Is there Momentum in Factor Premia?

Evidence from International Equity Markets

Adam Zaremba[a] (corresponding author), Jacob Shemer[b]

[a]Poznan University of Economics and Business, al. Niepodleglosci 10, 61-875 Poznan, Poland, e-mail: adam.zaremba@ue.poznan.pl

[b]AlphaBeta, e-mail: kobyshemer@gmail.com

Abstract

This study examines the momentum effect in the returns of factor premia representing a broad set of stock market strategies. Using cross-sectional and time-series tests, we investigate the performance persistence of market, value, size, momentum, low-risk, and quality premia within a sample of 24 international equity markets for the years 1990–2016. We provide strong evidence that the top performing factors continue to outperform the worst performing factors both in individual equity markets and in the cross-country framework. The momentum in factor premia is largely explained by the classic stock-level momentum effect.

Keywords: momentum, factor premium, asset pricing, value, size, quality, low-volatility, style momentum, performance persistence, international equity markets, market efficiency, return predictability

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1. Introduction

The momentum effect is the tendency of assets with good past performance to continue to overperform in the future and of assets with poor past performance to continue to underperform. It is one of the most robust and pervasive stock market anomalies ever discovered. The effect has been documented across many stock markets (Chui et al., 2010) and asset classes (Asness et al., 2013). It is a strategy that has worked well for more than two centuries. Chabot et al. (2008) proved that momentum was profitable even in the Victorian age, and Geczy and Samonow (2016) have made a tremendous research effort to demonstrate that momentum has been present in the U.S. equity market since 1800.

This paper examines the momentum effect in a novel environment: equity factor premia. We show that the factors that drive returns in equity markets are not random: they are determined by an underlying pattern stemming from the momentum effect.

We thus examine returns on six asset-pricing factors which are widely recognized and backed up by solid theoretical and empirical evidence: market excess return (MKT), small minus big (SMB), high minus low (HML), up minus down (UMD), betting against beta (BAB), and quality minus junk (QMJ). These factors correspond with equity market risk premia and numerous anomalies related to company size, value effect, momentum effect, low-volatility effect, and quality effects, respectively.[1] All of these have been examined in numerous international markets and asset classes, and represent a broad panel of cross-sectional effects in equity markets.

To assure the comprehensiveness of our results, we base our investigations on data from 24 individual, developed equity markets for the years 1990–2016. Our study relies on a series of cross-sectional and time series tests. We build zero-investment long-short portfolios

[1] For size, value, and momentum, see Fama and French (2012), de Groot et al. (2012), Cakici et al. (2013), and Asness et al. (2013). For low-volatility, see Haugen and Baker (2012) and Frazzini and Pedersen (2014). Finally, for quality, see Asness et al. (2014).

assuming long (short) positions in factors which performed best (worst) in the past, and evaluate their performance against the four-factor asset-pricing model (Carhart, 1997) and against a naive benchmark of all of the factors. We examine the factor momentum using three approaches: (a) in the returns on the six factors in individual countries, (b) in the returns on factors of one type across the 24 countries, and (c) in a pooled sample of 144 assets (i.e., the six factors across the 24 countries).

The paper aims to contribute in three ways. First, we reexamine the concept of momentum in styles (Chen & De Bondt, 2004; Teo & Woo, 2004; Tibbs et al., 2008; Clare et al., 2010; Chen et al., 2012; Kim, 2012; Chao et al., 2012) and anomalies (Zaremba & Szyszka, 2017; Zaremba, 2015; Avramov et al., 2017). We rework and generalize this approach: instead of testing the performance persistence of individual anomalies, we investigate the momentum in the returns on popular factor premia—which explain the abnormal returns on a broad spectrum of cross-sectional patterns. The returns on individual anomalies might be derived from common sources and would therefore display significant correlation in returns. Meanwhile, a number of studies have indicated that the large number of cross-sectional patterns can be reduced to a smaller number of dimensions; a plethora of anomalies could therefore be explained by a small number of relatively uncorrelated asset-pricing factors (see Fama & French, 1996; Hou et al., 2015).

Second, we markedly extend the geographical scope of earlier studies. We study the momentum effect in factor premia (later called the factor momentum) in international equity markets. Most equity anomalies and return patterns have been discovered and initially documented in the U.S. market. Meanwhile, they usually fare poorly in out-of-sample studies (Welch & Goyal, 2008; McLean & Pontiff, 2015). In particular, Li et al. (2016) and Jacobs (2016) show that only a fraction of them prove profitable in international markets. Thus, by examining the robustness of the momentum in factors, our goal is to provide new insights into international asset pricing.

Third, we offer a new explanation of the factor momentum. Despite the existing research, there is no single, broadly accepted explanation for the momentum found across investment strategies. Barberis and Shleifer (2003) suggest that some investors categorize risky assets into different styles and allocate funds based on relative past performance. Thus, the investors move into styles that have provided good returns in the past and finance this shift by withdrawing funds from styles that have underperformed. Barberis and Shleifer (2003) also assume that these fund flows affect prices and imply an autocorrelation in style returns. Peng and Xiong (2006) argue that due to limited attention, investors tend to focus more on market-level and sector-level information than on firm-specific information, whereas Teo and Woo (2004) attribute style momentum to performance chasing. On the other hand, Kim (2012) interprets the style momentum as being consistent with underreaction models. Finally, Avramov et al. (2017) indicate that due to investors' learning as well as improvement in liquidity, the profitability of investment strategies may decline with time. Thus, the momentum strategy might be used as a tool to select the most robust cross-sectional patterns.

In contrast with these views, we hypothesize that factor momentum is a manifestation of the standard momentum effect. In other words, we assume that if the momentum effect is present in the returns on individual stocks, then one should rationally expect the momentum phenomenon to also exist in the portfolios of these stocks, including factor portfolios.

The major findings of this study can be summarized as follows. First, we provide strong evidence for the factor momentum in international markets. In the majority of the investigated countries, the past top performing factors continue to outperform the worst performing factors. The phenomenon is significant throughout the entire period, in sub-periods, and under various breakpoints, weighting schemes, and ranking periods (although admittedly, it is the strongest for the 12-month ranking period). Despite this significance, however, the factor momentum portfolios do not outperform the naive benchmark of all the anomalies on a risk-adjusted basis. Furthermore, the application of the four-factor model reveals that the returns on the standard momentum UMD factor are the key drivers of the momentum in factor premia. In other words, the factor momentum proves to be a manifestation of the standard momentum effect.

Second, we document the strong momentum effect across countries when a single factor or multiple factors are considered. The phenomenon exists in the returns on MKT, SMB, HML, and QML, and is particularly strong in the BAB returns. It is not present in UMD, however. In other words, we find no "momentum in momentum," which is consistent with our hypothesis that the factor momentum is a manifestation of the classic stock-level momentum. The cross-country factor momentum effect is also as robust as the momentum in individual countries, but this can still be largely explained by the UMD factor. With the notable exception of the BAB factor, the application of the four-factor model dramatically diminishes the abnormal returns, thus making them predominantly insignificant. Even when we consider all of the 144 international factors (six factors in 24 countries), the adjusted returns are more than 50% lower than the raw returns and retain their significance only in the equal-weighting scheme.

To sum up, this paper contributes in two ways. First, we document the momentum effect in factor premia in a comprehensive international sample. Second, we provide an explanation for this phenomenon by showing that it is a manifestation of the standard stock-level momentum pattern. The results are important from both an academic perspective and a practitioner's perspective.

The rest of the article has the following structure. The next section, Section 2, provides a description of the data and the methods employed. Section 3 presents the findings and discussion. Finally, Section 4 concludes the paper.

2. Data and Methods

This study investigates the persistence of factor premia around the world. Thus, we first formed factor momentum portfolios and then examined them with asset-pricing models.

In this section, we first discuss the data sources and sample preparation. We then present the methods for constructing the portfolios of factors as well as the cross-sectional and time-series tests we applied. Finally, we outline our robustness checks.

2.1. Data Sources and Sample Preparation

In this study, we used international monthly returns on factor portfolios sourced from the AQR Library (AQR, 2016). Our models rely on six distinct factors derived from cross-sectional data: the market factor (MKT), small minus big (SMB), high minus low (HML), up minus down (UMD), betting against beta (BAB), and quality minus junk (QMJ).[2]

The market risk factor R_{mt} was calculated as the excess return of a capitalization-weighted portfolio formed from all securities in the sample over the one-month Treasury bill rate. In order to compute the next four factors (i.e., SMB, HML, UMD, and QMJ), the companies were sorted at time *t*-1, on their B/M ratio, size (total stock market capitalization), momentum (lagged cumulative return in months *t*-12 to *t*-2), and overall quality score. Big companies and small companies were defined as those with a capitalization above and below the median at time *t*-1, respectively. The B/M ratio breakpoints were the 30th and 70th percentiles of the B/M ratio for all companies measured at time *t*-1. The intersection between the independent 2×3 sorts on size and the B/M ratio produced six portfolios—*SG*, *SN*, *SV*, *BG*, *BN*, and *BV*, where *S* and *B* indicate small and big, and *G*, *N*, and *V* indicate growth, neutral, and value (bottom 30%, middle 40%, and top 30% of B/M), respectively. The next step was to compute monthly capitalization-

[2] The mean pair-wise correlation between the factor returns in individual countries in our sample is close to zero, and it amounts to −0.03 on average.

weighted returns for all six portfolios. Finally, we calculated the *t*-month return on the size factor (i.e., SMB) as the mean return on the three small company portfolios from the 2×3 size-B/M sorts, minus the mean return on the three big company portfolios. The return on value factor (i.e., HML) was the difference between the mean return on value portfolios (BV and SV) and the mean return on growth portfolios (BG and SG). The two remaining factors—UMB and QMJ—were calculated the same way as HML with the exception that instead of the B/M ratio, the stocks were sorted on momentum and overall quality score, respectively.

Finally, to form the BAB factor, all securities in a given country were ranked on their beta estimates and assigned to one of two portfolios: high-beta and low-beta. Next, the returns were weighted by the ranked betas for each portfolio so that the higher-beta (lower-beta) securities have greater (lesser) weights in the high- (low-) beta portfolios. Both portfolios were then rescaled to have a beta of one. The return on the BAB factor was measured as the return on a long-short self-financing portfolio which was long (short) in the low- (high-) beta portfolios.[3]

Our study is based on stock market returns in 24 developed countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. We used monthly returns as they provided us with a reasonable number of observations to ensure the power of the conducted tests and allowed us to avoid an excessive exposure to micro-structure issues. The sample period of returns on the factor portfolio ran from July 1990 to February 2016 (308 monthly observations), as available. All the returns were expressed in USD.[4]

[3] The detailed description of the construction of factor portfolios is available at AQR (2016).
[4] The indicated 308-month period includes both the sorting period and the evaluation periods. Because we need to discard the first months to form the initial portfolio, the actual length of the time series of evaluated returns varies from 248 to 307 months, depending on the corresponding ranking period (from 1 to 60 months).

2.2. Cross-Sectional Tests

We started our investigation with simple monthly regressions in the style of Fama and MacBeth (1973). The univariate regressions are based on the following formula:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-k:t-1} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the return on factor i in month t, $R_{i,t-k:t-1}$ is the mean monthly return on portfolio i from month t-k to t-1, and β_0 and β_1 are regression parameters.[5] We applied these regressions in two approaches: (a) to the six various factors in individual countries; and (b) to single or multiple factors across the 24 examined countries. In each case, we considered a spectrum of different periods, k, ranging from 1 to 60 months.

2.3. Time-Series Tests

Having examined the basic cross-sectional relations with the Fama-MacBeth regressions in the first pass, we then continued with the time-series tests. In other words, we examined the performance of portfolios of factors that were formed on the basis of their past returns. We applied the time-series tests in three distinct approaches: (a) within the sets of the six various factors (MKT, SMB, HML, UMD, BAB, and QMJ) in individual countries (approach A); (b) within sets of factors of a single type (e.g., SMB) across the 24 countries (approach B); and (c) in the pooled sample of all 144 assets that includes all six factors across 24 countries (approach C). In each of the approaches, we ranked the factors on the basis of their cumulative past returns, and we formed quantile portfolios of the factors that performed best and worst in the past. We then formed long-short zero-investment portfolios, assuming long (short) positions in the top

[5] All of the calculations in this and any further regressions are based on log-returns and their parameters and corresponding t-statistics are always based on the Newey-West estimator (Newey & West, 1987).

(bottom) factors.[6] The portfolios were reviewed and rebalanced on a monthly basis. Finally, we examined the monthly log-returns on these portfolios with two different asset-pricing models.

The first model was the four-factor model, which was originally developed by Carhart (1997). It is described with the following regression:

$$R_{p,t} = \alpha_p + R_{f,t} + \beta_{MKT,p} \cdot MKT_t + \beta_{SMB,p} \cdot SMB_t + \beta_{HML,p} \cdot HML_t + \beta_{UMD,p} \cdot UMD_t + \varepsilon_{p,t}, \quad (2)$$

where $R_{p,t}$ is the return in month t on the examined portfolio of factors p; $\beta_{MKT,p}$, $\beta_{SMB,p}$, $\beta_{HML,p}$, $\beta_{UMD,p}$, and α_p are the model-estimated parameters; and $\beta_{MKT,p}$ is analogous, but not equal, to the CAPM beta. $\beta_{MKT,p}$, $\beta_{SMB,p}$, $\beta_{HML,p}$, and $\beta_{UMD,p}$, are measures of exposure to MKT_t, SMB_t, HML_t, and UMD_t risk factors. In approach A (i.e., the six factors in the individual countries), we used factor portfolios derived from data from each individual country. In contrast, in approaches B and C (which considered a broad range of countries), we employed global factors based on data from the 24 countries obtained from the AQR Library (AQR, 2016).

The major aim of using the four-factor model is to investigate the role of stock level momentum as the driver of factor momentum. Controlling for the stock-level UMD factor allows us to compute its contribution to the abnormal returns on the factor momentum. Importantly, the more recent five-factor model by Fama and French (2015) does not include the stock-level momentum factor.

The second model is an ad-hoc benchmark model. In this approach, we examine whether our factor momentum portfolios outperform a naive benchmark of all the factors considered. The model is represented by the following formula:

$$R_{i,t} = \alpha_i + \beta_{B,i} \cdot B_t + \varepsilon_{i,t}, \quad (3)$$

where $\beta_{B,i}$ and α_i are the model-estimated parameters, while B_t is the return on the benchmark in month t. The precise composition of the benchmark depends on the particular approach: in

[6] The factor portfolios are composed of long and short legs by their nature, so taking the short position in a factor means taking a short position in its long leg and a long position in its short leg.

approach A it includes the six factors from each given country, in approach B it consists of 24 factors of one type derived from each of the 24 countries, and in approach C it is composed of all of the 144 assets. The benchmark components are always weighted using the same method as the evaluated portfolio (i.e., using equal weights according to capitalizations).

2.4. Robustness Checks

To verify our results, we performed a set of robustness tests at various stages of the research.

Equal-weighting versus capitalization-weighting. The momentum portfolios in approach A were always equally weighted. However, in approaches B and C we additionally considered capitalization-weighted portfolios. The returns in the capitalization-weighting schemes were weighted according to the total market value of equity in a given country at t-1.[7]

Alternative breakpoints. We examined the selected portfolios of factors based on their past performance with the use of three different quantile portfolios. In approach A, our base method assumed long (short) portfolios including the two top (bottom) factors out of six. The robustness checks also encompassed portfolios of the one and three top (bottom) factors. In approaches B and C, the portfolios encompassed 10%, 20%, and 30% of the past best/worst performers, which translated to approximately two, five, and seven (14, 29, and 43 for approach C) factors. In this case, our base method was to form portfolios based on 20% of factors, while the 10% and 30% breakpoints were employed as alternative solutions.

Performance within sub-periods. We split our sample into two equal periods: July 1990–April 2003 and May 2003–February 2016. We applied this check at various stages of this study and verified whether the results held within the subsamples.

[7] Data sourced from AQR (2016).

Alternative ranking periods. We examined 10 different formation periods used for ranking the factors portfolios. This involves trailing 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 months, with 12 months as our base choice (for reasons explained later).

Importantly, the outcomes of many robustness checks, including the performance within sub-periods and alternative ranking periods, uncovered no qualitative differences in results. In such cases, for brevity, we do not report the effects of robustness checks.

3. Results

The results section is divided into two major parts. First, we discuss the factor momentum in individual countries (approach A), then we focus on the performance of factors across many countries (approaches B and C).

3.1. Factor Momentum in Individual Countries

To start with, let us concentrate on the results of the Fama-MacBeth regressions reported in Table 1. This table displays the coefficients of regression for factors in the 24 individual countries using 10 different time periods for past returns (ranging from one month to 60 months). The results show that the future returns on the factors indeed depend on their past performance: the better the past performance, the higher the future returns. The relationship is positive in nearly all of the country-sorting period combinations, and is predominantly significant for the majority of calculation variants.

[Insert Table 1 here]

Although there is a positive and robust autocorrelation of returns across different time horizons, it is not equally strong. The average regression coefficients are the highest for the 12-month sorting period. In this sorting period, they were equal to 0.31, and the corresponding average *t*-statistic amounted to 2.59. In this case, the relationship was significant in 21 of the

24 countries examined, with the exceptions being Italy, Japan, and the Netherlands. Importantly, our results are consistent with studies on momentum in other major asset classes, which also suggest that this phenomenon is particularly strong when the sorting period amounts to 12 months.[8] Consequently, we used the 12-month ranking period as the base period in our later examinations. In other words, our default trading approach focuses on a 12-month formation and one-month holding period. We also performed extensive robustness checks to demonstrate that the specific choice of sorting period is of secondary importance and that our results hold for the alternative sorting periods.

Table 2 presents the performance of zero-investment factor momentum portfolios in the 24 examined countries (Panel A) in comparison with the respective benchmark portfolio (Panel B). The mean monthly returns are positive in all the examined countries, and in 15 of them, the mean returns significantly depart from zero. The average monthly return on the factor momentum portfolios is 0.89% with the corresponding average *t*-statistic equal to 2.19. The Sharpe ratios vary across countries with an average of 0.47.

[Insert Table 2 here]

Although the returns on factor momentum portfolios are very impressive, the benchmark portfolios also display very good performances. However, the mean monthly returns are markedly lower than in the case of the factor momentum portfolios (0.55%), and the volatilities are notably lower. The average standard deviation amounts to 1.95%, more than three times lower than in the case of factor momentum strategies. In consequence, the lower volatility translates to Sharpe ratios that are more than twice as high, with the average annualized ratio equaling 1.01. This observation suggests that although there is strong evidence that past top performing factors continue to outperform in the future, the naive portfolio which weights all of the factors equally, may still display a better risk-return profile.

[8] See the work of Goyal and Wahal (2015).

The examination of the zero-investment factor momentum portfolios with the asset-pricing models provides further insights into the performance (Table 3). The application of the four-factor model (Panel A) sheds light on the sources of the factor momentum profits. Although the coefficients corresponding to MKT, SMB, and HML are close to zero and predominantly insignificant, the factor momentum strategies in all the countries show clear and significant positive exposure to the UMD factor. The average regression coefficient equals 0.71 (average *t*-statistic equals 8.82). As a result, the risk adjusted performance of the factor momentum strategies is significantly reduced in comparison to the outcomes in Table 2. The mean monthly alpha is only 0.19% and is insignificant in 19 of the 24 tested countries (the exceptions are Denmark, Greece, Hong Kong, Singapore, and Sweden). This observation indicates where the factor momentum payoffs come from: the profitability of this strategy stems from the simple stock-level momentum effect. In other words, the factor momentum appears to be just another manifestation of the standard momentum phenomenon. If the momentum is observed in individual stock returns, it is also visible in the returns of their portfolios, including the asset-pricing factor portfolios.

[Insert Table 3 here]

Panel B of Table 3 reports the results of the application of the benchmark model to the factor momentum strategies. The intercepts from this model are insignificant in almost all cases, which is in line with the intuition from the analysis of the Sharpe ratios in Table 2. The average exposure to the benchmark portfolio is 1.16 and the mean alpha is only 0.21, with the corresponding mean *t*-statistic amounting to 0.38. To sum up, the factor momentum strategies do not significantly outperform the naive benchmark of all the equal-weighted factors.

3.2. Factor Momentum across Multiple Countries

Let us now concentrate on approach B (i.e., the examinations of the momentum in returns on a factor of one type across multiple countries). Table 4 reports the results of the investigations using Fama-MacBeth regressions.

[Insert Table 4 here]

We observe a significant relationship between past and future returns on five of the factors—BAB, MKT, SMB, HML, and QMJ. The phenomenon is strongest for the BAB factor, but the regression coefficients are also significant for MKT, SMB, HML, and QMJ, even when the sorting period is as long as 24 months. The only exception is the UMD factor. For these portfolios, the study documents no significant relationship between past and future performance. In other words, there is no momentum in momentum. Counterintuitively, this observation also supports the idea that the primary source of factor momentum is the standard momentum effect. Once we account for the momentum effect in the stocks, no further momentum is observable in the factor portfolios.

In general, the autocorrelation is strongest for the 12-month sorting period, which is in line with the observations in approach A. The average regression coefficient in this ranking period equals 0.18, with the average corresponding *t*-statistic amounting to 3.64.

The last column of Table 4 depicts the results of the Fama-MacBeth regressions within the pooled sample of all the factors in all the countries (i.e., approach C). The relationship is positive and significant for sorting periods spanning from one to 48 months, which is consistent with the results of the individual factors. The regression coefficients are also highest in the case of the 12-month ranking period (the regression coefficient amounts to 0.24 with the respective *t*-statistic equaling 4.57). To sum up, the results presented in Table 5 indicate the presence of strong momentum effect in asset-pricing factors across multiple countries. The effect is visible for the BAB, MKT, SMB, HML, and QMJ factors, as well as in the pooled sample, but not for the UMD factor.

Table 5 uncovers the return characteristics of the zero-investment portfolios formed from factors across multiple countries (Panel A), along with the respective benchmarks that encompass the considered factors in all 24 countries (Panel B). The equal-weighted factor momentum strategies deliver positive and significant mean monthly returns for all the factors, except for the UMD factor. The mean monthly returns are the largest for the BAB portfolios, with the mean returns equaling 1.38% monthly. In general, the mean of the average returns on the strategies in the equal-weighting approach is 0.62%, which proves slightly higher than the returns on the benchmark portfolios (0.55%). Nonetheless, the benchmark portfolios are also less volatile (the monthly standard deviation equals 2.71% as compared to 3.62% for the factor momentum strategies), and so it is also characterized by higher Sharpe ratios.

[Insert Table 5 here]

The performance of the capitalization-weighted factor momentum portfolios is largely consistent with the equal-weighted ones. Interestingly, even the mean raw returns on the momentum strategy in the UMD factors prove significantly profitable in this case (although the mean monthly returns are fairly low and amount to 0.39%). Also interesting is that the spread between the returns on factor momentum portfolios and the benchmark portfolios is even higher—the average returns are 0.68% (0.45%) per month for the factor momentum (benchmark) portfolios. Consequently, the Sharpe ratios of the factor momentum and benchmark portfolios are nearly identical, amounting to 0.54 and 0.53, respectively. In summary, Table 5 provides strong evidence supporting the factor momentum in multiple countries. The countries with top (bottom) performing factors continue to outperform (underperform), but the profitability and risk-return profile of the factor momentum and benchmark portfolios are insignificant.

Table 6 presents an examination of the factor momentum portfolios in approach B with the four-factor and benchmark models. Interestingly, the traditional momentum strategy proves to be the crucial driver of the factor momentum effect in this case as well. Whether in the equal-weighting (Panel A) or capitalization-weighting (Panel B) approach, all the strategies display a notable and significant exposure to the UMD factor. Consequently, the alphas are close to zero—or not significantly different from zero—for five of the six tested factors: MKT, SMB, HML, UMD, and QMJ.[9] The only exception is the BAB factor. In this case, the cross-country factor momentum strategy delivers a positive and significant alpha amounting to 1.01% (1.36%) per month in the equal-weighting (value-weighting) approach. The size of the abnormal returns basically resembles the raw returns on these portfolios reported in Table 5.

[Insert Table 6 here]

Interestingly, the cross-country factor momentum strategies yield positive returns even after adjusting for the exposure to our naive benchmark. Five (four) of the six investigated types of factors deliver positive and significant intercepts from the benchmark model in the equal-weighting (capitalization-weighting) approach. Again, the best performing strategy is based on the BAB portfolios, which deliver mean monthly returns amounting to 0.99% and 1.86% when the portfolios are equal-weighted and capitalization-weighted, respectively. On the other hand, the only strategy that does not outperform the benchmark is the factor momentum implemented in country-specific UMD factors. This observation should not be astonishing, as the results in Table 5 already show that there is no momentum in momentum that could form the basis of a profitable country factor rotation strategy.

Finally, let us now concentrate on approach C (i.e., the momentum phenomenon in the pooled sample of the six factors in all 24 countries). Table 7 reports the returns on the zero-investment portfolios under various considerations. Clearly, our investigation confirms a visible momentum effect in the factor returns. The mean monthly returns are positive and highly

[9] Specifically, in the case of SMB, the intercept is insignificant in the capitalization-weighting approach and very low but significant in the equal-weighting approach (α_{4F} = 0.34%, t-stat = 1.67).

significant, and range from 1.27% to 0.99% (1.28%–1.01%) in the equal-weighting (capitalization-weighting) approach, depending on the portfolio formation breakpoint chosen (i.e., 10%, 20%, or 30%). The returns are highest for the 10% breakpoint and lowest for the 30% breakpoint. Importantly, these mean returns are more than twice as high as the payoffs of respective benchmarks, which yield 0.55% and 0.45% in the case of equal-weighted and value-weighted portfolios, respectively. Nevertheless, the benchmark returns are also much less volatile, and their standard deviation is more than four times lower than those of the factor momentum strategies. Consequently, the benchmark portfolios are characterized by noticeably higher Sharpe ratios than the factor momentum portfolios.

[Insert Table 7 here]

The superior risk-return profile of the benchmark portfolios is also reflected in the abnormal returns on the factor momentum strategies relative to the benchmark model. All the factor momentum portfolios—either equal-weighted or capitalization-weighted—display benchmark betas strongly exceeding unity. This exposure results in very small intercepts, and the alphas from the benchmark model are predominantly close to zero.

The performance of the factor-momentum portfolios is also strongly reduced by the four-factor model (in line with the observations in approaches A and B), and this effect is more pronounced for the capitalization-weighted portfolios. All the strategies reveal very strong exposure to the global UMD factor, and thus the respective betas are close to one. Accordingly, the alphas from the four-factor model in the equal-weighting approach are two times lower than before the adjustment, but they still depart significantly from zero. In the capitalization-weighted approach, the decline in abnormal returns is even stronger. Thus, the alphas on the 10%-breakpoint and 30%-breakpoint are no longer significantly different from zero. In other words, even when we consider as many as 144 individual factor portfolios, the explanatory power of the standard momentum factor is very strong and detrimental to the abnormal returns.

4. Concluding Remarks

The aim of this study was to comprehensively examine and explain the momentum effect in factor premia in 24 developed equity markets around the world. We have shown that there is a solid momentum phenomenon in the factor premia in both individual countries and across multiple countries. The top performing factors visibly outperform the worst performers, and the effect was strongest within a 12-month sorting period. The performance persistence of the factors is strong and robust to many considerations. Nevertheless, the factor momentum phenomenon is explained by the standard stock-level momentum strategy; after adjusting the returns with the UMD factor, the alphas are predominantly insignificant. The momentum phenomenon is particularly strong for BAB factors in the cross-country framework, and is practically nonexistent in the UMD factors.

The study has, nevertheless, two limitations of potentially high importance. First, the study period includes two major financial crises (i.e., the dot-com bubble of 2000 and the global financial crisis of 2008), which casts some doubt on its representativeness of long-term equity performance. Second, the calculations in this paper do not account for any trading costs, though some of the factor rotation strategies may implicitly assume high turnover.

Besides the new insights into asset pricing in international equity markets, the results are of particular importance for stock market practitioners. The conclusions of this paper can be used by investors with international mandates who pursue quantitative factor strategies in international markets.

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References

AQR (2016). AQR Library - Data Sets. Available at: https://www.aqr.com/library/data-sets (accessed 23 March 2016).

Asness, C.S., Frazzini, A., & Pedersen, L.H. (2014). *Quality minus junk*. Available at SSRN: http://ssrn.com/abstract=2312432 or http://dx.doi.org/10.2139/ssrn.2312432 (accessed 16 May 2016).

Asness, C.S., Moskowitz, T.J., & Pedersen, L.H. (2013). Value and momentum everywhere. *Journal of Finance*, 68(3), 929-985.

Avramov, D., Cheng, S., Schreiber, A., & Shemer, K. (2017). Scaling up market anomalies. *Journal of Investing*, 26(3), 89-105. https://doi.org/10.3905/joi.2017.26.3.089

Baker, N.L., & Haugen, R., A. (2012). *Low risk stocks outperform within all observable markets of the world*. Available at SSRN: http://ssrn.com/abstract=2055431 or http://dx.doi.org/10.2139/ssrn.2055431 (accessed 16 May 2016).

Barberis, N. & Shliefer, A. (2003). Style investing. *Journal of Financial Economics*, 68, 161-199.

Blitz, D.C. & van Vliet, P. (2008). Global tactical cross-asset allocation: Applying value and momentum across asset classes. *Journal of Portfolio Management*, 35(1), 23-38.

Cakici, N., Fabozzi, F.J., & Tan, S. (2013). Size, value, and momentum in emerging market stock returns. *Emerging Markets Review*, 16, 46-65.

Carhart, M.M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1), 57 – 82.

Chabot, B., Ghysels, E., & Jagannathan, R. (2008). Price momentum in stocks: Insights from Victorian age. *NBER Working Paper No. 14500*. Available at: http://www.nber.org/papers/w14500 (accessed 20 October 2015).

Chao, H.-Y., Collver, C., & Limthanakom, N. (2012). Global style momentum. *Journal of Empirical Finance*, 19(3), 319-333. Available at: http://dx.doi.org/10.1016/j.jempfin.2012.02.001

Chen, H.S. & De Bondt, W. (2004). Style momentum within the S&P-500 index. *Journal of Empirical Finance*, 11, 483-507.

Chen, L.H., Jiang, G.J., & Zhu, X. (2012). Do style and sector indexes carry momentum? *Journal of Investment Strategies*, 1(3), 67-89.

Chui, A.C.W., Titman, S., & Wei, J.K.C. (2010). Individualism and momentum around the world. *Journal of Finance*, 65(1), 361-392.

Clare, A., Sapuric, S., & Todorovic, N. (2010). Quantitative or momentum-based multi-style rotation? UK experience. *Journal of Asset Management*, 10, 370-381.

de Groot, W., Pang, J., Swinkels, L.A.P. (2012). The cross-section of stock returns in frontier emerging markets. Journal of Empirical Finance, 19(5), 796-818.

Fama, E.F. & French, K.R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51(1), 55-84.

Fama, E.F. & K. R. French (2012). Size, value, and momentum in international stock returns. Journal of Financial Economics, 105(3), 457–472.

Fama, E.F. & MacBeth, J.D. (1973). Risk, return and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607-636.

Frazzini, A. & Pedersen, L.H. (2014). Betting against beta. *Journal of Financial Economics*, 111, 1-25.

Geczy, C. & Samonov, M. (2016). Two centuries of price-return momentum. *Financial Analysts Journal*, 72(5), 32-56.

Goyal, A. & Wahal, S. (2015). Is momentum an echo? *Journal of Financial and Quantitative Analysis*, 50(6), 1237-1267. Available at: http://dx.doi.org/10.1017/S0022109015000575

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3), 650-705. https://doi.org/10.1093/rfs/hhu068

Jacobs, H. (2016). Market maturity and mispricing. *Journal of Financial Economics*, 122(2), 270-287. https://doi.org/10.1016/j.jfineco.2016.01.030

Jacobs, H., Regele, T., & Weber, M. (2015). *Expected skewness and momentum*. Available at SSRN: http://ssrn.com/abstract=2600014 or http://dx.doi.org/10.2139/ssrn.2600014 (accessed 16 May 2016).

Kim, D. (2012). Cross-asset style momentum. *Asia-Pacific Journal of Financial Studies*, 41(5), 610-636.

Li, P.M., Zhang, Q., Cai, C.X., & Keasey, K. (2016)., Understanding asset pricing anomalies across the globe: The role of newswatchers. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2839799 (accessed 27 January 2017).

McLean, D.R. & Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71, 5-32.

Newey, W.K., West, K.D. (1987). A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 703-708.

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, 103, 429-453.

Peng, L. & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3), 563-602.

Teo, M. & Woo, S.-J. (2004). Style effects in the cross-section of stock returns. *Journal of Financial Economics*, 74(2), 367-398. http://dx.doi.org/10.1016/j.jfineco.2003.10.003

Tibbs, S.L., Eakins, S.G., & DeShurko, W. (2008). Using style momentum to generate alpha. *Journal of Technical Analysis*, 65, 50-56.

Welch, I. & Goyal A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21, 1455-1508.

Zaremba, A. & Szyszka, A. (2016). *Is there momentum in equity anomalies? Evidence from the Polish an emerging market*. Research in International Business and Finance, 38, 546-564. https://doi.org/10.1016/j.ribaf.2016.07.004

Zaremba, A. (2015). *The momentum effect in country-level stock market anomalies*. Economic Research, forthcoming. Available at SSRN: http://ssrn.com/abstract=2621236 or http://dx.doi.org/10.2139/ssrn.2621236 (accessed 27 January 2017).

Zaremba, A. (2016). Investor sentiment, limits on arbitrage, and the performance of cross-country stock market anomalies. *Journal of Behavioral and Experimental Finance*, 9, 136-163.