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Investor Behavior in the Norwegian Equity Market

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Preface

THIS paper is written as part of the course *TIØ4900 - Master Thesis, Financial Engineering* at the Norwegian University of Science and Technology (NTNU) during the spring of 2014. The course is mandatory for students enrolled in the master program *Industrial Economics and Technology Management* following the *Financial Engineering* specialization. The paper investigate investor behavior in the Norwegian stock market, with special emphasis on the disposition effect and herd behavior by the use of acknowledged methods from the behavioral finance literature and data from different sections of the Norwegian Stock Exchange. The paper has been prepared in LaTeX and different editors of the Microsoft Office 2010 suite.

We would like to thank our supervisor, Associate Professor Einar Belsom at the Department of Industrial Economics and Technology Management for his valuable advice and guidance.

Trondheim, May 14, 2014

Sammenfatning

Atferdsfinans er et fagområde som studerer hvordan forskjellige psykologiske faktorer påvirker finansiell beslutningstaking i finansmarkeder. I denne masteroppgaven er atferdsfinans brukt som utgangspunkt for en studie av investorers atferd i det norske aksjemarkedet, med fokus på to separate temaer innen fagområdet: The Disposition Effect og Herd Behavior. The Disposition Effect er en utvidelse av Prospektteori, og omhandler investorers tendens til å selge vinneraksjer for tidlig og holde på tapere for lenge. Herd Behavior beskriver hvordan investorers flokkmentalitet fører til at de tar beslutninger basert på hvordan flertallet handler, og ikke nødvendigvis basert på sin personlige informasjon. Oppgaven er delt i to separate artikler, hvor begge bruker datamateriale fra Oslo Børs for å undersøke om det finnes tilfeller av henholdsvis the disposition effect og herd behavior i Norge. Ved å inkludere bevismateriale fra det norske aksjemarkedet vil denne masteroppgaven bidra til å utvide den eksisterende litteraturen om investoratferd i industriland. Gjennom bruken av flere utvalg av aksjer på Oslo Børs over perioden januar 2000 til desember 2013, finner vi spredte bevis for the disposition effect og ingen bevis for herd behavior i Norge. Dette indikerer at the disposition effect og herd behavior ikke påvirker priser og volumer i det norske markedet i betydelig grad, noe som er konsistent med tilsvarende studier i andre industriland. Resultatet kan delvis forklares med at investorer i disse landene har tilstrekkelig tilgang til variert informasjon og investeringsmuligheter i enkeltaksjer, og delvis med at det kreves bedre modeller i atferdsfinans for å undersøke investoratferd i reelle aksjemarkeder.

Abstract

We examine investor behavior in the Norwegian equity market by studying two behavioral finance phenomena: The Disposition Effect and Herd behavior. Both utilize market data from Oslo Stock Exchange. This thesis will contribute to the existing literature on investor behavior by including evidence from Norway, characterized as a developed market. In the disposition effect paper, the methodology employed on the data examines the relationship between volume at a given point in time, and volume that took place in the past at different stock price levels. In the second paper focusing on herd behavior, a model that analyses the relationship between cross-sectional absolute deviations of asset returns and the corresponding market returns is used for the main part, while the final part combines the volume perspective from the disposition effect study with relevant assumptions for detecting herd behavior.

The empirical analysis of the disposition effect presents scattered evidence, suggesting that the disposition effect exists to some extent in Norway. In addition, the evidence for tax-loss-selling, representing the opposite prediction of the disposition effect, is limited. Equivalently, by using the cross-sectional approach for detecting herd behavior we find no evidence of herding in the Norwegian market. In addition, no significant signs of herding are found in the investigation of herding through a volume perspective. Our results for the disposition effect and herd behavior in Norway suggests that they are not powerful factors in determining equity returns and volumes in the market, coinciding with similar empirical research on developed markets. This can partly be explained by sufficient access to diverse information and investment opportunities on individual stocks, and partly by the lack of comprehensive empirical models.

Contents

Introduction

The central unifying concept of finance is asset valuation. Standard (or modern) finance, originating from the 1950s, has introduced an avalanche of financial theories such as the Efficient Market Hypothesis (EMH), the capital asset pricing model (CAPM), arbitrage pricing theory and option-pricing models (Olsen, 1998). Modern finance theories assume that the world is dominated by rational investors focusing on expected utility maximization, and the models tie together finance and the entire economy in elegant theories using rational expectations (Shiller, 2003).

According to standard finance theorists, rational decision-makers make optimal use of all available information. As a result, all agents achieve their optimum, and equilibrium is reached in the market as price equals value. Fama (1970) remarks that even though ingenuous investors may push security prices away from intrinsic values, more sophisticated traders will find it worthwhile to correct any mispricing. This perspective is called the Efficient Market Hypothesis (EMH), and it states the premise that all available information has already been reflected in a security's price or market value. It can be noted that the EMH does not assume that all investors are rational, but it does assume that markets are rational (Ritter, 2003). To eliminate the effect of irrational traders who for instance follow trends, smaller elements of 'smart money' offset the actions by selling when the irrational optimists buy, and vice versa (Shiller, 2003).

One of several conditions for capital market efficiency is that all information is available to the market participants. Fama (1970) acknowledges that this is not descriptive of markets in the real world, but he argues that market efficiency is still applicable if a 'sufficient number' of investors have access to available information, and he claims that this condition exist to some extent in reality. In his article, Fama performs an analysis of empirical evidence for market efficiency, and concludes that the evidence in support of the efficient market model is extensive. However, Shiller (2003) remark that in the 1970s, some finance journals started to report anomalies that did not seem to be in accordance with the efficient markets theory. Thaler (1999) discusses different areas in the real world that seems at odds with the theory: the large volume traded each day, the excess volatility observed for stocks and bonds, the paying of dividends, the large equity premium and the partial predictability of future returns.

Anomalies affect fundamental decisions, so they are of interest and importance to economists in finance and other sectors (Fromlet, 2001). Misvaluations are often identified by arbitrageurs in an effort to make money, and in practice their trading maintains efficient markets, but misvaluations are of two types: those that are recurrent or arbitrageable and those that are nonrepeating and long-term in nature. According to Ritter (2003), trading strategies can keep a pretty efficient market for the recurrent misvaluations, but it is impossible to identify the other misvaluations until they have passed.

Fama (1998) asserts that the reported anomalies are only chance results, consistent with the market efficiency theory. In his paper, he discusses recent studies on market inefficiency, claiming that since the evidence and arguments on anomalies split roughly even between over- and underreaction, they can be attributed to chance, which is predicted by market efficiency. In addition, long-term anomalies are sensitive to methodology, and tend to disappear when exposed to different techniques and measurements. Fama's counter-argument towards critics of the EMH is that market efficiency can only be replaced by a better model of price formation that specifies judgment biases in investor behavior and capture the anomalies observed in the markets in a better way than the simple EMH. So far, the anomalies literature has not accepted the discipline of an alternative hypothesis, and Fama concludes that the predictability of the EMH still holds up rather well.

In recent years, the modern finance paradigm has been challenged by a new and now established field, Behavioral Finance, which has provided evidence that contradicts the notions of efficient markets through the introduction of psychological aspects. De Bondt et al. (2008) write that behavioral finance theories study the nature and quality of financial judgments and choices made by individual economic agents, and examine what the consequences are for financial markets and institutions. It is evident from multiple incidents and crises in financial markets that investment portfolios are frequently distorted, with consequent excess volatility in stock and bond prices, and it will be problematic to discuss these without reference to investor psychology. Thaler (1999) emphasizes that the contribution of behavioral finance is not to diminish the fundamental work that has been done by pioneers of the modern financial theory, but rather to extend it and make it more realistic by adding a human element.

According to Baker and Nofsinger (2002) traditional finance typically focus on how investors should behave, while behavioral finance examine how people actually behave in a financial setting and is, therefore, descriptive. Moreover, behavioral finance incorporate observable, systematic and very human departures from rationality (either because of preferences or because of mistaken beliefs) into models of financial markets and behavior (Ritter, 2003). Statman (1999) argues that normal people are not always rational, that is: (1) they do not always care about utilitarian characteristics, but rather value-expressive ones, (2) they do not have perfect self-control, (3) they are confused by cognitive errors, and (4) are sometimes averse to regret. Such 'noise traders' can affect security prices. Therefore, behavioral finance assumes, in contrast to EMH, that in some circumstances financial markets are informationally inefficient (Frankfurter and McGoun, 2002).

Most published behavioral finance studies have an empirical component and show a high predictive value, but are criticized due to their lack of robustness (Van der Sar, 2004). Usually in behavioral finance, observed anomalous behavior at an individual level of decision-making is used to construct a behavioral model for a higher aggregate, while the standard finance approach aims at deriving theorems with a broad reach by starting from a specific set of assumptions (Van der Sar, 2004). At the same time, the behavioral finance literature is expanding rapidly, and deviations from the standard decision-making models are being classified into several broad categories (Baker and Nofsinger, 2002). For instance, cross-sectional return predictability on the basis of historical factors such as prior return performance and market capitalization is studied in several theories, and is difficult to reconcile with the rational expectation hypothesis (Van der Sar, 2004).

Our aim in this thesis is to contribute to the literature by studying two specific fields within behavioral finance, i.e. psychological biases, which can be observed in financial markets. These are The Disposition Effect and Herding Behavior, and they will be presented as two separate papers related to the Norwegian stock market.

The disposition effect is a theory of a cognitive bias introduced in 1985 by Shefrin and Statman as an extension of a broad psychological theory of decision-making under risk, called Prospect Theory. The disposition effect postulates that investors avoid actions that will make them feel regret and seek actions that will give them pride, and as a result they are predisposed to ride losers too long and sell winners too early (Shefrin and Statman, 1985). Herd behavior, on the other hand, transpires when individual investors make investment decisions based on the actions of other investors, i.e. 'follow the crowd', while ignoring pertinent information such as news or financial reports (Ricciardi and Simon, 2000). By doing this, the investor can reduce emotional reactions or feelings if the stock declines substantially in value, since a group of investors also lost money on the bad investment. The disposition effect and herd behavior have in common that they are partly based on investors aversion to regret.

This thesis will use theory and earlier empirical studies of the disposition effect and herding behavior on foreign stock markets as a foundation for similar empirical tests in the Norwegian stock market. To our knowledge, we are the first to examine these two theories over the specific time period in Norway. The contribution of this thesis is thus to extend the existing literature on investor behavior by including evidence from the Norwegian Equity Market.

In the disposition effect paper, stock market data for the thirty smallest firms by equity value as of January 2014 is collected over a period of three years, and the methodology employed on the data examines the relationship between volume at a given point in time, and volume that took place in the past at different stock price levels. In the second paper focusing on herd behavior, multiple data sets are collected covering various stock categories and time periods, where the focus is particularly on firm size, market sectors and the financial crisis. The main part of the herd behavior paper uses a model that analyses the relationship between cross-sectional absolute deviations of asset returns and the corresponding market returns, while the final part combines the volume perspective from the disposition effect paper with relevant assumptions for detecting herd behavior.

Examination of investor behavior based on behavioral finance can grant investors a higher degree of understanding regarding price and volume information in financial markets. A study of investor behavior in Norway is important as share prices and volumes are substantially affected by market participants' investment behavior and thus can be linked to possible market inefficiencies.

The thesis is divided into two papers, presenting the studies of the disposition effect and herd behavior respectively. Each paper is separated into relevant sections and undersections, which introduces each field, describes the theory and empirical methodologies in detail and presents the results. Both papers also include a separate conclusion, before the main conclusion of the thesis and recommendations for future work is presented in the end.

Paper 1: The Disposition Effect in the Norwegian Equity Market

Abstract

In this paper, the disposition effect in the Norwegian equity market is examined. This is done by the application of prices and turnover for the thirty smallest firms by equity value on Oslo stock exchange as of January 2014, from January 2010 to December 2013. We apply a methodology which examines the correlation between volume at a given point in time and volume that took place in the past at different stock price levels, where the focus is specifically on abnormal turnover defined as the portion of a firm's trading volume that cannot be explained by common market influences.

The results from the empirical analysis present evidence of the disposition effect in some return intervals. When studying daily values, the disposition effect is more visible in December than January, and observed deviations can be a result of tax-loss selling. Monthly values for the entire year are also investigated in the analysis, providing no significant evidence of the disposition effect, with February being an exception. The scattered result can be a result of a dilution of the disposition effect by momentum strategy traders. When focusing on the returns closest to the investors' reference points, the disposition effect becomes more visible. In summary, the evidence suggests that the disposition effect is not an important factor in determining equity returns and volumes in the Norwegian market.

1 Introduction

Traditional financial theory has a tendency to concentrate on how asset prices are determined using models based on rationality, and thereby ignore the question of how investors actually behave (Shefrin and Statman, 1984). The expected utility theory is a well-known example, as it presents principles of rational choice with strong normative appeal, but with serious limitations as a predictive device of investor behavior (Loomes and Sudgen, 1982). That is, classic economic theories assume that the relevant agents to a problem act (on average) according to a normative solution to a problem, while Thaler (1980), among others, argue that descriptive models for the experts are quite different from the models for the novice or intermediate. While expected utility theory tries to characterize optimal behavior, other theories have been proposed in later years which aim to solely describe or predict behavior.

Serious questioning of modern finance as a paradigm started when Prospect Theory, introduced in 1979 by Kahneman and Tversky, was imported into studies of asset pricing, describing several departures from the expected utility maximization upon which modern finance has been based (Frankfurter and McGoun, 2002). The theory predicts "normatively unacceptable consequences", and is thus a *prescriptive* study of preferences (Kahneman and Tversky, 1979). Prospect theory, and similar theories, presents challenges to the theory of rational choice, because it is often far from clear whether the observed investor behavior should be treated as errors or biases, or whether it should be accepted as valid elements of human choice (Kahneman and Tversky, 1982).

One of the main features of prospect theory is that it has a value function defined on gains and losses relative to a reference point, i.e. it focuses on changes in wealth rather than the level of wealth (Ritter, 2003). In 1985, the theory was extended into a wider theoretical framework by Shefrin and Statman (1985) called The Disposition Effect, and this effect has eventually become part of the general folklore about investing (Shefrin and Statman, 1985). The disposition effect theory studies the implications of prospect theory in real financial markets, and combines it with other behavioral finance theories such as The Theory of Regret, Mental Accounting and Overconfidence (Shefrin and Statman, 1985). For instance, if investors are faced with the possibility of losing money, they often take on riskier decisions due to loss aversion to avoid the regret of having made a bad investment choice (Ricciardi and Simon, 2000).

According to Shefrin and Statman (1985), investors exhibit a disposition to sell winners too early and ride losers too long, i.e. they time the realization of gains differently from the realization of losses. Van der Sar (2004) suggests that "the occurrence of the disposition effect can demonstrate that what a security *has* done may be more important for the choice to sell or to hold than what it is *likely* to do". That is, the disposition effect is an implication of prospect theory, where traders will lock in gains by closing out profitable investments quickly, while holding on to losing investment in hopes that they will turn around (Bloomfield, 2006).

In relation to financial markets, it can be assumed that the disposition effect affects trading volumes, because the number of shares sold will be larger for winning assets than for losing assets (Camerer and Weber, 1998). In addition, the disposition effect might drive short-term momentum, as the tendency to hold losers slows reactions to bad news, while a rapid selling of winners slows reactions to good news (Bloomfield, 2006). That is, the rate at which private information on a stock is incorporated into prices is delayed (Odean, 1998).

The main purpose of this paper is to use theory on the disposition effect and earlier empirical methodology from foreign stock markets as a foundation for an empirical test of the disposition effect in the Norwegian stock market. A similar test of Norway is performed by Nygaard (2011), but while he uses an accounts dataset of household investors, this paper will focus on the smallest capitalization stocks on the stock market.

The empirical analysis will use stock market data for the thirty smallest firms by equity value as of January 2014. The data period is from January 2010 to December 2013, and data is collected from the Oslo stock exchange. The model that will be used to detect the disposition effect in Norway was originally formulated by Ferris et al. (1987), who performed the analysis on US stocks in 1988. In short, the methodology examines the relationship between volume at a given point in time, and volume that took place in the past at different stock price levels. In particular, volume levels at previous price levels are taken into account in predicting the level of abnormal volume at a given point in time.

The test for disposition effect in Norway will be performed over the entire year, with specific focus on December and January. This is done to account for the tax-loss-selling hypothesis, which has competing implications for the stock market in December. That is, according to the tax-loss-selling hypothesis, the volume of trading in stocks with capital losses will exceed the volume of stocks with capital gains in December (Ferris et al., 1987). In January on the other hand, the disposition effect and the tax-loss-selling hypothesis predicts the same trading pattern.

The next two sections of this paper, section 2 and 3, review previous literature concerning the disposition effect. In section 2, the underlying behavior finance phenomena related to the disposition effect are described, as well as factors in financial markets that can be misinterpreted as the disposition effect. Section 3 presents different elements in markets that can affect the measurement of the disposition effect, and counter-effects working against the empirical evidence. In section 4, the methodology and data used in the empirical analysis is described, and in section 5 the results are presented and discussed. Section 6 provides a conclusion.

2 The Disposition Effect

In 1985 Shefrin and Statman introduced a wide theoretical framework called The Disposition Effect. The theory concerns a general disposition to hold losers too long and sell winners too quickly, and it has eventually become a fundamental feature in behavioral finance and one of the most robust facts about the trading of investors (Barberis and Xiong, 2009). The disposition effect was originally presented as an extension of Prospect Theory, introduced a decade earlier by Kahneman and Tversky (1979), by placing its features into a broader scope. More specifically, the disposition effect also includes some other behavioral elements that support the main hypothesis of realizing winners too early and keeping losers too long, such as Regret Aversion, Mental Accounting and Overconfidence. In addition, the framework involves a study of real-world financial markets that ascertains if the disposition effect can be detected in actual trading (Shefrin and Statman, 1985). According to Ferris et al. (1987), investors affected by the disposition effect are eager to realize stocks with gains, but reluctant to realize stocks having losses. That is, they seek risk when faced with losses and avoid risk for certain gains (Camerer and Weber, 1998). Shefrin and Statman (1985), Barberis and Xiong (2009), Ferris et al. (1987) and Dhar and Zhou (2006) among others, have tried to determine whether this assumption holds, even when the perceptions of standard rational theory predicts otherwise, and it is one of the most widely documented biases in investor behavior (Dhar and Zhou, 2006). In particular, the disposition effect investor-type holds more shares than his rational counterpart in the case of a paper capital loss, and less shares in the case of a capital gain (Grinblatt and Han, 2002). Shefrin and Statman (1985) remark that while the standard neoclassical framework of utility is prescriptive, the disposition effect hypothesis should be understood as being descriptive (Shefrin and Statman, 1985).

Since the disposition effect is founded on the main elements of prospect theory, the first part of this section will look deeper into the underlying assumptions of this theory. In addition, the other behavioral finance elements that are strongly linked to the disposition effect will be described, namely The Theory of Regret, Mental Accounting and Overconfidence. Thereafter, other explanations of the observed trading pattern identified as the disposition effect is reported, such as a belief in mean reversion.

2.1 Prospect Theory

Prospect theory was introduced in 1979 by Kahneman and Tversky as an alternative descriptive model to expected utility theory, which until then had dominated the analysis of decision making under risk. The central idea of utility theory is that each outcome of a decision gives rise to a particular utility, and that utility is not necessarily a linear function of outcomes (Kahneman and Tversky, 1982). In addition, the traditional utility literature assumes that people behave as rational expected utility maximizers (Shapira and Venezia, 2001). In their article, Kahneman and Tversky (1979) claim that utility theory, being a normative model of rational choice, is not an adequate descriptive model of economic behavior under risk. The model might describe how consumers should choose, but it does not necessarily describe how they actually *do* choose (Thaler, 1980).

A central concept in both utility theory and prospect theory is that the highest monetary expectation does not always correspond to the highest expected utility (Kahneman and Tversky, 1982). However, Kahneman and Tversky (1979) present in their study results where over half of the respondent's preferences systematically violated the axioms of expected utility theory. As a matter of fact, the observed violations of conventional expected utility theory are neither small-scale or randomly distributed, indicating that people's choices are affected by factors that are mis-specified by conventional theory (Loomes and Sudgen, 1982). Thaler (1980) argues that the rational economic model of consumer behavior does a poor job of predicting the behavior of the average consumer, as it is, in essence, a model of robot-like experts ignoring rules-of-thumb and heuristics. Prospect theory, on the other hand, attempts to take into account a very complex and demanding world for human decision makers (Thaler, 1980).

According to Kahneman and Tversky (1979), decision-making under risk can be viewed as a choice between prospects, and if the decision maker does not discover that his preferences violate the decision rules he wishes to obey, several anomalies discovered in the financial markets are expected to occur. Thus, mental illusions should be considered the rule, rather than the exception (Thaler, 1980). In prospect theory, the value of each outcome of a decision is multiplied by a decision weight that is usually a function of stated probability, but which can be influenced by other factors as well.

2.1.1 Gains and Losses, and the use of a Reference Point

The cornerstone of prospect theory is that people perceive outcomes from choices as gains and losses, i.e. changes of wealth, rather than as final states of wealth (Kahneman and Tversky, 1979). This way of thinking is a deviation from the original assumption where utilities are assigned to final-asset positions, and was originally proposed by Markowitz in 1952. Markowitz argues that both rich and poor people will behave essentially the same when taking chances of a small loss for a small chance of a larger gain, only differentiating in their interpretation of 'large' and 'small'.

In prospect theory, the initial asset position usually serves as a reference point for the definition of gains and losses, implying that the location of this point is of great importance for the analysis (Shefrin and Statman, 1985). Specifically, the reference point depends not only on current wealth, but also on impressions, judgments and responses, making it a "ubiquitous psychological phenomenon" (Kahneman and Tversky, 1982). As a consequence, according to Kahneman and Tversky (1979), the value of a particular change is a function of two arguments: the reference point and the magnitude of the change from that reference point. The result is that people usually adapt to a limited view of the outcomes of decisions (Kahneman and Tversky, 1982).

It is important to note that the formulation of prospects and the expectations of the decision maker can affect the location of the reference point. For instance, a tendency called the 'isolation effect', where people discard components that are shared by all prospects under consideration, can lead to inconsistent preferences (Kahneman and Tversky, 1979). In addition, a fixation on specific factors, e.g. stock prices, is a specific behavioral phenomenon called 'anchoring' (Baker and Nofsinger, 2002). This makes the presentation of choices a critical factor in decision analysis, since a change in the reference point can alter the preference order for prospects (Kahneman and Tversky, 1979).

2.1.2 Risk Aversion versus Risk-Seeking behavior

Observed behavior and experimental studies, for instance by Kahneman and Tversky ((1979), (1982)), Odean (1998) and Camerer and Weber (1998), indicate that people are risk averse in choices involving sure gains, and risk seeking in choices involving sure losses, a feature that is inconsistent with utility theory (Kahneman and Tversky, 1979). Thus, there is an impressive amount of evidence that risk attitudes depend on the reference point. In the case of a gain, each extra dollar gained adds less value than the preceding one, favoring risk aversion. The case is similar for losses, where each dollar lost causes a smaller change in value than the preceding one, and in this case the result is a risk-seeking preference (Kahneman and Tversky, 1982). The exception is in cases involving very small probabilities (Thaler, 1980).

Another property of prospect theory is that when it comes to attitudes towards changes in welfare, losses seem to loom larger than gains (Kahneman and Tversky, 1982). This means that the pleasure associated with gaining a sum of money appears to be less influencing than the aggravation experienced in losing the same amount (Kahneman and Tversky, 1979). For instance, Shefrin and Statman (1984) note in their study that this behavior is consistent with the observation that announced increases in dividends have a much less evident effect on market value than do announced dividends decreases. The difference between gains and losses can also explain why out-of-pocket costs and opportunity costs are not treated equivalently, which they should according to rational theory. Opportunity costs are underweighted because they are treated as foregone gains, while out-of-pocket costs are viewed as losses and are thus more heavily weighted (Thaler, 1980). This illustrates how the structure of a problem may affect choices, even if the outcomes are identical when evaluated with respect to final asset positions (Thaler, 1980).

2.1.3 The Value Function

As a consequence of the observed behavior described above, Kahneman and Tversky (1979) present a new version of the value function, which associates a subjective value to any amount that is gained or lost. To account for the definition of gains and losses, the value function is defined on deviations from the reference point (Kahneman and Tversky, 1979). Risk seeking in the negative domain below the reference point is accompanied by risk aversion in the positive domain above, and the curvature of the function relates subjective values to objective outcomes (Kahneman and Tversky, 1979). Gains are represented in the positive domain, where the value function is concave and progressively flatter as the amount of the gain is increased, i.e. a shape that favors risk aversion. Similarly, losses are represented in the negative domain by a convex function favoring risk-seeking behavior (Kahneman and Tversky, 1982). The shape of the function is similar to that presented by Markowitz (1952), but his function had concave and convex regions in both regions of the value function (Shefrin and Statman, 1984).

Another feature of the value function illustrates the asymmetry in the response to losses compared to gains, i.e. that losses have a larger subjective effect, by a greater steepness in the graph in the loss domain (Kahneman and Tversky, 1982). By combining these properties, decision makers employ and behave as if maximizing a value function that is S-shaped, having a steeper graph on the loss side implying that people are generally risk-averse (Kahneman and Tversky, 1979). An illustration of a hypothetical value function is shown in Figure 2.1.

If a person's preferences instead follow the axioms from utility theory, that is, decisions are formulated in terms of final assets, the reference point will be shifted to zero and the value function will probably be concave everywhere. This eliminates risk-seeking behavior (Kahneman and Tversky, 1979). Kahneman and Tversky (1982) also remark that the described pattern doesn't always prevail in the cases of low probabilities, because they are commonly overweighed relative to certainty. The probability weighting function in prospect theory takes care of this feature by overweighting low probabilities and thus "parsimoniously captures the simultaneous demand many individuals have for both lottery tickets and insurance" (Barberis and Xiong, 2009).

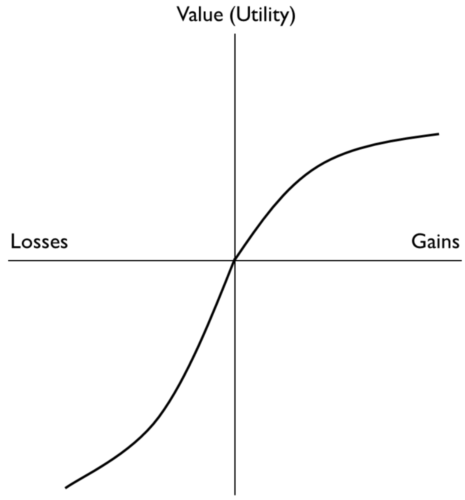

Figure 2.1: Hypothetical value function

2.1.4 Risk Aversion

As noted earlier, in relation to the value function, risk aversion is equivalent to a concave function and is related to the realization of gains (Kahneman and Tversky, 1979). In particular, a person is risk averse if a certain prospect is preferred over any risky prospect (Kahneman and Tversky, 1979). Kahneman and Tversky (1982) point out that the difference between possibility and impossibility, and between possibility and certainty is more significant than comparable differences in intervening probabilities. Kahneman and Tversky (1979) explain this behavior by a tendency called the 'certainty effect', where people underweight outcomes that are merely probable and overweight outcomes that are considered certain. In particular, risk-averse decision makers usually prefer a certain gain even if the possible gamble has a higher 'monetary expectation', and thus choose a risky venture only when the monetary expectation is sufficiently high to compensate for the risk (Kahneman and Tversky, 1982). This implies that prospect theory would make a risk-averse individual pay more for the complete elimination of uncertainty than his risk attitude alone would indicate (Shefrin and Statman, 1984). In contrast, when decision makers must choose between a sure loss and a probability of a large loss, they demonstrate risk-seeking preferences (Kahneman and Tversky, 1982).

2.2 The Theory of Regret

Regret theory is a model of choice under uncertainty that is strongly linked to prospect theory and the disposition effect, due to the concept of regret aversion. Loomes and Sudgen (1982) proposed the theory in 1982 as an alternative theory to prospect theory, in the light of the accumulated evidence showing consistent violations of certain axioms of expected utility theory. They remark that regret theory has a remarkably simple structure compared to prospect theory, while it still maintains predictive power and generality by supporting experimental evidence and having a greater appeal to intuition. The two fundamental assumptions of regret theory are: (1) many people experience regret, and (2) they try to anticipate and take account of this sensation when making decisions under uncertainty (Loomes and Sudgen, 1982). In particular, it is assumed that individuals have a 'choiceless utility function', which is essentially what Bernoulli understood by 'utility' (psychological experience associated with the satisfaction of desire), and a 'modified utility function' which incorporates the increment or decrement of utility corresponding with the sensation of rejoicing or regret (Loomes and Sudgen, 1982). Consequently, the degree of regret depends on the difference between the choiceless utility of 'what is' and the choiceless utility of 'what might have been'. The individual's experience of rejoicing or regret is thus a result of an act of choice, and someone who does not feel regret will simply maximize expected choiceless utility (Loomes and Sudgen, 1982).

It is worth noting that Loomes and Sudgen (1982) argue that regret theory is a model of *rational* choice under uncertainty, as they define the explained behavior as being both predictable and rational. They believe that people who experience regret and who seek to maximize expected modified utility by taking those feelings into account do not behave, in any meaningful sense of the word, irrational – even when the regret theory predicts certain violations of conventional expected utility theory. According to Loomes and Sudgen (1982), it is rather that the conventional axioms represent an unnecessarily restrictive definition of rationality. In addition, the experience of regret is just an experience, and cannot properly be described in terms of rationality in the same way as concrete choices (Loomes and Sudgen, 1982). However, Loomes and Sudgen (1982) note that regret theory cannot explain all of the behavioral regularities revealed by experimental research, e.g. by Kahneman and Tversky, into choice under uncertainty.

In prospect theory, regret can be modelled through induced changes in the reference point (Thaler, 1980). According to Shefrin and Statman (1985), aversion to regret is an important explanation to why many investors find it difficult to realize losses, because the very act of doing so is evidence of a wrong judgment in the past. The positive counterpart to regret is pride, induced when investors close a stock account at a gain, but if the stock continues to rise the feeling of pride is reduced by the regret of having sold to quickly (Shefrin and Statman, 1985).

Odean (1998) also discovers that investors are most reluctant to realize their greatest losses and suggests that it is due to regret aversion. Equivalently, investors' aversion to regret may influence them not to buy additional shares of big winners, as the potential regret becomes greater by the difference between the original and additional purchase price (Odean, 1998). An example is presented by Shefrin and Statman (1984) for the case of choosing between the use of dividends or gains from sold stocks to buy a television. According to financial theory, dividends and receipts from selling a stock are perfect substitutes, but evidence indicates that the sale of stocks causes more regret and therefore regret-averse investors will prefer consumption from dividends (Shefrin and Statman, 1984).

2.2.1 Taking Responsibility of an Action

As noted earlier, Loomes and Sudgen (1982) suggest that regret is mainly a result of an act of choice. Therefore, a particular feature of regret theory is that the regret associated with an action (such as buying a losing stock) tends to be more intense than regret from inaction or a missed opportunity (such as not buying a winning stock) (Kahneman and Tversky, 1982). As a result, the prospect theory value function changes when an individual feels responsible for the outcome of a gamble: A gain leads to an extra value stemming from pride, while a loss leads to a stronger sense of regret and less value (Shefrin and Statman, 1984). Therefore, Thaler (1980) proposes that the possibility of regret makes individuals reluctant to make decisions in which they feel responsible for the final outcome. This can be used to relate regret theory to the formal analysis of prospect theory, as it is easier to mentally delete an event from a chain of occurrences than to insert an event to the chain, i.e. it is easier to imagine not taking an action than to imagine taking one (Shefrin and Statman, 1984).

Making a choice becomes a special kind of decision-making cost which can be reduced by avoiding trades where the outcomes can cause regret (Thaler, 1980). Kahneman and Tversky (1982) thus claim that actions taken under restrictions or by following conventional rules generate less regret than when losses have occurred by making unconventional and innovative choices. The wish to avoid regret from selling a stock can for instance explain why some investors would be willing to pay a premium for cash dividends (Shefrin and Statman, 1984). Still, Shefrin and Statman (1984) point out that a decision involving responsibility will sometimes be preferred, since the odds attached to the gamble must be taken into account.

In their experimental study, Camerer and Weber (1998) separate between deliberate selling and automatic selling, the last being the case where shares are automatically sold after each period and subjects have to rebuy them (at the same price). They discover that the disposition effect is greatly reduced in the 'automatic selling' condition, which is in contrast with rational thinking where a decision maker should behave identically in both conditions (given no transaction costs). Subjects who must sell assets deliberately exhibit greater disposition effect because they have a reluctance to incur losses and thus "blow out the flame of hope with their own breath" (Camerer and Weber, 1998).

2.3 Mental Accounting

Grinblatt and Han (2005) suggest that the leading explanation for the disposition effect is prospect theory combined with a behavioral phenomenon known as 'mental accounting'. The framework of mental accounting was constructed by Thaler (1985) as a foundation for the way decision-makers frame decisions. Thaler (1985) developed the model using a hybrid of cognitive psychology and microeconomics, and suggests that a mental accounting system induces individuals to violate simple economic principles. Accordingly, decision-makers tend to segregate the different types of decisions into separate mental accounts, before applying prospect theoretic decision rules to each account separately, ignoring possible interactions. In the world of finance, a new mental account is opened when a stock is purchased, and the asset purchase price serves as a reference point for indicating gains and losses (Shefrin and Statman, 1985). In addition, the normative principle of fungibility, where money is not supposed to have labels attached, is relaxed in the mental accounting framework (Thaler, 1985). Consequently, even when an investor trades several stocks, he receives a separate component of utility from the trading profit of each stock (Barberis and Xiong, 2009). This sort of sequential analysis seems to be a good description of behavior (Thaler, 1985).

As shares are exchanged between investors, the reference point is updated (Grinblatt and Han, 2005). Thus, an investor's behavior is altered by his current position in wealth, not by either his lifetime winnings or losing nor by some event allocated to a different account altogether such as an increase in salary (Thaler, 1985). By using a reference point, the theory also capture 'mere' framing effects that affect choices, since choices often depend on the way a problem is posed as much as on the objective features of the problem (Thaler, 1985). In addition, the loss aversion feature can illustrate mental accounting, since one of the major obstacles standing in the way of loss realization of a particular investment is the reluctance to close a mental account at a loss (Shefrin and Statman, 1985).

Thaler (1985) investigates values of outcomes, and specifically whether jointly or separate valuation of gains and losses produces greater utility, referred to as integration or segregation of outcomes. He presents four principles: segregate gains, integrate losses, cancel losses against larger gains and segregate 'silver linings' (losses and gains of similar amounts). In the case of gains, it is desirable to have each gain evaluated separately, and in the case of losses the concavity of the loss function implies that adding a loss to an existing loss will have smaller impact. In fact, mental accounting can be regarded as part of an individual's solution to self-control problems.

Barberis and Xiong (2009) also suggests that mental accounting can explain why investors are reluctant to immediately transfer the proceeds from selling a stock to another similar stock (called 'tax swaps'). In theory, loss aversion from selling a losing stock could be reconciled by a purchase of a stock with similar characteristics, so that a tax loss could be realized while the risk exposure is maintained. However, since the stocks are segregated into separate mental accounts, such a tax swap requires that one mental account is closed at a loss, which people are reluctant to do (Odean, 1998).

2.4 Overconfidence

Ben-David and Doukas (2006) study the mechanism that links investor overconfidence to the disposition effect, with focus on institutional investors. They point out that this analysis is important not only because of the relative economic importance of institutional investors[1], but also because they are believed to be immune to behavioral biases and motivated by incentives and agency motives. Ben-David and Doukas (2006) document that institutional investors show signs of overconfident trading when stocks have ambiguous information, and as a result exhibit greater disposition effect. The explanation, according to Ben-David and Doukas (2006), is that overconfidence leads professional investors to overestimate the precision of their private information signals and update their beliefs asymmetrically between favorable and unfavorable signals: Price increases are interpreted as confirmation of beliefs, leading investors to sell shares as they believe their valuation has been fully incorporated in the market, while price decreases are discounted, leading investors to hold on to their shares as they believe other market participants have not realized the true valuation yet (Ben-David and Doukas, 2006).

The overestimation of information precision also leads to intensified differences in opinion among investors, which, in turn, causes trading. Consequently, investor overconfidence generates the high trading volume observed in financial markets, and it encourages investors to trade asymmetrically between gains and losses (Ben-David and Doukas, 2006). In addition, Ben-David and Doukas (2006) note that the disposition effect intensifies with information ambiguity[2], as it elicits investor overconfidence. This also indicates that when information ambiguity is low, investors accept the market's valuation less reluctantly, and thus put more weight on the public valuation signal and sell more loser stocks to cut losses. Still, it is worth noting that institutional investors might condition their trading decisions on past performance because of institutional characteristics and constraints unrelated to overconfidence. The asymmetry in trading gains and losses can for instance be due to institutional explicit and implicit compensation structures, agency issues (known as window dressing), rebalancing considerations, stock liquidity, transaction costs and sensitivity to taxes (Ben-David and Doukas, 2006).

2.5 Other Phenomena explaining the Disposition Effect

As mentioned earlier, evidence of the disposition effect is found in several studies. However, it is worth noting that the observed trading pattern, i.e. holding on to losers and selling winners, may have other behavioral or rational explanations. This section briefly describes some of them.

[1] Institutional investors represent the largest class of investors in the marketplace (Ben-David and Doukas, 2006).

[2] Here, information ambiguity is meant in the sense of parameter uncertainty.

2.5.1 A belief in Mean Reversion

Prospect theory is not the only possible explanation for the observed fact that investors sell shares after they rise and keep them if they fall. One hypothesis is based on informed trading, namely that investors may sell a winning stock believing that its price reflects the favorable information they had when buying, or hold a depreciating stock rationally believing that the market has not yet incorporated their information into price (Odean, 1998). This hypothesis is incompatible with the momentum effect, which is empirically documented by Odean (1998), and thus the investors are on average mistaken. Still, the disposition effect can be a result of an irrational belief in short-term mean reversion where investors misperceive probabilities of future change (Odean, 1998).

In general, it can be difficult to make a clear distinction between prospect theory and a belief in mean reversion when testing for the disposition effect, and it may be that investors themselves do not always separate them; an investor holding on to a losing stock might convince himself that the stock will mean revert rather than admit an aversion to realize a loss (Odean, 1998). It can be noted that mean reversion also applies to stocks that an investors does not already own, implying that investors believing in mean reversion will tend to buy stocks that have previously declined (Odean, 1998). While the disposition effect only predicts variation in the number of shares sold, the experiments performed by Camerer and Weber (1998) allow them to investigate how stock price movements affect buying behavior. Results from their design indicate that if subjects buy stocks expecting mean-reversion, their belief is wrong because price changes across all stock were actually positively autocorrelated.

According to De Bondt and Thaler (1985), a contrarian strategy of buying past losers and selling past winners will achieve abnormal returns because individuals tend to overreact to information, but Jegadeesh and Titman (1993) argue that their evidence can be explained by systematic risk of the contrarian portfolios and the size effect. In addition, significant abnormal returns, i.e. apparent success of contrarian strategies, due short-term return reversals may reflect a lack of liquidity, a lead-lag effect, rather than overreaction. Jegadeesh and Titman (1993) presents evidence that the profits can be attributed to delayed stock price reactions to firm-specific information, implying that the market is inefficient.

2.5.2 Post-Earnings Announcement Drift (PEAD)

Frazzini (2006) study the effect of corporate news announcement on stock prices, based on the observed fact that prices subsequent to positive news often show positive abnormal drift and that negative news generate negative market reactions followed by negative drift, since no unified rational or irrational explanation has won general acceptance. According to Frazzini, investors who display the disposition effect can generate this post-earnings announcement drift (PEAD) anomaly as a result of stock price 'underreaction': The investors want to lock in the paper gain for a stock that increases in value following good news, which depresses its price, and they are reluctant to sell a stock that decreases following bad news so that any trading occur at a temporarily inflated price. Consequently, disposition investors tend to generate return continuation by dampening the transmission of information (Frazzini, 2006). Positive (negative) news travels slowly across assets trading at large capital gains (losses), which generates positive (negative) post-event return predictability (Frazzini, 2006).

Frazzini (2006) remarks that the price drift depends on the news content (i.e. if it is positive or negative) and the difference between the current price and the reference price. In particular, the disposition effect makes a scenario-specific prediction about the sign of the underreaction pattern: The post-announcement drift following earnings surprises is significantly higher when the news and capital gains overhang have the same sign, and its magnitude is directly related to the amount of unrealized gains or losses (Frazzini, 2006). Finally, Frazzini (2006) notes that there are alternative explanations to the observed underreaction, for instance that some stocks have "loyal" holders who sell rarely, or that some stocks have low turnover and are generally illiquid (overhang is negatively correlated with turnover). However, none of the illiquidity factors can explain the asymmetry in the price response – i.e. that there are different directions for positive and negative news – which is consistent with the disposition effect (Frazzini, 2006).

2.5.3 Other Explanations

Barber and Odean (2000) presents evidence that individual investors trade too frequently, even when it is costly, and some of this trading has been explained by the disposition to sell winners. However, excess trading that is categorized under the disposition effect can be due to statistical artifacts or have other explanations, and there are often competing plausible hypotheses to explain it (Camerer and Weber, 1998). One of them is the belief in mean-reversion explained above, and others are presented in this section.

The first hypothesis is that the disposition effect is actually an instance of portfolio rebalancing (Barberis and Xiong, 2009). Investors may sell some appreciated stock after large price increases to restore diversification in their portfolios (Lakonishok and Smidt, 1986). However, Odean (1998) casts doubt on this explanation for two reasons: (i) rebalancing is usually a partial change of a stock position, so that investors who are rebalancing will usually only sell a portion of their stock position; still, the disposition effect remains strong even when their study is restricted to sales of entire stock holdings and (ii) the disposition effect is exhibited more strongly among less sophisticated investors, which is a contradiction if rebalancing is the most tactical thing to do (Barberis and Xiong, 2009).

Investors' reticence to sell losers may also be explained by transaction costs. This is because trading costs tend to be higher for lower priced stocks, and losing investment are more likely to be lower priced than winning investments (Odean, 1998). In addition, Lakonishok and Smidt (1986) suggest that professional managers who are compensated based on performance may realize gains to ensure that they are not lost by subsequent market downturns, and similarly that corporate investors time the realization of capital gains and losses so as to produce desirable accounting results - so called "window dressing".

The issues mentioned in this section are investigated by Odean (1998), among others, and his results indicate that the most obvious explanations fail to capture important features of the data. The disposition effect is still observed when the data is controlled for rebalancing and share price, so the excess trading in markets appear not to be justified by portfolio rebalancing or a desire to avoid high transaction costs (Odean, 1998).

3 Measuring the Disposition Effect

The disposition effect is a behavioral phenomenon composed of the main features of prospect theory, such as value being defined over gains and losses and the use of a reference point, and other theories trying to explain the psychology of investors. The theory of regret, mental accounting and overconfidence are all important contributors to the realization of the disposition effect in stock markets. At the same time, empirical results identified as evidence of the disposition effect can in some cases be due to other market phenomena instead, such as portfolio rebalancing, window dressing or belief in mean reversion. This makes it challenging to create a precise measure of the disposition effect in real markets.

This section will present more elements that affect the measurement of the disposition effect in stock markets. The first part describes how the choice of assumptions and data, such as annual or realized values and investor types, can affect the significance of the disposition measure. In addition, there exists several strategies in stock markets that operate in a direction contrary to the disposition effect, and the second part of this section will look deeper into two of these counter-effects: the momentum strategy and tax-loss-selling.

3.1 Factors affecting Empirical Analyses of the Disposition Effect

As mentioned earlier, the aversion to loss realization and quest for pride, together with an asymmetry between the strength of pride and regret, leads to a S-shaped value function where investors defer losses to postpone regret, and realize gains to hasten the feeling of pride (Shefrin and Statman, 1985). In a financial setting, the stock's purchase price is a natural reference point for evaluating investment alternatives (Camerer and Weber, 1998). An appreciating stock will move along the concave part of the value function, where it is sold if its expected return no longer justifies the risk of the stock. Similarly, a decreasing stock will move to a more convex part of the function, where it will be held by the investor even if its expected return falls below a price that would justify the original purchase. In this case, to motivate the sale the investor must lower his expected return further (Odean, 1998).

The implication of the disposition effect is that some investors sell good-performing stocks that often continue to do well, and keep poor performing stocks, perhaps even investing more in them, that continue to perform poorly (Baker and Nofsinger, 2002). The result is that trading volume tends to grow during a bull market, and tends to fall if the market turns (Ritter, 2003).[3] Camerer and Weber (1998) explore the case where investors adjust their reference points according to stock price changes and thus evaluate gains and losses with the current price being the reference point. They argue that in such a case there should be no disposition effect, because a loss averse investor will always sell for equal chance gambles, i.e. winners and losers will be treated identically (Camerer and Weber, 1998). Thus, according to Camerer and Weber (1998), the disposition effect will only arise when the reference point is a price of a previous period and when investors show prospect theoretic risk preferences. Therefore, it is obvious that the disposition effect should not be present in an efficient market, as the weak form of the efficient market hypothesis implies that past prices provide no information about future returns, since these past prices paid have become sunk costs by the time of sale (Shapira and Venezia, 2001).

Odean (1998) notes that the disposition behavior of individual investors can affect market prices, but that the extent depends on the trading activities of other market participants, so the economic significance of the disposition effect is likely to be greatest for the individuals. At the

[3] As an example, trading volume in the Japanese stock market fell by over 80% from the late 1980s to the mid-1990s (Ritter, 2003).

same time, when substantial trading takes place, the disposition effect may contribute to market stability around the current price, since this price becomes the investors' reference point: If the stock falls below the reference point, the supply of potential sellers is reduced, slowing further price decreases, while if the stock rises the supply of sellers is increased, slowing further price increases (Odean, 1998). Consequently, people tend to reverse or substantially alter their revealed disposition toward risk if gains turn into losses or vice versa.

3.1.1 Annual versus Realized Gains and Losses

As noted earlier, prospect theory is a potentially important ingredient in a model of the disposition effect. While the link between them has been discussed informally in many articles, Barberis and Xiong (2009) study in more detail under what conditions prospect theory predicts a disposition effect, to formalize the link in a rigorous model. In particular, they find that there are particular circumstances where the disposition effect does not seem to hold. They present evidence that if the expected return of a stock is high, an investor with a function that is only mildly concave in the region of gains will take a large gamble on the stock and thus take more risk.

On the other hand, Barberis and Xiong (2009) argue that the disposition effect is relevant in the cases when (i) there are many trading periods, (ii) expected stock return is low, which lowers the risk-aversion to buy the stock, (iii) the degree of loss aversion is high, so that the investor takes a less aggressive position in the risky asset, and (iv) the value function has increased concavity for gains and convexity for losses, so that the investor takes a smaller position in gains and a larger position in losses. Barberis and Xiong (2009) also distinguish between paper gains/losses and realized gains/losses in relation to perceived utility, which are not considered different in the traditional framework, and find that a model defining prospect theory over realized gains and losses is more probable to find evidence of the disposition effect.

3.1.2 Differences across Individuals

As noted earlier, many studies of the disposition effect have been performed using field data, and one of the most convincing is done by Odean (1998) who uses several different tests on large samples from a large discount broker. However, even as the data comprise independence across investors, the conclusions are based on aggregate results. According to Dhar and Zhou (2006), using aggregate data across all traders to arrive at a mean disposition effect is not entirely representative for individual investors because of systematic differences in trading heuristics across individuals. Odean (1998) also points out that cross-sectional variation will be concealed by aggregate descriptions of average investors, in particular because the realized gains of one investor does not necessarily correspond to the proportion of losses realized for the same investor. Consequently, idiosyncratic differences between each individual investor are not captured and no direct insights into individuals decision-making processes is offered (Camerer and Weber, 1998). Accordingly, Dhar and Zhou (2006) suggest that there is a wide dispersion in the disposition bias across individuals, and explain this in terms of underlying investor characteristics. Specifically, they study if trading frequency and different investors' literacy about financial markets can be possible explanations of the variation in individual disposition effect, and their results show that trading frequency, high income and/or a high occupational status tends to reduce the bias.

The reason why wealthier individuals who work in professional occupations exhibit significantly smaller disposition effect, is that such demographic characteristics are correlated with better access to information, an understanding of stock investments and/or access to financial advice (regardless of education and knowledge) (Dhar and Zhou, 2006). Shapira and Venezia (2001) also analyze the difference between individual and professional investors with the argument that accepted financial theories predict that markets are mainly driven by decisions made by professionals who are, it is argued, likely to be rational. They find that the disposition effect is stronger for the individual investors, but that also professional investors exhibit the effect. In addition, they confirm the result of Dhar and Zhou (2006), namely that the disposition effect is significantly weaker in the managed group, indicating that professional training and experience may reduce judgmental biases. In addition, the returns of the independent group were far more correlated with the market than the returns of the managed group, indicating a tendency for individuals to 'follow the herd' rather than choosing stocks based on their merit (Shapira and Venezia, 2001). Moreover, the managed portfolios were better diversified, thus appearing less risky (Shapira and Venezia, 2001). In general, a lack of knowledge about investment valuation usually leads to a reliance on the price paid as inferring value and a belief that past prices affect future returns (Dhar and Zhou, 2006). Even if 'cognitive illusions', such as the reference point effect, are not easy to eliminate through learning, awareness of these illusions and consequences of decisions can lead to behavior modification (Dhar and Zhou, 2006).

The consequences of Dhar and Zhou's (2006) evidence is that less sophisticated investors (in the market sense) having higher disposition effect will experience lower after-tax returns than what they could possibly obtain. A possibility for amateur investors is to become a client of a professional trader, and thus face a trade-off between the superior knowledge and expertise of the professional, and the possible payment for unnecessary transactions (Shapira and Venezia, 2001). In addition, Shapira and Venezia (2001) suggest that market models could be extended to include investors with varying degrees of biases or information, not only general rational and irrational (noise) traders.

The conclusion of Dhar and Zhou (2006) and Shapira and Venezia (2001) is in contrast with the results of Ben-David and Doukas (2006) in the earlier section describing overconfidence, since Ben-David and Doukas indicate in their article that institutional investors' overconfidence is a driver of the disposition effect as it leads them to prefer trading past winners to past losers. At the same time, Ben-David and Doukas point out that the predictive power of prospect theory relies on an appropriate assumption about the reference price, implying that tests for the disposition effect are tests of joint hypothesis of both risk preferences and reference price. Therefore, they find that institutional investors do not exhibit the disposition effect on average when the historic purchase price of stocks is used as the reference for calculation of gains and losses, but that they seem to be reluctant to sell losers when the ever-high price is set as a reference. Thus, Institutional investors are reluctant to sell stock after prices have decreased from the peak level (Ben-David and Doukas, 2006).

3.1.3 Trading Frequency

Another feature of the aggregated mean method is that more weight is assigned to frequent traders, and Dhar and Zhou (2006) find a negative relationship between trading frequency and the magnitude of the disposition effect. A reason for this can be that frequent traders have a greater understanding of the role of market forces in setting stock prices, and consequently have a better appreciation for the concept of market efficiency, leading them to adjust the reference point in direction of the current price and thus to a smaller disposition bias (Dhar and Zhou, 2006). Shapira and Venezia (2001) also discover that the number of transactions and turnover rate indicate that professionals are significantly more active than the independent investors, and they present several explanations: (i) professionals are more overconfident, (ii) professionals want to signal that they are doing some work to preserve their jobs, (iii) professionals have lower trading costs, and (iv) professionals hold a larger number of stocks. In any case, Shapira and Venezia (2001) find that the annualized overall returns of the managed group were significantly higher than those of the independent group and that it can specifically be attributable to the managed accounts' behavior in the losing transactions. Finally, Dhar and Zhou (2006) indicate that some of the anomalies in markets can be alleviated by an increased trading frequency, but Barber and Odean (2000) discover in their study however, that trading is costly and thus hazardous to investors wealth.

3.2 Counter-Effects

Some strategies suggest the opposite behavior of the disposition effect, namely to sell losers and keep winners in order to earn profits. In this section, two of these strategies will be presented. One of them is based on a belief in continuance of existing trends in the marked, and the other is based on a rational consideration of tax issues.

3.2.1 Momentum Strategies

Jegadeesh and Titman (1993) propose that profitable trading strategies that select stocks based on their past returns will exist if stock prices either overreact or underreact to information, and that the profitability of such strategies depends on the efficiency of the stock market. The market is efficient if the profits of a strategy may be attributed to compensation for bearing systematic risk, not to past prices (Jegadeesh and Titman, 1993).

The disposition effect has been linked to pricing phenomena such as stock-level-momentum (Barberis and Xiong, 2009). Grinblatt and Han (2002) explains momentum as the persistence in stock returns over horizons between three months and one year. Disposition effect behavior can in some ways be regarded as the opposite of a profitable momentum strategy, as a momentum trader will take a long position in a stock with an upward trending price and vice versa. The momentum strategy is based on the intuition that the relatively high returns experienced by some securities can be expected to continue, since realized returns contain a component related to expected returns (Jegadeesh and Titman, 1993). Odean (1998) presents evidence that momentum trading can be a profitable strategy, because the average returns of past winners often continue to be high in subsequent periods. Consequently, if disposition prone investors hold on to losers believing that they will outperform their winners in the future, they behave irrationally because persistent evidence suggests otherwise (Odean, 1998). Similarly, they seem to have irrational beliefs when they sell past winners, even if it is because they lower their estimate of the stocks expected return, since the winners continue to outperform the losers they keep in subsequent months (Barberis and Xiong, 2009).

At the same time, Jegadeesh and Titman (1993) find evidence that the long-term returns are higher for the stock in the loser portfolio, revealing that the excess returns of past winners dissipate over a longer-term horizon. Similarly, the flow of information over short horizons is usually too small to generate large gains or losses across stocks (Grinblatt and Han, 2005). This means that in a momentum strategy, it is most profitable to use intermediate horizon past returns for portfolio formation (Grinblatt and Han, 2002). In addition, the reference point converges to the market price faster the higher the turnover, as the recent updating of the reference prices shifts the demand function closer to the rational benchmark in the subsequent round of trading (Grinblatt and Han, 2005).

Grinblatt and Han (2002) propose that if some investors are subject to the disposition effect and thus create a 'capital gains overhang' in the market, this can actually be the key variable generating profitability for the momentum strategy. Trading that arise because of the disposition effect may account for the tendency of past winning stocks to subsequently outperform past losing stocks, i.e. the correlation between past returns and variables, as stocks with large aggregate unrealized capital gains tend to have higher expected return than stocks with large aggregate unrealized losses (Grinblatt and Han, 2002). For instance, Grinblatt and Han (2005) find in their empirical analysis that the return-based momentum effect disappears once the disposition effect is controlled for. The disposition effect induces demand perturbation, because the demand is not perfectly elastic when some investors have higher demand for losing stocks. Such interference in otherwise rational demand functions has implications for equilibrium prices (Grinblatt and Han, 2005). In particular, the disposition effect creates a spread between a stock's fundamental value and its market price, and a spread convergence implying that stocks with large past price increases have higher expected returns. A momentum strategy makes use of this spread and the succeeding predictable prices, to generate profits that depend on the path of past stock prices (Grinblatt and Han, 2002). Grinblatt and Han (2002) therefore suggest that as the number of disposition agents is reduced, the fundamental value will converge to the equilibrium market price.

As the disposition demand is determined by the future realization of the fundamental value, there is no way to anticipate the demand in advance, so to prevent the model from collapsing rational agents must have some degree of risk aversion (Grinblatt and Han, 2002). Moreover, even when fully rational arbitrageurs have full knowledge of the existence of disposition investors, they will not eliminate the impact on the equilibrium as they cannot ascertain when reference prices, and hence market prices, will converge to fundamental values (Grinblatt and Han, 2005). In addition, the trading done by rational arbitrageurs will be restrained by limited capital or incomplete information, or they rather anticipate the impact of positive feedback traders on demand and thus further destabilize prices by front-running them instead of bringing the prices in line with fundamental values (Grinblatt and Han, 2005).

3.2.2 Tax Considerations

Tax considerations have in some cases been used to explain the unaccountable high trading volume that is observed in financial markets (e.g. Barber and Odean (2000)). It is well known that gains and losses are taxed when the investor sells the stock, not when gains and losses actually occur (Constantinides, 1984). Therefore, taxable investors have an incentive to realize losses and, according to the prevailing view, should avoid realizing gains (Lakonishok and Smidt, 1986). According to Constantinides (1984), the optimal strategy for tax reasons and zero transaction costs is to: (1) defer realization of short-term capital gains and (2) realize a capital loss and repurchase the stock.

The tax-loss selling hypothesis predicts a greater propensity to hold profitable investments to postpone taxable gains, and to sell stocks with losses because the realized losses can offset taxable gains in other assets (Barberis and Xiong, 2009). In contrast, the disposition effect proposes the opposite behavior, namely that people has a reluctance to realize losses and thus act as if they are trying to maximize their taxes (Ritter, 2003). Consequently, for taxable investments the disposition effect is suboptimal, being at odds with optimal tax-loss selling, and predicting that people behave differently than if they paid attention to tax consequences (Odean, 1998).

Lakonishok and Smidt (1986) study the relationship between trading volume in a given month and price changes in earlier months, and try to analyze if it is created by the response of investors to capital gains taxes or by non-tax reasons. Whatever explanation, investors seem to respond to past price changes by being more or less willing to trade (Lakonishok and Smidt, 1986). The results of Lakonishok and Smidt (1986) show that taxes do influence turnover, but that there are other more important motives for trading. As noted above, capital gains taxes create incentives to realize losses and in some circumstances to defer realizing gains, but Lakonishok and Smidt (1986) find that winners tend to have higher abnormal volume than losers, i.e. there exists a positive cross-sectional correlation between past price changes and current volume. This relationship is contrary of tax-related responses, and is rather expected if non-tax-related motives are predominant. According to Lakonishok and Smidt (1986), there are several factors that limit the extent of tax-induced trading: short-term losses may need to be carried forward to future years (reducing the tax benefits), investors may be reluctant to realize losses early in the year as they do not know what the exact consequences will be, high transaction costs may reduce the incentives to trade, and finally there are taxpayers who do not report realized capital gains on their tax returns.

At the same time, Dyl (1977) presents analyses suggesting that investors take capital gains tax liabilities into consideration and that tax incentives also exist for the initiation of transactions. Shefrin and Statman (1985) discover that the observed patterns of loss and gain realization in real markets are consistent with a combination of the disposition effect and tax considerations – it cannot be explained by one of them alone. In addition, investors' after-tax portfolio performance can be improved with a better awareness of the disposition effect (Dhar and Zhou, 2006).

Constantinides (1984) find that in the presence of transaction costs, tax-loss selling predicts a seasonal pattern in trading volume. According to the optimal trading policy, the volume of loss realizations should peak in December before the end of the tax year, then fall off drastically in January before gradually increasing again (Constantinides, 1984). This assumption is confirmed in studies by Constantinides (1984) and others (e.g. Dhar and Zhou, 2006). Equivalently, tax-*gain* selling decreases at the end of the year as traders postpone sales to avoid being taxed on the gains in the current tax year (Ferris et al., 1987). As investors' trading in the month of December is affected by tax-selling considerations, the volume of losing stocks will be relatively high as opposed to what is predicted by the disposition effect (Ferris et al., 1987). The consequence is a reduced disposition effect in the end of the tax year because tax factors play a larger role (Barberis and Xiong, 2009). This is confirmed in several studies, for instance by Constantinides (1984), Ferris et al. (1987), Lakonishok and Smidt (1986), and Grinblatt and Han (2005), and implies that market prices move closer to fundamental values in December (Grinblatt and Han, 2005).

In January, on the contrary, the disposition effect predicts the same trading pattern as the tax-loss selling hypothesis, namely that the volume of trading in stocks with capital gains will be higher than for losses (Ferris et al., 1987). The selling pressure of gains in January may or may not affect the stock price, but if irrationality or ignorance among investors is assumed, the seasonal pattern in trading volume maps into a seasonal pattern in stock prices where small stocks experience positive abnormal returns in January, particularly known as the 'January anomaly' (Constantinides, 1984). Lakonishok and Smidt (1986) argue that the seasonal variance in the strength of relationship between past prices and current turnover is evidence that tax-related motives also influence trading volume.

Several authors (e.g Constantinides, 1984) seem to believe that the loss realization in December is consistent with rational behavior, because of the additional year's interest involved. However, Dhar and Zhou (2006) find that both taxable and tax-deferred accounts exhibit similar disposition effect, indicating that individuals' behavior is not changed because of tax considerations in particular. In addition, Shefrin and Statman (1985) criticise the rational explanation by arguing that December has no special role in models based upon rational behavior. The framework individuals presented by Shefrin and Statman (1985) have a rational desire to take advantage of the tax consequences of gain and loss realization, but are also affected by the disposition effect and thus have an aversion for loss realization even if they recognize the tax benefits of doing so (Odean, 1998). The concentration of loss realization in December can therefore rather be explained by a perceived deadline characteristic where investors exert 'self-control' by requiring themselves to override their disposition to keep losers (Shefrin and Statman, 1985).

Jegadeesh and Titman (1993) also propose an additional explanation for the increased loss realization in December, namely that it is partly due to price pressure arising from portfolio managers selling their losers for window dressing reasons. Similarly, the high turnover for winners in January may be due in part to the high frequency of annual results and analysts' recommendations released at this time (Lakonishok and Smidt, 1986). Finally, Grinblatt and Han (2002) find that momentum strategies appear to be most effective in December, because of an additional perturbation in demand arising from tax-loss selling.

As noted earlier, tax considerations and the disposition effect operate in opposite directions, and this also relates to short-term and long-term conduct. The disposition effect suggests that investors hold on to their losing investments and close out profitable gains quickly, to lock in gains. In contrast, tax considerations propose that gains should be realized only when they are long-term and that losses should be realized while they are short-term. According to Lakonishok and Smidt (1986) and Constantinides (1984), the volume for winners should be especially large in the first month after the winner has become long-term, so that future losses will be short-term, and they refer to this as an 'insurance motive'. The study by Shefrin and Statman from 1979 find no significant differences associated with various durations, implying that investors seem to be subject to the disposition effect. Still, they point out that this result could be due to a small portion of tax-motivated trades in the market, or that those investors subject to the disposition effect offset the contribution from others.

4 Methodology and Data

As mentioned earlier, several authors have tried to measure the disposition effect in stock markets, and many of them presents results in favor of the hypothesis that some investors hold on to losers too long and sell winners too quickly. This section presents the methodology and data used to perform the analysis of the disposition effect in the Norwegian equity market. After an introduction of abnormal turnover, the main model is presented and the relevant data material is described.

4.1 Methodology

In the examination of the disposition effect in Norway, the correlation between prices and trading volume will be investigated. The methodology was introduced by Ferris et al. (1987), who performed the analysis on US stocks in 1988, and is designed to test for the predictions of the disposition effect using trading volumes and price performance.

Relationship between Normal and Abnormal Trading Volume

There are many factors that may influence the normal trading volume for a specific firm, i, both internal and external. Dyl (1977) points out that the number of shares a firm has outstanding, as well as the number of shareholders and how closely the firm is held, are probably the primary internal factors. When it comes to external factors, determinants that influence more than one stock, such as information about political events and economics, affect companies. This results in increased trading volumes because the information changes investors' expectation, and thereby their desired portfolio (Dyl, 1977). In his study of the information content of annual earnings announcements, Beaver (1968) finds that the correlation between market wide events (external factors) and a firm's specific trading volume is significantly different from zero. Therefore, one should always consider external factors in any definition of normal trading volume (Dyl, 1977).

To calculate the expected or normal trading volume for a given stock, i, when taking into account that external factors may influence the trading volume, an ordinary least square regression is used where the daily turnover for stock i at day t (V_{it}) is regressed on the market turnover (V_{mt}) at day t.[4] The linear regression for the normal trading volume is defined as:

$$V_{it} = A_i + B_i V_{mt} + e_{it} \tag{4.1}$$

where

$$V_{it} = \frac{\text{Number of shares of stock i traded on day t}}{\text{Total number of shares of stock i outstanding on day t}}$$

$$V_{mt} = \frac{\text{Number of shares of all stocks traded on day t}}{\text{Total number of shares of all stocks outstanding on day t}}$$

$$e_{it} = \text{Abnormal turnover for stock i on day t}$$

The abnormal turnover, e_{it}, from (4.1) is defined as the portion of a firm's trading volume that cannot be explained by market influences (Beaver, 1968). From (4.1), the abnormal turnover can be expressed as the difference between the actual trading volume for stock i observed at day t, V_{it}, and the conditional expected trading volume given by:

[4] The use of turnover is to prevent stock splits to have any effect on the results.

$$E(V_{it}|V_{mt}) = A_i + B_i V_{mt} \tag{4.2}$$

Negative (positive) e_{it} indicates that the trading volume for stock i was abnormally below (above) the daily average (Dyl, 1977).

The Emprical Model

In the search for the disposition effect in the Norwegian equity market, the relation of the abnormal turnover for a stock i at its given price, P_{it}, to its past turnover is examined. This is done by a classification of the past price for the stock at an earlier trading day n, P_{in}, into eight different price ranges around P_{it}. The ranges are defined as:

Range 1: $P_{it} < P_{in} \leq (1+x)P_{it}$

Range 2: $(1+x)P_{it} < P_{in} \leq (1+2x)P_{it}$

Range 3: $(1+2x)P_{it} < P_{in} \leq (1+3x)P_{it}$

Range 4: $(1+3x)P_{it} < P_{in}$

Range 5: $P_{it} \geq P_{in} > (1-x)P_{it}$

Range 6: $(1-x)P_{it} \geq P_{in} > (1-2x)P_{it}$

Range 7: $(1-2x)P_{it} \geq P_{in} > (1-3x)P_{it}$

Range 8: $(1-2x)P_{it} \geq P_{in}$

That is, if the price on a past trading day, n was greater than on day t, it is classified in one of the ranges 1 through 4. Similarly, prices lower than on day t would fall in one of the ranges 5 through 8.

For every day t, the price P_{in} on each past trading day n going back a year from day t, is classified into its corresponding range according to P_{it}, and thereafter the belonging turnover for that day is assigned to the range. After this, all volume assigned to each range is added up, so that the final product is eight cumulative turnover numbers representing the total abnormal turnover that occurred in each range. These eight cumulative turnover numbers are then used in the following regression:

$$e_{it} = \alpha_0 + \beta_1 T_{1it} + \beta_2 T_{2it} + \beta_3 T_{3it} + \beta_4 T_{4it} + \beta_5 T_{5it} + \beta_6 T_{6it} + \beta_7 T_{7it} + \beta_8 T_{8it} + u_{it} \tag{4.3}$$

Where T_{jit} is the cumulative turnover for stock i for all the trading days over the past year when its price was in range j.

When analyzing the abnormal turnover, the closing price is used and x is set to 0.075[5]

A drawback with this model is the assumption that the security was bought on day n and sold on day t, since obviously that is usually not the case. Buyers at a past price may sell before or after day t, and this makes the cumulative turnovers, T_{jit}, noisy variables. However, since volumes at all prices are affected in this way, the results will most likely have no significant bias because of this problem (Ferris et al., 1987).

To investigate the possibility that the disposition effect is visible in the Norwegian stock market, a hypothesis around the regression coefficients, β_j, is formed. If the variables β_1 to β_4 are negative, the investors are holding on to the losing securities, which support the appearance of abnormal behavior. On the other hand, if the coefficients are positive the investors are selling the losing securities, and the disposition effect hypothesis will be rejected. In addition, if the coefficients are positive in December this supports the tax-selling hypothesis. Similarly, if the variables β_5 to β_8 are positive, the investors are selling the winning securities, which is predicted

[5]Ferris et al. (1987) found no significant difference when changing the x to 0.05 or 0.10.

by the disposition effect. Accordingly, the hypothesis that is tested is defined in the following way:

$$\beta_j < 0 \text{ for j} = 1,...,4 \text{ and } \beta_j > 0 \text{ for j} = 5,...,8$$

4.2 Data

The data used to examine the existence of the disposition effect in the Norwegian equity market are prices and turnover for the thirty smallest firms by equity value as of January 2014. The data covers the period from January 2010 to December 2013 and is collected from the Oslo stock exchange (Oslobors, 2014)[6]. The reason for examining the thirty smallest firms on the Norwegian stock exchange, is because the stocks belonging to small market capitalization firms are characterized by more volatile return patterns, and therefore it will be a higher chance of detecting abnormal investor behavior in these stocks (Ferris et al., 1987).

[6] The stocks that are chosen have been listed the whole period, and are traded sufficiently.

5 Results

In this section, the results from the empirical analysis will be presented, but first there will be a short discussion around choices that are made and noise that might affect the results.

5.1 Choices and Noise that can affect the Results

Some choices have been made for the analysis due to regression robustness, convenient data separation and non-trading days.

The first choice is done to obtain more power for the regression. In particular, data for one trading day is pooled from three different years instead of one, and as a result there will be ninety observations for each trading day. This implies that unexpected events will have less impact on the overall results.

The second choice is regarding the separation of the data. The last day of the year is used as a crossroad for the analysis, meaning that the last trading day in December is the last trading day for all the three years that the stocks are pooled from, and the first trading day in January is the first trading day for all the three years, i.e. irrespective of the specific date. Consequently, some of the last trading days placed in the January category will consist of some days from January and some from February, and the same will apply for the first trading days in December. This is a result of a different number of trading days in the three years the data are pooled from. Therefore, the regression results for the days in the beginning of the months for August to December, and the regression results for the last days of the months for January to June should be interpreted with caution.

Third, since the smallest firms per equity value are chosen, the data consists of several days with no trading activity. At the same time, to be able to do the analysis a closing price is needed for all the trading days. Therefore, the closing price for the non-trading days is set equal to the closing price on the previous day.

There are several factors that make the results noisy. For instance, the noise in the data might be a result of counter-effects, such as tax-loss selling or momentum strategies, that can erase (or in some cases increase) the symptoms of disposition effect. First, tax-loss selling will dilute the results of the disposition effect in December, since the two trading patterns contradict each other. Both effects can be present in the market, but not be visible, because of the contradictory symptoms. One the other hand, tax-gain selling will strengthen the results of the disposition effect in January, because both trading patters predict the same behavior for January. Secondly, the momentum strategy will dilute the symptoms of the disposition effect during the entire year, since investors following this strategy will do the opposite of investors prone to the disposition effect.

Another factor that can bias the results is illiquidity, linked to the choice about the non-trading days. In Table 1, the average number of non-trading days for each month for each year the data is pooled from is listed together with average for all the years. From Table 1, it can be seen that there is on average about three non-trading days each month.

Table 1: Average non-trading days for each month

Month	'10	'11	'12	'13	Average
January	2.4	3.4	2.4	3.8	3.0
February	3.1	2.1	2.7	3.3	2.8
March	2.9	2.9	3.2	3.9	3.2
April	1.4	2.4	3.3	4.5	2.9
May	1.5	2.7	4.1	3.6	3.0
June	2.6	2.5	4.6	3.4	3.3
July	2.9	3.9	5.6	4.2	4.1
August	2.8	3.6	5.2	3.7	3.8
September	2.6	3.6	4.4	2.8	3.4
October	2.1	3.9	4.9	2.4	3.3
November	1.6	3.2	3.6	2.0	2.6
December	1.8	2.4	2.0	1.5	1.9

These non-trading days can both positively and negatively influence the evidence of the disposition effect in the Norwegian market. The reason is that the existence of non-trading days implies a less liquid company, which means that the stocks belonging to these firms can be harder to trade. Therefore, even if an investor wants to sell his stocks when his utility is above (disposition effect) or below (rational) origo, he might not be able to do it because nobody wants to buy it.

5.2 Daily Values

According to the hypothesis, the disposition effect is present in the Norwegian equity market if the first four beta coefficients, excluding the intercept, are negative, and the last four are positive. In Table 2, the regression coefficients for December are switching between positive and negative values for all the trading days. Consequently, the results do not point in one clear direction. The January results are also scattered, and it can be noted that the January coefficients are on average less significant than the December coefficients. In summary, the disposition effect in Norway is more visible in December than in January, but there are some deviations in the results and so a distinct conclusion cannot be made.

Still, the results present some interesting findings. Starting with the December results, the first four coefficients are on average more negative than positive, suggesting that the majority of the investors hold on to their losing investment, in accordance with the disposition effect. The only exception is β_3, which is predominantly positive, indicating that investors sell their investments when the return is in the interval (-15%, -22.5%). This exception can be a result of the tax-loss selling effect, which is realistic since a loss in this order of magnitude can give a significant tax gain that is worth more to the investor than his pride.

Regarding the last four coefficients for December, coefficient 5 and 7 are predominantly significant and positive, while coefficient 6 and 8 are less significant and predominantly negative. This indicates that investors sell their stocks when the return is either in the interval (0% - 7.5%) or (15% – 22.5%), and predominantly keep their stocks if the return is between 7.5% and 15%, or higher than 22.5%. The fact that investors sell when the return is in the first of the last four intervals (e.g. close to origo) can be explained by the steepness of the utility curve in figure 2.1, since the loss if the price moves in the left direction is much bigger than the profit if the price moves to the right. The slope of the utility curve gets less steep further away from the origin, which can explain why investors hold on to their investments in the higher intervals, since their loss if the price moves in the left direction is not nearly as big as it is in the fourth interval.

Table 2: Daily values for December and January for the thirty smallest firms on OSE

Trading day	α_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	R^2_{Adj}	DW
						December					
1	-0.00069 (0.0161)*	-0.01510 (0.0809)	0.03921 (0.0000)***	-0.02192 (0.1401)	0.00042 (0.3332)	0.01455 (0.0196)*	-0.05681 (0.0000)***	0.05824 (0.0000)***	-0.00340 (0.1390)	0.5449	1.7129
2	-0.00080 (0.0059)**	-0.00919 (0.1885)	-0.01515 (0.1122)	0.06526 (0.0000)***	-0.00123 (0.0057)**	0.01247 (0.0354)*	-0.02531 (0.0550)	0.00589 (0.6540)	0.00272 (0.2074)	0.3476	1.7869
3	-0.00076 (0.2880)	0.00370 (0.8690)	0.02341 (0.3120)	0.03691 (0.1340)	-0.00192 (0.1330)	0.02176 (0.1900)	-0.02983 (0.2810)	0.00047 (0.9870)	0.00229 (0.520)	0.0862	1.7583
4	-0.00078 (0.2062)	-0.01476 (0.5525)	-0.02114 (0.3931)	0.06566 (0.0000)***	-0.00059 (0.4985)	00596 (0.6424)	-0.07775 (0.0000)***	0.11488 (0.0000)***	0.00497 (0.0752)	0.7738	1.9265
5	-0.00090 (0.1548)	-0.03458 (0.1022)	0.02223 (0.0249)*	0.00985 (0.5256)	-0.00139 (0.1187)	0.08214 (0.0000)***	-0.07361 (0.0000)***	0.04983 (0.0000)***	-0.00444 (0.1088)	0.665	1.8109
6	-0.00031 (0.6093)	0.02682 (0.1175)	-0.01226 (0.6085)	0.03690 (0.0799)	-0.00277 (0.0317)*	-0.01124 (0.3796)	-0.06392 (0.00025)***	0.06198 (0.0000)***	00850 (0.0015)**	0.297	1.6391
7	-0.00056 (0.2507)	-0.03910 (0.0083)**	0.07707 (0.0009)***	-0.04373 (0.0466)*	0.00118 (0.2776)	0.01960 (0.0835)	-0.01002 (0.3518)	0.02620 (0.0364)*	-0.00403 (0.0165)*	0.2705	2.2515
8	-0.00072 (0.0044)**	-0.01305 (0.0431)*	0.03114 (0.0000)***	-0.01977 (0.0201)*	0.00045 (0.3515)	0.01371 (0.0002)***	-0.03266 (0.0000)***	0.02963 (0.0002)***	0.00012 (0.8902)	0.6305	1.4865
9	0.00271 (0.1863)	-0.12768 (0.0472)*	-0.09177 (0.3522)	0.00121 (0.9889)	0.01142 (0.0015)**	0.01561 (0.6889)	0.06234 (0.2189)	0.04591 (0.4998)	-0.01713 (0.0073)**	0.1765	2.1411
10	-0.00113 (0.0148)*	-0.13629 (0.0000)***	0.19448 (0.0000)***	-0.08115 (0.0108)*	0.01372 (0.0000)***	0.05089 (0.0118)*	-0.03582 (0.1960)	0.08019 (0.0921)	-0.01207 (0.0458)*	0.8077	2.1428
11	-0.00154 (0.1371)	-0.04939 (0.0868)	0.11932 (0.0000)***	-0.11992 (0.0001)***	-0.00230 (0.2557)	0.12663 (0.0000)***	-0.02807 (0.3926)	-0.12038 (0.0066)**	0.03141 (0.0076)**	0.8248	1.8889
12	-0.00289 (0.0924)	-0.07037 (0.1100)	-0.04100 (0.4907)	0.1922 (0.0118)*	-0.0191 (0.0001)***	0.38806 (0.0000)***	-0.46152 (0.0000)***	0.26041 (0.0000)***	-0.03151 (0.0000)***	0.8344	1.974
13	-0.00431 (0.00219)**	-0.07070 (0.0141)*	-0.08124 (0.1813)	0.13108 (0.0352)*	-0.00042 (0.9150)	0.31044 (0.0000)***	-0.14791 (0.0007)***	0.08306 (0.0406)*	-0.00571 (0.3511)	0.9436	2.007
14	-0.00148 (0.0109)*	0.09707 (0.0000)***	-0.10434 (0.0000)***	0.09016 (0.0000)***	0.00550 (0.0018)**	-0.00960 (0.3643)	0.02069 (0.1722)	0.01978 (0.0296)*	-0.00596 (0.0122)*	0.9165	1.448

15	-0.00106	0.01807	-0.04742	0.04468	0.00715	0.02752	-0.06016	0.04208	0.00092	0.7609	2.0742
	(0.0691)	(0.1580)	(0.0697)	(0.0000)***	(0.0005)***	(0.0516)	(0.0033)**	(0.0039)**	(0.6125)		
16	-0.00002	-0.00202	-0.06600	0.01670	0.00066	0.07298	-0.08660	0.04330	-0.00080	0.3510	1.7681
	(0.9810)	(0.9022)	(0.0240)*	(0.0494)*	(0.7273)	(0.0003)***	(0.0028)**	(0.0333)*	(0.6757)		
17	-0.00343	-0.01992	-0.02635	0.30275	-0.01878	0.1653	-0.03292	-0.03692	0.00762	0.7905	2.0551
	(0.0087)**	(0.4201)	(0.7034)	(0.0000)***	(0.0001)***	(0.0000)***	(0.4905)	(0.3156)	(0.0407)*		
18	-0.00110	-0.03208	0.00705	0.09152	-0.00532	0.07078	-0.02595	0.06175	-0.01248	0.8407	1.8797
	(0.1981)	(0.0881)	(0.9011)	(0.0135)*	(0.1604)	(0.0000)***	(0.0715)	(0.0041)**	(0.0046)**		
					January						
1	-0.00055	-0.00112	0.00518	-0.00464	0.00386	-0.00541	-0.05086	0.02248	-0.00089	0.2581	1.4632
	(0.1858)	(0.9334)	(0.5934)	(0.8327)	(0.0708)	(0.6453)	(0.0043)**	(0.0023)**	(0.7386)		
2	0.00001	-0.01153	0.00436	0.00870	-0.00049	-0.00604	-0.01444	0.00153	0.01110	0.3096	1.6729
	(0.9860)	(0.3680)	(0.5910)	(0.6420)	(0.8150)	(0.5380)	(0.2820)	(0.8700)	(0.0000)***		
3	-0.00058	-0.01521	-0.00010	-0.00359	0.00395	0.00991	-0.01491	-0.02714	0.02048	0.05941	1.7017
	(0.0571)	(0.0052)**	(0.9882)	(0.8223)	(0.0293)	(0.3681)	(0.1351)	(0.0017)**	(0.0000)***		
4	-0.00014	-0.00030	-0.01625	-0.00591	0.00403	0.01445	-0.03041	-0.03433	0.01771	0.2402	1.5887
	(0.7810)	(0.9856)	(0.5447)	(0.5561)	(0.1508)	(0.3940)	(0.2070)	(0.0161)*	(0.0000)***		
5	-0.00020	-0.02767	0.00385	0.00393	-0.00019	0.01297	0.01532	-0.02774	0.00900	0.3258	1.8413
	(0.5037)	(0.0060)**	(0.7782)	(0.5043)	(0.8993)	(0.1643)	(0.2215)	(0.0007)***	(0.0000)***		
6	-0.00036	-0.01967	-0.00306	0.00282	-0.00095	-0.00636	0.01862	0.00113	0.00419	0.3222	1.5419
	(0.1508)	(0.0100)**	(0.7862)	(0.5860)	(0.2541)	(0.5426)	(0.0393)*	(0.8457)	(0.0082)**		
7	-0.00113	-0.02715	0.00271	0.03783	0.01417	-0.00707	0.00567	-0.01587	0.00765	0.8423	1.5683
	(0.0020)**	(0.0003)***	(0.7333)	(0.0625)	(0.0000)***	(0.6590)	(0.6492)	(0.08048)	(0.0003)***		
8	-0.00033	-0.02342	-0.00809	0.00804	-0.00014	0.00892	0.01749	0.00522	-0.00125	2374	1.8031
	(0.2292)	(0.0001)***	(0.4541)	(0.1499)	(0.9132)	(0.5243)	(0.1094)	(0.3904)	(0.4255)		
9	-0.00050	-0.03227	-0.22001	0.01221	0.00887	0.31692	-0.13271	-0.00823	-0.00841	0.2543	2.124
	(0.7862)	(0.6820)	(0.1460)	(0.7491)	(0.2853)	(0.0000)***	(0.0407)*	(0.8508)	(0.4884)		
10	-0.00053	-0.00943	-0.02191	0.00348	0.00009	0.01249	-0.00775	0.00175	0.00633	0.3033	1.0635
	(0.0896)	(0.3039)	(0.0003)***	(0.5963)	(0.9266)	(0.2113)	(0.4701)	(0.7726)	(0.0036)**		

11	-0.00013	-0.02379	-0.01219	0.01409	-0.00356	0.01325	0.03791	-0.00568	-0.00058	-0.0333	1.9895
	(0.8550)	(0.2940)	(0.4920)	(0.3520)	(0.2610)	(0.4610)	(0.1770)	(0.6850)	(0.9030)		
12	-0.00035	-0.01607	0.00174	-0.00488	0.00108	0.00607	-0.00361	-0.00478	0.00484	0.0734	1.5957
	(0.1509)	(0.0380)*	(0.7383)	(0.7073)	(0.4348)	(0.3767)	(0.7576)	(0.3928)	(0.0034)**		
13	-0.00011	-0.20945	-0.01008	0.03484	0.00772	0.21427	-0.18777	0.00898	0.06747	0.4854	1.7412
	(0.9399)	(0.0.0000)***	(0.7071)	(0.2776)	(0.1403)	(0.0000)***	(0.0052)**	(0.7844)	(0.0000)***		
14	-0.00009	-0.06100	0.07382	-0.01460	0.00055	-0.00457	-0.01497	-0.01857	0.02388	0.3259	1.8515
	(0.9012)	(0.0205)*	(0.0016)**	(0.1888)	(0.8775)	(0.7984)	(0.6425)	(0.2295)	(0.0000)***		
15	-0.00053	-0.14687	0.00314	0.01609	0.02043	0.36115	-0.49497	0.00898	0.02235	0.3741	2.1887
	(0.8481)	(0.0568)	(0.9573)	(0.7779)	(0.0682)	(0.0000)***	(0.0010)**	(0.8867)	(0.2095)		
16	-0.00077	-0.00010	-0.01869	-0.00202	-0.00571	-0.00674	0.06443	0.01073	-0.00447	0.4493	1.8430
	(0.0162)*	(0.9882)	(0.0012)**	(0.7538)	(0.0000)***	(0.4456)	(0.0000)***	(0.1511)	(0.0533)		
17	-0.00004	-0.0020	-0.02579	-0.00020	-0.00006	-0.00059	0.02113	0.00590	-0.00420	0.2418	1.8601
	(0.9036)	(0.7461)	(0.0003)***	(0.9738)	(0.9461)	(0.9472)	(0.1413)	(0.3807)	(0.05469)		
18	-0.00029	0.01969	-0.04450	0.00581	0.00648	-0.01583	0.03906	-0.01389	-0.00189	0.2614	1.9455
	(0.4979)	(0.0615)	(0.0001)	(0.4764)	(0.0000)***	(0.1432)	(0.2327)	(0.2552)	(0.5396)		
19	-0.00035	0.08969	-0.02210	-0.03469	-0.00457	0.04633	-0.09399	0.02095	-0.01088	0.1079	2.2174
	(0.7670)	(0.00178)**	(0.6131)	(0.0556)	(0.1100)	(0.0800)	(0.2600)	(0.5229)	(0.2258)		
20	-0.00027	0.00120	-0.01379	-0.01061	-0.00116	-0.00079	0.00272	0.00252	-0.00324	0.3207	1.3201
	(0.3359)	(0.8768)	(0.1723)	(0.0109)*	(0.0579)	(0.8856)	(0.8767)	(0.7305)	(0.1362)		
21	-0.00082	0.00301	-0.02090	0.01168	0.00157	0.00652	0.06400	-0.00923	-0.01093	0.2982	2.1015
	(0.0608)	(0.8160)	(0.2913)	(0.0862)	(0.3479)	(0.5607)	(0.0000)***	(0.3187)	(0.0012)*		
22	-0.00033	-0.00953	0.01843	-0.00301	-0.00212	-0.02393	0.09928	-0.01510	-0.01444	0.5018	1.7009
	(0.4129)	(0.4006)	(0.1431)	(0.6981)	(0.0758)	(0.0322)*	(0.0000)***	(0.0314)*	(0.0000)***		

***Level of significance is within 0.1%

**Level of significance is within 1.0%

*Level of significance is within 5.0%

In January, half of the investors hold on to their stocks in all of the intervals, while the other half sells their stocks. The only coefficient that is separate from the others is β_1, which is noticeably more negative than positive. This results suggests that the disposition effect for January is only visible in the first interval (-7.5%, 0), since in this interval the majority of the investors hold on to their investment.

5.3 Monthly Values

The monthly values in Table 3 are calculated by averaging the daily values for each month. β_1 is negative for all the months except June, which indicates that the majority of the investors in the Norwegian equity market have a tendency to hold on to their losing stocks when the loss is of smaller magnitude. February is the only month where the evidence for the disposition effect is truly visible. For the rest of the months, the regression coefficients change between positive and negative values for the last seven coefficients.

The figures below present the number of positive and negative coefficients sorted by quarters and separated between the first and last four regression coefficients. For the first four coefficients presented in Figure 5.1, it can be seen that there are predominately more negative coefficients than positive, but that there is no significant dominance. In Figure 5.2, where the last four coefficients are presented, the positive coefficients are far from dominating. In particular, for two of the quarters there are actually more negative coefficients than positive. In consequence, no precise conclusion about the presence of the disposition effect in the Norwegian stock market during these months can be made.

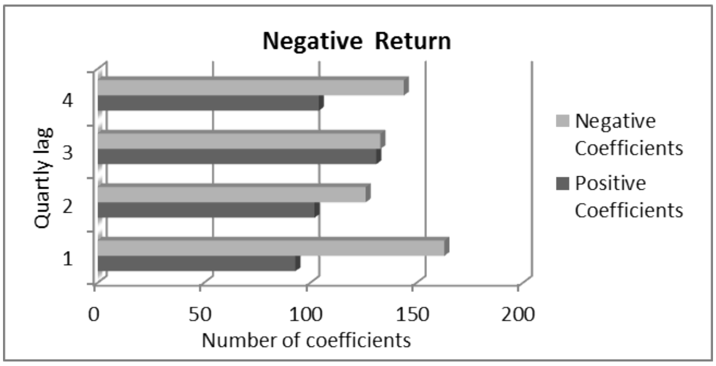

Figure 5.1: Number of positive and negative coefficients for the first four regression coefficients, sorted by quarters

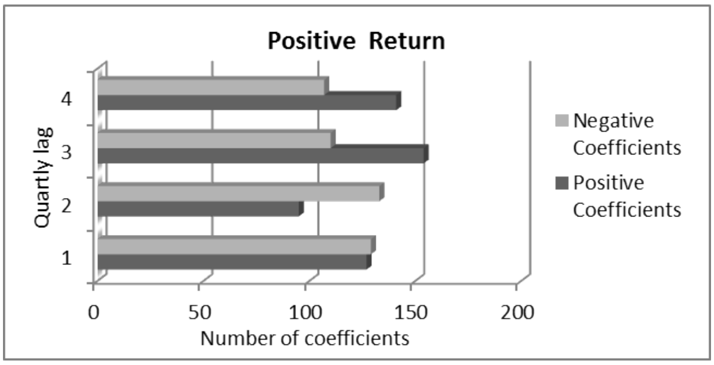

Figure 5.2: Number of positive and negative coefficients for the last four regression coefficients, sorted by quarters

Table 3: Monthly values for the thirty smallest firms on OSE

Month	α_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	R^2_{Adj}	DW
January	-0.00037	-0.03374	-0.01588	0.00622	0.00334	0.05099	-0.04071	-0.00497	0.00968	0.3259	1.7435
	(0.4936)	(0.3055)	(0.4730)	(0.5560)	(0.3929)	(0.4010)	(0.2287)	(0.4220)	(0.1904)		
February	-0.00021	-0.00659	-0.00131	-0.00551	-0.00184	0.01953	-0.01520	0.00121	0.00374	0.2969	1.8608
	(0.5011)	(0.3249)	(0.5117)	(0.4816)	(0.0790)	(0.2117)	(0.2393)	(0.3672)	(0.2246)		
March	-0.00031	-0.00926	-0.00992	0.00773	-0.00069	0.01680	-0.00543	0.00683	-0.00376	0.2567	1.7479
	(0.4242)	(0.2004)	(0.2350)	(0.4143)	(0.3135)	(0.3387)	(0.2916)	(0.4487)	(0.2709)		
April	-0.00076	-0.01812	-0.01153	0.00936	0.00075	0.02127	-0.00493	-0.01858	0.01090	0.5628	1.7532
	(0.2582)	(0.3378)	(0.1865)	(0.2094)	(0.0866)	(0.3466)	(0.1504)	(0.2696)	(0.2019)		
May	-0.00036	-0.01055	-0.00780	0.00227	0.00131	0.00719	-0.00104	-0.12443	-0.00403	0.3142	1.7068
	(0.4356)	(0.2151)	(0.1129)	(0.2523)	(0.2038)	(0.2432)	(0.3883)	(0.2286)	(0.3434)		
June	-0.00046	0.00648	0.00005	-0.01802	0.00091	-0.00012	-0.00894	-0.00247	0.00136	0.3530	1.5725
	(0.2753)	(0.3470)	(0.3591)	(0.2327)	(0.3564)	(0.4167)	(0.3218)	(0.3587)	(0.3254)		
July	-0.00057	-0.03366	-0.02400	-0.01682	0.00914	0.02536	-0.01698	-0.01195	0.00770	0.49908	1.7535
	(0.2718)	(0.0935)	(0.1263)	(0.2141)	(0.1502)	(0.1309)	(0.1964)	(0.2133)	(0.3183)		
August	-0.00119	-0.03345	-0.01826	-0.07426	0.01206	0.05741	0.00829	-0.00220	0.02216	0.5909	1.8462
	(0.2355)	(0.3450)	(0.1580)	(0.1637)	(0.0664)	(0.1366)	(0.2459)	(0.3264)	(0.2208)		
September	-0.00098	-0.01326	-0.02236	0.00966	0.00705	0.01757	-0.03820	0.03234	0.02157	0.6973	1.7940
	(0.3297)	(0.2633)	(0.2282)	(0.0949)	(0.0853)	(0.2790)	(0.1877)	(0.1928)	(0.1619)		
October	-0.00006	-0.00511	-0.01540	0.00193	0.00057	-0.00018	-0.02249	-0.00901	0.00842	0.34582	1.7248
	(0.6052)	(0.3669)	(0.2919)	(0.4078)	(0.3101)	(0.4286)	(0.2118)	(0.3243)	(0.2890)		
November	-0.00010	-0.05338	-0.02258	0.01993	0.00068	0.08885	-0.05847	0.04173	-0.00490	0.3604	1.9998
	(0.4729)	(0.1904)	(0.3569)	(0.3272)	(0.3230)	(0.1624)	(0.1570)	(0.1986)	(0.2458)		
December	-0.00116	-0.02714	0.00010	0.04435	-0.00074	0.07653	-0.06476	0.04427	-0.00217	0.6034	1.7928
	(0.1798)	(0.2105)	(0.2319)	(0.1142)	(0.2118)	(0.1371)	(0.1809)	(0.1518)	(0.2064)		

5.4 The Disposition Effect in a Smaller Frame

The conclusion regarding the existence of the disposition effect in the Norwegian Equity market has been drawn from the results by the use of the hypothesis, i.e. that coefficient β_1 to β_4 should be less than zero, and coefficient β_5 to β_8 should be above zero. So far, as the results presented above show, no distinct conclusion about the disposition effect can be made

At the same time, if the focus is concentrated on the area where the utility curve is steepest, i.e. around origo, the results might be different. For the steepest part, only β_1, and β_5, are of interest. A reason for looking at the interval covered by β_1, i.e. the first negative interval, is that investors are most likely affected by the disposition effect on different levels. Therefore, β_1, which represents the interval where investors have the most to gain if the stock market goes upward again, would therefore catch everyone, even those that are just partly affected by the disposition effect. An argument for looking at the first positive interval, covered by β_5, is that most investors affected by the disposition effect would probably sell their shares already in this interval, since it is in this interval they have the most to lose by holding on to their shares. Therefore, with this argument in mind, the betas in the subsequent intervals are less likely to be positive, i.e. investors selling their shares, since these coefficients reflect more rational investors' behavior.

From Table 3, 11 out of 12 months had a negative β_1, and 10 out of 12 months had a positive β_5. In Figure 5.3 and 5.4, the number of positive and negative coefficients for β_1, and β_5 for each month is shown. The results point in the direction of the disposition effect for both β_1, and β_5. For β_1, 69% of the coefficients were negative, and for β_5, 64% of the coefficients were positive. This indicates that the majority of the investors hold on to their shares when the return is between 0 and -7.5%, and sell their stocks when the return is between 0 and 7.5%. From Figure 5.3 and 5.4, it is clear that the disposition effect is more visible in the months November and December. According to Table 1, these months have the lowest number of non-trading days, meaning that there is a small chance that the result is caused by illiquidity.

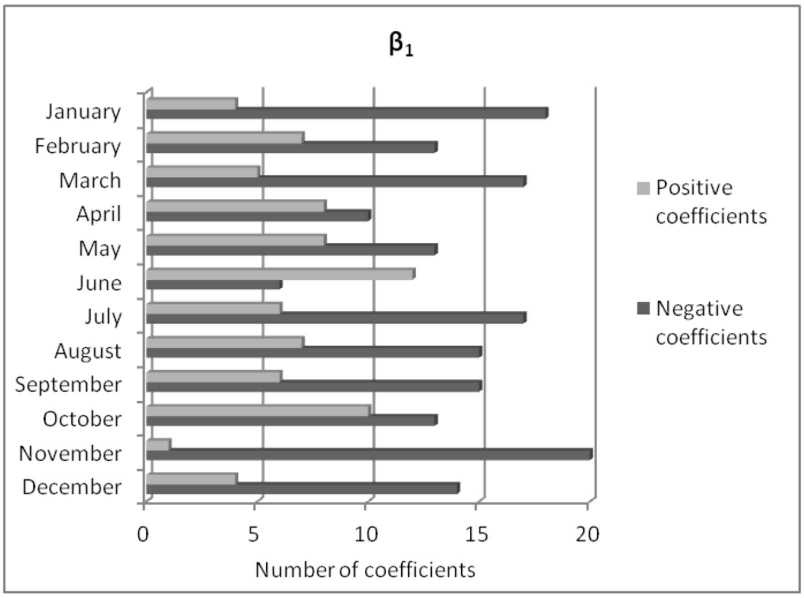

Figure 5.3: Number of positive and negative coefficients for β_1 for each month

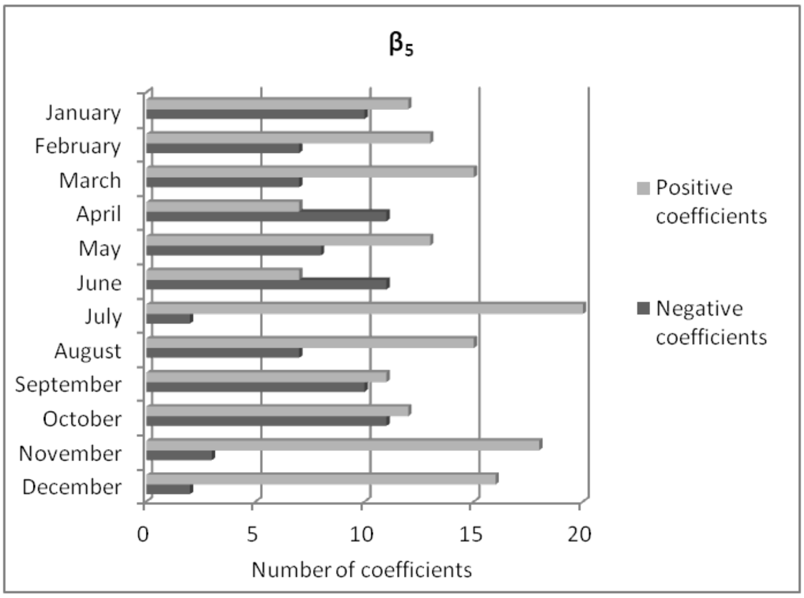

Figure 5.4: Number of positive and negative coefficients for β_5 for each month

In a more statistical perspective, one can assume that the coefficients are random variables which follow a binomial distribution with parameters n and p, $\beta \sim$ B(n, p). p = 50%, is the probability for one successive outcome, and n = 249, is the number of trials.

The cumulative probability for β_1, and β_5 is then:

$$Pr(\beta_1 > 170) = 1.8391E - 10$$

$$Pr(\beta_5 > 159) = 4.0104E - 06$$

From the results in this section, more evidence supporting the disposition effect in the Norwegian equity market is presented. Even with the noise from the methodology, and the possible counter-effects diluting the evidence of the disposition effect, the cumulative probability presented above makes it clear that the high number of negative signs for β_1 and positive signs for β_5 is far from random. This strengthens the conclusion that there is evidence of the disposition effect in the steepest part of the utility curve in Norway.

6 Conclusion

This paper has attempted to analyze the investment behavior of market participants in Norway, particularly by measuring the extent of the disposition effect. In simple terms, investors who exhibit the disposition effect demonstrate a strong preference for realizing winners rather than losers. There is a growing literature indicating that the disposition effect is useful for explaining several asset pricing anomalies, and the main contribution of this paper is to provide more evidence to the investigation of the disposition effect in developed markets, here represented by Oslo Stock Exchange. The paper aims to understand as clearly and analytically as possible how a perturbation of investors' demand for a stock due to the disposition effect generates deviations from the rational equilibrium. More specifically, it has been examined how past price increases (decreases) have a positive (negative) impact on trading volume.

The disposition effect occurs because investors use their purchase price as a reference price, and are reluctant to realize losses due to regret aversion. The theory presented in this paper is combining several behavioral finance and real market aspects to support and explain the disposition effect theory and several aspects of it. In addition, challenges when measuring the disposition effect are presented, such as counter-effects that exist in financial markets.

The empirical analysis has attempted to measure the extent of the disposition effect in Norway, and the research is based on the idea that investors' response to past price patterns might create a relationship between trading volume in a given day and previous price changes. The results present scattered evidence, suggesting that the disposition effect exists to some extent in Norway. That is, the findings weakly support the results of Shefrin and Statman (1985) and are inconsistent with EMH. As suggested by Dhar and Zhou (2006), the variation in the evidence for the disposition effect is partly due to differences in trading frequency and demographic characteristics that proxy for knowledge about investment products. The evidence for tax-loss selling, representing the opposite prediction of the disposition effect, is limited. Therefore, it can be inferred that tax-induced traders form a minor portion of all traders, or that those who typify the disposition effect offset their contribution.

The observed phenomena can be explained by investors' deviations from expected utility theory, but they cannot completely rule out other theories. For instance, investors might misperceive probabilities of future price change, e.g. they may think losing stocks will bounce back and winning stocks will fall (i.e. a belief in mean reversion). As mentioned in section 2, there are a number of other non-disposition related motives that could account for the relationship between past price changes and volume, such as rebalancing of portfolios, trading strategies based on past prices (e.g. the momentum strategy) and psychological theories that are not accounted for in this paper. Moreover, it is highly possible that multiple phenomena exist synchronously in the stock market. The diverging evidence for the disposition effect illustrate the requirement for a more sophisticated model of investor behavior and more specific data material, such as individual investor trading records.

An important objective for subsequent studies should be to identify the motives that account for the trading patterns that are observed in this paper, as it would be interesting to separate the disposition effect and other effects more carefully. In addition, market microstructure models, such as the disposition effect model in this paper, assuming the existence of noise traders (irrational) and informed traders (rational) could be enriched by incorporating investors with varying degrees of biases or information (Shapira and Venezia, 2001). Finally, it can be noted that the findings in favor of the disposition effect can help investors to obtain higher returns, as they are informed of the existence of the disposition bias and its implications, and can adjust their trading accordingly.

Paper 2: Herd Behavior in the Norwegian Equity Market

Abstract

In this paper, we examine herding behavior in the Norwegian equity market. This is done by applying daily data and volumes from OBX covering the period from January 2000 to December 2013, separated into four different data sets. We apply two different methologies to the data, where the first analyses the relationship between cross-sectional deviations of asset returns and the corresponding market returns, based on the assumption that dispersions are low when individual returns herd around the market. The second method is based on idiosyncratic returns and abnormal turnover for individual stocks, justified by the assumption that herd behavior leads to increased trading volumes.

Using the approaches, we find no significant evidence of herding in the Norwegian market. When adjusting for up and down markets, the evidence suggests asymmetric behavior in the market, but no presence of herding. The results from applying quantile regression to estimate the herding equation for multiple market conditions are also inconsistent with the presence of herding. Since theory suggests that herding may be more prevalent during extreme market conditions, we also specifically test for herd behavior during the financial crisis in 2008 and get compatible results. The same conclusion also applies for the method based on abnormal turnover. Our evidence supports the predictions of rational financial models, and suggests that herding is not an important factor in determining equity returns in the Norwegian market. The results coincide with similar empirical research on developed markets, and can partly be explained by sufficient access to diverse information and investment opportunities on individual stocks in this market.

1 Introduction

On November 8, 2007, Renewable Energy Corporation reached all time high with a share price of NOK 301 on the Norwegian stock market. Two months later the share price was down to NOK 125. During less than 100 days the share price had dropped by almost 60 percent, and 4 years later the share price was down to NOK 0.628. Looking at the bigger picture, the same behavior can be found earlier in this decade, during the dotcom crisis, and in 2008 during the financial crisis. The observed phenomenon can be characterized by a rapid expansion followed by a contraction, and is given the name *economic bubble* after the first evidence of its occurrence in March 1637 under tulip mania (Garber, 1990).

Economic bubbles and other anomalies in financial markets occur for several reasons, and they have been a popular research topic in finance for many years. Lux (1995) explains the emergence of bubbles as a self-organizing process of contagion among traders, leading to equilibrium prices which deviate from fundamental values. Further, he postulates that there is one basic economic variable, namely returns, that decide the speculators' readiness to follow the crowd. If the returns are above average, a more optimistic attitude arises among speculators that foster the disposition to overtake others positive view, and vice versa. The willingness of a speculator to imitate the observed decision of others or movements in the market, rather than to follow his own views and information, is called herd behavior.

According to Fromlet (2001), the concept of herd behavior may be the most generally recognized observation on financial markets in a psychological context, especially during financial crises. For private investors, the underlying reason for herd behavior is often lack of accurate information and the assumption that the "majority is always right". In the case of money managers, the damage done to a reputation after bad decisions can always be limited if the manager is in line with the consensus.

The main purpose of this paper is to use theory on herding behavior and earlier empirical studies from foreign stock markets as a foundation for empirical tests of herding behavior in the Norwegian stock market. To our knowledge, we are the first to examine herding behavior in the Norwegian market, so the contribution of this paper is to extend the existing literature on investor herds to include evidence from Norway. Another reason for studying the Norwegian market is to examine herding behavior in an economy that is highly sensitive to oil prices and supported by oil revenues. In addition, Oslo Stock Exchange has an unique position for companies in the Energy, Shipping and Seafood sectors. It is the largest European marketplace for shipping securities and the world's largest marketplace for seafood securities (Oslobors, 2013).

The empirical analysis will use stock market data and market portfolio data from the Oslo Stock Exchange, in particular daily asset returns and turnover. The first sample includes 54 of the most traded securities on the exchange, collected from the OBX over the period 03.01.00 - 28.06.13. The second sample consists of the stocks that were on the Norwegian stock market by 31.08.13, that also existed during the financial crisis, covering the period from January 2008 to December 2010. The third sample is created by separating out the stocks that form the five largest sectors on Oslo Stock Exchange from the second sample. The fourth and final sample consists of the thirty smallest firms on Oslo Stock Exchange by equity value as of January 2014. Based on a comprehensive literature research, three different models will be employed on the data. The first two models are cross-sectional models that measure herding on the basis of individual return dispersion from market return. The third model focuses on individual shares, and measures herding based on idiosyncratic return and abnormal turnover.

The first model was introduced by Christie and Huang in 1995, and measures herd behavior under extreme market moves based on the cross-sectional standard deviations of returns (CSSD) in relation to the market return. The second model is an extension of the CSSD model, proposed by Chang et al. (2000), which examines the existence of herding by analysing the relationship between cross-sectional absolute deviations (CSAD) of asset returns and the corresponding market returns. The last model is inspired by the work of Chen et al. (2004), where herding is investigated from a volume perspective. The CSAD model will be the main focus in the empirical analysis of this paper, and it will be combined with quantile regression to allow for the study of different market conditions. The focus will be to investigate herding behavior in the Norwegian market, in addition to different market sectors, during the financial crisis.

The remainder of this paper is organized as follows: Section 2 presents a review of the previous literature concerning herd behavior. Section 3 summarizes previous empirical work on investor herds in stock markets. Section 4 provides the details of the testing methodologies employed to detect herding, and describes the data collection. Section 5 reports the results from the empirical analysis and discusses the findings. Conclusions and recommendations for further work are presented in section 6.

2 Herding Behavior

Shiller (2003) writes that one of the particular concerns related to the performance of stocks in the market has been the observed excess volatility, relative to what would be predicted by the efficient markets model. Investment portfolios are frequently affected by excess volatility in stock and bond prices, and examples include: the stock market crash of 1987, the dot-com bubble and the financial crisis of 2008.

The focus in this paper is on herd behavior, a concept that can be linked to the extreme volatility and destabilization that is sometimes observed in markets (Lao and Singh, 2011). Herd behavior is thus a signal of market inefficiency, affecting share prices and influencing the accuracy of stock valuation (Chang et al., 2000). Herding can be defined as an investment strategy based on individuals imitating other investors' actions or the market consensus, without paying attention to their own belief or information, even if one believes the market is wrong (Bikhchandani and Sharma, 2000). The psychology underlying herd behavior is that individual investors assume other investors have access to better information than themselves, hence that increases or decreases in stock prices resulting from investor trading is reflecting the correct market conditions. The motivation for herding is related to the number of other people already partaking in a given action, and Rook (2006) presents research explaining how people solve the mental conflict of a perceived wrong answer by using the heuristic "the majority is always right".

2.1 Spurious and Rational Herding

It is important to note that spurious herding will occur in markets when groups facing similar information take similar decisions. This is not herding according to the definition given earlier, because the investors are making individual decisions from publicly known information (Bikhchandani and Sharma, 2000). It is important to distinguish between spurious herding and intentional herding, because it is the latter that can lead to excess volatility in markets, and thus will be the focus in this paper. In addition, according to Devenow and Welch (1996) herding behavior is not necessarily in conflict with rational behavior, which is an underlying assumption in the EMH. Investors may rationally herd in the direction of others who they believe are better informed, thus engage in optimal decision-making, and money managers may rationally herd to maintain their reputation and position. In addition, Hirshleifer and Teoh (2003) note that market efficiency does not mean perfect foresight; a fully rational market may react to information that the investor has failed to perceive. However, some phenomena in asset pricing are difficult to explain rationally, indicating that share prices are affected by irrational investors ignoring their own information and blindly following other's decisions (Chang et al., 2000).

2.2 Institutional Herding

The market consists of both professionals and non-professionals, where professionals tend to herd to avoid underperforming their peers, and non-professionals herd because they are less informed on market conditions (Shiller, 2003). According to Scharfstein and Stein (1990), professional managers will follow the herd if they are concerned about their reputation, and the compensation scheme and terms of employment for money managers are often such that imitation, i.e. herd behavior, is rewarded. More specifically, managers that follow the herd can share the blame if they make an unprofitable decision and thus reduce their significant risk of being dismissed, because external observers conclude that the bad outcome occurred by chance (Lakonishok et al., 1992). This confirms the quotation by Keynes (1936): 'it is better to fail conventionally than to succeed unconventionally'. Although this behavior is rational from the perspective of managers, it is inefficient from a market standpoint because the money managers herd towards the first managers' decisions, not revealing their private information. A way to test for herd behavior among money managers is to examine if decisions of professional money managers are more closely correlated over time compared to the decisions of private investors who are unconcerned about their reputation (Scharfstein and Stein, 1990). However, Hirshleifer and Teoh (2003) note that correlated individuals are most likely just influenced by common information from some noisy variable on trades.

Lakonishok et al. (1992) suggest that herding might be more prevalent among institutions than among individuals, because institutional investors know more about each other's trades than individuals do, and because the signals reaching institutions are more correlated. The authors point out that herding among institutions can have a stabilizing effect if the investors all react to the same fundamental information, or if they all respond to the same irrational individual investor moves, resulting in a more efficient market. This is related to the previously described rational herding, indicating that institutions are in a better position to evaluate fundamentals because they are exposed to a variety of news reports and analyses.

In their study, Lakonishok et al. (1992) find little evidence of herding among money managers, concluding that professionals possibly use a variety of trading styles, resulting in uncorrelated trading decisions. In addition, it may be a better chance of detecting herd behavior among managers at a more aggregate level, since they may be better able to observe actions at this level. Hirshleifer and Teoh (2003) point out that the reputational approach can also make some money managers intentionally deviate from the industry benchmark, especially very good or very poor managers daring to choose a risky project.

2.3 Information Cascades

In relation to herd behavior, several authors describe the concept of *information cascades* (see e.g. Bikhchandani and Sharma, 2000), that is, herd behavior arising from informational differences. According to Hirshleifer and Teoh (2003) herd behavior is defined as "converge in behavior", while information cascading means "ignoring private information signals". Information cascades occur when the decisions of investors acting early influence the actions of the majority, making individuals ignore their own private information. This definition makes such behavior idiosyncratic because random events combined with the choices of the first few investors determine what individuals will herd on (Bikhchandani and Sharma, 2000). This will increase the volatility in the market, especially if it becomes clear that the first investors made the wrong decision, resulting in people herding in the opposite direction.

Once a cascade starts, only the investment decision of early investors is reflected in the asset prices. So although the prices in the market reflect all public information, the price does not reveal the private information of all investors, in theory resulting in a complete 'information blockage', but more presumably resulting in unduly slow information aggregation (Hirshleifer and Teoh, 2003). This means that poor decisions will be made in the market, even if the signals possessed by the participants could be assembled to determine the right decision, because these signals are not revealed and reflected in the prices. Individuals understand perfectly well that the information in the market is inadequate, but they rather privately optimize than take into account their effects upon the public information pool (Hirshleifer and Teoh, 2003). One way to prevent a cascade is that the participants in the market use a variety of decision rules, providing a greater diversity of actions after a cascade starts.

Hirshleifer and Teoh (2003) remark that if there is uncertainty regarding the accuracy of information in the markets, informational cascades can arise even when investors are rational.

Specifically, investors having very noisy information will herd, often mistakenly believing that most other investors have accurate information. Also, if there are limits to the investors' attention, or the information that they receive is hard to process, the investors may be pressed to join an information cascade and thus engage in imperfect rationality. Still, fully rational models of cascades or herding cannot explain the anomalous evidence regarding excess volatility. To explain such return patterns, market imperfections or failures in human rationality must be included.

2.4 Positive-Feedback Trading

A concept closely related to herd behavior is *feedback trading*, defined by Nofsinger and Sias (1999) as a special case of herding resulting when variables correlated with lag returns, such as decisions of previous traders, act as a common signal for investors. Positive-feedback trading, or trend chasing, is a trading strategy driven by a concept from the behavioral literature; the belief that trends are likely to continue. Such behavior can lead to investors buying overpriced stocks and selling underpriced stocks, contributing to a further divergence of prices away from fundamentals (Lakonishok et al., 1992). Positive-feedback trading can be explained by loss aversion, making investors herd to past winners and away from past losers, or by managers following the herd to protect their reputation. Such behavior may eventually lead to a price bubble, as explained earlier. At the same time, Bikhchandani and Sharma (2000) emphasize that positive-feedback strategies may be rational if the participants are exploiting the persistence of returns observed in the market when new information arrives.

At any level of herding, individuals are more likely to destabilize prices if they follow strong positive-feedback strategies (Lakonishok et al., 1992). Destabilization of prices increase the long-run price volatility, since prices move away from their fundamental value, so positive-feedback trading have the potential to explain the excess volatility observed in financial markets (Nofsinger and Sias, 1999). Even if only small amounts of herding and positive-feedback are detected, one cannot rule out the possibility of large price impacts from the trading strategies. However, positive-feedback trading is not necessarily a destabilizing strategy in the cases where stocks underreact to news, and it can in some cases be explained as a response to recent price increases, without necessarily causing these increases. From their analysis, both Lakonishok et al. (1992) and Nofsinger and Sias (1999) find evidence for institutional investors' engaging in herding and positive-feedback trading only for small stocks, while the trading strategies for large stocks are probably most important since they constitute the bulk of most holdings and trading.

2.5 Market Stress and Price Bubbles

Christie and Huang (1995) and Chang et al. (2000) among others, suggest that the formation of herds is more likely during periods of market stress. During extreme market movements, individuals are more prone to suppress their own private information in favour of the market consensus, creating a clustering of individual returns around the market return. Thus, herd behavior can also be defined as a contagious emotional response to stressful events, especially when a critical number of individuals have a particular behavior, leading to a tipping in favor of one behavior versus another (Hirshleifer and Teoh, 2003). In addition, Christie and Huang (1995) assume that herd behavior is a very short-lived phenomenon and that herding responds asymmetrically to extreme market movements. These assumptions are confirmed in several empirical studies of herding (e.g. Chang et al., 2000). Chiang and Zheng (2010) also find that a crisis can trigger herding activity in the country of origin, and then produce a contagion effect spreading the crisis to neighbouring countries.

In his paper, Shiller (2003) suggests that if the herd behavior is not interrupted, the prices of an asset will continue to deviate from its fundamental value, i.e. equilibrium, and over a longer time period this may produce a speculative *price bubble*. It is common to assume that price bubbles arise because of investors' speculative behavior, but Hott (2009) shows in his paper that price bubbles can arise merely because of herding behavior without any speculative incentives involved. The price bubble can be caused by institutional investors that after a herd year continues to practice destabilizing behavior for several years (Nofsinger and Sias, 1999), and irrational private investors who do not react to informative signals, but to the market 'mood', believing that they are receiving a positive signal when the market mood increases. Eventually, such positive-feedback trading creates an unsustainable overvaluation of the assets, leading to a bursting of the price bubble. The consequences of herding behavior, pulling stock prices away from their equilibrium values and creating bubbles, are often causing substantial damage to a country's economy and investors (Balcilar et al., 2013).

3 Empirical analysis of Herding

The literature review presented in the previous section provides possible explanations of herding and situations when herd behavior is likely to occur. It is evident that there are several reasons why investors participate in herd behavior, both institutional and private market actors, and it is also important to note that herd behavior is not necessarily irrational. Still, the theory cannot give a clear answer to the extent of actual herd behavior in financial markets. To be able to answer this, it is necessary to develop methodologies for testing of herd behavior and perform empirical analyses. In the last decades, there has been increased interest and research in this area, and a selection of the most acknowledged methodologies and analyses is presented in this section.

Empirical analysis of herding behavior has received attention in studies examining the group behavior of investors in financial markets. This is based on the possible consequences of such behavior; markets failing to make the market price and fundamental value converge, resulting in greater instability and inefficiency. Chang et al. (2000) emphasize the implication of finding evidence of herding for investment strategies, namely that a larger number of assets must be included in a portfolio in order to achieve the same degree of diversification than in an otherwise normal market. Most empirical studies of herd behavior measure whether clustering of decisions is taking place in securities markets, using a pure statistical approach. An important challenge to empirical work on herding is to separate it from correlation in trades, resulting from some external factor independently influencing investors' actions in parallel without any interaction between the market participants (Hirshleifer and Teoh, 2003).

3.1 The CSSD and CSAD Models

Extensive research has investigated the level of herding behavior in developed and undeveloped markets. One of the first papers to perform empirical studies on a market is written by Christie and Huang (1995), who introduce a new measure of herding and applies it on the US market. Their test for herding relies on the assumption that because dispersion quantifies the average proximity of individual returns to the mean, the presence of herd behavior is revealed when individual returns follow the lead of the portfolio returns. Specifically, they look for herding by testing whether securities' return dispersions are significantly lower than average during periods of extreme market movements, and this is done by performing a linear regression on the dispersion related to the extreme tails of the returns distribution. The rationale is that individuals are more likely to suppress their own beliefs in favor of the market consensus in periods of market stress, and thus herds are more likely to form in these periods. The study of Christie and Huang (1995) finds evidence for asymmetric behavior of dispersion during times of market stress, but no evidence of significant herding in the US market, concluding that herding is not an important factor in determining equity returns during periods of market stress.

Chang et al. (2000) extends the work of Christie and Huang (1995). They continue to examine the relationship between equity dispersion and the overall market return, measured as cross-sectional absolute deviation, but proposes a more powerful approach that uses a non-linear regression specification. Their model is called the Cross Sectional Absolute Deviation Model (abbreviated CSAD), and is used as a foundation in several later empirical studies. They also examine herding in an international context by extending the data to include both developed and developing financial markets. Chang et al. (2000) find evidence of herding in the two emerging countries, South Korea and Taiwan, partial evidence for Japan and no evidence for the developed countries, US and Hong Kong. The differences between market conditions may partly be the result of incomplete information disclosure in the emerging markets, where macroeconomic information tends to play a significant greater role in the decision making process of market participants (Chang et al., 2000).

3.2 Extending the CSAD Model

Chiang and Zheng (2010) are the first to examine herding behavior across national borders, arguing that financial markets are somehow interdependent, especially during high-volatility periods. The paper uses a modified version of the approach applied by Chang et al. (2000), testing the cross-sectional stock return dispersions in relation to a set of explanatory variables, including absolute domestic stock returns and foreign market influences. Chiang and Zheng (2010) also test specifically for herding during turbulent periods, based on the suggestion by Christie and Huang (1995) that herding will be more prevalent during periods of market stress. Their results confirm this theory by finding evidence of herding activity triggered by market crises.

Following the approach of Chang et al. (2000), Chiang et al. (2010) examine herding behavior of investors in Chinese stock markets. The authors separate the market in A-share investors and B-share investors to test the hypothesis that foreign or institutional investors (B-share investors) are more rational and have diverse information to assess. The results confirm that herding behavior in the A-share market is more consistent, since it consists of local investors who tend to herd due to lack of fundamental information, and that B-share investors herd only during down markets. Chiang et al. (2010) also employ a quantile regression on the data, to include information about the tails of the returns distribution and thus create more robust results. The quantile regression provides a more complete picture of the conditional distribution between return dispersion and independent variables. Herding activity is observed in lower quantiles for periods of market stress, and the B-share markets appear to be more variable conditional on different quantiles, suggesting that using a mean level of the data to examine herding behavior may produce a deceptive statistical inference.

Saastamoinen (2008) also builds on the standard methodology of Chang et al. (2000) by using quantile regression in his empirical analysis. He argues that quantile regression enables the examination of effects in different points of the market returns distribution, such as the median and extreme quantiles, and that quantile regression may be more efficient when the distribution of errors is non-normal. In his paper, Saastamoinen (2008) study the market in Finland, characterized as a remote stock exchange suffering from low liquidity, arguing that such a market more easily triggers herd behavior. From his analysis, Saastamoinen (2008) find evidence of herding in the lower tail of the stock return distribution, but he emphasizes that a possible explanation for his results could also be, for example, correlated adjustments to new information.

Lao and Singh (2011) look for evidence of herding behavior in the Chinese and Indian stock markets. These markets are characterized as inefficient, having low standards of information disclosure. Consequently, investors may be inclined to herd towards perceived informed investors, leading to abnormal volatility in the markets. The paper uses the method proposed by Chang et al. (2000), adjusted with AR(1) to avoid auto-correlated time-series data which can lead to inaccurate estimation of the coefficients. Lao and Singh (2011) measure herding during extreme market conditions, increasing and decreasing markets and high and low volume state. They also try to capture the effect of the global financial crisis, confirming that herding behavior may occur when uncertainty in the market is high. The study finds that herding behavior is present in both the Chinese and Indian stock markets, and that it is greater during extreme market conditions.

3.3 Other Empirical measures of Herd Behavior

Balcilar et al. (2013) proposes a dynamic herding approach, testing for herding under regime switching and with concentration on the Gulf Arab stock markets. The study suggests that these frontier markets have a different structure than developed markets, and that the market can be divided into three regimes; low, high and extreme or crash volatility. The authors estimate a three-state Markov-switching model for the cross-sectional dispersion of stock returns in the stock markets, and examine the relationship between the market returns and return dispersions during different market regimes. The final part of the study looks into cross-market effects and examines possible herding spillover effects in the markets. This is similar to what was done in the study by Chiang and Zheng (2010), but in this case regime switching is included. The regime-based tests yield significant evidence of herding under the crash regime for all of the markets except Qatar which herds under the high volatility regime, and the cross-market herding analysis supports herding co-movements and not spillovers.

A new approach to detect and measure herding is proposed by Hwang and Salmon (2004), and it is based on the cross-sectional dispersion of the factor sensitivity of assets within a given market. The approach is called the state space model, and is similar to Christie and Huang (1995) to the extent that it exploits the information held in the cross-sectional movements of the market. However, the state space model focuses on the cross-sectional variability of factor sensitivities rather than returns, which makes it free from the influence of idiosyncratic components and allows for herding during not only periods of extreme market movements. Hwang and Salmon (2004) apply the model to an analysis of herding in the US and South Korean stocks markets, and find evidence of herding towards the market portfolio in both up and down markets for both markets.

Demirer et al. (2010) study the Taiwanese market, representing an emerging yet relatively sophisticated market, and they also look for herding evidence within each specific industry in the market. They find that the linear model proposed by Christie and Huang (1995) provides no evidence of investor herds, while the results from the non-linear model proposed by Chang et al. (2000) provide support for herding, and that the herding effect is more prominent during periods of market losses. Demirer et al. (2010) also employ the state space model suggested by Hwang and Salmon (2004), including two control variables; market volatility and market return. The results from this model further support the results from the non-linear model, indicating robust evidence for herding in Taiwan, and implying that herding in the Taiwanese stock market can occur under normal market periods in addition to periods of market stress.

Another alternative approach to test for herding behavior, presented by Bhaduri and Mahapatra (2013), uses symmetric properties of the cross-sectional return distribution to identify herding. The methodology is based on the idea that the security returns tend to be more symmetric towards the market return under herding, and more specifically it uses the cross-sectional absolute mean-median difference to capture the symmetry of ensemble return distribution. The symmetry in the cross sectional distribution would imply that this difference would tend to zero and the lack of linear relation between this difference and the market return is used to identify herding. The argument for this proposed measure is that it is less prone to the presence of securities with extreme returns in the portfolio, and hence provides a more reliable measure of herding. The empirical test performed by Bhaduri and Mahapatra (2013) examine herding on the Indian equity market, and the results provide evidence of the presence of herd behavior during periods of extreme price movements.

Following many others, Chen et al. (2004) investigate the issue of herding behavior through returns, but they also include a trading volume perspective. Inspired by Christie and Huang (1995) they use cross-sectional dispersion to test for herding, focusing on idiosyncratic returns instead of total returns. In addition, Chen et al. (2004) argue that trading volume in the market provides important information in a different dimension than returns, and is a necessary condition for the existence of herding behavior. Accordingly, they test if the cross-sectional dispersion is negatively correlated with trading volume, while pointing out that increased information flow could affect the results. In the empirical analysis, Chen et al. (2004) study the Chinese stock market, claiming that its institutional characteristics provide a unique perspective to study herd behavior due to the separation between domestic and foreign investors. From the empirical test, Chen et al. (2004) find evidence supporting the presence of herding behavior in China, in particularly for foreign participants, suggesting that in the presence of inefficient information disclosure, foreigners tend to herd due to lack of fundamental and private information on firms. Chen et al. (2004) also find strong support for herding activities when trading volume is involved and informational effects are controlled for.

3.4 Combining Herd Behavior and Positive-Feedback Trading

Lakonishok et al. (1992) examine trading patterns of institutional investors, focusing on the prevalence of herding and positive-feedback trading. They test for herding by assessing the degree of correlation across money managers in buying and selling a given stock, indicating that individual herding is present if money managers tend to end up on the same side of the market in a given stock. In addition, herding is tested by examining the fraction of purchasing behavior of an individual money manager that can be explained by the actions of others. For the analysis of positive-feedback trading, Lakonishok et al. (1992) looks at excess demand, and their test examines the relationship between money managers' demand for a stock and the past performance of that stock. The tests are done on pension funds in the NYSE, justified by the fact that there is more scope of finding herding and positive-feedback trading in homogenous groups where each member faces a similar decision problem, and each member can observe the actions of other members in the group. From the results, Lakonishok et al. (1992) find weak evidence for herding and somewhat stronger evidence for positive feedback-trading in smaller stocks, and no evidence in larger stocks. This can be explained by the fact that there is less public information about these stocks, and that money managers dump poorly-performing stocks to improve the appearance of their portfolios. At the same time, herding clearly leads to correlated trading, but the reverse need not to be true (Bikhchandani and Sharma, 2000).

Nofsinger and Sias (1999) perform a similar analysis as Lakonishok et al. (1992), evaluating herding in the NYSE by looking at increases and decreases in institutional ownership resulting from institutional investors herding to a stock or individual investors herding away from a stock. In the study, the authors attempt to differentiate the 'price impact' of herding from intraperiod positive-feedback trading, and their results suggest that institutional investors' herding impacts prices to a greater extent than individual investors', and/or that the institutional investors engage in positive-feedback trading to a greater extent. Their results show that there is a strong positive relation between returns and annual changes in institutional ownership, interpreting this as evidence of positive-feedback trading among institutional investors. Still, Nofsinger and Sias (1999) point out that the change in fractional institutional ownership may not reflect herding, but rather an investor taking a large position in a security.

3.5 Measurement Problems

The results from the empirical studies presented above show some evidence of herding behavior in stock markets. The model proposed by Christie and Huang (1995) does not reveal any strong evidence of herding, while the non-linear expansion of this model, the CSAD model, provides some positive results. By extending the CSAD model with quantile regression or lagged variables, several later studies find more evidence of herding. In other studies, various measures of herding have been developed presenting somewhat positive results, in particular when trading volume is included. Some studies have also included a test for positive-feedback trading, a concept that is linked to herd behavior, and find stronger evidence for this. Much of the empirical research on herding behavior has been done in the context of developing countries. In these countries, one is likely to find a greater tendency of herding, due to a lack of sufficient investment opportunities and because rapid and accurate information is hard and costly to obtain (Balcilar et al., 2013). It is also important to note that many studies look for evidence of a particular form of herding, and the absence of evidence supporting this form does not imply that other types of herding do not exist.

Two reasons for possible understating of herd behavior are: (1) that the trading volumes are too low for certain stock markets and periods, and (2) that the investors considered are too heterogeneous (Bikhchandani and Sharma, 2000). When performing empirical studies on herd behavior in markets, it is difficult, if not impossible, to find the particular motive behind a trade that is not driven by fundamental laws in the EMH. According to Bikhchandani and Sharma (2000), it may be possible to separate out unintentional herding by allowing for changes in 'fundamentals', but further differentiation among the causes of herding from an analysis of a data set on asset holdings and price changes is challenging. This means that there is a lack of a direct link between herd behavior theory and the empirical specifications used for testing, and it is hard to distinguish intentional herding from participants' common responses to publicly known information. To be able to examine herd behavior correctly, proprietary information from the investors on their investment strategies is required, but to keep the markets functioning in a proper way, this information cannot be published – and so proper examination of herd behavior in stock markets will remain difficult.

4 Methodology and Data

This section presents the methodologies that have been used in this study and the data that has been analysed

4.1 CSSD and CSAD

In 1995, Christie and Huang introduced a method to detect the existence of herd behavior in equity returns. They proposed that individual stock returns dispersions from the overall market return is predicted to be relatively low when herding behavior occurs. The rationale behind this argument is based on evidence from social psychology on the behavior of individuals in groups. The evidence suggests that even when a decision conducted by a group is perceived as wrong by an individual, the individual often suppress his own beliefs and follows the group's decision. When translating this into investments decision making, herding will be present when individuals do their investments based solely on the action of the overall market, and without considering their own fundamentals. The method Christie and Huang (1995) employed is based on cross-sectional standard deviations of returns (CSSD), and it will be the first method used in this study. The dispersion measure is defined as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}} \tag{4.1}$$

where $R_{i,t}$ is the observed return on stock i at time t, $R_{m,t}$ is the market return, and N is the number of stocks in the portfolio.

According to Christie and Huang (1995), herd behavior will be most visible during periods of market stress, or extreme market moves. This is because during such periods individual securities' returns are more likely to cluster around the market return, since there is a higher probability that investors suppress their own private information in favor of market consensus. Christie and Huang (1995) use the following regression to test for herding under such circumstances:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{4.2}$$

where α describe the average dispersion of the sample excluding the region covered by the dummy variables (β_1, β_2). D_t^L and D_t^U takes the value one if the return of the market portfolio on day t lies in the extreme lower (L) or upper (U) tail of the return distribution, and zero otherwise.

The capital asset pricing model (CAPM), representing the rational market model, predicts that the dispersion of individual securities will increase with the absolute value of market return. The increase is given by the CAPM beta coefficient (β), reflecting the tendency of security's returns to respond to swings in the market. By the same analogy, the rational asset pricing model predicts that the coefficients for the dummy variables (β_1, β_2) will be significantly positive in periods of market stress, since the dummy variables are designed to capture the differences in investor behavior during extreme market moves versus normal market (Chiang et al., 2010). This contradicts the theory of herd behavior, which predicts statistically significant negative values for the coefficient of β_1 and β_2 during such periods, as investors will herd towards the market return.

One of the challenges with Christie and Huang's theory is the definition of extreme returns. They use 1% and 5% in their study, but emphasize that this choice is relatively arbitrary since there is no correct definition of what extreme market return is. This stems from the fact that investors differ in what they see as an extreme return (Chiang et al., 2010). Another challenge with CSSD is that the methodology only captures herding during extreme market moves, while herding may occur to some extent over the whole sample period, only being more visible during market stress. The final challenge with CSSD is its sensitivity to outliners, which may affect the reliability of the results.

The next method applied in this study was proposed by Chang et al. in 2000. They use the cross-sectional absolute deviation (CSAD) as an alternative measure of dispersion. This method corrects the second challenge with CSSD, i.e. that CSSD is a very stringent test and therefore requires the dispersion to be far from linear to detect herding, which only occurs during periods of market stress (Chang et al., 2000). Instead of just testing for herding during extreme market conditions (lower and upper tail), the methodology suggested by Chang et al. (2000) is constructed to detect herding over the entire distribution of market returns. CSAD is defined as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \tag{4.3}$$

From equations (4.1) and (4.3), it can be seen that the formula for CSSD assigns a much higher weight to large deviations from the market returns than to small because each divergence is squared, while the CSAD formula gives a proportional weight to each deviation according to deviation size.

Christie and Huang (1995) challenged the rational asset pricing model when it comes to its statement about increasing dispersion between individual securities and market portfolio return. Chang et al. (2000) challenge the CAPM assumption further by claiming that the linear and increasing relation between equity return dispersion and market return will not hold under periods of market stress. Instead, a non-linear increasing or even decreasing relation can be detected between the dispersion and market return. Hence, they proposed an alternate test of herding, which include an additional regression parameter to capture any non-linearity, and therefore the test is based on a quadratic relationship between $CSAD_t$ and $R_{m,t}$:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \epsilon_t \tag{4.4}$$

The non-linear relationship will be reflected by a statistical significant and negative value of γ_2, and this non-linear relation will indicate the existence of herding. A positive γ_2 will either indicate that the regression is not able to capture herding due to incorrect premises, or that the CAPM is not completely valid in the Norwegian market.

4.1.1 Herding during other Market Conditions

Herding may be asymmetric under different market conditions, so it can be useful to divide the data into subsets. The regression model in equation (4.4) restricts γ_1 to be the same for both down and up market, i.e. no asymmetry allowed. To allow for asymmetric herding, equation (4.4) can be rewritten to the following equations:

$$CSAD_t^{Down} = \alpha + \gamma_1|R_{m,t}| * D_t^L + \gamma_2 R_{m,t}^2 * D_t^L + \epsilon_t \qquad \text{if } R_{m,t} < 0 \tag{4.5}$$

$$CSAD_t^{Up} = \alpha + \gamma_1|R_{m,t}| * D_t^U + \gamma_2 R_{m,t}^2 * D_t^U + \epsilon_t \qquad \text{if } R_{m,t} > 0 \tag{4.6}$$

where $D_t^L = 1$, if the market return lies in the extreme lower tail of the distribution on day t, otherwise 0, and $D_t^L = 1$, if the market return lies in the extreme upper tail of the distribution on day t, otherwise 0.

4.1.2 Quantile Regression

In the previous section different methods to detect herding have been explored. A common aspect of these methods is that the regression line passes through the average or 'center of gravity' of the points. Quantile regression (QR) models allows one to see far more than is possible using a simple regression. The difference between a general regression and QR is that the regression line in a quantile regression will pass through a quantile of the points rather than the mean of the sample (Alexander, 2008). Therefore, by finding several quantile regression lines, a more complete picture of the return distribution and the relation between $CSAD_t$ and $R_{m,t}$ will be given. Consequently, QR explores the issue that herding behavior may be sensitive to a certain quantile of stock dispersions. QR also solves the problem regarding what the rightfully definition of extreme market returns are, since it provides a tool for estimating the effects on the dependent variable over the entire return distribution. QR is a more efficient and robust estimation method compared to the ordinary least squares (OLS) method for several reasons. For instance, QR is more efficient when the distribution of regression errors is non-normal, and financial data does not usually pass the test of normality (Saastamoinen, 2008). Also, OLS focuses on the mean as a measure of location and lacks information about the tails of a distribution, meaning that extreme news in financial markets can significantly affect the tail values and thus distort the estimated results, while QR is robust to the presence of outliers (Chiang et al., 2010). Using the notation introduced by Chiang et al. (2010), quantile regressions for estimating $CSAD_t$ and a set of explanatory variables, X_t, for τ quantiles are characterized as:

$$CSAD_t(\tau|x) = \alpha_\tau + \gamma_{1,\tau}|R_{m,t}| + \gamma_{2,\tau} R_{m,t}^2 + \epsilon_{t,\tau} \tag{4.7}$$

In equation (4.7), X_t represents a vector of the right-hand-side variables in the equation. With this method, the conditional distribution of the dependent variable $CSAD_t$ is characterized by different values of the τ^{th} quantile. When $\tau = 0.5$, the QR becomes the median regression.

4.2 Herding based on excessive turnover

In this section, an alternative approach to detect herding behavior will be presented. It is built on the hypothesis that herding will lead to increased trading volume in individual stocks. So far, the methods used have been based on the assumption that a change in prices is a plausible condition for the existence of herding, but Chen et al. (2004) noted that it is not a necessary condition. Trading volume, in contrast, is an essential premise for the existence of herding behavior, since it is a voluntary coordinated action (Chen et al., 2004). According to Bessembinder et al. (1996) trading volume is not always required for price formation, i.e. price reactions can occur without trading volume, implying that a measure of herding solely based on prices will have several biases that can be overcome by the inclusion of volume measures. Therefore, the new approach will use volume, specifically turnover, to investigate herd behavior. Another feature of this new approach is that the focus will be on individual shares aggregated over time. This is based on the close relation between volume and firm-specific information that is found by Bessembinder et al. (1996).

From the assumptions above, a new test for herd behavior based on idiosyncratic returns and abnormal turnover for individual stocks is introduced, called the IR model. The test consists of two parts, where the first part is based on the intuition that abnormal turnovers will be autocorrelated in the case of herding in the markets. This is because trading volume due to the earlier actions of some investors can serve as a common signal that other investors can follow, with the belief that it is in their best interest to follow the crowd. The second part of the test, also the main part, is based on the comprehension that the idiosyncratic return for an individual stock will move in the opposite direction of abnormal turnover when herding occurs.

Part I:

The first step is to estimate abnormal trading volume for each share, using a 'market model' regression for volume proposed by Ferris et al. (1987):

$$V_{it} = A_i + B_i V_{mt} + e_{it} \tag{4.8}$$

where

$$V_{it} = \frac{\text{Number of shares of stock i traded on day t}}{\text{Total number of shares of stock i outstanding on day t}}$$

$$V_{mt} = \frac{\text{Number of shares of all stocks traded on day t}}{\text{Total number of shares of all stocks outstanding on day t}}$$

$$e_{it} = \text{Abnormal turnover for stock i on day t}$$

e_{it} is interpreted as the fraction of the outstanding stock of i, traded on day t after removing the effects of market-wide events (Ferris et al., 1987).

Next, autocorrelation in the abnormal turnover is measured by the regression:

$$e_{it} = \rho_1 + \rho_2 e_{it-1} + \mu \tag{4.9}$$

Where autocorrelation is detected if ρ_2 is positive and significant.

After measuring the autocorrelation in the abnormal turnover, the first part of the test is done. If the autocorrelation is significant and positive, herding might be present in the firm and the second part of the test should be executed.

Part II:

The main method for detecting herd behavior is based on the assumption that when herding occurs, individual investors usually suppress their own firm-specific information, resulting in a more uniform change in security returns. The result is a reduced level of individual security returns in relation to the market.

Inspired by the work of Chen et al. (2004), a measure of idiosyncratic returns (IR) for each individual share is proposed:

$$IR_{it} = |\epsilon_{it}|$$

where ϵ_{it} is the idiosyncratic return from a market model[7]. By using idiosyncratic return, it is possible to separate out the returns that cannot be explained by common factors in the market.

It is important to note that an increase in information flow could also lead to a high trading volume. This will be refered to as 'informational trading', which is trading resulting from differential information among investors. According to Bessembinder et al. (1996), differences in traders' private information will increase trading volume and the dispersion measure, e.g. the opposite prediction of herd behavior. Therefore, to account for the informational effect, an additional variable will be used to measure the change in abnormal turnover.

To detect herd behavior, the following empirical model is suggested:

$$IR_{it} = \alpha + \beta_1 IR_{it-1} + \beta_2 e_{it} + \beta_3 \Delta e_{it} + err. \tag{4.10}$$

The regression is performed for each year of the data period. By doing this, it is possible to remove some of the noise from daily trading values, while still being able to analyze variation in herding in relation to overall market behavior over time. The lagged IR variable is used to control for autocorrelation in the residual.

The prediction for herding behavior, controlled for informational trading, calls for a negative β_2 and a positive β_3.

There are some limitations to the model that needs to be mentioned. The most obvious weakness when it comes to a measure of herd behavior in relation to volume, is that trading volumes in financial markets are determined by several factors, such as (i) traders' exogenous liquidity needs, (ii) public and private information flows and (iii) cross-sectional differences in agents' beliefs and opinions regarding value and their interpretation of common signals. Obviously, it is difficult to separate these factors from each other.

In addition, it can be noted that trading volume is not normally distributed, but that log-transformed volume adheres more closely to the properties of the normal distribution (Bessembinder et al., 1996). Therefore, to account for a possible heteroscedasticity in the residual, log-transformed values can be used in the regression.

4.3 Data

Using the methodologies introduced above, herding in the Norwegian stock market will now be investigated using daily end-of-day stock prices and volume data. There will be four different sets of data that will be analyzed, and all the data is obtained from the Oslo Stock Exchange (OSE). The timeframe for the data used is from January 2000 to December 2013.

The first set of data consists of 54 individual shares during the period 03.01.00 to 28.06.13[8]. The period covers the dotcom bubble in early 2000 and the financial crisis, and will therefore represent both a bear and bull market. The shares used in the sample have been or still are a part of the OBX index over the given period. The OBX index consists of the 25 most traded, and thus the largest and most liquid, stocks on the Norwegian Stock Exchange. However, since not all shares in the OBX have been part of the index over the entire period, the least liquid stocks and the stocks that have been a part of the OBX for a short time have been removed from the data set.

[7] In this case, the idiosyncratic return is the residual from the capital asset pricing model (CAPM).
[8] A complete list of the stocks can be found in the appendix.

The second sample of data consists of stocks that were listed on Oslo Stock Exchange during the financial crisis and were still listed by 31.08.13. In this paper, the financial crisis is set to the period from January 2008 to December 2010. In the third set of data, the stocks from the second dataset that were a part of one of the five largest sectors on OSE as of 31.08.13 are separated into their respective sector. The five largest sectors are: Energy, Industrials, Information Technology, Finance and Consumer Staples. The final sample of data is the thirty smallest firms by equity value as of January 2014 that were listed on Oslo Stock Exchange from January 2010 to December 2013.

To use the first two methods presented above, a parameter that represents the overall market performance is needed. In this paper, the Norwegian equity market will be presented by the OSEAX index. This is an index that consists of all the shares on Oslo Stock Exchange, and is therefore the best representation of the market. In Figure 4.1, OSEAX is shown for the sample period.

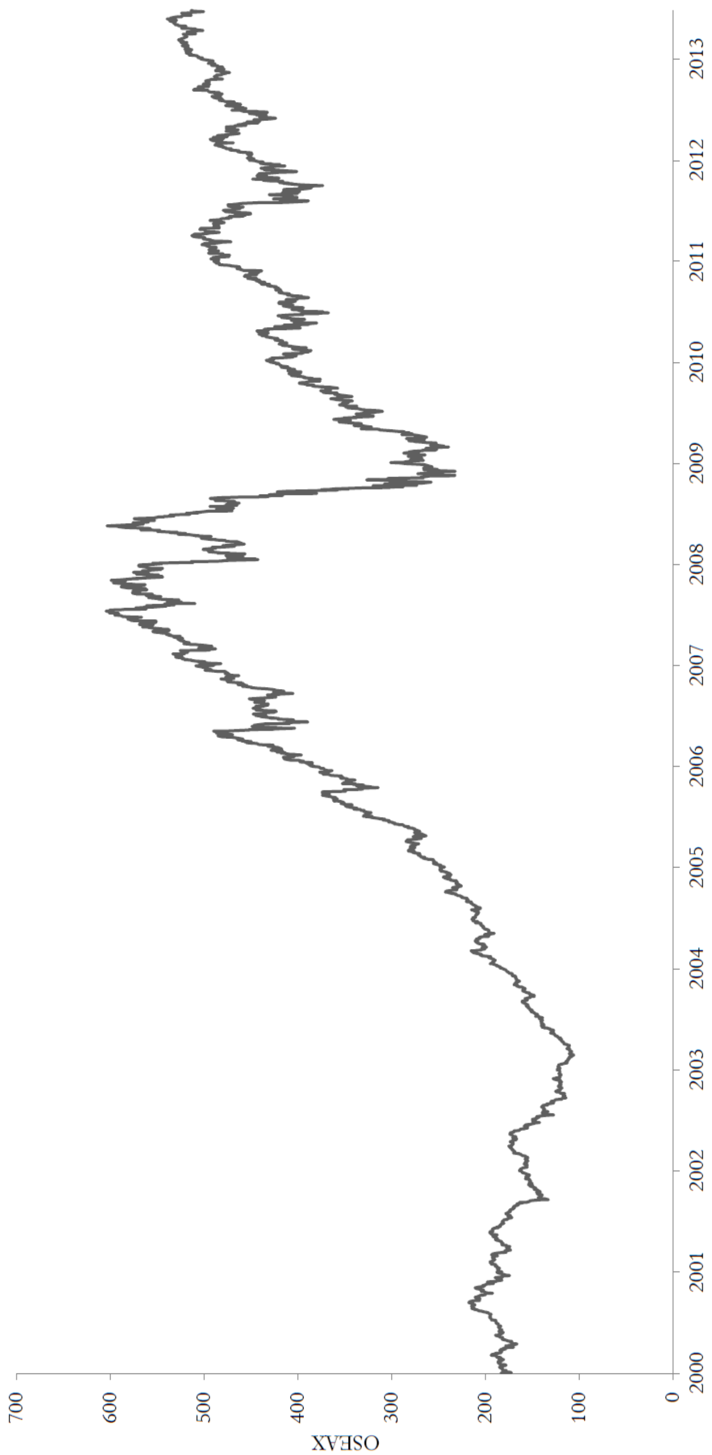

Figure 4.1: OSEAX over the sample period

5 Results

This section presents the results from the empirical analysis. Four different data sets have been analyzed using the methodologies presented in section 4. Both CSSD and CSAD have been applied to the first dataset containing the OBX shares. For the sample covering the financial crisis and the sector sample, only the CSAD approach has been used. Finally, the IR model has been applied to the sample consisting of the thirty smallest firm on OSE.

5.1 Results from the OBX

In the investigation of herding in the OBX, the main results for the selection of 54 stocks that are or have been a part of OBX during the period from January 3, 2000 to June 28, 2013 will be presented.

5.1.1 Descriptive Statistics

Table 1: Descriptive statistics for the Norwegian equity market

Statistics	CSSD	CSAD
Median	0.02581	0.01810
Mean	0.02959	0.01988
Max	0.21251	0.07921
Min	0.01001	0.00779
Variance	0.00022	0.00006
St.dev	0.01474	0.00777
Skewness	3.25496	1.83193
Kurtosis	23.2748	5.71082
Jarque-bera	64261.6	2944,92
ADF	-6.04444[1]	-4.76666[2]
Observations	3385	3385

[1]p-value: 0.0100
[2]p-value: 0.0100

In Table 1, the univariate statistics for the CSSD and CSAD of returns for Norway is reported. For CSSD, the value ranges from a low of 1.0% to a high of 21.3%, and for CSAD the values are 0.8% and 7.9% respectively. So the CSAD has a smaller span. In general, the CSSD and CSAD have small volatilities, but CSSD is characterized by a slightly higher magnitude of standard deviation having a value of 1.5% compared to 0.8% for CSAD. A low standard deviation may suggest that there are few unusual cross-sectional variations due to unexpected news in the market (Chiang and Zheng, 2010). In addition, the calculation of the average CSSD is higher than the average for CSAD, suggesting higher market variations when using the CSSD model. Moreover, the Augmented Dickey-Fuller test (ADF) indicates that both series are stationary at every significance level.

5.1.2 Results from the CSSD Model

Durbin-Watson testing of the first data analysis shows that the time-series seems to be autocorrelated. Consequently, the subsequent analyses and the results presented in the next sections are adjusted for autocorrelation with AR(1).

Table 2 provides the regression estimates for the CSSD model in equation (4.1) for the overall sample. The upper and lower one and five percentiles of the market return is used to represent market stress. The first column presents results under the 1% criterion for extreme returns, and the second column presents results under the 5% criterion. The estimates of β_1 and β_2 for both criteria are positive, and the p-values confirm that the coefficients are statistically significant. This implies that the return dispersion tend to increase during extreme price movements. These findings are consistent with Christie and Huang (1995), and as mentioned in section 4, these results contradict their definition of herd behavior which requires a decrease in dispersion levels. Rather, in this analysis the dispersions are higher than average during days characterized by extreme returns, as predicted by the rational asset pricing model, i.e. CAPM. It is most apparent for the 1% criterion, as it produces higher estimates for β_1 and β_2, but at the same time, the beta coefficients for the 5% criterion are estimated with more observations compared to the 1% criterion.

Table 2: Regression results for cross-sectional standard deviation

1% Criterion		5% Criterion	
Coefficients	CSSD	Coefficients	CSSD
α	0.01557 (0.0000)***	α	0.01518 (0.0000)***
β_1	0.01737 (0.0000)***	β_1	0.00900 (0.0000)***
β_2	0.01817 (0.0000)***	β_2	0.00933 (0.0000)***
AR(1)	0.46334 (0.0000)***	AR(1)	0.45974 (0.0000)***

***Level of significance is within 0.1%

5.1.3 Results from the CSAD Model

The linear CSSD model fails to capture the possible non-linear correlation between individual asset returns and the market return. In order to make a more comprehensive evaluation of the level of herding in Norway, the non-linear CSAD model is utilized.

Table 3: Regression results for cross-sectional absolute deviation

Coefficients	CSAD
α	0.00567 (0.0000)***
γ_1	0.18922 (0.0000)***
γ_2	0.73066 (0.01360)*
AR(1)	0.60677 (0.0000)***

***Level of significance is within 0.1%
*Level of significance is within 5%

The results in Table 3 show the parameter estimation from using the CSAD model over the entire return sample, together with consistent p-values. The non-linear coefficient γ_2 is significantly positive within 5%, indicating an increasing relation between return dispersions and the market return and thus implying that there is a low degree of herding in the Norwegian market. This finding is consistent with the assumption that herding behavior is less present in developed markets, and may be due to the increasing number of experienced investors in Norway and the influence of institutional investors having better information sources. It is also found that the coefficient on the linear term, $|R_{m,t}|$, i.e. γ_1 is significantly positive, so that $CSAD_t$ increases with $|R_{m,t}|$.

5.1.4 Herding Behavior under Up and Down Markets

Table 4 represents estimation results for the CSAD-based model when the market is divided into up and down state.

Table 4: Regression results for cross-sectional absolute deviation in UP and DOWN markets

Up market		Down market	
Coefficients	CSAD	Coefficients	CSAD
	Panel A: 1% Criterion		
α	0.00631 (0.0000)***	α	0.00634 (0.0000)***
γ_1	0.18106 (0.0068)***	γ_1	0.19770 (0.0063)**
γ_2	0.30775 (0.7620)	γ_2	-0.10769 (0.9131)
AR(1)	0.67770 (0.0000)***	AR(1)	0.67526 (0.0000)***
	Panel B: 5% Criterion		
α	0.0.00641 (0.0000)***	α	0.00642 (0.0000)***
γ_1	0.12232 (0.0001)***	γ_1	0.10989 (0.0001)***
γ_2	1.21821 (0.0401)*	γ_2	1.11954 (0.0178)*
AR(1)	0.66521 (0.0000)***	AR(1)	0.66267 (0.0000)***

***Level of significance is within 0.1%
**Level of significance is within 1.0%
*Level of significance is within 5.0%

The γ_2 coefficient associated with D^U captures the change in investor behavior associated with extreme upward price movements, and the same concerns the γ_2 coefficient associated with D^L. For the up market, γ_2 is positive for both the 1% criterion and the 5% criterion. As mentioned earlier, the positive coefficient is indicative of an increase in the CSAD measure, providing no evidence for herd behavior. For the down market, the γ_2 coefficient is negative at the 1% criterion, but the corresponding p-value indicates that the result is not significant. The evidence from Table 4 thus confirms the provisional conclusion that the model is unable to detect herding in Norway. It is also of interest to compare the coefficients in the up and down markets to test the hypothesis that $\gamma_1^{UP} = \gamma_1^{DOWN}$ and $\gamma_2^{UP} = \gamma_2^{DOWN}$, to examine whether the market presents an asymmetric reaction at different market states. At the 5% extreme market criteria, the rate of increase in the up market is larger than that of the down market, suggesting that the dispersion in returns are on average wider in an up market day, relative to a down market day. This represents an asymmetric reaction to good and bad macroeconomic news; however there is still no clear proof of herding.

5.1.5 Quantile Regression

Table 5 contains regression estimates when using the quantile regression method. For instance, setting $\tau = 90\%$ corresponds to the top 10% of the high returns. The estimated statistics suggest that the coefficient for γ_2 is positive and statistically significant at the 0.1% level for the quantile $\tau = 10\%$, positive and statistically significant at the 5% level for quantiles $\tau = 25\%$, $\tau = 50\%$ and $\tau = 75\%$, and negative but insignificant for the quantile $\tau = 90\%$. As previously discussed, this implies that return dispersion increases under all market conditions, and accordingly provides a larger foundation for the conclusion that Norwegian investors are less likely to herd. The evidence in Table 5 also indicates that the estimated coefficient varies with the quantile levels. The median quantile ($\tau = 50\%$) is close to the mean values of the least squares estimation that has been used in the other testing herding equations in this section. The variation in coefficients suggests that examining herding behavior using a mean or median level of the data may produce a deceptive statistical inference. In addition, as noted earlier the quantile regression provides a more complete picture of the conditional distribution between independent variables and return dispersion (Alexander, 2008).

Table 5: Quantile regression results for cross-sectional absolute deviation

Quantiles	α	γ_1	γ_2	AR(1)
$\tau = 10\%$	0.00444	0.13849	0.94368	0.41777
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
$\tau = 25\%$	0.00491	0.12922	1.56237	0.49732
	(0.0000)***	(0.0000)***	(0.0190)*	(0.0000)***
$\tau = 50\%$	0.00551	0.15110	1.31734	0.59896
	(0.0000)***	(0.0000)***	(0.0354)*	(0.0000)***
$\tau = 75\%$	0.00599	0.17596	1.18660	0.72501
	(0.0000)***	(0.0000)***	(0.0208)*	(0.0000)***
$\tau = 90\%$	0.00685	0.24455	-0.08296	0.84151
	(0.0000)***	(0.0000)***	(0.8644)	(0.0000)***

***Level of significance is within 0.1%
*Level of significance is within 5.0%

5.1.6 Level of Herding during the Global Financial Crisis

This section will examine the hypothesis that the magnitude of herding behavior is higher during the recent global financial crisis, because investors are more likely to herd when there is high uncertainty in the market (see e.g. Christie and Huang, 1995). The global financial crisis made the Norwegian market highly volatile and uncertain in the period from 2008 to 2010 as shown in Figure 4.1. To capture the effect of the global financial crisis on OBX stocks, herding behavior is measured during two different periods, covering a smaller and larger part of the crisis period, and this is illustrated in Table 6. Panel A shows the results from the period January 2008 to

December 2008, presenting an insignificant herding behavior through the coefficient for γ_2. The results in Panel B, presenting a positive and insignificant coefficient for γ_2 supports the results from Panel A. Thus, the testing approach finds no evidence for herding behavior in OBX during the global financial crisis in Norway.

Table 6: Regression results for cross-sectional absolute deviation during the financial crises

Panel A: Jan. 08 to Dec. 08		Panel B: Jan. 08 to Dec. 10	
Coefficients	CSAD	Coefficients	CSAD
α	0.00709 (0.0000)***	α	0.00564 (0.0000)***
γ_1	0.06563 (0.4890)	γ_1	0.21370 (0.0000)***
γ_2	-1.26346 (0.5920)	γ_2	0.53139 (0.2460)
AR(1)	0.73386 (0.0000)***	AR(1)	0.59517 (0.0000)***

***Level of significance is within 0.1%

5.2 Results from the Norwegian Equity Market during the Global Financial Crisis

When examining the stocks in the OBX, no evidence of herding is found. This does not necessarily imply that herding does not exist in the Norwegian market. There are several possible reasons why herding is not discovered so far in this paper: The model used may not capture the type of herding that can form around other indicators than the market return, or an irrelevant subset of the market is investigated.

Lao and Singh (2011) found that herding was more likely to appear during days of high trading volume, suggesting that there is a higher probability of investors herding in a more liquid market. Therefore, it is relevant to ask if the current interpretation of herding behavior in the Norwegian market will change when a broader market perspective is introduced.

The stocks in the OBX index cover only the most liquid part of the Norwegian market. In this section, the Norwegian equity market during the global financial crisis will be examined[9]. Accordingly, not only the most liquid stocks will be included, but also less liquid stocks.

5.2.1 Descriptive Statistics

In Table 7, descriptive statistics for the Norwegian equity market during the financial crisis is presented. CSAD range from 1.17% to 7.34%. These values deviate only slightly from the OBX CSAD values, which is a little surprising, considering that this period covers the global financial crisis. One would expect larger deviations for this period, since it was characterized by stock prices dropping significantly from day to day. On the other hand, the analysis explores a total of 144 shares on Oslo Stock Exchange during this period, and therefore there are more stocks averaging out the results. The variance for this period is a little higher than for the OBX CSAD variance, which is reasonable since the time period covered in this section is much shorter. Moreover, the Augmented Dickey-Fuller (ADF) test indicates that the data is non-stationary at

[9]The data set only includes stocks that were still listed on the Oslo Stock Exchange by 31.08.13.

all significance levels. This means that the t-ratios might have severe bias (Alexander, 2008). At the same time, the p-value is high, which indicates that this result is highly uncertain.

Table 7: Descriptive statistics for the Norwegian equity market

Statistics	CSAD
Median	0.02201
Mean	0.02510
Max	0.07342
Min	0.01168
Variance	0.00009
St.dev	0.00966
Skewness	1.80435
Kurtosis	3.64969
Jarque-bera	427.228
ADF	-2.6811[1]
Observations	753

Period: Jan. 2008 to Dec. 2010
[1]p-value: 0.2900

5.2.2 Results from the CSAD Model

The results in Table 8 are the parameter estimations from using the CSAD model on the Norwegian equity market. In both panels the non-linear coefficient γ_2 is positive and statistically insignificant. This result reinforces the conclusion that when applying the CSAD model to the Norwegian market, no evidence of herding is found.

Table 8: Regression results for cross-sectional absolute deviation

Panel A: Jan. 08 to Dec. 08		Panel B: Jan. 08 to Dec. 10	
Coefficients	CSAD	Coefficients	CSAD
α	0.00742 (0.0000)***	α	0.00840 (0.0000)***
γ_1	0.33025 (0.0000)***	γ_1	0.37765 (0.0000)***
γ_2	0.72725 (0.1430)	γ_2	0.35395 (0.2630)
AR(1)	0.47439 (0.0000)***	AR(1)	0.42305 (0.0000)***

***Level of significance is within 0.1%
*Level of significance is within 5%

5.2.3 Quantile Regression

In Table 9, the results from quantile regression for the two respective periods are presented. For the period from January 2008 to December 2008, the coefficient for γ_2 is positive and statistically significant for the quantiles $\tau = 10\%$, $\tau = 25\%$, while it is positive and statistically insignificant for the quantiles $\tau = 50\%$, $\tau = 75\%$ and $\tau = 90\%$. Since the coefficients are either positive or statistically insignificant, it is not possible to make any conclusion about investor herding behavior in the Norwegian equity market during the financial crisis. The same conclusion holds for the period January 2008 to December 2010. Here, the coefficients for γ_2 for all quantiles are positive and statistically insignificant, except for $\tau = 90\%$ where γ_2 is negative and insignificant. The results further strengthen our earlier findings that the Norwegian market does not appear to indulge in herd-type trading. At the same time, the model seems not to enable contradiction of herding, so no distinct conclusion can be made.

Table 9: Quantile regression results for cross-sectional absolute deviation

Coefficients	$\tau = 10\%$	$\tau = 25\%$	$\tau = 50\%$	$\tau = 75\%$	$\tau = 90\%$
			January 08 to December 08		
α	0.00722 (0.0000)***	0.00783 (0.0001)***	0.00632 (0.0000)***	0.00794 (0.0000)***	0.00703 (0.0000)***
γ_1	0.26787 (0.0000)***	0.23987 (0.0000)***	0.30674 (0.0000)***	0.29828 (0.0000)***	0.29821 (0.0001)***
γ_2	1.35928 (0.0477)*	1.67962 (0.0180)*	1.01437 (0.1780)	1.21853 (0.1062)	1.31208 (0.1845)
AR(1)	0.34062 (0.0000)***	0.38821 (0.0000)***	0.29786 (0.0000)***	0.54271 (0.0000)***	0.67585 (0.0000)***
			January 08 to December 10		
α	0.00759 (0.0000)***	0.00820 (0.0000)***	0.00884 (0.0000)***	0.00884 (0.0000)***	0.00962 (0.0000)***
γ_1	0.32401 (0.0000)***	0.34805 (0.0000)***	0.35314 (0.0000)***	0.34955 (0.0000)***	0.46794 (0.0618)
γ_2	0.86409 (0.0192)*	0.60308 (0.2134)	0.74490 (0.1927)	0.69885 (0.2013)	-0.54887 (0.4885)
AR(1)	0.30390 (0.0000)***	0.33627 (0.0000)***	0.42060 (0.0000)***	0.49637 (0.0000)***	0.53502 (0.0000)***

***Level of significance is within 0.1%
*Level of significance is within 5.0%

5.3 Sector Analysis

So far in this paper, no analysis of market segments has been done. At the same time, it is well known that the Norwegian market is heavily over-represented by companies related to the energy market, because of Norway's strong position within oil production. Therefore, another relevant question to ask when examining herding behavior in the Norwegian market, is if herding can be observed in specific sectors of the market. Accordingly, in this section the five largest sectors on Oslo Stock Exchange (OSE) during the financial crisis are examined.

The five largest sectors on OSE are shown in Table 10 in descending order, together with the results for each sector. The definitions of the different sectors are given in the Global Industry Classification Standard (GICS), which is an international industry taxonomy for public companies, and the definitions are used worldwide (MSCI, 2013). The Energy sector is the largest sector on OSE and approximately 33% of the companies listed on the Norwegian stock exchange are in this sector. The second largest sector, Industrials, is almost half the size of the Energy sector, while IT, Financials and Consumer Staples are around 1/3 of the size. In Consumer Staples, 13 out of 14 companies are related to fish production.

Table 10: Regression results for cross-sectional absolute deviation

Sectors	α	γ_1	γ_2	AR(1)
Energy	0.00813	0.33284	0.23773	0.46225
	(0.0000)***	(0.0000)***	(0.6280)	(0.0000)***
Industrials	0.01107	0.48269	0.64923	0.24619
	(0.0000)***	(0.0000)***	(0.1740)	(0.0000)***
Information Technology	0.01463	0.29770	1.64748	0.28521
	(0.0000)***	(0.0000)***	(0.0157)*	(0.0000)***
Financials	0.00649	0.50828	-0.29405	0.31759
	(0.0000)***	(0.0000)***	(0.6000)	(0.0000)***
Consumer Staples	0.00983	0.38251	1.04220	0.30439
	(0.0000)***	(0.0000)***	(0.1740)	(0.0000)***

***Level of significance is within 0.1%
*Level of significance is within 5.0%
Period: Jan. 2008 to Dec. 2010

In Table 10, the non-linear coefficient, γ_2, is only significant for the information technology sector, and no herding is detected since the coefficient is positive. For the rest of the sectors the coefficient for γ_2 is not statistically significant, and therefore no indication of the existence of herding in these sectors is found.

5.4 Herding based on Excessive Turnover

In this section, the results from the investigation of herding from a volume perspective are presented. The data used is the thirty smallest firms on OSE as of January 2014. The reason for the choice of small capitalization stocks is based on the finding by Bessembinder et al. (1996), namely that firm-specific information has larger proportional effect on the volume of small firms, and the suggestion of Chen et al. (2004) that herding occurs more easily among small stocks because of less available information.

According to the market efficiency hypothesis, news affecting the price and thereby the turnover of a stock should be incorporated in the new stock price after a very short time. This means that in an efficient market, what happened yesterday should already be reflected in the equilibrium price, and not affect investors behavior the following day. From the regression in equation 4.9, autocorrelation in the daily data is detected by a positive and significant ρ_2. In the analysis, ρ_2 is positive for all thirty firms that are investigated, and significant for 83.33% of them[10]. This indicates that the market efficiency hypothesis is not applicable to the smallest firms on the OSE, i.e. that their prices and turnover are affected by investors' behavioral biases.

Accordingly, it is interesting to investigate further. This is done by an examination of the idiosyncratic return and turnover relationship through the regression model 4.10.

[10]Details can be found in Appendix D.

Table 11: Herding and turnover effects in the thirty smallest firm on OSE for 2010 - 2011

Firm	2010				2011			
	α	β_1	β_2	β_3	α	β_1	β_2	β_3
DIAG	0.03577	0.19415	1.66722	5.07613	0.02421	0.22887	-0.24291	4.32082
	(0.0000)***	(0.0022)**	(0.4608)	(0.1118)	(0.0000)***	(0.0003)***	(0.8926)	(0.0313)*
NMG	0.02904	0.17637	-2.10065	1.68035	0.07860	0.21549	-65.9138	36.9876
	(0.0000)***	(0.0054)**	(0.8224)	(0.9025)	(0.0000)***	(0.0006)***	(0.0103)*	(0.1018)
REPANT	0.03387	0.03938	16.1193	-0.68407	0.03791	0.11100	7.68016	1.60728
	(0.0000)***	(0.5380)	(0.0000)***	(0.8070)	(0.0000)***	(0.08080)	(0.000)	(0.2474)
DOM	0.02253	-0.23427	112.277	-34.9853	0.01866	0.28202	0.94870	31.0368
	(0.0000)***	(0.0004)***	(0.0000)***	(0.0011)**	(0.0000)***	(0.0000)***	(0.9563)	(0.0399)*
ECHEM	0.03055	0.01802	1.39636	-0.15506	0.03582	0.20812	-1.24054	0.73399
	(0.0000)***	(0.7777)	(0.0531)	(0.8822)	(0.0000)***	(0.0009)	(0.5066)	(0.7459)
COMROD	0.01440	0.13585	0.97802	0.36994	0.00847	0.09319	-0.22261	0.05651
	(0.0000)***	(0.0332)*	(0.0607)	(0.1761)	(0.0000)***	(0.1350)	(0.6740)	(0.6460)
RGT	0.02710	0.01471	5.28126	1.91734	0.03446	-0.03465	9.85756	1.87792
	(0.0000)***	(0.8124)	(0.0000)***	(0.0017)**	(0.0000)***	(0.5769)	(0.0000)***	(0.0433)*
EMS	0.03044	0.12871	13.2920	-8.41090	0.05446	0.05966	28.3672	41.8364
	(0.0000)***	(0.0428)*	(0.3658)	(0.6931)	(0.0000)***	(0.3450)	(0.1029)	(0.0153)*
BLO	0.02700	0.44683	40.4090	-18.5390	0.04179	0.16530	-16.3804	279.590
	(0.0297)*	(0.0000)***	(0.3661)	(0.7738)	(0.1048)	(0.0081)**	(0.8767)	(0.0239)*
OTS	0.02193	0.17294	-0.40966	10.9417	0.03007	0.15117	1.81170	15.2823
	(0.0000)***	(0.0057)**	(0.8587)	(0.0010)**	(0.0000)***	(0.0161)*	(0.6865)	(0.0085)**
COV	0.01491	0.13342	17.7079	8.24561	0.01110	0.20324	3.73555	2.05976
	(0.0000)***	(0.0403)*	(0.0000)***	(0.0054)**	(0.0000)***	(0.0014)**	(0.0114)*	(0.0688)
NAVA	0.02950	0.12588	1.84048	-0.26848	0.03661	-0.00346	1.75279	-0.27545
	(0.0000)***	(0.0473)*	(0.0050)**	(0.5804)	(0.0000)***	(0.9564)	(0.0008)***	(0.4701)
SBX	0.02596	0.15208	0.89725	5.67306	0.04355	0.15986	3.85252	5.88286
	(0.0000)***	(0.0143)*	(0.4984)	(0.0007)***	(0.0000)***	(0.0114)*	(0.3311)	(0.2088)
SCI	0.01349	0.21920	-1.06706	7.37303	0.02906	0.13875	12.1893	4.01196
	(0.0001)***	(0.0005)***	(0.8575)	(0.18627)	(0.0000)***	(0.0281)*	(0.2599)	(0.6766)
ITX	0.03530	-0.00629	1.81249	0.03120	0.01486	0.25806	0.17111	0.18170
	(0.0000)***	(0.9220)	(0.0000)***	(0.9180)	(0.0000)***	(0.0000)***	(0.8270)	(0.7670)

PDR	0.02212 (0.0000)***	0.21384 (0.0007)***	2.17663 (0.09205)	0.67347 (0.47501)	0.03776 (0.0000)***	0.12801 (0.0396)*	13.0021 (0.0005)***	12.0564 (0.0006)***
BERGEN	0.02101 (0.0000)***	0.16376 (0.0052)**	1.13621 (0.0000)***	-1.42176 (0.0087)**	0.01926 (0.0000)***	0.16332 (0.0090)**	0.75185 (0.0932)	0.59826 (0.7212)
NAUR	0.02336 (0.0000)***	0.06024 (0.3450)	0.34700 (0.7370)	0.29641 (0.8420)	0.01494 (0.0034)**	0.03547 (0.5755)	-1.47164 (0.2652)	1.81136 (0.2574)
NIO	0.04031 (0.0000)***	-0.08856 (0.1662)	6.55234 (0.0009)***	-0.84273 (0.5490)	0.02252 (0.0000)***	0.20560 (0.0013)**	0.22733 (0.5463)	-0.28374 (0.2864)
BIRD	0.03219 (0.0000)***	0.16777 (0.0075)	1.26361 (0.0304)*	-0.85052 (0.0444)*	0.02922 (0.0000)***	0.33021 (0.0000)***	1.39665 (0.0601)	0.19133 (0.7310)
PSI	0.2219 (0.0000)***	0.11027 (0.0833)	0.67932 (0.1723)	0.17185 (0.6344)	0.02566 (0.0000)***	0.19348 (0.0017)**	1.58271 (0.0176)*	2.16950 (0.0001)***
BOR	0.00823 (0.0000)***	0.23671 (0.0002)***	26.408 (0.0054)**	6.43722 (0.3598)	0.01126 (0.0000)***	0.02599 (0.6845)	17.0078 (0.0046)**	-2.69556 (0.5306)
ITE	0.01286 (0.0000)***	0.30414 (0.0000)***	1.59428 (0.3692)	3.11337 (0.0187)*	0.01109 (0.0000)***	0.32370 (0.0000)***	3.00186 (0.0733)	1.82178 (0.1695)
REACH	0.03729 (0.0000)***	0.20508 (0.0010)***	-82.5001 (0.2485)	514.328 (0.0000)***	0.05990 (0.0000)***	0.05793 (0.3560)	11.9470 (0.8060)	3.71227 (0.9270)
APP	0.02254 (0.0000)***	0.24382 (0.0001)***	1.45605 (0.1450)	3.35756 (0.0000)***	0.02982 (0.0000)***	0.12994 (0.0395*)	1.10372 (0.6699)	2.46904 (0.1946)
IMSK	0.01049 (0.0000)***	0.18594 (0.0033)**	17.0999 (0.0033)**	5.18215 (0.2841)	0.01154 (0.0000)***	0.19151 (0.0019)**	25.8192 (0.0000)***	-4.56430 (0.1693)
BEL	0.00983 (0.0000)***	0.05094 (0.4244)	3.36330 (0.0295)*	0.89341 (0.4415)	0.00945 (0.0000)***	-0.04236 (0.5060)	20.1543 (0.0000)***	0.20648 (0.9450)
AQUA	0.01862 (0.0000)***	0.16259 (0.0103)*	0.26085 (0.1016)	0.18885 (0.2033)	0.02143 (0.0000)***	0.25410 (0.0000)***	0.76675 (0.0116)*	0.77058 (0.0083)
KIT	0.01742 (0.0000)***	0.10232 (0.1080)	0.05102 (0.4550)	0.01856 (0.7010)	0.02090 (0.0000)***	0.09682 (0.1250)	-0.35759 (0.8750)	2.11793 (0.2850)
FUNCOM	0.02420 (0.0000)***	0.25025 (0.0000)***	0.82609 (0.0075)**	1.33924 (0.0002)***	0.02984 (0.0000)***	0.15566 (0.0197)*	1.23629 (0.0000)***	0.49864 (0.0463)*

***Level of significance is within 0.1%
**Level of significance is within 1.0%
*Level of significance is within 5.0%

Table 12: Herding and turnover effects in the thirty smallest firm on OSE for 2012 - 2013

Firm	2012				2013			
	α	β_1	β_2	β_3	α	β_1	β_2	β_3
DIAG	0.05204	0.27239	9.66361	10.03694	0.02671	0.11058	2.48570	0.91919
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0788)	(0.0000)***	(0.0030)**
NMG	0.02575	0.02678	9.52095	3.00324	0.02416	0.23395	14.5833	8.92045
	(0.0000)***	(0.6704)	(0.0000)***	(0.0071)**	(0.0000)***	(0.0003)***	(0.0000)***	(0.0006)
REPANT	0.02458	0.19107	2.45650	4.47558	0.02392	0.17954	11.2672	-2.13737
	(0.0000)***	(0.0021)**	(0.0101)*	(0.0013)**	(0.0000)***	(0.0044)**	(0.0003)***	(0.3422)
DOM	0.02414	0.00767	22.9507	0.25573	0.01688	0.10012	-21.0325	40.9943
	(0.0000)***	(0.9040)	(0.3200)	(0.9880)	(0.0000)***	(0.1180)	(0.8130)	(0.5520)
ECHEM	0.01390	0.17780	-10.3942	9.58266	0.03579	0.26482	0.55706	1.05533
	(0.4685)	(0.0047)**	(0.0157)*	(0.0731)	(0.0000)***	(0.0000)***	(0.0002)***	(0.0000)***
COMROD	0.00761	0.08205	0.01845	0.98579	0.02496	0.11055	0.15009	1.38474
	(0.0737)	(0.1916)	(0.9841)	(0.0189)*	(0.0000)***	(0.0842)	(0.3174)	(0.0000)***
RGT	0.02607	0.16688	4.65435	1.26110	0.02853	-0.08776	2.56847	-0.17039
	(0.0000)***	(0.0096)**	(0.0000)***	(0.0599)	(0.0000)***	(0.1720)	(0.0000)***	(0.5350)
EMS	0.03208	0.13265	22.0725	11.5256	0.02782	0.07572	12.0001	-1.5904
	(0.0000)***	(0.0306)*	(0.0000)***	(0.0001)***	(0.0000)***	(0.2360)	(0.0000)***	(0.4630)
BLO	0.03190	0.20472	-29.2871	21.8624	0.03689	0.20722	6.19476	4.26984
	(0.0004)***	(0.0015)**	(0.4379)	(0.4242)	(0.0000)***	(0.0008)***	(0.0000)***	(0.0000)***
OTS	0.04653	0.07043	7.32719	-2.71957	0.02387	0.18919	1.92301	-0.83533
	(0.0000)***	(0.2592)	(0.0000)***	(0.0092)**	(0.0000)***	(0.0024)**	(0.0003)***	(0.0423)*
COV	0.00939	0.20738	11.4337	1.07545	0.01459	0.08969	24.2494	0.15166
	(0.0000)***	(0.0033)**	(0.0000)***	(0.6230)	(0.0000)***	(0.1380)	(0.0000)***	(0.9560)
NAVA	0.02495	0.10925	1.86024	0.01983	0.02177	0.11340	1.54372	0.06491
	(0.0000)***	(0.0854)	(0.0460)*	(0.9760)	(0.0000)***	(0.0817)	(0.0000)***	(0.7380)
SBX	0.02581	0.20081	0.62404	0.14242	0.01900	0.12021	1.19573	0.3340
	(0.0000)***	(0.0015)**	(0.0006)***	(0.3063)	(0.0000)***	(0.0599)	(0.0020)**	(0.2767)
SCI	0.03733	0.16061	28.9295	-0.33989	0.02490	0.09412	2.59007	-0.12875
	(0.0000)***	(0.0116)*	(0.0006)***	(0.9586)	(0.0000)***	(0.1420)	(0.0000)***	(0.8400)
ITX	0.02235	0.13183	0.54497	0.03044	0.01855	0.10975	1.76147	0.55711
	(0.0000)***	(0.0377)*	(0.0233)*	(0.8602)	(0.0000)***	(0.0846)	(0.0000)***	(0.0770)

PDR	0.03750	0.17164	30.5312	28.5512	0.02709	0.21139	6.25267	0.91920
	(0.0000)***	(0.0065)**	(0.0093)**	(0.0066)**	(0.0000)***	(0.0008)***	(0.0003)***	(0.5019)
BERGEN	0.01954	0.17376	0.69986	-2.43139	0.03732	0.04896	28.4474	-0.44271
	(0.0000)***	(0.0058)**	(0.1873)	(0.6585)	(0.0000)***	(0.3560)	(0.0000)***	(0.5790)
NAUR	0.05275	0.18624	6.96619	2.40931	0.04038	0.41232	0.42738	1.33813
	(0.0000)***	(0.0035)**	(0.0054)**	(0.4528)	(0.0000)***	(0.0000)***	(0.0041)**	(0.0000)***
NIO	0.02926	0.10388	2.47222	-0.19182	0.02032	0.24086	3.11495	0.06916
	(0.0000)***	(0.1020)	(0.0289)*	(0.8097)	(0.0000)***	(0.0001)***	(0.0050)**	(0.9392)
BIRD	0.03378	0.17971	3.74259	-0.96110	0.03520	0.18246	2.80426	2.77720
	(0.0000)***	(0.0045)**	(0.0000)***	(0.1843)	(0.0000)***	(0.0025)**	(0.0000)***	(0.0000)***
PSI	0.03336	-0.03231	-0.05107	0.75074	0.01424	0.19943	3.79790	3.31906
	(0.0000)***	(0.6120)	(0.9570)	(0.2640)	(0.0000)***	(0.0016)**	(0.0173)*	(0.0113)*
BOR	0.00805	0.07140	7.90638	0.73595	0.00508	0.17391	1.62147	-1.04298
	(0.0000)***	(0.2620)	(0.0398)*	(0.7866)	(0.0000)***	(0.0067)**	(0.0530)	(0.0862)
ITE	0.01525	0.20881	7.16745	2.80173	0.01226	0.23189	2.53071	-0.48165
	(0.0000)***	(0.0009)***	(0.01963)*	(0.2471)	(0.0000)***	(0.0002)***	(0.0218)*	(0.5438)
REACH	0.05440	0.20107	75.8527	60.2187	0.02691	0.11318	13.3124	15.9916
	(0.0000)***	(0.0014)**	(0.0000)***	(0.0002)***	(0.0000)***	(0.0716)	(0.0192)*	(0.0035)**
APP	0.02421	0.04358	8.51821	-3.85732	0.02965	0.00051	-1.41200	1.00446
	(0.0000)***	(0.4896)	(0.0016)**	(0.0455)*	(0.0000)***	(0.9940)	(0.3240)	(0.3890)
IMSK	0.00523	0.23023	0.76580	-0.04127	0.00703	0.28202	0.95354	-0.88019
	(0.0000)***	(0.00027)***	(0.0403)*	(0.8744)	(0.0000)***	(0.0000)***	(0.0095)**	(0.0008)***
BEL	0.01086	14858	31.6156	10.9946	0.01548	0.02146	14.3859	5.72611
	(0.0000)***	(0.0182)*	(0.0000)***	(0.0197)*	(0.0000)***	(0.7318)	(0.0000)***	(0.0030)**
AQUA	0.05291	0.02247	3.69647	1.82704	0.02750	0.07808	0.56623	0.49128
	(0.0000)***	(0.6800)	(0.0000)***	(0.0000)***	(0.0000)***	(0.1110)	(0.0000)***	(0.0000)***
KIT	0.01624	0.17156	1.12559	3.48466	0.01572	0.19061	7.62431	-0.94426
	(0.0000)***	(0.0067)**	(0.7756)	(0.2939)	(0.0000)***	(0.0026)**	(0.1177)	(0.8045)
FUNCOM	0.03675	-0.14358	1.74139	0.28675	0.03367	0.00705	0.99513	0.19234
	(0.0000)***	(0.0212)*	(0.0000)***	(0.0823)	(0.0000)***	(0.9130)	(0.0000)***	(0.1080)

***Level of significance is within 0.1%
**Level of significance is within 1.0%
*Level of significance is within 5.0%

Herd behavior is present in a firm if β_2 is negative. From Table 11 and 12, β_2 is only negative and significant for two out of thirty firms from 2010 to 2013: Nickel Mountain Group (NMG) in 2011 and Eitzen Chemical (ECHEM) in 2012. Given the results of the two firms' β_3 for the same year, the results most surely do not descend from informational trading. Accordingly, herding is only visible in one out of four years, and only for two out of thirty firms, suggesting that the probability that investors indulge in herd behavior is quite small.

On the other hand, the results from equation 4.9, show something different. The autocorrelation is highly significant and positive for almost all of the thirty firms. A reason for this can be that the positive autocorrelaion arise from something other than herd behavior, or it can be that the regression model in 4.10, is not able to catch the evidence of this abnormal behavior. Regardless of this, the results found in this section strengthens the findings in the former sections, namely that herd behavior is not visible in the Norwegian equity market.

6 Conclusion

In this paper, the investment behavior of market participants in Norway, with regard to the investors' tendency to exhibit herd behavior, has been examined. Herd behavior is a concept used to explain the scenario in which investors, rationally or irrationally, confirm with aggregate market behavior. The main contribution of this paper is to provide more evidence to the investigation of herding behavior in developed markets, represented by Oslo Stock Exchange. The first part of this paper aims to obtain a valuable understanding of investors' herding behavior through a review of earlier literature, and presents preferred explanations and testing methodologies for herding.

In the empirical test, the CSSD methodology proposed by Christie and Huang (1995) and the extended version introduced by Chang et al. (2000), namely the Cross-Sectional Standard Deviation (CSAD) model, has been applied to the data, together with an excessive turnover model inspired by the work of Chen et al. (2004). The data used consist of four samples covering different stock categories and time periods from the Norwegian stock market.

The analysis finds no evidence of herding in the Norwegian stock market. The results from the CSSD and the CSAD approach are congruent, even when we take autocorrelation and different market conditions into account. We also find that the global financial crisis did not seem to affect the level of herd behavior in Norway, and this also applies when we consider the entire OSE and market sectors over the period. This can partially be explained by the fact that the economic downturn was not as severe in Norway as in many other industrial countries, because of a range of fiscal and monetary measures that were implemented. In addition, no significant signs of herding is found in the investigation of herding through a volume perspective (the IR-model), which strengthens the results given by the cross-sectional approaches. The results from the IR-model also reduces the possibility that arbitrageurs are offsetting the price deviation that might arise from unexperienced investors herding towards small capitalization stocks, since this would have been captured by the model.

Our evidence supports the predictions of rational financial models, and suggests that herding is not an important factor in determining equity returns in the Norwegian market. Still, the results do not preclude that herding exists in Norway, because an explanation for not detecting herd behavior could be that herding has a tendency to form around other indicators than the market census (Christie and Huang, 1995), and our model seems not to enable contradiction of herding. Accordingly, no distinct conclusion can be made.

The results should be interpreted cautiously, as there are limitations to the analysis that needs to be considered. First, the inclusion of a higher number of stocks and a longer time period could have resulted in different findings. Also, the uncertain indication of non-stationarity in one of the data sets that is discovered could be investigated further, and if necessary the data could be made stationary or a rolling regression could be carried out. Beyond these limitations, the empirical study was also not able to categorize the market volatility in terms of investor types, making it impossible to differentiate between herding by private and institutional investors. Even if these limitations were removed, the greatest challenge for empirical studies on herd behavior is to determine the cause of herding, and whether herding was intentional or unintentional. The present and most other studies have concentrated on price patterns and volume only, while proper tests for herding require data on how investors communicate with each other and how individuals follow one another in time, controlled for 'fundamental changes'.

A natural extension of our empirical analysis in section 5 would be to include more stocks and extend the time horizon of the analysis. In addition, it would be worthwhile to differentiate between large and small firms, since earlier studies suggest that informational asymmetries could be more evident among small companies (see e.g. Saastamoinen, 2008). Suggested future research also includes the implementation of an international model that compares the Norwegian market to other global markets, especially less developed countries. Finally, it would be interesting to compare the current findings with those obtained from other methodologies, as alternative methods might result in different results.

Conclusion

We have examined the investment behavior of market participants in the Norwegian equity market, with specific regard to the investors' tendency to exhibit two separate behavioral finance phenomena: The Disposition Effect and Herding Behavior. In general, behavior finance theories try to explain finance and investing from a human perspective, with the argument that finance must reflect the way that people really behave - and normal people usually do not behave rationally (Frankfurter and McGoun, 2002). Psychology-based finance models are developing, with the rationale that whatever investors do is going to be psychological. At the same time, despite the growing progress, behavioral finance is still at an early stage (Van der Sar, 2004).

Behavioral finance can be regarded as a moderate, agnostic approach to study financial markets (Thaler, 1999). It is difficult to be agnostic without accepting the existence of the underlying 'religion' (i.e. standard finance theory) and making it the benchmark against which everything is judged. The financial market anomalies demonstrate the need for a change of focus from market efficiency to behavioral modeling, as sentiment impacts the prices and volumes of all assets. Some behavioral finance theoreticians suggest that behavioral finance will not be a separate discipline, but will instead increasingly be part of 'mainstream' finance (Ritter, 2003).

However, Bloomfield (2006) indicates that no behavioral alternative will ever match the coherence, parsimony and power of traditional efficient markets theory, because psychological forces are too complex. In addition, a major criticism of behavioral finance is that it is a concoction of numerous psychological effects, sometimes contradictory, so that no matter what happens in the market, there is a psychological effect that can be mustered to explain it (Frankfurter and McGoun, 2002). Accordingly, it is possible to ex post explain anomalies in the markets by finding a behavioral finance theory that fits the facts, and behavioral finance lacks a common accepted definition. For instance, there is no single preference framework to accommodate the features of the behavioral finance phenomena studied in this thesis, i.e. the disposition effect and herding behavior. Nevertheless, behavioral researchers in finance continue to document and refine our understanding of how psychological forces influence individual behavior in financial settings.

From the results in this thesis, it can be presumed that there exists a few incidents of psychological factors, specifically the disposition effect and herd behavior, affecting prices and volumes in the Norwegian stock market. At the same time, it is difficult to make a distinct conclusion, as the thesis has only scratched the surface in understanding financial decision making in Norway from a behavioral viewpoint. The evidence from the tests leads to further questions, for example what the factors are that lead to different reactions among Norwegian investors, and who is trading with the investors that are prone to the behavioral biases? In addition, it would be interesting to compare the results from Norway with other countries to investigate if the biases affect different cultures in different ways, as experiences and history can affect financial decision-making (Baker and Nofsinger, 2002).

There are probably other explanations for the results presented in this thesis, as the evidence does not allow for distinguishing between several behavioral finance hypotheses about investor behavior. Given that our analysis suggests that investor expectations in Norway are systematically biased, further research that attempts to identify explanations for the empirical evidence in Norway beyond the disposition effect and herding behavior would be of interest. Still, there is a long way to go from the level of understanding we have now to the day when it is possible to fully comprehend investor behavior - if that day ever comes.

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Appendices

A Stocks in the OBX index

Table A: Stocks in the OBX index

Ticker	Name	Ticker	Name
STL	Statoil	DNB	DNB
TEL	Telenor	SDRL	Seadrill
YAR	Yara International	NHY	Norsk Hydro
GJF	Gjensidige Forsikring	RCL	Royal Caribbean Cruises Ltd.
ORK	Orkla	SUBC	Subsea 7 S.A.
SCH	Schibsted	MGH	Marine Harvest
AKSO	Aker Solutions ASA	FOE	Fred. Olsen Energy ASA
STB	Storebrand	PGS	Petroleum Geo-Services
TGS	TGS-NOPEC Geophysical Company	DNO	DNO International
DETNOR	Det norske oljeselskap	PRS	Prosafe
ALGETA	Algeta ASA	NAS	Norwegian Air Shuttle
REC	Renewable Energy Corporation	PLCS	Polarcus
EMGS	Electromagnetic Geoservices	SONG	Songa Offshore
FRO	Frontline Ltd.	CEQ	Cermaq
GOGL	Golden Ocean Group	QEC	Questerre Energy Corporation
KOA	Kongsberg Automotive Holding	NPRO	Norwegian Property ASA
NSG	Norske skogindustrier	AKER	Aker ASA
TOM	Tomra Systems	SNI	Stolt-Nielsen Limited
JIN	Jinhui Shipping and Transportation	ELT	Eltek
EKO	Ekornes	TAD	Tandberg Data
ELK	Elkem	TAA	Tandberg ASA
OCR	Ocean Rig	FAST	Fast Search and Transfer
FJO	Fjord Seafood ASA	TAT	Tandberg Television
SME	Smedvig ASA	AIK	Aktiv Kapita ASA
OPC	Opticom ASA	NER	NERA ASA
EDBASA	EDB Business Partner	AHM	Amersham plc
TCO	TeleComputing ASA	VIS	Visma ASA

B Durbin-Watson results

Table C: Durbin-Watson results

Regressions	Without AR(1)	With AR(1)
CSSD 1%	1.1139 (0.0000)***	2.247 (1.0000)
CSSD 5%	1.1128 (0.0000)***	2.245 (1.0000)
CSAD OBX	0.8236 (0.0000)***	2.3569 (1.0000)
CSAD UP 1%	0.6710 (0.0000)***	2.4439 (1.0000)
CSAD DOWN 1%	0.7209 (0.0000)***	2.493 (1.0000)
CSAD UP 5%	0.7004 (0.0000)***	2.4226 (1.0000)
CSAD DOWN 5%	0.7520 (0.0000)***	2.4828 (1.0000)
CSAD OBX Panel A	0.5859 (0.0000)***	2.6197 (1.0000)
CSAD OBX Panel B	1.0162 (0.0000)***	2.3857 (1.0000)
CSAD Panel A	0.8808 (0.0000)***	1.7113 (0.0100)**
CSAD Panel B	1.0294 (0.0000)***	1.9613 (0.2902)
CSAD Energy	1.2139 (0.0000)***	2.2454 (0.9996)
CSAD Industrials	1.4198 (0.0000)***	2.0004 (0.4955)
CSAD Infor. Tech.	1.5209 (0.0000)***	2.1842 (0.9940)
CSAD Financials	1.4006 (0.0000)***	2.2060 (0.9975)
CSAD Consumer	1.6596 (0.0000)***	2.2896 (1.0000)

***Level of significance is within 0.1%
**Level of significance is within 1.0%

C Autocorrelation in abnormal turnover

Table E: Autocorrelation

Firm	γ_2	Firm	γ_2
DIAG	0.42448 (0.0000)***	PDR	0.15462 (0.0000)***
NMG	0.30458 (0.0000)***	BERGEN	0.03906 (0.2163)
REPANT	0.48281 (0.0000)***	NAUR	0.58292 (0.0000)***
DOM	0.51024 (0.0000)***	NIO	0.01186 (0.7074)
ECHEM	0.69580 (0.0000)***	BIRD	0.29156 (0.0000)***
COMROD	0.02932 (0.3534)	PSI	0.11321 (0.0003)***
RGT	0.23876 (0.0000)***	BOR	0.08274 (0.0087)**
EMS	0.39910 (0.0000)***	ITE	0.08326 (0.0083)**
BLO	0.22930 (0.0000)***	REACH	0.56298 (0.0000)***
OTS	0.19913 (0.0000)***	APP	0.11626 (0.0015)**
COV	0.24218 (0.0000)***	IMSK	0.01211 (0.7014)
NAVA	0.17926 (0.0000)***	BEL	0.30660 (0.0000)***
SBX	0.14649 (0.0000)***	AQUA	0.51715 (0.0000)***
SCI	0.67974 (0.0000)***	KIT	0.00096 (0.9758)
ITX	0.13304 (0.0002)***	FUNCOM	0.54618 (0.0000)***

***Level of significance is within 0.1%
**Level of significance is within 1.0%