Filtered Momentum Strategy*

Sangwon Suh†

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Abstract

In this paper, we propose a new method to improve the conventional momentum strategy. The new method modifies the conventional momentum strategy by filtering out equities with low predictability of momentum signal for future momentum profits. We apply the new method into equity data and find that the new momentum strategy significantly outperforms the conventional strategy. The outperformance of the new method is robust to various specification changes. We also conduct additional analyses to supplement the main results.

Keywords: Momentum, Sorting, Filtered sorting, Portfolio performance.

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†School of Economics, Chung-Ang University; Email: ssuh@cau.ac.kr.

1 Introduction

A momentum strategy bets on the ability of past returns to predict future returns and prescribes to buy past winners and to sell past losers among a cross section of assets. Momentum profits have been tested across multiple time periods, in many markets, and in numerous asset classes. A large body of literature has documented significantly positive and pervasive momentum profits.[1] Momentum strategies are also widely used by practitioners (e.g., Grinblatt and Titman (1989, 1993)).

Motivated by significant profits of the momentum strategy, there exists literature which aims to improve momentum profits. For example, a double sort strategy based on a combination of momentum and reversal signals was examined in commodity futures contracts (Bianchi, Drew, and Fan (2015)) and in international equity market indices (Malin and Bornholt (2013)). Balvers and Wu (2006) proposed a parametric combination of momentum and mean reversion and applied it into international equity market indices. Rachev, Jašić, Stoyanov, and Fabozzi (2007) and Choi, Kim, and Mitov (2015) modified the momentum strategy by sorting based on reward-risk measures. De Groot, Karstanje, and Zhou (2014) used term-structure information to implement momentum strategy in commodity futures contracts. Blitz, Huij, and Martens (2011) proposed sorting stocks according to their past residuals instead of gross returns to produce more stable momentum profits. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) proposed new momentum strategies to manage momentum crash risks. Suh and Kim (2017) used investor sentiment to improve momentum profits and prescribes decisions to make more (less) investment with optimistic (pessimistic) sentiment. Our paper is related to this literature. In this paper, we propose a new way to improve momentum profits by using a filtered sorting method.

[1] For example, Jegadeesh and Titman (1993) and Asness (1994) sorted firms on the basis of three- to 12-month past returns and showed momentum profits in U.S. common stock returns from 1965 to 1989. Jegadeesh and Titman (2001) also documented momentum profits in a later period from 1990 to 1998. Israel and Moskowitz (2013) extended the period from 1927 to 1965 and from 1990 to 2012. Momentum profits were also documented in industry portfolios (Moskowitz and Grinblatt (1999)), in developed and emerging equity markets (Rouwenhorst (1998; 1999)), in country indices (Asness, Liew, and Stevens (1997)), in currencies (Okunev and White (2003)), in commodities (Erb and Harvey (2006)), and in exchange traded futures contracts (Moskowitz, Ooi, and Pedersen (2012)). Asness, Moskowitz, and Pedersen (2013) also reported momentum profit evidences across multiple markets and asset classes.

The profitability of the momentum strategy crucially relies on the predictive ability of past returns (momentum signal) for future returns. We guess that its predictive ability may differ across a cross section of assets and vary over time. In this paper, we try to improve the momentum strategy based on this conjecture. Suh (2017) proposed a filtered sorting method and used it into a currency carry trade strategy in which the new method first filters out currencies with low predictability of forward discount and then implements the usual currency carry trade strategy only with a subset of selected currencies. He documented evidences that the new currency carry trade strategy significantly improves portfolio performance. Since the filtered sorting method can be applied into a wide range of information variables for sorting, we will apply it to momentum signal for improving the momentum strategy. We expect that the filtered sorting method can enhance the predictive ability of momentum signal and thus improve momentum profits. We call this new momentum strategy as the "filtered" momentum strategy.

We apply the filtered momentum strategy into U.S. individual stocks. Our empirical results reveal several findings. First, the predictive ability of momentum signal for future returns turns out to be sufficiently differentiated across equities. Second, the new momentum strategy can significantly improve the momentum profits. Third, the relative outperformance of the new momentum strategy is robust to various specification changes. We obtain similar results in the presence of transaction costs and with various ways of momentum portfolio formation and filtered sorting. Our new strategy has an advantage of offering investors an effective way of enhancing momentum profits. Our result also deepens the puzzle related with momentum anomalies.

The rest of this paper is organized as follows. Section 2 introduces the new "filtered" momentum strategy and compares it with the usual momentum strategy. Section 3 explains the data to be used in our empirical analysis, presents performance results of the new strategy relative to the conventional one and analyzes the mechanism behind the relative outperformance of the new strategy. In Section 4, we provide results for some robustness checks and from additional analyses. We consider the effect of transaction costs on momentum profits and alternative filtering methods. Section 5 concludes the paper.

2 Methodology

2.1 Momentum portfolios

To construct momentum portfolios, we follow the methodology of Jegadeesh and Titman (1993). Specifically, we sort all stocks in ascending order based on their returns for the past J months (from $t-J-1$ to $t-2$) in each month t. We skip month $t-1$ in order to allow one month between the end of the formation period and the beginning of the holding period, which helps to avoid microstructure biases. We form ten equal-weighted portfolios with stocks belonging to each of these sorts. We call the tenth decile ($P10$) as the "winner" portfolio and the first decile ($P1$) as the "loser" portfolio. Every month, the momentum (MOM) strategy prescribes to form a long-short portfolio by going long in the winner portfolio and short in the loser portfolio. We construct overlapping portfolios by holding the long-short portfolio for K months and by revising $1/K$ of the stocks; that is, we close the positions in the winner and loser portfolios initiated in month $t-K$, open those initiated in month $t-1$, and carry over the rest from the previous month. The (overlapping) momentum portfolio return at t, $R_{MOM,t}$, is computed as

$$R_{MOM,t} = \frac{1}{K}\sum_{k=1}^{K}\left[R10_{t-k,k} - R1_{t-k,k}\right], \tag{1}$$

where $R10_{t-k,k}$ ($R1_{t-k,k}$) denotes the return at time t of the tenth (first) decile portfolio which is formed at $t-k$. In our analysis, we consider eight cases: $J = 6, 11$ and $K = 1, 3, 6, 12$.[2]

2.2 Filtered momentum portfolios

The filtered momentum (FMOM) strategy consists of two stages to form momentum portfolios. In the first stage, we assess the predictive ability of momentum signal (past J-month

[2] For example, Antoniou et al. (2013) consider three cases with $J = 6$ and $K = 3, 6, 12$. French and Daniel and Moskowitz provide momentum portfolio results with $J = 11$ and $K = 1$ in their web pages. Jegadeesh and Titman (1993) form 16 momentum portfolios with $J = 3, 6, 9, 12$ and $K = 3, 6, 9, 12$. We believe that our choice is typical one in the literature.

returns) for future returns and then sort out assets with low return predictability from the set of investable assets. In the second stage, we employ the usual method of forming momentum portfolios with the equities selected in the first stage.

To assess the ability of momentum signal to predict the return for K-month holding period, we employ an indicator called as the *signal ratio*. The signal ratio is a count-based index of predictive ability of an information variable; it is formally defined as the ratio of the difference between the number of correct predictions and the number of incorrect predictions to the total number of periods for assessment. By construction, the signal ratio ranges from -1 to 1, and the higher the signal ratio the greater the predictive ability of momentum signals. Since the momentum strategy bets on the belief that past winners (losers) would lead to positive (negative) returns, we regard the prediction as "correct" if the momentum signal and the next $K-$month holding period return have the same sign and as "incorrect" otherwise. More formally, the signal ratio $\omega_{j,t}$ at time t for equity j is computed as

$$\omega_{j,t} = \frac{1}{M} \sum_{m=1}^{M} \left[I_{s_{j,t-m-K} \times f_{j,t-m-K} > 0} - I_{s_{j,t-m-K} \times f_{j,t-m-K} \leq 0} \right], \tag{2}$$

where I_A is an indicator function to indicate one when the condition A holds and zero otherwise, and M is the number of assessment periods. The momentum signal for asset j at time $t-m-K$ is denoted by $s_{j,t-m-K}$ which indicates its past J-month return from $t-m-K-J$ to $t-m-K-1$, while $f_{j,t-m-K}$ denotes asset j's future K-month holding period return from $t-m-K+1$ to $t-m$. The signal ratio is computed with a rolling window to capture a potential time-varying characteristics of the predictive ability of momentum signals.

We sort out assets with signal ratio less than a threshold level $\overline{\omega}_t$ at each month t. We use historical long-short portfolio returns to determine the threshold level for asset selection. Formally, the threshold level $\overline{\omega}_t$ at each month t, is determined as a level to maximize the historical average return of the long-short portfolio:

$$\overline{\omega}_t \in \arg\max_{\overline{\omega}} \frac{1}{t-J-K-2} \sum_{\tau=J+K+2}^{t-1} \left[R10_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right) - R1_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right) \right], \tag{3}$$

where $S(\overline{\omega})$ indicates the set of assets available for investment when the threshold level $\overline{\omega}$ is applied for equity selection, and $R1_{\tau-K,K}(S(\overline{\omega}))$ and $R10_{\tau-K,K}(S(\overline{\omega}))$ denote the returns of $P1$ and $P10$ with the set of assets $S(\overline{\omega})$ at month τ, respectively, which are formed at $\tau - K$ and held for K-month holding period. If the signal ratios change over time, the threshold level $\overline{\omega}_t$ would also change over time. The threshold level can be easily found via a grid search over the range $[-1,\ 1]$.

Lastly, the return of the FMOM at month t is computed as

$$R_{FMOM,t} = \frac{1}{K}\sum_{k=1}^{K}\left[R10_{t-k,k}\left(S\left(\overline{\omega}_{t-k}\right)\right) - R1_{t-k,k}\left(S\left(\overline{\omega}_{t-k}\right)\right)\right]. \tag{4}$$

Note that the FMOM strategy prescribes decisions to dynamically change the set of equities to form momentum portfolios.

3 Empirical analysis

3.1 Data

We will apply the FMOM strategy into the U.S. individual equities. We use all common stocks (share codes 10 and 11) listed in the New York and American Stock Exchanges from the Center for Research in Security Prices (CRSP) monthly file. The sample time period is from January 1967 to December 2015. We delete all stocks that are priced less than \$1 at the beginning of the holding period.

3.2 Portfolio performance

In this subsection, we compare the portfolio performances of both strategies in various ways.

Summary statistics. Figure 1 shows cumulative returns of the MOM and the FMOM strategies for each of eight momentum portfolio formation cases over the sample period. Remarkably, the FMOM strategy shows cumulative returns which have grown much faster that those of the MOM strategy in all cases. Table 1 presents summary statistics of the profits from both strategies. The MOM strategy generates significantly positive and high mean returns (ranging from 7% to 15% per annum) in all cases, which is consistent with the literature on momentum strategy. More interestingly, the FMOM strategy yields much higher mean returns (ranging from 30% to 81% per annum) than the MOM strategy in all cases. Although the FMOM strategy yields higher volatilities than the MOM strategy, the Sharpe ratios of the FMOM strategy (ranging from 0.37 to 0.85) are higher than those of the MOM (ranging from 1.03 to 2.45) in all cases. The MOM profit tends to be more negatively skewed than the FMOM profit, while the former has fatter tail than the latter (except for the 12-month holding period). The profits of both strategies tend to be smaller for a longer holding period.

Risk-adjusted returns. We examine whether the higher returns of the FMOM strategy simply reflect more loadings on economic risk factors. To account for the effect of risk-taking on momentum profits, we compute risk-adjusted (filtered) momentum profits from the CAPM, Fama-French 3-factor model (FF3), and Fama-French-Carhart 4-factor model (FF4). In accordance with Cooper, Gutierrez, and Hameed (2004), we regress momentum profits on asset pricing risk factors and use factor loadings and factor realizations to estimate risk-adjusted excess return for each momentum portfolio and hold-period month, from which we then compute the risk-adjusted (filtered) momentum profits of overlapping momentum portfolios.

Table 2 presents the CAPM, FF3, and FF4-adjusted (filtered) momentum profits. While the risk-adjusted returns of the MOM strategy are significantly positive in all cases, the risk-adjusted returns of the FMOM strategy are much greater than those of the MOM strategy. For 6-month formation ($J = 6$) and 6-month holding period ($K = 6$) as an example, the MOM profits are 15.2% (CAPM), 15.5% (FF3), and 12.4% (FF4) per annum while the FMOM profits are 57.6% (CAPM), 58.3% (FF3), and 53.7% (FF4). The difference between the risk-adjusted returns of both strategies is positive and highly significant in all cases. This result implies that the higher returns of the FMOM strategy (relative to the MOM strategy) remain robust to these risk-adjustments.

Investment horizon. One-period analysis holds true for multi-periods only under some restrictive assumptions.[3] With general (and realistic) situations, it would be desirable to measure performance over an appropriate horizon. In that sense, it would be legitimate to compare cumulative returns of both strategies as shown in Figure 1, if an investor's investment horizon coincides with the sample period. However, this investment horizon seems unrealistically too long. On the other hand, one-month horizon seems to be too short, with which performances are measured and shown in Table 1. Although investment horizons are various, we will consider two horizons (5- and 10-year) to deliver more realistic results in this analysis. Figure 2 shows the time trend of 10-year rolling cumulative return of both momentum strategies. The Internet Appendix (Figure A3) also illustrates the cases with 5-year horizon. With 10-year horizon, the FMOM strategy delivers better performance than the MOM strategy in all periods and all cases. These results also hold for the cases of 5-year horizon.

Hypothesis tests. Figure 3 illustrates empirical densities of both momentum profits with 10-year horizon. The MOM strategy yields positive returns in most chances. While the FMOM returns tend to be more dispersed than the MOM returns, they distribute over a much higher range than the MOM returns in all cases. We obtain similar results for the case with 5-year horizon which is demonstrated in the Internet Appendix (Figure A4). Although the Sharpe ratio (SR) has been popularly used as a performance measure, it does not distinguish between a downside risk and an upside potential and unduly penalizes high volatility even when it is associated with positive and high returns, which is not a risk, but rather a potential gain. To take into account this consideration, we not only use the SR but also other measures for formal hypothesis tests.

The downside risk (or downside deviation), DR, measures the risk that returns are less

[3] For example, if returns follow an identically and independently normal dirstibution, then a one-period analysis can also hold for multi-periods. For both momentum profits, we draw qq-plots (Figure A1 in the Internet Appnedix) and autocorrelation function (Figure A2 in the Internet Appnedix) and perform several normality tests (Anderson–Darling test, Jarque–Bera test, Kolmogorov–Smirnov test, and Shapiro–Wilk test) and serial independence tests (Breusch-Godfrey test and Ljung-Box test), whose results are reported in the Internet Appnedix (Table A1). All of these results significantly support the alternative hypotheses that momentum profits are non-normal and serially dependent.

than a target return level T. Formally, the DR is defined as

$$DR = \left[\int_{-\infty}^{T} (T - r)^2 f(r)\, dr \right]^{1/2}, \tag{5}$$

where $f(r)$ denotes the density of the (F)MOM returns.

The Sortino ratio (SO), a variant of the SR, penalizes only with downside risk, unlike the SR.[4] Specifically, the SO is defined as

$$SO = \frac{R - T}{DR}, \tag{6}$$

where R indicates average (F)MOM returns.

The upside potential ratio (UP) penalizes upside gains (relative to a target return) with downside risk. The UP is computed as

$$UP = \frac{\int_{T}^{\infty} (r - T) f(r)\, dr}{DR}. \tag{7}$$

Lastly, the omega ratio (OM) measures the ratio of upside gain to downside loss relative to a target return and is formally defined as

$$OM = \frac{\int_{T}^{\infty} (r - T) f(r)\, dr}{\int_{-\infty}^{T} (T - r) f(r)\, dr}. \tag{8}$$

Based on the above four measures, we formally test the null hypothesis that both momentum strategies equally perform against the alternative hypothesis that the FMOM performs better than the MOM strategy. The p-value is calculated using a bootstrapping method.[5] Table 3 presents the hypothesis test results based on the four performance measures and for eight cases with 10-year horizon. For performance comparison, we set the target return as the mean return of the MOM strategy (Panel A), with which the SO is zero, and the OM

[4] Refer to, for example, Sortino and Price (1994).

[5] We employ a block bootstrapping method to account for potential serial dependence. We also conduct a bootstrapping method assuming serial independence for robustness check. We find that both results are qualitatively similar in our analysis.

is one for the MOM strategy. The SR of the FMOM strategy is significantly higher than that of the MOM strategy for all cases. Moreover, the other three performance measures amount to infinity with zero downside deviation, rejecting the null hypothesis and supporting the alternative hypothesis. That is, the FMOM strategy outperforms the MOM strategy by providing significant relative upside gains. Alternatively, we set the target return as the mean return of the FMOM strategy (Panel B), which yields zero SO and unity OM for the FMOM strategy. With this alternative target return level, we can obtain finite values for the measures and still reach the same results. We also obtain similar results for the case with 5-year horizon (which are presented in Table A2 of the Internet Appendix).

3.3 Understanding the performance improvement

In this subsection, we analyze the mechanism through which the FMOM strategy outperforms the MOM strategy.

Distribution of signal ratios. Since the filtered sorting method relies on the notion that return predictability is sufficiently differentiated across assets, we first examine whether it is the case for individual equities. Figure A5 (in the Internet Appendix) shows empirical densities of the signal ratios of the sample equities over the sample period, and Table 4 presents the summary statistics. It reveals that the sample equities are sufficiently differentiated with respect to the signal ratio. For the case of 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$) as an example, the average signal ratio ranges from -0.54 to 0.66 with the mean (75th percentile) signal ratio of 0.037 (0.112), and 62.5% of equities show positive signal ratios. While many equities show a high signal ratio, many other equities also show a low or even negative signal ratio. This fact implies that sorting out such equities could help to improve portfolio performance. Signal ratios across equities tend to be not only more dispersed but also higher on average with a longer holding (or formation) period.

Accuracy ratios. To better understand the performance improvement by the FMOM strategy from the view of the signal ratio, Figures 4 and 5 show average signal ratios of decile portfolios for both the MOM and FMOM strategies, respectively. The MOM decile portfolios show an uneven distribution of average signal ratios. Interestingly, the tenth decile portfolio shows relatively high signal ratio. Similarly, the first decile portfolio shows relatively high signal ratio, compared to its adjacent decile portfolios.[6] As Figure 5 illustrates, the signal ratio becomes much higher in the FMOM decile portfolios, which results from filtering out low signal-ratio equities. Unlike the MOM case, the signal ratio distributes more evenly in the FMOM case.

To take a closer look at the link between the signal ratio and portfolio performance, we devise a measure (called as *accuracy ratio*) to indicate how accurately equities are allocated into portfolios. The accuracy in equity allocation is determined in an ex-post sense. That is, bottom 10% equities based on *realized* returns should be accurately allocated into the first decile portfolio (P1), the next 10% equities should be allocated into the second decile portfolio (P2), and so on. Thus, these accurate portfolios are unreal but ex-post optimal. The accuracy ratio (AR1) indicates the ratio of the number of equities belonging to their accurate portfolios to the total number of equities available at each period. Specifically, the AR1 is defined as

$$AR1_{d,t} = \frac{\#\left\{j \,\middle|\, j \in P_{d,t} \cap P_{d,t}^{opt}\right\}}{\#\left\{j \,\middle|\, j \in P_{d,t}\right\}}, \tag{9}$$

where decile portfolios are indexed by $d\,(= 1, ..., 10)$, individual equities are indexed by j, the set of equities belonging to d-th decile portfolio is denoted by P_d, P_d^{opt} denotes the ex-post optimal d-th decile portfolio, and $\#\{\cdot\}$ denotes the number of elements of a set $\{\cdot\}$. Note that the AR1 is 0.1 for a benchmark case where allocation is randomly made or based on uninformative signals.

In addition, an alternative accuracy ratio (AR2) measures the allocation inaccuracy by the difference between the decile numbers of two portfolios: ex-post optimal and signal-based momentum portfolios. We divide the decile number difference by the uninformative mean difference, therefore the AR2 is zero for the uninformative benchmark case. Formally, the

[6] Together with the fact that signal ratios are positive on average, this feature might contribute to a high performance of the MOM strategy.

AR2 is computed as

$$
\begin{aligned}
AR2_{d,t} &= 1 - \frac{\sum_{j \in P_{d,t}} \left| d - d^{opt}(j) \right|}{MD_d \times \# \left\{ j \,|\, j \in P_{d,t} \right\}}, \\
MD_d &= \frac{1}{10} \sum_{i=1}^{10} \left| i - d \right|,
\end{aligned}
\tag{10}
$$

where $d^{opt}(j)$ denotes the decile number of ex-post optimal decile portfolio for j-th equity belonging to d-th decile portfolio, and MD_d denotes the uninformative mean difference of decile numbers for the d-th decile portfolio. Obviously, a positive AR indicates a more accurate portfolio allocation than the benchmark uninformative allocation, and both AR measures are bounded above by one.[7]

Figure 6 contrasts the mean accuracy ratios (AR1 and AR2) of decile momentum portfolios over the sample period for both strategies. For both accuracy measures, the MOM strategy shows a higher accuracy across decile portfolios than an uninformative allocation, which contributes to its high profits.[8] The FMOM strategy shows a much higher accuracy across decile portfolios, compared not only to the uninformative allocation but also to the MOM strategy for both accuracy measures. This result implies that a filtered sorting in the FMOM portfolios not only increases signal ratios but also improves accuracy ratios.

Distribution of equity returns. If filtering out equities with low signal ratio significantly alters return characteristics of equities, then it may also affect relative performance of the FMOM strategy. We examine whether return characteristics of equities before and after the filtering-out differ each other or not. Figure 7 contrasts two empirical densities of equity returns with and without a filtering for the case of 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$), and Table A3 (in the Internet Appendix) shows the summary statistics for eight cases of momentum portfolio formation. In all cases, the fil-

[7] While the $AR1_d$ is bounded below by -1, the $AR2_d$ has a variable lower bound which depends upon the decile number d.

[8] While the average signal ratios of the MOM strategy unevenly distribute across decile portfolios, the accuracy ratios distribute more evenly. This discrepancy is attributable to the fact that the signal ratio should be constructed based on relative ranks of predictive values to be consistent with the accuracy ratios whereas it is constructed based on the direction of prediction.

tering does not significantly change characteristics of equity return distribution. This result implies that performance improvement by the FMOM strategy mainly comes from accuracy improvement in portfolio allocation.

Signal ratio thresholds. The threshold of the signal ratio for equity selection is optimally determined based on historical portfolio performance at each month and thus is time-varying. We use an initial 36-month period ($M = 36$) to compute the signal ratio. To maintain a minimum level of diversification, we include at least 100 equities (i.e., minimum ten equities in each portfolio) for forming the new portfolios. Figure 8 illustrates the time trend of the signal ratio threshold (Panel A), the proportion of equities included in the FMOM portfolios relative to the MOM portfolios (Panel B), the number of stocks included in the FMOM (Panel C) and in the MOM (Panel D) strategies for the case of momentum portfolio formation with 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$).[9]

As shown in Figure 8, the signal ratio threshold is time-varying, ranging from 0.2 to 0.4., which explains the fact that the average signal ratios exceed 0.3 across decile FMOM portfolios in Figure 5. Panel C shows that the condition of minimum required number of stocks is binding in many periods. The proportion of equities included in the FMOM portfolios has remained low, ranging between 5% and 10% in most periods.

4 Robustness and additional analyses

In this section, we provide results for some robustness checks and from additional analyses.

4.1 Transaction costs

In our above analysis, we do not take into account of the effects of transaction costs on momentum profits. We first investigate whether the FMOM strategy requires more trade volume for its implementation than the MOM strategy. Then, we formally conduct hypothesis tests based on profits net of transaction costs. Intuitively, since the FMOM strategy

[9] For other cases, we obtain similar results which are omitted for brevity.

changes position according to more accurate signals, is may require few trades. On the other hand, it uses only a few selected equities, and the selection itself might incur additional trades. Due to these two opposite effects, it is an empirical issue whether the FMOM strategy would require more trade volume than the MOM strategy.

Table 5 shows the trade volume of both strategies which is measured as the ratio to investment amount. Since both momentum strategies construct a long-short portfolio, the maximum trade volume for both strategies is four (which occurs when selling all existing stocks and buying new stocks in the long position and closing all existing stocks and opening new stocks in the short position). For overlapping portfolio, trade volume would decrease with a longer holding period (because it requires only partial rebalancing each period), and the maximum trade volume is $4/K$ for a K-month holding period. We find that both strategies incur similar trade volume. Noteworthily, the FMOM strategy incurs more trade volume than the MOM strategy only for a short holding period ($K = 1$) but less trade volume for the other holding periods ($K = 3, 6, 12$). On the other hand, the FMOM strategy shows higher volatilities in trade volume than the MOM strategy.

Following DeMiguel, Garlappi, and Uppal (2009), we assume transaction costs of 50 basis points.[10] Table 6 shows summary statistics of the momentum profits net of transaction costs. The momentum profits significantly decrease after deducting transaction costs. For the case of 6-month formation period ($J = 6$) and 6-month holding period ($K = 6$) as an example, the mean annualized MOM and FMOM net returns are 10.4% and 52.9% which are lower by 3.5%p and 3.8%p than the corresponding gross returns, respectively. Although transaction costs significantly reduce momentum profits, both momentum strategies still yield positive and high net returns. Moreover, Table A4 (in the Internet Appendix) shows that the formal hypothesis test results based on net returns (with 10-year horizon) are similar to those with gross returns. In sum, the relative outperformance of the FMOM strategy still holds in the presence of transaction costs.

[10] More recently, DeMiguel, Nogales, and Uppal (2014) assumed proportional transaction cost rates of 10 bps and 5 bps, reflecting the fact that transaction costs tend to decrease over time. Similarly, Fleming, Kirby, and Ostdiek (2003) assumed 1 bp cost, and Frazzini, Isreal, and Moskowitz (2015) assumed 10 bps. However, we assume a high level of transaction costs (50 bps) to obtain conservative results. Alternatively, Lesmond, Schill, and Zhou (2004) inferred costs indirectly from observed trading behavior.

4.2 Alternative filtering criteria

We have determined the signal ratio threshold level by maximizing the historical average return of the long-short portfolio (Avg) as (3). Since this method is not unique, we will consider alternative filtering criteria and examine how results are sensitive to various filtering criteria. Particularly, we consider the four performance measures used for hypothesis tests as alternative filtering criteria. For example, we use the SR measure to determine threshold $\overline{\omega}_t^{SR}$ as follows:

$$\overline{\omega}_t^{SR} \in \arg\max_{\overline{\omega}} \frac{\overline{\Delta}_t}{\sigma_t(\Delta)}, \tag{11}$$

with

$$\begin{aligned}
\overline{\Delta}_t &= \frac{1}{t-J-K-2} \sum_{\tau=J+K+2}^{t-1} \Delta_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right), \\
\sigma_t^2(\Delta) &= \frac{1}{t-J-K-3} \sum_{\tau=J+K+2}^{t-1} \left(\Delta_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right) - \overline{\Delta}_t\right)^2, \\
\Delta_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right) &\equiv R10_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right) - R1_{\tau-K,K}\left(S\left(\overline{\omega}\right)\right),
\end{aligned}$$

where Δ denotes the return of the long-short portfolio with its sample mean of $\overline{\Delta}$ and sample standard deviation of $\sigma(\Delta)$. Similarly, we use the other measures SO, UP, and OM to determine thresholds.[11] In addition, we also consider a signal ratio threshold of zero (Pos). Note that it is the minimum threshold level to include informative signals and thus constructs the largest set of equities.

Table 7 presents summary statistics of the FMOM strategy with alternative filtering criteria, and Figure 9 shows the cumulative momentum profits. Several observations emerge. Table 8 shows the results of hypothesis tests for the FMOM strategies with alternative filtering criteria and with two target criteria: the "Pos" and the "SR". First, the FMOM strategy still outperforms the MOM strategy with alternative filtering criteria.[12] Second,

[11] We omit formal expressions for these measures for brevity.

[12] We believe that this result is clear from Figure 9 and Table 7 and omit formal hypothesis testing for brevity.

while the FMOM with the "Pos" criterion outperforms the MOM strategy, it is inferior to other optimal criteria which is statistically confirmed in Table 8. Third, the "SR" criterion yields not only a lower mean return but also a lower volatility than other optimal criteria. The hypothesis test results in Table 8 show that the "SR" criterion is inferior to other optimal criteria based on measures other than the SR. Fourth, optimal criteria other than the "SR" show similar performances.[13]

4.3 Alternative signal ratio windows

Next, we are interested in analyzing the informativeness of the "rolling" signal ratio in improving portfolio performance. We examine whether the FMOM performance is sensitive to the length of rolling window for computing signal ratios. A short window could appropriately capture a potential time-varying feature whereas a long window can reap an estimation efficiency. It is an empirical issue to determine an optimal window length or to examine the effect of the window length on performances. We consider alternative windows other than the benchmark 3-year rolling window: 5-year, 10-year, and recursive windows.

Figure 10 shows the cumulative momentum profits of the FMOM strategy with alternative signal ratio windows as well as the MOM strategy, and Table 9 presents the summary statistics. Several remarks are in order. First, although the length of window for computing signal ratio affects the performance of the FMOM strategy, the FMOM strategy still outperforms the MOM strategy for all alternative windows. Second, a 3-year short window tends to deliver relatively better performance, compared with a longer window. For $J = 6$ and $K = 1$ as an example, the FMOM annualized mean return with 3-year window amounts to 71.8% whereas those with 5-, 10-year, and recursive windows are 58.1%, 56.7%, and 55.3%, respectively. This result implies that the predictive ability of momentum signals exhibits a time-varying feature. Third, recursive window tends to yield relatively better performance with a longer holding period. For $J = 11$ and $K = 12$ as an example, the recursive window delivers 30.6% which is close to that of 3-year window (29.7%) whereas those with 5- and

[13] This result may be related with the fact that the condition of the minumim number of 100 equties to be included is binding in many periods. The criteria may become similar with this binding condition, even though they may significantly differ without it.

10-year windows are 26.9% and 24.6%, respectively.

4.4 Alternative minimum numbers of equities

As Panel C of Figure 8 shows, the benchmark minimum number of equities (of 100) is binding in many periods. In this subsection, we examine whether the performance of the FMOM strategy is robust to the choice of the minimum number of equities. We consider several alternative minimum numbers of equities: 10, 50, and 200.

Figure 11 shows cumulative momentum profits (net of transaction costs) of the MOM strategy as well as the FMOM strategy with alternative minimum numbers of equities, and Table A6 (in the Internet Appendix) provides the summary statistics. Several findings emerge. First, the relative outperformance of the FMOM strategy (over the MOM strategy) is robust to various minimum numbers of equities. Second, while the returns from the FMOM strategy with fewer equities tend to be more volatile, they are also higher on average, particularly for short holding periods. Third, taken together the effects of more volatile but higher returns, the FMOM strategy with fewer equities tend to outperform the strategy with more equities, for which Table A7 (in the Internet Appendix) presents formal hypothesis test results. Noteworthily, this result implies that the filtering in the first stage is an "informative" selection, and thus it is not contradictory to diversification benefits. A related evidence will be provided in the next subsection.

4.5 Uninformative filtering

In this subsection, we consider the FMOM strategy with an uninformative filtering.[14] While both the "informative" and "uninformative" FMOM decile portfolios are constructed with the same number of equities, the latter portfolios contain equities that are randomly selected in the first stage.[15] Figure 12 shows cumulative momentum profits of the MOM strategy

[14] If we employ a signal-ratio-based filtering in the first stage to implement the FMOM strategy, we refer to it as an "informative" FMOM strategy. In constrast, an "uninformative" FMOM strategy does not utilize any information variable in the first filtering stage.

[15] As a random sampling, we select equities with an equal interval in our data which contain equities sorted based on "permno" in the CRSP data file.

and the informative and uninformative FMOM strategies. The uninformative FMOM strategy is inferior to the informative FMOM strategy. This result implies that the signal-ratio based filtering is informative and significantly contributes to the profitability of the FMOM strategy. Interestingly, the uninformative FMOM strategy is also inferior to the MOM strategy. This relative underperformance of the uninformative FMOM strategy comes from the losses of diversification benefits with fewer equities. In sum, while diversification benefits explain the difference between the MOM and the uninformative FMOM strategies, the informativeness of the signal-ratio-based filtering explains the difference between the informative and uninformative FMOM strategies. Further, the signal-ratio-based filtering contributes to momentum portfolio improvements more significantly than diversification benefits.

4.6 Momentum crash

It has been well documented that a momentum strategy runs a risk of a profit plunge during a short period (often referred to as "momentum crash"), although it offers significant excess profits at other times.[16] As shown in Figure 13, a momentum crash occurred in 2009 within our sample period. Like the MOM strategy, the FMOM strategy also incurred a momentum crash. However, while the momentum crash could not be fully recovered for the MOM strategy, the FMOM strategy could recover the losses from the momentum crash within three or four years. This rapid recovery from the crash is attributable to a fast growth of the FMOM portfolios.

Recently, Suh and Kim (2017) suggested a sentiment-based momentum strategy which prescribes decisions to make decisions to make more (less) investment with optimistic (pessimistic) sentiments. If a pessimistic signal from sentiment correctly precedes the occurrence of a momentum crash, then the sentiment-based MOM (SMOM) strategy will reduce investments and thus can avoid or mitigate momentum crashes. We can apply the SMOM to the FMOM and call it "sentiment-based filtered" momentum (SFMOM) strategy. Figure 13 contrasts the time trend of cumulative returns of the SFMOM strategy with those of the

[16] See Grundy and Martin (2001), Barroso and Santa-Clara (2015), and Daniel and Moskowitz (2016) for the explanations about momentum crashes. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) also propose new momentum strategies to manage momentum crash risks.

(F)MOM strategy. A combination of the FMOM strategy with the SMOM strategy offers better performances, without incurring momentum crashes.

5 Conclusion

In this paper, we employ a filtered sorting method to form momentum portfolios of equities. The new method first filters out equities with low predictive ability of past returns for future returns. Then, the usual sorting method is applied to form momentum portfolios. Indeed, predictive ability of momentum signals sufficiently differ across a cross section of equities, and the new method works well for momentum portfolio improvements. Empirical evidences with actual data imply that the new momentum strategy significantly outperforms the conventional momentum strategy. We also present evidence that the outperformance of the new method over the conventional one is robust to various specification changes.

While this paper suggests that the new two-stage method is applicable to equity momentum portfolios, it can be used for other trade strategies, other asset classes, or in other markets. This research line would be worthwhile to explore in the future.

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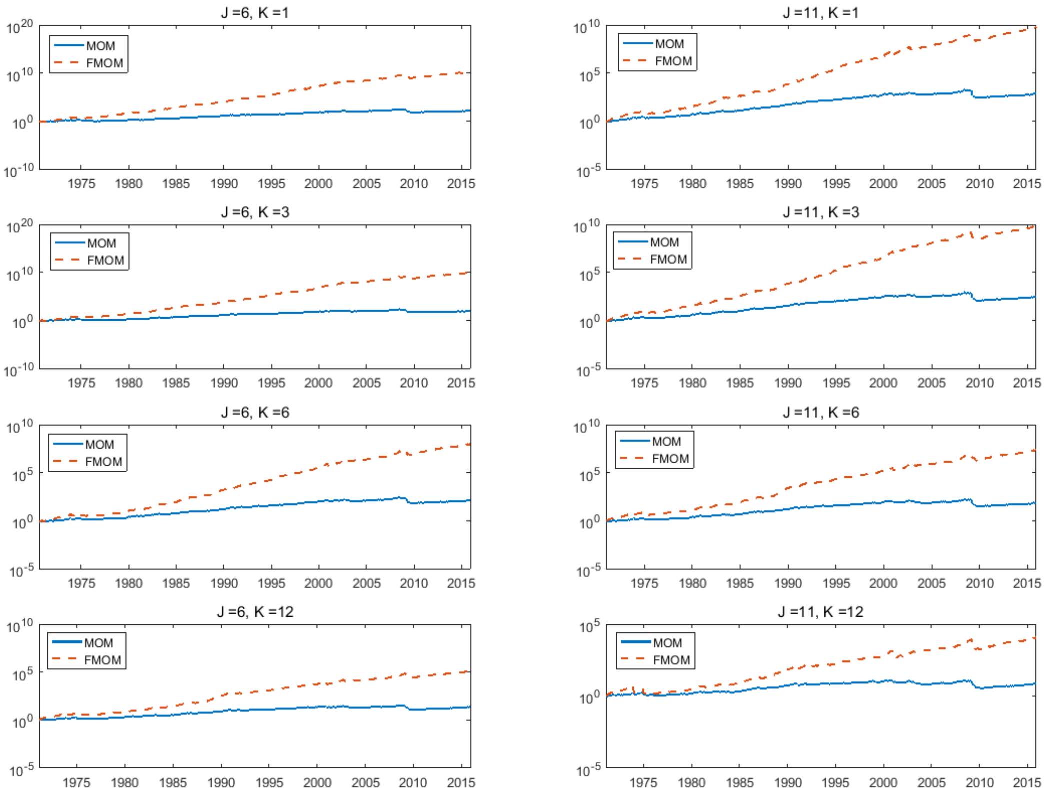

Figure 1. Cumulative momentum profits. This figure shows the time trend of cumulative return of the momentum (MOM) and the filtered momentum (FMOM) strategies. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

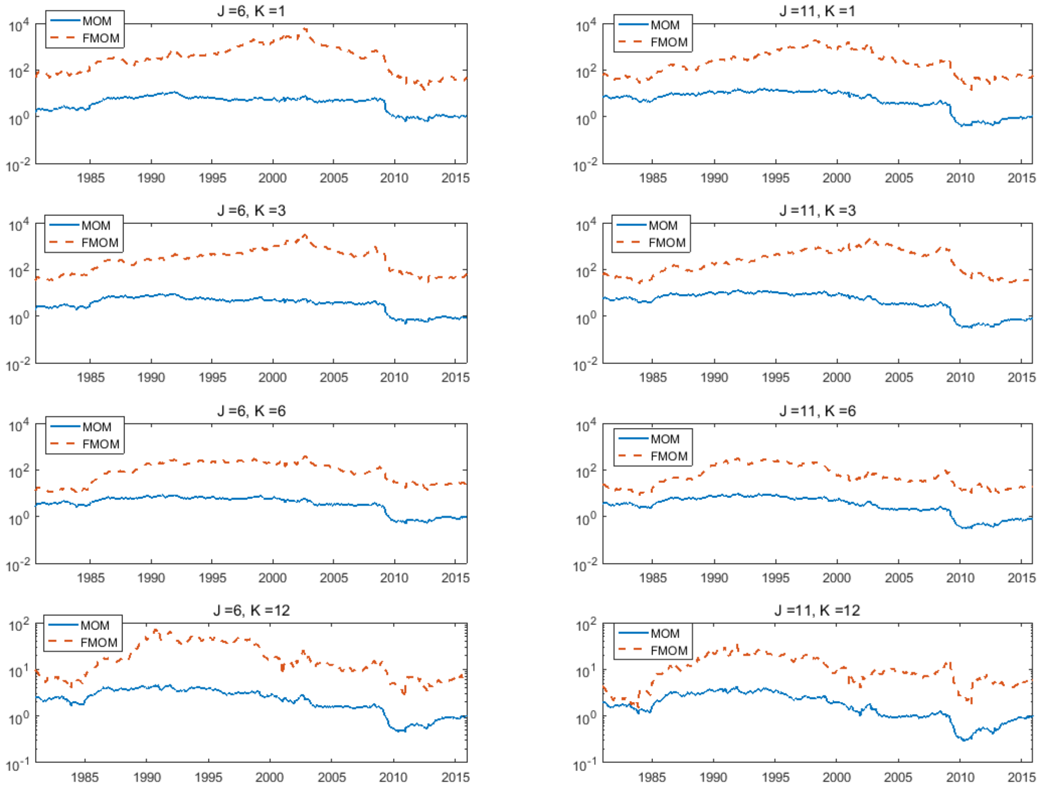

Figure 2. Rolling cumulative momentum profits. This figure shows the time trend of 10-year rolling cumulative return of the momentum (MOM) and the filtered momentum (FMOM) strategies. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

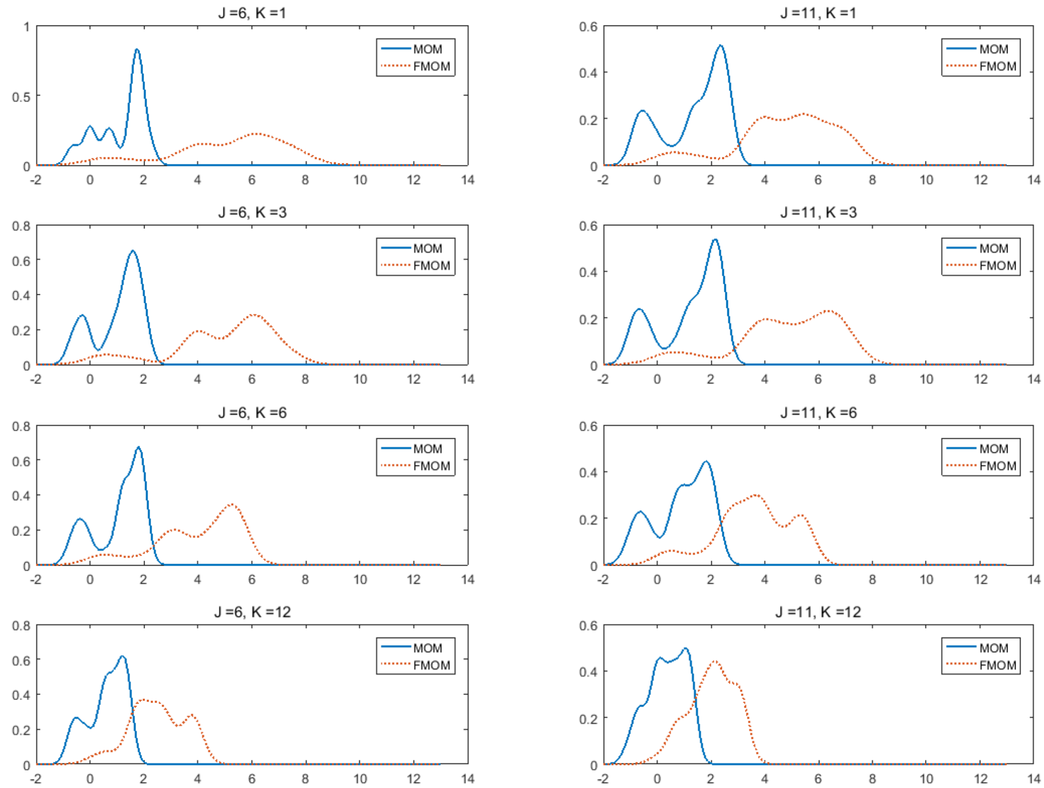

Figure 3. Probability density of rolling cumulative momentum profits. This figure shows the (kernel-smoothing) density function of 10-year rolling cumulative log return of the momentum (MOM) and the filtered momentum (FMOM) strategies. 10-year rolling cumulative log return is indicated in x-axis. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

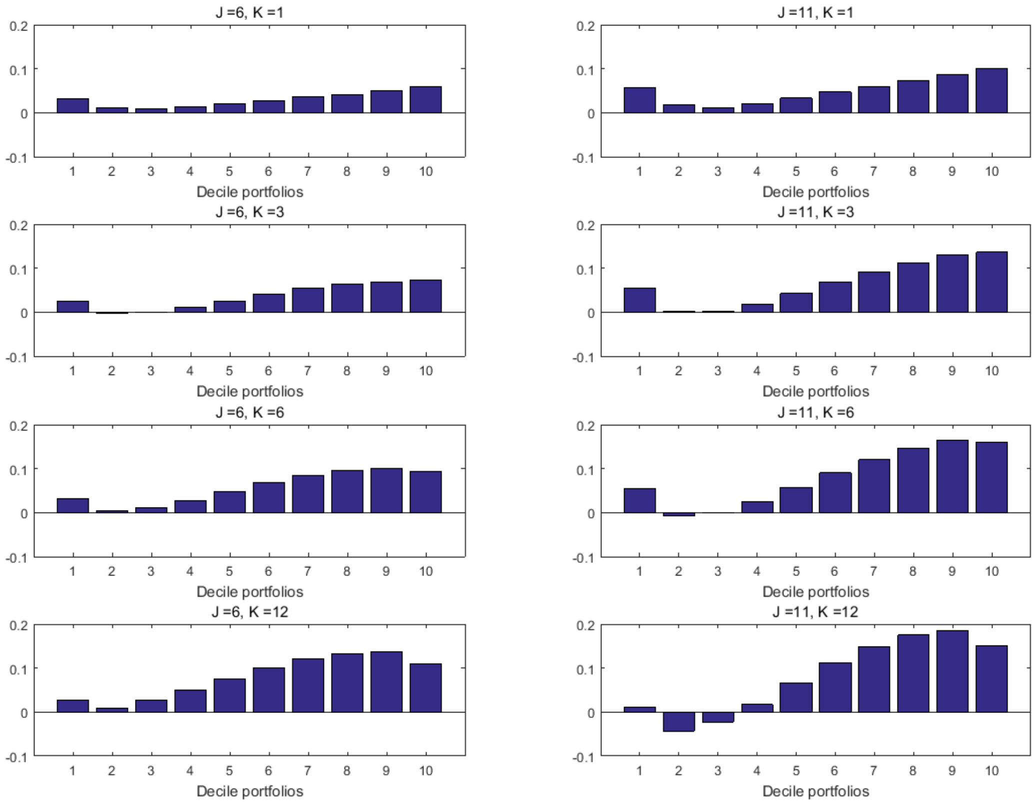

Figure 4. Average signal ratios of decile momentum portfolios. This figure shows the average signal ratios of decile momentum portfolios from the MOM strategy. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

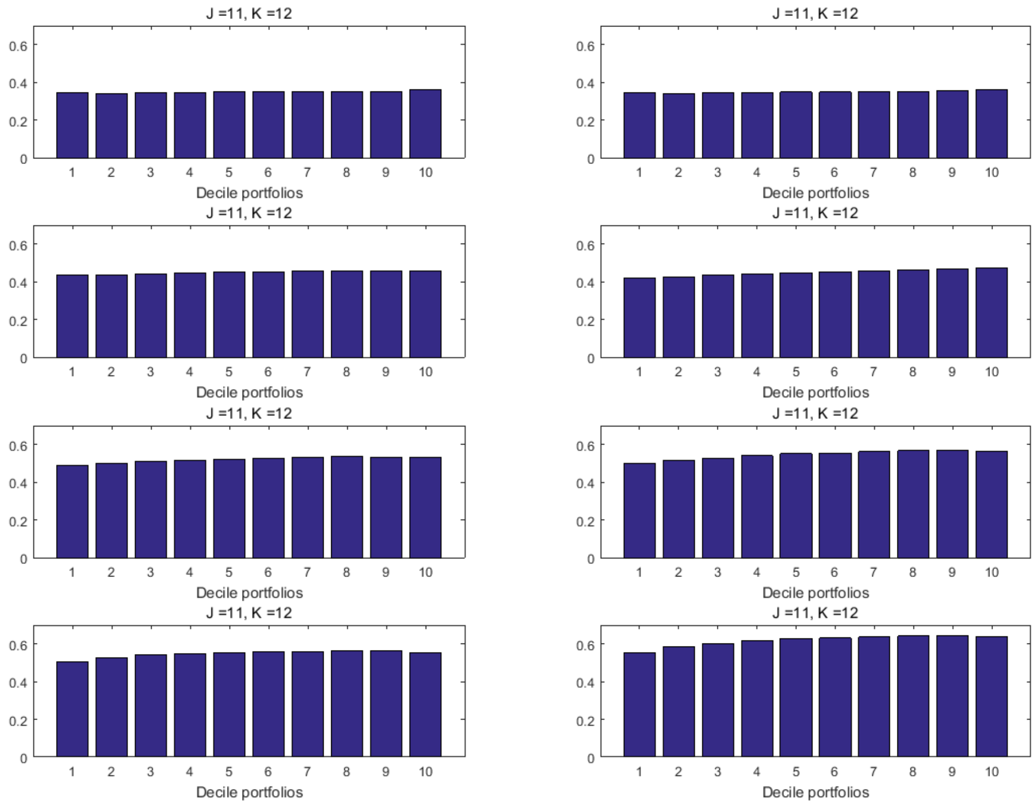

Figure 5. Average signal ratios of decile filtered momentum portfolios. This figure shows the average signal ratios of decile momentum portfolios from the FMOM strategy. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

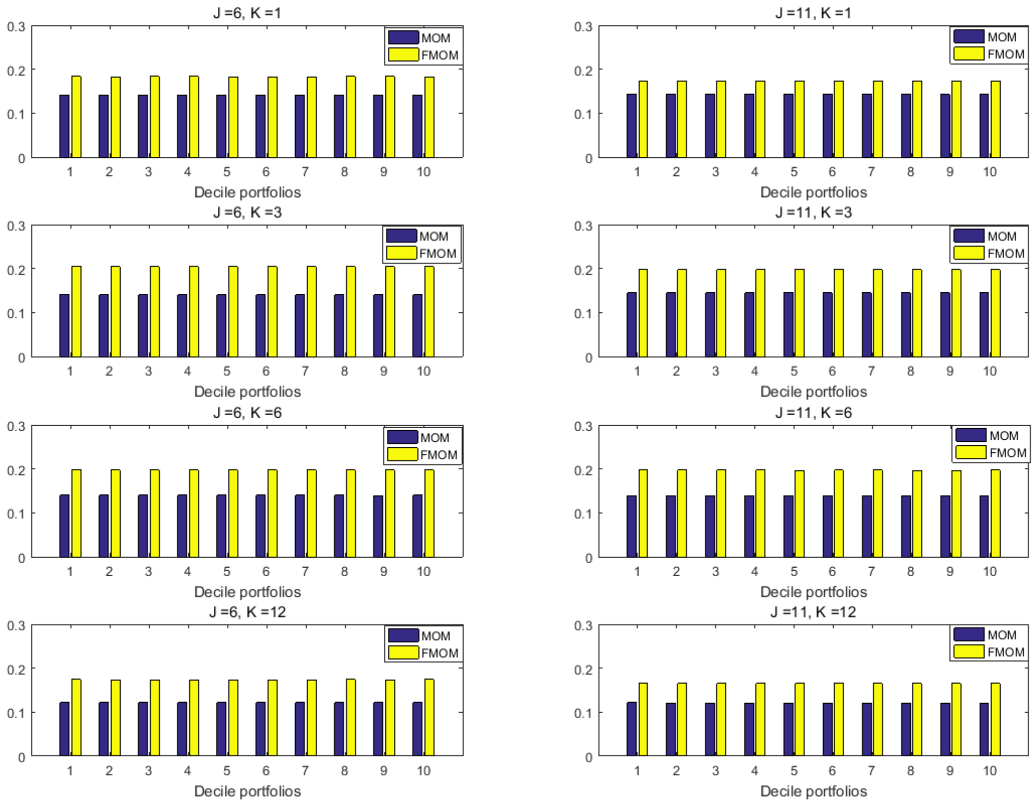

Figure 6-1. Accuracy ratios of decile filtered momentum portfolios: AR1. This figure contrasts the accuracy ratio (AR1) of decile momentum portfolios for both strategies. The accuracy ratio AR1 is specified as (9). Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

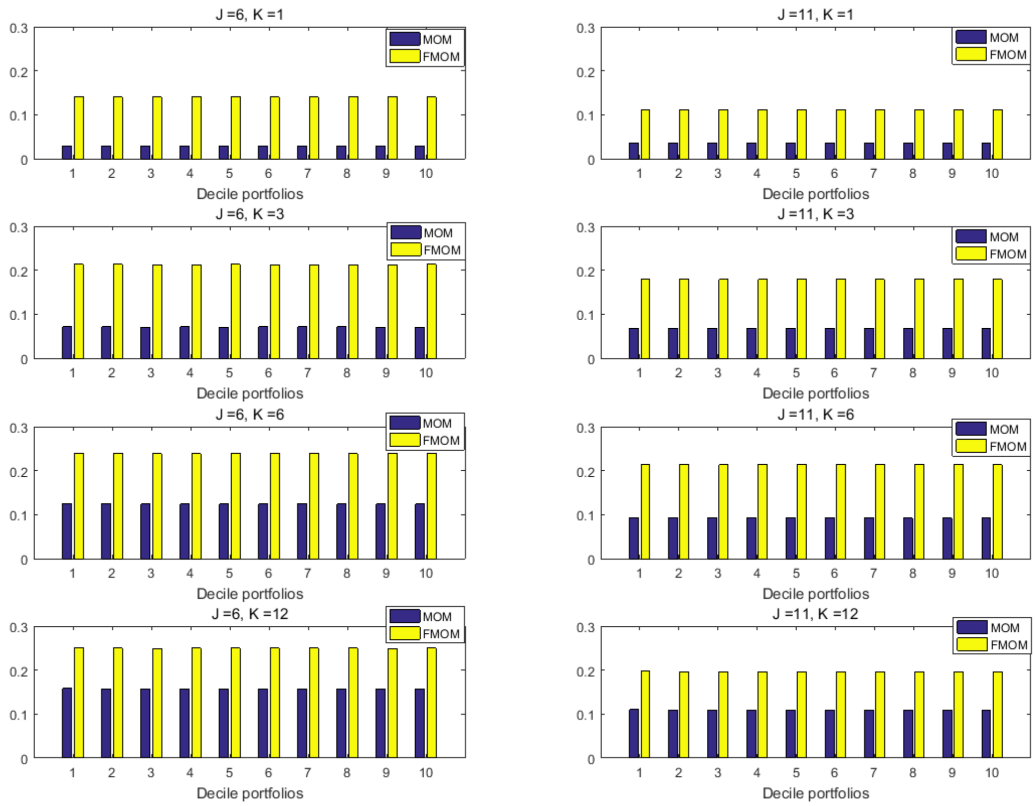

Figure 6-2. Accuracy ratios of decile filtered momentum portfolios: AR2. This figure contrasts the accuracy ratio (AR2) of decile momentum portfolios for both strategies. The accuracy ratio AR2 is specified as (10). Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

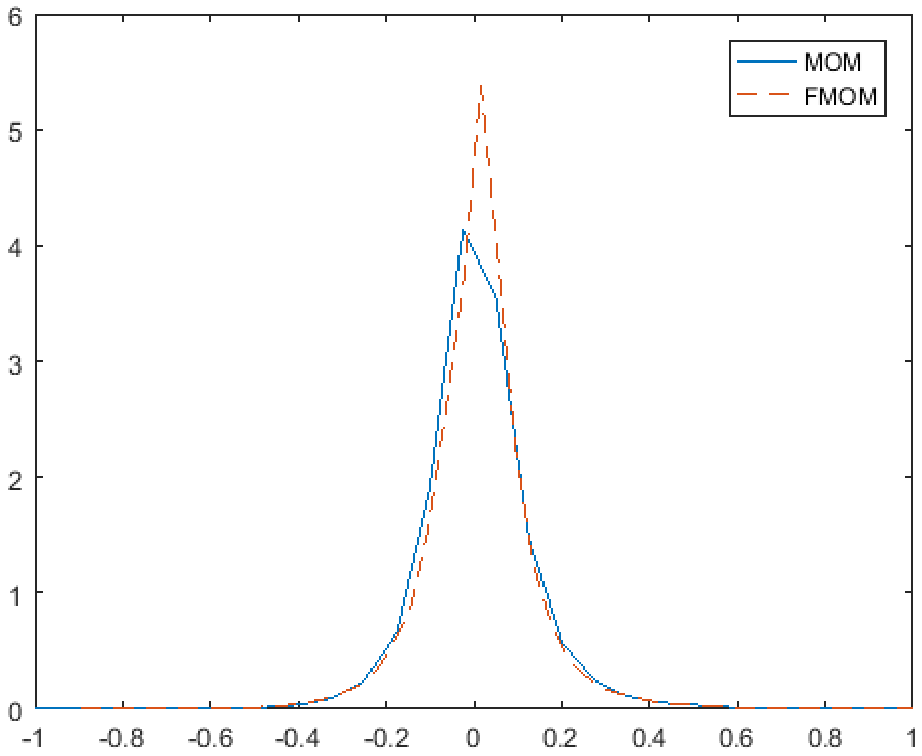

Figure 7. Empirical distributions of individual stock returns in (filtered) momentum portfolios. This figure shows the (kernel-smoothing) density function of one-month log returns of equities belonging to the MOM and the FMOM strategies. The case of momentum strategy is considered with 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$).

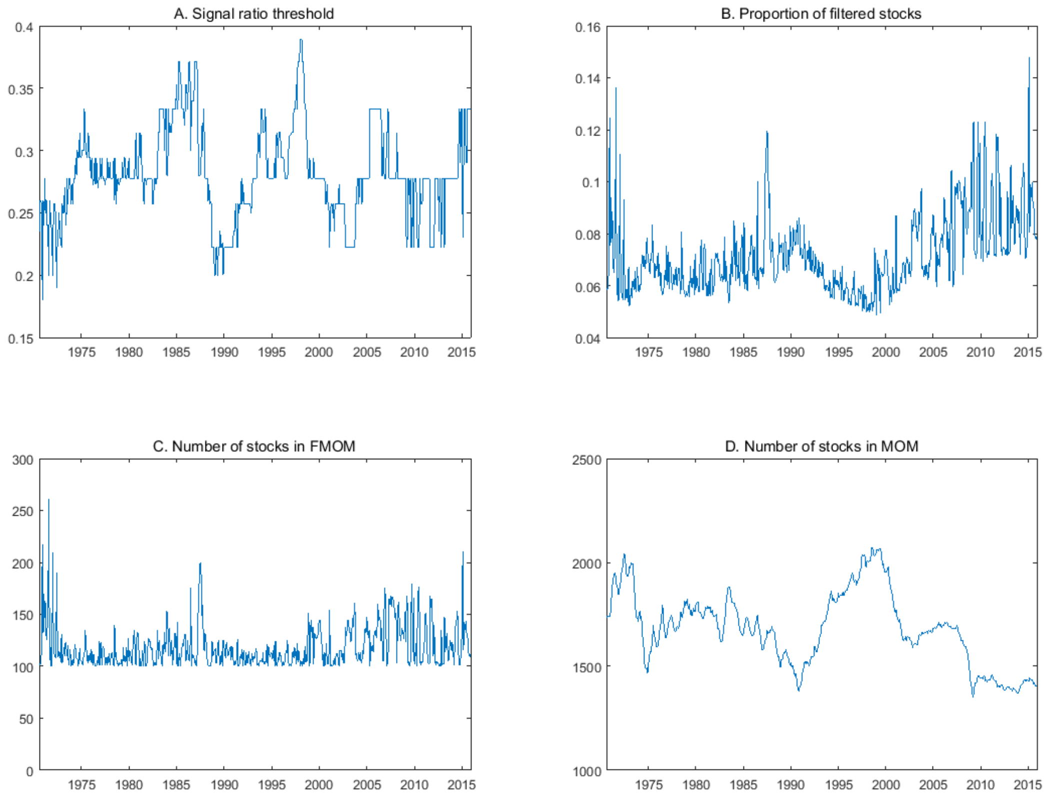

Figure 8. Time variation of signal ratio thresholds and the number of stocks in (filtered) momentum portfolios. This figure shows the time trend of the signal ratio threshold (Panel A), the proportion of equities included in the FMOM portfolios relative to the MOM portfolios (Panel B), the number of stocks included in the FMOM (Panel C) and in the MOM (Panel D) strategies. The case of momentum strategy is considered with 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$).

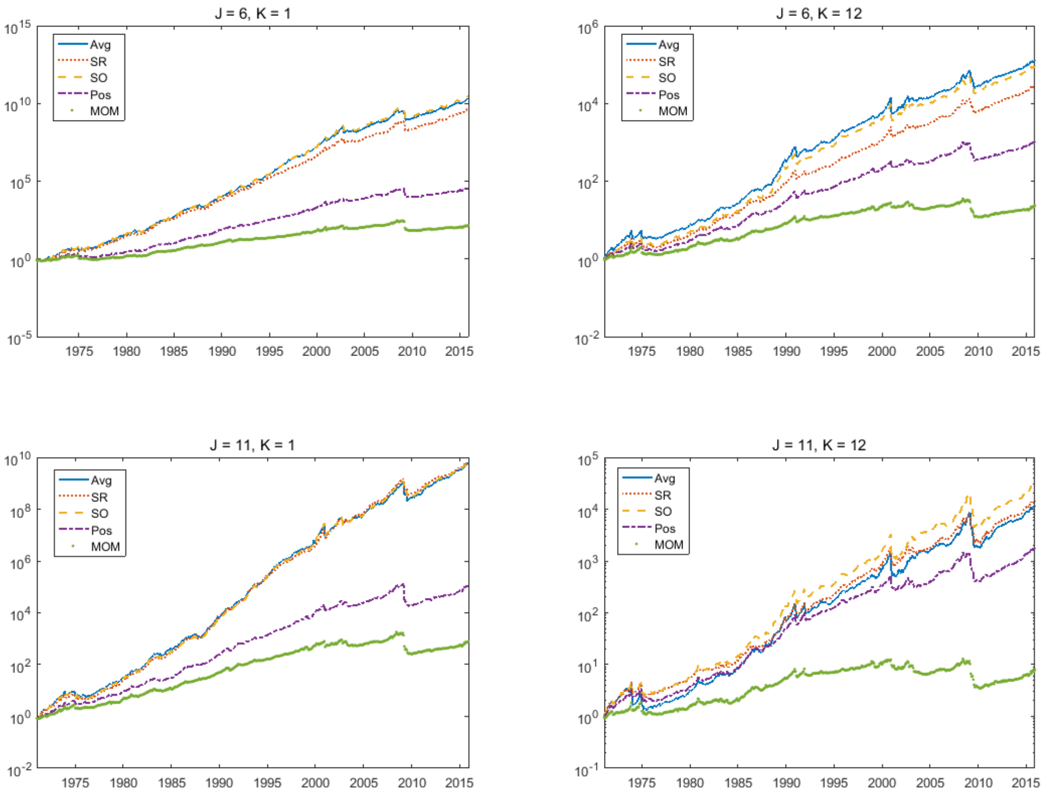

Figure 9. Cumulative momentum profits: Alternative filtering criteria. This figure shows cumulative momentum profits of the MOM strategy as well as the FMOM strategy with alternative filtering criteria. For the FMOM strategy, the "Avg" filtering criterion denotes (3). Performance measures such as SR and SO are also used as alternative filtering criteria. The "SR" filtering criterion denotes (11). The "Pos" filtering criterion indicates signal ratio threshold of zero. Four cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

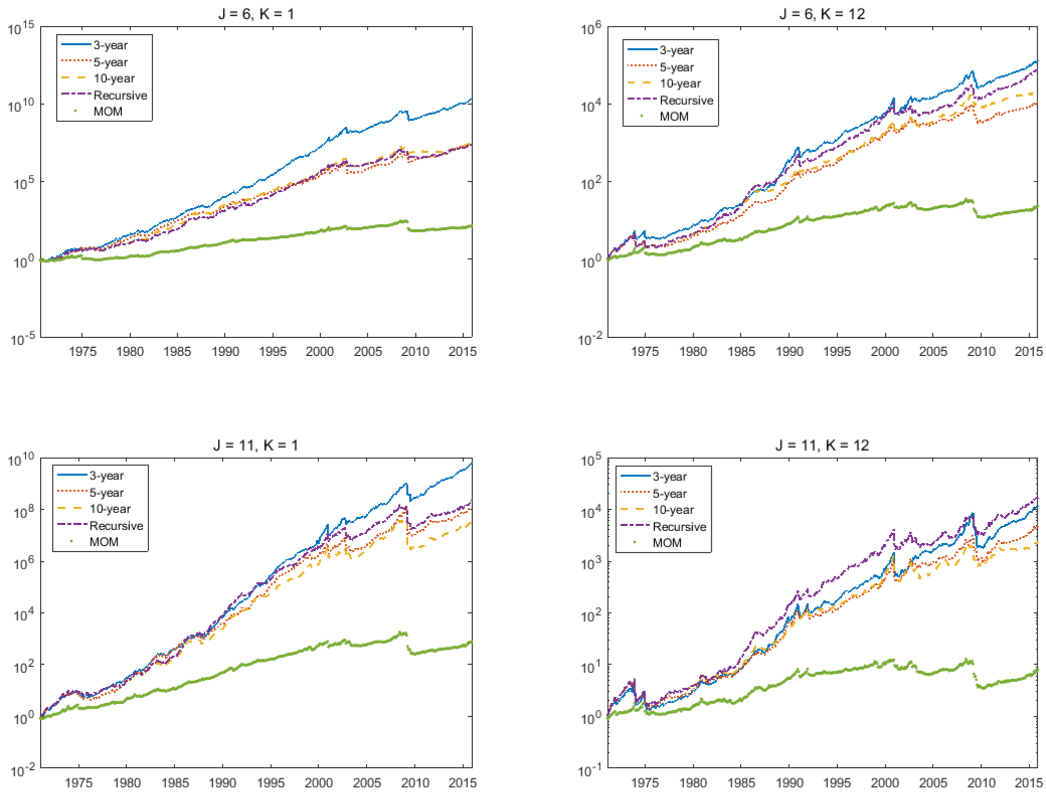

Figure 10. Cumulative momentum profits: Alternative signal ratio windows. This figure shows cumulative momentum profits of the MOM strategy as well as the FMOM strategy with alternative signal ratio windows: 3-year, 5-year, 10-year, and recursive windows. Four cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

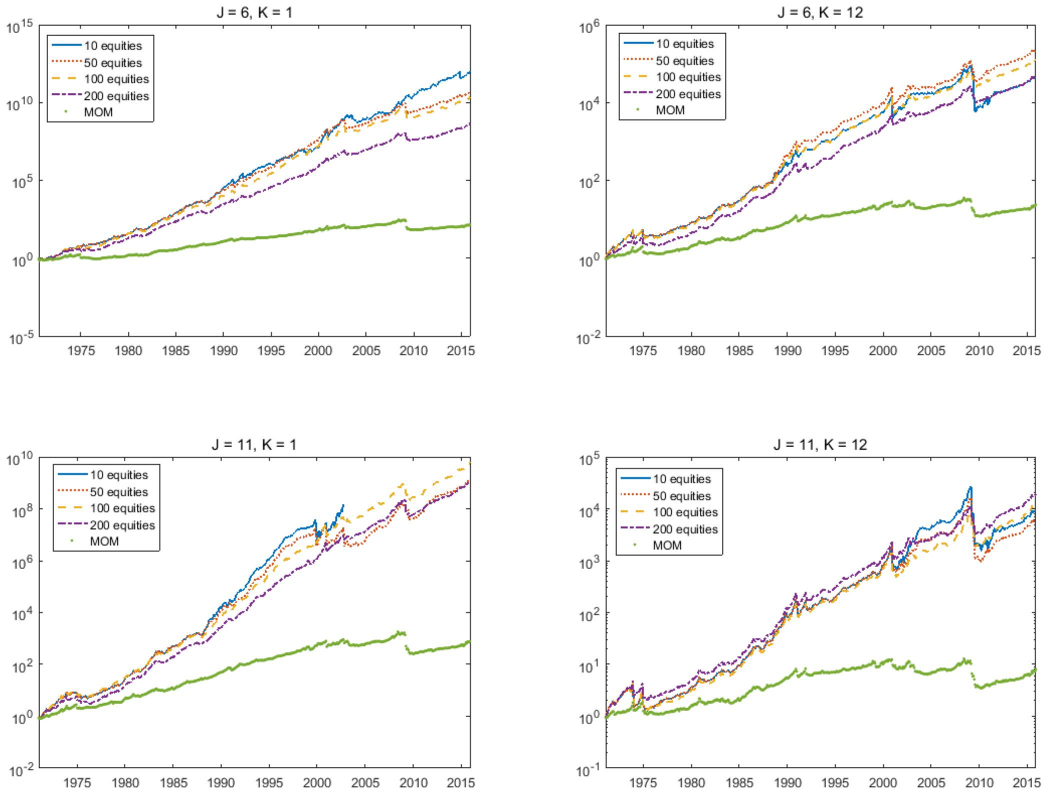

Figure 11. Cumulative momentum profits: Alternative minimum numbers of equities. This figure shows cumulative momentum profits (net of transaction costs) of the MOM strategy as well as the FMOM strategy with alternative minimum numbers of equities. Four cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

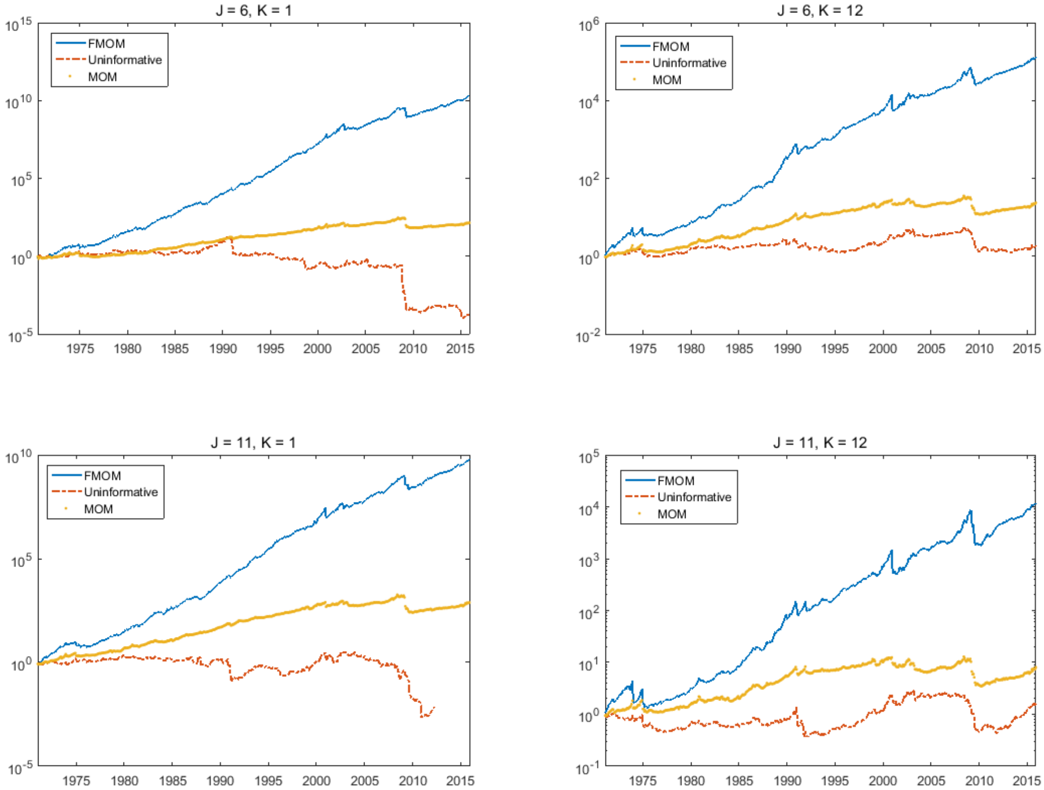

Figure 12. Cumulative momentum profits: Uninformative filtering. This figure shows cumulative momentum profits of the MOM strategy, the FMOM strategy, and the FMOM with an uninformative filtering. Four cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

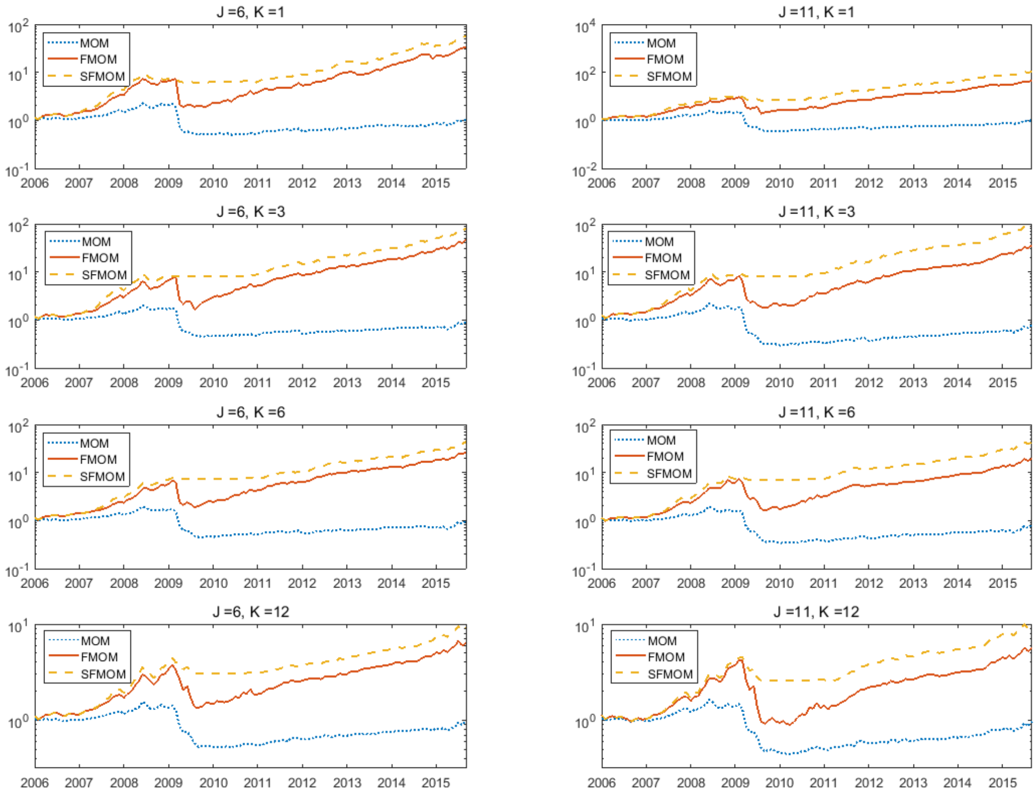

Figure 13. Momentum crashes and semtiment-based filtered momentum strategy. This figure shows the time trend of cumulative momentum profits of the MOM strategy, the FMOM strategy, and the sentiment-based FMOM (SFMOM). Refer to the text for the explanation about the SFMOM strategy. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

Table 1. Summary statistics of momentum profits

This table shows summary statistics of the momentum (MOM) and the filtered momentum (FMOM) profits, including mean, median, standard deviation (SD), skewness, kurtosis, autocorrelation coefficient with lag one (AC(1)), and the Sharpe ratio (SR) of the annualized return over the sample period. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

	(J, K)							
Statistics	$(6, 1)$		$(6, 3)$		$(6, 6)$		$(6, 12)$	
	MOM	FMOM	MOM	FMOM	MOM	FMOM	MOM	FMOM
Mean	14.88	81.38	13.44	75.61	13.90	56.76	8.70	34.86
(t-val)	4.18	11.52	4.01	12.57	4.56	10.94	3.58	7.96
Median	25.01	95.63	21.06	86.70	22.33	61.30	15.12	41.12
SD	22.50	35.67	21.30	30.87	19.32	28.20	15.65	25.47
Skew	-2.82	-1.59	-2.69	-1.71	-2.49	-2.19	-1.97	-2.40
Kurt	23.23	12.63	21.35	14.29	19.54	17.01	13.52	18.55
AC(1)	0.03	-0.04	0.01	0.01	0.04	-0.01	0.04	0.02
SR	0.66	2.28	0.63	2.45	0.72	2.01	0.56	1.37
	(J, K)							
Statistics	$(11, 1)$		$(11, 3)$		$(11, 6)$		$(11, 12)$	
	MOM	FMOM	MOM	FMOM	MOM	FMOM	MOM	FMOM
Mean	19.63	75.98	16.86	74.00	12.80	52.68	6.62	29.66
(t-val)	5.22	11.43	4.72	12.47	3.90	9.72	2.38	6.08
Median	27.91	82.43	25.89	82.28	20.86	57.89	13.77	35.93
SD	23.19	33.94	22.27	30.46	20.79	29.71	18.10	28.94
Skew	-2.57	-1.69	-2.44	-1.40	-1.99	-1.35	-1.90	-2.75
Kurt	22.08	13.51	20.50	11.06	15.06	9.56	12.68	20.15
AC(1)	0.06	-0.03	0.07	0.02	0.07	-0.01	0.05	0.00
SR	0.85	2.24	0.76	2.43	0.62	1.77	0.37	1.03

Table 2. Risk-adjusted returns of momentum strategy

This table shows risk-adjusted (filtered) momentum profits from CAPM, Fama-French 3-factor model (FF3), and Fama-French-Carhart 4-factor model (FF4). We regress momentum profits on asset pricing risk factors and use factor loadings and factor realizations to estimate risk-adjusted excess return for each momentum portfolio and hold-period month, from which we then compute the risk-adjusted (filtered) momentum profits of overlapping momentum portfolios. The risk-adjusted alpha indicates an annualized return in percentage. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period. The t-value (in the bracket) of the significance of momentum profits and the difference between profits are calculated using Newey-West (1987) standard errors, where the lag is set to $K-1$.

	CAPM			FF3			FF4		
(J,K)			FMOM			FMOM			FMOM
	MOM	FMOM	- MOM	MOM	FMOM	- MOM	MOM	FMOM	- MOM
(6,1)	18.20	85.32	67.12	21.24	90.95	69.71	6.47	63.01	56.54
	[5.28]	[10.73]	[11.39]	[6.18]	[11.29]	[11.52]	[3.64]	[11.05]	[11.04]
(6,3)	15.57	77.41	61.84	16.86	80.25	63.39	11.66	71.25	59.59
	[4.69]	[9.39]	[10.21]	[5.10]	[9.65]	[10.31]	[4.64]	[9.90]	[10.28]
(6,6)	15.15	57.55	42.39	15.54	58.28	42.73	12.38	53.70	41.32
	[4.45]	[7.31]	[7.55]	[4.58]	[7.39]	[7.58]	[4.36]	[7.47]	[7.57]
(6,12)	9.21	34.33	25.12	9.32	34.61	25.29	7.63	32.92	25.29
	[3.18]	[5.14]	[5.38]	[3.22]	[5.18]	[5.40]	[2.96]	[5.20]	[5.42]
(11,1)	21.34	78.91	57.58	25.60	85.33	59.73	9.01	59.20	50.19
	[5.72]	[10.56]	[10.37]	[6.95]	[11.26]	[10.42]	[5.56]	[10.94]	[10.21]
(11,3)	17.98	75.68	57.70	19.68	78.62	58.94	13.77	69.21	55.43
	[4.76]	[9.22]	[9.90]	[5.27]	[9.50]	[9.97]	[5.00]	[9.76]	[9.94]
(11,6)	13.36	53.30	39.94	14.06	54.37	40.31	10.65	48.88	38.23
	[3.61]	[6.68]	[7.11]	[3.82]	[6.80]	[7.14]	[3.45]	[6.80]	[7.06]
(11,12)	6.56	29.25	22.70	6.81	30.15	23.33	5.13	28.26	23.13
	[2.16]	[4.59]	[4.97]	[2.25]	[4.71]	[5.06]	[1.88]	[4.67]	[5.06]

Table 3. Hypothesis testing

This table shows the results of hypothesis tests with null hypothesis that both momentum (MOM) and filtered momentum (FMOM) strategies equally perform and with alternative hypothesis that the FMOM performs better than the MOM strategy based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). The p-value is calculated using a block bootstrapping method. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period. "Inf" indicates positive infinity which can occur with zero downside deviation. Two target return levels are considered: average MOM return (Panel A) and average FMOM return (Panel B).

(J,K)	SR			SO			UP			OM		
	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val
A. Target = average MOM return												
(6, 1)	4.57	2.57	0.00	Inf	0.00	0.00	Inf	0.54	0.00	Inf	1.00	0.00
(6, 3)	5.20	2.20	0.00	Inf	0.00	0.00	Inf	0.49	0.00	Inf	1.00	0.00
(6, 6)	4.87	2.10	0.00	Inf	0.00	0.00	Inf	0.45	0.00	Inf	1.00	0.00
(6, 12)	3.93	1.46	0.00	Inf	0.00	0.00	Inf	0.52	0.00	Inf	1.00	0.00
(11, 1)	4.93	2.15	0.00	Inf	0.00	0.00	Inf	0.49	0.00	Inf	1.00	0.00
(11, 3)	4.60	1.80	0.00	Inf	0.00	0.00	Inf	0.48	0.00	Inf	1.00	0.00
(11, 6)	4.63	1.53	0.00	Inf	0.00	0.00	Inf	0.51	0.00	Inf	1.00	0.00
(11, 12)	4.39	0.98	0.00	Inf	0.00	0.00	Inf	0.57	0.00	Inf	1.00	0.00
B. Target = average FMOM return												
(6, 1)	4.57	2.57	0.00	0.00	-0.99	0.00	0.62	0.00	0.00	1.00	0.00	0.00
(6, 3)	5.20	2.20	0.00	0.00	-0.99	0.00	0.58	0.00	0.00	1.00	0.00	0.00
(6, 6)	4.87	2.10	0.00	0.00	-0.98	0.00	0.55	0.00	0.00	1.00	0.00	0.00
(6, 12)	3.93	1.46	0.00	0.00	-0.97	0.00	0.60	0.00	0.00	1.00	0.00	0.00
(11, 1)	4.93	2.15	0.00	0.00	-0.98	0.00	0.62	0.00	0.00	1.00	0.00	0.00
(11, 3)	4.60	1.80	0.00	0.00	-0.98	0.00	0.63	0.00	0.00	1.00	0.00	0.00
(11, 6)	4.63	1.53	0.00	0.00	-0.97	0.00	0.61	0.00	0.00	1.00	0.00	0.00
(11, 12)	4.39	0.98	0.00	0.00	-0.96	0.00	0.56	0.00	0.00	1.00	0.00	0.00

Table 4. Summary statistics of signal ratios

This table shows summary statistics of empirical densities of the average signal ratios of individual equities over the sample period. The proportion of positive signal ratios is denoted by "$Pr[sr > 0]$". Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

(J, K)	Mean	SD	Percentile					$Pr[sr > 0]$
			Min	25%	50%	75%	Max	
(6, 1)	0.037	0.132	-0.540	-0.041	0.035	0.112	0.659	0.625
(6, 3)	0.045	0.179	-0.608	-0.060	0.044	0.149	0.844	0.607
(6, 6)	0.063	0.211	-0.743	-0.065	0.059	0.186	0.925	0.618
(6, 12)	0.081	0.230	-0.816	-0.062	0.068	0.220	0.944	0.636
(11, 1)	0.058	0.133	-0.551	-0.024	0.056	0.138	0.667	0.687
(11, 3)	0.072	0.185	-0.664	-0.045	0.067	0.179	0.797	0.666
(11, 6)	0.085	0.231	-0.811	-0.062	0.078	0.219	0.941	0.646
(11, 12)	0.083	0.283	-0.816	-0.103	0.070	0.258	1.000	0.609

Table 5. Trade volume

This table shows the trade volumes of both momentum (MOM) and filtered momentum (FMOM) strategy for 10-year investment horizon which are measured as the ratio to investment amount. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

(J, K)	MOM				FMOM			
	Mean	SD	Min	Max	Mean	SD	Min	Max
(6, 1)	1.49	0.18	1.00	2.20	1.52	0.37	0.50	2.73
(6, 3)	0.80	0.07	0.63	1.06	0.70	0.13	0.27	1.10
(6, 6)	0.52	0.03	0.33	0.62	0.43	0.06	0.29	0.61
(6, 12)	0.26	0.02	0.17	0.30	0.21	0.03	0.13	0.28
(11, 1)	1.09	0.14	0.75	2.00	1.24	0.32	0.30	2.40
(11, 3)	0.60	0.06	0.42	0.89	0.58	0.11	0.23	0.94
(11, 6)	0.41	0.04	0.31	0.55	0.36	0.05	0.17	0.50
(11, 12)	0.26	0.02	0.17	0.30	0.20	0.03	0.13	0.27

Table 6. Momentum profits net of transaction costs

This table shows summary statistics of annualized return (in percentage) from both momentum (MOM) and filtered momentum (FMOM) strategies. Portfolio returns are measured net of transaction costs which are assumed to be 50 basis points. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

Statistics	(J, K)							
	$(6, 1)$		$(6, 3)$		$(6, 6)$		$(6, 12)$	
	MOM	FMOM	MOM	FMOM	MOM	FMOM	MOM	FMOM
Mean	5.16	66.25	8.15	68.72	10.40	52.92	7.03	33.22
(t-val)	1.51	9.80	2.49	11.65	3.46	10.32	2.91	7.63
Median	14.03	77.20	15.44	79.93	18.34	57.38	13.40	39.28
SD	22.50	35.68	21.30	30.90	19.33	28.21	15.65	25.48
Skew	-2.80	-1.57	-2.68	-1.70	-2.49	-2.18	-1.97	-2.39
Kurt	23.09	12.55	21.29	14.20	19.54	16.98	13.52	18.54
AC(1)	0.03	-0.03	0.01	0.02	0.04	-0.01	0.04	0.02
SR	0.23	1.86	0.38	2.22	0.54	1.88	0.45	1.30
Statistics	(J, K)							
	$(11, 1)$		$(11, 3)$		$(11, 6)$		$(11, 12)$	
	MOM	FMOM	MOM	FMOM	MOM	FMOM	MOM	FMOM
Mean	12.16	63.88	12.78	68.30	10.10	49.50	4.99	28.14
(t-val)	3.33	9.93	3.64	11.69	3.11	9.22	1.80	5.80
Median	20.43	69.79	21.87	76.63	17.94	54.79	12.00	34.49
SD	23.21	34.02	22.28	30.50	20.80	29.72	18.10	28.94
Skew	-2.56	-1.67	-2.43	-1.40	-1.99	-1.34	-1.90	-2.75
Kurt	22.03	13.37	20.51	11.02	15.08	9.55	12.69	20.14
AC(1)	0.06	-0.03	0.07	0.02	0.07	-0.01	0.05	0.00
SR	0.52	1.88	0.57	2.24	0.49	1.67	0.28	0.97

Table 7. Summary statistics of momentum profits with alternative filtering criteria

This table shows summary statistics of the momentum (MOM) and the filtered momentum (FMOM) profits. For the FMOM strategy, the "Avg" filtering criterion denotes (3). The four performance measures (SR, SO, UP, and OM) are also used as alternative filtering criteria. The "SR" filtering criterion denotes (11). The "Pos" filtering criterion indicates signal ratio threshold of zero. Two cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

	$(J, K) = (6, 1)$						
Statistics	MOM	FMOM					
		Avg	SR	SO	UP	OM	Pos
Mean	14.88	81.38	73.56	82.48	80.68	81.72	30.77
(t-val)	4.18	11.52	11.57	11.76	11.48	11.76	7.31
Median	25.01	95.63	86.12	95.63	91.96	95.62	41.07
SD	22.50	35.67	32.83	35.30	35.55	35.08	24.97
Skew	-2.82	-1.59	-1.85	-1.54	-1.54	-1.53	-2.41
Kurt	23.23	12.63	14.27	12.45	12.32	12.55	19.29
AC(1)	0.03	-0.04	-0.05	-0.03	-0.04	-0.03	0.01
SR	0.66	2.28	2.24	2.34	2.27	2.33	1.23
	$(J, K) = (11, 12)$						
Statistics	MOM	FMOM					
		Avg	SR	SO	UP	OM	Pos
Mean	6.62	29.66	27.96	31.05	31.19	30.68	21.27
(t-val)	2.38	6.08	6.80	6.82	6.82	6.76	5.94
Median	13.77	35.93	37.47	38.35	39.26	38.12	31.57
SD	18.10	28.94	24.54	26.85	26.95	26.80	21.91
Skew	-1.90	-2.75	-2.14	-2.47	-2.46	-2.49	-2.17
Kurt	12.68	20.15	14.23	17.85	17.71	17.90	13.01
AC(1)	0.05	0.00	0.04	0.03	0.03	0.04	0.07
SR	0.37	1.03	1.14	1.16	1.16	1.14	0.97

Table 8. Hypothesis testing: Alternative filtering criteria

This table shows the results of hypothesis tests with null hypothesis that the filtered momentum (FMOM) strategies with an alternative filtering criterion and the target criterion equally perform and with alternative hypothesis that the FMOM with an alternative criterion performs better than the FMOM strategy with the target criterion based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). The p-value is calculated using a block bootstrapping method. The momentum portfolio formation is considered with 6-month formation period ($J = 6$) and 1-month holding period ($K = 1$).

$(J, K) = (6, 1)$								
Filtering	SR		SO		UP		OM	
criterion	stat	p-val	stat	p-val	stat	p-val	stat	p-val
A. Target = Pos								
Avg	4.565	0.000	Inf	0.000	Inf	0.000	Inf	0.000
SR	5.766	0.000	Inf	0.000	Inf	0.000	Inf	0.000
SO	4.486	0.000	Inf	0.000	Inf	0.000	Inf	0.000
UP	4.637	0.000	Inf	0.000	Inf	0.000	Inf	0.000
OM	4.424	0.000	Inf	0.000	Inf	0.000	Inf	0.000
B. Target = SR								
Avg	4.565	0.967	0.790	0.000	1.329	0.000	2.467	0.000
SO	4.486	0.975	0.909	0.000	1.445	0.000	2.693	0.000
UP	4.637	0.958	0.752	0.000	1.292	0.000	2.392	0.000
OM	4.424	0.980	0.865	0.000	1.416	0.000	2.569	0.000
Pos	3.561	1.000	-0.963	1.000	0.000	0.994	0.000	0.973

Table 9. Summary statistics of momentum profits with alternative signal ratio windows

This table shows summary statistics of the profits of the momentum (MOM) and the filtered momentum (FMOM) strategies of the annualized return over the sample period with alternative signal ratio windows: 3-, 5-, 10-year, and recursive windows. Two cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

	$(J, K) = (6, 1)$				
Statistics	MOM	FMOM			
		3-year	5-year	10-year	Recursive
Mean	14.88	81.38	58.05	56.70	55.30
(t-val)	4.18	11.52	8.62	8.66	8.48
Median	25.01	95.63	66.14	59.10	64.69
SD	22.50	35.67	36.42	35.58	35.59
Skew	-2.82	-1.59	-1.92	-1.25	-0.92
Kurt	23.23	12.63	14.75	10.06	7.32
AC(1)	0.03	-0.04	-0.03	-0.06	-0.05
SR	0.66	2.28	1.59	1.59	1.55
	$(J, K) = (11, 12)$				
Statistics	MOM	FMOM			
		3-year	5-year	10-year	Recursive
Mean	6.62	29.66	26.87	24.59	30.60
(t-val)	2.38	6.08	5.67	5.35	6.11
Median	13.77	35.93	34.65	34.15	41.91
SD	18.10	28.94	28.37	27.77	29.58
Skew	-1.90	-2.75	-2.60	-2.55	-2.21
Kurt	12.68	20.15	20.08	19.78	16.59
AC(1)	0.05	0.00	-0.02	-0.04	-0.06
SR	0.37	1.03	0.95	0.89	1.03

Internet Appendix to

"Filtered Momentum Strategy"

September 2017

Abstract

This appendix presents supplementary results not included in the main body of the paper.

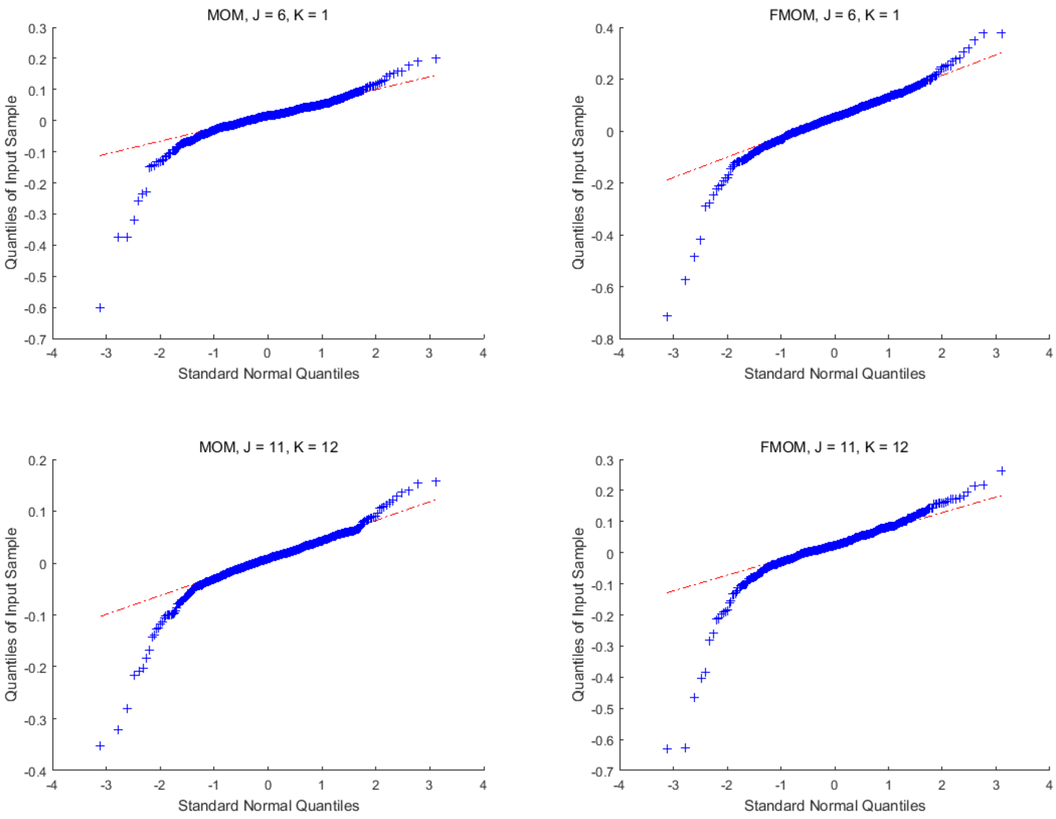

Figure A1. QQ-plot of momentum profits. To test normality, this figure shows the qq-plots of the returns of the momentum (MOM) and the filtered momentum (FMOM) strategies. Several cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

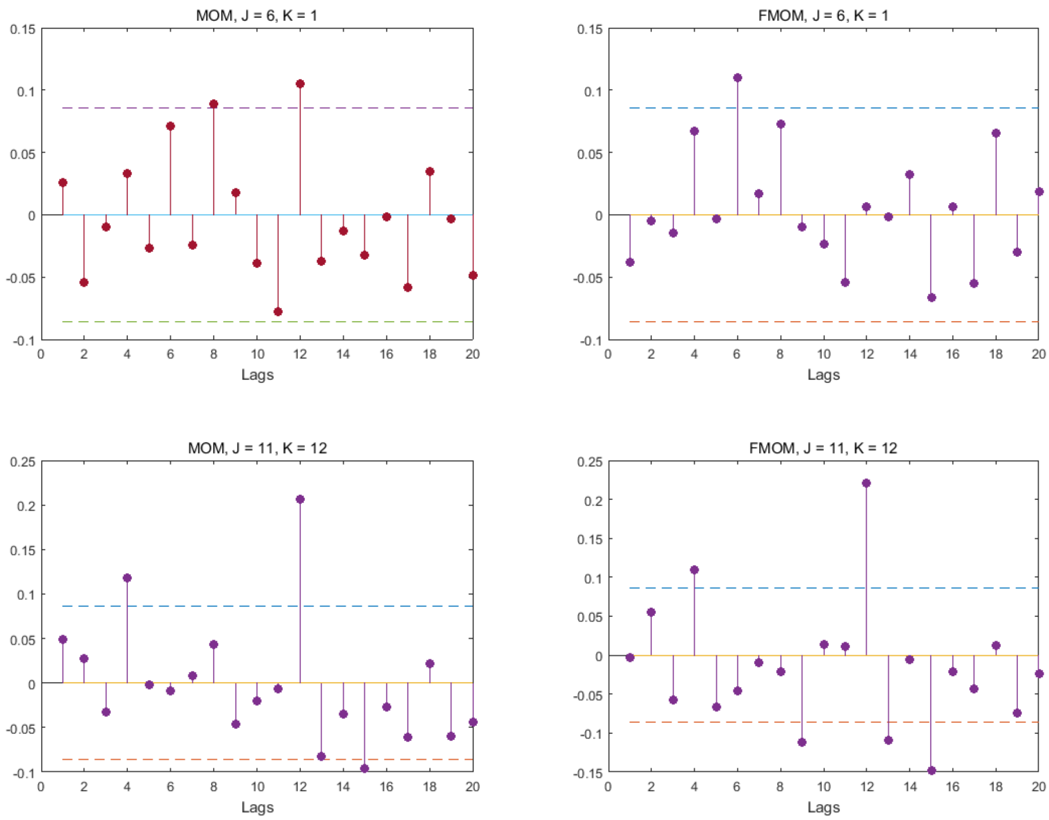

Figure A2. Autocorrelation function of momentum profits. To test serial independence, this figure shows the autocorrelation coefficients and their 95% confidence intervals of the returns of the momentum (MOM) and the filtered momentum (FMOM) strategy. Several cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

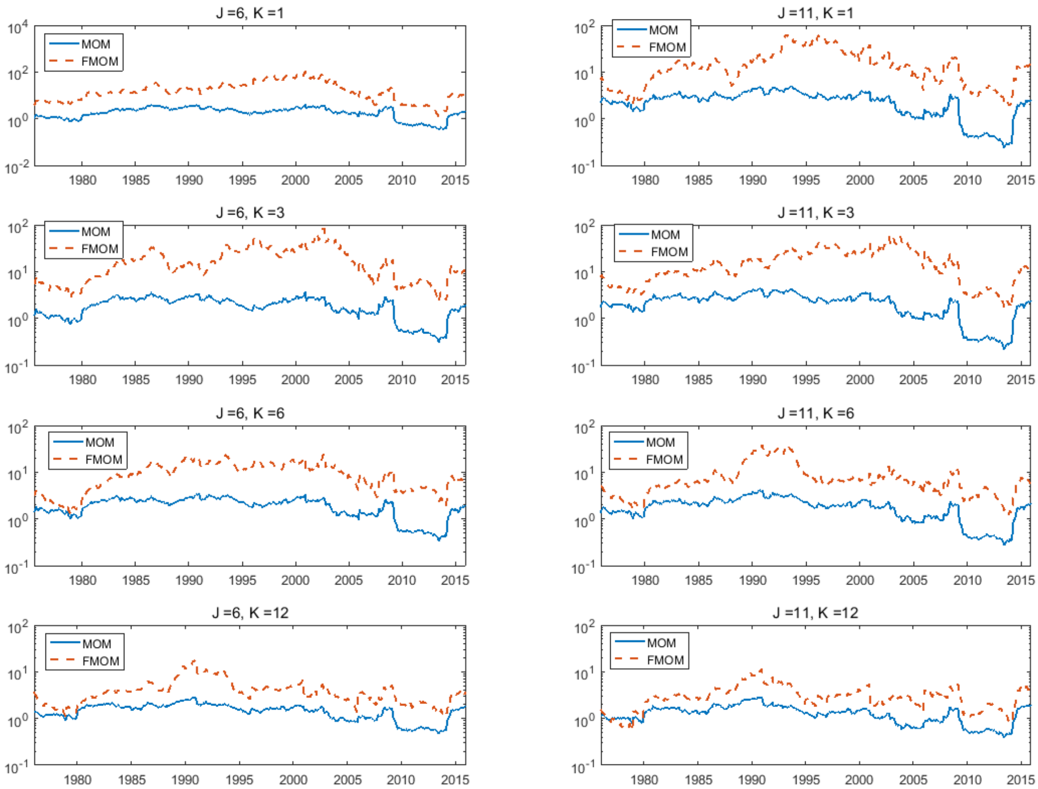

Figure A3. 5-year rolling cumulative momentum profits. This figure shows the time trend of 5-year rolling cumulative return of the momentum (MOM) and the filtered momentum (FMOM) strategies. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

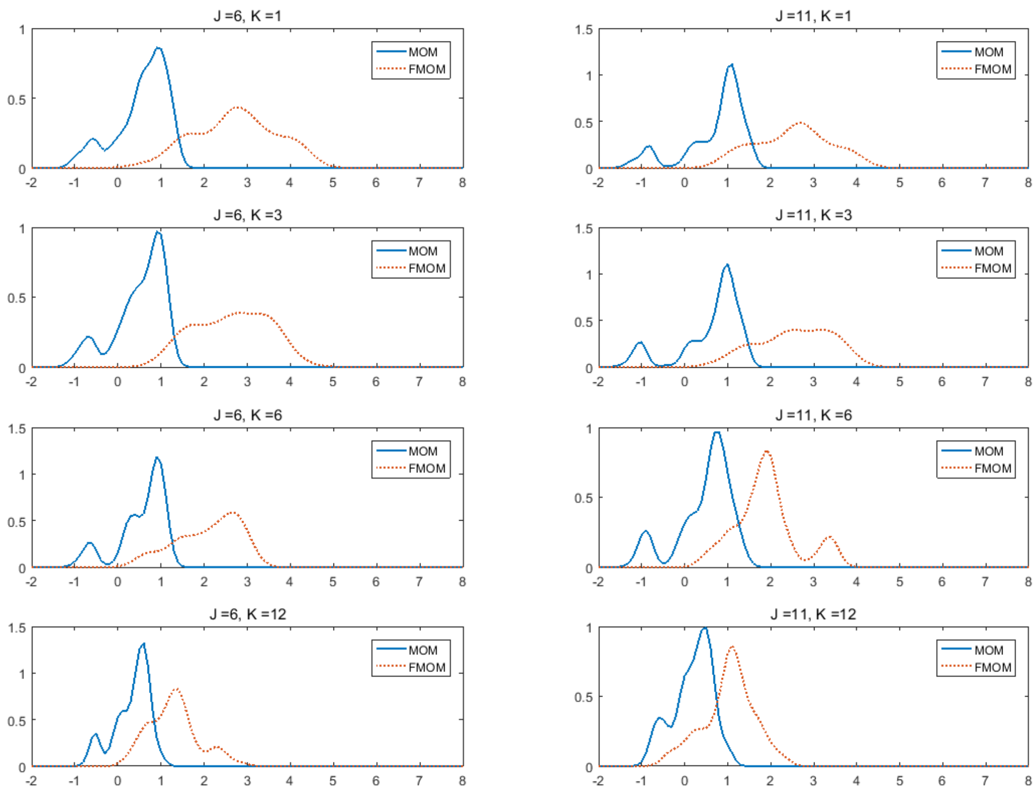

Figure A4. Probability density of 5-year rolling cumulative momentum profits. This figure shows the (kernel-smoothing) density function of 5-year rolling cumulative log return of the momentum (MOM) and the filtered momentum (FMOM) strategies. 5-year rolling cumulative log return is indicated in x-axis. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

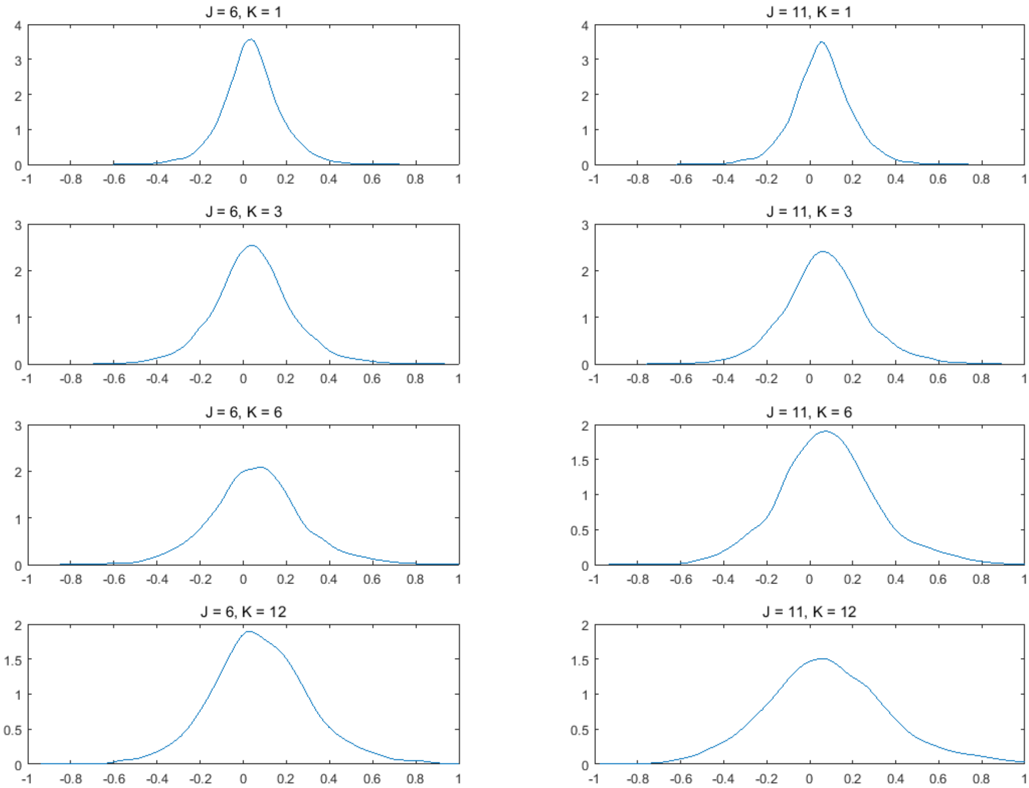

Figure A5. Probability density of signal ratios. This figure shows the (kernel-smoothing) density function of signal ratios of the sample equities over the sample period. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

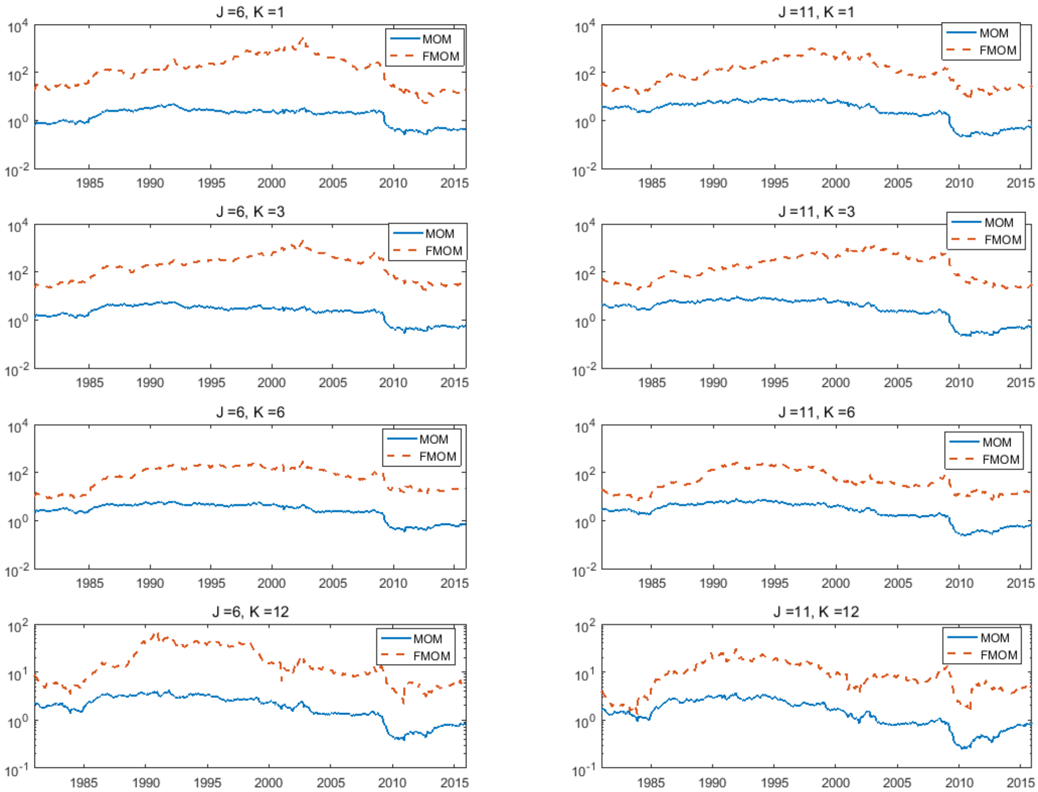

Figure A6. 10-year rolling cumulative net momentum profits. This figure shows the time trend of 5-year rolling cumulative return of the momentum (MOM) and the filtered momentum (FMOM) strategy. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

Table A1. Normality and serial independence tests of momentum profits

This table shows the normality test results for both momentum (MOM) and filtered momentum (FMOM) profits. We employ several normality tests, including Anderson–Darling test (AD), Jarque–Bera test (JB), Kolmogorov–Smirnov test (KS), and Shapiro–Wilk test (SW). We also conduct serial independence tests such as Breusch-Godfrey (BG) and Ljung-Box (LB) tests where we choose the number of lags at which the maximum of absolute autocorrelation coefficients is attained. Eight cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

(J, K)	Normality tests								Serial independence tests			
	AD		JB		KS		SW		BG		LB	
	stat	p-val	stat	p-val	stat	p-val	stat	p-val	stat	p-val	stat	p-val
A. MOM												
(6,1)	17.36	0.00	10013	0.00	0.43	0.00	0.80	0.00	22.25	0.03	21.15	0.05
(6,3)	18.77	0.00	8301	0.00	0.44	0.00	0.80	0.00	20.40	0.06	20.24	0.06
(6,6)	17.79	0.00	6773	0.00	0.44	0.00	0.82	0.00	5.91	0.21	5.58	0.23
(6,12)	14.58	0.00	2831	0.00	0.45	0.00	0.85	0.00	28.67	0.00	29.21	0.00
(11,1)	13.68	0.00	8782	0.00	0.44	0.00	0.83	0.00	9.74	0.05	9.78	0.04
(11,3)	13.65	0.00	7426	0.00	0.44	0.00	0.84	0.00	11.81	0.02	12.45	0.01
(11,6)	13.26	0.00	3629	0.00	0.44	0.00	0.86	0.00	13.59	0.01	13.99	0.01
(11,12)	13.40	0.00	2428	0.00	0.44	0.00	0.86	0.00	34.91	0.00	36.09	0.00
B. FMOM												
(6,1)	7.56	0.00	2336	0.00	0.42	0.00	0.80	0.00	9.43	0.15	10.08	0.12
(6,3)	10.39	0.00	3159	0.00	0.42	0.00	0.80	0.00	15.87	0.04	14.11	0.08
(6,6)	9.01	0.00	4890	0.00	0.44	0.00	0.82	0.00	14.55	0.48	13.90	0.53
(6,12)	13.07	0.00	5949	0.00	0.42	0.00	0.85	0.00	22.99	0.03	23.68	0.02
(11,1)	9.14	0.00	2741	0.00	0.43	0.00	0.83	0.00	12.37	0.34	10.47	0.49
(11,3)	5.78	0.00	1640	0.00	0.42	0.00	0.84	0.00	19.94	0.17	19.76	0.18
(11,6)	7.25	0.00	1131	0.00	0.42	0.00	0.86	0.00	7.52	0.11	7.68	0.10
(11,12)	17.08	0.00	7284	0.00	0.42	0.00	0.86	0.00	45.18	0.00	47.81	0.00

Table A2. Hypothesis testing based on 5-year rolling cumulative returns

This table shows the results of hypothesis tests with null hypothesis that both momentum (MOM) and filtered momentum (FMOM) equally perform and with alternative hypothesis that the FMOM performs better than the MOM strategy based on 5-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). The p-value is calculated using a block bootstrapping method. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

(J,K)	SR			SO			UP			OM		
	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val
A. Target = average MOM return												
(6, 1)	3.39	1.45	0.00	Inf	0.00	0.00	Inf	0.52	0.00	Inf	1.00	0.00
(6, 3)	3.55	1.28	0.00	Inf	0.00	0.00	Inf	0.50	0.00	Inf	1.00	0.00
(6, 6)	3.36	1.37	0.00	181.26	0.00	0.00	181.33	0.48	0.00	2681.13	1.00	0.00
(6, 12)	2.61	1.01	0.00	134.32	0.00	0.00	134.40	0.50	0.00	1742.25	1.00	0.00
(11, 1)	3.45	1.52	0.00	Inf	0.00	0.00	Inf	0.47	0.00	Inf	1.00	0.00
(11, 3)	3.36	1.26	0.00	Inf	0.00	0.00	Inf	0.46	0.00	Inf	1.00	0.00
(11, 6)	3.05	1.07	0.00	9153.11	0.00	0.00	9153.16	0.48	0.00	200744.40	1.00	0.00
(11, 12)	2.61	0.66	0.00	60.51	0.00	0.00	60.62	0.53	0.00	567.02	1.00	0.00
B. Target = average FMOM return												
(6, 1)	3.39	1.45	0.00	0.00	-0.98	0.00	0.62	0.00	0.00	1.00	0.00	0.00
(6, 3)	3.55	1.28	0.00	0.00	-0.98	0.00	0.60	0.00	0.00	1.00	0.00	0.00
(6, 6)	3.36	1.37	0.00	0.00	-0.96	0.00	0.54	0.00	0.00	1.00	0.00	0.00
(6, 12)	2.61	1.01	0.00	0.00	-0.94	0.00	0.58	0.00	0.00	1.00	0.00	0.00
(11, 1)	3.45	1.52	0.00	0.00	-0.96	0.00	0.57	0.00	0.00	1.00	0.00	0.00
(11, 3)	3.36	1.26	0.00	0.00	-0.96	0.00	0.61	0.00	0.00	1.00	0.00	0.00
(11, 6)	3.05	1.07	0.00	0.00	-0.94	0.00	0.59	0.00	0.00	1.00	0.00	0.00
(11, 12)	2.61	0.66	0.00	0.00	-0.93	0.00	0.55	0.00	0.00	1.00	0.00	0.00

Table A3. Summary statistics of the individual stocks in (filtered) momentum portfolios

This table shows summary statistics of one-month returns of equities belonging to the MOM and the FMOM strategies. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

(J, K)		Mean	SD	Skew	Percentile						
					Min	10	25	50	75	90	Max
(6, 1)	MOM	0.010	0.129	1.447	-0.981	-0.124	-0.056	0.004	0.068	0.145	6.407
	FMOM	0.015	0.131	1.708	-0.867	-0.118	-0.046	0.013	0.068	0.142	3.000
(6, 3)	MOM	0.010	0.129	1.447	-0.981	-0.124	-0.056	0.004	0.068	0.145	6.407
	FMOM	0.015	0.123	1.356	-0.981	-0.107	-0.040	0.012	0.067	0.136	3.000
(6, 6)	MOM	0.010	0.129	1.447	-0.981	-0.124	-0.056	0.004	0.068	0.145	6.407
	FMOM	0.017	0.119	1.492	-0.981	-0.102	-0.039	0.013	0.068	0.137	3.000
(6, 12)	MOM	0.010	0.129	1.447	-0.981	-0.124	-0.056	0.004	0.068	0.145	6.407
	FMOM	0.019	0.113	1.063	-0.981	-0.095	-0.036	0.015	0.069	0.134	2.429
(11, 1)	MOM	0.010	0.127	1.443	-0.981	-0.123	-0.055	0.005	0.067	0.143	6.407
	FMOM	0.018	0.128	1.899	-0.848	-0.111	-0.042	0.016	0.070	0.140	3.000
(11, 3)	MOM	0.010	0.127	1.443	-0.981	-0.123	-0.055	0.005	0.067	0.143	6.407
	FMOM	0.018	0.119	1.121	-0.981	-0.101	-0.038	0.015	0.070	0.137	2.429
(11, 6)	MOM	0.010	0.127	1.443	-0.981	-0.123	-0.055	0.005	0.067	0.143	6.407
	FMOM	0.018	0.115	1.359	-0.981	-0.097	-0.037	0.015	0.068	0.133	2.450
(11, 12)	MOM	0.010	0.127	1.443	-0.981	-0.123	-0.055	0.005	0.067	0.143	6.407
	FMOM	0.018	0.110	1.569	-0.981	-0.091	-0.035	0.015	0.067	0.129	3.994

Table A4. Hypothesis testing based on 10-year rolling net returns

This table shows the results of hypothesis tests with null hypothesis that both momentum (MOM) and filtered momentum (FMOM) equally perform and with alternative hypothesis that the FMOM performs better than the MOM strategy based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). Portfolio returns are measured net of transaction costs which are assumed to be 50 basis points. The p-value is calculated using a block bootstrapping method. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

(J,K)	SR			SO			UP			OM		
	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val	FMOM	MOM	p-val
					A. Target = average MOM return							
(6, 1)	4.10	1.24	0.00	Inf	0.00	0.00	Inf	0.49	0.00	Inf	1.00	0.00
(6, 3)	5.57	1.44	0.00	Inf	0.00	0.00	Inf	0.47	0.00	Inf	1.00	0.00
(6, 6)	5.76	1.55	0.00	Inf	0.00	0.00	Inf	0.47	0.00	Inf	1.00	0.00
(6, 12)	4.14	1.10	0.00	Inf	0.00	0.00	Inf	0.54	0.00	Inf	1.00	0.00
(11, 1)	4.95	1.32	0.00	Inf	0.00	0.00	Inf	0.51	0.00	Inf	1.00	0.00
(11, 3)	4.85	1.30	0.00	Inf	0.00	0.00	Inf	0.50	0.00	Inf	1.00	0.00
(11, 6)	5.07	1.16	0.00	Inf	0.00	0.00	Inf	0.53	0.00	Inf	1.00	0.00
(11, 12)	5.28	0.68	0.00	Inf	0.00	0.00	Inf	0.59	0.00	Inf	1.00	0.00
					B. Target = average FMOM return							
(6, 1)	4.10	1.24	0.00	0.00	-0.99	0.00	0.59	0.00	0.00	1.00	0.00	0.00
(6, 3)	5.57	1.44	0.00	0.00	-0.99	0.00	0.58	0.00	0.00	1.00	0.00	0.00
(6, 6)	5.76	1.55	0.00	0.00	-0.98	0.00	0.54	0.00	0.00	1.00	0.00	0.00
(6, 12)	4.14	1.10	0.00	0.00	-0.97	0.00	0.59	0.00	0.00	1.00	0.00	0.00
(11, 1)	4.95	1.32	0.00	0.00	-0.98	0.00	0.59	0.00	0.00	1.00	0.00	0.00
(11, 3)	4.85	1.30	0.00	0.00	-0.98	0.00	0.61	0.00	0.00	1.00	0.00	0.00
(11, 6)	5.07	1.16	0.00	0.00	-0.97	0.00	0.63	0.00	0.00	1.00	0.00	0.00
(11, 12)	5.28	0.68	0.00	0.00	-0.96	0.00	0.60	0.00	0.00	1.00	0.00	0.00

Table A5. Hypothesis testing: Alternative filtering criteria

This table shows the results of hypothesis tests with null hypothesis that both momentum (MOM) and filtered momentum (FMOM) equally perform and with alternative hypothesis that the FMOM performs better than the MOM strategy based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). Portfolio returns are measured net of transaction costs which are assumed to be 50 basis points. The p-value is calculated using a block bootstrapping method. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

$(J, K) = (11, 12)$								
Filtering	SR		SO		UP		OM	
criterion	stat	p-val	stat	p-val	stat	p-val	stat	p-val
A. Target = Pos								
Avg	4.394	0.000	5.703	0.000	6.026	0.000	18.621	0.000
SR	4.505	0.000	3.225	0.000	3.577	0.000	10.169	0.000
SO	4.450	0.000	7.632	0.000	7.908	0.000	28.664	0.000
UP	4.428	0.000	8.038	0.000	8.315	0.000	29.978	0.000
OM	4.612	0.000	6.890	0.000	7.163	0.000	26.305	0.000
Pos	2.991	0.463	0.000	0.480	0.628	0.474	1.000	0.480
B. Target = SR								
Avg	4.394	0.566	0.588	0.000	1.078	0.000	2.198	0.000
SR	4.505	0.451	0.000	0.496	0.571	0.493	1.000	0.496
SO	4.450	0.510	0.958	0.000	1.430	0.000	3.028	0.000
UP	4.428	0.529	1.015	0.000	1.487	0.000	3.152	0.000
OM	4.612	0.344	0.831	0.000	1.299	0.000	2.778	0.000
Pos	2.991	0.998	-0.646	0.992	0.106	0.984	0.141	0.966

Table A6. Summary statistics of filtered momentum profits with alternative minimum numbers of equities

This table shows summary statistics of the filtered momentum (FMOM) profits (net of transaction costs) of the annualized return over the sample period with alternative minimum numbers of equities: 10, 50, 100, and 200 equities. Four cases of momentum portfolio formation are considered with a $J-$month formation period and a $K-$month holding period.

	$(J, K) = (6, 1)$				$(J, K) = (6, 12)$			
Statistics	Minimum number of equities				Minimum number of equities			
	10	50	100	200	10	50	100	200
Mean	107.83	90.63	81.38	63.21	36.77	37.57	34.86	30.69
(t-val)	10.33	10.70	11.52	11.11	6.69	7.89	7.96	7.99
Median	106.15	105.87	95.63	72.13	40.64	41.12	41.12	37.49
SD	49.14	41.71	35.67	30.31	31.75	27.45	25.47	22.68
Skew	-0.48	-1.58	-1.59	-1.77	-3.06	-2.37	-2.40	-2.20
Kurt	7.54	12.10	12.63	13.87	28.73	20.18	18.55	14.67
AC(1)	-0.02	-0.10	-0.04	-0.03	-0.09	-0.05	0.02	0.02
SR	2.19	2.17	2.28	2.09	1.16	1.37	1.37	1.35
	$(J, K) = (11, 1)$				$(J, K) = (11, 12)$			
Statistics	Minimum number of equities				Minimum number of equities			
	10	50	100	200	10	50	100	200
Mean	102.64	79.90	75.98	67.39	32.28	30.52	29.66	29.37
(t-val)	9.73	9.63	11.43	11.64	5.59	5.52	6.08	6.71
Median	103.88	87.42	82.43	82.92	39.94	38.76	35.93	35.41
SD	50.13	41.87	33.94	30.31	33.90	32.68	28.94	25.98
Skew	-1.84	-2.19	-1.69	-2.10	-2.89	-3.13	-2.75	-2.17
Kurt	17.71	17.11	13.51	16.50	20.57	23.03	20.15	15.06
AC(1)	-0.03	-0.01	-0.03	-0.02	-0.02	0.02	0.00	0.03
SR	2.05	1.91	2.24	2.22	0.95	0.93	1.03	1.13

Table A7. Hypothesis testing: Alternative minimum number of equities

This table shows the results of hypothesis tests with null hypothesis that two filtered momentum (FMOM) strategies with the benchmark minimum number of equities of 100 and with alternative minimum numbers of equities equally perform and with alternative hypothesis that the latter performs better than the former, based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). Portfolio returns are measured net of transaction costs which are assumed to be 50 basis points. The p-value is calculated using a block bootstrapping method. Eight cases of momentum strategies are considered with a $J-$month formation period and a $K-$month holding period.

(J, K)	# Equities	SR		SO		UP		OM	
		stat	p-val	stat	p-val	stat	p-val	stat	p-val
(6,1)	10	0.45	0.76	0.13	0.01	0.58	0.00	1.29	0.01
	50	0.47	0.68	0.05	0.19	0.48	0.23	1.12	0.17
	200	0.49	0.54	-0.13	0.97	0.32	0.93	0.71	0.97
(6,3)	10	0.50	0.69	0.12	0.01	0.54	0.02	1.28	0.01
	50	0.50	0.71	0.04	0.27	0.44	0.41	1.09	0.26
	200	0.56	0.45	-0.10	0.93	0.34	0.85	0.77	0.93
(6,6)	10	0.45	0.60	0.11	0.01	0.51	0.04	1.28	0.01
	50	0.48	0.48	0.06	0.13	0.46	0.20	1.15	0.11
	200	0.46	0.57	-0.08	0.91	0.36	0.78	0.81	0.90
(6,12)	10	0.28	0.75	0.02	0.35	0.38	0.60	1.05	0.33
	50	0.34	0.46	0.03	0.28	0.43	0.34	1.07	0.27
	200	0.36	0.36	-0.04	0.68	0.39	0.52	0.91	0.67
(11,1)	10	0.41	0.74	0.13	0.01	0.51	0.05	1.33	0.00
	50	0.41	0.76	0.02	0.28	0.42	0.42	1.06	0.27
	200	0.51	0.28	-0.05	0.77	0.38	0.66	0.88	0.77
(11,3)	10	0.51	0.46	0.14	0.01	0.61	0.00	1.30	0.00
	50	0.53	0.35	0.04	0.19	0.50	0.19	1.10	0.18
	200	0.50	0.52	-0.09	0.87	0.36	0.83	0.81	0.88
(11,6)	10	0.38	0.44	0.09	0.06	0.52	0.07	1.20	0.05
	50	0.39	0.38	0.05	0.17	0.47	0.22	1.11	0.15
	200	0.40	0.34	-0.03	0.61	0.39	0.64	0.92	0.62
(11,12)	10	0.25	0.58	0.02	0.30	0.39	0.48	1.06	0.29
	50	0.25	0.60	0.01	0.40	0.37	0.58	1.02	0.39
	200	0.30	0.32	-0.01	0.51	0.42	0.36	0.98	0.50