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# Factor-based Investing – Insights from Investing in the Euronext 100 Index

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## **Abstract**

Within this work, performance of factor-based investing is assessed using the Euronext 100 index in the years from 2002 to 2018. First, single-factor portfolios are constructed using momentum, size, value, betting-against-beta and short-term reversals strategies. The performance of these portfolios is quite patchy. Only the momentum factor proved itself successful in achieving abnormal returns with and without industry adjustments.

Further, multi-factor portfolios are evaluated. The industry adjusted multi-factor portfolio performed really well especially when combined with the market portfolio. The portfolios based on regression-based return forecasts perform well with and without industry adjustments. Analog to the multi-factor model these good performances still benefit from combining these portfolios with the market.

An investor would suffer from transaction costs if he traded on these strategies. To account for these costs an estimate is introduced based on the trading activity of the portfolios and the bid-ask spreads in the stock market. However, the performance correction based on these estimates does only harm the portfolios slightly and does not eliminate the usefulness of the portfolios. As a result, the paper concludes that factor-based long-short portfolios can serve as a nice tool for investors to increase their portfolio performance especially if combined with the market portfolio.

**Keywords:** factor investing, long-short portfolios, return forecasting, transaction cost estimate

## **1. Introduction**

### **1.1 Factor-based investing**

Factor-based or characteristic-based investing has become more and more important to practitioners to build a portfolio which yields abnormal returns. The Capital-Asset-Pricing-Model (CAPM) was built in order to explain the differences in stock returns. Since its introduction the CAPM has been challenged by many papers. Fama and French (1992, 1996) built the Fama-French three-factor model and later the Fama-French five-factor model. Within these models they included more factors besides the market risk of the CAPM to explain stock returns. While it is still debatable which factor model is best, it has been proven that other factors like size can contribute to the explanation of the differences in returns in the cross-section (Banz, 1981). Based on earlier findings regarding relevant factors, factor-based portfolios have managed to outperform portfolios of stock market indexes (Centineo & Centineo, 2017) (Koedijk, Slager, & Stork, 2016). Over time the number of factors with some explanatory power has grown into a large universe of hundreds and hundreds of factors (Harvey, Liu, & Zhu, 2016). Characteristic-based portfolios with a large number of characteristics have also proven to yield abnormal returns. Nonetheless, most papers find that only a few robust factors can approximate stock returns quite well in comparison to a large number of characteristics (Freyberger, Neuhierl, & Weber, 2017). Further, using a limited number of factors and understanding the economic reasoning behind these factors offers the advantage of also comprehending their persistence (Koedijk, Slager, & Stork, 2016). As machine learning techniques are getting better and better, recent literature implemented these techniques in order to select significant factors to predict returns. Freyberger, Neuhierl, and Weber (2016) use adaptive group least absolute shrinkage and selection operator and find that out of 24 characteristics only between six and eleven provide independent information. Whether it is better to use the whole universe of available characteristics or a smaller number of robust and economically justified factors, highly depends on the final goal of the investor. Absolute

return funds, which primarily do not set their focus on the risks to which they get exposed, may choose to include beyond many characteristics whereas funds or investors with given risk targets may focus on only some factors (Koedijk, Slager, & Stork, 2016) (Gorton, Lewellen, & Metrick, 2012).

## **1.2 Long-short strategies**

Many individuals and investors still care about their exposure to the market. The most prominent method to reduce the exposure to the market risk are long-short strategies. The idea of a long-short strategy is to go long overperforming stocks and sell underperforming stocks. Since the portfolio goes long as well as short in stocks with exposure to the market movements, the portfolio itself should then be relatively neutral to movements of the market. Over time long-short portfolios have become one of the most successful tools applied by investors (Shubert, 2006). Investors may use factor-based forecasts or tilting methods to identify the long and short positions, respectively. Significant performance improvements of stand-alone long-short portfolios can be achieved when investing in a combination of a long-short portfolio with a long position in the market. This effect is driven by the low or negative correlation between the long-short portfolios and the market portfolio (Beaver, McNichols, & Price, 2016). However, many investors (e.g. pension funds, private individuals) are limited in taking short positions. Clarke, de Silva, and Thorley (2016) built a factor-based long-short portfolio with restricted short positions allowed. They take a total long-position of 120 and a total short-position of only 20. However, most of the factor-based sharp ratio can be captured. They show further that even with the presence of a large number of very liquid exchange traded funds (ETFs) investors still benefit from trading individual stocks.

## **1.3 Economic motivation and performance evidence of the included factors**

Within this paper five factors (momentum, size, value, betting-against-beta, and short-term reversals) are selected and used to build different portfolios.

### **1.3.1 Momentum**

Momentum is probably the most famous factor. The idea is that stocks which outperformed in the past (winners) will continue to outperform in the future and stocks which underperformed in the past (losers) will continue to underperform in the future. The time horizon of past data which is used in order to identify winners and losers varies between three to 12 months. Literature offers evidence that this strategy of buying winners and selling losers has proven to be a successful strategy to realize abnormal returns (Jegadeesh & Titman, 1993). There are different economic explanations for this anomaly. First, if this phenomenon was widely known and traded upon, it should persist. Investors who simply follow the trend will cause past winners to outperform in the future and past losers to underperform in the future. Secondly, investors underreact to news. As a result, stocks with a relative high price in comparison to their past high price should outperform and stocks with a relatively low price in comparison to their past high price should underperform (George & Hwang, 2004). The first explanation is the most compelling and intuitive one.

### **1.3.2 Size**

Banz (1981) established the idea of a negative correlation between size and average returns. Looking at the average returns of companies with a high market equity (big firms), their returns are too low with respect to their beta estimates of the CAPM. Respectively, the average returns of companies with a low market equity (small firms) realize higher returns than the return estimates given by the CAPM. Evolving on the findings of Banz (1981) further research has been done and supported the negative relation between the size of a company and its average return (Fama & French, 1992). Even though subsequent literature identified a declining effect, the effect is still significant (Davis, Fama, & French, 2000). The size effect is seen by some literature as a systematic risk, other explanations might be that it is just correlated with other factors which capture some contribution to returns.

### **1.3.3 Value**

The value premium is a very prominent factor and definitely a characteristic that contributes to the explanation of Warren Buffet's success over the past decades. Literature provides evidence that firm's book-to-market ratio of equity is positively correlated with average returns (Rosenberg, Reid, & Lanstein, 1985) (Chan, Hamao, & Lakonishok, 1993). The strategy to go long stocks with a high book-to-market equity ratio (value stocks) and to go short stocks with a low book-to-market equity ratio (growth stocks) showed even stronger results than obtained by the size effect (Fama & French, 1992). Multiple potential explanations have been established over the years. Chan and Chen (1991) introduced a distress factor which captures risk. Firms struggling in the eyes of the market, which is characterized by a low market value and thus, a higher book-to-market ratio have higher expected returns. An additional reasoning is that investors like growth stocks and dislike value stocks and therefore, cause growth stocks to be overpriced and value stocks to be underpriced (Daniel & Titman, 1997). As a result, the overpriced growth stocks will have lower risk-adjusted returns than the underpriced value stocks. Another story tells that investors are irrational and overreact to the past performance of firms attributing irrationally low prices to weak firms (high B/M ratio) and irrationally high prices to strong firms (low B/M ratio). The correction of this irrational behavior then leads to the value premium observable in the markets.

### **1.3.4 Betting-against-beta**

Frazzini and Pedersen (2014) found that a portfolio which goes long leveraged low-beta stocks and goes short high-beta stocks realizes significant positive risk adjusted returns. Other literature also provides evidence for the existence of the betting-against-beta anomaly (Buchner & Wagner, 2016). The most plausible and intuitive reason behind this phenomenon is the fact that many investors (e.g. pension funds, private investors) are limited in the amount of leverage they can take. These leverage constraints force restricted investors who aim for high returns to invest in high-beta stocks. The demand for high-beta stocks then causes the prices of high-beta

stocks to rise relatively to low-beta stocks and leads to a CAPM alpha associated with low-beta stocks. Support to this theory also gives the high demand for leveraged ETFs (Frazzini & Pedersen, 2014). At the same time, the existence of leveraged ETFs poses a threat to the persistence of the betting-against-beta anomaly since investors who cannot take leverage themselves can now indirectly leverage low-beta stocks. If one wants to trade on this strategy it will be beneficial to carefully observe future reactions to the leveraged ETFs becoming very liquid.

### **1.3.5 Short-term Reversals**

Jegadeesh (1990) found evidence that short-term reversals can be observed in the stock market. Meaning that stocks that performed very poorly over the most recent past will on average yield higher risk-adjusted returns than stocks that performed extraordinary well over the most recent past. Economically this pattern could be explained by fire sales of stocks caused by falling prices and excessive price declines combined with a subsequent rebound. Another potential explanation is that a higher volatility and liquidity provisions are associated with very poorly performing stocks and therefore, poorly performing stocks become riskier. A third explanation could be that institutional investors are influenced by past return performances.

## **2. Data**

The used sample consists of all stocks included in the Euronext 100 Index (N100) at the month under consideration. The data is obtained from Bloomberg L.P. for the period from February 2002 to August 2018. All data is obtained on a monthly basis if applicable. The traded stocks on the Euronext 100 are updated monthly to ensure to only include traded stocks into the portfolio at any point in time. Since certain information are not updated monthly the latest update within a 12 months timeframe is used or the relevant field is marked as not applicable. In order to obtain the stock returns, build the factors, and execute relevant performance analysis the following information was obtained: price per stock, total market cap, betas with respect to the N100 looking at a two years period, members of N100, bid-ask-spreads, dividends, book-

to-market ratio all per month and stock if applicable. Further to get a proxy for the risk-free rate the Bloomberg risk-free rate for France is used.

### 3. Methodology

#### 3.1 General Definitions and abbreviation

The following indices will be used throughout this paper:

*t* = rolling index that controls for the different months

*i* = rolling index which controls for all the individual stocks considered

*ind.* = {Financials; Consumer Staples; Consumer Discretionary; Industrials;

Materials; Technology; Health Care; Communications; Utilites; Energy}

The monthly returns ( $r_{i,t}$ ) are obtained as a ratio of the stock prices at the end of the previous month ( $p_{i,t-1}$ ), the stock price at the end of the current month ( $p_{i,t}$ ) and distributed dividends ( $D_t$ ) if applicable:

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1} + D_{i,t}}{p_{i,t-1}}$$

The market return ( $r_{m,t}$ ) is obtained as the weighted average of the monthly returns ( $r_{i,t}$ ) of all members of the N100 in the previous month. The weights are measured on the actual market capitalization one month before the considered month.

$$r_{m,t} = \frac{1}{total\ market\ cap_{N100,t-1}} * \sum_i (r_{i,t} * market\ cap_{i,t-1})$$

To calculate the monthly alphas of each stock ( $\alpha_{i,t}$ ) the stock's beta with respect to the N100 ( $\beta_{i,t}$ ) is used and the risk-free rate of France functions as a proxy for the risk-free rate ( $r_{f,t}$ ). The stock's alpha is then defined by the difference of the realized return and the CAPM estimate.

$$\alpha_{i,t} = r_{i,t} - (\beta_{i,t} * (r_{m,t} - r_{f,t}) + r_{f,t})$$

The portfolio return ( $r_{portfolio}$ ) is calculated using the compounded annual growth rate (CAGR) for the constructed portfolio. Therefore, an initial investment ( $IV$ ) of one and the final value ( $FV$ ) one would have obtained by investing in the portfolio over the time horizon from September 2010 to August 2018 are used.

$$r_{portfolio} = \left(\frac{IV}{FV}\right)^{\frac{1}{8}} - 1$$

The average market return ( $r_m$ ) and the average risk-free ( $r_f$ ) rate are annualized using the same method.

### 3.2 Factor Construction

For the factor construction, only past data is used to be in an out-of-sample scenario. This means all relevant investment decisions could have been made at the respective point in time without knowing any future data.

The momentum factor ( $MOM_{i,t}$ ) is calculated as the sum of realized monthly returns ( $r_{i,t}$ ) in the past months. The returns are considered in the time frame from 10 months until two months before the considered month. If returns were only applicable for some but at least one of these nine previous months the momentum factor would be the average of the available returns.

$$MOM_{i,t} = \sum_{t-2}^{t-10} r_{i,t}$$

The next factor, size ( $SMB_{i,t}$ ), was built using the market capitalization of the respected stock of the previous month.

$$SMB_{i,t} = market\ cap_{i,t-1}$$

The value factor ( $HML_{i,t}$ ) can be drawn from the average book-to-market ratio ( $\frac{B}{M}_{i,t}$ ) of the previous nine months. If book-to-market ratios were only applicable for some but at least one of these nine previous months the value factor would be the average of the available book-to-market ratios.

$$HML_{i,t} = \frac{1}{n} \sum_{t-9}^{t-1} \left( \frac{B}{M_{i,t}} \right)$$

Using the beta ( $\beta_{i,t-1}$ ) of the previous month with respect to the Euronext 100 index calculated over a two-year frame the betting-against-beta factor ( $BAB_{i,t}$ ) was built.

$$BAB_{i,t} = \beta_{i,t-1}$$

The last factor which is considered in this paper is short-term reversals ( $STR_{i,t}$ ). To construct the short-term reversals factors

the returns ( $r_{i,t}$ ) of the previous month are used.

$$STR_{i,t} = r_{i,t-1}$$

### 3.3 Portfolios/ Investment decisions

Based on these factors several portfolios are constructed.

#### 3.3.1 Single-factor portfolios

The more basic portfolios are the single-factor portfolios which are built based on the signals of one factor. For the decision rule which stocks to go long and which stocks to go short, first a ranking is performed. This ranking allocates a rank ( $rank_{factor,i,t}$ ) to each stock based on the value of the different factors. The ranking is done in a way, that the highest value gets the first rank and the lowest value gets the last rank looking at only one month at a time.

$$rank_{factor,i,t} =$$

$$\{1|factor_{i,t} = highest; 2|factor_{i,t} = second\ highest; \dots; n|factor_{i,t} = nth\ highest\}$$

To build a portfolio weights ( $W_{factor,i,t}$ ) are assigned to each single stock. The weights for each factor are defined in the following.

For the momentum factor ( $MOM_{i,t}$ ) portfolio and the value factor ( $HML_{i,t}$ ) portfolio:

$$W_{factor,i,t} = \{0.2|1 \leq rank_{factor,i,t} \leq 5; -0.2|n - 5 \leq rank_{factor,i,t} \leq n; 0, otherwise\}$$

For the size factor ( $SMB_{i,t}$ ) portfolio and the short-term reversals factor ( $STR_{i,t}$ ) portfolio:

$$W_{factor,i,t} = \{0.2|n - 5 \leq rank_{factor,i,t} \leq n; -0.2|1 \leq rank_{factor,i,t} \leq 5; 0, otherwise\}$$

For the betting-against-beta factor ( $BAB_{i,t}$ ) portfolio a multiplier ( $l_{BAB}$ ) is added to control for the smaller betas of the long positions. The multiplier then also identifies the amount of leverage ( $L_{BAB}$ ) an investor needs to take ( $L_{BAB} = l_{BAB} - 1$ ). The factor  $l_{BAB} (= 1.996)$  is defined as the ratio of the first and third quartile of the observed betas in the period from February 2002 to August 2008 which is before the investment decisions are made. It is also used for the industry adjusted weights for the betting-against-beta portfolio.

$$W_{BAB,i,t} = \{0.2 * 1.996 | n - 5 \leq rank_{BAB,i,t} \leq n; -0.2 | 1 \leq rank_{BAB,i,t} \leq 5; 0, otherwise\}$$

The single-factor portfolios are then constructed by investing into the stocks based on their assigned weights. A positive weight represents a long position in the considered stock and a negative weight a short position in the considered stock, respectively. As a result, we obtain long-short portfolios for each individual factor. The overall long position for each month accumulates to one and the overall short position of each month accumulates to minus one.

### 3.3.2 Industry adjusted single-factor portfolios

In order to not only minimize the market risk but also industry specific risk factors, industry adjusted portfolios are constructed. At first all stocks are grouped into ten different industries. Industry specific ranks ( $rank_{ind.,factor,i,t}$ ) are assigned to each stock.

$$rank_{ind.,factor,i,t} = \{1 | factor_{ind.,i,t} = highest; \dots; n | factor_{ind.,i,t} = nth\ highest\}$$

The investment rule is always to go long one stock and short one stock in the respective industry. The decisions are made by the following rules.

For the momentum factor ( $MOM_{i,t}$ ) and the value factor ( $HML_{i,t}$ ) industry adjusted portfolio weights ( $W_{MOM,ind.,i,t}$  and  $W_{HML,ind.,i,t}$ ) are defined in the following manner:

$$W_{ind.,factor,i,t} = \{0.1 | rank_{ind.,factor,i,t} = 1; -0.1 | rank_{ind.,factor,i,t} = n; 0, otherwise\}$$

For the size factor ( $SMB_{i,t}$ ) and the short-term reversals factor ( $STR_{i,t}$ ) industry adjusted portfolio weights ( $W_{SMB,ind.,i,t}$  and  $W_{STR,ind.,i,t}$ ) are defined in the following manner:

$$W_{ind.,factor,i,t} = \{0.1 | rank_{ind.,factor,i,t} = n; -0.1 | rank_{ind.,factor,i,t} = 1; 0, otherwise\}$$

For the betting-against-beta factor ( $BAB_{i,t}$ ) industry adjusted portfolio weights ( $W_{BAB,ind.,i,t}$ ) are defined in the following manner:

$$W_{ind.,BAB,i,t} = \{0.1 * 1.996 | rank_{ind.,BAB,i,t} = n; -0.1 | rank_{ind.,BAB,i,t} = 1; 0, otherwise\}$$

The industry adjusted portfolios are then built by buying or shorting a stock based on the decision rule embraced by the weights. To ensure comparability to the not industry adjusted single-factor portfolios the overall long position for each month again accumulates to one and the overall short position of each month accumulates to minus one.

### 3.3.3 Equally weighted multi-factor portfolios

Advancing from the single-factor portfolios equally weighted multi-factor portfolios are built. The weights for the multi-factor portfolio ( $W_{multi\ factor,i,t}$ ) are a composition of the weights for the single-factor portfolios.

$$W_{multi\ factor,i,t} = \frac{1}{5} * \sum_{factor} (W_{factor,i,t}),$$

$$for\ factors = \{MOM, SMB, HML, BAB, STR\}$$

Analog to the above applied methodology an industry adjusted equally weighted multi-factor portfolio is built. The portfolio weights for the industry adjusted multi-factor portfolio ( $W_{multi\ factor,ind.,i,t}$ ) are constructed under the following rule:

$$W_{multi\ factor,ind.,i,t} = \frac{1}{5} * \sum_{factor} (W_{ind.,factor,i,t}),$$

$$for\ factors = \{MOM, SMB, HML, BAB, STR\}$$

Based on the weights, portfolios are built with a long position in positive weighted stocks and short positions in negative weighted stocks. The amount of the long or short position is exactly the amount of the respective weight.

Additionally, a mixed portfolio is constructed that invests a total amount of 0.5 in the multifactor portfolio and 0.5 in the market portfolio (N100). This is done for both the simple and the industry adjusted multi-factor portfolio.

### 3.3.4 Portfolios based on regression forecasts

In addition, a more sophisticated approach is applied. In order to control for different predictive powers of each factor, the factors ( $MOM_{i,t}, SMB_{i,t}; HML_{i,t}, BAB_{i,t}, STR_{i,t}$ ) are set as explanatory variables against the depended variable return ( $r_{i,t}$ ). With the use of an ordinary least square (OLS) regression coefficients for each individual factor are obtained. The OLS is updated every two years to ensure the consideration of enlargements in the data base. The observation periods for each regression start in November 2002 and end in August 2010, August 2012, August 2014 and August 2016, respectively. The factor coefficients ( $b_{MOM,t}, b_{SMB,t}, b_{HML,t}, b_{BAB,t}, b_{STR,t}$ ) then function as base for the return estimates ( $r_{i,t}^e$ ).

$$r_{i,t}^e = b_0 +$$

$$b_{MOM,t} * MOM_{i,t} + b_{SMB,t} * SMB_{i,t} + b_{HML,t} * HML_{i,t} + b_{BAB,t} * BAB_{i,t} + b_{STR,t} * STR_{i,t}$$

The return estimates are then ranked with respect to the relevant month ( $rank_{r^e,i,t}$ ).

$$rank_{r^e,i,t} =$$

$$\{1|r_{i,t}^e = highest; 2|r_{i,t}^e = second\ highest; \dots; n|r_{i,t}^e = nth\ highest\}$$

The weights for the portfolio based on the return estimates ( $W_{r^e,i,t}$ ) are then constructed using the above obtained ranking.

$$W_{r^e,i,t} = \{0.2|1 \leq rank_{r^e,i,t} \leq 5; -0.2|n - 5 \leq rank_{r^e,i,t} \leq n; 0, otherwise\}$$

These weights then are translated in long or short positions based on their sign. A positive sign translates into a long position and a negative sign into a short position.

Analog to above an industry adjusted portfolio is constructed. The following rankings ( $rank_{r^e,ind.,i,t}$ ) and weightings ( $W_{r^e,ind.,i,t}$ ) are used.

$$rank_{r^e,ind.,i,t} = \{1|r_{ind.,i,t}^e = highest; \dots; n|r_{ind.,i,t}^e = nth\ highest\}$$

and

$$W_{r^e,ind.,i,t} = \{0.1 | rank_{r^e,ind.,i,t} = 1; -0.1 | rank_{r^e,ind.,i,t} = n; 0, otherwise\}$$

Each stock will then be bought or shorten based on its weight. The resulting long-short portfolios are long a total amount of one and short a total amount of minus one. Further equally weighted mixed portfolios with the market are constructed.

### 3.3.1 Benchmarking and performance evaluation

To evaluate the performance of the above constructed portfolios some ratios and a benchmark are used. The CAPM beta of the relevant portfolio ( $\beta_{portfolio}$ ) is used to define a benchmark portfolio which consists of two components being the market portfolio (N100) ( $W_{r_m,t}$ ) and the risk-free rate ( $W_{r_f,t}$ ). The weights for each component are defined as follows:

$$W_{r_m,t} = \beta_{portfolio}$$

and

$$W_{r_f,t} = (1 - \beta_{portfolio})$$

Using the described benchmark portfolio several ratios are introduced to measure the performance. The Sharpe ratio tries to calculate a risk-adjusted return. To obtain the ratio the difference of the annualized portfolio return ( $r_{portfolio}$ ) and the annualized risk-free return ( $r_f$ ) is set into relation to the portfolios annualized standard deviation ( $\sigma_{portfolio}$ ).

$$sharpe\ ratio_{portfolio} = \frac{r_{portfolio} - r_f}{\sigma_{portfolio}}$$

Another possibility to assess the return of a portfolio ( $r_{portfolio}$ ) is the information ratio (IR) which compares the performance of a portfolio to the performance of its benchmark ( $r_{benchmark}$ ) and the standard deviation of the differences in returns ( $\sigma_{r_{portfolio} - r_{benchmark}}$ ).

$$IR_{portfolio} = \frac{r_{portfolio} - r_{benchmark}}{\sigma_{r_{portfolio} - r_{benchmark}}}$$

In order to control for transaction costs an annualized average transaction cost estimate ( $tc^e$ ) is calculated based on the average percentage of the portfolio that has to be traded every month

and the average bid-ask spread an investor is confronted with by investing in the Euronext 100 index.

$$tc^e = 12 * \frac{1}{n} \sum_t \left( \frac{\# \text{ stocks traded}_t}{\text{total \# stocks in portfolio}_t} \right) * \frac{\frac{1}{n} \sum_t (\emptyset \text{bid} - \text{ask spread}_{N100,t})}{2}$$

To evaluate the significance of the portfolio returns a t-statistic is introduced. The relevant critical values for this statistic are  $t_{crit,0.975,96}=1.985$  and  $t_{crit,0.025,96}=-1.985$  executing a two-sided t-test with an alpha of 0.05.

#### 4. Portfolios' Performances

The investment periods for all portfolios start in September 2010 and end in August 2018. Hence the overall duration is eight years.

To get a first idea about the market conditions, the market return and the risk-free rates are assessed. The return an investor would have gotten if he had invested in the market is 6.6% per year. An investment in the risk-free asset yield 0.8% per year. The standard deviation of such a market investment is 0.127 and the Sharpe ratio is 0.453. The market has a positive kurtosis and a negative skewness over the considered time horizon. Based on the obtained t-statistic of 5.525 a conclusion can be made that the returns a market portfolio yields are significantly positive based on a two-sided t-test with an alpha of 0.05.

<i>Portfolio</i>	<i>Market<sub>N100</sub></i>	<i>Portfolio<sub>risk free</sub></i>
<i>Average annualized return (r)</i>	0.066	0.008
<i>CAPM beta (β)</i>	1	0
<i>Standard deviation (σ)</i>	0.127	0.011
<i>Sharpe ratio</i>	0.453	NA
<i>Kurtosis</i>	0.198	0.276
<i>Skewness</i>	-0.226	-0.293
<i>t-statistic</i>	5.525	7.764

#### 4.1 Single-factor portfolio performances

The portfolio based on the single-factor momentum managed to yield a positive annual return for both the not industry adjusted and the industry adjusted portfolio of 0.128 and 0.090 and excess returns based on the CAPM of 0.165 and 0.120, respectively. It is not surprising that the industry adjusted portfolio suffers a decrease in return since it does not allow to go long several stocks of a well performing industry and short several stocks of a badly performing industry. However, the industry adjustments decrease the volatility of the portfolio as the annualized standard deviation changes from 0.275 to 0.193. In the big picture the Sharpe ratio is lower for the industry adjusted portfolio (0.426) than for the not industry adjusted portfolio (0.436) and information ratio favors the not adjusted portfolio (0.640) over the adjusted portfolio (0.464), too. Summing up, the momentum factor portfolios manage to allow a higher sharp ratio then their benchmarks. Yet, these high Sharpe ratios are driven by a highly negative correlation between the market and the portfolio ( $\beta_{MOM} = -0.774$  and  $\beta_{MOM,ind.} = -0.658$ ) which translates in short positions in the market portfolio. These negative relations are specific to this sample and might not always occur as there is no economic reasoning which would justify this. Other literature has found positive betas for momentum portfolios.

<i>Portfolio</i>	<i>Portfolio<sub>MOM</sub></i>	<i>Benchmark<sub>MOM</sub></i>	<i>Portfolio<sub>MOM,ind.</sub></i>	<i>Benchmark<sub>MOM,ind.</sub></i>
<i>Average annualized return (r)</i>	0.128	-0.036	0.090	-0.030
<i>CAPM alpha (<math>\alpha</math>)</i>	0.165	0.000	0.120	0.000
<i>CAPM beta (<math>\beta</math>)</i>	-0.774	-0.774	-0.658	-0.658
<i>Standard deviation (<math>\sigma</math>)</i>	0.275	0.098	0.193	0.084
<i>Sharpe ratio</i>	0.436	-0.453	0.426	-0.453
<i>Information ratio (IR)</i>	0.640	NA	0.464	NA
<i>Kurtosis</i>	-0.048	-1.395	0.227	-1.359
<i>Skewness</i>	0.025	0.087	-0.010	-0.190
<i>t-statistic</i>	5.628	-4.063	5.327	22.403

The size factor does not perform well. For both portfolios without and with industry adjustment the annualized average returns are negative ( $r_{SMB} = -0.167$  and  $r_{SMB,ind.} = -0.083$ ). Both betas are positive but almost zero for the industry adjusted portfolio with 0.033. The CAPM alpha of

the not adjusted portfolio is very low with -0.206. A lot better but still negative is the alpha when adjusted for industry specific risk ( $\alpha_{SMB,ind.} = -0.093$ ). In line with the other findings the industry adjustments also improve the kurtosis and skewness as the kurtosis measure is decreased and the skewness measure increased. Despite the fact that these results are very disappointing and highly speak against the size factor, it has to be said that they are not completely unexpected. Banz (1981) already mentioned in his finding that the effect is mostly carried by the difference of very small firms on the one hand and very large firms on the other hand. The considered sample of the Euronext 100 index does not contain very small firms and thus, eliminates the biggest effect already by its composition.

<i>Portfolio</i>	<i>Portfolio<sub>SMB</sub></i>	<i>Benchmark<sub>SMB</sub></i>	<i>Portfolio<sub>SMB,ind.</sub></i>	<i>Benchmark<sub>SMB,ind.</sub></i>
<i>Average annualized return (r)</i>	-0.167	0.040	-0.083	0.010
<i>CAPM alpha (<math>\alpha</math>)</i>	-0.206	0.000	-0.093	0.000
<i>CAPM beta (<math>\beta</math>)</i>	0.545	0.545	0.033	0.033
<i>Standard deviation (<math>\sigma</math>)</i>	0.219	0.069	0.117	0.004
<i>Sharpe ratio</i>	-0.798	0.453	-0.784	0.453
<i>Information ratio (IR)</i>	-0.921	NA	-0.426	NA
<i>Kurtosis</i>	1.026	1.749	-0.267	0.558
<i>Skewness</i>	-0.774	1.657	-0.181	1.303
<i>t-statistic</i>	-6.919	-0.679	-6.656	-361.865

Better results are received with the value factor portfolios. The simple portfolio yields an annualized average return of 0.022 whereas when controlled for industry risk the portfolio yields an annualized average return of 0.067. Looking at the CAPM these returns translate into a negative excess return of -0.6% for the not industry adjusted portfolio and a positive excess return of 4.3% for the industry adjusted portfolio. In addition, the industry adjustments manage to decrease volatility from a standard deviation of 0.276 to 0.137. Hence, the obtained Sharpe ratio (Sharpe ratio  $HML = 0.049$  and Sharpe ratio  $HML,ind. = 0.431$ ) as well as the information ratio ( $IR_{HML} = -0.022$  and  $IR_{HML,ind.} = 0.157$ ) are higher for the portfolio which is industry adjusted. In conclusion, the industry adjustments do significantly improve the overall performance of portfolios constructed using the value factor.

<i>Portfolio</i>	<i>Portfolio<sub>HML</sub></i>	<i>Benchmark<sub>HML</sub></i>	<i>Portfolio<sub>HML,ind.</sub></i>	<i>Benchmark<sub>HML,ind.</sub></i>
<i>Average annualized return (r)</i>	0.022	0.028	0.067	0.024
<i>CAPM alpha (<math>\alpha</math>)</i>	-0.006	0.000	0.043	0.000
<i>CAPM beta (<math>\beta</math>)</i>	0.339	0.339	0.273	0.273
<i>Standard deviation (<math>\sigma</math>)</i>	0.276	0.043	0.137	0.035
<i>Sharpe ratio</i>	0.049	0.453	0.431	0.453
<i>Information ratio (IR)</i>	-0.022	NA	0.157	NA
<i>Kurtosis</i>	0.497	-0.790	0.201	-0.937
<i>Skewness</i>	-0.360	0.579	-0.325	-0.718
<i>t-statistic</i>	2.142	1.793	5.319	13.920

Looking at the betting-against-beta portfolios the industry adjustments translate into a clear advantage against the not adjusted portfolio. While the return of the not adjusted portfolio is significant negative with -8.5% the industry adjusted return is significant positive with 2.6%. Combined with a slightly negative beta ( $\beta_{BAB,ind.} = -0.046$ ) the industry adjusted portfolio has an alpha of 2.0%. The Sharpe ratio (Sharpe ratio  $_{BAB,ind.} = 0.098$ ) and the information ratio (IR  $_{BAB,ind.} = 0.065$ ) are quite low but positive. The negative betas especially in the simple portfolio may be a hint that the low beta stocks were not leveraged enough. Yet, higher leverage positions would have borne higher risks and it is not certain if it had improved the portfolio performance.

<i>Portfolio</i>	<i>Portfolio<sub>BAB</sub></i>	<i>Benchmark<sub>BAB</sub></i>	<i>Portfolio<sub>BAB,ind.</sub></i>	<i>Benchmark<sub>BAB,ind.</sub></i>
<i>Average annualized return (r)</i>	-0.085	-0.009	0.026	0.006
<i>CAPM alpha (<math>\alpha</math>)</i>	-0.076	0.000	0.020	0.000
<i>CAPM beta (<math>\beta</math>)</i>	-0.295	-0.295	-0.046	-0.046
<i>Standard deviation (<math>\sigma</math>)</i>	0.313	0.038	0.179	0.006
<i>Sharpe ratio</i>	-0.296	-0.453	0.098	-0.453
<i>Information ratio (IR)</i>	-0.242	NA	0.065	NA
<i>Kurtosis</i>	0.150	0.008	1.027	-0.845
<i>Skewness</i>	0.199	0.821	-0.470	0.106
<i>t-statistic</i>	-1.210	0.904	2.283	-79.940

The biggest difference by adjusting for industries has shown up in the case of portfolios based on short-term reversals. The annualized average returns changed from large and significant negative ( $r_{STR} = -0.174$ ) to significant positive ( $r_{STR,ind.} = 0.071$ ). The same improvements can

also be observed for the CAPM alphas with a change from an alpha of -0.199 to an alpha of 0.080. Analog the Sharpe ratio (Sharpe ratio  $_{STR} = -0.847$  and Sharpe ratio  $_{STR,ind.} = 0.469$ ) and information ratio (IR  $_{STR} = -0.915$  and IR  $_{STR,ind.} = 0.377$ ) improved drastically. The industry adjustments also managed to decrease the excess kurtosis of the portfolio and turn the negative skewness positive. As shown by these ratios the not adjusted portfolio suffers highly from some extreme negative outliers. Why the returns have switched sign cannot be explained by the current literature.

Portfolio	Portfolio $_{STR}$	Benchmark $_{STR}$	Portfolio $_{STR,ind.}$	Benchmark $_{STR,ind.}$
Average annualized return ( $r$ )	-0.174	0.025	0.071	-0.009
CAPM alpha ( $\alpha$ )	-0.199	0.000	0.080	0.000
CAPM beta ( $\beta$ )	0.295	0.295	-0.308	-0.308
Standard deviation ( $\sigma$ )	0.215	0.038	0.133	0.039
Sharpe ratio	-0.847	0.453	0.469	-0.453
Information ratio (IR)	-0.915	NA	0.377	NA
Kurtosis	3.645	0.762	0.627	-0.575
Skewness	-1.112	1.302	0.672	-0.472
t-statistic	-7.463	-1.142	5.652	-44.376

## 4.2 Multi-factor portfolio performance

As an extension to the single-factor portfolios the multi-factor portfolios are constructed and their performance is analyzed. Based on the observations above it is not completely unexpected that the performance of the multi-factor portfolio is patchy. The return of the not industry adjusted portfolio is negative ( $r_{mult.fact.} = -0.031$ ). This combined with a positive beta of 0.038 leads to very poor ratios (Sharpe ratio  $_{mult.fact.} = -0.383$  and IR  $_{mult.fact.} = -0.403$ ). On the other hand, the industry adjusted portfolio performs quite well. With a positive annualized average return of 4.4% and a negative beta of -0.125 the alpha is highly positive with 4.3%. Also remarkable is the low volatility of this portfolio ( $\sigma_{mult.fact.,ind.} = 0.063$ ). It is by fare the lowest volatility of the considered portfolios which may make it interesting for investors who only want to allow for little variation in their portfolios. It also has a high sharp ratio (Sharpe ratio  $_{mult.fact.,ind.} = 0.573$ ) and a high information ratio (IR  $_{mult.fact.,ind.} = 0.418$ ).

<i>Portfolio</i>	<i>Portfolio</i> <sub>mult.fact.</sub>	<i>Benchmark</i> <sub>mult.fact.</sub>	<i>Portfolio</i> <sub>mult.fact.,ind.</sub>	<i>Benchmark</i> <sub>mult.fact.,ind.</sub>
<i>Average annualized return (r)</i>	-0.031	0.011	0.044	0.001
<i>CAPM alpha (α)</i>	-0.042	0.000	0.043	0.000
<i>CAPM beta (β)</i>	0.038	0.038	-0.125	-0.125
<i>Standard deviation (σ)</i>	0.104	0.005	0.063	0.016
<i>Sharpe ratio</i>	-0.383	0.453	0.573	-0.453
<i>Information ratio (IR)</i>	-0.403	NA	0.418	NA
<i>Kurtosis</i>	7.254	0.559	0.893	-1.260
<i>Skewness</i>	-1.282	1.161	0.065	-0.515
<i>t-statistic</i>	-2.475	21.556	7.042	-16.347

Building on the findings of Beaver, McNichols and Price (2016) the mixed portfolio ( $Portfolio_{mf,mixed}$ ) that invest equally in the multi-factor long-short portfolios and the market portfolio has an improved performance in comparison to a full investment in the multi-factor model. Especially the industry adjusted mixed portfolio performs really well. The sharp ratio increases (Sharpe ratio  $_{mf,mixed,ind.} = 0.789$ ) and the information ratio ( $IR_{mf,mixed,ind.} = 0.484$ ) improves as well. These nice ratios are partly due to the fact that the volatility of the mixed portfolio is very low ( $\sigma_{mf,mixed,ind.} = 0.063$ ). Also, when benchmarked against the market portfolio it performs well. The market portfolio has a Sharpe ratio of 0.453 which is below the sharp ratio of the industry adjusted mixed portfolio of 0.789. Particularly the lower standard deviation which is just under one half of the market portfolio's ( $\sigma_{N100} = 0.127$ ) is a quite nice effect and contributes to the lucrativeness of the portfolio.

<i>Portfolio</i>	<i>Portfolio</i> <sub>mf,mixed</sub>	<i>Benchmark</i> <sub>mf,mixed</sub>	<i>Portfolio</i> <sub>mf,mixed,ind.</sub>	<i>Benchmark</i> <sub>mf,mixed,ind.</sub>
<i>Average annualized return (r)</i>	0.020	0.038	0.058	0.033
<i>CAPM alpha (α)</i>	-0.018	0.000	0.025	0.000
<i>CAPM beta (β)</i>	0.514	0.514	0.432	0.432
<i>Standard deviation (σ)</i>	0.084	0.065	0.063	0.055
<i>Sharpe ratio</i>	0.134	0.453	0.789	0.453
<i>Information ratio (IR)</i>	-0.354	NA	0.484	NA
<i>Kurtosis</i>	0.909	-0.634	0.271	-1.443
<i>Skewness</i>	-0.527	0.062	-0.042	-0.271
<i>t-statistic</i>	2.661	6.128	9.047	-2.304

### 4.3 Portfolios based on return forecasts

Based on the above-mentioned regression the following coefficients are obtained. Except the coefficients for the betting-against-beta factor all factors do have significant coefficients. Also interesting is the fact that all coefficients have a positive sign which is against some of the economic reasoning done before but in line with the results of the single-factor analysis.

Regression data	Intercept	MOMi	BABi	STRi	SMBi	HMLi
02/02 to 08/10	-0.00505	0.00817*	0.00091-	0.07074*	0.00547*	0.01098*
02/02 to 08/10	-0.00118	0.00612-	0.00172-	0.08072*	0.00366*	0.00240-
02/02 to 08/12	-0.00050	0.00708*	0.00107-	0.07250*	0.00272-	0.00466*
02/02 to 08/14	-0.00034	0.00590*	0.00186-	0.06359*	0.00276-	0.00320*

\*significant based on a 95% confidence

The portfolios based on the regressions achieve higher annualized average returns ( $r_{r^e} = 0.109$  and  $r_{r^e,ind.} = 0.105$ ) than the market portfolio ( $r_m = 0.066$ ). The CAPM beta of the industry adjusted portfolio is quite low with 0.169. But the performance ratios of the portfolios are harmed by a relatively high standard deviation of 0.208 and 0.228, respectively. The Sharpe ratio (Sharpe ratio  $r^e = 0.500$  and Sharpe ratio  $r^e,ind. = 0.426$ ) favors the not industry adjusted portfolio due to the higher annualized average return. However, the information ratio (IR  $r^e = 0.377$  and IR  $r^e,ind. = 0.444$ ) turns pro industry adjustments. All in all, the results do show that long-short portfolios based on return forecasts could be an interesting tool when an investor wants to limit his exposure to the market.

Portfolio	Portfolio $_{r^e}$	Benchmark $_{r^e}$	Portfolio $_{r^e,ind.}$	Benchmark $_{r^e,ind.}$
Average annualized return (r)	0.109	0.034	0.105	0.018
CAPM alpha ( $\alpha$ )	0.075	0.000	0.087	0.000
CAPM beta ( $\beta$ )	0.442	0.442	0.169	0.169
Standard deviation ( $\sigma$ )	0.201	0.056	0.228	0.022
Sharpe ratio	0.500	0.453	0.426	0.453
Information ratio (IR)	0.377	NA	0.444	NA
Kurtosis	0.788	-1.322	-0.552	-1.219
Skewness	-0.184	0.151	0.313	0.481
t-statistic	5.530	9.049	4.923	44.857

Following the method applied before a mixed portfolio ( $Portfolio_{r^e,mixed}$ ) is built by equally investing into the long-short portfolio of the return forecasts and the market portfolio. Similar improvements to the ones observed above show up. The mixed portfolios show returns of ( $r_{r^e,mixed} = 0.093$  and  $r_{r^e,mixed,ind.} = 0.094$ ) and at the same time a lower standard deviation ( $\sigma_{r^e,mixed} = 0.161$  and  $\sigma_{r^e,mixed,ind.} = 0.152$ ). As a result, the information ratios improve to values of 0.432 and 0.526, respectively and the Sharpe ratios improve to values of 0.527 and 0.567, respectively. The industry adjusted portfolio has an advantage over the not industry adjusted portfolio, but the differences are marginal compared to the differences in the multi-factor portfolio. This advantage is strengthened by the negative kurtosis and positive skewness of the industry adjusted portfolio.

<i>Portfolio</i>	<i>Portfolio<sub>r<sup>e</sup>,mixed</sub></i>	<i>Benchmark<sub>r<sup>e</sup>,mixed</sub></i>	<i>Portfolio<sub>r<sup>e</sup>,mixed,ind.</sub></i>	<i>Benchmark<sub>r<sup>e</sup>,mixed,ind.</sub></i>
<i>Average annualized return (r)</i>	0,093	0,050	0,094	0,042
<i>CAPM alpha (α)</i>	0,043	0,000	0,052	0,000
<i>CAPM beta (β)</i>	0,727	0,727	0,591	0,591
<i>Standard deviation (σ)</i>	0,161	0,100	0,152	0,099
<i>Sharpe ratio</i>	0,527	0,502	0,567	0,428
<i>Information ratio (IR)</i>	0,432	NA	0,526	NA
<i>Kurtosis</i>	0,091	-1,324	-0,385	-1,267
<i>Skewness</i>	-0,353	0,130	0,107	0,332
<i>t-statistic</i>	5,471	5,331	5,855	5,140

## 5. Transaction Costs

The above presented strategies all require active trading since some of the positions change monthly. Unlike an investment in the market portfolio the long-short portfolios will suffer from transaction costs. In order to adjust for some of the transaction costs an estimate is introduced and will serve as a correction of the actual returns such a portfolio would have yield to an investor. For the single-factor portfolios, the transaction cost estimates range between 0.1% and 1.6% reductions of the annualized average return of the portfolios. It is not surprising that short-

term reversals strategies require more active trading than size strategies since returns are way more subjected to changes than the firm size.

<i>Portfolio</i>	<i>Portfolio<sub>MOM</sub></i>	<i>Portfolio<sub>SMB</sub></i>	<i>Portfolio<sub>HML</sub></i>	<i>Portfolio<sub>BAB</sub></i>	<i>Portfolio<sub>STR</sub></i>
Simple portfolio $tc_e$	0.007	0.002	0.001	0.005	0.016
Industry adjusted $tc_e$	0.006	0.003	0.002	0.005	0.015

A more detailed look is now taken with regards to the well performing mixed portfolios of the multi-factor portfolios mixed with the market portfolio and the portfolios based on return estimates with the market portfolio.

Even if adjusted for transaction costs the industry adjusted multi-factor mixed portfolio has significant positive returns. Further, it manages to have a higher Sharpe ratio ( $sharpe\ ratio_{mf,mixed,ind.}^{corr.} = 0.751$ ) than the market alone ( $sharpe\ ratio_{N100} = 0.453$ ).

<i>Portfolio</i>	<i>Portfolio<sub>mf,mixed</sub></i>	<i>Benchmark<sub>mf,mixed</sub></i>	<i>Portfolio<sub>mf,mixed,ind.</sub></i>	<i>Benchmark<sub>mf,mixed,ind.</sub></i>
<i>Average annualized return (r)</i>	0.020	0.038	0.058	0.033
<i>Transaction costs (<math>tc^e</math>)</i>	0.003	NA	0.002	NA
<i>Corrected average annualized return (<math>r^{corr.}</math>)</i>	0.017	0.038	0.056	0.033
<i>CAPM alpha (<math>\alpha^{corr.}</math>)</i>	-0.021	0.000	0.023	0.000
<i>CAPM beta (<math>\beta^{corr.}</math>)</i>	0.514	0.514	0.432	0.432
<i>Standard deviation (<math>\sigma^{corr.}</math>)</i>	0.084	0.065	0.063	0.055
<i>Sharpe ratio<sup>corr.</sup></i>	0.103	0.453	0.751	0.453
<i>Information ratio (<math>IR^{corr.}</math>)</i>	-0.403	NA	0.437	NA
<i>Kurtosis<sup>corr.</sup></i>	0.909	-0.634	0.271	-1.443
<i>Skewness<sup>corr.</sup></i>	-0.527	0.062	-0.042	-0.271
<i>t – statistic<sup>corr.</sup></i>	2.360	6.128	8.673	-2.304

The mixed portfolios of the return estimates and the market both have significant positive returns after adjusting for transaction costs ( $r_{r^e,mixed}^{corr.} = 0.087$  and  $r_{r^e,mixed,ind.}^{corr.} = 0.088$ ). However, the transaction costs are higher than in the portfolio above. This is due to the fact that the portfolios based on return estimates require more trading. The Sharpe ratios are 0.485 and 0.526 and hence, higher than the Sharpe ratio of the market alone. Unlike the not industry adjusted return-based portfolio and the portfolios assessed above, the industry adjusted return-based portfolio has a negative Kurtosis and a positive Skewness.

<i>Portfolio</i>	<i>Portfolio<sub>r<sup>e</sup>,mixed</sub></i>	<i>Benchmark<sub>r<sup>e</sup>,mixed</sub></i>	<i>Portfolio<sub>r<sup>e</sup>,mixed,ind.</sub></i>	<i>Benchmark<sub>r<sup>e</sup>,mixed,ind.</sub></i>
<i>Average annualized return (r)</i>	0,093	0,050	0,094	0,042
<i>Transaction costs (tc<sup>e</sup>)</i>	0,007	NA	0,006	NA
<i>Corrected average annualized return (r<sup>corr.</sup>)</i>	0,087	0,050	0,088	0,042
<i>CAPM alpha (α<sup>corr.</sup>)</i>	0,036	0,000	0,046	0,000
<i>CAPM beta (β<sup>corr.</sup>)</i>	0,727	0,727	0,591	0,591
<i>Standard deviation (σ<sup>corr.</sup>)</i>	0,161	0,100	0,152	0,099
<i>Sharpe ratio<sup>corr.</sup></i>	0,485	0,502	0,526	0,428
<i>Information ratio (IR<sup>corr.</sup>)</i>	0,364	NA	0,463	NA
<i>Kurtosis<sup>corr.</sup></i>	0,091	-1,324	-0,385	-1,267
<i>Skewness<sup>corr.</sup></i>	-0,353	0,130	0,107	0,332
<i>t – statistic<sup>corr.</sup></i>	5,060	5,331	5,448	5,140

The observed portfolios did not lose their attractiveness after adjusting for transaction cost. However, the transaction cost estimates do not include the cost of time an investor has to take to invest in these portfolios. As the portfolios are only traded on a monthly basis and have a quite simple decision rule this additional cost should not change the general conclusion which will be drawn based on the findings above.

## 6. Conclusion

Within this work the factors momentum, size, value, betting-against beta and short-term reversals are assessed in different contexts. When examined individually only the momentum factor performed well with and without industry adjustments. The other factors all benefited from the introduction of industry adjustments. However, the size factors performed very poorly with and without the industry adjustments.

In line with the findings of the single-factor portfolios the multi-factor portfolio performance improves drastically when adjusted for the industries. The industry adjusted multi-factor portfolio is superior to the market based on the CAPM and also achieves a higher Sharpe ratio than the market portfolio. Especially the low volatility of the portfolio makes it an interesting investment for investors who want to keep the volatility of their portfolio low. Even though the performance further accelerates if the industry adjusted multi-factor model is combined with

the market portfolio. An equally weighted portfolio of the both improves all obtained measures and thus, strengthens the argument for the usefulness of a multi-factor based long-short portfolio.

Unlike the multi-factor portfolios, the portfolios based on return estimates performs well with and without the industry adjustments. The performance measures improve further when the portfolios are combined into an equally weighted portfolio with the market. The portfolios manage to have higher returns than the market and only a slightly higher volatility. As a result, the portfolios may be very appealing to investors who want to achieve higher returns than the market allows for but have leverage restrictions.

After deducting transaction which occur due to bid-ask spreads in the market the mixed portfolios do not lose their attractiveness. This leads to the conclusion that these strategies are indeed a nice tool for investors. Investors can profit from using these relatively simple trading strategies. The main advantage of the mixed portfolios drives from the relatively low correlation between the market and the portfolios. Low correlations are not surprising in this context as the portfolios are constructed with the idea to eliminate at least some portion of the market risk. However, the negative correlation between the industry adjusted multi-factor model originates mainly from the large negative beta of the momentum portfolio. This relation between momentum strategies and the market is quite specific to this sample and cannot be expected to always be found.

Comparing the two approaches using a simple multi-factor model or a regression-based model both managed to create improvements compared to an investment in the market alone. A clear advantage for one or the other cannot be found since the different measures are in disagreement. The main advantage of the regression-based approach is the fact that factors which cannot be found in the sample will not influence the regression estimates and thus, not harm the portfolio. The not industry adjusted multi-factor portfolio suffers largely from factors which are not

present in the observed sample whereas the portfolios based on the return estimates either disregards these factors or rather changes the sign of the relation.

As a final recommendation, simple multi-factor strategies should only be used if the investor has strong reasons to believe that the used anomalies are present in the considered market and industry adjustments should be used as they offer a clear advantage. If an investor wants to trade on a larger set of factors without a strong background for the relevant market it will be beneficial to use a regression-based strategy. This will allow for corrections of irrelevant or bad factors.

The stock picking allowed for improvements of the performance compared to a simple investment in the market. As a result, it can be recommended to think about some stock picking with quite simple decision rules as an addition to the overall portfolio of an investor. The portfolios presented, established themselves as alternatives for private investors. They are not associated with large transaction costs and do neither need excessive computing power nor extremely large data bases. On a final note this work encourages private investors to consider simple factor-based portfolios as an alternative to investments in large hedge funds.

This work would benefit from enlargements of the sample as well as enlargements of the included factors. Some factors (e.g. size) may highly benefit from increasing the considered market. A larger sample considering also stocks outside of Europe may then also be adjusted for country specific risk factors. It would be interesting to see if similar benefits which came with the industry adjustments would show up for the country adjustments as well. Further, it would also be interesting to see if the use of betas with respect to different markets (e.g. the global S&P 1500) will change the performances. Another interesting enhancement would be the eliminate and introduce factors of the multi-factor model based on their performance in the recent past and frequently update these decisions. Based on the results above further improvements may be possible.

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