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Eureka! A Momentum Strategy that Also Works in Japan

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Abstract

This article explores an alternative definition of momentum that is calculated using the idiosyncratic returns from market regressions. By removing the return component due to market beta exposure, this new definition of momentum reduces the volatility of momentum strategies and generates sizeable four-factor alphas. These results hold in a sample of 21 countries, in addition to U.S. data. Most interestingly, the findings also hold in Japan, where previous studies have failed to find any significant power for traditional momentum strategies.

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The momentum effect of Jegadeesh and Titman [1993] is one of the strongest and most pervasive phenomena in the financial literature. Researchers have verified its existence among even the largest and most liquid stocks in the U.S. market (Fama and French [2008]), in industry (Moskowitz and Grinblatt [1999]) and style (Lewellen [2002]) portfolios, and in different countries and asset classes (Rouwenhorst [1998], Griffin, Ji, and Martin [2003], Chui, Wei, and Titman [2000], Fama and French [2011], and Asness, Moskowitz, and Pedersen [2011]). According to *The Economist* [2011], momentum "drives a juggernaut through one of the tenets of finance theory, the efficient-market hypothesis."

In this paper, I explore an alternative, yet simple, measure of momentum. Whereas the usual definition of momentum involves the cumulative *raw* return over months $t-12$ and $t-2$,

$$MOM_{i,t} = \prod_{j=2}^{12}\left(1 + r_{i,t-j}\right) - 1, \tag{1}$$

the alternative definition starts with simple regressions inspired by the capital asset pricing model (CAPM) of Sharpe [1964] and Lintner [1965],

$$r_{i,t} - r_t^f = \alpha + \beta\left(r_t^M - r_t^f\right) + \varepsilon_{i,t}, \tag{2}$$

and defines idiosyncratic momentum as the cumulative idiosyncratic return over the same period of time,[2]

$$IMOM_{i,t} = \prod_{j=2}^{12}\left(1 + \varepsilon_{i,t-j}\right) - 1. \tag{3}$$

I follow the literature and skip the most recent month in both definitions to avoid the reversal, or contrarian, effect usually present in stock returns (e.g., Jegadeesh [1990] and Lo and MacKinlay [1990]).

[2] In the rare occasions when $\varepsilon_{i,t-j} < -1$, the definition of $IMOM_{i,t}$ breaks down and the stock is removed from the portfolios. An alternative definition using $\varepsilon^*_{i,t-j} = \max\left(\varepsilon_{i,t-j}, -0.99\right)$ results in minor improvements in performance.

This seemingly small change in definition generates a significant improvement in the performance of momentum strategies. In particular, it reduces in most cases the standard deviation of long–short portfolios by a factor of two. Similar to traditional momentum strategies, these gains are not restricted to small or illiquid stocks and remain strong even in U.S. large-cap stocks.

Strategies formed on idiosyncratic momentum are almost uncorrelated with the market portfolio and the size and value factors of Fama and French [1993]. They have a relatively high correlation with traditional momentum strategies, but their low volatility and equivalent or superior average returns result in highly significant risk-adjusted alphas: four-factor regressions including the momentum factor of Carhart [1997] explain less than half of their total average returns.

Using Fama and MacBeth [1973] regressions I show that idiosyncratic momentum cannot be explained by the strong negative correlation in previous-month returns (Jegadeesh [1990] and Lo and MacKinlay [1990]). Further, *IMOM* subsumes *MOM* and the alternative momentum definition used by Novy-Marx [2011]—a firm's performance 12 to 7 months prior to portfolio formation—in all size groups.

Most importantly, I also show that *IMOM* works better than *MOM* in an international sample of 21 developed countries. The main improvement in performance, as in the U.S. sample, comes via a sharp reduction in volatility, generating large and highly significant alphas in regressions that are controlled for each country's market and traditional momentum portfolios. Given the high correlation between these two signals—the monthly cross-sectional Spearman rank correlation is, on average, 0.7—*IMOM* tends to work better in large countries or in countries with a broad cross-section of stocks to choose from. Idiosyncratic momentum works even in Japan, where previous studies have failed to find any significant power for traditional momentum strategies.

Intuition suggests that the main driver of the enhanced performance I find in my analysis is the reduced exposure of idiosyncratic momentum to market movements. Grundy and Martin [2001] and

Daniel and Moskowitz [2011] showed that hedging the beta exposure directly through the market portfolio increases the performance and reduces the volatility of momentum strategies. The approach that I follow achieves a similar effect, but it does so indirectly via stock selection and does not require any additional investments.

Daniel and Moskowitz [2011] showed further that momentum strategies tend to experience long periods of poor performance following market downturns and contemporaneously with market rebounds. They call this effect a "momentum crash." The reason for the underperformance, according to the authors, is the optionality embedded in the "losers" portfolio; investors who sell this portfolio short get rewarded during market downturns, but suffer big losses in market rebounds. By selecting stocks that exhibit better idiosyncratic performance, $IMOM$ avoids, to a large extent, companies whose outperformance is due mostly to a high market beta.

Other researchers have also formed momentum portfolios based on factor regressions, but using more complicated construction rules. Moreover, to the best of my knowledge this is the first study to analyze these alternative momentum strategies in an international sample.

Grundy and Martin [2011], for instance, ran five-year regressions and calculated momentum as the horizon-specific alpha between $t-7$ and $t-2$.[3] Strategies constructed according to their measure of momentum showed slightly higher average returns and lower volatility relative to traditional momentum. However, the most significant improvements came only after the authors calculated risk-

[3] More specifically, they run factor regressions as in

$$r_\tau = \alpha_0 D_\tau + \alpha_1(1 - D_\tau) + \beta f_\tau + \varepsilon_\tau,$$

where

$$D_\tau = \begin{cases} 1: & \text{if } \tau \in \{t-7, \dots, t-2\}; \\ 0: & \text{otherwise,} \end{cases}$$

and pick winners and losers based on α_0.

adjusted profits, which included offsetting positions in the factors used in the regressions.[4] This last piece of evidence confirms the significant risk-adjusted performance (three-factor and four-factor alphas) found here for portfolios formed on the basis of idiosyncratic momentum.

Blitz, Huij, and Martens [2011] showed superior performance of momentum strategies using the residuals of regressions on the three factors of Fama and French [1993]. They correctly argued that the exposures to the Fama and French factors “can be reduced by ranking stocks on residual stock returns instead of total returns.” The findings here show that the vast majority of the improvements they found can be attributed *exclusively* to exposure to the market portfolio, confirming the evidence of Daniel and Moskowitz [2011].

I. Data

Monthly returns and market capitalizations of individual U.S. companies are from CRSP (starting in 1964) and international returns and market capitalizations in U.S. dollars are from Datastream (starting in 1972). The risk-free rate and the four U.S. risk factors—market (MKT), size (SMB), value (HML), and momentum (UMD)—are obtained from the Kenneth French website.[5] For each country in the international sample I calculate the market portfolio as the capitalization-weighted index of all stocks with a valid return and existing market capitalization on the previous month. I use the U.S. risk-free rate to calculate excess returns in all countries, because the data are in U.S. dollars. The regressions in Equation (2) are estimated using three years of data.[6] Both momentum signals require 11 valid

[4] Their hedging positions suffer from look-ahead bias, as future months are used in the calculation of the coefficients. In separate tests, they calculate “feasible-hedged” returns using past data, but these returns retain less than half of the magnitude of the original, unfeasible, improvements.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] Small improvements can be obtained by using longer horizons in the regressions, but even one year is enough for most results presented here.

observations, thus only stocks with a full previous year of data are included in the portfolios each month.

Following Fama and French [2008], I divide U.S. stocks into micro caps, small caps, and large caps using as breakpoints the 20^{th} and 50^{th} percentiles of market capitalization among NYSE stocks. The smallest group represents, on average, 3% of the U.S. sample in market capitalization terms, the medium group 7%, and the large group 90%.

The international sample consists of 21 developed countries.[7] To avoid the selection of illiquid stocks in the international portfolios, I restrict each country sample by using two methodologies that mimic the U.S. breakpoints. The first methodology selects the top half largest stocks in each country. Some countries have a limited number of stocks in the early years, so I further require a minimum of 50 stocks (25 after the market-capitalization screening) in order to select stocks for the first month of that country's sample.

The second methodology ranks stocks and selects a sample that contains at least 90% of the total market capitalization of that country. Because the second approach is more restrictive, I report individual results only for four countries that consistently have more than 50 stocks that satisfy the requirements (France, Germany, Japan, and the United Kingdom). The remaining countries are pooled into four distinct groups: northern Europe (Denmark, Finland, Norway, Sweden, and Ireland), central Europe (Austria, Belgium, Netherlands, and Switzerland), southern Europe (Greece, Italy, Portugal, and Spain) and other (Australia, Canada, New Zealand, and Singapore).

II. U.S. Results

[7] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Sweden, Singapore, Spain, Switzerland, and the United Kingdom.

Table 1 shows average excess returns and *t*-statistics (in parentheses) for five quintile portfolios sorted on *IMOM* and for the long–short winners-minus-losers (WML) portfolio formed as the difference between quintiles 5 and 1. Stocks are equally weighted (first row) or value weighted (second row) within each portfolio. The monotonically increasing pattern of returns is clear and the WML portfolios have annualized returns of 18% and 17%, respectively. The *t*-statistics are impressive at roughly 8 and 7, respectively, translating into annualized Sharpe ratios in excess of one over the 47 years in the sample.

<Table 1 here.>

Table 2 investigates whether these results can be attributed to exposure to common risk factors. Regressions 1 and 4 use only the market, regressions 2 and 5 use the three factors from Fama and French [1993], and regressions 3 and 6 add the momentum factor (*UMD*) of Carhart [1997]. Regressions 1 and 2 show that the equally weighted WML portfolio is negatively correlated to the market, as is common in momentum strategies; weakly and positively correlated to SMB, indicating a weak dependence on smaller stocks; and weakly and positively correlated to HML, indicating a weak dependence on growth stocks. Regressions 4 and 5 show that the value-weighted WML portfolio also has a negative correlation with the market, but unlike the EW portfolio, the value-weighted WML portfolio is uncorrelated with SMB and HML.

The common pattern in all four regressions is a strong and highly significant alpha. All four regressions have an alpha above 18% and a *t*-statistic above 7. The more interesting results, however, come from regressions 3 and 6, which show strong and statistically significant loadings on *UMD* at 0.64 (EW) and 0.87 (VW), but also strong and statistically significant annualized alphas at roughly 11% and 9%, respectively. The R-squareds jump from less than 0.1 to 0.55 (EW) and to 0.63 (VW) when the momentum factor is included. These results indicate that the WML portfolios are correlated with traditional momentum strategies, but more than half of their total average returns still remain after controlling for a momentum factor.

<Table 2 here.>

To investigate the dependence of idiosyncratic momentum on small stocks, **Table 3** reports similar statistics on micro, small, and large stocks, following the definitions of Fama and French [2008]. Panels A and B of Table 2 show the results for quintiles sorted on idiosyncratic momentum (*IMOM*), and Panels C and D show the results for quintiles sorted on traditional momentum (*MOM*). A clear pattern emerges from a comparison between the unadjusted performances of the portfolios: in most cases, *IMOM* delivers only a minor increase in average returns, but the *t*-statistics are increased by a factor of two, indicating a sharp reduction in volatility. In the interest of space, only the alphas from the CAPM, three-factor, and four-factor regressions are shown in the risk-adjustment tests. Traditional momentum strategies have large and significant CAPM and three-factor alphas, but four-factor regressions provide mixed evidence; EW alphas are small and insignificant for micro- and large-cap stocks, whereas VW alphas are large and significant in micro caps and negative and significant in large caps. Idiosyncratic momentum strategies, however, have positive and significant alphas in all six portfolios. Although the *IMOM* strategy in large-cap stocks have relatively smaller alphas, the traditional *MOM* strategies show that the risk adjustment due to the momentum factor tends to overstate the correction in this size group. The final verdict is clearly favorable for *IMOM*, because its strategies are profitable among all size groups, even after controlling for the traditional momentum factor.

<Table 3 here.>

Table 4 uses Fama–MacBeth regressions to investigate whether *IMOM* can be explained by other short- or medium-term price signals. Fama [1976] showed that the coefficients from Fama–MacBeth regressions can be interpreted as average returns on a long–short portfolio that hedges out

the risk exposure of the remaining variables. The first column in Table 4 reports the results for all stocks, and the next three columns report the results for the three size groups. Jegadeesh [1990] and Lo and MacKinlay [1990], among others, showed a strong negative serial correlation in monthly stock returns due to microstructure effects, and Novy-Marx [2011] showed that the performance in the first 6 of the previous 12 months has a stronger explanatory power than momentum on the cross-section of stock returns. I denote the former as $r_{i,t-1}$ and the latter as *MOM2*, which is calculated as

$$MOM2_{\mathrm{i,t}} = \prod_{\mathrm{j=7}}^{12} \left(1 + \mathrm{r_{i,t-j}}\right) - 1. \tag{4}$$

Panel A of Table 4 reports the base cases with regressions of each individual variable, and Panel B reports regressions that include all variables simultaneously. Confirming the evidence presented earlier, *IMOM* shows a strong and consistent annualized performance of 19% across all size groups in individual regressions. The stronger performance among large stocks reported in Table 4 in comparison to the results reported in Table 3 can be attributed to the fact that Fama–MacBeth regressions tend to assign heavier weights to stocks with stronger *IMOM* signals, unlike value- or equal-weighted strategies. Individually, the performances of *MOM* and *MOM2* are lower, but still statistically significant. The previous month's return is a strong forecaster, especially among micro caps, but is likely not useful in practice; I use it in my analysis to control for any possible criticisms that *IMOM* is driven by microstructure, price-rebound, or bid-ask effects. Joint regressions drive home the argument by showing that *IMOM* is still strong and statistically powerful in all size groups, with annualized performances in excess of 10% and *t*-statistics of 3 (large stocks), 5 (small stocks), 7 (micro stocks), and 6 (market). The other two momentum variables are small and mostly insignificant, showing that *IMOM* is a more powerful predictor for the cross-section of stock returns. The only exception is *MOM2* among large stocks, with a coefficient of 7% and a *t*-statistic of 2.34.

<Table 4 here.>

All previous strategies involved signals and weights that were recalculated on a monthly basis, so the next step is to investigate how persistent those signals are. To answer this question, **Figure 1** shows average returns and *t*-statistics for value-weighted WML portfolios sorted on both *IMOM* and *MOM*, up to 12 months after the portfolios are formed. In the first month we see a difference of roughly 3 percentage points (17% versus 14%) between the average returns of the two strategies and, more importantly, a difference in *t*-statistics of 7 versus 4, which confirms the previous finding that *IMOM* achieves a slightly superior performance with a much lower standard deviation. In subsequent months the performances of both strategies are similar and decrease slowly—revealing the unsurprising deterioration of the signals over time—but we can still observe a significant difference in *t*-statistics that persists at least 6 months after the portfolios are formed.

<Figure 1 here.>

The differences between *MOM* and *IMOM* portfolios become even starker when their risk-adjusted performances are compared. **Figure 2** shows large and significant four-factor alphas in the case of *IMOM* portfolios, starting at 9.19% (*t*-stat of 5.81) in the first month and slowly decreasing over time to 5.57% (*t*-stat 2.90) in the sixth month. In comparison, the alphas of *MOM* portfolios in the first six months are all below 4% and their *t*-statistics rarely climb above 2. Starting at seven months after portfolio formation, the two strategies look similar, with decaying and mostly insignificant alphas.

<Figure 2 here.>

Idiosyncratic Momentum as a Risk Factor

The previous results show that the portfolios formed on *IMOM* provide higher average returns and lower volatility than portfolios formed on *MOM* and, more importantly, that their outperformance cannot be explained by the traditional momentum factor (*UMD*). To investigate whether a factor created on the basis of the information contained in *IMOM* subsumes *UMD*, I follow the definition of *UMD* and create six portfolios using one breakpoint on size (50th percentile among NYSE stocks) and two breakpoints on *IMOM* (30th and 70th percentiles among NYSE stocks). The idiosyncratic momentum factor, *IUMD*, is then calculated as the average of the return differential between the extreme portfolios in each size group,

$$IUMD_t = \frac{1}{2}(r_t^{SH} - r_t^{SL}) + \frac{1}{2}(r_t^{BH} - r_t^{BL}). \tag{5}$$

Next, I run individual regressions of the five quintiles sorted on either *IMOM* or *MOM* on each factor separately to check whether *IUMD* or *UMD* loadings line up with average expected returns. Not surprisingly given the similarity between the two signals, **Table 5** shows a strong correlation (above 95% in all cases) between the average returns of both types of quintile portfolios and the coefficients on both factors. This characteristic indicates that cross-sectional R-squared, a commonly used measure to compare the explanatory power of competing risk factors, is not an effective statistic in this case.

As an alternative, I follow the recommendation in Lewellen, Nagel, and Shanken [2010], who argued that the magnitude of the estimated risk premiums should be taken seriously. I therefore compare the estimated risk premiums to the average returns of the factor as an additional evaluation criterion. Because of the small number of portfolios (five) in this case, and because of the high correlation between dependent variables and regressors, I choose a simple approach to calculate the implied cross-sectional risk premiums. Instead of running cross-sectional regressions, I calculate the ratio between the spread in average returns and the spread in factor loadings. This ratio suffices to show which factor performs best in terms of the magnitude of its risk premium. Below I confirm the results with traditional time-series tests.

<Table 5 here.>

The spread between quintiles 5 and 1 is represented by the column labeled WML. Panel A of Table 5 shows a spread in average annualized returns of 14% and spreads in factor loadings of 1.45 (*UMD*) and 1.87 (*IUMD*). Approximating the true regression slopes, the risk premiums required by each factor are 9.65% for *UMD* and 7.45% for *IUMD*. These are reasonable numbers and indicate that both factors seem to work relatively well. Panel 2, however, paints a different picture. Quintile portfolios sorted on *IMOM* show a spread in *IUMD* loadings of 1.56, almost twice the spread in *UMD* loadings of 0.82, resulting in approximated risk premiums of 11.09% and 21.23%, respectively. The latter is not feasible, as I show next, and indicates that *IUMD* provides a better adjustment for portfolios with exposure to traditional or idiosyncratic momentum.

Next, I use time-series spanning tests (regressions) to confirm the evidence that an idiosyncratic momentum factor, *IUMD*, is capable of explaining not only portfolios formed on idiosyncratic momentum, *IMOM*, but also on traditional momentum, *MOM*. **Table 6** reports that IUMD earns an average return (risk premium) of 11.05%, not much higher than the 8.64% of *UMD*. But IUMD achieves its superior performance with twice the statistical significance—7.79 versus only 3.88—and confirms the finding that *IMOM* generates portfolios with lower volatilities. The second and third rows of Table 6 show that regressions using *UMD* alone and *UMD* combined with market, size, and value factors can explain less than half of the risk premium of *IUMD*, leaving alphas of 6.77% (*t*-stat of 7.49) and 5.61% (*t*-stat of 6.52). The fifth and sixth rows show results for opposite tests (i.e., regressions of *UMD* on *IUMD* alone and on *IUMD* combined with market, size, and value factors). Interestingly, the alphas are also statistically significant—*t*-statistics of 3.28 and 2.31—but are negative, –4.84 and –3.20. Interpreting these results literally, the negative risk-adjusted performance of *UMD* implies that it can be substituted by *IUMD* in four-factor regressions. More pragmatically, however, it could still be argued that the inverse of *UMD* should be included in addition to *IUMD* and MKT, SMB, and HML.

<Table 6 here.>

Figure 3 plots the cumulative return of $100 invested in the market portfolio and in each of the two legs (long and short) of *IUMD* and *UMD*. Comparing the returns of the individual components with the market portfolio, it is clear that the positive average returns earned by both factors are not concentrated in the short portfolios but are also earned in the long portfolio, confirming the evidence from previous studies of momentum. Moreover, *IUMD* achieves its higher average annualized return of 2.41% relative to *UMD* from a combination of both legs: outperformance of 1.15% by the long portfolio and underperformance of 1.26% by the short portfolio (not reported in the tables or figures). Less noticeable from the graph is the source of the lower (monthly) volatility of *IUMD* (2.80%)—when compared to the volatility of *UMD* (4.39%). Not only are both legs less volatile—5.35% versus 5.51% on the long side and 5.97% versus 6.43% on the short side—but the correlation between each component of the same factor is also higher—0.88 for *IUMD* versus 0.74 for *UMD*.

Momentum Crashes

It is easy to understand that momentum strategies that rely on recent idiosyncratic performance avoid stocks that performed well (poorly) due only to a high (low) beta, but it is not clear why this choice should result in improved performance or reduced volatility. The financial literature is only starting to understand how momentum strategies interact with, or are exposed to, the market portfolio. Grundy and Martin [2001], followed by Daniel and Moskowitz [2011], provided the first satisfactory answer to this question by showing that momentum strategies tend to experience long periods of poor performance following market downturns and contemporaneously with market rebounds. The reason for the underperformance, according to Daniel and Moskowitz, is the optionality embedded in the "losers" portfolio; investors who sell this portfolio short are rewarded during market downturns, but suffer big losses—momentum crashes—when the market rebounds.

Table 7 provides a brief view of this effect and shows the 10 worst-performing months for the *UMD* factor since 1965. Confirming Daniel and Moskowitz's argument, 9 of the 10 months happened right after a period of steep market decline, measured as the previous 12-month return, followed by a sharp market recovery in the current month. It is also worth mentioning that 7 of the 10 months happened in the last 10 years. The performance of the idiosyncratic momentum factor (*IUMD*) is still negative in 9 of the 10 months, but the losses are significantly reduced in all occasions. For instance, when *UMD* fell 34% in April of 2009, *IUMD* only lost 11%.[8] By avoiding stocks in the losers portfolios that have large negative returns originated by a combination of high betas and market declines, *IUMD* reduces the volatility and skew in its distribution of returns.

<Table 7 here.>

III. International Results

Traditional momentum strategies are profitable in many countries around the world (Rouwenhorst [1998], Griffin, Ji, and Martin [2003], Chui, Wei, and Titman [2000), and Fama and French [2011]). I use an international sample with 21 countries to check the robustness of *IMOM* and to study its similarities and differences with *MOM*. As explained in Section II, in order to guarantee that the results are not limited to micro or illiquid stocks, two size screens are imposed on the data. The first screen sorts stocks in each country by their market capitalization and removes the bottom half of the stocks. The remaining stocks are then sorted on either *MOM* or *IMOM*, and 5 quintile portfolios are formed by equally weighting the stocks within them. The return on a zero-investment, winners-minus-losers (WML)

[8] The top-five losses of *IUMD* are the same as in Table 6; *IMOM* does not generate severe losses in other months.

portfolio is calculated as the difference between quintile portfolios 5 and 1. I further require a minimum of 25 stocks in each country, so that each quintile has at least 5 stocks. This last requirement allows a better comparison between *IMOM* and *MOM*, because with a reduced number of stocks, the two signals are hard to disentangle.

The second size screen also sorts stocks according to their market capitalization, but selects a sample that contains at least 90% of the total market capitalization in that country. Because this second approach is more restrictive, I report individual results only for four countries (France, Germany, Japan, and the United Kingdom), which consistently have more than 50 stocks that satisfy the requirement, and pool the remaining countries into four distinct groups: northern Europe, central Europe, southern Europe, and other. Quintile and WML portfolios are then formed as described in the first size screen.

Table 8 reports results for the first size screen. The first four columns show the number of existing monthly returns in each portfolio as well as the average, minimum, and maximum number of stocks in each country over time. The United Kingdom has the longest time series with 465 monthly observations, followed by eight countries with 453 monthly observations. Finland has the shortest time series (237), followed by Portugal (267), Austria (269), Greece (273), and New Zealand (273). The restriction on the minimum number of stocks in each country (25) reduces the sample size in 7 of the 21 countries. Japan and the United Kingdom have the largest average number of stocks: 1,114 and 767, respectively. Canada has few stocks (36) in the early years of the sample, but the number increases quickly, reaching second place (1,481) after Japan (1,969) in later years. Some countries continue to have a limited number of stocks even in the later years of the sample: Ireland (41), Portugal (54), Austria (63), Finland (75), and New Zealand (77).

<Table 8 here.>

The next two columns in Table 8 indicate the similarity of the two strategies formed on *MOM* and *IMOM*. Every month I calculate the rank Spearman correlation between the two signals in each country and then report the average and standard deviations of the monthly time series. The averages are strikingly similar across countries and relatively stable over time. Not surprisingly, sorting stocks on *MOM* and *IMOM* produces rankings that have a correlation of roughly 70%. More surprisingly, however, is the subsequent performance of the stocks that are assigned to the winners and losers portfolios (quintiles 5 and 1).

The average returns and *t*-statistics on the WML portfolios formed on *MOM* are shown in the next two columns of Table 8. Confirming the evidence in previous studies, traditional momentum strategies work well in the vast majority of countries. Average returns are often above 12% per year (1% per month) with *t*-statistics in excess of 2. Some of the best performers are Denmark, Portugal, Australia, Canada, and New Zealand. Notably, *MOM* shows impressive *t*-statistics even in large countries such as the United Kingdom (5.99), Germany (5.97), and France (4.41). The two exceptions in the sample are Ireland and Japan. The failure of traditional momentum strategies in Japan has been the topic of recent articles (e.g., Asness [2011] and Asness, Moskowitz, and Pedersen [2011]).

Finally, WML portfolios formed on *IMOM* are shown in the last two columns of Table 8. Average returns are higher in 13 of the 21 countries and, more importantly, *t*-statistics increase in all countries except for New Zealand and are statistically significant in all 21 countries. The most surprising result is the relative success of the *IMOM* strategy in Japan, where it generates an average return of 7.37% and a *t*-statistic of 3.11. The most significant improvements in performance are in Ireland, Singapore, Greece, and Japan, and the largest increases in *t*-statistics are in Singapore, Canada, France, and the United Kingdom.

The results in Table 8 show a consistent improvement in the performance and, in particular, the volatility of strategies that use *IMOM* versus *MOM*. The results presented in Table 8 also indicate a high correlation between these two signals. To study whether the performance of *IMOM* remains significant after controlling for the correlation between these two strategies, **Table 9** reports results of the following regressions for each country:[9]

$$WML_t^{IMOM} = \alpha + \delta WML_t^{MOM} + \beta MKT_t + \varepsilon_t. \quad (6)$$

The results are very similar to previous findings in the U.S. sample: βs are slightly negative and often statistically insignificant; δs are close to 0.5 and highly statistically significant; and R-squareds range from 40% to 60% in most cases. Most importantly, alphas are close to or above 50% of the total average return and are statistically significant. The only exceptions are New Zealand, Spain, and Norway. The statistical significance of alpha is strongly correlated with country sample length and, more importantly, with the average number of stocks in a country, which reinforces the earlier claim that a broader cross-section of stocks improves the ability to disentangle *IMOM* from *MOM*.

<Table 9 here.>

An extra benefit of limiting each country's exposure to market beta and, consequently, to momentum crashes is reducing the correlation between the WML portfolios of different countries. Using the same portfolios from Tables 8 and 9, I calculate two correlation matrices: the first one includes all *MOM* portfolios and the second one includes all *IMOM* portfolios. In the interest of space, **Table 10** shows only the average and standard deviation of correlations for each country, excluding the diagonal. The portfolios formed according to *IMOM* display, on average, half of the correlation of portfolios

[9] An alternative method would be to construct a country momentum factor similar to *UMD* in the United States. However, the regression in Equation (6) provides a better comparison between *IMOM* and *MOM*, because both portfolios are formed using the same universe of stocks and the same number of breakpoints (quintiles), thus generating similar relative spreads between winners and losers.

formed according to *MOM*. Further, the standard deviation of the correlations shows no significant differences across the two types of portfolios.

<Table 10 here.>

Combining the lower correlations between portfolios (Table 10) with the lower standard deviations of each portfolio (Table 8), one can quickly see the potential in cross-country portfolios. Here I follow a simple strategy and construct an equally weighted portfolio of individual countries. **Table 11** reports the results. Although the two combinations of country portfolios formed according to either *MOM* or *IMOM* share annualized average returns of roughly 15 percent, the latter displays a significantly higher *t*-statistic of 13.68 versus only 7.53 for the former.

<Table 11 here.>

To show that idiosyncratic momentum works even among the most liquid stocks in each country, **Table 12** repeats the same analysis from Tables 8 and 9 in the reduced and more restrictive sample composed of eight countries and regions. The United Kingdom has 465 monthly observations and all other portfolios have 453 monthly observations. The average number of stocks ranges from 89 in Germany to 620 in Japan, and the minimum (maximum) number of stocks ranges from 25 (248) in northern Europe to 287 (973) in Japan. Traditional momentum strategies are profitable in all countries and regions with the usual exception of Japan. Idiosyncratic momentum strategies show modest improvements in performance but more meaningful improvements in statistical significance. The *IMOM* strategy in Japan has an average return of 6.48% with a *t*-statistic of 2.59. Results from the regression in Equation (6) also yield alphas from 4% to 9% with *t*-statistics well above 3.

<Table 12 here.>

In summary, the evidence from the international sample reinforces the findings from the U.S. sample. Strategies based on idiosyncratic momentum achieve similar or higher average returns than other momentum strategies, but with a reduction in volatility. Because of the positive correlation between *IMOM* and *MOM*, these factors result in positive and statistically significant risk-adjusted performances (alphas). Finally, *IMOM* seems to be the first momentum-related strategy that shows a consistent performance in Japan.

IV. Conclusion

Over the last two decades, momentum strategies have intrigued academics and practitioners for their simplicity and impressive performance, but their unexpected and sizeable losses have also attracted attention, especially during the recent financial crisis.

In this article, I describe a powerful yet simple method for reducing the volatility and the magnitude of the losses associated with momentum strategies by ranking stocks based on their idiosyncratic performance. This approach significantly reduces the exposure of such strategies to the momentum crashes described by Daniel and Moskowitz [2011].

I show that the strong performance of idiosyncratic momentum is not constrained to U.S. stocks, but also holds in an extended sample of 21 countries including Japan, where traditional momentum strategies have failed.

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Table 1: WML Portfolios

This table reports excess returns (annualized, percent) and *t*-stats (in parentheses) for five portfolios sorted on idiosyncratic momentum (*IMOM*) and for the long–short portfolio of winners minus losers (WML). Stocks within each portfolio are equally weighted in (1) and value weighted in (2). U.S. sample, 1965–2011.

	Losers	2	3	4	Winners	WML
(1) EW	-0.34	6.54	9.21	12.15	17.77	18.11
	(-0.08)	(2.15)	(3.52)	(4.62)	(5.36)	(8.79)
(2) VW	-5.50	3.02	3.95	6.44	11.83	17.33
	(-1.50)	(1.17)	(1.79)	(2.88)	(4.25)	(6.99)

Table 2: WML Portfolios Factor Regressions

This table reports alphas (annualized, percent), coefficients, and *t*-stats (in parentheses) for six regressions of long–short portfolios (WML) sorted on idiosyncratic momentum (*IMOM*) on the market (MKT), size (SMB), value (HML), and momentum (UMD) factors. Stocks are equally weighted in the first three regressions and value weighted in the last three. U.S. sample, 1965–2011.

	Alpha	MKT	SMB	HML	UMD	R-squared
(1) EW	18.98	-0.18				0.04
	(9.38)	(-5.04)				
(2) EW	18.48	-0.13	0.14	-0.11		0.06
	(9.06)	(-3.36)	(2.36)	(-2.05)		
(3) EW	11.24	-0.01	0.35	-0.12	0.67	0.55
	(7.79)	(-0.42)	(8.35)	(-3.21)	(24.56)	
(4) VW	18.85	-0.32				0.09
	(7.94)	(-7.48)				
(5) VW	18.28	-0.30	0.10	0.00		0.09
	(7.58)	(-6.47)	(1.48)	(0.05)		
(6) VW	9.19	-0.15	0.37	-0.01	0.84	0.63
	(5.81)	(-4.92)	(8.00)	(-0.21)	(28.16)	

Table 3: WML Portfolios in Size Groups

This table reports, for all three size groups, average excess returns (annualized, percent) and *t*-stats (in parentheses) for five quintiles sorted on idiosyncratic momentum (*IMOM*). For the long–short portfolio of winners minus losers (WML), it also shows CAPM, three-factor and four-factor alphas (annualized, percent) and *t*-stats (in parentheses). The size groups are created using NYSE breakpoints at the 20th and 50th percentiles. U.S. sample, 1965–2011.

	Losers	2	3	4	Winners	WML	CAPM alpha	3F alpha	4F alpha
					Panel A: EW - *IMOM*				
Micro	0.04	7.58	10.68	14.59	20.00	19.95	20.95	20.24	13.58
	(0.01)	(2.18)	(3.49)	(4.87)	(5.50)	(9.05)	(9.71)	(9.34)	(7.85)
Small	-1.57	6.72	8.91	11.47	15.69	17.26	17.98	17.48	10.25
	(-0.40)	(2.20)	(3.28)	(4.13)	(4.45)	(8.77)	(9.24)	(8.85)	(7.60)
Large	-0.42	5.50	6.76	7.76	11.94	12.35	13.04	12.33	4.91
	(-0.13)	(2.21)	(2.91)	(3.29)	(4.12)	(6.32)	(6.74)	(6.32)	(3.88)
					Panel B: VW - *IMOM*				
Micro	-7.88	4.13	8.57	12.00	17.59	25.47	26.45	25.49	18.24
	(-1.80)	(1.21)	(2.85)	(4.11)	(4.86)	(12.09)	(12.84)	(12.31)	(12.26)
Small	-1.59	6.42	8.76	11.39	15.67	17.27	18.00	17.44	10.07
	(-0.41)	(2.10)	(3.24)	(4.14)	(4.51)	(8.68)	(9.16)	(8.74)	(7.48)
Large	-0.53	3.71	3.63	5.73	10.85	11.37	12.00	11.54	3.91
	(-0.18)	(1.61)	(1.68)	(2.58)	(4.02)	(5.33)	(5.66)	(5.40)	(2.60)
					Panel C: EW - *MOM*				
Micro	6.39	7.62	9.80	13.42	16.54	10.16	11.50	12.96	0.48
	(1.24)	(2.09)	(3.20)	(4.57)	(4.79)	(3.01)	(3.46)	(3.87)	(0.22)
Small	0.61	6.85	8.89	11.06	14.39	13.78	14.30	16.49	3.48
	(0.15)	(2.28)	(3.26)	(3.87)	(3.85)	(4.71)	(4.88)	(5.70)	(2.93)
Large	2.17	5.38	5.83	6.94	11.68	9.52	9.85	11.91	-0.80
	(0.66)	(2.13)	(2.50)	(2.90)	(3.67)	(3.30)	(3.41)	(4.27)	(-0.75)
					Panel D: VW - *MOM*				
Micro	-5.64	3.62	7.59	10.97	15.37	21.02	22.52	24.16	10.47
	(-1.15)	(1.00)	(2.47)	(3.72)	(4.37)	(6.39)	(6.99)	(7.43)	(6.11)
Small	1.06	6.44	8.47	10.91	14.46	13.40	13.91	16.10	2.75
	(0.26)	(2.15)	(3.13)	(3.87)	(3.89)	(4.49)	(4.65)	(5.46)	(2.35)
Large	2.18	3.51	3.83	5.84	9.48	7.30	7.54	9.62	-3.53
	(0.71)	(1.50)	(1.75)	(2.54)	(3.19)	(2.46)	(2.53)	(3.34)	(-3.22)

Table 4: Fama–MacBeth Regressions

This table reports, for all stocks and for the three size groups, Fama–MacBeth regression coefficients (annualized, percent) and *t*-stats (in parentheses) using three different momentum definitions—idiosyncratic momentum (*IMOM*), traditional momentum (*MOM*), and Novy-Marx's (2011) momentum (*MOM2*)—and previous month return (r(t-1)). Panel A contains regressions that include one variable at a time, whereas Panel B reports regressions that include all four variables jointly. The size groups are created using NYSE breakpoints at the 20^{th} and 50^{th} percentiles. U.S. sample, 1965–2011.

	ALL	Micro	Small	Large
Panel A: Individual Regressions				
IMOM	19.18	19.44	19.73	19.53
	(10.57)	(11.27)	(9.67)	(7.23)
MOM	6.04	5.14	8.34	9.08
	(2.74)	(2.24)	(4.09)	(3.69)
MOM2	8.28	6.40	11.59	15.57
	(4.03)	(3.29)	(5.32)	(5.33)
r(t-1)	-55.39	-69.37	-22.12	-22.85
	(-10.83)	(-13.50)	(-3.95)	(-3.39)
Panel B: Joint Regressions				
IMOM	12.68	13.93	13.19	10.10
	(6.25)	(7.25)	(5.11)	(3.06)
MOM	-0.94	-2.82	2.08	0.17
	(-0.30)	(-0.89)	(0.69)	(0.05)
MOM2	1.30	0.40	1.19	7.03
	(0.67)	(0.21)	(0.53)	(2.34)
r(t-1)	-58.86	-72.92	-24.77	-30.94
	(-11.92)	(-14.22)	(-4.66)	(-5.11)

Table 5: Excess Returns and Factor Loadings

This table reports average excess returns of five quintile portfolios sorted on either *MOM* (Panel A) or *IMOM* (Panel B) and their regression coefficients on *UMD* and *IUMD* factors. The column WML (winners minus losers) reports the spread between quintiles 5 and 1, and the column Slope reports the spread in excess returns divided by the spread in coefficients.

	Losers	2	3	4	Winners	WML	Slope
				Panel A: *MOM* Portfolios			
Excess Return	-3.68	2.31	3.91	6.56	10.26	13.94	
***UMD* Coefficient**	-1.07	-0.70	-0.31	0.02	0.38	1.45	9.65
***IUMD* Coefficient**	-1.62	-1.04	-0.58	-0.18	0.25	1.87	7.45
				Panel B: *IMOM* Portfolios			
Excess Return	-5.50	3.02	3.95	6.44	11.83	17.33	
***UMD* Coefficient**	-0.63	-0.39	-0.20	-0.03	0.19	0.82	21.23
***IUMD* Coefficient**	-1.31	-0.86	-0.44	-0.06	0.25	1.56	11.09

Table 6: Spanning Tests

This table reports alphas (annualized, percent), coefficients, *t*-statistics (in parentheses), and R-squareds of regressions of factors on factors. IUMD is the factor constructed using idiosyncratic momentum, and MKT, SMB, HML, and UMD are the traditional market, size, value, and momentum factors, respectively. U.S. sample, 1965–2011.

Dependent	**Independent Variables**						**R-squared**
Variable	**Alpha**	**IUMD**	**UMD**	**MKT**	**SMB**	**HML**	
IUMD	11.05						
	(7.79)						
IUMD	6.77		0.50				0.60
	(7.49)		(29.19)				
IUMD	5.61		0.52	-0.03	0.04	0.22	0.66
	(6.52)		(31.91)	(-1.68)	(1.75)	(8.85)	
UMD	8.64						
	(3.88)						
UMD	-4.84	1.22					0.60
	(-3.28)	(29.19)					
UMD	-3.20	1.26		-0.03	-0.05	-0.39	0.67
	(-2.31)	(31.91)		(-1.12)	(-1.26)	(-10.18)	

Table 7: UMD Extreme Months

This table shows losses of Carhart's [1997] momentum factor (UMD) and the corresponding returns of the market in the previous year, the market in the same month, and the risk factor based on idiosyncratic momentum (IUMD) in the same month.

Year	Month	MKT Previous Year (%)	MKT (%)	UMD (%)	IUMD (%)
2009	4	-39.40	11.04	-34.75	-11.29
2001	1	-16.10	3.41	-25.01	-16.44
2002	11	-14.99	6.01	-16.31	-8.39
1975	1	-33.50	13.58	-13.80	2.07
2009	5	-35.88	6.73	-12.49	-7.09
2009	3	-44.95	8.76	-11.51	-5.06
1973	7	-11.84	5.06	-11.50	-8.50
2003	5	-14.16	6.26	-10.77	-5.50
1980	3	17.61	-13.23	-9.61	-5.54
2003	4	-24.72	8.18	-9.44	-2.84

Table 8: International Sample Summary Statistics and WML Portfolios

This table reports, for each country, the number of months with enough information to construct the momentum portfolios; the average, minimum, and maximum number of stocks in each month; the average and standard deviations of the monthly Spearman rank correlations between *MOM* and *IMOM*; and the average return (annualized, percent) and *t*-stats of portfolios constructed using traditional momentum (*MOM*) and idiosyncratic momentum (*IMOM*). Each month, only the top half of stocks in terms of market capitalization in each country is included in the sample. The long (short) leg of each portfolio includes the top (bottom) 20% of stocks according to *MOM* or *IMOM*, and both legs are equally weighted. January 1972–September 2011.

	Months	# Stocks			Monthly Rank Correlation		*MOM*		*IMOM*	
		Average	Min	Max	Average	Std. Dev.	Mean	*t*-stat	Mean	*t*-stat
AUSTRALIA	453	355	60	954	0.68	0.11	19.88	6.10	19.94	7.95
AUSTRIA	269	47	25	63	0.61	0.21	13.72	2.46	16.81	4.18
BELGIUM	315	63	25	80	0.71	0.13	17.75	4.58	16.44	5.43
CANADA	453	634	36	1481	0.66	0.11	19.50	5.24	22.70	8.56
DENMARK	281	96	43	117	0.71	0.14	24.45	6.10	24.47	7.64
FINLAND	237	56	25	75	0.68	0.17	12.06	1.94	15.60	3.04
FRANCE	453	245	46	471	0.70	0.10	14.10	4.41	16.93	7.37
GERMANY	453	263	76	516	0.70	0.13	16.63	5.97	17.59	8.43
GREECE	273	114	29	168	0.66	0.17	18.18	2.88	24.01	4.83
IRELAND	290	36	25	41	0.71	0.16	8.83	1.24	18.06	3.15
ITALY	453	90	33	149	0.71	0.13	17.82	5.03	17.12	5.98
JAPAN	453	1114	384	1969	0.72	0.10	2.08	0.67	7.37	3.11
NETHERLANDS	453	84	53	121	0.70	0.13	16.80	5.20	14.71	6.22
NEW ZEALAND	273	53	27	77	0.66	0.20	18.72	4.11	17.52	4.03
NORWAY	332	67	25	109	0.64	0.32	15.94	3.30	16.41	3.70
PORTUGAL	263	39	25	54	0.63	0.14	21.93	3.21	15.39	3.45
SINGAPORE	333	163	46	317	0.66	0.18	10.31	2.07	16.38	5.46
SPAIN	283	68	29	84	0.72	0.13	9.44	2.21	9.08	2.62
SWEDEN	303	130	25	231	0.69	0.14	14.61	2.79	16.87	3.97
SWITZERLAND	453	88	29	149	0.70	0.13	13.49	4.85	12.21	5.61
UNITED KINGDOM	465	767	416	1169	0.71	0.09	15.93	5.99	15.89	8.81

Table 9: International Sample Regressions

This table reports coefficients (*t*-stats), alphas (annualized, percent), and R-squareds from regressions of a long–short portfolio sorted on idiosyncratic momentum (*IMOM*) on the market portfolio in each country and the long–short portfolio sorted on traditional momentum (*MOM*) in each country. January 1972–September 2011.

	Alpha	*t*-stat	*MOM*	*t*-stat	Market	*t*-stat	R-squared
AUSTRALIA	10.71	5.19	0.48	16.64	-0.03	-1.16	0.38
AUSTRIA	11.41	3.21	0.36	9.35	0.08	1.75	0.25
BELGIUM	5.96	2.93	0.60	20.62	-0.01	-0.47	0.59
CANADA	14.57	6.91	0.45	17.43	-0.11	-3.52	0.41
DENMARK	9.02	4.21	0.63	20.97	0.00	0.14	0.62
FINLAND	11.20	3.07	0.54	14.08	-0.16	-4.65	0.52
FRANCE	11.31	6.21	0.44	16.56	-0.07	-3.01	0.41
GERMANY	9.30	6.18	0.52	20.96	-0.06	-3.02	0.53
GREECE	14.87	3.89	0.51	14.22	-0.03	-0.85	0.43
IRELAND	14.47	2.94	0.42	9.86	-0.02	-0.32	0.28
ITALY	5.65	3.02	0.63	25.98	0.05	2.19	0.60
JAPAN	6.35	4.28	0.59	26.27	-0.05	-2.38	0.61
NETHERLANDS	6.21	3.76	0.53	22.69	-0.06	-2.22	0.56
NEW ZEALAND	2.89	1.03	0.75	20.84	0.08	2.13	0.62
NORWAY	5.61	1.87	0.69	20.73	-0.02	-0.52	0.57
PORTUGAL	10.60	2.50	0.24	6.30	-0.10	-1.81	0.14
SINGAPORE	12.44	5.38	0.39	14.65	-0.01	-0.46	0.43
SPAIN	3.51	1.54	0.61	19.21	-0.03	-1.13	0.58
SWEDEN	9.12	3.54	0.61	21.36	-0.12	-3.98	0.65
SWITZERLAND	4.95	3.33	0.58	23.73	-0.07	-3.04	0.57
UNITED KINGDOM	6.41	6.39	0.58	34.26	0.03	2.48	0.72

Table 10: WML Country Portfolio Correlations

This table reports the average and standard deviation of correlations between each country's winners-minus-losers (WML) portfolio and all the other countries'.

	MOM		*IMOM*	
	Average Correlation	**Std. Dev. Correlation**	**Average Correlation**	**Std. Dev. Correlation**
AUSTRALIA	0.28	0.09	0.14	0.08
AUSTRIA	0.30	0.09	0.15	0.07
BELGIUM	0.33	0.12	0.14	0.08
CANADA	0.28	0.09	0.16	0.09
DENMARK	0.33	0.09	0.19	0.09
FINLAND	0.35	0.13	0.22	0.11
FRANCE	0.41	0.13	0.26	0.11
GERMANY	0.38	0.12	0.25	0.12
GREECE	0.21	0.06	0.10	0.06
IRELAND	0.35	0.10	0.14	0.10
ITALY	0.33	0.11	0.16	0.08
JAPAN	0.19	0.05	0.07	0.05
NETHERLANDS	0.39	0.13	0.22	0.10
NEW ZEALAND	0.14	0.06	0.04	0.05
NORWAY	0.30	0.11	0.18	0.10
PORTUGAL	0.19	0.08	0.09	0.06
SINGAPORE	0.24	0.07	0.09	0.07
SPAIN	0.35	0.12	0.20	0.09
SWEDEN	0.35	0.13	0.22	0.12
SWITZERLAND	0.39	0.13	0.22	0.10
UNITED KINGDOM	0.43	0.12	0.26	0.10

Table 11: Cross-country Portfolios

This table reports average returns and t-statistics (in parentheses) for portfolios formed by equally weighting the winners-minus-losers (WML) MOM or IMOM portfolios of each country.

	MOM	*IMOM*
Average Return	14.41	15.67
***t*(Return)**	(7.53)	(13.68)

Table 12: International Sample Regressions 2

This table reports, for each country or group, the number of months with enough information to construct the momentum portfolios; the average, minimum, and maximum number of stocks in each month; and the average return (annualized, percent) and *t*-stats of portfolios constructed using traditional momentum (*MOM*) and idiosyncratic momentum (*IMOM*). It also shows coefficients (*t*-stats), alphas (annualized, percent), and R-squareds from regressions of the *IMOM* portfolio on the market portfolio in each country and the *MOM* portfolio in each country. Each month, only the largest stocks are selected so that the sample contains at least 90% of the total market capitalization in each country. The long (short) leg of each portfolio includes the top (bottom) 20% of stocks according to *MOM* or *IMOM*, and both legs are equally weighted. Northern Europe includes Sweden, Norway, Finland, Ireland, and Denmark. Central Europe includes Austria, Belgium, Netherlands, and Switzerland. Southern Europe includes Greece, Italy, Portugal, and Spain. The group Other includes Australia, Canada, New Zealand, and Singapore. January 1972–September 2011.

	Months	# Stocks			*MOM*		*IMOM*		Regression						
		Average	Min	Max	Mean	*t*-stat	Mean	*t*-stat	Alpha	*t*-stat	*MOM*	*t*-stat	Market	*t*-stat	R-squared
CENTRAL EUROPE	453	119	74	165	12.71	4.24	11.39	5.87	7.12	4.30	0.36	14.09	-0.04	-1.39	0.32
FRANCE	453	91	53	172	9.85	2.98	12.47	4.92	7.53	4.18	0.54	20.79	-0.04	-1.92	0.52
GERMANY	453	89	61	133	11.63	3.63	12.74	5.60	7.68	4.50	0.47	18.82	-0.06	-2.55	0.46
JAPAN	453	620	287	973	1.90	0.59	6.48	2.59	5.51	3.60	0.61	27.58	-0.04	-2.08	0.63
NORTHERN EUROPE	453	130	25	248	15.50	4.65	15.27	6.00	8.65	4.34	0.48	17.36	-0.11	-3.87	0.43
OTHER	453	350	77	740	14.08	4.17	13.23	7.32	9.60	6.16	0.28	13.36	-0.06	-2.56	0.29
SOUTHERN EUROPE	453	133	28	245	17.57	4.09	17.37	5.58	8.18	3.65	0.52	21.39	0.02	0.64	0.51
UNITED KINGDOM	465	238	154	352	7.33	2.51	9.02	4.55	4.81	3.94	0.54	28.10	0.03	1.89	0.63

Figure 1 – This chart shows the average returns (annualized, percent) and *t*-stats for the value-weighted long–short portfolio (WML) formed on idiosyncratic momentum (*IMOM*) and traditional momentum (*MOM*) up to 12 months after formation. U.S. sample, all size groups, 1965–2011.

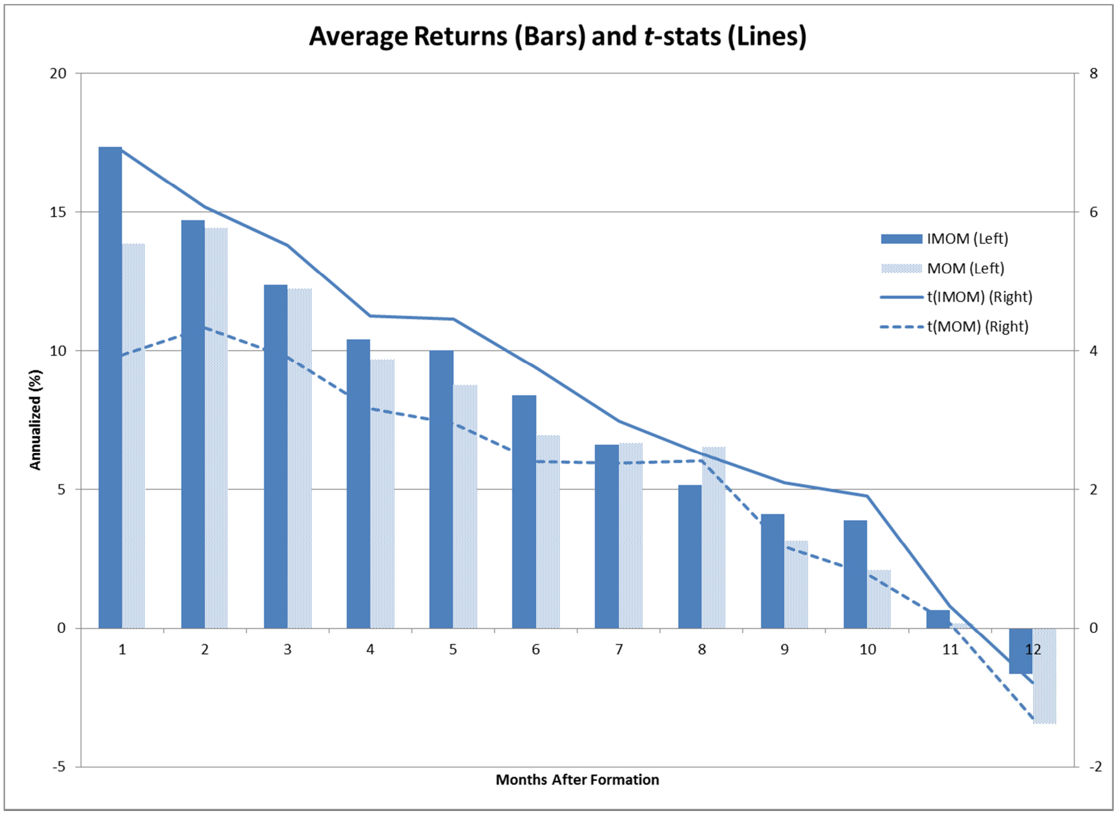

Figure 2 – This chart shows four-factor alphas (annualized, percent) and *t*-stats for the value-weighted long–short portfolio (WML) formed on idiosyncratic momentum (*IMOM*) and traditional momentum (*MOM*) up to 12 months after formation. U.S. sample, all size groups, 1965–2011.

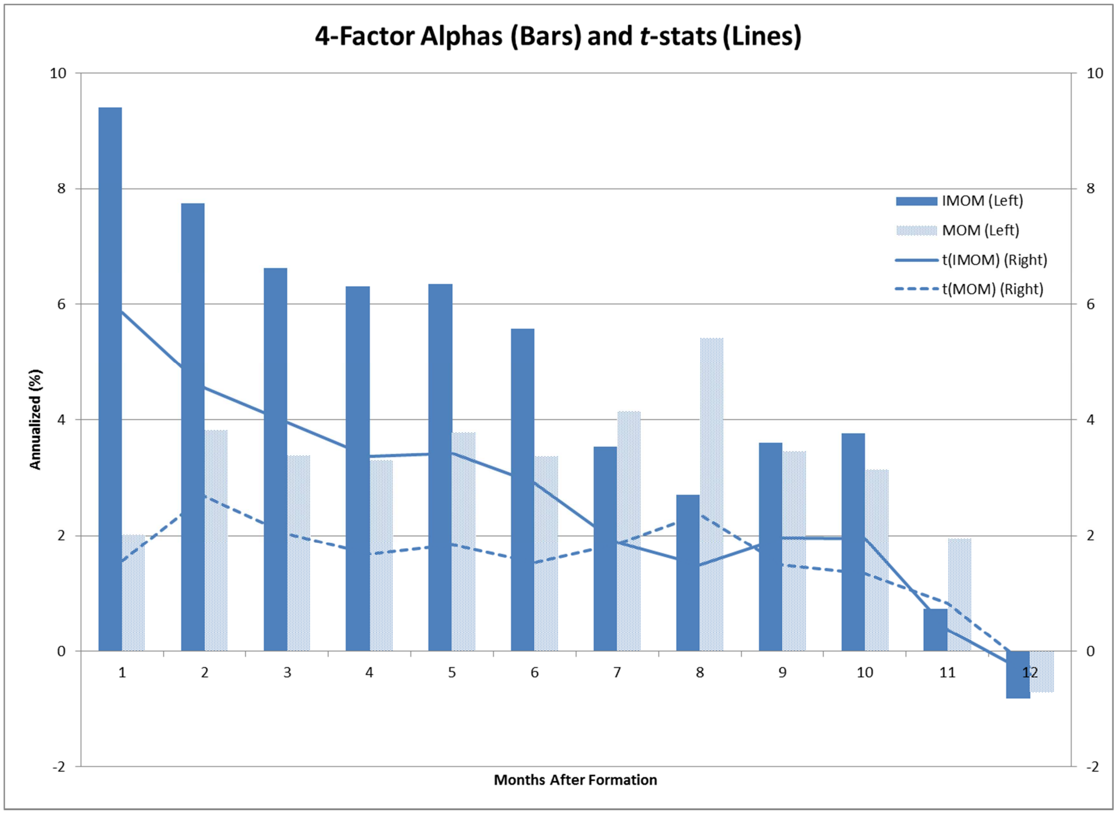

Figure 3 – This chart shows the cumulative performance of $100 invested in January 1965 in each of five portfolios: market, long and short legs of UMD, and long and short legs of IUMD.