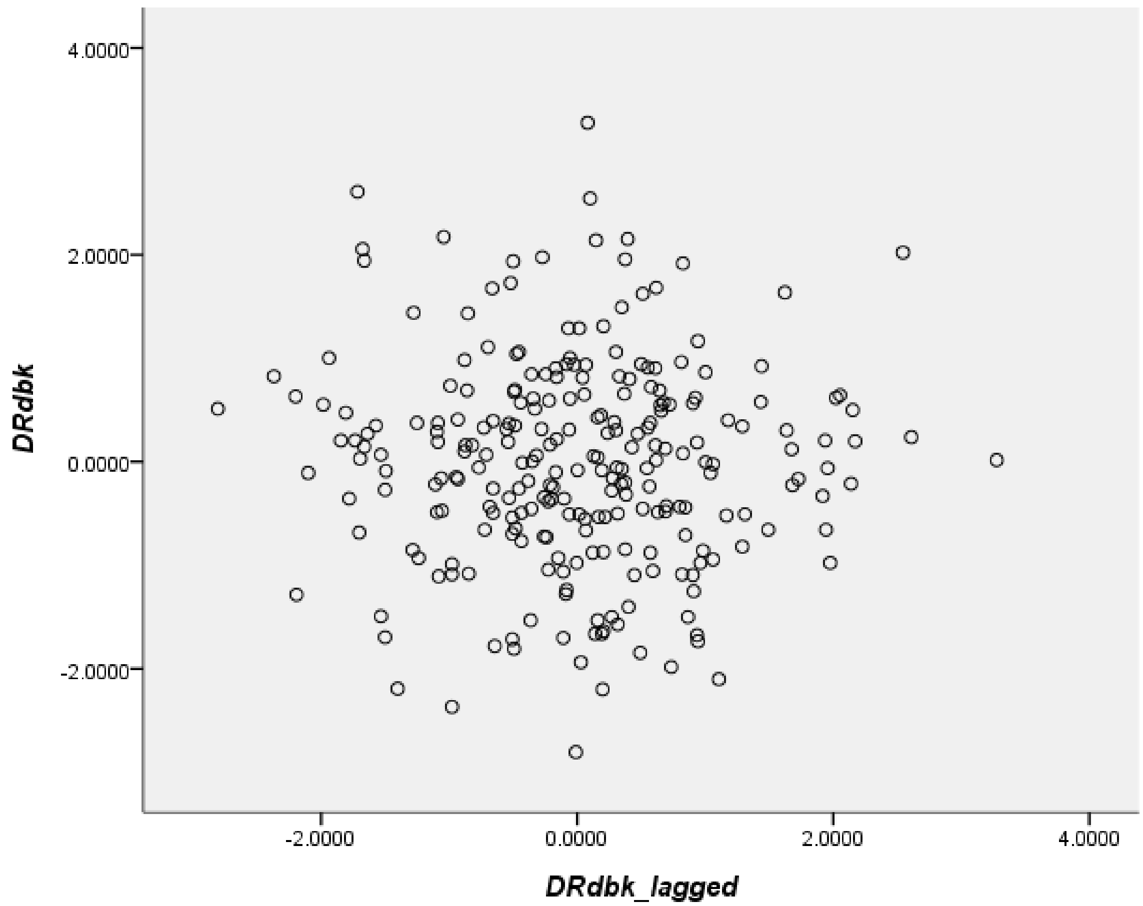


4.3.2.1.5.2 Deutsche Bank

4.3.2.1.5.2.1 Assumptions of Autocorrelation

The variable representing the daily stock returns of Deutsche Bank, *DRdbk,* had been ascertained already earlier to be a measurable quantitative variable. According to the scatterplot of $DRdbk_{t-1}$ against *DRdbk*, which can be seen in Figure 42, the existence of a particular relationship between the two variables is not suggested. While nonlinearity is not observed, the assumption of homoscedasticity seems to be fulfilled and striking outliers are not spotted.

Figure 42: Scatterplot of $DRdbk_{t-1}$ against *DRdbk*



4.3.2.1.5.2.2 Autocorrelation Coefficient of *DRdbk*

The necessary assumptions were adhered to; hence, the 1-day autocorrelation coefficient of the daily returns in Deutsche Bank stocks, *DRdbk*, was calculated. This coefficient shows a value of -0.028 but does not differ from zero to a significant degree (p=0.655). A linear relationship between 1-day lagged daily stock returns and contemporary daily stock returns is not suggested by this second robustness check, either.

4.3.2.1.5.2.3 Simple Linear Autoregression

The related simple linear autoregressive model was derived accordingly.

$$DRdbk_t=-0.028DRdbk_{t-1} \tag{21}$$

Being equal to the autocorrelation coefficient, the slope coefficient does not differ from zero to statistically significant degree (p=0.655). Again, daily stock returns have not been found predictable by their own 1-day lagged values.

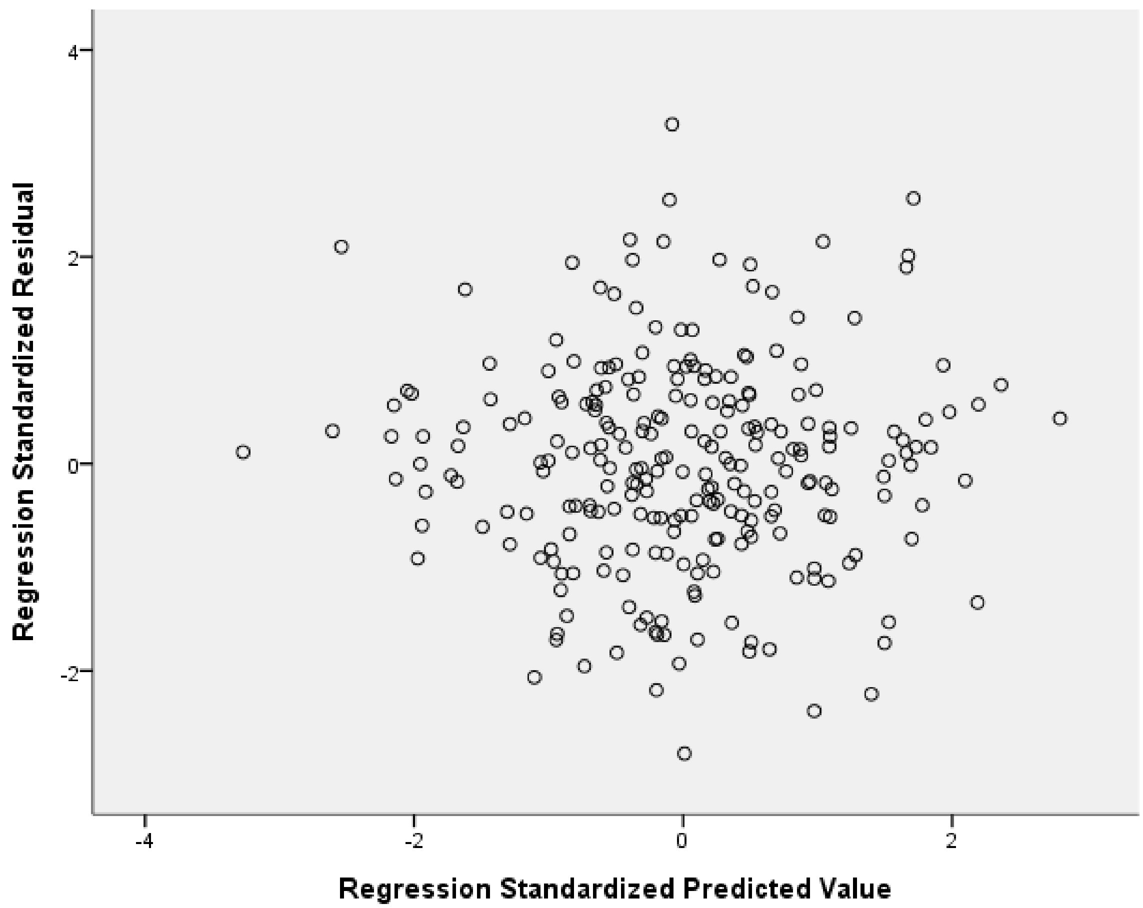
4.3.2.1.5.2.4 Evaluation of the Simple Linear Autoregressive Model

The coefficient of determination, R-squared, holds a value of 0.001. Accordingly, 0.1% of the variability in the daily stock returns of Deutsche Bank, *DRdbk*, is explained by their 1-day lagged values, whereas 99.9% of the variability remains unexplained.

The standard deviation of the regression residuals indicates a value of 0.9988132. This value is only marginally lower than the standard deviation of the dependent variable, *DRdbk*, itself, which equals 0.9992124, given that the first trading day of the year was excluded. Against this background, this autoregressive model is also incapable of explaining a linear relationship between 1-day lagged daily stock returns and daily stock returns.

The scatterplot of residuals, which can be seen in Figure 43, does not illustrate critical patterns. The data points appear to be fairly equally distributed without hinting at nonlinearity or deviations from homoscedasticity. At least, the appropriateness of ordinary least squares regression to the underlying data set appears to be given.

Figure 43: Scatterplot of Predicted Values against Residuals (Autoregression – Second Robustness Check)



4.3.2.1.6 Résumé

As consolidated in Table 6, which represents the autocorrelation and simple linear autoregression results based on equations 19 to 21, the autocorrelation coefficient or slope coefficient, respectively, is not different from zero to a statistically significant degree. This is true both for the primary analysis and for the two robustness checks. Since prior short-term stock returns do not constitute a factor in explaining contemporary short-term stock returns, persistence in stock returns was not assumed.

Table 6: Autocorrelation Coefficients/Slope Coefficients

	DR	*DRcbk*	*DRdbk*
DR_{t-1}	0.008		
$DRcbk_{t-1}$		0.069	
$DRdbk_{t-1}$			-0.028

*Significant at 10%

**Significant at 5%

***Significant at 1%

4.3.2.2 MULTIPLE LINEAR REGRESSION

As shown in the preceding autoregressive analysis, virtually none of the variability in daily stock returns, *DR*, is accounted for by a simple linear autoregressive model that includes 1-day lagged daily stock returns, DR_{t-1}, as the explanatory variable. Against this background, it also seemed reasonable from a statistical perspective to introduce further independent variables that have the potential to explain at least part of the variability. According to the outline in Chapter 3, a multiple linear regression model was constructed. With regards to after-hours disagreement, the recoded variable was used again.

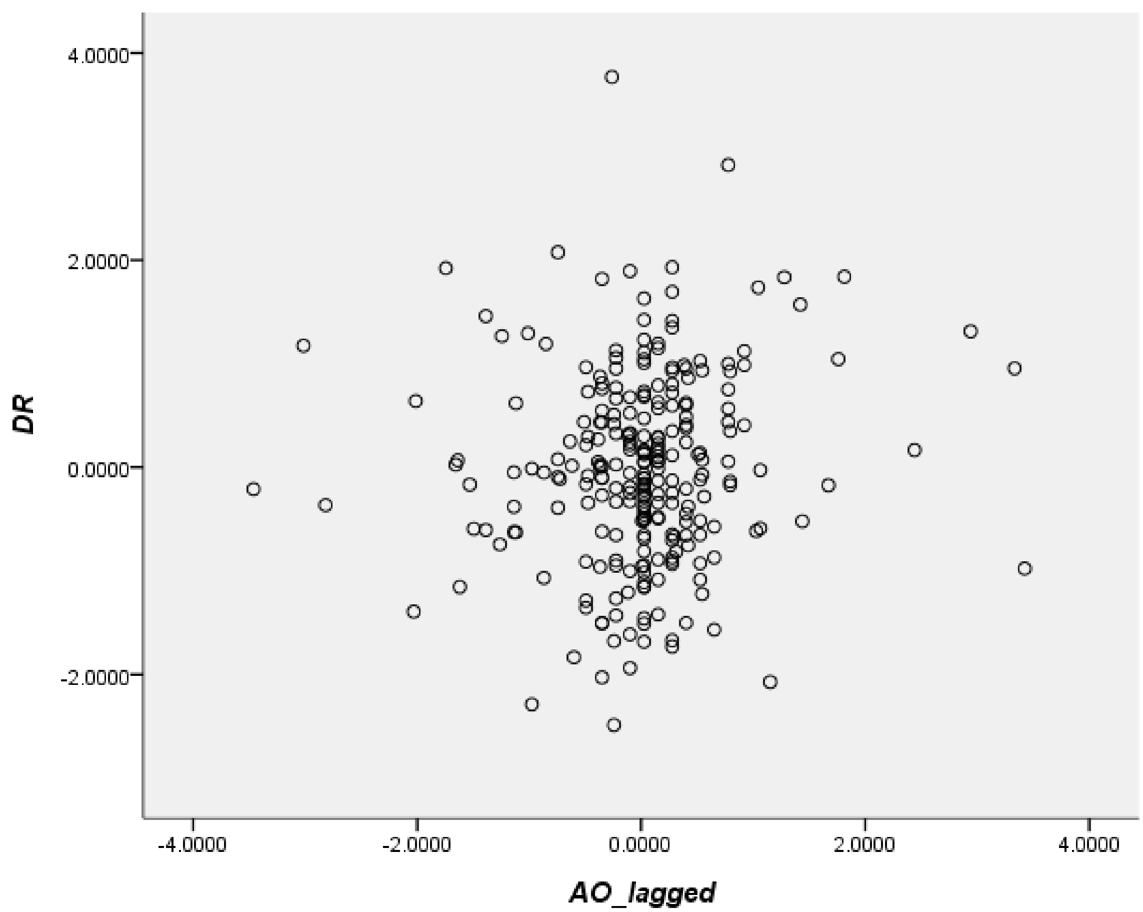
$$DR_t=\beta_0+\beta_1(DR_{t-1})+\beta_2(AO_{t-1})+\beta_3(APV_{t-1})+\beta_4(AD\_recoded_{t-1})+\beta_5(DTV_t)$$
$$+\beta_6(DV_t)+\beta_7(AW_t)+\beta_8(M_t)+\beta_9(DN_t)+\varepsilon_t \qquad (22)$$

4.3.2.2.1 Assumptions of Multiple Linear Regression

All variables introduced into this multiple linear regression model, except for daily corporate news, *DN*, had been ascertained already earlier in preceding analysis to adhere to the quantitative variables condition. Since the variable for daily corporate news, *DN*, was coded as an indicator variable, it could be integrated into the regression model.

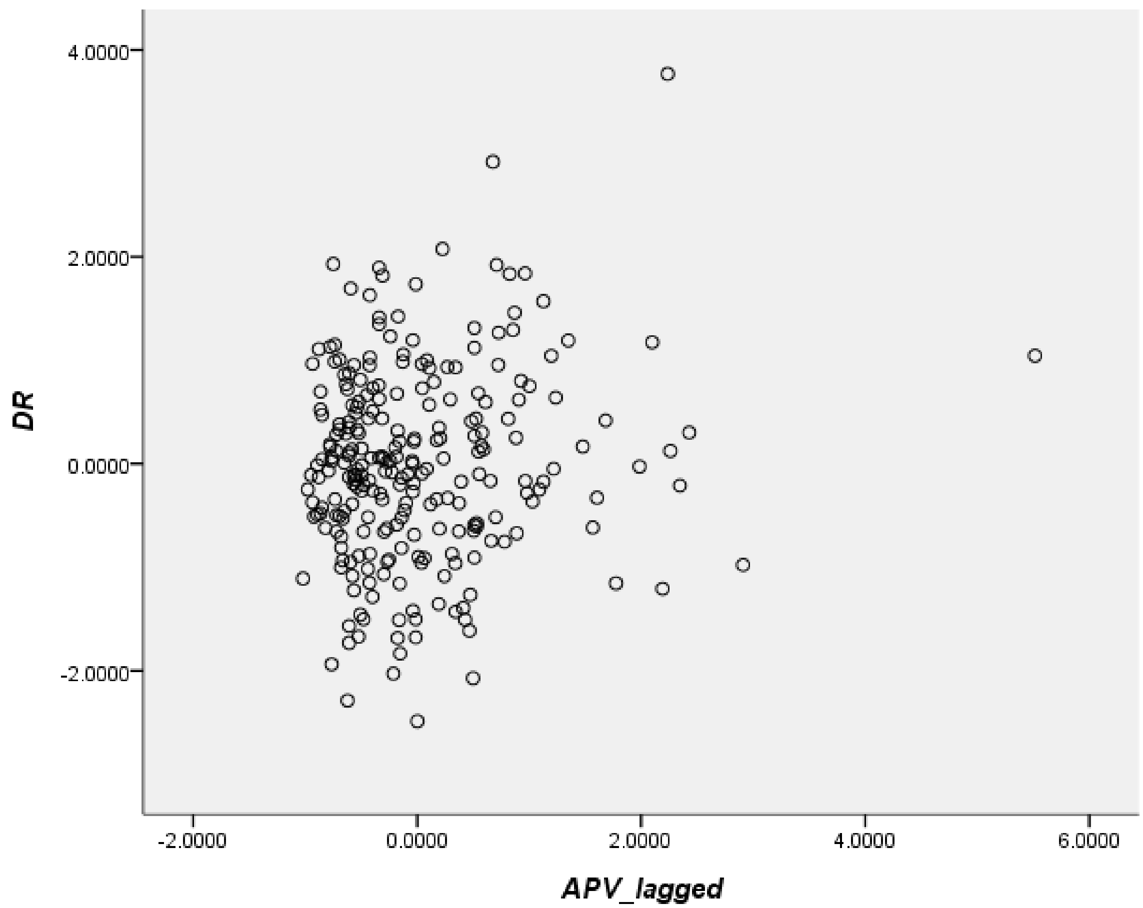
The assumptions concerning linearity, outliers and homoscedasticity in the relationship of each independent variable with the dependent variable were checked by inspecting the relevant scatterplots. As shown in Figure 44, according to the scatterplot of AO_{t-1} against *DR*, an association between these variables is not suggested. While nonlinearity and outliers are not observed, the assumption of homoscedasticity is adhered to.

Figure 44: Scatterplot of AO_{t-1} against *DR*



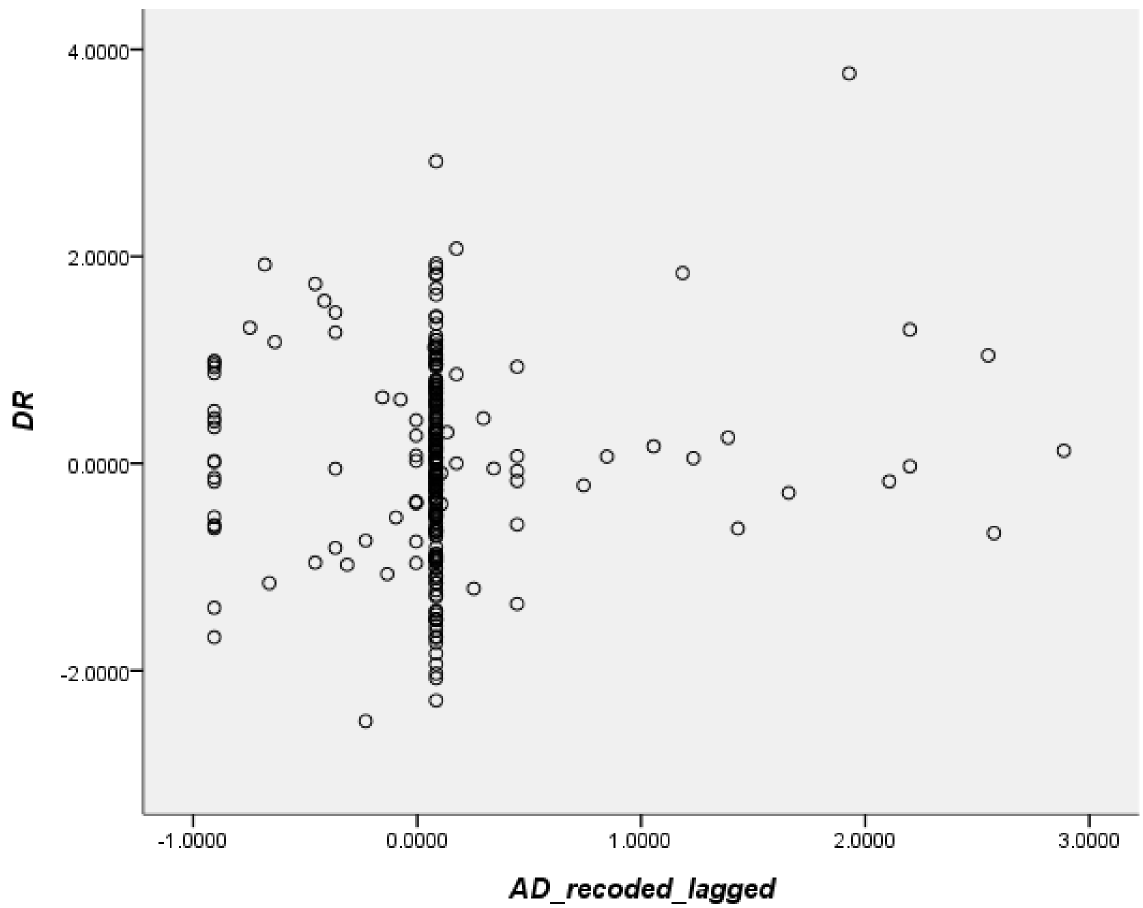
Considering the scatterplot of APV_{t-1} against *DR*, which can be seen in Figure 45, neither a linear pattern, nor a nonlinear pattern is observed. While the assumption of homoscedasticity does not appear to be violated, the rightmost and the topmost data points might be considered as outliers, however. Still, these data points do not deviate substantially from the remainder of data points.

Figure 45: Scatterplot of APV_{t-1} against *DR*



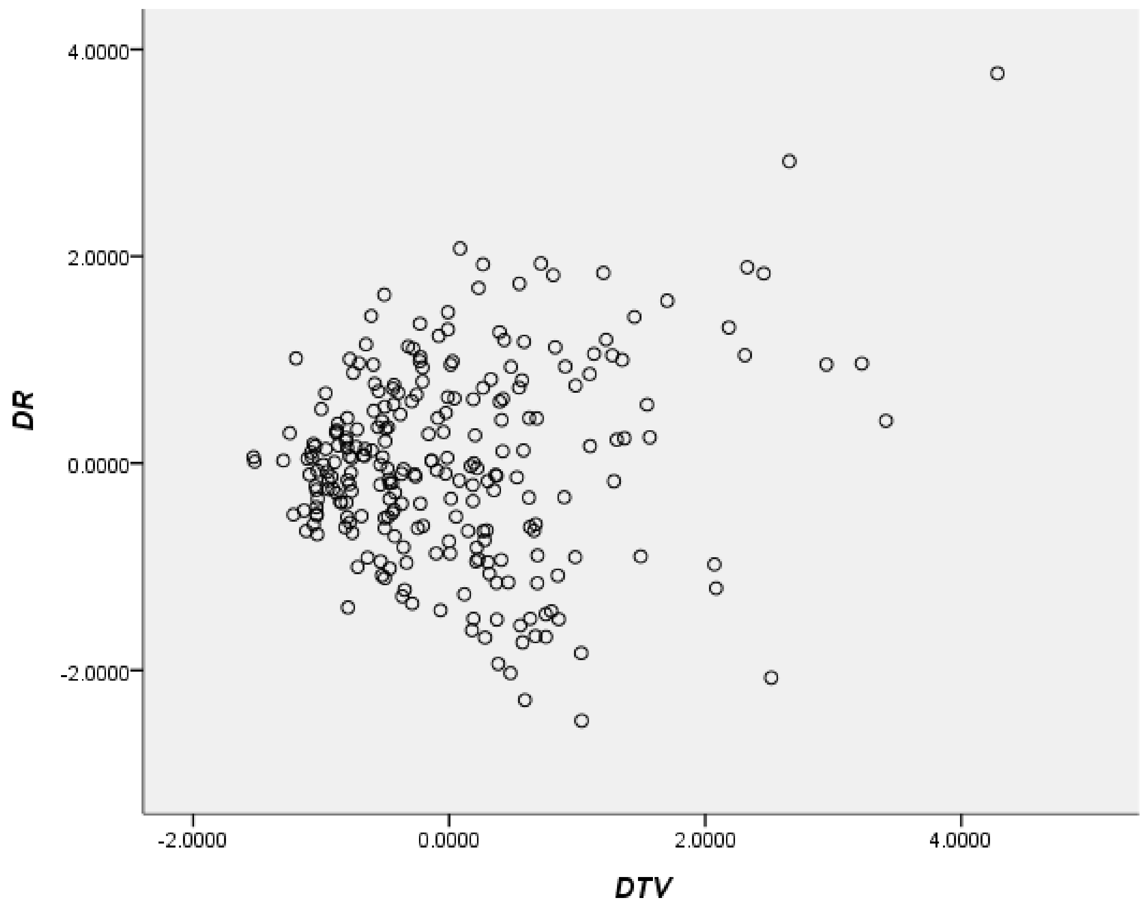
According to Figure 46, the scatterplot of $AD\_recoded_{t-1}$ against *DR* illustrates that both variables are fairly unrelated to each other. These variables are characterized neither by linear, nor by nonlinear association. The topmost data point might be regarded as an outlier; however, it is not particularly salient. The assumption of homoscedasticity seems to be fulfilled.

Figure 46: Scatterplot of $AD\_recoded_{t-1}$ against *DR*



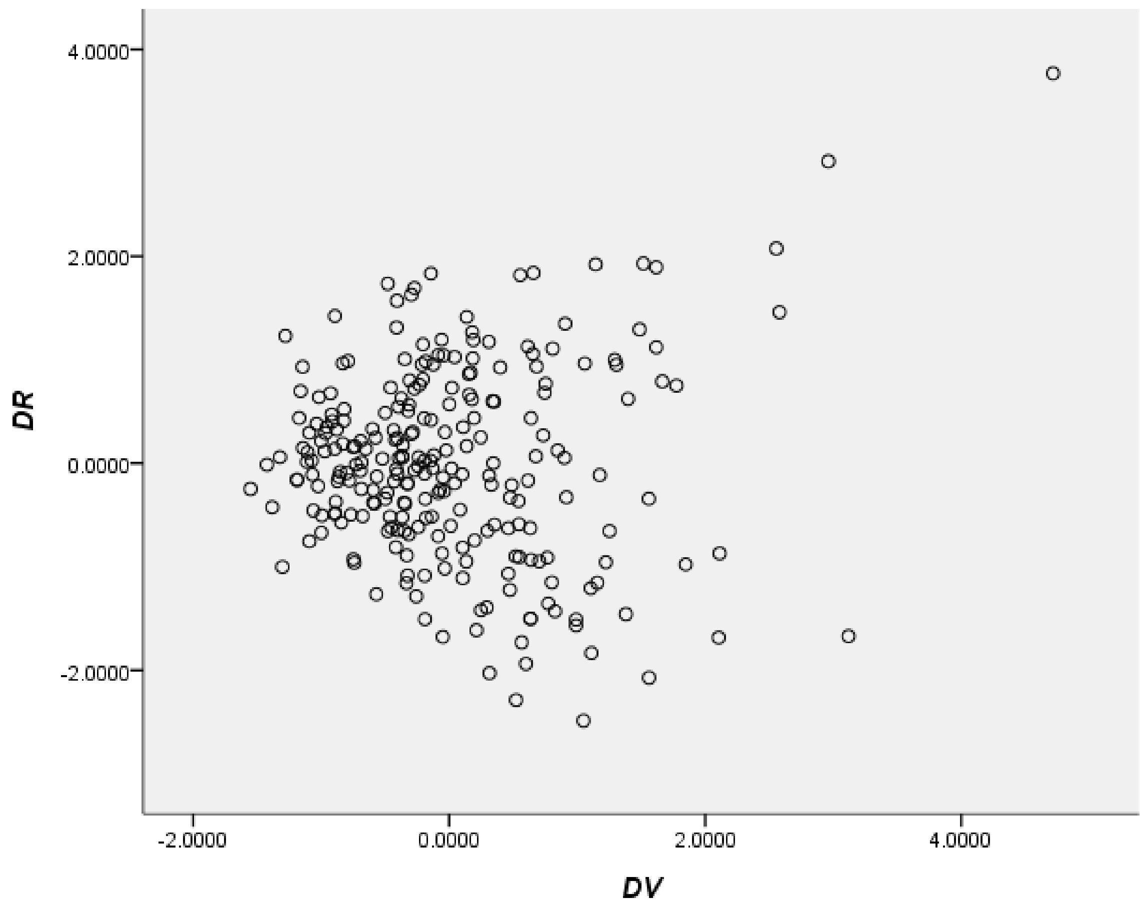
As shown in Figure 47, the scatterplot of *DTV* against *DR* indicates, while nonlinearity is not suggested, that the variance of the data points is not unambiguously constant. The variance seems to become somewhat larger with increasing values of the independent variable. On the other hand, when the data point in the right upper corner, which might be considered as an outlier, is removed, a potential violation of the homoscedasticity condition becomes less obvious.

Figure 47: Scatterplot of *DTV* against *DR*



Considering Figure 48, nonlinear features are not detected but the relationship between *DV* and *DR* seems to be characterized by a slight deviation from homoscedasticity. Similar to the preceding scatterplot in Figure 47, when the potential outlier in the right upper corner is removed, the appearance of increasing variance is weakened. Interestingly, just as in the preceding case, the outlying data point refers to 19 January 2012. This day is a special day in that corporate news of Commerzbank was released on this day. While after-hours weighted opinion shows only an above average value on this day, other stock market and message board variables indicate remarkably high values.

Figure 48: Scatterplot of *DV* against *DR*



By and large, in none of the relationships between the individual independent variables with the dependent variable, a material violation of the assumptions concerning linearity, outliers and homoscedasticity is assumed to have occurred. The relevant assumptions are at least approximately met.

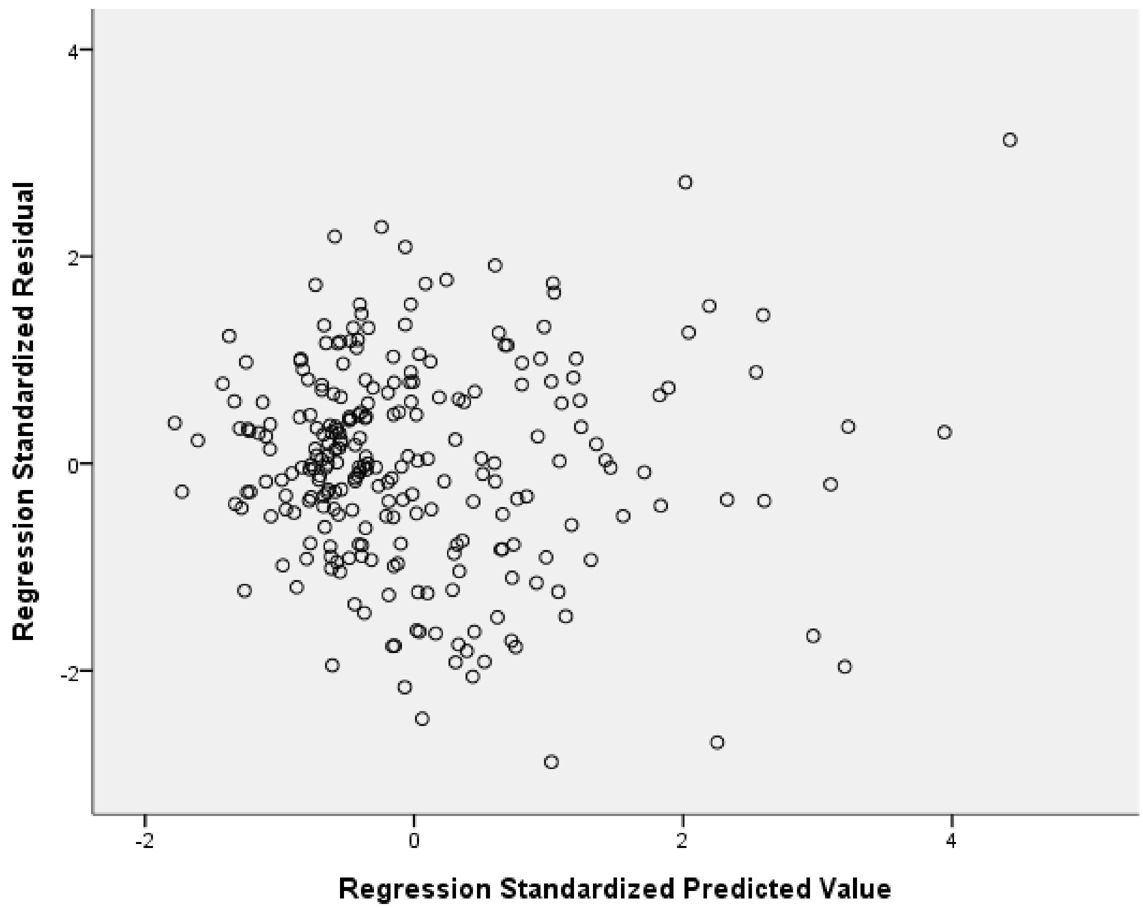
The requirement regarding the ratio of cases to independent variables is fulfilled, too. Since 252 trading days are included in this multiple linear regression model and nine independent variables were introduced, the ratio equals 28, which clearly exceeds the minimum ideal ratio of 20 (Coakes & Ong, 2011).

According to the VIF values of the independent variables, a serious degree of multicollinearity is not suggested. While *DTV* is associated with the highest VIF value, the exhibited value of 2.112 is not problematic (O'Brien, 2007).

Considering multivariate outliers, nine degrees of freedom are relevant to Mahalanobis Distance in this multiple linear regression model. As the critical chi-square value at an alpha level of 0.001 is 27.88 (Tabachnick & Fidell, 2007), 8 outliers were identified. As stated earlier, such a number of outliers is acceptable for a multiple linear regression model that involves 252 cases, and it was not considered necessary to construct an alternative model that corrects for the outliers (Coakes & Ong, 2011).

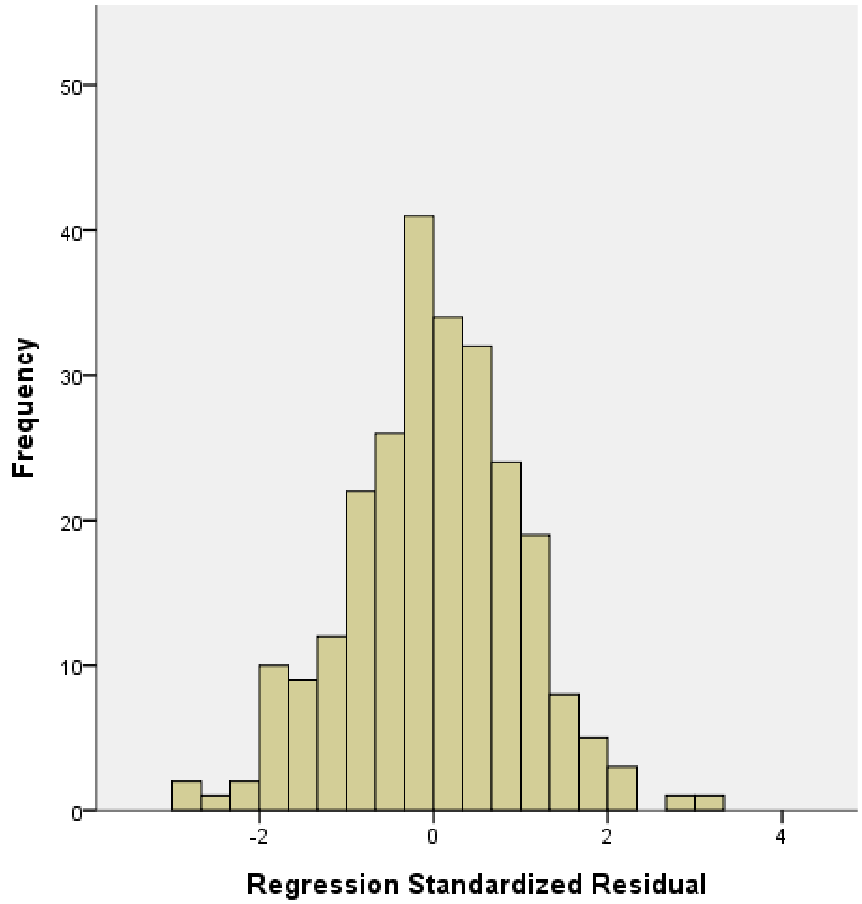
Finally, concerning the assumptions of linearity, homoscedasticity, independence and normality of the residuals, the scatterplot of residuals, as shown in Figure 49, was first inspected. Neither nonlinearity, nor a deviation from homoscedasticity is suggested here.

Figure 49: Scatterplot of Predicted Values against Residuals (Second Multiple Regression)



According to the Durbin-Watson test statistic, which shows a value of 1.981, material serial correlation, thus a violation of the independence assumption, was rejected (Vogt & Johnson, 2011). While inspecting the histogram of the distribution of residuals in Figure 50, a substantial deviation from normality is not observed. The distribution is unimodal and fairly symmetric in shape.

Figure 50: Histogram of Distribution of Residuals (Second Multiple Regression)



4.3.2.2.2 Interpretation of the Regression Coefficients

As elaborated above, the assumptions of multiple linear regression are adhered to at least in an approximate sense. Therefore, the regression model was accepted as initially proposed in equation 22. An overview of the results of the regression is supplied in Table 7.

Table 7: Regression Results (Second Multiple Regression)

Intercept	-0.059
DR_{t-1}	-0.050
AO_{t-1}	0.074
APV_{t-1}	0.064
$AD\_recoded_{t-1}$	0.039
DTV	0.142
DV	-0.022
AW	0.098
M	-0.015
DN	0.103
N	252
R-squared	0.043

*Significant at 10%

**Significant at 5%

***Significant at 1%

4.3.2.2.2.1 Lagged Daily Stock Returns, DR_{t-1}

The coefficient of 1-day lagged daily stock returns, DR_{t-1}, has not been found to be significantly different from zero (p=0.495). For that reason, 1-day lagged daily stock returns were not assumed to represent a factor in predicting contemporary daily stock returns.

4.3.2.2.2.2 The Remaining Regression Coefficients

As far as the other regression coefficients are concerned, neither the negative constant term (p=0.513), nor the positive coefficient of AO_{t-1} (p=0.424), nor the positive coefficient of APV_{t-1} (p=0.469), nor the positive coefficient of $AD\_recoded_{t-1}$ (p=0.739), nor the positive coefficient of *DTV* (p=0.128), nor the negative coefficient of *DV* (p=0.799), nor the positive coefficient of *AW* (p=0.428), nor the negative coefficient of *M* (p=0.922), nor the positive coefficient of *DN* (p=0.683) is different from zero to statistically significant degree. None of the independent variables that were introduced into the multiple linear regression model is a significant factor in predicting daily stock returns.

4.3.2.2.3 Evaluation of the Multiple Linear Regression Model

The coefficient of determination holds a value of 0.043, which means that 4.3% of the variation in daily stock returns, *DR*, is explained by the variation in the independent variables. While this value represents some improvement over the simple autoregressive model, 95.7% of the variability remains unexplained by the multiple regression model. As far as adjusted R-squared is concerned, a value of 0.008 is indicated. The F-test statistic exhibits a value of 1.219 that is not statistically significant (p=0.284); hence, the null hypothesis that none of the regression coefficients is significantly different from zero cannot be rejected (De Veaux, Velleman & Bock, 2008). This multiple linear regression model is no superior to modeling daily stock returns, *DR*, simply by their mean value.

4.3.2.2.4 Robustness Checks: Multiple Linear Regression at Individual Stock Levels

Consistent with the earlier analyses, robustness checks were carried out for this multiple linear regression model.

4.3.2.2.4.1 Commerzbank

The first robustness check includes the data of Commerzbank stocks. With regards to after-hours disagreement, the recoded variable was employed again.

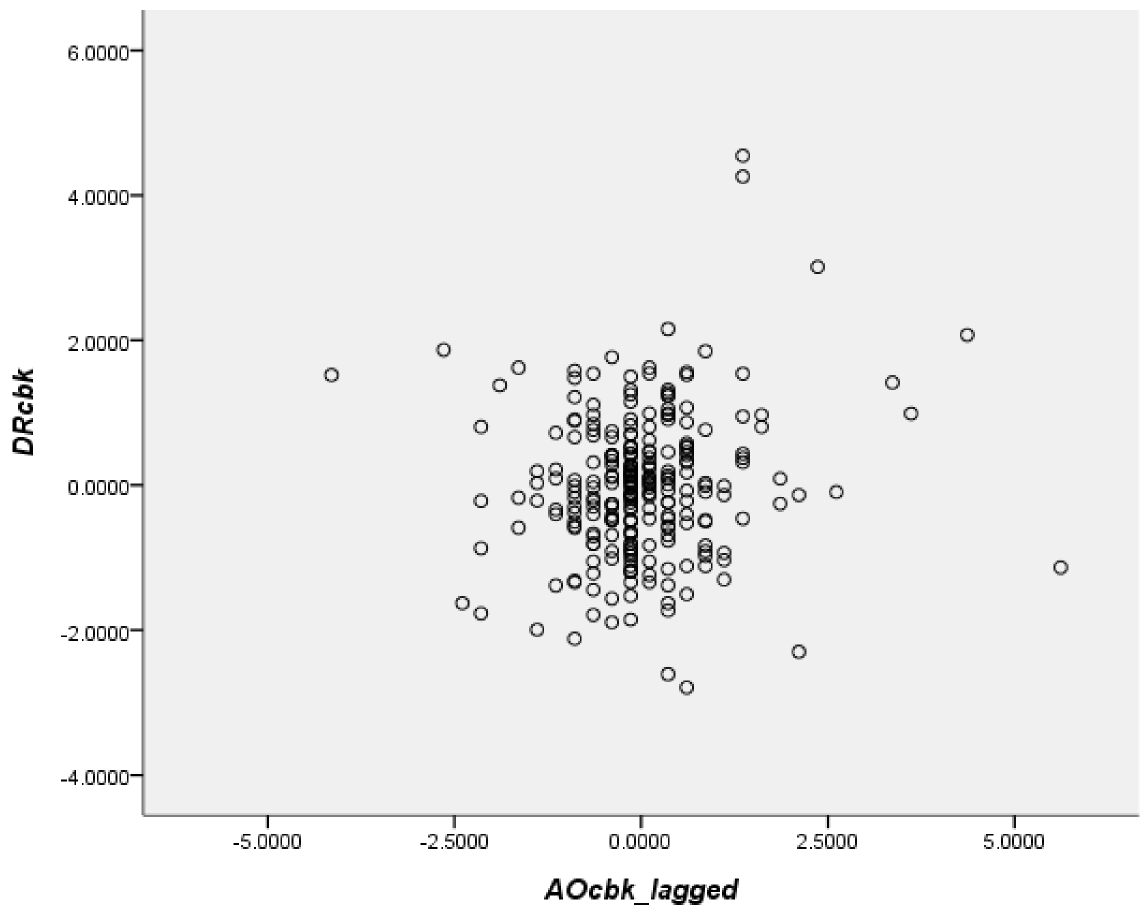
$$\begin{aligned} &DRcbk_t=\beta_0+\beta_1(DRcbk_{t-1})+\beta_2(AOcbk_{t-1})+\beta_3(APVcbk_{t-1}) \\ &+\beta_4(ADcbk\_recoded_{t-1})+\beta_5(DTVcbk_t)+\beta_6(DVcbk_t)+\beta_7(AW_t)+\beta_8(M_t) \\ &+\beta_9(DNcbk_t)+\varepsilon_t \end{aligned} \tag{23}$$

4.3.2.2.4.1.1 Assumptions of Multiple Linear Regression

Except for daily corporate news, *DNcbk*, all variables used in this first robustness check had been ensured already earlier to represent measurable quantitative variables. Since the categorical variable *DNcbk* was coded as an indicator variable, it could be employed in the multiple regression model.

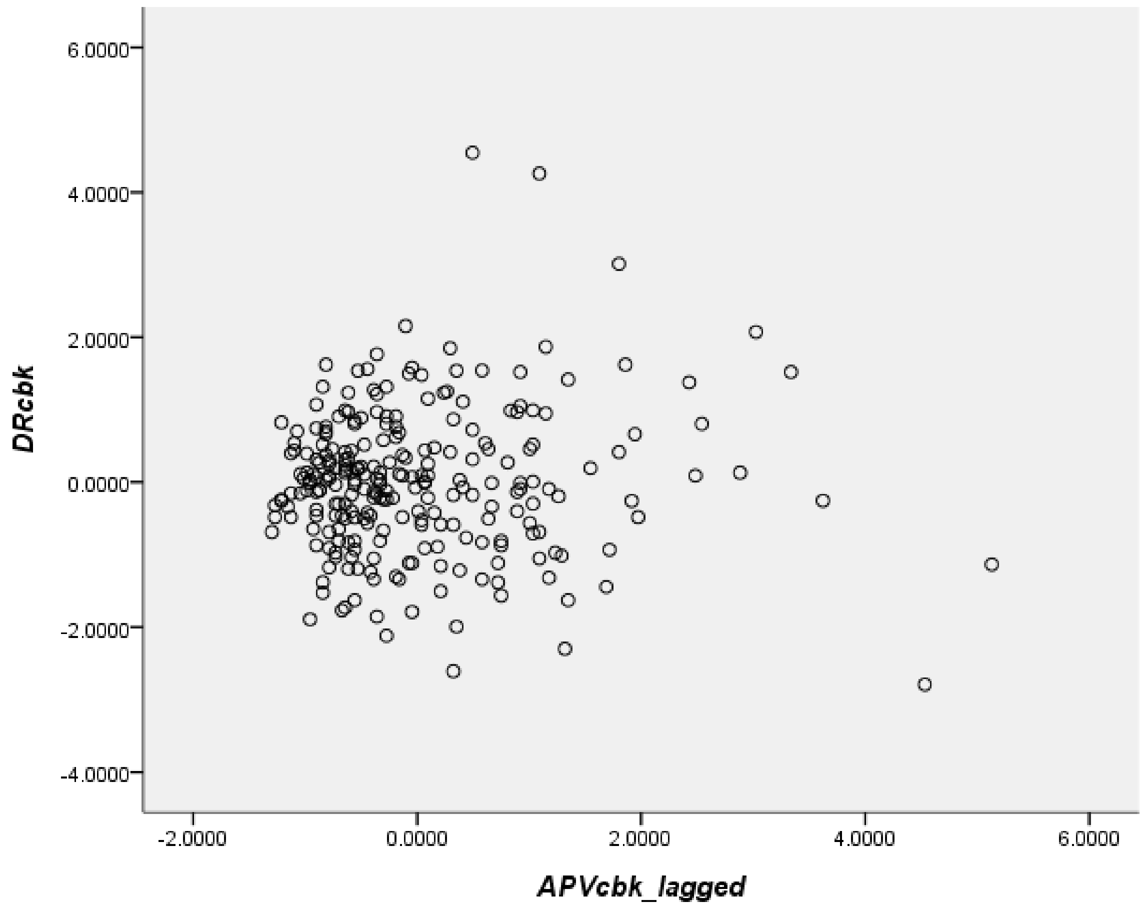
For the purpose of checking the linearity, outlier and homoscedasticity conditions, relevant scatterplots were again inspected. According to the scatterplot of $AOcbk_{t-1}$ against *DRcbk*, as shown in Figure 51, problematic features are not observed. A nonlinear association is not identified and striking outliers or a deviation from homoscedasticity are not suggested.

Figure 51: Scatterplot of $AOcbk_{t-1}$ against *DRcbk*



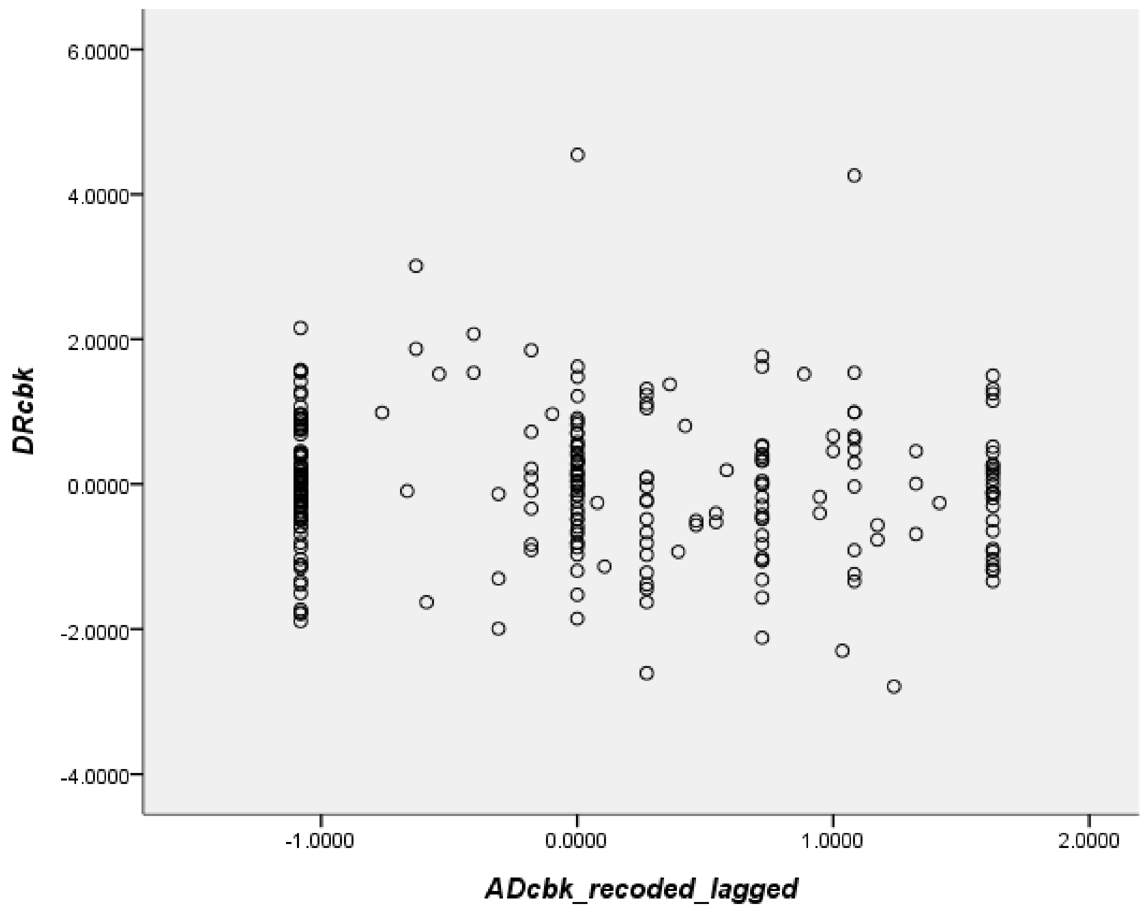
The scatterplot of *APVcbk*$_{t-1}$ against *DRcbk,* which can be seen in Figure 52, does not imply either a linear or a nonlinear relationship. It might be argued that the variance of the data points increases somewhat; however, when the two rightmost data points, which might constitute outliers, are removed, the deviation from homoscedasticity virtually disappears.

Figure 52: Scatterplot of *APVcbk*$_{t-1}$ against *DRcbk*



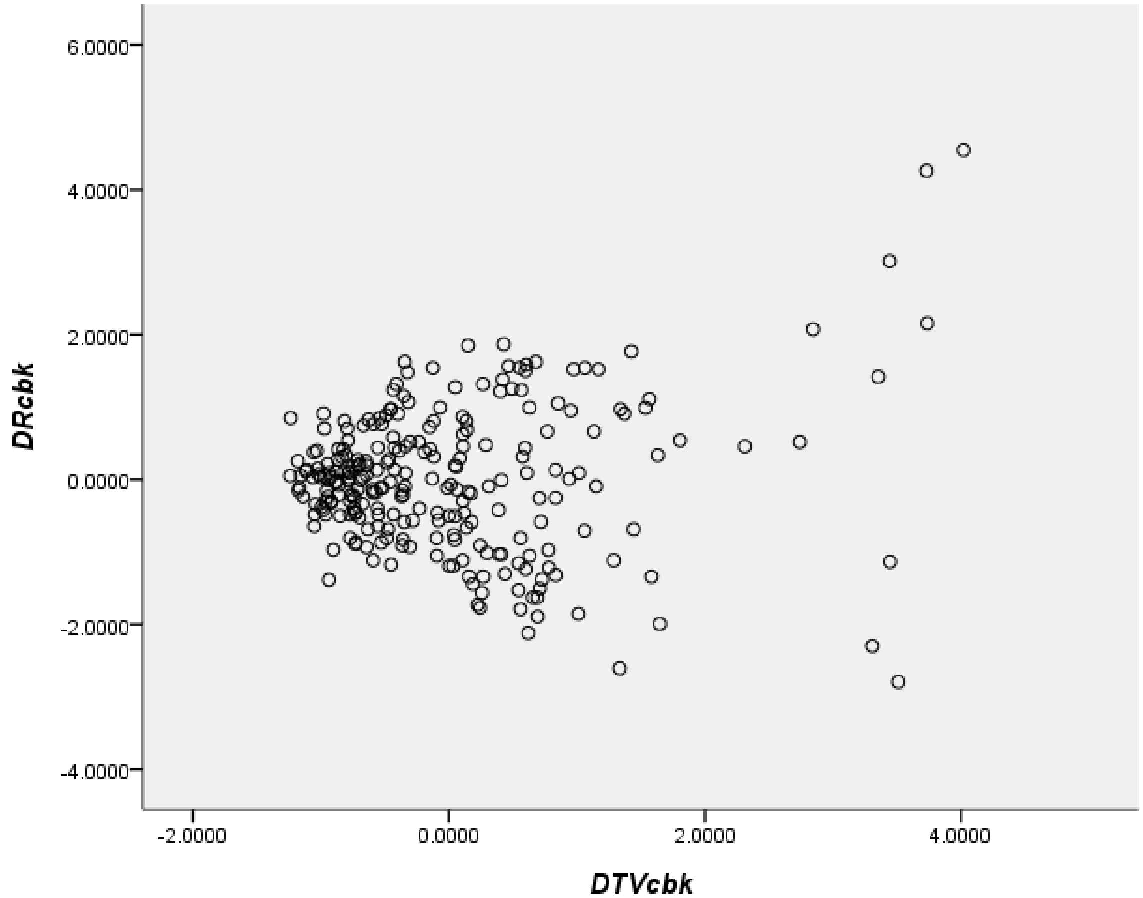
According to the scatterplot of *ADcbk_recoded*$_{t-1}$ against *DRcbk* in Figure 53, critical patterns with regards to linearity, outliers and homoscedasticity are not identified.

Figure 53: Scatterplot of *ADcbk_recoded*$_{t-1}$ against *DRcbk*



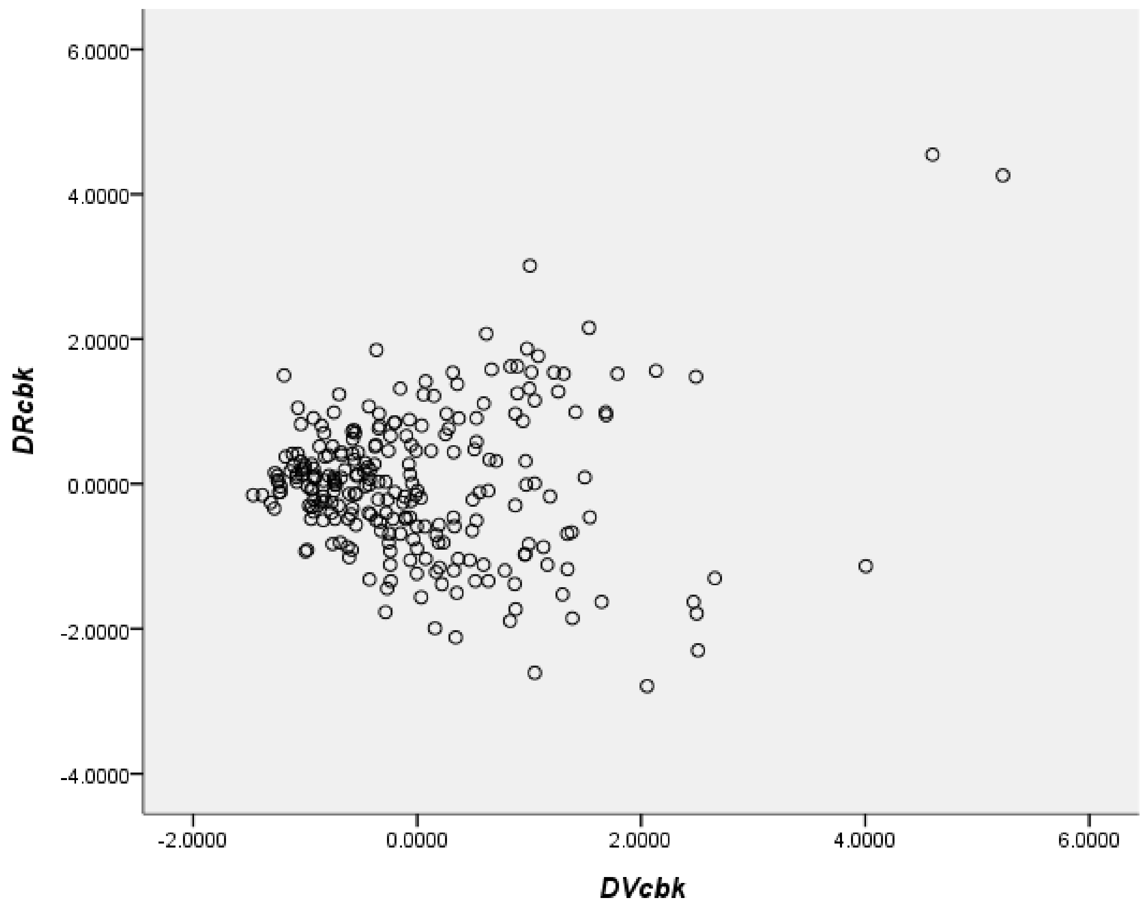
As far as the scatterplot of *DTVcbk* against *DRcbk* in Figure 54 is concerned, while nonlinear features are not observed, the variance of the data points tends to become larger with increasing values of *DTVcbk*. However, if the high leverage points in the right corner of the scatterplot are removed, a deviation from homoscedasticity is no longer observed. Overall, the relationship between *DTVcbk* and *DRcbk* seems to be similar to that of the equivalent variables in the primary model; that is, the relationship between *DTV* and *DR*.

Figure 54: Scatterplot of *DTVcbk* against *DRcbk*



As shown in Figure 55, although the scatterplot of *DVcbk* against *DRcbk* does not hint at nonlinearity, it also shows somewhat increasing variance in the data points. If two potential outliers in the upper right corner of the scatterplot are deleted, the impression of changing variance becomes weakened.

Figure 55: Scatterplot of *DVcbk* against *DRcbk*



Overall, in none of the relationships between each of the independent variables with the dependent variable, a material violation of the assumptions with respect to linearity, outliers and homoscedasticity is supposed to have occurred. The relevant assumptions are at least approximately fulfilled.

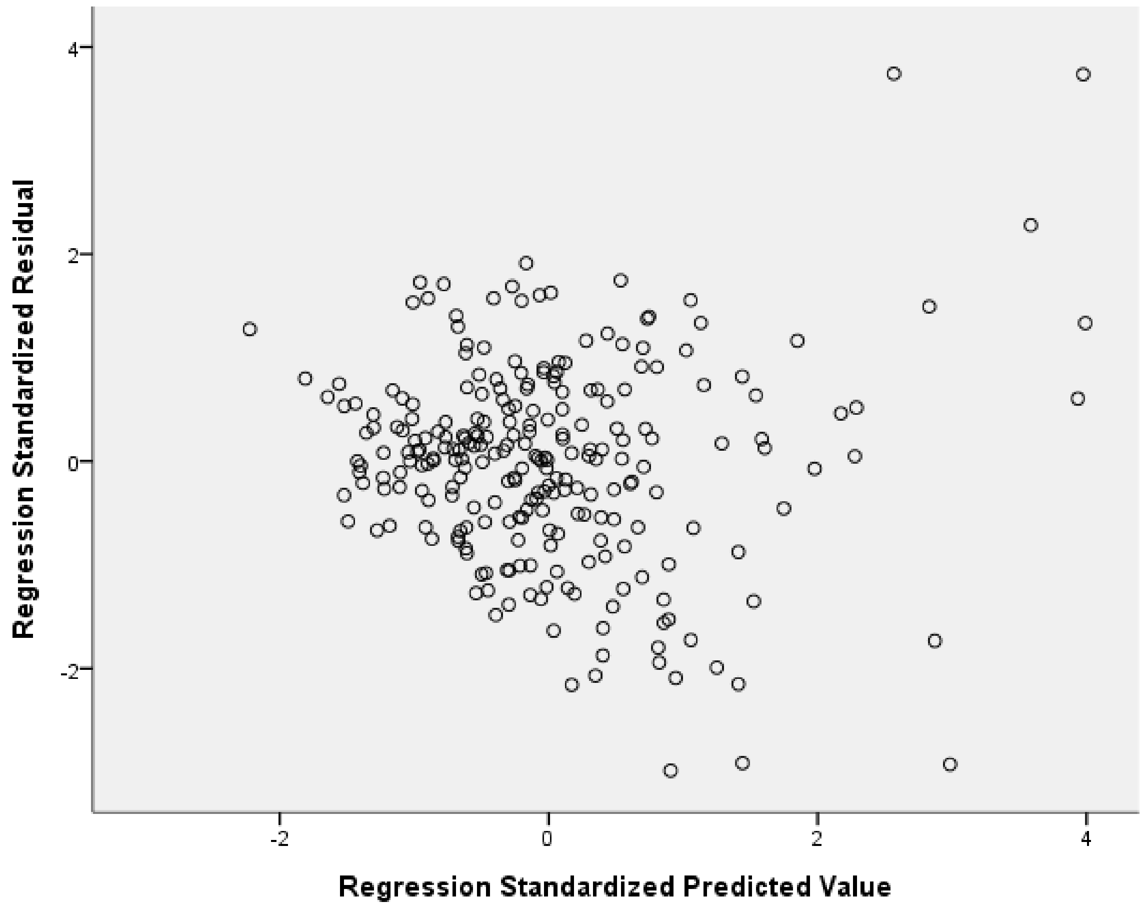
The underlying structure of the multiple linear regression models in the robustness checks remains unchanged compared to the primary model. The ratio of cases to independent variables is therefore identical to that in the primary model and exceeds the minimum ideal ratio.

The highest VIF value is again exhibited by the variable that is associated with daily stock trading volume. *DTVcbk* shows a VIF value of 2.679, which does not hint at a critical degree of multicollinearity (O'Brien, 2007).

As to Mahalanobis Distance, nine degrees of freedom are relevant again, which implies a critical chi-square value of 27.88 at an alpha level of 0.001 (Tabachnick & Fidell, 2007). Fourteen multivariate outliers are identified, which does not appear to be excessive, given the number of 252 cases (Coakes & Ong, 2011). Again, it was not deemed necessary to construct an alternative multiple regression model that corrects for the outliers.

As shown in Figure 56, according to the scatterplot of residuals, a nonlinear relationship is not suggested. However, the variance of the data points seems to increase somewhat. When potential outliers in the upper right corner are removed, the impression of changing variance tends to disappear.

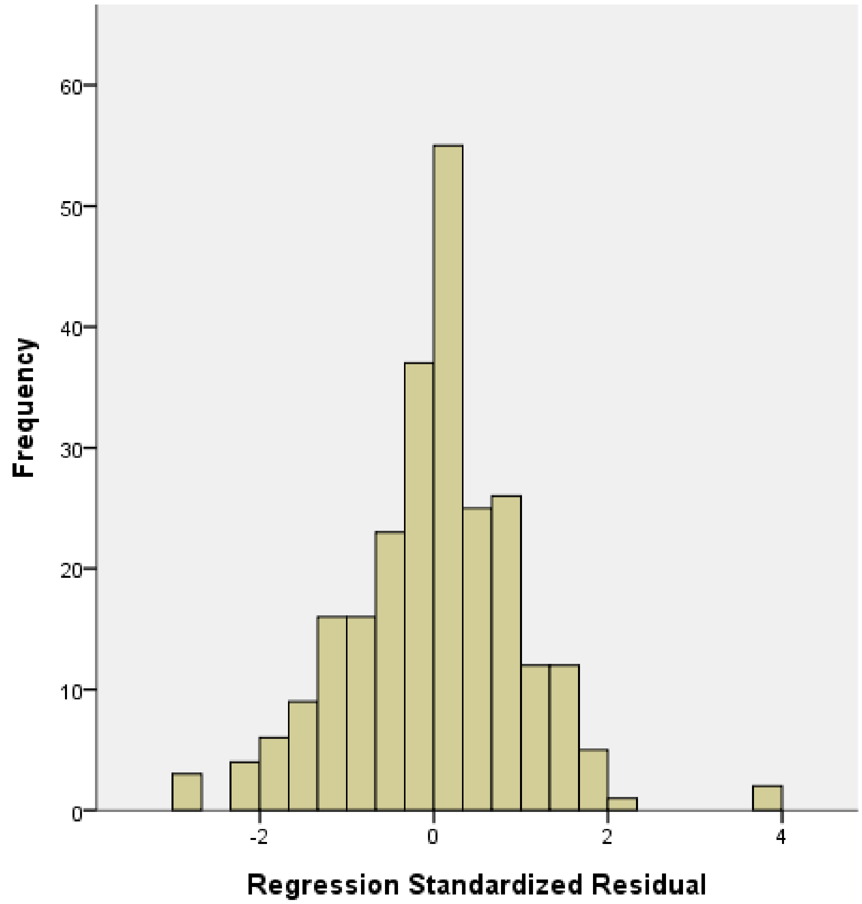
Figure 56: Scatterplot of Predicted Values against Residuals (Second Multiple Regression – First Robustness Check)



With respect to independence of residuals, the Durbin-Watson test statistic indicates a value of 2.010. As this value implies virtually no serial correlation at all (Durbin & Watson, 1950), the independence condition was supposed to be fulfilled.

The histogram illustrating the distribution of the regression residuals, which can be seen in Figure 57, shows that this distribution approximately follows the normal distribution. Although the distribution is relatively peaked, it is at least symmetric and unimodal in shape.

Figure 57: Histogram of Distribution of Residuals (Second Multiple Regression – First Robustness Check)



4.3.2.2.4.1.2 Interpretation of the Regression Coefficients

The assumptions of multiple linear regression were at least roughly met in this first robustness check; hence the multiple linear regression model was set up as originally devised in equation 23. The results of the regression are summarized in Table 8.

Table 8: Regression Results (Second Multiple Regression – First Robustness Check)

Intercept	-0.020
$DRcbk_{t-1}$	-0.001
$AOcbk_{t-1}$	0.033
$APVcbk_{t-1}$	-0.067
$ADcbk\_recoded_{t-1}$	-0.083
DTVcbk	0.193*
DVcbk	0.011
AW	0.079
M	-0.070
DNcbk	-0.186
N	252
R-squared	0.043

*Significant at 10%

**Significant at 5%

***Significant at 1%

The coefficient of 1-day lagged daily stock returns, $DRcbk_{t-1}$, does not differ from zero to a statistically significant degree (p=0.991). Similar to the primary model, 1-day lagged daily stock returns were not considered a significant factor in explaining contemporary daily stock returns.

As far the other regression coefficients are concerned, neither the negative constant term (p=0.831), nor the positive coefficient of $AOcbk_{t-1}$ (p=0.686), nor the negative coefficient of $APVcbk_{t-1}$ (p=0.400), nor the negative coefficient of $ADcbk\_recoded_{t-1}$ (p=0.239), nor the positive coefficient of *DTVcbk* (p=0.063), nor the positive coefficient of *DVcbk* (p=0.898), nor the positive coefficient of *AW* (p=0.544), nor the negative coefficient of *M* (p=0.667), nor the negative coefficient of *DNcbk* (p=0.576) is significantly different from zero. None of the independent variables suggested for the multiple linear regression model in this first robustness check is a significant factor in explaining daily stock returns.

4.3.2.2.4.1.3 Evaluation of the Multiple Linear Regression Model

According to the coefficient of determination, R-squared, 4.3% of the variability in the daily stock returns of Commerzbank, *DRcbk*, can be attributed to the independent variables. The remaining 95.7% of the variability is not accounted for by the regression model, however. Adjusted R-squared shows a value of 0.008. The F-test statistic indicates a value of 1.212 but it is not statistically significant (p=0.288). As none of the regression coefficients has been found to be significantly different from zero, this multiple linear regression model is no superior to modeling the daily stock returns of Commerzbank, *DRcbk*, simply by their mean value.

4.3.2.2.4.2 Deutsche Bank

The second robustness check involves Deutsche Bank stocks. Again, the recoded variable of after-hours disagreement was employed.

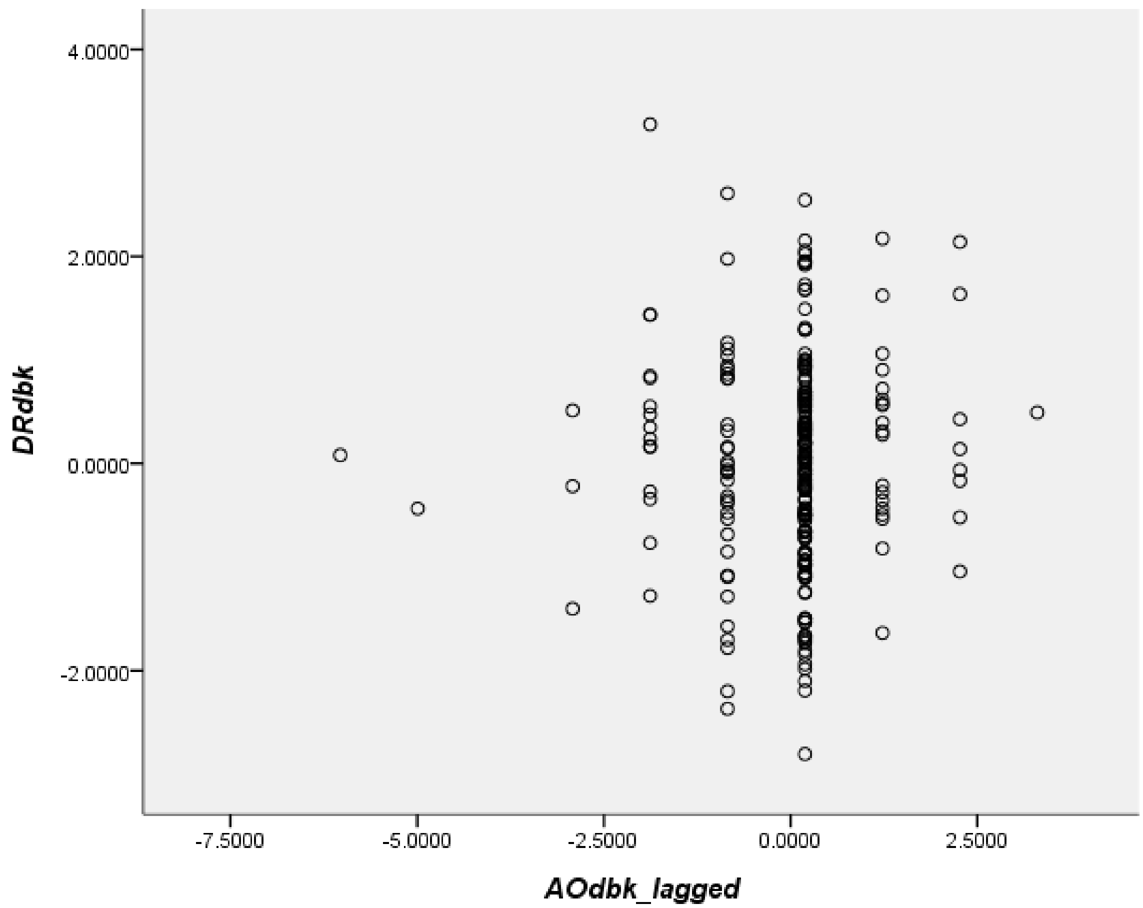
$$\begin{aligned} DRdbk_t &= \beta_0+\beta_1(DRdbk_{t-1})+\beta_2(AOdbk_{t-1})+\beta_3(APVdbk_{t-1}) \\ &+\beta_4(ADdbk\_recoded_{t-1})+\beta_5(DTVdbk_t)+\beta_6(DVdbk_t)+\beta_7(AW_t)+\beta_8(M_t) \\ &+\beta_9(DNdbk_t)+\varepsilon_t \end{aligned} \tag{24}$$

4.3.2.2.4.2.1 Assumptions of Multiple Linear Regression

Except for the variable representing daily corporate news, *DNdbk*, all variables incorporated into this second robustness check had been ensured already earlier to constitute measurable quantitative variables. Since the categorical variable *DNdbk* was coded as an indicator variable, it could be used in the multiple linear regression model.

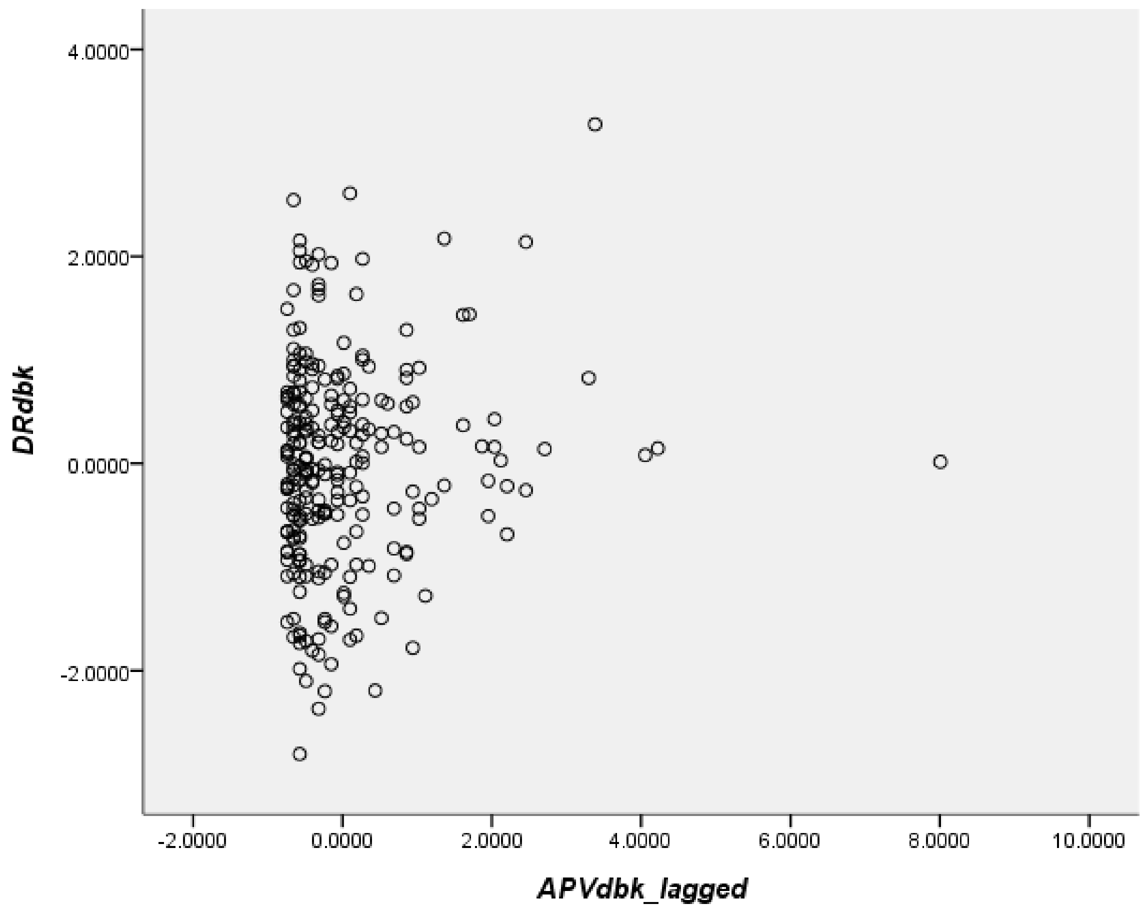
When inspecting the scatterplot of $AOdbk_{t-1}$ against *DRdbk*, as shown in Figure 58, critical patterns are not observed. Nonlinearity and striking outliers are not suggested and the homoscedasticity condition is fulfilled.

Figure 58: Scatterplot of $AOdbk_{t-1}$ against *DRdbk*



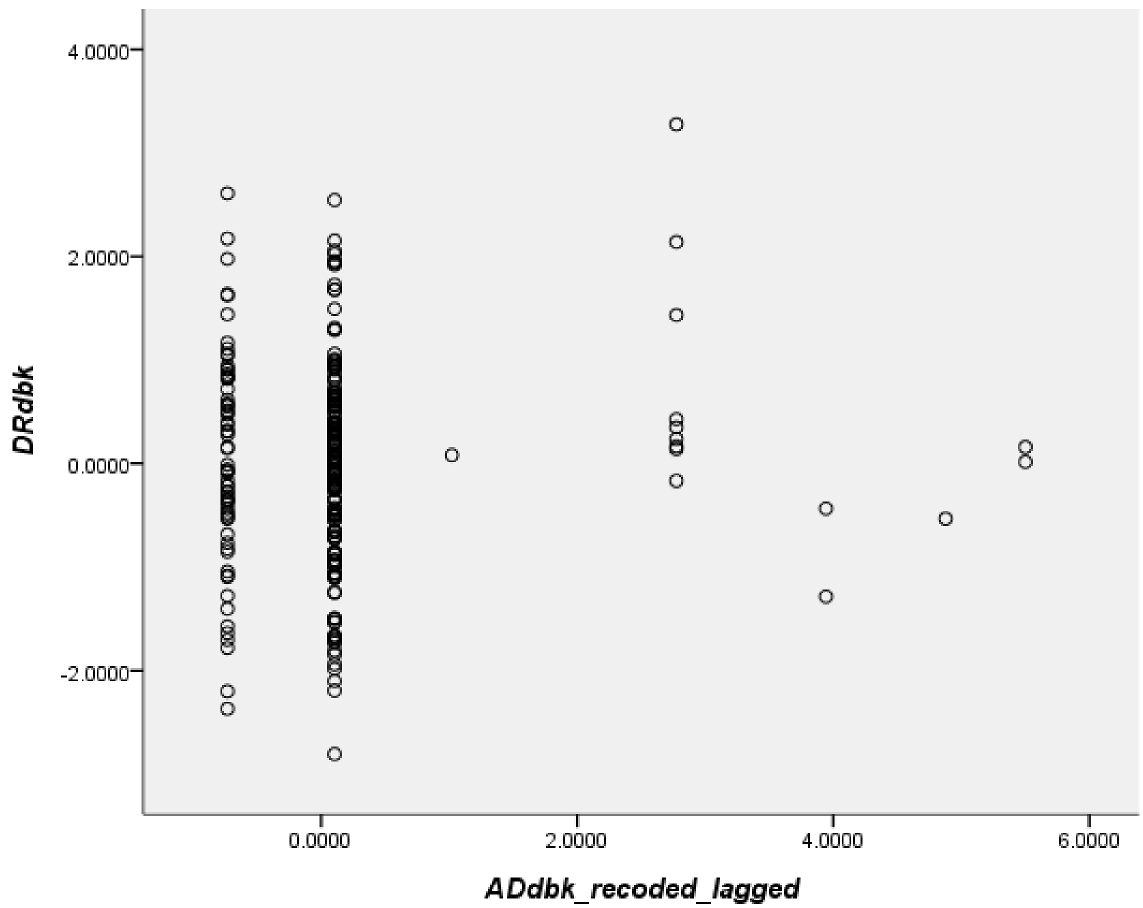
According to the scatterplot of $APVdbk_{t-1}$ against *DRdbk*, which can be seen in Figure 59, nonlinearity is not suggested. It might be argued that the rightmost and the upmost data point reflect outliers. While these outliers are not particularly striking, homoscedasticity appears to be roughly given.

Figure 59: Scatterplot of *APVdbk*$_{t-1}$ against *DRdbk*



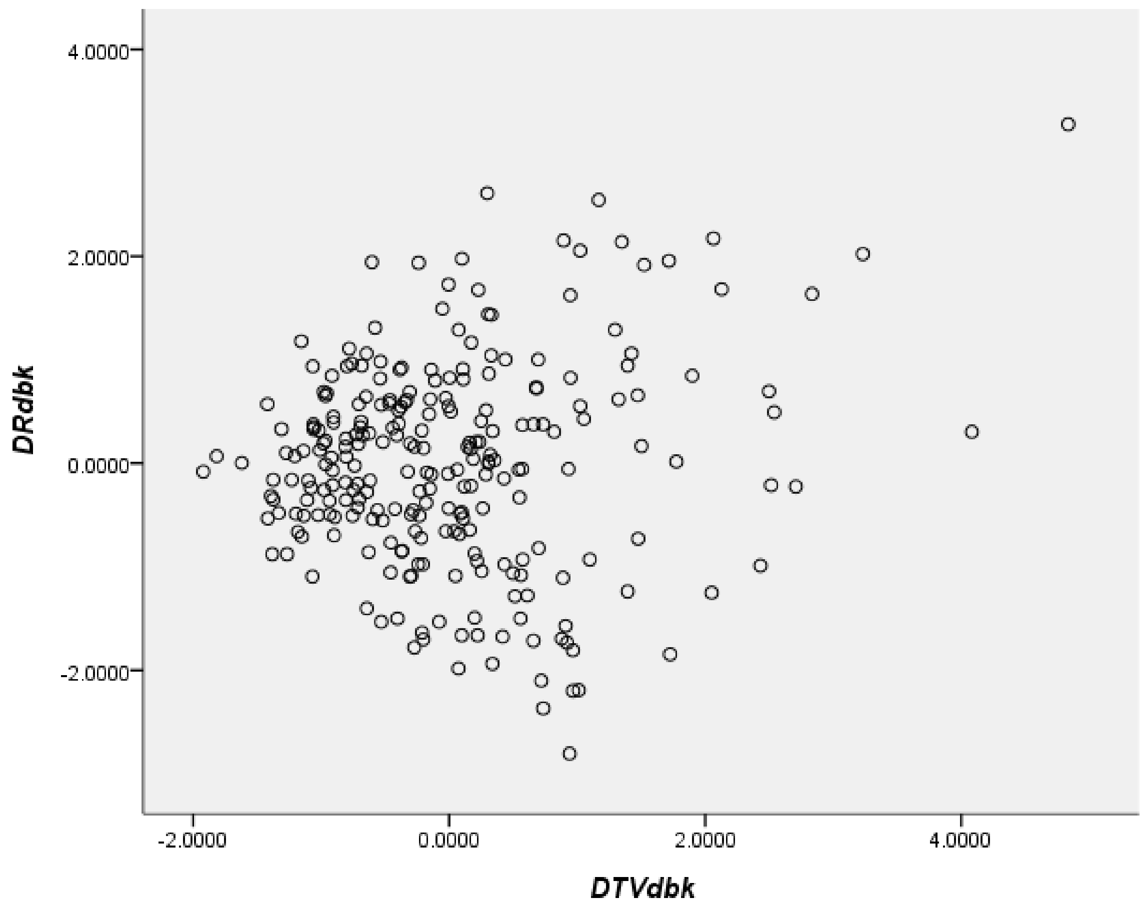
The appearance of the scatterplot of *ADdbk_recoded*$_{t-1}$ against *DRdbk,* as shown in Figure 60, illustrates the fact that various missing values of after-hours disagreement were replaced by mean substitution and that certain other values of after-hours disagreement also occurred more than once. Furthermore, nonlinear features, outliers or a violation of the homoscedasticity condition are not suggested.

Figure 60: Scatterplot of *ADdbk_recoded*$_{t-1}$ against *DRdbk*



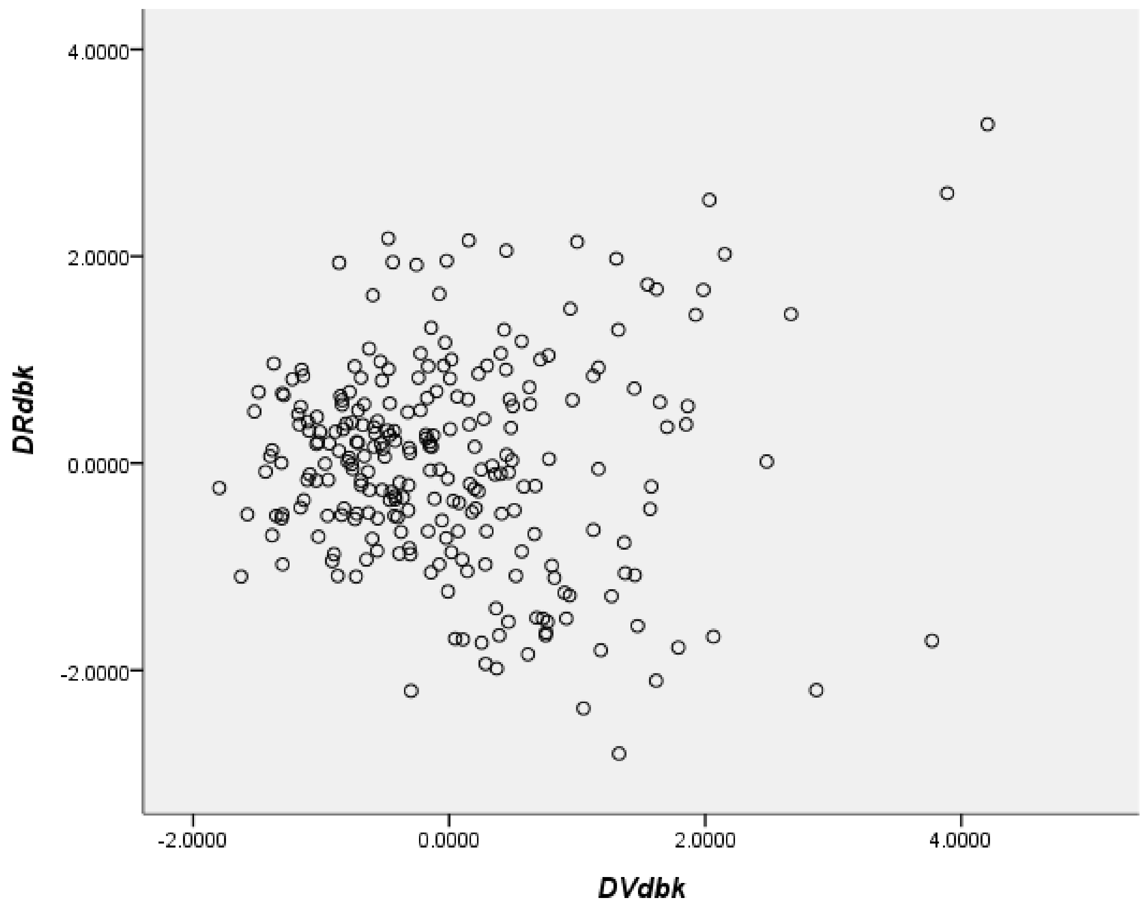
According to the scatterplot of *DTVdbk* against *DRdbk*, which can be seen in Figure 61, neither nonlinearity, nor a deviation from homoscedasticity is identified. However, it might be argued that the data point in the upper right corner represents an outlier.

Figure 61: Scatterplot of *DTVdbk* against *DRdbk*



When analyzing the scatterplot of *DVdbk* against *DRdbk*, as shown in Figure 62, problematic patterns are not observed except for two potential outliers in the right upper corner. However, these data points are not particularly salient. It is not observed either nonlinearity or a violation of homoscedasticity.

Figure 62: Scatterplot of *DVdbk* against *DRdbk*



By and large, in none of the individual relationships between each independent variable with the dependent variable, the assumptions concerning linearity, outliers and homoscedasticity are assumed to be substantially violated. The necessary assumptions are at least approximately met.

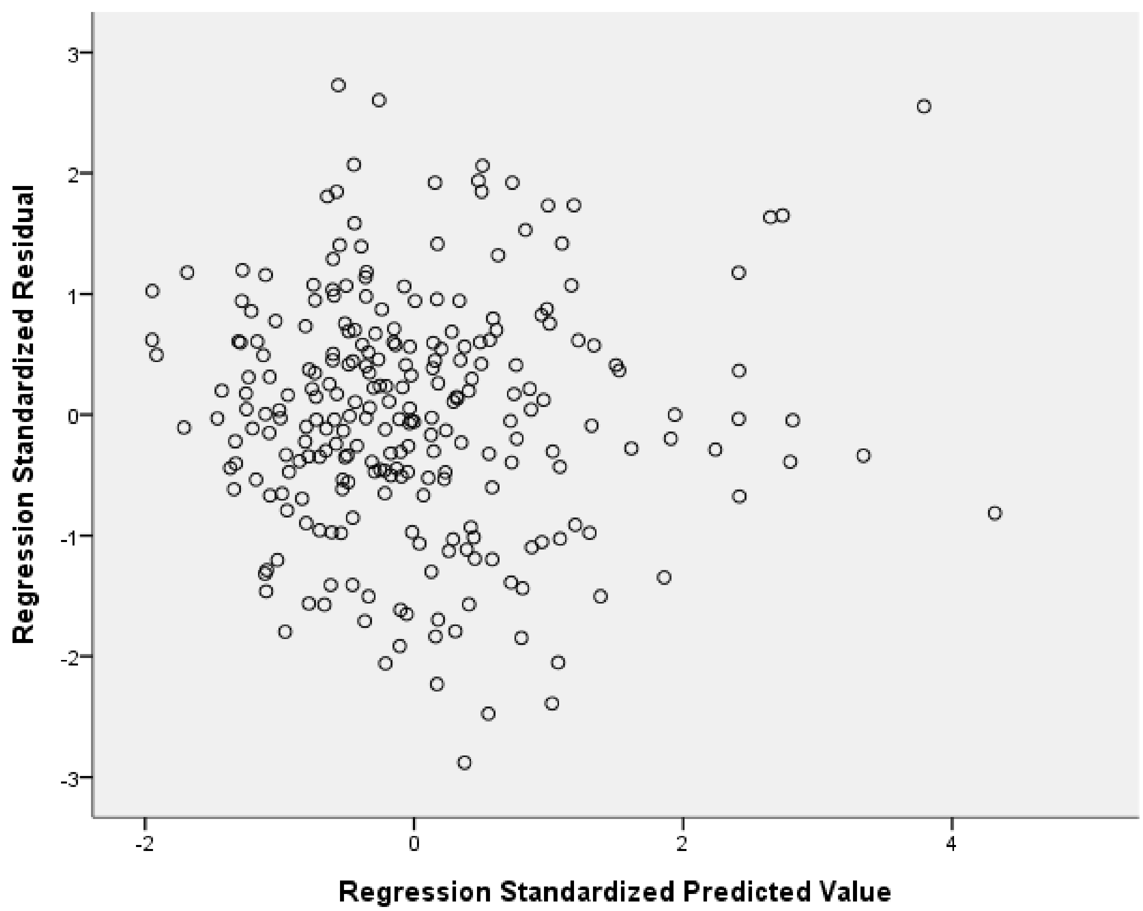
As stated earlier, the minimum ideal ratio of cases to independent variables is exceeded in the robustness checks. The highest VIF value in this second robustness check refers to daily stock trading volume, *DTVdbk*. As this VIF value amounts to only 1.480, multicollinearity was not suspected to adversely affect the regression model (O'Brien, 2007).

Regarding Mahalanobis Distance, nine degrees of freedom are relevant and the critical chi-square value equals 27.88, given an alpha level of 0.001 (Tabachnick & Fidell, 2007).

Accordingly, 13 multivariate outliers are suggested, which is unobjectionable and roughly comparable to the first robustness check.

As shown in Figure 63, the scatterplot of residuals does not indicate critical patterns regarding linearity and homoscedasticity.

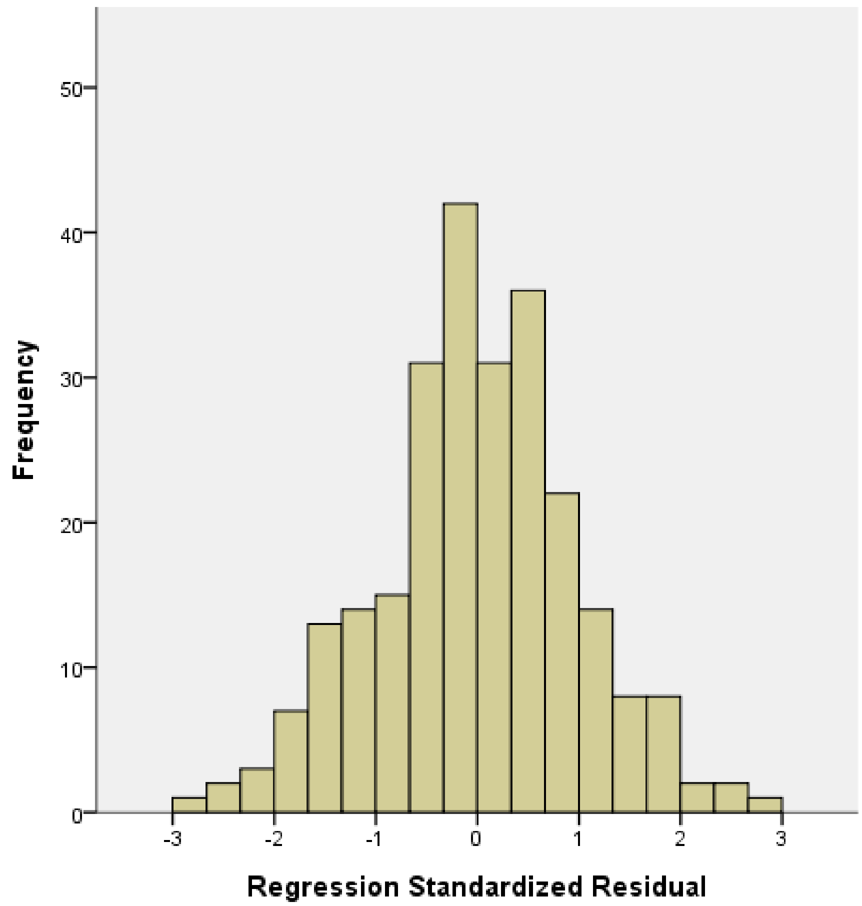
Figure 63: Scatterplot of Predicted Values against Residuals (Second Multiple Regression – Second Robustness Check)



As the Durbin-Watson test statistic shows a value of 1.985, material serial correlation is not suggested (Durbin & Watson, 1950). The residual values were assumed to be independent of each other.

Finally, as the histogram of the distribution of residuals, which can be seen in Figure 64, indicates symmetric shape, this distribution was supposed to follow the normal distribution at least in an approximate sense.

Figure 64: Histogram of Distribution of Residuals (Second Multiple Regression – Second Robustness Check)



4.3.2.2.4.2.2 Interpretation of the Regression Coefficients

The assumptions of multiple linear regression were adhered to at least in an approximate sense in this second robustness check; thus, the regression model was set up as initially suggested in equation 24. An overview of the results of the regression is supplied in Table 9.

Table 9: Regression Results (Second Multiple Regression – Second Robustness Check)

Intercept	-0.049
$DRdbk_{t-1}$	-0.069
$AOdbk_{t-1}$	0.046
$APVdbk_{t-1}$	0.098
$ADdbk\_recoded_{t-1}$	-0.005
DTVdbk	0.137*
DVdbk	-0.051
AW	0.102
M	-0.034
DNdbk	0.060
N	252
R-squared	0.037

*Significant at 10%

**Significant at 5%

***Significant at 1%

The regression coefficient that refers to 1-day lagged daily stock returns, $DRdbk_{t-1}$, is not significantly different from zero (p=0.306). Again, 1-day lagged daily stock returns are no significant predictor of contemporary daily stock returns.

With regards to the other regression coefficients, neither the negative constant term (p=0.609), nor the positive coefficient of $AOdbk_{t-1}$ (p=0.517), nor the positive coefficient of $APVdbk_{t-1}$ (p=0.191), nor the negative coefficient of $ADdbk\_recoded_{t-1}$ (p=0.942), nor the positive coefficient of *DTVdbk* (p=0.075), nor the negative coefficient of *DVdbk* (p=0.501), nor the positive coefficient of *AW* (p=0.447), nor the negative coefficient of *M* (p=0.835), nor the positive coefficient of *DNdbk* (p=0.907) differs from zero to a statistically significant degree. None of the explanatory variables introduced into the multiple linear regression model is a significant factor in explaining daily stock returns.

4.3.2.2.4.2.3 Evaluation of the Multiple Linear Regression Model

The coefficient of determination, R-squared, shows a value of 0.037, which means that 3.7% of the variability in the daily stock returns of Deutsche Bank, *DRdbk*, is explained by the independent variables. Similar to the primary model and the first robustness check, a large proportion of the variability is not accounted for, in this instance 96.3%. Adjusted R-squared is associated with a value of 0.002. The F-test statistic exhibits an insignificant value of 1.044 (p=0.406). While none of the regression coefficients has been found to differ from zero to a significant degree, this multiple linear regression model does not represent an improvement over modeling the daily stock returns of Deutsche Bank merely by their mean value.

4.3.2.2.5 Résumé

As consolidated in Tables 6 to 8, the variables representing lagged daily stock returns do not differ from zero to a statistically significant degree. While this is true both for the primary model and for the two robustness checks, the results from the autocorrelation analysis have been supported. Prior daily stock returns could not be demonstrated to represent a significant factor in explaining contemporary daily stock returns.

Since none of the other variables in the multiple linear regression model is significantly different from zero, either, daily stock returns appear to follow a random walk (Fama, 1965a). In contrast with short-term private investor sentiment, short-term stock returns do not seem to be predictable.

The implications that arise from the findings of the data analysis in this Chapter are discussed in detail in Chapter 5. The limitations of this research study are also outlined in Chapter 5.

CHAPTER 5: DISCUSSION

5.1 INTRODUCTION

In this chapter, the findings of the data analysis from Chapter 4 are interpreted and discussed. Moreover, the limitations associated with this research study are elaborated.

5.2 FINDINGS OF THE DATA ANALYSIS

As the data analysis provides the basis for answering the research questions, the research results were interpreted at length. In the following, first, the two research questions are directly addressed. Then, the broader implications of the research findings are discussed. Finally, ancillary issues also suggested by the results of the data analysis are elaborated.

5.2.1 DOES EXTRAPOLATION BIAS EXIST AMONG PRIVATE INVESTORS?

5.2.1.1 EMPIRICAL RESULTS

According to the data analysis in Chapter 4, private investor sentiment towards future short-term stock returns depends upon most recent short-term stock returns. Private investors appear to refer to and disproportionately extrapolate past stock returns for the purpose of forming expectations for future stock returns. In specific, after-hours sentiment among private investors, as exhibited in stock message boards, has been shown to be positively predicted by the preceding daily closing stock returns. For that reason, the first research question of whether extrapolation bias exists among private investors must be affirmed.

5.2.1.2 RESULTS IN THE LIGHT OF EXISTING STUDIES

While several existing studies address medium-term and long-term extrapolation bias, only few studies analyze extrapolation bias specifically on a short-term daily basis. Grinblatt and Keloharju (2000) support the existence of extrapolation bias concerning daily stock returns. They report that foreign investors in the Finnish stock market tended to purchase stocks that had appreciated the preceding trading day, whereas these investors tended to sell stocks that had depreciated the preceding trading day. As such foreign investors were supposed to include professional investors rather than private investors, Grinblatt and Keloharju (2000) did not find domestic private investors to be affected by short-term extrapolation bias. Even more, Finnish private investors were prone to opposite contrarian behavior while they tended to buy recent losers but were likely to sell recent winners.

According to Hibbert, Daigler and Dupoyet (2008), a negative association exists between daily stock returns and the implied volatilities of related stock options. This finding hints at short-term extrapolation bias among the participants in stock markets. Unfortunately, Hibbert, Daigler and Dupoyet (2008) do not differentiate between private investors and professional investors. Das, Martínez-Jerez and Tufano (2005) who also analyzed stock message boards suggest that private investors might show a tendency to extrapolate previous stock returns.

5.2.2 DOES EXTRAPOLATION BIAS BY PRIVATE INVESTORS HAVE AN EFFECT ON THE MARKET PRICES OF STOCKS?

5.2.2.1 EMPIRICAL RESULTS

Since the data analysis does not support positive autocorrelation in daily stock returns, the evidence of extrapolation bias by private investors identified earlier in this study does not appear to be reflected in the pricing of stocks. For that reason, the second research question of whether extrapolation bias by private investors has an effect on the market prices of stocks must be negated.

5.2.2.2 RESULTS IN THE LIGHT OF EXISTING STUDIES

Several existing studies underline the finding that daily stock returns do not show positive autocorrelation. Early empirical research by Fama (1965b) found no evidence of daily stock prices being autocorrelated. More recent research in the context of a developing market could not demonstrate autocorrelation in daily stock returns, either (Hasan, 2004). Following Tumarkin and Whitelaw (2001), who also analyzed stock message boards, US technology stocks do not appear to be autocorrelated.

By way of contrast, other research posits that daily stock prices are characterized by positive autocorrelation. Erdinc (2006) reports positive autocorrelation in the daily returns of the developing Turkish stock market. According to Watanabe (2002), even the daily stock returns in developed economies, such as Japan, tend to be autocorrelated. However, while he found positive autocorrelation in an environment of low price volatility, autocorrelation turned negative during periods of high volatility. Assuming that volatility is lower during bull markets than during bear markets (Kearns & Pagan, 1993), Watanabe's (2002) finding is inconsistent with Erdinc (2006), who posits that positive autocorrelation tends to be more pronounced during bear markets than during bull markets. It appears that the degree of liquidity and competition in a market plays a role for whether stock returns are positively autocorrelated or not. According to DePenya and Gil-Alana (2007), the originally positive autocorrelation in daily Spanish stock returns dissipated over time, as the Spanish stock market became more efficient.

5.2.3 BROADER IMPLICATIONS OF THE RESEARCH FINDINGS

Following from the research results in Chapter 4, more general issues are broached than merely those that narrowly refer to answering the research questions. More specifically, the research results provide support for the existence of the random walk hypothesis and efficient markets. On the other hand, while this study was able to distinguish between private and professional investors, the irrationality of private investors is hinted at and the concept of *homo economicus* is rejected.

5.2.3.1 RANDOM WALK HYPOTHESIS AND MARKET EFFICIENCY ISSUES

This study demonstrates that although private investors are impaired by extrapolation bias, the market prices of stocks remain unaffected. Since stock returns were not found to be predictable, the random walk hypothesis (Fama, 1965a) cannot be rejected for this sample. Recent empirical research underlines that daily stock prices tend to follow a random walk. Respective evidence was provided both for developed markets (for instance, Auer & Schuster, 2011) and for developing markets (for instance, Tabak, 2003). On the other hand, Lo and MacKinlay (1988) rejected the random walk hypothesis, as they found evidence of serial correlation in the weekly returns of US stocks. A tendency towards price behavior that contradicts the random walk hypothesis also appears to have emerged ever since the most recent financial crisis in the markets of frontier economies (Auer & Schuster, 2011).

Against the background of price behavior consistent with the random walk in this study, EMH is assumed to dominate in its weak form. According to weak-form EMH, while all available information with respect to past returns is always reflected in current market prices, trading rules that merely incorporate past returns data cannot be profitable (Fama, 1970). In practice, profitability will not be given at least after taking account of transactions costs (Joo & Dickinson, 1993).

Provided that private investors actually take the investment decisions that are consistent with their opinions, they can be assumed to purchase stocks when their sentiment is positive and sell stocks when their sentiment is negative. If only private investors participated in the stock market, private investor sentiment would inevitably have an impact on the market prices of stocks. Following high private investor sentiment, prices would be bid up, whereas following low private investor sentiment, prices would be bid down. However, this price behavior is not suggested by the research findings in this study, which show that subsequent stock prices are uncorrelated with private investor sentiment. Obviously, the private investors investigated in this study were not representative of the marginal investor; hence their biases were unlikely to move prices. Other classes of investors are likely to exist who counteract the behavior of private investors and offset the effects of biased private investor extrapolation on the market prices of stocks. More sophisticated investors, probably professional investors, seem to carry out arbitrage transactions and promptly correct for overreactions caused by private investors. Given the stocks examined in this sample are highly liquid blue-chip stocks, there are no apparent limits to arbitrage that may impinge upon the ability of sophisticated investors trading away any mispricing (Shleifer & Vishny, 1997).

An alternative explanation for why market prices remain unaffected after private investors have become impaired by extrapolation bias is available. Different behavioral biases, which have opposing effects on market prices, might occur simultaneously. As some biases implicate investor overreaction while others entail investor underreaction (Chan, Frankel & Kothari, 2004), it cannot be ruled out that they perfectly offset each other and the combined effect of behavioral biases on market prices is zero. Finally, it is also possible that part of a mispricing caused by extrapolation bias is offset by an opposing bias, with the remainder of the mispricing being eliminated by arbitrageurs.

5.2.3.2 PRIVATE INVESTORS VS. PROFESSIONAL INVESTORS

Following the preceding argument, it appears likely that at least some professional investors are not affected by extrapolation bias and enter into stock market transactions that offset those of private investors. The supposition that professional investors are less likely to rely on the biased extrapolation of past stock returns than private investors is also suggested by previous research (Bange, 2000; Chen, Kim, Nofsinger & Rui, 2007).

On the other hand, Grinblatt and Keloharju (2000) report that professional investors rather than private investors are prone to extrapolating past stock returns into the future. Although Chen, Kim, Nofsinger and Rui (2007) show, again consistent with the results in this study, that private investors are generally more susceptible to extrapolation bias than professional investors, they also demonstrate that the degree of experience among private investors tends to be positively related to their susceptibility.

5.2.3.3 INVESTOR RATIONALITY VS. INVESTOR IRRATIONALITY AND THE CONCEPT OF HOMO ECONOMICUS

As Grinblatt and Keloharju (2000) posit that buying past winners and selling past losers leads to superior investment performance, investor extrapolation may well involve reason. Chen, Kim, Nofsinger and Rui (2007) argue that irrational investors are associated with lacking predictive abilities and produce inferior investment returns.

Considering the second multiple regression model of this study in Chapter 4, the coefficient of lagged after-hours weighted opinion is not significantly different from zero, which suggests lacking predictive abilities of private investors. Even more, the p-value of 0.424 is far from indicating any statistical significance. The inability of private investors to forecast subsequent stock returns is confirmed by the two robustness checks, where the respective coefficients of lagged after-hours weighted opinion are not significantly different from zero, either. It is concluded that private investors act in an irrational manner while they extrapolate past stock returns for the purpose of forming expectations regarding future stock returns. Such behavior contradicts the concept of *homo economicus*, which assumes rational behavior and an unambiguous promotion of self-interest (Ng & Tseng, 2008).

The notion that private investors lack predictive capabilities is consistent with past research. According to Bange (2000), the portfolio allocation decisions by private investors do not hint at the ability to correctly forecast stock returns. Moreover, Benartzi (2001) reports that the extent to which US employees invest retirement savings into the stocks of their own company is uncorrelated with the company's future stock performance. Similarly, it has been demonstrated in the context of a developing market that the stocks purchased by private investors tend to underperform the stocks sold by private investors (Chen, Kim, Nofsinger & Rui, 2007). Specifically with respect to stock message boards, Tumarkin and Whitelaw (2001) show that the opinions of board participants do not imply predictive capabilities.

5.2.4 RESEARCH FINDINGS ANCILLARY TO THE RESEARCH QUESTIONS

Since the two multiple regression models in this study also include independent variables that are not directly related to the research questions, conclusions can be drawn that go beyond extrapolation bias. The coefficients of some of the independent variables have been found to be significantly different from zero, which suggests that certain relationships exist. In the following, the multiple regressions that explain private investor sentiment and stock returns, respectively, are addressed one after the other.

5.2.4.1 FINDINGS WITH RESPECT TO PRIVATE INVESTOR SENTIMENT

Regarding private investor sentiment, particular relationships are suggested by the regression results. Those findings that indicate statistical significance in a consistent fashion, across both the primary analysis and the robustness checks, are considered to be unambiguous. By way of contrast, findings that are not invariably significant or that would be significant only at an alpha level of 0.10 are deemed ambiguous. An alpha value of 0.10 for the purpose of determining statistical significance constitutes a less rigid alternative to the commonly used alpha value of 0.05 (Dallal, 2001).

5.2.4.1.1 Unambiguous Relationships

Considering the first multiple regression model, one unambiguous relationship is identified. While the coefficient for lagged private investor sentiment has been found to be significantly different from zero, private investor sentiment showed persistence over time. The robustness checks confirm this finding, as the related coefficients indicate statistically significant positive values, too. This discovery implies autocorrelation and persistence in investor sentiment, which is consistent with past research (Tumarkin & Whitelaw, 2001; Das, Martínez-Jerez & Tufano, 2005). Investor sentiment appears to be predictable and seems to develop trends.

5.2.4.1.2 Ambiguous Relationships

Four ambiguous relationships have been uncovered with respect to private investor sentiment. These relationships involve message board posting volume, disagreement among private investors, seasonal effects and weekday effects. First of all, according to the second robustness check of the first multiple regression, the volume of postings uploaded is negatively associated with private investor sentiment to a statistically significant degree. This means that message board participants tend to upload fewer postings when sentiment is high and tend to upload more postings when sentiment is low. However, this finding is not true for the primary regression model, nor is it true for the first robustness check. In the primary regression, although the coefficient for after-hours posting volume is also negative, it is statistically insignificant. In the first robustness check, the related coefficient is positive but statistically insignificant. Therefore, only ambiguous evidence hints at a negative relationship between message board posting volume and private investor sentiment. Considering past research, private investor sentiment has been suggested to be positively associated with the volume of postings uploaded in stock message boards (Antweiler & Frank, 2004; Das, Martínez-Jerez & Tufano, 2005; Das & Chen, 2007). While a positive relationship is not confirmed by the results of this study, it cannot be excluded that the inconsistence with prior research is attributable to the restricted sample in this study.

Moreover, the coefficient for private investor disagreement has been shown to be significantly positive in the second robustness check. This finding implies that high levels of disagreement tend to coincide with high levels of sentiment, whereas low levels of disagreement tend to coincide with low levels of sentiment. However, both in the primary regression and in the first robustness check, the related coefficient is statistically insignificant. While the coefficient is positive in the primary regression, it is negative in the first robustness check. Therefore, only ambiguous evidence exists regarding a positive relationship between disagreement among private investors and private investor sentiment. It should be noted that the validity of the research results might be impaired here to a certain degree since various values for after-hours disagreement were missing in the dataset and needed to be replaced. As previous studies suggest that disagreement among stock message board participants is negatively related to private investor sentiment (Das & Chen, 2007), the findings in this study regarding disagreement are inconsistent with past research.

The coefficient of the dummy variable that indicates autumn or winter is positive both in the primary regression model and in the two robustness checks. Since this variable is significantly different from zero only in the first robustness check, merely ambiguous evidence exists that private investor sentiment is higher during autumn and winter on average than during spring and summer. This finding is not consistent with past research, with different existing studies suggesting that investor sentiment is generally lower during the dark season of the year as a result of mood effects (for instance, Lo & Wu, 2010). It is possible that this inconsistency is due to industry-specific factors that occurred during 2012 when the Eurozone crisis reached its peak and particularly impaired the banking sector (Ahmad, Sehgal & Bhanumurthy, 2013).

As far as the indicator variable for Mondays is concerned, although the coefficient of this variable is not different from zero at an alpha level of 0.05, it is positive at an alpha level of 0.10 in the first robustness check. This finding implies an ambiguous tendency for private investor sentiment to be higher on average on Mondays, which is somewhat supported by the fact that, even though statistically insignificant, the related coefficients in the primary regression model and in the first robustness check also show positive signs. Nonetheless, the turn of investor sentiment to be higher on Mondays seems to be inconsistent with existing studies, as past research reports that a ‘Monday effect’ leads to significantly lower investor mood on the first trading day of the week (Gondhalekar & Mehdian, 2003). It might be possible that the dominance of the Eurozone crisis during 2012 facilitated the occurrence of another surprising result.

5.2.4.2 FINDINGS WITH RESPECT TO STOCK RETURNS

Similar to the first multiple regression model, which explains private investor sentiment, the second multiple regression model also suggests certain relationships that go beyond extrapolation bias. In the following, both the unambiguous findings and the ambiguous findings, as defined earlier, are discussed.

5.2.4.2.1 Unambiguous Relationships

None of the independent variables in the second multiple regression model exhibits coefficients that are significantly different from zero at the 0.05 confidence level. Therefore, there is no evidence of any unambiguous relationships.

5.2.4.2.2 Ambiguous Relationships

One ambiguous relationship is discovered in the second multiple regression. Although the coefficient for trading volume is insignificant at an alpha level of 0.05, at an alpha level of 0.10 it is significantly positive both in the first and the second robustness check. It can be assumed that a certain tendency exists for trading volume and stock returns to be positively associated. This means that high trading volume tends to coincide with high stock returns, whereas low trading volume tends to coincide with low stock returns. Past research documents a positive relationship between trading volume and stock returns (Chordia, Roll & Subrahmanyam, 2000). The ambiguous results reported in this study provide some evidence to support past research.

5.3 LIMITATIONS OF THE STUDY

All research is likely to be affected by certain limitations (Bryman & Bell, 2011). While every study is generally prone to bias by the researcher to unconsciously influence the research results in an anticipated direction (Wilholt, 2009), particular features of a study tend to be associated with specific limitations.

In the following, sample, methodology and methods of analysis that were chosen for this study are challenged with respect to limitations. When generalizing from the research findings of this study, it should always be accounted for the relevant limitations.

5.3.1 SAMPLE

In this study, German blue-chip bank stocks were analyzed throughout the year 2012. It cannot be ruled out that significantly different research results would have emerged, which would have led to different conclusions, if another industry, market segment, year and/or country had been selected. The limitations regarding the chosen sample are discussed in the following. As they affect the generalizability of the research results, these limitations relate to the external validity of the study (Bryman & Bell, 2011).

5.3.1.1 SAMPLE SIZE

Although the size of the sample appears sufficiently large from a statistical perspective, it covers only 1 year, which inevitably restricts variability. If the sample had included a few consecutive years, the impact of the specifics of individual years would have become weakened. Variability is also restricted by the fact that the DAXsubsector Credit Banks index, whose stocks were included in the sample, was composed of only two stocks (Deutsche Börse, 2014).

5.3.1.2 BANKING SECTOR REPRESENTATIVE OF OVERALL STOCK MARKET?

It is questionable whether stocks from the banking sector are representative of the overall stock market. This is particularly true for the year 2012 when the banking industry was severely impaired by the Eurozone crisis (Reichlin, 2014). The overall stock market increased by almost 30% during the course of the year, as reflected in the DAX index. However, blue-chip bank stocks increased only by approximately 14%, as indicated by the DAXsubsector Credit Banks index.

5.3.1.3 FOCUS ON BLUE-CHIP STOCKS

Irrespective of industry affiliation, blue-chip stocks tend to share common characteristics and differ from the stocks that belong to other segments of the market. For instance, the prices of small-cap stocks have generally been found to react more sharply than blue-chip stocks to recommendations or changes in recommendations by securities analysts (Womack, 1996).

5.3.1.4 ENVIRONMENT OF EUROZONE CRISIS

During the year 2012, the Eurozone crisis reached its peak (Ahmad, Sehgal & Bhanumurthy, 2013). While stock prices were characterized by sharp swings, the participants in financial markets exhibited significant uncertainty. It is possible that private investors would have displayed unbiased behavior under normal market conditions, as the degree of biased extrapolation has been shown to be related to risk (Andreassen & Kraus, 1990).

5.3.1.5 CULTURAL ISSUES

Particular cultural environments seem to facilitate the occurrence of certain behavioral biases. While private investors from China have been found to be prone to extrapolation bias (Chen, Kim, Nofsinger & Rui, 2007), private investors from Finland could not be demonstrated to be susceptible to this bias (Grinblatt & Keloharju, 2000). Even in the case of cultures that are rather related, such as Germany and the US, biased behavior tends to prevail to varying degrees (Sowinski, Schnusenberg & Materne, 2011).

5.3.2 METHODOLOGY

In addition to the sample, the methodology of the study entails certain limitations. These limitations, which relate to the specific research design as well as measurement issues, are explained in the following.

5.3.2.1 LIMITATIONS IN THE RESEARCH DESIGN

This study is delimited by the particular philosophical perspective that underlies the research design. Moreover, the study‘s internal validity is affected by the specifics of the research design.

5.3.2.1.1 Philosophical Perspective

As this study incorporates hypothesis testing and relies on a research strategy that is primarily quantitative, it is characterized by deductive positivistic reasoning. However, deductive positivistic reasoning tends to be restricted to challenging existing concepts, in this case extrapolation bias, whereas the development of new theories is unlikely to be supported (Bryman & Bell, 2011).

5.3.2.1.2 Internal Validity of Correlational Studies

Since the research design of this study is correlational, conclusions as to cause-and-effect relationships cannot be drawn easily, which compromises internal validity (De Veaux, Velleman & Bock, 2008). It is true that the existence of associations between variables can be revealed by correlational studies; however, it cannot be inferred unambiguously that particular changes in a variable have actually been caused by particular changes in another variable. Only experimental research designs have the potential to demonstrate causal effects, as they account for omitted variables that might in fact be responsible for a suggested association. Unfortunately, the correlational research design in this study is not immune to omitted variable bias (Clarke, 2005).

5.3.2.2 MEASUREMENT ISSUES AND TECHNICAL SPECIFICS OF THE VARIABLES

Further limitations in the methodology of this study concern the way the constructed variables have been measured as well as related technical specifics. In this regard, the proxy for private investor sentiment, the chosen number of lags in the autocorrelation analysis and the specific computation of stock returns are addressed.

5.3.2.2.1 Proxy for Private Investor Sentiment

It was assumed that the sentiment of private investors can be inferred effectively from the postings uploaded in stock message boards. However, it cannot be ruled out that only a certain subset of private investors participates in stock message boards and that this subset is not representative of the underlying population of private investors. It is possible that the sentiment associated with message board participants differs materially from the sentiment exhibited by private investors.

5.3.2.2.2 Autocorrelation Lags

As far as the autocorrelation of stock returns is concerned, past research reports that different lag lengths are likely to produce different and possibly contradictory results. While a 1-day lag is likely to lead to results that differ from the results generated by a 1-week lag, autocorrelation coefficients may even change sign dependent upon the time frame considered (Kraizberg & Kellman, 1999). Obviously, certain findings that relate to short-term stock returns cannot be generalized beyond the short term.

5.3.2.2.3 Calculation of Stock Returns

Since this study analyzes short-term stock returns, more specifically daily stock returns, over a horizon of merely 1 year, it was desisted from computing abnormal daily stock returns. Raw daily stock returns were considered a reasonable basis for constructing the variables for the statistical analysis. Although deemed unrealistic, it cannot be excluded, however, that the risk-free interest rate and/or the market risk premium have changed materially throughout the year 2012. Such changes might have caused drift in the spread between raw returns and abnormal returns, which would have biased the research results.

5.3.3 METHODS OF ANALYSIS

Two broad methods of analysis were employed in this study. First, QCA was applied to the stock message board postings. Second, different statistical techniques were used for analyzing the quantitative data. The respective limitations of these methods of analysis are outlined in the following.

5.3.3.1 LIMITATIONS OF QCA

QCA entails limitations to the extent that private investor sentiment was gradated for classification purposes. Furthermore, it cannot be ruled out that a certain degree of subjectivity emerged during the qualitative coding of the stock message board postings.

5.3.3.1.1 Gradation of Private Investor Sentiment

Three sentiment categories had been pre-determined for classifying the stock message board postings. As explained in Chapter 3, it was distinguished between postings that imply ‘short-term positive sentiment’, postings that imply ‘short-term negative sentiment’ and postings that imply ‘neither short-term positive sentiment, nor short-term negative sentiment’. Since further refinement within each of these categories was not done, both slightly positive (negative) postings and clearly positive (negative) postings regarding the short term were assigned to the same category. Using separate categories for slightly positive (negative) postings and clearly positive (negative) postings would have allowed for greater differentiation. It cannot be ruled out that the research results of this study would have changed materially if more nuanced categories had been introduced. On the other hand, it appeared that employing more gradated categories would have impaired coding consistency and thus the reliability of the study.

5.3.3.1.2 Subjectivity in Coding

As far as the coding of the stock message board postings through QCA is concerned, a pilot phase including consistency checks was conducted. Nevertheless, it cannot be ruled out that a certain degree of subjectivity was involved in the interpretation and classification of the postings. It cannot be excluded, either, that during the course of the coding, bias developed that caused systematic distortions over time.

5.3.3.2 LIMITATIONS IN QUANTITATIVE STATISTICAL TECHNIQUES

The limitations concerning the quantitative statistical techniques include the assumptions of correlation and regression, the focus on linear associations in the data analysis, the specific assumptions made with respect to statistical significance and the approach towards the missing data in the underlying dataset.

5.3.3.2.1 Correlation and Regression Assumptions

As described in Chapter 4, the data underlying this research study only approximately meets the assumptions of linear statistical inference. More specifically, the existence of outliers cannot be negated entirely in some cases and homoscedastic tendencies are partly observed. Furthermore, it cannot be ruled out that the assumption of normality regarding the variables included in the correlation and regression analysis is ultimately relevant although its importance has been disputed (Nefzger & Drasgow, 1957). The main variables, which directly address the research questions, after-hours weighted opinion and daily stock returns, approach normality closer than the remainder of variables.

5.3.3.2.2 Focus on Linear Associations

Linear correlation and ordinary least squares regression, which were relied on for the data analysis in this study, are only able to discover linear relationships (De Veaux, Velleman & Bock, 2008). As financial time series, for instance stock returns, have been found to exhibit nonlinear features and possibly chaotic structures, it cannot be excluded that significant associations remained undetected in the underlying data set (Hasan, 2004).

5.3.3.2.3 Assumptions Concerning Statistical Significance

With regards to the statistical significance of the correlation and regression coefficients, an alpha value of 0.05 had been pre-selected. Although this alpha value is fairly common in scientific research (Dallal, 2001), relying on a different value would have changed interpretations of the research results. At an alpha value of 0.10, for instance, a larger number of the regression coefficients would turn statistically significant, whereas at an alpha value of 0.01 fewer coefficients would be significant.

5.3.3.2.4 Missing Data

The variables for after-hours disagreement are compromised by various missing values. While mean substitution was used for replacing the missing values, this technique has been found to bias a data set to a certain degree (Olinsky, Chen & Harlow, 2003). It cannot be ruled out that a technique other than mean substitution (Coakes & Ong, 2011) would have altered part of the research results in a material way.

CHAPTER 6: CONCLUSION

6.1 OVERVIEW

This research study investigated whether financial market participants are affected by behavioral bias when forming expectations for future stock returns and whether such bias impacts on market prices. Specifically, the existence of extrapolation bias among private investors and its effect on stock prices were tested. An innovative methodology was introduced, which incorporated the content analysis of stock message board postings in a qualitative fashion. The subsequent quantitative data analysis relied on conventional statistical techniques given a deductive positivistic perspective. This study contributes to the highly topical controversy between neoclassical finance and behavioral finance, as it addresses the rationality of investors and the efficiency of financial markets.

Below, the theoretical contributions following from the research findings and the associated policy implications are elaborated. Recommendations as to future research are also given against the background of the limitations of this study.

6.2 THEORETICAL CONTRIBUTIONS

This research study provides a few theoretical contributions. It contributes to the literatures on behavioral bias, market efficiency, private versus professional investors, investor rationality and investor sentiment.

6.2.1 LITERATURE ON BEHAVIORAL BIAS

The results reported in this study provide evidence that investors are susceptible to behavioral bias. As the sentiment among the participants in stock message boards concerning future stock returns was found to be positively predicted by prior stock returns, private investors tended to be affected by extrapolation bias. This finding is consistent with the behavioral finance paradigm, and appears to be at odds with the neoclassical finance paradigm (Statman, 2005).

6.2.2 EFFICIENT MARKETS LITERATURE

The study also contributes to the efficient markets literature. The second research question of whether extrapolation bias by private investors has an effect on the market prices of stocks was negated because short-term stock returns were not found to be positively autocorrelated. Since negative autocorrelation was not detected, either, and daily stock returns could not be explained by any of the variables that were introduced, short-term stock returns were concluded to follow a random walk. Anomalous pricing was not identified and the weak-form EMH appears to prevail (Fama, 1970).

6.2.3 PRIVATE VS. PROFESSIONAL INVESTORS LITERATURE

Another theoretical contribution refers to the issue of whether private investors, who tend to be less sophisticated than professional investors, are more prone to behavioral biases than professional investors. It was inferred from the research results that private investors are more susceptible to extrapolation bias during financial decision-making than professional investors. As the biased behavior of private investors was not found to be reflected in inefficient prices, it was argued that professional investors arbitrage away any mispricing opportunities. The finding that private investors are more prone to biased behavior than professional investor is consistent with most prior research (for instance, Kempf, Merkle & Niessen-Ruenzi, in press).

6.2.4 LITERATURE ON INVESTOR RATIONALITY

This study also contributes to the literature regarding the rationality of financial market participants. As extrapolating private investors could not be shown to possess predictive abilities and achieve superior investment returns, their judgment and decision-making was deemed to involve irrational behavior. Rational behavior, on the other hand, would be assumed to involve predictive abilities with respect to future stock returns. The concept of *homo economicus*, which is associated with exclusively rational behavior, was rejected (Ng & Tseng, 2008).

6.2.5 INVESTOR SENTIMENT LITERATURE

Another theoretical contribution relates to the literature on investor sentiment. Persistence in investor sentiment was discovered in this study, as short-term private investor sentiment has been found to be autocorrelated. Obviously, private investor sentiment tends to follow trends. Persistence in private investor sentiment is also suggested by prior research (Tumarkin & Whitelaw, 2001; Das, Martínez-Jerez & Tufano, 2005).

6.3 POLICY IMPLICATIONS

Following the results of this research study, a few policy recommendations are suggested in addition to the theoretical contributions outlined above. While private investors have not been found to possess predictive abilities when taking investment decisions, they appear to be compromised by irrational extrapolation bias. Becoming aware of biased judgment is assumed to constitute a first step in improving investment behavior and achieving enhanced investment results. Therefore, effective private investor education is recommended to mitigate irrational behavioral bias.

Private investors seem to be disadvantaged in the financial marketplace. They have not been found to take investment decisions according to their own best interests, allowing rational arbitrageurs to profit by offsetting the biased transactions of unsophisticated private investors. It might be argued that a more level playing field between private investors and professional investors is necessary to ensure the lasting confidence of all participants in the financial marketplace, especially in the context of the recent financial crises. If the vast majority of private investors stay away from the stock market, an efficient allocation of resources will become compromised; which would be likely to ultimately result in welfare losses for the entire economy.

6.4 RECOMMENDATIONS FOR FUTURE RESEARCH

Against the background of the limitations of this research study, further research appears necessary in the area of behavioral finance. In specific, it is recommended to substantiate the findings of this study by conducting additional research on extrapolation bias among private investors that covers a different sample and a different study period. The study period used in this study was dominated by the Eurozone crisis; a crisis that severally impacted on European banking stocks, which were the stocks examined. It would be interesting to find out whether research findings that are similar to the results in this study emerged during noncrisis market periods.

While this study reports that private investors in general are affected by extrapolation bias, it is worthwhile investigating whether different categories of private investors are affected to varying degrees. In this context, the distinctive factors that support the susceptibility to extrapolation bias should be explored.

In essence, contrary to the still widely accepted concept of *homo economicus*, the claim that all financial market participants always take decisions in a completely rational manner, this research study demonstrates that probably a significant part of the market participants exhibits irrational biases. Although capital market efficiency remains unimpaired given at least some actors in the market exist who instantly correct for arising mispricing and behave according to the demanded ideal, those affected by behavioral bias do not act according to their own best interests.

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