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DOES THE FROG BOIL IN EUROPE?

Frog-in-the-pan momentum and Stoxx Europe 600

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ABSTRACT:

Momentum is one of the most studied and robust anomalies in financial markets. There have been numerous studies that tries to increase its performance by adding other both risk- and behavioral based variables. One of the behavioral based variables is information discreteness by Da et al. (2014), which measures the relations between positive and negative return days. Information discreteness acts as proxy for investors limited information processing capacity.

Aim of the thesis is to study wether double sorting a portfolio first by momentum and then by information discreteness generate risk-adjusted returns on European markets. This thesis also extends the existing literature by studying another sample period and different continent.

Using the constituents of Stoxx Europe 600 index as test assets and time-period from 11/2005 to 8/2019, test portfolios are formed by double sorting stocks into quantiles first by its J-month cross-sectional momentum and then by the ID measurement. A total number of test portfolios is 25 per formation and holding period. Returns of the test portfolios are then regressed against Fama and French (1993 & 2015) factor models that also includes the momentum factor. Also, average returns, return distributions and firm characteristics in test portfolios are studied.

Information discreteness based momentum strategy does not generate risk-adjusted returns. In every tested portfolio, alpha is not significantly different from zero. The momentum factor is mostly the only factor with a significant loading, which indicates that that factor drives the returns of the test portfolios. Mean returns of the double sorted portfolios, both long only and long-short, are mostly higher than their plain momentum benchmark returns.

KEY WORDS: momentum, limited attention, behavioral finance

1. INTRODUCTION

Momentum has been one of the most robust anomalies in the finance literature during the past few decades after Jegadeesh and Titman (1993) brought the anomaly to the wide public. After the original documentation of the anomaly, there have been numerous studies that tries to increase its profitability by taking other variables into account. One potential addition to the momentum is information discreteness by Da, Gurun and Warachka (2014) that combines the momentum with the behavioural models. My purpose in this thesis is to examine whether the performance of traditional price momentum could be increased in the European markets by taking into account the quality of the past J-month returns of the stock, measured by information discreteness.

Before the information discreteness-based momentum could be studied more closely, I have to introduce the original anomaly – the momentum. The anomaly is normally implemented by cross-sectionally rank the assets and then buying the assets that have performed well during the past 3 to 12 month and sell the assets that have declined during the past 3 to 12 month, and then holding the equal-weighted long-short portfolio for 1 to 12 months. Jegadeesh and Titman (1993) found, for example that simple anomaly of constructing the portfolio based on the past 12-month performance and then hold the portfolio for 3 months could generate on average 1,31 percent per month in the US markets in 1965–1989.

Even though Jegadeesh and Titman (1993) constructed their portfolios based on pure past return or skipping only one week before the construction, nowadays it is a standard practise to skip one month before the construction (see e.g. Asness et al. 2013, Da et al. 2014, Hillert, Jacobs and Müller 2014). This procedure is due to the fact that over a short time period, stock markets tend to reversal, which is caused for example behavioural biases of investors or microstructures of the markets (see e.g. Brennan and Subrahmanyam 1996, Grinblatt and Moskowitz 2004, and Hou and Moskowitz 2005).

The findings of Jegadeesh and Titman (1993) has been confirmed ever since across the globe in many different time periods, in the different asset classes, in time-series, combined with other anomalies and even other anomalies have been exhibited to follow momentum pattern. In the European stock markets, Rouwenhorst (1998) found that the 12/3 strategy generates on average 1,35 percent per month when Fama and French (2012) found that the performance of 12/1 strategy is on average 0,92 percent per month. On country index level, for instance, Asness et al. (2013) found the average excess return of 8,7 percent per year on the 12/1 strategy.

When in the standard momentum literature assets are ranked based on cross-sectional returns, in the time series momentum, trading decisions are based on purely the past return of the asset itself. On the future contracts, Moskowitz, Ooi and Pedersen (2014) discovered that past 12-month return of the asset is a great predictor of the assets next month return. That very same effect is also found on the common stocks, where Lim, Wang and Yao (2018) found that the value weighted time series momentum generates on average 0,76 percent per month. It was also found that both the performance of time series and cross-sectional momentum could be increased by combining the both strategies and generate on average 1,74 percent per month (Lim et al. 2018).

Gupta and Kelly (2019) took the research even further as they found both the time series and cross-sectional momentum effect on factor level. It was discovered that the performance of the factor investing could be increased by actively selecting the factors based on its past performance or selecting the factors that have better performed relative to other factors (Gupta and Kelly 2019).

Even though the momentum generates significantly positive robust returns even after risk adjustments and it has been founded in many different markets and time periods, it has weaknesses as the strategy is highly sensitive to crashes that could almost wipe out many years of profits. For instance, Daniel and Moskowitz (2016) found in their sample that the worst month for momentum had a massive decline of –74,36 percent at August 1932 and –45,52 percent at April 2009. Barroso and Santa-Clara (2015) found similar returns from their sample. As a result of the weaknesses of the momentum, both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) founded two different risk managed momentum strategies mitigating the drawbacks of the traditional momentum. For example, Barroso and Santa-Clara (2015) designed risk-managed momentum strategy, where they scale up the momentum strategy to have a constant risk exposure.

As the evidence shows, the momentum is clearly a stock market anomaly, but what is the true return driver behind the anomaly? After the discovery of the anomaly, there have been numerous explanations for it, both “soft” or behavioural and information-based explanations, and “hard” or economic and risk explanations. For example, Hillert et al. (2014) argued that the financial media is causing the momentum, but also investors personality (Chui, Titman and Wei 2010), underreactions (Hong and Stein 1999), market sentiment and -constraints (Stambaugh, Yu and Yuan 2012) and even institutional and foreign investors (Baltzer, Jank and Smajlbegovic 2019) have been offered to explain the anomaly on the behavioural basis. Economic and risk explanations for momentum are for example offered by Moskowitz and Grinblatt (1999) as they argued that industries may cause momentum, Maio and Philip (2018) offered economic activity and Garcia-Feijoo, Jensen and Jensen (2018) found that funding conditions could be explanations for it.

Many of the explanations for momentum and other anomalies on the financial markets are based on the behavioural explanations and information, so these two have been taken to view of this thesis, especially the latter one, as information is widely an accepted factor that affects the prices of the assets (see e.g. efficient market hypotheses by Fama 1970). Therefore, economic and risk-based models are out of the scope of his thesis (see e.g. Asness et al. 2013, for discussion on risk-based explanations). Many of the largest markets in the world, for example the government bonds, oil and indices, adapts very quickly to new information, when the markets for smaller firms and firms with otherwise less attention adapts much slower (Hong and Stein 1999, Hong, Lim and Stein 2000). This gradual flow of information, as argued for example by Hong and Stein (1999) and Da et al. (2014), is one source of momentum.

According to the efficient market hypotheses (Fama 1970), the changes in the asset prices are driven by the new information that arrives at the markets. Da et al. (2014) uses the frog-in-the-pan (FIP thereafter) anecdote to describe the effect of the limited information processing capacity. When the frog is put on the pot with boiling water, it would immediately try to jump out of that pot, but if the water is slowly heated to the boiling point, the frog ignores the change in the temperature and slowly became cooked. This is the same that happens to investors as they notice some dramatic event, they immediately react to that new information, but when the small changes happen during a longer period, it would be adapted much slower.

Da et al. (2014) argues that, this is due to the limitations of investors' attention and ability to process new information, investors do not recognize continuous gradual positive information that firms produce and hence underreact, which on the one hand, keeps the momentum going (see chapter 3.1 for complementary discussion). On the other hand, when the firm release sporadically extremely good news, that is they produce discrete information that attracts a lot of public, media and analyst coverage, lots of investors runs to trade on that information and causes them collectively to overreact on that information (Da et al. 2014). As a result, the evidence suggested by Da et al. (2014), the discrete information is more exposed to long-term reversals compared with continuous information.

Da et al. (2014) expressed that the investors capability to process information is main determiner of the k parameter, which measures the relative frequency of the information signals. Information is continuous whenever the signals are below k and discrete when the signals are above k. As the information processing limitations increases, the k also increases, which indicates that the investor is more likely to miss greater amount of continuous information. As there are no common way to measure investors information processing capabilities, Da et al. (2014) used information discreteness as proxy.

To measure information discreteness, Da et al. (2014) have come up with the Information discreteness measurements (ID). It measures the sign of the returns of the formation period and how the returns are distributed to positive and negative days. If the formation period returns are mainly driven by certain sign return days, then the information is continuous. On the other hand, when the returns are constantly changing between positive and negative, the returns are more likely to be discrete.

1.1. Research question, hypothesis and contribution

Traditional momentum strategies are based on purely the past returns of the asset no matter how volatile the past returns are. For example if we have two different return series of the stocks A and B, where A={2,2,2,2,2,2,2} and B={1,1,1,1,1,1,8}, it could be easily see that the return series of A is much smoother than B, and intuitively A could be expected to continue its smoother increase whereas B's future prices have much more uncertainty, even though both series got the ID of -1. More discussion about ID measurement is on chapter 4.2.

In the post 1980 sample period, Da et al. (2014) found that ID momentum produces 9,1 percent (t-stat 6,35) six month return after portfolio construction in the lowest ID portfolio (i.e. the portfolio of the most continuous information) and 11,75 percent (t-stat 8,55) Fama and French Three-factor alpha. Following the methodology of Da et al. (2014) I form my hypothesis:

H1: FIP momentum produce significant risk adjusted returns

This thesis extends the recent academic research in two ways. First, the original paper byDa et al. (2014) focuses only on the US data, but I extend the research to the international level as I use the European data. Second, I will test the strength of the anomaly after original publication. As argued by Mclean and Pontiff (2016), academic research seems to decrease or vanish the out-of-sample returns of the anomalies in the US, but according to Jacobs and Müller (2019) these anomalies stays strong outside of the US both out-of-sample and post-publication. My final contribution is to test whether the performance of the FIP momentum differs with different formation- and holding periods, as Da et al. (2014) only focuses on the 6-month formation and holding period.

1.2. Structure of the thesis

The rest of the thesis is constructed as follows. In chapter two, theorethical background of the thesis is introduced. Chapter three, goes trough behavioral models behind the momentum. Data and methodology are outlined in chapter four and empirical findings are discussed in chapter five. Lastly, chapter six concludes the whole thesis and discusses more on the results.

2. THEORETHICAL BACKGROUND

To better understand the possible explanations of the momentum, it is vital to under-stand the theoretical framework of the markets where the anomaly works and the framework how the assets in these markets are priced. It is practical to first understand how the markets should work in theory and have a reference point that can be used to compare how these potential violations deviate from the state that the theory offers. To do so, this chapter first concentrates collectively on the market-wide efficiency and then move focus on the pricing and the returns of the individual assets. For example, findings by Celiker, Kayacetin, Kumar and Sonaer (2016) have shown that news about the cash flows, and the finding that changes in dividends (Asem 2009) are indeed very an important driver behind the momentum.

2.1. Efficient market hypotheses

The main function of the markets is to allocate the ownership of the economy's capital stock (Fama 1970). In the completely efficient markets, the prices should reflect all available information. The most well-known theory of the market efficiency is the efficient market hypotheses introduced by Fama (1970). The efficient market hypotheses states that there are three different versions of the theory: weak form, semi-strong form and strong form. The main differences between the different forms are what kind of information is already included in the prices (Fama 1970).

On the weak form of the efficient market hypotheses, the market prices of the securities contain all historical information that is available at the time (Fama 1970). That means on the other words that the trading strategy, that uses the past prices of the security, should be unprofitable, which is not the case in reality as could be seen for example in the momentum strategy. The weak form of the efficient market hypotheses also drops the floor from the technical analysis and trend following strategies that uses the past performance of an asset as signals for profitable trading strategies.

Semi-strong form of the efficient market hypotheses states that the current market price of the securities fully reflects all public information that is available at the time, in addition to the information on the weak form. This form of the theory assumes that all the events and the information that will have an influence on the market price will be fully incorporated into the price of an asset immediately after the announcement of the event or the new information (Fama 1970). This leads to the situation where the markets should not have any under- or overreactions because the information adjusted prices of the assets should be on the right level, so the rational investors have no incentives to trade too much.

The strongest form of the efficient market hypotheses suppose that the market price of an asset contains all possible information, both public and private, that is available at the time. This form assumes that there are no expected exceed trading profits available for an individual investor, because of the investor's superior insider information supply (Fama 1970). As Fama (1970: 409) has pointed out that this form is not "an exact form of reality", but more like an ideal state of the world that could be used to test the deviations from it, for example to test whether an individual investor or a group of investors will have access to private information.

As a result of the practical limitations of Fama's (1970) different forms of the market efficiency, Grossman and Stiglitz (1980) offered an alternative argument that the markets cannot be fully efficient and reflect all available information. Their main argument against the efficient market hypotheses is that the price of the information costly. They argued that if the markets would be fully efficient, that is the prices contains all available information, and the information is costly, then no-one has incentive to acquire information. If no-one acquires the information, then there will not be any "informed investors" who will trade, and if there are no trading, how the prices of the securities could contain any information? (Grossman and Stiglitz 1980.)

It seems to be that the arguments against the efficient market hypotheses are quite robust, but they still leave an open question how then it is so difficult to beat the markets? Malkiel (2003) have concluded many studies of the performance of the mutual funds and discovered that the performance of the mutual funds is neither consistent, nor they can outperform the markets. For example, many funds that are outperformed the index in the 1980's were underperformer in the 1990's. Also, it was discovered that the studies about the performance of the mutual funds are biased because of the survivorship bias. (Malkiel 2003.)

The main arguments against the efficient market hypotheses are the anomalies, or in the other words, predictable patterns that seem to outperform the markets in-the-sample. However, as found by Mclean and Pontiff (2016), the out-of-sample performance of most anomalies are much lower than in-the-sample, and the performance get even worse after the publication of the article that introduces the anomaly. They found that on average the out-of-sample performance in 26 percent lower than in the sample, and even 58 percent lower after the publication (Mclean and Pontiff 2016).

The academic debate for and against the efficient market hypotheses is endless swamp where no right answer would never be found. As Fama (1970) pointed out that the strongest form of the hypothesis is clearly false, but he raised a question in his updated paper on efficient market hypotheses (1991) that it is impossible to test pure efficiency in the markets. All the tests that have been done are done with the different forms of equilibrium models. The question Fama (1991) raised is the market inefficient or are the models wrong, that tries to break down the efficient market hypotheses?

To conclude, Malkiel (2003) pointed out that the markets can sometimes deviate from the efficient levels, but in the long run it will always reverse back to where the market is efficient. Also, both Malkiel (2003) and Fama (1991) accepted the fact that there are factors that clearly prevent the markets be fully efficient, for example the cost of information and trading. In addition, Mclean and Pontiff (2016) concluded that post publication expected returns are the highest on trading strategies that are costly to implement in practice, which potentially could explain the consistence in the momentum strategies that involves of trading of hundreds or thousands of stocks both long and short. This leaves the spot in theory, that allows the information based FIP momentum to be at least profitable on the theoretical level.

2.2. Stock pricing models

Dividend discount model

The assumptions of the dividend discount models are that the current value of the common share is the present value of its expected future dividends. The equation 1 presents the simple dividend discount model, where the price of the stock at time t, P_t, is the perpetual sum of its expected dividends at time $t+1$, and every paid dividend is discounted with the discount factor $(1+r)^t$, where r is the average of the expected return of the stock or internal rate of return on expected dividends (Fama and French 2015).

(1) $$P_t = \sum_{t=1}^{\infty} E(DIV_{t+1})/(1+r)^t$$

This simple model takes dividends as taken and does not take a stand on the changes in dividends. It also assumes that the expected future dividends reflect a possible change in market value and in other meaningful factors that affect the market value of the stock (Bodie et al. 2014). The model also shows that if two companies have the same expected dividends, but different market prices, from equation 1, it could be seen that the firm with lower market value has the higher expected rate of return.

If it could be unrealistically expected that the dividends paid by the stock will grow with the steady rate of g, the model 1 could be modified to following form, where other factors are as in the model 2 (Bodie et al. 2014).

(2) $$P_t = E(DIV_{t+1})/r - g$$

For practical reason, usually dividends can be estimated with moderate accuracy over a medium period of time and then the dividends are expected to grow with steady rate g. This can be interpreted with combining models 1 and 2 to get a model 3. For illustrative purpose, four years of expected dividends are used.

(3) $$P_t = \sum_{t=1}^{3} E(DIV_t)/(1+r)^t + 1/(1+r)^3 * E(DIV_4)/r - g$$

Dividends and especially changes in the dividend policies are very followed and expected information that the firms have to publish regularly. Analysts try to predict them as accurately as possible, investors are allocating their wealth based on the pay-out policies and financial media tries to publish news and analysis based on the announcements, so it is easy to understand the importance of them in the information-based momentum strategy. To have an example of a different type of information, let's consider two types of firms: firms that have very long and steady dividend growth history, or so-called dividend-aristocrats, and firms that have never paid any dividends. If these dividend-aristocrats announces that next year their dividend will grow with the expected steady rate, the markets are not expected to react to the announcement strongly. On the other hand, if these non-paying firms announce that their they start to pay dividends, the market reaction would be much stronger and the probability to overreaction is much stronger.

Free cash flow models

A free cash flow is the cash flow produced by the company which it can pay out to its investors when the investments, which are necessary to the growth of the company, have been made. The model could be seen as an extension of the dividend discount model as it also takes into the consideration of the cash flows of the company that the company itself invests, which are important to the future growth of the company. The model does not take into consideration how much the company pays dividends or buys its own shares back, but rather it tells the limits within these actions can be made (Brealey et al. 2017). The free cash flow model is especially useful for evaluating companies that do not pay dividends such as smaller growth firms.

The free cash flow model can be used to evaluate the price of the equity capital or the whole company. If only the equity capital is used, then the free cash flow is discounted with the cost of equity and if the whole company is evaluated then the cash flows are discounted with the *weighted average cost of capital* which takes the after-tax cost of debt into consideration. In the model 4, $E(FCF_{t+1})$ denotes the expected free cash flow at the time t+1 and WACC is the weighted average cost of capital, which is expressed at the model 5

(4) $$P_t = \sum_{t=1}^{\infty} E(FCF_{t+1})/(1 + WACC)^t$$

(5) $$WACC = (1 - T_c) * r_d * D/V + r_e * E/V,$$

Where Tc is the company's tax rate, r_d is the after-tax cost of debt, D is outstanding debt, r_e is the cost of equity capital, E is the outstanding equity capital and V is the sum of D and E.

The same logic behind the importance of dividends applies to the cash flow models, because the cash flows are very important part in the equity valuation. Many equity valuation models are mainly based on the information about the financial statements, which are the mandatory announcements that are required by law. Also, all the public companies have an obligation to inform all the information that a rational investor would use to make investment decisions (Market Abuse Regulation 2014/596). It is easy to see that the cash flows and dividends, in addition to information that affects previous two are very closely followed by investors and financial media, which are the main users and distributors of the new information. As the FIP momentum is based on the information discreteness of the firms, all the changes in the information produced by firms are potential sources of the overreaction that the strategy tries to avoid.

2.3. Asset pricing models

Capital Asset Pricing Model

According to Brealey et al. (2017:888), Capital Asset Pricing model by Sharpe (1964) and Lintner (1965) is one of most important theories of modern finance. The model works as a link between the expected return and systemic risk of a stock, where the excess return over the risk-free rate of a stock is its beta times markets risk premium. The model is expressed in the model 6:

(6) $$R_i - r_f = \beta_i (R_m - r_f)$$

Where R_i is the return of a stock, r_f is the risk-free rate, β_i is the beta coefficient of stock i and R_m is the return of a market.

The assumptions behind the model are listed below and one can see that these are very unrealistic, so these assumptions should be seen more like a benchmark of the perfect capital markets. Also, as discussed in the market efficiency chapter, the model clearly fails to price stocks at least partly due to concerns raised by for example, Black, Jensen and Scholes (1972) and Fama (1991), but it is still widely used among practitioners (Bodie et al. 2014).

1. Investors are rational portfolio optimizers
2. All investors have same investing horizon and homogenous expectations
3. Investors can lend and borrow at a steady risk-free rate
4. All assets are publicly held, and all securities could be traded
5. Short selling is allowed
6. All information is public
7. There are no transaction costs or taxes

None of the assumptions are true, for example investors are not rational as they tend to under- and overreact to different types of news, investors tend to have very different investment horizons, and investment loans are not available for everyone neither are short selling. Also, the main component of the model, the beta coefficient, is not forecasting the average returns correctly as low beta stocks earns higher average return than higher beta stocks (Black et al. 1972) and it is time varying (Bollerslev, Engle and Wooldridge 1988). Even though the strict assumptions drop the floor behind the model, it is still one of the most important factors of the more up-to-date asset pricing models for example, Fama's and French's three and five factor models (1993 and 2015), which tries to explain the average returns that CAPM left unexplained.

Fama and French 3 factor model

Three factor model by Fama and French (1993) is an extension of the traditional capital asset pricing model, where the returns of the assets are explained, in addition to market risk premium, with the size factor and book-value factor. The size factor (SMB, Small minus big) is the difference between the returns of the portfolio of small firms and large firms. The book-value factor (HML, High minus low) is the difference between the returns of the portfolio of the high book-to-market firms and low book-to-market firms. The model is expressed as in the equation 7:

$$R_{i,t} - R_{rf} = \alpha_i + \beta_i(R_m - R_{rf})_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{7}$$

Where the left-hand side is the excess return of the asset i at time t, α is the abnormal return of the asset i, $\beta_{i,m}$ is the loading of the market factor, s_i is the loading to size factor, h_i, is the loading to book-value factor and ε is a residual term with zero mean.

Fama and French (1993) used the median NYSE market capitalization as break points to define the different size portfolios. Fama and French (1993) added the size factor to their model, as it was discovered that the size of the firm is explaining the returns (see Banz 1981 for original discussion). Especially, the returns of smaller firms were a challenge for the traditional Capital asset pricing model, which was the motivation to add the size factor as proxy for the common risk factor in their asset pricing model (Fama and French 1993).

Fama and French (1992) found that book-equity-to-market (B/M) seems to have an explanatory power on average stock returns, and especially combined with the size factor, they are explaining other factors, such as earnings per share (E/P) and leverage, that tries to explain average returns in the stock markets. Fama and French (1992) argued that all of these four studied factors, B/M, size, E/P and leverage are all scaled versions of price of a stock, so some of them must be redundant. In the multivariate tests the relation with average returns and B/M and size stayed robust after the inclusion of other tested factors (Fama and French 1992).

Size and B/M factors are closely related to momentum strategy. Momentum is found to be stronger among smaller firms (see e.g. Jegadeesh and Titman 1993 and 2001, Hong et al. 2000). This finding implies that if the FIP momentum portfolios are also driven by smaller firms, the strategy should load strongly on that factor. Also, as found by Jegadeesh and Titman (2001), the long leg of 6/6 momentum portfolio has smaller loading than the short leg, which implies that short leg is driven by smaller firms. One argumentation behind the relative strength of the smaller firms in momentum strategy is that they are not so widely followed by analysts and informed investors and therefore the information they produce are less effectively spread across the markets (Hong et al. 2000).

Value strategy, or the strategy that buys low B/M stocks or long-term losers, is an opposite view of the momentum strategy that buys and sells the short-term movers. The profitability of the value strategy has been confirmed many times (see e.g. Fama and French 1992) and it is working very well with the momentum strategy across different asset classes, as these two strategies are negatively correlated (Asness et al. 2013). Interestingly, Jegadeesh and Titman (2001) found that both extreme winners are losers both loads negatively to B/M factor, compared with "middle" portfolios that load positively. This indicates that extreme portfolios are more driven by growth firms (low B/M) than value firms (high B/M). Reactions to all Fama and French (1993) factors implies that the short side of the momentum strategy is riskier, as it loads more strongly on all Fama and French factors compared long side (Jegadeesh and Titman 2001).

Fama and French 5 factor model

If the asset pricing model prices all the assets correctly, the α of the model should be zero for all securities and portfolios that the model tries to price. Unfortunately, Fama and French (1993) three factor model fails price the variations caused by the profitability and investments of the companies. Due to this mispricing, Fama and French (2015) added two new factors for their asset pricing model: profitability and investment factors. The profitability factor is the difference of the diversified portfolio of robustly and weakly profitable firms and investment factor is the difference between the portfolios of conservatively investing firms and aggressively investing firms. Five factor model is presented in the equation 8:

(8) $$R_{i,t} - R_{rf} = \alpha_i + \beta_i\left(R_m - R_{rf}\right)_t + s_i SMB_t + h_i HML_t + r_i RMW_i + c_i CMA_i + \varepsilon_{i,t}$$

Where the other factors are as in the equation 7, but r_i is the loading of profitability factor and c_i is the loading of the investment factor. (Fama and French 2015.)

To understand the logic and importance of two new factors, the dividend discount model 1 could be extended to take into account of equity earnings per share at time t, Yt, and the change in book equity, dBt, where we got that expected dividends at time t+1 are the expected equity earnings per share minus the change in the book equity (Fama and French 2006). Model 1 is now 9, which is more precise:

$$P_t = \sum_{t=1}^{\infty} E(Y_{t+1} - dB_{t+1})/(1+r)^t \tag{9}$$

If both sides of model 9 are divided with book equity at time t¸ we got the model 10, where it is easily seen that market-to-book-equity, is dependent from the profitability of the firm (equity earnings per share) and the investments of the firm (change in the book equity). For more precise discussion about the model could be found from Fama and French (2006).

$$\frac{P_t}{B_t} = \frac{\sum_{t=1}^{\infty} E(Y_{t+1} - dB_{t+1})/(1+r)^t}{B_t} \tag{10}$$

Gross profitability or revenues minus costs of goods sold is discovered to be a very robust return factor and offers a good hedge against the traditional value factor, as these two strategies took the opposite views of the profitability of the assets. This is a result from the fact that traditional value strategy buys inexpensive assets when selling expensive assets, but in the gross profitability, it buys profitable assets and sells unprofitable assets. (Novy-Marx 2013.)

It is argued that the "gross-profits is the cleanest accounting measure of true economic profitability" (Novy-Marx 2013: 2) and therefore tells more about the future profitability of the firm, even though the net profits of the firm might be much smaller than the competitors. Novy-Marx (2013) argues that highly gross-profitable firms could have, for example, much higher research and development or advertisement expenses than its more net-profitable competitors. These expenses are closely related to future bottom line profits. (Novy-Marx 2013.)

The expected investments of the firms are negatively correlated with the expected future returns. Theoretically, this can be derived from the model 10 as there is four term in the extended dividend discount model: expected profitability (Y), expected investments (dB), B/M (inverse of P/B) and the expected return of the firm (r). When profitability and B/M terms are fixed, then increase in expected return decreases the expected investments by the firm. This negative correlation between two variables is confirmed empirically for example, by Titman, Wei and Xie (2004) and Ahorani, Grundy and Zeng (2013).

For example, Chen, Yu and Wang (2018) tested how “plain momentum” loads on five factors. On all firm samples, both profitability and investment factors are redundant with t-values of -0,11 for RMW and 0.77 for CMA. Interestingly, for large firms only, RMW become important with the loading of -0.21 and t-value of -2.09 indicating that momentum is more driven by weakly profitable firms. On the other hand, small firms load positively on the investment factor with factor loading of 0,3 with t-value of 2.39, indicating that smaller firms invest conservatively. Other factors behavior is mostly in line with Jegadeesh and Titman (2001).

3. BEHAVIORAL EXPLANATIONS

The next chapter focuses on investors psychology to understand the information processing and behavioural return drivers behind the stock markets anomalies. Especially the FIP momentum is mainly driven by behavioural biases, especially under- and overreactions, it is mandatory to understand the theory behind these biases. Therefore, the research on behavioural finance is taken as a view in this chapter and risk-based explanations have less weight. While some of the covered theories are not directly linked to already known explanations of the momentum, they are still covered as it widens the view in the topic and possibly offers not yet offered explains to anomaly.

3.1. Under and overreactions

Predictable short to medium and longer run return patterns has been in the interest of the financial academia and these patterns are tried to be explained with traditional asset pricing models. Traditional models have clearly failed to explain these patterns so new angles have been taken. For example, Hong and Stein (1999) took a behavioral view on the topic, as they came up with theory about how the heterogenous agents interact with each other's. Their goal was not to model the psychology of the agents and took the cognitive bias as taken. To model the interaction between different types of investors, they split the investor population to two types of investors: the newswatchers and momentum traders. The main difference between two types of investors is that newswatchers trades based on the changes of the fundamentals or when new information arrives, and momentum traders' trades only based on the prior price changes of the asset (Hong and Stain 1999.)

Neither of these investors' types is fully rational as expected by traditional models. Rather, in their model, investors irrationality is due to limited capability to process public information and how they react to it. Newswatchers trades are based on forecasts that they have done from the news about the future values of the fundamentals and they do not give a weight to the price of the stock. Momentum traders are opposite as they cannot process any fundamental data and their forecast are based purely on the simple changes of past prices (Hong and Stain 1999.)

In the model, Hong and Stein (1999) assumed that new information diffuses slowly within the newswatchers and the speed how the new information diffuse, differs on how many newswatchers there are. They used a residual analyst coverage after size control as the proxy of the information flow. Hong and Stein (1999) discovered that momentum is in fact more profitable and the effect lasts longer within the stocks with the lowest information flow. This indicates that when the information flow is slow the markets tend to underreact at first. This major underreaction, on the one hand, attracts the momentum traders and when more momentum traders rush to trade, on the other hand, makes them collectively to overreact. Authors argued that the profitability of the momentum strategies depends on how early on the "momentum cycle" the traders jump in. On the earlier stages of the cycle, momentum traders are reacting to initial underreaction of new information and on the later stages' traders are reacting on the price changes caused by early birds, which is the reasoning to overreaction (Hong and Stain 1999.)

The gradual flow of information could be seen as a part of the wider concept of the disagreement of the information or disagreement models (Hong and Stein 2007). Disagreement models are based on three different psychological mechanisms: gradual information flow, limited attention and heterogenous priors. Even though these different mechanisms are based on different theoretical and empirical concepts, they still share common factors. The main features of these models are the importance of the differences in the investor's beliefs. Hong and Stein (2007) argued the importance of these disagreement models in a following way: as a majority of the traditional pricing models clearly fails to explain most of the trading volume, there has to be some other factors that explains the volume, which according to Hong and Stein (2007), is the disagreement about the value of the stocks.

In the 2007 article, Hong and Stein took the views of the original 1999 article even further when they introduced two new types of investors: specialists and generalist. They used the analysis by Huberman and Regev (2001) as an extreme example of the gradual flow of information among the different types of the investors. On the example, a small biotechnology firm was mentioned in the front-page story on New York Times (NYT) that was about the break-through in cancer research. This story made the price of the firm rocketing from 12$ to 52$ per share. The most interesting part of the example was that this story contained 5-month-old information, as that research was originally published in a scientific journal five months before the story in NYT. This original publication made the stock price move higher, but actual rocketing happened only after the NYT story (Huberman and Regev 2001). Hong and Stein (2007) suggested that investors who reacted to the original publication were the specialists and those who rushed to trade after the NYT story was the generalists.

The limited attention model assumes that investors are not able to process all available in-formation because they are “cognitively-overloaded” and thereby they only pay attention to a small set of available information (Hong and Stein 2007). Even though limited attention is closely related to gradual information flow, but it pays less attention to the dynamics of the diffusion of the information. As argued by Hong and Stein (2007), the importance of the media is closely linked to limited attention as the “attention-grabbing” news release will increase the trading volume more than its less sensational but equal content news. Hong and Stein (2007) also used an article by DellaVigna and Pollet (2009) as an example of limited attention. DellaVigna and Pollet (2009) found that trading volume after earnings announcements on Fridays are lower than on other days of the week, which suggest that investors are underreacting to this news because the weekend disrupts their attention.

Third part of the disagreement model, introduced by Hong and Stein (2007), is the heterogenous priors. Heterogenous priors mean that even though investors might get the same public information at the same time, their beliefs about the contained information might differ a lot. As an example Hong and Stein (2007: 121) used three investors with different expectations about the firm earnings announcement. Suppose that the earnings are 10 percent and the investors have the following expectations: first expected no increase, second expected 10 percent increase and third expected 20 percent increase. From the example, it can be seen that for one investor, earnings were a positive surprise and for another it was negative surprise. Every one of these investors has to up-date their models and therefore they have to trade with each other. This, on the other hand, increases the trading volume on the markets. This is the total opposite compared with traditional rational agent models (see e.g. chapter 2), where the new information should decrease disagreement among investors (Hong and Stein 2007.)

As already pointed out by Hong and Stein (1999 & 2007), different investors have different beliefs and expectations of the information on certain stocks. According to the Bayesian framework, investors' expectations and beliefs will be updated based on their earlier beliefs in addition to new information. The process how this update will happen depends on how strong the uncertainty of prior beliefs is and how uncertain is the new information. Heterogeneity of these beliefs, as measured by the dispersion of analyst forecasts of earnings, is shown to be robust predictor of the momentum returns, since the monthly difference between high and low dispersed momentum portfolios is 0,55 per-cent with t-statistic of 3.59. Also, it was found that loser stocks have higher heterogeneity of beliefs compared to winners (Verardo 2009.)

When Hong and Stein (1999 & 2007) studied how the heterogenous agents interacts with each other, Daniel, Hirshleifer and Subrahmanyam (1998) took a different view as they formed a theory of the markets over- and underreacts to new information about how these reactions are derived from overconfidence and biased self-attribution. They defined an overconfident investor as a person who overestimates his forecasts that are based on the private information signals. These private signals are either confirmed or disconfirmed after the public information is announced, and depending of the outcome, his confidence will overly rise or fall only slightly. This asymmetry between the results of the confirming and disconfirming public information is called biased self-attribution (Daniel et al. 1998.)

This overconfidence on private signals is causing the stock markets first to overreact and when the noisy public information signals arrive, only a part of that initial overreaction is corrected, which leads to delayed underreaction. This "overreaction-underreaction" pattern is, for example, linked to negative long-run autocorrelations and unconditional excess volatility. On the other hand, if this noisy public information confirms, on average, more than disconfirms the private signals, it could trigger the continuation in initial overreaction, which is linked to positive short-run autocorrelations (momentum) before the delayed reversal (Daniel et al. 1998.)

Barberis, Shleifer and Vishny (1998) extended the behavioral finance literature by introducing their model for investor sentiment. Their investor sentiment model explains both under- and overreactions and it is based on two psychological theories: representativeness and conservatism. Compared with for example Daniel et al. (1998), investor sentiment model first assumes that investors underreact to news, but as this news are forming the same sing patterns, investors overreacting to these, as they overly optimistically expect them to continue even though if it is highly improbable (Barberis et al. 1998.)

First psychological model Barberis et al. (1998) used is conservatism, first introduced by Edwards (1968), that is a psychological theory, in which individuals slowly adapts their beliefs when they find new evidence. In the concept of Barberis et al. (1998), when investors get new information, they update their models correctly, but too little compared to “rational benchmark”, which causes them to collectively underreact and therefore drives the momentum further. The second model, introduced by Tversky and Kahneman (1974), is the representative heuristic, which one “manifestation” is that people seem to see patterns in random data. Barberis et al. (1998) suggest that this representativeness is the reasoning behind the long-term reversals as investors do not face the fact that long streaks of same sing news cannot continue forever.

The investor sentiment model assumes that earnings or other corporate information follows a random walk, but the investor is not aware of that. The investor believes that these earnings are moving between two different regimes, where the first regime is a state where earnings are “mean-reverting” and the second regime is a state where the earnings are trending. The probability to move from one regime to another is fixed in the investors mind. The model also assumes that at any point of time, the earnings of the firm are more probably staying in one regime than change. Every time new earnings announcement is released, the investor uses this new information to update his beliefs about the regime where he is. (Barberis et al. 1998.)

3.2. Cultural differences

Behavioural biases that investors face (see e.g. Daniel et al. 1998, Barberis et. al. 1998 and Hong and Stein 1999), could be caused by differences in cultures where the investors live and therefore this cultural environment is a potential factor that affects stock returns (Chui et al. 2010). As proxy for the cultural environment, authors studied how the

Hofstede's (2001) individualism index explains the returns of the momentum strategy. Chui et al. (2010) argued that individualism is closely related to overconfidence and self-attribution bias, which has been shown to be a potential driver in momentum returns (Daniel et al. 1998). Also, some Asian countries have caused problems to the momentum (see e.g. Asness et al. 2013) and at the same time these countries have lower index values compared with western countries, which is the motivation of the study (Chui et al. 2010).

The individualism index is significant predictor of the momentum returns as the difference between the highest and lowest 30 percent individualistic countries is 0.65 percent per month with t-statistic of 4.3. These results are very robust, as they also compared other country-related measurements that might explain the results, such as economic development, information uncertainty and development and integrity of the country's financial markets, and still found that the individualism stay significant momentum returns explanator. Findings hold even after excluding these Asian countries or including only developed countries. Also, there seems to be long-term reversals in the momentum portfolios (see e.g. Daniel et al. 1998 and Hong and Stein 1999 for behavioural models), these reversals are stronger on more individualistic countries (Chui et al. 2010.)

3.3. Investors attention

Investors' attention is an important part of the decision-making process, as already briefly discussed in chapter 3.1. But how individual and institutional investors decide what stocks they buy or sell? Barber and Odean (2008) offers a view that stock that attracts individual investors' attention is more likely to be bought than sold, compared with the institutional investors, where both actions are equal likely. This difference between two types of investors is resulted from the fact that buying, and selling are fundamentally two different actions, as opposed to the views of the traditional models. This difference is also more meaningful to individual investors, as they face more search problems and constraints (Barder and Odean 2008.)

Investors have limited cognitive resources and therefore they cannot process all available information. Consequently, investors tend to focus on the stocks that have attracted their attention in some way, as there is cognitively an efficient way to reduce that potential universe of stocks to buy. On the other hand, when they face a situation, where stocks have to be sold, the universe is mostly the stocks that the investor already owns, so the “attention-crabbing” is not so important factor than for example the past returns of the stocks (Shefrin and Statman 1985). They found that the actual buying behaviour of individual investors is what was expected, as on the most attention attracting days individuals are the net buyers, when the “attention-crabbing” was measured by trading volume, extreme price changes and news coverage (Barder and Odean 2008.)

Da, Engelberg and Gao (2011) took on a different view on the investors’ attention and used Googles Search Volume Index (SVI) as proxy for the direct attention of certain stocks, compared more indirect measures used by Barber and Odean (2008). Da et al. (2011) argued that their proxy is more precise than other indirect measures, as for example stock returns and trading volumes could be related to other factors than attention, and even though some firm might be in a news article, it does not guarantee that the investor will actually read it. This is not the case with SVI, where the searcher of the information is unquestionably paying attention on the subject of the search (Da et al. 2011.)

SVI is especially a good attention indicator among individual investors, as found in the difference between changes in SVI and trading behaviour of the investors. As founded from the retail execution reports from Security and Exchange Commission, Individual investors tend to concentrate on specific market centres compared with more sophisticated investors. They also confirmed the hypothesis of Barber and Odean (2008) that individual investors are the net buyers among the “attention-crabbing” stocks, as they found that the stocks with a high increase in abnormal SVI outperform their peers more than 30 basis point during two weeks after the increase. It was also founded that this effect is stronger on stock that are more traded by individual investors and by the end of the year that initial price pressure is almost completely reversed (Da et al. 2011).

When Da et al. (2011) looked at the investor attention from the view of an individual investor, Ben-Rephael, Da and Israelsen (2017) extended the investor attention literature to cover institutional investors. Individual investors mostly rely on free information sources like Google when institutional investors use more sophisticated information sources as for example Bloomberg or Thomson Reuters. Azi et al. (2017) used user profiles from Bloomberg Terminal as their proxy for the investors' attention and came up with the abnormal institutional attention (AIA) as a measurement that captures attention by institutional investors.

To get the best possible comparativeness with Da et al. (2011), Ben-Rephael et al. (2017) used a very similar sample. They found that both measurements (SVI and AIA) are positively and significantly correlated, but still only explains about 2 percent of each other's variation. Then, AIA is more correlated with institutional trading volume than total trading volume, which indicates that AIA measures directly institutional investors' attention. Also, it was founded that AIA actually leads the SVI, what underlines the fact that institutional investors have more resources and incentive to more quickly pay attention to new information.

AIA is also very good predictor of the underreactions on the new information as institutional investors are those who tries to react more quickly, trade more and are less constrained than retail investors. Ben-Rephael et al. (2017) discovered that when new information does not attract the attention of institutional investors, prices are more likely to exhibit patterns, for example post-announcement drifts, that are related to underreaction. They found that the strategy, that goes long on positive news and short on negative news on days that does not attract attention, could generate 63 to 95 basis points significant returns over five to ten days after the news, compared with opposite strategy, where the returns are not significant. This finding confirms that underreactions are driven by limited attention (Ben-Rephael et al. 2017.)

Investors have clearly limited capacity to process information and therefore paying attention only on certain types of information. There are still a lot of other factors, in addition on economic factors, that disrupt the attention of investors. Huang, Huang and Lin (2019) founded that large national lottery jackpots attracts a lot of individual investors' attention and therefore causes the markets to pay less attention on firm level information. Peress and Schimdt (2018) had similar findings when they studied the effects of sensational news on stock markets. They found that on days with sensational news, for example trading activity and liquidity was much smaller in comparison with other days (Peress and Schmidt 2018).

Investors' moods have an effect on investors’ attention. For example, sport sentiments can also distract the investors' mood, as was founded by Edmans, Carcìa and Norli (2007). They found that international soccer games have economically and significant effects on stock markets for example, especially when losing an important match on important games (Edmans, Carcìa and Norli 2007). Also, the weather has an impact on a mood. Sunshine has significant effect, as there is a negative relationship between cloudiness and stock returns, even after controlling other weather conditions (Hirshleifer and Shumway 2003).

In addition, that different types of investors react on different types of information with a different degree, this investors’ attention is also influenced by seasonal patterns. There is not just a constant degree of attention that is given to specific type on information at certain time, if the information content exceeds some unit of information. Liu and Peng (2015) pointed out that investors’ attention is strongly following seasonal patterns as Fridays and summer holidays (July and August) exhibit predictable reactions when measured by “abnormal attention”.

On Fridays, investors’ pay much less attention to earnings announcements compared with other trading days of the week, even after controlling that there are less announcements and less “baseline attention” on Fridays. This Friday pattern is in line with the findings of DellaVigna and Pollet (2009). Summer months have a similar pattern, as attention is significantly much lower during these months even when July is the seconds busiest earning announcement month. Interestingly, even though the baseline attention is lower on these summer holiday months, reactions between announcement days and non-announcements days do not differ from other months (Liu and Peng 2015.)

3.4. Seosanality of stock returns and momentum

Even though financial markets do not sleep during the summer months, there is still strong evidence that many participants are "gone fishin'" as suggested by Hong and Yu (2009). They studied trading activity and mean returns during the summer holiday months (3rd quarter on the Northern Hemisphere and 1st quarter on the Southern Hemi-sphere) around the world and discovered that both measures are significantly lower during these months. Especially, these findings were the strongest among the largest markets in Northern America and Europe. It was also discovered that lower activity and returns are in fact due to summer vacations, as air-travel passenger travel and hotel occupancy rates predicted significantly well the summer month dummy, which on the other hand, was significant variable explaining both trading activity and mean returns. Hong and Yu (2009) argued that their "Gone fishin'" effect is related to "Sell in May and Go Away" effect by Bouman and Jacobsen (2002), as both studies found that trading activity is in fact lower during summer months.

One important driver behind the annual seasonal patterns on the stock markets is well known psychological disorder called seasonal affective disorder (SAD) or more commonly known from its milder version: winter blue (Kamstra, Kramer and Levi 2003). Many psychological studies have shown that SAD is closely related to the length of the day and to many depression symptoms, which on the other hand are linked to risk-aversion and "sensation-seeking" propensity (see Kamstra et al. 2003) for more discussion). Interestingly, there are strong evidences that the effects of SAD are asymmetrically distributed around the winter solstice. Kamstra et al. (2003) argued that during the fall period investors who are affected by SAD reduce the riskiness of their portfolios and moving their wealth to the safer assets, as the length of the day is decreasing. Around the winter solstice, when the length of the day starts to again increase, which boosts the mood of the investors, and they again move their wealth back to riskier assets, that is linked to higher returns on the markets (Kamstra et al. 2003).

Findings by Kamstra et al. (2003) supports this argue, as the SAD has positive and significant impact on the mean returns, but the fall dummy decreases as one move further away from the equator, for example Sweden (59 degrees north) has lower value than

Germany (50 degrees north) and New Zealand (37 degrees south) has lower value than South Africa (26 degrees south). Also, when the risk-aversion is linked to SAD effect, then an asset pricing model, that allows a price of the risk vary, should capture SAD effect. This, indeed, is the case as when the conditional capital asset pricing model that allows time-varying in market risk and in price of risk captures the SAD effect completely (Garret, Kamstra and Kramer 2005).

As there are clearly behavioural factors that cause seasonal patterns in the stock markets, how these patterns exploit trading opportunities? For example, Heston and Sadka (2008) found that if a stock has above-average return on a specific month, this same month tend to have above-average returns at annual intervals. Also, the January effect has been founded to be very consistent calendar anomaly (see e.g. Moller and Zilca 2008 for discussion on the January effect) that have affected other stock market anomalies such as the momentum (e.g. Jegadeesh and Titman 1993 & 2001) and long-term reversals (De Bondt and Thaler 1985 & 1987). For example, Jegadeesh and Titman (2001) found that momentum have an average -1,69 percent (t=-2,49) return on Januaries, when in between February and December an average return is 1.26 percent (t= 8.31).

Yao (2012) took a closer look on the January effect as he studies what kind of impact it has on momentum. Two different formation periods are used in the study, as short-term (t-2 to t -6) and intermediate-term (t-7 to t-12) momentum strategies were studied separately. One of the main findings was that these two different strategies have a different exposure to differently sized stocks, as the short-term momentum is more exposed to size effect than the intermediate-term strategy on January. Also, January has strong negative autocorrelation and non-January months has strong positive autocorrelations, which underlines the well-known fact that the momentum loses money on Januaries. In addition, Yao (2012) found that, after controlling the January effect, intermediate-term autocorrelation seems to disappear, which might be one of the reasons why it is an established practice in momentum literature to use a prior 6-month returns.

3.5. Some evidence from the behavioral models

Jegadeesh and Titman (2001) extended their earlier (1993) research to study more closely potential explanations for momentum and to tackle the questions about the reliability of the results. As the extended momentum returns are consistent with the earlier work, they focused more on reversals and how it could be explained by different theories. For example, behavioral theories by Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) all predict that there is a return reversal after the intermediate holding periods. This is what Jegadeesh and Titman (2001) indeed found, as cumulative momentum returns are on average negative 13 to 60 months after the formation date (ranges from -0,13 percent per month with t-statistic of -1,93 to -0,38 percent per month with t-statistic of -4,45). Also, this reversal effect is stronger among smaller firms and weaker among larger firms, which on the other hand, is consistent with the momentum as the effect is stronger among smaller firms. This small firm dominance in the momentum might be due to higher volatilities of these firms, so the extreme values are more likely among these firms (Jegadeesh and Titman 2001).

Hong et al. (2000) tested the predictions of the gradual information flow model by Hong and Stein (1999) and found that momentum is stronger among small to medium size (peaking at the 3rd smallest decile) firms compared with the largest and the smallest firms, which is in line with the findings of Jegadeesh and Titman (1993 & 2001). They also discovered, as predicted, that momentum is stronger among the firms that have low analyst coverage. The most interesting finding was that the firms with less analyst coverage seem to react stronger on the bad news than on the good news. For example, 1,05 percent of the monthly profitability of the total 1,43 percent came from the “losers” side of 3rd decile winner minus loser portfolio. They argued that this phenomenon might be due to the fact that when there is less or no analyst coverage, the executives of the firms are major spreader of the information. When the firm has something positive to announce (e.g. positive profit warning), then the executives are more likely to make much more noise about this news compared with the situation when the firm has something negative to announce (e.g. lawsuit), when they most likely announce only what is required by law (Hong et al. 2000.)

The model of the gradual flow of the information is also tested using the information from the option markets. Chen and Lu (2017) rationalized their approach by that the measures used by Hong et al. (2000) are static rather than dynamic, which is more the true nature of information diffusion speed. Chen and Lu (2017) used the growth of implied volatility of call options as proxy for the information diffusion. They argued that large moves in the implied volatility reflects the positions and beliefs of information of informed traders. Test portfolios are then formed by sorting stock with the largest growth or decline in implied volatility, where the "winners" were the stock with the highest growth and the "losers" were the stock with the largest decline. These enhanced portfolios generated 1,25 to 1,78 percent monthly alphas after risk adjustments and are mainly driven by the long leg of the long-short portfolios, which is interestingly the opposite of the findings of Hong et al. (1998) (Chen and Lu 2017.)

In addition to the past market data, momentum and reversals are also studied in the laboratory setting. Bloomfield, Tayler and Zhou (2009) established laboratory experiments that are based on the Hong and Stein's (1999) model of the gradual flow of information, where they studied how informed and uninformed investors behave in different settings. Bloomfield et al. (2009) observed that actual behavior of investors is mostly in line with the predictions by Hong and Stein's (1999) model, as gradually spreading news is driving the momentum. They also discovered that long-term reversals arise when the uninformed investors make their trades, as they are overreacting to the new information. Even though the behavior patterns are in line with the model, the causes are not as Bloomfield et al. (2009) found that uninformed traders are behaving more like contrarians than momentum traders. Bloomfield et al. (2009: 2536) explained that this finding is due to the fact that "The uninformed traders' contrarian reactions… lasts longer than the informed traders' reaction…" and thereby getting prices starts to reverse.

The media plays an important role in the stock markets as suggested by Hong and Stein (2007). Also, the importance of the information is shown to be an important factor in the momentum returns. In this context Hillert et al. (2014) studied how media coverage, measured by the number of articles on the specific firm in well-known newspapers, affects the momentum returns. They found that over the six month holding period, the media-based momentum portfolio generated on average 1,02 percent (t=3,61) per month in the highest covered decile portfolio compared with only 0,33 percent (t= 1,42) in the lowest covered decile portfolio, also the difference between the highest and the lowest decile portfolios is 0,68 percent with t-statistic 3,7. In addition, Hillert et al. (2014) found that the reversal effect is stronger among higher covered stocks, which indicates that this type of momentum is potentially driven by overconfidence, overreactions and limited attention as, for example, suggested by Daniel et al. (1998), Barber and Odean (2008) and Da et al. (2011).

4. DATA AND METHODOLOGY

This chapter describes the data and portfolio construction methodology. First sub-chapter introduces the data in a detailed way and briefly discusses its major drawbacks. Second sub-chapter introduces the information discreteness measurement, the main component of the portfolio construction, and its alternative.

4.1. Data

My data contains the constituents of the Stoxx Europe 600 index from the end of January 2004 to the end of August 2019. I will use the constituents of the Stoxx Europe 600 index as proxy for the largest 600 firms from the European region. My data methodology loosely follows the methodology of Asness et al. (2013: 933–934), as they focused on the "a very liquid set of securities that could be traded for reasonably low cost at reasonable trading volume size" to have a conservative result, as the momentum is shown to stronger on smaller firms. Also, focusing on the largest sample of stocks, makes this strategy easier to implement on practise, as for example, many of the smallest stocks are, or almost are, impossible to sell short.

As different academic papers use different definition for European markets, I will use the definition of Stoxx Europe. The Stoxx Europe 600 contains firms from 17 countries of the European region: Austria, Belgium, Denmark, Finland, France, Germany, Ire-land, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom. Also, due to the index construction method, the Stoxx Europe 600 index contains the stocks that are both the largest and the most liquid stocks, as every stock within "the STOXX universe" is assigned to the Stoxx's own "Free float factor" to reduce free-float market capitalization to the actual number of shares that are available to trade (Stoxx 2019). For example, this Free float factor excludes the shares that are owned by the company itself, governments and other long-term owners that own more than 5 percent of the total market capitalization (Stoxx 2019).

Because of data availability issues, I have to use this same set of firms to the whole study period. Therefore, the data is under a survivorship bias, as it does not contain firms that are delisted during the study period. This leads to the situation, where the results of the study might be too optimistic or pessimistic. The number of firms at the beginning of the sample is 348 and at the end, there are 533 firms after excluding stocks that are less than 5$ at the beginning of each month. Also, I have formed the first test portfolios at the end of November 2005, to have at least 2/3 of the firms from the constituents of the index at the data collection date. Afterall, firms should have at least 12 to 24 months of return data to be included in portfolios due to the portfolio construction methods.

In addition to the daily price data, I have accounting based data for market-to-book ratio, market capitalization, revenues, total assets, return-on-equity ratio and firm-based data for exchange, equity type, sector, listing currency and symbol. Accounting based data is either quarterly or semi-annual, depending on the release frequency. All data came from Thomson Reuters DataStream. For risk adjustments, I use the factors from French's database. To compare the results, both firm data and factor data is in United States dollars, so I have a view of an American investor.

4.2. Methodology

As already briefly discussed on the introduction, I use the Information discreteness measurement by Da et al. (2014) as my proxy for the quality of the past returns. ID is determined in the equation 11:

(11) $$ID = sign(PRET) * (\%neg - \%pos), \text{ where}$$

(12) $$\%pos = mean \sum_{t-251}^{t} positive \begin{cases} 1, if\ r_{t,t-1} > 0 \\ 0, otherwise \end{cases}$$

(13) $$\%neg = 1 - \%pos$$

Where sign(PRET) is the sign of the cumulative return of the past twelve skipping the most recent month and have values +1 when the PRET is > 0 and -1 when the PRET is

<0. %neg (%pos) is the percentage of negative (positive) days during the twelve-month formation period (I use 21 trading days per month, as an average of trading days per month). Negative (positive) days are days, when the daily return is negative (positive) and got a value of 0(1). Percent positive is a rolling mean of a sum of positive days, and as zero return days are handled as a negative, then percent negative is just 1 minus percent positive. Because my data set contains only the largest and most liquid stocks, I handle zero days as negatives, which is opposite than Da et al. (2014) as they handle them as an own group and do not count them on the equation. My decision is based on the fact, that zero returns days are in my sample mostly national holidays or other market-wide events and not the result of illiquidity as discussed by Lesmond, Ogden, and Trzcinka (1999).

The magnitude of the daily returns is ignored by equally weighting each observation. Therefore, the ID got values from -1 to +1, where -1 is the most continuous information and +1 is the most discrete information. It is important to notice that ID only measures how continuous the information is and not how the stock is performed. For example, if stocks A's past twelve month return is positive (sign[PRET] = +1) and 60 percent of days are positive, it got ID of +1*(0,4-0,6) = -0,2 when stock B's with negative twelve month return (sign[PRET] = -1) and 60 percent negative days, got also ID of -0,2 (-1*[0,6-0,4]).

To follow the methodology of Jegadeesh and Titman (1993) and Da et al. (2014), test portfolios are formed in a following way. At the beginning of each month, all stocks are ranked by their past J- month return to five different portfolios: the winner and the loser quantiles and three neutrals between two extremes (Jegadeesh and Titman 1993 used deciles and Da et al. 2014 used quantiles). I will use the wider portfolios than Jegadeesh and Titman (1993), as my sample is much smaller than their, so my results are not so driven by the most extreme values. After the rank by past J-month return, each portfolio is sub-derived by the ID to five sub portfolios. A total number of portfolios per J-month formation period and K-month holding period is therefore 25 from continuous losers (low ID and low J-month return) to discrete winners (high ID and high J-month return). For robustness checks, I will also test other formation methods.

Da et al. (2014) uses 6-month formation period and 6 month holding periods and Jegadeesh and Titman (1993) used all combinations of one to four quarters formation and holding periods totaling of 32 different portfolios but focusing on 6/6 portfolios. To follow these methodologies, first I will test the performance of all 25 portfolios with four different combinations of formation and holding periods, and then I will focus more on 6/6 portfolios. Da et al. (2014) computed the ID by using past twelve-month returns, I will test if it changes the results to match the formation period of the ID and the past return portfolios and I will test to double the formation period, as a robustness check.

As I have a quite short study period, I will use the methodology of Jegadeesh and Titman (1993:68) to increase the power of my tests, so I will include "portfolios with overlapping holding periods". This means that at every time t, I will have J different portfolios: a portfolio that is formed at time t as well as portfolios that are formed at previous J-1 months. Therefore, I have to weight each stock with a factor of 1/J, as there are stocks that are in more than 1 portfolio at a given time.

For risk adjustments, I will use the factors from the Ken Frenches database. I will use 4 different models: Fama's and French's three-factor model (1993), the three-factor model plus, the momentum factor, Fama's and French's five-factor model (2015) and the five-factor model that includes the momentum factor. All the factor data is from French's (2019) online database.

4.3. Methodology of alternative ID measurement

The ID measurement by Da et al. (2014) is based on the relation between the same and the different sign daily returns. Even though the whole idea of the ID measurement is based on that investors' miss small amount of information that firms produce, the ID still does not take into consideration magnitude of these same sign returns.

Alternative ID measurement by Da et al. (2014) takes also in the consideration magnitude of the returns, by weighting each sign of the return with a decreasing weight. Before the weighting is done, absolute values from returns are taken to make sure that both, the same magnitude positive and negative returns, have the same weights. The smallest return quantile got a weight of 5/15, next got the weight of 4/15 and so on till the highest quantile, that got a weight of 1/15. Weighting is arbitrarily chosen to strictly follow a methodology of Da et al. (2014).

After the weighting is done, I take one-year (252 trading days) rolling sum of these weighted signs and multiply it by the sign of the one-year return on that same period. After that, this whole equation is divided by 252 to have a daily alternative ID measurement. After all, the alternative ID measurement is as in equation 13.

(14) $$ID_{mag} = -{}^{1}/_{N} * sign(PRET) * \sum_{i}^{N} sign(return_i) * w_i$$

5. EMPIRICAL FINDINGS

This chapter shows the empirical findings of the study. The first sub-chapter reports the results for different formation and holding periods for both long only and long-short portfolios. Second sub-chapter reports the summary statistics for firm-characteristics in long-only six months formation and holding period portfolios. The next sub-chapter reports multivariate time-series regressions on Fama and French factors. Lastly, the rest of the chapter discusses the results of different portfolio formation methods.

5.1. Summary statistics for different formation and holdin periods

Table 1 reports the long-only portfolios monthly mean returns and corresponding t-statistics, standard deviations, skewness's and kurtosis. In this table, I have tested four equal length formation and holding period pairs: three and three, six and six, nine and nine, and twelve and twelve months, and four different double sorted extreme quantile portfolios (continuous winners and losers, discrete winners and losers) plus traditional momentum quantiles. I have focused on these formation periods and portfolios for simplicity, because all combinations of one to four quartiles would totalled 16 different combinations plus 25 combinations from 5*5 quantiles would have totalled 16*25 = 400 different portfolios.

Double sorting the portfolios first by past J months return and then by ID have mixed results. On longer formation and holding periods, especially discrete winners outperform traditional momentum portfolios, whereas continuous do not. Almost every long-only portfolio has a positive and significant return when formation and holding period is six-months or longer. For example, nine- and twelve-month discrete winners have the average returns of 1,086 and 1,242 percent per month with the t-statistics of 6,170 and 7,667. On the other hand, the shortest formation and holding periods are mostly the least profitable strategies among tested portfolios and also have the lowest t-statistics among all, when two portfolios are insignificant (continuous losers, with t-statistic of 1,806 and discrete losers with t-statistic of 1,775) on usual significant levels.

The differences between continuous and discrete portfolios are unexpectable, as Da et al. (2014: 2184) find that continuous portfolios outperform discrete ones with relatively wide margin, when I find the opposite. Even though the differences are not as found by Da et al. (2014), there are differences between average returns, but that difference is not always statistically different from a zero. For example, in the six-month formation and holding period, the difference between continuous and discrete losers is -0,185 but t-statistic is only -1,613. On the other hand, on the winners' side on 12 months holding and formation period, the difference between continuous and discrete is -0,437 with t-statistic of -6,411, so the comprehensive conclusion about the differences of the average returns of long-only portfolios cannot be made. Also, these findings questions formation and holding periods used by Da et al. (2014), as six months is not the best possible option in all cases.

Summary statisctics for different formation/holding period long only portfolios

J/K		Continuous loser	Discrete loser	Continuous winner	Discrete winner	Winner	Loser
3/3	Mean	0,569	0,474	0,582	0,606	0,614	0,618
	T.stat	1,806	1,775	2,466	2,858	2,829	2,207
	Standard dev.	4,051	3,427	3,026	2,723	2,791	3,590
	Skewness	0,708	-0,953	-0,494	-1,034	-0,694	0,118
	Kurtonis	5,143	5,325	4,099	3,593	3,203	5,503
6/6	Mean	0,518	0,703	0,875	0,939	0,872	0,700
	T.stat	1,911	2,917	4,014	4,815	4,338	2,834
	Standard dev.	3,449	3,069	2,774	2,484	2,555	3,141
	Skewness	1,529	0,878	-0,884	-1,090	-0,933	1,225
	Kurtonis	8,013	5,826	3,076	2,099	2,588	7,034
9/9	Mean	0,611	0,584	0,886	1,086	0,974	0,687
	T.stat	2,464	2,835	4,763	6,170	5,663	3,026
	Standard dev.	3,122	2,591	2,339	2,219	2,164	2,859
	Skewness	2,219	0,832	-0,790	-0,641	-0,784	1,555
	Kurtonis	10,316	3,080	1,238	0,383	0,944	6,857
12/12	Mean	0,537	0,639	0,805	1,242	0,966	0,713
	T.stat	2,872	3,294	4,909	7,667	6,192	3,733
	Standard dev.	2,332	2,420	2,044	2,018	1,944	2,387
	Skewness	1,004	0,884	-0,319	-0,441	-0,600	0,937
	Kurtonis	4,170	2,552	0,287	0,195	0,528	3,433

Table 1. Summary statistics for different formation and holding periods – long-only portfolios. The final sample period is from 30/11/2005 to 30/08/2019. Portfolios are formed in a following way: at the beginning of each month, every stock is ranked by its past K-month raw return, skipping one month, then sub-ranking is done with the ID measurement, which is the product of the sign of the past 12-month return, skipping one month, and the difference between the proportion of negative and positive days. Therefore, ID got values between -1 and 1, where lower values of ID indicate that information is continuous and higher values indicate that information is discrete. After all, a portfolio of stocks is held for J-months. At any point of time, there are J different portfolios, so the return of the portfolio is divided by J to have a monthly average return.

Riskiness of the long-only portfolios is decreasing when the formation and holding period is increasing. For example, in the lowest ID portfolios (continuous) the standard deviation of loser portfolio decreases from 4,051 to 2,332 and in winner portfolio it decreases from 3,026 to 2,044 when one move from 3/3 to 12/12. Risk-characteristics of the portfolios differs quite a lot when the return distributions are more closely investigated with skewness and kurtosis. Most of the loser portfolios have positive skewness, which indicates that these distributions have long positive tail, or on the other words, these portfolios have a positive tail risk. Also, losers have much higher kurtosis, or their return distributions are leptokurtic.

On the other hand, winner portfolios have skewness lower than zero, which means that these portfolios have negatively tailed distribution and these portfolios are more exposed to negative events than losers' side. Shorter formation and holding periods have higher kurtosis compared with longer periods, so these shorter portfolios have more extreme events than longer ones. ID affects a little to these shape of the return distribution measurements, as plain momentum winners and losers' skewness's and kurtosis are approximately in the middle of continuous and losers. For example, in the 9-month holding and formation period, average skewness for continuous and discrete losers is 1,526 and for plain momentum loser, skewness is 1,555.

Summary statistics for different formation/holding period long-short portfolios

J/K		Continuous winner minus continuous loser	Continuous winner minus discrete loser	Discrete winner minus continuous loser	Discrete winner minus discrete loser	Winner minus loser
3/3	Mean	0,013	0,109	0,036	0,132	-0,004
	T.stat	0,074	0,858	0,178	0,947	-0,031
	Standard dev.	2,322	1,627	2,618	1,784	1,597
	Skewness	-1,262	-0,175	-2,000	-0,330	-2,692
	Kurtosis	6,205	1,002	12,111	5,221	17,209
6/6	Mean	0,356	0,172	0,420	0,236	0,172
	T.stat	2,065	1,240	2,279	1,555	1,284
	Standard dev.	2,197	1,764	2,347	1,929	1,705
	Skewness	-2,055	-1,622	-3,502	-2,941	-3,808
	Kurtosis	10,713	5,222	17,894	14,840	21,485
9/9	Mean	0,275	0,302	0,475	0,502	0,287
	T.stat	1,488	2,223	2,547	3,789	2,000
	Standard dev.	2,332	1,711	2,353	1,670	1,807
	Skewness	-3,077	-1,543	-3,675	-2,200	-3,948
	Kurtosis	14,555	5,005	18,455	8,213	19,506
12/12	Mean	0,268	0,166	0,705	0,603	0,253
	T.stat	2,045	1,249	5,140	4,502	2,237
	Standard dev.	1,638	1,662	1,713	1,673	1,414
	Skewness	-1,753	-1,820	-2,012	-1,950	-3,248
	Kurtosis	6,567	5,743	8,097	7,119	14,338

Table 2. Summary statistics for different formation and holding periods – long-short portfolios. The final sample period is from 30/11/2005 to 30/08/2019. Portfolios are formed in a following way: at the beginning of each month, every stock is ranked by its past K-month raw return, skipping one month, then sub-ranking is done with the ID measurement, which is the product of the sign of the past 12-month return, skipping one month, and the difference between the proportion of negative and positive days. Therefore, ID got values between -1 and 1, where lower values of ID indicate that information is continuous and higher values indicate that information is discrete. After all, a portfolio of stocks is held for J-months. At any point of time, there are J different portfolios, so the return of the portfolio is divided by J to have a monthly average return.

The performance of long-short portfolios is reported in table 2, where I have compared four different winners minus loser long-short portfolios and the plain momentum portfolio as a benchmark. The winner minus loser portfolio with continuous information (low ID) returned on average 0,013 (3/3 portfolio) to 0,268 (12/12 portfolio) percent per month with t-statistics from 0,074 (3/3 portfolio) to 2,045 (12/12 portfolio), when discrete equivalents have returned on average 0,132 (t-statistic 0,947 for 3/3 portfolio) to 0,603 (t-statistic 4,502 for 12/12 portfolio) percent per month. In both cases, only two out of four portfolios are significant, 6/6 and 12/12 for continuous and 9/9 and 12/12 for discrete. The discrete winner minus loser portfolio outperforms its continuous equivalents in three out of four cases. Only exception is 6-month holding and formation period, where discrete portfolio is not significantly different from zero (mean is 0,236 with t-statistic of 1,555).

Surprisingly, in most formation and holding periods that are significant, discrete winner minus continuous loser is the best performing portfolio. For example, that portfolio has returned on average 0,705 percent per month with t-statistic of 5,140 in 12-month formation and holding period, when corresponding return on the 6-month portfolio is 0,420 percent with t-statistic of 2,279. In the 9-month holding and formation period, discrete winner minus loser is the best performing portfolio with the monthly average return of 0,502 percent with t-statistic of 3,789. All though, it has to be pointed out that the differences are still very small and for example, two sample t-test indicates that difference in means between two best-performing portfolios in 6-month formation and holding period is not significant (t-statistic of -0,253).

Even though the returns of the ID portfolios are much smaller than in Da et al. (2014), these portfolios still outperform its plain momentum equivalent. For example, in 6-month winner minus loser portfolios, there is only one portfolio, continuous winner minus loser, where the return is actually lower than in plain momentum. Return of that portfolio happens to be also insignificant, so every portfolio with a significant return outperforms the plain momentum. This is also true for longer formation and holding periods.

Double sorting the plain momentum portfolios with ID decreases the riskiness of the portfolios as measured by the shape of the return distribution. In every formation and holding period, the plain momentum portfolio is the most negatively skewed and has the highest kurtosis, indicating that extreme events have a major impact on the portfolio. From ID portfolios, the highest return comes mostly with the highest risk, as discrete winner minus continuous loser is mostly the riskiest portfolio, when the opposite is true for continuous winner minus discrete loser.

Different return distributions of winners and losers are a cause the riskiness of the long-short portfolios. Long legs, or the winners, are highly negatively skewed, when short legs, or losers, are positively skewed. Also, the short legs have much higher kurtosis, which combined with positive skewness, indicates that there are much more extreme positive events than in the long legs of the portfolios. This combined with the negative skewness of long legs and the fact, that these extreme events happen to happen at the same time, is the source of the riskiness of long-short momentums or the so-called momentum crashes (see e.g. Daniel and Moskowitz 2016 for further discussion).

Interestingly, continuous losers are more exposed to this phenomenon compared with discrete losers. Also, discrete winners are riskier than continuous ones. This could be rationalized in a following way. The continuous losers are firms which return patterns is mainly driven by many losing days. These firms have produced a lot of negative news for a long time and therefore investors and analysts have a very pessimistic view on these firms. When one of these firm's managed to turn their direction, the stock price could skyrocket in a very short period of time. On the other hand, these discrete winners are the firms, which stock price have a lot of variability. There might be, for example, be rumours about major acquisition, which increases the share price a lot, but when the actual news came out that there is no news, the price will drop dramatically. Combining this two rationalizing's could explain the riskiness of the discrete winners minus continuous losers' portfolio.

5.2. Long-only portfolios summary statistics for firm characteristics

Table 3 reports summary statistics for long-only portfolios with the formation and holding period of six months. Statistics are calculated for ID, M/B ratio and market cap which is a logarithm of 10. ID acts as proxy for the discreteness of the information, M/B is market-to-book-value statistic that is a “value factor” and a market cap act as size proxy. ID is calculated in as equation 11 and its closer description is in chapter 4.2. Market-to-book-value is a monthly market capitalization of the stock divided by its latest book-value and a market cap is a tenth logarithm of a monthly market capitalization.

As expected of Da et al. (2014), every continuous portfolio has lower ID than its discrete counterpart in every reported percentile. Continuous losers have the mean (median) ID of -0,108 (-0,102) when discrete ones have 0,038 (0,043) . On the winners’ side, corresponding numbers are -0,116 (-0,110) and 0,028 (0,030). Differences between means are highly statistically significant as losers have t-statistic of -53,445 and winners have t-statistic of -49,822. These findings are in line with the findings of Da et al. (2014: 2184) as they find that average ID among discrete firms is about 0,03 and in among continuous firms it is about -0,10.

Market-to-book-value are in line with the momentum literature, as especially winners got larger values indicating that those are “growth” stocks and losers got smaller values, indicating that those are more “value” stocks. Also, continuous stocks are more growth as winners have a mean (median) of 3,865 (3,529) and more value as losers have a mean (median) of 0,955 (2,039) than discrete ones , where winners have a mean (median) of 3,633 (3,157) and losers have a mean (median) of 2,256 (2,456) although differences between the means of winners and losers are not significant (t-statistic for winners 0,791 and -1,060 for losers). Extreme values have a higher impact on the continuous losers’ portfolio, and therefore the difference between mean and median is much wider than in other portfolios.

As the sample contains mostly the largest and the most liquid stocks in the European region, the size of the firms is relatively stable among all portfolios. There are still statistically significant differences in means, when for example, the difference between continuous and discrete winners is significantly different from zero with t-statistic of 5,466. Although corresponding t-statistic for losers is just 0,506. The difference between continuous winners and losers is also insignificant with practically zero t-statistic, but difference between discrete winners and losers is significant with t-statistic of -4,886. These findings indicate, that size could explain some of the difference between returns.

Characteristics of different long-only portfolios

Statistic		**Continuous loser**	**Discrete loser**	**Continuous winner**	**Discrete winner**
ID	Mean	-0,108	0,038	-0,116	0,028
	Median	-0,102	0,043	-0,110	0,030
	Standard dev.	0,027	0,023	0,028	0,024
	Min.	-0,195	-0,063	-0,186	-0,031
	Pctl(25)	-0,122	0,031	-0,138	0,008
	Pctl(75)	-0,089	0,051	-0,094	0,046
	Max	-0,056	0,083	-0,062	0,088
M/B	Mean	0,955	1,783	3,865	3,633
	Median	2,039	2,456	3,529	3,157
	Standard dev.	7,578	6,640	1,790	3,335
	Min.	-52,249	-58,871	1,276	-4,969
	Pctl(25)	1,377	1,900	2,937	2,546
	Pctl(75)	2,613	2,974	4,315	4,097
	Max	9,938	7,478	17,630	27,540
Mkt Cap	Mean	6,915	6,905	6,914	6,803
	Median	6,932	6,918	6,905	6,810
	Standard dev.	0,181	0,195	0,185	0,182
	Min.	0,181	0,195	0,185	0,182
	Pctl(25)	6,815	6,781	6,789	6,671
	Pctl(75)	7,044	7,027	7,043	6,930
	Max	7,323	7,395	7,370	7,160

Table 3. Characteristics of firms in different long-only portfolios. The final sample period is from 30/11/2005 to 30/08/2019. ID measurement is the product of the sign of the past 12-month return, skipping one month, and the difference between the proportion of negative and positive days. Therefore, ID got values between -1 and 1, where lower values of ID indicate that information is continuous and higher values indicate that information is discrete. M/B or the Market-to-book-value is a monthly market capitalization of the stock divided by its latest book-value and a market cap is a tenth logarithm of a monthly market capitalization.

5.3. Regression analysis for long-short portfolios

Table 4 and 5 reports the performance of the long-short strategies after Fama and French (1993 and 2015) and momentum factor risk-adjustments. Returns of the long-short portfolios are regressed on different combinations of European Fama and French, and momentum factors, where all factor returns are monthly returns from French (2019) online library. The first and the third model are factor models by Fama and French (first model is from F&F 1993 and third model is from F&F 2015), and second and fourth models adds the momentum factor to latter models. The second model is originally introduced by Carhart (1997) and mostly referred as Carhart's four-factor model, but I will use the term FF3 + WML to consistent interpretation. Detailed factor construction methods can be found on original papers by Fama and French (1993 and 2015). All standard errors and t-values are Newey and West (1987) adjusted with a lag of 6 following a methodology of Da et al. (2014).

Table 4 shows that the risk-adjusted alphas for long-short continuous and discrete portfolios are insignificant, even though the average monthly returns are mainly significant. This indicates that explanatory factors mainly explain returns of the long-short strategies. For the continuous portfolio, the momentum factor is the only factor with significant loading. A positive loading of 0,158 (t-statistic 3,762) for FF3 plus the momentum factor and a loading of 0,188 (t-statistic 5,081) for FF5 plus the momentum factor indicates that the winner's leg of the factor is driving the returns on continuous long-short portfolio.

In the discrete portfolio, the momentum factor has again positive and significant loading of 0,194 (t-statistic 5,389) for FF5 and a loading of 0,232 (t-statistic 5,524) for FF5 plus the momentum factor. In FF5 model, the strategy has a negative and significant loading of -0,092 with t-statistic -2,275 on the market excess return factor. Also, in FF5 plus the momentum factor model, the strategy has a negative and significant loading of -0,338 with t-statistic of -2,600 on the investment factor, in addition to the negative and significant loading on the market factor and positive and significant loading on the momentum factor. These risk factors indicate that this discrete long-short portfolio is driven by aggressively investing short-term winners and this strategy offers a small hedge against the market movements.

Adjusted R-squared shows that every of the tested models do a very bad work to explain the variability in the continuous portfolio. Values are practically zero, and in the FF5 even a negative. Adding the momentum factor slightly increases the value, but it does not change the picture. For the discrete portfolio, situation is a somewhat better. Traditional Fama and French (1993 and 2015) models still does a very bad work, but adding the momentum factor increases the values, as FF3 plus the momentum have the value of 17,9 percent and FF5 plus the momentum have the value of 20 percent, which are reasonable values. F-statistics tell the similar story than R-squared about the power of the models. Insignificant F-statistics for the continuous portfolio means that these models do not have any predictive capability. On the discrete portfolio, these two models that best explain the variability also have the highest F-statistics.

As Da et al. (2014) have only FF3 risk-adjustments, it is only meaningful to compare FF3 risk-adjusted returns. Neither continuous nor discrete long-short portfolio have the significant returns, which is not completely in line with the findings of Da et al. (2014). Because Da et al. (2014) do not report their factor loadings, I cannot compare the results in more detailed way. They find that discrete portfolios have insignificant FF3 alpha in their full sample, but when they study more recent sample period, also discrete portfolio has significant alpha. As my FF3 and other alphas are in both cases insignificant, I have to reject my hypotheses 1 that the strategy that sorts stocks by its six-month past return and then by its ID measurement and holds these stocks for six months do not generate risk-adjusted returns. These findings mean that sub-sorting momentum portfolios by ID do not increase the risk-adjusted performance of the plain momentum strategy in this sample.

Combining continuous and discrete portfolios increases the profitability of the long-short portfolios compared with pure continuous or discrete portfolios, as already shown in table 2. Although, it could be seen from table 5 that both combination portfolios have insignificant alphas, which means that these neither of the portfolios can generate significant risk-adjusted returns. Strategies have similar loadings on Fama and French (1993 & 2015) factors and on the momentum factor than in the pure portfolios. Again, the momentum factor has both positive and significant loadings in both portfolios and for both models than include the factor. For discrete winners minus continuous losers, the investment factor has a significantly negative loading of -0,327 and t-statistic -1,970. For this portfolio, market factors have close to significant loadings but not enough at 5 percent level. The same is true for investments factor loading in continuous winner minus discrete loser portfolio.

Time series regression for winner minus loser portfolios on Fama and French factors: continuous minus continuous and discrete minus discrete

	Dependent variable: Continuous winner minus continuous loser				Dependent variable: Discrete winners minus discrete losers			
Model:	*FF3*	*FF3+WML*	*FF5*	*FF5+WML*	*FF3*	*FF3+WML*	*FF5*	*FF5+WML*
Constant	0,260	0,142	0,285	0,194	0,158	0,014	0,211	0,099
	0,743	*0,472*	*0,934*	*0,764*	*0,551*	*0,051*	*0,805*	*0,414*
Market	-0,040	-0,010	-0,051	-0,041	-0,078	-0,040	**-0,091**	**-0,079**
	-1,000	*-0,294*	*-1,000*	*-0,872*	*-1,696*	*-1,143*	*-2,275*	*-2,548*
SMB	0,094	0,107	0,080	0,064	-0,036	-0,020	-0,058	-0,079
	1,237	*1,574*	*0,930*	*0,877*	*-0,439*	*-0,247*	*-0,734*	*-1,068*
HML	-0,070	0,030	-0,060	0,116	-0,117	0,007	-0,136	0,081
	-0,547	*0,240*	*-0,302*	*0,703*	*-0,745*	*0,050*	*-0,638*	*0,529*
RMW			-0,029	-0,052			-0,098	-0,126
			-0,166	*-0,323*			*-0,731*	*-1,068*
CMA			-0,075	-0,269			-0,098	**-0,338**
			-0,532	*-1,805*			*-0,676*	*-2,600*
WML		**0,158**		**0,188**		**0,194**		**0,232**
		3,762		*5,081*		*5,389*		*5,524*
R2	0,029	0,080	0,030	0,094	0,097	0,199	0,101	0,230
Adjusted R2	0,010	0,056	-0,001	0,059	0,080	0,179	0,072	0,200
Residual Std.Error	2,184	2,132	2,196	2,129	1,831	1,730	1,838	1,707
F Statistic	1,548	**3,383**	0,960	**2,661**	**5,622**	**9,694**	**3,499**	**7,664**

Table 4. Time series regression results on Fama and French factors. The final sample period is from 30/11/2005 to 30/08/2019. Dependent variable is the pure winner minus loser long-short portfolio and independent variables are the Fama and French factors obtained from French database. Four different models are tested: Fama and French (1993) three factor model (FF3), FF3 + the momentum factor, Fama and French (2015) five factor model (FF5) and FF5 plus the momentum factor. Factor loadings are on the top and on the bottom, t-statistics are in italic. Bolded values are significant at 5 percent level. All standard errors and t-statistics are Newey and West (1987) adjusted.

Time series regression for winner minus loser portfolios on Fama and French factors: continuous minus discrete and discrete minus continuous

	Dependent variable: Continuous winner minus discrete loser OLS				Dependent variable: Discrete winners minus continuous losers OLS			
Model:	*FF3*	*FF3+WML*	*FF5*	*FF5+WML*	*FF3*	*FF3+WML*	*FF5*	*FF5+WML*
Constant	0,083	-0,078	0,071	-0,049	0,335	0,234	0,425	0,342
	0,318	*-0,338*	*0,283*	*-0,239*	*0,855*	*0,655*	*1,304*	*1,188*
Market	-0,048	-0,006	-0,051	-0,039	-0,070	-0,044	-0,090	-0,081
	-0,923	*-0,143*	*-1,214*	*-1,147*	*-1,892*	*-1,517*	*-1,765*	*-1,761*
SMB	0,056	0,074	0,055	0,034	0,002	0,013	-0,034	-0,049
	0,659	*0,914*	*0,775*	*0,576*	*0,027*	*0,191*	*-0,358*	*-0,583*
HML	-0,073	0,065	-0,036	0,196	-0,114	-0,028	-0,160	0,001
	-0,575	*0,602*	*-0,196*	*1,496*	*-0,630*	*-0,163*	*-0,623*	*0,005*
RMW			0,050	0,021			-0,178	-0,198
			0,336	*0,163*			*-0,798*	*-0,961*
CMA			-0,024	-0,280			-0,150	**-0,327**
			-0,110	*-1,718*			*-1,111*	*-1,970*
WML		**0,217**		**0,248**		**0,136**		**0,172**
		7,750		*7,515*		*3,487*		*4,649*
R2	0,048	0,198	0,049	0,222	0,056	0,089	0,064	0,111
Adjusted R2	0,03	0,177	0,018	0,192	0,038	0,066	0,034	0,076
Residual Std.Error	1,73	1,593	1,74	1,578	2,290	2,257	2,295	2,244
F Statistic	2,639	**9,626**	1,595	**7,344**	**3,091**	**3,813**	2,115	**3,209**

Table 5. Time series regression results on Fama and French factors. The final sample period is from 30/11/2005 to 30/08/2019. Dependent variable is the pure winner minus loser long-short portfolio and independent variables are the Fama and French factors obtained from French database. Four different models are tested: Fama and French (1993) three factor model (FF3), FF3 + the momentum factor, Fama and French (2015) five factor model (FF5) and FF5 plus the momentum factor. Factor loadings are on the top and on the bottom, t-statistics are in italic. Bolded values are significant at 5 percent level. All standard errors and t-statistics are Newey and West (1987) adjusted.

5.4. Different length of the ID formation period

ID construction methods by Da et al. (2014) uses daily returns for past year. In this sub-chapter, ID formation period is matched to the formation period of PRET and doubled, to test if the length of the formation period of ID affects the results. Results of this comparison are reported in table 6, where panel A reports the results of original construction period, panel B reports the results of shorter construction period and finally, panel C reports the results of longer construction period.

Shortening the formation period does not change the performance, as the results show that shorter formation periods have even lower and less insignificant results than the original formation period. For example, the long legs of the long-short portfolios have lower returns and the short leg have higher returns than in longer formation periods, which means that long-short returns are much smaller. None of the shorter formation period average returns or risk-adjusted returns is significant as can be seen from table 6, panel B.

There are a couple of interesting findings, when increasing the formation period of ID. First, discrete and continuous long-short portfolios changes places, as now the discrete long-short portfolio has a positive and statistically significant average return of 0,315 (t-statistic 2,042) per month, when the continuous portfolio has insignificant and close to zero return. This is totally different to original formation period length, where the continuous portfolio has a positive and significant return, when discrete portfolio return is insignificant. Secondly, risk-adjusted returns are again insignificant, as alphas are not significantly different from zero, even though t-statistics are larger than in the shorter formation period and mainly similar than in original length, as could be seen from table 6, panel C.

Lastly, in unreported time-series regressions, factor loadings for different formation period portfolios are mostly in line with the original formation period. In both formation period and for every model that includes the momentum factor, that factor has positive and significant loading. For the shorter discrete long-short portfolio, only other factor that have positive loading is the size factor for FF5 where SMB has a loading of 0,12 with a t-statistic of 1,967. Other models for that portfolio have almost significant SMB factor loadings. On the other hand, for longer formation periods, the investment factor has negative loading that is mostly significant or closely significant at 5 percent level. Also, the adjusted R-squared and F-statistics are in line with the original formation periods, so increasing or decreasing the formation period from the original length do not have any meaningful effect on the results.

5.5. Alternative ID methodology

Table 7 reports the returns of the alternative ID measurement. It can be easily seen that the alternative ID measurement does not increase the profitability of the strategy. Actually, it gets even worse than in the original ID. The only exception is the alternative ID continuous loser portfolio, which have a higher return than in the original equivalent. As the losers' side has a higher return and the winners' side lower returns, the long-shorts are even worse. All long-short returns are insignificant, both before and after risk adjustments. Even chancing the “arbitrary” weighting scheme does not have any impact on the results, as unreported results are practically equally bad as reported results. Therefore, only conclusion that can be made about the alternative ID measurement is that it is useless.

5.6. Alternative ID construction methods

Because some modifications to the original ID construction method were made, the results of original methods are reported here. First, I handle zero return days as negatives, so here those are handled as an own group. Therefore, the difference part in equation 11 differs a bit from the methodology that I used. The average returns are mostly in line with my previous methodology. The losers' returns are slightly higher, and winners' returns are slightly lower than in table 1, so long-short returns are also lower than in table 2. The same is true for the risk-adjusted returns as alphas are practically the same in both methods. Also, factor loadings follow the similar path, as the same factors have approximately the same loadings and significant levels.

Comparison of different ID formation periods

Panel A: conditionally double sorted portfolios with ID formation length of 252 days

	Winner	Loser	Avg ID	Winner minus loser	T-stat	FF3 Alpha	T-stat	FF3 + WML Alpha	T-stat	FF5 Alpha	T-stat	FF5 + WML Alpha	T-stat
Discrete	0,939	0,703	0,033	0,236	1,555	0,158	0,551	0,014	0,051	0,211	0,805	0,099	0,414
Continuous	0,875	0,518	-0,112	0,356	2,065	0,260	0,743	0,142	0,472	0,285	0,934	0,194	0,764
Continuous minus discrete				0,172	1,240	0,083	0,318	-0,078	-0,338	0,071	0,283	-0,049	-0,239
Discrete minus continuous				0,420	2,279	0,335	0,855	0,234	0,655	0,425	1,304	0,342	1,188

Panel B: conditionally double sorted portfolios with ID formation length match the lenght of momentum formation period (126 days)

	Winner	Loser	Avg ID	Winner minus loser	T-stat	FF3 Alpha	T-stat	FF3 + WML Alpha	T-stat	FF5 Alpha	T-stat	FF5 + WML Alpha	T-stat
Discrete	0,880	0,790	0,043	0,090	0,560	0,002	0,007	-0,129	-0,512	0,022	0,090	-0,072	-0,344
Continuous	0,786	0,570	-0,149	0,216	1,154	0,123	0,291	0,000	0,001	0,183	0,523	0,093	0,317
Continuous minus discrete				-0,004	-0,024	-0,098	-0,323	-0,248	-0,954	-0,088	-0,337	-0,193	-0,885
Discrete minus continuous				0,310	1,637	0,223	0,566	0,119	0,340	0,294	0,886	0,213	0,742

Panel C: conditionally double sorted portfolios with ID formation length of twice as Da et al. (2014) (504 days)

	Winner	Loser	Avg ID	Winner minus loser	T-stat	FF3 Alpha	T-stat	FF3 + WML Alpha	T-stat	FF5 Alpha	T-stat	FF5 + WML Alpha	T-stat
Discrete	0,842	0,527	0,022	0,315	2,042	0,315	1,006	0,170	0,646	0,309	1,058	0,198	0,835
Continuous	0,673	0,603	-0,083	0,071	0,487	0,059	0,219	-0,042	-0,179	0,137	0,612	0,049	0,263
Continuous minus discrete				0,146	1,015	0,146	0,502	-0,012	-0,050	0,170	0,599	0,043	0,208
Discrete minus continuous				0,239	1,432	0,228	0,695	0,140	0,468	0,275	1,007	0,203	0,825

Table 6. Average returns and risk-adjusted returns for different ID formation periods. The final sample period is from 30/11/2005 to 30/08/2019. Risk-adjusted returns are the constants from time-series regressions against Fama and French factors. Dependent variable is either the pure or combination winner minus loser long-short portfolio and independent variables are the Fama and French factors obtained from French database. All standard errors and t-statistics in regressions are Newey and West (1987) adjusted.

Comparison of different ID formation methods

Panel A: conditionally double sorted portfolios. First by PRET and then by ID

	Winner	Loser	Avg ID	Winner minus loser	T-stat	FF3 Alpha	T-stat	FF3 + WML Alpha	T-stat	FF5 Alpha	T-stat	FF5 + WML alpha	T-stat
Discrete	0,939	0,703	0,033	0,236	1,555	0,158	0,551	0,014	0,051	0,211	0,805	0,099	0,414
Continuous	0,875	0,518	-0,112	0,356	2,065	0,260	0,743	0,142	0,472	0,285	0,934	0,194	0,764
Continuous minus discrete				0,172	1,240	0,083	0,318	-0,078	-0,338	0,071	0,283	-0,049	-0,239
Discrete minus continuous				0,420	2,279	0,335	0,855	0,234	0,655	0,425	1,304	0,342	1,188

Panel B: conditionally double sorted portfolios. First by PRET and then by alternative ID

	Winner	Loser	Avg ID	Winner minus loser	T-stat	FF3 Alpha	T-stat	FF3 + WML Alpha	T-stat	FF5 Alpha	T-stat	FF5 + WML alpha	T-stat
Discrete	0,706	0,711	0,017	-0,006	-0,036	0,010	0,036	-0,122	-0,524	0,041	0,155	-0,053	-0,255
Continuous	0,863	0,726	-0,020	0,137	0,930	0,134	0,462	0,046	0,168	0,141	0,538	0,074	0,297
Continuous minus discrete				0,152	0,888	0,171	0,487	0,050	0,166	0,238	0,735	0,153	0,577
Discrete minus continuous				-0,020	-0,147	-0,028	-0,119	-0,125	-0,587	-0,056	-0,239	-0,131	-0,609

Table 7. Average returns and risk-adjusted returns for different ID formation methods. The final sample period is from 30/11/2005 to 30/08/2019. Risk-adjusted returns are the constants from time-series regressions against Fama and French factors. Dependent variable is either the pure or combination winner minus loser long-short portfolio and independent variables are the Fama and French factors obtained from French database. All standard errors and t-statistics in regressions are Newey and West (1987) adjusted.

6. CONCLUSION

Price momentum has been one of the most robust and widely studied anomaly in the financial markets since it has been founded by Jegadeesh and Titman in 1993. Its existence has been confirmed numerous times in different markets and in different asset classes (e.g. Asness et al. 2013). There are also numerous studies that tries to increase its performance by taking other variables into consideration, such as volatility (e.g. Barroso and Santa-Clara 2015), industries (e.g. Moskowitz and Grinblatt 1999) and information flow (e.g. Da et al. 2014).

My goal is to test does the information discreteness, introduced by Da et al. (2014), has an effect on the performance of the price momentum. Information discreteness is a difference between proportion of losing and winning in days during last year times the sign of the last year returns skipping one month (Da et al. 2014). More precisely, I test does it affect the risk-adjusted returns. My results do not support my hypothesis that this strategy does generate risk-adjusted returns.

Surprisingly, both pure continuous and discrete long-short portfolios and combination portfolios are mainly driven by the momentum factor. In every tested model that includes the momentum factor, it is mostly the only factor with significant loading. A positive loading for the momentum factor means that the long leg of the factor, or the winners, are driving my portfolios. This is actually true, when I look at the long-only portfolios, where both winners and losers have positive and significant returns, which, on the other hand, means that the losers' side is decreasing the returns from winners' side in long-short portfolios.

Also, in two out of four long-short portfolios, the investment factor has a negative and significant loading, which indicates that these portfolios are driven by the short leg of the factor or the aggressively investing leg. In one portfolio, discrete long-short, the market factor has also negative and significant loading. This is quite interesting, that only one portfolio had the significant market factor loading, which could indicate that the other models are market neutrals. Other factors, such as value, size and profitability all have insignificant loadings in every tested model and in every tested portfolio. There is a potential explanation for these, as other factors, such as the momentum factor explains the variability in these factors. If this is true, then traditional factor models by Fama and French (1993 and 2015) should have significant loadings on these factors, which is not the case. Therefore, these factors are just redundant to explain the returns of the portfolios.

Recall from the introduction, that the idea of information discreteness is based on the investors' limited capacity to process information and that information flows gradually because of that limited processing capacity. Also, the firms in the sample are the largest and the most liquid, and therefore have a very broad coverage by financial media and analysts, and that is why the price formation process is most likely as efficient as it could be in the European region. Therefore, the relative frequency of the information signal, or the k parameter is likely to much smaller than among smaller and less attractive firms. This, on the other hand, leads to the situation, where most of the information is discrete, which explains the better performance of the discrete portfolios, especially on the winners' side.

Other potential conflict between my results and Da et al. (2014) results is data mining. Mclean and Pontiff (2016), for example, estimated that there is 32 percent decline in returns after the anomaly is published in the academic journal. They also argued that the decline is larger for anomalies that contain illiquid stocks, with high idiosyncratic volatility, which are usually the smallest stocks (for more discussion on the dominance of microcaps, see e.g. Hou, Xue and Zhang 2018). As my sample contains only the most liquid stocks, and the results of Da et al. (2014) are potentially driven by illiquid and smaller ones, then this might also explain the difference between results.

As far as I know, there are not any public and peer-viewed studies, that tries to replicate the results of Da et al. (2014). This might be due to the fact that these results are not found in different samples of stocks, markets or study periods. This, on the other hand, leads to the important question on the reliability of the finance literature. For example, Harvey, Liu and Zhu (2016) argued that it is very difficult to publish a paper in the academic journal that did not found any results. Also, the research in academic journals are heavily skewed to new research on the cost of verifying existing results, which decreases the reliability of the research, as the existing results are rarely confirmed.

Due to the data availability problems, a very complementary conclusion cannot be made. My data sample contains the constituents of the index at data gathering date, which is the 9th of September 2019. Therefore, as the sample length increases, the data is more and more biased due to survivorship bias. This means that the sample only contains firms that have survived to this data gathering date, and therefore exclude firms that have been dropped from the index for some reason. Depending on the reason for the drop, the results are likely to be either too optimistic or pessimistic. For example, if the drops are more likely to be due to mergers or acquisitions, then the target firms are likely to be dropped at a reasonable price, compared with the situation, where the drop has happened because the firm has been declared to bankrupt, when the price of the firm is practically zero. In the first case, the results are too pessimistic and in the latter case, too optimistic.

There have to be further research, before the final conclusion of the usefulness of information discreteness measurement can be made. Especially, the sample should be much wider, include also dropped firms, and include micro, small and medium cap firms to test if the results are driven by one of these limitations. Also, the reliability of the results can be increased by having a longer sample period, as I had to shorten it quite a lot to have a reasonable number of firms.

Even though the results of this study are not as expected, it is not completely useless. It has to pointed out that the plain momentum returns are still mostly lower than in the momentum portfolios, which are subdivided by the information discreteness measurement. Also, as my sample contains the largest and the most liquid firms in Europe, these firms are only potential targets for the largest investors in the European markets. Many of the largest investors simply cannot invest in the small or medium cap firms. Also, other potential users of the results could contain the developers of investment products, such as ETFs, where the underlying asset is an index.

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