9. THE IMPACT OF MOMENTUM FACTORS ON MULTI ASSET PORTFOLIO[1]

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Abstract

This article examines a global momentum-based allocation strategy across a broad range of asset classes. It is necessary to break away from a fixed asset allocation because of these unusual and unforeseen market movements, like the tech bubble during the late 1990s and the financial market crisis in 2008. With the dramatic decline in value across all asset classes, the neoclassical capital market theory lost its reputation. This research shows that a dynamic asset allocation process offers an attractive risk-return profile. Furthermore, this work seeks to demonstrate that the classical diversification is not appropriate and in a multi-asset portfolio, asset classes should be managed dynamically. The predictive power of the factors, absolute and relative momentum, is evaluated and analysed in a multi asset context. The data history ranges from 1992 to 2015. The calculations are based on the momentum of various equity markets (World, Emerging Markets, REIT`s), government bonds (US-Treasuries), foreign currencies (JPY/USD, EUR/USD) and commodities (energy, industrial metals, precious metals, agricultural commodities and livestock). Absolute and relative momentum portfolios are constructed using those three asset classes (p_{1-3}) that present the highest relative or absolute monthly ex-post return within the entire investment universe (p_{1-8}). The research indicates that both absolute and relative momentum strategies are suitable approaches for constructing and managing high performing multi-asset portfolios, especially it was proved by the outperformance of the portfolios during "dot com" bubble, financial crises of 2008.

Keywords: factor allocation, momentum, multi-asset, portfolio theory, dynamic asset allocation.

JEL Classification: F21; F37; G12; G17

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[1] *Some tables and figures are available only online as Supplementary Appendix (http://www.rjef.ro)*

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Introduction

The conventional portfolio theory by Markowitz aims to reach the optimum diversification of risk by diversifying an investor's capital (Markowitz, 1952). This relies on the assumption that the core characteristics of the assets (mean, variance, and covariance) remain constant over time. Later based on Markowitz' findings (1952), the Capital Asset Pricing Model (CAPM) is formulated by Sharpe (1964). This model provided investors with the first quantitative tool for structuring a portfolio by postulating diversification and a blend of risky and non-risk investments. Several portfolio management strategies have been derived from this approach. Among them are the 60/40 portfolio and the buy-and-hold strategy, which involves a static weighting of investments Brightman (2012). Ang, Brandt and Denison (2014) illustrate that due to the complete market capitalization of all stocks listed on the different exchanges and all U.S. Treasury securities that the 60/40 portfolio split is very common. This consists of an allocation of 60% to equities and 40% to bonds. It is called a weighted portfolio, according to the market capitalization of each asset class and conforms to the CAPM, i.e., the market capitalization of bonds in the United States is about 40% and of stocks approximately 60% of the entire market capitalization (due to its well established data-history only US-data used, World Bank and US Treasury Department). The 60/40 weighting fluctuates over time as performance for bonds and equities differs, but it is re-evaluated monthly. The term 'multi-asset' is traditionally associated with rigid portfolio structures such as those employed by endowment funds. In such portfolios, the multi-asset approach aims to generate a superior risk and return profile. However, the various financial crises over the past 15 years have exposed the weaknesses of such rigid portfolio weightings. Portfolios with fixed allocations have turned out to be insufficiently robust judged by conventional risk criteria due to the individual causes and singularities of the individual crises. Neither multi-asset portfolios nor 60/40 strategies have been able to prevent huge, even though temporary, losses. In addition, market analysis has shown that static type portfolios and that a static design of inherent diversification into a 60/40 portfolio has failed and has led to a suboptimal risk-efficient portfolio in every period under review. This means that the assumption of the core characteristics of assets (mean, variance, and covariance) and the premise of the normal distribution of returns has to be questioned and that any negative or positive skew in the distribution of returns needs to be considered. Furthermore, the 'prospect theory' of behavioural finance proposed by Tversky and Kahnemann (1979), explains that investors react much more strongly to losses than to profits. Thus, the unstable core assumptions of 'modern portfolio theory' and the corresponding unrealistic assumptions represent an immense problem for investors, as static 60/40 portfolios fail to provide a comprehensive solution. The implementation of a static allocation concept is clearly inadequate when applied to the more extreme financial cycles that have occurred in recent years. The proposal put forward in this paper is for the implementation of a dynamic multi-asset allocation.

The main research question addressed in this article is to test whether a dynamic multi-asset portfolio (consisting of equities such as MSCI World; MSCI Emerging Markets; FTSE NAREIT; commodities such as Gold & S&P GSCI; government bonds such as US Treasury; currencies such as JPY/USD; EUR/USD) whose investments are chosen by relative momentum and absolute momentum can achieve a significant excess of return compared to the (static) reference portfolio, with the focus on the performance of the dynamic portfolio during the dot com crisis and financial crisis of 2008. The rest of this paper is organised as follows: Section 2 summarises previous work and provides theoretical framework, Section 3 presents the data and methodology employed, Section 4 presents the results and Section 5 provides the conclusions.

Theoretical Framework

Markowitz (1952) portfolio selection theory builds upon the mathematical analysis of diversification, which is used to identify the optimal portfolio structure. Using various assumptions in its mathematical model, the aim is to calculate the weight of various financial assets (or instruments) in a portfolio in order to achieve an optimal diversification. In this portfolio context, the mathematical relation between risk and return is demonstrated. Markowitz (1952) concluded that for determining a portfolio's total risk and the diversification effect, the variance of the return of the individual investments and the correlation are necessary. Tobin's separation theorem demonstrates that the risk-enhanced part of the portfolio for any investor always corresponds with the composition of the market portfolio (Tobin, 1958).[4] The Capital Asset Pricing Model (CAPM) is built on the assumptions of the portfolio theory and the separation theorem by Tobin (1958). The latter, in its basic version, was developed independently and almost concurrently by Sharpe (1964), Lintner (1965) and Mossin (1966). Fama and French (1993) developed a three-factor regression model that explained the excess return on a stock compared to a risk-free interest rate by using three factors: market capitalization, valuation and company size. Carhart (1997) later added another factor – momentum – to this model. This further increased the significance of the excess return and was known as the 'four-factor regression model'.

The momentum factor can be traced back at least to the 18th century and describes the fact that the stocks that generated positive excess returns in the past will generate positive excess returns in the future and vice versa.[5] That is, the ex-post winners are the future winners, while the ex-post losers will be the ex-ante losers. More precisely, the effect based on the premise of significant auto-correlations of asset returns and states that assets which achieved an outperformance over the last 6 to 12 months will continue their outperformance in the future and, equivalently, assets which underperformed over the last 6 to 12 months will continue to do so going forward.

DeBondt and Thaler (1985, 1987) documented that long period past losers would outperform long period past winners. Jegadesh (1990) and Lehman (1990) stated that stocks selected based on the previous week or month return tend to outperform. However, Lo and MacKinlay (1990) point out that the large number of the huge returns found by Jegadeesh (1990) and Lehmann (1990) happened due to the delayed reaction of the stock price to the common factors. The success of the mutual funds analysed by Grinblatt and Titman (1989, 1991), as well as the power of Value Line ranking (Copeland

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[4] *The market portfolio includes every type of asset available in the global financial market, with each asset weighted in proportion to its total market value. As a market portfolio is completely diversified, it is only subject to systematic risk (risk that affects the market as a whole) and not to unsystematic risk (the risk inherent to a particular asset class).*

[5] *David Ricardo (1772-1823) quoted "Cut your losses; let your profits run on".*

and Mayers, 1982; Stickel, 1985) suggested the abnormal returns provided by the relative strength strategies.

The momentum factor of Jegadeesh and Titman (1993) is one of the most controversial but also the most recognized anomalies in financial markets. It shows that US-stocks that have performed well recently will carry on performing well in the future. The above authors select stocks according to their performance in testing periods ranging from 3 to 12 months and hold the portfolio for the following 3 to 12 months. They build a long portfolio of the past "winners" and a short portfolio of the past "losers" and show an average outperformance of 12% per year with this strategy. Fama and French (2012) stated that there are also value and momentum premiums for the international stock markets. Moskowitz and Grinblatt (1999) documented momentum strategies effect in the industrial level.

Another issue is that since the publication of the Jegadeesh and Titman (1993) paper, empirical evidence has identified the momentum factor in various asset classes, markets and throughout time, not only including stocks also REITS, commodities, currencies, bonds and art. The existence of momentum in commodities is reported by Pirrong (2005) and Erb and Harvey (2006) as well as in research papers by Miffre and Rallis (2007). Momentum effects have also been documented for government bonds by Asness, Moskowitz, Ooi and Pedersen (2012) and for corporate bonds by Jostova, Nikolova, Philipov and Stahel (2010). The momentum effect in currency was tested and verified by Menkoff, Lucio, Schmeling and Schrimpf (2011) and Okunev and White (2003) for example. The momentum effect was also demonstrated for REITS by Beracha and Skiba (2011).

The momentum factor creates return pattern which cannot be explained by the CAPM of Sharpe (1964) and Lintner (1965) and the three-factor model of Fama and French (1993) and therefore is called a financial market anomaly. This implies that it cannot explain the excess return of the factor as a function of more risk as an additional risk of the strategy could not be demonstrated. Hardly any other financial market anomaly has been tested as early as the momentum effect. For example, Lemperiere *et al.* (2014) had already tested the effect for equity index and commodity markets since the 1800.

Nevertheless, the momentum factor separates the academic world. Some determine the excess-return of the momentum factor as function of risk, others argue in terms of a financial market anomaly (Behavioural finance). Liu and Zang (2008) finds for example an increased loading of the momentum assets to systematic risk, macroeconomic supply and demand frictions, positive feedback loops between risk assets, and economic growth and even in the market microstructure and provide evidence that high momentum stocks have excess exposure to macro growth risk. The behavioural finance theory (BF) explains the autocorrelation effects due to psychological feedback mechanism and with it the BF supported the financial market anomaly concept (Malkiel, 2003). Investors tend to sell winners too early and hold on to losers. Barberis, Shleifer and Vishny (1998), as well as Hong and Stein (1999) investigate the under-reaction phenomenon and justify momentum with short-term under-reaction of market participants when processing information. Gradual development of these response phases lead to temporary autocorrelation, i.e. momentum. It can be observed that asset prices tend to return to their long-term average — the explanation being the overreaction of investors. This means that over an extended long-term horizon, a short-term under-reaction is corrected (Barberis, Shleifer & Vishny, 1998; Hong, Lim & Stein, 2000; Hirshleifer & Subrahmanyam, 1998).

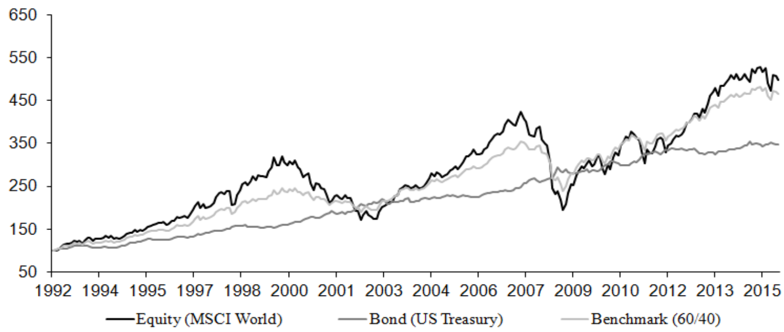
Hirshleifer and Subrahmanyan (1998) show another bias responsible for the momentum effect is called over-confidence bias, which is based on the idea that investors overvalue their own opinions compared to public signals. As a result, stock prices overreact to private information signals and under react to public signals, creating a short term momentum. The trends can continue if the risk management strategies keep on selling in down markets and buying in up markets (Garleanu and Pedersen, 2007). It is documented by Liu and Zhang (2008) that momentum continues to outperform due to high-momentum assets show greater sensitivity to the macroeconomic factors. Momentum will continue as a "pervasive phenomenon" until there will be large deviations from the fundamental price as a result of market reversal (Vayanos and Woolley, 2013).

2.1. Momentum in a Multi-Asset Context

As noted above, the momentum effect is one of the most researched capital market phenomena. Simultaneously one of the most controversial but also one of the most recognised anomalies in financial markets and has attained a broad acceptance after the work of Jegadesh and Titman (1993). The literature not only identifies the effect of equities, but also the effect on whole equity sectors, investment styles, as well as commodities, currencies, and fixed income markets.[6] However, the momentum phenomenon has mostly been demonstrated with individual securities rather than in a multi-asset context (Fama and French, 2012; Frazzini and Pedersen, 2010; Moskowitz, Ooi and Pedersen, 2012). The simplest multi-asset portfolio is the 60/40 portfolio (benchmark). Figure 1 illustrates the simulated cumulative return of a 60/40 portfolio since the year 1992.

Figure 1

Cumulative Return of the 60/40-Portfolio (Benchmark) Compared to Market Indices



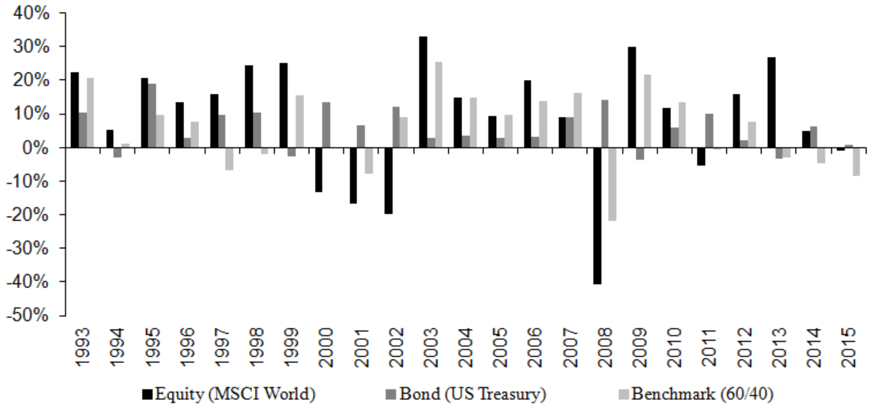
Source: Authors' calculation.

[6] *Fama & French (2008) evaluated the momentum effect for U.S. equities; Moskowitz & Grinblatt (1999) for equity sectors; global equities were examined by Griffin, Ji & Martin (2005); commodities by Pirrong (2005), currencies by Menkoff et al. (2011); government bonds by Asness, Moskowitz & Pedersen (2012); corporate bonds by Jostova, Nikolova & Philipov (2010); and REITs were analysed by Beracha & Skiba (2011).*

The equity portion of the portfolio is represented by the MSCI World Index and the fixed income portion by the US Treasury Index. The simulation demonstrates that the combination of two different asset classes suffers significant losses over a 23-year period. For example, between 2000 and 2002 as well as in 2008 and 2011, the 60/40-portfolio had to partially digest large losses (Figure 2). In aggregate, the simulation shows that the diversification effect is not sufficient enough to avoid losses across all economic cycles.

Figure 2

Annual Returns



Source: Authors' calculation.

In the following, we test the relative and absolute momentum and their capability of managing a multi-asset portfolio.

Data and Methodology

The empirical tests in this study are designed to meet the requirements of flexible multi-asset portfolios. The momentum factors are evaluated for the following asset classes: Equities (MSCI (Morgan Stanley Capital International) World; MSCI (Morgan Stanley Capital International) Emerging Markets; FTSE NAREIT (Financial Times Stock Exchange National Association of Real Estate Investment Trusts); Commodities (Gold; S&P GSCI (Standard & Poor's Goldman Sachs Commodity Index)); Government Bonds (US Treasury); Currencies (JPY/USD; EUR/USD).

In this paper monthly data from MSCI Inc., S&P, FTSE International Limited, the European Public Real Estate Association (EPRA), NAREIT and Bloomberg were collected. The data history ranges from 1992 to 2015.

The MSCI World includes over 1,613 constituents from 23 countries and captures large and mid-caps. The stocks are weighted according to their market capitalisation. The index covers approximately 85% of the free float-adjusted market capitalization in each country. The index was launched on March 1986 and the index is rebalanced. The large and mid-capitalization cut off points are recalculated during May and November semi-annual index reviews.

The MSCI Emerging Markets contains over 825 stocks and captures large and mid-caps across 21 Emerging Market (EM) countries. EM countries include: Brazil, Chile, China, Colombia, the Czech Republic, Egypt, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand and Turkey. The index is rebalanced and the large and mid-capitalization cut off points are recalculated during May and November semi-annual index reviews.

For REIT's (Real Estate Investment Trusts), the FTSE Index will be used, which includes 300 stocks from 20 countries. The index is designed to represent real estate equities worldwide and to track the performance of listed real estate companies and REITS. The index constituents are free-float adjusted and liquidity, size and revenue are screened and also weighted according to market capitalization.

The commodity index of S&P includes 24 different commodity futures from the fields of energy, industrial metals, precious metals, agricultural commodities and livestock. The commodities are weighted according to the value of their annual production volume with the current price. It is designed to be investable by including the most liquid commodity futures. The S&P GSCI is a total return index and widely recognized as the leading measure of general commodity proce movements and inflation in the world economy. The S&P GSCI is one of three most commonly used index according to Erb and Harvey (2006). The Gold Spot price is quoted as US Dollars per Troy Once.

The government bond index is the Bloomberg US Treasury Bond Index. The index is a rules-based, market-value weighted index engineered to measure the performance and characteristics of fixed rate coupon U.S. Treasuries which have a maturity greater than 12 months. Yields are yield to maturity and pre-tax. The rates are comprised of Generic United States on-the-run government (bill, note, bond) indices.

The Euro, JPY and USD are the most liquid currencies and downloaded from Bloomberg. The US Cas Indieces LIBOR Total return 3 month is used as cash surrogate. The index is generated using the theory that a basket of cash is invested daily at the prevailing LIBOR maturity rate. Interest is compounded daily.

The indices are always return indices and therefore the dividends are included.

The portfolios are sufficiently diversified and the most attractive asset classes are dynamically selected. The momentum factor is used to generate a buy or sell signal at time t_0 and for every selected asset class the return is realized in t_1. The portfolio is re-balanced at the beginning of each month based on the momentum factor of each asset class. The aforementioned 60/40 portfolio is used as a reference portfolio (benchmark). We also construct a benchmark that is obtained from the previously mentioned asset classes, and those classes are equally weighted (equal weight).

3.1 Relative and Absolute Momentum Portfolio Combinations

At the end of each month, three of aforementioned asset classes with the highest ex-post momentum were selected to construct the portfolio for the following month. The selection criteria was the highest ex-post momentum for the past 12 months $(\mathrm{n} = 12\ \mathrm{months})$ and throughout the entire universe of assets a with $\mathrm{a}\,\epsilon\{1,2,3,\ldots,8\}$. As a common measure of the momentum only the past 12 months return on the asset was used in this paper (Jegadesh and Titman, 1993; Asness, 1994; Fama & French, 1996; Grinblatt & Moskowitz, 2004; Asness *et al.*, 2013).

This provides a relative comparison for the various momentum factors of the individual asset classes as the momentum factors for the individual asset classes a have the same dimension and therefore are comparable.

The *relative momentum* is a cross-sectional or relative strength measure and it predicts the future returns of an asset class relative to other asset classes. The portfolio is re-balanced every month.

The asset classes with the highest ex-post momentum are selected for the past 12 months ($n = 12$ months) throughout the entire universe of assets a with $a \in \{1,2,3,\ldots,8\}$. *Absolute momentum* is constructed at the end of each month, the asset classes which achieved a positive absolute momentum $MOM > 1$ throughout the entire universe of assets a with $a \in \{1,2,3,\ldots,8\}$ are chosen for the portfolio. If all asset classes a are $MOM < 1$, the portfolio should be invested in the money market (cash).

The absolute and relative momentum portfolios are computed as follows:

$$MOM = \frac{p_a(t)}{p_a(t-12)} \tag{1}$$

where: $p_a(t)$ = the closing price of the asset "a" at the end of the month t , and $p_a(t-12)$ = the closing price of the asset at end of the month$(t-12)$,

However, the selection criterion for absolute and relative strategies is based on the peculiarities of both of them mentioned earlier.

There are more complicated methods for measuring absolute momentum (Baltas and Kosowski, 2012), but we determine the strategy by selecting only asset classes with a positive value (Antonacci, 2013). Absolute momentum is also called trend-following, which is recognised in the academic community (Brock, Lakonishok and LeBaron, 1992; Lo, Mamaysky, and Wang, 2000; Zhu and Zhou, 2009; Han, Yang and Zhou, 2013).Therefore, the hurdle rate is zero and the calculations are time series. By using absolute momentum future returns of an asset class are tried to be predicted based on the past return of the asset class. Rebalancing occurs monthly to increase cost effectiveness.

3.2. Sharpe Ratio and Alpha of the Relative Momentum and Absolute Momentum Strategies

To test the performance of both strategies the Sharpe ratio and Alpha were used. The calculation of the 'Sharpe' ratio, return and risk are combined into a single ratio:

$$SR = \frac{R_{P,t} - R_F}{\sigma_P} \tag{2}$$

with

$R_{P,t} =$ Portfolio return in time period t ;

$R_F =$ Yield of the riskless interest rate

$\sigma_P =$ Volatility of the realised portfolio returns

The 'alpha' is calculated as given by the CAPM equation whereby the risk is defined as the 'beta':

$$A_P = R_{P,t} - E(R_{P,t}) + \varepsilon_P = R_{P,t} - \left(R_F + \left[(R_{E,t} - R_F)\right] \times \beta_P\right) + \varepsilon_P \tag{3}$$

where:

$R_{E,t} =$ Benchmark return in the time period t

β_P = Beta factor of the annual portfolio returns

$E(R_{P,t})$ = Expected portfolio return in time periode t

ε_P = a random variable, the error term

3.3 F-test and t-test

The F test null hypothesis H_0 is based on the assumption that the variances are equal. The alternative hypothesis H_1 assumes that σ_1^2 and σ_2^2 vary. The null hypothesis of two random samples is:

$H_0: \sigma_1^2 = \sigma_2^2$

with $\sigma_1^2 = Variance\ 1$ and $\sigma_2^2 = Variance\ 2$. The 'F parameter' is the quotient of the estimated variances $\hat{\sigma}_1^2$ und $\hat{\sigma}_2^2$ thus:

$$F = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2} \quad (4)$$

The 't-test' null hypothesis is based on the assumption that all mean values of the population are equal

$H_0 : \mu_1 = \mu_2$ or the alternative hypothesis

$H_1 : \mu_1 \neq \mu_2$.

The formula for 't-test' is:

$$t_{df} = \frac{\bar{X}_1 - \bar{X}_2}{\hat{\sigma}_{\bar{X}1-\bar{X}2}} \quad (5)$$

with $\bar{X}_1 - \bar{X}_2 = empirical\ mean\ value\ difference$

and $\hat{\sigma}_{\bar{X}1-\bar{X}2} = estimated\ standard\ error\ of\ the\ mean\ value\ difference$

It will be tested in two samples whereby the arithmetic mean figures of this feature are significantly different.

Results

4.1 Relative Momentum Results

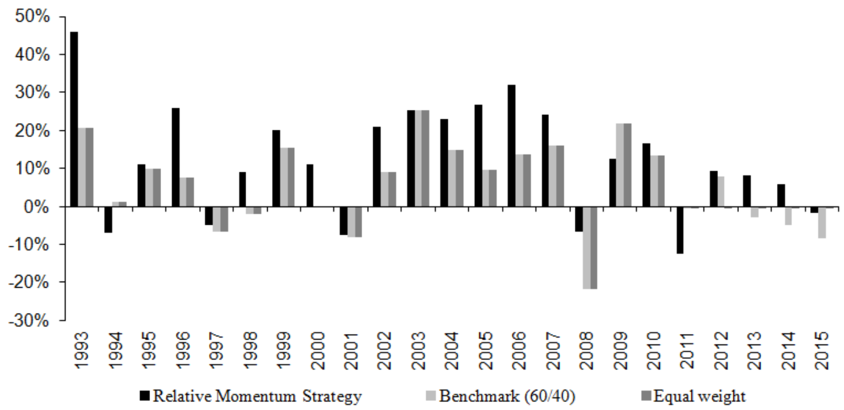
The performance of the dynamic multi-asset portfolio (Figure A1 - online Supplementary Appendix) indicates a superior result compared to both the benchmark and the equally-weighted portfolio. During the years of strong performance in the equity markets in the late 90s up to the year 2000, this strategy only generated mixed returns. During periods of declining equity markets, excess returns could be earned continuously.

The annual return figures (Figure 3) illustrate considerable differences between the strategy and the benchmark as well. It is striking that besides the excellent developmental period experienced between 1999 and 2008, the weakest performance was achieved in the year 2011. Due to the fact that the equally-weighted portfolio and the benchmark performed significantly better, the poor return is attributable to the momentum factor, which generated a negative relative return in the years 1994, 2001, 2011. However, the simulation clearly shows that the momentum factor generates a significant excess return during the period overall. Whereas the equally-weighted portfolio and the benchmark generated an annual return of 5.4% and 6.9%, respectively, the strategy's return was 11.7% (Table 1[7]). Also, in 65.4% of the months, a positive return was produced. Thus, the frequency of positive returns is higher (Figure 4).

The descriptive statistics table reveals the differences between the two portfolios. Skewness of the benchmark is greater and thus inferior and it shows the asymmetry of the return distribution. The kurtosis is a curvature parameter and suggests a 60/40 benchmark. This can also be observed when looking at the minimum values. However, a significant difference between the maximum figures is observed can be interpreted as being superior for the momentum strategy. Overall, the relative momentum strategy delivers an excellent return-risk profile and demonstrates its relevance as an asset allocation tool.

Figure 3

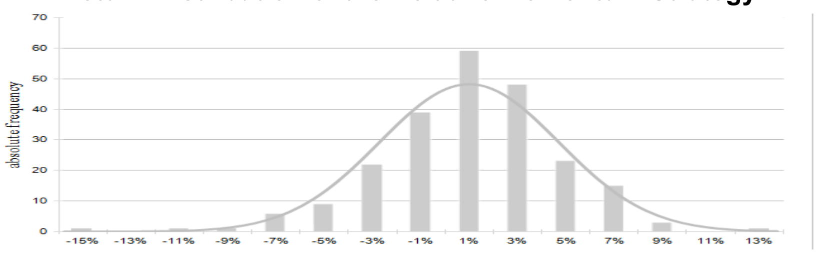
Annual Returns for the Relative Momentum Strategy



Source: Authors' calculation

Figure 4

Return Distribution of the Relative Momentum Strategy



Source: Authors' calculation.

In absolute terms, the 'alpha' of the strategy is positive and, compared with the 'alpha' of the benchmark, can also be categorised as above-average. The 'Sharpe' ratio is clearly positive and is superior in comparison. The risk-adjusted excess return is therefore also significantly greater than that of the benchmark (Table 3).

[7] *All tables are available online as Supplementary Appendix (http://www.rjef.ro)*

The strategy's maximum drawdown (the peak-to-trough decline during a specific period) is significantly lower. Although, Figure A2 (online Supplementary Appendix) also shows that temporarily higher losses can be experienced, especially during the Euro zone debt crisis.

4.1.1. Relative Momentum 'F-test' and 't-test' Results

The 'F-test' discloses that the variances differ significantly and are therefore rather inhomogeneous; 't-test' has a significance value of 0.097, which renders it improbable that both mean values vary systematically. The null hypothesis H_0, which is based on the assumption that the variances are equal, is rejected as a consequence of which the 'p' value of 0.097 can be taken to be significant. That means, it is likely that both mean figures systematically vary from each other.

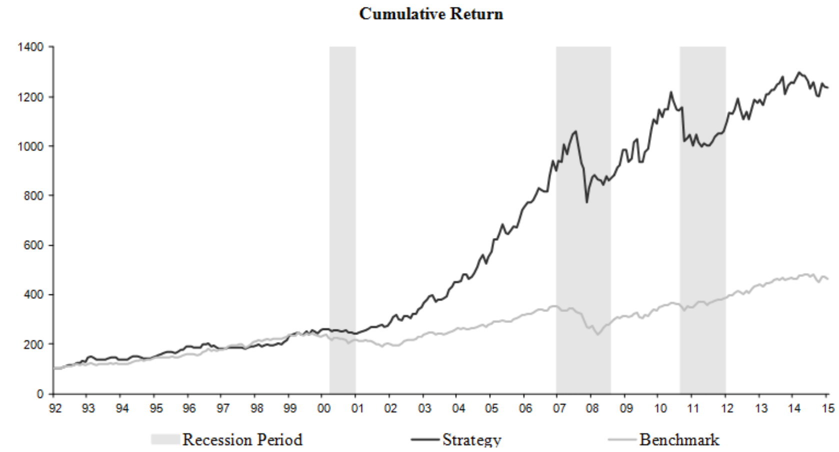
4.1.2 Robustness Test of Relative Momentum in Different Economic and Market Environments

The risk figures provide a mixed picture. While the volatility is highest for the strategy, the beta to the benchmark is low. The beta reveals the positive selection qualities of the factor as it is lower during periods of weak stock market and higher during periods of strong stock market (Figure A4 - online Supplementary Appendix). However, there is empirical evidence that the beta factor and therefore the risk premium of stocks and bonds are time-varying (Bekaert & Hoerova, 2013, Bollerslev, Sizova &Tauchen, 2012; Viceira, 2007). Nevertheless, it can be stated that the ratio analysis of the relative momentum strategy demonstrates the high forecasting quality of the strategy. The volatility increases after the financial market crisis of 2008 (Figure A3 online Supplementary Appendix), but decreases significantly after 2011. The volatility development can be classified as stable. Grouard, Levy and Lubochinsky (2003) also investigate the volatility pattern and verify the connection between macroeconomic uncertainty, financial shocks and uncertainty about geopolitical development and the stock market volatility.

Figures 5 to 7 show that the relative momentum strategy evidenced an outperformance even during periods of stock market turmoil. During the dot-com bubble the factor adds value in absolute and relative terms. The dot-com bubble (also referred to as the internet or technology bubble) was a speculative boom and bust cycle in the stock markets across the developed world that started in approximately 1997 and reached its peak in March 2000. During this period certain equity sectors, mainly in technology, telecommunication and internet, saw a rapid rise in value.

Figure 5

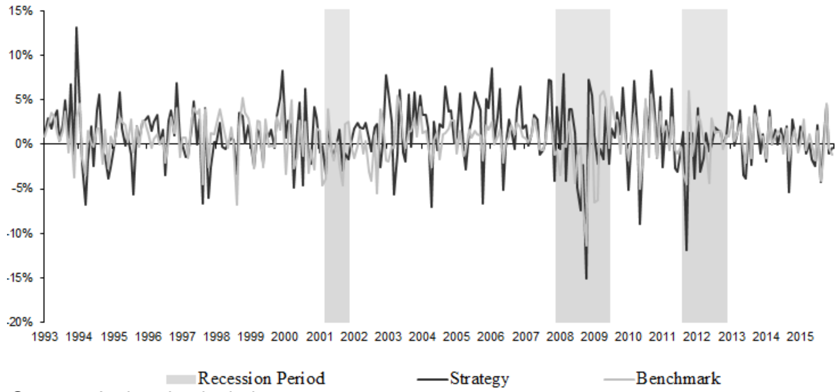
Cumulative Return



Source: Authors' calculation.

Figure 6

1-Month Returns (in NBER Recessions)

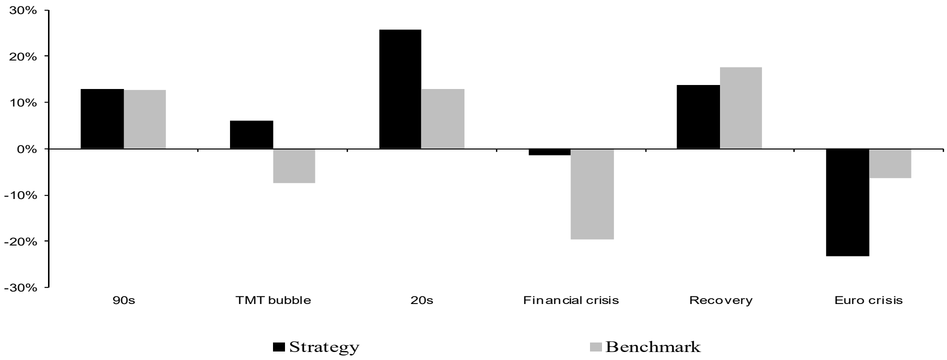


Source: Authors' calculation.

In the financial crisis of 2008 the factor cannot protect the invested capital, but compared to the benchmark the results are nevertheless superior. It can be observed that until the Euro zone's debt crisis of 2011 the strategy performed considerably better during periods of market and economic crisis.

Figure 7

Up and Down Markets – Annualized Returns

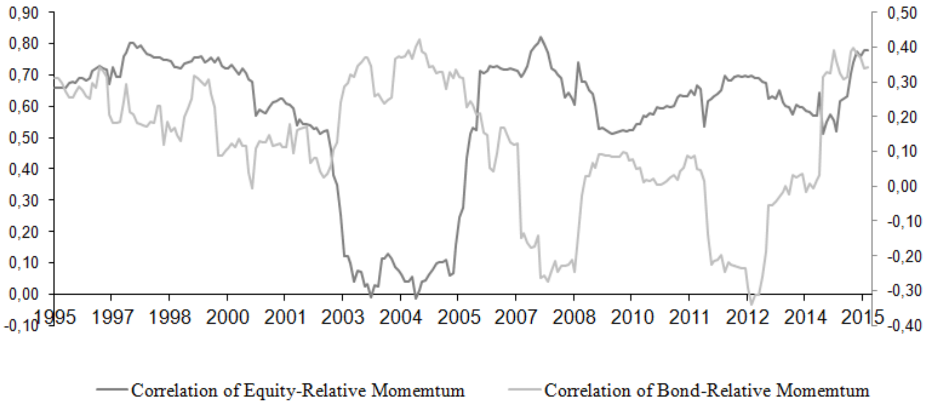


Source: Authors' calculation.

Figure 8 shows the 3-year rolling correlation analysis of Equity-Relative Momentum and Bond-Relative Momentum. The analysis reveals that the relative momentum strategy shifts dynamically between risky and non-risky assets. The asset allocation of the strategy also demonstrates the positive selection quality of the momentum factor and can be considered as the main performance driver. In years of turbulent equity markets, risky assets are systematically removed and in years of positive stock market and a positive macro-economic environment, the factor allocates more to risky assets. The performance table shows that the superior performance of the strategy does not only depend on the flexible allocation between bonds and equity. The asset allocation figure reveals that the selection of gold in the early 1990`s and for examples REIT`s in the 2010 supports the return of the strategy.

Figure 8

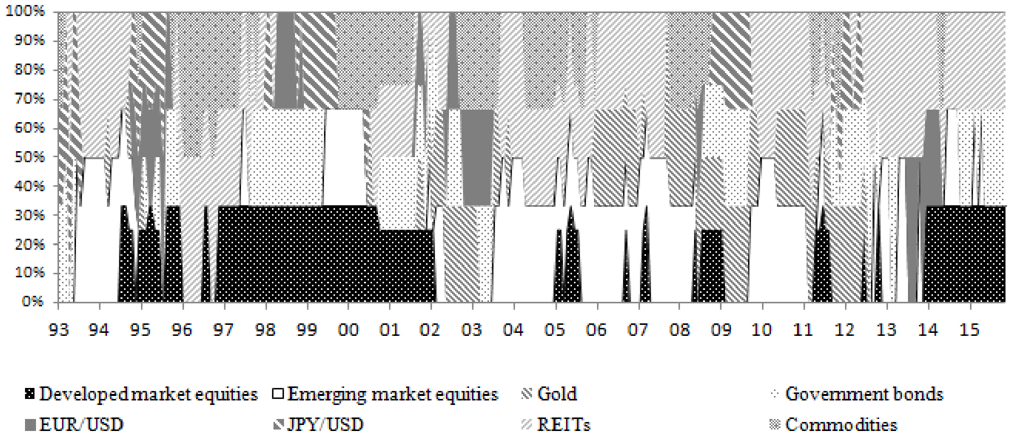
Correlation of Relative Momentum



Source: Authors' calculation.

Figure 9

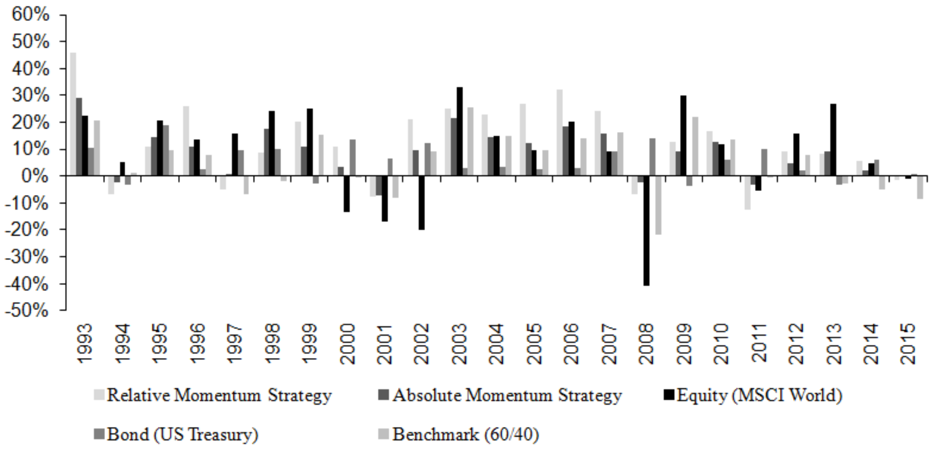
Asset Allocation – Relative Momentum



Source: Authors' calculation.

Figure 10

Annual Returns



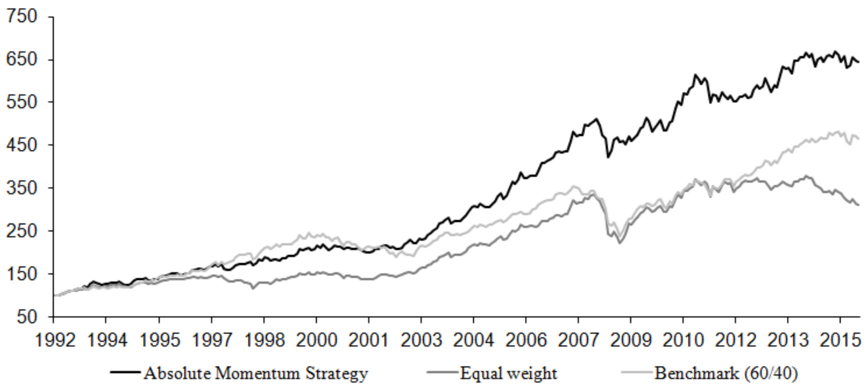
Source: Authors' calculation.

4.1. Absolute Momentum Results

Our ex-post analysis of the returns achieved shows that the cumulative return of the strategy is significantly higher than both the equally weighted benchmark and the reference portfolio. Figure 11 confirms the positive characteristics of the strategy, especially in the periods of large market drawdowns. In the years 1997-1998, as well as in the years 2000 and 2002, the portfolio achieved positive returns. In the year 2008, when markets declined significantly, the strategy only lost marginally in value. The comparison with the equally weighted portfolio proves that this was due to the absolute momentum factor and not to the diversification effect. In the year 2009, however, when equity markets performed well, the strategy results were partially below average.

Figure 11

Cumulative Returns of the Absolute Momentum Strategy

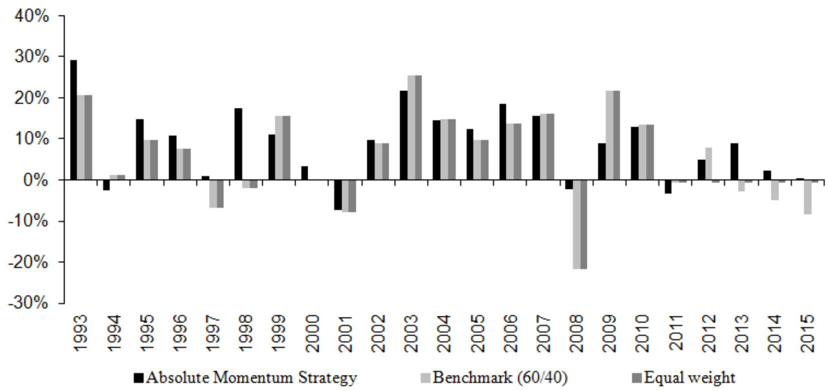


Source: Authors' calculation.

Figure 12 shows the annualised returns, which are significantly above those of the comparative benchmark. Table 5 shows that absolute momentum factor generates excess return during the overall period (it was 8.51%). However, it is lower in comparison to the relative momentum factor.

Figure 12

Annual Returns for the Absolute Momentum Strategy

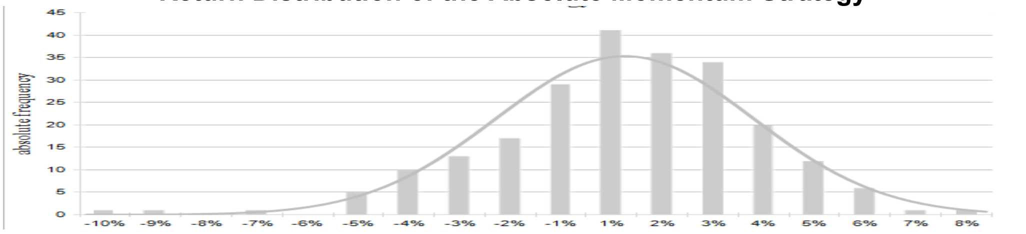


Source: Authors' calculation.

The return distribution of the absolute momentum strategy (Figure 13) displays a considerably smaller spread than the relative momentum strategy. The results show that 66.5% of the returns are positive, representing a clear positive distribution of the returns.

Figure 13

Return Distribution of the Absolute Momentum Strategy



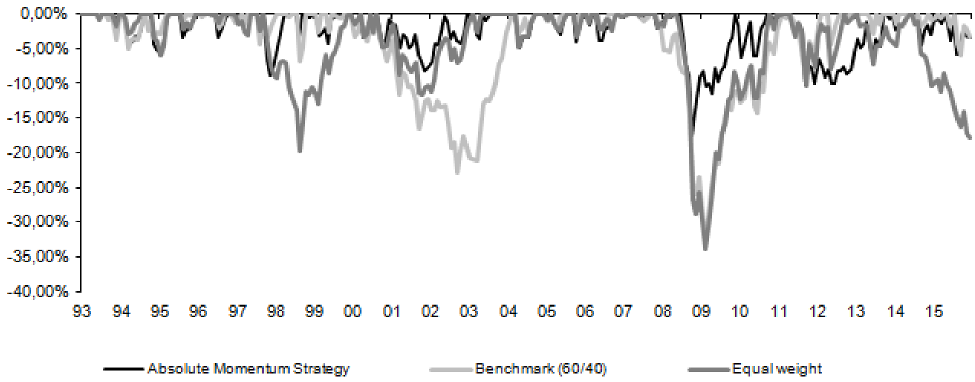
Source: Authors' calculation.

The mean value of the benchmark (Table 6) are classified as superior under return aspects. The return of the worst month is -9.4%, while the value for the benchmark is -11.4%, also the best months show a significant difference of 6.0% and 7.1%, respectively. Both measures evidenced the high consistency of the return risk profile. Both skewness and the kurtosis favour the strategy. Right skewed return distributions rejected by investors with decreasing absolute risk aversion. Lower returns (in comparison to the relative momentum strategy) are apparent with a comparatively high probability in both cases. The strategy is superior in all measures, which demonstrates the high selection quality of the factor in the context of multi-asset allocation.

In accordance with the greater excess-return, and in contrast to the reference portfolio, a positive 'alpha' can be observed, both in absolute and in relative terms. In accordance with the greater returns and the lower risk, the 'Sharpe' ratio is positive. This is consistent with the results found by Antonacci (2014), and is almost twice the value of the benchmarks (Table 7).

Figure 14

Maximum Drawdown



Source: Authors' calculation.

An interpretation of the maximum drawdown will complete the positive risk characteristics. By applying the strategy, the risk of a significant maximum loss can be reduced considerably. The graph does not only verify the results, but highlights the high degree of consistency. Within the whole observation period, the strategy had some loss by the end of Eurozone debt crisis and at the start of the recovery period.

4.2.1 Absolute Momentum 'F-test and 't-test' Results

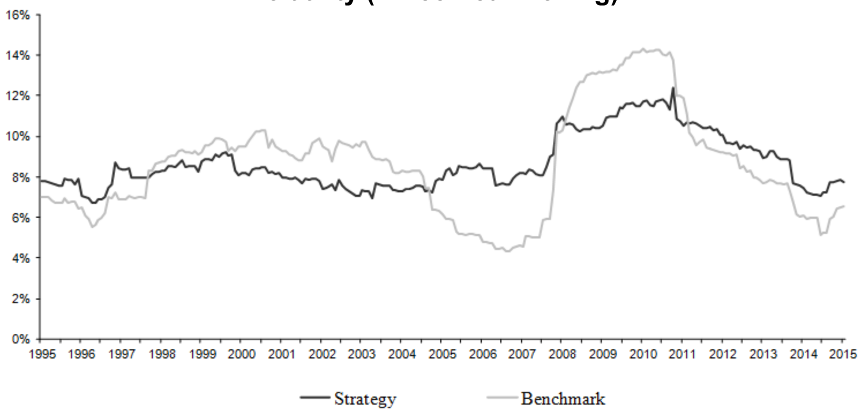
The results of the 'F' and 't-tests' shown in Table 8 indicate that the variance homogeneity can be rejected, and that the variance estimation of the 't-test' ('heterogeneous variance estimation') is the same. However, as this shows a *p* value of 0.39, it is unlikely that both mean figures systematically vary from each other. Thus, the null hypothesis cannot be rejected.

4.2.2 Robustness Test of Absolute Momentum Strategy in Different Economic and Market Environments

Momentum strategy also benefits the management of risk. A lower volatility and a lower beta show a lower risk of the strategy and a risk reducing element in the portfolio context. On average the volatility is lower than that of the benchmark, but it increases after the financial crisis. Beta also shows positive selection properties. The strategy participates in strong stock markets, whereas in weak periods the beta is successively reduced. Figures 15 to 17 show the risk-reducing property of the absolute momentum strategy in times of recession and market meltdown. In the financial crisis of 2008 and during the dot-com bubble the invested capital could be protected, losses were incurred only during the Euro zone debt crisis. The strategy was also very successful in the long-term recovery period in the 2000s. A strong absolute performance can also be observed in the 1990s. However, in the fast and volatile upside movement after the financial crisis of 2008, the absolute momentum factor was not overwhelmingly successful. Nonetheless, overall, the high quality of the selection properties can be noted.

Figure 15

Volatility (Three Year Rolling)



Source: Authors' calculation.

Figure 16

Beta (Three Year Rolling)

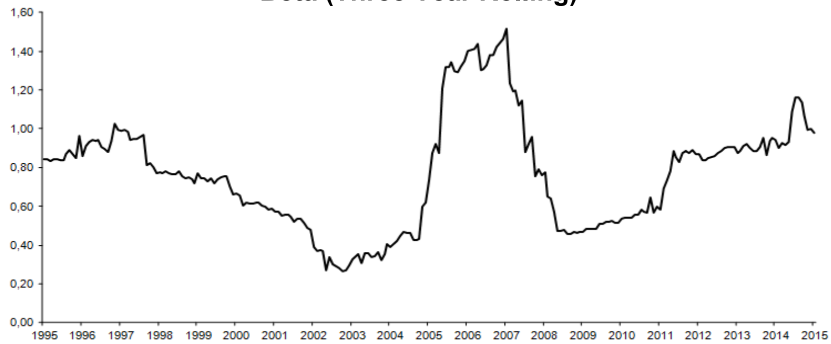
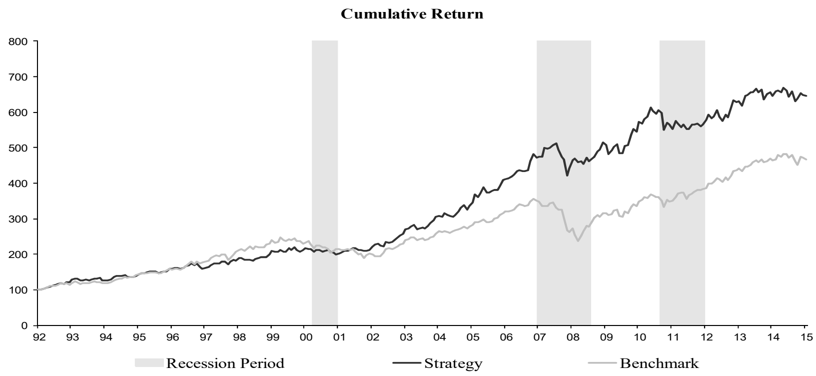


Figure 17

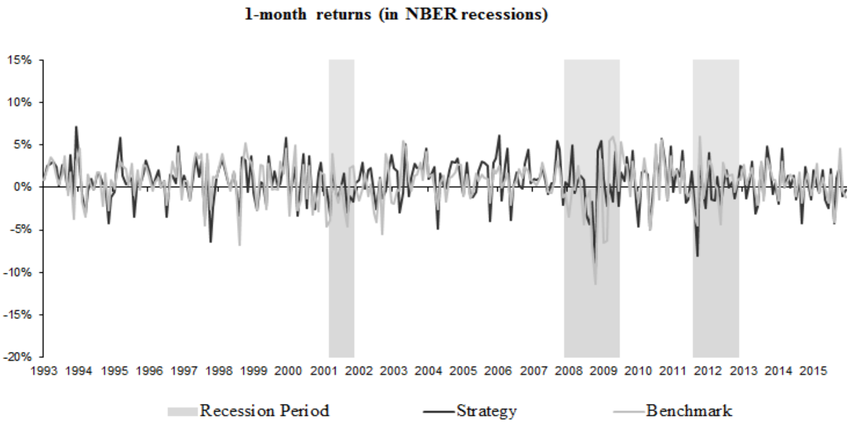
Cumulative Return



Source: Authors' calculation.

Figure 18

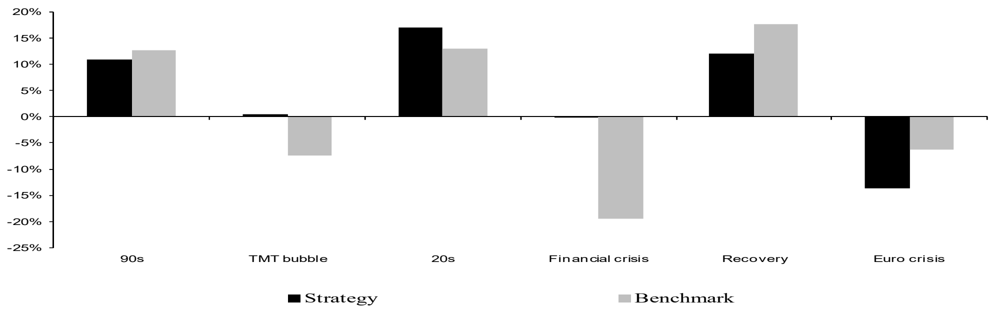
1-Month Returns (in NBER Recessions)



Source: Authors' calculation.

Figure 19

Up and Down Markets – Annualized Returns

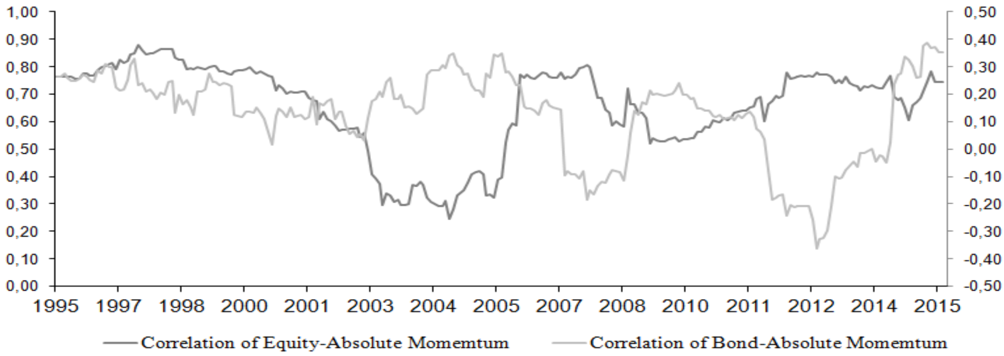


Source: Authors' calculation.

Figure 20 presents a 3-year rolling correlation analysis and shows a very dynamic allocation between risky and non-risky asset. Figure 21 demonstrates how the assets are allocated over time. A well-diversified portfolio can be observed which also documents the high selection quality. In periods of economic slowdown and weak equity markets the factor prefers less risky asset classes and vice versa. For example, exposure to equities is either significantly reduced or even completely removed during downturn periods such as the financial crisis of 2008. The performance table in conjunction with the correlation analysis demonstrates that the performance depends on multi asset weighting and not only on bond and equity allocation. The allocation in gold especially in years of high inflation is obvious.

Figure 20

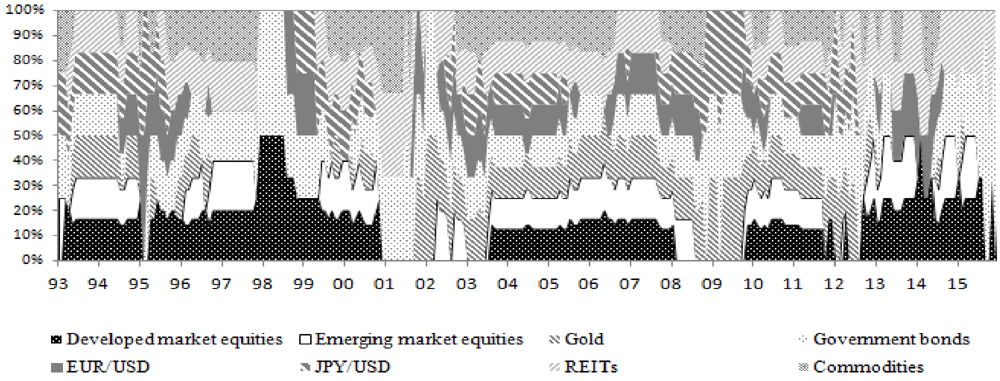
Correlation of Absolute Momentum



Source: Authors' calculation.

Figure 21

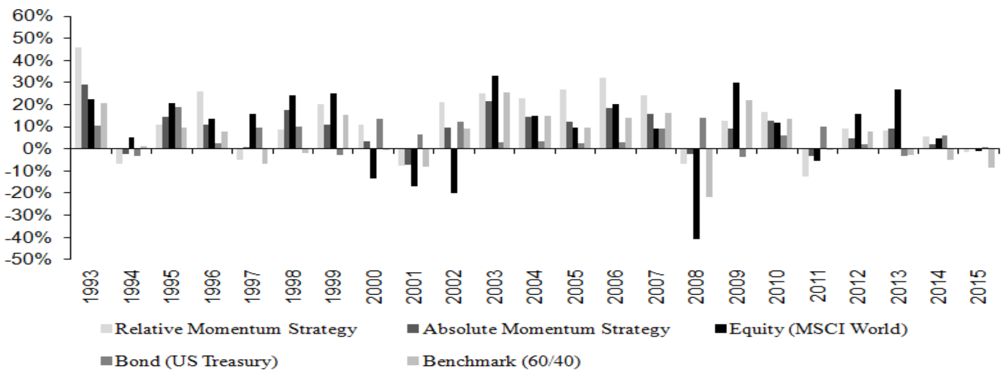
Asset Allocation: Absolute Momentum



Source: Authors' calculation.

Figure 22

Annual Returns



Source: Authors' calculation.

Conclusion

We modelled the construction of two multi-asset portfolios that were assumed to be invested in equities, government bonds, currencies, and commodities, in which the asset allocation decision was driven by the momentum factor. For one portfolio, we used relative momentum to select the three asset classes that were expected to provide the highest returns for the next month. For the second portfolio, we based our allocation decision on the highest absolute momentum, allocating either to the asset classes with the highest absolute momentum or to cash in cases in which no asset class showed a positive absolute momentum.

The work described here combines the principles of modern portfolio theory (diversification) with a review of the efficiency of the momentum approach behavioural finance strategies. The return and risk characteristics of the two portfolios were compared to the widely employed 60/40 benchmark and a broadly diversified portfolio.

The results demonstrate that the returns of both momentum strategies are superior to a 60/40 benchmark as well as the broadly diversified but static portfolio.

The performance tables in conjunction with the correlation analysis demonstrate that the performance depends on multi-asset weighting and not only on bond and equity allocation. The allocation in gold, especially in years of high inflation, is of interest.

The maximum drawdown in both cases is smaller than the benchmarks, although only the volatility of the absolute momentum strategy is superior (it has a lower volatility than the relative momentum strategy). If investors select asset classes based on relative momentum, the returns will be more volatile. The skewness in both cases is significantly less compared to the 60/40 benchmark.

Both absolute and relative momentum strategies gave good results between 1999 and 2008. However, a slowdown and weak performance was realised in the year 2011. It was demonstrated that until the Euro zone's debt crisis the strategy performed considerably better than the benchmarks, especially during periods of market and economic crisis.

In conclusion, both absolute and relative momentum strategies offers a valuable asset allocation tool for constructing and managing high performing multi-asset portfolios, especially it was proved by the outperformance of the portfolios during "dot com" bubble and financial crises of 2008.

Further research on the momentum would be of value, as would exploration of absolute and relative risk premia strength while building the portfolios via novel modelling methods such as Risk Parity, Maximum diversified Method and the Maximum Sharpe Ratio Method within a dynamic asset allocation context.

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