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Rivals as Allies: Combining Fundamental and Technical Analysis for Stock Investing

Bachelor thesis

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Abstract

The main aim of this thesis is to perform a detailed investigation of certain investment strategies based on European stock data. There are four investment strategies overall that are examined from the performance perspective: momentum strategy, momentum strategy with BOS ratio filtering, fundamental buy and hold strategy using F_SCORE and a key combined strategy incorporating all the methods mentioned above. After the estimation of Fama and French three-factor model for the combined strategy using the aggregated group of stocks, it can be inferred that in the case of a monthly rebalancing this strategy generates statistically significant monthly risk-adjusted return of 0.938%. For the three-month, six-month and nine-month holding periods the conclusion for the aggregated group of stocks is similar - in all of these cases the combined strategy also generates statistically significant risk-adjusted returns. Based on further comparative testing of strategies for the aggregated group of stocks, it can be stated that the combined investment strategy significantly outperforms all other strategies in terms of returns, especially in the case of a one-month holding period.

Keywords:	portfolio analysis, fundamental analysis, technical analysis, stock investing, empirical testing
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Abstrakt

Hlavním cílem této práce je analýza vybraných investičních strategií a jejich testování na evropských datech. Celkem se jedná o čtyři strategie, které jsou zkoumány a porovnány z hlediska ziskovosti: dvě strategie založené pouze na technické analýze s využitím dat o minulých ziscích, objemech obchodů a poměru BOS, jedna strategie vycházející výhradně z fundamentální analýzy, konkrétně z ukazatele F_SCORE a klíčová kombinovaná investiční strategie založená na spojení všech výše zmíněných metod. Na základě zkoumání kombinované investiční strategie na souhrnné skupině akcií pomocí Fama-French tři-faktorového modelu lze tvrdit, že v případě jednoměsíční rebilance tato strategie generuje statisticky signifikantní nadměrné výnosy ve výši 0,938% měsíčně. Pro tříměsíční, šestiměsíční a devítiměsíční doby držení je závěr pro souhrnnou skupinu akcií podobný - ve všech těchto případech kombinovaná strategie rovněž generuje signifikantní nadměrné výnosy. Po komparativním testování jednotlivých strategií na souhrnné skupině akcií lze konstatovat, že kombinovaná strategie signifikantně překonává všechny ostatní strategie z hlediska výnosů, zejména v případě jednoměsíční rebilance.

Klíčová slova: analýza portfolia, fundamentální analýza, technická analýza, investice do akcií, empirické testování

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Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, April 22, 2019

Signature

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Project of Bachelor Thesis

Author:	**Igor Buinevici**
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Title:	**Rivals as Allies: Combining Fundamental and Technical Analysis for Stock Investing**

Goals of the thesis:

Research question and motivation

Fundamental analysis and technical analysis are two main methodologies used for evaluation of securities and financial markets. Fundamental analysis is based on obtaining and examining information from financial statements, in order to make investment decisions. Technical analysis, in contrast, aims especially at the assessment of historical market data and forecasting future market movements. There are a substantial number of studies dedicated separately to either fundamental or technical analysis, but it is very difficult to find academic papers that do not have a wall of separation between these concepts. The lack of detailed examination in that area served as a reason for further investigation. The main research question of this thesis is going to be: "Is the strategy based on a combination of methods involving fundamental and technical analysis efficient in terms of profitability and risks?". The study will focus on integration of techniques of both analyses into one strategy, evaluation of corresponding investment decisions and their empirical testing.

Contribution

There are a limited number of studies dedicated to this topic, even though they essentially illustrate that investment strategies based on both types of analysis not only outperform strategies based on either individually, but generate highly abnormal returns. Despite such valuable implications, the depth of research on combination of both techniques is limited and there is a scope for further investigation. The main contribution of the thesis will consist of several parts. The European equity market has not yet been thoroughly examined in this particular area. This investigation will provide further insight for equity analysts and new options in strategy choice based on empirically tested results. Therefore the contribution to the literature will be considerable from both theoretical and practical perspectives.

Methodology

The main part of the empirical section will be dedicated to the construction of a stock portfolio using both fundamental and technical analysis and subsequent evaluation of strategy performance, involving an econometric investigation of related factors. The European stock data will be collected and, based on its compound analysis involving both concepts, the portfolio will be determined and examined. Finally, the described empirical evaluation will follow based on which the investment inference will be formulated.

Synopsis:

1. Introduction
2. Literature Review
3. Theoretical part
   - 3.1 Description of fundamental analysis
   - 3.2 Description of technical analysis
   - 3.3 Investment strategies combining both techniques
4. Empirical part – portfolio evaluation and econometric investigation
5. Conclusion

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1 Introduction

Fundamental and technical analysis are often considered to be two sets of investment strategies that should not intersect. The main reason is that these techniques are substantially different from various perspectives.

Fundamental analysis is used in order to determine the future value or real value of stocks using accounting information about certain company. The goal is to find a true value of a particular investment instrument (whether it is undervalued or overvalued) in order to obtain a premium by buying or selling shares in a right moment. Investment strategies based on fundamental analysis mostly concentrate on a long time frame. On the contrary, pure technicians[1] endeavour to predict future price movements of a stock without using fundamentals[2] but rather by looking at specific signals in data or in graphs. They are generally not interested in a real value of a certain stock and pay attention especially to price patterns. The vast majority of strategies based on technical analysis are therefore concentrated on short periods of time.

Nevertheless, there are sophisticated investors and traders who are persuaded that it is necessary to use all types of available techniques in order to obtain the best investment strategies and a broader picture of possible outcomes. Moreover, there are several ways how to combine different types of analysis depending on a preference and experience of an investor. In one related paper (Bollinger, 2005) there was introduced a type of a compound analysis called "rational analysis" that combines not only fundamental and technical analysis but also behavioural and quantitative ones (computer-based testing of technical strategies that is now generally considered to be a part of technical analysis).

There are studies that empirically demonstrated the possibility of earning abnormal returns and beating the market using combined strategies. Some of them are implementing more advanced methods of machine learning -

1 Investors or traders that use only technical analysis tools.

2 Qualitative and quantitative information from financial statements used for investment analysis.

genetic algorithms, for instance as in work Contreras et al. (2012), others are using momentum strategies[3] mixed with fundamentals, as Wang et al. (2014), though both leading to excess returns. In the work of Bettman et al. (2009) fundamental and technical analysis are combined in order to construct a better stock valuation model using explanatory variables based on both types of analysis.

One can find a handful of real life examples how technical analysis can support fundamental analysis. Among the most prominent one is Enron case, where the financial statements were significantly manipulated. Whereas a fundamental investor was rather certain that a fall in stock price is not related to any fundamental danger, technical traders had already closed their positions or shorted the stock after recognising several alarming signals. This is one of the many reasons mentioned in various papers (e.g. Bollinger, 2005; Lloyd, 2013, etc.) why in some cases it is not only recommended but is even necessary to check the information that can be provided by different types of analysis.

This particular paper is dedicated to the area of combined investment strategies. More specifically, the potential of the strategy combining fundamental and technical analysis is investigated. Both types of analysis were proven to be useful in determining winner and loser stocks. Each of these methods is given its precisely defined role in portfolio construction process. Fundamental analysis is implemented as a method of stock picking. On the other hand, technical information is used in order to determine the correct time for entering the market to get potential momentum effect and provide further filtering.

There is not an extensive amount of literature related to the academic research of this topic, though there are several papers that present a detailed insight into specific categories of combined investment strategies. These and other studies relevant to the research are going to be mentioned and analysed in section 2 that is dedicated to the literature review. The attention

3 Strategies primarily based on past returns information.

is paid both to influential works that investigated separately fundamental and technical analysis and to those examining the capacity of combined information.

The following part of the study (section 3) provides a theoretical description of the key concepts of fundamental analysis, technical analysis and possible combinations of the techniques that are going to be implemented in the study. Initially, both notions are analysed separately as a foundation for investigation and subsequently more sophisticated combined models are elaborated.

The next section 4 discusses in more detail the data and methodology that are going to be used in the thesis. In this case the data needs a rather careful treatment, therefore a separate subsection is dedicated to the description and explanation of the dataset. In the methodology part the portfolio construction process is discussed, from both perspectives of fundamental and technical analysis. Subsequently, portfolios are constructed and examined from the perspective of relative efficiency in terms of returns. At this stage, Fama and French three-factor model is the main instrument to estimate the excess returns of the respective strategy and test their statistical significance. Afterwards, the performance of strategies is compared in terms of returns using the paired t-test.

Finally, the results are interpreted along with a detailed financial explanation. Based on that, a conclusion is formulated summarising the entire output from the thesis. The results can play an important role in the literature of combined investment strategies. This thesis differentiates itself from other literature on the topic of combined strategies, as to the best of author's knowledge it is the first study that empirically tests such a strategy on the European dataset. Furthermore, it can be useful not only in the academic environment but also in the professional one, especially for the development of alternative investment strategies.

2 Literature Review

In this section there is an extensive outline of the literature related to the thesis, describing the usage and testing of different ways how to combine fundamental and technical analysis (starting with valuation models and ending with particular strategies and stock picking methods).

Despite the limited supply of the academic works related to the topic of combined investment strategies, these studies generally demonstrate remarkable empirical results from various perspectives. Bettman et al. (2009) were broadly examining the possibility of extending the equity valuation model integrating fundamental and technical analysis. In their inference they stated that their model of stock valuation is outperforming both types of analysis, when either of them is used in isolation, implying that both techniques can be used as complements rather than substitutes. Mashiqa et al. (2015) constructed a hybrid valuation model using both types of analysis based on data from Johannesburg Stock Exchange. They concluded based on study results that investors can enhance the return potential of their portfolios by taking an advantage via implementing both fundamental and technical information in decision-making process.

The article of Chen et al. (2016) provides an investigation of mixed investment strategies.[4] Authors are combining an improved momentum strategy (based on BOS ratio[5] defined in theory as liquidity buy volume to liquidity sell volume, proposed by Wu, 2007) with fundamental indicator called F_SCORE, developed by Piotroski and described in the paper Piotroski (2000), and G_SCORE suggested by Mohanram (2005). The result of their empirical testing demonstrates that the proposed strategy selects stocks possessing more information than market can reflect in time (information spotted just by technical analysis) and outperforms the momentum strategy in terms of returns.

4 In this thesis similar methodology of the portfolio construction and empirical testing as in Chen et al. (2016) is used.

5 BOS ratio is thoroughly described in section 3, dedicated to the theoretical background.

F_SCORE is based on three attributes of company's financial health that were defined in the following way: profitability, leverage/liquidity/source of funds and operating efficiency. Overall, there are nine binary variables each being in one of these categories and implying either positive or negative information about possible future stock prices and profitability. After determining the potential of the company, the main intuition behind the Piotroski (2000) financial indicator is that shortening expected losers and buying expected winners in high book-to-market portfolios can generate excess returns.

G_SCORE follows very similar logic, though it is implemented mostly for low book-to-market portfolios (used for growth stocks). It demonstrated similar high efficiency in differentiation between losers and winners. Analogous strategy as described in previous paragraph, though based on *G_SCORE* indicator, also shows potential for generating excess returns (20.6% yearly), however, these often flowed from the short positions. As it is a stock-picking method for growth stocks it has eight variables and some of them are different from those in *F_SCORE*, more precisely: R&D, capital expenditures and advertising expenditures are not part of *F_SCORE*.

Analogous study was conducted on Taiwanese data in the work of Wang et al. (2014). Authors use modified fundamental assessment techniques based on *F_SCORE* and *G_SCORE* that were named *KG_SCORE* and *MG_SCORE*. These indicators are combined with already mentioned technical analysis instrument - *BOS* ratio, which plays a role of a proxy for adverse selection between informed and uninformed investors. After performing an empirical investigation they concluded that portfolios constructed based on their methodology beat the market in a long-term horizon, providing investors with excess returns.

There are also various studies that are dedicated to more advanced methods, especially from the vantage point of technical analysis. Lam (2003) constructed a backpropagation algorithm based on both fundamental and technical analysis that should serve to predict the financial performance of an investment. Author also additionally included in the model certain macroeconomic variables, but they did not prove to be useful in predictions. Nevertheless, the resulted neural network that integrated both fundamental and technical analysis significantly outperformed minimum benchmark that was set by authors and based on a highly diversified investment strategy.

The researchers in the study of Contrerás et al. (2012) programmed a genetic algorithm (referred to as Evolutionary Algorithm) that combines different fundamental and technical indicators. This work similarly used an advanced methodology and the conclusion was consistent with the previously mentioned papers – developed trading system not only outperformed buy and hold strategy[6] but also boosted the investment outcome in 65% of companies. Vanstone et al. (2004) were also applying artificial neural networks based on fundamental analysis indicators in order to select securities in the Australian stock market.

The recent paper of Eiamkanitchat et al. (2016) described the decision system based on fundamental and technical analysis tools that was tested on Taiwan stock market. Authors created a several step stock-picking system based on fundamental analysis and used technical factors in order to determine the right time for investment. They concluded that this model is effectively filtering high-performance stocks.

Another conclusion related to the topic was drawn in the study of Sagi and Seasholes (2007). Researchers were testing momentum strategies for a group of companies determined by the following firm-specific attributes: costs, revenues, growth and shutdown options. Strategies proposed by authors were more successful than traditional momentum strategies, outperforming them on average by 5% per year. Asem (2009) was examining in his work how momentum profits are related to the payment of dividends. He came to the conclusion that stock markets demonstrate lower momentum profits for dividend paying firms and higher for those companies that did not pay dividends. The next important finding was brought by Asness et al. (2013),

6 Means buying and holding a stock for a longer time period, mostly at least one year.

where authors examined value and momentum investing. They discovered that these types of strategies are negatively correlated and therefore can partially neutralise common variation.

Marasović et al. (2011) created their own portfolio optimisation model based on Markowitz (1952) inference with additional combination of fundamental and technical factors. They stated that both types of analysis are complementary as in combination they provide more information for efficient portfolio optimisation. Nevertheless, in each stage one type of analysis can be more important than another. Authors concluded that in their strategy it is better to start with stock-picking using fundamental analysis and then choose the right timing with technical analysis that will correct for the lack of dynamics in Markowitz mean-variance optimisation model.

Combined strategies are not only limited to stocks, they can also serve well in another types of markets, for instance currency markets. Zwart et al. (2008) performed a thorough research in emerging currency markets and particularly, what economic value can be extracted from technical and fundamental variables. In the conclusion authors stated that if these two types of information are combined, then the risk-adjusted performance of the investment strategies can be significantly improved. Additionally, there is an extensive amount of papers that were examining the implementation of individual strategies in isolation, particularly in portfolio management as Griffin et al. (2005), Jegadeesh and Titman (1993), etc.

The efficient market hypothesis (especially its strong form) is a theoretical concept that can be considered to be contradictory to some real world cases,[7] therefore investors and traders are striving to explore different opportunities in the markets that can be examined by both fundamental and technical analysis. Similarly, there does not exist an ideal strategy and it is important to be cautious while drawing conclusions about both mixed strategies involving several types of analysis and those using exclusively either fundamental or technical information. A convenient example is Malkiel (2003), where it

7 Various market anomalies can be found in a number of papers as Ball (1978), Ariel (1990), etc.

was mentioned in the conclusion that markets can be more efficient and less predictable than many authors of academic papers believe. Therefore, it is always necessary to take into consideration the correctness of methodology and be aware of different aspects that can distort results,[8] which this study strongly endeavoured to account for.

8 As survivorship bias, data-snooping bias etc.

3 Theoretical Background

3.1 Fundamental Analysis

When investor or analyst wants to determine a real value of a particular investment, fundamental analysis is one of the key tools how to realise it. It is possible to trace one of the first prominent works highlighting the importance of fundamental analysis already at the beginning of 20$^{\text{th}}$ century. Security Analysis book of Graham and Dodd (1934) emphasises the significance of fundamental information for valuation of securities. That was one of the first works that drew a large attention to fundamental analysis, resulting in a quickly expanding amount of academic and professional research in this area.

Fundamental analysis is a generally used method for the long-term investments. That is one of the reasons why short-term traders seem to ignore it. Though, it was empirically shown in different studies[9] that fundamental analysis can be very useful, especially as a stock picking mechanism for subsequent long-term or short-term investments. Therefore, Graham (2015) indicates another reason, why many technicians avoid fundamental analysis. It is primarily the subjectivity of judgment and lack of clear signal when to buy or sell particular security, whereas in technical analysis signals are relatively straightforward, though, at the same time, never guarantee a successful outcome.

In order to correctly decide about particular investment based on fundamental information it is necessary to perform a sophisticated investigation of the stock targeted for a purchase. This initially involves understanding both economic trends in a whole economy and specific sector characteristics (related to macroeconomic indicators). Afterwards, the most challenging step for all investors comes – analysis of the particular company. However, it is true, as Lloyd (2013) and Graham (2015) mentioned, that there are many sources potentially providing investor with a thorough fundamental

9 Many of these studies were mentioned in the literature review, though in relation to combined investment strategies (e.g. Chen et al., 2016; Piotroski, 2000, etc.).

analysis reports carried out by professionals. Nevertheless, it does not mean that it is right to invest without performing own investigation.

Fundamental analysis of the respective stock consists generally of careful examination of different financial statements (balance sheet, income statement, cash flow statement, statement of shareholder's equity) and ratios based on data extracted from them. The main goal is to evaluate the healthiness of a certain company, how good are performance, efficiency, liquidity, profitability and will they continue to develop in the same manner or not. Nevertheless, fundamental analysis involves more complex assessment to be done for correct decision-making. In order to have a broad picture of the company's financial situation it is always necessary to look at long-term historical information, footnotes, management reports etc. Therefore, as itself, fundamental analysis becomes a rigorous task. On the other hand, it brings a lot of advantages to investors and analysts, who can perform it correctly and efficiently. Deep research of company's fundamental information provides investor with a better understanding of the business he wants to buy a stake in. Furthermore, fundamental analysis is based on numbers from financial statements, and provided they are not manipulated, which should be generally the case, it brings an objective picture of a company's financial situation.

One of the other main advantages is a long-term factor – investor is putting money in a financially sound company and despite the fact that there are some endless short-term fluctuations, the long-term growth is driven by fundamentals. On the contrary, fundamental investing has its flaws that should be also taken into account for the correct analysis. Besides the fact that it usually requires a significant amount of time for proper investigation and the procedures are far from standardised, all financial statements of publicly listed companies are mostly issued four times a year. The timing can play an important role as in the middle of the periods you can look into the figures that do not represent the current financial position of a company. Furthermore, most valuation models are based on various assumptions (as going concern) and universally cannot account for different externalities (legal, economic etc.). Last but not the least, earnings manipulation can make all complex investigation meaningless. If this is the case, as it happened with Enron, fundamental analysis does not give an objective picture of the firm's state and inference based on it is incorrect (Bollinger, 2005).

Despite the fact that fundamental analysis has some disadvantages it still remains one of the key tools for long-term investors, and the corresponding methods are developing across the time with the data accessibility. The key fundamental analysis instrument that is going to be discussed in this thesis stems from the paper of Stanford accounting professor Piotroski (2000).

In some cases it is not necessary to have a precise valuation of a stock, but it is sufficient to know how to distinguish winner stocks from loser stocks. Subsequently, the long position is taken for the winner stocks, whereas losers are shorted in a determined time frame.[10] There were not many standardised procedures in the fundamental analysis that in addition appeared to be successful. Piotroski (2000) enlarged the financial literature with a new fundamental-based strategy that proved to be effective under certain conditions.

Piotroski proposed a special indicator called F_SCORE that can efficiently pick winner stocks among high book-to-market firms and provide investors with significant excess returns. In the study Piotroski (2000) it was mentioned that the distribution of returns can be shifted to the right increasing investor's mean returns by 7.5% annually, in case financially strong firms with high book-to-market ratio are selected. Overall, the proposed strategy generated return of 23% annually during the time period from 1976 until 1996 and appeared to be robust in time, as indicated by author.

Furthermore, the conducted research resulted in an inference both useful academically (especially for the subject of the efficient market hypothesis) and practically. In particular, the conclusion suggests that stock market

10 Sometimes only the long or short position is taken into consideration. In this thesis the long position is examined in different strategies.

initially underreacts to historical information. The main reason is presence of a positive relationship between the initial historical information and both future firm performance and reactions around quarterly earnings announcements. Specifically, it was shown that one-sixth of the difference in annual returns between predetermined strong and weak companies is earned during the four three-day intervals around quarterly earnings announcements. On the whole, result suggests that historical information is not entirely incorporated into prices in a timely manner.

The particular indicator that was used in order to distinguish winners from losers, initially among value firms (with high book-to-market ratio), as it was mentioned, is named F_SCORE. It consists of nine binary factors based on the fundamental information about certain company. The procedure, how the composite score is constructed is summarised in the following Table 1.

Table 1: F_SCORE description

Variables of F_SCORE:	*Fundamental meaning*	$FS_k = 1,\ k = 1, \dots, 9$	$FS_k = 0,\ k = 1, \dots, 9$
$FS_1 = F\_ROA$	ROA	$ROA > 0$	$ROA \leq 0$
$FS_2 = F\_CFO$	CFO	$CFO > 0$	$CFO \leq 0$
$FS_3 = F\_\Delta ROA$	ΔROA	$\Delta ROA > 0$	$\Delta ROA \leq 0$
$FS_4 = F\_ACCRUAL$	Size of CFO_{sc} and ROA	$CFO_{sc} > ROA$	$CFO_{sc} \leq ROA$
$FS_5 = F\_\Delta LEVER$	Δ(Long-term debt/ Total assets)	$\Delta LEVER < 0$	$\Delta LEVER \geq 0$
$FS_6 = F\_\Delta LIQUID$	ΔCurrent ratio	ΔCurrent ratio > 0	ΔCurrent ratio ≤ 0
$FS_7 = EQ\_OFFER$	ΔTotal shares outstanding	ΔTotal shares outstanding ≤ 0	ΔTotal shares outstanding > 0
$FS_8 = F\_\Delta MARGIN$	ΔGross margin	ΔGross margin > 0	ΔGross margin ≤ 0
$FS_9 = F\_\Delta TURN$	ΔTotal asset turnover	ΔTotal asset turnover > 0	ΔTotal asset turnover ≤ 0

F_ROA: This indicator is measuring performance of a company in terms of ROA (return on assets). If ROA in current year is positive, then the variable has value 1, otherwise it is 0. Alternatively, instead of ROA it is possible to just use net income (without scaling it by total assets). The variable is included, since net income is the base measure of company's efficiency.

F_CFO: This indicator is measuring performance of a company in terms of CFO (cash flow from operations). If CFO (it can be also scaled by total assets) in current year is positive, then the variable has value 1, otherwise it is 0. CFO plays an important role because it shows current business health, specifically, how well it can handle its operating expenses. Moreover, it is more difficult to manipulate CFO than net income and stable company in most cases has to constantly generate cash from operating activities.

$F\_\Delta ROA$: This indicator is measuring dynamic performance of a company in terms of a change in ROA, i.e. $(ROA_t - ROA_{t-1})$, where t denotes year. If ROA in current year is higher than in previous, then the variable has value 1, otherwise it is 0. It determines the sustainability of profit growth.

$F\_ACCRUAL$: This indicator is determining the quality of respective company's earnings by the relation between CFO_{sc} (scaled by total assets) and ROA. Piotroski (2000) highlights that this variable is particularly important and refers to Sloan (1996), who empirically confirmed that if earnings are driven by positive accrual adjustments (net income is greater than operating cash flow), then it is a serious signal of bad profitability in the future. The more persistent is cash flow in net profits, the better is the reflection of company's performance (CFO is more difficult to manipulate). Therefore, the variable is 1 if $CFO_{sc} > ROA$, and 0 otherwise.

$F\_\Delta LEVER$: This indicator measures both leverage and ability of a company to meet its future obligations. It is defined as the change in the ratio of long-term debt to total assets (leverage ratio). If leverage ratio in current year is lower than in previous year, then the variable has value 1, otherwise it is 0. If financially distressed company has excessive external financing it is a warning sign that it is unable to generate sufficient internal funds. As Piotroski (2000) points out that firm is less financially flexible with an increasing long-term debt.

$F\_\Delta LIQUID$: This indicator measures dynamics in liquidity capacity of a company in terms of changes in current ratio that is current assets divided by current liabilities at the end of the fiscal year. If current ratio in this year is higher than in preceding, the variable has value 1, and 0 otherwise. Piotroski (2000) assumes that if there is an improvement in liquidity (increase in current ratio) the firm has better ability to cope with current debt obligations.

EQ_OFFER: This indicator also measures financing abilities of a company along with dilution. It is equal to 1 in case a company did not issue common shares in a year preceding portfolio formation. Firstly, firms in financial distress are signalling that they are not able to generate enough internal funds in order to meet future liabilities if they issue additional equity (similar to long-term debt). Secondly, shareholders want to avoid dilution and prefer companies that do not issue additional shares often.

$F\_\Delta MARGIN$: This indicator measures operating efficiency of a company in terms of a change in gross margin. If gross margin in this year is higher than in previous year, then the variable has value 1, otherwise it is 0. Piotroski (2000) mentions that increase in gross margin means either optimisation of various cost structures (factors of production, inventory, etc.) or higher price for the product sold, in each case signifying better performance.

$F\_\Delta TURN$: This indicator also measures operating efficiency of a company but in a relatively distinct terms, specifically, change in asset turnover ratio (sales/total assets). If current year's asset turnover ratio is greater than in preceding year, then the variable has value 1, and 0 otherwise. Increase in asset turnover ratio means either better operating efficiency (decrease in assets for the same amount of sales) or higher sales (can signify better market conditions).

The cumulative F_SCORE is the sum of all above mentioned variables, i.e.

$$\begin{aligned} F\_SCORE = & F\_ROA + F\_CFO + F\_\Delta ROA + F\_ACCRUAL + F\_\Delta LEVER + \\ & F\_\Delta LIQUID + EQ\_OFFER + F\_\Delta MARGIN + F\_\Delta TURN. \end{aligned}$$

3.2 Technical Analysis

The tools of technical analysis appeared in the financial literature a long time ago with one of the oldest sources known as Joseph de la Vega's accounts of the Dutch markets from 17$^{\text{th}}$ century. Despite such a long existence the sharpest development of the technical analysis came after the invention of computers, so that more advanced techniques of data examination were accessible.

Technicians are using historical market information primarily about prices, volumes and turnovers in both quantitative form as datasets and visual form as charts, in order to find certain patterns in time series. Generally, technical analysis is used for short-term trading and it has a vast amount of techniques for recognition of different buy or sell signals starting from simple one as moving averages and ending with more advanced as neural networks.[11] It strives to discover certain trends in the security price pattern and believes that fundamental factors are already reflected by market before investors react.

The main instruments used by technical analysts are generally related to transformations and visualisations of two key variables - price and volume, for instance: relative strength index, stochastic oscillator, candlesticks etc. Some prominent academic studies as Fama (1970) and Griffioen (2003) undermine the predictability power of technical analysis as it is inconsistent with the weak form of the efficient market hypothesis. However, based on the amount of work produced in this area, many researchers and traders still believe in its ability to determine trading opportunities, even if it cannot be used for price predictions.

One of the most used types of strategies in technical trading is called a momentum strategy. It is related to the market anomaly that past stock-winners often keep winning and past stock-losers keep losing. For instance, Jegadeesh and Titman (1993) were examining sixteen investment periods based on monthly data on stocks from the New York Stock Exchange (NYSE). They declared that if investor takes a short position in the past loser stocks and long position in the past winner stocks in the prior period from three to twelve months, then this portfolio generates significant returns in the next

11 Many of large investment companies develop their own technical analysis and high-frequency trading tools that are not available to public (Lloyd, 2013).

three to twelve months. Their trading strategy generated abnormal returns through the period from 1965 to 1989.

Similarly, and even more relevant for this study, Rouwenhorst (1998) was examining internationally diversified portfolios with stocks chosen from twelve European countries between the years 1978 and 1995. He concluded that the portfolio of past winner stocks outperformed the portfolio of past loser stocks by approximately 1% per month. Therefore, it can be inferred that price momentum is not an individual effect of one market, as European results were very similar to those drawn from United States data. Nijman et al. (2004) were also investigating European market but from another perspective. Authors mainly analysed what effects drive positive expected returns based on momentum strategies. It was concluded that individual stock effects are primary drivers of excess returns, whereas industry and country momentum proved to be less important. Doukas and McKnight (2005) were conducting an out-of-sample investigation in order to explain momentum effect related to stock returns in the European market. They inferred that there are two important factors influencing momentum - failure of investors to update their beliefs after realising publicly available information and gradual spreading of individual company's information.

Chui, Titman and Wei (2010) were researching different momentum strategies in the international environment, specifically, the effect of cultural differences on returns of momentum strategies. Authors used a special individualism index[12] associated with self-attribution bias and overconfidence. They found that individualism is positively related to volume, volatility and magnitude of momentum profits.

Momentum was largely examined in the academic literature, starting with the relation of past trading volumes and prices with future returns (Grinblatt and Moskovitz, 2004) and ending with the investigation of momentum returns in international markets (Daniel et al., 1998). Lee and Swaminathan (2000) conducted a research similar to the study of Daniel et al. (1998) based

12 Measuring cross-country cultural differences, proposed by Hofstede (2001).

on data of NYSE and AMEX[13] stocks from 1968 through 1995. Authors stated that past trading volume is an important connection between value and momentum strategies. More precisely, high-volume stocks tend to be overvalued by the market and low-volume stocks undervalued by the market, implying that expectations of investors affect not only returns of a stock, but, additionally, its trading activity. Moreover, Lee and Swaminathan (2000) concluded that past trading volume can predict persistence and magnitude of price momentum and low-volume winners, similarly as high-volume losers, can experience faster reversals.

Even though there is a substantial amount of variables and transformations used for momentum investing, the one that was already mentioned in the literature review is implemented in this thesis, specifically, BOS ratio. It is related to several results present in the above mentioned papers about the importance of trading volume and price momentum for future stock performance.

In order to define properly BOS ratio it is necessary to introduce some theory in the basis of this concept. The key role in explanations play propositions mentioned in Wu (2007) concerning the adverse selection and information asymmetry. Author constructed the model in which there are distinguished informed and uninformed investors, each facing a fixed transaction cost denoted as c. If supply shocks of different magnitude occur, they are absorbed by each of uninformed investors, who make fixed adjustments of a shares. However, none of them observes the total trading volume and cannot precisely recognise the size of the shock through holdings. The adjustment of each investor depends on the size of a shock.

Because individual holdings will not correspond exactly to the aggregate supply shock, price becomes less informative. On the other hand, the demand of informed investors shifts and changes the allocation without affecting the prices. Thus investors with lack of information will face a price-independent adverse selection. In other words, none of uninformed investors will observe

13 The American Stock Exchange.

the total trading volume, therefore price will not incorporate promptly all the information available in the market and will remain at the same level regardless of contemporaneous shocks. Even though, the efficient market hypothesis tells that in a standard asset-pricing model no risk-adjusted returns can be predicted, Wu (2007) theoretically derives in his proposed model that in case $\frac{c}{a} \sim 0$ (i.e. $a \gg c$, transaction costs are substantially lower than the value of adjustment) is true, then

$$E(r_t) = -cov(r_t, \pi_t),$$

where r_t represents return at time t and $\pi_t = \frac{V_t}{E(V_t)}$ with V_t denoting the unsigned aggregate volume of trades and $E(V_t)$ is its expected value, both at time t. This formula is not contradicting the semi-strong version of the efficient market hypothesis, since returns that are observed via prices are different from the marginal investor's returns. Wu (2007) claims that returns should be the most predictable when high information asymmetry is accompanied by unbalanced trades of non-informed investors, driving the momentum effect.

Wu (2007) states that due to the presence of the information asymmetry between uninformed and informed investors, when informed investors are trying to sell their excessive long positions in winner stocks, uninformed investors are not willing to buy those for offered price. Thus, informed investors have to sell their stocks for lower prices than the reasonable price they expected to get, in order to compensate uninformed investors. It might take some time until prices adjust to their reasonable level, thus causing momentum effect for winner stocks. On the other hand, when informed investors are closing their short positions in loser stocks by purchasing them back, uninformed investors are not selling those, unless informed investors raise their bids. Therefore, there is a similar momentum effect for loser stocks in the next periods.

It was subsequently evidenced that there are two attributes that account for momentum of stocks having extreme past performance. The first is the fact that information asymmetry and extreme stock performance act conjointly. Specifically, even after extreme returns are observed the level of information asymmetry stays high for a certain time afterwards. The second attribute is that informed investors are expected to have concentrated excessive positions in preceding periods. Therefore, these holdings deviating from neutral position will stimulate a flow of non-information-driven trades. Hence, coming to the possible way to estimate the momentum strength examining how informed investors are taking advantage of additional information they possess.

Generally, information driven buys are having smaller effects on price if they are accompanied by liquidity sells and vice versa. Wu (2007) defines BOS ratio as liquidity buy volume divided by liquidity sell volume[14] and states that it can approximate the extent to what informed investors benefit from their additional information. It follows that the higher BOS ratio is, the larger is momentum effect for loser stocks and alternatively, the lower BOS ratio is, the larger is momentum effect for winner stocks. Wu (2007) proposes an empirical proxy for BOS ratio of i^{th} stock in month t based on above mentioned findings and it is defined as

$$BOS_t^i = cov\left(r_t^i, \frac{\nu_t^i}{E(\nu_t^i)}\right),$$

where r_t^i is return of i^{th} stock in month t, then ν_t^i is total trading turnover (value of monthly trading volume in a given currency)[15] of i^{th} stock in month t, and $E(\nu_t^i)$ denotes the expected value of ν_t^i that is empirically estimated as an average trading turnover for stock i calculated using data from last twelve months. More precisely, in order to calculate $E(\nu_t^i)$ and $cov\left(r_t^i, \frac{\nu_t^i}{E(\nu_t^i)}\right)$ monthly observations $(r_{t-(12-m)}^i, \nu_{t-(12-m)}^i)$, $m = 1, ..., 12$, are used, in other words, twelve months directly preceding the portfolio formation period. The procedure is repeated each time when portfolio is rebalanced.

14 Liquidity buys and liquidity sells are those performed by uninformed investors, providing liquidity to the market.

15 In this thesis only Euro currency is used, as the European stock market is examined and also for the calculations to be consistent and standardised.

The detailed interpretation of the resulting number is following. If the BOS ratio of loser stock is high, or of winner stock is low, in relative terms (mostly compared in terms of percentiles) that means uninformed investors will not trade with informed ones for the initial price. Subsequently, abnormal momentum returns are expected to be spotted as high BOS ratio signifies the substantial degree of information asymmetry for loser stocks, and low BOS ratio has the same effect for winner stocks. Chen et al. (2016) mentioned the relation of this argument to the literature about the link of momentum strategies and valuation uncertainty. They referred to Daniel et al. (1998) who concluded that momentum effect can appear due to the bias stemming from the case when investors give higher weight to the information consistent with their estimates and underweight the information that is different from their views. Some studies (Daniel and Titman, 1999, etc.) show that the momentum strategy is more efficient for low book-to-market companies, however, Chen et al. (2016) proclaim in their study that BOS ratio can be effectively used for both high and low book-to-market firms to achieve considerable portfolio performance. In this study, stocks are examined both in aggregate and separated into low book-to-market and high book-to-market firms.

3.3 Combined Strategies

Many investors, traders and researchers stick to the one type of investment analysis, though recently more and more papers started to be dedicated to the area of combined strategies (as it was mentioned with the particular examples in the literature review). Even though it may seem that it is difficult to combine fundamental and technical analysis because of some contradictions, such as time horizon inconsistencies and different conceptual bases, each method can be successfully used in some steps of investment decision-making. There are various possible ways how to separate combined strategies into several categories. In this thesis the preference is given to Petrusheva and Jordanoski (2016) dividing mixed strategies into two groups.

The first one is related to the case when investor applies principally fundamental analysis for choosing appropriate stocks and constructing portfolios. In this situation technical analysis can be used in order to find the right time when to enter the market. Sometimes the correct timing could be much more important than the investment itself, as mentioned in Petrusheva and Jordanoski (2016). The second category is when investor uses primarily technical analysis. In this case, if a certain signal or pattern is recognised, technical trader can check for fundamental information about the company of interest in order to be sure that it is a right investment. Therefore, both types of analysis can efficiently work in the sequential manner based on the preferences of investor. Authors of the above mentioned paper concluded that advantages of both fundamental and technical analysis can be combined in order to construct an optimal strategy. Bollinger (2005) mentions one more approach that could have been potentially considered. Even if a certain portfolio was constructed exclusively based on fundamental factors, technical analysis can be used to manage the risks of this portfolio (limit the left part of the return distribution with stop signals).

In case of this particular study, the strategy that is relatively close to the first group of combined strategies defined above is implemented. Both types of analysis have their own different assumptions and instruments, though in this thesis the advantages of both methods are used in order to construct an optimal strategy that has to be superior, in terms of performance, to the usage of either fundamental or technical analysis in isolation. Based on the literature review there is a number of papers that agreed on the high efficiency of the mixed strategies and this thesis has to support and enhance their contribution to the finance-related academic literature. The detailed methodology based on the notions introduced and defined in this section is described in the following empirical section of the study.

4 Empirical Investigation

4.1 Data

The main aim of this study is to examine the European stocks. Therefore, the dataset includes information on constituents of the STOXX Europe 50 index for the period from 2010 to 2018. This index was chosen based on several criteria. All member stocks have high turnover that is important for correct investigation. Even though index constituents are considered to be large-cap stocks they have a significant variation in the book-to-market ratio and that is favourable for the study. Moreover, many constituents are listed at different European stock exchanges, thus this sample represents a relatively diverse group of stocks. The entire dataset was manually constructed from the Thomson Reuters Eikon database that is considered to be a reliable source[16] for financial data, and can prevent from appearance of additional biases that are stemming from various data gathering issues (such as measurement errors etc.).

There are several important points that should be treated with attention. Firstly, F_SCORE cannot be used for financial companies such as banks or insurance companies, therefore these should be dropped from the analysis.[17] In the dataset there are five insurance companies and eight banks that will be omitted from the list. As a result, there are thirty seven stocks that pass to subsequent investigation. Secondly, as the key information needed for calculation of F_SCORE is in financial statements it is necessary to remark that there are two companies (Vodafone Group PLC and National Grid PLC) whose financial year ends on 31st of March, whereas the rest of the firms close their books on 31st of December. The initial portfolio construction begins after 31st of March 2011. Thirdly, there is one company that had an IPO on 24th of May 2011, therefore it could be a part of the

16 Thomson Reuters data are extensively used in a large number of papers published in various high-reputation finance-related journals such as: Journal of Finance, Journal of Financial Economics etc.

17 Some of F_SCORE variables are not well applicable for financial companies, e.g. change in asset turnover ratio and change in gross margin. There exists an alternative measure $BSCORE$, having different structure than F_SCORE, proposed by Mohanram (2016) for banks, though it is not analysed in this study due to a small number of banks in the sample.

portfolio just after this date. The companies Unilever NV and Unilever PLC that are also constituents of the dataset operate as a single entity, though legally they are two different enterprises (having different stock prices) and therefore are treated separately in the analysis.

In order to calculate F_SCORE for current period it is necessary to use certain data from the previous year's financial statements. Specifically, even though data collection period starts from 2010, portfolio construction period begins on 31$^{\text{st}}$ of March 2011 for the reason that some variables should be calculated using preceding year's data. The entire gathered set of data for fundamental analysis consists of variables of interest for F_SCORE (described in the subsection dedicated to the fundamental analysis) that come from balance sheet, income statement and cash flow statement of a respective company. Additionally, returns, trading volumes and financial ratios data (primarily P/B ratio, i.e. price-to-book ratio) are collected for each portfolio constituent, as it is subsequently used for technical analysis and evaluation of strategies' performance.

4.2 Methodology

All the main concepts needed for the analysis were described in the theoretical part of the thesis, therefore they can be now used in this section dedicated to the detailed explanation of the methodology.

As the first step, for the period since March 2010 until September 2018 at the end of each fiscal year the P/B ratio is calculated to determine the value and growth stocks. Specifically, the median P/B ratio for the year using all stocks is calculated and those stocks that are below the median are considered to be value stocks and those above are growth stocks. As each year P/B ratio changes, which entails variation of the median, some stocks switch their category. This procedure is performed additionally, since F_SCORE was initially declared to be an efficient method of stock-picking for high book-to-market firms (low price-to-book) that are value stocks, though in this thesis the efficiency of the method is also tested for growth stocks and mainly aggregated data, as in many of previous studies it was proved to be an efficient method of stock-picking also for low book-to-market firms. Moreover, there was not any precise definition of the "high book-to-market firm" and since most of the papers were tested on American data this term may have slightly different characteristics in the European stock markets.

In each year the number of value stocks is nineteen, except for 2010 for which there were eighteen value stocks. Overall, after filtering out all financial firms there were 37 stocks, therefore in all years the number of growth stocks was eighteen and just in 2010 there were nineteen growth stocks.[18] In the following Table 2 there are summary statistics of the dataset.

Table 2: Summary statistics

Variables:	*Mean*	*Median*	*Standard deviation*	*Minimum*	*Maximum*
ROA	0.0767	0.0612	0.0681	-0.0638	0.4779
CFO_{sc}	0.1056	0.1014	0.0680	-0.1160	0.4942
P/B	3.9361	2.6625	4.8083	0.4653	68.2348
Asset turnover ratio	0.6898	0.6300	0.3058	0.0800	2.2400
Current ratio	1.2186	1.1700	0.4049	0.4600	2.8000
Gross margin	0.4839	0.4910	0.2213	-0.1620	0.8500
Leverage ratio	0.1934	0.1748	0.1115	0	0.5124
F_SCORE	5.5541	6	1.4204	2	9
BOS	-0.0019	-0.0013	0.0060	-0.0628	0.0341

The majority of the firms in the dataset were profitable, with the distribution of returns having a heavy right tail. The distribution of CFO_{sc} (scaled by total assets) is slightly more symmetric with an average value higher than that of ROA. Similarly, both median and mean of P/B ratio are much farther from the maximum than from the minimum, signifying the right skewness. Based on the current ratio and gross margin medians it is possible to say that at least half of the firms operate efficiently in terms of liquidity and sales. Most of the companies have a positive long-term debt,

18 Despite the fact that the number of stocks in categories stays the same for certain period, some stocks switch their category from year to year, please refer to the Table A1 in Appendix.

but regarding to the median at least half of all firms have their leverage ratio below 0.18 and no firm has the value above 0.52. The median value of F_SCORE is 6 and in fact it is also the mode, signifying that many stocks have a potential of high future earnings, since in Piotroski (2000) it was empirically demonstrated that company's F_SCORE equal to 6 was the marginal conditional value for the stock to generate excess returns. Based on the BOS ratio summary statistics it is possible to say that the distribution is more shifted to the left comparing to American data examined by Chen et al. (2016), where both mean and median were close to zero but positive.

In the following part there is an explanation of the econometric technique used in this study. In order to test the efficiency of each strategy that is presented in the thesis, Fama and French three-factor model, developed by Fama and French (1992), is used. It is defined as

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \theta_i SMB_t + \gamma_i HML_t + e_{i,t},$$
$$t = 1, 2, ..., n,$$

where $R_{i,t} - R_{f,t}$ is the excess return of a given portfolio i (portfolio return minus risk-free rate) and $R_{m,t} - R_{f,t}$ is the excess market return (market return minus risk-free rate). SMB_t in original paper is referred to as "small minus big" factor and it is mimicking returns for the size, i.e. "small firm effect" representing the difference between the returns on big-stock and small-stock portfolios (where size is determined by the market capitalisation) with similar weighted-average book-to-market equity. HML_t, on the other hand, means "high minus low" factor, that is supposed to represent the risk factor for returns related to book-to-market equity, i.e. spread of returns between growth- and value- stock portfolios. Regarding the coefficients, α_i is risk-adjusted return of portfolio i, then β_i, θ_i and γ_i are corresponding factor loadings. The model can be estimated using simple OLS[19] for time series, entailing standard regression procedures and assumptions.[20]

19 For Fama and French three-factor model different estimation procedures are used, though OLS with exogeneity and stationarity assumptions is prevailing in literature (Jiao and Lilti, 2017; Koutmos, 2019, etc.). The model has to be estimated separately for each strategy, i.e. i is fixed.

20 In order not to get a substantial bias in the analysis, the data on the factors is separately gathered from the official Kenneth R. French data library, where all factors were calculated for the European market based on Bloomberg data.

Subsequently, I determine the momentum strategy compounded portfolio as a first foundation for further analysis, following the similar procedure as in Chen et al. (2016). Each stock is included in the portfolio if it has previous twelve-month annualised returns above the median of past twelve-month annualised returns of all stocks[21] in respective month. Portfolio is monthly rebalanced according to the main criterion that all stocks-constituents should be in the top 50 percentile of past twelve-month annualised returns based on all stocks in the respective month. Each month portfolio has different constituents and since there are overall 91 months in the examined period, there are 91 sub-portfolios (one for each month) that create together one compounded portfolio.

The next stage is calculation of F_SCORE indicator using the methodology from the paper Piotroski (2000), which was extensively described in the theoretical section of the study. This measure is the basis for the next benchmark strategy - buy and hold strategy with yearly rebalanced portfolio based on F_SCORE. Contrary to the paper of Chen et al. (2016), where fundamental score strategy was not evaluated individually for longer holding period, in this case it is included in the analysis in order to have at least one basis for comparison from both purely fundamental and technical analysis.

The following step is testing of the BOS ratio momentum strategy. In this thesis the portfolio construction process also follows the analogous procedure as in the paper of Chen et al. (2016). When the winner and loser stocks are determined based on past twelve-month annualised returns, stocks are additionally sorted within each group based on BOS ratio. Precisely, there is a monthly rebalanced portfolio with long position for winner stocks having lower than monthly median BOS ratio for a given month in the respective category.

For the final testing of the combined investment strategy all the methods mentioned above are incorporated in the special sequential way. Similarly, as in previous cases, portfolio is monthly rebalanced,[22] initially, based on

21 Stocks that are initially considered in the analysis.
22 Transaction costs are not analysed directly, only considered through the assumption for BOS ratio.

two criteria - only the stocks with past twelve-month returns above the median and also BOS ratio within the respective group below the median are selected. Subsequently, stock is included in the portfolio if its F_SCORE is above 6, i.e. final portfolio is constructed based on the intersection of the three groups appearing after each step. This value is chosen as it is the marginal F_SCORE that proved to be successful in obtaining excess returns after stock picking in Piotroski (2000). As in previous cases, compounded portfolio is constructed by aggregating 91 monthly sub-portfolios. For all strategies and periods, portfolios are equally-weighted, meaning that the same amount is invested in each stock fulfilling the necessary criteria.

All strategies with monthly rebalancing are evaluated for both the aggregated group of stocks and separate groups consisting just either of value or growth stocks. Moreover, there are additionally introduced results for longer holding periods: three-month, six-month and nine-month.

4.3 Performance Analysis

In order to demonstrate the behaviour of some previously found relationships directly from the dataset, especially concerning the variables based on which portfolios are constructed, there are presented Spearman rank-order correlations in the following Table 3 and Table 4.

Table 3: Spearman correlation 1

	F_SCORE	FS_1	FS_2	FS_3	FS_4	FS_5	FS_6	FS_7	FS_8	FS_9	CR
F_SCORE	1	0.25213***	0.28637***	0.63231***	0.27367***	0.42653***	0.21839***	0.25724***	0.44445***	0.40556***	0.15284***
FS_1	0.25213***	1	-0.04766	0.15246***	-0.11450**	0.15084***	0.14037**	-0.02093	-0.06083	0.02903	0.12249**
FS_2	0.28637***	-0.04766	1	0.04626	0.41625***	0.04485	-0.06209	0.13243**	0.04910	0.03315	0.01179
FS_3	0.63231***	0.15246***	0.04626	1	-0.09105*	0.19085***	0.07278	0.01156	0.19672***	0.27878***	0.14430**
FS_4	0.27367***	-0.11450**	0.41625***	-0.09105*	1	0.02519	-0.08319	-0.04587	0.06951	0.07053	-0.06776
FS_5	0.42653***	0.15084***	0.04485	0.19085***	0.02519	1	-0.18154***	-0.07688	0.05421	0.08055	0.13229**
FS_6	0.21839***	0.14037**	-0.06209	0.07278	-0.08319	-0.18154***	1	-0.03395	-0.06248	-0.11174**	0.01000
FS_7	0.25724***	-0.02093	0.13243**	0.01156	-0.04587	-0.07688	-0.03395	1	0.02549	-0.14273**	-0.03142
FS_8	0.44445***	-0.06083	0.04910	0.19672***	0.06951	0.05421	-0.06248	0.02549	1	0.00846	0.06098
FS_9	0.40556***	0.02903	0.03315	0.27878***	0.07053	0.08055	-0.11174**	-0.14273**	0.00846	1	0.07285
CR	0.15284***	0.12249**	0.01179	0.14430**	-0.06776	0.13229**	0.01000	-0.03142	0.06098	0.07285	1

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In the Table 3, FS_1 to FS_9 are fundamental signals (binary variables) of F_SCORE, presented in the same order as in the Table 1 from theoretical part. CR means end year capital returns from stocks. Statistical significance is denoted based on p-values from correlation significance test. Precise p-values for all pairs are reported in Appendix in the Tables A2 and A3.

Table 4: Spearman correlation 2

	F_SCORE	*BOS*	*3M*	*1M*	*12P*
F_SCORE	1	-0.06608***	0.00192	-0.00161	0.10395***
BOS	-0.06608***	1	-0.03403**	-0.02704**	0.25983***
3M	0.00192	-0.03403**	1	0.53206***	0.06081**
1M	-0.00161	-0.02704**	0.53206***	1	0.04157**
12P	0.10395***	0.25983***	0.06081**	0.04157**	1

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In the Table 4 BOS represents BOS ratio, *3M* - three-month future stock returns, *1M* - one-month future stock returns and *12P* - previous twelve-month annualised stock returns.

It can be seen from the Table 3 that past stock performance is positively correlated with the companies' financial position measured by F_SCORE. Furthermore, among the individual binary variables influencing F_SCORE, one is especially highly correlated with the aggregate measure - FS_3, which is change in ROA (correlation is equal to 0.63231). Similarly, FS_5 (change in leverage), FS_8 (change in gross margin) and FS_9 (change in asset turnover ratio) have strong correlations with F_SCORE - all larger than 0.4.

Several important things can be observed from the Table 4. Firstly, BOS ratio is negatively correlated with both one-month (*1M*) and three-month (*3M*) returns that is consistent with Chen et. al (2016) and Wu (2007), as this measure is being the part of the basis for the compound strategy. On the other hand, it is not possible to draw a conclusion about correlation of F_SCORE with *1M* and *3M* due to the absence of statistical significance. Additionally, since past twelve-month returns are positively correlated with both three-month and one-month returns, momentum returns will be potentially observed, based on the conclusion of Jegadeesh and Titman (1993).

Furthermore, BOS ratio and F_SCORE are negatively correlated and none of past returns, BOS ratio and F_SCORE is substantially correlated with each other (all these correlations appear to be below 0.26) signifying that they can potentially capture different information about the stock, i.e. respective company's characteristics. Therefore, it can be expected that the combined strategy incorporating several variables will outperform not only the momentum strategy using the information just about past returns, but also the other two strategies used in isolation. In this particular case there are some different characteristics of data (mostly in terms of magnitudes), though the necessary relations are all consistent with the analysis of Chen et al. (2016) and Wang et al. (2014).

In the next part of this section there are presented empirical results of investment strategies' testing. The first strategy, which can be considered to be one of the benchmark measures, is the momentum strategy. As it was described above, it means that portfolio is formed from the companies being in the top 50 percentile of past twelve-month annualised returns, based on returns of all analysed stocks in the respective month, and it is monthly rebalanced. In the following Table 5 the results of Fama and French three-factor model for this strategy are reported.

Table 5: Momentum strategy

	Dependent variables:		
	Excess "aggregated" returns	*Excess "value" returns*	*Excess "growth" returns*
	Aggregated	*Value*	*Growth*
$R_m - R_f$	0.52257^{***}	0.57780^{***}	0.57720^{***}
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	-0.83285^{***}	-0.70996^{***}	-0.71490^{***}
	$p = 0.00000$	$p = 0.00018$	$p = 0.00016$
HML	-0.32588^{***}	-0.01029	-0.00803
	$p = 0.00663$	$p = 0.94340$	$p = 0.95582$
α	0.00471^{*}	0.00344	0.00340
	$p = 0.05339$	$p = 0.24885$	$p = 0.25499$
Observations	91	91	91
Adjusted R^2	0.57355	0.51916	0.52002

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In the first column *Aggregated* group means estimation results for all stocks without separation on growth and value, in the second column *Value* means that the model is estimated just for the value stocks and similarly in the third column *Growth* means just for the growth stocks respectively.[23] The alpha (α) coefficient in Table 5 is of the most interest - it is directly the portfolio risk-adjusted rate of return. The precise p-value for alpha corresponding to the aggregated group of stocks is 0.05339 (p-values are reported below the estimated coefficients), so it is possible to consider it close to being statistically significant at 5% significance level. The interpretation of the coefficient is that on average this momentum portfolio beats the market benchmark in terms of returns at the monthly rate of 0.471%.

Moreover, strong statistical significance of the other variables can be seen from the first column of the Table 5 - $R_m - R_f$ (its coefficient is often referred to as market beta), SMB and HML factors.[24] On the other hand, it is not possible to say that the strategy beats the market for separated groups of value and growth stocks, since alpha is not statistically significant at any reasonable significance level (both p-values are above 0.24).

For the subsequent strategy an additional variable is introduced - BOS ratio. The next set of portfolios is constructed taking the momentum strategy as the basis, proceeding with further filtering using BOS ratio (as it was mentioned in the methodology part, only the stocks within the top 50 percentile of previous twelve-month annualised returns and subsequently the bottom 50 percentile of BOS ratio for a given group in respective month are chosen) and performing monthly rebalancing. The results of Fama and French three-factor model for this strategy are summarised in the Table 6.

From the Table 6 it can be seen that in this case alpha is similar to the momentum strategy, but seems to be slightly higher, provided it is assumed that alpha is still statistically significant at sufficiently low significance level (in

23 As a dependent variable in each of the models there are considered only expected returns of the analysed group, i.e. *"aggregated"*, *"value"* or *"growth"*. Similar rules apply for the next three tables.

24 Other coefficients are also reported for completeness and since they characterise respective portfolios, but their detailed interpretation is beyond the scope of this text. *Adjusted* R^2 is used instead of R^2 to demonstrate goodness-of-fit (though these are in all estimated models very close to each other).

Table 6: *BOS* momentum strategy

	Dependent variables:		
	Excess "aggregated" returns	*Excess "value" returns*	*Excess "growth" returns*
	Aggregated	*Value*	*Growth*
$R_m - R_f$	0.53922^{***}	0.58148^{***}	0.57951^{***}
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	-0.82732^{***}	-0.72886^{***}	-0.74517^{***}
	$p = 0.00000$	$p = 0.00032$	$p = 0.00024$
HML	-0.34922^{***}	-0.11145	-0.10398
	$p = 0.00614$	$p = 0.47518$	$p = 0.50470$
α	0.00476^{*}	0.00289	0.00274
	$p = 0.06542$	$p = 0.36797$	$p = 0.39285$
Observations	91	91	91
Adjusted R^2	0.55234	0.47236	0.47526

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

this case p-value is 0.06542). Nevertheless, the difference is too small to draw any precise conclusion about the relative performance of these strategies.

In the subsequent Table 7, the returns of the fundamental buy and hold strategy with yearly rebalanced portfolio based on F_SCORE are presented. Similarly as in previous cases, in the first column there are excess returns of the aggregated group of stocks, in the second column there are excess returns of value stocks and in the third of growth stocks respectively, and alpha is the main coefficient of interest.

Table 7: Fundamental b&h strategy

	Dependent variables:		
	Excess "aggregated" returns	*Excess "value" returns*	*Excess "growth" returns*
	Aggregated	*Value*	*Growth*
$R_m - R_f$	0.59815^{***}	0.70591^{***}	0.51267^{***}
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	-0.77225^{***}	-0.64190^{***}	-0.90041^{***}
	$p = 0.00000$	$p = 0.00026$	$p = 0.00000$
HML	-0.21834^{**}	0.05634	-0.50179^{***}
	$p = 0.03384$	$p = 0.67672$	$p = 0.00002$
α	0.00457^{**}	0.00379	0.00540^{**}
	$p = 0.03052$	$p = 0.17381$	$p = 0.01719$
Observations	91	91	91
Adjusted R^2	0.68809	0.63759	0.61572

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

As it can be seen - the strategy outperforms the market both for the aggregated group of stocks and growth stocks, being statistically significant at 5% significance level. There is not any statistically significant evidence that group of value stocks outperforms the market benchmark. One of the possible reasons is that since the key examination period starts shortly after the crisis, growth stocks tend to perform well in mid-cycle slowdown, late cycle pick-up and beat value stocks in shorter holding period (based on the industry studies of BlackRock, 2014; Brush, 2007, etc.). The other reason can be just characteristics of this particular sample.

In the next part of the analysis Fama and French three-factor model is estimated for the combined strategy that incorporates both fundamental and technical analysis. As it was mentioned previously, all portfolios are sorted based on the momentum strategy and BOS ratio criteria and then the additional filtering based on F_SCORE is performed, in other words, taking the stocks with F_SCORE above 6. The results for all groups of stocks are provided in the Table 8.

The combined investment strategy generates on average monthly excess return of 0.938% based on alpha coefficient from Fama and French three-factor model estimated on the aggregated group of stocks (as opposed to 0.457%,

Table 8: Combined fundamental and technical strategy

	Dependent variables:		
	Excess "aggregated" returns	*Excess "value" returns*	*Excess "growth" returns*
	Aggregated	*Value*	*Growth*
$R_m - R_f$	0.62638^{***}	0.66759^{***}	0.57556^{***}
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	-0.96575^{***}	-0.59557^{**}	-0.95195^{***}
	$p = 0.00014$	$p = 0.02523$	$p = 0.00000$
HML	-0.10943	0.03217	-0.73876^{***}
	$p = 0.57222$	$p = 0.87811$	$p = 0.00000$
α	0.00938^{**}	0.00374	0.00586^{*}
	$p = 0.02019$	$p = 0.38647$	$p = 0.06153$
Observations	91	91	91
Adjusted R^2	0.42820	0.38249	0.50295

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

0.476% and 0.471% of previously tested strategies). Moreover, in this case alpha is close to being statistically significant at 1% significance level, with p-value of 0.02019, comparing to p-values of 0.03052, 0.06542 and 0.05339 from other strategies. The result for growth stocks can be also considered to be marginally statistically significant, beating the market in terms of returns at the monthly rate of 0.586%. There is not any statistically significant evidence that can be drawn for value stocks. Nevertheless, the combined strategy generates on average almost 1% of monthly risk-adjusted returns. There is no perfect collinearity among the used time series and also there is neither evidence of heteroskedasticity nor serial correlation in residuals after performing the necessary tests (Breusch-Pagan and Breusch-Godfrey). Based on Augmented Dickey-Fuller test, there is no unit root in any of the time series used for regression analysis in the thesis (also, the time series are not autocorrelated, as follows from the autocorrelation function).

In the next part holding periods are extended to three-month, six-month and nine-month. Since in this case portfolio is rebalanced every three, six and nine months respectively, there will be no stocks in some months in the portfolios of separated groups of growth and value stocks. Therefore, this analysis is performed using aggregated data and similarly, Fama and French three-factor model is estimated for respective holding periods and strategies. The results for three-month holding period are reported in the Table 9.

Table 9: Three-month holding period, the aggregated group

	Dependent variables:			
	Excess mom. returns	*Excess BOS mom. returns*	*Excess fund. b&h returns*	*Excess combined returns*
$R_m - R_f$	0.58761***	0.65449***	0.59815***	0.64480***
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	−0.81379***	−0.83568***	−0.77225***	−0.89875***
	$p = 0.00000$	$p = 0.00000$	$p = 0.00001$	$p = 0.00000$
HML	−0.40392***	−0.47978***	−0.21834**	−0.25549*
	$p = 0.00061$	$p = 0.00033$	$p = 0.03384$	$p = 0.06065$
α	0.00440*	0.00470*	0.00457**	0.00687**
	$p = 0.06229$	$p = 0.07735$	$p = 0.03052$	$p = 0.01476$
Observations	91	91	91	91
Adjusted R^2	0.62404	0.60546	0.68809	0.59889

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In the first column there is an output for the simple momentum strategy (momentum abbreviated as mom.), in the second column - the BOS momentum strategy (the simple momentum strategy with subsequent BOS ratio filtering), in the third - the fundamental b&h (buy and hold) strategy and in the last column - the combined strategy. It is evident that the combined strategy has the value of alpha equal to 0.00687 (which means monthly risk-adjusted returns being almost 0.7%). Furthermore, it is strongly statistically significant (close to being significant at 1% significance level, since p-value is 0.01476). The momentum and BOS momentum strategies generate 0.44% and 0.47% of monthly risk-adjusted returns respectively (provided the significance level of 10% is considered to be sufficiently low). In this table and also in the following tables for longer holding periods, results for the fundamental buy and hold strategy are the same as in the Table 7 (because it has yearly rebalanced portfolios) and these are included for easier comparison.

The next Table 10 summarises the Fama and French three-factor model estimation results for six-month holding period with the columns corresponding to respective strategies as in the Table 9.

Similarly as in the previous cases, the combined investment strategy generates on average 0.726% of monthly significant excess returns, compared to 0.435% and 0.457% of the momentum and fundamental b&h strategies

Table 10: Six-month holding period, the aggregated group

	Dependent variables:			
	Excess mom. returns	*Excess BOS mom. returns*	*Excess fund. b&h returns*	*Excess combined returns*
$R_m - R_f$	0.61481***	0.71923***	0.51815***	0.63741***
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	−0.87691***	−0.88569***	−0.77225***	−0.90041***
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
HML	−0.45508***	−0.59095***	−0.21834**	−0.22529*
	$p = 0.00005$	$p = 0.00000$	$p = 0.03384$	$p = 0.09298$
α	0.00435**	0.00240	0.00457**	0.00726***
	$p = 0.04828$	$p = 0.33257$	$p = 0.03052$	$p = 0.00917$
Observations	91	91	91	91
Adjusted R^2	0.67973	0.67466	0.68809	0.61256

Remark: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

(the results for the fundamental b&h strategy are the same due to yearly rebalancing). Furthermore, in this instance risk-adjusted returns of the combined strategy are statistically significant even at 1% significance level.

In the subsequent Table 11 the results of Fama and French three-factor model are reported for all strategies, where portfolios are constructed with nine-month holding period using the aggregated group of stocks.

Table 11: Nine-month holding period, the aggregated group

	Dependent variables:			
	Excess mom. returns	*Excess BOS mom. returns*	*Excess fund. b&h returns*	*Excess combined returns*
$R_m - R_f$	0.64507***	0.69628***	0.59815***	0.62981***
	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$	$p = 0.00000$
SMB	−0.75678***	−0.78113***	−0.77225***	−0.85291***
	$p = 0.00000$	$p = 0.00003$	$p = 0.00000$	$p = 0.00000$
HML	−0.48388***	−0.50602***	−0.21834**	−0.24183*
	$p = 0.00002$	$p = 0.00056$	$p = 0.03384$	$p = 0.08043$
α	0.00479**	0.00378	0.00457**	0.00590**
	$p = 0.02908$	$p = 0.19469$	$p = 0.03052$	$p = 0.03846$
Observations	91	91	91	91
Adjusted R^2	0.68100	0.57363	0.68809	0.57560

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

From the Table 11 it is evident that the combined strategy has alpha of 0.0059 (risk-adjusted returns being 0.59% monthly and p-value is 0.03846). The BOS momentum strategy, as in the previous estimation, does not provide statistically significant excess returns. Thus, in this case among other strategies it is possible to draw conclusion about the simple momentum strategy that generates statistically significant excess returns as high as 0.479% monthly, being statistically significant at 5% significance level, and the fundamental b&h strategy where results are the same as in previous tables.

There is one additional remark related to the estimation results. The returns from the combined fundamental and technical strategy seem to decline with the increasing holding period for the aggregated group of stocks, except for six-month holding period, which appears to be an exception (one-month risk-adjusted return is 0.938%, three-month is 0.687%, six-month is 0.726% and nine-month is 0.59%). This evidence is consistent with Chen et al. (2016).

In the final part of the thesis, the paired t-test is performed in order to compare strategies among each other in terms of returns. The main hypotheses are that the combined investment strategy outperforms other strategies in terms of returns in one-month, three-month, six-month and nine-month holding periods. In this specific instance a one-sided alternative is used (i.e. mean difference is greater than zero), because it is more natural in this situation given the hypotheses construction. The time series used in this test do not have unit root and are not autocorrelated (as it was declared before). They can be deemed to be approximately normally distributed based on the graphical check (Q-Q plot) or, alternatively, Shapiro-Wilk test (that in this case provides the same conclusion as Q-Q plot, i.e. that the time series can be considered to be approximately normally distributed) and have no substantial outliers. Therefore assumptions for the application of the paired t-test can be considered to be fulfilled.

The comparative test results for value and growth stocks for one-month holding period are not reported since these groups did not, generally, provide any statistically significant results neither in this instance nor in previous investigation. Therefore the results of the paired t-test for all examined holding periods and strategies based on the aggregated group of stocks are reported in the following Table 12.

Table 12: Paired t-test, the aggregated group

	Holding period:			
	one-month	*three-month*	*six-month*	*nine-month*
Combined - Mom.	0.00443**	0.00366**	0.00207*	0.00047
	$p = 0.03786$	$p = 0.04605$	$p = 0.09853$	$p = 0.43962$
Combined - BOS mom.	0.00423**	0.00286*	0.00317*	0.00120
	$p = 0.04577$	$p = 0.06827$	$p = 0.05421$	$p = 0.25138$
Combined - Fund. b&h	0.00434**	0.00381**	0.00234*	0.00161
	$p = 0.03289$	$p = 0.04832$	$p = 0.08170$	$p = 0.19115$

Remark: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Column names determine the holding period corresponding to the respective pairs of strategies being tested. Row names denote all pairs of strategies for which the paired t-test of returns is performed: *Combined - Mom.* means the relative performance of the combined strategy and the momentum strategy is tested, *Combined - BOS mom.* means testing the relative performance of the combined strategy and the momentum strategy with *BOS* filtering and, finally, *Combined - Fund. b&h* stands for the test of the relative performance of the combined and fundamental buy and hold strategies.

From the test results it is directly apparent that for the aggregated group of stocks the combined investment strategy significantly outperforms all other strategies in terms of returns in one-month holding period at 5% significance level (given the one-sided alternative). In case of three-month holding period the combined strategy also generates on average higher statistically significant returns than the momentum, the *BOS* momentum (in this case provided p-value of 0.06827 is considered to be sufficiently small) and the fundamental buy and hold strategies. Similarly, for six-month holding period the conclusion can be considered to be analogous, though all p-values increased (in this case outperformance can be inferred only at 10% significance level for all strategies). Finally, there is no evidence that the combined strategy has higher statistically significant returns than other strategies in case of nine-month holding period at any reasonable significance level.

5 Conclusion

In this thesis the profitability and risk analysis of various investment strategies is performed. After accomplishing the empirical testing it is possible to infer based on the evidence drawn from the aggregated group of stocks that the strategy incorporating both fundamental and technical modes of analysis significantly outperforms the strategies using either in isolation, especially in the case of a one-month holding period. Moreover, for the same holding period the combined strategy generates on average statistically significant monthly risk-adjusted return of 0.938% (measured in terms of alpha from Fama and French three-factor model estimated on the aggregated group of stocks). For three-month, six-month and nine-month holding periods the inference from Fama and French three-factor model is analogous, though the returns seem to decline with the increasing holding period. The results are important from both academic and professional perspectives. Firstly, to the best of author's knowledge, it is the first paper testing this type of combined strategies on the European data and demonstrating its statistically significant performance. Secondly, the inference can be potentially useful for both investors and analysts providing them with an alternative procedure for portfolio management, specifically, on how to improve momentum strategies by additionally applying fundamental analysis.

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Data source:

The dataset used in the thesis was manually constructed based on the information from the *Thomson Reuters Eikon* database. Data on the factors that were used in the estimation of Fama and French three-factor model were collected from the official K. French Data Library that can be retrieved at: *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

Disclaimer:

All investments, especially in the stock markets, involve substantial degree of risk. The primary purpose of this thesis is purely academic and it should not be considered as an investment advice. The author is not liable for any potential losses stemming from the application of the described methods and the whole responsibility lies on an individual making particular investment decisions.

Appendix

Table A1: Growth and value stocks

Name of stock:	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
I. ABB Ltd	Growth	Growth	Growth	Growth	Growth	Value	Value	Growth	Growth
II. Air Liquide SA	Growth	Growth	Growth	Growth	Value	Value	Value	Value	Growth
III. Airbus SE	Value	Value	Value	Value	Growth	Growth	Growth	Growth	Growth
IV. Anheuser Busch Inbev NV	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
V. ASML Holding NV	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
VI. AstraZeneca PLC	Growth	Growth	Growth	Value	Growth	Growth	Growth	Growth	Growth
VII. BASF SE	Value	Value	Value	Growth	Value	Value	Value	Value	Value
VIII. Bayer AG	Value	Value	Value	Growth	Growth	Growth	Growth	Value	Value
IX. BP PLC	Value	Value	Value	Value	Value	Value	Value	Value	Value
X. British American Tobacco PLC	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Value
XI. Daimler AG	Value	Value	Value	Value	Value	Value	Value	Value	Value
XII. Deutsche Telekom AG	Value	Value	Value	Value	Value	Value	Value	Value	Value
XIII. Diageo PLC	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XIV. Eni SpA	Value	Value	Value	Value	Value	Value	Value	Value	Value
XV. GlaxoSmithKline PLC	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XVI. Glencore PLC	Growth	Growth	Value	Value	Value	Value	Value	Value	Value
XVII. L'Oreal SA	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XVIII. LVMH Moet Hennessy Louis Vuitton SE	Value	Growth	Value	Growth	Value	Value	Value	Growth	Growth
XIX. National Grid PLC	Growth	Value	Growth	Value	Value	Value	Value	Value	Value
XX. Nestle SA	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXI. Novartis AG	Value	Value	Value	Value	Value	Growth	Value	Value	Value
XXII. Novo Nordisk A/S	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXIII. Reckitt Benckiser Group PLC	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXIV. Rio Tinto PLC	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXV. Roche Holding AG	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXVI. Royal Dutch Shell PLC	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXVII. Safran SA	Value	Value	Value	Value	Growth	Growth	Growth	Growth	Growth
XXVIII. Sanofi SA	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXIX. SAP SE	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXX. Schneider Electric SE	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXXI.Siemens AG	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXXII.Telefonica SA	Growth	Growth	Growth	Value	Value	Value	Growth	Value	Value
XXXIII. Total SA	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXXIV. Unilever NV	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXXV. Unilever PLC	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth	Growth
XXXVI. Vinci SA	Value	Value	Value	Value	Value	Value	Value	Value	Value
XXXVII. Vodafone Group PLC	Value	Value	Value	Value	Value	Value	Value	Value	Value

This table provides information on whether the respective stock was growth or value at the end of a given year.

Table A2: Spearman correlation 1, p-values

	F_SCORE	FS_1	FS_2	FS_3	FS_4	FS_5	FS_6	FS_7	FS_8	FS_9	CR
F_SCORE	–	0.00001	0.00000	0.00000	0.00000	0.00000	0.00020	0.00001	0.00000	0.00000	0.00855
FS_1	0.00001	–	0.41559	0.00839	0.04753	0.00912	0.01633	0.73068	0.30349	0.60667	0.03548
FS_2	0.00000	0.41559	–	0.42197	0.00000	0.43608	0.28295	0.02220	0.39447	0.55980	0.84022
FS_3	0.00000	0.00839	0.42197	–	0.09685	0.00083	0.23123	0.80014	0.00057	0.00000	0.01311
FS_4	0.00000	0.04753	0.00000	0.09685	–	0.75074	0.18886	0.36894	0.28284	0.30294	0.24599
FS_5	0.00000	0.00912	0.43608	0.00083	0.75074	–	0.00149	0.20827	0.32813	0.14582	0.02306
FS_6	0.00020	0.01633	0.28295	0.23123	0.18886	0.00149	–	0.52749	0.26455	0.04721	0.86421
FS_7	0.00001	0.73068	0.02220	0.80014	0.36894	0.20827	0.52749	–	0.62386	0.01834	0.59097
FS_8	0.00000	0.30349	0.39447	0.00057	0.28284	0.32813	0.26455	0.62386	–	0.82477	0.29655
FS_9	0.00000	0.60667	0.55980	0.00000	0.30294	0.14582	0.04721	0.01834	0.82477	–	0.21217
CR	0.00855	0.03548	0.84022	0.01311	0.24599	0.02306	0.86421	0.59097	0.29655	0.21217	–

This table provides information about p-values from correlation significance test for variables of F_SCORE and past end-year capital returns of stocks.

Table A3: Spearman correlation 2, p-values

	F_SCORE	BOS	$3M$	$1M$	$12P$
F_SCORE	–	0.00017	0.91323	0.92703	0.00672
BOS	0.00017	–	0.04031	0.04792	0.00000
$3M$	0.91323	0.04031	–	0.00000	0.03561
$1M$	0.92703	0.04792	0.00000	–	0.04982
$12P$	0.00672	0.00000	0.03561	0.04982	–

This table provides information about p-values from correlation significance test for F_SCORE, BOS ratio, future three-month returns ($3M$), future one-month returns ($1M$) and past twelve-month annualised stock returns ($12P$).