The Momentum Effect

An empirical study of the momentum effect in sectors and the influence of investor attention

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Executive summary

The purpose of this thesis is to investigate the momentum effect on a sector level and address the issue whether attention can be an explanatory variable. The relationship between momentum and attention is analyzed for the total period 2004-2018, while also a deep diving into different market states. The different market states are an up-market period and a down-market period, which provides a more comprehensive understanding of the market.
The thesis is based on a theoretical framework within behavioral finance, considering the irrationality in human behavior when reacting to information as well as in decision making. From this, Jegadeesh and Titman (1993) investigated the momentum effect and their methodology will be the essence in the creation of momentum portfolios. We composed portfolios for the US stock market for 11 different sectors based on the SP500. Furthermore, three attention measures were chosen to conduct the analysis of the relationship between momentum and attention; trading volume, analyst recommendation and market cap, where trading volume has the main focus since it is a more direct measure. Attention as an explanatory variable were examined by a linear relationship along with a regression showing the effect of a change in attention on momentum return as the dependent variable.

The results showed positive momentum returns for all the sectors for the total period and up-market. For the down-market, positive momentum returns were found, though with lower returns and a few negative for some sectors. A positive linear relationship between attention and momentum were found; higher attention generates a positive effect on momentum return. This was present for the total period and up-market indicating that attention can be an explanatory variable for momentum. In the down-market this linear relationship faded and instead of higher attention having a positive effect on momentum, almost all sectors except for one exhibited negative effect on momentum return if attention increased, why attention no longer is an explanatory variable for the momentum effect when looking at a down-market state.

The evidence could be related to over- and underreaction driven momentum, where especially overreaction driven momentum could be the explanation for the up-market and underreaction driven momentum for the down-market.

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Chapter 1

Introduction

1.1 Introduction

Modern Portfolio Theory (MPT) has over the last decades been through a transition and is now challenged from new academic theory, research and empirical analysis. The many strict (and unrealistic) assumptions contained in theories of the efficient frontier, CAPM, efficient market hypothesis (EMH) and the rational investor combined with clear evidence of anomalies in the financial markets, have led to the emergence of behavioral finance. One of these anomalies is the momentum effect; stocks, which have performed well in the past, keep performing well and the opposite for stocks, which performed poorly. A winning investment strategy could therefore be to buy the historical best performing stocks and sell the poorest performing stocks. The strategy is that winners keep winning and losers keep losing. Jegadeesh and Titman tested this strategy in 1993 and since then several studies have found momentum effects in different stock markets all over the world.

The momentum effect has mainly been elaborated on a country level. Dividing the countries into different sectors and investigate the presence of momentum within each sector, have not been executed to the same degree. The thesis will examine if there is a momentum effect on a sector basis and furthermore investigate if some sectors have more momentum than others. Possible explanations of the results are conducted. The momentum effect has so far not been explained by one reason. But several theories within behavioral finance, focusing on human behavior and irrational tendencies, which can lead individuals to over- or underreact to information, and thereby affect stock prices and breaking the assumption of rationality, have increasingly got more and more consideration both in academic circles and financial institutions. Recent papers have expanded the analysis to include an attention parameter measured as trading volume, analyst recommendation and market cap in order to deepen the explanation of momentum. This thesis will conduct an analysis between momentum and attention since empirical evidence shows that attention is an important factor in determining the development of stock prices due to investors reaction to information. Therefore, the question whether there is a positive relationship between momentum and attention will be addressed, indicating that attention could be an explanatory variable for momentum. Furthermore, evidence shows that the momentum effect varies in different market states. This thesis will perform a deep dive into attention and momentum and examine if there is the same relationship between attention and momentum in both up-markets and down-markets.

We test this by analyzing the SP500 for the period 2004-2018 and divide the stocks into 11 different sectors. First, the creation of momentum portfolios for the different sectors is conducted based on the Jegadeesh and Titman paper (1993). Second, the relationship between momentum and attention is investigated by a correlation graph to see whether there is a positive linear relationship between momentum and attention. Furthermore, regressions have been run to see what effect attention has on momentum as the dependent variable. These analyses have been done for both the total period and the subperiods.

We find that all the different sectors exhibit momentum effect but on varying levels. Attention is also found to be a possible explanation for momentum in the total period and in the up-market. The results are supportive of attention being an important factor for investors reaction to information regarding under- and overreaction. The results show the positive linear relationship between momentum and attention along with the regression showing that attention has a positive effect on momentum return. In the down-market, the momentum effect is lower. The relationship between attention and momentum has faded. Attention is rejected as an explanatory variable for momentum in down-markets, instead theories about investor underreaction is discussed.

Our study contributes to the literature on momentum anomaly, by demonstrating that investor attention is related to the phenomena and are supportive of the existing theories within behavioral finance regarding investor over- and underreaction as possible explanations. Further it contributes to the literature which investigates the momentum effect in different market states and shows that momentum is higher in up-markets and with attention as an explanatory variable. Finally, it adds to the litterateur of inattention in down-markets where attention is not found to be a possible explanation.

The paper is organized as follows. The remainder of this chapter will present the problem statement together with the sub problems and a delimitation. Chapter 2 reviews Modern Portfolio Theory (MPT) and an introduction to behavioral finance. Chapter 3 is a review of the related empirical and theoretical literature on momentum and the existing possible explanations based on behavioral biases, together with theories of momentum in different market states. Chapter 4 presents the data and the method to conduct the analysis of momentum and attention. Chapter 5 goes through the results for the total period and the up- and down-markets followed by a robustness check. Chapter 6 contains a discussion and interpretation of the results in relation to the chosen literature from chapter 3. Chapter 7 concludes the paper.

1.2 Problem statement

A well-documented anomaly in the US stock market is the momentum effect. Instead of focusing on the country level, this thesis moves further down and split the country level into sectors to investigate the momentum effect among 11 different sectors in the US market for the period 2004 – 2018. Furthermore, a possible explanation for the momentum effect will be investigated with attention as the explanatory variable. To get a deeper understanding of the momentum effect and the possible relationship to attention, different market states will be included in the analysis.
The essence of this thesis is to provide an answer to the following question:
How is the momentum effect on a sector level, furthermore will some sectors have more momentum than others and can attention be an explanatory variable for the momentum effect?

In order to answer the problem statement, this thesis will investigate four different sub questions:

1. *How is the momentum effect measured and what explanations are uncovered in the literature?*

2. *How can stock portfolios for the US sectors based on momentum trading strategies be created and tested?*

3. *What role can attention have as a possible explanatory variable for the momentum effect, and how can changes in attention affect the momentum result for each sector?*

4. *Is higher attention associated with an increased momentum return, and what influence does the different market states have on the results?*

1.3 Delimitation

In the making and processing of this thesis, some delimitations were necessary in order to simplify and secure the quality and consistency of the many data, while also complying with the time limits of the project.

The US equity market has been chosen as the market to investigate. The US equity market is by far the largest in the world with a market share of approximately 50% (Statista, 2019). Furthermore, the US equity market is very diversified and in combination with many globally and international oriented companies the market is a good representative for global equities. Due to the big data volume, if including all stocks in the US market, we chose to focus only on the SP500 index, which should give a good representative picture. A big advantage in choosing this index is, that the availability and quality of data is very high and goes historically a long time back. Within this index, focus is on the different market sectors. As regards classification of sectors, the Morningstar sector category was chosen and together with the Bloomberg stock classification, stocks were categorized in their respective sectors. The time period is limited to 2004-2018. This period is a 14-year timeline and covers different market states. Therefore, this period seems reasonable for an analysis of attention in both up- and down-markets.

The thesis is only covering the momentum effect as regards to price momentum effect. For pricing momentum effect, the strategy is that stocks are bought or sold based on past returns, so historical data for earlier performance is required. From now on when the notion of momentum effect is stated, it refers to price momentum effect.

Regarding the methodology applied in the paper, we have limited the portfolio formation to follow the approach and ideas of Jegadeesh & Titman (1993). In this way, a well-documented and comparable method is applied, and the quality of the testing is secured. Not exploring further methods to test for the momentum effect for SP500 in the time period 2004-2018 seems like a fair assumption since the method used already has been proven and tested throughout the years. The paper also discusses the underlying reasons for the momentum effect and includes earlier stated behavioral models and ideas, as well as a test for attention as an explanatory variable for momentum.

The formation of the portfolios and testing of the 16 trading strategies stated by Jegadeesh & Titman (1993) have some assumptions. Risk is not included as an explanatory variable in the formation and calculation. At the same time, transaction costs and taxes are not incorporated in the data processing. This is due to earlier tests which conclude, that including these factors do not change the results, and therefore to simplify the data processing it has been decided to leave them out. We are aware that the assumptions are not aligned with reality, but they simplify the testing of the momentum effect.

As the focus is on behavioral finance to be an explanatory factor of the momentum effect, the paper will review and present a limited selection of behavioral models. In the paper, attention is especially in focus, and how it affects the momentum effect, also referring to different market states, up- and down-markets. Together behavioral finance, individual's reactions to news and attention will create a discussion of the momentum effect in different market states and possible explanatory variables. The models chosen are described in the literature, but only a limited selection was possible, due to the size and time of the paper.
Decisions also had to be made regarding the measurements of attention. In earlier papers and financial theories, we have found sources of what variables to measure. Trading volume and analyst coverage are the primary measures for attention applied in this thesis. Together with the behavioral theory focusing on investors' reactions to news and different market states, it will all add to the answering of the problem statement.

Chapter 2

Financial Theory

This section will focus on the theory of market efficiency, which is one of the milestones in financial theory. Section 2.1 will examine the efficient market hypothesis presented by Fama in 1970, the random walk hypothesis and investor rationality. Section 2.2 will present the CAPM and factor models. Last section 2.3 introduces behavioral finance and some of the main heuristics.

2.1 Market Efficiency

2.1.1 Market Efficiency hypothesis

The Efficient Market Hypothesis (EMH) was presented in 1970, by Eugene F. Fama in the paper "Efficient Capital Markets: A review of Theory and Empirical Work". The key idea is, that for the market to be called efficient, prices of securities must "fully reflect" all available information (Fama, 1970).

According to Fama (1970), the theory of efficient markets is described as investing in a fair game model. Earlier work states market equilibrium conditions as an expression of expected returns. Therefore equation *1* says that the expected value of a security, given the level of what information is fully reflected in the price, equals the predictive price of the security *j* at time *t*. By multiplying the price of *j* at time *t,* by the equilibrium expected return plus 1, will add up to the combined future price,

$$E\left(\tilde{p}_{j,t+1}|\phi_{t}\right) = \left[1 + E\left(\tilde{r}_{j,t+1}|\phi_{t}\right)\right]p_{jt} \qquad (1)$$

The idea of equation *1* is to achieve that no matter what model is chosen for expected return the measure of ϕ, defined as level of information fully reflected in the price, will be applied in completion of equilibrium expected return (Fama, 1970).

Both the sequence of $\{x_{jt}\}$ and $\{z_{jt}\}$ are stated to be a "fair game", given the level of information stated to be reflected in the term ϕ.

$$x_{j,t+1} = p_{j,t+1} - E\left(p_{j,t+1}|\phi_t\right) \qquad (2)$$

$$E(\tilde{x}_{j,t+1}|\phi_t) = 0 \qquad (3)$$

And

$$z_{j,t+1} = r_{j,t+1} - E\left(\tilde{r}_{j,t+1}|\phi_t\right) \tag{4}$$

$$E(\tilde{z}_{j,t+1}|\phi_t) = 0 \tag{5}$$

Equation *2*, $x_{j,t+1}$, represents the excess market value of the security *j* at time *t +1*. The equation states that in an efficient market, the difference between the observed and expected price equals $x_{j,t+1}$. Equation *3* shows that in an efficient market the expected excess value of x_j, given the level of ϕ, will be zero. Equation *4* replicates that $z_{j,t+1}$ is the return from *t* to *t+1.* Similar to the expected excess value, the expected value of excess return given the level of ϕ is zero, compared to equation *5*. The expected value of total excess market value at time *t+1,* given the set of information fully reflected, equals zero (Fama, 1970). In relation to this, when they all lead to expectations of zero excess return, it should not be possible to outperform the market. All investors have equal access to information and prices are fully reflecting changes, why earnings of abnormal returns should not be possible. Expected value of excess returns is zero and defined as a "fair game" with no outperforming.

EMH can be divided in three different versions; the weak, semi-strong and strong form. They all define what version of efficiency the capital market is in, depending on the level of available information, which is defined for each of them (Bodie et al., 2014).
The purpose of the three levels was to test EMH depending on different criteria to the availability of information (Fama, 1970).
The first version is the **weak-form** defined as all available information in the form of historical market trading data, all past data about prices and trading volume (Bodie et al., 2014). This can be related to the random walk hypothesis, which states that all price changes are random and unpredictable. That is supportive of the assumption of the weak-form, where no past prices can be used to predict future prices and earn abnormal returns (Bodie et al., 2014).
Next version referred to, is efficiency in a **semi-strong** form. Here all information reflected in a stock price is assumed to be all publicly available information, in the sense of past prices, fundamental data on product line, management quality, financial performance, setup and decision related details for the firm (Bodie et al., 2014 and Fama, 1970).

In the **strong-form** all information possible relevant for the firm, even inside information, is assumed to be incorporated and fully reflected in the price. This version is seen as more extreme and harder to fulfil (Bodie et al., 2014). The version is not completely concluded to be valid and fully able to support the EMH (Fama, 1970).

The random walk theory lies closely to EMH and supports the efficient market since no systematic over- or underreactions towards stocks should happen (Horne & Parker, 1967). The random walk theory deals with the idea of how movements of stock prices are following a random walk. All price changes are assumed to be non-predictable, independent over time and a random process (Bodie et al., 2014 and Horne & Parker, 1967). According to the theory it is not possible to uncover a price pattern to predict future prices based on history (Horne & Parker, 1967). Prices will reflect all information and only adjust to new announcements. Therefore, it is not possible to obtain any form for profit or abnormal returns from historical prices, when prices follow a random walk in reality. Referring to Burton G. Malkiel news are directly implemented and reflected in stock prices, but since they are unpredictable the prices reflected hereby should be unpredictable and random (Malkiel, 2003). In the text presented earlier by Fama, it is stated, that the random walk hypothesis can be seen as an extension of the "fair game" efficient market model (Fama, 1970). The random walk is presented in the clarification of the weak-form version of efficiency in the text by Fama and focuses on the unpredictable information that is directly incorporated in the stock price, so no excess profit can be made.

2.1.2 Investor rationality

Rational decision-making is one of the cornerstones in financial theory. The overall assumption is that all individuals and firms will aim towards maximizing their own utility. They all base decisions on all relevant information and are independent from each other, they only seek for their own best interest (Ackert & Deaves, 2009).
When focusing on expected utility theory, focus is on the rational investor in relation to dealing with risk. Most people are willing to take on risk, if they are compensated for it. In that sense, they go for investing in stocks that match their risk profile. They will go for the stock with the highest possible expected return at a given level of risk; they will not accept the same return at a higher risk. If a person takes on a riskier investment, the return is expected to increase to compensate for

a higher risk (Ackert & Deaves, 2009). Investors can be divided into three risk profiles: Risk averse, risk seeker and risk neutral. For a risk-averse person the uncertainty about the future value makes the person rather have a lower expected wealth of *x* than different percentage chances of a lower or higher wealth, with uncertainty of the outcome (Ackert & Deaves, 2009). A risk-seeker is more willing to take on more risk, and deal with uncertainty, and consequently expect a higher return from their investment. Investors prefer having the opportunity of increasing wealth to higher level, than the wealth they can obtain with certainty (Ackert & Deaves, 2009). **Risk-neutral** investor's profile is in between the two earlier mentioned. Investor rationality add to the idea of market efficiency. Rational investors are an important supporter to fulfill the condition for market efficiency and have been used in several financial models (Ackert & Deaves, 2009). Over the years the rational investor has been questioned, due to the increasing examination of human behavior. In behavioral finance, humans are considered to behave irrational.

2.2 Financial Models

2.2.1 CAPM

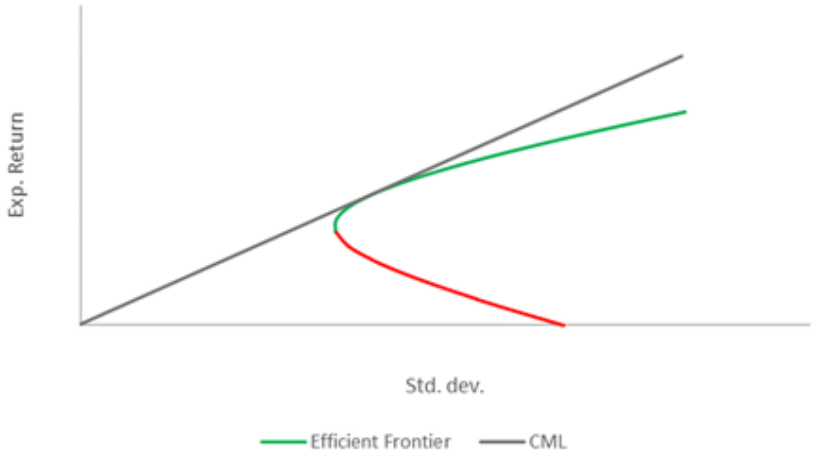
In 1952 Harry Markowitz changed the view of portfolio theory by creating optimal portfolios based on diversification. Later the CAPM was introduced by William Sharpe, John Lintner and Jan Mossin (Bodie et al., 2014). The CAPM is a further development of Markowitz portfolio theory and it provides an estimate of the relationship between risk and return.

The model assumes an efficient capital market:

1. There is no tax or transaction cost
2. Relevant information is available for everybody in the market
3. Investors can borrow or lend at the risk-free rate and no risk of bankruptcy
4. Homogeneous expectations
5. Investors are risk averse and base their decisions on the mean-variance rule

The relationship between risk and return is further explained by the efficient frontier, which is created based on expected returns and a covariance matrix.

Figure 1: Efficient Frontier
The figure shows the efficient frontier (green) and the capital market line (CML)



The efficient frontier shows a combination of all available assets, which are efficient (green line). Therefore, an investor should hold a portfolio on the efficient frontier where the weights are achieved by Markowitz optimization. The risk-free asset was introduced in the model and used to calculate risk premiums and is an alternative investment to the risky assets. When investors have the same investing universe it would provide them with an identical efficient frontier. Combined with an identical risk-free rate it would lead investors to draw an identical capital market line (CML), which shows the risk premiums of efficient portfolios. If all investors are choosing the same risky portfolio it must be the market portfolio, which is a value-weighted portfolio of all assets (Bodie et al., 2014). The market portfolio is located where CML tangent the efficient frontier.
The CAPM provides the expression for the expected return-beta:

$$E(r_i) = r_f + B_i * \left(E(r_M) - r_f\right) \tag{6}$$

Where $E(r_i)$ is the expected return, r_f the risk-free asset, B_i the systematic risk and $E(r_M)$ is the expected return for the market portfolio (Bodie et al., 2014). The formula shows that the expected return only depends on the systematic risk. Nonsystematic risk can be eliminated in a portfolio by diversification and in the market portfolio the nonsystematic risk is removed.

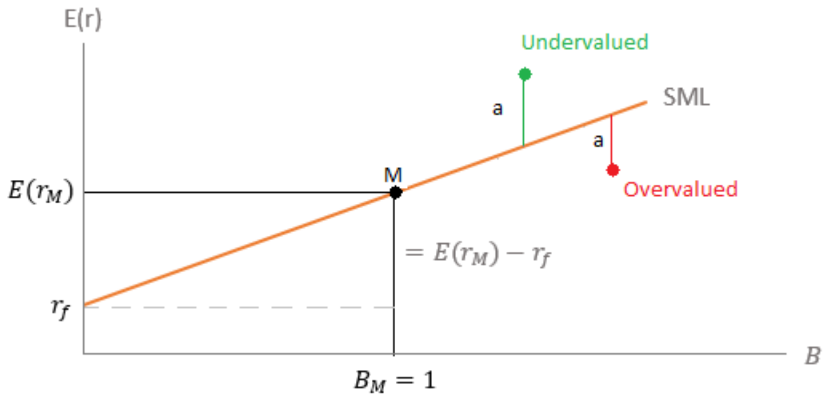
Beta, the systematic risk, is calculated as: $B_i = \frac{cov(R_i,R_M)}{\sigma_M^2}$.

The market portfolio has a beta of 1: $B_i = \frac{cov(R_M,R_M)}{\sigma_M^2} = \frac{\sigma_M^2}{\sigma_M^2}$ (Bodie et al., 2014).

Where B_i is the assets beta, σ_M^2 is the variance of the market portfolio and $cov(R_i, R_M)$ is the covariance between the assets expected return and the market portfolios expected return.

A portfolio with a beta greater than 1 is seen as riskier or more exposed to changes in market conditions, where a portfolio beta less than 1 is more defensive (Bodie et al., 2014).
The security market line (SML) shows the relationship between expected return and beta. Since the beta of the market portfolio equals 1, the slope of the SML is the risk premium of the market portfolio.

Figure 2: Security Market Line
The figure shows the security market line and the slope



SML shows individual asset risk premiums and when the market is in equilibrium all assets must lie on the SML. Assets above the SML are undervalued and asset under the SML are overvalued. The difference is the alpha coefficient (Bodie et al., 2014).

The focus in the CAPM is the positive relationship between beta (risk) and expected return, the higher the beta, the higher expected return. Over the years many empirical tests of this relationship have been conducted, but the results show a flat or negative relationship (Howard, 2014). Based on the piling evidence, that beta is not a proven measure of risk, Fama & French recommended not to use the CAPM and beta in practical matters. Furthermore, breaking down the beta it consists of (1) the market and stock return correlation and (2) the variance of the market. Subsequently volatility can be viewed as investors' reactions to market events, why beta can be related to a measure of emotions (human reactions) rather than risk (Howard, 2014).

2.2.2 Factor models

Partly to the letdown of beta not being a measure of risk, other proposals for risk measures have been provided by factor models. In 1993 Eugene Fama and Kenneth French used firm specific characteristics as proxies for systematic risk. The characteristics were chosen based on past evidence showing some predict power of average returns. The three characteristics chosen in their model are;

1. Excess return for the market portfolio, $R_{Mt} = E(r_M) - r_f$
2. Small minus big (SMB), which is the difference in return of a small stock portfolio compared to a large stock portfolio.
3. High minus low (HML), which is the difference in return of a portfolio based on high book to market ratio stocks (value stocks) compared to a portfolio of low book to market stocks (growth stocks).

The three-factor asset pricing model:

$$E(r_i) - r_f = a_i + b_i[E(r_M) - r_f] + s_i E[SMB] + h_i E[HML] \tag{7}$$

Where $E(r_i) - r_f$ is the excess return (R_{it}) and b_i, s_i and h_i are the betas (Bodie et al., 2014). Firm size (SMB) and book to market ratio (HML) was chosen based on past evidence showing a relationship between the two firm characteristics and deviations in average returns, which led to going long in small stocks and shorting big stocks (SMB) and consequently going long in value stocks and shorting growth stocks (HML). Reason is that average returns of small firms and firms with high B/M have been observed to be higher than predicted by SML (Bodie et al., 2014). Fama & French used market cap to predict alpha coefficients in the CAPM. The evidence shows that the smaller the firm (market cap) the higher the alpha (excess return). Therefore, the size factor can be viewed as an anomaly that counter the CAPM. The systematic risk factors in the model are therefore firm size, B/M and the market index where the betas of the model should capture the overall risk.

In 1993 Jegadeesh and Titman published their article showing the momentum effect in the market, which was a further violation of the efficient market hypothesis. Creating portfolios based on past winners and losers and then holding the portfolio 3-12 month provided positive significant excess return. This was a factor, which was not explained by the three-factor model.

In 1997, the three-factor model was extended with one more factor; the momentum factor (Carhart, 1997). The Carhart four-factor model added the momentum factor, since it was found to be an anomaly, which was not accounted for in the Fama-French three-factor model. The momentum factor was created by buying the winners and selling the losers and thereby capture the momentum effect.

Carhart four-factor regression model:

$$E(r_i) - r_f = a_i + b_i\left[E(r_M) - r_f\right] + s_i E[SMB] + h_i E[HML] + p_i E[PR1YR] \qquad \text{(8)}$$

Where, PR1YR is the factor for one-year momentum in stock returns (Carhart, 1997).

These factors are not true return factors, but rather proxies. In reality, what stock returns are based on is the investors' decisions to buy and sell (Howard, 2014). Since it is not possible to observe what investors are thinking or why they act as they do, measurable proxies can instead be identified, and in the case of the factor models it is market cap, SMB, HML and the momentum. With the use of proxies to explain price movements, measuring risk got more complicated, since the question is whether the additional return earned can be explained by for example an opportunity for enhanced return, risk premium or as the relation between economy and the market (Howard, 2014). Therefore, the factor models can explain the relation between return and other variables, but not regarding whether risk or other return factors has been identified. For example, with the SMB, where small cap stocks have a higher return than large cap stocks, this could both be due to a better opportunity or higher risk. Therefore, whether the factor models measure risk or opportunity is unknown (Howard, 2014). Risk and opportunity are tangled together, making it hard to come up with a certain measure of risk and the introduction of behavioral finance makes it even more complicated (Howard, 2014).

2.3 Behavioral Finance

The above theories have historically dominated modern finance, but recent evidence has made researchers question the traditional view and whether markets are efficient. Anomalies and irrationality have become of greater interest, which have led to a further investigation of how human psychology and behavior influence financial decision-making. Anomalies in the market introduces controversy to market efficiency and in behavioral finance people are no longer rational but "normal" which means that they tend to behave irrational (Pompian, 2012).

2.3.1. Prospect theory

In 1979 Daniel Kahneman and Amos Tversky presented a critique to the traditional expected utility theory of decision making under risk by introducing prospect theory (Kahneman & Tversky, 1979). Where utility theory assumes that people act in a specific way (normative model), prospect theory focus on what people do in reality and creates models based on the observations (positive model). Kahneman and Tversky therefore argue that utility theory is not a correct descriptive model; that is why they come up with an alternative (Kahneman & Tversky, 1979).

Prospect theory is based on three aspects of observed behavior (Ackert & Deaves, 2009):

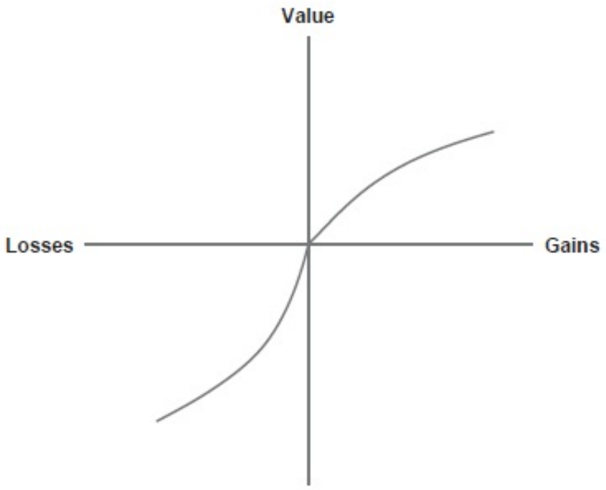
1) People can change in risk attitude (sometimes a person can display risk aversion and other times be risk seeking).

2) People exhibit different risk attitudes between gains and losses. Therefore, it is the change in wealth that people care about, not the specific wealth (people use a reference point relative to gains and losses when valuating prospects).

3) People exhibit loss aversion, they feel a loss stronger than a gain when the value is the same. For people to exhibit risk neutrality between a possible gain and a possible loss, the gain must be more than two times greater than the loss.

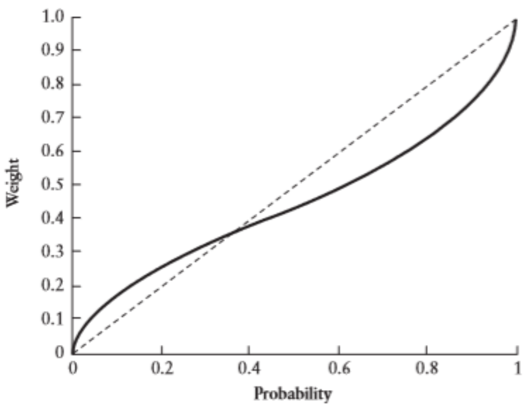
Prospect theory creates a model for decision-making under risk which integrates the observed behavior above. The focus on gains and loses relative to the reference point is the essences of the value function, which replaces the utility function that focuses on the level of wealth where the value function focuses on changes in wealth. The three key aspects above provide the value function with the necessary input, which creates a function that is concave (risk averse) in the positive domain and convex (risk seeking) in the negative domain (Ackert & Deaves, 2009).

Figure 3: The Value Function
The figure shows the value function of prospect theory



The value on the vertical axis is determined by changes in wealth relative to the reference point, not just wealth as in utility theory. The function is steeper in the loss domain due to loss aversion. Another difference between utility theory and prospect theory is the use of decision weights which is a function of probabilities, where utility theory uses simple probabilities (Ackert & Deaves, 2009). When determining the value of a prospect, decision weights incorporates overweighting of low probabilities. When probabilities for a payoff are low, people tend to shift from risk aversion in the positive domain to risk seeking. Similarly, when there is a low probability of a loss, people tend to shift from risk seeking in the negative domain to risk aversion. Prospect theory confronts this observation by introducing a nonlinear weighting function (Ackert & Deaves, 2009).

Figure 4: Weighting Function
The figure shows the weighting function of prospect theory



The weighting function introduces two additional controversies to utility theory. The certainty effect which is the difference between probably outcomes and certain outcomes. People overweight certain outcomes compared to probable ones, why the slope of the weighting function is steep close to certainty (slope > 1). The other controversial focus on highly unlikely events, where it is found that overweighting of probabilities is greatest for low probabilities, which also leads to a steep slope close to zero (slope > 1). Based on the above the slope is relatively flat in the middle (slope < 1) (Ackert & Deaves, 2009).

2.3.2. Heuristics

Since the evolvement of the efficient market theory and CAPM, psychology and sociology has become of greater interest when trying to understand decision-making. The rational human has been questioned and the assumptions about information level and sharing is for some models critical. The CAPM model as described earlier, assumes that people can investigate the market and incorporate all the required input for the model, here among expected return and standard deviation for all assets. Only then can the investor decide; but the world is full of uncertainty and limited time, which are factors that need to be accounted for. Given limited time combined with uncertainty, people have unconsciously developed heuristics or "rule of thumbs" to guide their decision-making. The problem with heuristics is the tendency to lead to biased decisions (Ackert & Deaves, 2009).

2.3.2.1. Overconfidence

The first bias is overconfidence which is probably the most robust finding and appear when people overestimate their own knowledge (Bazerman & Moore, 2013). Events such as stock market bubbles or the high trading tendency on the stock market, despite the cost, has been explained by overconfidence (Bazerman & Moore, 2013). People think they have some better information than others or that they are just better than others to choose the right investment. This leads overconfidence to be divided in three groups:

1) Overprecision

Happens when people are too confident in their decisions and can lead them to ignore other evidence. The results of overprecision can be narrow confidence intervals and in the markets, it can be an explanatory factor for increasing trading turnover despite the cost of trading. Overprecision can therefore lead investors to think they have the correct answer of market predictions, which increases focus on trading (Bazerman & Moore, 2013).

2) Overestimation

Happens when people think they are better or smarter than they are, which can lead to overestimation of accomplishments or their knowledge within a given area. Overestimation can also lead the person to think that they have full control over a situation, when they have very little control. Furthermore, it can lead a person to be optimistic biased, which is when people are too optimistic regarding the future. Here the concept "defensive pessimism" also plays a role, which is the tendency that people shield themselves from dissatisfaction (Bazerman & Moore, 2013).

3) Overplacement

Happens when people think they are better than others within a given area. This is especially present in a competitive context and can lead people to be too focused on competing with others, for example in the stock market, because they think that they are better (Bazerman & Moore, 2013).

2.3.2.2. Representativeness

Representativeness heuristic is when people are trying to figure out for example whether an object or a person is representative for a group or class. People tend to use stereotypes when making these decisions (Kahneman & Tversky, 1974). Related to investor behavior, the same tendency can be spotted when investors are trying to determine the success of a company. The investor will categorize the company based on a familiar classification for example as a value stock and then make decisions based on that classification. This will lead to ignorance of other factors that could influence the success of the company. In sum, investors use stereotypes when making their financial decisions (Pompian, 2012).

People also use the representativeness heuristics in relation to sample size, for example when evaluating the probability of a specific investment outcome, the investor does not account for the sample size. Some call this the "law of small numbers", since the investor incorrectly assumes that a small sample size is representative for the population.

The bias is also present in forms of misconceptions related to change, for example a random sequence is expected to portray the real characteristics of the sequence; e.g. tossing a coin (Kahneman & Tversky, 1974). This can be related to investor behavior, where individuals tend to see patterns in random sequences, for example if a company's earnings have increased over the past years, the individual tend to think they have found a trend and that it will continue (Pompian, 2012).

The representativeness heuristics is also related to predictability, for example when trying to predict the expected value of a stock. Given a description of a company, people will tend to predict better performance for a company with a good description rather than one with a mediocre. The favorableness of the description is not affected by the reliability or accuracy of the prediction of the description, this is why peoples estimates will not consider the reliability of that prediction (Kahneman & Tversky, 1974).

2.3.2.3. Conservatism

Conservatism is another psychological bias, where people tend to hold on to their prior views or estimates and do not account for new evidence (Pompian, 2012). In the market, investors can tend to hold on to previous information regarding a stock or a company's earnings announcement and do not incorporate newly received information if it negatively affects the prior ones. This bias can lead investors to underreact to new information, since they do not update their prior beliefs, but rather persevere them (Pompian, 2012). The implication for the investor will be that too much attention will be given to forecast, rather than focusing on new information.

Investor mistakes that can appear due to conservatism bias is (Pompian, 2012);

1. The investor holds on to prior forecast or information without being able to adapt new information, which for example can lead the investor to cling to an optimistic belief and will not incorporate potentially negative news.
2. If the investor reacts to new information, it will be done too slowly which for example can lead the investor to hold on to a losing stock too long.
3. The conservatism bias can be related to the tendency that individuals get troubled when confronted with complex data, so they choose the easy way by just sticking to their original belief.

2.3.3 Investor over- and underreaction

In 1985 Richard Thaler and Werner De Bondt discovered evidence of investor overreaction to information (Pompian, 2012). By analyzing data, they found over the last five years stocks with very low returns had constantly outperformed stocks with very high previous returns. Barberis, Vishy and Shleifer supported the evidence by observing that it would be a good strategy to buy previous losers based on a three to five-year period, since they would outperform over the next years.

This tendency can be explained by investor overreaction. Investors can tend to become too optimistic when incorporating positive news which can lead the company's stock price to be pushed to an unusually high level. Over the following years, the optimistic belief will be corrected, and the stock price will decrease. The same tendency can be observed regarding loser stocks where investors have been too pessimistic (Pompian, 2012).

Barberis, Vishny and Schleifer also find evidence that investors can tend to underreact to some news. This is found for both positive and negative news. When a company announces higher quarterly earnings investors will push the stock price up but not up to the fair level, while the stock will gradually drift upward over the coming period. The same evidence can be found when a company announces bad news for example a cut in dividend. The stock price will fall but not to the correct level, why it will keep falling for the subsequent months.

This evidence again shows, that markets are not efficient due to anomalies such as over- and underreaction. Investor behavior and anomalies will be further investigated in the coming literature review.

Chapter 3

Literature Review

This chapter is reviewing earlier literature and relevant studies about momentum and attention to uncover the important points and evidence from earlier papers. The aim is to give a brief overview of the relevant literature used later in the paper and the theories behind this thesis. It is a chosen selection of the academic papers read through this process, which were found relevant and important to present to give an overview and insights that are used later in the analysis. The main papers presenting momentum by Jegadeesh & Titman are guiding the method for setting up momentum strategies and creating the ponder of over- and underreaction combined with attention in different market states to be the key of the momentum effect.

The chapter is structured as follows; section 3.1 uncovers evidence of momentum in the US equity market, showing the method of momentum portfolio creations and trading strategies in the time frame of 1965-1998, plus further research opening for the behavioral models as explanations for the momentum effect. Section 3.2 uncovers several behavioral model suggestions with focus on psychological biases and over- and underreactions in different market states. In this section, different measurements for attention are uncovered as keys to creating momentum profits. Section 3.3 expose the idea of up- and down-markets, investigating momentum in different market states. Lastly section 3.4 summarizes and combines the uncovered papers and their key points.

3.1 Momentum in Stock Markets

Jegadeesh & Titman, 1993, "Returns to Buying Winners and Selling losers: Implications for Stock market Efficiency" is a main paper for documenting momentum investment strategies that generates a positive return when buying stocks that are performing well and selling stocks that are performing poor, over a time period of 3-12 months look back and holding period. Focus is a short-term period for creating abnormal returns based on price movements. The paper sets up the methodology for forming portfolios in relation to the momentum strategy and shows an analysis of the strength for the trading strategies varying between 3-12 months lag and holding period. With an examination period from 1965 to 1989, data is collected 23 months prior 1965 for stocks

on NYSE and AMEX, to enable the creation for the 12/12 strategy. The relative strength of each trading strategy has been tested. In total there are 16 different strategies to create a portfolio. They are based on four different combinations of selecting and holding stocks from their return over the past 3, 6, 9 and 12 months as look back period (denoted as J months) and then deciding a holding period varying within same time measure (denoted as K months). Therefore, referred to as J-month/K-month strategy when later shown in the table. The construction of the portfolios is classified from a ranking of each security included in the sample based on their returns in the last J-months. All securities get evaluated based on their performances the last J-months and from here divided into equally weighted ten decile portfolios. The top performers are in the winner decile and the worst performing are in the loser decile. From here the idea is to buy the winner portfolio and sell the loser portfolio. This gets rebalanced over the tested period, where the bought securities are held for K months, before the actual return from doing the strategy is calculated. For the analysis, they see all portfolios as zero-cost portfolios. All portfolios in the different combination of J/K strategies showed positive returns and all statistically significant, except the 3-month/3-month strategy. The best performing relative strength strategy was 12-months/3-months with 1.31% per and the result is significant with a t-test of 3.74. Strategy 6-months/6-months is chosen as a representative strategy for all presented trading strategies and is used throughout the paper at further analysis and tests. It stated a return of 0.95% per month and a yearly abnormal return of 11.40% with t-stat 3.07. For the analysis done in the period 1965-1989, Jegadeesh & Titman (1993), concludes that using the trading strategy of buying winners from chosen J months and selling losers generates abnormal returns that are significant.
The text comments that profitability from the relative strength strategies are concluded not to be related to systematic risk of the strategies. Lastly, reflections of investor behavior are discussed. Links to over- and underreaction about firm news are presented. Reflecting on whether investors underreact to information about short-term and overreact to information related to long-term firm perspective. It is also discussed whether transactions in connection to rebalancing creates an overreaction for prices when buying winners and selling losers. Both ideas are not concluded, but encouragement for further research to identify explanations of the investor behavior is stated in Jegadeesh & Titman (1993).

Jegadeesh & Titman, 2001a, "Profitability of momentum strategies: An evaluation of alternative explanations" is a follow up paper, that tests the conclusion of momentum profits from Jegadeesh & Titman (1993), in the period 1990-1998. The momentum strategies are still profitable, which backs up the conclusions from the 1993 paper. The aim is to assure that the results are not due to conspirations of data mining. The paper sums up the reflection of Jegadeesh &Titman (1993) and the capability of rejecting the efficient market hypothesis with their results. By testing a new time period, using the 6/6 strategy and overlapping portfolios which still includes the previous period the strategy is still seen as profitable. Therefore, the momentum trading strategy is concluded not to have been incorporated in investors approach on a level that can eliminate the idea and possibility of obtaining abnormal return. The post-holding period is being tested to see if an extended period to 13-60 months will be affected by return reversal. The conclusion is that an investor will lose the abnormal returns over the extended time frame and returns are negative. Therefore, the 3-12 months approach is the best strategy for momentum. Besides testing the strategy in a new time frame and an extension of the post-holding period, the paper also looks into later proposed explanation models, provided as behavioral models. The emphasized models are presented by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) focusing on investors behavior and reaction to news and information, which will be presented later in the literature review. Even though the explanation comes close and Jegadeesh & Titman results can be supporting, they keep a caution (Jegadeesh & Titman, 2001a).

Jegadeesh & Titman, 2001b, "Momentum" sums up and extends the papers above from 1993 and 2001(a). It recaps earlier findings and evidences of momentum and the 3-12 months momentum strategies. The paper sets up a few tests for explaining momentum by risk, but the winners do not seem to be more risky than the losers. A new angle is the industrial momentum, they evaluate the idea that some industries have higher momentum than others and therefore outperform the low momentum industries. Some earlier papers by Moskowitz and Grinblatt (1999) and Grundy and Martin (2001), have discussed that momentum profits can be due to industry momentum. Other factors than behavioral models are investigated, here among firm size, price level, quality and type of information is evaluated and presented. When controlling for size, greater momentum for smaller firms is found. Furthermore, a new area investigated is the evidence for earnings momentum and relation to return momentum. Referring to Chan, et al. (1996) it is stated that there is a correlation between the variables for earnings and price momentum. The paper concludes that the momentum effect is one of the strongest anomalies challenging EMH. A lot of investigation, interest and document details has been provided to document the relationships. Both behavioral models and different stock characteristics has been proven to be correlated with the momentum profit. But no definite conclusion and knowledge has been obtained yet.

3.2 Behavioral Explanations

3.2.1 Overreaction and underreaction

J. Bradford De Long, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation" question the view of rational speculators to be the ones stabilizing assets prices. As well as expectations of rational speculators to fight destabilizing and make sure prices of assets will obtain full adjustment and return to their fundamental values. Positive feedback traders are the ones destabilizing prices; they follow the strategies of buying when prices are going up due to extrapolative expectations and sell when prices are going down. But, in this paper, rational speculators are also included in the destabilizing part and therefore challenging earlier works statement. The rational investors trades will affect the extrapolative expectations of the feedback traders about the future. When rational speculators are informed and get good news, they act on them in the belief that by making a purchase today, which will drive prices higher than fundamental value, then tomorrow positive feedback traders will react by buying due to increases in prices and drive prices even higher. In that sense some of the rising is rational but some is a mix of rational speculators expectations and positive traders' reactions, "Trading by rational speculators destabilizes prices because it triggers positive feedback trading by other investors" (De Long et al., 1990, p. 380). The model presented is running over a four-period timeline 0-3. Period 0 is the reference point where the fundamental value is zero, from here period 1 is the one where rational speculator gets a signal, news about period 2. In Period 2, the actual value is uncovered and lastly period 3 has no trading and payouts or payments are received according to the position they decided to hold of the stock, this is the long-run where prices are stabilizing to fundamental values. In relation to earlier mentioned ideas, this paper also states that the model has a positive correlation with stock returns in the short-run and negative correlations are seen in the long-run when prices return. Overreaction to news and for asset prices to rise above fundamental values are stated due to news triggering trade expectations from rational speculators, which encourage positive feedback traders in buying the stock. The article adds to the challenges and questioning of the assumptions for an efficient financial market. The power of rational speculators to stabilize prices is not possible according to this paper. The rational speculators will in the presence of positive feedback investors "…jump on the bandwagon and not to buck the trend" (De Long et al. 1990, p. 393).

Kent Daniel, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, "Investor Psychology and Security Market Under- and Overreactions" uncover a psychological and behavioral view on momentum. It adds perspective to the idea of challenging the view of assets being priced rationally and prices reflecting all public available information. The purpose of the paper is to develop a psychological theory for the security markets, that will help explaining the anomalies present, put them in various contexts and find new meanings and explanations. The roots of the theory are investor overconfidence and biased self-attribution. The definition of an overconfident investor is stated as overestimation of private information signals accuracy, but not public signals. Self-attribution bias is that the investor only sees good news and forecast as own success and confidence will grow further; but if public information is not aligned with prediction then confidence will not fall similarly, "The psychological evidence indicates that people tend to credit themselves for past success, and blame external factors for failure" (Daniel et al., 1998, p. 1845). The paper focuses on the combination of under- and overreaction and how they play together. Models are setup and defined to prove the positive relationship between overreaction and short-term momentum and underreaction to public signals causing long-term reversal. Public information will over time draw the price back to the true value. The investors are overconfident to private signals and the confidence of the investors gets lifted if the public information confirms the same sign as the private information. They refer and compare evidence back to the findings of Jegadeesh and Titman (1993). Their finding of momentum being related to delayed price reaction for firm related information is contrary with the finding in this paper. Momentum here is not happening due to late reaction, but overreaction to information and later a public information can push up the overreaction from private signals. Finally, Daniel et al. (1998) argues that the models will work best for less liquid assets and securities. This relates to earlier mentioned expectation for small stocks to have higher momentum. The inefficiency for small stocks and less liquid assets supports the idea that they have higher information asymmetry which according to this paper is concluded to be related positively to momentum and reversal (Daniel et al., 1998).

Nicholas Barberis, Andrei Shleifer and Robert Vishny, 1998, "A model of investor sentiment" present a model which focuses on investor sentiment and how investors create beliefs. The model is consistent with findings of both underreaction and overreaction to news in stock prices. Research in underreaction finds that over 1-12 months prices underreact to news, due to a slow incorporation of the news. Whereas evidence from overreaction indicates that over greater time periods such as 3-5 years, prices overreact to patterns in news, for example stocks that have experienced a pattern of good news will become overvalued, which will lead to lower average returns in the future (Barberis et al., 1998). This contradicts EMH since investors can exploit this tendency in the market and thereby earn abnormal returns without further risk. This leads to the challenge, which is to understand how an investor forms belief that led to both under- and overreaction. Barberis et al. propose a model of investor sentiment, that is consistent with especially evidence on the heuristic representativeness and conservatism bias explained in section 2.3.2. The paper examines the representativeness heuristic and the tendency that individuals find patterns in random sequences. Barberis et al. argues that the heuristic can lead investors to believe, that if a company consistently announces extraordinary earnings, it will continue to do well in the future. Furthermore, they discuss how the conservatism bias can give rise to momentum due to investor underreaction. Combined it can lead stock prices to become overvalued, which in the long run will lead stocks that prior have had high returns to have lower/negative returns.

The model is based on one investor and one asset, where the beliefs of this investor influence the prices and returns. The assets earnings follow a random walk, but the investor is not aware of this, instead the investor thinks that earnings operates between two states. In the first state, earnings are mean-reverting (Model 1) and in the second state, earnings will trend, which means they can rise more after an increase (Model 2) (Barberis et al., 1998). For every period the investor observes the earnings and forms beliefs about which state he or she is in based on the observations/information.

The model provides evidence that supports the paper from Griffin and Tversky (1992). They made a model where individuals would update beliefs based on strength and weight of new information. Strength is defined as salience and extremity parts of the evidence, while weight is defined as statistical informativeness (ex. sample size) (Barberis et al., 1998). The model shows that individuals have too much attention on the strength of evidence rather than focusing on the statistical weight, when they are making their forecast. For example, is it assumed in the model that earnings announcement (corporate announcement) have low strength but high statistical weight, which means that stock prices underreact to these types of news. On the contrary a consistent pattern of good or bad news, for example a consistent pattern of good or bad earnings announcement, are related to high strength and low weight, which means that stock prices overreact.

Related to the model in the paper, Model 1 provides effects that are consistent with the conservatism bias. The investor does not react enough on individual earnings announcement, which is related to low strength and high weight (underreaction). In contrast, when the investor focuses on Model 2, the behavior is described as the one of the representativeness heuristics. After consistent good or bad news, investor forecasts are based on Model 2, which led to capture the prior news in a too long horizon. This is in line with the representativeness heuristic where investor associate past growth with future growth, which is related to high strength and low weight (overreaction) (Barberis et al., 1998). The model presented can therefore both lead to underreaction and long-term overreaction, it depends on the stream of past information.

Harrison Hong and Jeremy C. Stein, 1999, "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets" has a purpose similar to Barberis et al. (1998) and Daniel et al. (1998) in creating models to explain investor behavior. The results contribute to papers that are trying to deal with the market efficiency models. Focus is a bit different compared to the two papers mentioned above, where focus is on the psychology of the represented agent, focus is now on the interaction between heterogeneous agents. Traders are divided into two groups, "newswatchers" who's forecasts are based on privately observed future elements, no current or past prices, and "momentum traders" who take actions based on past price fluctuations. The paper concludes to accomplish merging of under- and overreaction, the model is split up, first showing the part where only newswatchers are present and time horizon is infinite. Information travels slowly across all newswatchers, but everyone is seen as well-informed, and it helps capturing the underreaction to private information. Underreaction is seen as a point of departure leading to the next inclusion of the model. If newswatchers themselves are not capable of incorporating prices in their forecasts, another group of traders can benefit. From here the momentum traders enter, and they take advantage of the underreaction. An arbitrage strategy helps them form excessive momentum in prices, which can cause an overreaction, "…the very existence of underreaction sows the seeds for overreaction…" (Hong & Stein, 1999, p. 2146). Momentum traders do not have an ongoing horizon like newswatchers, they have a timeline of *j* periods holding stocks until time *t+j*, therefore the early momentum traders can affect later momentum buyers negatively. Prices are driven up due to purchases, misleading next comers "good news" that are not there, which encourage later buyers to buy. Therefore, all momentum traders will not benefit, because they have no knowledge of what stage in the news cycle they are entering. This paper concludes in accordance with Jegadeesh and Titman (1993) that momentum is most profitable for smaller stocks, who proceed information more slowly. A figure shows, that slower information proceeding gives a higher short-run return correlation. On the other hand, the overvalue of stocks are higher and therefore the reversal in the long-run is bigger. This model and theory conclude the same as earlier papers, that there is a positive correlation in the short-run and a negative, reversal, in the long-run. The paper focus on the externalities that comes up when different traders interact with each other. It shares the focus and goal of creating a model that captures continuations in assets prices as well as reversal. A short-run underreaction to slowly traveling news about future elements will cause an overreaction in the long-run, due to momentum strategies creating arbitrage.

Wesley S. Chan, 2003, "Stock price reaction to news and no-news: drift and reversal after headlines" uses headlines from public news to investigate the effect on companies monthly returns and compare to companies with similar return but with no public news.
Chan raises the question whether returns after big public news and returns after huge price movements (unaccompanied by public news) would differ and if they do, what that tells us about investors responds to information (Chan, 2003). This is examined by combining portfolios of

returns from the two sources of stimuli; The public news (identified from headlines) and large movements in prices (with no public news). The portfolios are formed each month based on momentum trading strategies and are investigated for any drift or reversal in contrast to no abnormal return (Chan, 2003). The findings show that stocks which experience news display momentum while no news stocks do not. Especially when exposed to bad news, a negative drift up to 12 months is spotted, where the drift is shorter for good news. This is interpreted as bad public news get slowly integrated in prices. Overreaction in price movements is found for stocks with no news as they reverse in the following month. In sum, the results show that after bad news a strong drift is found, due to a slow reaction from investors and after huge movement in prices (unaccompanied by public news) a reversal is spotted (Chan, 2003).

The paper relates the results to two strains; The drift, caused by the slow response from investors to new information and the reversal effect, caused by overreaction to price shocks leading to increasing trading volume. The three major theories within the field are Daniel et al. (1998), Barberis et al. (1998) and Hong & Stein (1999) documented above. The results are consistent with the findings in Daniel et al. (1998); investors are only paying attention to news that support their prior beliefs (ignoring the headline balance) and they overreact to private signals (price shocks). The evidence is however more supportive of the research done by Hong and Stein (1999), that some investor groups react slowly to news and others are feedback traders. This provides evidence on what information makes investors change expectations (Chan, 2003).

3.2.2 Attention

Charles M. C. Lee and Baskaran Swaminathan, 2000, "Price Momentum and Trading Volume" shows that trading volume is an important factor for momentum. They investigate how trading volume (measured as turnover ratio) can be used to forecast returns for price momentum portfolios. The paper is divided into two parts, first it is investigated how past return and past trading volume can be used to predict future returns over intermediate and long horizons. Second, alternative theories are considered (Lee & Swaminathan, 2000).

The paper finds that even though high volume companies have lower future returns, the opposite is found to be true in the past. Their evidence shows, that trading volume can be connected to market misperception regarding companies' future earnings. It is revealed that low volume stocks are undervalued by the market and in contrast high volume stocks are overvalued. This contributes to the paper of Jegadeesh and Titman (1993), since a reversal is found over long-time horizons. It contrasts the view that price momentum is due to underreaction, instead their evidence shows that parts of the initial price momentum is better explained by overreaction, since they find no reversal through the third year after the formation of the portfolio, but instead over years 3 through 5 past winner portfolios underperform past loser portfolios. Therefore, the expectations of the investor affect both the returns and trading activity (Lee & Swaminathan, 2000).

Furthermore, the paper finds no relation to the known views (fueling hypothesis and diffusion hypothesis) about volumes effect on momentum. The fueling hypothesis is an implicit assumption from Daniel et al. (1998) and De Long et al. (1990) where high trading volume will "fuel" momentum (higher momentum), when assumed trading volume is viewed as a proxy for positive feedback trading (activity for overconfident investors). Here the paper instead finds that it is true among loser stocks, but not for winner stocks. The loser stocks with high volume continue to lose for longer periods than loser stocks with low volume, while winner stocks with high volume continue to win for a shorter horizon than winner stocks with low volume (Lee & Swaminathan, 2000). The diffusion hypothesis is related to the paper of Hong & Stein (1999), which shows that momentum should be greater for slow information diffusion stocks. In relation to trading volume, they would predict that low volume stocks would create higher momentum, assuming that the lack of trading would lead to insufficient information diffusion. The results in the paper is consistent with Hong & Stein (1999) for winner stocks but not for losers, since they find that winners with low volume have higher momentum and loser with low volume have less momentum. Furthermore, the paper provides evidence that price momentum performs better for high volume stocks and does not correspond to the diffusion hypothesis (that volume can be used as an information diffusion proxy) (Lee & Swaminathan, 2000).

In summation, the paper finds that volume "fuels" momentum for losers only and that volume support information "diffusion" for winners only (Lee & Swaminathan, 2000).

Niklas Karlsson, George Loewenstein, Duane Seppi, 2009, "The ostrich effect: Selective attention to information" uncover the behavior of investors in reaction to good and bad news. The way investors wish to "know" and be aware of news through what information they wish to acquire. Focus is the monitoring of investors' portfolios in up- and down-markets. The assumption is that investors prefer to collect information and news in up-markets and ignore them in down-markets. The model aims to explain the selective attention, where investors can decide what information to collect and control the impact on their utility. The decision of what information wants to be acquired is linked to investor psychology. The assumption is that people "shield" themselves from bad news, which they do not want. The term "ostrich effect" is used to explain the tendency of people to "put their heads in the sand" to avoid further information. The opposite is the case in up-markets, where investors will actively seek information. This is why investor account monitoring is asymmetric in up- and down-markets. The model refers to utility theory and sees three different ways attention can be affected. First, an impact effect on utility depends on several factors as; the content of information, the psychological and context factors. Second, referred to the reference point, is an updating effect for utility by attention. The more attention the faster the update, in down-markets inattention will cause a slow adjustment. Lastly, risk aversion effect will experience a negatively impact on utility due to a negative movement away from a reference point. In the model, investors can delay knowing about news until date 2, but they will eventually get the news, only timing can be decided until final point of date 2. The hypothesis proven is that investors will have a higher reason and be more likely to check news, information and their portfolios in up-markets than down-markets. The model is tested on the US and Scandinavian markets, both meeting the hypothesis that more people showed interest in logins during up-markets. Reflections for the model to be extended to multiple periods, from two periods, will give a better decision for when to monitor and attend for investors. People are set to pay selective attention to information in their approach of utility maximization. This paper is a part of the theories which uncovers how investors are responding to information and processing it.

Kewei Hou, Lin Peng and Wei Xiong, 2009, "A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum" is focusing on investor attention in up- and down-markets to explain the profitability of price and earnings momentum. From here, due to the focus of this thesis, only results on price momentum will be reviewed. The finding is that price momentum is more profitable in up-markets for high volume stocks due to attention from investors, which can create an overreaction. The opposite is the case of down-markets, where less attention is paid and therefore an underreaction is stated to be happening. Referring to the ostrich effect presented by Karlsson et al. (2005), (the paper presented above is the version published in 2009), the paper uses this term to explain why investors are paying more attention in up-markets. Attention is a necessary factor for overreaction to be present and drive the price momentum, investors can only react if they actually pay attention. To measure investor attention and incorporate it in the formation of portfolios, the paper uses trading volume. The idea is, investors can only be able to actively trade if they actually pay attention, and therefore trading volume should reflect higher price momentum. Trading volume is defined as monthly turnover, the number of shares that was traded, volume, divided by the total amount of shares that was issued at that moment and possible to be traded. Trading volume is used to rank and form portfolios out from an attention perspective. Additional measures for attention and factors that can affect momentum profits are for example size (market cap) and analyst coverage. As mentioned earlier a long-term reversal is assumed to occur for prices that will be corrected from an overreaction. Through tests and regressions, the findings of the paper support their hypothesis and price momentum profits are related to overreaction from investors which is more exposed for high turnover stocks, so "…overreaction-driven price momentum strengthens with investor attention" (Hou et al, 2009, p. 14). Regressions also confirmed that price momentum is more significant present and profitable in up-markets, which also is in accordance with the findings of Cooper et al. (2004). It is found that investor attention has an important role for stock price reactions. With little investor attention present, stock prices are seen to underreact to news, and on the other side investor attention causes overreaction and leads to price momentum.

3.3 Up- & Down-markets

Michael J. Cooper, Roberto C. Gutierrez and Allaudeen Hameed, 2004, "Market States and Momentum" investigate momentum profits in different market states and test theories of overreaction for short-run momentum and long-run reversal of stock returns (Cooper et al., 2004). Based on the theories from Daniel et al. (1998) and Hong & Stein (1999) the paper tests their hypothesis that overreaction is the reason for the observed return patterns.

The results from Daniel et al. (1998) shows that increased overconfidence lead to short-run momentum and long-run reversal. Extended to different market states it is found that overconfidence is more pronounced in up-markets, which leads to a greater overreaction and thereby higher momentum profits in the short-run (Cooper et al., 2004). Hong & Stein (1999) can likewise be related to market states, since their model also predicts changes in prices over different states. By examining changes in risk aversion, it is found that decreasing risk aversion is related to further delayed overreaction which increases momentum profits. Assuming decreasing risk aversion and increasing wealth, this model corresponds to the results that momentum profit is higher in up-markets (Cooper et al., 2004). Based on this theory the paper examines if the market state has influence on the momentum profit. Two states are defined; up state, where lagged three-year market return is non-negative and down state, where three-year lagged market return is negative (Cooper et al., 2004).

They find that momentum profit is highly dependent on the market state. Results show, that profit from momentum in the short run only exist in the up state. This is consistent with both Daniel et al. (1998) and Hong & Stein (1999) that the market state has an influence on the momentum profit (Cooper et al., 2004). Furthermore, in up-market the paper finds evidence that the momentum profit reverses in the long run, which is consistent with Jegadeesh and Titman (2001a) and Lee and Swaminathan (2000). In down-markets the evidence shows that even though momentum is absent at the short run, the results still show a long run reversal. Therefore, overreaction is found to explain a great part of the momentum and reversal, but it is not found to be the whole explanation. The implication is that reversal in the long-run is not found only to be present due to past momentum corrections (Cooper et al., 2004).

3.4 Summary

Chapter 3 is reviewing a selection of literature seen as relevant for this thesis' scope and focus. The key ideas from each paper are uncovered and presented. The papers are divided into different sections depending on the aim and findings, showing the focus and goal of the papers. The findings are summed up here.

Jegadeesh & Titman (1993) is one of the main papers. The momentum investment strategies are defined and tested over the period 1965-1989 and documented. Portfolios are created based on the 3-12-months lag/hold periods, defined from now as J-month/K-month strategies. This paper defined the methodology for testing momentum and creating short-term abnormal returns based on price movements and ranking of each security's performance. In this paper the 6/6 -months strategy is chosen to represent all trading strategies and perform further tests. Two additional papers were made from Jegadeesh & Titman (2001a and 2001b). Jegadeesh & Titman (2001a), is a follow up paper extending the tested time period and confirming momentum also to be present from 1990-1998. Therefore, the earlier conclusions are confirmed, and the idea of a momentum strategy approach are not fully incorporated in all investors mind to eliminate the effects of the strategy. Lastly, the paper introduces the idea of behavioral models to uncover the relationship between momentum and behavior of investors. Jegadeesh & Titman (2001b), sums up earlier findings. It adds the angle of industry momentum being an interesting factor of how momentum for stocks can be explained by the industry they belong to. Another finding of the papers is that smaller firms tend to be more exposed to momentum compared to larger firms. Momentum is seen as one of the strongest anomalies within finance which challenge the EMH.

Then focus shifts to behavioral models and possibilities of using them as explanations for momentum and investors behavior. Daniel et al. (1998), presents a psychological theory explaining anomalies as investor overconfidence and biased self-attribution. Investors focus on their own success and confidence is growing with good news, but the opposite change in attitude is not present when bad news occur. Models prove overreaction and short-term momentum has a positive relationship and underreaction to public signals causing long-term reversal. De Long et al. (1990), sets focus on two different trading types, rational speculators and feedback traders, challenging the idea that rational speculators are stabilizing asset prices. Here, both trading types contribute to destabilization in the market. Rational speculators react on good news, buying the assets and drive prices up higher, hereafter feedback traders purchasing due to price increase, driving prices even higher. A positive correlation of stock return in the short-run and negative correlations in the long-run for price returns are seen, due to the overreaction of news driving asset prices above the fundamental value.

Barberis et al. (1998), states a model of investor sentiment on how investors form beliefs. Focus is on heuristic representativeness and conservatism bias. Heuristic leads people to find patterns and believe that consistent extraordinary earnings will keep growing in the future. This can lead to overvalued stocks. The conservative biased investors do not react completely to individual earnings announcement, which creates an underreaction. Hong & Stein (1999), adds to the behavioral models' explanations by focusing on the relationship between heterogeneous agents. "Newswatchers" are the first actors and their non-ability to incorporate news and underreaction will be taken advantage of by "momentum traders". The slow reaction and processing of news causes the underreaction in the short-run and will cause an overreaction in the long-run due to the momentum strategies creating arbitrage. Chan (2003) investigates how headlines from public news can affect momentum. The findings are that stocks with news show momentum and in contrast no-news stocks did not display momentum. The evidence was especially significant for negative markets, where information was slowly integrated in prices and overreaction was found for no-news stocks.

For investors to over- and underreact to news, their role of paying attention is an important factor. Lee & Swaminathan (2000) finds a relationship between trading volume and momentum. Their evidence shows that price momentum performs better for high volume stocks. When looking at loser portfolios volume increase momentum and when looking at winners, volume helps information to be slowly integrated.

Karlsson et al. (2009), discusses behavior of investors when reacting to good and bad news. Findings are that in down-markets investors will avoid bad news, using the "ostrich effect" and shield themselves from bad news. The opposite for up-markets, investors will seek good news and pay more attention, which will create a faster update and adjustment related to their utility. For down-markets inattention is assumed to cause slower adjustments. It is argued that people have a selective attention to information in process of utility maximization. Hou et al. (2009) uncover attention in up- and down-markets as explanatories for price momentum. Findings are that up-markets are more profitable due to attention creating overreaction and the opposite for down-markets where less attention causes underreaction. Trading volume, analyst coverage and size (market cap) are factors suggested to measure investor attention.

Cooper et al. (2004), uncovers definitions of the two market states, up- and down-states. Momentum profits are highly dependent on the market states. Short-run profit only exists in up-state, and it reverses in the long-run. Down-markets show an absence of momentum in short-run, but reversal in the long-run.

Summed up the selected academic articles delivers strong evidence that the momentum effect is present in different market states and can be explained by over- and underreactions from investors. Attention seems to be an important element in explaining momentum and a common denominator for all papers, although approached from different angles and assumptions.

Chapter 4

Data & Method

This chapter presents the data and the methodology for portfolio construction together with the momentum strategies. To investigate our problem statement, data from all sectors in the market are extracted and momentum portfolios are created based on the Jegadeesh & Titman (1993) method. To see whether higher attention increases momentum, measurements for attention have been chosen based on the above literature review. Trading volume and analyst recommendation are the main attention measurements and size (market cap) is used as a robustness check. Regressions and linear trend lines are used in order to investigate the relationship between attention and momentum.

This chapter is structured as follows; section 4.1 presents the data and uncovers the collection and decisions during the data processing. Section 4.2 contains the constructions of momentum portfolios according to Jegadeesh & Titman (1993). Section 4.3 focuses on regressions and tests of the relationship between attention and momentum. Lastly, section 4.4 discusses the method and data processing and uncovers critical points.

4.1 Data presentation

The examined period goes from 2004-2018 and to enable the investigation to start in 2004 for all the 16 different strategies, lagged return data for 23 months is required for the 12/12 strategy. Our hypothesis that higher attention increases momentum is based on the paper from Hou et al. (2009), which showed that attention would be higher in up-markets than down-markets due to overreaction in up-markets. Based on this we wanted a period that contained both an upgoing market and a downward going market. Cooper et al. defined the two market states up and down as a period of 3-years of non-negative returns and a 3-years period of negative returns. Based on this the total period goes from 2004-2018, the up-market period from 2012-2014, which had the highest positive return for a 3-year period, and a down-market period from 2007-2009.

To investigate the problem statement, data for all the sectors in the US market is needed. The US market is chosen since the Jegadeesh & Titman (1993) paper investigates the US market and confirms that momentum is present. Furthermore, the SP500 is chosen as a representative index for the US market. SP500 contains all the sectors and thereby provide the opportunity to create portfolios for each sector on a comparable level. By choosing the SP500 we control for the small firm effect and achieve more comparable portfolios.

The sectors are chosen based on the categories from Morningstar, which have divided the market in 3 “super” indexes and contains 11 sectors in total which are non-overlapping. The 3 “super” indexes are categorized based on their sensitivity to market conjunctures. The 3 indexes are: cyclical, defensive and sensitive. The cyclical index is the most volatile and corresponds relatively heavy on the state of the economy. If the market is going well, the cyclical sectors tend to expand and opposite when the markets are negative. Therefore, the stocks tend to be riskier and their betas are higher than 1. This is contrary to the second index “defensive”, which contains sectors that provide essential goods and services, which always is in demand regardless of the market state. The stocks tend to be less risky and have betas lower than 1. The sensitive index has sectors which contain stocks that tend to be in between cycle and defensive stocks. They are not overly affected by market downturns, but more than the defensive sectors, why they often have a beta close to 1. Some of the sectors can be exposed to more political, environmental or social issues. (Morningstar, 2011).

The sectors categorized as Cyclical:

- Consumer Discretionary:

  Companies such as auto manufacturers, restaurants, entertainment or retail stores as for example Ford Motor Company or McDonalds.

- Financials:

  Companies such as banks, asset management or insurance. Companies that provides a financial service as for example J.P. Morgan.

- Materials:

  Companies, which manufactures chemicals or building materials, such as BHP Billiton.

- Real Estate:

  For example mortgage firms or property management, such as Westfield Group.

The sectors categorized as Defensive:

- Consumer Staples:

  For example companies that manufactures essential goods such as food or beverage or household/ personal items such as Procter & Gamble.

- Healthcare:

  Companies within pharmaceuticals, biotechnology or hospitals such as Pfizer.

- Utilities:

  Companies that provide water, electricity or gas such as PG&E Corporation.

The sectors categorized as sensitive:

- Communication services:

  Companies that provide fixed-line or wireless networks along with internet access such as AT&T.

- Energy:

  Companies that generate oil or gas and field services such as ExxonMobil.

- Industrial:

  Companies that produces machinery, industrial products or hand-held tools, but also transportation or logistics companies such as Boeing or Siemens.

- Information Technology

  Companies that provide systems and applications for computers or manufacturing of data storage products and networking products such as Goggle or Microsoft.

Now the sectors have been identified, the next step is to extract the different data necessary for our investigation. To compare our momentum portfolios returns with the return if we just had bought an equally weighted portfolio for each sector in SP500 without rebalancing, we have extracted the monthly price for all the stocks in the SP500 from Bloomberg and calculated the returns as the relation between two closing prices minus 1; $E(r) = \frac{P_{t+1}}{P_t} - 1$. Furthermore, we have extracted three monthly measures for attention from Bloomberg; Trading volume (TV), analyst recommendation (AR) and market cap (MC). Trading volume is the average number of trades for a given month and analyst recommendation is the total number of recommendations given for each specific stock and market cap is the firms market capitalization or market value (value of a company's outstanding shares) which is used as a measure of firm size. In this way, we capture both the attention from the private investor and the institutional investor by applying trading volumes and analyst recommendations. Market cap is used as robustness check. The three measures of attention are based on the paper from Hou et al. (2009).

4.2 Momentum Portfolio

We use the methodology from Jegadeesh & Titman (1993), to investigate the momentum effect in all 11 sectors within the SP500 index for the time period 2004-2018. The aim is to create portfolios for each sector and test whether the momentum effect was present and profitable to use as an investment strategy. This is the foundation for our further investigation on the relationship between different factors and momentum.

4.2.1 Portfolio creations

Portfolios are created based on the defined trading strategies of Jegadeesh & Titman (1993). The best trading strategy is to follow a time period of 3-12 month. It gets further documented and tested in the paper Jegadeesh & Titman (2001a), where test results showed that using 13-60 months did not give positive abnormal returns and were not profitable. Therefore, using 3-12 months lookback and holding period is the one applied here. The portfolios made are based on the trading strategy defined as J-month/K-month strategy over their past 3, 6, 9 or 12-months stock returns.

J-months stands for the lookback period, it is the formation period where the previous performance of each stock is valued. Based on the previous performance and return, all stocks get ranked and from here the best stocks are picked to be included in the portfolio. They get divided into a top and bottom decile depending on their performance and rankings. Due to the decision of looking at SP500, the amount of stocks available in each of the 11 sectors are smaller than the total sample of stocks in the original paper by Jegadeesh & Titman (1993). Therefore, the original 10% disposition in deciles can give a risk of obtaining too few stocks in some sector portfolios, which might not be representative. Therefore, it has been decided to deviate from the original text, Jegadeesh & Titman (1993), and create portfolios containing 25% from top and bottom quartile, to include a higher number of stocks and aim for a more representative picture (Morningstar, 2015).

K-months is the holding period of the portfolio and comes after the J-month formation. Possible holding periods are 3, 6, 9 or 12 months similar to the J-months formation period. Together the combination of J/K-strategy creates 16 different trading strategies. We have chosen to produce results for all 16 strategies, for each sector, over the period of 2004-2018. They all have a formation period equal to the number of months stated as *J-months* and a holding period with the number showing *K-months*. When starting off, the portfolios created for each of them, will look back the number of months stated and rank stocks depending on their performance/returns. From here, the top quartile and bottom quartile will be formed, consisting of 25% in the top, called winners and 25% of the worst performers in the bottom, called losers. The winners in the top are bought and the losers in the bottom are sold. Hereafter the portfolios are held for *K-months* and the outcome from this investment strategy will be presented. The table presented later in our results will follow the strategy buying the top quartile and selling the low quartile. The number displayed in the table is the return of the zero-cost portfolio from using this strategy, already consisting of the difference between winners and losers. From here, one trading strategy has been selected to give a further analysis and interpretation of the results from the momentum test on all 11 sectors. The selected J/K-months strategy is the 6/6 strategy, which is also the most used and investigated strategy in other papers and seen as being representative for all trading strategies (Jegadeesh & Titman, 1993).

In the analysis the use of overlapping holding periods has been applied, where trading strategies contain both portfolios from the current month and the past K-1 month (Jegadeesh & Titman, 1993). Every month the portfolios established t-K months ago are rebalanced, when the K-holding period is over. The trading strategy is formed as an equally weight of the portfolios active at the time. This is due to the opportunity to increase the significance of the results by using more observations and adding power to the test. Also, most papers are applying this approach, including Jegadeesh & Titman (1993), why we wish to follow their proven methodology.

The investigation of the 16 strategies are as mentioned for the period 2004-2018, and therefore covering both up- and down-markets. In order to test and elaborate further, the 6/6-strategy was chosen as being representative for the trading-strategies. Regressions on the returns for the entire period are conducted, and a further investigation of sub periods is carried out. The sample period will be divided into different periods of 3 years, to test different market states and effects on the momentum results. Still using 25% as our inclusion criteria for the number of stocks and overlapping portfolios.

4.2.2 Data processing

To investigate the problem statement a big amount of data is needed. Momentum portfolios for each sector is going to be created and due to the many conditions, the easiest way to obtain the results, is through a data program. R-studio and Excel have been chosen as tools for the programming and organization of data.

First, the Bloomberg terminal in Excel was used to take out data on the index members of SP500. The formula; =BDS("SPX Index","INDX_MEMBERS"), generated all the tickers in the index. The function "GICS_SECTOR_NAME" ensured that all tickers got assigned one of the 11 sectors.

The tickers were sorted among all the different sectors, which provided an overview of the total number of tickers included in each sector. This gave a clear overview of the number of companies in each sector. From this, the earlier mentioned decision of including 25% from the tickers in top and bottom quartiles, instead of 10%, were implemented. This was done in order to obtain a more representative investigation and higher significance of the results.

Due to the complexity and many conditions in the creation of the momentum portfolios returns, the coding and programming was done in R-studio. Through inspiration from different programs and our own knowledge of the R-studio program, the portfolio momentum returns were calculated.

For each sector the code was run with the ticker names belonging to each sector. First, the currency was defined as USD, since the SP500 is an US index. Symbols were called in for all tickers from the connection between R-studio and Yahoo Finance. The symbols called in were then adjusted to monthly closing prices for the tickers, and from here the monthly returns were calculated via the rate of change, ROC. When the returns were calculated, data was made for each of the four possible look back periods, J-months. ROC over the past 3-months, 6-months, 9-months and 12-months were calculated.

Next step was to rank each of the tickers in the four different data sheets for each of the J-months. A ranking for each of the four J-months strategies were made over the dataset of the performances. The best performer of all tickers for that month, received the rank number of 1, the second-best performer number 2 etc. This ranking was made for every monthly return, by ranking all tickers compared to each other based on their monthly return over the J-month stated for the dataset.

When the ranking was done, the code could select the tickers which got ranked as the top and bottom quantiles, so it was possible to identify, which stocks should be bought and sold. The 25% of assets, that was calculated from the total number of tickers in each sector, defined how many was to be included in the portfolio. This number was inserted manually every time the code was ran for a sector, since the total number of tickers differed between sectors.

Momentum returns were calculated for each case depending on J-months being 3, 6, 9 or 12-months. The code for the momentum portfolios incorporates the rankings for buy and sell along with defining how many K-months to hold. The code was ran for each defined trading strategy. This result presented the return of our momentum test and showed the zero-cost portfolio combining the buy and sell strategy. The average monthly return for each trading strategy was produced by taking the average of the monthly momentum returns for each portfolio. The momentum result for the strategy using J-months lookback period and K-months holding period created the momentum return over the time period 2004-2018. The result was created together with a t-test for each of the momentum returns showing the significance of the results.

This test had to be run for all 11 sectors, one sector at a time.

The results are gathered in tables made in Excel, to give a more readable and comparable layout.

The results and tables from our calculations and data processing will be presented in chapter 5.

4.2.3 Significance measurement

To determine the statistical significance of the presented momentum returns from using the J/K-months strategy, the t-test for each return was reported in the table. The t-test was possible to calculate and get displayed in R-studio together with the returns for each of the 16 J/K-months trading strategy cases.

The t-tests are made over the average monthly return of our momentum results. It is possible to compare the significance level of the returns between different trading strategies for each sector, but also between the sectors themselves. Whether or not the returns will be positive or negative is unknown, which is why we have a two-sided t-test.

The null hypothesis is that the result of the test will be equal to zero, but if the t-test can reject the hypothesis, the result of the return obtained can be said to be statistically different from zero. The higher the t-test value the more significant is the results.

The hypothesis is:

$$H_0: \mu = 0 \; versus \; H_1: \mu \neq 0$$

Where μ is the momentum return.

And the t-value is calculated as (Stock & Watson, 2015):

$$t = \frac{\bar{Y} - \mu_{Y,0}}{SE(\bar{Y})}, \qquad where \; SE(\bar{Y}) = \frac{\sigma_Y}{\sqrt{n}}$$

The hypothesis will be evaluated on a 5% significance level, based on the t-test against the critical value of 1.96 for a two-sided test. If t-test > 1.96 the null hypothesis will be rejected at a 5% significance level (Stock & Watson, 2015).

4.3 Econometrics

In the above section the first part of the problem statement has been investigated, which is whether some sectors have more momentum than others. Now the next part of the problem statement can be investigated, which is whether this momentum effect can be explained by higher attention. To investigate the relationship between the above calculated momentum returns and the three attention measures, regressions and correlation graphs have been created.

4.3.1 Regressions

To investigate what effect attention has on momentum, linear regressions have been run. The linear regressions model is as follows: $Y_i = B_0 + B_1 X_i + u_i$.
Where $B_0 + B_1 X_1$ is the population regression line, Y is the dependent variable, X is the independent variable, B_0 is the intercept and B_1 is the slope. Here the slope is the change in Y given a unit change in X and the intercept is the value of the population regression when X = 0. The error term (u_i) incorporates all the other factors besides X which determines the value of Y (Stock & Watson, 2015).
Three different regressions will be ran. All the regressions contain momentum return as the Y variable (dependent variable). The first regression has trading volume as the X variable (independent variable), the second regression has analyst recommendation and as a robustness check the third regression has market cap. In this way, the regression will show whether return increases, when attention increases.
Before running the regressions, data must be adjusted. A common approach when analyzing economic time series is to take the natural logarithm (LN) or the changes in LN (Stock & Watson, 2015). The reason is, that often economic time series show exponential growth and thereby increases with a percentage over the years. Therefore, it is beneficial to convert the time series, so it is proportional (or percentage changes) to the original series, which can be done by calculating the natural logarithm (Stock & Watson, 2015).
The extracted data is transformed based on the above. As described in the beginning of this section returns are calculated as $E(r) = \frac{P_{t+1}}{P_t} - 1$. The return is therefore the change in the price over time. Based on this, we kept the same methodology for our three attention measures, which means the change in trading volume, analyst recommendation and market cap have been

calculated. By doing this, we get a more comparable framework, and everything in a percentage. To be able to take the natural logarithm, we need positive numbers. This is why the growth rate has been calculated based on the percentage change and then the natural logarithm has been calculated. The percentage change of the time series Y_t between the periods $t-1$ and t is $100\Delta\ln{(Y_t)}$ (Stock & Watson, 2015). The regressions are therefore based on LN to changes in price (return) and to the three attention measures.

As noted in the literature review, it can take time before prices gets updated, which is why a lag effect has been investigated for the attention measures. The first lagged value is denoted Y_{t-1} and the j[th] lag is denoted Y_{t-j} and is the lagged value j periods ago (Stock & Watson, 2015). The lagged values have been investigated up to six lags and it was found that lagging the attention measure one period (month) provided the best results, since the lags from thereon only decreases the return (Appendix 1).

The three linear regressions models with a single regressor (X) are defined as:

$\ln{(Momentum\ Return_t)} = B_0 + B_1\ln{(\Delta trading\ volume_{t-1})} + e$

$\ln{(Momentum\ Return_t)} = B_0 + B_1\ln{(\Delta Analyst\ recommendation_{t-1})} + e$

$\ln{(Momentum\ Return_t)} = B_0 + B_1\ln{(\Delta Market\ cap_{t-1})} + e$

The interpretation is that a 1% change in X is associated with a B_1 % change in Y.

4.3.2. Regression approach

To estimate the unknown slope and intercept, two different approaches are used in R. First, the linear regression model has been run using the ordinary least squares approach (OLS). Second, the linear regression model has been tested using panel data in the form of Random effect.

4.3.2.1 Ordinary least squares

To get the regression line as near to the observed data as possible, the OLS estimator is useful. By "near", it means how close we can get to the data, which is measured by the sum of squared errors when Y have been predicted given X (Stock & Watson, 2015). The OLS regression line is:

$$\widehat{Y_i} = \widehat{B_0} + \widehat{B_1}X_i \ and\ \widehat{u_i} = Y_i - \widehat{Y_i}$$

The intercept $\widehat{B_0}$, slope $\widehat{B_1}$ and the residual $\widehat{u_i}$ is based on a sample of *n* observations of X_i and Y_i. Therefore, they are estimators of the unknown true population intercept, slope and error term

(Stock & Watson, 2015). The OLS estimators ($\widehat{B_0}$ and $\widehat{B_1}$) have been calculated by minimizing the total squared mistakes $\sum_{i=1}^{n}(Y_i - b_0 - b_1X_i)^2$ (Stock & Watson, 2015).

There are four least squares assumptions (Stock & Watson, 2015):

1) Conditional distribution of u_i given $X_1, \dots, X_{ki}$ has a mean of zero. This means that sometimes Y_i can be above or under the population regression line, but in general should be on the line.

2) It is distributed as independently and identically (i.i.d) random variables $(X_{1i}, \dots, X_{ki}, Y_i), i = 1, \dots, n$.

3) It is unlikely to experience large outliers.

4) There is no perfect multicollinearity, which is a situation where it is impossible to calculate the OLS estimator. Perfect multicollinearity can happen if one regressor is a perfect linear function of the other regressors.

The problem with the OLS is the possibility for omitted variable bias. If data is unavailable or not included in the regression, then the OLS estimator of the regression coefficient can be exposed to omitted variable bias. This occur when two conditions are satisfied (Stock & Watson, 2015):

1) When the omitted variable is correlated with the regressor (X variable).

2) When the omitted variable is a determinant of the dependent variable (Y variable).

To meet this bias, a special type of data is needed, which is called panel data. This data can control for some omitted variables without really observing them (Stock & Watson, 2015).

4.3.2.2. Panel data

A reason to use panel data is to meet the problem of omitted variable bias. Using panel data requires a different setup for the analyzed data. The data are for *n* different entities, which are observed at T different periods (Stock & Watson, 2015). Now the data are stacked under each other, which enables us to investigate the data in a different way. To keep track of the data, the notation has changed and now two subscripts are used; entity is denoted *i* (first subscript) and time period is denoted *t* (second subscript). This gives us Y_{it} and is the Y variable that is observed for the i^{th} of *n* entities in the t^{th} of T periods (Stock & Watson, 2015). Each entity is observed at more time periods and when focusing on changes in the dependent variable (Y) it enables the removal of omitted variables across entities, but are consistent over time (Stock & Watson, 2015). A balanced panel is used, since the same time period is available for all entities. There are different methods of controlling for omitted variable bias in panel data; Fixed effects regression model and Random effects regression model (Stock & Watson, 2015).

The fixed effects regression model can control for omitted variables when they for example vary among entities (e.g. in this case sectors) and are consistent over time. It has an intercept for every entity (*n* intercepts*)* which can be denoted as a set of binary variables. The purpose is that the binary variables should "absorb" the impact of the omitted variables which changes among the entities but are consistent over the time period, why the purpose is to eliminate the fixed effect a_i, which stands for an unobserved effect (Stock & Watson, 2015). This gives the following regression (unobserved effect model) with a single dependent variable:

$$Y_{it} = B_1 X_{it} + a_i + u_{it}$$

Where $a_1, \dots, a_n$ are the unknown intercept or the fixed effects, which shall be estimated. The unobserved effect, a_i, is correlated with the X_{it} variable and fixed over time (Stock & Watson, 2015). The dependent variable Y_{it} can be the momentum return and X_{it} are the attention measure, for example trading volume. The subscript *i* is denoted as the sector and *t* is the time period. Adding further dependent variables gives the following model (Wooldridge, 2015):

$$Y_{it} = B_1 X_{it1} + B_2 X_{it1} + \cdots + B_k X_{itk} + a_i + u_{it}$$

There are four assumptions of the fixed effect regression which extend the four least squares assumptions stated earlier (Stock & Watson, 2015):

1) Error term u_{it} has conditional mean zero, given all T values of X for an entity, which states that there is no omitted variable bias.

2) Is that the entities are identically distributed but independently of another entity variable(i.i.d.).

3+4) Are analogous to the third and fourth assumption of the least squares.

The most important assumption is number two which contrast assumption two under least squares, under panel data the variables are independent among entities but not within an entity $(e.g. can\ X_{it}\ be\ correlated\ over\ time\ in\ an\ entity)$ where the least square assumption state that the observations are independent (Stock & Watson, 2015).

Until now the fixed or non-random models have been in focus, but sometimes, as in panel data or economic problems, the variables are often random, which leads to the random effect regression model (Tong et al., 2011).

The random effect regression model in panel data have the independent variables (X) as random variables. This model considers when the entity factors are viewed as unobserved heterogeneity (unobserved variation) and are therefore presented by a random variable (Matyas, 2017). Again beginning with an unobserved effects model (Wooldridge, 2015):

$$Y_{it} = B_0 + B_1 X_{it1} + \cdots + \mathrm{B_k X_{itk}} + \mathrm{a_i} + \mathrm{u_{it}}$$

Where an intercept is included, which enables the assumption that the unobserved effect a_i has zero mean. In the fixed effect model, the focus was to eliminate a_i since in that model it is thought of as being correlated with X_{it}. Now in the random effect model, a_i is thought of as being uncorrelated with the independent variables in the entire time period, why the equation above is transformed to the random effects model, by the assumption that the unobserved effect a_i is uncorrelated with the independent variables, $Cov(X_{it}, a_i) = 0$ (Wooldridge, 2015). The random effects model contains all the assumptions from the fixed effect model but adds the assumption that a_i is uncorrelated with the independent variables.

It is a discussion point whether to choose a random or fixed effect model. A normal way is to treat a_i as a fixed effect if it is going to be estimated for each entity or as a random effect if it is viewed as a random variable. This leads to the approach that the random effects model should be used if there is a hypothesis that a_i (the unobserved effect) is uncorrelated with the explanatory variables (X_{it}) otherwise a fixed effect model should be used (Wooldridge, 2015).
In the decision making the procedure of the data sampling can also be discussed. If the X-variable is known and certain then a fixed effect model is useful since the setup is known and fixed. Contrary if the sampling is random and the X-variable is not fixed at for example a certain level then the random effects model is useful (Tong et al., 2011). Overall, when considering large data sets and the observations is a sample from a larger population, the random effects model is a good fit (Matyas, 2017). Based on these considerations the random effects model has been chosen as the second way to run the linear regression, since our variable is a sample (SP500) of the US market and we do not know whether there is a correlation between a_i and the dependent variable.

To ensure random effect is the right choice of panel data model, a Hausman test has been ran over the regressions for fixed effect and the random effect in R-studio. The Hausman test investigates the difference between a_i and X_{it} , since the fixed effects model is consistent when a_i and X_{it} are correlated and then the Random effects model is inconsistent, a significant difference indicates evidence against the random effects model. Therefore, the Hausman test sets the two hypotheses (Wooldridge, 2002):

$$H_0: Cov(a_i, X_{it}) = 0$$

$$H_1: Cov(a_i, X_{it}) \neq 0$$

The null hypothesis states that the unobserved effect a_i is uncorrelated with the explanatory variables, why the random effect model is the best fit, while the alternative hypothesis states the opposite, indicating that the fixed effect model is the best fit. The Hausman test has been tested on a 5% significance level and from R-studio the Hausman test gave a p-value of 0.08166. Since the p-value > 0.05, the test fails to reject the null hypothesis; this is why a random effects model is chosen.

Both the OLS regression and the Random effect have been run using R.

4.3.3. Significance

To test the significance of the regression results the standard error, t-test and p-value have been used.

The standard error (SER) is a measure for the spread of the observations around the regression line. For the OLS regression the standard error is calculated by using the OLS residuals $\widehat{u_1}, \dots, \widehat{u_n}$ since the regression errors $u_1, \dots u_n$ are unobserved (Stock & Watson, 2015).

$$SER = \frac{SSR}{n-2} \qquad where\ sum\ of\ squared\ residuals,\ SSR = \sum_{i=1}^{n} \widehat{u_i^2}$$

The standard error used in the random effect model are clustered standard errors (Matyas, 2017). The word "clustered" is used because the standard errors accept that the regression errors have an arbitrary correlation in a grouping (cluster), but the regression errors are assumed to be uncorrelated across clusters (Stock & Watson, 2015). Related to panel data the cluster is based on an entity, why it allows for heteroskedasticity (the variance of the distribution of u_i given X_i is not constant over time) and arbitrary autocorrelation in an entity, but the standard errors across entities are uncorrelated. This is related to assumption two of panel data, which allow for serial correlation of u_{it} within an entity (Stock & Watson, 2015). The standard error will be reported in a parenthesis under the value of B_1 for the regressions.

The t-test is again based on a two-sided test, since it is investigated whether attention influences return:

$$H_0: B_1 = 0$$

$$H_1: B_1 \neq 0$$

where B_1 is the output (slope) of the regression, the effect of an increase in attention on the momentum return.

To reject the null hypothesis would imply large positive values of the t-statistic, which is calculated as described in section 4.2.3. Again, the critical value is 1.96, indicating a rejection of the null hypothesis if t-test > 1.96 (Stock & Watson, 2015).

The evaluation of whether our results are significant is in this situation based on the p-value categorization from R, where both the t-test and p-value are stated. The significance level is divided into three groups, depending on whether the p-value is greater or smaller than the three different significance levels; a 0.1% level which gives three stars (***), a 1% level which gives two stars (**), a 5% level which gives one star (*) and from 10% significance level zero stars is given and it is not significant.

4.3.4 Correlation graphs and tables

A different approach to investigate the relationship between momentum return and attention is to see if there is a linear positive relationship. This is done by taking the average of the momentum return and the attention measures for each sector, then a table has been created where the sectors have been ranked in descending order. Next the sectors have been plotted in a diagram where the y-axis is the momentum return and the x-axis is the attention measure. This has been done for all the attention measures for the total-, up- and down-periods. Here the hypothesis is that there should be a linear tendency between momentum return and attention for the total and up-market period, but not for the down-market period, which will be further discussed in chapter 6.

4.4 Critic and adjustments

We are aware that our results are based on historical numbers, which means that it does not necessarily say anything about the future. Furthermore, the results are based on a zero-cost portfolio, which means that the extra cost for rebalancing the momentum portfolio is not accounted for in the return and taxes are also neglected. No tax or transaction cost is an unrealistic assumption, but in theory it is easier to work with and based on the findings from the Jegadeesh & Titman (1993) paper, which states that momentum is still present if cost is accounted for, it seems fair to make that assumption.

The time period of 14 years seems acceptable since it covers multiple business cycles, economic trends and periods with both increasing and decreasing macroeconomic growth. Furthermore, the period contains several geopolitical crises such as Greece, Brexit and the financial crisis, why the period seems acceptable. If a longer period had been chosen even more adjustments would have been made to the SP500 index. Since some of today's stocks in the SP500 were not in the index through the total period, it has been necessary to make adjustments when forming the momentum portfolios. Stocks which were not present in the SP500 index in 2004 have been replaced with stocks within the same category (large cap) and same sector. This was done by extracting the index for each sector and adding the category for market cap (small, medium and large) along with the inception date of the stock. The number of stocks which have been replaced is 123. This can be criticized, since the SP500 index no longer reflects the real one, but the SP500 is changing all the time and the selection of stocks which have replaced the 123 stocks is within the same sector and category (large, well consolidated and liquid firms), in doing this the purpose of this thesis is not disturbed. The calculation of the momentum portfolios is as described based on the Jegadeesh & Titman (1993) paper. This led to the creation of the winner portfolio (buy) and loser portfolio (sell), which together created the return of our zero-cost portfolio, where the stocks of the winner portfolio (25%) was bought and stocks from the loser portfolio (25%) was sold. The Jegadeesh & Titman (1993) paper use 10%, we chose 25% otherwise our portfolios had a risk of being too small. This can be justified by evidence from the book "Investment Analysis and Portfolio Management" by Frank Reilly and Keith Brown (2003), which showed that a portfolio containing around 12 to 18 stocks, would get 90% of the benefit from diversification (Morningstar, 2015). Other studies say around 20-30 stocks (Financial Times, 2013).

Chapter 5

Results & Analysis

This chapter presents and interprets the results and outputs from the performed tests and data processing. The chapter will combine the results from different tests and investigations to give an analysis. Tables and figures will be presented and investigated with the aim to test if momentum is present in all sectors in the chosen time period 2004-2018 and also to determine the relationship between attention and the momentum effect. The chapter is structured as follows; section 5.1 uncovers momentum returns for all 11 sectors and shows the momentum effect for the time period 2004-2018. It shows overall results for the 16 trading strategies uncovered in Jegadeesh & Titman (1993). The 6/6-months trading strategy is investigated in more detail. Section 5.2 continues the analysis of the momentum effect with focus on attention as an explanatory variable. This section values the relationship between attention and momentum returns and carries out a check for a linear tendency. Attention is measured based on trading volume and analyst recommendation. Section 5.3 investigates momentum returns and the relationship between return and attention in different market states. Two sub-periods are chosen to represent an up-market and down-market period. Section 5.4 forms a robustness check of the earlier presented results in the different sections. Suggestions of other ways to measure and perform tests is uncovered and used to validate and support the earlier presented results.
Finally, section 5.5 summarizes the findings of the tests, analysis and results presented.

5.1 Momentum returns

In this section the results from our momentum test will be presented and uncovered.
Based on the method section, a total overview of all the 16 strategies from Jegadeesh and Titman (1993) is produced.

Table 1: Momentum returns

The table shows the 16 J/K-trading strategies ranked by the average of all the strategies with t-test in the parenthesis.

Ranked by Average Monthly Return

Strategy (J=lag/K = Hold)	3/3	6/3	9/3	12/3	3/6	6/6	9/6	12/6	3/9	6/9	9/9	12/9	3/12	6/12	9/12	12/12	Ranked by average
Healthcare	0.01307	0.0177	0.01772	0.01526	0.01913	0.01952	0.01618	0.01634	0.01732	0.01442	0.01501	0.01523	0.01457	0.01373	0.01579	0.01662	0.01610
	(3.6694)	*(4.7305)*	*(4.6198)*	*(4.0687)*	*(5.1639)*	*(5.0854)*	*(4.2309)*	*(4.2106)*	*(4.6808)*	*(3.8080)*	*(3.7488)*	*(3.8228)*	*(3.8417)*	*(3.4451)*	*(3.9636)*	*(3.9998)*	
Information Technology	0.01692	0.01599	0.0164	0.01542	0.01401	0.01501	0.01376	0.01325	0.01485	0.01381	0.01287	0.01395	0.01434	0.01341	0.01267	0.01335	0.01438
	(3.9278)	*(3.5695)*	*(3.6445)*	*(3.5682)*	*(3.1440)*	*(3.2811)*	*(3.1476)*	*(2.9906)*	*(3.2591)*	*(3.1044)*	*(2.8442)*	*(3.0751)*	*(3.2930)*	*(2.9384)*	*(2.7787)*	*(2.9954)*	
Materials	0.01079	0.01127	0.01286	0.01116	0.01593	0.01727	0.01238	0.01373	0.01352	0.01426	0.01401	0.0141	0.01256	0.01243	0.01361	0.01346	0.01333
	(2.0751)	*(2.2066)*	*(2.5411)*	*(2.1683)*	*(3.1152)*	*(3.3658)*	*(2.2584)*	*(2.605)*	*(2.4627)*	*(2.6188)*	*(2.5591)*	*(2.5689)*	*(2.2542)*	*(2.2955)*	*(2.5692)*	*(2.5079)*	
Industrials	0.01365	0.01267	0.01237	0.01278	0.01205	0.01382	0.0132	0.01307	0.01369	0.01325	0.01437	0.01249	0.01281	0.01274	0.0121	0.01323	0.01302
	(3.395)	*(3.0706)*	*(3.0609)*	*(3.0632)*	*(2.7996)*	*(3.2807)*	*(3.1190)*	*(3.0701)*	*(3.2014)*	*(3.0236)*	*(3.3842)*	*(3.0152)*	*(2.9195)*	*(3.0236)*	*(2.7699)*	*(3.0173)*	
Real Estate	0.01289	0.01356	0.0134	0.01244	0.01424	0.01233	0.01136	0.01104	0.0132	0.01161	0.0125	0.01441	0.01291	0.01131	0.01335	0.01231	0.01268
	(2.7785)	*(2.7925)*	*(2.9680)*	*(2.6850)*	*(2.9499)*	*(2.6856)*	*(2.3791)*	*(2.3320)*	*(2.7893)*	*(2.4890)*	*(2.7408)*	*(3.2897)*	*(2.6358)*	*(2.4401)*	*(3.0115)*	*(2.7885)*	
Consumer staples	0.01366	0.01371	0.01308	0.01192	0.01165	0.01362	0.01119	0.01253	0.01242	0.01171	0.011996	0.01221	0.01196	0.01124	0.01193	0.01501	0.01249
	(4.9084)	*(4.869)*	*(4.6327)*	*(4.294)*	*(4.0633)*	*(4.8962)*	*(3.9982)*	*(4.5062)*	*(4.6471)*	*(4.188)*	*(4.533)*	*(4.3936)*	*(3.958)*	*(3.7473)*	*(4.0701)*	*(5.4534)*	
Communication Service	0.01454	0.01291	0.01233	0.0114	0.01028	0.01091	0.01076	0.01127	0.0142	0.01101	0.01004	0.0126	0.01095	0.01047	0.01396	0.01349	0.01195
	(3.4312)	*(3.2109)*	*(3.0867)*	*(2.7050)*	*(2.3494)*	*(2.6052)*	*(2.4470)*	*(2.5610)*	*(3.258)*	*(2.5022)*	*(2.2722)*	*(2.8265)*	*(2.4681)*	*(2.3949)*	*(3.1249)*	*(3.0202)*	
Utilities	0.01007	0.01175	0.01096	0.01131	0.01123	0.0107	0.01235	0.01138	0.01014	0.01081	0.01097	0.01076	0.01147	0.01129	0.010838	0.01149	0.01109
	(3.3298)	*(3.8862)*	*(3.5047)*	*(3.7485)*	*(3.7207)*	*(3.4436)*	*(4.1078)*	*(3.5262)*	*(3.2109)*	*(3.4731)*	*(3.4013)*	*(3.3695)*	*(3.8160)*	*(3.5127)*	*(3.3500)*	*(3.6719)*	
Consumer Discretionary	0.01106	0.01189	0.01101	0.00996	0.01254	0.01362	0.009	0.00825	0.01286	0.00934	0.01036	0.01148	0.00993	0.01043	0.01147	0.01094	0.01088
	(2.7084)	*(2.9292)*	*(2.7976)*	*(2.5288)*	*(2.9338)*	*(3.2815)*	*(2.1573)*	*(2.0197)*	*(2.9276)*	*(2.2102)*	*(2.4517)*	*(2.7812)*	*(2.1336)*	*(2.4089)*	*(2.6529)*	*(2.4728)*	
Energy	0.011098	0.009226	0.01054	0.00941	0.009159	0.01183	0.00915	0.009439	0.013298	0.010999	0.010109	0.01188	0.0091	0.009033	0.01315	0.01041	0.01049
	(1.8029)	*(1.5246)*	*(1.7892)*	*(1.6415)*	*(1.5149)*	*(2.0087)*	*(1.5833)*	*(1.6427)*	*(2.1982)*	*(1.8465)*	*(1.6563)*	*(1.9755)*	*(1.5665)*	*(1.5193)*	*(2.2077)*	*(1.7263)*	
Financials	0.00824	0.00646	0.00621	0.00597	0.00904	0.0092	0.00866	0.00764	0.00914	0.00771	0.00896	0.01018	0.00927	0.00956	0.01023	0.0107	0.00857
	(1.6816)	*(1.5735)*	*(1.5387)*	*(1.5478)*	*(1.9948)*	*(2.1897)*	*(2.1483)*	*(1.8154)*	*(2.0614)*	*(1.8244)*	*(2.1003)*	*(2.3864)*	*(2.0688)*	*(2.2035)*	*(2.3509)*	*(2.5106)*	

Table 1 presents all the momentum returns for the 16 zero-cost trading strategies for each sector. This is the momentum returns produced in R-studio by using the trading strategies uncovered in Jegadeesh & Titman (1993). All 16 strategies for all the 11 sectors have produced positive returns, and most of them show a high t-test and are significant at the 5% level. Exceptions are the sectors Financial and Energy, which have lower t-test, why the returns are not significantly different from 0 at the 5% level. Both sectors are also ranked as having the lowest average return over all the 16 strategies. The top three sectors when ranked based on the highest average return from all trading strategies are Healthcare, Information Technology and Materials.

Based on Jegadeesh & Titman (1993) strategy 6/6 is elected for further analysis. The work includes a more readable analysis and layout to investigate and interpret on. Also looking at table 1 it is one of the few strategies which have significant results for all sectors at the 5% level.

Table 2: Momentum returns (6/6 strategy)
The table shows the selected J/K-trading strategy 6/6, ranked in descending order.

Ranked by avg. Return

Strategy (J=lag/K = Hold)	6/6
Healthcare	0.01952 *(5.0854)*
Materials	0.01727 *(3.3658)*
Information Technology	0.01501 *(3.2811)*
Industrials	0.01382 *(3.2807)*
Consumer staples	0.01362 *(4.8962)*
Consumer Discretionary	0.01362 *(3.2815)*
Real Estate	0.01233 *(2.6856)*
Energy	0.01183 *(2.0087)*
Communication Service	0.01091 *(2.6052)*
Utilities	0.01070 *(3.4436)*
Financials	0.0092 *(2.1897)*

The 6/6 strategy is chosen, and Table 2 present the returns ranked in descending order. Compared to the average return of all the 16 strategies, Healthcare, Materials, Information Technology and Industrial are still ranked as top four and Energy, Utilities and Financials are still ranked as part of the bottom four. This table gives an indication of the sectors performances compared to each other and shows that the returns vary across different sectors in the US market.

As described in the method section, the average return for each sector has also been calculated, if an investor just bought the stocks (index portfolio) and kept them for the entire period (2004-2018). To see whether the momentum portfolios has performed better than the index portfolios, the excess return has been calculated for the 6/6 strategy (Table 3).

Table 3: Excess return
The table presents the monthly excess return between the momentum portfolio and index portfolio.

Strategy (J=lag/K = Hold)	6/6
Materials	0.0080
Consumer staples	0.0060
Healthcare	0.0060
Utilities	0.0047
Industrials	0.0034
Information Technology	0.0032
Real Estate	0.0031
Consumer Discretionary	0.0025
Financials	0.0024
Energy	0.0023
Communication Service	0.0012

An investor who had invested in the momentum portfolio rather than the index portfolio would have obtained a higher average monthly return for all the sectors (Table 3). The same four sectors are in the top five of table 2 as in the table for the excess return, where Healthcare and Materials both are in top three. As with the bottom five, the same four sectors are represented, where Financials and Communication Service are in bottom three. This table outlines the performances and underbuilt the earlier presented tables. It indicates clearly that the top performers in our analysis are Materials, Healthcare, Industrials and Consumer Staples when looking at both table 2 and 3. As well as Financial, Energy and Communication Service are the worst performers. These sectors are interesting to follow in the further analysis of the attention perspective.

5.2 Momentum returns and attention

Momentum has now been documented to be present for all the sectors in the investigated period. Next comes the investigation of what factors that can explain the momentum effect. The thesis will focus on attention as the explanatory variable. Based on Hou et al. (2009) the relationship between momentum returns and attention measured as Trading Volume and Analyst Recommendation will be investigated and the 6/6-months strategy will be used for the calculations.

5.2.1. Momentum return and trading volume

Table 4 & Figure 5: Relationship between momentum returns and trading volume
The table shows average monthly returns ranked in descending order for trading volume. The figure shows the linear relationship between momentum return and attention (trading volume).

Strategy (J=lag/K = Hold)	6/6	Ranked by Trading volume
Real Estate	0.01233 *(2.6856)*	0.24705
Information Technology	0.01501 *(3.2811)*	0.23298
Healthcare	0.01952 *(5.0854)*	0.23152
Industrials	0.01382 *(3.2807)*	0.20968
Materials	0.01727 *(3.3658)*	0.20468
Consumer Discretionary	0.01362 *(3.2815)*	0.20289
Consumer staples	0.01362 *(4.8962)*	0.19115
Financials	0.0092 *(2.1897)*	0.18906
Communication Service	0.01091 *(2.6052)*	0.18198
Energy	0.01183 *(2.0087)*	0.14767
Utilities	0.01070 *(3.4436)*	0.14621

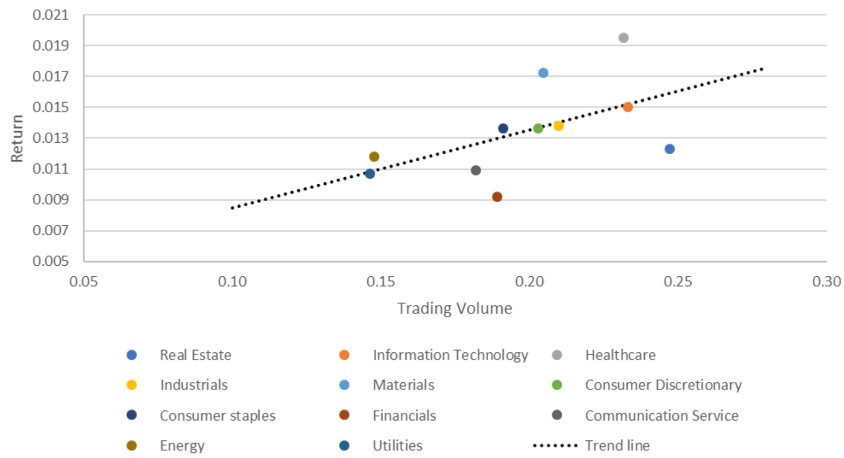


Table 4 provides an overview of the 6/6 strategy and trading volume, where the table has been ranked in descending order according to trading volume. Especially Real Estate, Information Technology and Healthcare have high trading volumes, where Energy and Utilities have low. Figure 5 supports the hypothesis by showing on average the assumed positive linear relationship between attention (trading volume) and momentum. From this figure Healthcare and Materials are above the trend line due to their relative high return compared to attention (trading volume).

Financials and Real Estate are both under the trend line. Based on their level of attention a higher return would have been expected.

A further analysis of trading volumes effect on return have been completed by the described regression in the method section (Table 5).

Table 5: Regression for return on trading volume
The regression shows the effect of attention (trading volume) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effect
Materials	0.1659***	0.1655
	(0.0029)	*(0.0034)*
Consumer staples	0.1440***	0.1454
	(0.0030)	*(0.0036)*
Healthcare	0.1425***	0.1464
	(0.0027)	*(0.0026)*
Energy	0.1355***	0.1302
	(0.0048)	*(0.0047)*
Consumer Discretionary	0.1282***	0.1299
	(0.0029)	*(0.0029)*
Utilities	0.1196***	0.1203
	(0.0032)	*(0.0045)*
Industrials	0.114***	0.1155
	(0.0029)	*(0.0030)*
Information Technology	0.1129***	0.1157
	(0.0028)	*(0.0027)*
Communication Service	0.1112***	0.1157
	(0.0039)	*(0.0032)*
Real Estate	0.0875***	0.0867
	(0.0026)	*(0.0027)*
Financials	0.0834***	0.0843
	(0.0027)	*(0.0032)*

The regression shows that when attention (trading volume) goes up by 1%, return increases with B_1%. This is further evidence that attention has a positive effect on momentum. The attention measure has been lagged one month (described in method section), to incorporate reaction time into the returns. Appendix 1 shows the slope for lag 2 to 6, which is decreasing, indicating that lag 1 is enough.
The table provides OLS and Random Effect (RE) results, both with standard error in the parenthesis and stars are given based on the p-value from R-studio (0.1% = ***, 1% =** and 5% =*). Ranking is done using OLS results and a rank correlation is shown in appendix 2 between the two regression types to indicate that the results are very close (correlation at 0.9613), which also can be seen from table 5. All results in the regression are significant at a 0.1% level.

Materials, Consumer Staples and Healthcare are the top three sectors where attention has the greatest influence on return. From the correlation figure 5, Materials and Healthcare are also the sectors placed with the highest ratio between return and attention. Consumer Staples is ranked number two in the regression and is lying close to the trend line.
Bottom are Real Estate and Financials, which also were the two sectors with lower expected returns compared to their relatively higher level of attention in figure 5. Along with Financials and Energy are Communication Services ranked as the third lowest in the regression line and can also be spotted under the trend line in figure 5. The other sectors are close to the trend line.
Compared to excess return Healthcare, Consumer Staples and Materials are also the top performers.

Summary of momentum

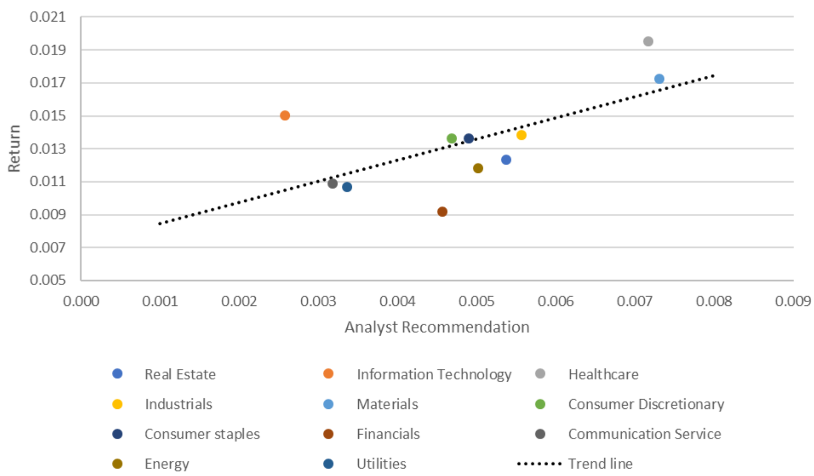
A linear tendency is spotted between momentum return and attention measured by trading volume, which supports the hypothesis. Healthcare and Materials has relatively higher return compared to attention while Financials and Real Estate have relatively low return compared to level of attention. The regression analysis shows that Materials and Healthcare are in top three as regards the effect of attention on return where Real Estate and Financial are the bottom two.

5.2.2. Momentum return and analyst recommendation

To further verify the positive linear relationship between attention and momentum, another investigation has been conducted where attention is measured by analyst recommendations.

Table 6 & Figure 6: Relationship between momentum return and analyst recommendation
The table shows average monthly returns ranked in descending order for analyst recommendation. The figure shows the positive linear relationship between momentum return and attention.

Strategy (J=lag/K = Hold)	6/6	Ranked by Analyst rec.
Materials	0.01727 *(3.3658)*	0.00731
Healthcare	0.01952 *(5.0854)*	0.00717
Industrials	0.01382 *(3.2807)*	0.00556
Real Estate	0.01233 *(2.6856)*	0.00537
Energy	0.01183 *(2.0087)*	0.00502
Consumer staples	0.01362 *(4.8962)*	0.00490
Consumer Discretionary	0.01362 *(3.2815)*	0.00468
Financials	0.0092 *(2.1897)*	0.00457
Utilities	0.01070 *(3.4436)*	0.00336
Communication Service	0.01091 *(2.6052)*	0.00318
Information Technology	0.01501 *(3.2811)*	0.00258



The table shows that Healthcare again is ranked in top three of the sectors with highest attention, which is fitting since it is the sector with highest return. Real Estate have been replaced with Materials compared to table 4, which makes more sense since Materials has the second highest return of the 6/6-strategy compared to Real Estate which is ranked as number seven. Information Technology has now been replaced with Industrial and is now ranked as the sector with the lowest attention despite having the third highest return compared to Industrial which is ranked as number four. Top five for analyst recommendation (Table 6) is aligned with top five for trading volume (Table 4), except for Information Technology which have almost switched placed with Energy which were ranked in the bottom for trading volume. Financials, Utilities and Communication Services are still in the lower end of the table for attention, which corresponds to the ranking in trading volume (Table 4).

From the figure the rough positive linear relationship between return and attention is again spotted. Healthcare has again relative lower attention compared to its high return and is together with Information Technology placed above the trendline. This time Materials is closer to the line. Financials is again placed under the trendline, where Real Estate now is closer to the line.

Looking at the excess return in Table 3, Materials and Healthcare are ranked as having the highest level of attention measured by analyst recommendation and have also the highest excess return for 6/6. Communication Services is in the bottom for analyst recommendation and has the lowest excess returns. Information Technology, which is the lowest ranked in analyst recommendation, is the median of excess returns.

Again, a further investigation of the relationship has been conducted by a regression between return and analyst recommendation (Table 7).

Table 7: Regression for return on analyst recommendation
The regression shows the effect of attention (analyst recommendation) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effect
Information Technology	4.1047***	4.0994
	(0.1966)	*(0.1459)*
Communication Service	2.6951***	2.7097
	(0.1499)	*(0.1177)*
Consumer Discretionary	2.6866***	2.6757
	(0.0516)	*(0.0801)*
Consumer staples	2.5795***	2.5693
	(0.0611)	*(0.0851)*
Healthcare	2.4503***	2.4224
	(0.1027)	*(0.0636)*
Materials	1.9468***	1.9413
	(0.0414)	*(0.0535)*
Real Estate	1.8458***	1.8289
	(0.0714)	*(0.0789)*
Industrials	1.8329***	1.8313
	(0.0668)	*(0.0673)*
Energy	1.6621***	1.6487
	(0.0437)	*(0.0729)*
Financials	1.6058***	1.5872
	(0.0880)	*(0.0927)*
Utilities	1.4990***	1.4953
	(0.0752)	*(0.0847)*

The regression shows a positive relation between analyst recommendation and return. An increase in analyst recommendations is associated with an increase in return and all the results are significant at the 0.1% level. The table provides OLS and RE results, both with standard error in the parenthesis and stars are given as described earlier. Ranking is completed in relation to OLS results, a rank correlation is shown in Appendix 2 between the two regression types. There is a very close correlation at 0.9909.

Ranked as having the greatest influence on return when analyst recommendation increases is Information Technology. This indicates that a small change in analyst recommendation will lead Information Technology's return to increase significantly, also relatively to the other sectors, which maybe can be an explanation for the relative high return compared to the relative low level of attention in figure 6. The result for Information Technology at 4.1047% can be viewed as an outlier, since the effect of a 1% increase in attention is 1.52 times greater than the effect for Communication Services at 2.6951 %, which is ranked as the second highest. Communication Services, Consumer Discretionary, Consumer Staples and Healthcare are all in the top and close to each other. In figure 6, they are all close to the trend line except for Healthcare which is above together with Information Technology.
Financials, Utilities and Energy are the three low performers in the regression, and in figure 6 they are all placed under the trend line.

Comparing the regression for trading volume and analyst recommendation, they have the same three sectors in the top five; Healthcare, Consumer Staples and Consumer Discretionary. Information Technology and Communication Service goes from bottom to top whereas Energy goes from top to bottom.

Summary of total period

The positive linear relationship between attention and momentum are spotted for both attention measures; trading volume and analyst recommendation. Healthcare and Materials are placed above the trendline for both scenarios, most significant for trading volume. Information Technology changes a lot when going from trading volume where it is placed on the trend line compared to analyst recommendation where it is placed above the trend line and has the relative highest return compared to level of attention (analyst recommendation). Financials and Real Estate are in both cases under the trend line. Overall it is concluded that the analysis for the total period shows clear and strong empirical evidence of a positive relationship between attention and momentum returns. An increase in the attention factor generates higher momentum returns.

5.3 Momentum returns in different market states

The total period confirmed the positive linear relationship between attention and momentum return. Now a subperiod investigation is conducted to see whether this relationship is stronger (more affective) in an up-market compared to a down-market, where the relationship is expected to fade (Cooper et al., 2004).

5.3.1. Up-market

The up-market period is chosen based on the definition from Cooper et al. (2004), which defined an up-market as a 3-year period with non-negative return, why the period 2012 – 2014 have been chosen as described in the method section.

The momentum portfolio return and the index portfolio return have again been calculated, but this time for the up-market period, to see whether the momentum portfolio performed better than the index portfolio.

Table 8: Excess return (Up-market)

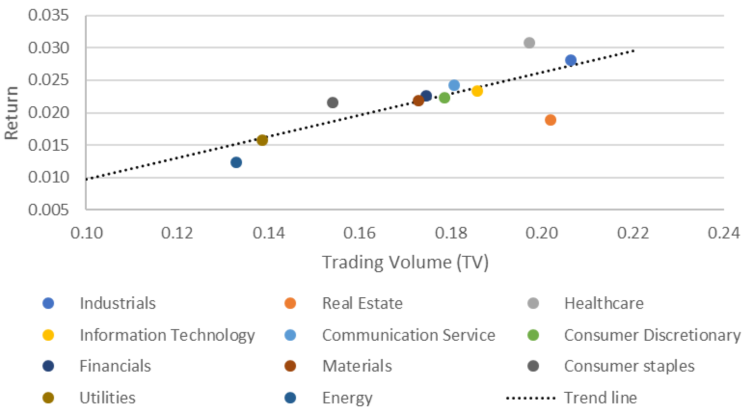
The table present the monthly excess return between the momentum portfolio and index portfolio for the up-market.

Sector	Momentum	Index	Excess Return
Industrials	0.0282	0.0180	0.0102
Materials	0.0219	0.0144	0.0075
Consumer staples	0.0216	0.0148	0.0068
Healthcare	0.0308	0.0243	0.0065
Information Technology	0.0233	0.0169	0.0065
Utilities	0.0157	0.0094	0.0063
Real Estate	0.0189	0.0127	0.0062
Energy	0.0124	0.0081	0.0043
Financials	0.0226	0.0194	0.0032
Consumer Discretionary	0.0223	0.0200	0.0024
Communication Service	0.0242	0.0224	0.0018
Avg. Return	0.0220	0.0164	0.0056

Materials, Consumer Staples and Healthcare are in the top four for the up-market period and the total period. Consumer Discretionary, Energy, Financials and Communication Services are in the bottom four for both. Therefore, the top and bottom positions for the excess returns are very similar for the two periods. Excess returns are on average higher for up-market than total period, which is expected since an up-market has a higher momentum effect (Cooper et al., 2004).

Table 9 & Figure 7: Relationship between momentum return and trading volume (Up-market)
The table shows average monthly returns ranked in descending order for trading volume. The figure shows the positive linear relationship between momentum return and attention for the up-market.

Sector	Return	TV
Industrials	0.02817	0.20645
Real Estate	0.01890	0.20196
Healthcare	0.03082	0.19723
Information Technology	0.02331	0.18578
Communication Service	0.02425	0.18073
Consumer Discretionary	0.02233	0.17872
Financials	0.02261	0.17450
Materials	0.02188	0.17286
Consumer staples	0.02161	0.15402
Utilities	0.01575	0.13865
Energy	0.01239	0.13284



The table shows the same top four sectors for attention as in the total period. Utilities and Energy are again ranked as the two lowest in the attention level, which corresponds to the total period. Indicating that the up-market and total period have the same tendencies. The returns are all positive and on average higher than the total period; up-markets average is 0.022 monthly and total period is 0.013 monthly.

The figure shows an even better positive linear relationship compared to the total period, supporting that the relationship between momentum and attention is stronger in up-markets. As with the total period, Real Estate is again spotted to have a lower return compared to attention level and Healthcare higher return compared to attention level. The other sectors follow a linear positive tendency.

As with the total period, a regression for return on trading volume has been conducted to further investigate the effect of an increase in attention on momentum (Table 10).

Table 10: Regression for return on trading volume (Up-market)
The regression shows the effect of attention (trading volume) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

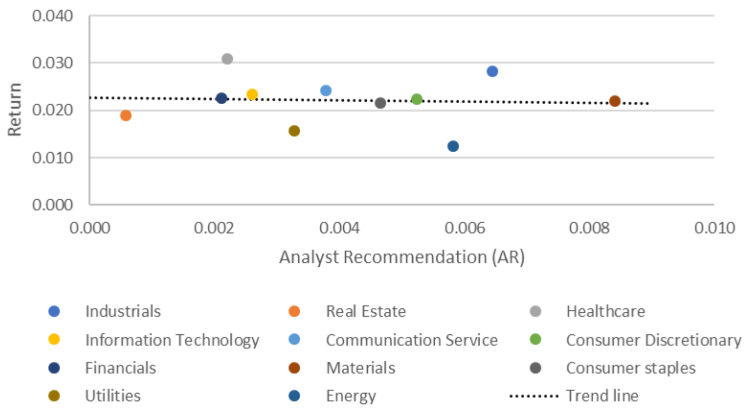
Sector	OLS	Random Effect
Industrials	0.2617***	0.2525
	(0.0156)	*(0.0127)*
Energy	0.2569***	0.2562
	(0.0306)	*(0.0193)*
Healthcare	0.2442***	0.2434
	(0.0136)	*(0.0119)*
Materials	0.2262***	0.2313
	(0.0141)	*(0.0158)*
Financials	0.2181***	0.2206
	(0.0162)	*(0.0153)*
Communication Service	0.2174***	0.2170
	(0.0100)	*(0.0123)*
Consumer staples	0.2157***	0.2146
	(0.0169)	*(0.0171)*
Utilities	0.2062***	0.2018
	(0.0143)	*(0.0199)*
Information Technology	0.2058***	0.2037
	(0.0152)	*(0.0144)*
Consumer Discretionary	0.1866***	0.1809
	(0.0118)	*(0.0144)*
Real Estate	0.1658***	0.1602
	(0.0128)	*(0.0164)*

All the results show a positive effect of an increase in attention on return with a 0.1% significance. Industrials, Healthcare and Materials are in top four of the regression which corresponds to the ranking of excess returns. Again, the regression is aligned with the total period, which also have Energy, Healthcare and Materials in the top four of the regression based on trading volume.
The bottom has changed, remaining is still Real Estate, but Financials is showing a stronger relationship in up-market between trading volume and return, than the total period. For the Energy sector an increase in attention has a relatively high effect despite the poor ranking in table 9. The high position in the regression tells that in the case of a 1% increase in attention the return of Energy will be affected with a high rate.
In general, the results show a stronger relationship for the up-market, which indicates that attention has a stronger effect on momentum in up-market.

As with the total period analyst recommendation is used as a second measure for attention to further investigate the relationship in an up-market (Table 11 and Figure 8).

Table 11 & Figure 8: Relationship between momentum return and analyst rec. (Up-market)
The table shows average monthly returns ranked in descending order for analyst recommendation. The figure shows the relationship between momentum return and attention for the up-market.

Sector	Return	AR
Materials	0.02188	0.00840
Industrials	0.02817	0.00645
Energy	0.01239	0.00582
Consumer Discretionary	0.02233	0.00523
Consumer staples	0.02161	0.00465
Communication Service	0.02425	0.00379
Utilities	0.01575	0.00328
Information Technology	0.02331	0.00261
Healthcare	0.03082	0.00220
Financials	0.02261	0.00212
Real Estate	0.01890	0.00058



The table shows that Materials and Industrials still are at the top compared to the total period for attention (analyst recommendation), otherwise it is not especially comparable.

Also, the figure is not comparable since it does not show the positive linear relationship as with the total period for analyst recommendation.

Table 12: Regression for return on analyst recommendation (Up-market)
The regression shows the effect of attention (analyst recommendation) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effect
Information Technology	7.6739***	7.2923
	(1.1441)	*(0.8749)*
Healthcare	7.3770***	7.4070
	(0.7127)	*(0.5606)*
Communication Service	5.5935***	5.2013
	(1.3330)	*(0.6550)*
Financials	5.2451***	5.1674
	(0.5122)	*(0.5263)*
Consumer staples	3.4913***	3.4384
	(0.2650)	*(0.3771)*
Industrials	3.3574***	3.3111
	(0.1445)	*(0.2260)*
Consumer Discretionary	3.2507***	3.2453
	(0.1438)	*(0.3377)*
Energy	2.9885***	2.8682
	(0.1586)	*(0.2596)*
Materials	2.2380***	2.2280
	(0.1628)	*(0.2169)*
Utilities	2.1081***	2.0707
	(0.1728)	*(0.2875)*
Real Estate	1.0212***	0.7614
	(0.9187)	*(0.6859)*

Based on the regression (Table 12), analyst recommendation still has a positive effect on momentum returns and the results are significant at the 0.1% level.
Especially Healthcare and Information Technology are standing out. Compared to the total market where Information Technology also was an outlier. As with the regression for the total period, a big difference in the effects between top and bottom can be ascertained.
Communication Service and Information Technology are again in the top compared to the total period.
Financials are still ranked higher compared to the total period, which also was the case in trading volume for up-market. Utility is also in the bottom for both when comparing up-market to total period.

5.3.2. Down-market

The down-market period is chosen based on the definition from Cooper et al. (2004), which defines a down-market as a 3-year period with negative return, why the financial crisis has been chosen (2007-2009) as described in the method section. As with the up-market the momentum portfolio return and index portfolio return have been calculated (Table 13).

Table 13: Excess return (Down-market)
The table present the monthly excess return for the momentum portfolio and index portfolio in the down-market.

Sector	Momentum	Index	Excess Return
Materials	0.0192	0.0049	0.0144
Information Technology	0.0113	0.0055	0.0058
Financials	0.0008	-0.0049	0.0057
Consumer Discretionary	0.0092	0.0056	0.0036
Utilities	-0.0010	-0.0025	0.0015
Consumer staples	0.0027	0.0023	0.0004
Healthcare	0.0071	0.0068	0.0003
Energy	0.0094	0.0097	-0.0003
Real Estate	-0.0027	0.0001	-0.0028
Communication Service	-0.0041	-0.0012	-0.0029
Industrials	0.0001	0.0039	-0.0038
Avg. Return	0.0047	0.0027	0.0020

Compared to the up-market's excess return, four sectors now have negative returns, indicating that it would have been better for an investor to just buy and hold the respective benchmarks. The momentum returns do in general not perform as well in the down-market compared to both the total period and the up-market. Materials and Information Technology are still in top five compared to the up-market period and Communication Service, Energy and Real Estate are still in bottom five.

Table 14 & Figure 9: Relationship between momentum return and trading volume (Down-market)
The table shows average monthly returns ranked in descending order for trading volume. The figure shows the relationship between momentum return and attention for the down-market.

Sector	Return	TV
Information Technology	0.0113	0.2360
Financials	0.0008	0.2022
Industrials	0.0001	0.1929
Consumer Discretionary	0.0092	0.1921
Healthcare	0.0071	0.1915
Communication Service	-0.0041	0.1758
Materials	0.0192	0.1700
Real Estate	-0.0027	0.1692
Consumer staples	0.0027	0.1660
Utilities	-0.0010	0.1441
Energy	0.0094	0.1196

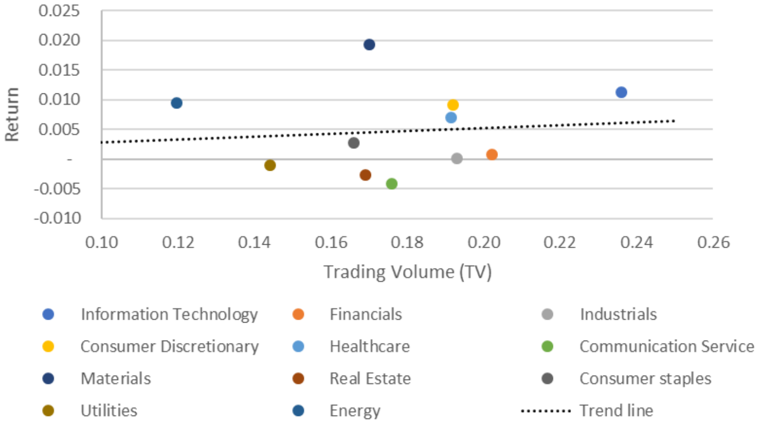


Table 14 shows the average return for a 6/6 strategy for the down-market period and ranked in descending order for trading volume. In down-market the greatest attention level is found in Information Technology, Financials and Industrials, who also have positive momentum returns. The lowest attention level is found within Utility and Energy, which respectively have negative and positive return.

The figure shows that the linear tendency is faded, which indicates that for down-markets an increase in attention does not necessarily lead to an increase in momentum.

To further investigate what an increase in attention (trading volume) does to momentum return a regression has been run for the down-market (Table 15).

Table 15: Regression for return on trading volume (Down-market)
The regression shows the effect of attention (trading volume) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effect
Materials	0.0099	0.0272
	(0.0502)	*(0.0173)*
Consumer Discretionary	-0.0112	-0.0201
	(0.0185)	*(0.0203)*
Information Technology	-0.0534*	-0.0491
	(0.0205)	*(0.0156)*
Healthcare	-0.0595**	-0.0509
	(0.0174)	*(0.0195)*
Financials	-0.0672**	-0.0768
	(0.0195)	*(0.0195)*
Consumer staples	-0.0835***	-0.0730
	(0.0156)	*(0.0238)*
Communication Service	-0.1179***	-0.1253
	(0.0226)	*(0.0226)*
Real Estate	-0.1591***	-0.1572
	(0.0182)	*(0.0190)*
Industrials	-0.1647***	-0.1468
	(0.0264)	*(0.0228)*
Utilities	-0.1680***	-0.1486
	(0.0220)	*(0.0327)*
Energy	-0.1733**	-0.1338
	(0.0616)	*(0.0382)*

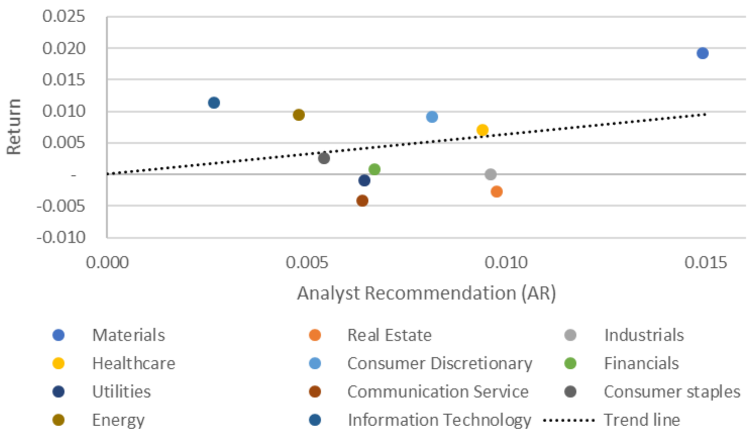
Table 15 shows that the effect of an increase in attention leads to a decrease in momentum for all sectors except Materials. The results are all significant except for Materials and Consumer Discretionary which are also ranked the highest.

Utilities and Energy are the bottom two in the regression and are also ranked as the bottom two for the level of trading volume (Table 14). Financials are now at the top in table 14 and ranked as the second sector to get the highest attention, but the regression table still shows that higher attention will lead to a decrease in return.

A further investigation will again be conducted for the down-market with attention measured as analyst recommendation (Table 16).

Table 16 & Figure 10: Relationship between momentum return and analyst rec. (Down-market)
The table shows average monthly returns ranked in descending order for analyst recommendation. The figure shows the relationship between momentum return and attention for the down-market.

Sector	Return	AR
Materials	0.0192	0.0149
Real Estate	-0.0027	0.0098
Industrials	0.0001	0.0096
Healthcare	0.0071	0.0094
Consumer Discretionary	0.0092	0.0081
Financials	0.0008	0.0067
Utilities	-0.0010	0.0064
Communication Service	-0.0041	0.0064
Consumer staples	0.0027	0.0054
Energy	0.0094	0.0048
Information Technology	0.0113	0.0027



Information Technology is again ranked as the sector with lowest attention when measured by analyst recommendation, which corresponds to the table for the total period. Materials and Industrials are in the top as with the up-market period. Real Estate is also ranked in the top despite the negative return.

This leads to figure 10, which matches the figure for trading volume and shows no positive linear relationship between momentum and attention (analyst recommendation).

Table 17: Regression for return on analyst recommendation (Down-market)
The regression shows the effect of attention (analyst rec.) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effect
Information Technology	2.5528**	1.0656
	(0.8419)	*(0.5642)*
Energy	0.8942	0.5072
	(0.9956)	*(0.5173)*
Financials	0.8310	0.4350
	(0.4687)	*(0.4425)*
Consumer Discretionary	0.5621*	0.4080
	(0.2570)	*(0.3430)*
Materials	0.2536	0.4322
	(0.3499)	*(0.2174)*
Healthcare	-0.1708	-0.0148
	(0.3237)	*(0.3327)*
Communication Service	-0.1825	-0.1979
	(0.3970)	*(0.3327)*
Consumer staples	-0.2447	-0.0793
	(0.3778)	*(0.4110)*
Utilities	-1.0093	-0.5059
	(0.5871)	*(0.4892)*
Industrials	-1.2915*	-0.8389
	(0.4983)	*(0.3278)*
Real Estate	-1.3669*	-1.1502
	(0.5077)	*(0.3341)*

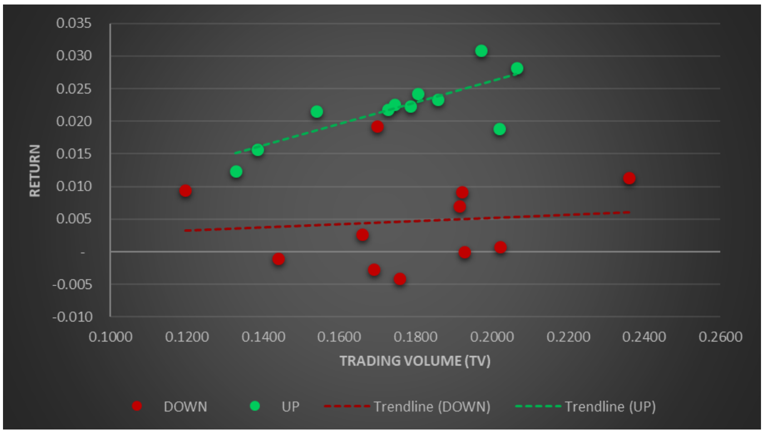
The regression supports the results from the regression on trading volume. The effect of an increase in attention leads to on average a lower and sometime negative effect on momentum. The results of this regression are on average not significant, only the sectors Information Technology, Consumer Discretionary, Industrial and Real Estate are significant.
Again, Information Technology has a higher effect on momentum return when attention (analyst recommendation) increases compared to the other sectors. The sector is showing a positive and significant effect.

Summary up- and down-market

The up-market showed the expected positive linear relationship between momentum and attention when measured as trading volume. Real Estate and Healthcare were the sectors which deviated most from the linear tendency due to respectively lower and higher return compared to level of attention, which corresponds to the results from the total period.

The down-market period verified that the positive linear relationship between momentum and attention had vanished both when measured as trading volume and analyst recommendation and for some sectors even indicating a negative effect.

Figure 11: Relationship between momentum return and trading volume (Up- and down-market)
The figure shows the relationship between momentum return and attention for up- and down-market, indicating a positive linear relationship for up-market, which vanishes for down-market.



5.4 Robustness check

This section provides a robustness check for the main results which first indicated that momentum was present based on the average of the monthly returns and second showed that higher attention leads to a higher momentum return. The robustness measure for attention is market cap (MC), which is chosen from the Hou et al. (2009) paper. The paper states that market cap could be used as a measure for attention, but trading volume and analyst recommendation provided a better measure, why market cap is chosen as a robustness check.

Instead of taking the average of the returns, the robustness measure is the compounded annual growth rate (CAGR), which measures an investments growth rate accounted for compounding and is calculated as (CFI, 2015):

$$CAGR = \frac{Ending\ Value}{Beginning\ Value}^{(\frac{1}{n})} - 1, \qquad where\ n = number\ of\ compounding\ periods$$

One of the advantages of CAGR is that it does not get affected by percentage changes in the investment period. On the contrary its disadvantage is that for investments with high risk, it can provide an unrealistic result due to the assumption of a constant growth rate. Based on this, CAGR is used as a comparison tool (CFI, 2015).
CAGR is calculated from the monthly returns for each trading strategy in R-studio. The result shows the growth of each trading strategy for the period 2004-2018. It is used as a measurement to check the validity of the average monthly returns presented earlier. It helps ensuring that the right conclusions are made by comparing the results and analysis of the sectors' performances.

5.4.1. Robustness check Total Period

Table 18: Momentum returns (CAGR)

The table shows the 16 J/K-trading strategies with the reported CAGR result. Ranked by the average of all strategies with t-test in the parenthesis.

CAGR return

Strategy (J=lag/K = Hold)	3/3	6/3	9/3	12/3	3/6	6/6	9/6	12/6	3/9	6/9	9/9	12/9	3/12	6/12	9/12	12/12	Ranked by average
Healthcare	0.01192	0.01645	0.0164	0.01399	0.01792	0.01822	0.01488	0.01501	0.01613	0.01316	0.01361	0.01383	0.01333	0.01236	0.01442	0.01525	0.01481
	(3.6694)	*(4.7305)*	*(4.6198)*	*(4.0687)*	*(5.3566)*	*(5.2012)*	*(4.3589)*	*(4.2106)*	*(4.8669)*	*(3.9604)*	*(3.7974)*	*(3.8228)*	*(3.9402)*	*(3.4102)*	*(3.8662)*	*(4.1985)*	
Information Technology	0.01525	0.01418	0.01457	0.01373	0.01225	0.01314	0.01207	0.01151	0.01303	0.01209	0.0111	0.01217	0.01272	0.01164	0.01091	0.01167	0.01263
	(3.9278)	*(3.5695)*	*(3.6445)*	*(3.5682)*	*(3.2598)*	*(3.3478)*	*(3.2013)*	*(2.9906)*	*(3.2229)*	*(3.1888)*	*(2.8427)*	*(3.0751)*	*(3.3105)*	*(2.7630)*	*(2.6886)*	*(2.9954)*	
Consumer staples	0.01296	0.01301	0.01236	0.01123	0.01093	0.01294	0.0105	0.01185	0.01181	0.01104	0.01139	0.01154	0.01117	0.01046	0.01119	0.01436	0.01180
	(4.9084)	*(4.869)*	*(4.6327)*	*(4.294)*	*(4.3057)*	*(5.0706)*	*(4.2006)*	*(4.5062)*	*(4.982)*	*(4.5036)*	*(4.7701)*	*(4.3936)*	*(3.8956)*	*(3.8311)*	*(3.9225)*	*(5.4534)*	
Industrials	0.01218	0.01112	0.01089	0.0112	0.01037	0.01225	0.01161	0.01145	0.01211	0.01159	0.01281	0.01099	0.01117	0.01122	0.0144	0.01155	0.01168
	(3.395)	*(3.0706)*	*(3.0609)*	*(3.0632)*	*(2.8145)*	*(3.2751)*	*(3.1102)*	*(3.0701)*	*(3.2837)*	*(3.1881)*	*(3.4813)*	*(3.0152)*	*(3.1589)*	*(3.1234)*	*(2.7635)*	*(3.0173)*	
Materials	0.00827	0.00883	0.01047	0.00871	0.013609	0.01489	0.0096	0.01177	0.01081	0.01159	0.01129	0.01134	0.00982	0.00984	0.01106	0.01085	0.01080
	(2.0751)	*(2.2066)*	*(2.5411)*	*(2.1683)*	*(3.1747)*	*(3.3665)*	*(2.2374)*	*(2.605)*	*(2.5044)*	*(2.5507)*	*(2.5537)*	*(2.5689)*	*(2.4372)*	*(2.4192)*	*(2.6714)*	*(2.5079)*	
Real Estate	0.01092	0.01141	0.01155	0.01046	0.01214	0.01044	0.00929	0.00903	0.01126	0.00969	0.01069	0.01275	0.01086	0.00947	0.01168	0.01066	0.01077
	(2.7785)	*(2.7925)*	*(2.9680)*	*(2.6850)*	*(3.1321)*	*(2.8373)*	*(2.5401)*	*(2.3320)*	*(2.9585)*	*(2.6885)*	*(2.7344)*	*(3.2897)*	*(2.9131)*	*(2.6329)*	*(3.1550)*	*(2.7885)*	
Communication Service	0.01291	0.01143	0.01088	0.00978	0.00856	0.00936	0.00904	0.00955	0.01254	0.00933	0.00835	0.01088	0.00928	0.00884	0.01226	0.01178	0.01030
	(3.4312)	*(3.2109)*	*(3.0867)*	*(2.7050)*	*(2.4085)*	*(2.7142)*	*(2.5266)*	*(2.5610)*	*(3.3839)*	*(2.4444)*	*(2.2903)*	*(2.8265)*	*(2.3120)*	*(2.1676)*	*(2.8677)*	*(3.0202)*	
Utilities	0.00924	0.01093	0.01007	0.01049	0.01042	0.00985	0.01155	0.01045	0.00927	0.00996	0.010049	0.00986	0.010697	0.010398	0.009927	0.01064	0.01024
	(3.398)	*(3.8862)*	*(3.5047)*	*(3.7485)*	*(3.8052)*	*(3.5261)*	*(4.1734)*	*(3.5262)*	*(3.3038)*	*(3.5777)*	*(3.432)*	*(3.3695)*	*(3.9319)*	*(3.5400)*	*(3.4061)*	*(3.6719)*	
Consumer Discretionary	0.00957	0.01041	0.00962	0.00858	0.0104	0.01211	0.00747	0.00677	0.01116	0.00778	0.00879	0.00999	0.00809	0.0088	0.00988	0.00929	0.00929
	(2.7084)	*(2.9292)*	*(2.7976)*	*(2.5288)*	*(3.0595)*	*(3.4036)*	*(2.2197)*	*(2.0197)*	*(2.9969)*	*(2.2881)*	*(2.4493)*	*(2.7812)*	*(2.0312)*	*(2.3514)*	*(2.6015)*	*(2.4728)*	
Energy	0.00756	0.00581	0.00734	0.00643	0.00588	0.00873	0.006197	0.00651	0.01012	0.007936	0.006873	0.00871	0.006244	0.006017	0.01012	0.00728	0.00736
	(1.8029)	*(1.5246)*	*(1.7892)*	*(1.6415)*	*(1.6102)*	*(2.0844)*	*(1.6651)*	*(1.6427)*	*(2.3900)*	*(2.008)*	*(1.7644)*	*(1.9755)*	*(1.8051)*	*(1.7465)*	*(2.3051)*	*(1.7263)*	
Financials	0.00609	0.0049	0.00471	0.0046	0.00721	0.00765	0.00721	0.00606	0.00741	0.00612	0.00736	0.00859	0.0075	0.00792	0.00859	0.00911	0.00694
	(1.6816)	*(1.5735)*	*(1.5387)*	*(1.5478)*	*(2.0794)*	*(2.241)*	*(2.293)*	*(1.8154)*	*(2.0726)*	*(1.9368)*	*(2.0788)*	*(2.3864)*	*(2.1806)*	*(2.1345)*	*(2.3706)*	*(2.5106)*	

The momentum returns calculated based on CAGR supports the main results, showing positive momentum return for all the 16 different trading strategies. Again, all the results are significant at a 5% significance level based on the t-test, except for Energy and Financials which provides insignificant results, but for the 6/6 strategy the results are significant. The sectors are again ranked based on their average returns (CAGR) of the 16 trading strategies and provide the same ranking as the momentum return calculated as average monthly returns.

As with the other results the 6/6 strategy are chosen and used for further analysis.

Table 19: Momentum returns (CAGR 6/6 strategy)
The table shows the CAGR returns for the 6/6 momentum strategy, ranked in descending order

Ranked by CARG

Strategy (J=lag/K = Hold)	6/6
Healthcare	0.01822 *(5.2012)*
Materials	0.01489 *(3.3665)*
Information Technology	0.01314 *(3.3478)*
Consumer staples	0.01294 *(5.0706)*
Industrials	0.01225 *(3.2751)*
Consumer Discretionary	0.01211 *(3.4036)*
Real Estate	0.01044 *(2.8373)*
Utilities	0.00985 *(3.5261)*
Communication Service	0.00936 *(2.7142)*
Energy	0.00873 *(2.0844)*
Financials	0.00765 *(2.241)*

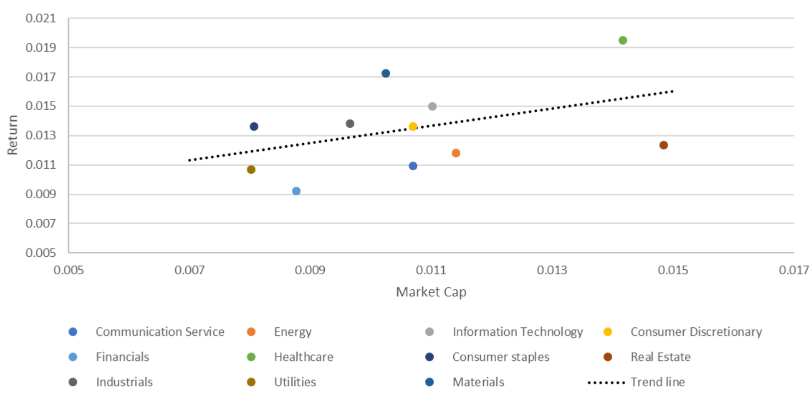
All the results are positive and significant at a 5% level. The CAGR returns shows the same tendency as the average return, the top three sectors are still the same as well as the bottom. Overall, the main results are a bit higher than the CAGR, but the robustness check still supports the main results, why the further analysis will use the average monthly return to get a more comparable robustness check.

To test the relationship between return and attention for the periods, the same tests with MC as a measure for attention will be performed. Tables, figures and regressions are presented here.

Table 20 & Figure 12: Relationship between momentum return and market cap.
The table shows average monthly returns ranked in descending order for market cap. The figure shows the relationship between momentum return and attention for the total market.

Strategy (J=lag/K = Hold)	**6/6**
Real Estate	0.01233 *(2.6856)*
Healthcare	0.01952 *(5.0854)*
Energy	0.01183 *(2.0087)*
Information Technology	0.01501 *(3.2811)*
Communication Service	0.01091 *(2.6052)*
Consumer Discretionary	0.01362 *(3.2815)*
Materials	0.01727 *(3.3658)*
Industrials	0.01382 *(3.2807)*
Financials	0.0092 *(2.1897)*
Consumer staples	0.01362 *(4.8962)*
Utilities	0.0107 *(3.4436)*

Ranked by MC
0.01484
0.01417
0.01141
0.01101
0.01070
0.01070
0.01024
0.00966
0.00877
0.00806
0.00802



Now the returns have been ranked according to market cap, to see if there is a relationship between MC and return. As with the table for trading volume Real Estate, Healthcare and Information Technology are in the top and Utilities and Financials are in the bottom. The sector which has changed the most is Energy, which was placed in the bottom for trading volume but now is in the top despite its lower return.

The figure again shows the rough linear tendency between attention (MC) and return. Compared to trading volume Financials and Utilities are in the lower end and below the trendline. Healthcare is again the sector which is most above the trend line with high attention and high return, whereas Real Estate again is spotted below the trendline despite the high attention. Overall, the robustness check supports the rough linear tendency.

Table 21: Regression for return on market cap
The regression shows the effect of attention (market cap) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effects
Materials	1.6737***	1.6669
	(0.0252)	*(0.0170)*
Consumer staples	1.6082***	1.6013
	(0.0097)	*(0.0190)*
Information Technology	1.4232***	1.4183
	(0.0111)	*(0.0161)*
Consumer Discretionary	1.3937***	1.3858
	(0.0166)	*(0.0153)*
Industrials	1.3847***	1.3771
	(0.0167)	*(0.0174)*
Healthcare	1.3602***	1.3580
	(0.0069)	*(0.0117)*
Utilities	1.3192***	1.3145
	(0.0148)	*(0.0235)*
Energy	1.1406***	1.1051
	(0.0175)	*(0.0177)*
Financials	1.0664***	1.0576
	(0.0152)	*(0.0192)*
Communication Service	1.0121***	1.0133
	(0.0132)	*(0.0136)*
Real Estate	0.8266***	0.8216
	(0.0085)	*(0.0119)*

The regression shows highly significant results at the 0.1% level. All the sectors have positive increase in return when attention goes up. Compared to the regression on trading volume, Materials and Consumer Staples are also the sectors which returns get most influenced by an increase in attention. Again, the bottom consists of Financials, Communication Service and Real Estate. Energy has changed a lot and this time fallen down the rankings and below the trendline in figure 12. Real Estate’s low position in figure 12, where the higher level of attention does not show the same performance in return, is supported by the lowest position in the regression.

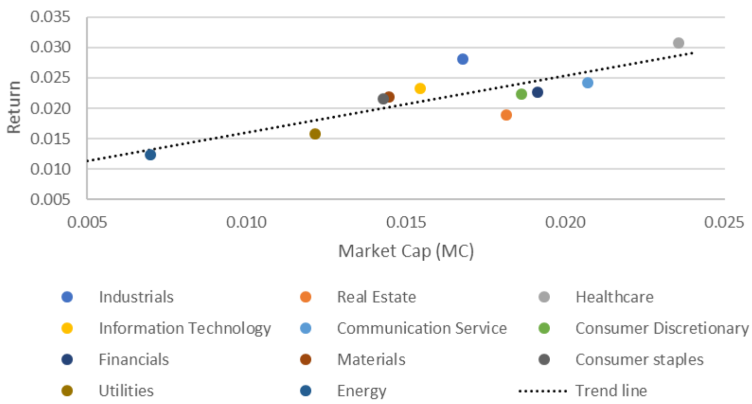
Overall the robustness check supports the main results for the total period, indicating a rough positive linear relationship between return and attention (MC). Again, displaying that Real Estate, Healthcare and Information Technology are in the top, although Real Estate has lower expected return. Utilities and Financials are in the bottom.

5.4.2 Robustness check (Up-market)

As with the main results an investigation of the relationship between return and attention (MC) for the up-market period is conducted.

Table 22 & Figure 13: Relationship between momentum return and market cap (Up-market).
The table shows average monthly returns ranked in descending order for market cap. The figure shows the relationship between momentum return and attention for the up-market.

Sector	Return	MC
Healthcare	0.03082	0.02356
Communication Service	0.02425	0.02069
Financials	0.02261	0.01913
Consumer Discretionary	0.02233	0.01863
Real Estate	0.01890	0.01816
Industrials	0.02817	0.01679
Information Technology	0.02331	0.01545
Materials	0.02188	0.01446
Consumer staples	0.02161	0.01428
Utilities	0.01575	0.01216
Energy	0.01239	0.00699



The table and figure show the positive linear relationship between momentum returns and attention (MC), which is even more pronounced compared to the total period.

Compared to the results for trading volume in the up-market period Healthcare is still in the top and Energy and Utilities in the bottom. An interesting change is that Financials is now in the top.

Table 23: Regression for return on market cap (Up-market).
The regression shows the effect of attention (market cap) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effects
Industrials	1.6478***	1.6049
	(0.0566)	*(0.0483)*
Utilities	1.4561***	1.4216
	(0.1038)	*(0.0845)*
Information Technology	1.4034***	1.4107
	(0.0512)	*(0.0575)*
Materials	1.3818***	1.3951
	(0.0502)	*(0.0560)*
Consumer staples	1.3166***	1.3263
	(0.0524)	*(0.0599)*
Healthcare	1.3015***	1.3022
	(0.0332)	*(0.0383)*
Energy	1.2790***	1.2905
	(0.0799)	*(0.0522)*
Financials	1.1339***	1.1246
	(0.0393)	*(0.0447)*
Consumer Discretionary	1.1336***	1.1438
	(0.0509)	*(0.0515)*
Communication Service	1.0968***	1.1034
	(0.0317)	*(0.0378)*
Real Estate	1.0553***	0.1613
	(0.0532)	*(0.0097)*

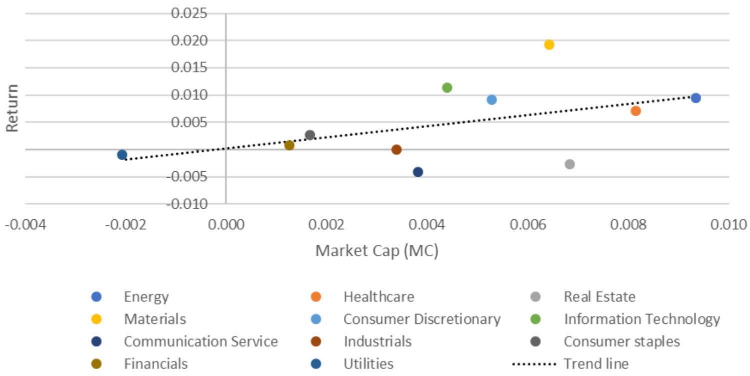
The regression for the up-market period for return on market cap shows that all the results are positive and significant a 0.1% level. Just like in the up-market period for trading volume Industrial is the sector with the biggest effect and Real Estate with the lowest.

5.4.3. Robustness check (Down-market)

Finally, the last robustness check is for the down-market period, to investigate if the positive linear relationship has disappeared as with the main results.

Table 24 & Figure 14: Relationship between momentum return and market cap (Down-market). The table shows average monthly returns ranked in descending order for market cap. The figure shows the relationship between momentum return and attention for the down-market.

Sector	Return	MC
Energy	0.0094	0.0093
Healthcare	0.0071	0.0081
Real Estate	-0.0027	0.0068
Materials	0.0192	0.0064
Consumer Discretionary	0.0092	0.0053
Information Technology	0.0113	0.0044
Communication Service	-0.0041	0.0038
Industrials	0.0001	0.0034
Consumer staples	0.0027	0.0017
Financials	0.0008	0.0013
Utilities	-0.0010	-0.0021



As expected the positive linear tendency has vanished in the down-market. Healthcare is still in the top, but now together with Energy, which was in the bottom for the up-market period. Utilities is still in the bottom, but now together with Financials which was in the top for the up-market. Compared to trading volume in the down-market, the level of attention is lower for market cap and negative for Utilities.

Table 25: Regression for return on market cap (down-market).
The regression shows the effect of attention (market cap) on return, where the standard error is indicated in the parenthesis and stars are given based on the significance level from the p-value (0.1% = ***, 1% =** and 5% =*).

Sector	OLS	Random Effects
Consumer staples	1.2295***	1.1590
	(0.1001)	*(0.1886)*
Industrials	1.1041***	1.0951
	(0.0704)	*(0.0844)*
Healthcare	1.0319***	1.0067
	(0.0858)	*(0.1343)*
Information Technology	0.9115***	0.8962
	(0.0765)	*(0.0850)*
Energy	0.8878***	0.8807
	(0.0791)	*(0.0702)*
Utilities	0.8818***	0.8657
	(0.0598)	*(0.1058)*
Real Estate	0.8164***	0.8216
	(0.0664)	*(0.0632)*
Communication Service	0.7591***	0.7631
	(0.0735)	*(0.0751)*
Materials	0.6990***	0.6876
	(0.1653)	*(0.0830)*
Financials	0.4952***	0.4982
	(0.0467)	*(0.0589)*
Consumer Discretionary	0.4017***	0.3963
	(0.0631)	*(0.0733)*

The regression is showing highly significant results at the 0.1% level. All the results are positive, indicating an increase in return when attention goes up. Contrary to trading volume, where the results were not so significant and in fact insignificant for some sectors. Also, the B_1 estimates were smaller and even negative for all the sectors except Materials, indicating the opposite, that return decreased when attention went up. Therefore, this robustness check does not support the main results, but it still indicates a lower effect of attention on return as the dependent variable, compared to the total period and up-market.

5.5 Summary

Chapter 5 is presenting and interpreting the results from the tests and investigation of the data. The first focus was to clarify whether momentum is present in all sectors. Section 5.1 concludes that all 11 sectors obtain positive momentum returns based on the average of the calculated monthly returns (Table 1). The results were significant except for Financials and Energy in some of the trading strategies. In the chosen 6/6 strategy for the further analysis all the results were significant.

The best performing sectors are Healthcare, Materials and Industrials. These sectors also have high excess returns when comparing the performance of the momentum return against the index return for each sector. Energy and Financial are the lowest ranking sectors and stay in the bottom of the figures. Momentum is concluded to be present for all sectors in the period of 2004-2018.

Next, an investigation of the momentum effect is being conducted with attention as the explanatory variable. Attention is measured as Trading Volume and Analyst Recommendation in section 5.2. The positive linear relationship between momentum and attention is seen for both attention measures. Healthcare, Materials and Industrials are again top performers and Healthcare and Materials lying above the trend line in figure 5. Financials and Real Estate are the ones responding with lower return compared to the level of attention, and not performing as high in the tables and figures. Overall, it can be concluded that for the total period 2004-2018, higher attention leads to higher momentum and the relationship between high performers and their attention is present.

Dividing the analysis into different market states (up and down) provided a further interpretation. The up-market (2012-2014) analysis supported the evidence of higher momentum returns in an up-market period. The attention measure was very aligned with the total period and supported the earlier findings showing that attention had a positive effect on momentum. As expected the down-market (2007-2009) had lower and even some negative momentum returns. The linear relationship between momentum and attention faded and the regression for trading volume even showed a negative impact of an increase in attention for some sectors. The investigation of the sub-periods in up- and down-market supported the idea of momentum returns being more present in up-markets and attention being a possible explanatory variable for the momentum effect. The results of the two market states will be further discussed in chapter 6.

Finally, the robustness check was made to support and uncover possible weaknesses of the earlier presented results. The results supported the earlier findings and not many variations between the tests were found. The results presented for momentum returns is seen as good and valid. Market Cap challenged earlier findings a little. The total market and up-market results supported earlier findings, but the MC robustness check for down-markets does not give the same conclusions as the earlier presented by TV and AR, since it shows some positive effect on return from attention, but it still indicates that the effect of attention is lower in down-market.

Overall, the sectors with high performance between attention and momentum are Healthcare, Materials and Industrials sectors, where the lowest ranked are Energy, Utilities and Financials. All 11 sectors are performing differently, and a higher level of momentum is seen present in some sectors compared to others. Generally, all sectors have momentum returns for the period 2004-2018. The linear relationship between attention and momentum returns is found present for the total period and the up-market. The down-market showed indication of this relationship fading and gives an opening for further investigation and discussion of attention in up- and down-markets.

Chapter 6

Discussion

This chapter will discuss the findings and results presented in chapter 5 and make connections to relevant literature and papers to get a deeper understanding of the results and their interpretation. The discussion will concentrate on the specific parts of our analysis that support earlier academic findings, as well as the variations and differences that have been disclosed. The interesting part is where the results can be supported or challenged by other research papers and tests, and if new findings and values are revealed. Section 6.1 will discuss the results and different literature and give a combined overview of all points and important conclusions derived from the study.

6.1 Discussion of results and literature

MPT started with Harry Markowitz as the main driver in 1952 when he presented the efficient frontier. Later Bill Sharpe recognized the Markowitz mean-variance optimization model as more than a tool to create investment portfolios. By introducing assumptions regarding investor rationality, market trading structure and information availability, Sharpe introduced the CAPM in 1965, a model for capital market equilibrium, which focused on the relationship between risk and return. Finally, Eugene Fama extended the concept of the rational investors and introduced EMH stating that all relevant information are fully reflected in market prices, which lead to the impossible scenario of earning excess returns. However, later academic research discovered multiple anomalies in the financial markets. The momentum effect is an anomaly well documented by many empirical studies. The introduction of behavioral finance formalized in an academic way the thoughts and ideas about anomalies and irrationality that challenged the whole foundation of MPT. A consequence of the entrance of anomalies to the market is a recognition of that investors and markets are not rational. In prolongation to the introduction of irrational markets, it becomes possible to earn excess returns. A deep dive into one element of the market and investor irrationality, the momentum anomaly with special focus on investors behavior and reactions to news in different market states, has been the purpose of this paper.

The financial theory section gave insights and the background to investigate the problem statement that the financial market is not efficient, investors are not rational and an anomaly in the form of momentum exits. Earlier academic literature and findings gave inspiration to the setup of the thesis and provided tools for analysis. Portfolios are created according to the methodology in Jegadeesh and Titman (1993), based on an irrational approach and not expecting markets to be efficient. The outcome of the tests helped to support earlier findings, but also deviations and points where the tests are not fully matching the expectations are revealed and highlighted. The market is unpredictable and defining an exact model is hard to do, since many variations and different factors are affecting investors' choices. In the rational perspective and theory, some parts and assumptions are not realistic towards the real market. Therefore, behavioral finance is a very good second dimension that adds on missing objectives and contributes with many important points to the financial theory. MPT does not account for anomalies, behavioral biases and unexpected events within the financial market. Findings of the thesis supports that anomalies like the momentum effect and possibilities of earning excess return is present in the market. The possible explanations are related to behavioral finance and human behavior.

The momentum effect in different sectors are the first results presented in this paper. The results showed that all the sectors had positive and significant returns for the 6/6 trading strategy in the total period. Furthermore, the performances of the momentum portfolios were also higher when compared to an investment in the sectors' individual indexes. The momentum return differs among the sectors: Healthcare, Materials and Information Technology are the top three. Communication Service, Utilities and Financials are the bottom three. Looking at excess return, Materials and Healthcare are still in top three, but now together with Consumer Staples. The bottom three still contain Financials and Communication Services, but now together with Energy. Overall, it is concluded that the momentum effect is valid for the time-period 2004-2018 in the US market as stated in Jegadeesh & Titman (1993). An interesting observation is that the level of the momentum effect differs between sectors. Moskowitz & Grinblatt (1999) supports the idea of different momentum levels within industries as well as the industry momentum affects the momentum within individual stocks and therefore the profitability of the individual stock's momentum strategy. In the paper individual stocks are stated to be more correlated within the

same industry, and a theory of momentum strategies being less diversified. (Moskowitz & Grinblatt, 1999).
The results are also interesting seen from a more practical angle. The results encourage to implement an investment portfolio in which the momentum strategy can be used profitable, not only in choosing the best performing sectors, but also to select the best performing stocks within these “winning” sectors. The analysis shows that, if the momentum strategy works well compared to other sectors, the greater the possibility to beat the comparable index (benchmark). A reason for different performances within sectors can also be related to behavioral biases as well as investors’ reactions and attention towards the different sectors.

The measurements used for attention have been Trading Volume (TV), Analyst Recommendation (AR) and Market Cap (MC). They have been selected due to the documentation and findings in the paper presented by Hou et al. (2009). The paper points out that TV is valued as the best measurement for attention and that AR and MC are alternative measures. The coverage of the attention measures differs. TV is regarded as a good and direct measure on the individual, private level, the number from the measurement reflects the actual actions and movements in the market. AR and MC are covering and giving input from a more public and institutional perspective. The results support that TV is the most reliable measurement as it represents the best and most significant positive linear relationship between momentum and attention for both the total market and the up-market. Therefore, TV is the most referred and used measure through the paper and the discussion. The analysis of AR did not give an indication of a linear positive relationship on return in the up-market. MC was chosen as a robustness check of the two tests based on TV and AR. It supported the findings in total market and up-market, but not as well in the down-market. The three measurements complement each other well and provide support for the results.

According to the results attention showed a positive linear relationship with momentum effect for the total market on all sectors. In Hou et al. (2009), attention is a necessary factor to analyze investor reactions in the market. The rationale behind this is that investors will only trade actively, if they actually are paying attention. Trading volume is a consequence of increased attention, and higher trading volume generates higher momentum. When attention is tested to be present, the momentum effect is more likely to happen (figure 5). The results for the total market confirm the idea that attention can be an explanatory variable for momentum returns. Lee & Swaminathan (2000), supports the findings of trading volume having an influence on the momentum profitability. According to Lee & Swaminathan (2000), the sectors with the highest trading volume are overvalued and sectors with the lowest trading volume are undervalued. From the figures showing the relationship between attention and return, the sectors lying above the trend line correspond to the assumption of being overvalued. The sectors below are assumed to be undervalued. This helps explaining why the sectors are performing differently. Looking at the total time-period Healthcare and Materials seem to be sectors that are "over-valued" while Real Estate and Financial are "under-valued". A more or less obvious link would be to assume that the more cyclical the sector is, the more responsive it is to changes in market. The cyclical sectors can experience a faster over- or underreaction, which can create momentum. However, the results do not fully support the assumption. The two most over-valued sectors – Healthcare and Materials - represents respectively defensive and cyclical stocks cf. Morningstars' classification of stocks into three "super" indexes: Cyclical, Sensitive and Defensive. The two most under-valued sectors are both cyclical. Including the third most over- and undervalued sectors – Information Technology and Communication Services – they are both characterized as Sensitive sectors.

Up- and down-markets are defined with reference to Cooper et al. (2004). The paper highlights the differences and the importance of a separate investigation of up- and down-market. The assumption is that momentum will be more profitable in the short-run for up-markets. Combining the findings from the two market states and attention, the results support the evidence that momentum is higher in up-markets and there is a positive linear relationship verified by the regressions of return on attention. The investigation of sub-periods, one up- and one down-market, shows different results for the relationship between momentum and attention as well as the conclusion for momentum being present and profitable for all sectors. The splitting of the results gives room for a narrower analysis and help looking into the different market states and effects on investors' behavior. Referring to Hou et al. (2009), up-markets should have a higher level of momentum and therefore a corresponding higher level of attention. As mentioned the linear positive relationship is higher for the up-market. However, the exact level of attention in the figures was not necessarily higher in the up-market compared to the down-market. The relationship tested in the regressions showed a clear difference in the tendency between the two market states, where up-markets had a positive linear relationship, which disappeared in down-markets. Overall, the empirical evidence points in the direction that attention can be appointed as an explanatory factor for momentum when the market is increasing. In down-markets the relationship between attention and momentum vanishes and there is no longer strong statistical evidence of a positive relationship. Karlsson et al. (2009) provides an explanation to why the relationship between momentum and attention contrasts in different market states. The "Ostrich effect" highlights how investors avoid bad news and try to shield themselves from the reality. In up-markets investors will seek information and respond more actively and faster. Therefore, a faster adjustment is assumed to happen in the up-market (2012-2014) contrary to the down-market (2007-2009). The assumption that investors respond differently to new information, depending on the market states, implies that investors pay less attention in the down-market, which is why the relationship fades.

The academic papers have different reflections about the causes of attention and how it affects investors' behavior.
They all support the idea that overreaction is linked to attention and a part of the explanation for the momentum effect. According to Cooper et al. (2004), the momentum effect seen in the up-market states can be explained by the overconfidence created in an up-market, which in turn generates overreactions from investors. Investors are increasingly self-confident due to a positive historical development, and keep believing it will continue. The excess demand leads to momentum profits in the short run. An explanation of why investors pay less attention in down-markets is found in Karlsson et al. (2009). Investors have less interest in negative information and try to shield themselves from uncomfortable news. The consequence is a more gradual and slower

adjustment of prices. People thereby underreact to news in the down-market, which is why the less attention also influences prices to a lesser degree and thereby the momentum effect vanish. Hou et al. (2009) stresses that attention is a prerequisite for overreaction to happen. The link to Karlsson et al. (2009) supports the idea that underreactions happen in the down-market and should be reflected in the trading volume. Hou et al. (2009) and Lee & Swaminathan (2000) support that higher trading volume should increase the momentum explained by overreaction from investors. The many earlier findings support the results of this paper and confirms the fact that attention, for the total market and an up-market, can be an explanatory variable. The positive linear relationship proven for the two periods are valid.
However, the analysis in this paper does not support the idea that attention and trading volume is lower in down-markets than in up-markets. This is one contradiction. Another is that although the trading volume was approximately the same in the two scenarios only in the up-market a positive relationship between trading volume and return is discovered. Therefore, the speed and extent of investors reaction to new information was similar in the two market states. A reason why the down-market is not showing a lower measure of attention, but only a different responding level, might be the chosen time-period, the financial crisis 2007-2009. The financial crisis exhibited a historical volatile and negative market development. It is an extraordinary period and is possibly not representable for a down-market. Trading volume was unusually high due to the extraordinary circumstances. Therefore, in this situation, trading volume itself is not a reliable measurement for attention causing momentum. In this context, the paper by Hou et al. (2009) makes a note stating, that it can be hard to measure a concrete effect from attention and that investors paying attention can be an expression of an overreaction more towards negative past returns than positive. The attention does not affect the returns to the same extent depending on the good and bad periods.

Attention is important as how investors react to information and subsequently the effect on momentum. Hou et al. (2009) divided attention into a dual role by showing that attention could make investors exhibit behavioral biases leading to overreaction, but inadequate attention could also lead to stock price underreaction, therefore the two roles is that attention interacts with overreaction, but also affect price underreaction. Consequently, attention can affect momentum and can be further investigated by looking at investors' over- and underreaction to information.

Behavioral models of investors reaction to news, analyzes how over- and underreaction can affect and explain momentum. Especially Daniel et al. (1998) and De Long et al. (1990) focus on investor overreaction, where Daniel et al. (1998) focuses on the behavioral biases' overconfidence and self-attribution bias as factors leading to overreaction and De Long et al. (1990) comes up with investors extrapolative expectations, where expectations make the investors incorporate their prior return into their expectations for the future. Linked to attention, for both mechanisms to create momentum, investors must be paying attention, since investors will not be able to overreact to private information or overly extrapolate stocks prior returns, if they do not pay attention to the stocks. Related to the evidence of the result section, overreaction can be a further explanation for the momentum found in the different sectors, since Hou et al. (2009) finds that high volume stocks (stocks which get traded a lot) exhibit stronger momentum due to overreaction. This can be supported by the evidence of this thesis, since the results show the positive linear relationship between momentum and attention, which means that the sectors with highest momentum and highest attention also are the sectors which have exhibited the strongest overreaction driven momentum. The results indicate that sectors like Healthcare and Materials are more exposed to overreaction driven momentum, than sectors like Financials and Real Estate (Figure 5). Reasons for the stronger overreaction driven momentum can be due to investors feeling more confident in some sectors than others (Moskowitz & Grinblatt, 1999). For example, investors who work in pharmaceutical companies, feel they have more knowledge or a better opportunity to gain information within that sector. Therefore, they may be more prone to exhibit overconfidence or self-attribution bias, which can lead to overreaction driven momentum. This can be further supported by the evidence that overreaction driven momentum is more present in up-markets than down-markets, which also is supported by the evidence from figure 7. It shows the strongest positive linear relationship between attention and momentum in up-market compared to the total period and in the down-market period. By incorporating investor attention into these theories, it is therefore a reliable conclusion that overreaction driven momentum, is often exhibited among stocks which have more attention (Hou et al., 2009). This is also supported by the result section where it is seen that overreaction driven momentum increases with trading volume. Contrary, in down-markets the study from Karlsson et al. (2009) showed that people pay less attention why the overreaction driven momentum is weaker. This is supported by the result in figure 9 showing the faded relationship between attention and momentum. Though the faded relationship is not due to people not paying attention, since the trading volume level is on average almost the same for up- and down-market, despite that the momentum return is lower and even negative for some sectors. The faded relationship can be supported by the evidence from the regression (table 15), showing that attention has a lower and even negative effect on momentum. Karlsson et al. (2009) can be related to underreaction, since evidence shows that people pay less attention in down-markets. Seen from the perspective of underreaction, especially the theories from Barberis et al. (1998) and Hong & Stein (1999) are interesting to investigate. Here attention is playing a role in the form of an investor attention that will generate an underreaction in stock prices. Barberis et al. (1998) and Hong & Stein (1999) use two different approaches to model investors' underreaction to information and show that investors tend to underreact to fundamental information or news about a company. This behavior leads price reaction to be lacking, why momentum is created when the information gradually gets incorporated into the price. Barberis et al. (1998) focuses on the conservatism bias and therefore underweight new received information and instead overweight the past information. A bit different approach is found in Hong & Stein (1999) where newswatchers are defined as individuals who create forecasts based on private information and that the private information slowly diffuses among the individuals. Building on the inattention base from Hou et al. (2009) they suggest that inattention can explain the slow-information diffusion mechanism which creates underreaction. As mentioned, our results do not support this idea, since on average the attention level is the same for up- and down-market, when attention is measured as trading volume.

The explanation by Barberis et al. (1998) for underreaction driven momentum, is a more likely argument for why the results shows positive momentum return and attention for the down-market. People trade on their prior beliefs and they pay attention, but not to the recent news. Instead they focus and trade based on prior news. This idea can help explain why some sectors have positive momentum in down-markets, and that the attention level is almost the same on average for the two periods.

Chan (2003) add a different perspective of underreaction as an explanation of why some sectors have positive momentum returns in down-markets. Evidence from the paper shows, that when stocks are exposed to news, there is momentum and specially when stocks are experiencing bad news, a long negative drift is spotted. Related to the result section for the down-market, this tendency can explain why some sectors have positive momentum returns. This is also supported by the Hong & Stein (1999) paper. Chan (2003) also supports the evidence, which shows overreaction driven momentum, since investors only pay attention to news which support their past beliefs and thereby overreact to private signals. This can relate to Daniel et al. (1998) and support the evidence in this thesis showing the positive linear relationship between momentum and attention.

Overall, the theory that overreaction driven momentum is related to attention as an explanatory variable for momentum gets support by the evidence of this thesis. The more uncovered question is the fact that the attention level is almost the same on average for up- and down-market. The positive momentum which some sectors exhibit in down-market can be explained by underreaction and a possible explanation for the attention level can be the conservatism bias where people use prior beliefs and will not update them based on bad news or news which do not correspond to their prior ones. Therefore, both momentum and attention can be present in a downward trending market, since investors trade based on their prior beliefs. Furthermore, as mentioned earlier the decision to use the financial crisis as the down-market period can have an influence on the level of attention. Though this thesis contributes to earlier findings, it is also challenging the inattention assumptions for down-markets. The idea of trading volume used as a measurement for attention can be doubtful in a time period where the trading volume is extremely high, as here with an extraordinary case (the financial meltdown in 2007-2009). This challenge the way of measuring attention. A more complex measurement and analysis can be necessary as tools for investigating the attention level.

In sum, the momentum trading strategy approach is working. It is profitable in most of the investigated periods for each of the 11 sectors. The investor's behavior and irrationality does influence the market, why attention has been found to be an explanatory variable. Therefore, it is important to uncover and account for investor behavior and reactions to news, since it significantly influences the development of stock returns in up- and down-markets. The momentum trading strategy is also created due to investor behavior, and different attention measurements have shown an impact on return. Even though not all tests showed the same results, the three tests supported each other and add to the earlier findings and literature.
As with other papers, there are some variation of the results and not all findings are exactly as expected. However, in prolongation of the analysis and discussions the paper gives good support to earlier findings and proves the effect attention has on stock returns and sectors performance. Attention can be used as an explanatory variable for further research of investors over- and underreaction to market news and states that investors will pay attention or shield themselves, which will have an impact on the financial market. Further, investors can use the evidence when creating momentum portfolios, since the results shows that not all sectors are performing at the same level, why some sectors are more profitable for momentum portfolios than others are.

Chapter 7

Conclusion

This thesis has addressed the issue of the momentum effect on a sector level and investigated the relationship between attention and momentum, in the search for a possible explanation for the momentum effect. Furthermore, the investigation was deepened by examining the effect and relationship in different market states.

Positive momentum returns have been found for all 11 sectors in the US market for the total time period 2004-2018. The momentum return varies among the sectors, indicating that some sectors are more exposed to the momentum effect than others. In the search for an explanation of the momentum effect, attention has been found to be an explanatory variable. The results showed a positive linear relationship between momentum and attention, indicating that the higher level of attention the higher momentum return. This was further proven by a regression analysis, showing that increases in attention had a positive effect on momentum return. A deeper analysis of the relationship between momentum and attention was conducted using subperiods; one up-market (2012-2014) and one down-market (2007-2009) period. The split into sub-periods revealed how different market states affect the results. The results of the deep dive confirmed the supporting theories that the momentum effect was higher in up-market compared to the down-market. Furthermore, the relationship between attention and momentum was improved in the up-market compared to the total period, indicating an even stronger relationship between momentum and attention as the explanatory variable. The results from the down-market partly confirmed the supporting theories. In the down-market the momentum effect was lower even negative for some sectors; Utilities, Real Estate and Communication services, but at the same time, the level of trading volume was relatively high in comparison. The regression showed a negative effect between momentum and attention for all sectors except Materials. The relationship between momentum and return had faded, but not due to inattention as stated in the supporting theories (Karlsson et al., 2009). The attention level was almost the same on average for the up-market and down-market, why the down-market is prone for further research. The chosen period can also be of interest since it represents the financial crises, which is an extreme case, where a lot of trades did happen due to many other exogenous factors, which affect the attention measure. Based on

the evidence of this thesis, it is concluded that in a down-market, attention is not an applicable measurement for momentum.
Theories regarding investor reaction to information is found to support the findings of this thesis. Overreaction is found as an explanation for momentum especially in the up-market and total period and supports attention as an explanatory variable. Investors will not be able to overreact to information, if they do not pay attention to the stocks. In this way attention and overreaction is linked. The underreaction theories can help explain why there is momentum in the down-market, but the inattention theory is not supported by this thesis.

Overall, momentum was present in the time period 2004-2018 for all sectors within the SP500 index. The zero-cost portfolios, with the 6/6-months strategy, were profitable on a highly significant level and the proposed behavioral models for attention were supportive in the analysis of the relationship between momentum returns and attention. The analysis and results on the total market and up-market were very much in line with the conclusions in the selected academic literature. The findings for the down-market were different. No relationship between momentum and attention was found, but the level of attention was still high. The level of attention differed between the sectors and affected their performance expressed both through the absolute and relative returns. Some sectors were more exposed to changes in the attention level than others, and it was revealed that the effect on return was higher, when the attention level changed. Earlier findings and behavioral models helped discuss and interpret the results. Over- and underreaction from investors was a reliable explanation as the cause for creating momentum and different effects in different market states. The findings of this paper support and challenge different parameters in the presented literature.

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Appendix

Appendix 1: Investigation of lags

1.1 Communication service

Lag 2:

```
> model.ComSer2 <- lm(ComSer_return ~ ComSer_lag_2, volume)
> summary(model.ComSer2)

Call:
lm(formula = ComSer_return ~ ComSer_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.58193 -0.20349  0.04424  0.20316  0.52938 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.514127   0.063058   55.73   <2e-16 ***
ComSer_lag_2 0.116091   0.003971   29.24   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2638 on 172 degrees of freedom
Multiple R-squared:  0.8325,	Adjusted R-squared:  0.8315 
F-statistic: 854.7 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3:

```
> model.ComSer3 <- lm(ComSer_return ~ ComSer_lag_3, volume)
> summary(model.ComSer3)

Call:
lm(formula = ComSer_return ~ ComSer_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.57877 -0.19651  0.04157  0.19798  0.50673 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.529957   0.062596   56.39   <2e-16 ***
ComSer_lag_3 0.115832   0.003965   29.21   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.264 on 172 degrees of freedom
Multiple R-squared:  0.8322,	Adjusted R-squared:  0.8313 
F-statistic: 853.3 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4:

```
> model.ComSer4 <- lm(ComSer_return ~ ComSer_lag_4, volume)
> summary(model.ComSer4)

Call:
lm(formula = ComSer_return ~ ComSer_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.57552 -0.20176  0.04566  0.19006  0.54528 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.546822   0.062108   57.11   <2e-16 ***
ComSer_lag_4 0.115486   0.003957   29.18   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2642 on 172 degrees of freedom
Multiple R-squared:  0.832,	Adjusted R-squared:  0.831 
F-statistic: 851.7 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5:

```
> model.ComSer5 <- lm(ComSer_return ~ ComSer_lag_5, volume)
> summary(model.ComSer5)

Call:
lm(formula = ComSer_return ~ ComSer_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.58604 -0.20255  0.04026  0.20319  0.52429 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.561950   0.061619   57.81   <2e-16 ***
ComSer_lag_5 0.115247   0.003949   29.18   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2642 on 172 degrees of freedom
Multiple R-squared:  0.832,	Adjusted R-squared:  0.831 
F-statistic: 851.6 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6:

```
> model.ComSer6 <- lm(ComSer_return ~ ComSer_lag_6, volume)
> summary(model.ComSer6)

Call:
lm(formula = ComSer_return ~ ComSer_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.57185 -0.19068  0.04319  0.20225  0.51563 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.575288   0.061002   58.61   <2e-16 ***
ComSer_lag_6 0.115133   0.003933   29.27   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2635 on 172 degrees of freedom
Multiple R-squared:  0.8328,	Adjusted R-squared:  0.8319 
F-statistic: 856.9 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.2 Consumer Discretionary

Lag 2:

```
> model.ConDis2 <- lm(ConDis_return ~ ConDis_lag_2, volume)
> summary(model.ConDis2)

Call:
lm(formula = ConDis_return ~ ConDis_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.61749 -0.13129  0.01592  0.17488  0.39633 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   3.78141    0.05250   72.03   <2e-16 ***
ConDis_lag_2  0.12996    0.00301   43.18   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2204 on 172 degrees of freedom
Multiple R-squared:  0.9155,	Adjusted R-squared:  0.915 
F-statistic:  1864 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3:

```
> model.ConDis3 <- lm(ConDis_return ~ ConDis_lag_3, volume)
> summary(model.ConDis3)

Call:
lm(formula = ConDis_return ~ ConDis_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.59640 -0.12497  0.01268  0.17244  0.41266 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.800974   0.052200   72.81   <2e-16 ***
ConDis_lag_3 0.129718   0.003012   43.07   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.221 on 172 degrees of freedom
Multiple R-squared:  0.9151,	Adjusted R-squared:  0.9146 
F-statistic:  1855 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4:

```
> model.ConDis4 <- lm(ConDis_return ~ ConDis_lag_4, volume)
> summary(model.ConDis4)

Call:
lm(formula = ConDis_return ~ ConDis_lag_4, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6355 -0.1263  0.0099  0.1803  0.3851 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.822507   0.052089   73.38   <2e-16 ***
ConDis_lag_4 0.129333   0.003024   42.76   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2224 on 172 degrees of freedom
Multiple R-squared:  0.914,	Adjusted R-squared:  0.9135 
F-statistic:  1829 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5:

```
> model.ConDis5 <- lm(ConDis_return ~ ConDis_lag_5, volume)
> summary(model.ConDis5)

Call:
lm(formula = ConDis_return ~ ConDis_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65603 -0.11763  0.00909  0.18184  0.36757 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.840829   0.051560   74.49   <2e-16 ***
ConDis_lag_5 0.129136   0.003012   42.87   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2219 on 172 degrees of freedom
Multiple R-squared:  0.9144,	Adjusted R-squared:  0.9139 
F-statistic:  1838 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6:

```
> model.ConDis6 <- lm(ConDis_return ~ ConDis_lag_6, volume)
> summary(model.ConDis6)

Call:
lm(formula = ConDis_return ~ ConDis_lag_6, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6273 -0.1188  0.0052  0.1752  0.3750 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.860876   0.051067   75.61   <2e-16 ***
ConDis_lag_6 0.128839   0.003002   42.91   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2217 on 172 degrees of freedom
Multiple R-squared:  0.9146,	Adjusted R-squared:  0.9141 
F-statistic:  1841 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.3 Consumer Staples

Lag 2

```
> model.ConSta2 <- lm(ConSta_return ~ ConSta_lag_2, volume)
> summary(model.ConSta2)

Call:
lm(formula = ConSta_return ~ ConSta_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.52455 -0.11803  0.05341  0.14992  0.34583 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.901013   0.049160   79.35   <2e-16 ***
ConSta_lag_2 0.145297   0.003236   44.90   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1939 on 172 degrees of freedom
Multiple R-squared:  0.9214,	Adjusted R-squared:  0.9209 
F-statistic:  2016 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.ConSta3 <- lm(ConSta_return ~ ConSta_lag_3, volume)
> summary(model.ConSta3)

Call:
lm(formula = ConSta_return ~ ConSta_lag_3, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5126 -0.1230  0.0471  0.1441  0.3374 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.918336   0.049329   79.43   <2e-16 ***
ConSta_lag_3 0.145126   0.003268   44.41   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1959 on 172 degrees of freedom
Multiple R-squared:  0.9198,	Adjusted R-squared:  0.9193 
F-statistic:  1972 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.ConSta4 <- lm(ConSta_return ~ ConSta_lag_4, volume)
> summary(model.ConSta4)

Call:
lm(formula = ConSta_return ~ ConSta_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.52284 -0.12435  0.04669  0.14643  0.31611 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.939421   0.049452   79.66   <2e-16 ***
ConSta_lag_4 0.144667   0.003297   43.88   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.198 on 172 degrees of freedom
Multiple R-squared:  0.918,	Adjusted R-squared:  0.9175 
F-statistic:  1926 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.ConSta5 <- lm(ConSta_return ~ ConSta_lag_5, volume)
> summary(model.ConDis5)

Call:
lm(formula = ConDis_return ~ ConDis_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65603 -0.11763  0.00909  0.18184  0.36757 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.840829   0.051560   74.49   <2e-16 ***
ConDis_lag_5 0.129136   0.003012   42.87   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2219 on 172 degrees of freedom
Multiple R-squared:  0.9144,	Adjusted R-squared:  0.9139 
F-statistic:  1838 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.ConSta6 <- lm(ConSta_return ~ ConSta_lag_6, volume)
> summary(model.ConSta6)

Call:
lm(formula = ConSta_return ~ ConSta_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.53721 -0.14367  0.03961  0.16224  0.33911 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.977036   0.049591   80.20   <2e-16 ***
ConSta_lag_6 0.144057   0.003348   43.03   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2016 on 172 degrees of freedom
Multiple R-squared:  0.915,	Adjusted R-squared:  0.9145 
F-statistic:  1852 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.4 Energy

Lag 2

```
> model.Energy2 <- lm(Energy_return ~ Energy_lag_2, volume)
> summary(model.Energy2)

Call:
lm(formula = Energy_return ~ Energy_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.58797 -0.14683  0.00565  0.14726  0.46696 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.449455   0.061530   72.31   <2e-16 ***
Energy_lag_2 0.129698   0.004926   26.33   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2228 on 172 degrees of freedom
Multiple R-squared:  0.8012,	Adjusted R-squared:  0.8001 
F-statistic: 693.3 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Energy3 <- lm(Energy_return ~ Energy_lag_3, volume)
> summary(model.Energy3)

Call:
lm(formula = Energy_return ~ Energy_lag_3, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6003 -0.1427  0.0070  0.1579  0.4718 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.458332   0.060899   73.21   <2e-16 ***
Energy_lag_3 0.129744   0.004903   26.46   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2219 on 172 degrees of freedom
Multiple R-squared:  0.8028,	Adjusted R-squared:  0.8017 
F-statistic: 700.4 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Energy4 <- lm(Energy_return ~ Energy_lag_4, volume)
> summary(model.Energy4)

Call:
lm(formula = Energy_return ~ Energy_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.60668 -0.14010 -0.00419  0.15528  0.46879 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.471181   0.060560   73.83   <2e-16 ***
Energy_lag_4 0.129448   0.004902   26.41   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2223 on 172 degrees of freedom
Multiple R-squared:  0.8022,	Adjusted R-squared:  0.801 
F-statistic: 697.4 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Energy5 <- lm(Energy_return ~ Energy_lag_5, volume)
> summary(model.Energy5)

Call:
lm(formula = Energy_return ~ Energy_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.61936 -0.14216 -0.00305  0.15287  0.51076 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   4.48331    0.05984   74.92   <2e-16 ***
Energy_lag_5  0.12921    0.00487   26.53   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2214 on 172 degrees of freedom
Multiple R-squared:  0.8037,	Adjusted R-squared:  0.8025 
F-statistic:   704 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Energy6 <- lm(Energy_return ~ Energy_lag_6, volume)
> summary(model.Energy6)

Call:
lm(formula = Energy_return ~ Energy_lag_6, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5920 -0.1420  0.0036  0.1492  0.5532 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   4.49903    0.05976   75.29   <2e-16 ***
Energy_lag_6  0.12867    0.00489   26.32   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2229 on 172 degrees of freedom
Multiple R-squared:  0.801,	Adjusted R-squared:  0.7999 
F-statistic: 692.5 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.5 Financials

Lag 2

```
> model.Fin2 <- lm(Fin_return ~ Fin_lag_2, volume)
> summary(model.Fin2)

Call:
lm(formula = Fin_return ~ Fin_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.63441 -0.14133  0.05799  0.15276  0.29425 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.091418   0.046650   87.70   <2e-16 ***
Fin_lag_2   0.084224   0.002868   29.37   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.191 on 172 degrees of freedom
Multiple R-squared:  0.8337,    Adjusted R-squared:  0.8328 
F-statistic: 862.5 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Fin3 <- lm(Fin_return ~ Fin_lag_3, volume)
> summary(model.Fin3)

Call:
lm(formula = Fin_return ~ Fin_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.60452 -0.13566  0.05348  0.15303  0.28334 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.104049   0.046353   88.54   <2e-16 ***
Fin_lag_3   0.083974   0.002866   29.30   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1914 on 172 degrees of freedom
Multiple R-squared:  0.833,    Adjusted R-squared:  0.8321 
F-statistic: 858.2 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Fin4 <- lm(Fin_return ~ Fin_lag_4, volume)
> summary(model.Fin4)

Call:
lm(formula = Fin_return ~ Fin_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.66642 -0.13767  0.05376  0.14727  0.30080 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.118362   0.046194   89.15   <2e-16 ***
Fin_lag_4   0.083602   0.002873   29.10   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1925 on 172 degrees of freedom
Multiple R-squared:  0.8312,	Adjusted R-squared:  0.8302 
F-statistic: 846.8 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Fin5 <- lm(Fin_return ~ Fin_lag_5, volume)
> summary(model.Fin5)

Call:
lm(formula = Fin_return ~ Fin_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65986 -0.13616  0.05529  0.15455  0.27569 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.13135    0.04573   90.35   <2e-16 ***
Fin_lag_5    0.08331    0.00286   29.13   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1923 on 172 degrees of freedom
Multiple R-squared:  0.8314,	Adjusted R-squared:  0.8305 
F-statistic: 848.4 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Fin6 <- lm(Fin_return ~ Fin_lag_6, volume)
> summary(model.Fin6)

Call:
lm(formula = Fin_return ~ Fin_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.62579 -0.13811  0.05416  0.15549  0.29303 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.143707   0.045267   91.54   <2e-16 ***
Fin_lag_6   0.083066   0.002848   29.16   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1921 on 172 degrees of freedom
Multiple R-squared:  0.8318,	Adjusted R-squared:  0.8308 
F-statistic: 850.6 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.6 Healthcare

Lag 2

```
> model.Health2 <- lm(Health_return ~ Health_lag_2, volume)
> summary(model.Health2)

Call:
lm(formula = Health_return ~ Health_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.56509 -0.19964  0.04876  0.17313  0.37018 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.359438   0.057344   58.58   <2e-16 ***
Health_lag_2 0.145983   0.002737   53.34   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2287 on 172 degrees of freedom
Multiple R-squared:  0.943,	Adjusted R-squared:  0.9427 
F-statistic:  2845 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Health3 <- lm(Health_return ~ Health_lag_3, volume)
> summary(model.Health3)

Call:
lm(formula = Health_return ~ Health_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.55711 -0.19241  0.05581  0.17971  0.41137 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.396805   0.057223   59.36   <2e-16 ***
Health_lag_3 0.145099   0.002747   52.83   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2308 on 172 degrees of freedom
Multiple R-squared:  0.9419,	Adjusted R-squared:  0.9416 
F-statistic:  2791 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Health4 <- lm(Health_return ~ Health_lag_4, volume)
> summary(model.Health4)

Call:
lm(formula = Health_return ~ Health_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.54574 -0.20911  0.05764  0.17833  0.42066 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.437583   0.057133   60.17   <2e-16 ***
Health_lag_4 0.144035   0.002758   52.23   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2333 on 172 degrees of freedom
Multiple R-squared:  0.9407,	Adjusted R-squared:  0.9403 
F-statistic:  2728 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Health5 <- lm(Health_return ~ Health_lag_5, volume)
> summary(model.Health5)

Call:
lm(formula = Health_return ~ Health_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.55047 -0.18891  0.06459  0.17458  0.41445 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.476284   0.056895    61.1   <2e-16 ***
Health_lag_5 0.143058   0.002762    51.8   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2351 on 172 degrees of freedom
Multiple R-squared:  0.9398,	Adjusted R-squared:  0.9394 
F-statistic:  2683 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Health6 <- lm(Health_return ~ Health_lag_6, volume)
> summary(model.Health6)

Call:
lm(formula = Health_return ~ Health_lag_6, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5549 -0.2013  0.0577  0.1763  0.4101 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.516084   0.056647   62.07   <2e-16 ***
Health_lag_6 0.142040   0.002766   51.35   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.237 on 172 degrees of freedom
Multiple R-squared:  0.9388,	Adjusted R-squared:  0.9384 
F-statistic:  2637 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.7 Industrial

Lag 2

```
> model.Ind2 <- lm(Ind_return ~ Ind_lag_2, volume)
> summary(model.Ind2)

Call:
lm(formula = Ind_return ~ Ind_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.61484 -0.15656  0.07215  0.15536  0.33597 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.923477   0.050106   78.30   <2e-16 ***
Ind_lag_2   0.115821   0.003087   37.52   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2197 on 172 degrees of freedom
Multiple R-squared:  0.8911,	Adjusted R-squared:  0.8905 
F-statistic:  1407 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Ind3 <- lm(Ind_return ~ Ind_lag_3, volume)
> summary(model.Ind3)

Call:
lm(formula = Ind_return ~ Ind_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.57722 -0.14991  0.08017  0.16021  0.37208 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.933243   0.050001   78.66   <2e-16 ***
Ind_lag_3   0.116072   0.003103   37.41   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2203 on 172 degrees of freedom
Multiple R-squared:  0.8905,	Adjusted R-squared:  0.8899 
F-statistic:  1399 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Ind4 <- lm(Ind_return ~ Ind_lag_4, volume)
> summary(model.Ind4)

Call:
lm(formula = Ind_return ~ Ind_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65151 -0.14130  0.07997  0.16194  0.37062 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.944468   0.049883   79.07   <2e-16 ***
Ind_lag_4   0.116214   0.003117   37.28   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2209 on 172 degrees of freedom
Multiple R-squared:  0.8899,	Adjusted R-squared:  0.8892 
F-statistic:  1390 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Ind5 <- lm(Ind_return ~ Ind_lag_5, volume)
> summary(model.Ind5)

Call:
lm(formula = Ind_return ~ Ind_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.65507 -0.15573  0.07509  0.16091  0.34137 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.95826    0.04977   79.54   <2e-16 ***
Ind_lag_5    0.11616    0.00313   37.11   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2219 on 172 degrees of freedom
Multiple R-squared:  0.889,	Adjusted R-squared:  0.8883 
F-statistic:  1377 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Ind6 <- lm(Ind_return ~ Ind_lag_6, volume)
> summary(model.Ind6)

Call:
lm(formula = Ind_return ~ Ind_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.62311 -0.15362  0.06797  0.16779  0.38177 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.969968   0.049403   80.36   <2e-16 ***
Ind_lag_6   0.116257   0.003129   37.16   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2216 on 172 degrees of freedom
Multiple R-squared:  0.8892,	Adjusted R-squared:  0.8886 
F-statistic:  1381 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.8 Materials

Lag 2

```
> model.Mat2 <- lm(Mat_return ~ Mat_lag_2, volume)
> summary(model.Mat2)

Call:
lm(formula = Mat_return ~ Mat_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.56684 -0.12388  0.00121  0.13138  0.41576 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.750611   0.044646   84.01   <2e-16 ***
Mat_lag_2   0.166247   0.003039   54.70   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1924 on 172 degrees of freedom
Multiple R-squared:  0.9456,	Adjusted R-squared:  0.9453 
F-statistic:  2992 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Mat3 <- lm(Mat_return ~ Mat_lag_3, volume)
> summary(model.Mat3)

Call:
lm(formula = Mat_return ~ Mat_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.51554 -0.13295 -0.00942  0.14566  0.41094 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.755961   0.043782   85.79   <2e-16 ***
Mat_lag_3   0.167137   0.003002   55.67   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1892 on 172 degrees of freedom
Multiple R-squared:  0.9474,	Adjusted R-squared:  0.9471 
F-statistic:  3099 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Mat4 <- lm(Mat_return ~ Mat_lag_4, volume)
> summary(model.Mat4)

Call:
lm(formula = Mat_return ~ Mat_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.56732 -0.12229  0.00784  0.13567  0.39390 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.768901   0.043233   87.18   <2e-16 ***
Mat_lag_4   0.167437   0.002985   56.10   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1879 on 172 degrees of freedom
Multiple R-squared:  0.9482,	Adjusted R-squared:  0.9479 
F-statistic:  3147 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Mat5 <- lm(Mat_return ~ Mat_lag_5, volume)
> summary(model.Mat5)

Call:
lm(formula = Mat_return ~ Mat_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.55026 -0.12447 -0.00624  0.14163  0.40364 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.780651   0.042094   89.81   <2e-16 ***
Mat_lag_5   0.167793   0.002925   57.36   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1839 on 172 degrees of freedom
Multiple R-squared:  0.9503,	Adjusted R-squared:   0.95 
F-statistic:  3290 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Mat6 <- lm(Mat_return ~ Mat_lag_6, volume)
> summary(model.Mat6)

Call:
lm(formula = Mat_return ~ Mat_lag_6, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5246 -0.1225 -0.0183  0.1350  0.4538 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.793194   0.041245   91.97   <2e-16 ***
Mat_lag_6   0.168111   0.002886   58.26   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1812 on 172 degrees of freedom
Multiple R-squared:  0.9518,	Adjusted R-squared:  0.9515 
F-statistic:  3394 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.9 Real Estate

Lag 2

```
> model.Real2 <- lm(Real_return ~ Real_lag_2, volume)
> summary(model.Real2)

Call:
lm(formula = Real_return ~ Real_lag_2, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.80866 -0.07465  0.03122  0.14363  0.39783 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.378646   0.052664   83.14   <2e-16 ***
Real_lag_2  0.086320   0.002839   30.40   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2222 on 172 degrees of freedom
Multiple R-squared:  0.8431,	Adjusted R-squared:  0.8422 
F-statistic: 924.3 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Real3 <- lm(Real_return ~ Real_lag_3, volume)
> summary(model.Real3)

Call:
lm(formula = Real_return ~ Real_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.78444 -0.08225  0.03419  0.13735  0.35185 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.393203   0.052806   83.19   <2e-16 ***
Real_lag_3  0.086129   0.002866   30.05   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2244 on 172 degrees of freedom
Multiple R-squared:   0.84,	Adjusted R-squared:  0.8391 
F-statistic: 903.3 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Real4 <- lm(Real_return ~ Real_lag_4, volume)
> summary(model.Real4)

Call:
lm(formula = Real_return ~ Real_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.79520 -0.08165  0.03918  0.14763  0.36804 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.408461   0.052792   83.51   <2e-16 ***
Real_lag_4  0.085903   0.002884   29.78   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2261 on 172 degrees of freedom
Multiple R-squared:  0.8376,	Adjusted R-squared:  0.8367 
F-statistic: 887.1 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Real5 <- lm(Real_return ~ Real_lag_5, volume)
> summary(model.Real5)

Call:
lm(formula = Real_return ~ Real_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.80333 -0.07772  0.03008  0.15619  0.37202 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.423732   0.052599   84.10   <2e-16 ***
Real_lag_5  0.085673   0.002893   29.62   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2272 on 172 degrees of freedom
Multiple R-squared:  0.8361,	Adjusted R-squared:  0.8351 
F-statistic: 877.1 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Real6 <- lm(Real_return ~ Real_lag_6, volume)
> summary(model.Real6)

Call:
lm(formula = Real_return ~ Real_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.78622 -0.08302  0.02485  0.14117  0.35892 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.438717   0.052438   84.65   <2e-16 ***
Real_lag_6  0.085471   0.002904   29.43   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2283 on 172 degrees of freedom
Multiple R-squared:  0.8344,	Adjusted R-squared:  0.8334 
F-statistic: 866.4 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.10 Information Technology

Lag 2

```
> model.Tech2 <- lm(Tech_return ~ Tech_lag_2, volume)
> summary(model.Tech2)

Call:
lm(formula = Tech_return ~ Tech_lag_2, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.7556 -0.1339  0.0408  0.1621  0.3692 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.646663   0.056214   64.87   <2e-16 ***
Tech_lag_2  0.115644   0.002954   39.15   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2343 on 172 degrees of freedom
Multiple R-squared:  0.8991,	Adjusted R-squared:  0.8985 
F-statistic:  1533 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Tech3 <- lm(Tech_return ~ Tech_lag_3, volume)
> summary(model.Tech3)

Call:
lm(formula = Tech_return ~ Tech_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.67158 -0.14520  0.05131  0.16488  0.38770 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.668930   0.055822   65.73   <2e-16 ***
Tech_lag_3  0.115228   0.002951   39.04   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2349 on 172 degrees of freedom
Multiple R-squared:  0.8986,	Adjusted R-squared:  0.898 
F-statistic:  1524 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Tech4 <- lm(Tech_return ~ Tech_lag_4, volume)
> summary(model.Tech4)

Call:
lm(formula = Tech_return ~ Tech_lag_4, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.79302 -0.12961  0.06083  0.16298  0.38593 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.693719   0.055645   66.38   <2e-16 ***
Tech_lag_4  0.114656   0.002959   38.74   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2365 on 172 degrees of freedom
Multiple R-squared:  0.8972,	Adjusted R-squared:  0.8966 
F-statistic:  1501 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Tech5 <- lm(Tech_return ~ Tech_lag_5, volume)
> summary(model.Tech5)

Call:
lm(formula = Tech_return ~ Tech_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.80238 -0.13347  0.04687  0.16150  0.38081 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.71651    0.05532   67.19   <2e-16 ***
Tech_lag_5   0.11418    0.00296   38.58   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2374 on 172 degrees of freedom
Multiple R-squared:  0.8964,	Adjusted R-squared:  0.8958 
F-statistic:  1489 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 6

```
> model.Tech6 <- lm(Tech_return ~ Tech_lag_6, volume)
> summary(model.Tech6)

Call:
lm(formula = Tech_return ~ Tech_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.74518 -0.13092  0.04561  0.16825  0.35103 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.739472   0.054703   68.36   <2e-16 ***
Tech_lag_6  0.113711   0.002945   38.62   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2372 on 172 degrees of freedom
Multiple R-squared:  0.8966,	Adjusted R-squared:  0.896 
F-statistic:  1491 on 1 and 172 DF,  p-value: < 2.2e-16
```

1.11 Utilities

Lag 2

```
> model.Util2 <- lm(Util_return ~ Util_lag_2, volume)
> summary(model.Util2)

Call:
lm(formula = Util_return ~ Util_lag_2, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.4357 -0.1319  0.0355  0.1335  0.2832 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.010415   0.044066   91.01   <2e-16 ***
Util_lag_2  0.120019   0.003445   34.84   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1637 on 172 degrees of freedom
Multiple R-squared:  0.8759,	Adjusted R-squared:  0.8751 
F-statistic:  1213 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 3

```
> model.Util3 <- lm(Util_return ~ Util_lag_3, volume)
> summary(model.Util3)

Call:
lm(formula = Util_return ~ Util_lag_3, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.45954 -0.12870  0.03623  0.13789  0.26022 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.02350    0.04413   91.18   <2e-16 ***
Util_lag_3   0.11972    0.00347   34.50   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1651 on 172 degrees of freedom
Multiple R-squared:  0.8737,	Adjusted R-squared:  0.873 
F-statistic:  1190 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 4

```
> model.Util4 <- lm(Util_return ~ Util_lag_4, volume)
> summary(model.Util4)

Call:
lm(formula = Util_return ~ Util_lag_4, data = volume)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.4257 -0.1310  0.0565  0.1338  0.2769 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.038592   0.044255   91.26   <2e-16 ***
Util_lag_4  0.119254   0.003501   34.07   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1669 on 172 degrees of freedom
Multiple R-squared:  0.8709,	Adjusted R-squared:  0.8702 
F-statistic:  1161 on 1 and 172 DF,  p-value: < 2.2e-16
```

Lag 5

```
> model.Util5 <- lm(Util_return ~ Util_lag_5, volume)
> summary(model.Util5)

Call:
lm(formula = Util_return ~ Util_lag_5, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.41271 -0.13834  0.04337  0.13160  0.26217 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.050955   0.044148   91.76   <2e-16 ***
Util_lag_5  0.118979   0.003512   33.88   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1677 on 172 degrees of freedom
Multiple R-squared:  0.8697,	Adjusted R-squared:  0.8689 
F-statistic:  1148 on 1 and 172 DF,  p-value: < 2.2e-16
```

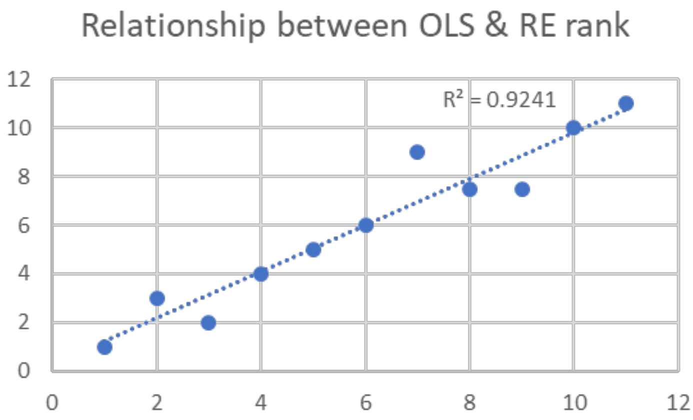
Lag 6

```
> model.Util6 <- lm(Util_return ~ Util_lag_6, volume)
> summary(model.Util6)

Call:
lm(formula = Util_return ~ Util_lag_6, data = volume)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.42314 -0.14759  0.04994  0.13625  0.29883 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.064616   0.044160   92.04   <2e-16 ***
Util_lag_6  0.118618   0.003533   33.57   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.169 on 172 degrees of freedom
Multiple R-squared:  0.8676,    Adjusted R-squared:  0.8668 
F-statistic:  1127 on 1 and 172 DF,  p-value: < 2.2e-16
```

Appendix 2: Rank Correlation

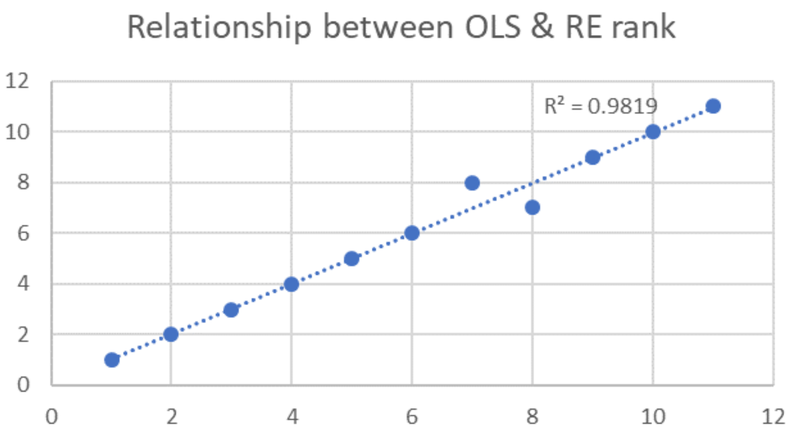
2.1 Regression Return on Trading Volume, rank correlation (Total Period)

Rank OLS	Rank RE
1	1
2	3
3	2
4	4
5	5
6	6
7	9
8	7.5
9	7.5
10	10
11	11
Spearman rank correlation	*0.9613*



2.2 Regression Return on Analyst Recommendation (Total Period)

Rank OLS	Rank RE
1	1
2	2
3	3
4	4
5	5
6	6
7	8
8	7
9	9
10	10
11	11
Spearman rank correlation	*0.9909*



2.3 Regression Return on Market Cap (Total Period)

Rank OLS	Rank RE
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
10	10
11	11
Spearman rank correlation	*1.0000*