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HYBRID INVESTMENT STRATEGY BASED ON MOMENTUM AND MACROECONOMIC APPROACH

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Hybrid Investment Strategy Based on Momentum and Macroeconomic Approach

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Abstract: The purpose of this research is to test the potential returns and robustness of an automated investment strategy. The strategy is based on momentum and macroeconomic approach, that consists of the technical core – momentum, and the additional macro screening, which is used to determine whether investment signals generate relevant investment opportunities or just technical noise. In order to check whether the macroeconomic factor is the value added to the momentum strategy, the hybrid approach is tested and compared with the simple momentum and the macroeconomic strategy alone and then assessed on a risk-adjusted return basis. The main aim of this paper is to answer the question, whether an investor can gain surplus risk-adjusted returns from merging short-term momentum strategy with the long-term macroeconomic approach. Strategies are based on the data for the selected companies from the S&P500 index in the period ranging from 02/01/1990 to 31/12/2018.

Keywords: investment strategy, momentum, macroeconomic indicators, algorithmic trading, risk adjusted returns

JEL codes: C4, C45, C61, C15, G14, G17

Note: The views presented in this text are those of the authors and do not necessarily represent those of Circus Consulting Group nor LHF project.

1. Introduction

The asset management industry is a highly competitive field in terms of technological advancement. It is especially distinguishable when we look at the disruption of the telecommunication industry – optic fiber to be precise, which led to the intensification of the competition in high-frequency trading. Nevertheless, along with the technical progress, the development of investment strategies goes, and new, different ways to develop investment signals and generate alpha¹ are built. Nowadays, managers and analysts focus on artificial intelligence, machine learning, and alternative data science techniques, but the beginning of automation and quantitative approach to trading, began in the 20th century and the momentum strategy was one of many profitable and theoretically efficient ways to execute it.

Momentum and contrarian strategies are based on deviations from the typical price movement. Typical, in a sense of a stable or average level. Whereas the contrarian strategy generates its profits from a mean reversion phenomenon and is considered rather a long-term approach (Chan 1988), the momentum – the core strategy used and discussed in this research – is a short-term approach, with the core assumption being in the simplest words, “stocks that outperform (underperform) will continue to do this for a certain period of time”. It means, that an investor should look for quick and short deviations from recent price levels and take a position based on the direction of this price movement.

The main purpose as well as the important innovation in this research is the use of macroeconomic extension in order to verify investment signals generated by the core momentum strategy. Whether the decision to buy or sell certain equity is on its way to execute, it is reasonable to include an additional set of macroeconomic indicators in order to either confirm or reject the signal (Ślepaczuk, et al. 2018). Given, that nowadays the implementation of technical strategies is broad, it is useful to examine, whether the momentum strategy can be enhanced. Research is based on the most liquid companies listed on the US stock exchange, hence when the outlook for the US economy is considered positive, long orders are going to be executed, otherwise when the outlook is negative, only short orders. A set of factors will be tested for its correlation with and impact on the US economy and then discussed in the next sections of this thesis.

The core hypothesis of this paper is *whether the momentum strategy can lead to better risk adjusted returns when supported by macroeconomic screening tool*. It was verified based

¹ The term used to describe investment strategies' ability to beat the market or the benchmark portfolios, often also referred to as “excess return”.

on data gathered from a broad pool of information accessible through online databases, such as Yahoo Finance or Bloomberg Service. To process the data and investment strategies, R 3.4.3. with additional libraries was used.

The following section of this research presents the literature review. Next, the theoretical framework including the details of the investment mechanism and the main hypotheses is presented. Then, we move to technical details and starts by explaining the datasets and the transformations needed to be done in order to proceed with the analysis. Before moving to the results, the earlier section is used to describe the methodology including the construction of macroeconomic extension and three strategies used in the analysis. The results section presents the comparison between simple momentum and enhanced momentum strategies, as well as the results of the macroeconomic strategy. Before the conclusion, the extensive sensitivity analysis is preformed, in order to check the robustness of the results. The final section concludes.

2. Literature Review

In this chapter, the most insightful and popular research papers connected to the momentum strategy will be summarized. Plenty of articles either outline the methodological issues or provide the empirical evidence for the profitability of this trend following strategy. Many articles test the robustness and emphasize the constraints of practical implementing e.g. the level of transaction costs or the liquidity analysis. Nevertheless, momentum is such a popular approach, that even the financial institutions, especially AQR Capital Management – the global investment firm – are conducting the research and provide more practical insights on this strategy.

One of the fundamental papers, that discusses the beginning of automated and technical trading strategies is the “Profitability of Momentum Strategies: An Evaluation of Alternative Explanations” published by Jegadeesh and Titman (1999). It successfully summarizes the phenomenon of momentum trading and provides basic information about the methodology. However, it regards mainly the theoretical side, rather than practical and empirical evidence, e.g. discussing the explanations and the theoretical rationale behind the momentum mechanism. Speaking of Jegadeesh’s momentum strategy legacy, it is important to emphasize, that they introduced the lookback periods for implementing this mechanism. He suggested, as it is widely known, that momentum should be implemented on a rather short-term basis, focusing on periods ranging from 3 to 12-months.

Contrary to that, Marshall and Cahan (2006) or Liu, et al. (2011), describe the 52-week strategy on international stock markets. In the first paper, the authors tested the Australian stock market and found out, that the momentum strategy is profitable, generating an average return of 2.14%, monthly. However, they emphasized, that this return is much bigger than the return from the same strategy ran on the US stock market. They consider this, as an argument for the author of this paper, that if this research is based on the US stocks, formation and holding windows should be shorter than 52 weeks. The second research based on the window of this length, test 20 different markets besides the US market, however, the risk-adjusted returns with estimated trading costs were ambiguous and were not easy to categorize and group results between developed, emerging, big nor small stock markets.

Many researchers tried to compare the momentum strategy with different approaches. One of those endeavors is described by Kang, Liu, and Ni (2002), where the authors investigate the potential returns in China. It is also worth mentioning, that they reversed common outlook and constructed the contrarian strategy on a shorter time horizon than the momentum. Ultimately, the authors have found out that the Chinese market is highly influenced by the overreaction effect, which enables the mean-reversion, contrarian strategy to be more profitable than the trend following, momentum strategy. Additionally, this Asian market is built upon a “lead-lag” structure, wherein in certain periods, large companies lead smaller ones and in different periods it is the opposite. The first statement is true for 1-8 week windows and the second one for 12-26 week windows. This indication however, does not add much value to this paper, because the research is focused on the group of the biggest companies in the US. Analyzing further the momentum research on Chinese stocks, the author found out, that Li, Qiu, and Wu (2010) performed research based on the 1994-2007 period, which did not suggest any profitability from this approach.

Another attempt to combine different strategies was conducted by the founder of AQR Capital Management and well-known author of technical strategies publications – Clifford Asness (1997), where he investigated “The Interaction of Value and Momentum Strategies”. The author of the publication above tried to measure the relation of value and momentum. Asness finds, that the strategies are negatively correlated. It means, that if an investment decision is based on the first methodology, the investor has to select the worst companies in terms of the second methodology as well. His research outline, that it is crucial to examine the correlation between the strategies, before an investor tries to merge them, in order to maximize profits from both approaches rather than create a loss on one’s portfolio.

Contrary to the above-described papers focused on momentum or contrarian strategies on the US market, Kość, et al. (2019) investigated those effects on the cryptocurrency market. The authors compared their strategies with four benchmarks including S&P500 Index, and concluded, that contrarian approach results in abnormal risk-adjusted returns, even after taking the transaction costs into account. However, their results were not robust after detailed sensitivity analysis. These results suggest, that the momentum and contrarian strategies can work great even on highly volatile assets.

It can be clearly seen, that the research focused on this investment technique is broad and insightful. Momentum factors are often used along with macroeconomics outlook assessment during screening and making short term asset allocation decisions. In terms of merging both, macroeconomics and momentum strategy, Liu and Zhang (2008) argue, that macro outlook does matter, however the other paper (Ji and Martin 2012) shows that there is no evidence, that momentum profits lie in macroeconomic risk.

All these arguments regarding the lookback window or the relation of momentum with macroeconomics, encouraged us to test the potential hybrid strategy and compare it in terms of risk-adjusted return and statistical significance.

3. Theoretical Framework

In this section, a theory connected to a broader strategy description is presented, focusing on the core assumptions that distinguish the momentum from other technical forms of generating investment signals and especially the contrarian strategy. Next, the basic framework for implementing such a strategy will be presented. Then, in the next part of the Theoretical Framework, hypotheses that are verified in this thesis will be presented in an elegant and concise form.

3.1. Investment Strategy

As it was previously stated, the mechanism to develop investment signals is built upon the momentum strategy concept. The core assumption of this approach is based on the price changes of an underlying instrument. There are at least two ways to investigate the price deviations.

The most popular technique is to observe the n -day rate of change (RoC^2) for each asset in the potential portfolio and select the winners or losers to perform trades. After calculating the n period RoC , the portfolio manager should cut off a certain number of observed assets and execute trades according to the methodology – long position on the winners (the highest positive RoC) and short position on the losers (the lowest RoC). If the assumption of trend following concept is correct, it will result in the profit from buying the companies that will continue to outperform the broader market and the profit from selling the underperformers. Equation (1) presents the n day RoC calculation method (between date t and $t - n$) used in further sections of this research.

$$n \text{ day } RoC = \frac{Value_t}{Value_{t-n}} - 1 \quad (1)$$

Using different, less popular approach, the strategy can be developed based on n -day Simple Moving Average (SMA_n) and x -days standard deviation channel. Thus, in order to implement it, one should build a corridor corresponding to recent prices. An example can be the corridor based on the SMA_n with an x -day rolling standard deviation added and subtracted from the SMA line. One should observe the price level on a rolling basis, and then execute trades on companies that “breaks” the bottom or ceiling of the corridor, expecting the trend to be continued, not reversed. That would be the example of a momentum approach.

The tendency, that momentum is strictly connected with the trend following hypothesis is known as the price persistence, meaning that a security price will continue to move in its present direction. In other words, the main rationale behind this strategy is that when a trend is established on a security or a broader market, there is a higher probability, that it would be continued.

The problem is that quantitative and technical strategies based on statistics, generate a number of false signals, not fundamentally correct, thus leading to wrong investment decisions. It can be referenced as a statistical noise. Therefore, an additional extension or verification of the signal can be useful in executing a certain method. In this research, an additional macroeconomic evaluation is proposed as a mechanism to verify pre-generated momentum signals. When a certain signal was noticed, meaning that the RoC is abnormally high or the price deviated from its moving average and created a sufficient gap, the macroeconomic condition of the US economy is evaluated. Such advancements enable us to

² RoC is generally expressed as the percentage ratio between the current value and the previous value. It can be calculated using discrete or continuous compounding.

increase the probability of correct investment signals, confirmed by the fundamental rationale – to purchase securities during the bull market and to sell them during the bear market. The algorithm describing the proposed hybrid strategy is presented as Formula (2). Summary of core Momentum Strategy and Macro Strategy can be found in Table 7. Given, that the technical mechanism is generating both buy and sell signals, (as it evaluates the best and worst RoCs,) the hybrid approach is always executing positions.

$$\left\{ \begin{array}{l} \text{buy signal from momentum} \wedge \text{bull market from macro.} \Leftrightarrow \text{long position} \\ \text{buy signal from momentum} \wedge \text{bear market from macro.} \Leftrightarrow \text{no any position} \\ \text{sell signal from momentum} \wedge \text{bear market from macro.} \Leftrightarrow \text{short position} \\ \text{sell signal from momentum} \wedge \text{bull market from macro.} \Leftrightarrow \text{no any position} \end{array} \right. \quad (2)$$

Before moving to further sections of this paper and especially the results, it is important to state, that in the current market condition, momentum or contrarian strategies, might result in weaker returns. It can occur due to technological advancement, the use of these approaches became more popular. In economics, the more users or consumers of certain products, the less value it starts to present. Many institutions have implemented those strategies, hence the current market imperfections and inefficiencies are less visible, than e.g. a decade ago. The market is more liquid, spreads are becoming tighter and mean reversion advances faster. Momentum strategy core assumption is based on the price anomaly and as the market becomes more liquid and the deviations are caught by quantitative or high-frequency trading companies, the returns tend to flatten. Hence, the statistical arbitrage strategies and those based on price fluctuations, in general, are supposed to be less profitable.

3.2. Hypotheses

In this section, the authors' leading ambition is to outline main hypotheses. In the conclusion section of this thesis, the assumptions regarding the results are addressed. Based on the results from the primary research and the sensitivity analysis these hypotheses will be verified.

The main hypothesis in this research is that *the momentum strategy – whether it is considered profitable or not – can lead to better risk adjusted returns when supported by macroeconomic screening tool*. One of the mistakes that can be made in developing the strategy with the best returns during backtesting is overfitting. Tweaking the model on historical prices will eventually provide worse forecasting ability. On the other side, we have the confirmation bias, meaning that the investor would stop improving its algorithm if it starts to provide sufficient returns. To address this, we decided that the strategy should be somehow

supported. And the idea is to balance short-term seeing statistical analysis with the more long-term fundamental approach. It can be worthwhile adding a macroeconomic assessment to provide a greater level of certainty, that buying the companies in a certain period of time, will result in profit as an outcome, because the broader economy is in the good condition.

Leveraging the fact, that a macroeconomic screening tool was built, we also decided to test the hypothesis of profits greater than zero from the sole macroeconomic strategy. When a signal is generated from the algorithm a long or short position on security such as index-tracking ETF (exchange-traded fund) can be executed for a period of time. That enabled us to test the tool in practice, checking whether it is profitable on its own or not. If the sole macroeconomic strategy will not be profitable, it would mean, that it does not have the ability to assess the outlook of the US economy and indicate whether the S&P500 Index will grow or decline. Verifying this hypothesis will also contribute to the understanding of the hypothesis regarding the hybrid approach and the final results of this research. The summary of hypotheses and research questions is presented below.

Hypothesis 1. The momentum strategy based on the S&P500 Index selected companies and RoC calculations provide risk-weighted returns greater than the benchmark.

Hypothesis 2. The macroeconomic strategy based on the index-tracking product and build upon the macroeconomic factor provide risk-weighted returns greater than the benchmark.

Hypothesis 3. The momentum strategy risk-weighted returns are better (bigger) when the strategy is supported by macroeconomic extension in comparison to a simple momentum strategy.

Research Question 1. Does changing the Formation and Holding Period influence the risk-weighted returns of the strategies?

Research Question 2. Does changing the Number of Traded Companies influence the risk-weighted returns of the strategies?

4. Data

This section is dedicated to describe two independent, however corresponding with each other datasets, that the paper is built upon. The data is gathered from different sources, but it does not affect the accuracy, neither the results of the research process. The first database is used to run the core momentum strategy (and it consists of equity time series) and the second one

provides the macroeconomic data and is based on the same period as equities. Both datasets are time series with the holidays and weekends excluded, thus the trading year has 252 days.

4.1. Equity Database

The first set consists of US equities and it is essentially the list of constituents of the S&P 500 Index, in the period starting from 02/01/1990³ and ending on 31/12/2018. Based on this time series, automated signals were generated, executed and closed during repositioning of the strategy.

However, working on certain types of data – here on the index time series – and especially on time series of this length, a survivorship bias problem has to be addressed. It is the logical error, that results in making the assumptions and analyzing only the objects that have “made through” some process, e.g. analyzing the airplane damages based on the airplanes that survived the failure. In other words, making assumptions based on the biased source of information, which is represented only by a certain number of objects, usually smaller than the whole spectrum. In this special case, the biased dataset would consist only of the “winners” – companies that survived since 1990 until now (which is 31/12/2018 in this research). This could affect the returns of the strategy, especially the one based on positive price deviations (momentum, which is a core mechanism in this research) in a negative way. However, this research paper is dedicated to investigating differences that arise when technical investment strategy implementation is merged with the long-term macroeconomic assessment. The authors are completely aware of this bias and tried to address the problem in the best way, by controlling the number and the list of the constituent companies, in order to make sure, that the results are comparable to each other.

The authors will compare the returns of different strategy implementations, but based on the same dataset. Moreover, complex databases, that address the problem are hardly accessible on an open source license and the process of implementing a bigger dataset would be more extensive in a technical sense. That being said, to create the set of companies, Bloomberg data was used and two separate datasets were compared to each other. The first dataset consisted of companies, that were part of the Index on 2nd Jan 1990, and the second one consisted of those present in the Index on 31st Dec 2018. The intersection of companies was derived, resulting in 146 companies listed continuously for 29 years. Then, daily time series for each company were downloaded automatically through Yahoo Finance, using

³ Dates in this paper are based on DD/MM/YYYY format.

getSymbols() function from quantmod R package. Columns representing the Adjusted Price were saved for future analysis, finally resulting in over 1 million daily observations for 146 equities. A complete list of companies can be found in Table A1, in the Appendix.

4.2. Macroeconomic Database

The second dataset consists of specially selected macroeconomic indicators. Its main goal is to verify and assess automatically generated investment signals. For the list of primarily selected factors, additional research is conducted in order to confirm and measure the impact they have on the US economy individually and in aggregate. The impact is needed to be measured in order to build a precise and accurate screening tool. Multiple regressions were run in order to set the weights for each indicator included in the final dataset. To provide consistency, in this section, only the technical side of the database is discussed, hence the rationale and arguments behind selecting each indicator are provided in the next section.

Certain indicators selected for the strategy have different frequency of the announcements. Some are quoted on a constant, daily basis, some are announced once in a week or once in a month. The authors derived the most frequent data for each indicator, and then, after regressions and significance analysis transformed the series, where it was needed, to provide daily data corresponding with equities. To explain the process, let us use the CPI indicator. It is announced on a monthly basis, hence to provide a synthetic daily time series, its levels were transformed on a fixed basis filling each day of the next month for which the announcement has been made. In other words, if the CPI announced on 01/03/1995 is at a certain level, this value is copied to every other day in this month up until 01/04/1995, when new numbers are announced. This is the best approach to maintain the daily data and provide a continuous assessment of the state of the US economy. However, the CPI is announced as a percentage change of the index between two periods. Some of the indicators are announced as the nominal values (e.g. M2 Money Supply). In that case, the authors calculated the RoC between the announcements and continued the procedure with the change level expressed in percentage. It is important to state, that we use an approach that replicated the growth rates for every day in the month and not filling the daily data with zeros. To summarize, we assume that the level of the indicator will remain the same, until the moment that the new official level is announced and then the data is updated. If the investment signal is generated on 15/03/1995, the algorithm would assess the US macroeconomic outlook based on the CPI level from 01/03/1995.

All data was primarily downloaded from the Federal Reserve Bank of St. Louis Economic Research (FRED) website excluding CRB Commodity Index, which daily data was downloaded from an open source stooq.pl website. Where it was needed (seasonal time series), we used Seasonally Adjusted type to perform analysis, in order to avoid seasonal bias and to ensure, that the indicators are the precise proxy of macroeconomic trend and are the representation of fundamental changes in the economy.

After merging the growth rates⁴ for each indicator into one matrix 7256 rows of macroeconomic data were created compared to 7303 in equity dataset. The discrepancy is present in the datasets due to the different sources and different types of data (announcements and equity price levels). Monthly announcements are artificially assigned to the last day of the month, whereas these days are sometimes non-trading days. The two datasets have been adjusted through the intersection of dates and creation of the continuous time series of equity and macroeconomic indicators, that consist of the same number of rows.

To address the problem, that certain time series were created after 1990, missing values from the beginning of 1990 to the first announcement or price level, were substituted with zeros. That way, in a future row means calculation, the weights of indicators would spread equally and would not affect the mean calculated in the next chapters. If a certain indicator's value is zero, it is skipped in calculating the mean, and its weight is transferred equally to the rest of the indicators. It is important to emphasize once again, that the analysis is completely based on the period over period changes, not the nominal values of the indicators. Daily data is used only in the momentum strategy, an earlier analysis of correlation and regressions against the S&P500 Index were run on original, weekly or monthly periodicity for each indicator.

The important challenge regarding the macroeconomic dataset is associated with macroeconomic lag. The idea behind the hybrid strategy is to blend long and short-term views based on the macroeconomic environment and technical signals. The problem arises when the mechanism is dealing with preliminary data, meaning when the market reacts earlier (before the forecast is announced). Moreover, the market (investors) react more to the difference between estimates and real data, than to the announced data itself. During a more complex analysis, it should be taken into account, as well as the fact, that part of the anticipation is already in the price of underlying assets. The macroeconomic data in this research is sourced on a daily, weekly or monthly basis. In other words, it aggregates the data and market

⁴ The growth rate is essentially the 1-period Rate of Change. In other words, it is the percentage change between the present value and the value from one period before.

behavior, to some point. This way, the problem is more likely to be skipped than addressed. However, the purpose of this screening is not to precisely forecast market movement in the moment of data announcement, but to assess a wide macroeconomic outlook on a certain period of time. Then, confirm or reject the primarily generated investment signals, by enhancing the core technical strategy.

Finally, although the used periodicity can work correctly during the strategy itself, it can cause problems, while assessing and investigating the impact of forecasting or explaining the US economy status. Analysis of correlations and the regression model are run on a monthly rate of indicator changes, hence there is fewer data provided and it can be less accurate. Additionally, the S&P500 Index is a highly liquid collection of companies, therefore aggregating the data to weekly or monthly returns, can lead to a less than the ideal view on its condition. Nevertheless, certain macroeconomic data is not published on a daily basis, but more rarely, on a weekly or monthly basis. A complete list of indicators and correlations⁵ can be found in Table 1.

Table 1. List of primarily selected macroeconomic indicators used in the research

Indicator	Form	Ticker	Freq. (n)	S&P500 Corr	Obs.
US Generic Government 10 Year Yield	RoC _n	10Y	W	0,2220	1510
US Generic Government 2 Year Yield	RoC _n	2Y	W	0,1998	1510
Thomson Reuters/CoreCommodity CRB Commodity Index	RoC _n	CRY	W	0,2740	1305
US Initial Jobless Claims SA	RoC _n	JOB	W	-0,0252	1510
Federal Reserve United States Money Supply M2 SA	RoC _n	M2	W	-0,0984	1510
CPI: Total All Items (Growth Rate Prev. Period, not SA)	Original	CPI	M	0,1767	348
US Employees on Nonfarm Payrolls Total SA	RoC _n	NFP	M	0,1305	348
S&P CoreLogic Case-Shiller Boston Home Price Index	RoC _n	Schiller	M	-0,0151	348
Average Hourly Earnings All Employees Total Private SA	Original	AHE	M	-0,1888	155

Note: Table 1 represents the indicators that were pre-selected for future analysis. Tickers are used to explain which variable (indicator) do we refer to. Frequency (Freq.) is the variable used to explain whether the data is based on weekly (W) or monthly (M) periods. Correlations are based on 1-period lagged indicator data based on the "Form". If the Form is "Original", it means, that the data is initially announced as RoC.

5. Methodology

In this section, we will present core research problems, that were faced during the development of this thesis. Touching upon the selection of macroeconomic indicators and strategy implementation, the underlying investment mechanism is explained thoroughly. The

⁵ Values are based on Pearson's correlation. Statistics are measured as a relation between RoC of the indicator and W/M S&P 500 Index RoC. RoCs are based on the Last Price data.

Performance Statistics section, summarizes the formulas used to interpret the results of this paper.

5.1. Performance Statistics

In this section, we explain, how the statistics used to measure the performance of the strategies are calculated.

$$\text{Cumulative Return (AbsRet)} = \frac{(1 + r_1)(1 + r_2) \dots (1 + r_n) - 1 = \text{prod}(1 + r_i) - 1}{\text{where } r_i \text{ is the daily return}} \quad (3)$$

$$\text{Annualized Return (ARC)} = \frac{\text{prod}(1 + r_i)^{\frac{252}{n}} - 1}{\text{where } n \text{ is the total no. of periods}} \quad (4)$$

$$\text{Maximum Drawdown (MD)} = \sup_{x, y \in \{[t_1, t_2]^2: x \leq y\}} \frac{P_x - P_y}{P_x}, \text{ where } P_t \text{ is price level} \quad (5)$$

$$\text{Annualized Standard Deviation (aSD)} = \sqrt{\text{var}(r_i)} * \sqrt{252} \quad (6)$$

$$\text{Information Ratio}^*(IR^*) = \frac{ARC}{aSD} \quad (7)$$

5.2. Macroeconomic Indicators Selection Process

Before the quantitative analysis will be conducted on the selected indicators (factors), it is worth mentioning that the rationale behind selecting these factors is to use them as an investment/macroeconomic proxy. Bearing in mind, that the purpose of this mechanism is to give a long-term view on the US economy and condition of the biggest companies especially, a natural place, to begin with, is the job market. Constituent companies of the S&P500 Index employ approximately 17% of the employees ready to work (Deutsche Bank assessment from 2015) and based on publicly available data, Walmart on its own has an employment base of over 2 million people. To address the job market situation, two leading indicators in this area can be good proxies and measurements. Initial Jobless Claims (JOBS) and Nonfarm Payrolls (NFP) to be precise. Apart from the employment itself, another important indicator related to the analysis is the real wage growth. Similarly, there are two leading indicators, that could be helpful – Average Hourly Earnings of All Employees (Private) (AHE) and Average Hourly

Earnings of Production and Nonsupervisory Employees (AHEPNE). Given that the former indicator is announced since 2006, we opted for the latter in order to have a full period of data. Additionally, tracking the average wage of production employees excluding the supervisors, can lead to a better understanding of a broader economy and help to include production outlook in the analysis. Unfortunately, the basic tests for the correlation between the S&P500 Index and the indicator mentioned as the second one (AHEPNE), showed results near zero. Addressing this and bearing in mind the highest possible accuracy for the research, finally, the Average Hourly Earnings of All Employees (Private) was selected. Addressing the lack of data, its time series was extended to begin in 1990, and filled with growth rate, which equals to zero. Thus, it will not affect the aggregating in further analysis, and the weights will distribute equally. This method was explained in the earlier section of this paper.

While describing the broader market it is important to mention two phenomena, that drives the US economy. The first one is connected to consumption. As the major part of the country wealth is driven by this part of the Gross Domestic Product, it is important to track the changes in US consumer spending and Consumer Price Index (CPI) is going to be used. Another important factor is the housing market. We are going to test the influence of Case-Schiller indicator which is the proxy of the real estate part of the economy. Focusing on the main drivers of production, another insightful tool can be the Commodity Index. It is important, given that the US is leading exporter and importer of crude oil and the Index assess the condition of other major commodities as well – 19 in aggregate, including groups of petroleum products, and diverse commodities such as Aluminum, Cotton, Live Cattle, Orange Juice and 15 more. The Index data is span across 1994 and 2019, hence the same procedure as for the wage growth indicator was applied.

Moving the focus to a more fundamental outlook, money supply, and government debt are key drivers of investors' attitude to the US economy. Hence, M2 Money Supply and Government Bond Yields for 2 and 10-year certificates are used.

After explaining the key drivers for the primary list of indicators, the analysis can move to the next step – the quantitative analysis of relevance of the selected macroeconomic gauges. In this section, the time series are downloaded keeping their natural frequency (time series is based on the announcement dates) then, if needed, changed to periodical RoCs, correlated and regressed against periodically corresponding S&P500 Index rate of change. The extension to daily data will be performed later, during the strategy tests.

The weight and therefore the importance of each factor have to be adjusted in order to maximize the added value of the macroeconomic extension. The first assessment is connected

to a simple Pearson's product – moment correlations. Results of `cor.test()` function, as well as the p-values are printed below in Table 2. The null hypothesis of this test is that the true correlation equals zero, and the alternative is that the true correlation is not equal to zero. At the beginning of the testing, the stationarity of the time series is checked using the Augmented Dickey-Fuller Test. The results, whether the time series is stationary or not, can be seen in the last column of the table. The stationarity was tested on the form of the time series used for the regressions and the analysis. The form of each indicator is presented in Table 1.

Table 2. Monthly Macroeconomic Indicators summary table

Ticker	Correlation	p-value	95% conf. interval	Stationarity
CPI	0,1767	0,0010	(0,073; 0,277)	Stationary (<0.010)
NFP	0,1305	0,0150	(0.026; 0.236)	Stationary (<0.010)
Schiller	-0,0151	0,7788	(-0.120; 0.090)	Nonstationary (0.698)
AHE	-0,1888	0,0190	(-0.337; -0.032)	Stationary (0.048)

Note: The table presents correlations between the indicators' and the S&P500 Index's rate of change, as well as the results of stationarity tests (ADF Test), performed to avoid problems in future analysis and regressions (p-values in the bracket). For the correlations, the p-values of the tests and confidence intervals are printed.

Analyzing the results, Schiller indicator becomes statistically insignificant for the further research, as the correlation between its monthly changes and the Index's RoCs is close to zero, and insignificant because p-value is bigger than the alpha significance level⁶ of 1%, 5% and even for 10%. We do not reject the null hypothesis of the test in the favor of alternative, hence true correlation of this indicator is equal to zero. In every other case, we reject the null hypothesis and confirm the alternative, that true correlation is different from zero for the rest of the indicators. Moreover, Schiller is not a stationary time series, which would lead to problems in building the linear model in further steps of this research.

Next, a linear regression model is built (Equation (8)), to assess the significance of the whole group of monthly indicators. The results of this regression can be found in Table 3.

$$\begin{aligned}
 \mathcal{Y}_{S\&P500\ Index\ RoC_Month} \\
 &= \beta_0 + \beta_{CPI}x_{CPI_ \%_Month} + \beta_{NFP}x_{NFP\ RoC_Month} \\
 &+ \beta_{AHE}x_{AHE_ \%_Month} + \varepsilon_t
 \end{aligned}
 \tag{8}$$

⁶ Significance level (alpha, α) is the probability of a Type 1 error, meaning that the null hypothesis is rejected, while it is true.

Table 3. Time series linear regression of monthly indicators

<i>p-value</i>	0,0000				
Adjusted R ²	0,1525				
Ticker	Estimate (Beta)	Standard Dev.	t-statistics	<i>p-value</i>	VIF
Intercept	0,005346	0,005572	0,959	0,3389	-
CPI	4,557652	1,028386	4,432	0,0000	1,027864
NFP	2,598450	1,757629	1,478	0,1416	1,019544
AHE	-4,379039	2,077910	-2,107	0,0367	1,008259

Note: The table represents basic statistics assigned to the regression model above. Variance Inflation Factor (VIF) is the measure of multicollinearity in the data. The values below 10 suggest a lack of multicollinearity.

The linear model is correct (p-value equals 0, hence the alternative hypothesis – the model being significant – is accepted). Residuals' distribution is characterized by the same attributes as normal distribution and the Shapiro test for these residuals is passed with p-value of 0.3836. Combining these results with the correlation analysis (Table 2), we decide to exclude Nonfarm Payrolls from further research. NFP is neither entirely significant in linear model nor the correlation is strong. Finally, we select two monthly indicators CPI and AHE for the macroeconomic screening tool.

Table 4. Weekly Macroeconomic Indicators summary table

Ticker	Correlation	<i>p-value</i>	95% conf. interval	Stationarity
10Y	0,2220	0,0000	(0,174; 0,269)	Stationary (<0.010)
2Y	0,1998	0,0000	(0,151; 0,248)	Stationary (<0.010)
CRY	0,2740	0,0000	(0,223; 0,323)	Stationary (<0.010)
JOB	-0,0252	0,3930	(-0,083; 0,037)	Stationary (<0.010)
M2	-0,0984	0,0001	(-0,148; -0,048)	Stationary (<0.010)

Note: The table presents correlations between the indicators' and the S&P500 Index's rate of change as well as the results of stationarity tests (ADF Test), performed to avoid problems in future analysis and regressions (p-values in the bracket). For the correlations, the p-values of the tests and confidence intervals are printed.

A similar analysis as for the monthly indicators is used for weekly data to determine the importance of each indicator. Applying the same procedures, tables with correlations and time series linear model of the selected indicators against the S&P500 Index can be found in Tables 4 and 5 respectively. Additionally, the formula for regression is presented in Equation (9).

The correlation coefficient between the S&P500 Index weekly changes and Initial Jobless Claims is not statistically significant. We decide to not use this indicator in further research. At this moment, it is worth reminding, that all weekly variables are stationary and the analysis can proceed to a linear model regression.

$\mathcal{Y}_{S\&P500\ Index\ RoC_Week}$

$$= \beta_0 + \beta_{10Y}x_{10Y\ RoC_Week} + \beta_{2Y}x_{2Y\ RoC_Week} + \beta_{CRY}x_{CRY\ RoC_Week} + \beta_{JOB}x_{JOB\ RoC_Week} + \beta_{M2}x_{M2\ RoC_Week} + \varepsilon_t \quad (9)$$

Table 5. Time series linear regression of weekly indicators

<i>p-value</i>	0.0000				
Adjusted R ²	0.1295				
Ticker	Estimate (Beta)	Standard Dev.	t-statistics	p-value	VIF
Intercept	0.002405	0.000681	3.533	0.0004	-
10Y	0.084913	0.023242	3.653	0.0002	2.161532
2Y	0.032606	0.011952	2.726	0.0065	2.116721
CRY	0.256559	0.027842	9.215	0.0000	1.193800
M2	-0.980574	0.289915	-3.382	0.0007	1.001223

Note: The table represents basic statistics assigned to the regression model above. Variance Inflation Factor (VIF) is the measure of multicollinearity in the data. The values below 10 suggest a lack of multicollinearity.

Finally, aggregating the results of correlations and regressions in Table 6, the decision is made to choose indicators with corresponding weights in the final macroeconomic outlook factor. Direction (Dir.) is the indicator of interpretation. If the direction is set to 1, the increase of the indicator means a positive outlook and the decrease means a negative outlook. Respectively, if the direction is set to -1, the increase of the variable denotes a negative outlook, and its decline denotes a positive outlook. Weights of monthly indicators are lower, due to less accurate indicating power due to bigger time lag. The formula used to calculate Macroeconomic Factor (Macro Factor) is shown in Equation (10). The Macro Factor is later smoothened using the ordinary Simple Moving Average technique in the strategies.

Table 6. Indicators selected to construct Macroeconomic Factor

Indicator	Form	Ticker	Weight	Freq.	Dir.
US Generic Government 10 Year Yield	1W Yield RoC	10Y	20%	W	1
US Generic Government 2 Year Yield	1W Yield RoC	2Y	20%	W	1
Thomson Reuters/CoreCommodity CRB Commodity Index	1W Price RoC	CRY	20%	W	1
Federal Reserve United States Money Supply M2 SA	1W Amount RoC	M2	20%	W	(1)
CPI: Total All Items (Growth Rate Prev. Period, not SA)	1M Change	CPI	10%	M	1
Average Hourly Earnings All Employees Total Private SA	1M Change	AHE	10%	M	(1)

Note: The table above summarizes the indicators selected after a complex analysis in this section of the paper. Weights are used to compute the cumulative mean, for each day in the analysis, which essentially is the Macro Factor. If the Direction is negative, the subtraction instead of addition was applied, when calculating the mean.

$$Macro\ Factor_t = \sum Weight_{Indicator} * Dir_{Indicator} Indicator's\ RoC_t \quad (10)$$

It is important to note here, that the main aim of this research is not to search for the exact relation between macroeconomic indicators and the S&P500 Index, but only the possible correlation, that is supposed to confirm the momentum investment signals. In order to avoid the spurious correlation problem, only stationary time series were an object of regression against other time series. After the transformation, the final correlation between the S&P500 Index RoCs and the Macro Factor RoCs was equal to 26.16%. Authors are aware, that the value could be higher, but at this point, it is sufficient to proceed to the next steps of the analysis.

5.3. Macroeconomic Strategy

In this section, the strategy development process will be explained step by step, meaning that we will describe developed algorithms and data processing thoroughly.

In order to build macroeconomic extension strictly corresponding to the core momentum strategy, from the downloaded data for selected indicators, we have to adjust time series to daily periods e.g. CPI, where the announcement is published once in a month. The assumption behind the transformation process is that until the next announcement, levels of the latest announcement are set as present ones in the daily database. Thus, the model's indicators concerning the US economy macroeconomic condition are at most delayed for one month, which is approximately 21 trading days.

Taking a step further, and constructing the macroeconomic screen, we calculate the weighted mean of underlying variables, based on the weights included in Table 6 and the formula no. 5. Next, we calculate the SMAs of the Macro Factor. SMAs are calculated using SMA() function from the TTR package. 1, 3, 6, 9 and 12-month moving averages were generated. The strategy used to evaluate the macroeconomic system is a simple construction of trend following methodology. When daily RoC of the Macro Factor is above the level of SMA, the long position is executed and if the factor is below – short position. Trading decisions are generated on a daily basis, but with the use of moving averages, the long or short portfolio is usually kept for more than one day. The strategy trades S&P500 Index and the benchmark is the simple Buy & Hold Strategy on the same product. The author's main assumption here is, that if the Macro Factor's components are changing in the positive direction, the US economy should do this as well.

5.4. *Momentum and Momentum + Macro Strategies*

For the purpose of verifying hypotheses stated at the beginning, two momentum strategies were developed. The first strategy is the simple long and short momentum strategy based on RoC value, and the second one is the same strategy but with the macroeconomic assessment (confirmation) attached to it. In the second approach, during trading periods, only positions confirmed by the macroeconomic outlook are executed, meaning that if the outlook is positive, the momentum strategy will execute only long positions, otherwise only the short positions. The first strategy based on n companies trades both the outperformers and underperformers, executing long and short positions (cumulatively trading $2n$ companies), while the second strategy trades only n best or worst companies depending on the Macro Factor value.

Based on Jegadeesh (2001), the best results for momentum can be achieved using 3 to 12-month formation and trading periods. Therefore, the author decides to test 6-month periods in the core analysis and different lengths in Sensitivity Analysis. During the Formation Periods, RoC matrices are calculated as well as Simple Moving Average of macroeconomic factor corresponding with formation period length. We calculate SMA to smoothen the values and provide a more stable outlook. During the Holding Periods, long and short positions are executed in the portfolio, and the rebalancing is at the end of this period (6 months in core analysis for both Formation Period of RoCs and Holding Period for holding the positions). Scheme for Momentum Strategy is represented as follows:

1. Ranking procedure (based on 6-month RoC) of the equities based on the n period Rate of Change using discrete compounding and daily data.
2. Selecting a fixed number ($n = 15$ in the core analysis) of top outperforming and bottom underperforming equities.
3. Next formation procedure during the trading period (6-month holding period in the core analysis).

Momentum + Macro Strategy assess, whether to perform only the long or only the short positions, taking into account, that long positions are executed during the rebalancing only when the macroeconomic factor is greater than zero, and short positions otherwise. During the analysis, the factor used to determine the direction for US economy was found to be either a positive (53,11% of factor values) or negative (46,89% of factor values) signal in terms of value (there was no value equal to zero), therefore there is always a decision. To calculate the cumulative return or equity line for the portfolio of companies, an equally

weighted mean was used. Below is Table 7, which summarizes the strategies in this paper. Regarding the Sensitivity Analysis, there is Table 8, which represent the variables changes and values, that were tested.

Table 7. Summary of the strategies

Name	Type	Data	Mechanism
Macroeconomic Strategy	Long / Short	Trading S&P500 Index	Based on the signal from Macro Factor, it takes either long or short position on the S&P500 Index. If the daily RoC of Macro Factor is above (under) SMA _n strategy executes short (long) position on the Index
Momentum Strategy	Long & Short	Trading the companies incl. in Table 1A.	Based on the signal from RoC _n ranking performs a long position on a number of best companies and short position on the same number of worst companies
Momentum + Macro Strategy	Long / Short	Trading the companies incl. in Table 1A.	Merges signals from Macro Factor and Momentum mechanisms, by either executing long position on the best companies, if the Macro Factor is greater than zero or short position on the worst companies, otherwise

Note: All strategies' benchmark is the Buy & Hold S&P500 index strategy.

Table 8. Table summarizing the choices of variables used in the strategy

Analysis	Variable	Level
Core Analysis	Formation Period	6 Months
	Holding Period	6 Months
	No. of Traded Companies	15 Companies
Sensitivity Analysis	Formation Period	3 and 9 Months
	Holding Period	3 and 9 Months
	No. of Traded Companies	5 and 25 Companies
SMA Length of Macro Factor		Matching Formation Periods

Note: Table represents the variables, that were changed in the Sensitivity Analysis in order to verify research questions posed at the beginning of this paper.

6. Results

The most important issue, is the possibility to compare the results from different strategies. From a broad list of indicators, Cumulative Return (Cum. Return, AbsRet), Annualized Return (Ann. Return, ARC), Annualized Standard Deviation (Ann. Std. Dev., aSD), Information Ratio*⁷ (IR*), and Maximum Drawdown (Max. Drawdown, MD) was used. The IR* and aSD are calculated for additional 5, 10 and 15-year periods as well. Especially important here, is the fact, that the risk-adjusted measures were used. If the strategies are not as profitable as the Buy & Hold S&P500 strategy in terms of the cumulative return, they may

⁷ The Information Ratio* is essentially the Information Ratio in the version for absolute return products, without the subtracted benchmark, which provides the results on a risk-adjusted basis.

have lower risk expressed in volatility (aSD) hence the risk-weighted return is much better to evaluate the performance.

It is important to state, that different lengths of Formation and Holding periods influence the strategies' return vectors length. The algorithm used to calculate RoCs and the ranking of companies operates on the full 3, 6 or 9-month periods, hence the vector for 9M Formation and Holding period is shorter than for the 3M. Therefore, the authors adjusted the equity lines of the Momentum and the Momentum + Macro Strategies to the same length, to provide fully comparable results and addressing the technical constraints set by the algorithm. Due to the formation of SMAs in the Macro Strategy, the results are calculated starting from 03/01/1991, to let the 12M SMA form during the first year of the analysis. In the end, for the purpose of comparison and to remain the consistency, all results in this thesis are based on a period starting from 03/01/1991 and ending on 03/01/2018.

Table 9. Results of the Macro Strategy

Variable	Period	6-Month SMA	B&H S&P500 Index
Cumulative Return (AbsRet)	Full	10.148	742.801
Annualized Return (ARC)	Full	0.359	8.222
Maximum Drawdown (MD)	Full	60.174	56.775
Annualized Standard Deviation (aSD)	Full	17.668	17.652
Information Ratio* (IR*)	Full	0.020	0.466
Annualized Standard Deviation	Last 15Y	18.314	18.311
	Last 10Y	20.368	20.362
	Last 5Y	11.988	11.967
Information Ratio*	Last 15Y	0.257	0.389
	Last 10Y	0.445	0.387
	Last 5Y	0.237	1.017

Note: The results above are represented in percentage values, except the Information Ratio*, which is presented in absolute value. These results cover the period from 03/01/1991 to 03/01/2018.

Table 9 and Figure 1 show the results of the Macro Strategy built upon a 6-month SMA (6M SMA) of Macro Factor (MF) and its benchmark. They enable us to notice, that compared to Index benchmark, the Macro Strategy has not generated abnormal returns. It has volatility (aSD) on the similar levels to the benchmark however, the annualized return is much lower, hence the risk-adjusted returns are much worse. The strategy MD was bigger compared to the benchmark since the beginning of the test and the drawdowns are aligned after the housing crisis in 2007. An important fact is that the Last 10Y IR* is higher for the Macro Strategy than for the benchmark. Those two facts suggest, that the Macro Strategy is performing not worse in terms of the risk, and better in terms of the risk-adjusted profit. It

may be caused by better performance of Macro Factor after the crisis – perhaps the indicators are more efficient after the decline in the economy and at the beginning of recovery.



Note: Cumulative Return axis is expressed in hundreds of percent, and the chart below presenting the drawdowns is expressed in percentage values. The 6M SMA equity line represents the line of Macro Strategy based on the Macro Factor 6-month SMA. The initial value for the Cumulative Return chart is 1.

Figure 1. Results of the Macro Strategy

Nevertheless, the hypothesis the authors wanted to verify was whether this trading mechanism based on the Macro Factor has any ability to gain risk-adjusted returns bigger than the benchmark and it certainly has not.

Now, let us see the results for both Momentum and Momentum + Macro strategies. They were built upon the core specifications, that Formation and Holding Periods length is 6 months and 15 companies were traded during the Holding Periods (cumulatively, 30 companies in the Momentum Strategy, without leverage).

Table 10. Results of the Momentum and the Momentum + Macro (n = 15, F. and H. 6M)

Variable	Period	Momentum	Momentum + Macro	B&H S&P500 Index
Cumulative Return (AbsRet)	Full	68.691	-14.997	742.801
Annualized Return (ARC)	Full	1.956	-0.600	8.222
Maximum Drawdown (MD)	Full	33.617	77.168	56.775
Annualized Standard Deviation (aSD)	Full	9.944	22.878	17.652
Information Ratio* (IR*)	Full	0.197	-0.026	0.466
Annualized Standard Deviation	Last 15Y	10.119	24.847	18.311
	Last 10Y	11.226	27.677	20.362
	Last 5Y	7.283	15.217	11.967
Information Ratio*	Last 15Y	0.357	0.110	0.389
	Last 10Y	0.223	0.210	0.387
	Last 5Y	0.267	0.396	1.017

Note: The results show the comparison between Momentum Strategies, one which is a simple long and short mechanism based on RoC ranking, and the second, enhanced version of this strategy, when based on the Macroeconomic Factor, the mechanism performs the trades, that correspond with macroeconomic outlook. These results cover the period from 03/01/1991 to 03/01/2018.



Note: Cumulative Return axis is expressed in hundreds of percent, and the chart below presenting the drawdowns is expressed in percentage values. Variable “n” represents the Number of Traded Companies in the strategies, “F.” is the length of the Formation Period and “H.” is the length of the Holding Period. The initial value for the Cumulative Return chart is 1.

Figure 2. Results of the Momentum and the Momentum + Macro Strategies

As can be seen in Table 10 and Figure 2, conversely to the authors’ hypothesis, the additional macroeconomic extension in its current form does not improve the results of the momentum strategy. It has a lower (negative) cumulative return, bigger drawdown, and standard deviations. From the graphical analysis of the chart, the higher volatility (represented

by drawdown) and flatter cumulative return can be seen. Overall, the risk-adjusted return from the enhanced strategy is worse based that the simple Momentum Strategy and the benchmark. The Momentum Strategy alone is fairly profitable, but not as much as the benchmark strategy, hence the hypothesis suggesting that Momentum Strategy produce better returns than the benchmark is rejected as well. In the next section, the authors will perform the Sensitivity Analysis, to make sure the decisions to reject hypotheses stated at the beginning are stable and robust.

7. Sensitivity Analysis

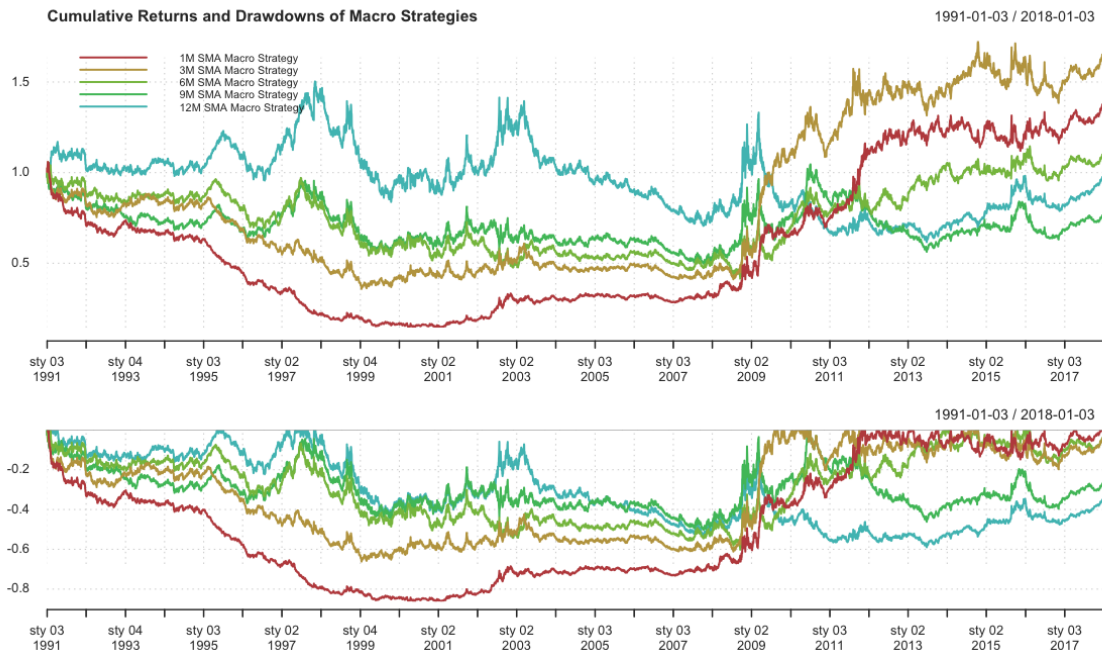
This section is devoted to check the robustness of the results from the strategies and compare them after the changes in initial assumptions– the number of companies selected to trade, the formation period and the holding period, to be precise. Below are tables and figures presenting and summarizing the returns for different values of those variables. For the reader convenience, the results from core analysis will be included as well. Table 11 presents the results for various length of SMA in the Macro Strategy.

Table 11. The results of Sensitivity Analysis for Macro Strategy

Strategy	AbsRet	ARC	aSD	MD	IR*
1M SMA	37.852	1.197	17.667	86.290	0.068
3M SMA	65.469	1.884	17.667	66.165	0.107
6M SMA	10.148	0.359	17.668	60.174	0.020
9M SMA	-23.465	-0.986	17.668	50.215	-0.056
12M SMA	-2.268	-0.085	17.668	58.967	-0.005
S&P500 Index	742.801	8.222	17.652	56.775	0.466

Note: Results are presented as percentage values except the Information Ratio*, which is presented in absolute values. These results cover the period from 03/01/1991 to 03/01/2018.

From the analysis of Table 11 and the Figure 3, it can be seen, that different length of SMAs in the Macro Strategy, generally speaking, lead to similar volatility (measured by aSD). The 3-month SMA is by far the best strategy, having the best statistics in comparison to the rest of the results. However, none of the 5 Macro Strategies has a risk-weighted return higher or even close to the benchmark, hence the Hypothesis (2) is rejected. A similar analysis was performed for Momentum and Momentum + Macro Strategy, this time however manipulating the Formation and Holding Period (F.&H. P.) lengths and the Number of Traded Companies (No.).



Note: Cumulative Return axis is expressed in hundreds of percent, and the chart below presenting the drawdowns is expressed in percentage values. The SMAs represent the equity line of Macro Strategy based on the Macro Factor n -month SMA, where n is 1, 3, 6, 9 or 12. The initial value for the Cumulative Return chart is set to 1.

Figure 3. Summary of different parameters for Macro Strategies

The third part of Table 12 contains the result of the best performing strategies, created after analyzing the results from the Sensitivity Analysis. Although the Momentum Strategy alone is at the peak of its performance at 9M F.&H. P., but the enhanced strategy is underperforming with this configuration. Hence to analyze the best ones, the length of 3M periods was selected. Benchmark results are included as well. Figure 4. and Figure 5. present the results of Sensitivity Analysis for different configurations of Momentum Strategies, while Figure 6 presents the best performing configuration. The equity line for the benchmark is excluded from the figures for the reader's convenience and to make the comparison between configurations easier.

Table 12. The results of Sensitivity Analysis for Momentum Strategies**F.&H. P. = 3/6/9 Months; No. = 15**

Strategy	F.&H. P.	AbsRet	ARC	aSD	MD	IR*
Momentum	3M	168.589	3.727	9.666	28.759	0.386
Mom. + Macro	3M	166.652	3.699	22.928	52.043	0.161
Momentum	6M	68.691	1.956	9.944	33.617	0.197
Mom. + Macro	6M	-14.997	-0.600	22.878	77.168	-0.026
Momentum	9M	215.115	4.343	9.715	39.218	0.447
Mom. + Macro	9M	-96.491	-11.668	24.365	96.677	-0.479
S&P500 Index	-	742.801	8.222	17.652	56.775	0.466

F.&H. P. = 6 Months; No. = 5/15/25

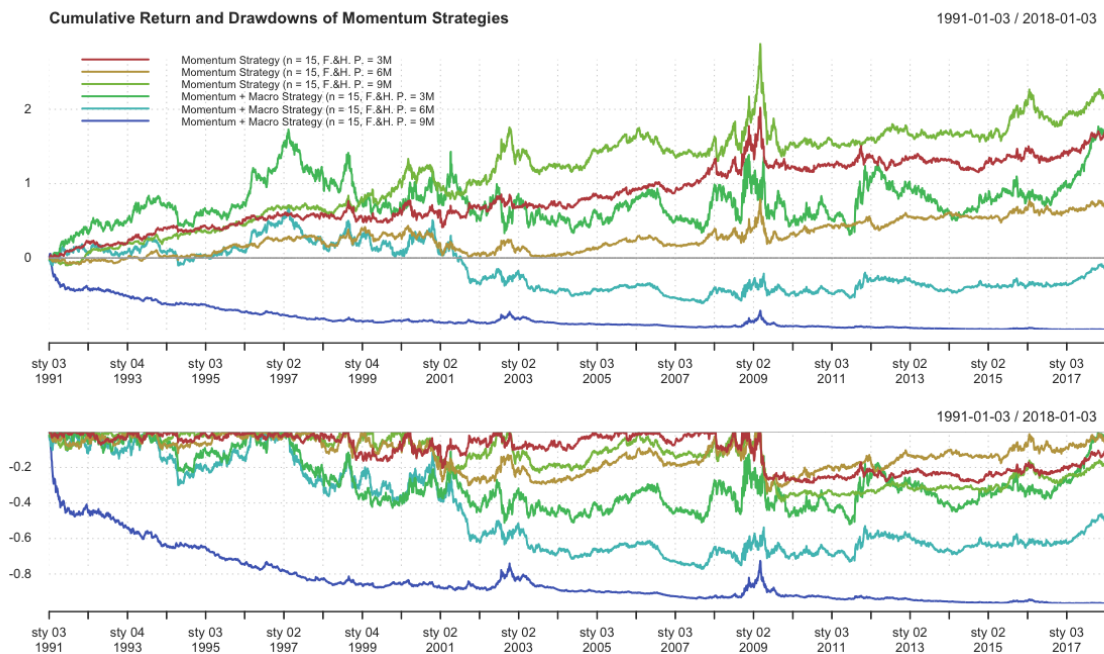
Strategy	No.	AbsRet	ARC	aSD	MD	IR*
Momentum	5	352.568	5.751	16.222	49.991	0.355
Mom. + Macro	5	140.891	3.310	30.347	68.819	0.109
Momentum	15	68.691	1.956	9.944	33.617	0.197
Mom. + Macro	15	-14.997	-0.600	22.878	77.168	-0.026
Momentum	25	56.329	1.669	8.077	31.758	0.207
Mom. + Macro	25	13.876	0.482	20.799	72.101	0.023
S&P500 Index	-	742.801	8.222	17.652	56.775	0.466

Best Performing Strategies (F.&H. P. = 3 Months; No. = 5)

Strategy	AbsRet	ARC	aSD	MD	IR*
Momentum	930.842	9.025	15.579	50.827	0.579
Mom. + Macro	374.410	5.936	29.286	66.301	0.203
S&P500 Index	742.801	8.222	17.652	56.775	0.466

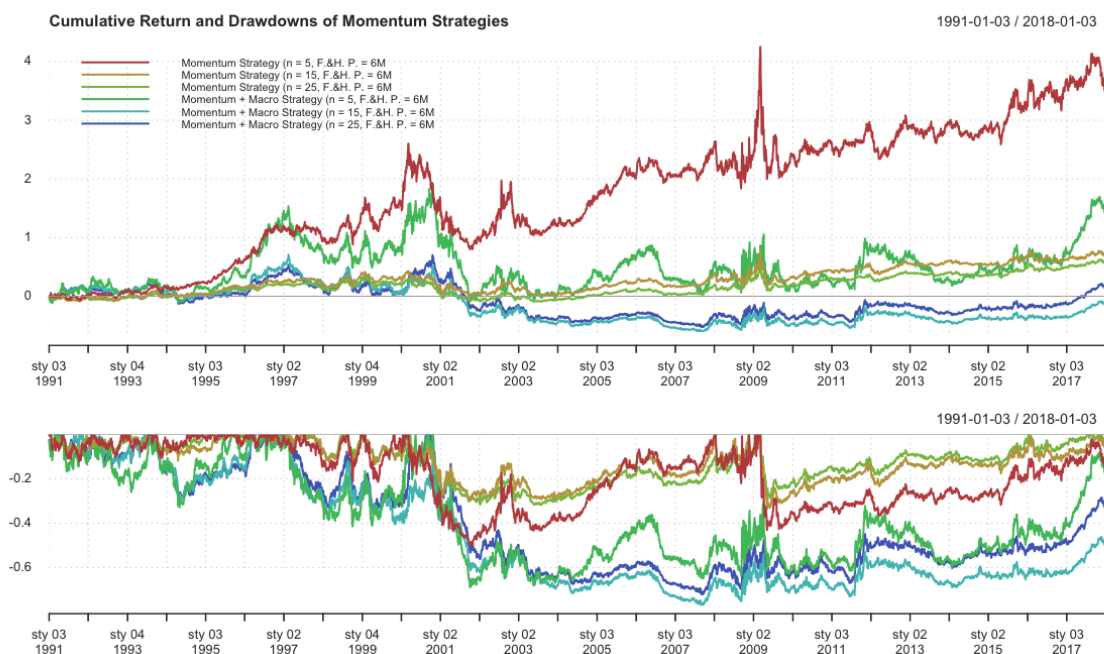
Note: Results are presented as percentage values except the Information Ratio*, which is presented in absolute values. To answer the research questions, we differentiated the number of traded companies, as well as the formation and holding periods. The table should be used to compare between the simple momentum and the enhanced momentum strategy as well as between the same type of strategy and different variables. These results cover the period from 03/01/1991 to 03/01/2018.

The observations of the worse performance of Momentum + Macro Strategy in comparison to the sole Momentum Strategy is persistent after the results of Sensitivity Analysis. With the increasing length of the F. and H. Periods, the hybrid approach results are worsening however, this pattern is not that clear in the classic approach (Momentum Strategy). The basic mechanism is at the peak of its performance at 3-month and 9-month length of F.&H. P. The Hypothesis (3) remains rejected, as the results of Sensitivity Analysis, did not deliver a different pattern. Changing the formation or holding periods length has a better impact on the returns for the simple Momentum Strategy, however, the Hypothesis (1) remains rejected as well because the strategy did not deliver abnormal or better risk-adjusted returns than the benchmark.



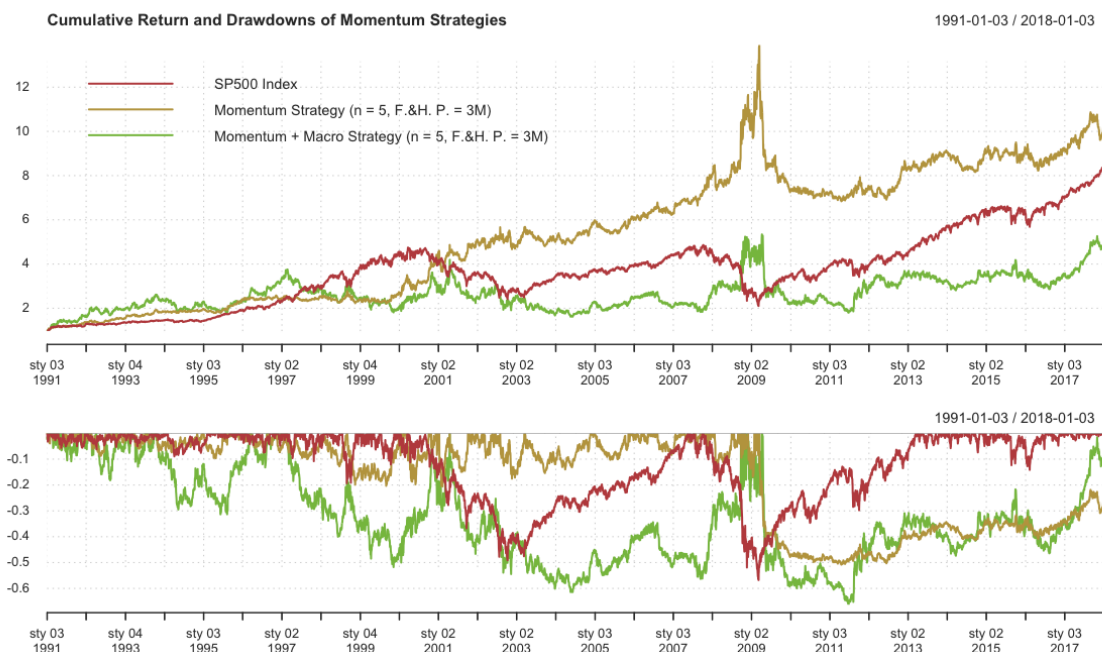
Note: Cum. Ret. axis is expressed in hundreds of percent, and the chart below presenting drawdowns is expressed in percentage values. Variable “n” represents the Number of Traded Companies in the strategies, “F.” is the length of the Formation Period and “H.” is the length of the Holding Period. The initial value for the Cumulative Return chart is set to 1.

Figure 4. Different Formation & Holding Period configuration in Momentum Strategies



Note: Cum. Ret. axis is expressed in hundreds of percent, and the chart below presenting drawdowns is expressed in percentage values. Variable “n” represents the Number of Traded Companies in the strategies, “F.” is the length of the Formation Period and “H.” is the length of the Holding Period. The initial value for the Cumulative Return chart is set to 1.

Figure 5. Different Number of Traded Companies configuration in Momentum Strategies



Note: Cum. Ret. axis is expressed in hundreds of percent, and the chart below presenting drawdowns is expressed in percentage values. Variable “n” represents the Number of Traded Companies in the strategies, “F.” is the length of the Formation Period and “H.” is the length of the Holding Period. The initial value for the Cumulative Return chart is set to 1.

Figure 6. Best Performing Momentum Strategies

In terms of manipulating the number of traded equities, the classic method is the best, when the number is the lowest, which is logical, however it is not that clear with the hybrid strategy. Its performance is not always worsening with the increase in the number of companies, because the results for No. = 25 are better than those for No. = 15.

Nevertheless, both strategies are at the peak of their performance with the smallest number of traded companies. The authors decided to compare the results of the best assumption settings to the benchmark. The classic momentum strategy has outperformed the benchmark in terms of the AbsRet and risk-weighted IR*, however one has to bear in mind, that this is the artificially created best-performing strategy during the backtest, hence it does not influence the confirmation or rejection of the hypotheses. Summarizing, both research questions are positively confirmed – changing the assumptions has an impact on the returns. The returns after the change of initial settings can be either better or worse.

8. Conclusion

The Momentum Strategy was enhanced with the additional macroeconomic extension (Macro Factor) in order to filter the investment signals. The indicators for Macro Factor were

thoroughly analyzed for its impact on the S&P500 Index and the US economy. Only the significant ones were selected and aggregated into the Factor. Next, the Macro Strategy, the Momentum Strategy and the Momentum + Macro Strategy were benchmarked with the S&P500 Index on the period starting from 03/01/1991 and ending on 03/01/2018. After the initial results, an extensive sensitivity analysis was conducted and the final results were adjusted.

Referring to the main hypotheses stated at the beginning of the paper, we can say that enhancing the momentum strategy with macroeconomic screening does not improve the returns (Hypothesis 3). The Momentum + Macro Strategy has consistent and worse results than the Momentum Strategy in terms of volatility (aSD), risk (MD) and the risk-weighted returns measured by the Information Ratio*. The first Hypothesis and the second one are rejected as well. Macro Strategy has worse performance than the simple Buy & Hold S&P500 Index benchmark, however, the better annualized risk-adjusted results during the last 10 years were observed. Momentum Strategy alone is by far the best performing strategy in this research, however, it could not beat the benchmark in terms of the IR* as well.

Referring to the rejection of the main hypothesis (3), we have to stress the way of enhancement, its technical implementation, the momentum strategy methodology and some additional issues regarding our database. Regarding the results of Momentum Strategies, the reader shall bear in mind, that the database has not included the best-performing companies from the 1990s, that became delisted before 2019 and the companies that went bankrupt before that date, what could have been the potential profits for the strategy. Nevertheless, adding a Macro Factor seem to diminish the returns and influence the volatility in a negative way. Regarding two research questions, that were analyzed in the Sensitivity Analysis. It was noticed that both changing the F.&H. Periods and No. variable has an impact on the results however, the direction is not always clear.

The reader of this paper should bear in mind, that the spectrum of possible outcomes and tests here is unlimited. Strategies can be tested on a more lagged time series, different weights, SMAs or F.&H. P. lengths. However, it is impossible to cover all the possible changes in this paper or even in a series of monographs. Therefore, it was decided to cover just the part of the possibilities and proved, that when this methodology is taken into consideration, the momentum strategy is superior.

Appendix

Table 1A. List of continuously listed companies on S&P500 Index used in the research

No.	Ticker	Full Name	No.	Ticker	Full Name
1	AAPL	Apple Inc	76	JNJ	Johnson & Johnson
2	ABT	Abbott Laboratories	77	JPM	JPMorgan Chase & Co
3	ADM	Archer-Daniels-Midland Co	78	JWN	Nordstrom Inc
4	ADP	Automatic Data Processing	79	K	Kellogg Co
5	ADSK	Autodesk Inc	80	KMB	Kimberly-Clark Corp
6	AEP	American Electric Power Co	81	KO	Coca-Cola Co
7	AIG	American Int. Gr Inc	82	KR	Kroger Co
8	AMD	Advanced Micro Devices Inc	83	LB	L Brands Inc
9	APD	Air Prod. & Chemicals Inc	84	LLY	Eli Lilly & Co
10	AVY	Avery Dennison Corp	85	LNC	Lincoln National Corp
11	AXP	American Express Co	86	LOW	Lowe's Cos Inc
12	BA	Boeing Co	87	MAS	Masco Corp
13	BAC	Bank of America Corp	88	MAT	Mattel Inc
14	BAX	Baxter Int. Inc	89	MCD	McDonald's Corp
15	BDX	Becton Dickinson and Co	90	MDT	Medtronic PLC
16	BF-B	Brown-Forman Corp	91	MMC	Marsh & McLennan Cos Inc
17	BLL	Ball Corp	92	MMM	3M Co
18	BMJ	Bristol-Myers Squibb Co	93	MO	Altria Group Inc
19	C	Citigroup Inc	94	MRK	Merck & Co Inc
20	CAG	Conagra Brands Inc	95	MRO	Marathon Oil Corp
21	CAT	Caterpillar Inc	96	MSI	Motorola Solutions Inc
22	CI	Cigna Corp	97	NEE	NextEra Energy Inc
23	CL	Colgate-Palmolive Co	98	NEM	Newmont Mining Corp
24	CLX	Clorox Co	99	NKE	NIKE Inc
25	CMCSA	Comcast Corp	100	NOC	Northrop Grumman Corp
26	CMI	Cummins Inc	101	NSC	Norfolk Southern Corp
27	CNP	CenterPoint Energy Inc	102	NUE	Nucor Corp
28	CPB	Campbell Soup Co	103	NWL	Newell Brands Inc
29	CSX	CSX Corp	104	OKE	ONEOK Inc
30	CVS	CVS Health Corp	105	ORCL	Oracle Corp
31	CVX	Chevron Corp	106	OXY	Occidental Petroleum Corp
32	D	Dominion Energy Inc	107	PCAR	PACCAR Inc
33	DE	Deere & Co	108	PCG	PG&E Corp
34	DIS	Walt Disney Co	109	PEG	Public Service Ent. Gr. Inc
35	DOV	Dover Corp	110	PEP	PepsiCo Inc
36	DTE	DTE Energy Co	111	PFE	Pfizer Inc
37	DUK	Duke Energy Corp	112	PG	Procter & Gamble Co
38	ECL	Ecolab Inc	113	PH	Parker-Hannifin Corp
39	ED	Consolidated Edison Inc	114	PHM	PulteGroup Inc

40	EIX	Edison Int.	115	PKI	PerkinElmer Inc
41	EMR	Emerson Electric Co	116	PNC	PNC Financial Services Gr.
42	ETN	Eaton Corp PLC	117	RTN	Raytheon Co
43	ETR	Entergy Corp	118	SHW	Sherwin-Williams Co
44	EXC	Exelon Corp	119	SLB	Schlumberger Ltd
45	F	Ford Motor Co	120	SNA	Snap-on Inc
46	FDX	FedEx Corp	121	SO	Southern Co
47	FL	Foot Locker Inc	122	SPGI	S&P Global Inc
48	FMC	FMC Corp	123	STI	SunTrust Banks Inc
49	GD	General Dynamics Corp	124	SWK	Stanley Black & Decker Inc
50	GE	General Electric Co	125	SYY	Sysco Corp
51	GIS	General Mills Inc	126	T	AT&T Inc
52	GLW	Corning Inc	127	TAP	Molson Coors Brewing Co
53	GPC	Genuine Parts Co	128	TGT	Target Corp
54	GPS	Gap Inc	129	TJX	TJX Cos Inc
55	GT	Goodyear Tire & Rubber Co	130	TMK	Torchmark Corp
56	GWW	WW Grainger Inc	131	TRV	Travelers Cos Inc
57	HAL	Halliburton Co	132	TXN	Texas Instruments Inc
58	HAS	Hasbro Inc	133	TXT	Textron Inc
59	HD	Home Depot Inc	134	UNP	Union Pacific Corp
60	HES	Hess Corp	135	UTX	United Technologies Corp
61	HON	Honeywell Int. Inc	136	VFC	VF Corp
62	HP	Helmerich & Payne Inc	137	VZ	Verizon Comms. Inc
63	HPQ	HP Inc	138	WBA	WalgreensBoots Alliance Inc
64	HRB	H&R Block Inc	139	WFC	Wells Fargo & Co
65	HRS	Harris Corp	140	WHR	Whirlpool Corp
66	HST	Host Hotels & Resorts Inc	141	WMB	Williams Cos Inc
67	HSY	Hershey Co	142	WMT	Walmart Inc
68	HUM	Humana Inc	143	WY	Weyerhaeuser Co
69	IBM	Int. Business Machines Corp	144	XEL	Xcel Energy Inc
70	IFF	Int. Flavors & Fragrances Inc	145	XOM	Exxon Mobil Corp
71	INTC	Intel Corp	146	XRX	Xerox Corp
72	IP	Int. Paper Co			
73	IR	Ingersoll-Rand PLC			
74	ITW	Illinois Tool Works Inc			
75	JCI	Johnson Controls Int. plc			

Note: Table 1A represents the companies, that were present in the S&P500 Index from the beginning to the end of the period used in this research. Listed tickers were used to download Adjusted Close price data for each individual company from Yahoo Finance platform, using the algorithm build in R statistical software.

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