The Idiosyncratic Momentum Anomaly

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ABSTRACT

This paper seeks to uncover the drivers of the idiosyncratic momentum anomaly. We show that: (i) idiosyncratic momentum is a distinct phenomenon that exists next to conventional momentum and is not explained by it; (ii) idiosyncratic momentum is priced in the cross-section of stock returns after controlling for established and recently proposed asset pricing factors, including the ones that explain a host of momentum-related anomalies; (iii) some of the prominent explanations for the momentum premium, such as crash risk, and investor overconfidence and overreaction linked to market states and dynamics cannot explain idiosyncratic momentum profits; (iv) long-term return dynamics of idiosyncratic momentum support the underreaction hypothesis for its existence; (v) idiosyncratic momentum generates robust returns across a range of developed and emerging markets.

Keywords: *asset pricing, idiosyncratic momentum, momentum crashes, risk management*
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1 Introduction

The momentum effect is one of the most pervasive asset pricing anomalies documented in the financial literature: stocks with the highest returns over the past six to twelve months continue to deliver above-average returns in the subsequent period (see Jegadeesh and Titman, 1993, 2001). Momentum strategies are known to exhibit significant dynamic exposures to systematic risk factors (styles). For instance, in bull markets high-beta stocks tend to, on average, outperform low-beta stocks, and a zero-investment momentum factor has a net positive exposure to the market factor. The opposite happens in bear markets. Such exposures can be particularly hurtful during style reversals: the Fama-French momentum factor returned -83% in 2009, when stocks that had suffered the largest losses during the financial crisis made a strong recovery.

Grundy and Martin (2001) show that dynamic hedging of the momentum strategy's market and size exposures substantially reduces the volatility of the strategy without a loss in return, but Daniel and Moskowitz (2016) show that the superior performance of their strategy is crucially dependent on the fact that they use ex-post factor betas to hedge these exposures. A hedging strategy based on ex-ante betas does not generate the same improvement. Gutierrez and Pirinsky (2007) propose an alternative method to reduce these systematic style tilts by making individual stock returns in the ranking period orthogonal to the three factors that explain a major part of the variation in average returns - the market, size, and value factors. Using this approach, the authors document that, after a similar performance in the first year after formation, this *idiosyncratic*[1] momentum strategy continues to generate abnormal returns for years, while the total return momentum strategy reverses strongly. Although their results suggest that the performance difference in the first year after formation is negligible, Blitz et al. (2011) observe that the idiosyncratic momentum strategy exhibits only half of the volatility of the conventional momentum strategy without a significant reduction in return, thus doubling the Sharpe ratio of the strategy. However, neither Gutierrez and Pirinsky (2007) nor Blitz et al. (2011) address one of the fundamental asset pricing questions, namely, if the idiosyncratic momentum is a distinct factor that expands the efficient frontier comprised of already documented factors. The inclusion of the total return momentum to the set of control variables in asset pricing tests is of paramount importance that was overlooked by previous studies, as it is

[1] Gutierrez and Pirinsky (2007) refer to this effect as abnormal return momentum, and Blitz et al. (2011) refer to it as residual momentum.

not a priori clear if idiosyncratic momentum contains information about expected returns that is not contained in total return momentum, or a linear combination of factors that form the basis of the established asset pricing models (such as the Fama and French, 2015, five-factor model) augmented with the total return momentum factor[2]. This is also in line with the arguments in Barillas and Shanken (2017, 2018) that all factors should be considered jointly. This paper provides strong evidence that the idiosyncratic momentum is a distinct phenomenon from the conventional momentum.

Using a set of time-series, cross-section, and factor-spanning tests, we show that the idiosyncratic momentum cannot be explained by any of the established asset pricing factors, such as market, size, value, operating profitability, and investment, even if the total return momentum factor is included. In fact, the idiosyncratic momentum subsumes the total return momentum in some tests, while the converse is never the case. The recently proposed alternative asset pricing models of Hou et al. (2015) and Stambaugh and Yuan (2017), which have been shown to explain the total return momentum, fail to explain its idiosyncratic counterpart.

Furthermore, we examine the links between the idiosyncratic momentum and its conceptually related idiosyncratic volatility anomaly and find a much weaker relationship between these two effects than between the idiosyncratic volatility and the total return momentum. We also find that, relative to the idiosyncratic momentum, the total return momentum tends to be invested in stocks of smaller market capitalization with higher levels of Amihud (2002) illiquity where the limits to arbitrage likely play a larger role in preserving the premium. While the idiosyncratic momentum is associated with a somewhat higher level of turnover, we show that the break-even transactions costs necessary to render it insignificant are 15% higher than for the conventional momentum. The idiosyncratic momentum stocks exhibit lower average level of the idiosyncratic volatility and higher market capitalization relative to the conventional momentum stocks, which have been shown to be, respectively, positively and negatively related to the transactions costs of a strategy by, for instance, Novy-Marx and Velikov (2016) and Frazzini et al. (2018). We conjecture that the transactions costs of trading the idiosyncratic momentum are likely to be lower than those of trading the conventional momentum. Therefore, we conclude that the total costs of trading the idiosyncratic momentum

[2] Gutierrez and Pirinsky (2007) and Blitz et al. (2011) apply only the Fama and French (1993) three factor model that was still the "industry standard" (Subrahmanyam, 2009, p. 45) back then.

are lower or at least no higher than those of trading the convectional momentum.

When examining the importance of factors with respect to which stock excess returns are orthogonalized in order to obtain idiosyncratic momentum scores, we find that the market is by far the most important one. This should not come as a surprise as it is the factor with the highest risk premium, volatility, and power in explaining the variation in returns in the time series. Adding size (SMB) and value (HML) factors further enhances risk-adjusted returns of the strategy, but RMW and CMA add value only marginally.

Moskowitz and Grinblatt (1999) show that industry portfolios exhibit significant momentum that is not subsumed by the individual firm momentum and other standard asset pricing factors. We test the strength of the idiosyncratic momentum on an industry level and find that, while present, it is less important than in the case of the conventional momentum. Consistent with this, we find that adding the industry portfolios to the set of factors against which we orthogonalize stock returns to lower the return of the idiosyncratic momentum strategy, but to lower the risk (volatility) even more thus leading to a higher Sharpe ratio. This indicates that the industry exposures in the idiosyncratic momentum do contribute to the risk of the strategy, but that this risk is not fully compensated by the market.

We also provide a fresh perspective on the various explanations for the momentum phenomenon that have been put forwarded in the literature. These include investor overconfidence, investor over- and underreaction, as well as risk-based explanations. Gutierrez and Pirinsky (2007) argue that idiosyncratic momentum is an underreaction phenomenon, caused by gradual diffusion of information, given their finding that abnormal returns do not reverse over multi-year holding periods. Prior research has established links between conventional momentum profits and investors' overconfidence, overreaction, and risk-based explanations. If idiosyncratic momentum is a distinct phenomenon that is driven by something else, such as investor underreaction, one would expect such links to be absent, or at least much less pronounced. If, on the other hand, idiosyncratic momentum and total return momentum are driven by the same underlying market mechanisms, the superiority of idiosyncratic might simply be due to more extreme exposures to these sources. We empirically test this and reject the latter hypothesis, i.e. we find that the strong link between conventional momentum and investors' overconfidence or overreaction, as well as risk-based explanations, is much weaker for idiosyncratic momentum.

Our results support the underreaction hypothesis. First, we iteratively run sixty Fama and MacBeth (1973) regressions with varying lags of the two momentum signals, controlling for the other known predictors of stock returns in the cross-section, and find that idiosyncratic momentum forecasts high short and long-term excess returns, while conventional momentum forecasts high short-term, and negative long-term excess returns. Second, as conventional and idiosyncratic momentum strategies are positively correlated, we argue that one can use idiosyncratic momentum as a signal to distinguish between momentum stocks with high future returns, that are more likely to be caused by underreaction, and those whose returns reverse, consistent with initial overreaction and long-term reversal. We find evidence in support of this argument and show that a portfolio that is long idiosyncratic momentum winners and short losers within past conventional momentum winners generates high, non-reverting returns over the next five years. On the other hand, a portfolio that is long conventional momentum winners and short losers within past idiosyncratic momentum winners generates negative long-term returns.

The final contribution of this paper is to document that idiosyncratic momentum shows robust out-of-sample performance in international developed and emerging equity markets. Our results are consistent with Chaves (2016), who finds strong results for a simplified definition of idiosyncratic momentum in 21 developed countries, in addition to the U.S.[3] In our study we use the original definition and apply it uniformly in all considered regions, including emerging markets, which have not been examined before. The work of Chaves (2016) also shows that the effect is robust to the methodological choices.

Conventional momentum is known to be ineffective in Japan, at least unconditionally, therefore giving rise to data mining results. In line with Chaves (2016) and the recent work of Chang et al. (2018) we find that idiosyncratic momentum does work in Japan. Chang et al. (2018) specifically examine idiosyncratic momentum in Japan and link it to explanations based on investor underreaction. We add to this existing literature by providing additional evidence for the underreaction explanation. Specifically, we show that, similar to the U.S., idiosyncratic momentum profits in international markets remain positive up to five years after portfolio formation, while conventional momentum profits already start reversing after less than one year. This paper is organized as

[3] Chaves (2016) considers one-factor (market) unscaled residuals estimated over the past 12-2 month window, whereas we use three-factor model volatility-scaled 12-2 month residuals estimated over the past 36 months.

follows: In section 2, we discuss various explanations for momentum that have been proposed in the literature and their links to idiosyncratic momentum. In section 3, we describe the data and methodology used to construct idiosyncratic momentum. In section 4, we presents results of asset pricing tests, and analyze importance of factors in residualization. In section 5, we show that none of the explanations for sources of the momentum premium hold for idiosyncratic momentum, and discuss the link between idiosyncratic momentum profits and underreaction. Section 6 presents international results, and section 7 concludes the paper.

2 Discussion

While momentum is one of the most pervasive asset pricing anomalies, it is also one of the least systematic, in the sense that the composition of the momentum portfolio is solely determined by the recent performance of the stocks in the investment universe. Kothari and Shanken (1992) show that past return sorted portfolios have significant time-varying exposure to systematic factors. Consequently, the long leg of momentum has positive exposures to the styles that performed well in the recent past, and the short leg is exposed to those that underperformed. An intuitive example is the relative outperformance of high-beta stocks in bull markets, and a contemporaneous underperformance of low-beta stocks. As a direct consequence of this, momentum can exhibit negative returns if the market experiences sharp turns.

Daniel and Moskowitz (2016) demonstrate that not only does the market beta of the momentum portfolio differ depending on the past market performance, but also that after bear markets, the beta of the momentum portfolio becomes even more negative when the market subsequently reverses. The authors assert that, in bear markets, the momentum portfolio behaves like a short call option on the market, meaning that it gains little if the market further declines, but if the market rises, the portfolios loses a lot. Moreover, they document that the loser portfolio is the predominant source of this optionality, and argue that this evidence is consistent with the theory of Merton (1974) in which common equity is viewed as a call option on the value of the firm. Especially after a bear market environment, stocks of the loser portfolio are not as deep in-the-money as stocks of the winner portfolio, and consequently have a stronger option-like behavior.

If this momentum crash risk is the driver of momentum returns, and idiosyncratic momentum is simply more exposed to this risk, the superiority of idiosyncratic momentum could be explained. However, since idiosyncratic momentum explicitly attempts to eliminate the time-varying style exposures that seem to be the source of the crash risk, it may also turn out to be less prone to crashes. We empirically test this hypothesis and find that idiosyncratic momentum is significantly less exposed to the crash risk. Consequently, this cannot be an explanation for its superiority over conventional momentum.

Cooper et al. (2004) find that momentum returns are positive following periods of positive market returns, and negative after periods of negative market returns, and argue that this behavior is consistent with the overreaction hypothesis for existence of the momentum premium. They further link the overreaction hypothesis to cognitive biases described in Daniel et al. (1998) and Hong and Stein (1999). Daniel et al. (1998) assume that investors are overconfident about their private information, and this overconfidence, together with self-attribution bias, leads to an overreaction that drives momentum returns. As overconfidence tends to be greater after bull than after bear markets, as argued in Gervais and Odean (2001), overreaction and, therefore, momentum returns, are higher after bull markets. In the behavioral model of Hong and Stein (1999) an initial underreaction to information, and subsequent overreaction, driven by momentum traders, leads to momentum returns. According to their model, overreaction, and momentum returns, are negatively correlated with the risk aversion of momentum traders. As risk aversion decreases with wealth (e.g Campbell and Cochrane, 1999), momentum returns should be higher after market increases.

We replicate and confirm the findings of Cooper et al. (2004) for conventional momentum; however, we find that in the case of idiosyncratic momentum, returns are still positive, albeit insignificant, after periods of negative market returns, and not statistically different from the returns after periods of positive market returns. Therefore, this overreaction explanation also does not apply to idiosyncratic momentum.

Asem and Tian (2010) further investigate the asymmetric momentum profits following bull and bear markets. They show that momentum returns for different market states (as shown in Cooper et al., 2004) are dominated by returns for different market dynamics, where the subsequent market return is also taken into account. They document that momentum returns are significantly higher when the market stays in the same condition than when it transitions to another state. Asem and Tian (2010) argue that this pattern is consistent with the model of Daniel et al. (1998), but not with the competing models of Hong and Stein (1999) or Sagi and Seasholes (2007) that predict high momentum returns in case of a market reversal after a bear market.

In the model of Daniel et al. (1998) traders receive public signals after trading a stock based on a private signal. If the public signal confirms their private signal, the investors attribute the success to their skills, however, they attribute non-confirming signals to bad luck. Because of this self attribution bias, traders become overconfident about their stock selection skills, and this overconfidence drives momentum. Asem and Tian (2010) argue that investors, on average, traded more based on positive (negative) private signals when the past market was positive (negative). Consequently, subsequent positive months should drive overconfidence more than subsequent negative months and vice versa. Therefore, momentum returns should also be higher for market continuations than for market reversals.

We validate the findings of Asem and Tian (2010) that results for different market states are dominated by results for different market dynamics, but again we show that idiosyncratic momentum is less affected by these market dynamics than its total return counterpart, which unequivocally indicates that overconfidence, if captured by these metrics, cannot explain it.

Gutierrez and Pirinsky (2007) argue that incentives of delegated wealth managers may lead them to underreact to firm-specific news, and overreact to relative (total) past returns. Using data on institutional ownership, they show that institutional investors buy/sell total return winners/losers significantly more than any other stock in the universe, a pattern that is largely absent in the case of their idiosyncratic momentum counterparts. This empirical observations is in line with the fact that institutional investors largely neglect firm-specific returns. The authors find that high momentum stocks with the smallest change in institutional ownership during the formation period are precisely those that have the highest long-term returns, and conversely, high momentum stocks that are bought the most by institutions during the formation period are those that exhibit the strongest reversals. Thus, long-term returns of momentum strategies depend on the level at which they are held by institutions[4]. As total return momentum stocks are subject to substantially higher changes in institutional ownership than idiosyncratic momentum stocks, the authors contend that this effect is driven by investor's overreaction, while the latter one can be attributed to underreaction.

We confirm the findings of Gutierrez and Pirinsky (2007) that while conventional momentum

[4]This assumes that institutions are marginal investors in the market.

forecast high short to medium-term returns, its significance drops to zero fairly quickly and, consistent with Jegadeesh and Titman (2001), turns into a long-term reversal after around one year following portfolio formation. In contrast, idiosyncratic momentum forecasts high (or at least non-negative) short and long-term returns. Differently from Gutierrez and Pirinsky (2007), we use Fama and MacBeth (1973) regressions with lagged conventional and idiosyncratic momentum signals (up to 60 lags). This approach enables us to control for other know predictors of stock returns, such as market beta, book-to-market, size, profitability, and investment. These results are consistent with the underreaction and overreaction hypothesis for idiosyncratic and conventional momentum, respectively.

Related to our work is that of Haesen et al. (2017) who document idiosyncratic momentum spillover effects from the equity to the credit market. In particular, they find that stocks with the highest past idiosyncratic returns are also future winners in the credit market. The momentum spillover effect, whereby companies whose stocks are past total return winners have high credit returns going forward, has been documented by Gebhardt et al. (2005), however, Haesen et al. (2017) show that this effect has a structural bias towards low-risk credits and is, consequently, dependent on performance of the credit market during the portfolio holding period. They also show that the default risk exposure of momentum spillover depends on the equity market return during the formation period. On the other hand, the idiosyncratic momentum spillover is substantially less exposed to these systematic biases, and cannot be explained by any of the other credit market factors, such as default and term, nor the Fama-French-Carhart[5] factors. Their results indicate that the idiosyncratic momentum spillover effect also stems from underreaction.

3 Data and methodology

3.1 Data

The data used in this study come from multiple sources. For the U.S. sample, we obtain security level information from the Center for Research in Security Prices (CRSP) from the end of December, 1925 till the end of December, 2015. We include all common shares (share codes 10 and 11) that are traded on the NYSE/AMEX, and NASDAQ exchanges (exchange codes 1, 2, and 3)

[5]Carhart (1997) introduces the momentum factor.

except those with beginning of month share price below \$1. For the bulk of the analysis we also exclude microcaps[6], defined as stocks with market capitalization below the 20th percentile market capitalization of NYSE-traded stocks, in order to dismiss concerns that our results are driven by tiny stocks that are out of reach for institutional investors, or market micro-structure issues.

We estimate market betas using univariate regressions of excess stock returns on the market factor over the most recent sixty months (minimum twenty-four). Size is defined as the natural logarithm of firms market capitalization (shares outstanding times price per share). The balance sheet and income statement information used in the cross-section tests stems from Compustats annual files. Book value is the sum of book value of stockholders equity, balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. If available, we use the redemption, liquidation, or par value to calculate the book value of preferred stock. Stockholders equity is obtained either from Moodys industrial manuals or Compustat. If it is not available, we measure stockholders equity preferably as the sum of book value of common equity and the par value of preferred stock, or the book value of assets minus total liabilities if the first one is not available. The book value of equity is then divided by the market capitalization calculated at the end of the previous calendar year to obtain the book-to-market ratio, which is further log-transformed. The 12-2 month total return momentum is the total return from month t-12 to t-2. Operating profitability is defined as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1, and investment (asset growth) is the percentage change in firms total assets from year t-2 to t-1. Accounting data for a given fiscal year are updated once a year at the end of June of the following calendar year. Idiosyncratic volatility is standard deviation of residuals from a regression of stock excess returns on the three Fama and French (1993) factor over the last month (twenty-two, minimum sixteen trading days). Amihud (2002) illiquidity measure is defined as the ratio of absolute stock return to its dollar volume averaged over the last month (twenty-two, minimum sixteen trading days).

As a proxy for the risk-free rate, we use the one-month U.S. Treasury bill rate that, together

[6] The only exception is when we construct the value-weighted idiosyncratic momentum factor, as, for consistency, we follow the standard Fama and French (1993) factor construction methodology, and they also do not exclude microcaps. The portfolios are, however, value-weighted and that ensures that micro-caps do not dominate the portfolio returns.

with the Fama-French factor returns that are used to construct idiosyncratic momentum in the United States, is obtained from the website of Professor Kenneth French[7]. The Hou et al. (2015) Q-factor model return series come from Professor Lu Zhang[8], and returns of the mispricing factors of Stambaugh and Yuan (2017) come from the website of Professor Yu Yuan[9].

3.2 Variable construction

We calculate idiosyncratic momentum in multiple stages, following the methodology of Gutierrez and Pirinsky (2007) and Blitz et al. (2011). First, each month, we estimate model (1) over the past 36-month window for all stocks in the investment universe. We require the full 36-month return history to estimate the model.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{mkt,i} \cdot (R_{mkt,t} - R_{f,t}) + \beta_{hml,i} \cdot R_{hml,t} + \beta_{smb,i} \cdot R_{smb,t} + \epsilon_{i,t} \tag{1}$$

In the second step, we calculate idiosyncratic returns as:

$$e_{i,t} = R_{i,t} - R_{f,t} - \hat{\alpha}_i\iota - \hat{\beta}_{mkt,i} \cdot (R_{mkt,t} - R_{f,t}) - \hat{\beta}_{hml,i} \cdot R_{hml,t} - \hat{\beta}_{smb,i} \cdot R_{smb,t} \tag{2}$$

Finally, the idiosyncratic momentum score is the last 12-2 month volatility-adjusted mean idiosyncratic return[10]:

$$IdiosyncraticMomentum_{i,t} = \frac{\sum_{t-12}^{t-2} e_{i,t}}{\sqrt{\sum_{t-12}^{t-2} (e_{i,t} - \bar{e}_i)^2}} \tag{3}$$

Our results are robust to a host of commonly used portfolio construction methodologies. For the base case, we form equal-weighted portfolios, and address some of the concerns associated with equal-weighting by excluding micro-caps, as defined in section 3.1, from the investment universe. Fama and French (2008) note that these are stocks that represent around 60% of the universe, but account for only 3% of total market capitalization. Equal-weighting ensures that portfolios have

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

[8] We thank Professor Lu Zhang for providing these return series.

[9] http://www.saif.sjtu.edu.cn/facultylist/yyuan/

[10] We follow Blitz et al. (2011) and scale residuals with their volatilities. This adjustment leads to a slight improvement in the signal, especially for the top portfolio, but our results do not hinge on it. In fact, the unscaled top-bottom idiosyncratic momentum portfolio generates absolute and risk-adjusted returns that are comparable in magnitude to those of the scaled version.

enough breadth, as returns on value-weighted portfolios can be heavily dominated by returns on a small number of very large stocks.

Furthermore, we validate our findings by constructing an idiosyncratic momentum factor following the portfolio construction methodology that Fama and French use to the construct the conventional momentum (WML) factor. Thus, the factor is based on the six size - idiosyncratic momentum sorted value-weighted portfolios, and it is a zero-investment portfolio that is long small and big (idiosyncratic) winners, and short small and big (idiosyncratic) losers. Portfolios are re-formed monthly and stocks are held for one month.

$$iMOM_t = \frac{1}{2}(Big_{idio}Winners_t + Small_{idio}Winners_t) - \frac{1}{2}(Big_{idio}Losers_t + Small_{idio}Losers_t) \quad (4)$$

We confirm that all conclusions in our paper remain qualitative unchanged if we use the value-weighted iMom factor portfolio, instead of the decile spread portfolio. The reason we opt to use the latter as a base case is because most papers that we reference and replicate in this paper use decile portfolios, and we do not want to depart from this choice. We do, however, challenge the robustness of this choice all-throughout.

We provide yet another robustness check, where we show that our results hold if we consider only large stocks - commonly defined as stocks with beginning-of-month market capitalization above the median market capitalization of NYSE-traded stocks.

Hou et al. (2018) find that many anomalies documented over the past decades do not survive these robustness tests, and that the strong results reported in the original studies are oftentimes driven by micro-caps. We establish that idiosyncratic momentum is not a micro-cap phenomenon, but a robust and pervasive effect that consistently shows up throughout the entire cross-section of US equities.

3.3 Motivating Results

In Table 1, we report descriptive statistics of the decile portfolios formed as univariate sorts on idiosyncratic, as well as total return momentum, over the 1963-2015 period. Results for the long sample (1929-2015) can be found in Table A1 in the appendix, and they are consistent with what we observe in the shorter sample.

INSERT TABLE 1 HERE

We observe a monotonically increasing pattern in excess returns, Sharpe ratios, and factor-adjusted returns (i.e. alphas) going from low (D1) to high (D10) idiosyncratic and total return momentum portfolios. The self-financing D10-D1 idiosyncratic momentum portfolio generates a monthly return of 0.98%, which is somewhat lower than that of total return momentum (1.07%), however, with a substantially lower volatility. The Sharpe ratio of the idiosyncratic momentum strategy is 0.29 per month, 77% higher than that of conventional momentum (0.17). The CAPM and three-factor alphas are higher for total return momentum, but the standard errors associated with these estimates are also substantially higher, resulting in lower t-statistics. Thus, idiosyncratic momentum generates more stable alphas. The Fama and French (2015) five-factor model is also unable to explain the extreme decile return spreads of the two strategies, and the pattern that we observe for other models is also present here: the t-statistic is substantially higher for idiosyncratic than for conventional momentum despite the lower abnormal return.

In order to ensure that our results are not driven by small, illiquid stocks, we also form decile portfolios that exclude stocks with market capitalization below NYSE median (i.e. if we only consider large-caps). Results reported in Table 2 show that our conclusions are not qualitatively affected by this alteration, although both strategies generate somewhat smaller returns in the large cap universe. Based on all these results, we conclude that, on a stand-alone basis, idiosyncratic momentum is a much stronger phenomenon that conventional momentum.

INSERT TABLE 2 HERE

4 Time-series, cross-section, and factor-spanning tests

4.1 Empirical Results

We conduct three tests to examine whether idiosyncratic momentum is a separate factor that expands the efficient frontier, i.e. that it cannot be subsumed by other asset pricing factors: the time-series GRS[11], cross-section Fama and MacBeth (1973), and factor-spanning tests. Fama

[11] Gibbons et al. (1989)

(2015) argues that time-series and cross-section asset pricing tests should be examined jointly as they provide unique perspectives that complement each other.

We first turn to the time-series GRS test where we test whether the idiosyncratic momentum decile portfolios have a joint alpha of zero. Thus, under the null hypothesis, the asset pricing model is able to perfectly explain returns of the test portfolios. All GRS test statistics are presented in the bottom rows of Table 1. With the CAPM and three-factor model GRS statistics of 7.72 and 7.12, respectively, we reject both asset pricing models at the most conservative significance levels, and conclude that they cannot explain the idiosyncratic momentum anomaly. The addition of the two new Fama French factors to the original 1993 three-factor set does not lead to a change in conclusion (GRS statistic of 5.70): the pattern in average returns generated by univariate idiosyncratic momentum sorts cannot be explained by any of the leading asset pricing models.[12]

We repeat the analysis with total return momentum sorted portfolios as test assets. The GRS statistics for each of the models are substantially smaller than for idiosyncratic momentum. For instance, the CAPM GRS test statistic for momentum deciles is 5.14, which is 33% lower than that of idiosyncratic momentum, and for the five-factor model, the GRS test statistic is 3.66, which is 36% lower.

The second test we consider is the Fama and MacBeth (1973) cross-section test, whereby, each month, we regress stock returns on a set of characteristics to obtain a time-series of coefficients, and subsequently calculate averages and corresponding t-statistics of the resulting time-series. The estimated slope coefficient can be interpreted as premia associated with a unit exposure to a factor (characteristic), holding all other factors constant. We include the following controls: market beta, natural logarithms of size and ratio of book to market equity, operating profitability, investment (asset growth), and the main variables of interest - idiosyncratic and total return momentum. All variables are winsorized at 1% and 99% levels, and t-statistics are calculated using Newey and West (1987) adjusted standard errors with a maximum lag of 3 months. Once again, we remove micro-caps from our analysis. Results are shown in Table 3.

INSERT TABLE 3 HERE

We note that all control characteristics have signs and magnitudes consistent with those reported

[12] In unreported test, we augmented the five-factor model with the conventional momentum factor and we still reject this model when we test it on idiosyncratic momentum portfolios.

in the literature. Stand-alone, both momentum strategies are highly economically and statistically significant regardless of the model specification. If we include both characteristics at the same time, idiosyncratic momentum emerges stronger with a higher t-stat, however, total return momentum remains significant. This suggests that there is information about average returns in idiosyncratic momentum that is not contained in total return momentum, and vice versa. In Table A2 in the appendix, we show that these results also hold over the long (1929-2015) sample.

Panel A of Table 4 presents results of a series of spanning tests where we regress idiosyncratic momentum factor returns on (i) three Fama and French (1993) factors; (ii) five Fama and French (2015) factors; (iii) five Fama-French factors and Carhart's momentum factor. In the next step, we reverse the position of total return and idiosyncratic momentum. For this analysis, we use the formal, value-weighted idiosyncratic momentum factor, as defined in equation (4), to ensure that our results are not driven by different portfolio concentrations, weighting schemes, or rebalancing frequencies.

INSERT TABLE 4 HERE

Unlike cross-section tests that do not provide robust evidence for one factor over the other, spanning tests strongly show that conventional momentum is redundant when we control for idiosyncratic momentum. While both factors have significant three- and five-factor alphas, the addition of idiosyncratic momentum to the five Fama-French factors renders total return momentum insignificant, while the converse is not true. Over the 1963-2015 sample, the five-factor model augmented with the total return momentum factor brings the alpha of idiosyncratic momentum to 0.35% per month (t-statistic of 5.55), while the five-factor model augmented with the idiosyncratic momentum factor brings the alpha of the total return momentum to -0.13% (t-statistic of -1.09). In Table A3 in the appendix, we show that these results also hold up in our long sample (1929-2015): the four factor model that includes the idiosyncratic momentum factor is fully able to capture average returns on the conventional momentum factor, while the converse is not the case.

Panels B and C show results of spanning tests where we consider the big and small legs of the two momentum factor separately, based on 2x3 portfolio sorts. For each of the factors, we construct *Big* factors by going long the big (above NYSE) portfolio with a favorable factor exposure (idiosyncratic and total return winners, value, high profitability, and conservative investment, receptively), and shorting the big unfavorable factor legs. The Big-Rf portfolio is the value-weighted portfolio of stocks with market capitalization above median capitalization of NYSE-traded stocks, financed by shorting the risk-free portfolio. Similarly for *Small* factors, we go long the small favorable factor legs, and short the small unfavorable ones. The Small-Rf is the value-weighted portfolio of stocks with market capitalization below median capitalization of NYSE-traded stocks, financed by shorting the risk-free portfolio. In these tests we find that the value-weighted idiosyncratic momentum factor subsumes the total return momentum factor holds for both big, as well as small-cap factors, while total return momentum does not subsume idiosyncratic momentum in neither sub-universe.

In Table 5 we examine whether the Q-factor model of Hou et al. (2015), or the model based on the mispricing factors of Stambaugh and Yuan (2017) are able to explain idiosyncratic momentum profits, by considering spanning tests based on these alternative asset pricing models. The Q-factor model consists of four factors - the market, size (ME), investment (IA), and profitability (ROE), and has been shown to explain returns of the conventional return momentum factor. Novy-Marx (2015) shows that the ROE factor that Hou et al. (2015) use is a convoluted proxy for profitability, as it mechanically incorporates earnings surprises through the use of quarterly earnings data, and consequently explains returns of the momentum factor. In Table 5, we confirm these results and also show that the Q-factor model is unable to explain returns of the idiosyncratic momentum factor. Over the January 1967 to December 2015 sample[13], the idiosyncratic momentum factor has a Q-factor alpha of 0.39% a month, with a t-statistic of 4.23[14].

We also find that the mispricing factors of Stambaugh and Yuan (2017) are unable to explain returns of the idiosyncratic momentum factor, while they have no issues with the conventional momentum factor. The model of Stambaugh and Yuan (2017) consists of the market, size, and two mispricing factors constructed from a set of 11 asset pricing anomalies. The first factor consists of six anomalies related to firms management and it is labeled as MGMT. The second factor is

[13] The sample starts in January of 1967 as the Q-factor model returns are available from that date.

[14] Hou et al. (2018) show that the Q-factor model leaves an insignificant return spread between the top and the bottom idiosyncratic momentum portfolios, although the intercept remains economically significant at 0.32% a month (t-statistic of 1.46). The reason these findings differ from ours is a difference in portfolio construction. Our idiosyncratic momentum factor is constructed following the standard Fama-French factor construction methodology based on 2x3 portfolio sorts, which is also used to construct the factors in the Q-factor model. Hou et al. (2018) use an idiosyncratic momentum portfolio based on value-weighted decile sorts with NYSE break-points, that excludes micro-caps, and consequently, their left hand side (idiosyncratic momentum) portfolio is significantly more large-cap tilted than the factors in the Q-factor model, on the right hand side of the spanning regression. Our comparison, on the other hand, is done using portfolios constructed in the same way.

constructed from anomalies that are less related to firms management, one of which is total return momentum, and it is labeled as PERF. Naturally, the PERF factor plays a prominent role in explaining returns on the conventional momentum factor. Nevertheless, in case of idiosyncratic momentum, this model leaves an alpha of 0.38% a month with a t-statistic of 4.15.

INSERT TABLE 5 HERE

We conclude that results of the asset pricing tests do not conclusively reject one factor in favor of the other, however, idiosyncratic momentum seems to pose an even bigger challenge to the standard asset pricing models than conventional momentum.

4.2 Relationship with idiosyncratic volatility

The idiosyncratic volatility anomaly of Ang et al. (2006) is conceptually related to the idiosyncratic momentum anomaly. Idiosyncratic volatility is defined as the standard deviation of residuals from a regression of stock excess returns on the three Fama and French (1993) factors over the last month, and it has been shown to be negatively related to future stock returns. In a well-specified expected return model, residuals should be a pure noise, but given that the three-factor model does not fully explain stock returns, Ang et al. (2006) postulate that the omitted information will be captured in the regression residuals. The intuition behind the idiosyncratic momentum is similar, however, the signal is calculated based on the average value of residuals over the last 12-2 months, scaled by their volatility over the congruent window, while idiosyncratic volatility is based on the volatility of residuals over a much shorter time-span. Since the idiosyncratic momentum corrects for the impact of the (longer term) idiosyncratic volatility, we test whether the difference between the idiosyncratic and the total return momentum comes from different exposures to the idiosyncratic volatility anomaly.

In order to address this, we calculate stocks' idiosyncratic volatilities following the methodology of Ang et al. (2006). Panel A of Table 6 shows the output of the Fama and MacBeth (1973) regression where we add the idiosyncratic volatility to the set of return predictors. We confirm the results of the prior studies, such as Ang et al. (2006) and Malagon et al. (2018) that the idiosyncratic volatility is rewarded in the cross-section of stock returns with a negative and highly statistically significant premium (t-statistic of -5.44). However, the addition of this factor does not change the conclusions regarding the two momentum factors - both remain priced and similar in magnitude to the estimates from the specification without the idiosyncratic volatility.

INSERT TABLE 6 HERE

We next construct an idiosyncratic volatility factor[15] following the same methodology used to construct the standard Fama-French factors, and our idiosyncratic momentum factor, and add it to the set of the other explanatory factors that we used in the factor spanning tests. In panel B of Table 6 we show that there is no significant relationship between the idiosyncratic momentum and volatility, and that therefore, the idiosyncratic momentum continues to exhibit a statistically significant alpha of 36 bps a month (t-stat of 5.64). We repeat the same analysis for the total return momentum and find a positive and significant relationship with the idiosyncratic volatility, which further lowers its alpha to -0.17 bps a month (t-stat -1.44) when we also control for the idiosyncratic momentum and other characteristics that form the foundation of the Fama and French (2015) model. We conclude that the relationship between the idiosyncratic volatility and the idiosyncratic momentum is in fact much weaker than its relationship with the total return momentum, and that consequently differences in idiosyncratic volatility cannot explain the superiority of the idiosyncratic momentum over its conventional counterpart.

4.3 Liquidity and transactions costs

Novy-Marx and Velikov (2016) show that momentum has higher trading costs compared to lower turnover strategies based on variables such as value or size. However, the after-trading-cost performance of momentum remains statistically different from zero even for a naive strategy implementation and even more so for the more sophisticated trading cost mitigation strategies. If trading costs for implementing idiosyncratic momentum are higher than for conventional momentum, the superiority of the idiosyncratic momentum could be explained by higher limits to arbitrage. Trading costs for a strategy depend on (i) the average transaction costs per trade and (ii) the turnover of the strategy. Below we address each of these two components.

Novy-Marx and Velikov (2016) and Frazzini et al. (2018) argue that transaction costs increase with the idiosyncratic volatility and decrease with the market capitalization of the stocks being

[15] The portfolio is long low idiosyncratic volatility small and big portfolio and short high idiosyncratic counterparts.

traded. The left panel of Figure 1 shows the average idiosyncratic volatility of stocks across the total and idiosyncratic momentum deciles, and the right panel shows the average market capitalization. There is a distinct (inverse) U-shaped pattern where the extreme deciles, winners and losers, exhibit higher (lower) levels of the idiosyncratic volatility (market capitalization), however, the effect is more pronounced for the total return, than for the idiosyncratic momentum. Furthermore, in unreported tests, we have found that the total return momentum on average also has a significantly higher level of Amihud (2002) illiquidity[16], which is considered to be a measure of price impact, and consequently stock-level liquidity and implicit trading costs. These results indicate that the average costs of trading the idiosyncratic momentum stocks should be lower, or at most as high as those of trading the conventional momentum stocks.

INSERT FIGURE 1 HERE

While the idiosyncratic momentum tends to be invested in stocks with, on average, lower transactions costs per trade than the constituents of the total return momentum strategy, it does come with a higher level of turnover. We find that the turnover of the conventional momentum strategy is 64% per month, and that of the idiosyncratic momentum is 87% per month[17]. Similar as in Grundy and Martin (2001) and Barroso and Santa-Clara (2015), we calculate the round-trip cutoff costs that would render the profits of both strategies insignificant at the 1% level. We find these break-even costs to be 63 basis points for the conventional momentum and 73 basis points for the idiosyncratic momentum. Therefore, the hypothetical transactions costs that would remove the significance of the profits of the idiosyncratic momentum would be 15% higher than for the conventional momentum despite its higher turnover. Having established above that the transactions cost of the average idiosyncratic momentum stock do not seem to exceed the ones of the conventional momentum, we conclude that higher trading costs cannot explain the superiority of the idiosyncratic momentum.

4.4 Importance of factors in residualization

Fama and French (1993, 1996) show that their empirically motivated three-factor model spans a wide range of equity portfolio returns, and claim that the market, size, and value factors represent

[16] Amihud's illiquidity measure is defined as the absolute daily return scaled by the dollar trading volume.

[17] We calculate turnover as the sum of the average one-way turnover of the short and the long leg.

systematic risk factors. With affirmations coming from more than two decades of new data, and evidence from international markets, no one can dispute that the three-factor model successfully manages to capture much of the variation in average returns. In order to isolate the stock specific momentum from the common style momentum, following Gutierrez and Pirinsky (2007) and Blitz et al. (2011), we opt to orthogonalize stock returns against these three factors. In fact, any well-defined model that captures commonalities in stock returns is eligible, including variance decomposition models, such as those based on principal component analysis. Factors such as market, size, and value impose a structure that is accepted in the financial literature, and this motivates our decision to prefer them over others. We do, however, recognize that not all factors contribute equally in this process. For instance, the market factor may be the strongest driver of systematic returns, which is reflected in its significance in the time-series regressions. In this subsection, we consider alternatives to the three-factor model. We recalculate idiosyncratic momentum using:

- market factor
- market, size, and value factors
- market, size, value, operating profitability, and investment factors

For each variable specification, we calculate equal-weighted, monthly-rebalanced decile portfolios, excluding micro-caps, and report the performance characteristics of the top, bottom, and top-bottom deciles in Table 7. As three years of factor returns are necessary to calculate idiosyncratic momentum, and operating profitability and investment factors are available from 1963, we start the analysis in July, 1966 for all three specifications. This enables us to make a fair comparison of the models.

INSERT TABLE 7 HERE

We note that most of the effect comes from the market factor. The inclusion of the two additional Fama-French factors leads to a further improvement as more of the stock specific momentum is isolated; however, the incremental value is greatly diminished. In fact, both return and volatility are reduced as we add more factors, but the risk reduction is much larger, resulting in a higher risk-adjusted return. This is further evidence that dynamic style exposures are not fully rewarded, or put differently, stock specific momentum dominates style momentum. The model that includes the profitability and investment factors generates a monthly Sharpe ratio that is 20% higher than if only the market factor is used.

The pattern in five-factor alphas is similar to the one we observe for raw returns: alpha decreases as we add more factors, however, t-statistics increase substantially. The D10-D1 portfolio alpha of the specification that only includes the market factor is 10% higher than if the five-factor model is used, but the t-statistic is 19% lower. Thus, with the five-factor model we are able to distill a stronger signal than with the market factor alone, which comes with the cost of lower return that is due to elimination of some rewarded style momentum.

Lastly, we consider the impact of adding industry portfolio returns to the three Fama and French (1993) factors that form our base case. Industry portfolios are generally considered to be important from a portfolio risk management perspective, as stocks within the same industry tend to co-move together, however, unlike other factors, there is no evidence that industry exposures are priced in the cross-section of stocks. We obtain the returns of the ten industry portfolios[18] from the website of Professor Kenneth French and add them to the three Fama and French (1993) factors. The reason for using ten industry portfolios is that a finer classification would result in too many independent variables in our regression, which is performed using 36 monthly return observations.

We find that the addition of the industry factors leads to a 25% drop in excess return of the idiosyncratic momentum on a long-short level, but an even bigger reduction in volatility, resulting in a marginal increase in the Sharpe ratio. We observe the same pattern for the CAPM, three- and five-factor alphas and the associated standard errors and consequently t-statistics. The significant drop in return seems to indicate that industry exposures of the strategy do matter, however, they are also not fully compensated by the market, given that the Sharpe ratio increases once they are removed. In the following subsection, we dive deeper into the relationship between the total return and idiosyncratic momentum anomalies and their industry exposures.

4.5 Industry effects

Moskowitz and Grinblatt (1999) document that industry portfolios exhibit significant momentum

[18]The ten industries are consumer non-durables, consumer durables, manufacturing, energy, high-tech, telecom, shops, healthcare, utilities, and other.

that is not subsumed by the individual firm momentum and other standard asset pricing factors, such as size and value. They conjecture that this finding implies that conventional momentum strategies are not well diversified, as winning (losing) stocks tend to come from the same industries.

In order to test the importance of industry effects when it comes to the idiosyncratic momentum, we split the signal into two: the allocation signal that is the average idiosyncratic momentum of the industry[19] assigned to each stock in that industry, and the selection signal that is equal to stock's idiosyncratic momentum in excess of that of its corresponding industry. The same signals are calculated for the conventional momentum. We then use the selection signal to form decile portfolios of *within-industry* momentum strategies, and the allocation signal to construct the *across-industry* strategy where the top portfolio consists of all stocks in the industry with the highest allocation signal, and the bottom portfolio consists of all stock in the industry with the lowest signal[20]. Table 8 shows the performance characteristics of these portfolios, as well as the portfolios based on the total signal for comparison.

INSERT TABLE 8 HERE

In the case of the conventional momentum, we observe a drop of 13% in excess return, in relative terms, going from the total to selection (within-industry) signal, most of it coming from the short side of the portfolio. However, we also observe an even larger drop in volatility of 16%, thus leading to a marginally higher Shape ratio of the within-industry strategy compared to the one based on the total signal. The across-industry strategy in fact performs significantly worse, with a Sharpe ratio of 0.11, which is 39% smaller than that of the based-case strategy[21].

When it comes to the idiosyncratic momentum we observe similar patterns - a drop in return when going from the total to the selection signal, which is more than offset by the drop in volatility, and a poor overall performance of the across-industry strategy.

We next run spanning regressions of the total and idiosyncratic momentum strategy returns on the across and within-industry corresponding long-short portfolios. Table 9 shows that in case of the idiosyncratic momentum, both signals are significant, albeit the selection strategy gets a much

[19] We use the standard 10 industry classification based on SIC codes.

[20] The *across-industry* strategy buys and sells entire industries. Consequently, the decile portfolios do not have the same number of stocks.

[21] We obtain quantitatively similar results when constructing a 12-1M industry momentum strategy using 10 value-weighed industry return portfolios from Professor Ken French's website.

higher coefficient (1.03 versus 0.14). In fact, the within-industry strategy alone fully spans the normal strategy, and this is not the case when only the across-industry strategy is used.

INSERT TABLE 9 HERE

When it comes to the total return momentum, we observe the same pattern, however, the importance of the across-industry effect appears to be larger. This finding is supported by the results of the Fama and MacBeth (1973) regressions where we include both the selection, as well as the allocation variables. Table 10 shows that in the case of the idiosyncratic momentum, only the selection part remains priced in the cross-section, while in the case of the total return momentum both do. In the regression where we include all four variables, only the allocation component of the idiosyncratic momentum is insignificant.

INSERT TABLE 10 HERE

We should note that our analysis differs from that of Moskowitz and Grinblatt (1999) in a number of ways. First, we consider the 12-2 month look-back window for both the idiosyncratic and total return momentum strategies to be consistent with the rest of our paper, whereas Moskowitz and Grinblatt (1999) find that industry momentum is stronger when a shorter look-back is used and the last month is not skipped. Second, we consider 10 industry portfolio classification to be consistent with the previous section where we add 10 industry portfolios to the set of factors against we residualize stock returns. Given that there are 36-monthly return observation that are used for these regressions, we cannot use finer industry grouping. Moskowitz and Grinblatt (1999) on the other hand use a finer industry classification based on 20 industries, which leads to a higher breadth of their industry momentum strategy. Nevertheless, we are able to confirm the importance of industry effects in the total return momentum strategy, however, we also find that in the case of idiosyncratic momentum these effects seem to be of lesser importance.

5 Explanations for the idiosyncratic momentum anomaly

In this section, we discuss and empirically test whether the most prominent explanations for the momentum phenomenon, which include momentum crashes, investor overconfidence, and over- and underreaction, also hold for idiosyncratic momentum. We conjecture that if both strategies are driven by the same underlying mechanisms, the observed performance differences could simply be due to different degrees of exposure to these sources. On the other hand, if the links between these explanations and idiosyncratic momentum are absent, the two strategies are more likely to be separate phenomena.

5.1 Momentum crashes

In Table 11, we replicate results of Daniel and Moskowitz (2016)[22] using conventional momentum decile portfolios by estimating the following regression:

$$R_t = \alpha_0 + \alpha_B I_{B,t} + [\beta_0 + I_{B,t}(\beta_B + I_{U,t}\beta_{B,U})] \cdot (R_{mkt,t} - R_{f,t}) + \epsilon_t \tag{5}$$

where I_B and I_U are dummy variables that indicate whether the past cumulative twelve-month return of the market portfolio is negative (I_B) and whether the subsequent month is non-negative (I_U). β_B indicates whether the market-beta differs after past bear markets, while $\beta_{B,U}$ indicates the extent to which the subsequent up- and down-market betas differ after such market.

INSERT TABLE 11 HERE

Consistent with their results, we find that the market beta of the momentum strategy is significantly lower (-0.58 with a t-stat of -5.28) after a bear market than after a bull market. If the market subsequently further declines, the point estimate for beta is -0.51 (= $\beta_0 + \beta_B$), but if the market reverses, the beta is additional -0.85 (t-stat -5.83) lower, resulting in overall beta of -1.36 (=$\beta_0 + \beta_B + \beta_{B,U}$). The predominant source of this optionality comes from the loser portfolio with a down-market beta of 1.52 (=1.31+0.21), and an up-market beta of 2.18 (=1.31+0.21+0.66). As the momentum strategy is short these losers, it exhibits the most negative market exposure precisely when the market recovers after bear markets. In unreported tests, we also find that the optionality is asymmetric; i.e. the market beta difference for subsequent up- and down-markets following bull markets is more than two times smaller in magnitude.

We apply the same methodology to idiosyncratic momentum portfolios and find that the beta differences are much smaller than in the case of conventional momentum, however, still statistically

[22] In their study, Daniel and Moskowitz (2016) use value-weighted portfolios. For consistency with the rest of the paper, we use equal-weighted portfolios, but note that our conclusions do not differ if we value-weight stocks.

significant. While the difference in market betas following bull and bear markets is only -0.18 (t-stat -3.10) the differences between up- and down-market betas following bear markets is -0.28 (t-stat -3.58) compared to -0.85 for conventional momentum. If the market further declines following a bear market, the point estimate of beta is -0.14 (=0.04-0.18), and if the market recovers, the beta is -0.42 (=-0.14-0.28). Thus, the (negative) beta adjustment for idiosyncratic momentum is about a third of what we found for conventional momentum. In unreported test, we find that idiosyncratic momentum also exhibits less time-varying beta following bull markets than conventional momentum.

In Figure 2, we show the cumulative returns of the two momentum strategies from July 1929 till December 2015. While the residualization process nearly eliminated the crash in the early 1930s, it was not fully effective in 2009 when momentum strategies exhibited one of their largest drawdowns in history. Nevertheless, the drawdown of idiosyncratic momentum was much smaller than that of conventional momentum. Taken together, our results indicate that crash risk cannot explain the superior performance of idiosyncratic momentum.

INSERT FIGURE 2 HERE

5.2 Market States and Dynamics

We now turn to the overreaction argument, as proposed in Cooper et al. (2004). We calculate average returns of the two momentum strategies[23] following bull (bear) markets, which are defined as periods with positive (negative) 36-month market returns[24], and present results in Table 12.

INSERT TABLE 12 HERE

In line with the results in Cooper et al. (2004), momentum returns are positive (1.32%) and significant following bull markets, and negative (-0.48%), though insignificant, following bear markets. In contrast, idiosyncratic momentum returns are positive in both cases (1.08% and 0.39%, respectively), although also insignificant after bear markets. Furthermore, the dispersion in returns following bull and bear markets is marginally significant for total return, but insignificant for idiosyncratic momentum. In term of economic significance, we observe that the average difference

[23] We use decile spread portfolios following Cooper et al. (2004).
[24] The choice of 36-month lookback window also follows Cooper et al. (2004).

between bull and bear markets is almost three times higher to total return, than for idiosyncratic momentum. This indicates that this overreaction argument is less strong for idiosyncratic momentum.

Asem and Tian (2010) show that results for different market states (as shown in Cooper et al., 2004) are dominated by results for different market dynamics, where the subsequent market return is also taken into account.[25] We now empirically test whether their findings apply to idiosyncratic momentum. Following the methodology proposed in Asem and Tian (2010), we define bull markets as periods in which the cumulative 12-month market return is positive, and bear markets in which it is negative. If the return during the subsequent month is positive, it is classified as an 'up' month, and if it is negative, it is a 'down' month. In Table 13, we show that the average return of momentum following market downturns (a down month following a bull market) is 0.09% (t-stat 0.33), and following market upturns (an up month following a bear market) is -4.55% (t-stat -4.26). On the other hand, the average return in an up month following bull markets is 2.03% (t-stat 9.31), and in a down month following bear markets is 5.41% (t-stat 9.34). This clearly illustrates that momentum delivers high returns in trending markets, and underperforms if markets reverse.

We test the sensitivity of idiosyncratic momentum to market dynamics and find that it delivers positive return in trending markets and also in market downturns. The return in down months following bull markets is 0.84% (t-stat 4.87), but, more importantly, return in up months following bear markets, which is particularly hurtful for conventional momentum, is -0.66% and statistically indistinguishable from zero (t-stat -1.49).

INSERT TABLE 13 HERE

We further test for differences in average returns of idiosyncratic and total return momentum in different market states and find that average returns of the conventional momentum significantly differs depending on the subsequent month, however, in case of idiosyncratic momentum the difference is only significant following bear markets, and still one third of that observed in the base of total return momentum. We also test the difference between the two strategies in each of the four cases and find that total return momentum delivers significantly higher returns in trending

[25] Hanauer (2014) finds similar results for Japan, Korea, Taiwan, and Turkey. In contrast, Cheema and Nartea (2017) report positive momentum returns exclusively after bear markets for Chinese A-shares. Furthermore, only in down months following bear markets, momentum returns are significantly different from zero.

markets, while idiosyncratic momentum significantly outperforms when market dynamics change.

Our results show that idiosyncratic momentum is substantially less affected by market dynamics (market continuations versus market reversals), which is not surprising given that idiosyncratic momentum is designed to exhibit smaller time-varying style exposures. Asem and Tian (2010) claim that the documented patterns for conventional momentum are in line with the investor overconfidence hypothesis, but this explanation also seems less applicable to idiosyncratic momentum.

5.3 Link with Underreaction

Gutierrez and Pirinsky (2007) argue that idiosyncratic momentum is grounded in behavioral, rather than risk-based explanations. They link idiosyncratic momentum profits to investors' underreaction to news (slow diffusion of information) given their observation that idiosyncratic momentum profits are sustained even 60 months following portfolio formation.[26] However, the authors do not control for the impact of other stock characteristics that could also be related to future returns. Conventional and idiosyncratic momentum strategies could be different along other dimensions, that is, they could be related to other stock level characteristics, that may be causing their returns to be sustained over longer periods.

In order to address this concern we run Fama and MacBeth (1973) regression of next month's stock excess returns on their lagged conventional and idiosyncratic momentum scores, and also other known predictors of stock returns, such as market beta, book-to-market, size, profitability, and investment. We iteratively run 60 such regressions, in each using lags of momentum signals ranging from 1 to 60 months. This approach is similar to that used in Ball et al. (2016) with the difference that we are focusing on the ability of lagged momentum signals, as opposed to lagged profitability, to predict future returns. In Figure 3, we show the point estimates of the slope coefficients (LEFT) and the corresponding t-statistics (RIGHT) of the conventional and idiosyncratic momentum characteristics at lags t-1 to t-60. All independent variables are winsorized at 1% and 99% levels, and standard errors are calculated using Newey and West (1987) correction with a maximum lag of 3 months. Results for the 1929-2015 sample are consistent with the ones from the shorter sample and can be found in Figure A in the appendix[27].

[26] Alwathainani (2012) shows that this also holds for consistent winners and losers.

[27] For the longer sample, we do not control for profitability and investment characteristics as they are not available in the COMPUSTAT database.

INSERT FIGURE 3 HERE

While conventional momentum forecasts high short to medium term returns, the power of conventional momentum drops to zero fairly quickly and, consistent with Jegadeesh and Titman (2001), turns into a long-term reversal after around one year following portfolio formation. In contrast, idiosyncratic momentum forecasts high, or at least non-negative, returns up to 40 months following formation. Figure 4 shows slope estimates for the two momentum signals when we do not control for other characteristics. In this scenario, we find much more significant results, clearly highlighting the importance of controlling for other characteristics, in particular value, that is closely related to the long-term reversal factor of De Bondt and Thaler (1985), which plays an important role for conventional momentum.

INSERT FIGURE 4 HERE

To further gauge the link between idiosyncratic momentum and underreaction, we hypothesize the following: although on the margin, total return momentum is caused by overreaction, as the two momentum strategies are positively correlated, there is a subset of firms with high momentum (henceforth: Mom) scores that are caused by underreaction, and a subset of high idiosyncratic momentum (henceforth: iMom) firms that are caused by overreaction. Using iMom as a proxy for momentum that is caused by underreaction, we construct portfolios by first restricting the stock universe to 20% of stocks with the highest total return momentum scores, and then within this group we sort stocks into five portfolios on their idiosyncratic momentum scores. We then construct an equal-weighted portfolio that is long iMom winners and short iMom losers within this high total return momentum universe, and tract the performance of this portfolio up to 60 months following portfolio formation[28]. Micro-caps, as defined in the data section, are excluded from the analysis. Similarly, we use Mom as a proxy for momentum that is caused by overreaction and construct a long-short total return momentum portfolio in a universe that is restricted to 20% of stocks with the highest idiosyncratic momentum scores. Results are presented in Figure 5.

Consistent with our hypothesis, we observe that the gap in outperformance of the top over the bottom iMom portfolio in the high Mom universe widens over time, and reaches 6% five years after

[28]We apply the overlapping portfolio approach, as used in Jegadeesh and Titman (1993).

initial portfolio formation (LEFT figure). Conversely, the gap between the top and the bottom Mom portfolio in the iMom universe quickly becomes negative (RIGHT figure), and continues to widen reaching -5.5% five years into the future. These results support the hypothesis that idiosyncratic return momentum is more likely to be attributable to investors' underreaction to firm specific returns, while in the case of total return momentum, overreaction seems to be a more plausible explanation.

INSERT FIGURE 5 HERE

6 International Evidence

We further test the robustness of our results in four broad regions: Europe, Japan, Asia Pacific (excluding Japan), and emerging markets. The investment universe consists of all constituents of the FTSE World Developed Index or S&P Developed BMI for Europe, Japan, and Asia Pacific, and for emerging markets, we use S&P/IFC Global Emerging Markets Index constituents[29]. The resulting universe consists of approximately 1600, 1200, 450, and 1200 stocks, on average, for Europe, Japan, Asia Pacific, and emerging markets, respectively.

We gather monthly gross stock returns in local currencies, as well as in U.S. dollars, taking into account dividends, stock splits, and other capital adjustments. Our stock return data sources are Interactive Data Exshare, MSCI, and S&P/IFS, in that order. Monthly returns are truncated at 500%. The free-float adjusted market capitalization data come from FTSE and S&P/IFC, and accounting data, that we need to construct the HML factor, are obtained from Worldscope, MSCI, and SP/IFC.

Within each region, we construct equal-weighted quintile portfolios by ranking stocks on idiosyncratic and total return momentum, respectively, in a country-neutral manner. This ensures that we do not have strong structural biases to any given country within the corresponding region. Both momentum measures are defined as for the U.S. stocks, and we use local returns to avoid introducing noise that is due to currency effects[30]. Portfolio returns are in U.S. dollars in excess

[29]Stocks that are included in the broad S&P Developed BMI index are usually also included in the FTSE World Developed Index. However, the S&P Developed BMI starts only in 1989. As we aim to obtain the longest possible time series we also include FTSE World Developed Index constituents that are available from December 1985 onwards.

[30]We construct regional Fama-French equivalent hedge factors by ranking stocks on their market capitalization and book-to-market ratio, respectively. Thereby, we define the size (small-minus-big, SMB) and value (high-minus-low,

of the one-month Treasury bill rate from January 1989 for Europe, Asia Pacific, and Japan, and January 1992 for emerging markets, till the end of December 2015. These results are reported in Table 14.

INSERT TABLE 14 HERE

Similar to our earlier results for the U.S., idiosyncratic momentum generates superior risk-adjusted top-minus-bottom returns relative to conventional momentum in all markets that we consider. While this sample period was very favorable for total return momentum, with returns in excess of 80 basis points per month in Europe, Asia Pacific, and emerging markets, idiosyncratic momentum still delivered high returns with a substantial reduction in volatility, resulting in substantially higher Sharpe ratios and t-statistics for CAPM and three-factor alphas. Our results are consistent with Chaves (2016), who finds strong results for a simplified definition of idiosyncratic momentum in international developed equity markets. We stick to the original definition and also consider emerging equity markets, which have not been examined before.

When we regress the conventional (idiosyncratic) momentum returns on the three-factor model augmented with an idiosyncratic (conventional) momentum factor, both strategies exhibit highly significant four-factor model alphas for Europe, Asia Pacific, and emerging markets. Our results, therefore, do not favor one momentum factor over the other for these regions and indicate that they behave like complements, as opposed to substitutes.

Our results are even more compelling for Japan. Similar to other studies (e.g. Griffin et al., 2003; Fama and French, 2012), we find momentum returns that are close to zero. Hanauer (2014) argues that different market dynamics in Japan, i.e. the prevalence of periods with market reversals compared to periods with market continuations, cause these overall low returns of momentum. He further documents that momentum returns are also significantly positive in Japan when the market stays in the same condition, but significantly negative when it reverses. As these market reversals occurred more frequently compared to the U.S. or European markets during our sample period, and conventional momentum tends to underperform idiosyncratic momentum during these periods (as shown in section 5.2), idiosyncratic momentum should show better performance. Indeed, idiosyncratic momentum generates a return of 0.44% per month which is statistically significant at

HML) factors as the return difference between the value-weighted top and bottom tercile.

the most conservative levels. Also, the CAPM, three-factor, and four-factor model regressions show highly significant alphas for idiosyncratic momentum while the ones for conventional momentum are insignificant. These results indicate that the reduced time-varying exposures to systematic risk factors of idiosyncratic momentum significantly enhance the effectiveness of the strategy to such an extent that it even becomes a successful momentum-related strategy in Japan. Our finding that idiosyncratic momentum is also effective in Japan, contrary to conventional momentum, is consistent with Chaves (2016) and Chang et al. (2018).

INSERT FIGURE 6 HERE

Figure 6 shows the results of Fama and MacBeth (1973) regressions with the lagged conventional and idiosyncratic momentum scores, controlling for the market beta, size, and value characteristics. In order to increase the breadth of the sample, we pull all regions together and include country-level dummy variables to absorb country specific effects. Similar to our findings for the US market, lagged values of idiosyncratic momentum forecast positive returns up to five years into the future, while those of total return momentum forecast negative returns already one year following portfolio formation, consistent with the under-reaction hypothesis for idiosyncratic momentum and overreaction hypothesis for conventional momentum. Also, without applying lags for either of the momentum signals, that is using standard Fama and MacBeth (1973) regressions, idiosyncratic momentum emerges stronger with a t-statistic of 4.20 while total return momentum is not priced with a t-statistic of 1.27. Our results are consistent with Chang et al. (2018), who link idiosyncratic momentum profits in Japan to investor under-reaction using different arguments.

7 Conclusion

Portfolios formed on idiosyncratic, as opposed to total past returns generate comparable average returns, with half the volatility of the conventional momentum strategy. We provide evidence that idiosyncratic momentum is a separate factor that expands the efficient frontier comprised of already established asset pricing factors, even if one accounts for conventional momentum. We further discuss and test some of the most prominent explanations that have been put forward for conventional momentum, and find that none of them hold for idiosyncratic momentum. In particular, we show that, unlike conventional momentum, idiosyncratic momentum profits are positive following bull, as well as bear markets, albeit insignificant in the latter case, and that they are substantially less affected by market dynamics, where the return in the month following a bull or bear market is taken into account. These findings go against the overconfidence and overreaction explanations for the anomaly. We also find substantially lower non-linear crash risk exposure embedded in idiosyncratic momentum than in its total return counterpart, which leads us to reject the hypothesis that superior performance of idiosyncratic over total return momentum can be explained by this risk source. Our empirical results support the underreaction hypothesis for the existence of the idiosyncratic momentum premium. We find that, controlling for other known predictors of stock returns in the cross section, conventional momentum forecasts high short term returns, but becomes insignificant quickly, and turns negative around one year following portfolio formation. On the other hand, idiosyncratic momentum forecasts high short and long-term returns. We also show that one can use idiosyncratic momentum to distinguish between past total return winners that are prone to long term reversal and those that are not.

The fact that we cannot conclusively reject one factor in favor of the other, and our inability to link these two momentum phenomena to the same underlying mechanisms, leads us to conclude that they behave more like complements than like substitutes. Finally, we document significant idiosyncratic momentum profits in international equity markets, including the one market where conventional momentum is known to be ineffective - Japan. We conclude that idiosyncratic momentum presents an even bigger challenge to the asset pricing literature, and that the underreaction explanation for the premium seems more likely than the various risk-based and behavioral explanations that have been proposed for conventional momentum.

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Table 1: Performance of Decile Portfolios

		Excess Return	Volatility	Sharpe Ratio	Alpha CAPM	t-stat	Alpha 3FM	t-stat	Alpha 5FM	t-stat
Idiosyncratic Momentum	D1	0.22	5.92	0.04	-0.38	(-3.48)	-0.53	(-5.81)	-0.47	(-5.04)
	D2	0.43	5.54	0.08	-0.13	(-1.47)	-0.30	(-4.26)	-0.32	(-4.43)
	D3	0.52	5.29	0.10	-0.03	(-0.41)	-0.20	(-3.58)	-0.24	(-4.17)
	D4	0.64	5.20	0.12	0.10	(1.28)	-0.08	(-1.62)	-0.11	(-2.14)
	D5	0.73	5.12	0.14	0.20	(2.66)	0.02	(0.39)	-0.03	(-0.72)
	D6	0.77	5.10	0.15	0.24	(3.21)	0.07	(1.69)	0.02	(0.42)
	D7	0.82	5.09	0.16	0.28	(3.97)	0.12	(2.80)	0.06	(1.49)
	D8	0.87	5.09	0.17	0.34	(4.46)	0.18	(3.94)	0.14	(2.99)
	D9	1.01	5.26	0.19	0.46	(5.74)	0.31	(5.66)	0.27	(4.74)
	D10	1.19	5.57	0.21	0.63	(6.70)	0.52	(7.32)	0.51	(6.86)
	D10-D1	0.98	3.33	0.29	1.00	(7.51)	1.05	(7.78)	0.98	(7.02)
	GRS				7.72	p-val 0.00	7.12	p-val 0.00	5.70	p-val 0.00
Total Return Momentum	D1	0.13	7.74	0.02	-0.58	(-3.29)	-0.81	(-5.12)	-0.59	(-3.72)
	D2	0.48	5.97	0.08	-0.11	(-0.92)	-0.32	(-3.17)	-0.30	(-2.89)
	D3	0.63	5.26	0.12	0.10	(1.03)	-0.12	(-1.59)	-0.18	(-2.33)
	D4	0.64	4.86	0.13	0.15	(1.85)	-0.06	(-1.01)	-0.13	(-2.32)
	D5	0.67	4.71	0.14	0.18	(2.47)	-0.01	(-0.21)	-0.10	(-1.96)
	D6	0.73	4.65	0.16	0.24	(3.58)	0.06	(1.28)	-0.05	(-1.19)
	D7	0.83	4.69	0.18	0.34	(4.97)	0.18	(3.76)	0.07	(1.58)
	D8	0.86	4.94	0.17	0.35	(4.53)	0.21	(3.77)	0.10	(1.85)
	D9	1.04	5.60	0.19	0.48	(4.58)	0.41	(5.19)	0.37	(4.57)
	D10	1.20	7.09	0.17	0.55	(3.33)	0.57	(4.60)	0.64	(5.07)
	D10-D1	1.07	6.42	0.17	1.14	(4.42)	1.37	(5.47)	1.23	(4.77)
	GRS				5.14	p-val 0.00	4.60	p-val 0.00	3.66	p-val 0.00

This table reports performance characteristics of decile portfolios constructed as univariate sorts on idiosyncratic and total return momentum, respectively. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. For each portfolio, we report returns in excess of the risk-free rate, volatility, ex-post Sharpe ratios, CAPM-, three-factor-, and five-factor alphas and corresponding t-statistics. Also reported are the GRS test statistics for each of the corresponding asset pricing models, where the test assets are total return and idiosyncratic momentum sorted deciles. Portfolios are equal-weighted and reformed monthly.

Table 2: Performance in the Large-cap Universe 1963-2015

		Excess Return	Volatility	Sharpe Ratio	Alpha CAPM	t-stat	Alpha 3FM	t-stat	Alpha 5FM	t-stat
Idiosyncratic Momentum	D1	0.20	5.55	0.04	-0.37	(-3.82)	-0.46	(-4.89)	-0.40	(-4.19)
	D2	0.39	5.16	0.08	-0.15	(-1.93)	-0.25	(-3.43)	-0.28	(-3.70)
	D3	0.52	5.05	0.10	-0.02	(-0.27)	-0.13	(-2.22)	-0.17	(-2.81)
	D4	0.56	4.82	0.12	0.05	(0.82)	-0.06	(-1.12)	-0.10	(-1.77)
	D5	0.65	4.77	0.14	0.14	(2.30)	0.02	(0.38)	-0.04	(-0.77)
	D6	0.70	4.82	0.15	0.19	(3.11)	0.06	(1.22)	0.00	(-0.03)
	D7	0.68	4.76	0.14	0.17	(3.16)	0.07	(1.39)	0.02	(0.46)
	D8	0.78	4.71	0.17	0.28	(4.56)	0.18	(3.29)	0.11	(2.01)
	D9	0.85	4.93	0.17	0.33	(4.99)	0.23	(3.84)	0.20	(3.21)
	D10	1.05	5.26	0.20	0.51	(5.81)	0.45	(5.38)	0.44	(5.04)
	D10-D1	0.85	3.59	0.24	0.88	(6.11)	0.91	(6.27)	0.84	(5.63)
Total Return Momentum	D1	0.16	7.05	0.02	-0.49	(-3.14)	-0.65	(-4.18)	-0.45	(-2.87)
	D2	0.51	5.50	0.09	-0.03	(-0.33)	-0.19	(-1.99)	-0.19	(-1.93)
	D3	0.56	5.03	0.11	0.05	(0.59)	-0.10	(-1.31)	-0.15	(-1.88)
	D4	0.55	4.68	0.12	0.07	(0.92)	-0.09	(-1.50)	-0.17	(-2.63)
	D5	0.58	4.53	0.13	0.10	(1.57)	-0.04	(-0.65)	-0.12	(-2.14)
	D6	0.66	4.43	0.15	0.19	(3.16)	0.06	(1.20)	-0.05	(-1.02)
	D7	0.66	4.51	0.15	0.18	(3.02)	0.07	(1.29)	-0.05	(-0.92)
	D8	0.69	4.65	0.15	0.21	(3.12)	0.13	(2.02)	0.02	(0.25)
	D9	0.85	5.18	0.16	0.32	(3.56)	0.30	(3.64)	0.26	(3.02)
	D10	1.14	6.64	0.17	0.53	(3.43)	0.60	(4.45)	0.65	(4.74)
	D10-D1	0.97	6.56	0.15	1.03	(3.90)	1.24	(4.86)	1.10	(4.20)

This table reports performance characteristics of decile portfolios constructed as univariate sorts on idiosyncratic and total return momentum, respectively, in the universe that excludes stocks with market capitalization below NYSE median. We include all large-cap common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015, except those with share price below $1, with valid total return and idiosyncratic momentum scores. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three factor model. For each portfolio, we report returns in excess of the risk-free rate, volatility, ex-post Sharpe ratios, five-factor alphas and corresponding t-stats, number of observations in each portfolio, and percent median market capitalization of each portfolio. Portfolios are equal-weighted and reformed monthly.

Table 3: Fama-MacBeth (1973) Regressions

	Intercept	Beta	ln(ME)	ln(BtM)	OP	INV	iMOM	MOM	R2	N
(i)	1.66	-0.05	-0.08	0.17				0.78	7.12	1447
	(3.50)	(-0.36)	(-2.45)	(2.61)				(4.76)		
(ii)	1.75	0.03	-0.08	0.09			0.91		6.33	1447
	(3.61)	(0.18)	(-2.42)	(1.25)			(5.85)			
(iii)	1.78	-0.08	-0.09	0.14			0.45	0.59	7.48	1447
	(3.75)	(-0.58)	(-2.68)	(2.19)			(3.39)	(3.14)		
(iv)	1.63	0.05	-0.10	0.20	0.84	-0.44		0.79	8.06	1417
	(3.53)	(0.39)	(-3.06)	(2.77)	(4.88)	(-5.59)		(4.69)		
(v)	1.71	0.13	-0.10	0.13	0.87	-0.38	0.89		7.28	1417
	(3.65)	(0.87)	(-3.05)	-1.60	(4.73)	(-4.73)	(5.82)			
(vi)	1.74	0.01	-0.10	0.18	0.84	-0.42	0.44	0.59	8.39	1417
	(3.76)	(0.11)	(-3.25)	(2.44)	(4.96)	(-5.4)	(3.38)	(3.09)		

This table reports the results of Fama-MacBeth (1973) regressions. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above the 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1; profitability is the ratio of operating profits and book equity at the fiscal year ending in t-1, and investment is growth in total assets for the fiscal year ending in t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Table 4: Spanning Tests

Panel A: All Stocks		Alpha	Mkt-Rf	SMB	HML	RMW	CMA	MOM	iMOM
Idiosyncratic Momentum	(i)	0.68	-0.06	0.02	-0.03				
		(7.71)	(-2.81)	(0.65)	(-0.90)				
	(ii)	0.64	-0.04	0.03	-0.10	0.04	0.16		
		(7.02)	(-1.92)	(0.80)	(-2.36)	(0.78)	(2.50)		
	(iii)	0.35	0.01	0.00	0.10	-0.07	-0.01	0.39	
		(5.55)	(0.60)	(-0.06)	(3.25)	(-2.10)	(-0.12)	(26.47)	
Total Return Momentum	(iv)	0.91	-0.19	0.01	-0.33				
		(5.44)	(-4.66)	(0.14)	(-5.44)				
	(v)	0.74	-0.13	0.07	-0.52	0.27	0.43		
		(4.32)	(-3.22)	(1.16)	(-6.41)	(3.08)	(3.55)		
	(vi)	-0.13	-0.08	0.03	-0.38	0.22	0.21		1.36
		(-1.09)	(-2.64)	(0.83)	(-6.81)	(3.65)	(2.51)		(26.47)
Panel B: Only Big Stocks		Alpha	Big-Rf		HML_B	RMW_B	CMA_B	MOM_B	$iMOM_B$
$iMOM_B$	(vii)	0.26	0.00		0.00	-0.11	0.17	0.38	
		(3.31)	(0.00)		(0.13)	(-3.16)	(4.53)	(22.34)	
MOM_B	(viii)	0.00	-0.06		-0.18	0.25	-0.17		1.16
		(-0.01)	(-1.82)		(-3.16)	(4.30)	(-2.64)		(22.34)
Panel C: Only Small Stocks		Alpha	Small-Rf		HML_S	RMW_S	CMA_S	MOM_S	$iMOM_S$
$iMOM_S$	(ix)	0.39	0.03		0.08	0.00	-0.01	0.41	
		(5.84)	(2.51)		(2.67)	(-0.16)	(-0.31)	(27.50)	
MOM_S	(x)	-0.06	-0.10		-0.28	0.07	0.20		1.33
		(-0.52)	(-4.63)		(-5.06)	(1.27)	(2.31)		(27.50)

This table presents the results of the time-series spanning tests. The idiosyncratic momentum (iMOM) factor is constructed using independent sorts of stocks into two size and three idiosyncratic momentum groups, where the size breakpoint is the NYSE median market capitalization, and the idiosyncratic momentum breakpoints are the 30th and 70th percentiles of idiosyncratic momentum for NYSE stocks. This process yields six value-weighted portfolios. The final idiosyncratic momentum factor is a zero-investment, equal-weighted portfolio that is long small and big (idiosyncratic) winners, and short small and big (idiosyncratic) losers. Portfolios are reformed monthly. All other factors are obtained from the website of Professor Kenneth French. The sample period runs from July 1963 to December 2015.

Table 5: Spanning Tests with Other Factor Models

		Alpha	Mkt-Rf	SMB/ME	IA	ROE	MGMT	PERF
Idiosyncratic Momentum	(i)	0.39	-0.01	0.09	0.12	0.33		
		(4.23)	(-0.69)	(3.01)	(2.43)	(9.35)		
Total Return Momentum	(ii)	0.13	-0.07	0.24	0.01	0.92		
		(0.79)	(-1.92)	(4.54)	(0.13)	(14.32)		
Idiosyncratic Momentum	(iii)	0.38	0.02	0.04			0.08	0.27
		(4.15)	(0.97)	(1.44)			(2.31)	(12.14)
Total Return Momentum	(iv)	-0.11	0.09	0.11			0.16	0.85
		(-0.80)	(2.57)	(2.49)			(3.14)	(25.37)

This table presents the results of the time-series spanning tests with Q-factor model and Stambaugh-Yuan mispricing factor model. The idiosyncratic momentum (iMOM) factor is constructed using independent sorts of stocks into two size and three idiosyncratic momentum groups, where the size breakpoint is the NYSE median market capitalization, and the idiosyncratic momentum breakpoints are the 30th and 70th percentiles of idiosyncratic momentum for NYSE stocks. This process yields six value-weighted portfolios. The final idiosyncratic momentum factor is a zero-investment, equal-weighted portfolio that is long small and big (idiosyncratic) winners, and short small and big (idiosyncratic) losers. Portfolios are reformed monthly. The Q factor model factors are obtained from Lu Zhang and Stambaugh-Yuan mispricing factors are obtained from the website of Yu Yuan. The sample period runs from January 1967 to December 2015, limited by the availability of the Q-factor model return series.

Table 6: Fama MacBeth (1963) and Spanning Regressions with Idiosyncratic Volatility

Panel A: Fama MacBeth Regressions											
	Intercept	Beta	ln(ME)	ln(BtM)	OP	INV	iMom	Mom	iVol	R square	N
coeff	2.41	0.1	-0.13	0.14	0.72	-0.39	0.42	0.61	-0.22	8.97	1417
t-stat	(5.71)	(0.85)	(-4.72)	(1.96)	(4.4)	(-5.08)	(3.33)	(3.32)	(-5.44)		
Panel B: Spanning Regressions											
	Alpha	Mkt-RF	SMB	HML	RMW	CMA	iMom	Mom	iVol	R2	N
Idiosyncratic Momentum	0.35	0.01	0.00	0.10	-0.07	-0.01		0.39		54.0	630
	(5.55)	(0.60)	(-0.06)	(3.25)	(-2.10)	(-0.12)		(26.47)			
	0.36	-0.01	-0.03	0.11	-0.04	0.01		0.39	-0.05	54.2	630
	(5.64)	(-0.36)	(-0.96)	(3.49)	(-1.06)	(0.32)		(26.11)	(-1.55)		
Total Return Momentum	-0.13	-0.08	0.03	-0.38	0.22	0.21	1.36			57.0	630
	(-1.09)	(-2.64)	(0.83)	(-6.81)	(3.65)	(2.51)	(26.47)				
	-0.17	0.02	0.18	-0.43	0.03	0.08	1.32		0.29	58.9	630
	(-1.44)	(0.73)	(3.77)	(-7.65)	(0.51)	(0.89)	(26.11)		(5.32)		

This table presents results of the Fama MacBeth (1973) time-series spanning tests with idiosyncratic volatility.

Panel A: We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above the 20th percentile of market cap of NYSE traded stocks and with share price above $1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1; profitability is the ratio of operating profits and book equity at the fiscal year ending in t-1, and investment is growth in total assets for the fiscal year ending in t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. Idiosyncratic volatility is defined as the volatility of residuals from regressions of stock returns on the three Fama and French (1993) factors over the last 22 (min 16) days. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Panel B: The idiosyncratic momentum and volatility factors are constructed using independent sorts of stocks into two size and three idiosyncratic momentum/volatility groups, where the size breakpoint is the NYSE median market capitalization, and the idiosyncratic momentum/volatility breakpoints are the 30th and 70th percentiles of idiosyncratic momentum/volatility for NYSE stocks. This process yields six value-weighted portfolios. The final idiosyncratic momentum/volatility factor is a zero-investment, equal-weighted portfolio that is long small and big (idiosyncratic) winners\low-volatility, and short small and big (idiosyncratic) losers\high-volatility portfolios. Portfolios are reformed monthly. All other factors are obtained from the website of Professor Kenneth French. The sample period runs from July 1963 to December 2015.

Table 7: Importance of Factors in Residualization

	Mkt-Rf			Mkt-Rf, SMB, HML			Mkt-Rf, SMB, HML, RMW, CMA			Mkt-Rf, SMB, HML, 10IND		
	D1	**D10**	**D10-D1**	**D1**	**D10**	**D10-D1**	**D1**	**D10**	**D10-D1**	**D1**	**D10**	**D10-D1**
Excess Return	0.13	1.23	1.09	0.20	1.15	0.95	0.22	1.15	0.93	0.32	1.04	0.71
Vol	6.28	5.89	4.35	6.06	5.65	3.37	5.98	5.61	3.09	5.73	5.41	2.28
Sharpe Ratio	0.02	0.21	0.25	0.03	0.20	0.28	0.04	0.20	0.30	0.06	0.19	0.31
Alpha CAPM	-0.47	0.66	1.13	-0.39	0.59	0.98	-0.37	0.59	0.96	-0.25	0.49	0.74
t-stat	(-3.77)	(5.67)	(6.31)	(-3.38)	(6.15)	(7.01)	(-3.33)	(6.32)	(7.49)	(-2.65)	(5.92)	(7.86)
Alpha 3FM	-0.59	0.57	1.17	-0.53	0.50	1.03	-0.51	0.49	1.00	-0.40	0.38	0.78
t-stat	(-5.23)	(6.50)	(6.51)	(-5.58)	(6.82)	(7.36)	(-5.79)	(7.12)	(7.75)	(-5.64)	(7.45)	(8.34)
Alpha 5FM	-0.50	0.56	1.06	-0.46	0.48	0.94	-0.47	0.49	0.96	-0.39	0.37	0.76
t-stat	(-4.31)	(6.18)	(5.78)	(-4.74)	(6.26)	(6.50)	(-5.16)	(6.83)	(7.17)	(-5.26)	(6.92)	(7.77)

This table reports performance characteristics of the top, bottom, and top-bottom decile portfolios constructed as univariate sorts on 12-2 month idiosyncratic return estimated using (i) one-factor model (CAPM), (ii) Fama-French (1993) three-factor model, (iii) Fama-French (2015) five-factor model over the past 36 months, (iv) Fama-French (1993) three-factor model augmented with 10 industry portfolios . We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1966 to December 2015 (as the RMW and CMA factor returns are available from July 1963 onwards and we need three years of data to calculate idiosyncratic momentum) above 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with valid total return and idiosyncratic momentum scores. For each portfolio, we report the return in excess of the risk-free rate, volatility, Sharpe ratio, and five-factor model alpha and slope coefficients with its associated t-stats. Portfolios are equal-weighted and reformed monthly.

Table 8 : Performance of Within Industry and Across Industry Strategies

			Excess Return	Volatility	Sharpe Ratio
Idiosyncratic Momentum	Total	D1	0.22	5.91	0.04
		D10	1.19	5.57	0.21
		D10-D1	**0.98**	**3.33**	**0.29**
	Within Industry	D1	0.24	5.88	0.04
		D10	1.13	5.50	0.21
		D10-D1	**0.89**	**2.69**	**0.33**
	Across Industry	D1	0.26	6.12	0.04
		D10	1.02	6.23	0.16
		D10-D1	**0.76**	**5.81**	**0.13**
Total Return Momentum	Total	D1	0.13	7.73	0.02
		D10	1.20	7.09	0.17
		D10-D1	**1.07**	**6.43**	**0.17**
	Within Industry	D1	0.23	7.47	0.03
		D10	1.15	6.88	0.17
		D10-D1	**0.93**	**5.39**	**0.17**
	Across Industry	D1	0.36	6.22	0.06
		D10	1.02	6.49	0.16
		D10-D1	**0.66**	**6.27**	**0.11**

This table reports performance characteristics of the top, bottom, and top-bottom decile portfolios constructed as univariate sorts on idiosyncratic and total return momentum signals within and across industries. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. For each portfolio, we report the return in excess of the risk-free rate, volatility and Sharpe ratio. Portfolios are equal-weighted and reformed monthly. Industry classification is based on first digit of the SIC codes provided by CRSP.

Table 9: Spanning Regressions with Within Industry and Across Industry Strategies

		Alpha	Across Industry	Within Industry	R square	N
Idiosyncratic Momentum	(i)	-0.05	0.14	1.03	0.90	630
		(-1.03)	(18.68)	(61.79)		
	(ii)	0.06		0.79	0.85	630
		(0.26)		(9.78)		
	(iii)	0.76	0.17		0.31	630
		(7.57)	(9.78)			
Total Return Momentum	(iv)	-0.01	0.19	1.03	0.95	630
		(-0.22)	(18.06)	(83.50)		
	(v)	0.08		0.62	0.93	630
		(0.38)		(15.89)		
	(vi)	0.62	0.46		0.42	630
		(3.42)	(15.89)			

This table presents results of the time-series spanning tests based on top-bottom decile portfolios constructed as univariate sorts on idiosyncratic and total return momentum signals within and across industries. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20^{th} percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted and reformed monthly. Industry classification is based on first digit of the SIC codes provided by CRSP.

Table 10: Fama MacBeth (1963) Regressions with Industry and Industry-Neutral Strategies

	Intercept	Beta	ln(ME)	ln(BtM)	OP	INV	$iMOM_S$	$iMOM_A$	MOM_S	MOM_A	R square	N
(i)	1.74	0.12	-0.10	0.12	0.85	-0.40	0.84	1.18			8.04	1417
	(3.71)	(0.88)	(-3.11)	(1.59	(4.72)	(-5.07)	(6.17)	(1.71)				
(ii)	1.54	0.04	-0.10	0.19	0.79	-0.47			0.72	1.59	8.83	1417
	(3.33)	(0.34)	(-3.10)	(2.66)	(4.63)	(-6.01)			(4.53)	(3.39)		
(iii)	1.77	0.01	-0.10	0.16	0.80	-0.44	0.44	0.55	0.52	1.33	9.70	1417
	(3.77)	(0.04)	(-3.39)	(2.29)	(4.78)	(-5.91)	(3.96)	(0.64)	(2.84)	(2.28)		

This table presents results of the Fama MacBeth (1973) regressions based on idiosyncratic and total return momentum selection and allocation signals. The allocation signal that is the average value of the industry assigned to each stock in that industry ($iMOM_A$ and MOM_A), and the selection signal that is equal to stock's signal in excess of that of its corresponding industry ($iMOM_S$ and MOM_S). Industry classification is based on first digit of the SIC codes provided by CRSP. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above the 20th percentile of market cap of NYSE traded stocks and with share price above $1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1; profitability is the ratio of operating profits and book equity at the fiscal year ending in t-1, and investment is growth in total assets for the fiscal year ending in t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Table 11: Momentum Crashes - Optionality in Bear Markets

	Total Return Momentum										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1
α_0	-0.91%	-0.37%	-0.12%	0.03%	0.05%	0.19%	0.23%	0.26%	0.37%	0.41%	1.32%
	(-5.76)	(-3.47)	(-1.41)	(0.4)	(0.77)	(2.77)	(3.4)	(3.71)	(4.25)	(3.13)	(6.33)
α_B	-0.53%	-0.91%	-0.66%	-0.51%	-0.36%	-0.27%	0.10%	0.01%	0.38%	0.88%	1.41%
	(-1.04)	(-2.63)	(-2.36)	(-2.08)	(-1.6)	(-1.27)	(0.44)	(0.06)	(1.33)	(2.06)	(2.09)
β_0	1.31	1.13	1.03	1.01	1.00	1.02	1.04	1.10	1.19	1.38	0.07
	(36.3)	(46.15)	(52.62)	(57.95)	(62.75)	(66.65)	(67.12)	(67.15)	(59.64)	(45.59)	(1.48)
β_B	0.21	0.20	0.18	0.19	0.11	0.06	0.02	-0.08	-0.18	-0.37	-0.58
	(2.49)	(3.53)	(4.08)	(4.71)	(3.11)	(1.56)	(0.61)	(-2.2)	(-3.98)	(-5.37)	(-5.28)
$\beta_{B,U}$	0.66	0.61	0.44	0.28	0.25	0.12	0.04	0.05	-0.09	-0.19	-0.85
	(6.02)	(8.15)	(7.31)	(5.3)	(5.1)	(2.63)	(0.92)	(1.08)	(-1.48)	(-2.03)	(-5.83)
	Idiosyncratic Momentum										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1
α_0	-0.60%	-0.30%	-0.15%	-0.04%	0.06%	0.09%	0.16%	0.17%	0.32%	0.44%	1.04%
	(-6.18)	(-3.74)	(-2.07)	(-0.53)	(0.81)	(1.29)	(2.05)	(2.2)	(4.32)	(5.32)	(9.25)
α_B	-0.28%	-0.18%	0.01%	-0.17%	-0.22%	-0.47%	-0.26%	-0.25%	-0.31%	0.28%	0.56%
	(-0.9)	(-0.68)	(0.02)	(-0.69)	(-0.89)	(-2.13)	(-1.05)	(-0.98)	(-1.27)	(1.05)	(1.55)
β_0	1.16	1.12	1.09	1.09	1.08	1.10	1.11	1.12	1.14	1.19	0.04
	(52.43)	(60.45)	(63.76)	(61.85)	(62.6)	(69.96)	(63.05)	(62.02)	(67.57)	(62.79)	(1.46)
β_B	0.09	0.08	0.16	0.07	0.09	0.03	0.01	-0.04	-0.06	-0.09	-0.18
	(1.74)	(1.96)	(3.96)	(1.84)	(2.36)	(0.69)	(0.22)	(-1.02)	(-1.6)	(-2.16)	(-3.1)
$\beta_{B,U}$	0.32	0.21	0.11	0.23	0.21	0.25	0.28	0.33	0.22	0.04	-0.28
	(4.69)	(3.73)	(2.04)	(4.19)	(3.98)	(5.13)	(5.11)	(5.93)	(4.29)	(0.61)	(-3.58)

This table presents these results of conditional regressions $R_t = \alpha_0 + \alpha_B I_{B,t} + [\beta_0 + I_{B,t}(\beta_B + I_{U,t}\beta_{B,U}) * (R_{mkt,t} - R_{f,t}) + \epsilon_t$, where the dependent variables are price and idiosyncratic long-short (decile) portfolios; $I_{B,t}$ and $I_{U,t}$ are dummies indicating whether the past cumulative twelve-month return of the market is negative ($I_{B,t}$) and whether the subsequent month is non-negative ($I_{U,t}$). β_B indicates whether the market beta differs after past bear markets, while β_U indicates the extent to which the subsequent up- and down-market betas differ after such market. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. Portfolios are equal-weighted and reformed monthly.

Table 12: Market States

		Past Bull MKT	Past Bear MKT	Diff
Total Return Momentum	mean	1.32	-0.48	1.80
	t-stat	(6.88)	(-0.53)	(1.93)
Idiosyncratic Momentum	mean	1.08	0.39	0.69
	t-stat	(11.09)	(0.98)	(1.67)

This table reports average returns and associated t-statistics of the idiosyncratic momentum (D10-D1), as well as total return momentum strategy following bull and bear markets, defined as in Cooper et al. (2004) as periods with positive (negative) 36-month market returns. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted and reformed monthly.

Table 13: Market Dynamics

Total Return Momentum				
		Up Month	Down Month	Diff
Past Bull MKT	mean	2.03%	0.09%	1.94%
	t-stat	(9.31)	(0.33)	(5.49)
Past Bear MKT	mean	-4.55%	5.41%	-9.97%
	t-stat	(-4.26)	(9.34)	(8.10)
Idiosyncratic Momentum				
		Up Month	Down Month	Diff
Past Bull MKT	mean	1.18%	0.84%	0.34%
	t-stat	(9.32)	(4.87)	(1.60)
Past Bear MKT	mean	-0.66%	2.27%	-2.94%
	t-stat	(-1.49)	(7.57)	(5.46)
Difference (iMom-Mom)				
		Up Month	Down Month	
Past Bull MKT	mean	-0.85%	0.75%	
	t-stat	(-4.96)	(3.58)	
Past Bear MKT	mean	3.89%	-3.14%	
	t-stat	(5.24)	(-6.65)	

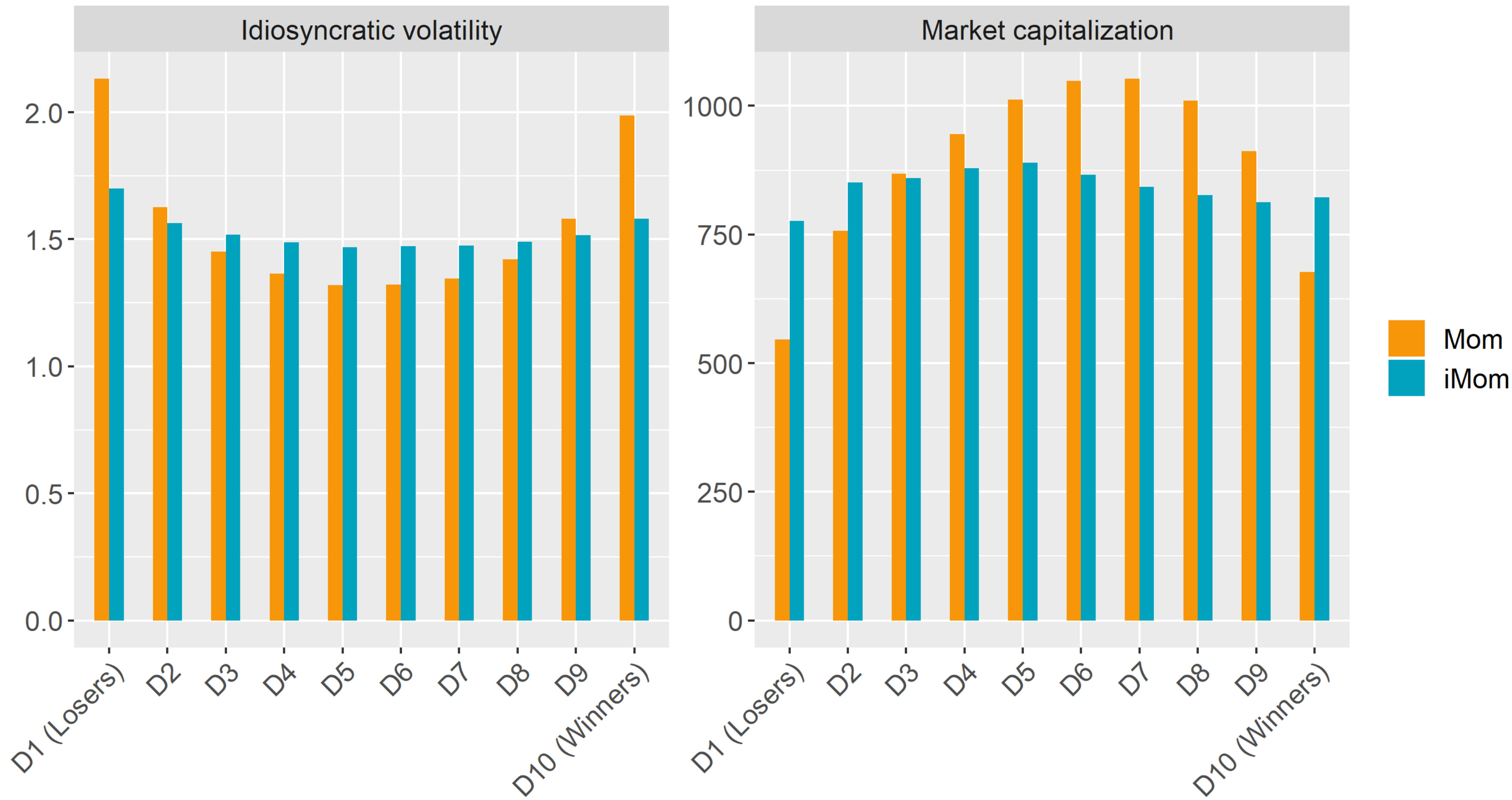
This table reports average returns and associated t-statistics of the idiosyncratic (D10-D1), as well as total return momentum strategy following market downturns (an down month following a bull market), market upturns (an up month following a bear market), and market continuations (an up month following a bull market and a down month following a bear market). Following Asem and Tian (2010), we define bull market as periods in which the cumulative 12-month market return is positive, and bear market in which it is negative. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20^{th} percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted and reformed monthly.

Table 14: International Results

			Excess Return	Vol	Sharpe Ratio	Alpha CAPM	t-stat	Alpha 3FM	t-stat	Alpha 4FM*	t-stat
Idiosyncratic Momentum	EUR	Q5	1.00	5.20	0.19	0.52	(5.19)	0.54	(8.71)	0.42	(7.89)
		Q1	0.13	5.91	0.02	-0.41	(-3.21)	-0.36	(-5.65)	-0.25	(-4.39)
		Q5-Q1	0.87	2.16	0.40	0.92	(7.91)	0.90	(8.61)	0.67	(7.94)
	JAP	Q5	0.28	6.59	0.04	0.39	(2.52)	0.21	(2.42)	0.13	(1.82)
		Q1	-0.16	7.18	-0.02	-0.04	(-0.20)	-0.32	(-4.02)	-0.24	(-3.84)
		Q5-Q1	0.44	2.69	0.16	0.43	(2.92)	0.53	(3.61)	0.37	(3.40)
	PCFxJP	Q5	1.09	6.41	0.17	0.40	(3.32)	0.65	(6.79)	0.63	(6.61)
		Q1	0.05	7.13	0.01	-0.70	(-4.52)	-0.31	(-3.07)	-0.24	(-2.55)
		Q5-Q1	1.04	2.73	0.38	1.10	(7.35)	0.96	(6.56)	0.87	(6.25)
	EM	Q5	1.14	6.62	0.17	0.60	(4.36)	0.58	(4.69)	0.41	(3.41)
		Q1	0.39	7.16	0.05	-0.18	(-1.02)	-0.21	(-1.44)	-0.11	(-0.76)
		Q5-Q1	0.75	2.30	0.33	0.78	(5.77)	0.79	(5.88)	0.53	(4.24)
Total Return Momentum	EUR	Q5	1.10	5.16	0.21	0.63	(5.30)	0.64	(6.72)	0.41	(6.80)
		Q1	-0.07	7.36	-0.01	-0.70	(-3.44)	-0.63	(-5.39)	-0.37	(-4.47)
		Q5-Q1	1.17	4.61	0.25	1.34	(5.57)	1.27	(6.59)	0.78	(6.97)
	JAP	Q5	0.07	6.40	0.01	0.18	(1.14)	0.12	(0.91)	0.00	(-0.01)
		Q1	0.01	8.64	0.00	0.15	(0.58)	-0.26	(-1.67)	-0.12	(-1.21)
		Q5-Q1	0.06	5.59	0.01	0.03	(0.10)	0.38	(1.39)	0.11	(0.76)
	PCFxJP	Q5	1.04	6.31	0.17	0.36	(2.89)	0.57	(5.09)	0.45	(4.54)
		Q1	-0.35	8.50	-0.04	-1.21	(-5.29)	-0.62	(-4.37)	-0.45	(-3.72)
		Q5-Q1	1.39	4.70	0.30	1.57	(6.32)	1.19	(5.52)	0.90	(5.19)
	EM	Q5	1.13	6.47	0.18	0.61	(4.43)	0.61	(4.72)	0.33	(2.81)
		Q1	0.32	8.17	0.04	-0.30	(-1.29)	-0.36	(-1.85)	-0.09	(-0.45)
		Q5-Q1	0.81	4.18	0.19	0.91	(3.82)	0.97	(4.32)	0.42	(2.14)

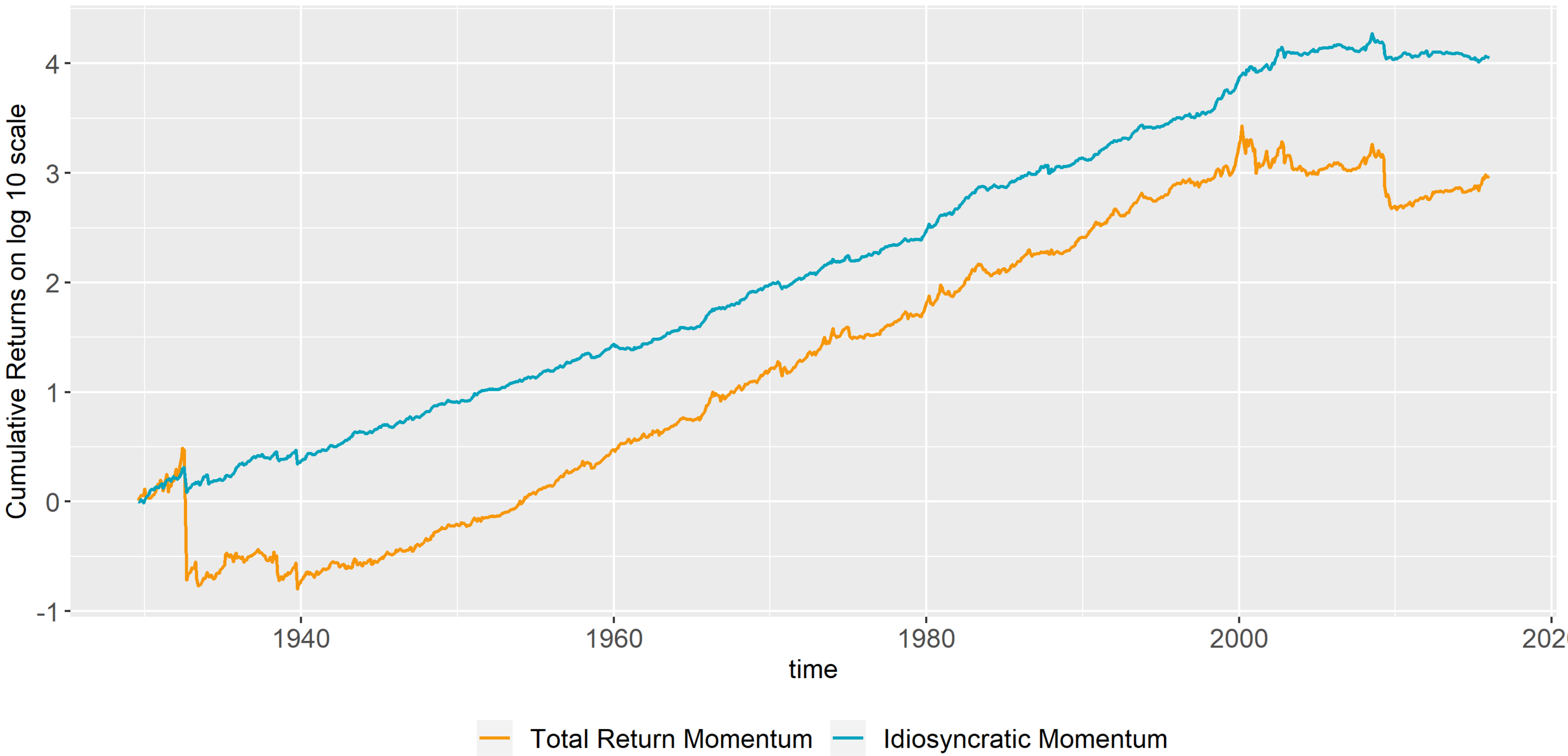
This table shows performance of total return and idiosyncratic momentum in international markets. We focus on four broad regions: Europe, Japan, Asia Pacific (excluding Japan) and emerging markets. Our universe consists of all constituents of the FTSE World Developed Index or S&P Developed BMI for Europe, Japan, and Asia Pacific, and for emerging markets, we use S&P/IFC Global Emerging Markets Index constituents. Our sample covers the period from the end of December 1989 to the end of December 2015 for Europe, Japan, and Asia Pacific, and from the end of December 1992 to the end of December 2015 for emerging markets. Within each region, we construct equally-weighted quintile portfolios by ranking stocks on idiosyncratic and total return momentum, respectively, in a country neutral manner. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the regional market, size, and value factors. Portfolio returns are in U.S. dollars in excess of the one-month Treasury bill rate.

Figure 1: Idiosyncratic Volatility and Market Capitalization across Deciles



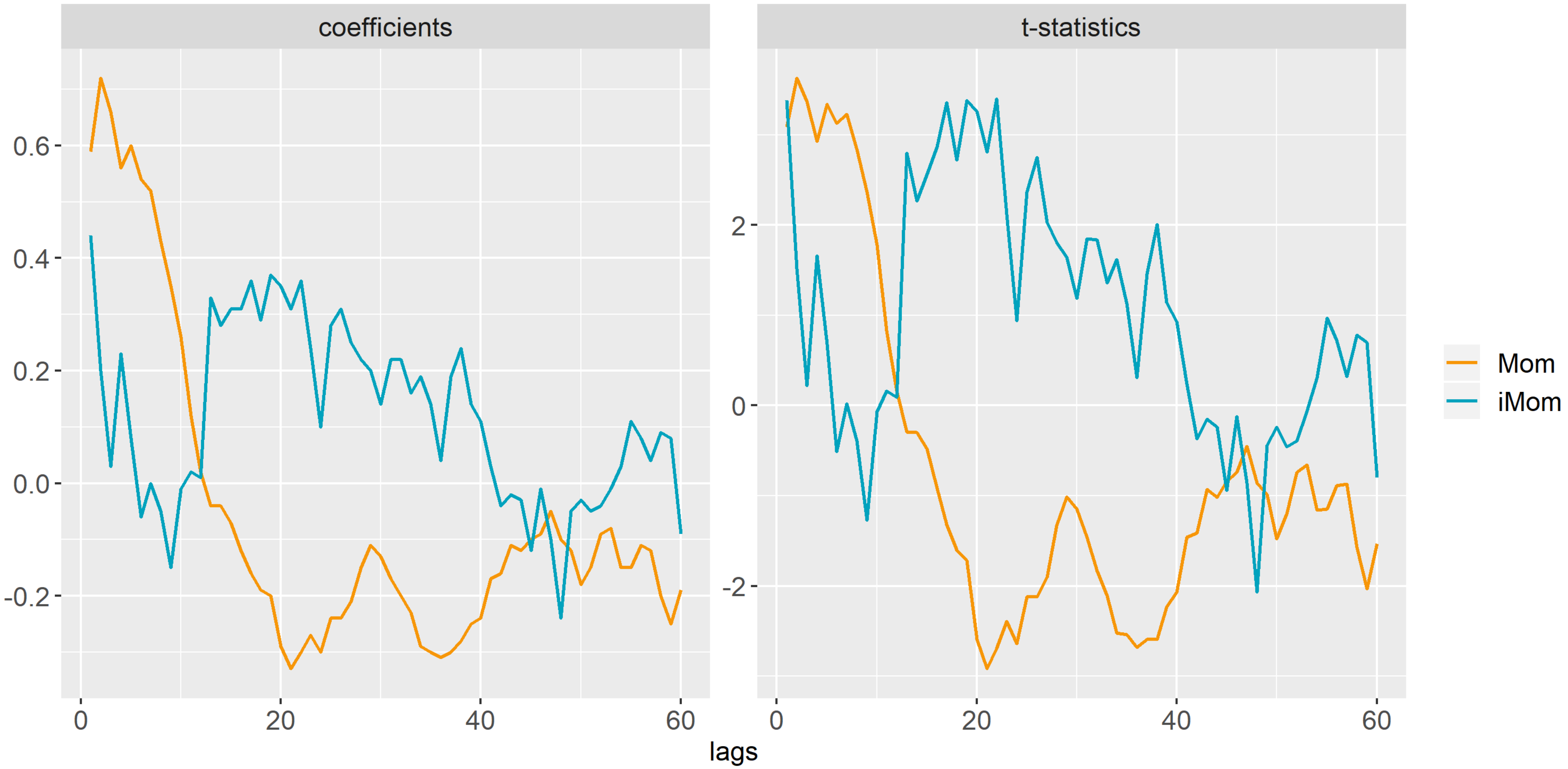
This figure shows the average level of the idiosyncratic volatility and market capitalization across deciles portfolios sorted on the total return and idiosyncratic momentum. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted and reformed monthly.

Figure 2: Cumulative Returns



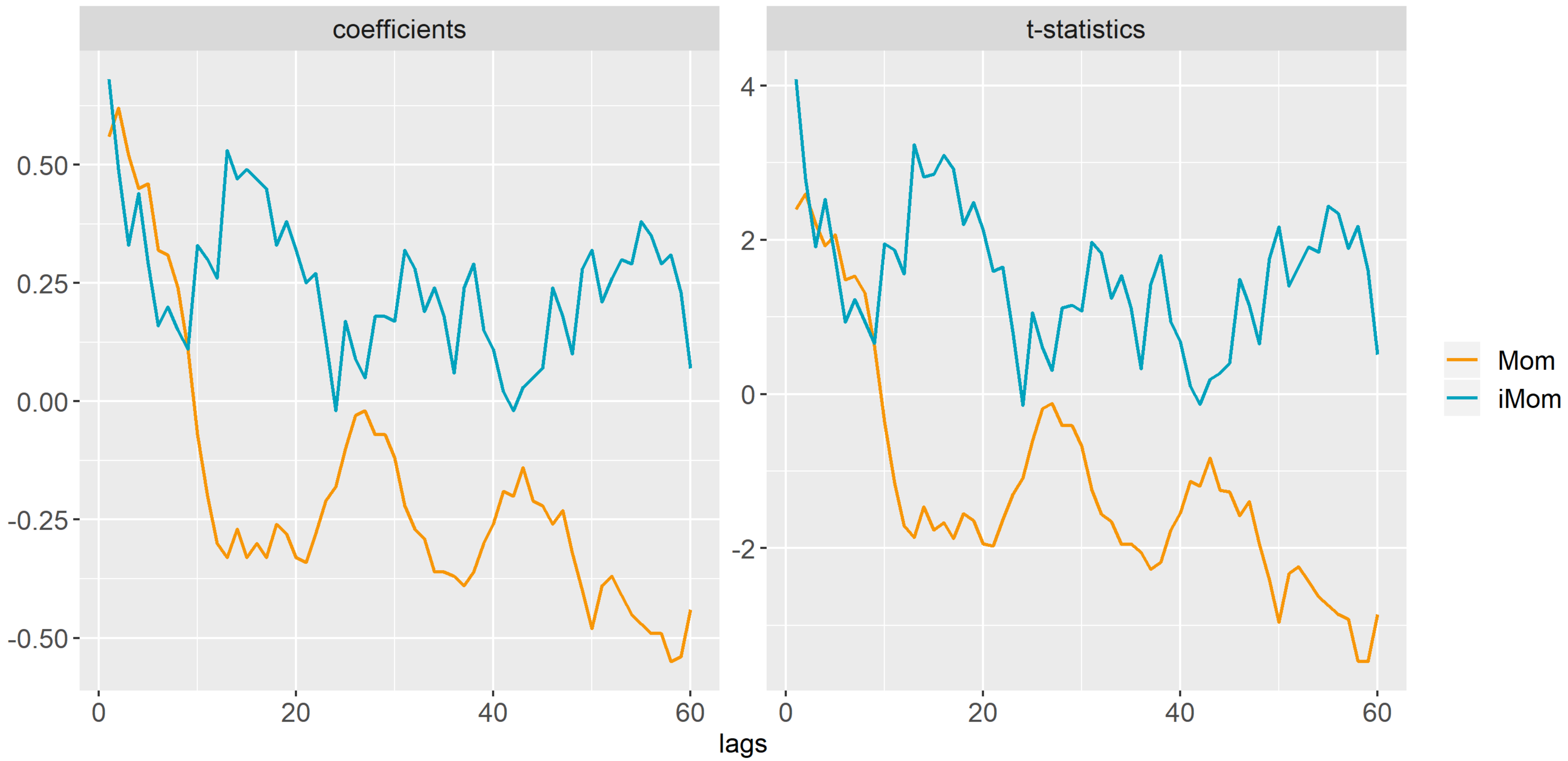
This figure shows cumulative outperformance of the top over the bottom total return and idiosyncratic momentum portfolios. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted and reformed monthly.

Figure 3: Fama and MacBeth (1973) Regressions with Lagged (i)Momentum Signals with Controls



This figure shows the Fama and MacBeth (1973) coefficients, and corresponding t-statistics on the lagged total return and idiosyncratic momentum characteristics. We iteratively run 60 such regressions with one lag-pair in each, with the following controls fixed at time t-1: beta, size, value, profitability, and investment. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20[th] percentile of market cap of NYSE traded stocks and with share price above $1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1; profitability is the ratio of operating profits and book equity at the fiscal year ending in t-1, and investment is growth in total assets for the fiscal year ending in t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Figure 4: Fama and MacBeth (1973) Regressions with Lagged (i)Momentum Signals without Controls

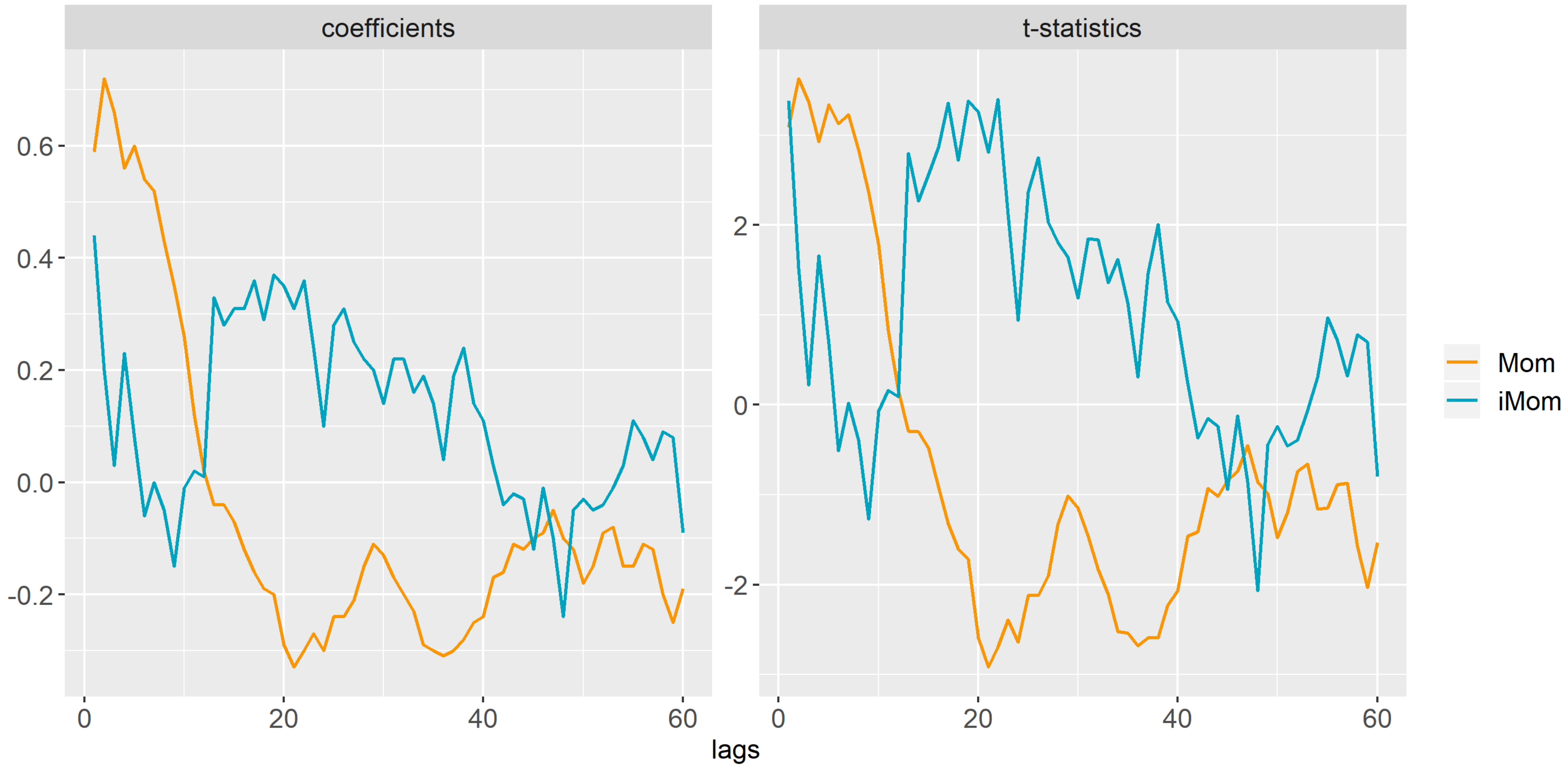


This figure shows the Fama and MacBeth (1973) coefficients, and corresponding t-statistics on the lagged total return and idiosyncratic momentum characteristics. We iteratively run 60 such regressions with one lag pair in each, with no other controls. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with non-missing characteristics. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Figure 5: Cumulative Performance in Restricted Universe

The left panel shows cumulative return of the top-bottom (qunitile) idiosyncratic momentum portfolio constructed in the restricted universe of stocks with 20% highest total return momentum scores; The right panel shows cumulative return of the top-bottom (qunitile) total return momentum portfolio constructed in the restricted universe of stocks with 20% highest idiosyncratic return momentum scores. We keep track of these portfolios up to 60 months following portfolio formation. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1963 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above $1, with valid total return and idiosyncratic momentum scores. Portfolios are equal-weighted. We apply the overlapping portfolio approach of Jegadesh and Titman (1993).

Figure 6: Fama and MacBeth (1973) Regressions with Lagged (i)Momentum Signals with Controls in International Markets



This figure shows the Fama and MacBeth (1973) coefficients, and corresponding t-statistics on the lagged total return and idiosyncratic momentum characteristics. We iteratively run 60 such regressions with one lag-pair in each, with the following controls fixed at time t-1: beta, size, value, and country dummies. We focus on four broad regions: Europe, Japan, Asia Pacific (excluding Japan) and emerging markets. Our universe consists of all constituents of the FTSE World Developed Index or S&P Developed BMI for Europe, Japan, and Asia Pacific, and for emerging markets, we use S&P/IFC Global Emerging Markets Index constituents. Our sample covers the period from the end of December 1989 to the end of December 2015 for Europe, Japan, and Asia Pacific, and from the end of December 1992 to the end of December 2015 for emerging markets. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-36 to t-1 (min t-12 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year lagged by at least 6 months and market cap also lagged by 6 months. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

APPENDIX

Table A1: Performance of Decile Portfolios 1929-2015

		Excess Return	Vol	Sharpe Ratio	Alpha CAPM	t-stat	Alpha 3FM	t-stat
Idiosyncratic Momentum	D1	0.31	0.08	0.04	-0.47	(-5.15)	-0.61	(-8.96)
	D2	0.52	0.07	0.07	-0.21	(-2.86)	-0.34	(-6.10)
	D3	0.61	0.07	0.09	-0.10	(-1.49)	-0.24	(-4.79)
	D4	0.76	0.07	0.11	0.05	(0.67)	-0.10	(-2.28)
	D5	0.84	0.07	0.12	0.13	(1.85)	-0.01	(-0.25)
	D6	0.86	0.07	0.13	0.15	(2.29)	0.01	(0.35)
	D7	0.98	0.07	0.14	0.27	(3.78)	0.12	(2.85)
	D8	1.04	0.07	0.15	0.32	(4.41)	0.18	(3.87)
	D9	1.13	0.07	0.17	0.42	(6.28)	0.30	(6.58)
	D10	1.27	0.07	0.19	0.58	(7.75)	0.50	(8.66)
	D10-D1	0.96	3.44	0.28	1.04	(9.94)	1.11	(10.80)
	GRS				12.85	0.00	12.04	0.00
Total Return Momentum	D1	0.32	0.10	0.03	-0.63	(-4.14)	-0.89	(-7.19)
	D2	0.60	0.08	0.07	-0.24	(-2.16)	-0.46	(-5.54)
	D3	0.70	0.07	0.10	-0.05	(-0.56)	-0.23	(-3.72)
	D4	0.75	0.07	0.11	0.05	(0.61)	-0.12	(-2.37)
	D5	0.76	0.06	0.12	0.09	(1.32)	-0.05	(-1.15)
	D6	0.84	0.06	0.14	0.19	(3.15)	0.08	(1.68)
	D7	0.91	0.06	0.15	0.27	(4.54)	0.17	(3.83)
	D8	0.97	0.06	0.16	0.33	(5.21)	0.25	(4.92)
	D9	1.13	0.06	0.18	0.48	(5.94)	0.43	(6.60)
	D10	1.33	0.07	0.18	0.65	(5.17)	0.63	(6.48)
	D10-D1	1.01	7.21	0.14	1.28	(6.05)	1.52	(7.80)
	GRS				6.46	0.00	6.88	0.00

This table reports performance characteristics of equal-weighted decile portfolios constructed as univariate sorts on idiosyncratic and total return momentum, respectively. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20^{th} percentile of market cap of NYSE traded stocks and with share price above \$1, with valid total return and idiosyncratic momentum scores. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. For each portfolio, we report returns in excess of the risk-free rate, volatility, ex-post Sharpe ratios, CAPM-, three-factor model alphas, and corresponding t-statistics. Also reported are the GRS test statistics for each of the corresponding asset pricing models, where the test assets are total return and idiosyncratic momentum sorted deciles. Portfolios are reformed monthly.

Table A2: 1929-2015 Fama-MacBeth (1973) Regressions

	Intercept	Beta	ln(ME)	ln(BtM)	iMOM	MOM	R2	N
(i)	1.60	0.02	-0.07	0.15			6.94	1076
	(3.95)	(0.16)	(-2.38)	(2.65)				
(ii)	1.70	0.03	-0.08	0.08	1.03		7.77	1076
	(4.19)	(0.23)	(-2.69)	(1.32)	(8.25)			
(iii)	1.58	-0.04	-0.08	0.16		0.87	8.64	1076
	(3.99)	(-0.32)	(-2.8)	(2.95)		(4.74)		
(iv)	1.65	-0.06	-0.08	0.12	0.71	0.46	9.09	1076
	(4.11)	(-0.49)	(-2.90)	(2.36)	(5.22)	(2.05)		

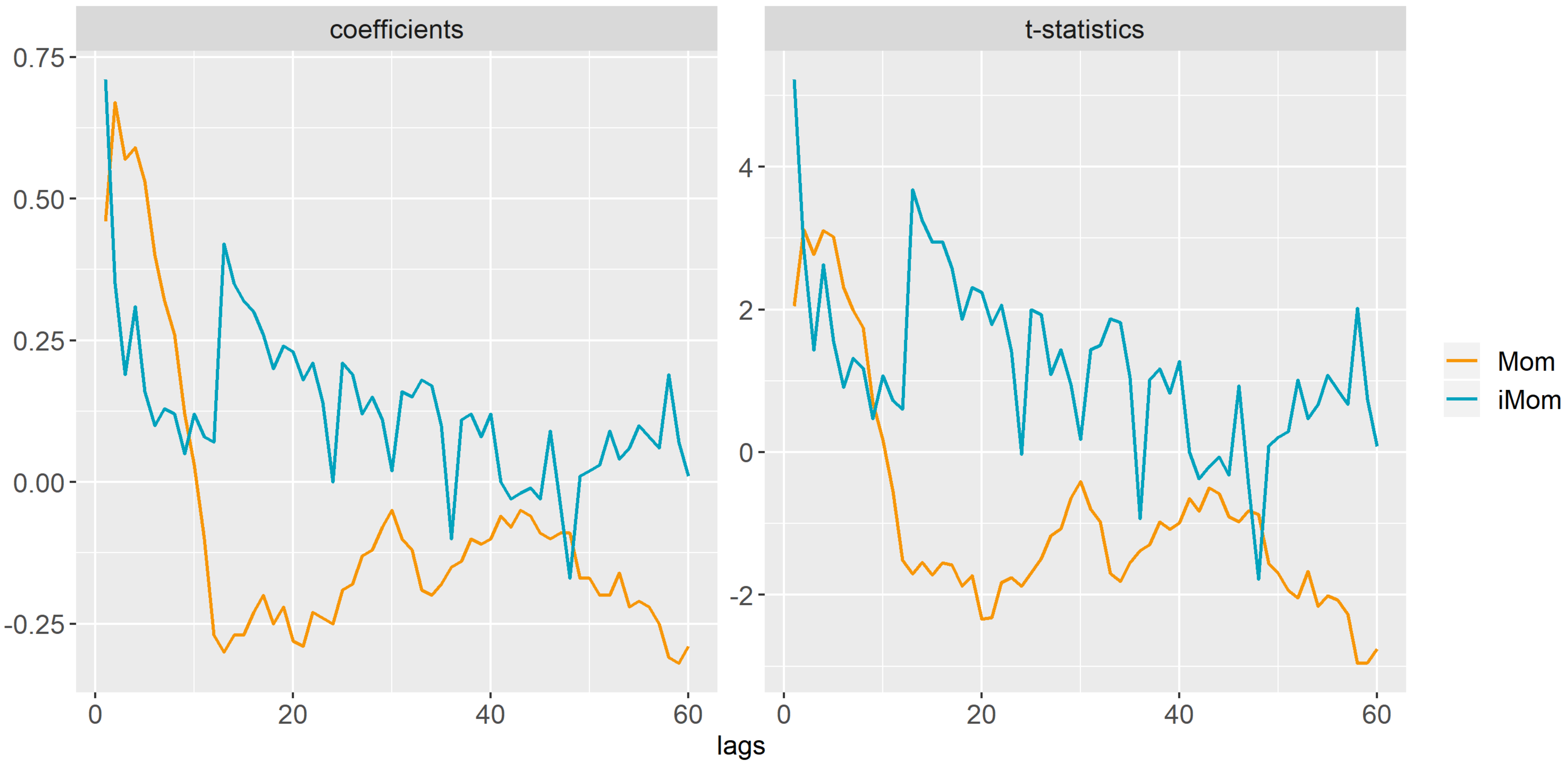
This table reports the results of Fama-MacBeth (1973) regressions. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.

Table A3: 1929-2015 Spanning Tests

Dependent Variable		Alpha	Mkt-Rf	SMB	HML	MOM	iMOM
Idiosyncratic Momentum	(i)	0.72	-0.05	0.03	-0.04		
		(10.33)	(-3.91)	(1.14)	(-2.25)		
	(ii)	0.37	0.03	0.04	0.12	0.35	
		(6.95)	(2.74)	(2.18)	(7.56)	(29.11)	
Total Return Momentum	(iii)	0.99	-0.23	-0.03	-0.46		
		(7.51)	(-8.96)	(-0.71)	(-12.30)		
	(iv)	0.08	-0.16	-0.06	-0.41		1.27
		(0.74)	(-8.48)	(-1.99)	(-14.51)		(29.11)

This table presents results of the time-series spanning tests. The idiosyncratic momentum (iMOM) factor is constructed using independent sorts of stocks into two size and three idiosyncratic momentum groups, where the size breakpoint is the NYSE median market capitalization, and the idiosyncratic momentum breakpoints are the 30th and 70th percentiles of idiosyncratic momentum for NYSE stocks. This process yields six value-weighted portfolios. The final idiosyncratic momentum factor is a zero-investment, equal-weighted portfolio that is long small and big (idiosyncratic) winners, and short small and big (idiosyncratic) losers. Portfolios are reformed monthly. All other factors are obtained from the website of Professor Kenneth French. The sample period runs from July 1929 to December 2015.

Figure A: Fama and MacBeth (1973) Regressions with Lagged (i)Momentum Signals with Controls



This figure shows the Fama and MacBeth (1973) coefficients, and corresponding t-statistics on the lagged total return and idiosyncratic momentum characteristics. We iteratively run 60 such regressions with one lag-pair in each, with the following controls fixed at time t-1: beta, size, and value. We include all common stocks traded on NYSE, AMEX, and NASDAQ exchanges from July 1929 to December 2015 above 20th percentile of market cap of NYSE traded stocks and with share price above \$1, with non-missing characteristics. Beta is the slope coefficient on the market factor estimated using univariate regressions of stock excess returns on the one-factor model (CAPM) from t-60 to t-1 (min t-24 to t-1). Size is the natural logarithm of firm's market capitalization at the end of month t, value is the natural logarithm of the ratio of firms book equity for the fiscal year ending in t-1 and market cap at the end of December of t-1. Total return momentum is defined as the 12-2 month total stock return and idiosyncratic momentum is the 12-2 month volatility-scaled idiosyncratic return estimated over past 36 months using the Fama-French (1993) three-factor model. All variables are winsorized at 1% and 99%. Reported are the average coefficients and t-statistics calculated using Newey-West corrected standard errors with a maximum of 3 lags.