

Analysis of the Factors Influencing Momentum Profits

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Abstract: In this paper, we provide further insight into the stock return momentum phenomena by investigating the sources of momentum profits. Applying statistical factor analysis, we identify the most important variables significantly affecting momentum profits: volatility and changes in the currency component of M1. We also document the periodic dynamics of momentum returns that is their inflation at quarter-, month- and year- ends and their deflation at quarter-, month- and year - beginnings.

Key words: momentum strategies, momentum effect, risk-adjusted criteria, factor models.

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1 Introduction

This paper analyzes and discusses the motivations of the profitability of momentum strategies in US market. In particular, we investigate and examine the factors that influence momentum profits. Doing so, we distinguish the main fundamental, macroeconomic and statistical variables which have an impact on momentum strategies based on optimal performance ratios (see Biglova, et al (2004b)).

Several empirical studies have shown that stocks with high returns over the past three to twelve months continue to perform well in future periods. Any momentum strategy is based on a mechanistic decision criterion for evaluating and ranking the stock performance. For example, Jagadeesh and Titman (1993) and Grundy and Martin (2001), use the cumulative return as criterion for ranking stocks into winner and loser portfolios. Alternatively to these analyses we apply performance ratios in the ranking process as shown by Biglova et al. (2004b). Since abnormal returns can be considered only if we assume that return distributions present heavy tails, the ranking criteria should consider the possibility that the return could have infinite variance. Therefore, our strategies use the performance ratios introduced in Biglova, et al (2004a), that are also applicable in the case of stable distributed returns (with finite mean) as criteria for constructing winner and loser portfolios. On the other hand, the existence of momentum strategies, based on the Rachev performance ratio have been empirically proved (see Biglova et al. (2004b)).

The contrasting interpretations of the possible causes of momentum effect have generated a heated debate in the recent literature (see Jagadeesh and Titman (1993), Rouwenhorst (1998) Griffin, et al. (2003)). A first justification given by Kahneman and Tversky (1982) and De Bondt and Thaler (1985) was based on market participants overreaction to information. However, Jegadeesh and Titman (1993) and others have shown that this motivation is insufficient to justify properly the higher returns achieved in momentum strategies. Moreover neither Fama and French (1996) or Chordia and Shivakumar (2002) multi-factor models (used to mimick portfolio returns), or the conditional CAPM (see Lewellen and Nagel (2004)) could explain the abnormal momentum returns.

In this paper, we investigate the major sources of momentum profits. Therefore first we determine the momentum profits with the Rachev ratio performance criterion applied at the components of the S&P500. To test which factors influence momentum profits, we examine the factors of the spread of the winner and loser portfolios. In particular we try to identify how momentum returns are related to fundamental, country-specific macroeconomic, and statistic factors. Finally we interpret those factors that better explain abnormal returns.

The remainder of the paper is organized as follows: Section 2 provides a brief description of the data and methodology and examines the profitability of momentum strategies. Section 3 provides an analysis of factors, that have an influence on momentum profits and Section 4 concludes the paper.

2 Algorithm of Momentum Strategies

In momentum strategies, there are the following three main decision steps (1) the length of the ranking or formation period, (2) the length of the holding or investment period, and (3) the ranking criterion. The strategy consists in selling losers and buying winners assets at the end of the ranking period and assessing their performance over the holding period. Biglova et al. (2004b) have shown that we obtain optimal length of the ranking period and holding period with “6-month/6-month” momentum strategy (also defined 6/6 strategy). This strategy involves evaluating returns over the past 6-months and holding the position for the next 6 months. Thus we first determine winners and losers based on prior returns in the ranking period, then the zero-investment, self-financing strategy generates momentum profits in the holding period. In particular, Bris et al. (2004) have shown that such zero-investment strategy is applicable in international equity investment management practice.

2.1 Description of the Data and Methodology

Usually in the momentum strategies literature, the stocks are ranked in ascending order. “Winners” are those stocks with the top 10% ranking-period returns and “losers” are those stocks with the lowest 10% ranking-period returns. Optimal winner and loser portfolios at formation are constructed and held for 6 months (the holding period). During the holding period, these portfolios are not rebalanced.

We consider all the stocks included in the S&P500 index over the 12-year time period from January 1992 to December 2003. Over that time period, there were more than 800 companies included in the index. However, we apply momentum strategies only on those companies that had a complete return history (3,026 observations). Therefore we have not included many of the components of the S&P500 index since they have shorter historical series with unequal histories. For the risk-free asset, we use daily observations of the one-month London interbank offered rate (US\$ Libor). We use daily log returns $r_t^i = \ln((S_t^i + D_{[t-1,t]}^i)/S_{t-1}^i)$ $i=0, \dots, N$; $t=1, \dots, T$ where S_t^i is the i -th stock price at time t , $D_{[t-1,t]}^i$ is the dividend on i -th asset during the period $[t-1, t]$, and r_t^0 is the risk-free log return valued at time t . Our procedure for implementation of momentum strategy is briefly summarized here below.

Step 1. Consider the matrix of excess returns $ER = [a_{i,j}]$ where $a_{i,j} = r_t^j - r_t^i$ is the i -th observation of the excess return ($i=1, \dots, T$ observations) on the j -th asset ($j=1, \dots, N$ assets)

Step 2. Divide the data into sub-periods equal to the length of the formation period. Compute the ranking ratio for each stock based on observations in this period and rank the stocks. The 10% of stocks with the highest ratio values will constitute winner portfolio, and the 10% stocks with the lowest ratio will form the loser portfolio.

Step 3. Form the zero-investment portfolios of winners and losers at the end of each formation period of 6-months (taking a long position in the winner top

decile portfolio and a short position in the bottom loser decile portfolio).

Step 4. Evaluate the performance of the winner and loser portfolios and of the zero-cost strategy at the end of each holding period taking into account the transaction costs.

2.2 Risk-Adjusted Criteria for Stock Ranking

In constructing a momentum portfolio, first we have to specify the criteria for forming a winner and loser portfolios. In previous studies the winners were those stocks with the highest past cumulative monthly returns over some ranking period (e.g., six-month monthly return for the six-month ranking period). Clearly this selection criterion does not consider the riskiness and the distributional behavior of the stock in the ranking period. Since abnormal returns can be considered only assuming heavy tailed return distributions, it would be more appropriate to develop a selection criterion applicable to non-Gaussian distributed asset returns. For example, stable non Gaussian distributions are fat-tailed and they do not admit finite variance even if they satisfy many of the properties of a Gaussian law. Moreover, stable distributions have been used to model both the unconditional and conditional returns, as well as theoretical framework of portfolio theory and market equilibrium models (see Rachev (2003)).

2.2.1 Alternative Risk Measures and Risk-Return Ratios

In the last years, several alternative measures have been proposed and used in portfolio theory to capture non-normality of asset returns (see Rachev et al (2008a) and the reference therein). Among these we recall a coherent risk measure, called Expected Tail Loss (ETL), also known as Total Value at Risk, Expected Shortfall, Conditional Value-at-Risk (CVaR) , is defined as

$$ETL_{\alpha}(X) = \frac{1}{\alpha} \int_0^{\alpha} VaR_q(X) dq,$$

where $VaR_q(X) = -F_X^{-1}(q) = -\inf \{x | P(X \leq x) > q\}$ is the Value-at-Risk (VaR) of the random return X . If we assume a continuous distribution for the probability law of X , then $ETL_{\alpha}(X) = -E(X | X \leq -VaR_{\alpha}(X))$ and thus, ETL can be interpreted as the average loss beyond VaR, see Rachev et al. (2008a). Expected tail loss conveys the information about the expected size of a loss exceeding VaR. For example, suppose that a portfolio's risk is calculated through the simulation. For 1,000 simulations and $\alpha = 0.95$, the portfolio's VaR would be the smallest of the 50 largest losses. The corresponding expected shortfall would be then estimated by the numerical average of these 50 largest losses.

These alternative risk-return performance measures can be used as criterion in forming momentum portfolios. One of these ratios is the Rachev ratio (denoted by R- ratio). This ratio with parameters α and β is defined as:

$$RR(\alpha, \beta) := RR_{(\alpha, \beta)}(r) := \frac{ETL_{\alpha 100\%}(r_f - r)}{ETL_{\beta 100\%}(r - r_f)},$$

where α and β are in $[0,1]$. Here, r denotes the return of a portfolio or asset over the given time horizon. The R-ratio is applied for different parameters α and β . The parameters α and β cover different significance levels of the right and left tail distribution, respectively. As observed by Rachev et al. (2008) investors that maximize the R-ratio prefer more than less and they are neither risk averse nor risk lover investors. The use of the R-ratio is largely justified by the investors behavior. As a matter of fact several empirical analyses have shown that investors who maximize this ratio increase their final wealth much more than using other performance ratios (see Biglova, et al (2004a)).

Biglova, et al (2004a) analyzed and compared the traditional Sharpe ratio (Sharpe (1994)) with alternative R-ratios for various parameter values that define different level of coverage of the tail of the distribution, demonstrating that statistical arbitrage approach based on alternative criterion generates more profitable momentum strategies than those based on the conventional cumulative or total return criterion. Results of that study are robust to transaction costs for both equal-weighted and optimized-weighted strategies. In particular, they find that empirically alternative R ratios outperform the cumulative return and the Sharpe ratio across all momentum strategies that they investigated, and measured by total realized return and independent performance measures over the observed period.

2.3 Optimization of Winner and Loser Portfolios Based on Risk-Return Criteria

Let us summarize our risk-adjusted criteria for construction of momentum strategies. First we identify winners and losers among the extreme deciles of stocks in S&P500 ordered with respect to the risk-return ratio measure. At any rebalancing time point , we solve two optimization problems where we still use the R-ratio as an objective function in the optimization. In particular, we maximize among the winners the R-ratio with α and β both equal to 0.05 and we minimize among the losers the same R-ratio. We choose these α and β since the empirical evidence has shown the possibility of momentum strategies for these values (see Biglova et al. (2004b)). Therefore, for any risk-return criterion, we can compute the optimal winner portfolio from the following optimization problem:

$$\begin{aligned} & \max_x RR_{(0.05, 0.05)}(x' r) \\ & \text{subject to} \\ & \sum_{i=1}^n x_i = 1; x_i \geq 0; i = 1, \dots, n \end{aligned} \tag{1}$$

and the following optimization problem to determine the loser portfolio:

$$\begin{aligned} & \min_x RR_{(0.05,0.05)}(x'r) \\ & \text{subject to} \\ & \sum_{i=1}^n x_i = 1; x_i \geq 0; i = 1, \dots, n \end{aligned} \tag{2}$$

where $x = (x_1, \dots, x_n)'$ represents portfolio weights in the winner and loser portfolios, respectively, and n is the number of stocks in winner or loser portfolio. Note that the constraint on positive weights is necessary since within the winner portfolio further short-selling is not plausible. The same holds for the loser portfolio.

By solving the two optimization problems above, we adjust the proportion of stocks in the winner and loser portfolio according to the obtained weights. We calculate the profits and the spread values between the winner portfolio and the loser portfolio for an optimized-weighted 6/6 strategy over the holding periods. We also take into account that the investor pays proportional transaction costs of 0.485% on the absolute difference of the changes of portfolio compositions (see Biglova et al. (2004b)). The sequence of the spread values (total 2865 observations: starting from observation on day 162 till observation on day 3026) is used as independent variable, which we intend to explain, in factor models described in Section 3.

3 Types of Factors influencing Momentum Profits and Their Estimation

Let us recall some basic facts on factor models (for more detailed information see Rachev et al (2008b)). In financial econometrics, the factors used in factor models can be divided into three categories: fundamental factors, macroeconomic factors, and statistical factors.

Macroeconomic factors are economic variables that would affect asset returns. In particular, macroeconomic variables are exogenous factors that influence the model variables but are not influenced by them. Among the macroeconomic variables we tested the following U.S. potential factors: exports, imports, inflation rate, currency component of M1, Industrial Production Index, S&P 500 dividend yield, corporate spread. Fundamental factors are variables that are derived from financial analysis and characterize the momentum strategy. As fundamental factors we used variables proxying for the effect of timing, the influence of volatility, and the influence of the market state. In contrast, the statistical factors are endogenous factors that should derive from the mathematical process. In particular, the statistical factors should be determined either with principal component analysis or with a factor analysis. These factors are hidden variables that can be seen as a linear combinations of all the variables and they often permit some important economic interpretations. Next, we describe how the various factors, that we obtain from an estimated factor model, influence momentum profits.

3.1 Fundamental factors: Influence of the effect of “timing” on momentum profits

In this subsection we employ a factor model to assess the effect of "timing" in momentum strategies.

It's well documented (see Haugen and Lakonishok (1988), Harris (1989), Musto (1997) Carhart et al. (2002) and the reference therein) that the “timing” could have an important influence on the amount of portfolio momentum strategy, in particular at year-end. The reasons are: the tax year change (see among other Roll (1983), Ritter (1983)), liquidity demands for the year end gifts and bonuses, capital requirements applied to year end portfolios (see Keim (1983), Roll (1983)). In particular, Harris (1989) finds that transactions prices systematically rise at the close and the effect is stronger for low-priced firms at month-ends. In order to identify the main fundamental “timing” factors that influence the momentum profits, we primarily analyze returns' behaviour over calendar years. The second target is investigating returns' behaviour over quarters, given their prominence in the press (e.g., the Wall Street Journal's quarterly pull-out section), in shareholder reports (e.g., the quarterly mailings to pension-plan participants), and elsewhere.

We test the year-end, quarter-end, and month-end patterns with simple dummy variable regressions. If momentum returns are inflated at quarter- and year- ends, we should observe abnormally high returns on the last day of each quarter and year, and abnormally low returns on the first day.

Let R_t be daily return of the spread. We run the following OLS-indicator-variable regression:

$$R_t = b_0 + b_1YEND_t + b_2YBEG_t + b_3QEND_t + b_4QBEG_t + b_5MEND_t + b_6MBEG_t + b_7WEND_t + b_8WBEG_t + e_t \quad (3)$$

where YEND is 1 when t is the last day of a year, and zero otherwise, YBEG is 1 when t is the first trading day of the year, and zero otherwise, QEND is 1 when t is the last of a calendar quarter other than the fourth, and zero otherwise, QBEG $_t$ is 1 when t is the first of a calendar quarter other than the first, and zero otherwise, MEND is 1 when t is the last of a month but not the last of quarter, and zero otherwise, MBEG is 1 when t is the first of a month but not the first of a quarter, and zero otherwise, WEND takes value of one when t is the last of a week but not the last of month, and zero otherwise, WBEG takes value of one when t is the first of a week but not the first of a month, and zero otherwise.

From the Table I it follows that the results indicate a strong two-day return reversal pattern across month-end, quarter-end, and year-end periods. The results are statistically significant at the 5% percent level.

The results are strongest for quarter- and year- ends: the coefficient b_1 has the largest estimated value of the coefficients while b_2 has the smallest estimated value. This suggests that investors should buy stocks on the second-to-last day of each year and sell the next day. If we use the strategy for a one-year holding

**Table I Winner minus Loser Momentum Returns around
year-, quarter-, month-, week- ends**

Coefficients of the Model 3.1								
beta0	beta1	beta2	beta3	beta4	beta5	beta6	beta7	beta8
0.0005	0.0160	-0.0089	-0.0026	0.0021	0.0010	-0.0005	0.0001	0.0005
Additional Statistics								
R-square statistic			F statistic		p value for the full model		Variance error	
0.0057			2.0628		0.0361		0.0003	

This Table reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. Additional statistics, indicating model's statistical significance are also presented: the R-square statistic (the R-square value is one minus the ratio of the error sum of squares to the total sum of squares), the F-statistic (Fisher criterion for the hypothesis test that all the regression coefficients are zero), p value for the full model, and an estimate of the error variance.

period, these results suggest that investors should rebalance their portfolios at the end of the year. The same situation is for the strategy with one month-holding period. Coefficient b5 the great value compared to other betas, and the coefficient b6 has the small value compared to other betas. It seems that they must be buying at the end of the month and selling soon after. The R-Square is 0.0057 indicating the model accounts for over 95% of the variability in the observations. The F statistic of about 2.06 and its p-value of 0.0361 indicate that it is highly unlikely that all of the regression coefficients are zero, and therefore the model is statistically significant.

To test whether the reversal pattern is significantly more intense at quarter-ends than at other month-ends, we rerun the nine regressions with the variables regrouped so that the second and third coefficients pick the marginal effect of being a quarter-end (including year end) in addition to being a month-end:

$$R_t = b_0 + b_1(YEND_t + QEND_t) + b_2(YBEG_t + QBEG_t) + b_3(YEND_t + QEND_t + MEND_t) + b_4(YBEG_t + QBEG_t + MBEG_t) + e_t \quad (4)$$

The results, in Table II, are statistically insignificant; therefore we don't analyze this model in detail. For our purpose, it is clear that year-, quarter-end momentum profits are inflated in that rebalancing of the portfolio at these periods delivers profits.

Table II Vector B of regression coefficients in the linear model $Y = X*B$

Coefficients of the Model 3.2				
beta0	beta1	beta2	beta3	beta4
0.0006	0.0012	-0.00008	0.0009	-0.0005
Additional Statistics				
R-square statistic	F statistic	p value for the full model	Variance error	
0.0004	0.3178	0.8661	0.00027	

This Table reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. Additional statistics, indicating model's statistical significance are also presented: the R-square statistic (coefficient of Multiple Determination is one minus the ratio of the error sum of squares to the total sum of squares), the F-statistic (Fisher criterion for the hypothesis test that all the regression coefficients are zero), p value for the full model, and an estimate of the error variance. According to F statistic and p value, this model is statistically insignificant.

3.2 Fundamental factors: Influence of the volatility on momentum profits

Financial markets sometimes appear quite calm and at other times highly volatile. Describing how this volatility changes over time is important and it can also influence momentum profits.

In this section we value with a factor model the influence of the volatility and statistical measures on "momentum effect". We consider here two cases. In Case 1 we compute the risk measures based on spread Data. In Case 2 we calculate the statistical measures for equally weighted portfolio (EVP) of all stocks, included in S&P500 index.

Let us denote the spread (winner-loser). As independent variables here we use the R-Ratio, Standard deviation and MAD (Mean-Absolute-Deviation).

OLS-indicator-variable regressions, we use, have the following forms:

$$R_t = \lambda_0 + \lambda_1(nominator_of_R_Ratio)_t + \lambda_2(denominator_of_R_Ratio)_t + e_t$$

$$R_t = \alpha_0 + \alpha_1(STD)_t + e_t$$

$$R_t = \gamma_0 + \gamma_1(MAD)_t + e_t$$

where $MAD(r - r_f) = E|r - r_f - E(r - r_f)|$ and STD is the standard deviation of momentum profits. Moreover, $((de)nominator_of_R_Ratio)_t$, $(STD)_t$, and

$(MAD)_t$ are calculated based on previous month's observations (22 observations) of momentum profits and for different values of the α and β R-Ratio parameters.

In Table III we check the hypothesis that all regression coefficients are zero. p value is very low for all of the cases, it means that the chance to have all coefficients zero is insignificant. The R-square value is one minus the ratio of the error sum of squares to the total sum of squares and very low for all of the cases. It means that the model explains the main part of the momentum returns' variance. Moreover, we can give the right interpretation of the statistical measures on the spread (case 1). As a matter of fact, volatility of the spread tends to decline the as momentum profits rises and it tends to increase as the stock market falls.

3.3 Fundamental factors: Influence of the state of economy on momentum profits

In this section we value the influence of the state of economy on "momentum effect". We first assume that the market follows a two states Markov Chain. Then we test the dependence of the momentum profits with being in a bull/bear market.

We consider two cases. In case 1 we use equally weighted portfolio (EWP) of all stocks components of the S&P500 to define the state of the market. In case 2 we use the spread between the winner and loser returns to define the state of the market.

Case 1: If the difference of returns of the equally weighted portfolio $r_t - r_{t-1}$ takes positive value, it means that there is bull-market at time t , if it takes negative value, we are in bear-market at time t . We analyze a total of 2864 equally weighted portfolio returns, except the data of the first ranking period.

Case 2: If the difference between the spread at time t and the spread at time $(t-1)$ $r_t - r_{t-1}$ takes positive value, it means that there is bull-market at time t , if it takes negative value, we are in bear-market at time t . We analyze a total of 2864 values of spread except the first ranking period.

Markov Chain: Assume, furthermore, that, at time t , the market is in state $s_t = j$ with probability $\lambda_{t,j}$, i.e.,

$$\Pr(s_t = j) = \lambda_{t,j}.$$

We assume that there are 2 states of the market (e.g., bull and bear). Thus, assume that the states of the market are generated by a Markov chain with 2 dimensional state space and transition matrix, where an element (i,j) is the probability of transition from state i to state j):

$$\begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}$$

**Table III Coefficients and statistics of the model
Influence of volatility on momentum profits of the next day**

Risk measures	Case 1 (spread)			Case 2(Equally weighted)		
	<i>coefficients</i>	<i>Intervals of coefficients</i>		<i>coefficients</i>	<i>Intervals of coefficients</i>	
R-Ratio(0.3,0.4)						
Lambda0	0,0012	-0,0002	0,0027	0,0000	-0,0009	0,0009
Lambda1	-0,0156	-0,0955	0,0644	-0,0017	-0,0881	0,0846
Lambda2	-0,0252	-0,1215	0,0711	0,0961	0,0018	0,1904
R-square statistic	0,0003			0,0022		
variance error	0,0003			0,0001		
R-Ratio(0.5,0.5)						
Lambda0	0,0013	-0,0002	0,0027	0,0000	-0,0009	0,0008
Lambda1	-0,0341	-0,1404	0,0721	0,0091	-0,1027	0,1208
Lambda2	-0,0224	-0,1279	0,0832	0,1092	0,0126	0,2058
R-square statistic	0,0003			0,0024		
variance error	0,0003			0,0001		
R-Ratio(0.1,0.1)						
Lambda0	0,0011	-0,0002	0,0024	0,0000	-0,0009	0,0008
Lambda1	0,0107	-0,0378	0,0591	0,0081	-0,0508	0,0670
Lambda2	-0,0325	-0,0877	0,0226	0,0446	-0,0153	0,1046
R-square statistic	0,0005			0,0016		
variance error	0,0003			0,0001		
STD						
Alpha0	0,0011	-0,0003	0,0024	0,0009	0,0002	0,0017
Alpha1	-0,0269	-0,1061	0,0523	0,0000	0,0000	0,0000
R-square statistic	0,0002			0,0001		
variance error	0,0003			0,0001		
MAD						
Gamma0	0,0012	-0,0002	0,0026	-0,0002	-0,0010	0,0007
Gamma1	-0,0494	-0,1662	0,0674	0,1266	0,0202	0,2330
R-square statistic	0,0002			0,0019		
variance error	0,0003			0,0001		

Table III reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. For each coefficient we give the confidence interval. Additional Statistics, indicating model's statistical significance are also presented: the R-square statistic (coefficient of Multiple Determination), and an estimate of the error variance.

where

$p = \Pr(\text{bull market next period} / \text{bull market today}) = \Pr(s_{t+1} = 1 | s_t = 1)$;

and, similarly,

$q = \Pr(\text{bear market next period} / \text{bear market today}) = \Pr(s_{t+1} = 2 | s_t = 2)$.

Table IV reports the transition matrix. According to the results, for *case 1*:

$p = \Pr(\text{bull market next period} / \text{bull market today}) = \Pr(s_{t+1} = 1 | s_t = 1) = 0,38706$;

and, similarly,

$q = \Pr(\text{bear market next period} / \text{bear market today}) = \Pr(s_{t+1} = 2 | s_t = 2) = 0,33218$.

For *case 2*:

$p = \Pr(\text{bull market next period} / \text{bull market today}) = \Pr(s_{t+1} = 1 | s_t = 1) = 0,33823$;

and, similarly,

$q = \Pr(\text{bear market next period} / \text{bear market today}) = \Pr(s_{t+1} = 2 | s_t = 2) = 0,33799$.

From Table IV we can't say that the state of the market in the next period(s) were predictable from current and past observations as the hypothesis of effective market consider. For example, the probability of being in a bull market next period may depend on the current state of the market. It is usually higher when we are currently in a bull market also. But our results show that the probability of being in a bull market next period is higher when we are currently in a bear market.

Fundamental factor analysis for bull market: In order to test the dependence of momentum profits on the hypothesis of being in a bull market (for both cases), we use OLS-indicator-variable regressions, with the following form:

$$R_t = \lambda_0 + \lambda_1(Var1)_t + e_t$$

Daily returns on each portfolio (winner and loser portfolios) are calculated and the dependent variable is the winner return minus loser return (total 2864 observations excepting the first ranking period). As independent variables we use a variable $(Var1)_t$ that takes value of 1 if we have the bull-market at time t , and zero otherwise. (We could also consider another variable Var2 that takes value of 1 if we have the bear-market at time t , and zero otherwise, but clearly this variable is linear dependent with Var1, since $Var2 = 1 - Var1$). Therefore we test here, whether the state of the market has an explanatory power for the momentum profit on the next day and the results are reported in Table IV.

The hypothesis that regression coefficients are zero is rejected for the one factor model in the case we use equally weighted portfolio of all stocks components of the S&P500 to define the bull state of the market. We do not get analogous result when we use the spread to identify the bull market. As a matter of fact, the p-value in case 2 is more than 14% and also statistic F is much lower than the value obtained with case 1. The R-square value is one minus the ratio of the error sum of squares to the total sum of squares and equal to 0.0013 and 0.0007.

Table IV Vector of regression coefficients in the linear model, estimated transition matrices and an additional statistics

	Case 1 (Equally weighted)	Case2 (Spread)
λ_0	0.0001	0.0011
λ_1	0.0012	-0.0009
Estimated transition matrices	$\begin{pmatrix} 0.3870 & 0.6129 \\ 0.6678 & 0.3321 \end{pmatrix}$	$\begin{pmatrix} 0.3382 & 0.6617 \\ 0.6620 & 0.3379 \end{pmatrix}$
R-square statistic	0.0013	0.0007
F-statistic	3.7291	2.1423
P value for the full model	0.0536	0.1434
an estimate of the error variance	0.0003	0.0003

Table IV reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described in Section 3.3. The estimated transition matrices and an additional Statistics, indicating Model's statistical significance is also presented: the R-square statistic (coefficient of Multiple Determination), the F-statistic (Fisher criterion for the hypothesis test that all the regression coefficients are zero), p value for the full model, and an estimate of the error variance.

It means that the model explains the most part of the momentum returns' variance, and therefore the influence of the other factors, which we didn't consider in this model is insignificant. Therefore the model is statistically significant for case 1.

3.4 Macroeconomic factors: Impact of Macroeconomic Variables on momentum profits

It's well known that macroeconomic variables affect security prices. The fundamental work of Fama (1986) has sparked considerable interest in studying the relation between stock markets and economic variables (see, among others, .Chen et.al. (1986)). In this section we investigate how momentum returns are related to country-specific macroeconomic factors for a sample of S&P500 data. We assume that momentum returns are described by a factor model and test, whether they can be predicted by independent. macroeconomic variables.

The macroeconomic data were obtained from COMPUSTAT over the 1992-2006 period. The set of macroeconomic variables includes exports, imports, inflation, Currency Component of M1, Industrial Production Index, Dividend yield of S&P 500 COMP LTD, corporate spread. We use returns series of macroeconomic data calculated using the following formula:

$$return_t = \ln(S_t/S_{t-1})$$

All macroeconomic data are obtained at the daily frequency since we analyze the data of momentum returns at this frequency. However we have monthly values of

Table V Summary statistics for macroeconomic variables

Variable	Mean	Standard Deviation	Minimum	Maximum
corporate spread	-0.0004	0.0050	-2.3269	2.3735
exports	0.0050	0.0004	-0.0591	0.0863
imports	0.0075	0.0003	-0.0497	0.0747
CPI (inflation)	0.0022	0.000007	-0.0080	0.0121
Currency Component of M1	0.0059	0.00003	-0.0120	0.0325
Industrial Production Index	0.0028	0.00002	-0.0132	0.0213
DIV (S&P 500 COMP-LTD)	0.0041	0.0948	-0.8713	0.8179
S&P 500 returns	0.0003	0.0055	-2.3747	2.3489

Table V summarizes statistics for returns of shares included in S&P 500, and for macroeconomic variables, the influence of which on momentum returns we analyze. The sample of shares includes total of 382 stocks traded on the American Stock Exchange during the period of January 1992 and December 2003. The sample of macroeconomic data covers the same period.

exports, imports, inflation, Currency Component of M1, Industrial Production Index, Dividend yield of S&P 500 COMP LTD from Federal Reserve Bank of St. Louis (Economic Research). Table V summarizes statistics for macroeconomic variables.

Since daily data are not available for the entire sample period, we interpolate monthly data into daily observations using simulating procedures based on estimated parameters of stable distribution for monthly returns.

Simulating of macroeconomic variables daily returns is based on three steps:

1. Estimation of the symmetric stable parameters of monthly returns, assuming that they are iid and symmetric.
2. Estimation of the symmetric stable parameters of daily returns α_{daily} , c_{daily} , $mean_{daily}$ using estimated parameters $\alpha_{monthly}$, $c_{monthly}$, $mean_{monthly}$ from the first step. We consider here 21 working days in a month and set:

$$\alpha_{daily} = \alpha_{monthly}; mean_{daily} = \frac{1}{n} mean_{monthly};$$

$$c_{daily} = n^{\frac{-1}{\alpha}} c_{monthly}$$

where α represents the index of stability for daily and monthly sequences of observations, c is the scale parameter, $mean$ is the location parameter for daily and monthly sequences of observations, and $n=21$ is the number of monthly observations.

3. Simulating 21 daily returns from symmetric alpha stable distribution with estimated parameters $(\alpha, c, mean)$ $x_1, \dots, x_{21}, x_{22}, \dots, x_{42}, \dots$, etc. We consider here two possible cases: the additive and the scale transformations, for rescaling the distribution to become for daily returns.

In the case of scale transformation we calculate first the sum $x_1 + \dots + x_{21}$ which will not be exactly the observed monthly value $m(1)$, but $x_1 + \dots + x_{21} = m(1)d_1 = D_1$. Then set $d_1 = \frac{D_1}{m(1)}$. In this case we use as daily returns the scaled values replacing x_i with x_i/d_1 . Important here is that for every monthly return $m(i)$ the normalizing constant d will be different, that is $d = d(m(i))$. In the case of additive transformation we calculate d_1 using the formula: $d_1 = \frac{m(1)-D_1}{21}$, and then replace x_i with $x_i + d_1$. Now the sum of the new shifted will sum to $m(1)$, but we will not change the extreme values so the index α of the new sequence of daily returns stay the same as the index α of the sequence of monthly returns. We have chosen the additive transformation to receive daily returns having monthly returns as in this case we received that parameter α is above 1 for daily returns and the mean is so small that it does not play role in the estimation process, even if it is slightly modified. In each period of time, t , the investor considers a set of 7 macroeconomic variables that may be useful for making a one-period-ahead forecast of momentum returns. In order to conduct this search over a large number of forecasting models in an efficient and timely manner, we used the ordinary least squares technique to estimate, in each period of time t , linear regression models of the following format:

$$R_t = \lambda_0 + \lambda_1 (exports)_t + \lambda_2 (imports)_t + \lambda_3 (inflation)_t + \lambda_4 (M1)_t + \lambda_5 (Ind_Prod_Index)_t + \lambda_6 (DIV)_t + \lambda_7 (Corp_spread)_t + e_t \quad (5)$$

where R_t denotes the variable of spread determined as the difference between winner and loser portfolios, and representing momentum returns, λ_i are factor loadings, indicating, how sensitive momentum returns are to its corresponding explanatory power, denoted in parenthesis, and e_{t+1} is the error term. Table VI represents vector of regression coefficients of the model.

Let us examine each of the variables in our regression. We have prior beliefs about the signs of the coefficients for some, but not all, of these variables.

Exports and imports : We expect that exports will have a positive coefficient, and imports will have a negative coefficient in our regression model. That is, when country's values of exports increase, there is a propensity for it's a stock prices increase in the world market. Similarly, when country's values of imports increase, the country may face with the bear tendency of its fond-market. In Table VI, we find, as expected, that momentum returns are significantly positive related to exports and significantly negative related to imports. Thus we can conclude that exports (imports) are associated with more (less) positive momentum profits.

Inflation: Inflation is defined as

Table VI Regression coefficients of the linear model and additional statistics

lambda 0	lambda 1	lambda 2	lambda 3	lambda 4	lambda 5	lambda 6	lambda 7
0.00057	0.44086	-0.2111	0.12556	0.43346	-0.52426	-0.00137	0.0003
R-square statistic				p value for the full model		an estimate of the error variance	
0.003				0.2749		0.00027	

Table VI reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. The additional statistics, indicating model's statistical significance is also presented: the R-square statistic (coefficient of Multiple Determination), p value for the full model, and an estimate of the error variance. We check the hypothesis that all regression coefficients are zero. p value is low, it means that the chance to have all coefficients zero is insignificant.

$$Inflation_t = \ln(CPI_t/CPI_{t-1}),$$

where CPI is a Consumption Price Index. According to the Fisher theory, if stocks provide a hedge against inflation, the relation between stock returns and inflation should be positive. Therefore, returns of optimal momentum strategies should be also positively correlated with Inflation rate. We find in Table VI, as it was expected, that inflation is positively related to momentum profits.

Currency Component of M1: We expect that M1 will have a positive coefficient in our regression model, as the growth of M1 means also the growth of inflation, which is positively correlated with the stock prices. We find in Table VI, as it was expected, that Currency Component M1 is positively related to momentum profits.

Industrial Production Index: We find in Table VI, that Industrial Production Index is negatively correlated with momentum returns.

Dividend yield of S&P 500 COMP LTD: This variable indicates the average dividend payments of S&P. We analyze momentum returns, constructed from the winner and loser portfolios of S&P shares. Our winner portfolio consists of the shares, which we have to buy, and our loser portfolio consists of the shares, which we have to sell at the moments of portfolio rebalancing. Therefore, it's very difficult to predict, whether dividend yield will have positive or negative correlation with momentum returns. We find in Table VI, that it's negatively correlated with momentum returns, but the coefficient of the regression is small enough to be treated as the noise.

Corporate spread: The corporate spread is the spread between the default able and default-free interest rate. Having series of 2-Year Treasury Constant Maturity Rate, 5-Year Treasury Constant Maturity Rate, 3-Year Treasury Constant Maturity Rate, and 3-Month Treasury Constant Maturity Rate we perform the PCA on them and find one factor, which explains most of them. We get one curve that represents most of the movements of the treasuries using Principal

Components Analysis. It is the first principal component. Then as corporate spread variable we use the difference between S&P 500 returns and this factor (the first principal component) indicating the behavior of Treasury Rates. On the other hand, Estrella and Mishkin (1998) find that the term spread (the long-term interest rate minus the short-term interest rate) is a good out-of-sample as well as in-sample predictor of recessions. In particular, they have shown there is a correspondence between a more positive term spread and a lower probability of recession, while a more negative term spread indicates a higher probability of recession. Thus we expect to see the same tendency for corporate spread also, and the positive correlation between the corporate spread and momentum profits.

As we can see from the coefficients of linear regression in Table VI, momentum returns inflate, if values of exports, inflation, currency component of M1, and corporate spread inflate and deflate, if value of imports, industrial production index, and dividends of S&P 500 COMP LTD inflate. These macroeconomic variables significantly affect momentum profits, and thus may be useful as predictors of momentum profits.

3.5 Fundamental and Macroeconomic factors: Impact of Fundamental and Macroeconomic Variables on momentum profits

In this Section we describe the model considering as the explanatory variables all fundamental and macroeconomic variables, described in previous Sections.

Let R_t be daily return of the spread, and run the following OLS-indicator-variable regression:

$$\begin{aligned}
R_t = & b_0 + b_1 YEND_t + b_2 YBEG_t + b_3 QEND_t + b_4 QBEG_t + b_5 MEND_t + \\
& + b_6 MBEG_t + b_7 WEND_t + b_8 WBEG_t + b_9 (nominator_of_R_Ratio)_t + \\
& + b_{10} (denominator_of_R_Ratio)_t + b_{11} (STD)_t + b_{12} (MAD)_t + b_{13} (Var1)_t + \\
& b_{14} (exports)_t + b_{15} (imports)_t + b_{16} (inflation)_t + b_{17} (M1)_t + \\
& + b_{18} (Ind_Prod_Index)_t + b_{19} (DIV)_t + b_{20} (Corp_spread)_t + e_t \quad (6)
\end{aligned}$$

Table VII represents vector of regression coefficients of the model and an additional statistics indicating Model's statistical significance. Obtained results confirm the results of previous Sections.

The hypothesis that all regression coefficients are zero is rejected, as follows from the value of the F statistic for 2841 and 20 factors. The p value is equal to 0.0149, and it means that the chance to have all coefficients zero is only 1.49%. The R-square value is one minus the ratio of the error sum of squares to the total sum of squares and equal to 0.0126. It means that the model doesn't explain only 1.26% of the momentum returns' variance, and therefore the influence of the other factors, which we didn't consider in this model is insignificant.

Table VII Regression coefficients of the linear model and additional statistics

beta 0	beta 1	beta 2	beta 3	beta 4	beta 5	beta 6	beta 7
0.0013	0.0187	-0.0088	-0.0031	0.0018	0.0012	-0.0006	0.00003
beta 8	beta 9	beta 10	beta 11	beta 12	beta 13	beta 14	beta 15
0.0003	-1.7557	-1.6811	3.1981	0.0779	0.0001	0.4833	-0.1726
beta 16	beta 17	beta 18	beta 19	beta 20			
0.0795	0.4922	-0.6311	-0.0012	-0.00012			
Additional Statistics							
R-square statistic		F statistic		p value for the full model		an estimate of the error variance	
0.0126		1.8112		0.0149		0.0002	

Table VII reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. The additional statistics, indicating model’s statistical significance are also presented: the R-square statistic (coefficient of Multiple Determination), the F-statistic (Fisher criterion for the hypothesis test that all the regression coefficients are zero), p value for the full model, and an estimate of the error variance.

3.6 Statistical Factors: Principal Components Analysis

In this section we investigate statistical factors, which are endogenous to the system and determined by principal component or factor analyses. We suppose that combinations of macroeconomic and fundamental variables, described in previous sections, form the statistical factors and estimate their influence on momentum profits. In such way we reduce the number of variables to analyze. For more detailed information according to the method of Principal Components (PCA) and Factor Analysis (FA) see Rachev et al.(2008b).

3.6.1 PCA for macroeconomic and fundamental factors

As independent variables (factors) we use here the following variables: variables, capturing effect of timing: YEND, YBEG, QEND, QBEG, MEND, MBEG, WEND, WBEG, variables, capturing the influence of volatility: nominator of R-RATIO denominator of R-RATIO, MAD STD, which are calculated based on previous month’s observations (22 observations) of momentum profits, variables, capturing the influence of the market state: VAR1, macroeconomic variables: EXPORTS, IMPORTS, INFLATION, CURRENCY COMPONENT OF M1, INDUSTRIAL PRODUCTION INDEX, DIVIDEND YIELD OF S&P 500 COMP LTD, CORPORATE SPREAD.

Let’s now proceed to perform PCA using the covariance matrix of variables. We have to compute the eigenvalues and the eigenvectors of the covariance matrix. The corresponding eigenvalue of eigenvectors is shown in Table VIII. Eigenvalues are listed in descending order; the corresponding eigenvectors go from left to right in the matrix of eigenvectors. Thus, the leftmost eigenvector

corresponds to the largest eigenvalue. The eigenvectors are normalized in the sense that the sum of the squares of each component is equal to 1. The sum of the squares of the elements in each column is equal to 1. If we form portfolios whose weights are the eigenvectors, we can form 20 portfolios that are orthogonal (i.e., uncorrelated). These orthogonal portfolios are called principal components. The variance of each principal component will be equal to the corresponding eigenvalue. Thus the first principal component (i.e., the portfolio corresponding to the first eigenvalue), will have the maximum possible variance and the last principal component (i.e., the portfolio corresponding to the last eigenvalue) will have the smallest variance. The 20 principal components thus obtained are linear combinations of the original series, $X = (X_1, \dots, X_N)'$ that is, they are obtained by multiplying X by the matrix of the eigenvectors. If the eigenvalues and the corresponding eigenvectors are all distinct, as it is the case in our illustration, we can apply the inverse transformation and recover the X as linear combinations of the principal components.

Table VIII shows also the total variance explained by a growing number of components. Thus, the first component explains 37.81% of the total variance, the first two components explain 64.31% of the total variance, 4 components explain 86% of the total variance, 8 components explain 98% of total variance, and so on. Now we can regress the dependent variable (the spread) with respect to the PCA factors with all 20 components, and receive the residuals processes for principal components. Then we fit PCA for residuals to see what is left from the systematic risk. Our results show, that we can use 10 principal components (9 of them were received in the first PCA analysis, one of them was received in the PCA analysis of residuals) to regress momentum profits.

3.7 Statistical Factors: Factor Analysis

Through principal components analysis we determined factors that explain most of the variance. In this section, we consider a factor analysis to determine the main statistical factors. See Rachev et al (2008b) for more detailed information.

Description of the algorithms and results: Consider the 20 time series and their 2865 observations, which were described in previous section. At first we have to compute the positive definite covariance matrix of initial data.

We have covariance matrix $C1$ (20x20) of our independent variables, which is strictly positive definite. Having calculated matrix $C1$ and supposing 8 factors we obtain maximum likelihood estimates of the factor loadings, $LAMBDA$, model with 8 factors. The (i,j)-th element of the 20-by-8 factor loadings matrix $LAMBDA$ is the estimated coefficient, or loading, of the jth factor for the ith variable. We calculate also maximum likelihood estimates of the specific variances in the 21-by-1 vector.

Table IX shows the factor loadings. Each row represents the loadings of the eight factors corresponding to each independent variable. The last column of the table shows the idiosyncratic variances.

The idiosyncratic variances are numbers between 0 and 1, where 0 means that the variance is completely explained by common factors and 1 that common

Table VIII Eigenvalues of the Covariance Matrix, and Percentage of the Total Variance Explained by a growing number of components based on the covariance matrix

Principal component	Eigenvalues of the Covariance Matrix	Percentage of variance explained	Percentage of total variance explained
P1	0.2497766256	37.8101294615	37.8101294615
P2	0.1750390363	26.4966692159	64.3067986775
P3	0.1143015042	17.3024784112	81.6092770887
P4	0.0315509332	4.7760468615	86.3853239502
P5	0.0291775816	4.4167789343	90.8021028844
P6	0.0240844090	3.6457959959	94.4478988803
P7	0.0119535440	1.8094769415	96.2573758219
P8	0.0115705633	1.7515029443	98.0088787662
P9	0.0052848687	0.8000010741	98.8088798403
P10	0.0038713418	0.5860273560	99.3949071962
P11	0.0038258707	0.5791441245	99.9740513207
P12	0.0001376654	0.0208392035	99.9948905243
P13	0.0000246788	0.0037357650	99.9986262893
P14	0.0000034206	0.0005177952	99.9991440845
P15	0.0000026583	0.0004023999	99.9995464844
P16	0.0000024769	0.0003749418	99.9999214262
P17	0.0000002326	0.0000352135	99.9999566397
P18	0.0000001852	0.0000280309	99.9999846706
P20	0.0000000302	0.0000045728	100.0000000000

Table IX A Factor Loadings and Idiosyncratic Variances

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Variance
<i>YEND</i>	-0.009338	-0.020519	-0.033579	-0.013775	-0.008253	-0.075705	-0.026133	0.019284	0.991151
<i>YBEG</i>	0.024226	-0.033802	-0.018359	-0.009530	-0.066951	-0.126668	0.030058	0.068763	0.977418
<i>QEND</i>	0.011794	-0.010967	-0.055297	-0.024185	-0.041929	0.039196	0.001103	0.025244	0.994308
<i>QBEG</i>	0.026761	-0.059329	-0.040552	-0.025478	-0.054331	0.034196	-0.062461	0.036916	0.989653
<i>MEND</i>	0.001823	-0.005822	-0.004831	0.996914	-0.001176	0.002759	-0.002901	0.001907	0.005000
<i>MBEG</i>	-0.029266	-0.091821	-0.038701	-0.038522	0.061959	0.026572	0.051729	-0.039145	0.985442
<i>WEND</i>	-0.000369	-0.009247	0.996714	-0.004940	-0.002410	0.001502	0.000069	0.033976	0.005000
<i>WBEG</i>	-0.000849	1.003606	-0.009228	-0.005728	0.002382	-0.000023	-0.000278	-0.108909	0.005000
<i>nominator of R-Ratio</i>	1.052038	0.000814	-0.002905	-0.000032	-0.230983	-0.010828	0.004321	-0.050045	0.005000
<i>denominator of R-Ratio</i>	0.243487	0.002200	-0.002159	-0.001081	0.866431	-0.005826	-0.003386	0.016695	0.005000
<i>MAD</i>	0.791471	0.001433	-0.002769	-0.001002	0.370343	-0.008415	0.001079	0.001113	0.005000
<i>STD</i>	0.947840	-0.003487	0.005621	0.003096	0.030727	0.018897	0.008682	0.358888	0.005000
<i>VarI</i>	-0.003698	-0.003178	0.000454	-0.008962	-0.021620	-0.034607	-0.021862	-0.003384	0.997909
<i>exports</i>	0.047187	0.022003	0.019950	-0.010567	-0.045633	0.009849	0.311761	0.030198	0.897241
<i>imports</i>	0.020750	-0.020497	-0.013330	-0.005991	0.042740	0.014218	0.332831	-0.020024	0.885416
<i>inflation</i>	-0.026972	0.000937	0.009580	0.017878	0.018976	-0.150489	0.086934	-0.041945	0.971634
<i>MI Currency Component</i>	-0.001434	-0.000750	0.001260	0.003223	-0.007393	0.790914	0.018139	0.079633	0.396793
<i>Industrial Production Index</i>	-0.058963	0.003274	-0.006017	0.015474	-0.025372	0.030086	0.278309	0.011978	0.918047
<i>Dividend yield of S&P 500 COMP LTD</i>	0.002918	-0.031758	0.001785	0.008777	0.018138	0.008910	-0.029552	-0.012870	0.997590
<i>corporate spread</i>	-0.010645	-0.010940	-0.039793	-0.005784	0.010896	-0.002456	0.044110	-0.001422	0.996488

Table IX presents the factor loadings. In bold we remark the highest absolute values for each factor.

factors fail explain variance.

From Table IX we can see that different factors influence momentum profits. Factors 1, 5 and 8 are associated with the influence of volatility, because loadings of MAD, STD, and R-Ratio are large for them, Factor 2, 3 and 4 indicate the influence of the “effect of timing”, factors 6 and 7 indicate the influence of the macroeconomic variables, mainly the influence of currency component M1 (factor 6) and the influence of the import, exports and industrial production (factor 7).

Let’s run the regression model for R_{t+1} - momentum returns, we intend to explain.

OLS-indicator-variable regression, has the following form:

$$R_{t+1} = b_0 + b_1(Factory1)_t + b_2(Factory2)_t + b_3(Factory3)_t + b_4(Factory4)_t +$$

Table X Vector B of regression coefficients in the linear model $Y = X*B$

beta0	beta1	beta2	beta3	beta4	beta5	beta6	beta7	beta8
0.001089	0.001394	-0.00269	0.001482	-0.00071	-0.03468	0.044082	-0.01072	-0.03387
R-square statistic					p value for the full model		an estimate of the error variance	
0.002260208					0.600857		0.000278	

Table X reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. The additional statistics, indicating model's statistical significance is also presented: the R-square statistic (coefficient of Multiple Determination), p value for the full model, and an estimate of the error variance. p value is equal to 0.60085, it means that the chance to have all coefficients zero is 60%. The R-square value is one minus the ratio of the error sum of squares to the total sum of squares and equal to 0.0023. It means that the Model explains the most part of the momentum returns' variance, and therefore the influence of the other factors, which we didn't consider in this Model is insignificant.

$$+b_5(Factor5)_t + b_6(Factor6)_t + b_7(Factor7)_t + b_8(Factor8)_t + e_{t+1}. \quad (7)$$

Table X shows that the most important influence on momentum profits have the factors 5, 6, 7 and 8. Factors 5 and 8 indicate the influence of volatility: momentum profits deflate, when volatility inflates and conversely. Factor 7 is linked with the macroeconomic factors: import, exports and industrial production. Factor 6 is associated with the influence of currency component M1: momentum profits deflate, when currency component M1 rises.

In order to improve the obtained results on this factor analysis we tested two methods of the stepwise regression: backward removal method and forward entry method, which provided the same results. Testing backward removal method we started with the whole model that includes all the 8 factors. At each step, after the initial step the removal criteria (p-value and R-square statistics) were computed for each factor to be removed from the model. Testing forward entry method, we started with the model included the regression intercept and one factor. At each step after the initial step the removal criteria were computed for each factor for entry in the model.

Results of the applications of this stepwise regression methodology are presented in Table XI.

Presented results confirm the most important influence of the volatility, "effect of timing" and the currency component's M1 changing on momentum returns.

Additional Statistics indicates model's statistical significance: p value is improved with respect to the previous factor analysis. The R-square value is one minus the ratio of the error sum of squares to the total sum of squares and equal to 0.002. It means that the model explains the most part of the momentum returns' variance, and therefore the influence of the other factors, which we didn't consider in this model is insignificant.

Table XI Vector B of regression coefficients in the linear model $Y = X*B$

beta0	beta1	beta2	beta3	beta4	beta5	beta6	beta7	beta8
0.001238	-0.01064	0.000906	0.000435	0	-0.015	0.038706	-0.01802	0
R-square statistic					p value for the full model		an estimate of the error variance	
0.002038					0.447587		0.000278	

Table XI reports coefficients (factor loadings), obtained by running OLS-indicator-variable regression, described above. These coefficients are obtained applying stepwise regression methodology. The additional statistics, indicating model's statistical significance is also presented: the R-square statistic (coefficient of Multiple Determination), p value for the full model, and an estimate of the error variance.

4 Conclusions

In this paper, we extend the momentum trading methodology and we analyze the main motivations of momentum effects. In particular, we use ratios based on the coherent risk measure of the expected shortfall to rank the risk-return profile of the individual stocks. These risk-return ratio criterion capture the distributional properties of stock returns at different threshold levels of the tail distribution. Furthermore, using the ratio criterion as the objective function in the portfolio optimization we propose an alternative methodology that optimizes weights in the winner and loser portfolios of momentum strategies. In order to analyze the source of momentum profits, we first tested the influence of several factors on momentum profits with the help of separate models. Then, we combined all factors in one model to see the "marginal" effect of a given explanatory variable.

We found that a set of fundamental, macroeconomic, and statistic variables significantly influence the momentum returns. We documented long-term yearly periodicity and intermediate-term quarterly and monthly periodicities of momentum returns, which inflate at quarter-, month- and year- ends and deflate at quarter-, month- and year - beginnings. From the analysis of volatility, it follows that as volatility rises, there is a propensity for the momentum profits to experience losses. Volatility tends to decline as the momentum profits rises and it tends to increase as the stock market falls. Analysis of the market state influence shows that momentum returns inflate, if the state of the market is bull and deflate, if the market is bear.

Our contribution to the literature on the macroeconomic determinants is twofold. First, we have found that several variables including exports, inflation, currency component of M1, corporate spread, imports, industrial production index, and dividends of S&P 500 COMP LTD, significantly influence on momentum returns.

Second, we employed a modeling approach to simulate daily data based on monthly sequences of initial returns. Such daily data set is not usually available

to an investor in real time. In the earlier literature, it has been common practice to use the monthly and year data set, but using daily data, in our opinion, can give us much more precise estimates.

To reduce a set of analyzed factors we used the Principal Component Analysis. PCA is interesting if in using only a small number of principal components, we nevertheless obtain a good approximation. That is, we used PCA to determine principal components but we used only those principal components that have a large variance as factors. Stated otherwise, we regressed the original series of spread data onto a small number of principal components. In this way, PCA implements a dimensionality reduction because it allows one to retain only a small number of components. By choosing as factors the components with the largest variance, we could explain a large portion of the total variance of spread data. We received that using 10 principal components allows to explain more than 99% of momentum returns.

To give an explanation in terms what factors explain what processes, we applied Statistical Factor Analysis, which concludes our work. Factor analysis, in contrast to the Principal Component Analysis, tends to reveal the exact factor structure of the data. We marked out the factors, which have the significant influence on momentum profits: In particular we observe the associated influence on volatility, on “effect of timing” and on macroeconomic variables.

On one hand, the results of this paper should help investors to be more profitable in optimal portfolio selection. In particular, the proposed analysis should force investors to more efficiently monitor and manage financial risks associated with a momentum strategy. On the other hand, the above discussion should be useful for politicians, central bankers and macroeconomists, to develop a better understanding of macroeconomic determinants of the source of momentum profits.

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