Enhanced Momentum Strategies

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Abstract

This paper compares the performance of three momentum risk management techniques proposed in the literature — idiosyncratic momentum, constant volatility-scaling and dynamic scaling. Using data for individual stocks from the U.S. and across 48 international countries, we find that all three approaches decrease momentum crashes, lead to higher risk-adjusted returns and raise break-even transaction costs. In a multiple model comparison test that also controls for other factors, idiosyncratic momentum emerges as the best momentum strategy. Finally, we find that the alpha stemming from volatility-scaling is distinctive from the idiosyncratic momentum alpha.

Keywords: Momentum, Momentum Scaling, Idiosyncratic Momentum, Risk Management

JEL Classifications: G12, G14, G15

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1 Introduction

The evidence for momentum is pervasive: Jegadeesh and Titman (1993) discover that past winner (loser) stocks tend to have relatively high (low) future returns. Momentum poses an explanatory problem on the Capital Asset Pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966), as well as on the Fama and French (1993, 2015) three- and five-factor models. Within the U.S., a long-short momentum factor generates an average raw return of 0.60% (Fama-French three-factor model (FF3FM) alpha of 0.87%) per month between January 1930 and December 2017. Positive momentum returns have also been identified for other equity markets and asset classes.[1]

Besides the relatively high profitability, momentum has occasionally experienced large drawdowns (crashes), i.e., persistent strings of negative returns. In 1932, the momentum factor for the U.S. equity market exhibited a drawdown of -67.10%. Also in 2009, the momentum factor for both the U.S. and international (ex-U.S.) equity markets experienced large losses. Grundy and Martin (2001) explain the risks of momentum by time-varying factor exposures. For instance, after bear markets the market betas of loser stocks tend to be higher than those of winner stocks. When the market rebounds after a bear state, the overall negative market sensitivity of the winner-minus-loser strategy generates negative strategy returns.[2] Grundy and Martin (2001) show that hedging out the momentum strategy's dynamic market and size exposures substantially reduces the volatility of the strategy without a loss in return, but

[1] Rouwenhorst (1998, 1999) finds that momentum strategies earn high abnormal returns in equity markets internationally, both in developed and in emerging markets. Moskowitz and Grinblatt (1999) document momentum for industry portfolios, Asness, Liew, and Stevens (1997) and Chan, Hameed, and Tong (2000) for country equity indices, Okunev and White (2003) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) for currency markets, and Erb and Harvey (2006) for commodity futures. Asness, Moskowitz, and Pedersen (2013) confirm these findings and uncover a common factor structure among momentum returns across asset classes. Chui, Titman, and Wei (2010) show that momentum is persistent worldwide except for Asia, and propose cross-country differences in individualism an explanation while Docherty and Hurst (2018) document that momentum is stronger in more myopic countries. Griffin, Ji, and Martin (2003) find that momentum returns cannot be attributed to macroeconomic risk factors, whereas Fama and French (2012) show that local momentum factors are superior to a global momentum factor in pricing regional size-momentum portfolios.

[2] Asem and Tian (2010) investigate the effect of market dynamics on momentum returns and document that there are higher momentum returns when markets continue in the same state than when they transition to a different states, i.e., market up (down) movements following bull (bear) markets, are associated with higher momentum returns.

Daniel and Moskowitz (2016), however, show that the superior performance of the dynamic hedged strategy depends on using ex-post factor betas to hedge these exposures. Daniel and Moskowitz (2016) more generally isolate this behavior by conditioning momentum on a stress dummy that indicates both past bear market states and high market volatility. The stress dummy has significant negative loadings when regressing momentum returns on it, indicating the conditional nature of momentum returns. Momentum crashes put extreme pressure on mean-variance optimizing momentum investors, both through the strategy's conditionally negative returns and its heightened volatility during these phases. The rationale to optimize the expected Sharpe is to either limit momentum return downturns, reduce the risk of momentum, or both.

The recent literature has focused on volatility-scaling of factors. This idea is based on the empirical observation that factor-return volatility is positively autocorrelated in the short term and that returns are relatively low when volatility is high, named the leverage effect.[3] Volatility-scaling strategies have been tested for single assets, factors, and asset classes.[4] Barroso and Santa-Clara (2015) study momentum strategies that are deflated by their realized volatility and scaled to a constant target volatility level. Realized volatility is calculated from past daily momentum returns and a proxy of future volatility. They find that Sharpe ratios more than double, while portfolio turnover only marginally increases. Daniel and Moskowitz (2016) extend the constant volatility-scaling approach by additionally taking the forecasted momentum return into account. The weights of their dynamic scaling are different than those of constant volatility-scaling because they can take on negative values. Daniel and Moskowitz

[3]See, among others, Engle (1982); Bollerslev (1987) for volatility autocorrelation and Bekaert and Wu (2000) for asymmetry in the risk to return relation.

[4]Moskowitz, Ooib, and Pedersen (2012) test volatility scaling at the security, not at the portfolio level. The goal is to prevent portfolios being dominated by only few assets with high volatility. Moreira and Muir (2017) highlight the advantage for mean-variance investors when scaling different equity long-short strategies by realized variance. Grobys, Ruotsalainen, and Äijö (2018) compare risk management strategies for industry momentum in the U.S. They find that industry momentum exhibits no time-varying beta (as standard momentum does) and that volatility-scaling improves its performance. du Plessis and Hallerbach (2016) find that the volatility-scaling of U.S. industries both lowers the industry momentum strategy's volatility and heightens its returns. Recently, Harvey, Hoyle, Korgaonkar, Rattray, Sargaison, and Van Hemert (2018) compare volatility-targeting strategies across different asset classes.

(2016) show that the dynamic strategy exceeds the Sharpe ratio achieved with the constant volatility-scaling strategy.[5]

Instead of scaling the standard momentum factor, a different way to potentially increase the risk-to-return relation is to change the portfolio sort criteria at the stock-level, yielding differently composed long-short portfolios. Gutierrez and Prinsky (2007) use orthogonalized stock returns (firm-specific abnormal returns) relative to a Fama-French three-factor model instead of raw returns during the formation period. They find that firm-specific momentum - or idiosyncratic momentum (iMOM)[6] - experiences no long-term reversals. In addition, Blitz et al. (2011) document that idiosyncratic momentum exhibits only half of the volatility of standard momentum without any significant decrease in returns. Finally, Blitz, Hanauer, and Vidojevic (2018) show that idiosyncratic momentum cannot be explained by the commonly-used asset pricing factors both in the U.S. (1926 to 2015) and internationally, claiming that idiosyncratic momentum is a separate factor that expands the efficient frontier comprised of already established asset pricing factors, including standard momentum.[7] Even though idiosyncratic momentum is conceptually different from standard momentum as shown by spanning test alphas, we aim to motivate idiosyncratic momentum as an additional strategy (besides the scaled versions of standard momentum) to manage momentum drawdowns and respectively maximize the performance of momentum.

This paper contributes to the literature in at least four aspects. First, we compare three momentum risk management strategies proposed in the literature — idiosyncratic momentum, constant volatility-scaling and dynamic scaling — using a uniform data set and methodology. We use both a long sample of U.S. and a broad sample of international stocks.

[5]However, Daniel and Moskowitz (2016) exploit ex-post information for calibrating their baseline model, disregarding the optimization set of a real-world investor. This forward-looking bias is addressed only perfunctory, giving rise to the question of a practical implementation.

[6]Gutierrez and Prinsky (2007) and Blitz, Huij, and Martens (2011) use the terms abnormal return momentum and residual momentum, respectively, but the definitions are identical.

[7]Chaves (2016) in this regard shows that also a simplified version of idiosyncratic momentum that is based on one-factor (market) unscaled residuals works. Blitz et al. (2018) confirm that most of the performance improvement comes from orthogonalizing returns with the market factor and that the inclusion of additional Fama-French factors leads to small further improvements as more of the stock specific momentum is isolated.

We then evaluate the momentum risk management strategies in different dimensions: return and risk characteristics including higher moments and maximum drawdowns, ex-post and Bayesian Sharpe ratio tests, as well as their implementability by avoiding look-ahead biases and investigating the break-even transaction cost, i.e., round-trip transaction costs that would render the strategy returns insignificant.

Second, we add to the replication literature by a large replication of standard momentum as well as strategies to improve its performance. According to Hou, Xue, and Zhang (2018), replication provides a contribution when extending existing studies out-of-sample. In this regard, the majority of asset pricing studies are covering solely the U.S. market. Karolyi (2016) argue that this implicitly creates a "home bias" for the U.S. market. Harvey (2017) gives additional rise to the replication argument by stating that many published results would not hold in the future, because of unreported tests, testing of multiple hypotheses, and data snooping. Harvey, Liu, and Zhu (2016) link data snooping concerns with the incentive to publish, generating a publication bias, and propose higher t-statistic hurdles. Lastly, Novy-Marx and Velikov (2016) state that most published factors with above a 50% turnover per month are not profitable after trading costs. Thus, transaction costs have the ability to subsume factors' profitability and even heighten the concerns for data snooping. Since we are conducting a comparison study, we do not aim at "p-hacking" to report significant results, but rather test already published volatility-management strategies. We use a uniform global dataset, an identical factor construction approach, and proceed with the same statistical tests (including the factors' transaction costs), reporting the results homogeneously across countries and strategies (factors). In this way, we overcome potential concerns of data mining, multiple hypothesis testing and Type I error concerns.

Third, we contribute to the ongoing debate about whether volatility-managed investment strategies yield higher Sharpe ratios than non-managed factors do.[8] Cederburg et al. (2019) examine 103 factors and find that volatility-management generates statistically significant

[8]See Cederburg, O'Doherty, Wang, and Yan (2019) for a literature overview about the volatility management of trading strategies.

Sharpe ratio improvements for only eight out of 103. Importantly, the authors show that the eight trading strategies all relate to momentum strategies.

Finally, we add to the current literature that looks for a parsimonious factor model that spans the tangency portfolio for traded factors, that does not retain redundant factors.

Our main findings can be summarized as follows. First, using a long sample of U.S. stocks from 1930 to 2017 and a broad sample of stocks from 48 international markets from 1991 to 2017, we show that all risk management strategies substantially increase Sharpe ratios. Furthermore, both skewness and kurtosis as well as maximum drawdowns decrease compared to standard momentum so that their distributions become more normal. Comparing the individual risk management strategies within samples, we find similar improvements for the long U.S. sample for Sharpe ratios and t-statistics (both roughly double compared to standard momentum) for all three approaches, while maximum drawdowns are reduced most by idiosyncratic momentum. For the broad sample, we document that idiosyncratic momentum outperforms all other strategies, as the improvements in Sharpe ratio and t-statistic for idiosyncratic momentum are more than twice as the improvements of volatility-scaling strategies and the reduction in maximum drawdowns is highest.

Second, maximum Sharpe ratio and factor comparison tests of the risk management strategies further confirm our results in favor of idiosyncratic momentum. Idiosyncratic momentum is assigned the highest weight in ex-post maximum Sharpe ratio tests for both the long and the broad sample, meaning that mean-variance optimizing investors would allocate most to the idiosyncratic momentum factor next to traditional factors such as the market, size, and value. Furthermore, the Bayesian Sharpe ratio tests as in Barillas and Shanken (2018) show that the models with the highest model probabilities include idiosyncratic momentum, and that idiosyncratic momentum shows the highest cumulative factor probability among the three momentum risk management approaches for both the long and the broad sample.

Third, our findings indicate that risk-managed momentum strategies should be at least as implementable as standard momentum. By calculating the transaction (break-even) costs that theoretically would render the strategies insignificant, we are able to directly compare the risk-managed momentum strategies with each other after taking portfolio turnover into account. Although all risk management strategies have higher average portfolio turnover compared to standard momentum, we document higher break-even costs due to higher (risk-adjusted) strategy returns.[9]

Finally, we find that the alpha generated by scaled momentum strategies is distinct from the idiosyncratic momentum alpha, as indicated by the economically and statistically significant alphas in pairwise mean-variance spanning tests. Furthermore, we show that scaling idiosyncratic momentum by its realized volatility further increases its Sharpe ratio. We find that even though residualizing of returns reduces the systematic exposure of the constructed idiosyncratic momentum factor, scaling the factor by its volatility generates even higher risk-adjusted returns, undermining the conceptual difference of the risk management approaches.

The following sections are structured as followed: Section 2 describes the data, factors, risk management strategies, and research methodologies. Section 3 presents our empirical results for the implemented strategies, maximum ex-post and conditional Sharpe ratio comparisons, turnover analyses, as well as mean-variance spanning tests and results for the scaled versions of idiosyncratic momentum to disentangle the effects of volatility scaling and residualizing. In Section 4 we assess the robustness of our results by applying the Fama-French five-factor model as a benchmark, using alternative portfolio construction methods (one-dimensional sorted decile/quintile portfolios), and investigating the momentum strategies on a country level. Section 5 concludes.

[9] Novy-Marx and Velikov (2016) find momentum to deliver significant after-transaction cost returns.

2 Data and Methodology

2.1 Data

The data analyzed in this paper is collected from various sources. We use a sample consisting of 58,431 stocks for 49 equity markets from July 1926 to December 2017. We refer to U.S. and ex-U.S. (international) equity data as long and broad sample with respect to differences in sample period availability and regional coverage. Both monthly and daily returns are measured in USD. The U.S. data comes from the Center for Research on Security Prices (CRSP) and covers July 1926 to December 2017. International data is collected from Thomson Reuters for the sample period July 1987 to December 2017. The country selection follows the Morgan Stanley Capital International (MSCI) Developed and Emerging Markets Indices. We include all countries that are classified as a developed or an emerging market at some point during the sample period.[10] More precisely, the countries are only part of the actual sample in those years in which they are part of the MSCI Developed and Emerging Markets Indices. The following countries are included: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, Indonesia, India, Ireland, Israel, Italy, Japan, (Republic of) Korea, Morocco, Mexico, Malaysia, Netherlands, Norway, New Zealand, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Russia, Singapore, South Africa, Spain, Switzerland, Sweden, Thailand, Turkey, Taiwan, United Arab Emirates, U.K. and U.S.

Our *long* U.S. sample includes all common equity stocks from NYSE, NYSE MKT (formerly: AMEX), and NASDAQ within the CRSP universe. We exclude all stocks with a CRSP share code (SHRCD) different than 10 or 11. If available, we use Fama-French factors from Kenneth French's website for the long sample, which leaves us with constructing momentum, idiosyncratic momentum, and a timely value factor.[11]

The *broad* international sample comprises market data from Datastream and accounting

[10] See https://www.msci.com/market-classification for details.

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

data from Worldscope. We process data through static and dynamic screens to ensure data quality. As a first step, we identify stocks by Thomson Reuters Datastream's constituent lists. We use Worldscope lists, research lists and, to eliminate survivorship bias, dead lists. Following Ince and Porter (2006), Griffin, Kelly, and Nardari (2010), and Schmidt, Von Arx, Schrimpf, Wagner, and Ziegler (2017), we apply generic as well as country-specific static screens to eliminate non-common equity stocks as well as dynamic screens for stock return and price data as described in Appendix A.1. The emerging market data is restricted to start only in July 1994.[12] In order for a security to be a regarded for the market, size, and value portfolios within the broad sample, securities are required to have a valid market capitalization for June y and December $t-1$ as well a positive book equity value for December $t-1$.

For both the long and the broad sample, we calculate momentum and idiosyncratic momentum and additionally require valid returns from $t-36$ to $t-1$.[13]

Finally, the countries are only part of the final sample in those months for which at least 30 stock-month observations are available after filters.[14] We end up with a total of 7,402,291 firm-month observations. Table 1 shows the descriptive statistics for the stocks in the final sample.

[Table 1 about here.]

2.2 Factor construction

Our approach for constructing the factor portfolios follows Fama and French (1993, 2012). We calculate the portfolio breakpoints for each country separately to ensure that the results are

[12] Griffin et al. (2010) and Jacobs (2016) apply the same sample starting point for emerging markets data, relying on the increased integration of emerging markets with world markets by 1994.

[13] The momentum factor requires return data from $t-12$ to $t-2$. We use this extended requirement to have a uniform data set for the construction of both standard and idiosyncratic momentum.

[14] Following Jacobs (2016), we thereby ensure that the six size-momentum portfolios contain at least five stocks on average. As a consequence, some countries (such as India, Hong Kong and Spain) are excluded from the sample for certain months. Jordan, Sri Lanka, Slovakia and Venezuela are excluded from the whole sample.

not driven by country effects. The market factor, RMRF, consists of value-weighted returns of all available (and valid) securities less the risk-free rate. All returns are in USD and excess returns are relative to the one-month U.S. Treasury bill rate. The size and value factors are constructed by six value-weighted portfolios using breakpoints on market capitalization and book-to-market. For every end-of-June of year y, we assign stocks among two size-sorted and three book-to-market sorted portfolios based on their market capitalization and book-to-market ratio, respectively. Market capitalization is from end of June of year y and the book-to-market ratio is calculated with market capitalization from end of December of year $y-1$ and book value from the fiscal year end of $y-1$. For the U.S., the size breakpoints are based on the NYSE median market capitalization and stocks are classified as big or small, indicated by B and S. For the broad sample, we follow Fama and French (2012, 2017) and define size breakpoints so that the largest (smallest) stocks cover 90% (10%) of a country's market capitalization. Moreover, all stocks are independently sorted into three portfolios (Growth, Neutral, and Value, indicated by G, N, and V) based on the country-specific 70% and 30% percentile breakpoints of book-to-market ratios. The breakpoints on book-to-market are calculated from NYSE (big) stocks only for the long (broad) sample. For the resulting six portfolios (BV, BN, BG, SV, SN, and SG), we calculate monthly value-weighted returns and construct the size (SMB) and value (HML) factor as zero-investment long-short portfolios from July y to end-of-June $t+1$:

$$
\begin{aligned}
SMB &= (SV + SN + SG)/3 - (BV + BN + BG)/3 \\
HML &= (BV + SV)/2 - (BG + SG)/2
\end{aligned}
\tag{1}
$$

Analogously to value, we categorize stocks based on the 70% and 30% percentiles of the past 12-2 month cumulative returns as Winner, Neutral and Loser (W, N, and L) stocks to form the momentum factor. We then calculate the monthly value-weighted returns for the 2x3 portfolios (BW, BN, BL, SW, SN, SL). Momentum is constructed by the long-short portfolio as $MOM = (BW + SW)/2 - (BL + SL)/2$ and - in contrast to SMB and HML -

rebalanced every month. Asness and Frazzini (2013) introduce the so-called HML-devil factor (denoted as HML_d). HML_d is comparable to HML but updates the market capitalization for the sorting criteria every month. Thus, stocks are sorted into portfolios based on their monthly updated book-to-market ratio. As stated above, we use the Fama-French factors from Kenneth French's website for the long U.S. sample. The momentum factor and risk management strategies, however, are constructed by ourselves based on independent double sort portfolios in order to ensure comparability. The sorts on the past 12-2 month returns are based on NYSE (big) stocks.

2.3 Risk management strategies

Volatility scaling aims to manage the realized volatility of an investment strategy. For cross-sectional (here: standard) momentum, realized volatility has been shown to have a positive (negative) correlation with future volatility (returns) and to be relatively high compared to other factors.[15] In this study we identify two potential channels for Sharpe ratio improvements by volatility scaling: volatility scaling lowers the overall ex-post volatility (named *volatility smoothing*) and heightens strategy returns due to negative correlation between volatility and returns (named *volatility timing*).[16] We apply the realized volatility of momentum strategy returns to control for volatility.[17] Combining these two channels, forecasted returns and variances (or volatilities) at the factor-level can generate scaling weights that increase the Sharpe ratio of momentum compared to a non-scaled strategy. Moreover, as a net-zero investment long-short strategy, momentum can be scaled without assuming leverage costs and the scaling can be interpreted as having a time-varying weight in the long and short

[15] See, among other, Barroso and Santa-Clara (2015) or Moreira and Muir (2017).

[16] Both channels do not directly consider the positive autocorrelation of momentum strategy returns, which is utilized for the dynamic momentum strategies.

[17] Alternatively one could use the individual volatility of all current holdings of the momentum strategy. However, using volatility at the strategy level is preferable for momentum due to the possibility of volatility timing (i.e., the negative relation between volatility and strategy returns, as shown in Bekaert and Wu, 2000). Individual volatilities are rather useful to control for realized volatility (volatility smoothing) of time-series momentum strategies (see, e.g., also du Plessis and Hallerbach, 2016, for U.S. industry portfolios). These strategies are scaled upward by volatility (not the inverse, as for cross-sectional momentum) due to the positive relation between volatility and returns.

legs. We explicitly distinguish between constant volatility-scaling and dynamic scaling.

Constant volatility-scaling, as proposed in Barroso and Santa-Clara (2015), adjusts the momentum portfolio to a constant target volatility level. The corresponding scaling weight for momentum in month t is defined as:

$$w_{cvol,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} \tag{2}$$

where σ_{target} is the full sample volatility of momentum and $\hat{\sigma}_t = \mathbb{E}_{t-1}[\sigma_t]$ is the forecasted respective expected volatility.[18] Since the forecasted volatility varies over time, the weights for the constant volatility-scaled momentum portfolio can take values between 0 (for $\hat{\sigma}_t = \infty$) and infinity (for $\hat{\sigma}_t = 0$). Following Barroso and Santa-Clara (2015), we calculate the monthly volatility forecast for month t from past daily realized returns of momentum in the previous six months (126 trading days):

$$\hat{\sigma}^2_{MOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t}}{126} \tag{3}$$

where $R^2_{MOM,d-j,t}$ is the squared realized daily return of momentum returns summed over the last 126 trading days. For robustness, we also use a one month look-back window (21 trading days) as in Moreira and Muir (2017). Constant volatility-scaled momentum over six months (cvol_{6M}) and constant volatility-scaled momentum over one month (cvol_{1M}) show the correspondingly weighted momentum strategies, where the return in month t is calculated using realized volatility:

$$R_{cvol,t} = R_{MOM,t} \cdot w_{cvol,t} \tag{4}$$

The dynamic strategy enhances the volatility forecasting of constant volatility strategies by additionally forecasting the expected return. Mean-variance optimizing investors optimize momentum as their investment asset according to the dynamic scaling weight that refers to

[18] By choosing the full-sample volatility of momentum as a target level, we (i) ensure that the strategy targets a constant risk over time and (ii) make the returns of the scaled and unscaled strategy comparable.

their expected Sharpe ratio.[19] We apply the dynamic approach from Daniel and Moskowitz (2016) and define the dynamic scaling weight for momentum in month t as:

$$w_{dyn,t} = \left(\frac{1}{2\lambda}\right) \cdot \frac{\hat{\mu}_t}{\hat{\sigma}_t^2} \tag{5}$$

where $\hat{\mu}_t = \mathbb{E}_{t-1}[\mu_t]$ ($\hat{\sigma}_t^2 = \mathbb{E}_{t-1}[\sigma_t^2]$) is the forecasted respective the conditional expected return (variance) of momentum, and λ is a static scalar scaling the dynamic strategy to the average volatility of momentum. The estimation of $\hat{\mu}_t$ and $\hat{\sigma}_t^2$ can be conducted either *in-sample* or *out-of-sample*. We apply both approaches to compare the performance, even though the *in-sample* estimation suffers from a look-ahead bias.[20] The return of momentum is forecasted, both *in-* and *out-of-sample*, with the following time-series regression:

$$R_{MOM,t} = \gamma_0 + \gamma_{int} \cdot I_{Bear,t-1} \cdot \sigma_{RMRF,t-1}^2 + \epsilon_t \tag{6}$$

where $I_{Bear,t-1}$ is a bear-market indicator that equals one if the cumulative past two year market return is negative (and zero otherwise), $\sigma_{RMRF,t-1}^2$ is the realized variance of RMRF over the past 126 days, γ_{int} is the regression coefficient on the interaction term of the two independent variables, and γ_0 is the regression intercept. The expected return ($\hat{\mu}_t$) is defined as the fitted values from the regression. Distinguishing between *in-sample* and *out-of-sample* estimation, the former refers to the whole momentum sample available for estimation of the regression and yields the mentioned look-ahead bias. The latter also uses fitted values but estimates Equation 6 on a monthly updating expanding-window basis.[21] To estimate the

[19] It is, however, an underlying assumption how investors end up with their return and variances forecasts respective how their expectations align for the weight components. Daniel and Moskowitz (2016) mention that investors optimize their objective function *in-sample* and unconditionally, which implies a forward-looking bias. In this regard, we additionally estimate return and variance *out-of-sample*.

[20] The estimation approaches will later on refer to the two strategies: dynamic in-sample-scaled momentum (dyn$_{IS}$) and dynamic out-of-sample-scaled momentum (dyn).

[21] In contrast to Daniel and Moskowitz (2016), we estimate an *out-of-sample* regression using the prior 36 months that are already necessary to constructing idiosyncratic momentum but drop the restriction of requiring at least one non-zero bear-market indicator observation to define the sample starting point. This was done to keep the same sample start date. In case the bear-market indicator is always zero within a subsample, the fitted values of the time-series regression simply equal the momentum returns on the LHS of

variance of momentum for the *in-sample* approach, we first estimate the generalized autoregressive conditional heteroskedasticity (GARCH) model introduced in Glosten, Jagannathan, and Runkle (1993). A feature of the model is that the variance process of the residuals is fitted while conditioning on the residual being negative, indicating a negative deviation of momentum returns from the return trend. We estimate the parameters within the GJR-GARCH model using maximum likelihood over the whole sample. In the second step, $\hat{\mu}_t$ is eventually estimated from the fitted values of an autoregressive model extended by the forecast of the calibrated GJR-GARCH. The processes of the model and details on the time-series regression in order to derive the *in-sample* volatility forecast ($\hat{\sigma}_t$) are provided in Appendix A.2. For the *out-of-sample* variance forecast of the dynamic strategy, we rely on the same approach as for the constant volatility-scaling strategies to overcome the look-ahead bias of the GARCH model forecast and use Equation 3 with a 126 day look-back window for $w_{dyn,t}$. We eventually derive dyn_{IS} and dyn as the dynamically weighted momentum strategies with their return in month t given by:

$$R_{dyn_{(IS)},t} = R_{MOM,t} \cdot w_{dyn_{(IS)},t} \tag{7}$$

Comparing cvol_{6M} and dyn as examples for the constant volatility-scaling and the dynamic strategy, the weights solely differ by $\mathbb{E}_{t-1}[\mu_t] = \hat{\mu}_t$. Hence, the scaling weights of the dynamic strategies can take on negative values when $\hat{\mu}_t < 0$. Figure 1 plots the corresponding weights for the whole sample and sub-samples. As expected, the dynamic weights vary more strongly than the constant volatility-scaling weights for both the long and broad sample. Figure 1b shows the weights during the Great Depression. Between July and August 1932, momentum in the U.S. exhibited returns of -41.90% and -37.19%.[22] The highly negative momentum returns in July 1932 drive down the weight for dyn from 0.79 to 0.14 by end-of-August 1932,

the regression equation.

[22] In previous months (March, April, and May 1932), the U.S. market factor rebounded from negative returns (-11.05%, -17.85% and -20.45%) to positive returns in July and August 1932 (33.87% and 37.09%). After strings of negative market returns, stocks assigned to the loser portfolio of momentum have on average higher market betas than stocks in the winner portfolio. Thus, after the positive market reversal in July 1932, short positions in the high beta stocks (within the loser portfolio) that yielded higher returns than low-beta stocks in the winner portfolio caused the long-short momentum portfolio to crash.

while the weight for cvol_{6M} only slightly decreases (0.44 to 0.41). Hence, an implemented dyn (cvol_{6M}) strategy effectively would have lowered momentum losses from -37.19% to -5.19% (-15.32%) in August 1932. For the broad sample, Figure 1d drafts a similar picture: the downward-scaled of dyn (assigning even negative weights) compared to cvol_{6M} is enhanced during periods of serially-autocorrelated momentum returns. This is especially the case after a bear market state turns positive (reversal).

Idiosyncratic momentum does not scale the standard momentum factor but applies a different sorting criterion at the individual stock level. The construction of idiosyncratic momentum is technically distinct from momentum (and volatility-scaled strategies) in that stocks within the long and short portfolios potentially differ. Instead of using the individual stocks' raw returns from $t-12$ to $t-2$, we orthogonalize them with respect to a Fama-French three-factor model. Thereby, stock returns are adjusted for their risk factor exposure. We follow Gutierrez and Prinsky (2007), Blitz et al. (2011), and Blitz et al. (2018) and regress the past 36 months' returns of all valid stocks within the investment universe on country-specific factors of the Fama-French three-factor model. Thus, the following time-series model is estimated for every stock i and month t using a rolling-window approach:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{RMRF,i} * RMRF_t + \beta_{SMB,i} * SMB_t + \beta_{HML,i} * HML_t + \epsilon_{i,t} \qquad (8)$$

The residuals of the time-series regressions, $\hat{\epsilon}_{i,t}$, can be interpreted as stock-specific idiosyncratic returns for stock i during month t. As in Gutierrez and Prinsky (2007), Blitz et al. (2011), and Blitz et al. (2018), we calculate the cumulative idiosyncratic return for each stock by scaling the 12-2 month idiosyncratic returns with their volatility:

$$\hat{\epsilon}_{12-1_{i,t}} = \frac{\sum_{j=2}^{12} \hat{\epsilon}_{i,t-j}}{\sqrt{\sum_{j=2}^{12} \left(\hat{\epsilon}_{i,t-j} - \bar{\epsilon}_i\right)^2}} \qquad (9)$$

We categorize each stock as a Winner, Neutral and Loser stock based on its cumulative idiosyncratic returns $\hat{\epsilon}_{12-1_{i,t}}$. Therefore, every stock is independently sorted into one of the 2x3 portfolios on size and cumulative idiosyncratic returns, namely BW_{idio}, BN_{idio}, BL_{idio}, SW_{idio}, SN_{idio}, and SL_{idio}. As for standard momentum, the 70% and 30% quantile breakpoints of cumulative idiosyncratic returns are calculated using big stocks only. The portfolios are rebalanced monthly and portfolio returns are value-weighted. Idiosyncratic momentum is then constructed as a factor analogously to momentum: long in $\frac{1}{2}(BW_{idio} + SW_{idio})$ and short in $\frac{1}{2}(BL_{idio} + SL_{idio})$.[23]

2.4 Methodology

We investigate the improvement of risk-management strategies for momentum returns based on a comprehensive set of methodologies. First, we evaluate different factors by means, t-statistics, higher moments (skewness and kurtosis) as well as maximum drawdowns. Second, we conduct ex-post and Bayesian maximum Sharpe ratio tests. Third, we compare risk-adjusted strategy returns with respect to the Fama-French three-factor model and conduct pairwise mean-variance spanning tests. Finally, we contrast the profitability of the different momentum strategies with their portfolio turnover to assess their capacity for potential transaction costs. This section presents the testing procedures:

With the ex-post Sharpe ratio maximization as in Ball, Gerakos, Linnainmaa, and Nikolaev (2016), we test which combination of factor sets has the highest ex-post Sharpe ratios. In the mean-variance efficient portfolio optimization, the economic significance of our factors is quantified by comparing how much an investor could gain from adding a certain factor to his investment opportunity set.

The ex-post optimization, however, does not test if the factors span each other in a time-conditional manner. Barillas and Shanken (2018) propose a Bayesian test to compare factor

[23] Within Section 4, we scale iMOM by its realized volatility with a six month look-back window to disentangle the alpha generating signals. To sustain homogeneity across analyses, all risk management strategies/factors are only used six months after their initial construction month. These six months correspond to the look-back window in order to scale iMOM by its realized volatility. Eventually, the long (broad) sample starts in 01/1930 (01/1991) although strategy returns are available from 07/1929 (07/1990) on.

models over time. In short, the posterior probabilities for models and/or factors are derived by evaluating the null hypothesis ($H_0 : \alpha = 0$) against the alternative ($H_1 : \alpha \neq 0$) under consideration of the expected Sharpe ratio increases by adding a factor. The methodology is structured in the following way: First, prior beliefs about potential increases in Sharpe ratios when adding factors to the investment opportunity set are assigned to the factors, considering the alternative hypothesis. The prior expected value for the increase in the squared Sharpe ratio, k, is:

$$k = \left(Sh_{max}^2 - Sh\left(f\right)^2\right)/N \tag{10}$$

where Sh_{max} is the target Sharpe value, Sh_f is the Sharpe of the market factor (Sh_{RMRF}) when taking the CAPM as a baseline model, and N is the number of factors. The prior for each factor is set so that Sh_{max} equals the sample Sharpe ratio of the market factor (Sh_{RMRF}) times 1.5 (4) for the long (broad) sample as baseline Sharpe multiple.[24] The benchmark scenario implies that the square root of the squared tangency portfolio's Sharpe ratio (spanned by the included factors) is 50% higher than the market's squared Sharpe ratio. Second, to see if a test asset (here: a factor) expands the efficient frontier, a so called Bayes factor (BF) is motivated.[25] By a derived regression density, the probability of a factor of generating alpha (H_1), and to be priced by factors in the current model (H_0), can be expressed as marginal likelihoods $ML\left(H_1\right)$ and $ML\left(H_0\right)$, respectively. The Bayesian factor relates the null hypothesis to the alternative by application of the Gibbons, Ross, and Shanken (1989) F-statistic. Hence, the ability of a factor to generate statistically significant alpha, under consideration of the prior beliefs and relative to other factors, is translated into posterior probabilities. Finally, the methodology yields two posterior results: model

[24] We choose a higher multiple for the broad sample as international factors benefit from diversification in regional factor returns. Cf. Fama and French (2012) and Hanauer and Linhart (2015) for the diversification potential in developed and emerging markets factor returns, respectively.

[25] The Bayes factor is defined as:

$$BF = \frac{ML\left(H_0\right)}{ML\left(H_1\right)} \tag{11}$$

where marginal likelihoods depend on the prior value k. For details on the methodology, see Barillas and Shanken (2018).

probabilities for all models under consideration with values between 0 and 1 (where the weights across all models sum up to one), and cumulative probabilities for every factor that assign values between 0 and 1 for every factor. The posterior probabilities give insights on a model's ability to price other factors, and on which factors are essential to build up the model in the first place.[26]

We apply a categorical model (not factor) perspective for the tests. The factors are restricted in a way where only one value and only one risk-managed momentum factor is allowed per model. This approach differs from the categorization in Barillas and Shanken (2018): we also prevent factors of the same category from being included in one model, however, we did not aggregate the results per factor category after all. The categorization (i) prevents overfitting since constant volatility-scaled momentum over six months and dynamic in-sample-scaled momentum are highly correlated, and (ii) enables us to measure the effect of installing solely one risk-management strategy for momentum.

To see the strategies' risk-adjusted performance, we calculate alphas for momentum and all risk-management strategies relative to a Fama-French three-factor model. Moreover, we conduct one-by-one comparisons of the strategies within mean-variance spanning tests including the Fama-French three-factor model factors. Hence, we regress returns of the test asset (e.g. momentum) on returns of the benchmark asset (e.g. idiosyncratic momentum) and the Fama-French factors within a linear time-series regression model.[27] The null hypothesis states that the test asset returns are spanned, i.e., that the intercept equals zero. If the null hypothesis is rejected and the intercept is statistically significantly different from zero, the test asset does outperform the benchmark asset as well as the Fama-French risk factors and

[26]For example, applying the methodology on the FF3FM model, Barillas and Shanken (2018) test all combinations obtainable from the three factors (RMRF, SMB, and HML) simultaneously against each other. The four factor combinations - {RMRF}, {RMRF HML}, {RMRF SMB}, and {RMRF HML SMB} - get assigned a prior probability of 1/4 and the value of k for the prior is implicitly given by Equation 11. For a baseline Sharpe multiple of 1.5 is chosen, Barillas and Shanken (2018) find posterior probabilities of 55.6% for {RMRF HML}, 43.4% for {RMRF HML SMB}, and less than 1% for the two remaining models. Thus, the FF3FM model is outperformed by the two-factor model without the size factor for the data tested. The Bayesian results are in line with the time-series regression results: there are highly significant and positive (insignificant) alphas when regressing HML (SMB) on RMRF.

[27]See, among others, Huberman and Kandel (1987).

extends the efficient portfolio frontier.

As in Grundy and Martin (2001) and Barroso and Santa-Clara (2015), we calculate the round-trip costs that would render the profits of the different momentum strategies insignificant at a certain α-significance level as

$$\text{Round-trip costs}_{\alpha=5\%} = \left(1 - \frac{1.96}{\text{t-stat}_s}\right) \frac{\bar{\mu_s}}{T\bar{O}_s} \quad (12)$$
[28]

where $\bar{\mu_s}$ is the average monthly return, $T\bar{O}_s$ is the average monthly turnover and t-stat$_s$ is the t-statistic of strategy s. Round-trip costs are advantageous since they define an upper border for the potential transaction costs instead of quantifying them directly. Only the strategy returns as well as the associated portfolio turnover are necessary input factors.[29] Moreover, statistical significance can be incorporated within the round-trip costs measure. Importantly, holding turnover fix, round-trip costs with reliance on the α-significance level increase for strategies with higher t-statistics and therefore, lead to a higher upper border.

3 Empirical results

3.1 Performance of the Strategies

In this section, we compare the risk-to-return performance improvement of risk management strategies for momentum in global markets. Table 2 depicts the return characteristics for the momentum strategies.

[Table 2 about here.]

For the long U.S. sample, the average monthly return of the standard momentum factor amounts to 0.60% with a highly significant t-statistic of 4.42. However, as Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) already show, momentum has also a

[28] We choose the Z-value of 2.58 (instead of 1.96 for the 5% level) for the 1% significance level.

[29] We calculate portfolio turnover as the sum of changes in the securities' weights within assigned long-short factor portfolios. The details of the turnover calculation are presented in Appendix A.3.

dark side. The high returns come with a very high kurtosis and a negative skewness, implying large drawdowns (fat left tails) such as the maximum drawdown for the momentum factor in 1932 of -67.10%. The returns of the standard momentum factor for the broad international sample show similar features. The average monthly return is 0.52% with a t-statistic of 2.99. The higher t-statistics for the U.S. sample can be attributed to the larger number of monthly observations, as indicated by almost similar Sharpe ratios (0.47 vs. 0.57). The momentum returns for the broad sample also exhibit a high kurtosis and a negative skewness but are more normal compared to their counterparts for the long sample. This is also reflected in the lower maximum drawdown in 2009 of -36.96%.

Comparing risk-management momentum strategies with standard momentum for both samples, all of them show significantly improved performance of momentum measured by the t-statistic and Sharpe ratio. Furthermore, skewness, kurtosis and as maximum drawdowns decrease as compared to standard momentum so that their distributions become more normal. For the long U.S. sample, we find similar improvements for Sharpe ratios and t-statistics (both roughly double compared to standard momentum) for all five approaches, with the highest Sharpe ratio of 0.95 for dynamic in-sample-scaled momentum and idiosyncratic momentum, while the maximum drawdowns are reduced most by idiosyncratic momentum. For the broad sample, we document that idiosyncratic momentum outperforms all other strategies, as the improvements in Sharpe ratio and t-statistic for idiosyncratic momentum are more than twice that of the improvements of volatility-scaling strategies and the reduction in maximum drawdowns is the highest.[30]

One main goal of this paper is to identify the risk-management strategy best suited for mean-variance optimizing momentum investors. As mentioned in Subsection 2.3, volatility scaling strategies are technically very similar. We observe that the results for constant volatility-scaled momentum over one month and constant volatility-scaled momentum over six months are very similar, with constant volatility-scaled momentum over six months having

[30] We additionally scale momentum for every country in the broad sample individually rather than scaling the aggregated time-series of all countries within the broad strategy. The results remain unchanged.

a slightly lower Sharpe ratio but also a suffering from slightly lower drawdowns. A different picture emerges for dynamic in-sample-scaled momentum and dynamic out-of-sample-scaled momentum. The forward-looking bias in dynamic in-sample-scaled momentum leads to higher returns and lower drawdowns for both the long and the broad sample. To further shed light on the similarity of returns, Table 3 shows pairwise correlation coefficients for both samples.

[Table 3 about here.]

As expected, cvol_{1M}, cvol_{6M} are highly correlated, as are dyn_{IS} and dyn, with correlation coefficients above 88%. The strong co-movement can be traced back to similar weights scaling the identical standard momentum factor. iMOM is not particularly correlated with the volatility-scaled strategies. We argue that it is plausible to categorize similar factors and thereby omit informationally-redundant factors. Besides redundancy, dyn_{IS} suffers from a forward-looking bias, sustaining the idea of focusing on dyn instead. Thus, we henceforth exclude cvol_{1M} and dyn_{IS} from our analyses, and only analyze cvol_{6M} and dyn as categorical factors for constant volatility-scaling and the dynamic strategy, as well as iMOM. This exclusion simplifies the interpretation of one-by-one comparisons, enables cross-validation with existing studies and eliminates the forward-looking bias of dyn_{IS}. We moreover include a monthly updated so-called HML-devil factor (HML_d) in our correlation analysis. Daniel and Moskowitz (2016) state that HML_d captures more variation of momentum than standard HML.[31] The more negative correlation between MOM and HML_d (compared to HML) is also shown for both our long and broad sample. Hence, we test our strategy returns against the FF3FM or the FF3FM and substitute HML by HML_d (denoted as FF_d).

Figure 2 displays the buy-and-hold returns of momentum and the proposed risk-management strategies for the long sample. All strategies are scaled to the average volatility of standard momentum for comparability reasons. For the U.S., all strategies increase in returns compared to momentum, with a clear outperformance of idiosyncratic momentum and dyn_{IS}.

[31] Cf. Daniel and Moskowitz (2016), p. 244.

The dyn_{IS} manages to hedge the momentum downturns in 2001 and 2008 and generates stable returns from the 1950s on. Idiosyncratic momentum has a steady return evolution, as expected by hedging out style exposure to the FF3FM factors. Both cvol_{6M} and dyn show a similar performance by construction, differing solely by the numerator in the scaling weight of dyn. In the global sample, idiosyncratic momentum clearly outperforms all volatility-scaling strategies, as shown in Figure 3.

3.2 Comparison of Factor Models

In this section, we analyze the factors from the viewpoint of a Sharpe-maximizing investors trading different momentum strategies and the FF3FM (resp. FF_d) factors. To measure the economic significance of factors, we calculate the ex-post maximum Sharpe ratios associated with different combinations. This approach distributes weights from zero to one to the regarded factors, where the weights in total sum up to one. Table 4 shows the weights and Sharpe ratios for the long U.S. sample in Panel A.

[Table 4 about here.]

The (annualized) Sharpe ratio of the market factor (RMRF) is 0.42 and it increases to 0.52 when extending it with the size factor (SMB) and both value factors (HML and HML_d). When adding momentum (MOM), the Sharpe ratio more than doubles (1.07) and the weight from HML is shifted to HML_d. A one-by-one inclusion of risk-management strategies to the size, value and momentum factors yields similar Sharpe ratios for all investment sets (about 1.24). However, cvol_{6M} and iMOM have the highest factor weights of 45% and 47%, respectively. Allowing all factors to be invested in, the Sharpe ratio peaks at 1.37 annually. Importantly, within the momentum strategies, iMOM contributes almost solely to the max Sharpe portfolio with an investment weight of 42%.

The following indications can be derived: (1) If an investor trades the base factors and at least one risk-managed momentum strategy, the achievable ex-post maximum Sharpe ratio of the investor is higher than if she traded the base factors along with the momentum factor. Depending on the base factors chosen (FF3FM or FF_d), adding a risk-managed factor yields similar Sharpe ratios across all risk-managed factors for the same base factors. Thus, an investor would do better by adding a risk-managed momentum factor to the investment opportunity set than by trading standard momentum. (2) In a comprehensive comparison, iMOM is assigned the highest weight, suggesting that iMOM substantially drives the achieved (ex post) mean-variance efficient portfolio with a Sharpe ratio of 1.45. Hence, an investor who is restricted to picking only one momentum strategy might favor iMOM over the other strategies.

A clearer picture emerges for the global sample, as depicted in Panel B of Table 4. iMOM clearly generates the highest Sharpe ratio (2.42) in one-by-one comparisons with other risk-management strategies. In the comprehensive factor comparison, iMOM is assigned an even higher weight than for the U.S. sample (52%), sustaining the implication that iMOM is superior in maximizing risk-adjusted returns for the overall (long and broad) sample.

Next, we investigate if the results also hold for time-conditional maximum Sharpe ratio tests. We apply the methodology of Barillas and Shanken (2018) to our factor time-series set. As mentioned earlier, we conduct categorical tests for value and the risk-management strategies. The results are thus comparable to the ex-post maximum Sharpe tests where we compare the FF3FM factors, momentum and one of the risk-management strategies. As a benchmark scenario, we use 1.5 (4) for the Sharpe multiple in our long (broad) sample, leading to $Sh_{max} = 1.5(4) \times Sh_{RMRF}$. Thus, the square root of the prior expected squared Sharpe ratio of the tangency portfolio from all eight factors[32] is assumed to be 50% (300%) higher than the Sharpe ratio of the CAPM. By increasing the Sharpe multiple to a maximum of six, the investors are assumed to believe in stronger mispricing, assigning relatively large probability to extreme Sharpe ratios. Figure 4 shows the posterior model probabilities and

[32]We consider RMRF, SMB, HML, HML_d, MOM, $cvol_{6M}$, dyn and iMOM, where HML and HML_d as well as $cvol_{6M}$, dyn and iMOM are treated as factors for categorical models. Thus, only one categorical factor is allowed to be included in within a model.

cumulative factor probabilities over time for the U.S. sample.[33] By starting with equal prior probabilities for every model, it takes some time until a substantial difference in the posterior probabilities emerges. The top panel shows the time-series of posterior model probabilities for the seven models with the highest probability by December 2017 (the end of the U.S. sample). We find that the model {RMRF HML_d MOM iMOM} performed best, ranking as the first after outperforming {RMRF iMOM} in the mid-1980s. Of the top seven models, five include iMOM as a factor. This hierarchy is further visualized by the bottom panel of Figure 4, which plots the sum of posterior probability for the models including the respective factor. Table 5 depicts the end-of-sample posterior model probabilities for the U.S. sample within Panel A. Even when increasing the Sharpe multiple, the best-performing model stays unchanged whereas weights even increase. Thus, when investors' prior mispricing beliefs are extremely high, among all risk-management strategies iMOM is solely picked as a factor and generates significant alpha relative to other factors. Stated differently, iMOM is also picked when extremely large Sharpe ratios are targeted.

[Table 5 about here.]

The time-conditional maximum Sharpe ratio tests for the broad sample provide even stronger evidence for idiosyncratic momentum. The top panel of Figure 5 shows that the model {RMRF HML_d iMOM} performed best with only a single downward peak after 2000. Importantly, idiosyncratic momentum is part of all the top seven models for the global sample. The bottom panel of Figure 1 highlights the importance of idiosyncratic momentum in terms of cumulative factor probability: its probability is close to one from the end of the 1990s to the end of the sample period. Table 5, Panel B depicts the end-of-sample global posterior model probabilities. Irrespective of the prior Sharpe multiple chosen, idiosyncratic momentum is part of the top-performing model, incorporating HML_d for the top three models. Overall, the model comparison tests as in Barillas and Shanken (2018) highlight the importance

[33]The U.S. (global) sample begins only in 03/1930 (03/1991) since the methodology requires 9 (=8 factors + 1) months to get the initial values. We end up with 48 models (since we categorize) and 8 factors for our analyses.

of idiosyncratic momentum both as a factor for asset pricing models, and as a profitable investment strategy. Clearly, for the broad sample, the stronger negative correlation with HML_d is key to the results obtained. As a potential caveat of the time-conditional maximum Sharpe ratio tests, it is noteworthy that we only consider the Fama-French-Carhart four-factor model (FFC4FM) either with HML or HML_d to proxy for value for the factor set, omitting other potential factors such as profitability or investment, as in Fama and French (2015) or Hou, Xue, and Zhang (2015). Nevertheless, our approach is valid in a sense that (i) we are only comparing risk-managed momentum strategies as additional factors and (ii) we start in January 1930 for the U.S. sample where data for other factors is limited. To ensure that our results are not driven by this choice, we add the profitability and investment factors to the factor set in Section 4.

3.3 Turnover and Transaction Costs

All momentum strategies — including idiosyncratic momentum — are constructed as zero-cost long-short strategies. The returns reported in Table 2, however, ignore transaction costs for implementing the strategies. As mentioned in Barroso and Santa-Clara (2015), "[o]ne relevant issue is whether time-varying weights induce such an increase in turnover that eventually offsets the benefits of the strategy after transaction costs." Table 6 shows the average (over time) one-way portfolio turnover of the long leg plus the short leg. We find that for all strategies, the legs on average generate a turnover of more than 50% per month when using value-weighted returns.[34] For the U.S. sample in Panel A, turnover increases for all risk-management strategies, especially for volatility-scaled strategies with a maximum of 82.22% monthly for dynamic out-of-sample-scaled momentum. The increase in turnover when investing in dynamic out-of-sample-scaled momentum but not in momentum yields a significant increase in turnover of 28.43 (82.22-53.79) percentage points. Similar results hold

[34] Our monthly turnover for momentum however is lower than the 74% in Barroso and Santa-Clara (2015). We trace back the difference to not using decile momentum portfolios, but forming HML-style portfolios based on 70/30% percentile breakpoints and double-sorts including size. We are able to validate the turnover for the equivalent sub-sample period using the more extreme decile breakpoints and single sorts.

true for the shorter global sample (from 01/1991 to 12/2017) in Panel B, where dynamic out-of-sample-scaled momentum generates a maximum average monthly turnover of 81.06%.[35] Idiosyncratic momentum also incurs higher portfolio turnover than standard momentum. Hence, we aim to investigate whether the increase in turnover offsets the benefits of volatility-scaling.

Round-trip costs describe transaction cost levels (in percent) that would render the strategies' returns statistically insignificant at confidence levels of 5% and 1%. Panel A of Table 6 shows that momentum investors within the U.S. are only 5% sure that their strategy will have positive net profits when transaction costs do not exceed 0.62% per month. Comparing the risk-management strategies, the transaction costs that would remove the statistical significance of profits (at the 5% level) are higher than for conventional momentum and highest for dynamic out-of-sample-scaled momentum (1.03%). When increasing the confidence level, a similar picture emerges. Panel B shows that for the global sample, idiosyncratic momentum clearly gives the highest bounds for all types of round-trip costs.

Our approach does not explicitly test the after-trading cost performance of the different momentum strategies nor does it analyze the effectiveness of transaction cost mitigation techniques.[36] Rather, this break-even cost study reveals how profitable each strategy remains when assuming a certain level of transaction costs. Stated differently, it simply defines an upper transaction cost bound for momentum investors. In this regard, Frazzini, Israel, and Moskowitz (2014) and Novy-Marx and Velikov (2016) show for the U.S. that even standard momentum, which reveals the lowest break-even round-trip costs within our analysis, is a profitable and thus implementable trading strategy. We transfer the profitability argument to standard momentum from the U.S. to the global sample and eventually argue that all risk management strategies are — as indicated by higher round-trip costs — are indeed

[35] The high turnover of dynamic out-of-sample-scaled momentum, for which scaling weights can also take on negative values (when return forecasts are negative), besides the high transaction costs implies that an investor would require considerably more leverage than for momentum or constant volatility-scaled momentum over six months to set up the strategy. Daniel and Moskowitz (2016) do not report any turnover or break-even cost statistics for their dynamic strategies.

[36] See Novy-Marx and Velikov (2016) for details on these two subjects.

implementable. Notably, we are aware of the following caveats with respect to our argumentation: the potential interaction effects between stock market volatility (and thus also realized volatility of momentum) and transaction costs (esp. bid-ask spreads) due to liquidity reasons, and differently-filled long and short portfolios for iMOM compared to standard momentum respective of its scaled versions.[37]

3.4 Disentangling the Strategy Effects

By comparing Sharpe ratios of momentum strategies, we only account for strategy-specific risk-to-return characteristics. However, Sharpe ratios give no insight on the risk-adjusted strategy return relative to a standard asset-pricing model. We conduct time-series regressions of momentum strategies on the FFC4FM including HML_d for value, as well as pairwise mean-variance factor spanning tests to better understand the relative importance of risk management strategies to check which factors are redundant. We proceed as follows: the test asset (factor 1) is regressed on the FFC4FM_d model and the benchmark asset (factor 2), whereby the FFC4FM_d factors plus factor 2 state the asset pricing model. In case the model generates an economically and statistically significant alpha, there is an omitted factor containing information relevant to price factor 1. In case the alpha is not significant, factor 1 is spanned by the respective asset pricing model, not generating any unexplained returns.

[Table 7 about here.]

Table 7 depicts momentum strategy alphas and corresponding t-statistics. The first column shows that cvol_{6M}, dyn_{IS} and iMOM generate significantly positive FFC4FM_d alphas for both the long and the broad sample. Factor spanning tests for the U.S. shown in Panel A reveal that cvol_{6M} and dyn_{IS} span each other, so that the alphas at least partially subsume each other. For the global sample in Panel B, dyn_{IS} is spanned by cvol_{6M}. The statistically significant spanning alphas for the remaining pairwise tests suggest that part of the strate-

[37]However, the long and short portfolio of the iMOM factor contains, as shown by Blitz et al. (2018), on average larger stocks with higher idiosyncratic volatility, indicating higher liquidity and lower transaction costs.

gies' returns cannot be explained by neither the $FFC4FM_d$ nor by other risk management strategies. This raises two questions: (i) whether the autocorrelation of returns, i.e., the difference in scaling weights between both scaled strategies, eventually matters in order to maximize Sharpe ratios, and (ii) to what extent are the alphas of volatility scaled strategies distinct from the alphas of the residualized momentum (iMOM). To tackle the latter issue, we disentangle the alphas of volatility scaling and residualizing. To accomplish this, we scale idiosyncratic momentum by its realized volatility to see if it yields another Sharpe ratio improvement. Table 8 shows the summary statistics for idiosyncratic momentum as well as the constant volatility-scaled and dynamic versions.

[Table 8 about here.]

The constant volatility-scaling of idiosyncratic momentum increases the Sharpe ratio by 24.21% (15.76%) for the U.S. (global) sample and also decreases both kurtosis and maximum drawdown returns. The reduced exposure of idiosyncratic momentum with respect to the market, size and value factors due to residualizing does not dissect the first time-series pattern observed for standard momentum: the negative volatility-to-return relation. This enables both volatility smoothing and timing for idiosyncratic momentum and motivates the constant volatility-scaling. Column three shows that the performance improvement is lower for the dynamic strategy than for the constantly-scaled version of idiosyncratic momentum. At least to some extent, the autocorrelation of returns (second pattern for momentum returns) seems to be neutralized by the style exposure reduction of residualizing. We find evidence that the alphas of volatility-scaled strategies are distinct from the alphas of idiosyncratic momentum, and both generic approaches can be independently applied for the risk management of momentum.

4 Robustness

4.1 Controlling for Profitability and Asset Growth

As Figure 4a shows for the time-conditional maximum Sharpe ratio tests, the cumulative factor probabilities vary substantially over time. In this regard, Barillas and Shanken (2018) use an even larger base set of 6 categorized factors (market, size, value, profitability, investment, and momentum) for their factor comparison. This begs the questions whether including profitability and investment as additional factors would affect our results.

Tackling the question of potentially omitted factors, we recalculate the maximum Sharpe ratio tests in Subsection 3.1 by extending the investment set by the profitability and investment factors: robust minus weak (RMW) and conservative minus aggressive (CMA). For the long sample, we use the data provided from Kenneth French, which restricts our sample to start in July 1963, when both factors became available. For the broad sample, we construct both factors country-neutral and analogous to the value factor using independent 2x3 sorts on size and the particular sorting criteria. Fortunately, the factors can be constructed from the original starting point of the broad sample in July 1990 on. Table 9 shows the results for a base set of 10 factors.

[Table 9 about here.]

For both the long and broad sample, idiosyncratic momentum is included in every one of the best seven investment sets for the corresponding baseline Sharpe multiple. This means that none of the other risk management strategies is considered to extend the investment opportunity set more than idiosyncratic momentum.

4.2 Single Sorts and Equal-Weighted Portfolio Returns

Up to this point, the analyses have aimed to compare momentum strategies based on 2x3 double sorts and value-weighted portfolio returns. Studies such as Jegadeesh and Titman

(2001), Rouwenhorst (1998), or Blitz et al. (2011) choose to construct equally-weighted decile portfolios to ensure that the resulting portfolios have sufficient breadth. In other words, value-weighted portfolio returns may be heavily driven by the returns of few very large stocks. The resulting up minus down strategy is even more concise in terms of return and crash behavior. This raises the question of whether idiosyncratic momentum also holds in a single-sorted long-short strategy and with equally weighted stock returns.

Hence, we construct momentum portfolios based on decile (quintile) sorts for the long (broad) sample. To prevent that the results are driven by micro stocks, we exclude them for every country.[38] For the U.S., we exclude all stocks with a market capitalization below the 20th percentile of the market capitalization distribution among NYSE stocks. For the global sample, we exclude the smallest stocks that jointly subsume 3% of the total market capitalization in the home country. The risk management strategies are installed as before, i.e., UMD is scaled based on its realized volatility (and predicted return for dynamically-scaled strategies) and iMOM is constructed from single sorts based on the scaled 12-2 month idiosyncratic returns from Equation 9. The results appear in Table 10.

[Table 10 about here.]

A similar pattern emerges for the one-dimensional sorted portfolios as for the standard setting: all risk management strategies roughly double the Sharpe ratios of UMD, both skewness and kurtosis are lowered, and the maximum drawdowns decrease significantly. Compared to the long sample, the broad sample yields especially pronounced differences across strategies with a more than 400% increase in the Sharpe ratio for the single sorted iMOM as compared to UMD.

[38] Fama and French (2008) note that micro stocks cover about 60% of the whole stock universe, but subsume only about 3% if the total market capitalization.

4.3 Country-Level Analysis

As highlighted by Chui et al. (2010), momentum is a persistent phenomenon around the world, except in Asia. To answer the question whether our results are driven by non-Asian countries or countries with high market capitalizations within the market cap-weighted broad international sample, we investigate the Sharpe ratios of momentum and risk management strategies as well as the maximum ex-post Sharpe ratio weights for every country individually. Panel A of Table 11 shows the factors' annualized Sharpe ratios analogously to Table 2.

[Table 11 about here.]

The factors with the highest (second highest) value are highlighted in dark (bright) grey. For developed markets, iMOM clearly has the highest or second highest Sharpe ratio for most of the countries. In contrast, the emerging market countries reveal no clear pattern. Panel B shows the country-specific results for the ex-post Sharpe ratio maximization test analogously to Table 4. More specifically, we only plot the weights for momentum and the three strategies for the specification where all eight factors enter the maximization test. In contrast to pure Sharpe ratios, the results also control for the FF3FM factors. The maximum weights are distributed equally between cvol_{6M} and iMOM for developed markets. In emerging market countries, cvol_{6M} clearly contributes mostly to the factor combination with the highest Sharpe ratio. We find that standard momentum is outperformed by all strategies, irrespective of the country or when controlling for other common factors.

From the list of individual countries, Japan might be the most interesting to examine in detail, because conventional momentum is considered ineffective in Japan. Similar to other studies (e.g. Griffin et al., 2003; Fama and French, 2012), we find that the performance of momentum is weak in Japan. This weakness presents a challenge for our momentum risk management strategies. Based on our analysis, idiosyncratic momentum emerges as the best momentum strategy by providing the highest Sharpe ratio. These results are even more compelling for the assigned maximum ex-post Sharpe ratio weight of 37%. In contrast, the two scaling approaches lead to smaller performance improvements.

5 Conclusion

The aim of examining volatility-scaling and residualizing momentum in this study is fourfold. First, we construct risk management strategies for momentum proposed in the literature that are found to work in the U.S. but have not yet been documented in a comprehensive international setting. Second, we assess the performance improvement of the strategies as compared to momentum in an absolute versus relative as well as in an unconditional versus conditional manner. Third, we investigate if momentum or risk-management strategy profits are robust to trading costs and calculate turnover and round-trip costs. Fourth, motivated by pairwise mean-variance spanning tests, we disentangle the potential Sharpe improvement of risk management strategies and additionally scale the residualized momentum strategy by its own volatility.

Using monthly stock returns for a total of 49 developed and emerging market countries and a sample period of about 28 years (89 years for the U.S.), our main findings can be summarized as follows: First, we show that all risk-management strategies substantially increase Sharpe ratios. Furthermore, higher moments and maximum drawdowns decrease as compared to standard momentum so that their distributions become more normal. Comparing the individual risk-management strategies within samples, we find similar improvements within the long U.S. sample for Sharpe ratios and t-statistics (both roughly double compared to standard momentum) across all three approaches, while maximum drawdowns are reduced mostly by idiosyncratic momentum. For the broad sample, we document that idiosyncratic momentum outperforms all other strategies, as the improvements in Sharpe ratio and t-statistic for idiosyncratic momentum are more than twice as the improvements of volatility-scaling strategies and the reduction in maximum drawdowns is highest.

Second, maximum Sharpe ratio and factor comparison tests of the risk-management strategies further confirm our results in favor of idiosyncratic momentum. Idiosyncratic momentum is assigned the highest weight in ex-post maximum Sharpe ratio tests for both the long and the broad sample, meaning that mean-variance optimizing investors would allocate most to the idiosyncratic momentum factor next to traditional factors such as the market, size, and value. Furthermore, the Bayesian Sharpe ratio tests as in Barillas and Shanken (2018) show that the models with the highest model probabilities include idiosyncratic momentum and that idiosyncratic momentum shows the highest cumulative factor probability among the three momentum risk-management approaches for both the long and the broad sample. However, pairwise factor spanning tests show that alphas generated by the volatility-scaled strategies are different from the alpha when using residualized returns.

Third, we tackle the difficulty of quantifying implied transaction costs. We apply the break-even round-trip cost metric of Grundy and Martin (2001). By calculating the transaction costs that theoretically would render the strategies unprofitable, we are able to directly compare the risk-managed momentum strategies with each other and relate them to existing quantifications of momentum trading costs. We find that all risk management strategies have higher average portfolio turnover compared to standard momentum but still higher break-even costs, driven by the increased strategy returns. Relying on the insights from research on transaction costs in the U.S., we conclude that all strategies should deliver significant after-transaction cost returns for the long U.S. sample.[39] For countries other than the U.S., studies have not comprehensively quantified transaction costs of anomalies.

Finally, scaling iMOM with its realized volatility enables us to investigate if (i) the autocorrelation of the strategy's returns and (ii) the negative risk-to-return relation known from standard momentum is also featuring residual momentum. In case solely the latter (both) feature(s) occur for iMOM, the constant volatility-scaled (dynamic) strategy would further improve its performance. We find that constant volatility-scaling of iMOM maximizes its performance.

[39]Research has found momentum to deliver significant after-transaction cost returns. Since round-trip costs of all risk management strategies are above those of momentum, we can derive the indication of profitability.

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Table 1: Descriptive statistics

The table presents summary statistics for the 49 countries of our CRSP, Datastream and Worldscope sample. Column 2 states the market affiliation according to MSCI, with DM as Developed Markets and EM as Emerging Markets. Columns 3, 4 and 5 report the total, minimum, and maximum number of firms per country, respectively. Columns 6 states the average mean size per country-month. Column 7 shows the average total size per country-month and column 8 reports these values in percentage of the respective total across countries. Size is measured as market capitalization in million USD. The last two columns report the start and end date of data availability for each country. Following Blitz et al. (2011), we require that firms have non-missing values for the following items: market value of equity, book-to-market, current month return, lagged month market capitalization and returns for the past 36 months.

Country	Market	Total no. firms	Min no. firms	Max no. firms	Mean size	Average total size	Average total size in %	Start date	End date
Argentina	EM	84	58	69	456	29961	0.09	2001-01-01	2009-06-30
Australia	DM	2414	82	1444	821	641446	1.99	1991-01-01	2017-12-31
Austria	DM	151	42	79	1071	68107	0.21	1993-01-01	2017-12-31
Belgium	DM	219	77	124	1968	201879	0.63	1992-01-01	2017-12-31
Brazil	EM	228	73	169	3031	363929	1.13	2002-01-01	2017-12-31
Canada	DM	3479	238	1889	815	789197	2.45	1991-01-01	2017-12-31
Chile	EM	237	72	164	943	140676	0.44	1997-01-01	2017-12-31
China	EM	2614	93	2521	1322	2332370	7.24	2000-01-01	2017-12-31
Colombia	EM	60	35	49	3076	138609	0.43	2009-09-01	2017-12-31
Czech Republic	EM	60	30	48	496	17301	0.05	2001-01-01	2006-01-31
Denmark	DM	304	119	189	945	137935	0.43	1993-01-01	2017-12-31
Egypt	EM	148	101	129	430	50389	0.16	2008-01-01	2017-12-31
Finland	DM	189	44	128	1865	203479	0.63	1997-01-01	2017-12-31
France	DM	1480	133	689	2086	1212744	3.76	1991-01-01	2017-12-31
Germany	DM	1363	158	738	1768	1019218	3.16	1991-01-01	2017-12-31
Greece	DM/EM	372	79	266	339	69444	0.22	1995-01-01	2017-12-31
Hong Kong	DM	1321	55	1164	544	383778	1.19	1995-01-01	2017-12-31
Hungary	EM	55	30	36	685	22228	0.07	2005-01-01	2016-08-31
India	EM	2999	231	2368	541	725268	2.25	1997-01-01	2017-12-31
Indonesia	EM	555	114	436	541	178170	0.55	1997-01-01	2017-12-31

[Continued on next page]

Country	Market	Total no. firms	Min no. firms	Max no. firms	Mean size	Average total size	Average total size in %	Start date	End date
Ireland	DM	76	30	42	1411	48885	0.15	1994-01-01	2012-05-31
Israel	DM/EM	482	71	389	495	131453	0.41	2004-01-01	2017-12-31
Italy	DM	492	144	238	2122	418863	1.30	1991-01-01	2017-12-31
Japan	DM	4927	984	3481	1183	3205293	9.95	1991-01-01	2017-12-31
Malaysia	EM	1232	125	860	388	219408	0.68	1993-01-01	2017-12-31
Mexico	EM	178	56	110	2020	197638	0.61	1999-01-01	2017-12-31
Morocco	EM	74	58	71	867	57223	0.18	2010-01-01	2014-06-30
Netherlands	DM	221	64	133	2879	277204	0.86	1991-01-01	2017-12-31
New Zealand	DM	198	46	112	385	35402	0.11	1999-01-01	2017-12-31
Norway	DM	353	43	156	1014	126730	0.39	1992-01-01	2017-12-31
Pakistan	EM	231	67	201	140	18084	0.06	1999-01-01	2009-06-30
Peru	EM	124	44	88	552	43173	0.13	2004-01-01	2017-12-31
Philippines	EM	287	76	221	498	95624	0.30	1997-01-01	2017-12-31
Poland	EM	627	72	456	447	108168	0.34	2002-01-01	2017-12-31
Portugal	DM/EM	127	39	87	1123	55045	0.17	1996-01-01	2017-12-31
Qatar	EM	42	41	42	3562	146914	0.46	2015-01-01	2017-12-31
Russia	EM	391	106	258	2866	549378	1.70	2009-01-01	2017-12-31
Singapore	DM	780	46	529	622	206569	0.64	1991-01-01	2017-12-31
South Africa	EM	671	127	329	1146	270405	0.84	1996-01-01	2017-12-31
South Korea	EM	2200	95	1674	496	479398	1.49	1993-01-01	2017-12-31
Spain	DM	277	97	141	3932	479909	1.49	1994-01-01	2017-12-31
Sweden	DM	709	87	394	1164	302209	0.94	1993-01-01	2017-12-31
Switzerland	DM	349	104	220	3944	786226	2.44	1991-01-01	2017-12-31
Taiwan	EM	1937	205	1623	590	552015	1.71	1998-01-01	2017-12-31
Thailand	EM	724	198	554	399	171452	0.53	1996-01-01	2017-12-31
Turkey	EM	424	62	337	600	145917	0.45	1998-01-01	2017-12-31
U.K.	DM	3413	975	1235	1833	2009162	6.24	1991-01-01	2017-12-31
U.S.	DM	18451	415	4995	1184	4123423	37.77	1930-01-01	2017-12-31
United Arab Emirates	EM	102	91	98	1955	188207	0.58	2015-01-01	2017-12-31

Table 2: Summary statistics for MOM and risk management strategies

The table presents the following summary statistics for MOM, cvol_{1M}, cvol_{6M}, dyn_{IS}, dyn and iMOM: (1) Average monthly returns (in %), (2) Corresponding t-statistics, (3) Annualized Sharpe ratios, (4) Skewness, (5) Kurtosis, and (6) Maximum drawdown (in %), defined as the maximum cumulative loss between a peak and subsequent downturn during the buy-and-hold resp. sample period. The analysis is performed from 01/1930 (01/1991) to 12/2017 for the long (broad) sample.

	MOM	cvol_{1M}	cvol_{6M}	dyn_{IS}	dyn	iMOM
Panel A: U.S. (Long) (01/1930 - 12/2017)						
Avg. Returns (in %)	0.60	1.12	1.09	1.21	1.11	0.64
t-Stat	4.42	8.27	8.07	8.93	8.24	8.90
Sharpe (annualized)	0.47	0.88	0.86	0.95	0.88	0.95
Skewness	-1.91	-0.15	-0.23	0.22	0.11	0.14
Kurtosis	19.46	1.22	2.08	4.32	7.23	10.50
Max. Drawdown (in %)	-67.10	-39.80	-35.88	-33.30	-39.66	-25.52
Panel B: Global (Broad) (01/1991 - 12/2017)						
Avg. Returns (in %)	0.52	0.92	0.88	0.97	0.76	0.71
t-Stat	2.99	5.33	5.09	5.64	4.42	8.57
Sharpe (annualized)	0.57	1.03	0.98	1.08	0.85	1.65
Skewness	-1.00	-0.14	-0.17	0.87	0.66	0.09
Kurtosis	5.50	1.53	0.37	3.80	7.52	1.16
Max. Drawdown (in %)	-36.96	-19.49	-15.11	-10.26	-23.74	-7.04

Table 3: Correlation coefficients

The table reports the time-series averages of the cross-sectional spearman correlation coefficients for the global sample between the following variables: RMRF (market factor), SMB, HML, HML_d, MOM, $cvol_{1M}$, $cvol_{6M}$, dyn_{IS}, dyn, and iMOM. For details regarding variable construction, see Section 2.2. The sample is described in Table 1. The analysis is performed from 01/1930 (01/1991) to 12/2017 for the U.S. (Global) sample and depicted within the upper (lower) triangle.

	RMRF	SMB	HML	HML_d	MOM	$cvol_{1M}$	$cvol_{6M}$	dyn_{IS}	dyn	iMOM
RMRF		0.27	0.02	0.07	-0.05	-0.02	-0.03	0.10	0.00	-0.09
SMB	-0.04		0.01	0.08	-0.03	-0.04	-0.04	0.00	-0.02	-0.04
HML	-0.01	-0.13		0.84	-0.18	-0.16	-0.15	-0.08	-0.13	0.02
HML_d	0.08	-0.11	0.74		-0.45	-0.42	-0.42	-0.29	-0.36	-0.18
MOM	-0.18	0.00	-0.10	-0.57		0.94	0.96	0.77	0.85	0.64
$cvol_{1M}$	-0.12	-0.03	-0.10	-0.55	0.94		0.98	0.87	0.93	0.62
$cvol_{6M}$	-0.12	-0.05	-0.09	-0.55	0.95	0.96		0.88	0.95	0.64
dyn_{IS}	0.11	0.00	-0.13	-0.42	0.64	0.71	0.75		0.92	0.54
dyn	0.01	-0.04	-0.10	-0.43	0.71	0.78	0.83	0.88		0.58
iMOM	-0.09	0.02	-0.05	-0.38	0.66	0.62	0.64	0.45	0.44	

Table 4: Maximum ex-post Sharpe ratios

The table presents the maximum ex-post Sharpe ratios that can be achieved by using different combinations of long-short portfolios (factors) and the weights required on each long-short portfolio to achieve the maximum Sharpe ratio. The following factors are included: RMRF (market factor), SMB, HML, HML_d, MOM, $cvol_{6M}$, dyn, and iMOM. For details regarding variable construction, see Section 2.2. The analysis is performed at monthly frequency from 01/1930 (01/1991) to 12/2017 for the U.S. (Global) sample.

RMRF	SMB	HML	HML_d	MOM	$cvol_{6M}$	dyn	iMOM	SR
Panel A: U.S. (Long) (01/1930 - 12/2017)								
1.00								0.42
0.31	0.24	0.45	0.00					0.52
0.13	0.00	0.00	0.39	0.48				1.07
0.09	0.03	0.00	0.35	0.08	0.45			1.24
0.10	0.00	0.00	0.35	0.27		0.27		1.23
0.11	0.00	0.00	0.24	0.18			0.47	1.24
0.08	0.00	0.00	0.23	0.00	0.12	0.14	0.42	1.37
Panel B: Global (Broad) (01/1991 - 12/2017)								
1.00								0.30
0.12	0.18	0.70	0.00					0.98
0.09	0.12	0.00	0.45	0.34				1.67
0.06	0.14	0.00	0.43	0.03	0.34			1.91
0.08	0.12	0.00	0.42	0.27		0.11		1.79
0.05	0.04	0.00	0.30	0.03			0.57	2.42
0.05	0.05	0.00	0.29	0.00	0.02	0.07	0.52	2.53

Table 5: Prior Sensitivity for the Model Probabilities with 8 Factors
The table displays changes in the prior and corresponding percentage model probabilities as in Barillas and Shanken (2018) for the seven models with the highest probability by December 2017 (the end of the sample period). The analysis is performed at monthly frequency from 01/1930 (01/1991) to 12/2017 for the U.S. (Global) sample in Panel A (B). The following prior multiples for the market Sharpe ratio, Sh_{RMRF} , are considered: 1.5, 2.0, 3.0, 4.0, 5.0 and 6.0. Models are based on the following factors: RMRF, SMB, HML, HML$_d$, MOM, cvol$_{6M}$, dyn, and iMOM. Models are restricted to contain not more than one factor from the following categories: value (HML or HML$_d$), risk-managed momentum (cvol$_{6M}$, dyn, or iMOM). The prior for each factor is set the following: $Sh_{max} = priormultiple \times Sh_{Mkt}$, where Sh_{Mkt} is the Sharpe ratio of RMRF within the sample and the mentioned prior Sharpe multiples are used. Sh_{max} is the square root of the squared tangency portfolio's expected Sharpe ratio (spanned by the factors included), implying the alphas of factors other than RMRF are non-zero. In line with the expected Sharpe ratios, we choose 1.5 (4.0) as the baseline Sharpe multiple for the U.S. (Global) sample.

	Prior Sharpe Multiple					
	1.5	2	3	4	5	6
Panel A: U.S. (Long) (01/1930 - 12/2017)						
RMRF HML$_d$ MOM iMOM	67.86	74.15	75.46	74.22	72.35	70.27
RMRF SMB HML$_d$ MOM iMOM	7.98	6.26	4.13	3.02	2.34	1.89
RMRF HML$_d$ iMOM	7.76	6.12	6.47	7.55	8.74	9.90
RMRF HML$_d$ MOM cvol$_{6M}$	5.99	6.16	6.04	5.87	5.69	5.51
RMRF HML iMOM	2.92	1.49	1.21	1.3	1.45	1.61
RMRF HML$_d$ cvol$_{6M}$	2.40	3.29	4.85	6.29	7.63	8.87
RMRF iMOM	1.75	0.57	0.45	0.56	0.73	0.94
Panel B: Global (Broad) (01/1991 - 12/2017)						
RMRF HML$_d$ iMOM	47.88	67.00	73.85	77.60	80.54	82.88
RMRF HML$_d$ MOM iMOM	11.85	14.97	13.40	11.61	10.15	8.97
RMRF SMB HML$_d$ iMOM	8.64	11.13	10.28	9.08	8.04	7.16
RMRF SMB HML$_d$ MOM iMOM	2.49	2.95	2.27	1.68	1.26	0.98
RMRF HML iMOM	13.09	2.60	0.14	0.02	0.01	0.00
RMRF HML MOM iMOM	1.93	0.50	0.04	0.01	0.00	0.00
RMRF SMB HML iMOM	2.42	0.44	0.02	0.00	0.00	0.00

Table 6: Turnover and break-even round-trip costs

The table presents the following turnover resp. trading cost measures for MOM, cvol_{1M}, cvol_{6M}, dyn_{IS}, dyn and iMOM: (1) Average long-short portfolio turnover (monthly, in %), (2) break-even round-trip costs significant at the 5% level, stating the upper border for trading costs so that the strategy is profitable with 5% significance, and (3) break-even round-trip costs significant at the 1% level. For details regarding measure construction, see Section 2.4. The analysis is performed from 01/1930 (01/1991) to 12/2017 for the long (broad) sample.

	MOM	cvol_{6M}	dyn	iMOM
Panel A: U.S. (Long) (01/1930 - 12/2017)				
Turnover (in %)	53.79	80.63	82.22	65.32
Round-trip costs at 5% sign. level (in %)	0.62	1.02	1.03	0.77
Round-trip costs at 1% sign. level (in %)	0.46	0.92	0.93	0.70
Panel B: Global (Broad) (01/1991 - 12/2017)				
Turnover (in %)	50.32	70.69	81.06	62.59
Round-trip costs at 5% sign. level (in %)	0.35	0.76	0.52	0.87
Round-trip costs at 1% sign. level (in %)	0.14	0.61	0.39	0.79

Table 7: Factor spanning tests

The table presents alphas and corresponding t-statistics from mean-variance spanning tests for the U.S. and Global sample. The dependent variables are the risk management momentum strategies as depicted in Panel A to C: cvol_{6M}, dyn, and iMOM. Independent variables are: RMRF (market factor), SMB, HML_d and MOM, as well as the risk management momentum strategies as benchmark assets. The independent factor set for each spanning test is shown above the respective results. For details regarding variable construction, see Section 2.2. The analysis is performed at monthly frequency over the time-series from 01/1930 (01/1991) to 12/2017 for the U.S. (Global) sample.

Ind. var.	FF_d+*MOM*	FF_d+*MOM* +$cvol_{6M}$	FF_d+*MOM* +*dyn*	FF_d+*MOM* +*iMOM*
Panel A: U.S. (Long) (01/1930 - 12/2017)				
$cvol_{6M}$				
α	0.42		0.06	0.37
t(α)	5.60		1.74	4.91
dyn				
α	0.60	0.06		0.55
t(α)	5.43	1.11		4.96
iMOM				
α	0.32	0.28	0.29	
t(α)	5.67	4.99	5.21	
Panel B: Global (Broad) (01/1991 - 12/2017)				
$cvol_{6M}$				
α	0.39		0.20	0.28
t(α)	4.34		3.18	2.86
dyn				
α	0.50	-0.04		0.56
t(α)	2.92	-0.34		2.97
iMOM				
α	0.54	0.49	0.55	
t(α)	8.17	7.37	8.18	

Table 8: Summary statistics for iMOM and scaled iMOM strategies

The table presents the following summary statistics for iMOM, and the corresponding scaled versions of iMOM: (1) Average monthly returns (in %), (2) Corresponding t-statistics, (3) Annualized Sharpe ratios, (4) Skewness, (5) Kurtosis, and (6) Maximum drawdown (in %), defined as the maximum cumulative loss between a peak and subsequent downturn during the buy-and-hold resp. sample period. The analysis is performed from 01/1930 (01/1991) to 12/2017 for the long (broad) sample.

	iMOM	iMOM_{cvol}	iMOM_{dyn}
Panel A: U.S. (Long) (01/1930 - 12/2017)			
Avg. Returns (in %)	0.64	0.80	0.74
t-Stat	8.90	11.11	10.23
Sharpe (annualized)	0.95	1.18	1.09
Skewness	0.14	0.16	0.96
Kurtosis	10.50	2.06	6.74
Max. Drawdown (in %)	-25.52	-14.25	-12.99
Panel B: Global (Broad) (01/1991 - 12/2017)			
Avg. Returns (in %)	0.71	0.82	0.77
t-Stat	8.57	9.93	9.31
Sharpe (annualized)	1.65	1.91	1.79
Skewness	0.09	0.64	1.57
Kurtosis	1.16	1.12	4.48
Max. Drawdown (in %)	-7.04	-5.17	-4.17

Table 9: Prior Sensitivity for the Model Probabilities with 10 Factors
The table displays changes in the prior and corresponding percentage model probabilities as in Barillas and Shanken (2018) for the seven models with the highest probability by December 2017 (the end of the sample period). The analysis is performed at monthly frequency from 07/1963 (01/1991) to 12/2017 for the U.S. (Global) sample in Panel A (B). The following prior multiples for the market Sharpe ratio, Sh_{RMRF} , are considered: 1.5, 2.0, 3.0, 4.0, 5.0 and 6.0. Models are based on the following factors: RMRF, SMB, HML, HML_d, MOM, RMW, CMA, cvol_{6M}, dyn, and iMOM. Models are restricted to contain not more than one factor from the following categories: value (HML or HML_d), risk-managed momentum (cvol_{6M}, dyn, or iMOM). The prior for each factor is set the following: $Sh_{max} = priormultiple \times Sh_{Mkt}$, where Sh_{Mkt} is the Sharpe ratio of RMRF within the sample and the mentioned prior Sharpe multiples are used. Sh_{max} is the square root of the squared tangency portfolio's expected Sharpe ratio (spanned by the factors included), implying the alphas of factors other than RMRF are non-zero. In line with the expected Sharpe ratios, we choose 1.5 (4.0) as the baseline Sharpe multiple for the U.S. (Global) sample.

	Prior Sharpe Multiple					
	1.5	2	3	4	5	6
Panel A: U.S. (Long) (07/1963 - 12/2017)						
RMRF HML_d MOM iMOM CMA RMW	34.62	45.75	47.13	46.51	45.47	44.15
RMRF HML_d iMOM CMA RMW	23.28	18.40	15.29	16.02	17.58	19.31
RMRF iMOM CMA RMW	10.08	2.46	0.99	0.92	1.04	1.23
RMRF HML iMOM CMA RMW	7.33	1.48	0.43	0.31	0.28	0.28
RMRF SMB HML_d iMOM CMA RMW	6.94	10.22	11.45	11.65	11.56	11.31
RMRF SMB HML_d MOM iMOM CMA RMW	6.79	13.55	16.04	14.51	12.47	10.62
RMRF HML_d MOM iMOM RMW	2.31	3.41	4.60	5.76	6.87	7.91
Panel B: Global (Broad) (01/1991 - 12/2017)						
RMRF HML_d iMOM CMA RMW	22.89	48.90	48.77	43.97	40.33	37.69
RMRF HML_d iMOM RMW	7.96	18.66	22.59	24.47	26.48	28.68
RMRF SMB HML_d iMOM CMA RMW	3.17	8.72	13.21	15.38	16.08	15.83
RMRF SMB HML_d iMOM RMW	1.07	3.25	6.09	8.64	10.75	12.33
RMRF HML_d MOM iMOM CMA RMW	3.18	6.23	5.17	3.91	3.06	2.47
RMRF HML_d MOM iMOM RMW	0.84	1.79	1.78	1.60	1.46	1.36
RMRF SMB HML_d MOM iMOM CMA RMW	0.48	1.19	1.45	1.39	1.22	1.03

Table 10: Summary statistics for UMD and risk management strategies
The table presents the following summary statistics for UMD, and the corresponding cvol_{1M}, cvol_{6M}, dyn_{IS}, dyn and iMOM: (1) Average monthly returns (in %), (2) Corresponding t-statistics, (3) Annualized Sharpe ratios, (4) Skewness, (5) Kurtosis, and (6) Maximum drawdown (in %), defined as the maximum cumulative loss between a peak and subsequent downturn during the buy-and-hold resp. sample period. The analysis is performed from 01/1930 (01/1991) to 12/2017 for the long (broad) sample.

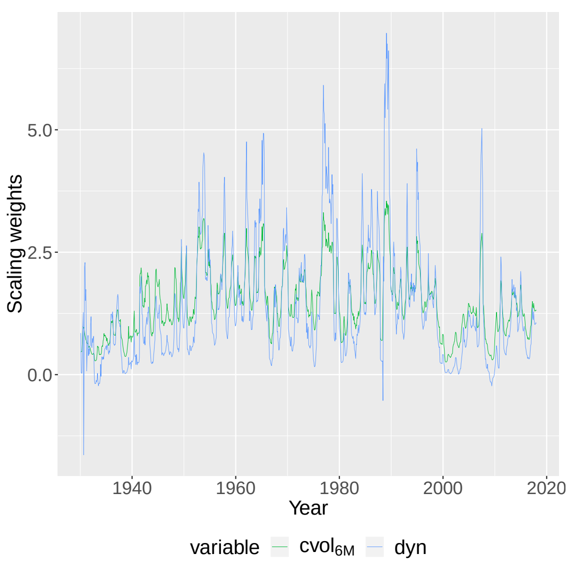
	UMD	cvol_{1M}	cvol_{6M}	dyn_{IS}	dyn	iMOM
Panel A: U.S. (Long) (01/1930 - 12/2017)						
Avg. Returns (in %)	1.11	2.11	2.05	2.39	2.11	0.92
t-Stat	4.98	9.45	9.18	10.69	9.43	8.82
Sharpe (annualized)	0.53	1.01	0.98	1.14	1.01	0.94
Skewness	-2.80	-0.62	-0.65	0.47	0.15	-1.52
Kurtosis	27.22	4.27	3.84	3.34	7.28	10.47
Max. Drawdown (in %)	-93.62	-51.89	-59.49	-45.18	-60.55	-42.73
Panel B: Global (Broad) (01/1991 - 12/2017)						
Avg. Returns (in %)	0.48	0.79	0.73	0.80	0.55	0.71
t-Stat	1.98	3.24	3.01	3.30	2.26	9.96
Sharpe (annualized)	0.38	0.62	0.58	0.64	0.44	1.92
Skewness	-0.53	-0.21	-0.28	2.99	-1.23	-0.12
Kurtosis	3.50	0.85	1.99	33.14	19.47	1.00
Max. Drawdown (in %)	-44.63	-32.31	-39.96	-39.76	-34.15	-8.58

Table 11: Sharpe ratios and Maximum ex-post Sharpe ratio weights
The table presents annualized Sharpe ratios as well as the weights required on each factor to achieve the maximum ex-post Sharpe ratio by using different factor combinations. The following factors are included: RMRF (market factor), SMB, HML, HML_d, MOM, $cvol_{6M}$, dyn, and iMOM. For details regarding variable construction, see Section 2.2. The analyses are performed at monthly frequency from 01/1991 (01/1930)) to 12/2017 for (the U.S.) all countries that have more than 120 observations for each factor. The maximum (second highest) factor Sharpe ratios and factor weights are indicated by darker (brighter) grew.

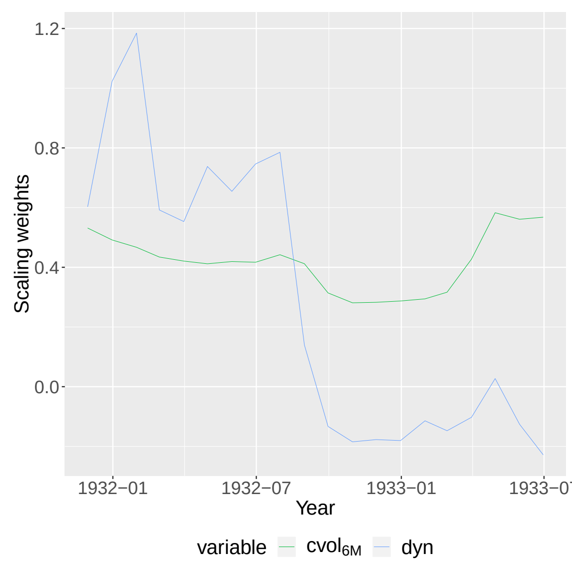
		Panel A: Sharpe ratios				Panel B: Max SR weights			
Country	Market	MOM	$cvol_{6M}$	dyn	iMOM	MOM	$cvol_{6M}$	dyn	iMOM
Australia	DM	1.28	1.51	1.44	1.78	0.00	0.17	0.11	0.36
Austria	DM	0.45	0.74	0.38	0.40	0.00	0.24	0.08	0.01
Belgium	DM	0.76	1.10	0.95	1.23	0.02	0.26	0.00	0.29
Canada	DM	0.71	1.10	1.01	1.10	0.00	0.30	0.08	0.21
Denmark	DM	0.61	0.88	0.65	0.92	0.00	0.29	0.01	0.29
Finland	DM	0.53	0.75	0.37	0.62	0.00	0.24	0.00	0.25
France	DM	0.44	0.80	0.69	0.95	0.00	0.21	0.06	0.29
Germany	DM	0.57	1.01	0.96	1.28	0.00	0.10	0.10	0.40
Hong Kong	DM	0.46	0.92	1.04	0.58	0.00	0.33	0.13	0.06
Ireland	DM	-0.02	0.32	0.20	0.34	0.00	0.22	0.06	0.33
Italy	DM	0.56	0.78	0.30	0.41	0.00	0.57	0.00	0.00
Japan	DM	-0.01	0.15	0.04	0.49	0.12	0.00	0.02	0.37
Netherlands	DM	0.31	0.61	0.51	0.42	0.00	0.37	0.02	0.11
New Zealand	DM	1.18	1.32	0.82	0.92	0.00	0.41	0.00	0.19
Norway	DM	0.63	0.78	0.58	1.01	0.00	0.16	0.06	0.27
Singapore	DM	0.09	0.56	0.57	0.73	0.00	0.23	0.08	0.25
Spain	DM	0.29	0.51	0.04	0.34	0.00	0.35	0.00	0.03
Sweden	DM	0.44	0.85	0.74	0.87	0.00	0.21	0.09	0.18
Switzerland	DM	0.46	0.74	0.57	0.85	0.00	0.05	0.10	0.36
U.K.	DM	0.79	1.26	1.18	1.32	0.00	0.19	0.07	0.37
U.S.	DM	0.47	0.86	0.88	0.95	0.00	0.12	0.14	0.42
Brazil	EM	0.21	0.42	0.47	0.15	0.00	0.30	0.22	0.00
Chile	EM	0.80	0.93	0.88	0.55	0.00	0.36	0.09	0.02
China	EM	-0.48	-0.26	-0.01	-0.01	0.00	0.16	0.00	0.11
Greece	EM	0.27	0.57	0.30	0.46	0.00	0.33	0.07	0.08
India	EM	0.59	0.92	1.01	1.38	0.00	0.00	0.17	0.50
Indonesia	EM	-0.07	0.38	0.18	0.49	0.00	0.24	0.07	0.18
Israel	EM	0.65	0.92	0.57	0.62	0.00	0.38	0.01	0.00
Malaysia	EM	0.20	0.86	0.88	0.74	0.00	0.39	0.00	0.15
Mexico	EM	0.38	0.62	0.82	0.56	0.00	0.11	0.21	0.10
Pakistan	EM	0.22	0.48	0.01	0.36	0.00	0.18	0.06	0.12
Peru	EM	-0.08	0.06	0.36	-0.06	0.00	0.09	0.08	0.05
Philippines	EM	0.06	0.32	0.06	0.27	0.00	0.10	0.07	0.13
Poland	EM	0.75	1.09	0.90	0.66	0.00	0.33	0.08	0.06
Portugal	EM	0.76	0.88	0.65	0.67	0.00	0.45	0.00	0.07
South Africa	EM	1.02	1.31	1.24	1.32	0.00	0.21	0.17	0.28
South Korea	EM	0.11	0.40	0.01	0.44	0.00	0.26	0.13	0.13
Taiwan	EM	0.21	0.46	0.63	0.37	0.00	0.14	0.32	0.22
Thailand	EM	0.24	0.62	0.70	0.66	0.00	0.20	0.18	0.11
Turkey	EM	-0.15	0.09	0.34	0.38	0.00	0.17	0.19	0.20

Figure 1: Static volatility-scaling and dynamic weights
This figure plots the weights on the momentum factor when scaling it to cvol_{6M} and dyn. For the U.S. sample, the weights range from 01/1930 to 12/2017 (Subfigure 1a) and are shown for times of high volatility, i.e. the 1930s (Subfigure 1b). For the Global sample, the weights range from 01/1991 to 12/2017 (Subfigure 1c) and are shown around the financial crisis in 2007/2008 (Subfigure 1d).

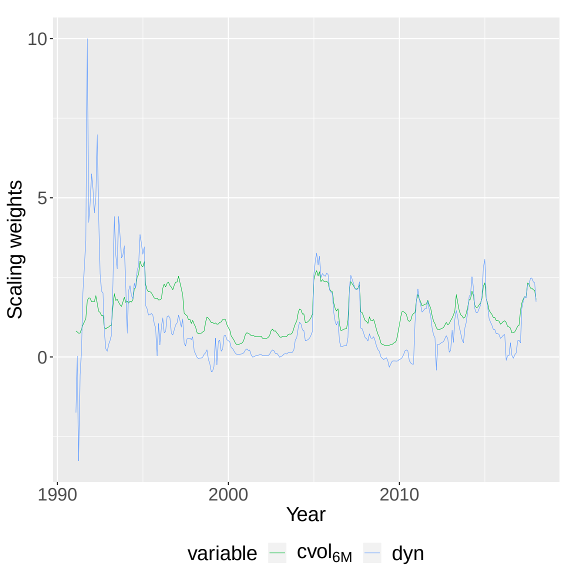
(a) U.S. (Long)



(b) U.S. (Long): 11/1931 - 06/1933



(c) Global (Broad)



(d) Global (Broad): 11/2007 - 09/2009

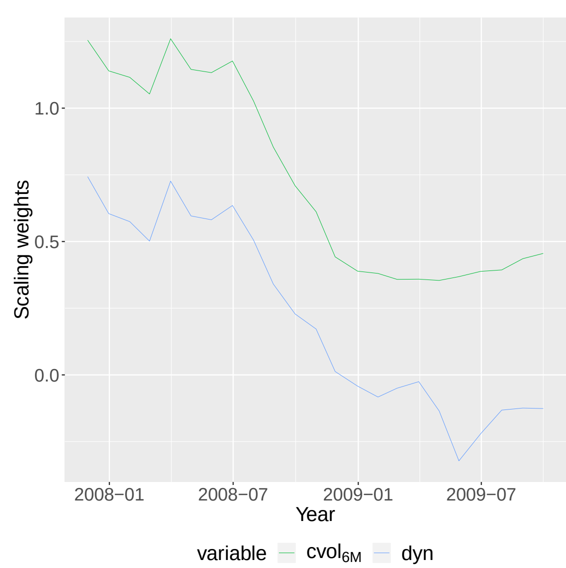


Figure 2: Cumulative Performance of the momentum strategies: U.S. (Long) This figure displays the cumulated performance of a $1 investment in each of the momentum strategies (plus the risk-free rate since, all momentum portfolio state zero-cost strategies) for the U.S. (Long) sample. The following strategies are comprised: MOM, cvol$_{6M}$, dyn and iMOM For details regarding variable construction, see Section 2.2. The sample period ranges from 01/1930 to 12/2017.

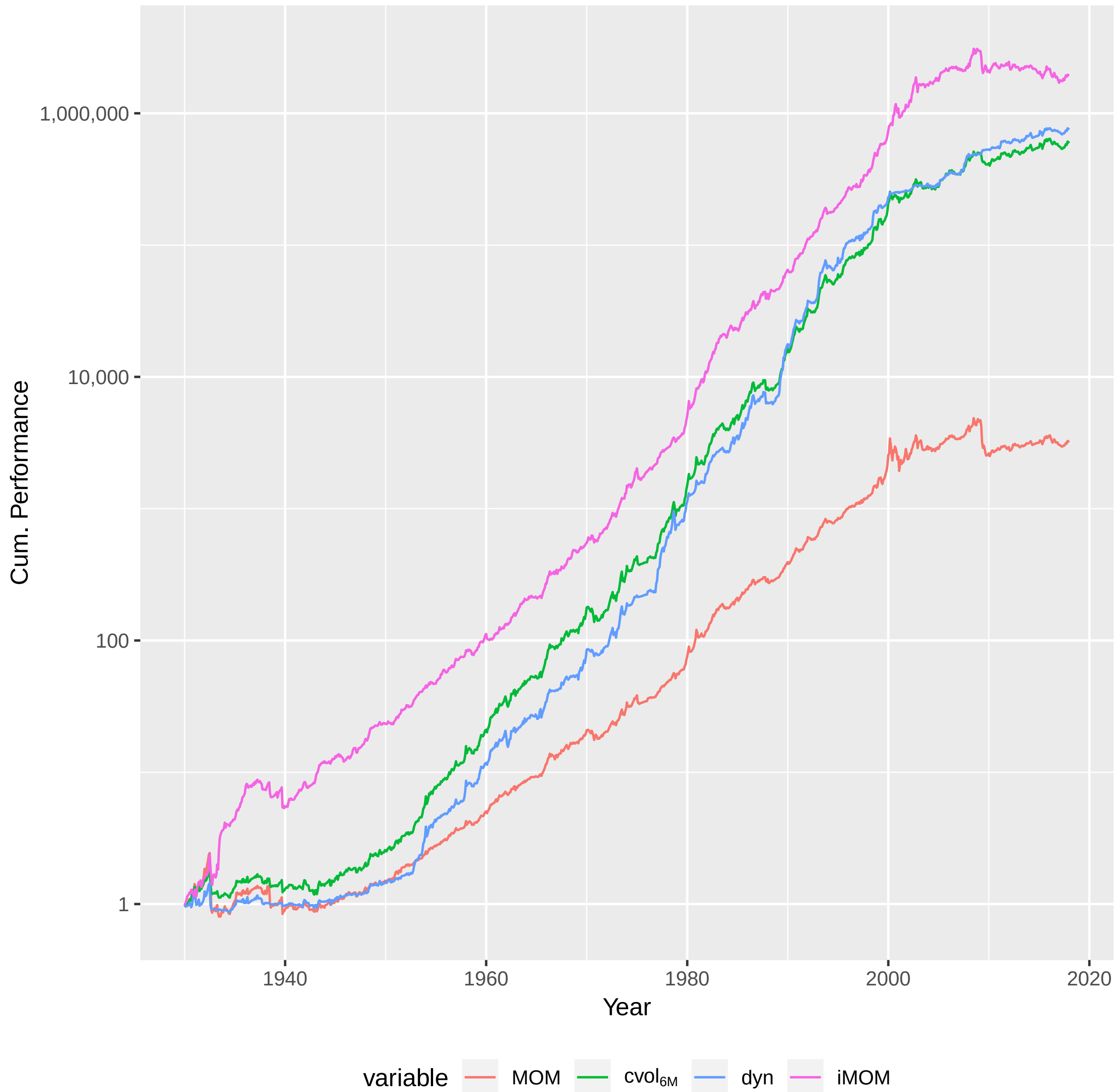


Figure 3: Cumulative Performance of the momentum strategies: Global (Broad) This figure displays the cumulated performance of a $1 investment in each of the momentum strategies (plus the risk-free rate since, all momentum portfolio state zero-cost strategies) for the Global (Broad) sample. The following strategies are comprised: MOM, $cvol_{6M}$, dyn and iMOM. For details regarding variable construction, see Section 2.2. The sample period ranges from 01/1991 to 12/2017.

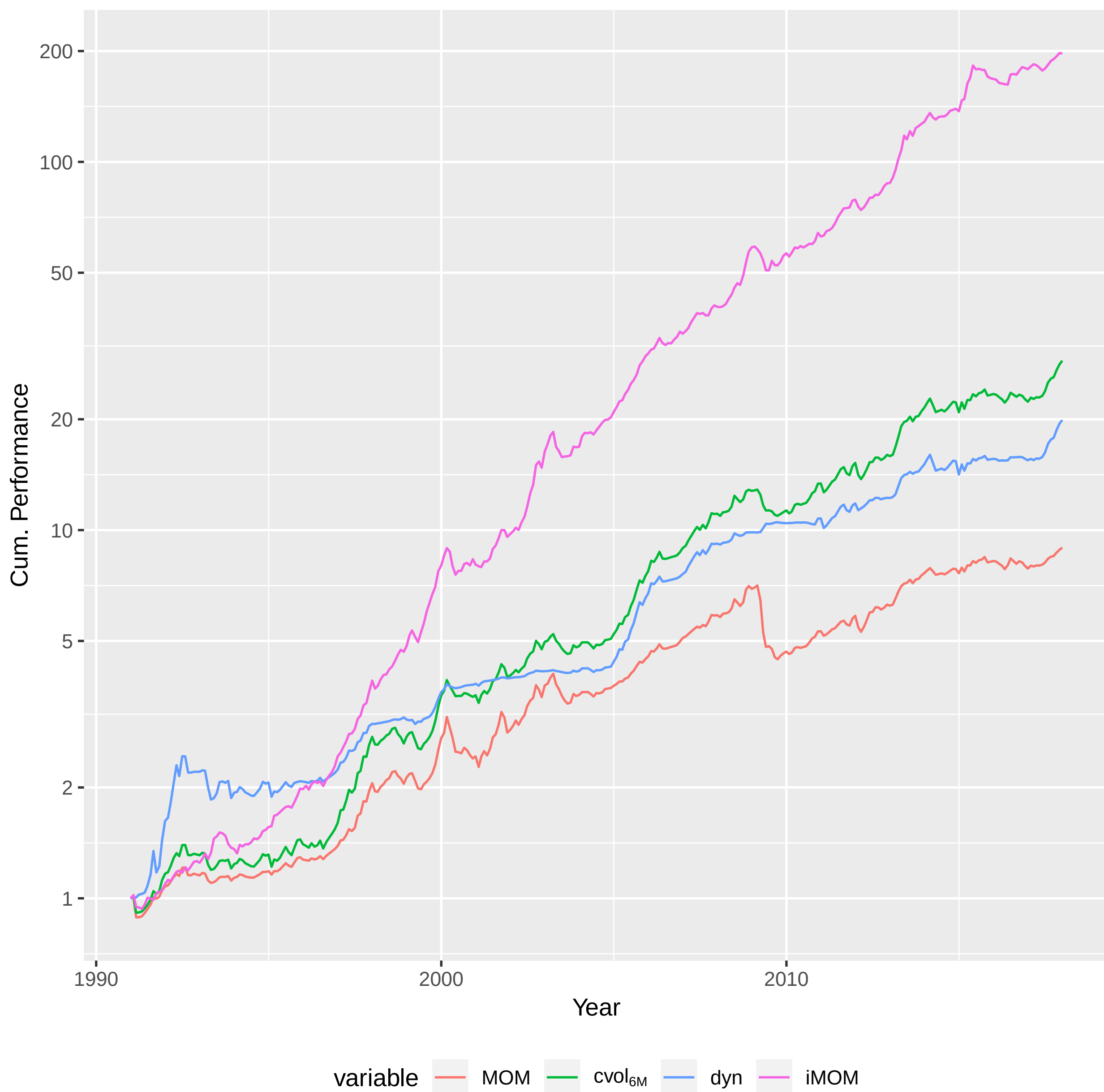
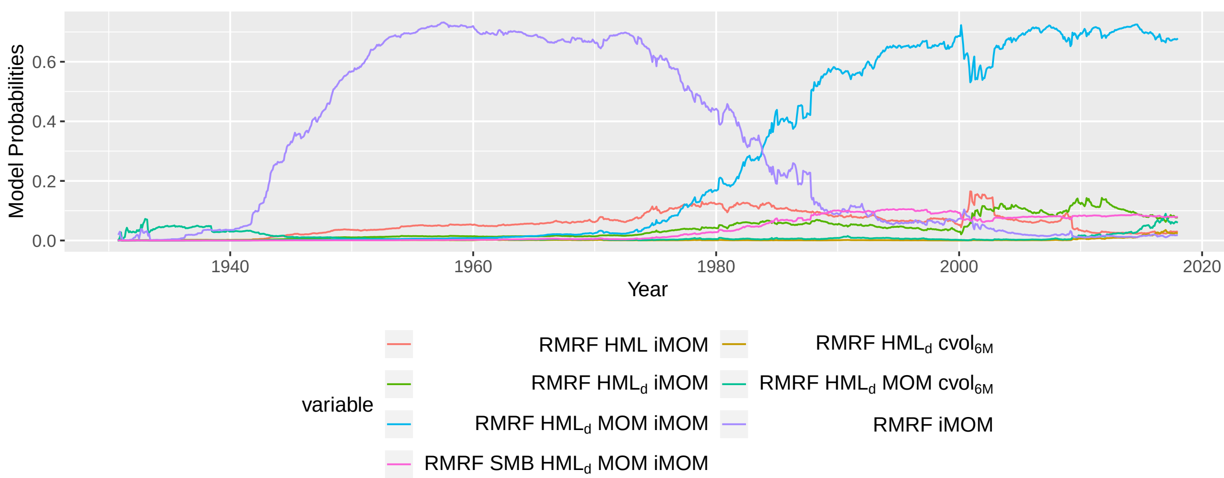


Figure 4: Model probabilities and cumulative factor probabilities for U.S. (Long) The top panel shows the time-series for posterior model probabilities of the seven models with the highest probability at the end of the U.S. sample. The plotted sample starts in 09/1930, and probabilities are calculated recursively at the end of each month up to 12/2017. Models are based on the following factors: RMRF, SMB, HML, HML_d, MOM, $cvol_{6M}$, dyn, and iMOM Models are restricted to contain not more than one factor from the following categories: value (HML or HML_d), risk-managed momentum ($cvol_{6M}$, dyn, iMOM). The bottom panel shows the time-series of cumulative posterior probabilities for factor. The prior for each factor is set the following: $Sh_{max} = 1.5 \times Sh_{Mkt}$, where Sh_{Mkt} is the Sharpe ratio of RMRF within the sample and the baseline Sharpe multiple (1.5) is used. Sh_{max} is the square root of the squared tangency portfolio's expected Sharpe ratio (spanned by the factors included) which is assumed to be 50% higher than the market's squared Sharpe ratio, implying the alphas of factors other than RMRF are non-zero.

(a) Model Probabilities



(b) Cumulative Factor Probabilities

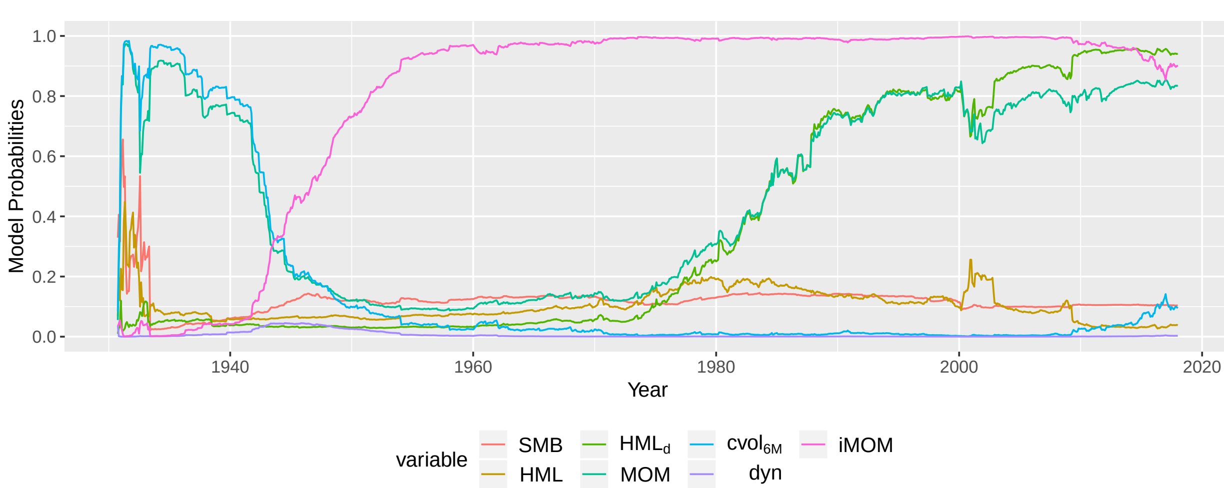
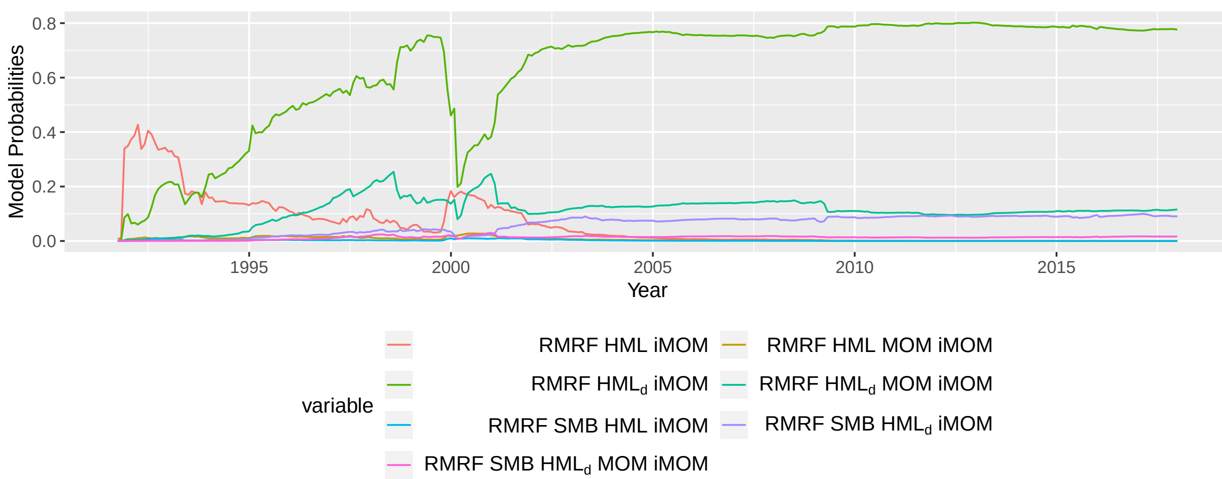
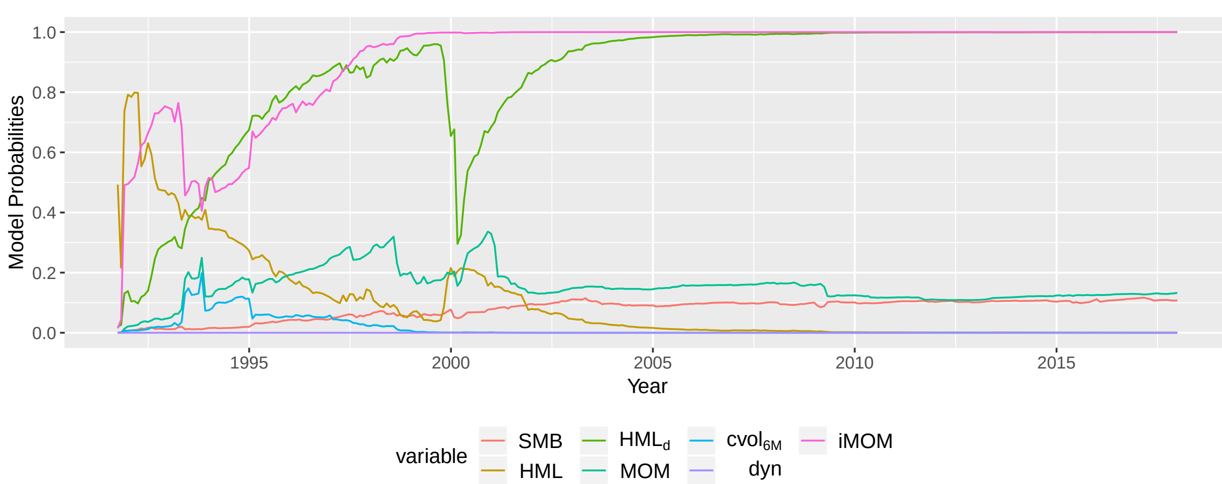


Figure 5: Model probabilities and cumulative factor probabilities for Global (Broad)
The top panel shows the time-series for posterior model probabilities of the seven models with the highest probability at the end of the Global sample. The plotted sample starts in 09/1991, and probabilities are calculated recursively at the end of each month up to 12/2017. Models are based on the following factors: RMRF, SMB, HML, HML_d, MOM, $cvol_{6M}$, dyn, and iMOM. Models are restricted to contain not more than one factor from the following categories: value (HML or HML_d), risk-managed momentum ($cvol_{6M}$, dyn, iMOM). The bottom panel shows the time-series of cumulative posterior probabilities for factor. The prior for each factor is set the following: $Sh_{max} = 4.0 \times Sh_{Mkt}$, where Sh_{Mkt} is the Sharpe ratio of RMRF within the sample and the baseline Sharpe multiple (4.0) is used. Sh_{max} is the square root of the squared tangency portfolio's expected Sharpe ratio (spanned by the factors included) which is assumed to be 300% higher than the market's squared Sharpe ratio, implying the alphas of factors other than RMRF are non-zero.

(a) Model Probabilities



(b) Cumulative Factor Probabilities



A Appendix

A.1 Datastream sample definition

Constituent lists

Datastream comprises three types of constituent lists: (1) research lists, (2) Worldscope lists and (3) dead lists. By using dead lists, we ensure to obviate any survivorship bias. For every country we use the intersection of all available lists and eliminate any duplicates. As a result, we have one remaining list for every country, which can subsequently be used in the static filter process. Table A.1 and Table A.2 provide an overview of the constituent lists for developed markets and emerging markets, respectively, used in our study.

[Table A.1 about here.]

[Table A.2 about here.]

Static screens

We restrict our sample to common equity stocks by applying several static screens as shown in Table A.3. Screen (1) to (7) are standard filters as common in the literature.

[Table A.3 about here.]

Screen (8) related to, among others, the following work: Ince and Porter (2006), Campbell, Cowan, and Salotti (2010), Griffin et al. (2010), Karolyi, Lee, and van Dijk (2012). The authors provide generic filter rules in order to exclude non-common equity securities from Thomson Reuters Datastream. We apply the identified keywords and match them with the security names provided by Datastream. A security is excluded from the sample in case a keyword coincides with part of the security name. The following three Datastream items store security names and are applied for the keyword filters: "NAME", "ENAME", and "ECNAME". Table A.4 gives an overview of the keywords used.

[Table A.4 about here.]

In addition, Griffin et al. (2010) introduce specific keywords for individual countries. Thus, the keywords are applied on the security names of single countries only. Exemplary, German security names are parsed to contain the word "GENUSSSCHEINE", which declares the security to be non-common equity. In Table A.5 we give an overview of country-specific keyword deletions conducted in our study.

[Table A.5 about here.]

Dynamic screens

For the securities, remaining from the static screens above, we obtain return and market capitalization data from Datastream and accounting data from Worldscope. Several dynamic screens that are common in the literature were installed in order to account for data errors mainly within return characteristics. The dynamic screens are shown in Table A.6.

[Table A.6 about here.]

A.2 GJR-GARCH volatility forecasts

To implement the dynamic in-sample-scaled momentum strategy, volatility of Momentum is forecasted via a GJR-GARCH model, calibrated in-sample over the whole Momentum return time-series. Therefore, as a first step, following Daniel and Moskowitz (2016), Momentum returns follow the process:

$$R_{MOM,t} = \mu + \epsilon_t \tag{13}$$

where the error term $\epsilon_t \sim \mathcal{N}\left(0, \sigma_t^2\right)$ is normally distributed, and the evolution of σ_t^2 is described by the process:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \left(\alpha + \gamma\mathcal{I}\left(\epsilon_{t-1} < 0\right)\right)\epsilon_{t-1}^2 \tag{14}$$

where $(\epsilon_{t-1} < 0)$ is an indicator that equals one if the error term in $t-1$ equals one if $\epsilon_{t-1} < 0$, and zero elsewise. The parameters μ, ω, α, γ and β are estimated on a country basis using a maximum likelihood estimator. In a second step, we estimate the volatility for the upcoming month resp. for 22 days within that month by an extended OLS autoregression including the past 126-day volatility of Momentum and the GJR-GARCH estimate:

$$\hat{\sigma}_{d_{22,t+1}} = \hat{\alpha} + \gamma_{GARCH,t}\hat{\sigma}_{GARCH,t} + \gamma_{d_{126,t}}\hat{\sigma}_{d_{126,t}} \tag{15}$$

where $\hat{\sigma}_{d_{22,t+1}}$ is the volatility forecast for month $t+1$, $\hat{\sigma}_{GARCH,t}$ is the volatility estimate from the first step, and $\hat{\sigma}_{d_{126,t}}$ is the past 126-day Momentum return volatility.

A.3 Turnover calculation

Specifically, (one-way portfolio) turnover in month t for both the long or short portfolio leg are calculated as:

$$Turnover_{t,Long(Short)} = 0.5 \times \sum_{i}^{N_t} |x_{i,t} - \tilde{x}_{i,t-1}| \tag{16}$$

where $x_{i,t}$ is the weight of stock i in the respective portfolio leg in month t (i.e., the value proportion since we use value-weighted portfolio returns), N_t amounts to the total number of stocks in the portfolio leg at month t, and $r_{i,t}$ is the return of stock i during month t, and $x_{i,\tilde{t}-1}$ is the weight at the end of month $t-1$ resp. at the beginning of month t, right before trading. We define $\tilde{x}_{i,t-1}$ as:

$$\tilde{x}_{i,t-1} = \frac{x_{i,t-1}\,(1 + r_{i,t-1})}{\sum_{i}^{N_t} x_{i,t-1}\,(1 + r_{i,t-1})} \tag{17}$$

The turnover of the long-short momentum strategies is then the sum of the average turnover in the long and short legs, i.e., the sum of $Turnover_{Long}$ and $Turnover_{Short}$. For the volatility-scaled strategies, the turnover is derived from Equation 16 by weighting the turnover in month

t with the corresponding strategy weight:

$$Turnover_{s,t,Long/Short} = 0.5 \times \sum_{i}^{N_t} |w_{scaled,t} x_{i,t} - w_{scaled,t-1} \tilde{x}_{i,t-1}| \tag{18}$$

Table A.1: Constituent lists: Developed markets

The table contains the Research lists, Worldscope lists and Dead lists of developed markets countries in our sample.

Country	Lists	Country	Lists
Australia	DEADAU	**Italy**	DEADIT
	FAUS		FITA
	WSCOPEAU		WSCOPEIT
Austria	DEADOE	**Japan**	DEADJP
	FOST		FFUKUOKA
	WSCOPEOE		FJASDAQ
Belgium	DEADBG		FOSAKA
	FBEL		FTOKYO
	FBELAM		JAPOTC
	FBELCM		WSCOPEJP
	WSCOPEBG	**Netherlands**	DEADNL
Canada	DEADCN1		FHOL
	DEADCN2		WSCOPENL
	DEADCN3	**New Zealand**	DEADNZ
	DEADCN4		FNWZ
	DEADCN5		WSCOPENZ
	DEADCN6	**Norway**	DEADNW
	FTORO		FNOR
	FVANC		WSCOPENW
	LTTOCOMP	**Portugal**	DEADPT
	WSCOPECN		FPOR
Denmark	DEADDK		WSCOPEPT
	FDEN	**Singapore**	DEADSG
	WSCOPEDK		FSIN
Finland	DEADFN		FSINQ
	FFIN		WSCOPESG
	WSCOPEFN	**Spain**	DEADES
France	DEADFR		FSPN
	FFRA		WSCOPEES
	WSCOPEFR	**Sweden**	DEADSD
Germany	DEADBD1		FAKTSWD
	DEADBD2		FSWD
	DEADBD3		WSCOPESD
	DEADBD4	**Switzerland**	DEADSW
	DEADBD5		FSWA
	DEADBD6		FSWS
	FGER1		FSWUP
	FGER2		WSCOPESW
	FGERIBIS	**United Kingdom**	DEADUK
	FGKURS		FBRIT
	WSCOPEBD		LSETSCOS
Hong Kong	DEADHK		LSETSMM
	FHKQ		LUKPLUSM
	WSCOPEHK		WSCOPEJE
Ireland	DEADIR		WSCOPEUK
	FIRL		
	WSCOPEIR		
Israel	DEADIS		
	FISRAEL		
	WSCOPEIS		

Table A.2: Constituent lists: Emerging markets
The table contains the Research lists, Worldscope lists and Dead lists of emerging markets countries in our sample.

Argentina	DEADAR	**Pakistan**	DEADPA
	FPARGA		FPAK
	WSCOPEAR		FPAKUP
Brazil	DEADBRA		WSCOPEPK
	FBRA	**Peru**	DEADPE
	WSCOPEBR		FPERU
Chile	DEADCHI		WSCOPEPE
	FCHILE	**Philippines**	DEADPH
	FCHILE10		FPHI
	WSCOPECL		FPHILA
China	DEADCH		FPHIMN
	FCHINA		FPHIQ
	WSCOPECH		WSCOPEPH
Colombia	DEADCO	**Poland**	DEADPO
	FCOL		FPOL
	WSCOPECB		WSCOPEPO
Czech Republic	DEADCZ	**Qatar**	DEADQT
	FCZECH		FQATAR
	FCZECHUP		WSCOPEQA
	WSCOPECZ	**Russia**	DEADRU
Egypt	DEADEGY		FRTSCL
	EGYPTALL		FRUS
	FEGYPT		FRUSUP
	WSCOPEEY		WSCOPERS
Greece	DEADGR	**Slovakia**	ALLSLOV
	FGREE		DEADSLO
	FGRMM		FSLOVAK
	FGRPM		WSCOPESX
	FNEXA	**South Africa**	DEADSAF
	WSCOPEGR		FSAF
Hungary	DEADHU		WSCOPESA
	FHUN		DEADKO
	WSCOPEHN		FKONEX
India	DEADIND		FKOR
	FBSE		WSCOPEKO
	FINDIA	**Sri Lanka**	DEADSL
	FINDNW		FSRILA
	FINDUP		FSRIUP
	FNSE		WSCOPECY
	WSCOPEIN	**Taiwan**	DEADTW
Indonesia	DEADIDN		FTAIQ
	FINO		WSCOPETA
	WSCOPEID	**Thailand**	DEADTH
Jordan	DEADJO		FTHAQ
	FJORD		WSCOPETH
	WSCOPEJO	**Turkey**	DEADTK
Malaysia	DEADMY		FTURK
	FMAL		FTURKUP
	FMALQ		WSCOPETK
	WSCOPEMY	**United Arab Emirates**	DEADAB
Mexico	DEADME		DEADDB
	FMEX		FABUD
	MEX101		FDUBAI
	WSCOPEMX		WSCOPEAE
Morocco	DEADMOR	**Venezuela**	DEADVE
	FMOR		FVENZ
	WSCOPEMC		WSCOPEVE

Table A.3: Static Screens

The table displays the static screens applied in our study, mainly following Ince and Porter (2006), Schmidt et al. (2017) and Griffin et al. (2010). Column 3 lists the Datastream items involved (on the left of the equality sign) and the values which we set them to in the filter process (on the right of the equality sign). Column 4 indicates the source of the screens.

Nr.	Description	Datastream item(s) involved	Source
(1)	For firms with more than one security, only the one with the biggest market capitalization and liquidity is used.	MAJOR = Y	Schmidt et al. (2017)
(2)	The type of security must be equity.	TYPE = EQ	Ince and Porter (2006)
(3)	Only the primary quotations of a security are analyzed.	ISINID = P	Fong, Holden, and Trzcinka (2017)
(4)	Firms are located in the respective domestic country.	GEOGN = country shortcut	Ince and Porter (2006)
(5)	Securities are listed in the respective domestic country.	GEOLN = country shortcut	Griffin et al. (2010)
(6)	Securities with quoted currency different from the one of the associated country are disregarded.[a]	PCUR = currency shortcut of the country	Griffin et al. (2010)
(7)	Securities with ISIN country code different from the one of the associated country are disregarded.[b]	GGISN = country shortcut	Annaert, Ceuster, and Verstegen (2013)
(8)	Securities whose name fields indicate non-common stock affiliation are disregarded.	NAME, ENAME, ECNAME	Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010) and Karolyi et al. (2012)

[a] In this filter rule also the respective pre-euro currencies are accepted for countries within the euro zone. Moreover, in Russia "USD" is also accepted as currency, besides "RUB".

[b] In Hong Kong, ISIN country codes equal to "BM" or "KY" and in the Czech Republic ISIN country codes equal to "CS" are also accepted.

Table A.4: Generic Keyword Deletions
The table reports the generic keywords, which are searched for in the names of all stocks of all countries. If a harmful keyword is detected as part of the name of a stock, the respective stock is removed from the sample.

Non-common equity	Keywords
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository Receipts	ADR, GDR
Preferred Stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit Trusts	.IT, .ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
ETFs	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly taken from Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD

Table A.5: Country-Specific Keyword Deletions

The table reports the country-specific keywords, which are searched for in the names of all stocks of the respective countries. If a harmful keyword is detected as part of the name of a stock, the respective stock is removed from the sample.

Country	**Keywords**
Australia	PART PAID, RTS DEF, DEF SETT, CDI
Austria	PC, PARTICIPATION CERTIFICATE, GENUSSSCHEINE, GENUSSCHEINE
Belgium	VVPR, CONVERSION, STRIP
Brazil	PN, PNA, PNB, PNC, PND, PNE, PNF, PNG, RCSA, RCTB
Canada	EXCHANGEABLE, SPLIT, SPLITSHARE, VTG\\., SBVTG\\., VOTING, SUB VTG, SERIES
Denmark	\\)CSE\\)
Finland	USE
France	ADP, CI, SICAV, \\)SICAV\\), SICAV-
Germany	GENUSSCHEINE
Greece	PR
India	FB DEAD, FOREIGN BOARD
Israel	P1, 1, 5
Italy	RNC, RP, PRIVILEGIES
Korea	1P
Mexico	’L’, ’C’
Malaysia	’A’
Netherlands	CERTIFICATE, CERTIFICATES, CERTIFICATES\\), CERT, CERTS, STK\\.
New Zealand	RTS, RIGHTS
Peru	INVERSION, INVN, INV
Philippines	PDR
South Africa	N’, OPTS\\., CPF\\., CUMULATIVE PREFERENCE
Sweden	CONVERTED INTO, USE, CONVERTED-, CONVERTED - SEE
Switzerland	CONVERTED INTO, CONVERSION, CONVERSION SEE
United Kingdom	PAID, CONVERSION TO, NON VOTING, CONVERSION ’A’

Table A.6: Dynamic Screens

The table displays the dynamic screens applied to the data in our study, following Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016) and Schmidt et al. (2017). If screens are adapted solely to monthly (daily) returns, this is indicated by m (d). Column 3 lists the respective Datastream items. Column 4 refers to the source of the screens.

Nr.	Description	Datastream item(s) involved	Source
(1)	We delete the zero returns at the end of the return time-series, which exist, because in case of a delisting Datastream displays stale prices from the date of delisting until the end of the respective time-series. We also delete the associated market capitalizations.	TRI, MV	Ince and Porter (2006)
(2)	We delete the associated returns and market capitalizations in case of abnormal prices (unadjusted prices > 1000000).	TRI, MV, UP	The screen originally stems from Schmidt et al. (2017), whereby we employ it on the unadjusted price.
(3m)	We delete monthly returns and the associated market capitalizations in case of return spikes (returns > 990%).	TRI, MV	Schmidt et al. (2017)
(3d)	We delete daily returns and the associated market capitalizations in case of return spikes (returns > 200%).	TRI, MV	Griffin et al. (2010)
(4m)	We delete monthly returns and the associated market capitalizations in case of strong return reversals, defined as follows: R_{t-1} or $R_t >= 3.0$ and $(1+R_{t-1})(1+R_t)-1 < 0.5$.	TRI, MV	Ince and Porter (2006)
(4d)	We delete daily returns and the associated market capitalizations in case of strong return reversals, defined as follows: R_{t-1} or $R_t >= 1.0$ and $(1+R_{t-1})(1+R_t)-1 < 0.2$.	TRI, MV	Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016)
(5)	We delete the associated returns and market capitalizations in case of a missing past-36-month return history.	TRI, MV	Blitz et al. (2011), Blitz et al. (2018).