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# Stock Market Volatility - Rationality and Irrationality

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**Abstract**

In this master thesis we examine the asymmetric volatility in stock market returns, i.e. why the stock market is more volatile in down turns than in up turns. By examining the Norwegian stock market, we find no support for the feedback hypothesis and conclude that the leverage effect at best is a weak explanation for the asymmetric volatility. We suggest that combining the traditional rational explanations with a behavioral approach will give a better understanding of the asymmetric volatility. Our data analysis supports prospect theory as a reasonable explanation for the asymmetric volatility in the market. Further, we find support for a heuristic explanation based on affect, representativeness and extrapolation bias. We also find a one day disposition effect, supporting a behavioral approach.

We want to thank our supervisor Kjell Jørgensen for his support and comments, and Oslo Børs for providing us with data.

## 1. Introduction

Asymmetric volatility refers to the phenomenon that stock price volatility tends to have a negative correlation with stock return (Hibbert, Daigler and Dupoyet 2008). When stock prices falls (rises), volatility tends to increase (decrease). The mainstream finance approach has developed two rational explanations for this phenomenon. The leverage hypothesis states that negative returns increase the leverage of the stock, and with more leverage, i.e. more risk, the stock gets more volatile (Black 1976). Low (2004) examines the leverage hypothesis and concludes that the leverage explanation for the asymmetric volatility is at best a weak one, and suggests a behavioral explanation. The other mainstream explanation for the asymmetric volatility is the volatility feedback hypothesis. Expected return rises when volatility rises, hence the stock price must fall assuming constant dividend (Brooks 2008). Campbell and Hentschel (1992) conclude that the volatility feedback normally has little effect on returns. Hibbert, Daigler and Dupoyet (2008) reject that the leverage hypothesis and the volatility feedback hypothesis could explain the asymmetric volatility adequately, and propose a behavioral explanation based on representativeness, affect and extrapolation.

Mainstream finance is based on assumptions of rational agents (Stracca 2004). While expected utility theory is based on how people should take decisions, Kahneman and Tversky have studied how people actually make decisions (Kahneman 2011). There seems to be a clear discrepancy between the underlying assumptions in the mainstream finance theory and how people really behave. Thaler (2000) predicts that Homo Economicus, the normative rational human model, will evolve into Homo Sapiens. It seems clear that people do not act according to the rational agent model, but can behavioral finance explain aggregated market behavior? According to prospect theory losses hurts twice as much as gains psychologically (Kahneman and Tversky 1979). In this paper we will examine whether this or potentially other behavioral explanations could explain the asymmetric volatility.

What effect that is the main determinant of the asymmetric volatility in stock markets still remains an open question. In this paper we expand on the existing literature by examining how the non-behavioral theories fit the Norwegian stock

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market and by focusing on the behavioral approaches that might explain the asymmetric volatility phenomenon.

Earlier studies propose different behavioral explanations of asymmetric volatility, such as the disposition effect (Boujelbene 2011), representativeness, affect, extrapolation bias (Hibbert, Daigler and Dupoyet 2008) and loss aversion (Low 2004). The different studies propose a behavioral explanation in the absence of a satisfying non-behavioral explanation. However, it seems like they do not compare the different potential behavioral explanations, and that the behavioral explanations are selected more or less coincidentally. We will in this thesis first examine the leverage hypothesis and the feedback hypothesis. If we could reject that the non-behavioral explanations fully could explain the asymmetric volatility, this would potentially support the behavioral explanations. Subsequently, we will do an analysis of the different behavioral theories and find the most plausible behavioral explanation.

We contribute to the existing literature by including all the most known potential explanations for the asymmetric volatility in one paper. This holistic approach makes it possible to compare the different theories, both rational and behavioral. We also analyze more detailed the relationship between prospect theory and aggregated market data than earlier studies.

The rest of this thesis is organized as follows. In section two we review the background and existing literature regarding the asymmetric volatility, the rationality discussion and the behavioral concepts. Section three and four describes methodology and data. Empirical results are presented in section five. The discussion and conclusion is presented in section six and seven, respectively.

## **2. Background and literature**

### ***2.1 – Volatility, the leverage hypothesis and the feedback hypothesis***

Within the field of finance, the most studied relationship is the one between risk and return. Firms and individuals constantly try to maximize the value of their investment by gaining the largest amount of return for the least amount of risk.

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Consequently, forecasting risk is important for asset allocation, risk management, and for taking bets on future volatility. In mainstream finance the variance or the standard deviation is used as the metric for risk, and hence the previous variance (volatility) is what is modeled in order to forecast risk. This can be done in numerous ways, whereby the simplest one is to use historical standard deviation.

To deal with “the implausible assumption of a constant one-period forecast variance”, Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, which recognizes that the volatility in stock markets is time varying. Since the introduction of the ARCH model, several hundred research papers applying this methodology to financial time series data have already appeared (Bollerslev, Chou and Kroner 1992). Several extensions to the model have also been introduced. Among the extensions, the perhaps best known, is the General ARCH, called the GARCH model. It was introduced by Bollerslev in 1986 and models the conditional variance as a weighted function dependent upon the long-term average volatility, the most recent innovation to volatility and the fitted variance from the model during the previous period.

Later, Glosten, Jagannathan and Runkle (1993) developed the GARCH model further, to involve an additional term that allowed for different impacts on the conditional volatility, depending upon if the return innovation was positive or negative. With this model it is possible to formally measure whether or not the volatility is symmetrical, and the impact on the conditional volatility.

Today, there exist numerous financial articles and empirical evidence suggesting that stock return volatility is negatively correlated with stock returns, with a greater asymmetric effect with negative return (Hibbert, Daigler and Dupoyet 2008). Black (1976) was among the first to criticize the use of constant volatility in financial models. He believed that stock returns were related to changes in volatility. In his research he found that as stock prices went down volatility went up (and vice versa), and he was the first one to introduce this as a leverage effect. The reasoning behind this argument relates to the fact that a decrease in the value of a leveraged firm generally causes a rise in the firm’s debt to equity ratio, which again causes the risk of the firm, or the volatility of the equity to rise. Later, Christie (1982) also found support for the negative relation between volatility of

the rate of return on equity and the value of equity, and he claimed that “it is in substantial part attributable to financial leverage”. However, Black (1976) and Christie (1982) as well as Schwert (1989) show that the financial and operating leverage cannot fully account for the predictive asymmetry of future volatility (Braun, Nelson and Sunier 1995).

An alternative explanation for the asymmetric volatility in stock returns is the volatility feedback hypothesis (time-varying risk premium theory). This theory states that if expected returns increases when stock price volatility increases, a rise in volatility should lead to a fall in stock prices. In other words, this theory suggests a reversed causality compared to the leverage effect; here the return shocks are caused by the change in the conditional volatility. French, Schwert and Stambaugh (1987) regress stock returns on unexpected changes in volatility and find a negative coefficient, which they attribute to volatility feedback. Campbell and Hentschell (1992) demonstrate the feedback hypothesis theoretically, showing that an increase in volatility causes negative returns. Their empirical findings suggest that volatility feedback is important in times of high volatility. However, they find that normally the volatility feedback effect has little effect on returns.

Numerous authors have further researched the asymmetric pattern in the stock market. Schwert’s (1989) findings suggest that there is an asymmetry in the volatility-return relation, meaning that negative returns correspond to a larger increase in volatility than do positive returns. Glosten, Jagannathan and Runkle (1993), uses their modified GARCH-type model to take this relationship into account. Their main result shows that a negative innovation to returns should lead to an increased conditional volatility, compared to a positive innovation of the same magnitude. Braun, Nelson and Sunier (1995) also test the asymmetric pattern with a modified GARCH model. They find that at the market level, volatility tends to rise strongly in response to bad news and fall in response to good news.

Further investigation on the topic highlights the opposite theories and how the empirical results differ from study to study. Figlewski and Wang (2000) study the leverage effect and in short they find that the leverage effect is really only a “down market effect” that may have little direct connection to firm leverage.



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Bekaert and Wu (2000), on the other hand, find asymmetry in the Japanese stock market and relate it to the volatility feedback hypothesis. They also test and reject the pure leverage model of Christie (1982).

Since their introductions, the leverage effect and the volatility feedback hypothesis have been heavily researched. Usually, only one of the theories is tested, and so far, the empirical results have been mixed, weak or inconclusive. The lack of conclusive evidence over the past has motivated us to research this field further, with focus on behavioral explanations.

Low (2004) studies the relation between option traders' risk perception and contemporaneous market conditions. He found that financial leverage (but not operating leverage) is a plausible explanation for the general negative risk-return relation, but that it is at best a weak explanation. He also suggests that a behavioral explanation, based on Kahnemans's "loss aversion" concept, could in fact be a more appropriate explanation. Further, Hibbert, Daigler and Dupoyet (2008) test both of the non-behavioral approaches. They find that neither the leverage hypothesis nor the volatility feedback hypothesis can adequately explain the asymmetric volatility. They propose a behavioral explanation, which involves representativeness, affect, and extrapolation bias. Another author, Boujelbene (2011), examines asymmetric volatility before and during the subprime crises and concludes that the disposition effect could explain the asymmetry.

What effect that is the main determinant of the asymmetric volatility in stock markets still remains an open question. In this paper we expand on the existing literature by examining how the non-behavioral theories fit the Norwegian stock market and by focusing on the behavioral approaches that may explain the asymmetric volatility phenomenon.

## ***2.2 – Rationality and irrationality***

The Homo Economicus model states that the market participants are rational unemotional agents (Thaler 2000). People in the real world are clearly not like this. However, applying the Homo Economicus assumption is not necessarily wrong if the markets are well described and predicted based on this assumption

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(Stracca 2004). Active portfolio strategies do not outperform passive strategies, at least when transaction costs are taken into account (Malkiel 1995). This could be viewed as an indicator that markets are rational and efficiently priced. However, market rationality in the beat-the-market sense does not necessarily mean that behavioral anomalies could not disturb rational asset pricing (Stracca 2004). In other words, the absence of arbitrage opportunities does not necessarily imply that the assets are rationally priced.

Black Monday, October 19<sup>th</sup> 1987, the New York Stock Exchange dropped with over 20% in the absence of any relevant news. Bubbles like this may indicate behavioral anomalies and irrational markets (Stracca 2004). According to Taleb (2007) “Black Swan events” are events that have a low degree of predictability and make a large impact. The dot-com bubble and the September 11<sup>th</sup> terrorist attack are other examples of Black Swan events. Most risk measures exclude the possibility of Black Swans. Before the stock market drop of over 20% in 1987, the standard deviation of S&P 500 was about 1%. Given a normal distribution, the 1987 crash would only happen one time every 4.5 billion years (Reider 2009). Risk measures of variance take into account the normal variation, but outliers and fat tails makes inference based on normal distributions false. Models excluding Black Swans give a false belief that we could measure uncertainty. Since Black Swans are not expected to happen we have no defense against it, as was shown by the subprime mortgage crises in 2008. What you don’t know and don’t expect is more relevant for the risk than what you do know.

Most market participants view loss as the true financial risk (Low 2004). In mainstream finance risk is measured by the variance. Higher variance includes both higher up and downturns. In reality investors are more concerned about the downside, and “upside volatility” is good. High volatility related to negative return, i.e. asymmetric volatility, might illustrate the discrepancy between the classical risk measure and how investors actually perceive risk.

Another explanation of asymmetric volatility could be that it simply reflects the reality of news. If negative news appears in clusters, volatility might be high when stock markets fall. The turmoil after the fall of Lehman Brothers in 2008 may be an example of falling markets with a lot of uncertainty and news with extreme

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impacts. In such times, asymmetric volatility may be a rational reflection of reality.

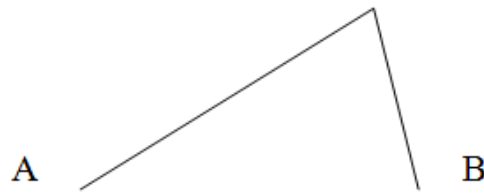
Mainstream economic theory assumes all participants are rational, but in reality they are not. A stock trading above its fundamental value may be rational to buy if you believe it would continue to grow. In other words, it may be rational to do something irrational. It is only rational to be rational when all other market participants are rational (Soros 2010). High growth periods might be driven by over-optimism and manias among the market participants and create bubbles (Kindleberger and Aliber 1978). Similarly, fear might induce cracks in the markets, through self-fulfilling prophecies.

While subjects such as physics have universal laws, economic laws are only valid under limited circumstances. Economic phenomena have thinking participants, natural phenomena don't. The thinking, or behavior, of the participants introduces an element of uncertainty that is absent in natural phenomena (Soros 2010).

### ***2.3 – The behavioral paradigm***

The literature sets the behavioral approach up against the non-behavioral approach. However, the two approaches must not necessarily be competing. Different perspectives may complement each other. Looking at figure 2.1, you could ask yourself if the mountain is slack or steep. From A's perspective it looks like the mountain is slack, but from B's perspective it looks steep. Which perspective is the right one? Obviously, neither A or B's perspective alone would give a good answer. Both behavioral and non-behavioral approaches may be necessary to get a good understanding of the asymmetric volatility and other qualities of the financial markets. Each approach may be useful depending on the problem under investigation (Stracca 2004).

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**Figure 2.1:** Complementing perspectives

Thomas Kuhn (1922-96) developed the concept of paradigms (Okasha 2002). A paradigm consists of a set of fundamental assumptions and theories that are accepted by the scientific community. The paradigm also affects study subjects, methodology and acceptable solutions. According to Kuhn, normal scientists do not test the paradigm, but simply accept the paradigm unconditionally and conduct their research within its limitations. Like all other sciences, finance also takes place in a specific period of time and is constantly evolving. Today's paradigm of finance makes us able to perceive the subject as we do. However, it also represents the limitations of our ability to fully understand the subject.

Research on behavioral finance is a rapidly growing field. The behavioral approach may be difficult to test and runs the risk of being unparsimonious (Tirole 2002). Can the behavioral approach explain aggregated market prices? Thaler (1999, 2000) predicts that Homo Economicus, the normative rational human model, will evolve into Homo Sapiens. He also postulates that economists will incorporate as much behavior into their models as they see in the real world, since doing otherwise would be irrational.

## ***2.4 – Behavioral concepts***

### *2.4-1 Prospect theory*

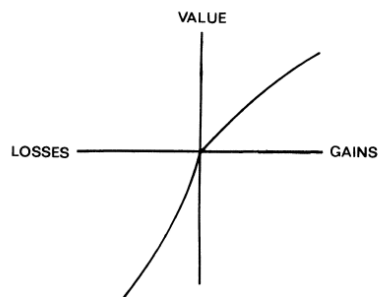
In his remarkable essay from 1738, Daniel Bernoulli introduced the expected utility theory (which he originally called “moral expectation”). This well-known theory tries to explain the relationship between the desirability of money (utility) and the actual amount of money. Bernoulli observed that most people are risk averse and that the risk aversion decreases with increasing wealth, and he pointed out that people often do not value uncertain prospects by their expected value (Kahneman 2011). The theory has been generally accepted as a normative model

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of rational choice, and widely applied as a descriptive model of economic behavior (Plous 1993; Kahneman and Tversky 1979).

Today, nearly 300 years later, this theory is still the prevailing one within financial economics. However, Kahneman and Tversky (1979) propose that this theory is seriously flawed. Further, they claim that the expected utility theory is not an adequate descriptive model. They introduce the alternative descriptive theory “prospect theory”, based on how individuals actually behave under decision-making involving risk. Instead of states of wealth, the prospect theory focuses on changes in wealth. When directly compared or weighted against each other, losses loom larger than gains (Kahneman 2011). The loss aversion ratio has been estimated in several experiments and is usually in the range of 1.5-2.5. Given a loss aversion ratio of for example two, people will require an upside twice of the downside in a gamble tossing a coin, in order to accept the gamble. Loss aversion might be an explanation for the asymmetric volatility.

**Figure 2.2:** A Hypothetical Value Function



The value function shows the (psychological) value of gains and losses (See figure 2.2). The graph exhibits two distinct parts, to the right and to the left of the reference point. The S-shaped form represents diminishing sensitivity for both gains and losses (Kahneman 2011), and it implies that people tend to be risk averse when it comes to gains, and risk seeking in the case of losses. Furthermore, it shows the loss aversion principle as the curve is a lot steeper in the loss region, than in the gain-area.

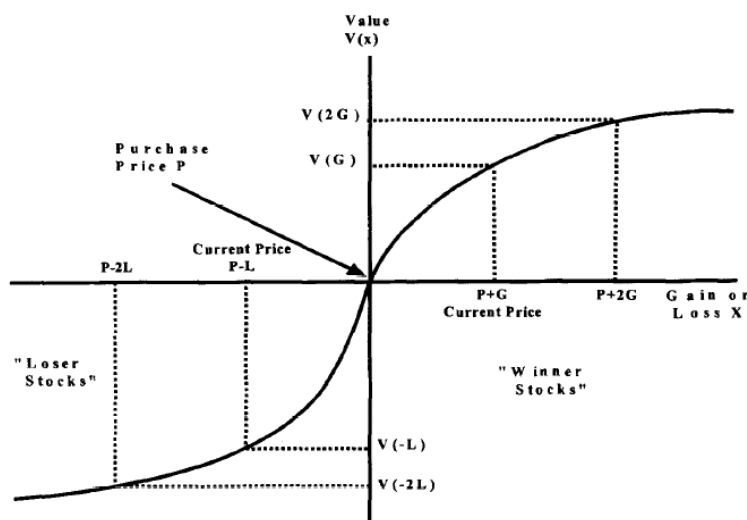
Kahneman (2011) divides our brain into System 1, which does the fast thinking, and the effortful and slower System 2, which does the slow thinking, monitors System 1, and maintains control as best it can within its limited resources.

Kahneman and Tversky have found that most people would reject a coin toss were they could win \$150 or lose a \$100, even though the expected value of the gamble clearly is positive. Kahneman claims that the rejection of this gamble is an act of System 2, but the critical inputs are emotional responses that are generated by System 1.

An interesting part of the analysis done by Kahneman and Tversky (1979) shows that a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise. In other words, he would be more risk seeking than normal. This is an effect that could heavily influence a trader's investment decisions, and it is all about the reference point. In figure 2.3 a), you can see the purchase price,  $P$ , and the possible outcomes  $P-L$  and  $P+G$ , with the associated psychological values. A stock having declined will be worth  $P-L$  if it is sold, and has an equal chance of being worth  $P-2L$  or  $P$  should it be kept. If your reference point is still the purchase price you will choose to keep the losing stock. The pain of a further loss is less than the pleasure of a recovery back to the purchase price, causing the risk seeking behavior. However, if you are in fact able to adjust the reference point to the new, lower, price you would prefer to sell the stock. In this case the psychological value of a loss hurts more than the pleasure a gain gives you (see figure 2.3 b)), and you would sell the stock since you are loss averse.

**Figure 2.3:** Prospect theory; the importance of the reference point

a)



b)

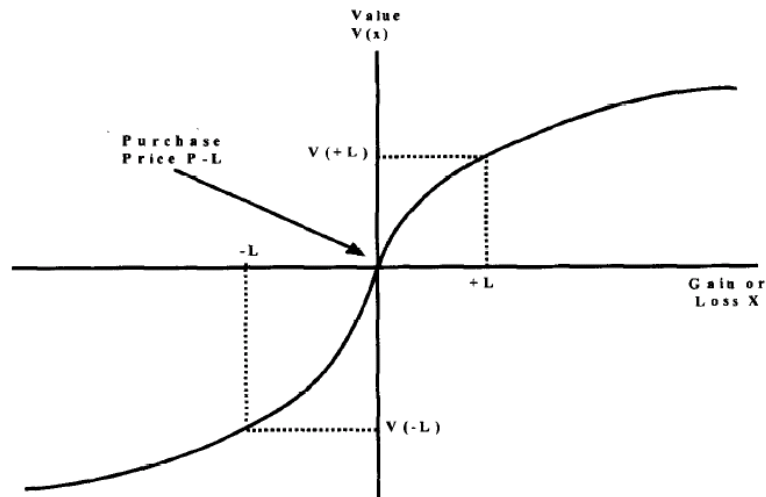


Figure 2.3 a) and b), illustrating the prospect theory, is a copy of figure 1 from Weber and Camerer (1998), and highlights the importance of the reference point, the risk seeking behavior in the domain of loss and the risk aversion in the domain of gain.

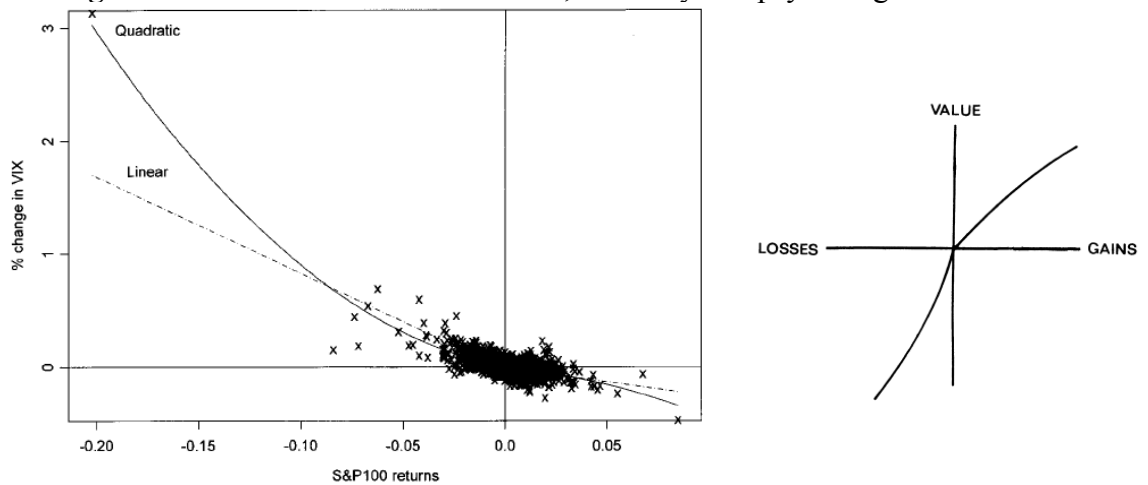
A value function that exhibits loss aversion predicts that for equal chance gambles the investor will always sell the lottery (Weber and Camerer 1998). According to Low (2004), loss aversion could translate into a greater responsiveness of downside price pressure on raising risk relative to the responsiveness of upside price pressure on lowering risk. Prospect theory is one of the behavioral explanations we will investigate as a potential explanation for the asymmetric pattern in volatility.

#### 2.4-2 Link between psychological value and volatility

Kahneman's psychological value graph is drawn based on individuals' decisions in experimental settings. Could prospect theory explain aggregated market data? Low's analysis of the relationship between return and volatility is shown in figure 2.4 beside Kahneman's hypothetical value function. Both graphs contain gains and losses, i.e. positive and negative return. However, Kahneman's graph have psychological value on the second axis while we find changes in volatility on Low's graph. What is the link between psychological value and volatility? The psychological value or the perception of gains and losses is one important element that could affect the investors' decisions. In Kahneman's experiments he has observed the participants' decisions and secondarily drawn the graph of the participants' psychological value. Decisions are observable, psychological value is not. However, the psychological value is the factor driving the decision in the

experiments. Hence, psychological value could affect decisions and the decisions are driving the stock prices in the markets and determine the volatility.

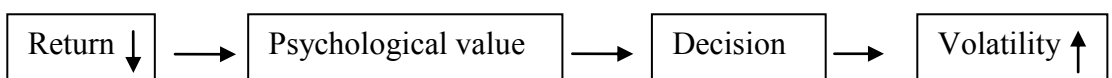
**Figure 2.4:** Similarities between return, volatility and psychological value.



The left graph is a copy of Low’s graph (Low 2004, page 535) and shows the relationship between % change in the VIX-index and return of S&P 100. The broken line represent regression  $\Delta VIX_t = \alpha + \beta_1 (R^-)_t$  and  $\Delta VIX_t = \alpha + \beta_1 (R^+)_t$  and the solid line represent regression  $\Delta VIX_t = \alpha + \beta_1 (R^-)_t + \beta_2 (R^-)^2_t$  and  $\Delta VIX_t = \alpha + \beta_1 (R^-)_t + \beta_2 (R^-)^2_t$  for positive and negative returns respectively. The regressions are similar to regression 5.3, 5.4, 5.6 and 5.7 in our analysis and are explained in detail in section “5.3 Testing of prospect theory”. The graph to the right is “The hypothetical value function” and is explained in section 2.4-1 as well as section 5.3.



Return and volatility are related in the markets. Could a behavioral explanation explain the asymmetric volatility? What is in the black box? It must necessarily be some kind of action or absence of action, because perception itself do not affect volatility. However, psychological value could affect decisions, and decisions affect stock prices and market volatility.



*2.4-3 Disposition effect*

Another behavioral explanation for the asymmetric volatility, found in the existing literature, is the “disposition effect”. It is defined as “the tendency of investors to ride losses and realize gains” (Boujelbène 2011), and is closely related to prospect



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theory. This effect was first found by Shefrin and Statman (1985), who examined decisions related to realizing gains and losses in a market setting. The effect has also been found in the market by Lakonishok and Smidt (1986), and by Weber and Camerer (1998) in an experimental setting.

According to Shefrin and Statman (1985), there exist four distinct elements that contribute to the disposition effect. That is, prospect theory, mental accounting, aversion to regret and self-control. As seen in figure 2.3 a), prospect theory predicts a behavior where investors sell winners and ride losers. This is due to the fixed reference point and the s-shaped valuation function. Mental accounting, a concept named by Thaler (1980), suggests that people tend to categorize, code and evaluate economic outcomes into different mental accounts. When a stock is purchased, for example, a new mental account is opened. The reference point will naturally be the purchase price, and a running score will be kept on this account, indicating gains or losses relative to the purchase price. Since people are reluctant to close a mental account with a loss, they will keep on to the stock until it has gained relative to the original purchase price. Mental accounting also helps explain why an investor is likely to refrain from readjusting his reference point for a stock (Shefrin and Statman 1985). Aversion to regret provides an important reason as to why investors may have difficulty with realizing both gains and losses. Lastly, self-control is an element investors employ in order to force themselves to realize losses, and thereby reducing the magnitude of the disposition effect.

For the purpose of explaining asymmetric volatility, we postulate that the asymmetry is caused by the changes in traded volume, triggered by the movement in prices. In the presence of investors subject to disposition effect, the market would be very liquid for winner stocks, and less liquid for loser stocks.

Consequently, a demand shock would have a greater impact on the volatility of a loser stock, than of a winner stock (Boujelbène 2011). Hence, according to existing theory, negative returns are related to an increase in volatility and vice versa. We hypothesize that mental accounting, as well as prospect theory and regret aversion leads to a disposition effect in the market, and will formally test this in our analysis.

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*2.4-4 Similarities between prospect theory and disposition effect*

In one of Kahneman's experiments (Kahneman 2011) he asked people what they would choose between winning 900 for sure or gamble with 90% probability of winning 1000. The participants also got the choice of losing 900 for sure or gamble with 90% probability of losing 1000. People tend to choose the certain alternative when confronted with the winning scenario and gamble in the loss scenario. The experiment reflects that people tend to be risk averse when it comes to gains, and risk seeking in the case of losses. Kahneman's hypothetical value function is convex in the domain of loss and concave in the domain of gain. This S-shape reflects the diminishing sensitivity of both gains and losses. In a situation where you have gained a lot, winning even more gives you relatively little increased value, psychologically. This reflects the risk aversion in the positive domain. In the case of a big loss, you would experience a severe pain, and losing even more would give you relatively little in additional pain. This reflects the risk seeking behavior in the domain of loss.

In the stock market an increasing stock price would represent a gain and a decreasing stock price would represent a loss. If people behave according to Kahneman's theory they would be risk averse when the stock goes up and risk seeking when the stock goes down. Selling represents the certain alternative and staying in the market represents the gamble. This implies that people would tend to sell winners and keep on to their losing stocks. This is exactly the same behavior as predicted by the disposition effect, where people tend to realize gains and ride losses.

Disposition effect could be seen as a manifestation of the prospect theory. But, at the same time, disposition effect is only one of the implications of prospect theory. Weber and Camerer (1998) point out that any test for disposition effects also tests the joint hypothesis of the prospect theory.

*2.4-5 The heuristics; affect, representativeness and the extrapolation bias*

The representativeness and affect heuristics as well as the extrapolation bias (described by Shefrin 2007) are other psychological phenomena that may explain the asymmetric volatility.

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The affect heuristic could lead managers to base decisions on instinct rather than a formal analysis, due to emotional associations with activities or positive/negative labels assigned to images, objects or concepts. Positive affect is related to labeling something as good and negative affect is related to labeling something as bad. Investors could for example label a decreasing stock as a bad stock. These labels have a strong influence on people's decisions (Shefrin 2007). People often base their decisions on affect heuristics rather than on an explicit analysis.

The representativeness heuristic leads managers to think of stocks of good companies as representative of good stocks, leading managers to expect higher returns from safer stocks. Representativeness affects investors to predict lower future volatility when market return has been high in the previous period (Shefrin 2007). Both the affect and representativeness reinforce each other when it comes to risk and return. Both lead managers to view the relationship between risk and return as being negative (as opposed to standard financial theory).

The extrapolation bias regards how people tend to give too much weight to the most recent events. The extrapolation bias is also called "the hot hand fallacy", overweighting past trends when forming forecasts. All the three heuristics have in common that they affect investors to believe that recent trends in the stock market will continue.

Hibbert, Daigler and Dupoyet (2008, 2257) postulates that "market returns influence the fear and exuberance of investors such that negative returns create fears of additional declines in the market, while positive returns create the exuberance of potential additional increases in the market, i.e. the representativeness associated with the momentum effects." They suggest that representativeness, the affect heuristic and the extrapolation bias causes asymmetric volatility.

Prospect theory and the disposition effect, as well as representativeness, the affect heuristic and the extrapolation bias have all been linked to the asymmetric pattern in volatility. We will further analyze how adequately these behavioral explanations can explain the asymmetry in volatility.

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### 3. Methodology

In this section we will outline the methodology we will use to test our theories and hypotheses.

#### 3.1 - GARCH

We will apply the GJR GARCH model developed by Glosten, Jaganathan and Runkle (1993) to test for asymmetric volatility in the Norwegian stock market. After running the conditional mean equation (See equation 3.1), we will use the estimated residuals further in the conditional variance equation (See equation 3.2). This period's volatility is dependent on the estimated  $\alpha_1$  and  $\beta$ , indicating the importance of the last period's shock and last periods' volatility respectively. Compared to the original GARCH model, the GJR GARCH contains a dummy variable that is activated when the last period shock is negative. In case of negative returns the dummy variable will be activated and lead to higher conditional variance, than in the case of a positive return. A significant positive  $\gamma$  will indicate the asymmetric pattern in volatility, where negative shocks leads to higher conditional volatility.

$$y_t = \mu + \phi y_{t-1} + u_t \quad (3.1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \quad (3.2)$$

where  $I_{t-1} = 1$  if  $u_{t-1} < 0$ , 0 otherwise.

#### 3.2 – *The leverage hypothesis, the feedback hypothesis and the heuristics*

##### 3.2-1 *The leverage hypothesis*

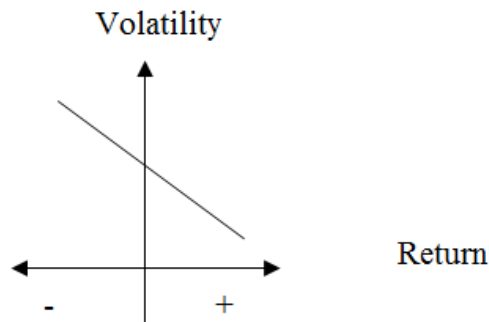
According to the leverage hypothesis a falling stock will lead to an increased debt to equity ratio and with increased risk the stock gets more volatile (Brooks 2008). We will classify the stocks in the OBX-index as low, medium or high leveraged, based on their debt to equity ratio. Further, we will run a GJR GARCH for each leverage group. According to the leverage hypothesis, we would expect more asymmetric volatility in groups with higher leverage.

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 3.2-2 *The heuristics, the feedback hypothesis and the leverage hypothesis*

Volatility tends to increase when markets fall and decrease when markets rise. The negative correlation is illustrated in figure 3.1. According to the leverage hypothesis, the leverage increases when a stock falls and this causes higher volatility. On the other hand, the feedback hypothesis postulates that increased volatility causes higher expected return, leading the stock price to decrease. Both effects involves a negative correlation between return and volatility, but with opposite causality. In contrast to a behavioral explanation based on heuristics, both the leverage and the feedback effects are longer-term lagged effects (Hibbert, Daigler and Dupoyet 2008). In other words, while the behavioral effect is more immediate, the non-behavioral explanations are more persistent.

**Figure 3.1:** The negative return-volatility relationship.



Earlier studies of asymmetric volatility and the negative correlation between volatility and return have used the Implied Volatility index on the S&P 500 (VIX) (See for example Low 2004 or Hibbert, Daigler and Dupoyet 2008). Bollen and Whely (2004) found that changes in implied volatility of S&P 500 options are most strongly affected by buying pressure for index puts. The heuristics affect investors to believe that existing trends will last. However, in falling markets this would affect the prices of both put and call options. The strong buying pressure for index puts and the increased implied volatility might be a result of the heuristics in combination with the effect of loss aversion or downside fear.

We will in our study use the implied volatility on the OBX-index as a proxy for the volatility in the market and use linear regression to test the heuristics, the leverage hypothesis and the feedback hypothesis (See equation 3.3).  $R_t$  is the current period's return on the OBX-index.

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 R_t + \beta_2 R_{t-1} + \beta_3 R_{t-2} + \beta_4 R_{t+1} + \beta_5 R_{t+2} + \varepsilon_t \quad (3.3)$$

Significant lagged effects would support the leverage hypothesis and significant lead effects would support the feedback hypothesis. If the lagged and lead effects are weak or not significant, this contradicts the leverage and the feedback hypothesis respectively and potentially supports a behavioral explanation. In other words, a weak or insignificant  $\beta_2$ ,  $\beta_3$ ,  $\beta_4$ , and  $\beta_5$  compared to  $\beta_1$ , will indicate that the leverage hypothesis and the feedback hypothesis are not fully able to explain asymmetric volatility. A strong and significant  $\beta_1$  would support the heuristic explanations.

### ***3.3 –Prospect theory***

According to prospect theory people are generally loss averse, risk seeking in the domain of loss and risk averse in the domain of gain. The theory has been widely explored and confirmed in experimental settings with single individuals. The question is whether the same patterns also could be found in aggregated market data. Based on the hypothetical value function, we have derived three empirical implications: (1) Positive and negative returns would have a significantly different impact on the implied volatility; (2) negative return will increase implied volatility more than positive return decreases volatility; and (3) there would be a significantly non- linear relationship between implied volatility and return. To test the prospect theory we will employ a relatively similar approach as Low (2004). The hypothesis and regressions will be outlined and explained in detail in section 5.3.

### ***3.4 – Disposition effect***

In our testing of a disposition effect in the OBX-index, we will use a similar approach as Lakonishok and Smidt (1986). We will collect daily trading volume and shares outstanding on all the companies listed on the OBX-index. From these figures we will compute the daily turnover for each of the shares and for the market portfolio (see eq. 3.4). These variables will further be used in regression 3.5 to compute the daily abnormal turnover for each stock. Here, the daily

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turnover for each stock is the dependent variable and the daily market turnover is the independent variable.

$$\text{Daily turnover}_{it} = \text{Daily volume}_{it} / \text{shares outstanding}_{it} \quad (3.4)$$

$$\text{VT}_{it} = \alpha_i + \beta_i \text{VTM}_t + \varepsilon_{it} \quad (3.5)$$

Since we are regressing the individual stock's turnover against the market turnover, the residuals in equation 3.5 will represent the abnormal turnover for each stock. The abnormal turnover will be positive if the particular stock had a higher turnover than the market, and vice versa. Further, we will use regression 3.6 to test for a disposition effect in the market. In other words, we will test if the abnormal turnover can be explained by the movement in prices, as predicted by the disposition effect. A binary variable will be generated in order to define a winner/loser stock, and be regressed against the dependent variable, the abnormal turnover. We will test this with different definitions of winner/loser stocks in order to capture different holding periods. Regression 3.6 shows the particular regression that will be run for each of the holding periods.  $\text{AVT}_{it}$  is the abnormal turnover of security  $i$  on day  $t$  and  $\text{DN}_{it}$  is a binary variable for security  $i$  on day  $t$ , receiving the value of 1 if  $P_t > P_{t-N}$  and 0 otherwise.

$$\text{AVT}_{it} = \alpha_i + \beta_i \text{DN}_{it} + \varepsilon_{it} \quad (3.6)$$

Other authors, such as Ferris, Haugen and Makhija (1988) have tested and found the disposition effect for smaller companies. A sample of smaller companies will potentially ease the likelihood of finding a disposition effect since these companies exhibit a higher volatility. However, we want to test if we can find the disposition effect in the OBX-index. In the case that winner stocks and loser stocks exhibit different trading volumes, this could lead to different reactions to demand shocks causing the asymmetric volatility. Hence, the relationship should be the following:

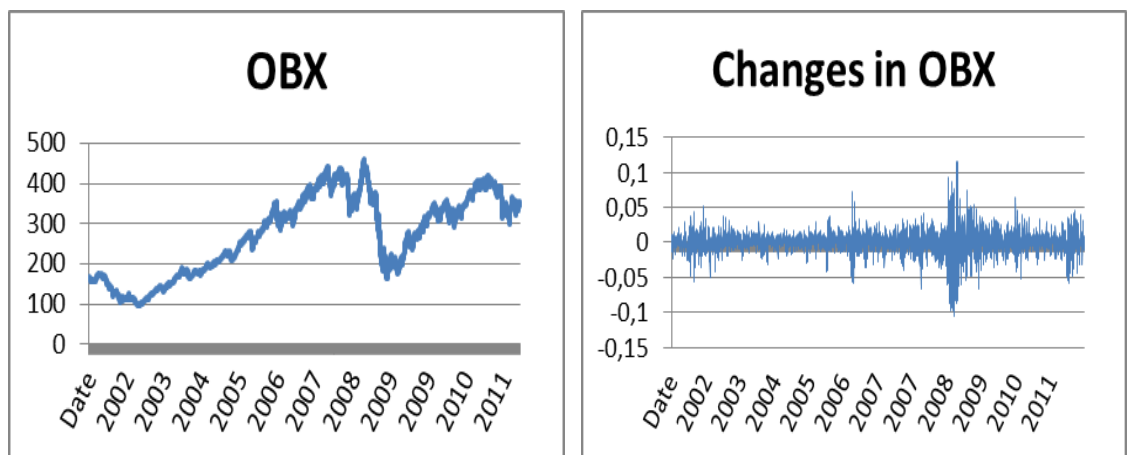
Price down (up)  $\rightarrow$  turnover down (up)  $\rightarrow$  volatility up (down).

## 4. Data

### 4.1 The OBX-index

We have collected daily values on single stocks and the OBX-index from the OBI database for the period 2002 to 2011. The OBX-index consists of the 25 most liquid stocks on Oslo Stock Exchange. Returns on single stocks are raw return adjusted for dividends and other corporate events, like stock dividends and stock splits. The negative relationship between return and volatility can be seen visually (See figure 4.1). We could observe from the two graphs that the volatility increases during drops in the stock market, as for example in 2008.

**Figure 4.1:** Development in the OBX-index from 2002 to 2011.



In the period from 2002 to 2011, the largest negative daily return on the OBX-index was -10.66%, whereas the largest positive return was 11.65% (See table 4.1). The changes in the OBX-index have a kurtosis of 5.61 indicating fat tails. The mean is below the median and the skewness is -0.34, both indicating more extreme negative returns than positive returns. In fact, the two most extreme returns are positive, but except from these two days the majority of extreme movements are related to negative returns (See table 4.2). One could, for example, observe that the number of days exceeding 5% negative return was 30 days, while the number of days exceeding 5% positive return was only 19 days.



**Table 4.1:** Descriptive statistics of the OBX-index 2002 to 2011.

	<b>Δ OBX</b>	<b>OBX</b>
Mean	0.05%	272.85
Median	0.14%	286.28
Min	-10.66%	95.34
Max	11.65%	462.70
Kurtosis	5.61	-1.29
Skewnes	-0.34	-0.12
Obs	2514	2514

**Table 4.2:** Number of days with large changes on the OBX-index 2002 to 2011.

<b>Limit</b>	<b># Positive</b>	<b># Negative</b>	<b>Limit</b>	<b># Positive</b>	<b># Negative</b>
2 %	226	230	7 %	7	11
3 %	83	103	8 %	4	10
4 %	33	52	9 %	3	4
5 %	19	30	10 %	2	1
6 %	13	19	11 %	2	0

A GJR GARCH showed asymmetry in the returns for the OBX-index in the period 2002 – 2011 (See table 4.3). The coefficients reported in the table are the asymmetric dummy terms. To check for market cyclical patterns in the asymmetric volatility we ran the model on a yearly basis. With the exception of 2003, all years showed a significant negative asymmetric pattern in volatility. We do not find any specific differences in asymmetric volatility in bull and bear markets.

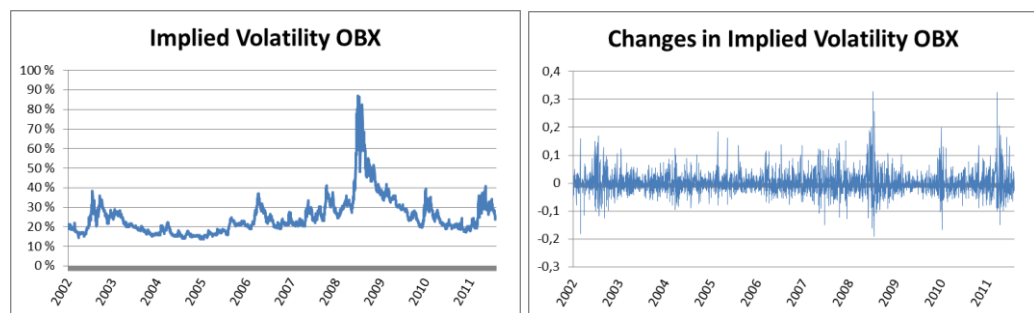
**Table 4.3:** Asymmetry on the OBX-index from 2002 to 2011.

<b>Year</b>	<b>Coefficient</b>	<b>P-value</b>
<b>2002-2011</b>	<b>0.1369</b>	<b>0.0000</b>
2002	0.0538	0.0000
2003	0.0105	0.6009
2004	0.2137	0.0001
2005	0.2112	0.0000
2006	0.2593	0.0000
2007	0.2176	0.0006
2008	0.1232	0.0063
2009	0.1435	0.0004
2010	0.2540	0.0000
2011	0.1296	0.0000

## 4.2 Implied volatility

Oslo Børs has also provided us with data on the implied volatility on the OBX-index. The implied volatility is derived indirectly from prices on put and call options on the OBX-index, using the Black & Scholes option pricing model. The variable indicates the expected volatility in the underlying index over the next 30 days, represented by an annualized standard deviation. Our data is relatively similar to the “Uro”-index reported in Dagens Næringsliv or the VIX-index on the S&P 500. The VIX-index have also been called “the fear gauge” or “the sentiment index” by the wall Street Journal (Low 2004), since it bursts up when the markets are falling and investors experience losses and uncertainty. Implied volatility captures the markets expectation of future volatility, in contrast to historical measures of volatility (Hibbert 2008). We also avoid potentially statistical errors as sampling error and misspecification errors. Similar to the bursts in volatility on the OBX-index in bear markets (See figure 4.1), the implied volatility also rises in falling markets, as for example in 2008 (See figure 4.2). In the turmoil during the fall of 2008, the implied volatility reaches its top of 87% and we also find the maximum change of 32.66% and the most negative change of -19.17% in this period (See table 4.4). The correlation between changes in implied volatility and changes in the OBX-index was 65% in the period 2002-2011.

**Figure 4.2:** Implied volatility on the OBX-index from 2002 to 2011.



**Table 4.4:** Descriptive statistics of implied volatility on OBX from 2002 to 2011.

	$\Delta$ Implied volatility OBX	Implied volatility OBX
Mean	0.9 %	25 %
Median	-0.18 %	22 %
Min	-19.17 %	14 %
Max	32.66 %	87 %
Kurtosis	5.86	8.44
Skewnes	1.00	2.39
Obs	2489	2490

### 4.3 Daily Turnover

From the OBI database we also collected data on shares outstanding and daily volume for the 25 companies listed on the OBX-Index. From this data we constructed a daily turnover variable for all the 25 companies. This variable was used to compute a daily abnormal turnover variable for each of the companies. Table 4.5 shows that the average daily turnover ranges from a low 0.19% for “Det Norske Oljeselskap” to a high of 1.83% for “Marine Harvest”. We will use the daily turnover data in our test of the disposition effect.

**Table 4.5:** Daily turnover for OBX companies from 2002 – 2011

Company name	Avg. daily turnover	St.dev
Aker Solutions	0.66%	0.60%
Algeta	0.41%	0.80%
Det norske Oljeselskap	0.19%	0.68%
DNB	0.37%	0.28%
DNO International	1.39%	2.08%
Electromagnetic Geoservices	0.47%	1.62%
Fred. Olsen Energy	0.44%	0.48%
Gjensidige Forsikring	0.20%	0.42%
Marine Harvest (Pan Fish)	1.83%	3.06%
Nopec International	0.86%	0.81%
Norsk Hydro	0.60%	0.35%
Norwegian Air Shuttle	0.47%	0.85%
Orkla	0.37%	0.31%
Petroleum Geo-Services	1.33%	1.28%
ProSafe	0.56%	0.91%
Renewable Energy Corporation	1.12%	1.01%
Royal Caribbean Cruises (RCCL)	0.27%	0.29%
Schibsted	0.31%	0.27%
Seadrill	0.95%	0.99%
Songa Offshore	1.09%	1.70%
Statoil	0.44%	0.38%
Storebrand	0.61%	0.69%
Subsea 7 (Stolt Comex Seaway)	0.80%	1.22%
Telenor	0.36%	0.42%
Yara International	0.93%	0.95%
<b>MARKET</b>	<b>0.75%</b>	<b>0.66%</b>

Table 4.5 shows the average daily turnover, standard deviation and the number of days with trade for each of the 25 companies and for the total index. The total sample is based on a period of 10 years, from 2002-2011.

## 5. Empirical results

### *5.1 Testing of the leverage hypothesis*

#### *5.1-1 The leverage hypothesis*

The leverage hypothesis states that negative returns increase the leverage of the stock, and with more leverage, i.e. more risk, the stock gets more volatile. To test this hypothesis we will group the OBX stocks into three groups, based on their debt to equity ratio. According to the hypothesis, we would expect more leveraged firms to have a higher degree of asymmetric volatility. We estimated a GJR GARCH for the individual years from 2007 to 2011 as well as for the whole sample period, rebalancing the stocks each year to account for changes in their debt to equity ratio.

#### *5.1-2 Results of the leverage hypothesis*

The dummy coefficients have to be significantly larger for a group with higher leverage to support the leverage hypothesis. Our results are mixed and often contradicting the leverage hypothesis (See table 5.1). For instance, in 2010, the asymmetric dummy coefficient is 0.32 for the group with medium leverage and 0.17 for the group with high leverage. Since the asymmetric volatility is lower for the group with the highest leverage we clearly have to reject that the coefficient is significantly higher. All the estimated coefficients marked with a grey shaded background are contradicting the leverage hypothesis. Consistent with earlier studies in our literature review, we conclude that the leverage hypothesis at best could be a weak explanation for the asymmetric volatility.

**H1: Stocks with high leverage will have higher asymmetric volatility.**

**Table 5.1:** Leverage and asymmetric volatility.

Leverage	2007	2008	2009	2010	2011	2007-2011
Low	0.1667** (0.0243)	0.2192*** (0.0056)	0.0645 (0.2490)	0.3305*** (0.0006)	0.1851*** (0.0000)	0.1475*** (0.0000)
Medium	0.2313*** (0.0049)	0.2793*** (0.0030)	0.0307 (0.5554)	0.3223*** (0.0007)	0.1876*** (0.0000)	0.1407*** (0.0000)
High	0.2506** (0.0209)	0.2719*** (0.0014)	0.1619** (0.0427)	0.1750*** (0.0080)	0.2456*** (0.0005)	0.1207*** (0.0000)

Table 5.1 shows the  $\gamma$  coefficient from the GJR GARCH model ( $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$ ), measuring the asymmetric volatility. The p-values are given in parenthesis in the table. The sample consists of stocks included in the OBX-index at the beginning of 2013. The stocks are grouped as low, medium and high leverage based on their debt to equity ratio each year. \* Indicates statistical significance at a 10% level, \*\* at a 5% level and \*\*\* at a 1% level.

### 5.1-3 Discussion of the leverage hypothesis

Based on our analysis it seems like the leverage effect at best could be a weak explanation for the asymmetric volatility. However, other potential factors might be dominating and disturb our results. Based on our analysis, we cannot determine if there is a small leverage effect or none at all. However, we do know that the leverage effect is not the dominating explanation for the asymmetric volatility. We will investigate the leverage hypothesis further in the next section by also testing the theory in a multiple regression.

## 5.2 Testing of the heuristics; representativeness, affect and extrapolation bias, the feedback hypothesis and the leverage hypothesis

### 5.2-1 The heuristics; representativeness, affect and extrapolation bias

According to traditional financial theory there is a positive relation between risk and return. A stock with higher risk has higher expected return. The heuristics are “rules of thumb” or “mental shortcuts” used instead of more explicit analyses. The affect and representativeness heuristics leads investors to believe low risk will give high return, i.e. a negative risk-return relationship. Current negative return affects investors negatively emotionally and the falling market is viewed as representative for the future. Extrapolation bias affects investors to extrapolate recent trends when forming future forecasts. People will be overly optimistic in bull markets and overly pessimistic in bear markets. All the three heuristics affects investors to believe that recent trends will last in the near future. Bollen and

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Whaley (2004) find that changes in implied volatility are directly related to net buying pressure from public order flow. They find that changes in implied volatility of S&P 500 options are most strongly affected by buying pressure for index puts. In falling markets, investors would buy put options for hedging and speculations in a much higher degree than they would buy call options in rising markets. Hence, the implied volatility would increase. This would lead to a negative risk-return relationship. The increased implied volatility related to rising put prices might be a result of the heuristics as well as loss aversion or downside fear.

We will use regression 5.1 to test the heuristics; representativeness, affect and extrapolation bias, as well as the feedback hypothesis and the leverage hypothesis. The model includes current, lagged and lead returns to explain the current implied volatility.

$$\Delta \text{Implied Volatility}_t = \alpha + \beta_1 R_t + \beta_2 R_{t-1} + \beta_3 R_{t-2} + \beta_4 R_{t+1} + \beta_5 R_{t+2} + \varepsilon_t \quad (5.1)$$

**H1: Current return on the OBX-index is the most important factor determining the contemporary implied volatility (Supports the heuristics and contradicts feedback and leverage).**

#### *5.2-2 The feedback effect and the leverage effect*

The feedback effect is a market effect, in contrast to the leverage effect that is a firm effect (Dennis et al. 2006). According to the feedback hypothesis, increased volatility in the stock market causes higher expected return, meaning that the volatility is the primary effect and the returns are secondary. The leverage effect has an opposite causation. Negative return increases the firm's leverage and this causes increased volatility, i.e. the return is primary and the volatility is secondary.

**H2: There is a significant negative relationship between lagged returns and contemporary implied volatility (Supports leverage hypothesis).**

**H3: There is a significant negative relationship between lead returns and contemporary implied volatility (Supports feedback hypothesis).**

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*5.2-3 Results of the heuristics, feedback and leverage*

The data supports the affect, representativeness and extrapolation bias heuristics. Hypothesis H1, “current return on the OBX-index is the most important factor determining the contemporary implied volatility”, is supported by the data. Current return ( $R_t$ ), with an estimated coefficient of -1.53, is the dominating factor determining the implied volatility, compared to the other estimated coefficients (See table 5.2). Falling stock markets will affect investors to believe it will continue to fall. Hence, put option prices will increase (protecting investors from further losses), reflecting the expectations of future increased volatility. The significant negative and dominating current return coefficient reflects the negative contemporary relationship between return and volatility.

**Table 5.2:** Heuristics, feedback and leverage.

Regression	Adj R <sup>2</sup>	Intercept	R <sub>t</sub>	R <sub>t-1</sub>	R <sub>t-2</sub>	R <sub>t+1</sub>	R <sub>t+2</sub>
Reg 5.1	0.4276	0.0017*	-1.5328*	-0.1722*	-0.0163	-0.0496	0.0223
		(2.7595)	(-42.8412)	(-4.8146)	(-0.4574)	(-1.3871)	(0.6232)

Table 5.2 shows the results from regression 5.1:  $\Delta \text{Implied Volatility}_t = \alpha + \beta_1 R_t + \beta_2 R_{t-1} + \beta_3 R_{t-2} + \beta_4 R_{t+1} + \beta_5 R_{t+2} + \epsilon_t$ . The model is relatively similar to Hibbert et al. (2008). Change in the implied volatility of the OBX-index is dependent variable for regression 5.1 and R is the return of the OBX-index. There is a 10 year sample period from 2002 to 2011. The t-values are given in parenthesis in the table. \* indicates statistical significance at a 1% level.

We find some evidence consistent with the leverage hypothesis while the feedback hypothesis is mainly contradicted by our analysis. However, the leverage hypothesis does not have a dominating explanatory role in determining the asymmetric volatility. Current return ( $R_t$ ) is the dominating factor determining the implied volatility, supporting hypothesis H1 (See table 5.2). Since both the leverage effect and the feedback effect are related to longer term lagged and lead effects, the strong effect from current return is contradicting that the leverage and the feedback effects are the main explanations for the asymmetric volatility. Hypothesis H2, “there is a significant negative relationship between lagged returns and contemporary implied volatility”, is partly supported by our data. The one day lag is statistically significant, supporting the leverage hypothesis. Hypothesis H3, “there is a significant negative relationship between lead returns and contemporary implied volatility”, is contradicted by our data. Both the one and two days lead are insignificant contradicting the feedback hypothesis. Overall

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our result shows no support for the feedback hypothesis, while the leverage hypothesis is at best a weak explanation for the asymmetric volatility.

#### *5.2-4 Conclusion on the heuristics, feedback and leverage*

The multiple regression model shows that the contemporary return is the dominating effect determining the implied volatility. Our analysis shows no support for the feedback hypothesis, while the leverage hypothesis is at best a weak explanation for the asymmetric volatility. This indicates that these rational theories are not the primary explanations for the asymmetric volatility. Our data are consistent with the heuristics; representativeness, affect and extrapolation bias.

### **5.3 Testing of prospect theory**

#### *5.3-1 Prospect theory*

The hypothetical value function (See figure 2.2) has three empirical implications: (1) Positive and negative returns would have a significantly different impact on the implied volatility; (2) negative return will increase implied volatility more than positive return decreases volatility; and (3) there would be a significantly non-linear relationship between implied volatility and return. The sample is based on the implied volatility on the OBX- index and the return on the OBX-index using daily data. (R+) consist of the whole sample removing all negative values and (R-) is the same sample removing all positive values.

#### *5.3-2 Loss aversion*

The first implication is derived from the reference point of the hypothetical value function. We expect to find a break point, i.e. that the two samples (reg. 5.3 and 5.4) with negative and positive returns would have significantly different slopes. To test the incremental effects we would run regression 5.5, which includes both regression 5.3 and 5.4. A significant  $\beta_3$  from regression 5.5 would indicate that the market reacts differently to gains and losses, consistent with the hypothesis. The second implication is related to the statement “losses loom larger than gains”. Loss aversion is expected to materialize with a steeper slope for the negative sample.



$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 R_t + \varepsilon_t \quad (5.2)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^-)_t + \varepsilon_t \quad (5.3)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^+)_t + \varepsilon_t \quad (5.4)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (D^+)_t + \beta_2 R_t + \beta_3 R_t (D^+) + \varepsilon_t \quad (5.5)$$

where  $(D^+) = 1$  if  $R_t \geq 0$ , 0 otherwise

**H1: Due to the reference point, changes in volatility should be significantly different for positive and negative returns.**

**H2: Due to loss aversion, the increase in volatility following negative return should be greater than the decrease in volatility following positive return.**

### *5.3-3 Risk seeking and risk aversion*

The third implication would be supported if we find a significant positive coefficient related to  $(R^-)^2$  and a significant negative coefficient related to  $(R^+)^2$  (See regression 5.6 to 5.9). A positive coefficient related to  $(R^-)^2$  implies a positive second derivative related to the negative sample and a negative coefficient related to  $(R^+)^2$  implies a negative second derivative related to the positive sample. This will imply the S-shape where negative return would have an exponentially increasing effect on implied volatility and positive return would have an exponentially diminishing effect on the reduction in implied volatility.

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^-)_t + \beta_2 (R^-)^2_t + \varepsilon_t \quad (5.6)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^+)_t + \beta_2 (R^+)^2_t + \varepsilon_t \quad (5.7)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^-)^2_t + \varepsilon_t \quad (5.8)$$

$$\Delta \text{ Implied Volatility}_t = \alpha + \beta_1 (R^+)^2_t + \varepsilon_t \quad (5.9)$$

**H3: Due to risk seeking in the domain of loss, the increase in volatility should be exponentially increasing (Convex function).**

**H4: Due to risk aversion in the domain of gain, the decrease in volatility should be exponentially decreasing (Concave function).**

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*5.3-4 Results of prospect theory*

Regression 5.2 has a significant negative beta coefficient of -1.53 reflecting the negative relationship between return and volatility (See table 5.3-1). When return goes up with one percent the implied volatility is expected to go down with 1.53 percent. In fact, all the linear slope coefficients in regression 5.2 to 5.7 are significantly negative, reflecting the negative relationship between return and volatility.

Our analysis supports hypothesis H1 and H2, reflecting the reference point and the loss aversion of prospect theory, respectively (See table 5.3-1). The negative sample has a slope coefficient of -1.86 and the positive sample has a slope coefficient of -1.13 (See reg. 5.3 and 5.4). The steeper slope related to losses reflects that losses looms larger than gains and supports hypothesis H2. Adjusted  $R^2$  for the negative sample is 38% and for the positive sample 16%. The higher adjusted  $R^2$  for the negative sample also reflects the greater relationship between return and volatility for negative returns. We use regression 5.5 to determine whether the two effects are significantly different. Regression 5.5 incorporates both regression 5.3 and 5.4. When there is negative return both the dummy variables are inactive. Hence, the constant and the slope coefficient of regression 5.5 are similar to regression 5.3. For positive returns the dummy variables are activated and we get the same coefficients for regression 5.5 as for regression 5.4 ( $-0.0026 + -0.0004 = -0.0030$  and  $-1.8649 + 0.7301 = -1.1348$ ). The significant slope dummy coefficient of 0.73 reflects that the markets react significantly different to gains and losses, and supports hypothesis H1 and the reference point aspect of prospect theory.

Hypothesis H3 and H4, reflecting the risk seeking behavior in the domain of loss and the risk aversion in the domain of gain are supported by our analysis (See table 5.3-1). For the negative sample we expected a positive coefficient related to  $(R-)^2$  (see reg. 5.6 and 5.8) and for the positive sample we expected a negative coefficient related to  $(R+)^2$  (See reg. 5.7 and 5.9). The signs of our estimated coefficients in regression 5.6 and 5.7 are opposite to our expectations and not significant. Testing for multicollinearity we got a VIF- value of 6.29 and 3.89 for the negative and positive sample, respectively. To avoid the multicollinearity problem we estimated regression 5.8 and 5.9. The estimated coefficients have

signs as expected and show a significant non-linear relationship, supporting hypothesis H3 and H4.

Excluding a relevant variable from a regression might lead to biased estimates, i.e. the squared terms might be biased excluding the linear terms in regression 5.8 and 5.9. However, we are mostly concerned about the significance level and not the values of the estimated coefficients. The reason that the squared terms are not significant in regression 5.6 and 5.7 is that the linear effect is the dominating one. In other words, it seems like loss aversion, i.e. that people don't like to lose, is a more fundamental effect than the risk seeking behavior in the domain of loss and the risk aversion in the domain of gains.

**Table 5.3-1:** Prospect theory. Sample 2002 to 2011.

Regression	Constant	R	R-	R+	(R-) <sup>2</sup>	(R+) <sup>2</sup>	Dummy	Dummy*R	Adj R <sup>2</sup>
Reg 5.2	0.0016*** (2.5804)	-1.5298*** (-42.602)							0.4222
Reg 5.3	-0.0026** (-1.9707)		-1.8632*** (-26.470)						0.3811
Reg 5.4	-0.0030*** (-2.6047)			-1.1348*** (-16.153)					0.1621
Reg 5.5	-0.0026** (-2.0946)	-1.8649*** (-27.639)					-0.0004 (-0.2146)	0.7301*** (7.3482)	0.4341
Reg 5.6	-0.0039** (-2.3464)		-2.0465*** (-12.871)		-2.9671 (-1.2852)				0.3815
Reg 5.7	-0.0018 (-1.3017)			-1.3015*** (-9.3906)		2.8685 (1.3949)			0.1627
Reg 5.8	0.0130*** (11.74385)				23.6800*** (21.6571)				0.2917
Reg 5.9	-0.0126*** (-14.0189)					-13.7801*** (-12.8139)			0.1083

Table 5.3-1 shows the estimated coefficients and their respective t-values in parenthesis for regression 5.2 to 5.9, using daily data from 2002 to 2011. The implied volatility on the OBX- index is dependent variable and the independent variables consist of return on the OBX-index. R represents the whole sample, (R+) consist of the whole sample removing all negative values and (R-) is the whole sample removing all positive values. The dummy is activated for positive returns. The t-values are given in parenthesis in the table. \* indicates statistical significance at a 10% level, \*\* at a 5% level and \*\*\* at a 1% level.

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### 5.3-5 Time variation of prospect theory

Further, we want to test if prospect theory has a different explanatory power in bull and bear markets. Boujelbene (2011) concludes that during the subprime crisis a behavioral explanation was more important for the asymmetric volatility, compared to the pre-subprime crisis period. We have estimated regression 5.3 to 5.5 each of the individual years in the 10 years period from 2002 to 2011, testing for stability over time (See table 5.3-2). The relationship between return and implied volatility for the positive sample in 2003 was actually positive. However, the relationship was weak and non- significant. Despite some lack of significance in 2004 and 2007, this analysis mainly supports Hypothesis H1 and H2 and our initial conclusions using the whole sample period. Further, we do not find any specific pattern related to potential differences between bull and bear markets.

**Table 5.3-2:** Prospect theory; Reference point and loss aversion, time consistency

Regression	Coefficient	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Reg 5.3	R-	-2.5082*** (-8.7506)	-1.9315*** (-4.9243)	-1.5095*** (-3.3818)	-2.3685*** (-7.0948)	-1.8858*** (-8.8341)	-2.7427*** (-8.7366)	-1.7250*** (-11.963)	-1.2784*** (-9.6466)	-2.5745*** (-8.9747)	-3.1844*** (-12.299)
Reg 5.4	R+	-1.6599*** (-3.8118)	0.0161 (0.0564)	-0.3417 (-0.6794)	-0.8445*** (-3.0238)	-1.0950*** (-5.5633)	-2.2817*** (-7.5298)	-1.0356*** (-6.1120)	-0.5614*** (-4.0728)	-1.7766*** (-8.9972)	-2.0709*** (-7.9792)
Reg 5.5	Dummy *R	0.8483* (1.6716)	1.9476*** (4.0770)	1.1678* (1.7380)	1.5240*** (3.5453)	0.8100*** (2.8163)	0.4663 (1.0770)	0.6893*** (3.0999)	0.7169*** (3.7192)	0.7978** (2.3484)	1.1135*** (2.9984)

Table 5.3-2 shows the estimated coefficients and their respective t-values in parenthesis for regression 5.3 to 5.5, using daily data from 2002 to 2011. The implied volatility on the OBX- index is dependent variable and the independent variables consist of return on the OBX-index. R represents the whole sample, (R+) consist of the whole sample removing all negative values and (R-) is the whole sample removing all positive values. The dummy is activated for positive returns. The t-values are given in parenthesis in the table. \* indicates statistical significance at a 10% level, \*\* at a 5% level and \*\*\* at a 1% level.

We have also estimated regression 5.8 and 5.9 each of the individual years in the 10 years period from 2002 to 2011, testing for stability over time (See table 5.3-3). Low found a relatively strong convex profile for extreme losses and a somewhat weaker concave profile for extreme gains (Low 2004). With exceptions of 2003 and 2004 in the cases of gains, our result shows the same relationship using Norwegian market data, supporting hypothesis H3 and H4. Similar to our results in table 5.3-2, we do not find any specific pattern related to potential differences between bull and bear markets.

**Table 5.3-3:** Prospect theory; Non- linearity, time consistency.

Regression	Coefficient	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Reg 5.8	(R-) <sup>2</sup>	52.9450*** (7.9446)	67.4235*** (5.6548)	68.9190*** (3.9897)	68.2109*** (7.3512)	33.6865*** (7.2182)	78.9232*** (7.6909)	17.9967*** (11.5324)	22.7643*** (9.1768)	67.3953*** (9.3400)	63.3598*** (11.1824)
Reg 5.9	(R+) <sup>2</sup>	-38.944*** (-3.4777)	1.8320 (0.1947)	-7.9869 (-0.3415)	-24.5859*** (-2.6716)	-16.5360*** (-4.50865)	-79.2328*** (-7.8752)	-9.6319*** (-5.5351)	-9.0924*** (-3.7017)	-34.5410*** (-7.6799)	-47.0050*** (-6.9281)

Table 5.3-3 shows the estimated coefficients and their respective t-values in parenthesis for regression 5.8 and 5.9, using daily data from 2002 to 2011. The implied volatility on the OBX- index is dependent variable and the independent variables consist of returns on the OBX-index. R represents the whole sample, (R+) consist of the whole sample removing all negative values and (R-) is the whole sample removing all positive values. The dummy is activated for positive returns. The t-values are given in parenthesis in the table. \* indicates statistical significance at a 10% level, \*\* at a 5% level and \*\*\* at a 1% level.

### 5.3-6 Discussion of loss aversion and causality

According to the efficient market hypothesis, markets are efficient when the assets are correctly priced and reflect all information (Bodie, Kane and Marcus 2008). Hence, the only thing that drives the stock prices is news. News is per definition unpredictable, hence the stock prices are following a random walk. It may be that on average more extreme news are following days with negative return than positive return. If that is the case, the asymmetric volatility may be a rational reflection of reality. It may also be other rational explanations that no-one have come up with yet. This is related to what is called an endogeneity problem, and could never be ruled out.

We would use Hume's classical example of the billiard table to enlighten the problem related to causality (Tollefsen, Syse and Nicolaisen 1997). A white ball is rolling over the table and hits the black ball. Then the black ball starts to roll. Can we say for certain that the white ball caused the movement of the black ball? According to Hume; No. Hume, the father of the empiric tradition, says we could only observe that the two balls are touching each other and that two movements are following each other in time. However, we could not observe the causality itself and therefore not have certain knowledge about the direct relationship. It might for example be some kind of "invisible hand" that caused the movement of the black ball. Hume's illustration is an extreme strict view of causality, but the story illustrates the same problem as we are facing. According to the loss aversion, we would predict asymmetric volatility and that the markets would react more severe to negative news compared to positive news. We do in fact also find

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this relationship. However, our methodology is based on correlations and it is difficult (if not impossible) to determine the causality with certainty.

### *5.3-7 Conclusion of prospect theory*

Our analysis supports prospect theory and the three empirical implications of the relationship between return and volatility. The reference point (H1), the loss aversion (H2), the risk seeking in the domain of loss (H3) and the risk aversion in the domain of gain (H4) are all supported by our analysis. The patterns in the market data are consistent with prospect theory. Hence, we conclude that prospect theory is a plausible explanation for the asymmetric pattern in volatility. Further, the loss aversion seems to be the strongest, or the most fundamental effect of prospect theory. The disposition effect can be seen as a manifestation of the risk seeking in the domain of loss and the risk aversion in the domain of gain. These effects will be further investigated in the next section.

## ***5.4 Testing of the disposition effect***

### *5.4-1 The disposition effect*

According to the disposition effect, investors tend to sell winners too early and hold on to losers for too long. In the case of disposition effects, we would expect to see the traded volume of a winner stock to increase, and the traded volume of a loser stock to decrease. Consequently, a demand shock would have a greater impact on the volatility of a loser stock, than of a winner stock, and we get asymmetric volatility.

We used the daily volume and shares outstanding to compute daily turnover for each of the 25 companies and for the market portfolio (see eq. 5.10). The daily turnover for each company was regressed against the market turnover, using eq. 5.11, in order to account for market-wide influences.  $VT_{it}$  is the turnover (volume traded) of security  $i$  on day  $t$ ,  $VTM_t$  is the market turnover on day  $t$ , and  $\varepsilon_{it}$  is the disturbance term for company  $i$  in day  $t$ . Equation 5.12 highlights that the disturbance term of eq. 5.11 represents the abnormal turnover.

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$$\text{Daily turnover}_{it} = \text{Daily volume}_{it} / \text{shares outstanding}_{it} \quad (5.10)$$

$$\text{VT}_{it} = \alpha_i + \beta_i \text{VTM}_t + \varepsilon_{it} \quad (5.11)$$

$$\varepsilon_{it} = \text{AVT}_{it} = \text{VT}_{it} - (\alpha_i + \beta_i \text{VTM}_t) \quad (5.12)$$

The abnormal turnover ( $\text{AVT}_{it}$ ) will be positive if the particular stock had a higher turnover than the market, and vice versa. Further, we want to analyze if the abnormal turnover can be explained by movement in prices, according to what is predicted by the disposition effect. In other words, we want to determine if stocks with declining prices did have a lower turnover rate than the stocks with increasing prices. We tested this by creating six different binary variables to account for a previous price change, and regressed this binary variable against the abnormal turnover. Each stock on a given day was sorted into either a winning stock or a losing stock, according to whether its price per share had increased or decreased in the previous  $N$  days. The values of  $N$  were chosen in order to capture different holding periods; 1, 3, 10, 30, 100 and 250 days. Equation 5.13 shows the particular regression that was ran for each of the six binary variables.  $\text{AVT}_{it}$  is the abnormal turnover of security  $i$  on day  $t$  and  $\text{DN}_{it}$  is a binary variable for security  $i$  on day  $t$ , receiving the value of 1 if  $P_t > P_{t-N}$  and 0 otherwise.

$$\text{AVT}_{it} = \alpha_i + \beta_i \text{DN}_{it} + \varepsilon_{it} \quad (5.13)$$

For each of the six definitions of winners and losers, the twenty-five companies will be sorted according to the  $t$ -values for their estimated beta coefficient. The firms are listed as having either a significant positive, negative or insignificant  $\beta$ -coefficient. In table 5.4 we have reported the  $t$ -values for the  $\beta$  coefficient from equation 5.13 for the 25 firms listed on the OBX-index. A significant positive  $t$ -value indicates that a winner stock had a higher abnormal return than a loser stock. Consequently, a significant positive  $t$ -value is supporting the disposition effect.

**H1: Stocks with a positive return will have a higher abnormal turnover than stocks with a negative return.**

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#### 5.4-2 Results of disposition effect

The one-day definition of winners and losers supports a disposition effect in the market. Out of the 25 firms listed on the OBX-index, 13 firms showed a significant positive beta. The other 12 proved insignificant, and the average t-value came out to be 2.02. The GJR GARCH showed asymmetric volatility in the OBX-index and the one day binary variable points in the direction of a positive relationship between price and daily volume (turnover), as is predicted by the disposition effect theory. Hence, it seems that we do find the following pattern:

Price down (up) → turnover down (up) → volatility up (down).

For the three-day binary variable the results are weakly supporting the disposition effect with 8 significant positive betas versus only 3 significant negative ones. However, the majority of 14 firms all have insignificant beta values. For the other four binary variables the results are more or less ambiguous. The firms are spread out almost equally to each of the three significance levels, showing no systematic pattern of a disposition effect.

**Table 5.4:** Number of firms on OBX with significant t-values for 2002-2011.

Winner/Loser Definition	2002 - 2011			Avg. t-value
	t < -1.96	-1.96 < t < 1.96	t > 1.96	
1 day	0	12	13	2.02
3 days	3	14	8	1.11
10 days	7	10	8	0.18
30 days	9	9	7	-0.30
100 days	10	8	7	-0.55
250 days	12	3	10	-1.17

Table 5.4 shows the t-values for the 25 beta-coefficients from equation 5.12 ( $AVTit = \alpha_i + \beta_i DNit + \epsilon_{it}$ ), sorted according to the six different definitions of a winner stock; 1, 3, 10, 30, 100 and 250 days period. A t-value above 1.96 indicates that we can reject the null hypothesis of no disposition effect, at the 5 % level.

The results show that there exists a positive significant relationship between the abnormal turnover and the movement in prices, for the one-day interval. Hence, if the stock price increased from yesterday to today, the abnormal turnover today will be higher than if the price had decreased. The results show clear differences with regard to the holding periods. It seems that a disposition effect is more easily found in short holding periods, at least for more liquid stocks like the ones on the OBX.



### *5.4-3 Conclusion of disposition effect*

Our analysis shows some evidence of a disposition effect in the OBX-index. For the one-day definition of a winner stock our findings supports a disposition effect in the market. For the three-day variable the results weakly supports a disposition effect. For the other four holding periods however, our findings show no clear pattern. Hence, we conclude that the disposition effect could be an explanation for the asymmetric volatility.

## **6. Discussion and future research**

### *6.1 Rational explanations*

Our analysis showed no support for the feedback hypothesis and we concluded that the leverage hypothesis at best could be a weak explanation for the asymmetric volatility. These findings are consistent with several previous studies (See part 1 and 2). In the absence of other rational explanations, this is a positive indicator for a behavioral explanation. However, we cannot exclude the possibility of other potential undetected rational explanations. Further, we cannot exclude the possibility that news is more extreme in bear markets, something that also would explain the asymmetric volatility rationally.

### *6.2 Contribution and discussion*

Earlier papers mostly investigate one or two explanations for the asymmetric volatility. Compared to these papers, our thesis is a more holistic approach testing all of the most known theories in one paper. Prospect theory is mentioned by Low (2004) as a potential explanation for the asymmetric volatility. However, he only mentions the theory while we go much deeper and more detailed into the relationship between prospect theory and the market volatility.

In this thesis we analyze both the prospect theory and the heuristics in one paper. The heuristic explanations are based on a greater price-sensitivity of put options compared to call options. Implicit in this explanation there is an element of downside fear and loss aversion. Hence, it might be difficult to separate the effect of the heuristics from the effect of prospect theory. In our study we have tested the heuristics and the prospect theory in two separate analyses. Separating the effects

from different behavioral explanations is difficult and is related to the unparsimonious problem of behavioral explanations. However, based on our data, quantitative analysis, and our more qualitative analysis it might seem like loss aversion is the most fundamental effect of the behavioral explanations for the asymmetric volatility.

The causality issue, discussed in detail in section 5.3-6, will always be a potential weakness for both the rational and the behavioral explanations. We do not know for certain that the observed patterns in the market data actually are caused by the specific theoretic explanation, although the data are consistent with our predictions. Based on loss aversion, for example, we would expect asymmetric volatility in the markets. However, we do not know for certain that the loss aversion actually causes the phenomenon.

Evidence of behavioral effects in the markets may influence other academics to be more skeptical of underlying assumptions of rationality in economic models and incorporate more behavioral aspects in future model development. Both the awareness of the existing theories' limitations and potential development of new more realistic theories may make the field of financial theory more useful for practitioners in the markets.

### ***6.3 Future research***

Psychological value and psychological perception affect the investors' decision making. How the decisions are affected in more detail, and which decisions that are affected can be studied closer in a stock trading setting. One could also study the differences between private and institutional investors, large and small stocks, and different securities with regard to the asymmetric volatility. The causality issue and the unparsimonious problem could also be investigated further.

## **7. Conclusion**

In this thesis we examine the asymmetric volatility in stock market returns, i.e. why the stock market is more volatile in down turns than in up turns. Our analyses show no support for the feedback hypothesis, while the leverage hypothesis is at best a weak explanation for the asymmetric volatility. This indicates that these rational theories are not the primary explanations for the asymmetric volatility, consistent with several earlier studies. We suggest that combining the traditional rational explanations with the behavioral approach will give a better understanding of the asymmetric volatility in the market. Our multiple regression (Reg. 5.1) shows that the contemporary relationship between return and implied volatility is the dominating one, supporting a behavioral explanation. The data are consistent with the heuristics; representativeness, affect and extrapolation bias. We also find support for prospect theory, including the loss aversion as well as the risk seeking behavior in the domain of loss and risk aversion in the domain of gain. The prospect theory is a well-established theory in experimental studies of single individuals' behavior and we find that aggregated market data also is consistent with the theory. The disposition effect, which could be viewed as a manifestation of the non-linearity of the prospect theory, is partly confirmed by our analysis. We find a significant one day disposition effect in approximately half of the stocks on the OBX- index. We suggest a behavioral explanation for the asymmetric volatility and based on our data and analyses, loss aversion seems like the most plausible explanation. Why is the market more volatile when it falls? The most likely answer is simply that people do not like to lose.

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