
Looking for Synergy with Momentum in Main Asset Classes

Lukas Macijauskas¹, Dimitrios I. Maditinos²

Abstract:

As during turbulent market conditions correlations between main asset-classes falter, classical asset management concepts seem unreliable. This problem stimulates search for non-discretionary asset allocation methods. The aim of the paper is to test whether the concept of Momentum phenomena could be used as a stand alone investment strategy using all main asset classes. The study is based on exploring historical prices of various asset classes; statistical data analysis method is used. Results of the current study reveal that, in comparison to passive portfolio, Momentum method can significantly increase compounded annual growth rates and, in most cases, to achieve this result with better risk/return ratios.

Key Words: Behavioral Finance, Momentum Investing, Asset Classes, Strategy, Tactical Asset Allocation, Methods

JEL Classification : G02, G11, G14, G15

1 Vilnius Gediminas Technical University Sauletekio ave. 11, LT-10223 Vilnius, Lithuania, Email: lukas@macijauskas.com

2 Technological Education Institute of Kavala Business School, Agios Loukas, 654 04, Kavala, Greece, Email: dmadi@teikav.edu.gr

1. Introduction

Recent decade proved to be one of the most problematic periods for asset managers since great depression. Global economy suffered two recessions where the recent one, which started in 2008, due to its large impact to global markets is often being pronounced as the Great recession. As a result almost all main financial markets felt abnormal turbulence which suddenly led to negative portfolio returns for absolute majority of investors.

The Capital Asset Pricing Model (CAPM) explains security prices by assuming rational behaviour on the part of investors (Sharpe 1964). Components of this behaviour, like mean-variance optimization, suggest investors must be able to solve complicated equations to construct optimal portfolios (Bodie et al. 2008). However, there are many articles with arguments that this concept is fragile (Michaud 1989; Farrelly 2006). As correlations during the peak of high economic uncertainty between main asset classes brake down (Taleb 2007; Campbell et al. 2002), rational behaviour is replaced by panic so even supposed to be well-diversified (rational) investors are experiencing huge losses in their investment portfolios (Dalbar 2010; Coaker 2007; Kindleberger and Aliber, 2005; Lowenstein 2001; Shiller 1984).

On the other hand As Vanguard's study (2011) shows, investors' behaviour during up-trending market conditions are noticeably irrational. Data from net cash flows to bond and equity mutual funds reveals that investors in market peaks tend to allocate significantly larger amounts of cash to equity funds than they do in down-trending markets. Thalassinou, Maditinos and Paschalidis (2012) have concluded for the existence of strong evidence in insider trading in the ASE.

As a matter of fact, just before the recent recession in 2008 net flow of cash to US equity funds during 2006-2007 reached 464 billion USD while in the bottom of dot.com bubble burst in 2001 and 2002 cash flow to equity funds was only 107 billion USD. Same tendency repeated in 2009 where cash flow was even negative. This indicates that instead of being rational and willing to buy stocks at significantly lower valuations like seen in 2001/2002 or 2009, majority investors decide to invest more aggressively near the peaks where valuations are much less attractive. We can conclude that majority of market participants in one way or another could be influenced by recent past market performance. Such irrationality can be explained by behavioural aspects where greed is one of the main driving factors (Shiller 2005).

Thus if we assume that systematic irrationality in the financial markets is one of the main factors that stimulate widening the scale of boom-bust cycles it is natural to look for such asset management methods in areas related to behavioural finance.

Investment community almost unanimously agree that diversification is one of the main factors influencing final portfolio results (Bernstein 2010; Faber and

Richardson, 2009; Darst 2007; Gibson 2007; Gibson 2007; Fraser-Sampson 2006; Bogle 2001; Jacquier and Marcus, 2001; Ibbotson et al. 2000) thus it is interesting to look for such investment management strategies that could not only potentially add value in one particular asset class but ideally generate synergetic effects using all main asset classes. One potential candidate concept for this task is the called momentum phenomena, where fundamental factors are completely ignored, and only combinations of past performance are used. In our case there will be an effort to evaluate if simply analyzing past 1, 3, 6, 9, 12 months rates of change we can achieve better compounded annual growth rates with overall better risk/return ratios than simply buying and holding all main asset classes in equal-proportion passive portfolio.

2. Literature Review on Momentum Investing

Growing stock market and rising activity of investors attracts more increasing attention by retail traders who look for simple investing methods (Dudzevičiūtė, 2004). This leads to rising demand for easy to use applications that could be implemented in real life investing decision-making algorithms. Technical Analysis (TA) apologists claim that one of possible answers to this demand could be found in behavioural finance based historical prices analysis and pattern recognition techniques which could indicate short term market tendencies in the near future. Technical analysis can be described as the various stock market forces interactions and their impact on share prices survey (Dzikevičius and Šaranda, 2010). The crowd of TA supporters is quite impressive and according to Taylor and Allen (1992) about 90 percent of market participants place some weight in it. Norvaišienė (2005) explains that TA factors are related to stock market conditions and are mainly focused on price changes, market volume, the demand and the supply of the stocks. So, the main reasoning of technical analysis supporters' could be determine as importance of historical analysis of stock rates that allow to ascertain cyclicity and future trends of a specified stock price making investment decisions (Jurevičienė and Albrichtaitė 2010).

However David Aaron in his book "Evidence-Based Technical Analysis: Applying the Scientific Method and Statistical Inference to Trading Signals" (2006) showed very clearly that absolute majority of complex technical analysis indicators fail to produce significantly better investment results than simple passive buy and hold strategy. He explained that increased mathematical complexity of such indicators add only illusionary benefits that could be detected for short periods of time. Unfortunately when filtered for data snooping, curve fitting and hindsight biases majority of indicators fall to over-optimization.

Thus it is important to search for such strategies that could not only show temporary theoretical benefits but also where algorithm logic could be explained using known

market patterns. Market inertia or more often called Momentum fall in this category. Strategies that rely on momentum have a very straight forward logic and can work because the market itself exhibits momentum (positive serial correlation) due to under reaction and overreaction at different time frames (Faber and Richardson, 2009).

Momentum strategies have been in existence for most of the twentieth century. Alfred Cowles and Herbert Jones described evidence of momentum in their work as early as the 1930s (1937). Gartley (1945) in his famous article named “Relative Velocity Statistics: Their Application in Portfolio Analysis” introduced methods of using momentum as a standalone strategy for stock selection. Levy (1968) enhanced previous works and published his own methodology called “The Relative Strength Concept of Common Stock Price Forecasting”.

Great summary of studies was presented by Elroy Dimson, Paul Marsh and Mike Staunton (2002) in their text on markets’ history „Triumph of the Optimists,, where they show that winners (top 20% past returns) beat losers (bottom 20%) by 10.8% per year in the UK equity market from 1956 – 2007. The greatest number of studies where researchers tried to verify momentum existence have been conducted with US stock market (Fama and French, 2008; Agyei-Ampomah 2007; Chen and DeBondt, 2004; Lewellen, 2002; Moskowitz and Grinblatt, 1999). Other authors also looked for evidence of momentum in international markets (Vanstone and Hahn, 2013; Chao et al. 2012; Naranjo and Porter, 2010) Narasimhan Jegadeesh and Sheridan Titman (1993) found that the Momentum effect has been evident in most major developed markets around the world. In their paper they showed that stocks that perform well (poorly) over a 3 to 12 month period continue to perform well (poorly) over the subsequent 3 to 12 months. Rouwenhorst (1998) demonstrated that momentum strategies can be profitable in the European market as well.

Anomaly of Momentum can be explained by under reaction to information which is well documented in several studies. Chan, Jegadeesh and Lakonishok (1996) showed that stock prices respond gradually to earnings news and that a substantial portion of the momentum effect is concentrated around subsequent earnings announcements. Hong, Lim and Stein (1999) using their analysis showed that under reaction of stock prices depends on analyst coverage, which is pronounced with bad news. Another probable reasoning of momentum phenomena comes from herding bias where investors tend to act with the masses (Ariely 2010). The herding behavior is well documented in the book by James Montier (2005) „Behavioural Investing: A Practitioner’s Guide to Applying Behavioural Finance “where he concludes that many retail investors purchase stocks based on their past returns, namely by buying past “winners”, and that even investment funds tend to follow the tendency of buying those stocks which performed well in recent past.

Thus momentum has already a big coverage and is quite popular issue in investment literature. However still majority of studies concentrate on research of momentum inside of one particular asset class (like stocks or bonds) therefore in this article concept of momentum will be used as strategic vehicle in building portfolios where combined positions of more than one asset class could be chosen. In this paper classical model will be expanded to more broad all asset class portfolio. Our primary goal for this article is to explore whether in combination of all asset classes (stocks, bonds, real estate sector, commodities and gold) it is possible to achieve better than passive-portfolio growth rates and evaluate if it can be generated with better risk/return ratios.

3. Data, Rules Specifications and Methodology

This paper is focused on a popular behavioral finance practical application used in building investment strategies – Momentum, and it's ability to act as alpha generating method in portfolios which include all main asset classes: stocks, bonds, real estate, commodities and gold. In this study we differentiate gold from commodities since these days more and more investors are looking for an alternative asset class to paper money and gold seen as most popular candidate for this role. So, in periods of possible inflationary breakout or economic/political volatility part of investment capital can be allocated to gold (Shayne 2010; Faber and Richardson, 2009).

We used monthly data series (closing prices for the month; provided by Bloomberg, MSCI Barra and NAREIT) and operated with following indices (used periods are shown in brackets):

Global stocks:

From 1976/01 to 2001/10 - MSCI World Developed Markets Index; from 2001/10 to 2014/02 MSCI World All Country Index.

Bonds:

The Barclays Capital Aggregate Bond Index (1976/01-2014/02).

Real Estate:

FTSE NAREIT Index (1976/01-2014/02).

Commodities:

S&P GSCI (Goldman Sachs Commodity Index) Total Return Index (1976/01-2014/02).

Gold:

Gold Spot Index (1976/01-2014/02).

As for a first step in our analysis for every asset class we will calculate various Momentum M variants using the following formula:

$$M(x) = \frac{P}{P_x} \quad (1)$$

where P is the last price of asset class index; P_x is the price of asset class index x months ago (last trading day of that month). In our analysis following Momentum variants will be analyzed: 1, 3, 6, 9, 12 (months) and a combination of 1+3+6+9+12 (we will note it as mix). It will be marked as M(1), M(3), M(6), M(9), M(12), M(mix).

Momentum can be considered as a trend indicator so the main rule (method) of it's usage is very intuitive – hold those assets (or asset classes) in investment portfolio only which have highest Momentum rating(s) (Faber and Richardson, 2009)

In this paper using various Momentum variations (M(1), M(3), M(9), M(12) and M(mix) series of portfolios that will hold only TOP 1, TOP 2, TOP 3 and TOP 4 (out of 5) asset classes will be constructed. All portfolios will consist of equal proportions (e.g. TOP 2 portfolio will consist of 50% of highest momentum asset class and 50% of second highest asset class; in TOP 3 portfolio all asset classes will take 1/3 of the overall portfolio and so on) and will be rebalanced on monthly basis. In order to properly evaluate profitability of Momentum in our study we will calculate most popular profitability indicator Compounded Annual Growth Rate (CAGR). As for the evaluation of risk we will calculate standard deviations (annualized) and Maximum Drawdown (MDD) measures for these portfolios.

While standard deviation (SD) is well-known and broadly used volatility/risk measure, exploring portfolio construction from the behavioral finance perspective it is also beneficiary to take into account MDD measure (Montier 2007) The definition of MDD is very intuitive.

Let the $P(t)$ be price of a given index at period t and $P_{\max}(t)$ the overall maximum of all prices up to this point in time:

$$P_{\max}(t) = \max_{\tau \leq t} P(\tau) \quad (2)$$

The MDD evaluated at time T is then defined as:

$$MDD = MDD(T) = \max_{t \leq T} \{P(t) / P_{\max}(t) - 1\} \quad (3)$$

The MDD is simply the loss suffered when the position is opened at a local price maximum, and sold at the next local minimum. The main idea behind adding MDD to our analysis is that by analyzing and considering methods that might have potential in helping managing maximum drawdowns, investors could avoid such irrational behaviour (Pompian 2006).

Finally, when all risk and return measures are calculated we will compare it to passive all-asset-class portfolio (our benchmark) where all asset classes (stocks, bonds, real estate, commodities and gold) have equal weights (each 20%) and are rebalanced on monthly basis. To evaluate the significance of these results we will use Welch's t test:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}, \quad (4)$$

Where:

\bar{X}_1 sample mean

s_i^2 sample variance

N_1 sample size.

The degrees of freedom v associated with this variance estimation is approximated using the Welch-Satterthwaite equation:

$$v = \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)^2}{\frac{\frac{s_1^4}{N_1^2 v_1} + \frac{s_2^4}{N_2^2 v_2}}{\frac{s_1^4}{N_1^2 (N_1 - 1)} + \frac{s_2^4}{N_2^2 (N_2 - 1)}}} \quad (5)$$

Here $v_i = N_i - 1$, the degrees of freedom associated with the i^{th} variance estimate.

4. Analysis

In this section we perform analysis of obtained test results and discuss their meaning and significance. Before going into details of momentum portfolios we make a quick review of our benchmark which is a passive all-asset-class portfolio where all asset classes (stocks, bonds, real estate, commodities and gold) have equal weights (each 20%) and are rebalanced on monthly basis.

Table 1. Risk and Return measures of all assets equal weighted passive portfolio

1976/01-2014/02	All assets equal weighted passive portfolio (benchmark)
CAGR	9.03%
Standard deviation (STDEV)	9.59%
Max Drawdown (MDD)	-38.79%
CAGR/STDEV	0.94
CAGR/MDD	0.23

Table 1 shows that in period of 1976/01-2014/02 such equal weighted portfolio generated 9.03% compounded annual growth rate (CAGR) with the maximum drawdown from peak to the bottom equal to -38.79% where annual standard deviation (STDEV) was 9.59%. This leads us to 0.94 CAGR/STDEV and 0.23 CAGR/MDD risk return ratios. In our tests these measures will be compared to momentum generated portfolios' parameters.

4.1. TOP 1 Asset Class Momentum Portfolios

Our first series of portfolios consist of only one highest momentum asset class (TOP 1 asset class momentum portfolio)

Table 2. Risk and Return measures of TOP 1 momentum portfolios [1976/01-2014/02]

TOP 1 momentum portfolios						
	M(1)	M(3)	M(6)	M(9)	M(12)	M(mix)
CAGR	10.2%	7.6%	9.8%	11.2%	15.1%	12.5%
Standard deviation (STDEV)	17.6%	18.7%	18.7%	19.4%	19.2%	19.4%
Max Drawdown (MDD)	-32.2%	-46.6%	-45.3%	-39.8%	-39.8%	-39.8%
CAGR/STDEV	0.58	0.41	0.52	0.58	0.79	0.64
CAGR/MDD	0.32	0.16	0.22	0.28	0.38	0.31

Table 2 presents that strategy where holding only one asset class with the highest momentum leads to noticeably increased profitability (only M(3) portfolio generated lower than 9.03% CAGR). These higher returns can be explained in higher standard deviations although MDD on average was very similar to our benchmark. By looking into our risk/return ratios we see that TOP 1 asset class momentum portfolios generated slightly higher CAGR/MDD ratios, but, on the other hand, CAGR/STDEV parameters decreased.

4.2. TOP 2 Asset Class Momentum Portfolios

Next we explore TOP 2 momentum portfolios' results where we hold only 2 highest momentum asset classes (50% each) and rebalance it on monthly basis (table 3).

Table 3. Risk and Return measures of TOP 2 momentum portfolios [1976/01-2014/02]

TOP 2 momentum portfolios						
	M(1)	M(3)	M(6)	M(9)	M(12)	M(mix)
CAGR	12.0%	12.5%	13.1%	14.9%	14.9%	14.3%
Standard deviation (STDEV)	12.6%	12.5%	12.8%	13.2%	13.2%	12.6%
Max Drawdown (MDD)	-28.6%	-30.2%	-29.3%	-37.5%	-36.7%	-27.5%
CAGR/STDEV	0.95	1.00	1.02	1.13	1.13	1.14
CAGR/MDD	0.42	0.41	0.45	0.40	0.41	0.52

Table 3 reveals that holding two asset classes with the highest momentum leads to significantly increased profitability with all variants (relative to benchmark 9.03% CAGR). These higher returns outpace slight increase in standard deviations and MDD on average were even lower than in our benchmark. Therefore we could conclude that in our case holding TOP 2 asset classes theoretically can not only increase profitability but also achieve it with relatively better risk/return ratios.

4.3. TOP 3 Asset Class Momentum Portfolios

The results of third portfolio series where every month three highest momentum asset classes (equal weightings in portfolio) are chosen are presented in table 4.

Table 4. Risk and Return measures of TOP 3 momentum portfolios [1976/01-2014/02]

TOP 3 momentum portfolios						
	M(1)	M(3)	M(6)	M(9)	M(12)	M(mix)
CAGR	12.6%	11.8%	11.8%	12.7%	12.7%	13.2%
Standard deviation	10.7%	12.4%	10.4%	11.3%	10.9%	10.5%
Max Drawdown	-26.9%	-	-	-	-31.1%	-26.9%

CAGR/STDEV	1.17	0.95	1.13	1.12	1.17	1.25
CAGR/MDD	0.47	0.44	0.44	0.37	0.41	0.49

Results from table 4 could lead to a conclusion that addition of one extra asset class in our momentum portfolio (in comparison to TOP 2 momentum portfolio) slightly decreases profitability but, because of lower standard deviations, increases overall risk/return ratios. It could be mentioned that CAGR/STDEV ratio of 1.25 is very rear in practice where ratio of 1 (in two digits annual growth rate area) is considered a very good performance even for the best in class asset managers.

4.4. TOP 4 Asset Class Momentum Portfolios

Our last series of portfolios consist of TOP 4 asset classes (out of 5 overall choices in our study). Every month we allocate 25% of portfolio funds to each of 4 highest momentum assets. Results are presented in table 5.

Table 5. Risk and Return measures of TOP 4 momentum portfolios [1976/01-2014/02]

TOP4 momentum portfolios						
	M(1)	M(3)	M(6)	M(9)	M(12)	M(mix)
CAGR	10.1%	9.7%	10.0%	10.6%	10.5%	10.8%
Standard deviation	10.0%	9.7%	10.0%	10.2%	10.2%	10.0%
Max Drawdown	-37.1%	-	-	-	-39.4%	-37.2%
CAGR/STDEV	1.01	1.00	1.00	1.05	1.03	1.08
CAGR/MDD	0.27	0.26	0.28	0.30	0.27	0.29

As we could expect, increase of asset classes in the portfolio makes it more diversified and balanced thus profitability should suffer. This is the case in our results as well. We can see that compounded annual growth rates for all variants are still higher than our benchmark portfolio, but, in comparison to other portfolios in our study (TOP 1, 2 and 3), this portion generates lowest yields. However decreased profitability comes with better risk measures and overall, we still have small advantage in comparison to our benchmark portfolio.

4.5. Summary of Analysis Results

After examining each set of portfolios (TOP 1, 2, 3 and 4) we could conclude our findings with statistical significance tests. Analysis showed that using simple momentum rules for each asset class it is possible to generate a synergetic effects in constructing dynamic portfolios.

Pooled results of CAGR differences between momentum portfolios and our benchmark are presented in table 5.

Table 5. Difference of CAGR between analyzed momentum portfolios and all assets equal weighted passive portfolio (benchmark)

	M(1)	M(3)	M(6)	M(9)	M(12)	M(mix)
TOP 1	1.2%	-1.4%	0.8%	2.2%	6.1%**	3.4%*
TOP 2	3.0%*	3.4%**	4.1%**	5.9%**	5.9%**	5.3%**
TOP 3	3.6%**	2.9%**	2.8%**	3.7%**	3.6%**	4.1%**
TOP 4	1.0%*	0.7%	1.0%	1.6%**	1.4%**	1.8%**

* Difference is significant at the 0.05 level (p-value < 0.05; 2-tailed)

** Difference is significant at the 0.01 level (p-value < 0.01; 2-tailed)

Table 5 shows that all (except TOP 1 M(3) portfolio) variants of portfolios managed to outperform all assets equal weighted passive portfolio benchmark. Best results generated by TOP 2 and TOP 3 momentum portfolios where in some cases outperformance almost reached 6% (In table 5 see: TOP 2 M(9) and TOP 2 M(12)). Results of TOP 2 and TOP 3 portfolios are statistically significant because calculated p-values are at least lower than 0.05 (majority lower than 0.01). However lowest reliability is seen in TOP 1 portfolio where only M(12) and M(mix) reached level of significant different (p-value < 0.05).

Thus we could conclude that optimal portfolios when using momentum with 5 main asset classes (stocks, bonds, real estate, commodities and gold) can be constructed using TOP 2 and TOP 3 approaches. Using only TOP 1 highest momentum asset class results have high deviation and lack statistical significance. TOP 4 portfolios suffer from over-diversification hence generated benefits are also noticeably less significant.

5. Conclusion

Studies show that in periods when market conditions are strongly deviated from historical norms investors tend to act irrationally. Thus, systematic irrationality reduction could be very beneficial to both retail and professional investors. Therefore non-discretionary investment strategies with links to behavioural finance concepts should be explored. While standard deviation is one of the main risk measures used by academia, in this article we argue that maximum drawdown, from behavioral finance perspective, is also relevant and should be considered seriously. Consequently, in this paper as a risk measure maximum drawdown was used in tandem with standard deviation.

Investigation presented in this study thoroughly explores concept of Momentum investing which is popular in technical analysis (TA) field. Unlike most studies

about Momentum phenomenon, in this paper this concept is examined in broadened way where traditional stocks/bonds portfolio was enhanced with addition of real estate, commodities and gold. In order to evaluate if using simple Momentum measurement rules synergy effects can be achieved and higher than passive portfolio compounded annual growth rates could be generated we used various portfolio construction combinations. Then risk and return measures were calculated and statistical significance was evaluated.

Results of this study reveal that Momentum method, when used as a dynamic investment portfolio (reconfigured and rebalance monthly) vehicle, in comparison to passive benchmark portfolio, can increase compounded annual growth rates, where in some cases outperformance reached 6%. Study revealed that best portfolios with highest statistically significant outperformance and best risk/return ratios, when using momentum with 5 main asset classes (stocks, bonds, real estate, commodities and gold), should be constructed using TOP 2 and TOP 3 approach.

In summary we can conclude that findings of this study go in tandem with other articles where researchers found evidence of momentum phenomenon. While the puzzle of why such anomaly is still evident in main financial markets remains unsolved, possible explanations may be found in basic human behavior where greed and fear are among most influential factors. Deepening the understanding of those human behavior aspects might help improve current financial models.

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