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**FACULTY OF BUSINESS STUDIES**  
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Jannika Kankare

**HETEROGENEOUS BELIEFS AND MOMENTUM PROFITS**  
**Evidence from S&P500 Index Survivor Stocks in 2002–2015**

Master's Thesis in  
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**UNIVERSITY OF VAASA****Faculty of Business Studies**

<b>Author:</b>	Jannika Kankare	
<b>Topic of the Thesis:</b>	Heterogeneous Beliefs And Momentum Profits	
<b>Name of the Supervisor:</b>	Vanja Piljak	
<b>Degree:</b>	Master's degree in Economics and Business Administration	
<b>Department:</b>	Department of Accounting and Finance	
<b>Major Subject:</b>	Accounting and Finance	
<b>Line:</b>	Finance	
<b>Year of Entering the University:</b>	2012	
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**ABSTRACT**

The momentum phenomenon is one of the most well documented anomalies in financial research. However, the driving forces behind the anomaly have yet to be indisputably recognized. The purpose of this Master's thesis is to investigate whether return continuation is derived from a situation where investors have heterogeneous beliefs or receive heterogeneous information. The dispersion of analysts' earnings forecasts is used as a proxy for heterogeneity of beliefs concerning a firm's fundamentals. The basic methodology is adopted from Verardo (2009).

The contribution of this study to prior research is to examine the relationship between momentum profits and heterogeneous beliefs in different states of the market. This method allows for a closer investigation of the state-dependent properties of the phenomenon. The research period ranges from 2002 to 2015 and is divided into three separate sub-samples according to the prevailing market state: pre-crisis, crisis and post-crisis periods. The research data consists of monthly stock returns of S&P 500 survivor stocks. The main independent variable, dispersion (DISP), is the coefficient of variation of analyst forecasts of earnings for the end of the current or the next fiscal year.

The purpose of the study is to provide an empirical link between momentum profits and heterogeneous beliefs using the dispersion of analysts' forecasts as the main variable to measure the relation between the diffusion of forecasts per given stock and return continuation in a portfolio setting and in a time-series regression framework. The results from portfolio analysis are further tested with multivariate time-series regressions featuring the Fama-French three-factor model to assess whether covariance with possible risk factors has an impact on momentum returns. The findings of this study confirm only partially those of previous research papers. The portfolio analysis results suggest that the momentum-dispersion strategy works only during a "normal" state of the market. During a crisis period, the strategy is unable to yield positive returns and the profitability pattern is reversed in the aftermath of a momentum crash.

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**KEYWORDS:** Momentum, heterogeneous beliefs, behavioral finance



## 1. INTRODUCTION

The momentum phenomenon, also known as price reversal and continuation, is the predictive power that past prices have on future returns. In other words, stock returns exhibit autocorrelation in various time periods. The term momentum refers to the short-run tendency of prices being positively autocorrelated in a time period that lasts less than one year. Long-term price reversals occur because prices are negatively autocorrelated in a period of three to five years. The predictable power of past prices is directly contradictory to the efficient market hypothesis in its weakest form. (Jegadeesh & Titman 1993, Fama 1970.)

It has been over 30 years since the momentum investing strategy was discovered by academics (Jegadeesh & Titman 1993, Asness 1994). Since then it has received a great deal of attention and sparked academic interest across the board in the field of finance, as there have been an abundance of studies documenting its presence and efficacy extending across over 40 countries and more than a dozen asset classes (Asness, Moskowitz & Pedersen 2013). Geczy and Samonov (2013) provide evidence of momentum in U.S. stocks with a time period ranging from as early as 1801 to 2010, calling their research “the world’s longest backtest”. While momentum is acknowledged as one of the most stable and extensively documented anomalies, there is ongoing debate regarding the causes behind momentum. A number of both traditional and behavioral theories have since emerged trying to justify the abnormal returns the momentum strategy continues to generate (Asness, Frazzini, Israel & Moskowitz 2014).

The proponents of the traditional finance paradigm believe in Von Neumann-Morgenstern expected utility theory and arbitrage assumptions. The traditional neoclassical view on financial models is rationality based – risk-averse investors utilize all available information effectively and their preferences conform to expected utility. They apply optimal statistical procedures to form their beliefs about the markets and assets. Using all publicly available information, investors are supposed to be able to make instantaneous and unbiased forecasts about future value of assets, which would lead to market prices fully reflecting the true value of assets at all times. (Fama 1970.)

Momentum, the tendency of past performance to continue in the short run and revert in the long run, challenges the credibility of the efficient market hypothesis especially since it is yet to be captured by any traditional asset pricing model. The proponents of the efficient markets have come up with a number of risk-based explanations for the anomaly. Most notably theories involving an undiscovered risk factor accounting for the abnormal returns (Schwert 2003), such as a common global risk factor and liquidity risk (Asness, Moskowitz & Pedersen 2013).

Behavioral finance is the paradigm that studies the financial markets using models that take into account the human factor. The advocates of this paradigm believe market operators to be imperfectly rational and their views are heavily rooted in studies on human cognitive psychology. Researchers studying the field of behavioral decision-making have produced a significant amount of evidence against individuals behaving as if they have Von Neumann-Morgenstern preferences or form judgments based on Bayesian principles. The biases that people have tend to cumulate into systematic errors that may account for much of the occurring anomalous phenomena that traditional risk-based models are unable to explain, such as the momentum anomaly. (Shefrin 2005.)

Heterogeneous beliefs are the product of various sets of traders forming different expectations about the future prices of assets. There are both rational and behavioral theories striving to explain the phenomenon. Heterogeneous beliefs may derive from receiving heterogeneous information or receiving identical signals, but interpreting them in different ways (Banerjee, Kaniel & Kremer 2009). One of the major causes of heterogeneous beliefs is sub-optimal learning of agents on the financial markets.

### 1.1. Prior research

The most notable previous research article related to this thesis is Verardo's (2009) study on heterogeneous beliefs and momentum profits. The study is conducted with monthly data from U.S. stocks listed on NYSE, AMEX, and NASDAQ indices during the period of 1984 to 2000. Using the dispersion of analyst forecasts as a proxy for heterogeneous beliefs, Verardo shows in a

portfolio setting and with predictive cross-sectional regressions that momentum profits are significantly larger for portfolios with higher levels of heterogeneity of beliefs. This suggests that there is a positive relationship between forecast dispersion and autocorrelation in returns. Verardo's findings are in line with the overreaction and self-attribution model of Daniel, Hirshleifer and Subrahmanyam (1998), the underreaction to public news model of Hong et al. (2000) and the parameter uncertainty model of Lewellen and Shanken (2002).

Other notable studies include the work by Allen, Morris and Shin (2006) and Banerjee, Kaniel, and Kremer (2009). Allen et al. examine the role of high-order expectations in an asset-pricing context with a REE model of financial markets and show that differences in high-order beliefs lead to price drifts. Banerjee et al. show theoretically that heterogeneous opinions paired with uncertainty about other traders' opinions create price drift in a dynamic setting. Hong, Lim and Stein (1999) propose that relevant information is scattered between numerous individuals and cognitive limitations prevent investors from interpreting what others know solely with data on market prices. This causes information to diffuse slowly, resulting in momentum. The authors also show that the momentum effect is most prevalent for low-attention stocks, such as small stocks and stocks with less analyst coverage.

## 1.2. Purpose of the study and intended contribution

How investors process information and update their beliefs is a central element of market efficiency, because it is directly reflected in asset prices and trading volume. The role of learning on the financial markets is increasingly important due to the exponentially increasing availability of information in today's world. The processing of information is both difficult to observe in an empirical setting as well as a broad concept comprising of different dimensions, such as attention, decision-making under uncertainty and dispersion of beliefs.

The purpose of this study is to strive to establish a link between return continuation and heterogeneous beliefs in S&P 500 survivor stocks to show that dispersion in analysts' forecasts contains information that can be used to predict future stock returns. The study replicates that of Verardo (2009) to some extent, as the dispersion of analyst forecasts is used as a measure of investors'

heterogeneous beliefs about a firm's fundamentals. The time period ranges from 2002 to 2015 and is divided into three sub-periods: pre-crisis, crisis and post-crisis periods. The purpose of the so-called sample split test is to illustrate the performance of both momentum and momentum-dispersion trading strategies in different market conditions. The results from portfolio analysis are further tested with multivariate time-series regressions featuring the Fama-French three-factor model to assess whether covariance with possible risk factors has an impact on momentum returns.

The contribution of this study to the existing literature is to provide a similar study to Verardo (2009) with newer data: the research methods are analogous to some extent, but the data is substantially different. The difference stems from the fact that the chosen time period features three distinct market states, where as the original study was conducted with only one time-period that did not feature any major momentum crashes. The sample period in this study is split into three separate periods to highlight the dependence of momentum returns on the state of the market, as well as its effect on the interdependence between return continuation and dispersion of beliefs. This analysis provides valuable insight on the varying, state-dependent properties of the relationship between return continuation and heterogeneous beliefs.

### 1.3. Research hypotheses

The hypotheses of this study are structured based on previous literature on the momentum trading strategy and its correlation with heterogeneous beliefs. According to previous research, the strategy should be more effective in the presence of belief heterogeneity regardless of the prevailing market situation. The first two hypotheses are designed according to this assumption:

**H1:** The momentum strategy is able to generate positive absolute return in all states of the market.

**H2:** Return autocorrelation in short-term cumulative individual stock returns is higher for stocks with a larger degree of heterogeneity of beliefs in all states of the market.

The subsequent hypotheses are more unique to this study and accentuate the novel contribution to the existing body of literature on the topic by focusing on the relationship between return continuation and heterogeneous beliefs across different states of the market. All hypotheses consider whether differences in beliefs exacerbate return continuation during specific sub-periods:

**H3:** Momentum profits are higher for stocks characterized by higher dispersion of analyst forecasts during the pre-crisis period.

**H4:** Momentum profits are higher for stocks characterized by higher dispersion of analyst forecasts during the crisis period.

**H5:** Momentum profits are higher for stocks characterized by higher dispersion of analyst forecasts during the post-crisis period.

#### 1.4. Structure of the thesis

The paper is organized as follows. The first chapter is an introduction to the topic and the thesis as a whole, containing information about the research subject in question, its main themes and relevant earlier research findings, as well as the motivation, purpose and intended contribution of this study. The research hypotheses are also introduced in the first chapter. Chapter two is the first part of the theory section of the thesis and introduces the concept of the Efficient Market Hypothesis (Fama 1970) as well as other cornerstones of the neoclassical finance paradigm. The third chapter focuses on the topic of heterogeneous beliefs. It begins with an introduction to the Bayesian theory of information updating and its modern approach in finance theory. The chapter also features a summary of the critique the theory has faced and the most significant known biases and violations related to it.

The fourth chapter sheds light on the behavioral implications of non-Bayesian information updating on the financial markets and relevant and widely documented behavioral biases concerning limited attention and sub-optimal learning. Chapter five discusses the price and earnings momentum anomaly, introducing relevant prior research findings and discussion between both

rational and behavioral explanations for the phenomenon. Special attention is focused on the relationship between heterogeneous beliefs and momentum.

Chapter six begins the empirical part of the thesis by introducing the data and methodologies used in the research. Chapter seven presents the results from the empirical research along with analysis and interpretation of these results as well as discussion on how they compare with relevant prior research findings. Finally, chapter eight concludes the thesis with a summary of the research findings and their implications.



## 2. THE EFFICIENT MARKET HYPOTHESIS

The neoclassicist finance paradigm seeks to understand financial markets by models that feature rational agents. In this context, rationality stands for two things. Firstly, in the face of new information, agents update their beliefs correctly according to Bayes' law. Secondly, based on those recently updated beliefs, agents make choices that are normatively acceptable according to the expected utility theorem. (Barberis & Thaler 2003: 1053.)

Modern finance is built around the idea of the Efficient Market Hypothesis (EMH), according to which investors are unable to earn above-average returns without accepting above-average risks. Introduced by Eugene Fama in 1965, the hypothesis argues that prices are driven into their correct value by competing investors seeking abnormal profits. The investors themselves are not viewed as rational, but the markets are. In its simplest form, the EMH states that security prices fully reflect all available information. In his seminal thesis of 1965, Fama defines the concept of an efficient market as follows:

"Independence of successive price changes is consistent with an "efficient" market, that is, a market where prices at every point in time represent best estimates of intrinsic values. This implies in turn that, when an intrinsic value changes, the actual price will adjust "instantaneously," where instantaneously means, among other things, that the actual price will initially overshoot the new intrinsic value as often as it will undershoot it."

Fama stated the sufficient conditions for capital market efficiency: First, there are no transaction costs in trading securities. Second, all available information is available to all market participants without a cost. Third, all agree on the implications of current information for the current price and distributions of future prices of each security. (Fama 1970.)

The Efficient Market Hypothesis was formed on the bases of earlier research findings, most notably Kendall's (1953) empirical studies on stock price behavior labeled "the random walk model". His studies were based on Bachelier's (1901) earlier mathematical findings that the movement of stock prices follow a random, Brownian motion. Kendall examines 22 UK stock and commodity price series and concludes "in series of prices which are observed at

fairly close intervals the random changes from one term to the next are so large as to swamp any systematic effect which may be present. The data behave almost like wandering series." This was the first time that the near-zero correlation of price changes was demonstrated.

Since the very first event studies, it has been empirically proven on numerous occasions that obtaining substantial profits can be made possible by early identification of new information. This is directly contradictory to the EMH. However, Jensen's (1968) analysis of 115 mutual funds over the period 1955-1964 concludes that even professionals were unable to "beat the market", since any informational advantage they have is consumed by costs and fees, thus leading to his conclusion that efficient markets prevail as long as abnormal profits do not persist ex post trading costs. Some incentive is still left for security analysis, since it is widely accepted that efficient markets do not rule out small abnormal returns. Minor market efficiencies have to be accepted for the concept of the hypothesis to work. (Dimson & Mussavian 1998: 3-5.)

## 2.1. Different forms of market efficiency

In his review Fama (1970) divides work on market efficiency into three categories based on the information processing capabilities of the stock market as reflected in the prices of securities. The first one concerns how well past returns predict future returns. In his later review *Efficient Capital Markets: II* (1991) Fama broadens the scope of the first form of market efficiency. Where weak-form tests only address the forecast power of past returns, the new category now more generally labeled *tests for return predictability* includes such variables as dividend yield and interest rates. The cross-sectional predictability of returns – tests of asset pricing models and anomalies discovered – are also addressed. Seasonalities in returns and claims of excessive volatility are also considered, since they are proved to have an effect on return predictability. According to the theory, when the markets are efficient in the weak form, abnormal profits cannot be obtained by applying technical analysis. On the other hand, it is theoretically possible to identify misvalued stocks by practicing fundamental analysis.

Under the semi-strong form of efficiency, prices will fully reflect all obviously available public information and adjust to any new information instantaneously and in an unbiased manner. Any overreactions and underreactions are to cancel each other out. Only individuals with access to monopolistic information could expect higher than average investment returns. (Fama 1970.) The tests were renamed as *event studies*, since the main focus is on such events as announcements of annual earnings and stock splits, and how quickly they have an effect on security prices, using the market model or capital asset pricing model as the benchmark. (Dimson & Mussavian 1998: 3-5.)

Finally, strong form tests concern whether some investors or groups with monopolistic access to information that is not reflected in market prices have an effect on security price formation. The tests were renamed in *Efficient Capital Markets: II* (Fama 1991) as *tests for private information*. In this theoretical context, if the strong form of market efficiency should prevail, no trader would be able to gain advantage on any sort of public or private information or research, thus making it impossible for investors to earn above-average returns without accepting above-average risks.

## 2.2. Debate surrounding the EMH

Empirical endeavor of testing the validity of the EMH began already in the early 1960s, even though the majority of the conducted studies seemed to further support the hypothesis, at least in the weak and semi-strong forms. However, there were a few important methodological issues pointed out. First, Kuhn (1970) granted a so-called “protective belt” for the prevailing paradigm in *The Structure of Scientific Revolutions*. An alternative paradigm will replace the prevailing paradigm only when mounting anomalies appear. This led the EMH dominating the academic scene in such proportions that any conflicting empirical studies were unlikely to become published. Additionally, it is nowadays being argued that the lacking of empirical evidence against the EMH in the 1960s was caused by a testing bias – market efficiency supported when the evidence is favorable and treated as part of the maintained hypothesis, insulated from falsification, when the evidence is unfavorable (Leroy 1989: 1614). (Lee & Yen 2008: 308-310.)

Also, challengers of the EMH have found possible evidence that improper statistical methods have been applied in researches supporting the theory. Taylor (1982) discovered that the empirical results support a price-trend hypothesis instead of the random walk hypothesis when autocorrelation coefficient  $r$  is replaced with the more powerful test statistic  $Q_k = n \cdot \sum r_i^2$ . He found that other test statistics refute random behavior due to not being designed to be powerful when there are trends. His conclusion applies to the conventional time-domain, frequency domain and non-parametric runs statistics. (Taylor 1982: 57.)

The fourth methodological issue is that empirical evidence against the validity of the hypothesis has been misinterpreted as support, most famously in Fama, Fisher, Jensen and Roll's (1969) study, where their evidence indicated a gradual, steady price response prior to split announcements. If the markets had indeed been semi-strong effective, share prices would have reacted to information promptly instead of gradually within a few months creating post-split excess returns as high as 30%. Conducting studies on seemingly nominal instead of truly nominal events makes it impossible to prove that price movements are inconsistent with the EMH. (Lee, Yen 2008: 310-311.)

Finally, it is to be noted that the definition of market efficiency has changed considerably since its establishment. However, it still remains the main source of controversy among the proponents of the two different schools of finance. Where as the advocates of the EMH focus on the absence of arbitrage opportunities as the main definition of efficient markets, proponents of behavioral finance tend to define it in a far more absolute manner, in terms of objectively correct prices that fully reflect all available information at all times (Shefrin 2005: 111).

### 2.3. Traditional asset pricing models

In textbooks with rational agents and frictionless markets the formation of stock prices is explained as follows: the current price of a share ( $P_0$ ) is derived from the expected dividend ( $D_1$ ) plus the future price ( $P_1$ ) discounted at the opportunity cost of capital ( $\rho$ ). Any fluctuation in prices is explained with both  $D_1$  and  $P_1$  having uncertain expectations, affected by any news that concerns

them. On top of that  $\rho$  also changes over time, because the compensation that investors require for risky assets is not constant. (De Bondt 1993: 356-357.)

In a rational asset valuation model, forecasts of  $D_1$  and  $P_1$  possibly contain random error, but it is never regarded as predictable. When investors decide to trade their stocks in an efficient market they always receive fair value, and thus the timing of the transaction seldom has any effect on it. (De Bondt 1993: 356-357.)

The traditional neoclassical assumptions about asset pricing are rationality based. In these models investors have fully rational preferences that conform to expected utility. The expected utility model is composed of a set of probability beliefs and a utility function. Rational investors utilize information efficiently and base their beliefs on the application of optimal statistical methods. In traditional asset pricing models, utility functions are concave functions of wealth levels, with concavity indicating the investors' risk aversion. (Shefrin 2005: 1-12.) Since traditional asset pricing theorists view investors free from bias in their use of information, observed pricing phenomena is attributed to fundamental risk or time varying risk aversion (Shefrin 2005: 365). The most well known of the general equilibrium models of the pricing of capital assets is mean-variance formulation originally developed by Sharpe (1964) and Treynor (1961).

Rational Expectations Equilibrium framework (REE) is used in the majority of asset pricing models. This means assumptions of individual rationality and beliefs that are consistent with the reality. To be able to figure out the correct distribution for the variables of interest, the agents need to have access to a sufficient amount of information and be able to process it accurately. (Barberis & Thaler 2003: 1053)

### 3. HETEROGENEOUS BELIEFS

Heterogeneous beliefs are the product of various sets of traders forming different expectations about the future prices of assets. There are both rational and behavioral theories striving to explain the phenomenon. Heterogeneous beliefs may derive from receiving heterogeneous information or receiving identical signals, but interpreting them in different ways (Banerjee, Kaniel & Kremer 2009). One of the major causes of heterogeneous beliefs is sub-optimal learning on the financial markets, which occurs when agents that face new information fail to update their beliefs according to the Bayesian principles described in this chapter.

#### 3.1. Bayesian information updating

Initially discovered by the 18th century British mathematician Thomas Bayes, the Bayes' law (alternatively Bayes' rule or Bayes' theorem) is a probability theory that describes the probability of an event based on related conditions. Also known as conditional probability or inverse probability, it provides a way to revise predictions in light of new or additional relevant evidence.

I. J. Savage created the modern approach to the Bayesian paradigm when he combined it with the Neumann Morgenstern utility maximization theory of 1947 into an axiomatized theory of decision-making under uncertainty. In his book *The Foundations of Statistics* (1954) he calls it "a highly idealized theory of the behavior of a 'rational' person with respect to decisions". (Slovic Lichtenstein 1970: 19-20.)

The basic principles of the Bayesian approach are that (1) probability is an informed judgment and (2) that the Bayes' theorem provides the optimal method for the revision of that judgment in the face of new information. Bayes' theorem is a normative model that provides a distribution of probabilities concerning a possible event. In economics, this distribution is combined with the theory of maximizing one's personal expected utility (Slovic & Lichtenstein 1970: 19-20).

Agents face constant uncertainty about parameters in the financial markets and strive to learn about these parameters by observing data and acquiring new information. Bayesian updating is the cornerstone of learning on the financial markets. It describes how rational agents update their beliefs in the face of new information, in other words learn about the assets and market. Learning is an important feature of the financial markets, since most parameters in financial models are subject to it. Learning is related to many financial market phenomena, such as volatility and predictability of asset returns, price anomalies and trading volume. (Pástor & Veronesi 2009: 1-5.)

In the neoclassical framework, agents utilize Bayesian techniques to formulate correct statistical judgments from the data at their disposal. When forming probability judgments, agents receive signals, which contain new information. They then consider it relative to their former beliefs, in other words the prior probability. After successfully implicating the new evidence into their prior belief, they have then formed the posterior probability. (Shefrin 2005: 15-32.)

According to the Bayes law,  $P(A|E)$  is derived from  $P(D|F)$  and the ratio  $P(F)$  divided by  $P(D)$ . The equation is designed as follows (Shefrin 2005: 15-32):

$$(1) \quad P(A|E) = \frac{P(A)P(E|A)}{P(E)}$$

$$= \frac{P(A)P(E|A)}{P(A)P(E|A) + P(A^c)P(E|A^c)}$$

$P(A|E)$  = Conditional probability of an event

$P(A)$  = Base rate information

$P(E)$  = Signal

Updating process in the financial markets features also the element of uncertainty, which can be described with variance. An agent's prior beliefs about a figurative parameter  $\theta$  are always normally distributed with mean  $\theta_0$  and variance  $\sigma_0^2$ . In line with the Bayes' law, after observing a T number of signals the agent's posterior beliefs are now normally distributed with mean  $\theta_T$

and variance  $\sigma_T^2$ . The revised mean  $\theta_T$  is the precision-weighted average of the prior mean and the signal. The revised variance  $\sigma_T^2$  becomes smaller with every new signal, because learning diminishes uncertainty. (Pástor & Veronesi 2009: 1-2.)

### 3.1.1. Signals

Signals are any new pieces of information, spread through for example earnings announcements, the media and social circles. The salience of signals is a measure of their relative strength. Salient signals enhance the processing of information and perceptual readiness. Investors are prone to buying shares that have previously caught their attention, due to prior performance for example, because salient information facilitates recall. The weight of signals is measured by their statistical significance in relation to prior information. (Hirshleifer 2001: 19-20.)

In the context of Bayesian information updating, the magnitude of price response to unanticipated events is due to the amount of novel information and the relative precision of market participants' prior and posterior expectations. Most classic pricing models are also based on the Bayesian assumption of the strength of the price impact of unanticipated news being relative to the precision of the signals presented in the news. (Hautsch & Hess 2004: 205-206.)

### 3.1.2. Critique

The Bayesian method of learning has long been regarded as an insufficient measure of how agents actually respond to new information and behave on financial markets. In addition to the method's lack of predictive power, researchers have found false and incomplete assumptions about how the Bayes law can be applied in real life.

Firstly, it has been noted that individual agents do not revise their beliefs in a uniform way. Secondly, there are a few biases that result from several agents systematically revising their beliefs in ways that are inconsistent with the model. For example, Kahneman and Tversky (1982) found that individuals often overreact to new signals and ignore prior data, as well as make



predictions according to what they call a simple matching rule: "The predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions". They call it the representativeness heuristic. They also state that overreaction is further strengthened due to the fact that people do not moderate extreme predictions by predictability, thus violating a statistical principal. There is also evidence on finance professionals, such as analysts and forecasters, being susceptible to the overreaction bias. (De Bondt and Thaler 1985: 793.)

### 3.2. Updating biases

Bayesian updating is the sole rational method of information updating and learning on the financial markets. It is theoretically sound, but there are deviations from optimal behavior when tested with individuals. Kandel and Pearson (1995) provide empirical evidence to prove false the assumption that agents interpret information identically. Their findings of abnormal volumes associated with interim earnings announcements, unrelated to the degree of price changes, are inconsistent with most existing models in which agents share identical interpretation of signals.

Researchers agree that suboptimal learning and information updating emerge from situations where individuals face incongruent and unfamiliar data, especially since most individuals have an aversion towards ambiguity. The subject and its economic consequences have been studied ever since the times of John Maynard Keynes, and have been linked to several market phenomena, such as investor disagreement, excessive optimism and the long-term overpricing of small-cap stocks. (De Bondt, Mayoral and Vallelado 2013: 108.)

Even sources of information can be biased, due to for example public excitement or conflicts of interest. Individual investors are prone to several systematic errors when it comes to updating new information. Inadequate updating of new information and failing to adjust for biased signal provision create mistakes in trading which cumulate to mispricing. A few major biases have been identified and scientifically proven. (Hirshleifer 2014: 20.)

### 3.2.1. Extrapolation bias

Extrapolation bias is also known as trend following and it stems from overweighting recent events relative to more distant events. It is closely linked to both representativeness and conservatism explained in the behavioral finance section of this thesis. In regards to financial markets, extrapolation bias causes people to derive conclusions from past price performance in a way that shows insufficient regression to the mean. (Shefrin 2005: 50-54.)

De Bondt (1993) examines how people form forecasts of future stock prices based on 48-month period stock price charts. He creates an incentivized study with students familiar with the efficient market hypothesis. The results indicate two important findings. Firstly, most subjects derive forecasts from trends or series that they perceive in the stock price data. Secondly, although most of the subjects prove to be betting on trends in varying levels, a notable proportion of participants predict price reversals. De Bondt labels these subjects "contrarians". This finding proves that people indeed do have heterogeneous predictions.

### 3.2.2. Selection bias

Investors' systematic tendency to create insufficiently diversified portfolios is well documented in financial literature. Blume, Crockett and Friend (1974) study a sample of over 17,000 investors to discover that merely 10.7 percent managed to create a portfolio featuring over 10 shares, whilst a staggering 50 percent held no more than two stocks. The empirical findings go against the proposed rate in several studies, in which over 30 stocks are required for a well-diversified portfolio (Statman 1987).

The main phenomenon concerning the selection of assets is known as *familiarity bias*, which describes the tendency of investors to discriminate against unfamiliar companies and markets. Individuals are prone to favor familiar assets because they appear to be easier to value correctly. For example, a study by Benarzi and Thaler (1997) shows that people invest an excessive amount of their retirement savings into the shares of the companies where they work. The

so-called habit of placing all of one's eggs in one basket is a severe case of failure of diversification, the basis of portfolio theory.

*Home bias* is a similar case, in which case investors fail to diversify geographically (De Bondt *et al.* 2013). According to Grinblatt, Keloharju and Linnainmaa (2011), people with less financial literacy and low cognitive abilities are especially prone to exhibit this bias. On the other hand, the tendency to favor domestic assets might also be completely rational and arise from practical issues, such as legal restrictions and transactions costs, associated with trading foreign assets.

The selection bias is closely linked to *belief perseverance*, which describes the tendency to hold on to one's opinion too strongly and for too long. Thaler (2005: 15) discovered that people disregard any information that disclaims their prior beliefs and try to avoid cognitive dissonance by not seeking contradictory evidence. When the contradictory evidence is overwhelming, most people slowly adapt to it while some prefer to disregard it completely.

### 3.2.3. Encoding bias

The bias connected to encoding of information is also known as *the information quality and ambiguity bias*. Both of these qualities are linked to situations that involve uncertain outcomes. Arnold, Fische and North (2010) study different reactions to soft (non-numerical) and hard (numerical) data in the context of initial public offerings of equity. They find out that ambiguous prospectuses cause further underpricing, which stems from doubt and divergence of opinion due to the information being more difficult to interpret. In some cases the underpricing effect may take several years to dissolve.

Unpredictability is a ubiquitous feature of financial markets, making ambiguity a key factor in all financial decision making. For example, various levels of ambiguity are always present in situations where the lack of information hinders the assessment of probabilities related to different future outcomes. The ever-increasing availability of information can also create ambiguity, especially if the information quality varies a lot. This is because people have limited information processing capacities and sometimes lack the ability to assess the validity and weight of each piece of information. (Shefrin 2002: 372-373.)

People have different intrinsic levels of ambiguity tolerance, but most exhibit aversion towards it. Ambiguity intolerance is strongly related to each individual's cognitive profile and often results in various decision-making paradoxes. Changes in confidence under ambiguity are found to be non-equivalent to changes in estimated risk in Bayesian learning. Ambiguity-intolerant investors react excessively to bad news, inducing skewness in returns (Epstein and Schneider 2008: 38).

In the context of Bayesian learning, it has been found in numerous studies that the quality of information is to be measured by its relative precision. Kim and Verrechia (1991) find significant differences in market reactions to announcements of known precision with the response to announcements of either unanticipated or ambiguous quality. This notion suggests that individual agents' market reactions are to a large extent driven by their prior beliefs and the way they utilize new information to update them.

## 4. BEHAVIORAL IMPLICATIONS

After years of financial research, it has become disconcertingly clear that the predictions of the simple traditional framework are not confirmed in the empirical data. In response to this, behavioral finance emerged as a new approach to financial markets. Since empirical irregularities are difficult to explain with the fully rational Bayesian learning model, a number of alternate models are represented in literature. The main argument of the advocates of behavioral finance is that traditional models should be altered to better reflect actual financial phenomena by using agents that are not fully rational. Their paradigm is based on two building blocks: (1) human cognitive and emotional psychology, which causes deviations from full rationality and (2) limits to arbitrage, which argues that dislocations caused by imperfectly rational traders are difficult to undo even for rational traders. (Barberis, Thaler 2003: 1052.)

Individual rationality consists of two assumptions. Using models in which some agents are not completely rational means testing hypotheses with agents that fail to update their beliefs correctly (in violation of the Bayes law) or make choices that are incompatible with the expected utility theorem, or both (Barberis & Thaler 2003: 1053). Since people have limited attention and information processing abilities, many relevant signals and features of the decision environment go unnoticed. This leads to several documented effects on market efficiency. (Hirshleifer 2014: 19.) This section will focus on two major behavioral finance phenomena related to suboptimal learning on the financial markets, representativeness and conservatism.

### 4.1. Overreaction and underreaction

De Bondt and Thaler (1985, 1987) were the first to discover stock price deviations from fundamental value due to investors extrapolating past performance. They found that investors tend to become excessively optimistic about past winners and in turn excessively pessimistic about past losers, resulting in misvaluation of stocks. Non-Bayesian learning has distinctive effects on asset prices. For example, excessive reliance on recent signals causes traders to ignore prior value-relevant evidence, which leads to overreaction to news. This overreaction is directly transferred into asset prices, causing short-

term overvaluation and subsequently long-run correction (Odean 1998: 1914). This chain of events also implies negative return autocorrelations. (Hirshleifer 2014: 12).

Lakonishok, Shleifer and Vishny (1994) propose that investors form expectations about stocks by naively extrapolating past performance. This means that they measure past performance with growth in sales and earnings and estimate future performance with stock-related ratios like price-to-earnings and book-to-market. This leads to stocks with strong past performance and estimated future performance become overvalued, and stocks that have shown worse performance in the past become undervalued. Shefrin and Statman (1998) test the hypothesis of naïve extrapolation, and find that investors tend to associate higher expected returns with better past performance measured by strong sales and earnings growth.

Fama (1998a, 1999b) questions the validity of these behavioral interpretations of over- and underreaction. He states that if the overreaction hypothesis is formulated to hold regardless of horizon, it is not backed by the data. He also argues that due to random variation, over- and underreaction of stock prices are approximately equally common and thus cancel each other out, evidently not resulting in any systematic deviation from efficient means of expected returns. He concludes that this evidence clearly points out that the behavioral hypotheses pose no threat to the EMH and rejects the notion of systematic price anomalies. Shefrin (2002: 865-89) in turn argues that Fama's notions might hold, if stocks displayed overreaction and underreaction in similar timeframes. But as the empirical evidence from numerous studies point out, stocks tend to systematically display short-term underreaction and long-term overreaction.

Investors' limited attention causes both over- and underreactions. Theories entail that overlooked good news are followed by positive abnormal returns and similarly overlooked bad news are followed by negative abnormal returns. The incidents often go hand in hand, in cases such as overreaction to salient news and underreaction to less salient news, as well as overreaction to accruals and underreaction to earnings components. (Hirshleifer 2014: 14-16.)

#### 4.1.1 Conservatism

Conservatism is the main behavioral bias related to non-Bayesian learning. It is the tendency to underweight new information relative to prior information, in which case base-rates are over-emphasized whilst new evidence is overlooked (Shefrin 2002: 19-20). The conservatism bias is also known as anchoring and adjustment, the failure to revise opinions when estimating probabilities in the face of new evidence. It has also been proven that financial professionals, such as analysts, are not immune to the human tendency to hold on to one's opinion. Analysts seem to anchor to their initial estimation and either conservatively incorporate new contradictory evidence to it, or fail to adjust efficiently. The same process concerns analysts' reactions to earnings announcements, when they also fail to sufficiently revise their initial opinions. (Shefrin 2002: 35-37.)

Basu (1997) uses stock returns to test how news from earnings announcements is incorporated in stock prices. He finds that investors react more efficiently to bad news. He also finds that conservatism and sensitivity of earnings are positively correlated, both increasing over time.

#### 4.1.2. Representativeness

Representativeness bias refers to the manner in which individuals rely heavily on stereotypes and past experiences when making judgments about the future under uncertainty. In finance, this causes investors to evaluate prospective investments based on factors like media coverage, company characteristics and recent returns. Representativeness is a behavioral bias of special importance, because it has such a significant effect on financial forecasting. (Shefrin 2005: 15-16.)

Kahneman and Tversky (1974) define representativeness bias as such that when facing uncertainty people make judgments on the basis of (1) the degree to which it is similar in essential properties to its parent population and (2) reflects the salient features of the process by which it is generated. They created a hypothesis that more representative events will be deemed more probable. Shefrin (2005: 38) concludes that when individuals rely on representativeness when making probability judgments they systematically violate the Bayes law, resulting in predictions that are insufficiently regressive to the mean.

According to the Bayes' law, the probability of two separate events D and F can be formed as follows:  $P(F|D) = P(D|F) P(F) / P(D)$ . The insensitivity to prior probability of outcomes is also known as base rate neglect. It occurs when individuals overweight the conditional probability  $P(D|F)$  at the expense of the prior probability  $P(F)$ . In more simple terms, individuals tend to underweight initial information in the face of new data (Shefrin 2002: 26-32). Individuals also have a habit of relying excessively on the strength of information signals thus overlooking their weight, also known as statistical significance. (Hirshleifer 2001: 14-15.)

According to the Bayes' law, prior probabilities have an important stance when determining an event's posterior probabilities. The discounting of the priors can be seen as evidence of human irrationality, or alternatively a rational reaction to perceived differences in the trustworthiness of base rates (Welsh 2007: 704).

#### 4.2. Cognitive models

Although investor behavior is defined in literature by rationality, their real-life decision-making seldom meets those high standards. Henceforth, what drives the financial markets is more often about sentiment and how the numerous market participants perceive news, rather than actual economic facts and phenomena. (De Bondt *et al.* 2013: 109.)

Cognitive models were created by researchers to simulate the decision-making process more realistically. These models feature specified stages of judgment and choice and strive to identify what drives them. They can be described as structured representations of behavioral finance studies and findings. (De Bondt *et al.* 2013.)

The model of Ozcan and Overby (2008) is divided into two parts, selection and encoding of data, and it is used to study the effect of partner diversity on stock market reactions to corporate alliance announcements. The selection part focuses on the level of similarity between the alliance partners. Extreme levels, regardless of direction, cause increased trading and pronounced price movements compared to more moderate levels. The encoding part of the model is centered on information clarity in terms of information diversity. Average



diversity is connected to ambiguity, which can produce either status quo bias or negative sentiment, or both. Extreme levels of diversity are regarded as distinct signals and linked to investor overconfidence, resulting in a U-shaped relationship between diversity and excess returns for firms with less and inverted U-shape for firms with more analyst coverage.

### 4.3. Implications on market efficiency

Everyday decisions made by investors are affected by several different factors, such as feelings, rationality, social interaction and cognitive limitations. The products of these factors are then turned into individual actions, which cumulate on the market and are reflected in asset prices. Research on behavioral finance has identified many driving factors behind financial decisions and biases that ensue from non-rational behavior. The empirical evidence presented is robust, but there is still controversy regarding how these individual level errors affect market efficiency on an aggregate level. (De Bondt *et al.* 2013: 99-100.)

Naturally, the extent on the effect of biases on market efficiency depends on which notion of market efficiency is used – are markets regarded as efficient when there are no opportunities for riskless arbitrage or does it require prices to reflect fundamental values and all available information (Shefrin 2005: 112). Even some former advocates of the EMH have now admitted that investors often do seem to make large errors that are reflected in prices. Furthermore, the vast empirical evidence on persistent price anomalies seem to prove the fact that markets are inarguably subject to systematic mispricing. (Daniel, Hirshleifer and Teoh 2002: 140-141.)

#### 4.3.1. Aggregation of individual biases

There are two conditions that have to apply for the markets to be efficient and both of them involve the distribution of individual level errors committed by investors. Firstly, errors committed by investors have to be non-systematic and result in a zero-value mean error. This implies that the market efficiently aggregates the errors. Secondly, the error-wealth covariance is required to be zero as well. If initial wealth is not evenly distributed, the magnitude of

individual level errors has to compensate for the differences in wealth effect for the errors to efficiently cancel each other out. These conditions are hypothetical at best, since empirical evidence shows that errors are in fact nonsystematic and the error-wealth covariance does not remain zero at all times. In fact, evidence shows that since deviations from these conditions are systematic, their aggregation on market level reinforces them in a cumulative manner instead of efficiently cancelling them. (Shefrin 2005: 115-122.)

Rational investors, also known as “smart money”, are a central part of efficient markets, because they are the ones driving prices back to fundamental value by profiting on arbitrage opportunities created by irrational traders. One factor hindering market efficiency is limits to arbitrage, which combines business risk, noise risk and several costs, such as transaction costs as well as both financial and cognitive costs related to information (De Bondt et al 2013: 102). Noise risk describes a situation where a rational arbitrageur cannot know how long and how severely prices will be dislocated from fundamental values. Wealth effect is a key part of this scenario, because it gives traders and their opinions about prices more weight. (Shleifer 2000: 12.)

Miller (1977) proposed a theory in which pessimistic investors are restricted by short sales constraints, which leads to prices reflecting a more optimistic valuation at all times. In his model, optimists suffer losses for holding the stock because their expectation on the value is inflated. Other price-optimism models have been presented later by for example Morris (1996) and Chen, Hong and Stein (2001). These models present the idea that a higher spread stems from stronger disagreement, and causes the price drift further away from fundamental value, eventually leading to lower returns in the future.

## 5. PRICE AND EARNINGS MOMENTUM EFFECT

Momentum anomaly is also known as return continuation or positive short-lag autocorrelation, and it describes the tendency of past performance to continue in the short run and revert in the long run. Momentum trading strategies continue to be profitable today, even though the phenomenon was discovered by academics some 50 years ago. These strategies are based on holding a so-called winner-portfolio consisting of stocks that have performed well during a certain time period that lasts less than one year and a loser-portfolio with stocks that have performed badly. Jegadeesh (1990) and Jegadeesh and Titman (1993) show that holding the winner portfolio generates excess returns for the next three to twelve months. If the holding period is longer than 12 months, the loser-portfolio is able to generate excess returns in turn. The authors conducted the study again in 2001 with more recent data and came up with similar results. Since its initial discovery, the medium-term momentum pattern has been documented across different markets and asset classes.

Price and earnings momentum effect was discovered when researchers examined more closely the driving forces behind the excess returns generated by certain types of value strategies. The initial belief was that the higher yields were due to the strategies bearing more fundamental risk, but it was found that they were able to exploit the cumulative effect of non-rational behavior by traders. (Lakoshnishok, Shleifer and Vishny 1994: 1541.)

### 5.1. Rational explanations for the momentum anomaly

The momentum anomaly has yet to be explained with purely rational and risk-based models. For example, the three-factor model by Fama and French (1996) cannot explain it, even though it can be used to explain several other anomalies. Rational explanations for the reversal effect are most often related to risk and limits to arbitrage.

Conrad and Kaul (1998) attribute profitable momentum strategies to cross-sectional dispersion in stock returns, which is why they also work in an efficient market setting. Explanations involving limits to arbitrage, such as trading costs

eliminating abnormal profits, are controversial because there are several studies with contradictory findings.

Some studies explain momentum profits with liquidity risk. Pastor and Stambaugh (2003) establish the link between sensitivity to liquidity fluctuations and above-average future returns. Additionally Sadka (2006) shows that momentum strategy performance is linked to liquidity shocks. Positive liquidity shocks induce better performance and vice versa. He attributes part of momentum profits to information quality and as compensation to the unexpected variations in the ratio of noise traders to informed traders.

## 5.2. Behavioral explanations for the momentum anomaly

The purely rational approach of the basic paradigm of asset pricing is being superseded by a more expansive approach based on the psychology of investors. Behavioral finance and traditional finance have very different views about asset pricing in general and especially the relationship between risk and return. In the behavioral approach, expected returns are determined by both risk and misvaluation. (Hirshleifer 2001: 2.)

There exists an abundance of behavioral explanations for the excess momentum profits. Explanations involving both under and overreaction are the most robust ones till date. For example, Barberis, Shleifer and Vishny (1998) demonstrate that investors initially underreact to new information, leading to short-term return continuation in prices. They subsequently overcorrect the initial mispricing, inducing reversals on the long-term. The authors conclude that investor sentiment is the main factor behind overreaction to new information.

The study by Daniel, Hirshleifer & Subrahmanyam (1998) implies that investors give excessive weight to private information signals, in other words overreact to them, and too little weight to public information signals thus underreacting to them. The authors demonstrate how short-run positive autocorrelations are consistent with long-run negative autocorrelations, because positive return autocorrelation stems from continuous overreaction.

Jiang and Zhang (2005) include the element of information quality in their model and conclude that the momentum effect is most prevalent for firms that have notable information uncertainty. Hong, Lim and Stein (1999) propose that relevant information is scattered between numerous individuals and cognitive limitations prevent investors from interpreting what others know using market prices. This causes information to diffuse slowly, resulting in momentum. In their study the interaction between two different types of traders is examined. The first type, labeled as “news-watchers”, only condition on signals about future cash flows. Their information is gradually incorporated into prices without causing any deviations from true value. The second type, labeled as naïve “momentum traders”, condition solely on a partial price history and whose trading causes price trends to initially overshoot and gradually adjust with time. The momentum effect is most prevalent for low-attention stocks, such as small stocks and stocks with less analyst coverage. (Hong & Stein 1999; Hong *et al.* 2000.)

### 5.3. Heterogeneous beliefs and momentum

Empirical studies provide evidence that there is a causal relationship between heterogeneous beliefs or heterogeneous information and phenomena such as price drifts and return continuation. The aggregate effect of heterogeneous beliefs on market efficiency has been studied and proven by for example by Williams (1977) and Goetzmann and Massa (2001). The results have shown that greater disagreement among investors is connected to prices being more strongly deviated from fundamental value (Verardo 2009: 819). A brief cross-section review on asset pricing models featuring agents with heterogeneous beliefs is provided in this chapter.

Asset pricing models based on rational expectations explain differences of opinion with private information. Alternative models, which often relax the assumption of full rationality, strive to explain price anomalies with more extensive views on the cause and effect of investor disagreement. One explanation suggests that the presence of noise dilutes signals of price related information and therefore causes a slower drift towards fundamental value. Noise can be any news, which are widespread and cause sentiment regardless of the fact that the signals are not related to fundamental prices. A more

intricate explanation takes into account the fact that in a dynamic rational expectations equilibrium (REE) model, in addition to their own forecasts, investors may need to forecast the forecasts of others. (Banerjee, Kaniel and Kremer 2009: 3708-3710.)

Milton Harris and Artur Raviv (1993) model trading in speculative markets with agents that have differences of opinion. The authors' motivation is to better understand how financial markets operate by examining the effect on the previously documented irregularities concerning the interplay between volume and price and their time-series properties. The authors use volume to measure market response to public announcements and focus on speculative trading as the most important factor behind activity surges. They presume that speculation arises from traders' disagreement concerning new information and the overall performance of the asset. They disregard information asymmetries as the primary source of disagreement and presume that it stems from individual level differences in interpreting data. The agents are thought to have identical prior beliefs about the returns of an asset and access to the same information, but update their beliefs according to their own model. Thus instead of using the rational Bayes model for updating beliefs, each individual assesses the relative importance of new information utilizing his or her own likelihood function.

The model has two basic functions both related to dispersion of beliefs. Firstly, individuals are more sensitive to information when their prior beliefs are diffuse. Secondly, speculative trading stems from the dispersion of traders' beliefs. With their model, the authors discover positive correlation between absolute price changes and volume. They also find that absolute price changes in the mean forecast payoff and volume are positively related and consecutive price changes show negative serial correlation. Their consecutive finding is that volume is positively autocorrelated and exhibits surges when the market opens after a period of being closed. With these results the authors are able to obtain underreaction to information that is contradictory to earlier information. It has been since established in numerous papers (for example Lee and Swaminathan 2000) that the momentum effect is more pervasive for stocks with higher trading volume.

The work of Allen, Morris and Shin (2006) build on the famous metaphor by Keynes (1936) in which he compares asset price generation on the financial markets to a beauty contest: "We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be". The metaphor implies that buying a stock is heavily motivated by the assumption that other investors find the stock attractive. High order beliefs, comprising of a circle of individuals' beliefs about other individuals' beliefs, are not a feature of classic asset pricing models. The purpose of the paper is to examine the role of high-order expectations in an asset-pricing context with a REE model of financial markets. The paper also builds on the work of Townsend (1983), who argues that agents forming beliefs about each other's beliefs cause serial correlation in unconditional forecast errors in a dynamic REE model.

Allen et al. (2006) examine this effect of slow aggregation of beliefs on the law of iterated expectations and find that it causes price drifts, such as post-earnings announcement drift and momentum. In their model, short-lived traders have access to private information, but underweight the information if they believe that it will not be reflected in asset prices. Forecasting the next period average forecast pushes prices further away from fundamentals, because too much weight is given to common public information, which coordinates the average expectations.

Banerjee, Kaniel and Kremer (2009) examine further the causal relationship between price drifts and the slow aggregation of heterogeneous beliefs and present contradictory evidence to that presented by Allen et al. (2006) and others. With their model, they find that a disagreement in high order beliefs is a necessary pre-condition for heterogeneous beliefs to cause price drifts. The authors are able to show theoretically that heterogeneous opinions paired with uncertainty about other traders' opinions create price drift in a dynamic setting. The authors argue that rational expectations equilibrium cannot feature price drift, because REE models always feature agents with access to information about asset prices. They also argue that the common prior assumption as well as the assumption that heterogeneous priors are common knowledge should both be relaxed. They advocate a difference of opinion (DO) model as a more potent substitute for the REE model. With their model, the authors were able to obtain momentum caused by agents ignoring the information contained in the

equilibrium price, because they were oblivious to the information of other agents.

Pástor and Veronesi (2003) adopt a different approach in explaining stock valuation related phenomena. In their model, they use the well-known Gordon growth formula with the assumption that it only works when the dividend growth is constant and known. They argue that stock prices are often inflated due to uncertainty regarding the growth factor. The authors use the market-to-book ratio (M/B) as an example subject to the uncertainty effect. They state that uncertainty about a company's future book value increases the ratio. The model also predicts that the M/B declines with time, because gaining more information about a company and its prospects reduces the uncertainty factor. As proof of this phenomenon they present evidence that the median M/B is significantly larger for younger firms than older firms. In a further study, Pástor and Veronesi (2006) extend their model to prove that extreme price fluctuations, also known as bubbles, are not due to market irrationality as often stated, but consistent with a rational general equilibrium model of learning. Interestingly the authors are able to confirm these theories using a model that features rational agents that update their beliefs according to the Bayes' law.

Verardo (2009) provides a link between investor disagreement and return continuation in a portfolio setting and a predictive regression framework using a cross-section of U.S. stock returns. In her model, heterogeneity of beliefs concerning a firm's fundamentals is measured by the rate of diffusion in earnings forecasts provided by financial analysts. The most significant finding demonstrates how portfolios with higher rates of heterogeneity generate significantly larger momentum returns. Verardo was the first to examine the empirical link between investor disagreements and return continuation. Her study adds to the body of theoretical models that have been able to establish a positive connection between heterogeneity of beliefs and price drift. The results are obtained with predictive cross-sectional regressions while controlling for commonly known factors behind the momentum effect, such as a stock's visibility, pace of information diffusion, ambiguity regarding fundamentals, information precision and volatility. The results can be regarded as robust, since the author is able to prove that short-sales constraints do not have an effect on them and that they cannot be explained by arbitrage risk.



Furthermore, Zhang (2006) examines the effect of information uncertainty on short-term stock price continuation. He discovers that greater levels of ambiguity in public signals cause increased stock price drift, supporting his hypothesis that underreaction to information is more prevalent in the face of new data that is difficult to intercept.

Ottaviani and Sorensen (2014) take an alternative approach to explaining anomalous price reactions to information. Instead of focusing on investors' differences in updating their beliefs in the face of new information, in other words updating their posterior beliefs, they focus on the aggregating effect of heterogeneous prior beliefs. They strive to achieve realistic pricing patterns and explain underreaction to information with a novel theoretical mechanism that features a binary market with traders that have heterogeneous beliefs and are subject to wealth effects. In their model, Ottaviani and Sorensen assume that all traders have concordant beliefs, which is to say that they interpret information rationally and identically. Any discrepancies in the traders' posterior beliefs are thus caused by differences in prior beliefs. The authors state that the reason why prices are not self-correlating and act as a posterior belief in the face of new information is because instead of acting as a constant "market prior" prices reflect the cumulative beliefs of traders and are subject to the marginal trader who moves against the information because of the wealth effect. Due to wealth constraints, demand for the outcome deemed more probable will decrease and demand for the outcome deemed less likely will increase due to changes in prices if traders are not willing to adjust their beliefs accordingly. The redistribution effect is stronger when traders' absolute risk aversion decreases with wealth. This is how heterogeneity in priors weakens the impact of information on the price, causing initial underreaction to news. Wealth effects thus assign an increased weight to traders with contrary beliefs to the new information, further strengthening the underreaction effect.

The model is able to show both short-term momentum and long-term reversal in both static and dynamic settings even in the absence of traders with suboptimal learning mechanisms. The traders in the model are all rational learners, but subject to different initial beliefs and wealth effects. The results put the role of suboptimal learning in price reactions in a questionable light, although the origin of the traders' heterogeneous prior beliefs seems somewhat artificial if they all share a similar information updating process. The model

omits several important features of actual financial markets, such as the occurrence of speculative retrade, and is also limited to reactions to public information and thus not directly applicable to a reality where traders have access to private information.

## 6. DATA AND METHODOLOGY

In this chapter, the data and methods of the study are presented in detail. The first part of the chapter is focused on describing the data used in this thesis, shedding light on the sources of the data, describing the databases and indices as well as forming the different sample sub-periods used for testing the data. Descriptive statistics are also presented in the first part. The second section is dedicated to introducing and describing in detail the various methods used for portfolio analyses as well as the regression analysis, which finalizes the empirical part of the study.

### 6.1. Data description

The study is conducted using data from S&P 500 “survivor stocks”, in other words stocks from the index selection in the year 2000 that continue to be featured in 2016. This, combined with other selection criteria, narrows the selection down to altogether 200 stocks. The use of survivor stocks ensures that all time periods feature the same stocks and are therefore fit for comparison. The S&P 500 Index is widely used in financial literature and often regarded as the most applicable single gauge of large-cap US equities and a suitable proxy for the market. The index represents almost 80% of available market capitalization while benchmarking for over 7.8 trillion US dollars. (Standard & Poor’s 2017.)

The main variable, dispersion (DISP), is the coefficient of variation of analyst forecasts of earnings for the end of the current or the next fiscal year, defined as the standard deviation of forecasts scaled by the absolute value of the mean (Verardo 2009). The dispersion variable represents investors’ heterogeneity of beliefs related to company fundamentals. In prior research, forecasts of earnings for the end of the current fiscal year are used, but in this study forecasts for the next fiscal year are used due to limitations in the data. Monthly logarithmic returns are calculated from stock price changes to allow testing for momentum profits. Stock-related and firm-level data include standard deviation, market value, book-to-market, turnover volume, volatility and beta. Observations with a zero mean forecast of earnings are discarded, but observations with negative mean forecast of earnings are included. Each firm is also required to have at

least two analyst forecasts at each point in time throughout the entire sample period.

The sample period consists of monthly data and covers fourteen years from 2002 to 2015. The period includes one major momentum crash, the subprime crisis, which began during the later half of 2007. The sample is split for testing in order to capture the effects of the varying market conditions. The sample period is broken down into three separate periods according to the state of the market at the time. The pre-crisis period spans from January 2002 to July 2007. The purpose of the pre-crisis period is to proxy for a “normal”, crisis-free state of the financial markets. Subsequently, the crisis period begins around the Quant Meltdown in August 2007 and ends with the depression of the stock market in March 2009. The post-crisis period is set from April 2009 to the end of the year 2015. Years 2000 and 2001 are left out due to the dot.com boom induced momentum crash, which would likely have a negative impact on the results for the pre-crisis period. The year 2016 is also omitted from the study due to data restrictions.

The stock related data is obtained from Datastream. Corresponding information on the monthly risk-free rate of interest and excess return on the market is obtained from the Kenneth R. French online data library, as well as the monthly Fama-French Three Factor Model values. The  $R_m - R_f$  factor, also known as the market premium, is formed of stocks incorporated in the U.S. and listed on NYSE, AMEX, and NASDAQ indices. The Fama-French risk factors are constructed by using six value-weighted portfolios formed on size and book-to-market. SMB (Small Minus Big) is formed by subtracting the average return of the three big portfolios from the average return of the three small portfolios. HML (High Minus Low) is calculated by subtracting the average returns of the two growth portfolios from the average returns of the two value portfolios. (French 2017.)

The data has been prepared using MS Office Excel. Subsequently Matlab was used for conducting the portfolio analysis. Finally the results have been tested using Eviews.

## 6.1.1. Descriptive statistics

Table 1 presents descriptive statistics for the data sample in the first sub-period, the pre-crisis period, ranging from the beginning of 2002 to July 2007. The mean and median dispersions are the lowest of the sub-samples, at 4.45 and 1.88 respectively. The average number of analyst coverage ranges from two to 45 forecasts per month. Mean consensus, the monthly mean forecast of earnings per share, at 2.38 here is the lowest of all sub-samples, but still stays relatively stable throughout the entire time period. Average return is positive but relatively modest at 0.67 percent per month.

**Table 1.** Descriptive statistics of the pre-crisis period. DISP is the average ratio between the standard deviation of analyst forecasts of earnings and the absolute value of the mean of the forecasts (coefficient of variation). Consensus is the monthly mean forecast of earnings per share. AN COV is the average number of monthly forecasts per share. VOL is average volatility and RET is the average monthly return.

	<b>DISP</b>	<b>Consensus</b>	<b>AN_COV</b>	<b>VOL</b>	<b>RET</b>
Mean	4.45	2.38	16.92	24.73	0.67
Median	1.88	1.97	16.00	23.24	0.87
Maximum	2,600.00	45.02	45.00	63.89	90.34
Minimum	0.00	-3.8	2.00	10.92	-102.08
Std. Dev.	29.32	2.94	6.85	7.75	7.91
Skewness	61.10	9.69	0.59	1.49	-0.99
Kurtosis	4,890.06	122.92	3.36	6.28	18.67
Observations	13,333	13,333	13,333	13,333	13,333

Table 2 presents the descriptive statistics for the crisis period ranging from August 2007 to March 2009. Interestingly, while the mean and median dispersion are both higher than during the pre-crisis period, the maximum dispersion is notably lower. This suggests that the dispersion is not driven by individual observations but rather increased amount of forecast dispersion in the sub-sample as a whole. The spread between maximum and minimum consensus is also at its highest, whilst the mean consensus remains relatively stable. Analyst coverage is at its lowest, averaging at 15.3 monthly forecasts per

company. Average volatility remains stable at 24.25, whilst the average monthly return takes a dive at -3.17 percent per month.

**Table 2.** Descriptive statistics of the crisis period. DISP is the average ratio between the standard deviation of analyst forecasts of earnings and the absolute value of the mean of the forecasts (coefficient of variation). Consensus is the monthly mean forecast of earnings per share. AN COV is the average number of monthly forecasts per share. VOL is average volatility and RET is the average monthly return.

	<b>DISP</b>	<b>Consensus</b>	<b>AN_COV</b>	<b>VOL</b>	<b>RET</b>
Mean	6.14	3.13	15.30	24.25	-3.17
Median	2.10	2.84	15.00	23.12	-1.55
Maximum	933.33	45.31	40.00	47.82	66.43
Minimum	0.00	-33.57	3.00	10.92	-137.92
Std. Dev.	25.72	2.78	5.70	6.77	12.71
Skewness	19.82	2.18	0.59	0.73	-1.78
Kurtosis	557.38	57.61	3.73	3.34	13.94
Observations	3,980	3,980	3,980	3,980	3,980

Finally, table 3 presents the descriptive statistics for the post-crisis period of altogether 81 months. Dispersion, averaging at 6.48, is at its highest of the entire sample period. Average consensus increases slightly, whilst the ratio of analyst coverage increases notably from the prior sub-samples, as the average number of monthly forecast is 19.79 during the crisis period. Average volatility is at its lowest at 22.59. The stocks also managed to generate positive return during the post-crisis period, averaging at 1.16 percent per month.

**Table 3.** Descriptive statistics of the post-crisis period. DISP is the average ratio between the standard deviation of analyst forecasts of earnings and the absolute value of the mean of the forecasts (coefficient of variation). Consensus is the monthly mean forecast of earnings per share. AN COV is the average number of monthly forecasts per share. VOL is average volatility and RET is the average monthly return.

	<b>DISP</b>	<b>Consensus</b>	<b>AN_COV</b>	<b>VOL</b>	<b>RET</b>
Mean	6.48	3.51	19.79	22.59	1.16
Median	1.90	3.01	19.00	21.83	1.31
Maximum	4,500.00	40.76	51.00	47.82	82.14
Minimum	0.00	-9.53	2.00	10.41	-46.04
Std. Dev.	52.71	2.85	7.25	6.72	7.27
Skewness	51.57	3.73	0.44	0.62	0.38
Kurtosis	3,701.78	34.10	3.49	3.16	8.28
Observations	16,119	16,119	16,119	16,119	16,119

## 6.2. Approach and model

The purpose of the study is to provide an empirical link between momentum profits and heterogeneous beliefs using the dispersion of analysts' forecasts as the main variable to measure the relation between the diffusion of forecasts per given stock and return continuation in a portfolio setting and in a time-series regression framework. The basic methodology is adopted from Verardo (2009) and adapted to suit the purpose of the study.

The total length of the data period is 168 months, split into sub-periods of 66, 21 and 81 months, respectively. The first step is portfolio formation by implementing so-called double sorts, where each month the stocks are initially divided into three momentum portfolios by sorting on terciles based on past cumulative returns. Subsequently, each of the momentum portfolios are further sorted independently by their dispersion into three equally weighted sub-portfolios, yielding a total of nine sub-portfolios. The decision of not dividing the samples into more portfolios for finer breakdown is justified by the risk of individual portfolios becoming too small, as there are only 200 stocks in the entire sample. A small number of stocks in a portfolio would likely result in the

portfolios becoming too undiversified and subsequently yielding larger standard errors in the test statistic (Dische 2002).

### 6.2.1. Portfolio formation

Portfolios are formed by sorting stocks on the basis of past returns and dispersion of analyst forecasts to test the hypothesis that heterogeneity of beliefs is related to momentum. In the first iteration, momentum portfolios are formed using the 12-7-1-momentum strategy introduced by Novy-Marx (2012), as his research findings show that momentum strategies based on intermediate past returns generate superior return compared to strategies based on immediate past returns. Zero-investment strategy returns are regarded as momentum profits. Rolling past raw returns are calculated for each of the 200 stocks, by using a ranking period from 12 to seven months prior and skipping the most recent month's return. Skipping the return from the most recent month has been a standard in momentum research since Asness (1994) to avoid the one-month reversal in stock returns due to liquidity and microstructure biases (Asness, Iltanen, Israel & Moskowitz, 2015). As the purpose of the strategy is to rebalance at the end of each month, the stocks are placed into three separate momentum portfolios by sorting on terciles based on the cumulative intermediate past returns. The three monthly momentum portfolios are the loser portfolio comprising stocks with the lowest cumulative return, the medium portfolio and the winner portfolio comprising of stocks with the highest cumulative return for the rolling past 12 to seven-month ranking period.

In the second iteration, the stocks are further sorted to terciles based on average analyst forecast dispersion for the corresponding time period as in the first sort. This yields altogether nine portfolios, as the initial three momentum portfolios are further divided into three sub-portfolios according to the amount of forecast dispersion.



**Table 4.** Portfolio formation

	<b>Low dispersion</b>	<b>Medium dispersion</b>	<b>High dispersion</b>
<b>Loser</b>	Portfolio 1	Portfolio 2	Portfolio 3
<b>Medium</b>	Portfolio 4	Portfolio 5	Portfolio 6
<b>Winner</b>	Portfolio 7	Portfolio 8	Portfolio 9

### 6.3. Time-series tests for momentum-dispersion portfolios

The final method for testing the hypotheses features multivariate regressions. Fama-French (1993) three-factor model is used to assess whether covariance with possible risk factors contains explanatory power over the obtained momentum returns. The excess returns independently for all of the nine portfolios as well as the spread between momentum returns for high and low dispersion portfolios act as dependent variables in the time-series regression, while the FF3 factors act as the independent, explanatory variables. Therefore altogether 30 time-series regressions will be performed. All of the regressions run in this thesis are Newey-West (1987) corrected for heteroskedasticity and autocorrelation.

$$(2) \quad (R_W - R_L)^{HIGH} - (R_W - R_L)_t^{HIGH} - (R_W - R_L)_t^{LOW} = \alpha_p + b_p (R_{Mt} - r_{ft}) + s_p SMB_t + h_p HML_t + \varepsilon$$

where  $(R_W - R_L)_t^{HIGH} - (R_W - R_L)_t^{LOW}$  = excess return for each portfolio or the difference in excess momentum returns between high- and low-dispersion portfolios (“spread”).

$R_{Mt} - r_{ft}$  = the equity market risk premium. It is calculated by subtracting the risk free interest rate from the aggregate equity return and represents the return from being long in equities at market capitalization weights. Basically it is the “spread” of return between all equities and all cash.

**SMB** = “small minus big” captures the size effect by representing the “spread” return of being long in small stocks and long in big stocks.

**HML** = “high minus low” represents value investing as a portfolio that is long in stocks with high book-to-market ratio and short in stocks with high book-to-market ratio.

$\varepsilon$  = Error term

## 7. RESULTS

This chapter presents the empirical findings and results obtained by using the data and statistical models that were presented in the previous chapter. The results from the portfolio analysis regarding plain momentum returns will be presented first, followed by the results from the momentum-dispersion portfolios. Finally the results from the time-series regressions will be presented.

### 7.1. Momentum returns

As the first step, portfolio analysis is performed in Matlab to determine the effectiveness of the momentum trading strategy during each time period. The Novy-Marx 12-7-1 momentum strategy is applied (Novy-Marx 2012), in which the three portfolios are formed by looking at an intermediate horizon for ranking past performance measured over the period from 12 to seven months prior and held for one month. With his findings, Novy-Marx (2012) challenges the traditional view of short-run autocorrelation as the primary source of the momentum phenomenon. However, he is still unable to demonstrate exactly what causes the link between recent and intermediate returns. The data is also tested with the widely used 6-1-1 momentum trading strategy, which combines the one-month holding period with a six-month ranking period. This is the strategy that is traditionally used in momentum studies and as the ranking period is based on more recent returns, it relies heavily on the tendency of prices to stay in motion. Similarly to the findings of Novy-Marx (2012), the obtained results are similar with both strategies, but stronger with the 12-7-1 strategy. Therefore only the results obtained with the 12-7-1 strategy are presented here.

The major downside to momentum strategy is the in-built risk of a momentum crash. These are the rare and persistent series of negative returns that occur when markets are in a state of crisis and mainly during the rebound phase after adverse market conditions, when prices of the so-called loser stocks bounce back faster than winner stocks, thus reversing the basic return pattern of the momentum strategy (Daniel and Moskowitz 2016). There have been two major momentum crashes since the beginning of the new millennium, first after the collapse of the tech bubble in the early 2000's and secondly after the financial

crisis of the late 2000's. Therefore, the realistic assumption in the onset of this study was that the results obtained with this data period would not fully reflect Verardo's (2009) findings, as the time period used in her study that spanned from 1984 to 2000 was relatively crisis-free.

#### 7.1.1. Momentum return in the pre-crisis period

The purpose of the pre-crisis sub period is to serve as an example of how efficient the momentum strategy is during a "normal", crisis-free state of the market. This is an important backdrop in understanding how the efficacy changes as the state of the market changes. Average monthly returns are reported for the winner portfolio, intermediate and loser portfolios. The average monthly momentum return is reported as the spread between the winner and loser portfolios. Table 4 confirms the presence of some significant portfolio returns in the first sub-sample, but the momentum spread is relatively low and insignificant. This may result from the sample being biased towards large firms.

**Table 5.** Momentum returns sorted into three portfolios based on past return during the pre-crisis period. Stocks are sorted into three portfolios based on past returns: R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio.

<b>Momentum portfolio</b>	<b>Return</b>	<b>p-value</b>
<b>R1</b>	<b>1.07 **</b> (2.51)	0.02
<b>R2</b>	<b>1.13 ***</b> (-3.407)	0.00
<b>R3</b>	<b>1.32 ***</b> (3.10)	0.00
<b>R3 – R1</b>	0.25 (0.74)	0.46

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

Furthermore, as the collapse of the tech bubble and the momentum crash that followed are so close to the beginning of the pre-crisis period, some of the aftermath can be seen to have an effect on the momentum returns presented in Table 4. All three portfolios produced positive returns significant at a 5% or 1% level, but the momentum spread, at only 25 basis points per month, is relatively low and insignificant. This is most likely due to the fact that while the winner portfolio (R3) did produce positive return (at 1.32 percent per month on average), the difference between the winner and loser portfolio is not substantial enough to enable significant returns with the momentum strategy. The markets have probably still been recovering from the recent momentum crisis during the earlier years of the pre-crisis period, resulting in the relatively faster rebound of the loser stocks, as presented by Daniel and Moskowitz (2016).

The first hypothesis, stating that the momentum strategy is able to generate positive absolute return in all states of the market, can already be rejected at this stage. The returns generated by the strategy of buying winners and selling losers does generate a positive return during the pre-crisis period, but the effect is statistically insignificant.

#### 7.1.2. Momentum return in the crisis and post-crisis periods

When comparing momentum returns from time periods with completely opposing market states, it is important to bear in mind that stocks are divided into momentum portfolios according to their performance relative to their peers. This method differs notably from the somewhat similar investment strategy of trend following, since where trend following takes the prevailing market trend into account and focuses on upswings and downswings, momentum investing consists of simply ranking the performance of stocks during a certain time period regardless of the market trend (Asness *et al.* 2014).

The effect of the market trend is well illustrated in the momentum portfolio returns presented in Table 6. During the crisis period, a typical “winner stock” was down only a few percent, therefore performing well relative to the other stocks that were substantially more down on average. Consequently, the momentum spread (R3-R1) for the crisis period is positive (at 0.33 percent) even though the momentum returns were negative for both the winner (R3) and loser (R1) portfolios, at -3.19 and -3.52 percent respectively. The momentum returns were quite insignificant during the crisis period, as the returns produced by the intermediate (R2) and winner portfolios were only significant at a ten percent level and the loser portfolio return and spread were not statistically significant at all.

I find that momentum returns are not significant for all of the sample sub-periods mostly due to the period during and after the market crash experiencing unexpectedly low momentum returns. The momentum anomaly's prevalence and robustness are found to be exceptionally stable and there are suggestions of momentum premium being part of the markets since their very beginning, well before becoming the subject of academic interest. However, despite the impressively stable long-term performance, the momentum

anomaly is also characterized by occasional longer periods of poor performance as well as occasional short spells of extreme performance. (Asness *et al.* 2014.)

**Table 6.** Momentum returns sorted into three portfolios based on past return during the crisis period. Stocks are sorted into three portfolios based on past returns: R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio.

Momentum portfolio	Return	p-value
R1	-3.52 (-1.68)	0.11
R2	-2.90 * (-1.83)	0.08
R3	-3.19 * (-1.99)	0.06
R3 – R1	0.33 (0.27)	0.79

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

The theory by Daniel and Moskowitz (2016) of loser stocks experiencing faster rebound than winner stocks after a momentum crash is again verified by the momentum portfolio return data from the post-crisis period. The loser portfolio (R1) produced 1.52 percent of monthly momentum return on average at a five percent significance level, while the winner portfolio (R3) produced merely 0.85 percent at a ten percent significance level, being surpassed also by the intermediate portfolio (R2) with 1.11 percent of average monthly momentum returns at a five percent significance level. Consequently, the momentum

spread (R3-R1) for this time period is negative at -0.67 percent and statistically insignificant.

**Table 7.** Momentum returns sorted into three portfolios based on past return during the post-crisis period. Stocks are sorted into three portfolios based on past returns: R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio.

Momentum portfolio	Return	p-value
R1	1.52 ** (2.43)	0.02
R2	1.11 ** (-3.49)	0.02
R3	0.85 * (3.89)	0.06
R3 – R1	-0.67 (-1.40)	0.17

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

The spring of 2009 marked the beginning one of the largest sustained drawdown periods for momentum investing (Daniel & Moskowitz 2016). As the spell lasted until March 2013, its effects are clearly visible in the results, especially in the relatively low return for the winner portfolio and consequently the negative and statistically insignificant momentum spread.

The rejection of the first hypothesis, stating that the momentum strategy is able to generate positive absolute return in all states of the market, is further backed by the evidence provided by the data from the crisis and post-crisis periods.



The spreads yielded by the strategy are not consistently positive across the market periods as well as statistically insignificant throughout the entire sample.

## 7.2. Momentum-dispersion returns

The results from portfolio strategies based on past returns and disagreement are presented in this section. Disagreement, or differences in investors' beliefs, is measured by dispersion in analyst forecasts of earnings. The initial hypothesis is that differences in beliefs exacerbate return continuation. I find that the efficacy of the strategy as well as the relation between past returns and disagreement show notable variation depending on the state of the market during the examination period. A positive relationship between momentum and forecast dispersion is found in the pre-crisis period data, absolutely no discernible relationship during the financial crisis period and finally a reversed outcome, where there is a negative relationship between momentum and forecast dispersion, in the post-crisis period data. The difference between the high-dispersion momentum spread and low-dispersion momentum spread, while positive during some sub-periods, fails to be significant. Therefore the relation between return continuation and disagreement during this sample period seems to be less robust and significant than what Verardo's (2009) findings suggest.

### 7.2.1. Momentum-dispersion return in the pre-crisis period

Almost all of the portfolios yield positive return during the pre-crisis period. The significance levels of the returns vary considerably, ranging from ten down to one percent. The winner portfolios generate more return than the loser portfolios on all levels of dispersion, resulting in positive momentum spreads. Whilst the low-dispersion momentum portfolios all generated positive returns significant at five or ten-percent level, the monthly momentum spread at 0.48 percent on average is statistically insignificant. The average monthly return yielded by the winner portfolio (R3) with intermediate dispersion (DISP2) is 1.73 percent and highly statistically significant at a one-percent level. The momentum spread (R3-R1) at the intermediate dispersion level is 0.99 percent and also significant. The high-dispersion (DISP3) winner portfolio generated an

average monthly return of 1.97 percent, highly significant at a one-percent level. The monthly average high dispersion momentum spread is 1.23 percent at a five-percent significance level. The difference in momentum returns between the high and the low dispersion portfolios is 75 bps per month, but statistically insignificant. Therefore the third hypothesis is not accepted.

**Table 8.** Pre-crisis momentum portfolios formed on past profits and forecast dispersion. Stocks are initially sorted into three portfolios based on past returns. R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio. The momentum portfolios are further independently sorted into portfolios based on the dispersion of analyst forecasts at the time of portfolio formation.

<b>Momentum portfolio</b>	<b>DISP1</b>	<b>DISP2</b>	<b>DISP3</b>	<b>DISP3-DISP1</b>
<b>R1</b>	<b>0.72 *</b> (1.90)	<b>0.74 **</b> (-2.52)	<b>0.75 *</b> (1.89)	
<b>R2</b>	<b>1.24 **</b> (2.62)	<b>1.05 ***</b> (2.81)	<b>1.08 **</b> (2.60)	
<b>R3</b>	<b>1.19 **</b> (2.13)	<b>1.73 ***</b> (3.89)	<b>1.97 ***</b> (3.47)	
<b>R3 – R1</b>	0.48 (1.23)	<b>0.99 ***</b> (2.98)	<b>1.23 **</b> (2.54)	0.75 (1.44)

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

### 7.2.2. Momentum-dispersion return in the crisis period

The momentum strategy yielded negative returns during the economically turbulent crisis period. The portfolios consisting of recent winner stocks were hit the hardest, generating large monthly negative returns on average, ranging from -3.7 percent in the high-dispersion portfolio to -4.2 percent in the low-

dispersion portfolio. The difference in momentum returns between the high and the low dispersion portfolios is 55 bps per month, but statistically insignificant. Hypothesis number four is thus rejected.

**Table 9.** Crisis period momentum portfolios formed on past profits and forecast dispersion. Stocks are initially sorted into three portfolios based on past returns. R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio. The momentum portfolios are further independently sorted into portfolios based on the dispersion of analyst forecasts at the time of portfolio formation.

<b>Momentum portfolio</b>	<b>DISP1</b>	<b>DISP2</b>	<b>DISP3</b>	<b>DISP3-DISP1</b>
<b>R1</b>	-2.46 (-1.24)	-1.95 (-1.57)	<b>-2.51 *</b> (-1.96)	
<b>R2</b>	-3.40 (-0.56)	-3.03 (-1.70)	<b>-3.20 *</b> (-1.95)	
<b>R3</b>	<b>-4.20 *</b> (1.81)	<b>-3.96 **</b> (-2.24)	-3.70 (-1.62)	
<b>R3 – R1</b>	-1.74 (-1.46)	<b>-2.02 ***</b> (-2.53)	-1.19 (-0.79)	0.55 (0.30)

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

### 7.2.3. Momentum-dispersion return in the post-crisis period

The loser portfolios (R1) generated both greater and more significant returns relative to the other momentum portfolios during the post-crisis period. The low-dispersion (DISP1) loser portfolio generated a monthly return of 1.60 percent on average, whilst the medium (DISP2) and high-dispersion (DISP3) loser portfolios generated 1.084 and 1.01 percent, respectively. All returns are highly significant at a one-percent level. This is most likely due to the earlier

mentioned effect of a relatively faster and more robust rebound of loser stocks after a momentum crash (Asness & Moskowitz 2016). The medium momentum portfolios (R2) also generated positive return during the post-crisis period. The low-dispersion portfolio generated a monthly return of 1.37 percent on average, whilst the medium and high-dispersion portfolios generated 1.13 and 0.94 percent, respectively. All returns are significant at a five-percent level. The winner portfolios (R3) managed to also generate positive return, but at a lower and less significant level than the other momentum portfolios. The low-dispersion portfolio generated an average monthly return of 1.38 percent, statistically significant at a ten-percent level. Equally significant, the medium portfolio generated 1.09 percent return on average. The high-dispersion winner portfolio managed to generate a mere 0.85 percent average monthly return that displayed no statistical significance. Due to the loser portfolios faring notably better than the winner portfolios during this time period, the momentum spreads were either negative or close to zero and statistically insignificant. The difference in momentum returns between the high and the low dispersion portfolios is 6 bps per month and statistically insignificant.

**Table 10.** Post-crisis momentum portfolios formed on past profits and forecast dispersion. Stocks are initially sorted into three portfolios based on past returns. R1 contains past losers and R3 past winners. R2 is the portfolio for the stocks with intermediary past performance. R3-R1 comprises profits from the momentum strategy of buying the winner portfolio and selling the loser portfolio. The momentum portfolios are further independently sorted into portfolios based on the dispersion of analyst forecasts at the time of portfolio formation.

<b>Momentum portfolio</b>	<b>DISP1</b>	<b>DISP2</b>	<b>DISP3</b>	<b>DISP3-DISP1</b>
<b>R1</b>	<b>1.60 ***</b> (3.36)	<b>1.08 ***</b> (3.12)	<b>1.01 ***</b> (2.77)	
<b>R2</b>	<b>1.37 **</b> (2.23)	<b>1.13 **</b> (2.44)	<b>0.94 **</b> (2.13)	
<b>R3</b>	<b>1.38 *</b> (1.75)	<b>1.09 *</b> (1.74)	0.85 (1.33)	
<b>R3 – R1</b>	-0.22 (-0.50)	0.01 (0.02)	-0.16 (-0.36)	0.06 (0.13)

\* Statistically significant at 10% level

\*\* Statistically significant at 5% level

\*\*\* Statistically significant at 1% level

### 7.3. Results for the time-series tests

This section presents the results from the time-series tests that were conducted in order to make sure that the results from the portfolio analysis are not driven by possible covariance with risk factors. Fama-French three-factor model is estimated for the momentum portfolio returns as well as the difference between high- and low-dispersion portfolio returns, net of the risk-free rate. Equation 2, presented earlier in the methodology section, describes the applied regression model in detail.

Performing a similar regression analysis, Verardo (2009) finds that winner and loser portfolios have roughly the same beta, whilst loser portfolios have higher

loadings on the risk factors. I find that the winner portfolio has a higher beta than the loser portfolio in each dispersion category throughout the entire sample. The findings are described in more detailed below.

The estimated coefficients for the results from the pre-crisis period are reported in Table 11. Notable findings from the sub-sample include that for the medium- and high-dispersion portfolios (DISP2 and DISP3), momentum returns for the winner portfolio (R3) stay positive and statistically significant after controlling for the effects of market risk, size and book-to-market characteristics. The spread between the winner and loser portfolio (R3-R1) remains statistically significant only for the high-dispersion portfolio. The loser portfolios seem to have slightly lower betas than the winner portfolios across all dispersion categories. The winner portfolios typically have higher (less negative) loadings on the SMB and HML factors. Overall, the adjusted  $R^2$  levels are solid for time-series regressions on the portfolios, but drop to low levels when concerning regression analysis on the spreads between winner and loser portfolios. The reported  $R^2$  levels are in line with the results from previous studies. In conclusion, the momentum return for high-dispersion stocks remains positive and statistically significant after controlling for market risk, size and value characteristics.

Table 12 presents the time-series regression results from the crisis period. The portfolio returns during the period are much lower to begin with, so it is no surprise that the estimates of the intercept reported in the time-series regression table are both low and statistically insignificant. Winner portfolios have higher betas than loser portfolios across all dispersion categories. Winner portfolios typically have lower loadings on the SMB factor and higher loadings on the HML factor, which is in line with Verardo's (2009) findings. The adjusted  $R^2$  levels are also similar.

The estimated coefficients for the results from the post-crisis period are reported in Table 13. The most evident observation is that in this sample, all spreads between the winner and loser portfolios are negative and one to ten percent statistically significant. The winner portfolios have higher betas as opposed to Verardo's study where winner and loser portfolios had similar betas. Winner portfolios also seem to have higher loadings on the SMB and HML factors, indicating that winner portfolio returns have higher covariance

with all of the risk factors featured in the model. The adjusted  $R^2$  levels are slightly lower than those reported by Verardo (2009).

**Table 11.** Pre-crisis time-series regressions including Fama-French (1993) three-factor model coefficient estimates for monthly excess returns for the momentum-dispersion portfolios. R1 is the loser portfolio, R2 the medium portfolio and R3 the winner portfolio. DISP1 is the portfolio for stocks with low dispersion, DISP2 for medium dispersion and DISP3 for high dispersion of analyst forecasts. The parameters are estimated as follows:  $(R_{pt} - r_{ft}) = a_p + b_p (R_{mt} - r_{ft}) + s_p \text{SMB}_t + h_p \text{HML}_t + e_{pt}$ . The intercept estimates are denoted as percentage points. T-statistics are shown in parentheses. All regressions are Newey-West (1987) corrected for heteroskedasticity and autocorrelation.

<b>Dispersion</b>	<b>Momentum Portfolio</b>	<b>a</b>	<b>b</b>	<b>s</b>	<b>h</b>	<b>Adj. R<sup>2</sup></b>
<b>DISP1</b>	<b>R1</b>	-0.05 (-0.18)	0.99 (9.08)	-0.30 (-3.62)	-0.13 (-0.87)	0.65
	<b>R3</b>	-0.04 (-0.12)	1.45 (11.82)	-0.12 (-0.61)	-0.20 (-0.88)	0.75
	<b>R3-R1</b>	0.00 (0.01)	0.46 (2.52)	0.17 (0.75)	-0.07 (-0.28)	0.21
<b>DISP2</b>	<b>R1</b>	0.18 (1.01)	0.79 (13.15)	-0.24 (-3.02)	-0.21 (-2.38)	0.71
	<b>R3</b>	0.62 (3.32) <sup>***</sup>	1.14 (9.74)	-0.07 (-0.49)	0.12 (1.11)	0.77
	<b>R3-R1</b>	0.45 (1.50)	0.34 (2.46)	0.17 (0.88)	0.33 (2.24)	0.21
<b>DISP3</b>	<b>R1</b>	-0.01 (-0.05)	0.92 (5.70)	-0.23 (-1.85)	-0.05 (-0.29)	0.52
	<b>R3</b>	0.60 (1.74) <sup>*</sup>	0.96 (7.08)	0.57 (3.17)	0.52 (1.93)	0.65
	<b>R3-R1</b>	0.61 (1.73) <sup>*</sup>	0.04 (0.18)	0.80 (4.69)	0.57 (1.87)	0.26
<b>DISP3- DISP1</b>	<b>R3-R1</b>	0.61 (1.11)	-0.42 (-1.20)	0.62 (2.38)	0.64 (1.47)	0.09



**Table 12.** Crisis period time-series regressions including Fama-French (1993) three-factor model coefficient estimates for monthly excess returns for the momentum-dispersion portfolios. R1 is the loser portfolio, R2 the medium portfolio and R3 the winner portfolio. DISP1 is the portfolio for stocks with low dispersion, DISP2 for medium dispersion and DISP3 for high dispersion of analyst forecasts. The parameters are estimated as follows:  $(R_{pt} - r_{ft}) = a_p + b_p (R_{mt} - r_{ft}) + s_p \text{SMB}_t + h_p \text{HML}_t + e_{pt}$ . The intercept estimates are denoted as percentage points. T-statistics are shown in parentheses. All regressions are Newey-West (1987) corrected for heteroskedasticity and autocorrelation.

<b>Dispersion</b>	<b>Momentum Portfolio</b>	<b>a</b>	<b>b</b>	<b>s</b>	<b>h</b>	<b>Adj. R<sup>2</sup></b>
<b>DISP1</b>	<b>R1</b>	1.09 (1.31)	1.16 (7.15)	-0.04 (-0.10)	0.43 (1.52)	0.77
	<b>R3</b>	0.33 (0.83)	1.22 (9.84)	-0.70 (-2.35)	1.19 (5.84)	0.91
	<b>R3-R1</b>	-0.76 (-0.98)	0.06 (0.33)	-0.66 (-2.37)	0.75 (2.07)	0.25
<b>DISP2</b>	<b>R1</b>	0.33 (0.87)	0.78 (12.38)	0.11 (0.61)	0.20 (1.81)	0.88
	<b>R3</b>	-0.50 (-1.38)	1.18 (20.44)	-0.09 (-0.85)	0.31 (3.14)	0.97
	<b>R3-R1</b>	-0.82 (-1.50)	0.40 (4.54)	-0.20 (-1.02)	0.11 (0.58)	0.43
<b>DISP3</b>	<b>R1</b>	-0.28 (-0.45)	0.91 (10.35)	0.04 (0.19)	-0.18 (-3.09)	0.92
	<b>R3</b>	0.30 (0.22)	1.38 (9.12)	-0.91 (-2.27)	0.26 (0.49)	0.64
	<b>R3-R1</b>	0.57 (0.47)	0.47 (3.35)	-0.95 (-2.54)	0.43 (0.79)	0.17
<b>DISP3- DISP1</b>	<b>R3-R1</b>	1.33 (0.79)	0.41 (1.57)	-0.29 (-0.59)	-0.32 (-0.39)	-0.09

**Table 13.** Post-crisis time-series regressions including Fama-French (1993) three-factor model coefficient estimates for monthly excess returns for the momentum-dispersion portfolios. R1 is the loser portfolio, R2 the medium portfolio and R3 the winner portfolio. DISP1 is the portfolio for stocks with low dispersion, DISP2 for medium dispersion and DISP3 for high dispersion of analyst forecasts. The parameters are estimated as follows:  $(R_{pt} - r_{ft}) = a_p + b_p (R_{mt} - r_{ft}) + s_p \text{SMB}_t + h_p \text{HML}_t + e_{pt}$ . The intercept estimates are denoted as percentage points. T-statistics are shown in parentheses. All regressions are Newey-West (1987) corrected for heteroskedasticity and autocorrelation.

<b>Dispersion</b>	<b>Momentum Portfolio</b>	<b>a</b>	<b>b</b>	<b>s</b>	<b>h</b>	<b>Adj. R<sup>2</sup></b>
<b>DISP1</b>	<b>R1</b>	0.33 (1.56)	0.90 (11.38)	-0.06 (-0.48)	0.13 (0.85)	0.71
	<b>R3</b>	-0.55 (-1.85)*	1.36 (12.16)	0.05 (0.35)	0.84 (4.07)	0.80
	<b>R3-R1</b>	-0.88 (-2.67)***	0.46 (4.41)	0.11 (0.75)	0.71 (4.41)	0.50
<b>DISP2</b>	<b>R1</b>	0.02 (0.13)	0.75 (18.70)	-0.07 (-0.96)	-0.15 (-2.16)	0.82
	<b>R3</b>	-0.65 (-2.33)**	1.22 (14.44)	0.15 (1.75)	0.39 (4.45)	0.89
	<b>R3-R1</b>	-0.67 (-1.83)*	0.46 (4.79)	0.22 (1.72)	0.54 (5.13)	0.54
<b>DISP3</b>	<b>R1</b>	0.02 (0.11)	0.70 (8.92)	-0.03 (-0.34)	-0.12 (-1.23)	0.65
	<b>R3</b>	-0.84 (-3.09)***	1.16 (14.83)	0.33 (2.30)	0.29 (1.90)	0.82
	<b>R3-R1</b>	-0.86 (-2.42)**	0.46 (4.10)	0.36 (1.94)	0.40 (2.62)	0.44
<b>DISP3- DISP1</b>	<b>R3-R1</b>	0.02 (0.04)	0.00 (-0.00)	0.25 (1.05)	-0.31 (-1.35)	0.00

## 8. CONCLUSIONS

Previous studies have been able to establish a link between heterogeneous beliefs and momentum profits by introducing the former as a variable to rational or behavioral asset pricing models. The main objective of this study was to further examine the relationship between investors' disagreement and return continuation by extending the empirical research to cover various different phases of the market. Both portfolio analysis and time-series regressions are used in this paper to test the relation in three different time periods. The time periods are separated as a sample split test to reflect pre-crisis, crisis and post-crisis periods as realistically as possible to capture the effects of momentum crashes and up and down periods comprehensively. Similarly to Verardo (2009), I use dispersion of analysts' forecasts as a measure of disagreement about a firm's fundamentals.

The study includes altogether five hypotheses. The first two were designed on the basis of previous research findings and concerned the performance of momentum strategy regardless of the state of the market as well as whether return autocorrelation in short-term cumulative individual stock returns is higher for stocks with a larger degree of heterogeneity of beliefs in all states of the market. According to the first hypothesis, Novy-Marx's (2012) 12-7-1 momentum strategy should be able to generate positive absolute returns regardless of the prevailing market condition. Portfolio analysis was performed separately for each research sub-period and the statistical evidence was soon found to insufficient or even contrary to the hypothesis. The most likely reason behind the contradictory findings is the presence of influence from two momentum crashes in the data, which reflects the findings of Daniel and Moskowitz (2016) regarding the relatively faster rebound of loser stocks in the aftermath of a momentum crash. The second hypothesis was also rejected, as it was found that the presence of heterogeneity did not increase momentum profits during all sub-periods. The causal relationship between heterogeneous beliefs and momentum profits was the most apparent during the pre-crisis period and reflected the findings of Verardo (2009). Further testing highlighted the state-dependent nature of the efficacy of the momentum-dispersion strategy.

The latter three hypotheses were ones that had not been previously tested in any other scientific study and considered whether differences in beliefs exacerbate return continuation during the three individual sub-periods. In other words, these hypotheses delve further into examining the state-dependency of momentum-dispersion returns. Interestingly, only the findings regarding the pre-crisis period mirrored those of Verardo's (2009). Analysis on the pre-crisis data shows that the strategy was able to generate positive returns especially for the medium and high-dispersion portfolios, for which the spreads were statistically highly significant. The most logical conclusion is that, unlike the latter two sub-periods, the pre-crisis period was relatively free of adverse effects from momentum crashes. However, the third hypothesis was still rejected because the statistical difference between the low-dispersion and high-dispersion spreads was not significant enough.

The momentum-dispersion portfolios did not yield positive return during the crisis period, most likely due to adverse market conditions. Interesting findings emerge from the post-crisis period, as the loser portfolios generated the highest return. The returns were also highly statistically significant. The medium portfolios also generated statistically significant positive return. The winner portfolios also generated positive returns, but at a relatively lower rate and with less significance. Interestingly, the low-dispersion portfolios generated the most return as compared to the medium- and high-dispersion portfolios. The results are completely opposite to those of the pre-crisis period as well as the initial hypotheses. This is most likely due to the effect of a relatively faster and more robust rebound of loser stocks after a momentum crash (Asness & Moskowitz 2016). Subsequently, the fourth and fifth hypotheses were both rejected.

One of the key motivations behind this study was to examine how well a prior research paper with highly robust results could be replicated with modern data. As it turns out, the substantial changes in the reality of financial markets are reflected in the results of this study. The vastly different results are most likely due to the presence of momentum crash effects in the data, but could also indicate that the use of analysts' forecasts as a proxy for investors' opinions is no longer straightforward, as many investors have begun to think differently about analysts' recommendations after the financial crisis. As the world keeps changing at an increasing pace, it is more important than ever that financial research strives to keep up.

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