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# Generalized Momentum Asset Allocation Model

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**Abstract**

In this paper we propose Generalized Momentum Asset Allocation Model (GMAA). GMAA is a new approach to construct optimal portfolio and is based on close examination of asset's returns distribution. GMAA tries to capture certain market phenomena and use information they contain as predictors for future returns. Our model is validated using MSCI Indexes with MSCI World Index set as a benchmark. We find results rather promising as we managed to significantly reduce portfolio volatility and obtain stable path of cumulative returns of portfolio. Our model outperforms benchmark in terms of Information Ratio or Maximum Drawdown. Detailed sensitivity analysis was conducted at the end of this paper and it shows that our strategy is sensitive to a few optimization parameters thus further research may be required.

**Keywords:**
asset allocation, diversification, momentum, trading strategy, capital asset pricing models, returns forecasting, efficient risk and return measures

**JEL:**
C53, G11, G14, G15, G23, C61, C22

## 1. Introduction

Since famous Markowitz article an asset allocation problem remains one of the most intriguing issues in quantitative finance. Dozens of techniques and formal models have been proposed and almost all of them were focused on optimal diversification strategy. In Modern Portfolio Theory optimal asset allocation is associated with reducing specific risk through appropriate diversification. It is well established that more than 90% of portfolio volatility can be attributed to asset allocation, or how an investor chooses to allocate investments among a variety of different asset classes (Ibbotson and Kaplan, 2000) so the main goal has to be to minimize this portfolio volatility, given certain level of profitability.

In this paper we propose Generalized Asset Allocation Model. Our approach is based on the momentum paradigm but also tries to capture other market phenomena (such as trend reversal) by exploiting characteristics of a single asset returns distributions. We use the following distribution moments: mean, variance (standard deviation), skewness and kurtosis. We use simple linear functions to combine all factors and apply grid search in order to find optimal parameters. We show backtests for considered models based on 26 country MSCI equity indexes. The main goal of this paper is to verify the hypothesis that using investment strategy based on distributional characteristics of analysed assets, we can outperform buy and hold strategy in terms of return to risk metrics.

The rest of the paper is organized as follows. Section 2 briefly reviews most recent literature dealing with asset allocation problem. Section 3 describes methodology and data used in our research. Section 4 presents empirical results of strategy we propose. In section 5 we conduct a detailed sensitivity analysis. Finally, section 6 concludes.

## 2. Literature review

In literature the process of asset allocation is often divided into two main groups: strategic asset allocation (SAA) and tactical asset allocation (TAA). Strategic asset allocation usually means to "buy and hold" assets and then systematically modify the portfolio, shorting investments in better performing asset classes and buying investments in lower performing asset classes, to get the portfolio back to its original asset allocation structure. On the other hand Tactical asset allocation is a far more active, forward-looking form of asset allocation that searches for modifying asset allocations to expose investors to equity building and to equity preservation opportunities dependent on macroeconomic and leading signals for various markets, sectors and asset classes.

TAA is dynamic approach to asset allocation. Unlimited methods can be applied for TAA. One of the most popular methods is momentum-based strategy. The strategy aims to capitalize on the continuation of existing trends in the market. The momentum investor believes that large increases in the price of a security will be followed by additional gains and vice versa for declining values. The momentum anomaly has been well known for centuries. The core of the momentum anomaly is that assets often continue their price momentum, defined as the change in price over a given look-back period (eg. 12 or 6 months). Therefore one should buy assets with the highest momentum and sell assets with the lowest momentum. Simple momentum strategy can be created by ranking assets based on last $m$ period returns and then holding them for $n$ periods. The performance of this kind of the strategy is well documented by academics and confirmed to be far superior to passive methods (Faber 2007, Fama 2010, and most recently Clare et al., 2014).

Beside simple approaches based on momentum, some more sophisticated methods have recently been considered for TAA. Most of these methods are based on the so-called minimum- or mean-variance models. Alternatively based on models that optimize some risk contribution or diversification measures, by choosing optimal weights $wi$ for each asset class $i$ under restrictions. An overview and demonstration of these methods can be found in Ang (2012). More advanced approach to asset allocation can be found in Butler (2012) who introduces the concept of

Adaptive Asset Allocation Model (AAAM) integrating three factors: momentum, volatility and correlation. The study shows the persistent outperformance of AAAM over the passive method. The most recent application of generalized momentum model can be found in Keller, Putten (2013). The authors extend the time series momentum (or trend following) model towards a generalized momentum model, called Flexible Asset Allocation (FAA), by adding new momentum factors to the traditional momentum factor based on the relative returns among assets. These new factors are called absolute momentum, volatility momentum and correlation momentum. They find FAA as much better investment approach than the buy and hold benchmark, both in terms of return and risk.

Interesting addition to the literature on asset allocation based on momentum can be found in Amaya (2011). The author use intraday data to compute weekly realized variance, skewness and kurtosis for individual equities and assess whether this week's realized moments predict next week's stock returns in the cross-section. Stocks are sorted each week according to their realized moments, form decile portfolios, and analyze subsequent weekly returns. They found a very strong negative relationship between realized skewness and next week's stock returns, and a positive relationship between realized kurtosis and next week's stock returns. An increasing body of literature indicates that momentum investing based on a wide range of asset classes may provide exceptional risk-adjusted returns.

## 3. Methodology and data

The asset allocation algorithm that we propose tries to capture certain market phenomena such as momentum and trend reversal. We argue that both are predictable by close examination of assets returns. In this research we focus on the first four moments of weekly returns distribution described by mean, variance (standard deviation), skewness and kurtosis. These four statistical measures, later mentioned as factors, are computed on rolling window (the width of the window is 26 weeks in a base scenario). Our aim is to find whether these factors can be used as predictors of momentum or trend reversal, if so, they would be extremely helpful to construct an investment portfolio. Below we present a brief description of our model.

Let *T* be a number of quarters during optimization window, then a single loop of algorithm consists of six steps:

1) For each time *t* in *{0,..,T}* all assets are ranked in descending order with respect to four factors,
2) For each time *t* in *{0,..,T}* and for each asset *j* a score is computed in a following way:

   $$S_{jt} = w_1 R_{1\,jt-1} + w_2 R_{2\,jt-1} + w_3 R_{3\,jt-1} + w_4 R_{4\,jt-1} \tag{1}$$

   where: $w_i$ is a weight for *i-th* factor and $R_{ijt}$ is a rank for *j-th* asset in time *t* with respect to *i-th* factor,
3) For each time *t* all assets are ranked in descending order with respect to scores,
4) *k* assets with the highest and *k* assets with the lowest score value form respectively: a long and a short position in our portfolio in time *t*. Each asset has an equal share in portfolio (1/2k).
5) Weights described in step (2) are chosen so as to maximize the Information Ratio of our portfolio over optimization window. The Information Ratio is defined as follows:

   $$IR_p = \frac{R_p}{\sigma_p} \tag{2}$$

   where: $R_p$ is mean portfolio return and $\sigma_p$ is a standard deviation of portfolio returns.

6) Using these chosen weights, we obtain scores for *T+1* period $(S_{jT+1})$ to construct an optimum portfolio (in a manner described in step (4)).

A procedure described above is repeated every quarter (every 13 weeks).

Due to technical reasons we have imposed a restriction on weights: they can vary only between –1 and 1, with a predetermined precision. This restriction should not have significant impact on results of our algorithm because we are interested in relative, not absolute, values of scores. We have chosen a grid search optimization technique because, in general, our objective function is not differentiable and may even be discontinuous in some regions. We are aware of the shortcomings of this approach, however it seems to be best suited to our model as results of algorithm are independent of starting points, and we do not have to impose any additional assumptions to ensure convergence.

Overall, there were 5 parameters that were not subjects of optimization, and all except fourth were analyzed in terms of the sensitivity of the model. These were:

1) optimization precision – default: 0.1, additionally: 0.05, 0.5, 1,
2) the width of factors rolling window – default: 26 weeks, additionally: 13, 52,
3) optimization window – default: 52 weeks, additionally: 26, 78,
4) rebalancing period – default: 13 weeks,
5) number of chosen assets (short and long) – default: 6, additionally: 3, 9

The numerical computations were performed using C++ and R languages. Initially, we struggled with the problem of weights optimization precision parameter due to the technical reasons. However during the research, it turned out that this factor plays insignificant role in enhancing performance metrics of the model.

We used data set containing weekly close prices of 26 MSCI Indexes at the period of ten years. A start date is set to January 1st, 2003 and February 28th, 2014 as an end date. Prices of all financial instruments are presented in USD. MSCI World Index is used as a benchmark. Transaction costs are assumed at the level of 0.1 % of invested capital in order to proxy real market conditions.

# 4. Results

## 4.1. Default Strategy

Firstly we conducted our procedure using default parameters, which are listed below:

1) optimization precision – 0.1,
2) the width of factors rolling window – 26 weeks
3) optimization window – 52 weeks
4) rebalancing period – 13 weeks
5) number of chosen assets (short and long) – 6

Performance metrics for the Default Strategy (model) are presented in table 1.

**Table 1.** Performance metrics for the Default Strategy

| **Default model performance** | **Annualized Return** | **Annualized St. Dev.** | **Information Ratio** | **MaxDD** | **Length of MaxDD** | **Net Information Ratio** |
|---|---|---|---|---|---|---|
| **Default Strategy** | ***0.036*** | ***0.055*** | ***0.65*** | ***0.086*** | ***7*** | ***0.566*** |
| **Benchmark** | ***0.046*** | ***0.183*** | ***0.254*** | ***0.511*** | ***26*** | |

**Annualized return** - the return an investment provides over a period of time, expressed as a time-weighted annual percentage. **MaxDD** – the largest single drop from peak to bottom in the value of a portfolio, before the new peak is achieved. **Length of MaxDD** – maximum loss duration indicates the number of quarters between the last maximum and the consecutive global maximum. **Information Ratio** – the ratio of portfolio return and standard deviation. **Net Information Ratio** – is Information Ratio adjusted by transaction cost

It is worth to notice that our strategy significantly reduce a risk (annualized standard deviation is more than three times lower, while maximum drawdown is less than one fifth of benchmark's). In terms of Information Ratio, our model clearly outperforms "buy and hold" strategy.

**Figure 1.** Equity Line for the Default Strategy vs B&H (benchmark) strategy

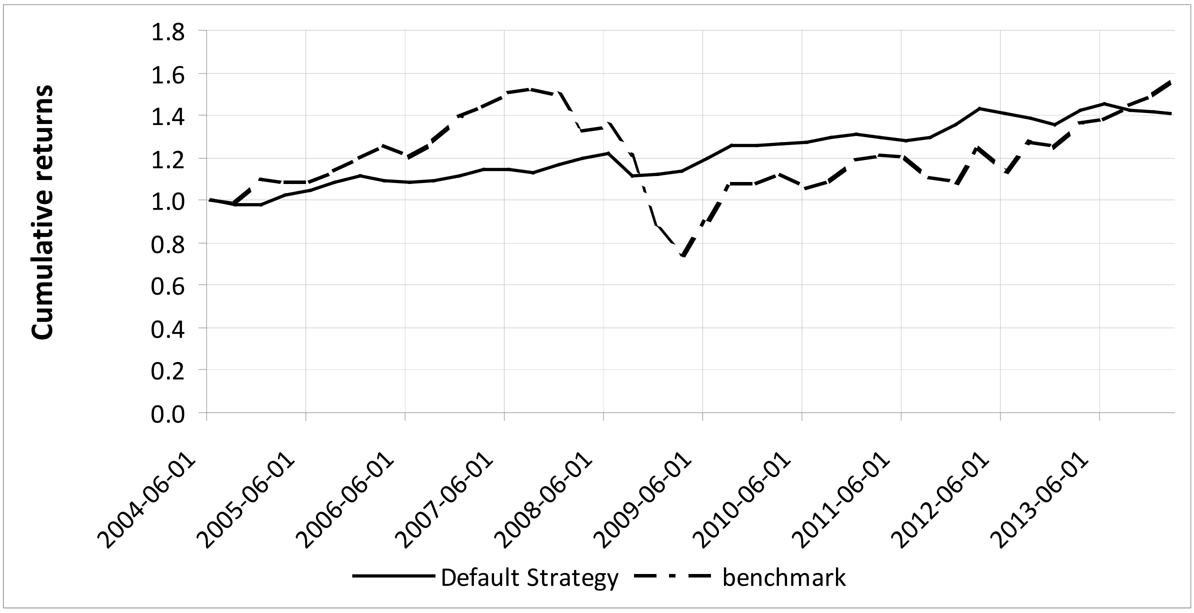
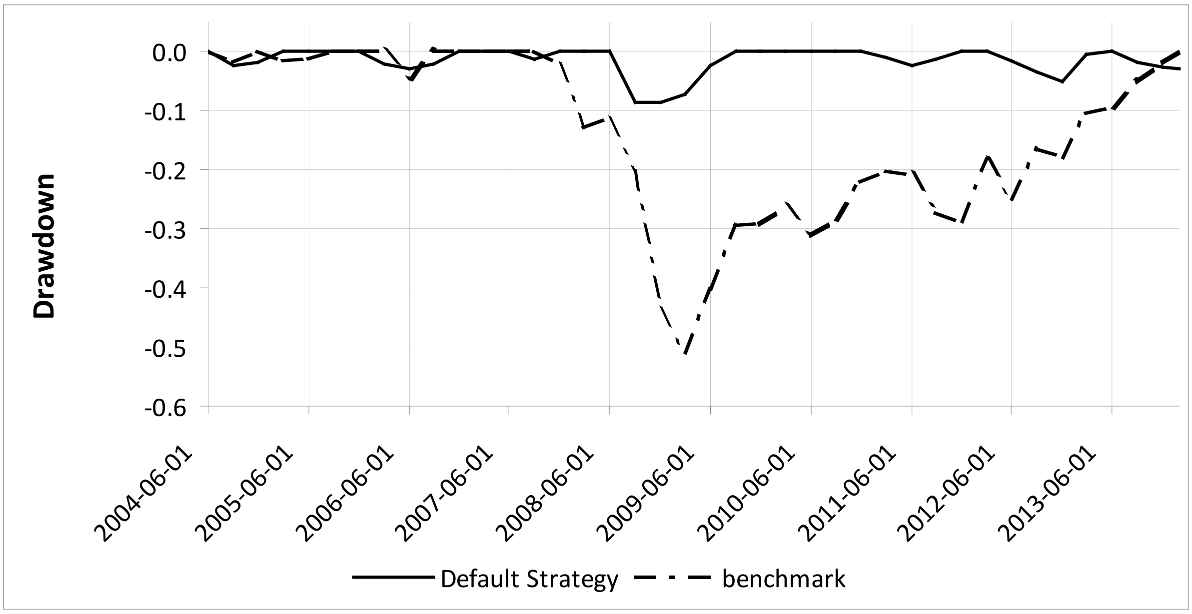



Figure 1 indicates that the cumulative return of both models is similar. However, the Default Model's performance is very stable across the whole period, while the benchmark's performance is more volatile and experienced large drawdown during the financial crisis in 2008-2009.

**Figure 2.** Maximum drawdowns for the Default Strategy vs B&H (benchmark) strategy




On figure 2 we can see that the Default Model's drawdown is significantly lower across the whole period, while the benchmark strategy experienced large drawdown during the financial crisis in 2008-2009 (more than 50%).

**Figure 3.** The relative performance of Default Strategy vs. Benchmark across time.

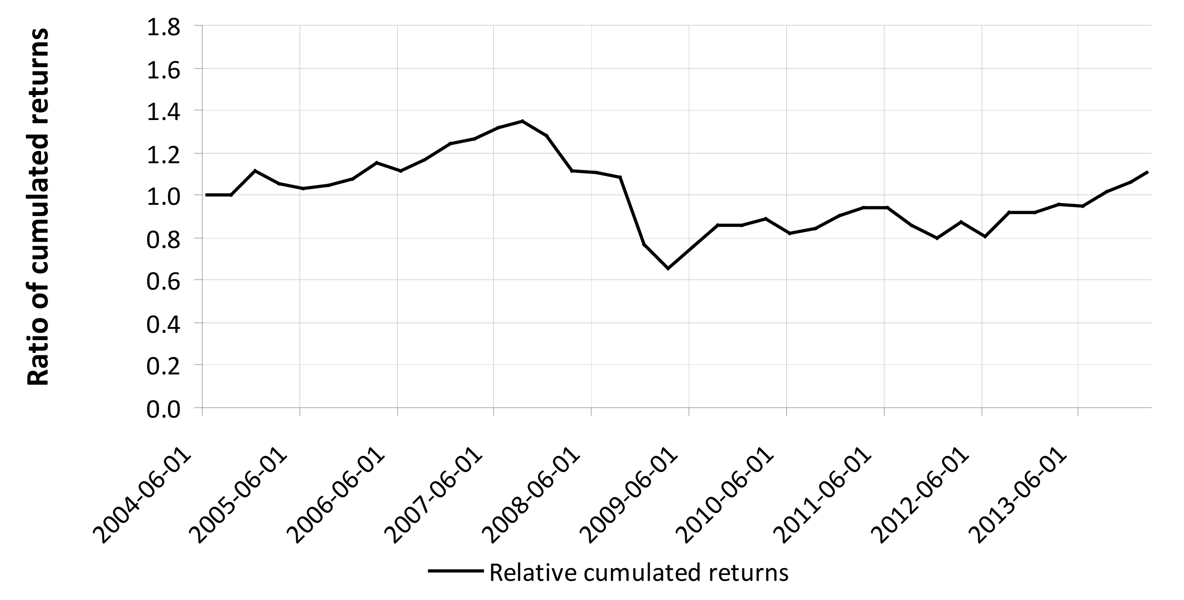
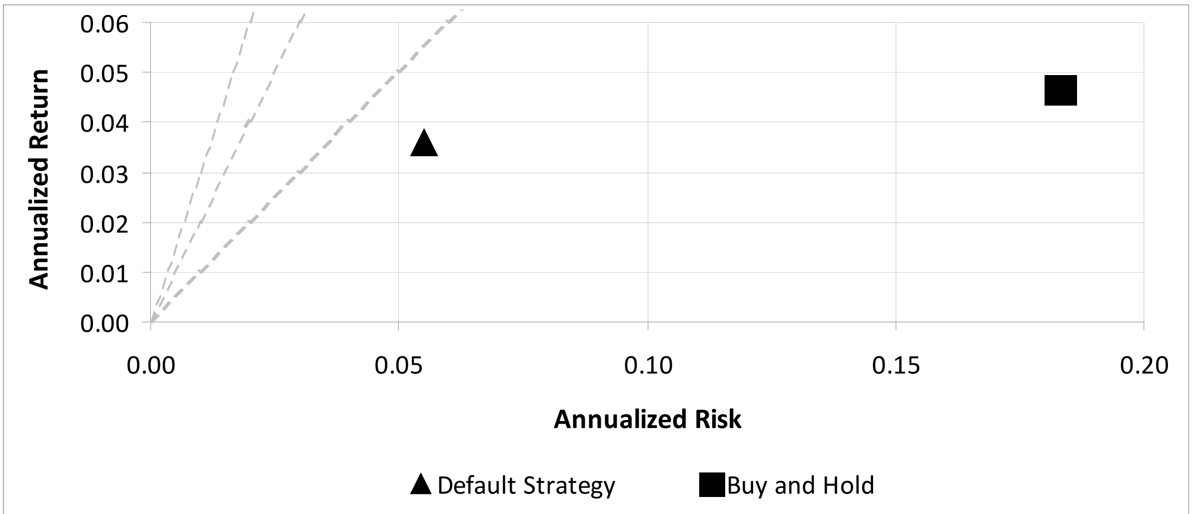


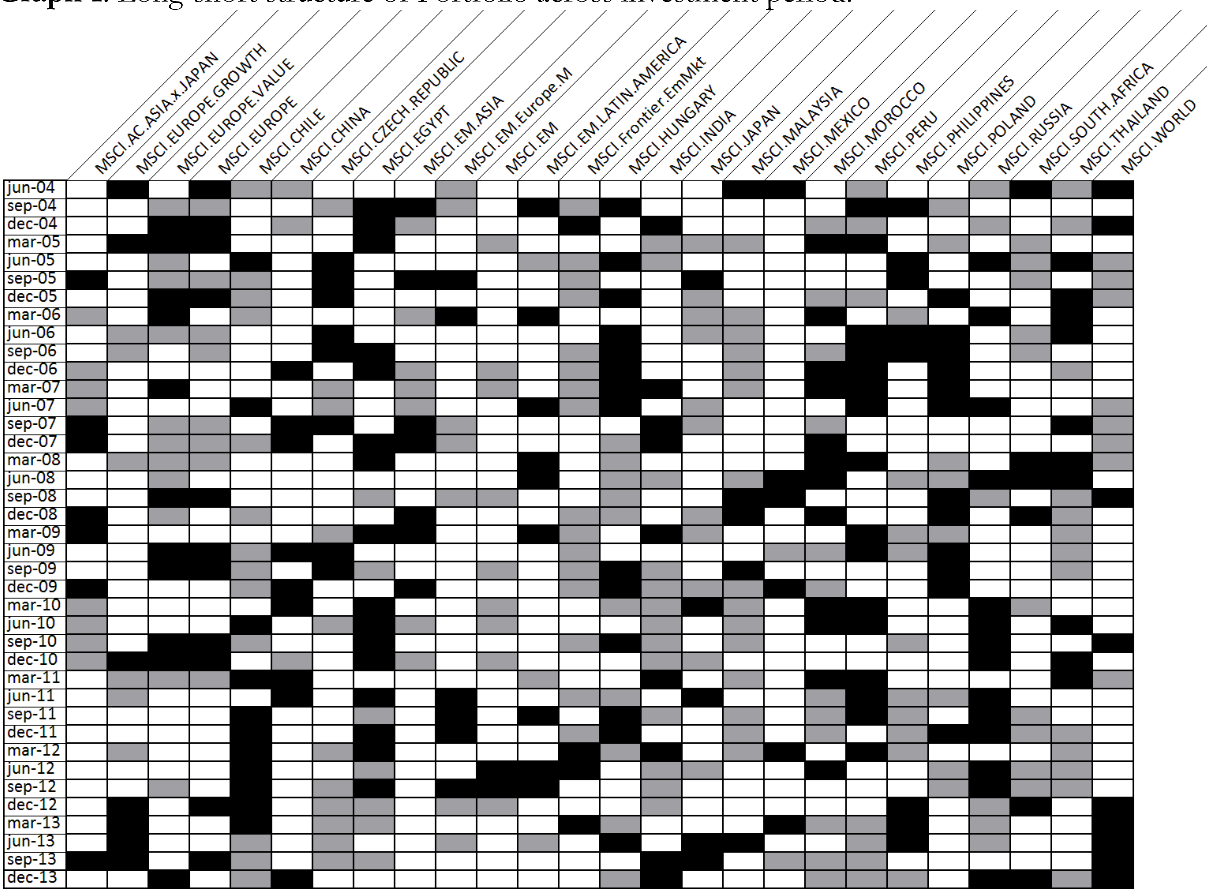

Figure 3 shows a relative cumulated returns line which is defined as a ratio between cumulative return of Default Strategy and Benchmark (value 1 means that the cumulative return equals cumulative return of the Benchmark). Values tend to fluctuate around one, so cumulative relative return of both models may be considered as quite similar. However, it is apparent that the Default Model outperformed the benchmark during the financial crisis in 2008-2009. On the other hand, after this period, when the market was rising, the benchmark outperformed the Default Model rather consistently.

**Figure 4.** The risk to return relation between Default Strategy and Benchmark




As we can see on figure 4, Default Model's relation of return to risk is far much attractive than the benchmark. The Default Model offers the similar level of annualized return with significant lower annualized risk.

**Graph 1**. Long-short structure of Portfolio across investment period.




On graph 1 we can observe changes of portfolio constituents across time. Long positions of assets are marked in black, while short ones in gray. The white field indicates that asset is not included in portfolio. We an observe that all indexes are allocated into portfolio during the analyzed period. Additionally, we can observe quite high turnover ratio and no any significant patterns of consequent selection of long or short positions for given countries.

## 4.2. Cross sectional analysis of the strategies. Above and below average.

The table 2 presents output (information ratios) calculated for each set of the parameters. Firstly, we calculated the average of all information ratios (avgAll). The output results which are above avgAll are bolded while the ones which are below avgAll are not bolded to visualize the best-worst set of parameters. The results in the table 2 present the overview of top and bottom strategies with regard to information ratio across all the parameters. We can observe that the top performances most often occur when 52 weeks period as an optimization window and 26 weeks as the width of factors rolling window are used. The results in the table 2 present the overview of below and above average strategies with regard to information ratio across all the parameters. The results support our previous analysis that 52 weeks period as an optimization window and 26 weeks as width of factors rolling window are the most promising values.

**Table 2.** Above/below average Information Ratio results.

| weights opt. prec. | width of factors roll. window | optimisation window | number of chosen assets 3 | 6 | 9 | Average |
|---|---|---|---|---|---|---|
| 0,1 | 13 | 26 | -0.21 | ***0.18*** | -0.02 | -0.02 |
| | | 52 | -0.07 | ***0.45*** | -0.05 | 0.11 |
| | | 78 | -0.22 | ***0.13*** | -0.23 | -0.1 |
| | 26 | 26 | 0.06 | ***0.27*** | ***0.31*** | 0.22 |
| | | 52 | ***0.41*** | ***0.56*** | ***0.42*** | 0.46 |
| | | 78 | 0.02 | ***0.11*** | ***0.16*** | 0.1 |
| | 39 | 26 | ***0.15*** | -0.13 | ***0.22*** | 0.08 |
| | | 52 | ***0.28*** | -0.17 | -0.02 | 0.03 |
| | | 78 | ***0.22*** | -0.28 | ***0.22*** | 0.06 |
| 0,5 | 13 | 26 | -0.07 | -0.21 | -0.09 | -0.12 |
| | | 52 | ***0.31*** | ***0.3*** | ***0.11*** | 0.24 |
| | | 78 | ***0.36*** | ***0.14*** | -0.2 | 0.1 |
| | 26 | 26 | ***0.25*** | ***0.31*** | ***0.17*** | 0.24 |
| | | 52 | ***0.51*** | ***0.45*** | ***0.45*** | 0.47 |
| | | 78 | -0.09 | 0.01 | ***0.51*** | 0.14 |
| | 39 | 26 | 0.06 | ***0.13*** | -0.27 | -0.03 |
| | | 52 | -0.04 | 0.03 | -0.03 | -0.01 |
| | | 78 | ***0.41*** | 0.07 | -0.1 | 0.13 |
| 1 | 13 | 26 | 0.01 | -0.04 | -0.02 | -0.02 |
| | | 52 | -0.1 | 0.09 | -0.23 | -0.08 |
| | | 78 | -0.39 | -0.31 | -0.65 | -0.45 |
| | 26 | 26 | ***0.24*** | ***0.36*** | ***0.36*** | 0.32 |
| | | 52 | ***0.47*** | ***0.31*** | ***0.23*** | 0.34 |
| | | 78 | -0.15 | ***0.6*** | ***0.49*** | 0.31 |
| | 39 | 26 | 0.04 | -0.29 | -0.11 | -0.12 |
| | | 52 | ***0.36*** | ***0.2*** | -0.19 | 0.12 |
| | | 78 | ***0.32*** | -0.03 | -0.2 | 0.03 |
| | | Average | 0.12 | 0.12 | 0.05 | |

## 5. Sensitivity Analysis

### 5.1. Sensitivity Analysis of the default strategy.

Table 2 showed overview of multiple strategies tested with various assumptions. Now, we focus on sensitivity analysis of Default Strategy with regard to four parameters: optimization precision – default: 0.1, the width of factors rolling window – default: 26 weeks, optimization window – default: 52 weeks and number of chosen assets (short and long) – default: 6. Four tables below show how Information Ratio of Default Strategy (marked in yellow) reacts to change in one parameter while the others are constant.

**Table 3.** The sensitivity of final results to optimization precision.

| weights opt. prec. | width of factors roll. window | optimisation window | number of chosen assets | Net Information ratio |
|---|---|---|---|---|
| *0,05* | *26* | *52* | *6* | *0,567* |
| *0,1* | *26* | *52* | *6* | *0,566* |
| *0,5* | *26* | *52* | *6* | *0,45* |
| *1* | *26* | *52* | *6* | *0,31* |

Analyzing Table 3 we discover that for weight optimization precision parameter below 0.1, the value of Net Information Ratio is not changing significantly. This fact is an additional proof that problem of time consuming calculation does not exist in our approach.

**Table 4.** The sensitivity of final results to the width of factors rolling window.

| weights opt. prec. | width of factors roll. window | optimisation window | number of chosen assets | Net Information Ratio |
|---|---|---|---|---|
| *0,1* | *13* | *52* | *6* | *0,45* |
| *0,1* | *26* | *52* | *6* | *0,56* |
| *0,1* | *39* | *52* | *6* | *-0,17* |

Table 4 shows that the strategy, where the value of width of factors rolling window parameter is set to 39 weeks, returns much worse results than default one. As we know from the literature of subject, one of the possible explanations is existence of business cycles at the financial markets.

**Table 5.** The sensitivity of final results to the length of optimization window.

| weights opt. prec. | width of factors roll. window | optimisation window | number of chosen assets | Net Information Ratio |
|---|---|---|---|---|
| *0,1* | *26* | *26* | *6* | *0,27* |
| *0,1* | *26* | *52* | *6* | *0,56* |
| *0,1* | *26* | *78* | *6* | *0,11* |

Above table confirms that the highest Net Information Ratio is obtained for default strategy, where the parameter optimization window is equal 52 weeks. Basing on the fact that this parameter describes the size of in-sample set, we can suspect that historical quotations from one year contain optimal amount of information to calibrate our model. Considering alternative values of optimization window parameter we see that data set covering 26 weeks is probably too small, while the data set containing information from previous 78 weeks is too noisy.

**Table 6.** The sensitivity of final results to the number of chosen assets.

| weights opt. prec. | width of factors roll. window | optimisation window | number of chosen assets | Net Information Ratio |
|---|---|---|---|---|
| *0,1* | *26* | *52* | *3* | *0,41* |
| *0,1* | *26* | *52* | *6* | *0,56* |
| *0,1* | *26* | *52* | *9* | *0,42* |

Last table shows that our model is not very sensitive to the number of chosen assets. As we see, in results from all three symmetric strategies, obtained Information Ratios are close to each other. However, also this time the highest value is generated for default set of parameters. Described fact can be used as an important argument for stability of symmetric strategies. To summarize, it is apparent that our algorithm is most sensitive to selection of width of factors rolling window and optimization window, while the change of weights optimization precision and number of chosen assets does not have significant impact on the performance.

## 5.2. Regression analysis: sensitivity of parameters

Additionally, we conducted a regression analysis in order to explain the variation of information ratios by different levels of strategy parameters. We created auxiliary dummy variables encoding different levels of parameters. Below we present coefficient estimates along with their standard errors and p-values. The variables which are significant at 0.05 confidence level are bolded.

**Table 7.** The sensitivity of obtained results on assumed parameters. Regression results.

| variable | default value | alternative value | coefficient | standard error | t- statistic | p-value |
|---|---|---|---|---|---|---|
| optimization precision | ***0.1*** | ***0.25*** | *-0.0668* | *0.0595* | *-1.12* | *0.264* |
| | | ***0.5*** | *-0.0052* | *0.0595* | *-0.09* | *0.931* |
| | | ***1*** | *-0.0488* | *0.0595* | *-0.82* | *0.414* |
| **width of factors rolling window** | ***26*** | ***13*** | *-0.2084* | *0.0515* | *-4.05* | ***0.000*** |
| | | ***39*** | *-0.2582* | *0.0515* | *-5.01* | ***0.000*** |
| **optimisation window** | ***52*** | ***26*** | *-0.2277* | *0.0515* | *-4.42* | ***0.000*** |
| | | ***78*** | *-0.1406* | *0.0515* | *-2.73* | ***0.008*** |
| number of chosen assets | ***6*** | ***3*** | *-0.0624* | *0.0515* | *-1.21* | *0.229* |
| | | ***9*** | *-0.1122* | *0.0515* | *-2.18* | ***0.032*** |
| **constant** | **-** | **-** | *0.5850* | *0.0665* | *8.79* | ***0.000*** |
| **test** | | | | | **statistic** | **p-value** |
| **Jarque-Bera test for residuals normality** | | | | | *0.23* | *0.892* |
| **Breusch-Pagan test for heteroskedasticity** | | | | | *0.03* | *0.861* |

Dependent variable was information ratio. Independent variables were dummy variables encoding different levels of parameters. Significance of variables tests: H0: coefficient equal 0. Jarque-Bera test for residuals normality: H0: residuals have Gaussian distribution. Breusch-Pagan test for heteroscedasticity: H0: residuals are homoscedastic

The results show that optimization precision step has not any impact on our strategy performance, so further thickening a grid would be pointless. This finding may be initially a little bit confusing, however we should keep in mind that the objective function is maximized using data from in-sample period and our strategy is evaluated on out-of-sample period. It is well known that over fitting during in-sample period often leads to worse out-of–sample results. The significance of width of factors rolling window and optimization window is rather coherent with previous conclusions, and supports our parameters default values choice. It is worth to notice that choosing too large number of assets actually lowers the information ratio this may indicate that there exists a reasonable limit of portfolio diversification.

## 5.3. The sensitivity to the level of leverage.

In financial economics term "leverage" is defined as the use of various financial instruments or borrowed capital, such as margin, to increase the potential return of an investment. The performance of Default Strategy suggests that it would be reasonable to increase leverage to obtain higher returns without taking extensive risk. In the Table 8, we analyzed how the increase in leverage impacts performance metrics of the default strategy.

**Table 8.** The sensitivity to the level of leverage.

| Performance | Annualized Return | Annualized St. Dev. | Information Ratio | MaxDD | Length of MaxDD | Net Information Ratio |
|---|---|---|---|---|---|---|
| **Default Strategy** | *0.036* | *0.055* | *0.65* | *0.086* | *7* | *0.566* |
| **Default Strategy with leverage 2:1** | *0.070* | *0.136* | *0.517* | *0.323* | *14* | *0.457* |
| **Benchmark** | *0.046* | *0.183* | *0.254* | *0.511* | *26* | |

While the usage of leverage increases annualized returns, we can observe deterioration of information ratio and maximum drawdown. However, the leveraged Default Strategy still outperforms the benchmark.

**Figure 5.** Equity Line for the Default Strategy with leverage 2 vs B&H (benchmark) strategy

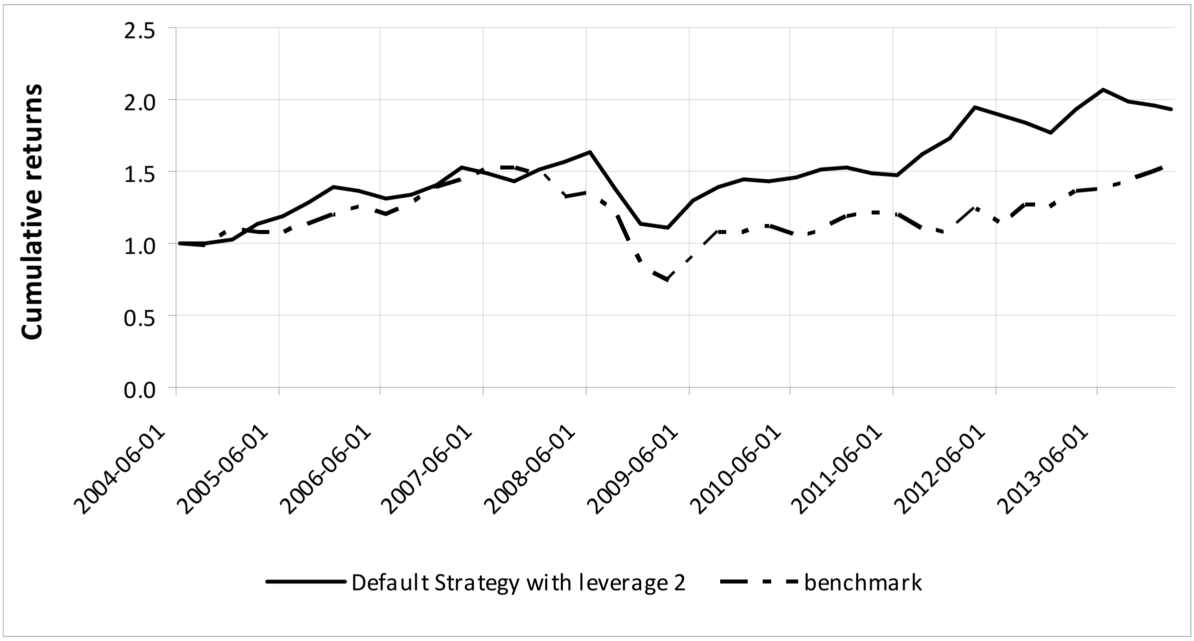



Figure 5 indicates that the cumulative return is higher for the Default Strategy with leverage 2. Additionally, the Default Model's performance is more stable across the whole period, with maximum drawdown at the level of 32%, while the benchmark's performance is more volatile and experienced large drawdown (51%) during the financial crisis in 2008-2009.

## 5.4. The Default Strategy vs Long-only and Long-hedged.

Additionally, we studied how our algorithm behaves while we open only long orders (12 long or 6 long) and also if there is any benefits to trade asymmetric balanced portfolio consisting of mostly long positions covered by some short positions (9 long and 3 short). Therefore, we constructed three strategies which mimic all the assumptions of the Default Strategy except for numbers of assets invested long and short. The results reveal the superior outperformance of the default model in terms of information ratio. Interestingly, we can observe higher information ratio and annualized return of the Strategy Only-Long 6-0 vs the Strategy Only-Long 12-0. This phenomenon can be explained by conjecture that the algorithm is most effective utilized by buying fewer number assets due to the proper process of ranking the assets. Finally, the performance of the Long-hedged strategy (Long-Short 9-3) shows minor improvement of annualized return, while information ratio is far lower than the default model. The results shows that the group of Only-long strategies has higher annualized return, however the risk is also higher.

**Table 9.** The results for various types of strategies.

| Performance | Annualized Return | Annualized St. Dev. | Information Ratio | MaxDD | Length of MaxDD | Net Information Ratio |
|---|---|---|---|---|---|---|
| **Default Strategy** | *0.036* | *0.055* | *0.65* | *0.086* | *7* | *0.566* |
| **Strategy Only-Long 12-0** | *0.088* | *0.187* | *0.473* | *0.434* | *26* | *0.448* |
| **Strategy Only-Long 6-0** | *0.108* | *0.201* | *0.539* | *0.445* | *13* | *0.511* |
| **Strategy Long-Short 9-3** | *0.044* | *0.104* | *0.427* | *0.307* | *26* | *0.382* |
| **Benchmark** | *0.046* | *0.183* | *0.254* | *0.511* | *26* | |

**Figure 6.** Equity Line for Only-Long 12-0 strategy vs B&H (benchmark) strategy

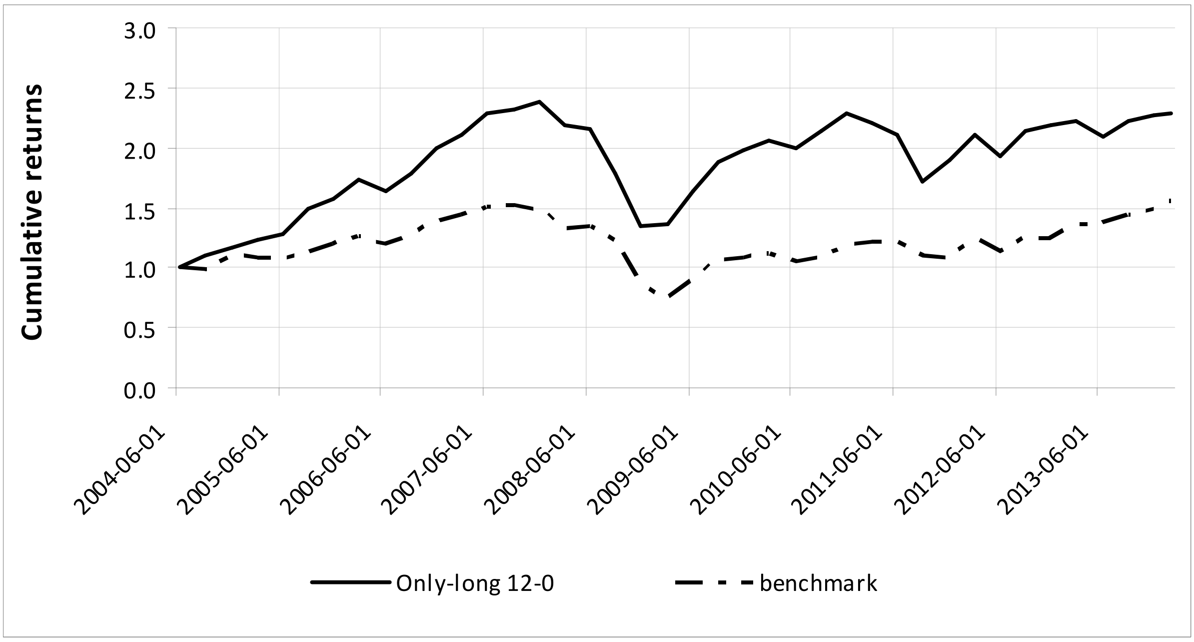


Figure 6 indicates that the cumulative return is higher for the Only-Long 12-0 strategy. Additionally, the maximum drawdown of Only-Long 12-0 strategy equals 43%, while the benchmark's performance is more volatile and experienced large drawdown (51%) during the financial crisis in 2008-2009. The level of annualized standard deviation is similar for both strategies. On figure 7 we can observe that the cumulative return is far higher for the Only-Long 6-0 strategy. Additionally, the maximum drawdown of Only-Long 6-0 strategy's equals 44%, while the benchmark's performance is more volatile and experienced large drawdown (51%) during the financial crisis in 2008-2009. The level of annualized standard deviation is slightly higher for Only-Long 6-0 strategy.

**Figure 7.** Equity Line for Only-Long 6-0 strategy vs B&H (benchmark) strategy

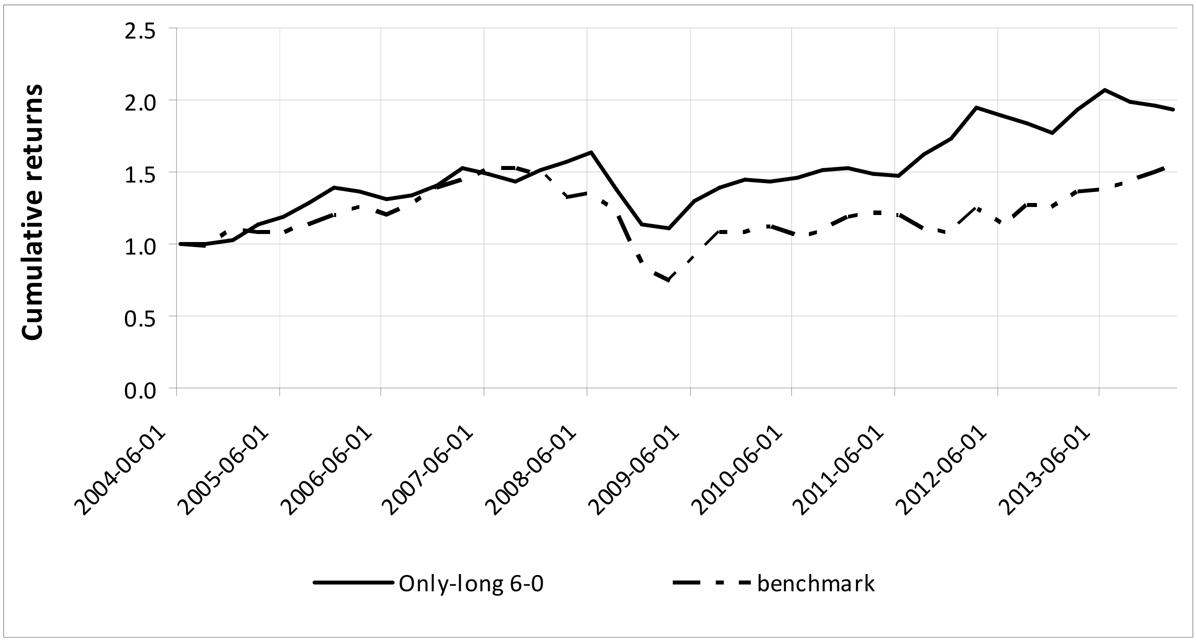



**Figure 8.** Equity Line for Long-Short 9-3 strategy vs B&H strategy

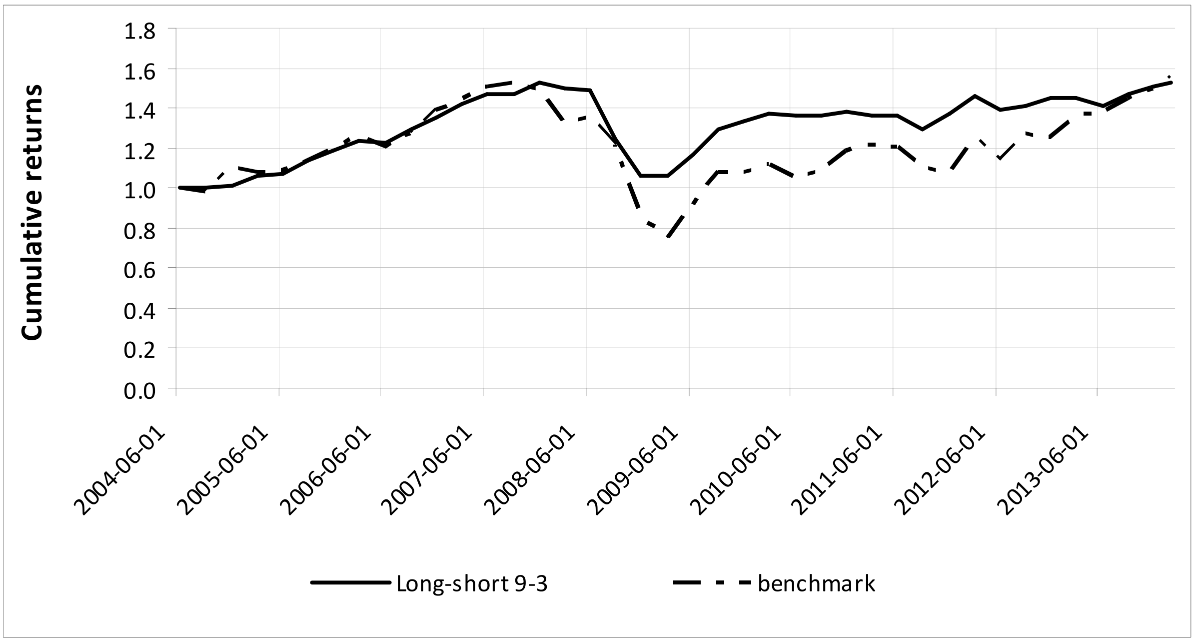


Figure 8 indicates that the cumulative return of the Only-Long 9-3 strategy is close to the benchmark at the eventually. Additionally, the maximum drawdown of Only-Long 9-3 strategy's equals 30%, while the benchmark's performance is more volatile and experienced large drawdown (51%) during the financial crisis in 2008-2009. The level of annualized standard deviation is far lower for Only-Long 9-3 strategy.

## 6. Conclusions

The initial results indicate that the default model overperforms the benchmark in terms of net information ratio which is 0.56 (0.25 in case of the benchmark). It is worth to notice, that the maximum drawdown of the default model is as low as 8.6% in comparison to 51% in case of the benchmark. This performance can be especially important for mutual funds managers whose clients may withdraw the capital in case of dramatic loss of funds. The sensitivity analysis signifies that we can obtain stable results if we use the following values of the parameters: the width of factors rolling window – 26 weeks, and optimization window – 52 weeks.

The asset allocation model we propose is particularly feasible as it requires a minimal possible set of data: series of close-to-close returns. Moreover, it is not computationally demanding as we have proved that thickening a grid does not significantly improve our strategy results.

The out-of-sample results in table 2 and table 3 suggest that there are some patterns that can be exploited after further research. Considering extension of our model, we propose to use alternative portfolio performance measures. Just to enumerate the most popular we should mention Roy's Safety First Ratio, Sortino Ratio or Treynor Ratio. Other interesting potential improvement is different shares of assets in traded portfolio. As was written in methodology, our model assumed that investments in portfolio had equal weights. Analyzing our approach based on factors model, some researchers would probably try to use other characteristics than mean, variance, skewness or kurtosis. Following the rule that only people who ask and look for answers can succeed, we encourage those researchers to continue our survey with alternative factors describing single assets.

In this research, we have studied different variants of the proposed Generalized Asset Allocation Model. Perhaps the greatest benefit of long-short tactical asset allocation is the reduction in volatility that accrues to this approach by being neutral to the market systematic risk. This in turn leads to substantial reductions in the maximum drawdown which an investor may experience. However, still the concern of a long-short strategy is performance relative to a benchmark. Our results show that the Default Strategy produces much lower drawdowns and higher information ratio than the comparable buy and hold strategy (in this case MSCI World Index). Importantly, the presented results include an approximation of transaction costs that an investor may incur at the real market.

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