A new momentum measurement in the Chinese stock market

ABSTRACT

Literature shows that the traditional momentum effect is absence in China, and our evidence also confirms this. However, considering the information of short-term investors’ consistent beliefs in price movements, we can capture a significant momentum effect. The short-term information horizon for reflecting the investor belief is relative to the longer information horizon of asset past performance in capturing basic momentum. By constructing an indicator of CB to reflect investors’ short-term consistent belief in price movements, we develop a new momentum indicator, CBMOM, as the product of short-term CB and long-run past returns. Based on the data from January 2000 to December 2020 in China, our results show that CBMOM has an advantage of capturing the momentum effect over the past-return measure. In particular, the momentum strategy based on CBMOM with the one-month CB and the one-year past return has the strongest profit. Furthermore, we examine the nonlinear impact of the synergy between CB and the one-year past return on stock returns. Specifically, the one-year past return has a greater positive impact as the cross-sectional CB level increases, but the significance is strong only for the highest-level CB.

**Keywords**: Momentum effect, Past returns, Investor belief, Cross-sectional returns

# Introduction

The momentum effect has been one of the widely studied anomaly. The robustness of momentum strategies is documented in many studies ([Rouwenhorst 1998](#_ENREF_39); [Fong *et al.* 2005](#_ENREF_21); [Antoniou *et al.* 2007](#_ENREF_3); [Asem & Tian 2010](#_ENREF_4); [Liu *et al.* 2011](#_ENREF_33); [Novy-Marx 2012](#_ENREF_37); [Asness *et al.* 2013](#_ENREF_5); [Barroso & Santa-Clara 2015](#_ENREF_8); [Avramov *et al.* 2016](#_ENREF_7); [Daniel & Moskowitz 2016](#_ENREF_15); [Butt & Virk 2017](#_ENREF_12); [Blitz *et al.* 2020](#_ENREF_10)). There is the momentum effect in many international markets and various asset classes ([Fong *et al.* 2005](#_ENREF_21); [Asness *et al.* 2013](#_ENREF_5)). However, the traditional momentum effect is absence in the emerging stock markets, including China ([Kang *et al.* 2002](#_ENREF_29); [Chui *et al.* 2010](#_ENREF_13); [Pan *et al.* 2013](#_ENREF_38); [Zhang *et al.* 2018](#_ENREF_44); [Butt *et al.* 2021](#_ENREF_11); [Gao *et al.* 2021a](#_ENREF_22); [Gao *et al.* 2021b](#_ENREF_23)). Based on the data from 2000-01 to 2020-12, we re-examine the momentum effect in China and also find insignificant evidence. In addition, the momentum effect based on the past one-year formation period (skipped the recent month for avoiding the short-term reversal effect) is relatively strong but still insignificant under the factor models.

Momentum theory believes that prices’ continuation is attributed to investors’ underreaction to information ([Hong & Stein 1999](#_ENREF_26); [Hong *et al.* 2000](#_ENREF_25); [Makarov & Rytchkov 2012](#_ENREF_34)). News-watchers trade based on the advantages of private information, while momentum traders buy/sell shares based on price realized up-/down- trends (past returns). However, the trading setting about momentum traders is too simple. Momentum traders are heterogeneous. Different momentum traders enter the market at different periods during price upward/downward trend and the strength of traders’ momentum beliefs are also distinct. When stock prices have experienced an extremely large upward/downward movement, due to the absence of private information momentum traders may worry about a potential price reversal in the future and not execute trend trading.

Intuitively, stock past performance is one of the sources for a momentum trader to form the buying or selling belief, and the short-term information that can reflect other investors’ beliefs may be another decision-dependence source to the momentum trader.

If momentum traders can conjecture other investors’ beliefs that are consistent with the price trend, they will be easier to execute a momentum strategy. Momentum traders who lack private information hope to achieve group advantage to alleviate concerns about potential price reversal or strengthen their momentum beliefs.

What kind of information that reflects investors’ consistent beliefs in price trend movements can be obtained by momentum traders and support their momentum belief? According to [Hong and Stein (1999)](#_ENREF_26), momentum traders make decisions based on the public and simply available price and trading information. For this consideration, in terms of a fixed-period price trend that momentum traders focus we think that low price volatility or dispersion in short-term prices is important information for momentum traders. This kind of information reflects that the overall investors have a relatively consistent belief or less disagreement in price trend movements, and indicate the higher probability of price continuation. The high-level consistent belief of investors indicates that investors agree with price trend movements whether actively or passively, in which prices show lower volatility around the price’s trend movements. The low-level consistent belief of investors demonstrates that investors disagree with each other about the expectation of stock prices, in which prices present higher dispersion around the price’s trend movements. Moreover, the short-term information that reflects recent investors’ consistent beliefs can satisfy the current/immediate needs of momentum investors to follow the crowd, thereby strengthening their momentum beliefs, instead of just depending on the long-term price performance. As momentum traders gradually execute their momentum strategies, the snowball will roll bigger and stock prices present a momentum effect because of the herding behavior of momentum traders.

Our basic hypothesis is that the shorter-term information of investors’ consistent belief enhances the momentum effect based on the long-term price performance. In this paper, we construct an indicator of CB to reflect investors’ consistent belief in price movements. The consistent belief measure is motivated by the conception of the heterogeneous belief and its properties ([Miller 1977](#_ENREF_35); [Shalen 1993](#_ENREF_40); [Diether et al. 2002](#_ENREF_17); [Berkman et al. 2009](#_ENREF_9); [Verardo 2009](#_ENREF_41); [Hibbert et al. 2020](#_ENREF_24)). A high heterogeneous belief indicates that investors have largely different opinions, and it is related to high volatility, high trading volume, the big divergence of analysts’ opinions, etc. The consistent belief is basically counter to the heterogeneous belief, where a higher consistent belief indicates lower-level disagreements among investors about future prices. Therefore, the CB is mainly characterized by low relative volatility based on the information of monthly highest, lowest, opening, closing prices. The negative relation between the consistent belief and volatility is opposite to the positive relationship between volatility and heterogeneous belief, where many studies also document the latter relationship ([Berkman *et al.* 2009](#_ENREF_9); [Atalla *et al.* 2016](#_ENREF_6); [Huisman *et al.* 2021](#_ENREF_28)). The volume information of capturing the investors’ participation is another character of CB, it could be as the confidence interval of the volatility part in CB, as well as avoiding part of liquidity issues.

By using a sample from 2000-01 to 2020-12, we first show that the traditional momentum effect based on traditional past performance is insignificant in China, in which the momentum effect based on the past one-year formation period is relatively strong but still insignificant. Then, we detect the role of short-term CB on the traditional momentum effect (based on past returns over twelve months). By factoring in CB, we find that for the 30% high-CB stocks, the traditional momentum effect is significant, where the average monthly return of the momentum strategy is 1.02% with a t-statistic of 2.77. For the 30% low-CB stocks, the traditional momentum is insignificant, and the strategy’s average return is only 0.16%. We further find that CB has a significant role on past losers and an insignificant role on past winners. This result indicates that in China, high CB is helpful to identify stocks that are underrated by investors.

We also construct a new momentum measurement, CBMOM, by combining the one-month CB and past return over one year (marked by MOM). We show that CBMOM has the advantage of capturing the momentum effect in China’s market. The results of univariate portfolios (in deciles) show that the CBMOM’s zero-investment momentum strategy earns significant average monthly returns of 1.26% and a significant FF5-adjusted alpha of 0.97%. Considering a set of firm characteristics, the CBMOM’s strategy can generate relatively stable profits. However, the momentum strategies based on MOM have no significant FF5-adjusted alpha at the 5% level of significance across all firm characteristics we mentioned.

Our results of Fama–MacBeth regressions further confirm that stocks’ CBMOM has a positive predictive ability on cross-sectional stock returns. In the cross-sectional regression with CB, MOM, CBMOM, and other control variables together, CBMOM has a positive coefficient with a t-statistic of 3.68, but MOM and CB have no significant coefficients. This result demonstrates that the synergy between MOM and CB is important for the momentum effect in China’s stock market. The impact of the synergy between CB and MOM on stock returns is nonlinear and not fully applicable to all CB levels. We further evaluate the difference of MOM’s impacts on cross-sectional stock returns under the restriction by the five levels of CB. As the cross-sectional CB level increases, MOM positively predict the cross-sectional stock returns with a greater coefficient, but the significance is strong only for the highest-level CB. This result supports our intuition that the momentum effect based on long-term past return performance is stronger when investors have relatively consistent belief or less disagreement in the short term.

Additionally, to strengthen and enrich our findings, we first show that the risk-adjusted approaches suggested by [Barroso and Santa-Clara (2015)](#_ENREF_8) and [Daniel and Moskowitz (2016)](#_ENREF_15) also can be used to improve the performance of momentum strategies based on our proposed measure CBMOM and the traditional measure MOM. Secondly, we also find that the impact of the short-term reversal effect on the CBMOM-based momentum effect is basically absent. Thirdly, the abnormal momentum profits by CBMOM are robust by the candidate factor models, including the 4-factor model proposed by [Liu *et al.* (2019)](#_ENREF_32), the reversal-based model suggested by [Lin *et al.* (2020)](#_ENREF_31), and the *q*-factor model of [Hou *et al.* (2015)](#_ENREF_27).

We have the following contributions. First, we demonstrate that investors’ consistent belief in price movements has a significant role in capturing momentum effects. Our paper is helpful to explain why the traditional momentum effect is insignificant in China. Second, we also develop a new momentum indicator, a unity of the short-term investors’ consistent belief and the long-term past returns. The new momentum indicator has an advantage in capturing cross-sectional momentum effects, and its performance is far better than that of the traditional indicator based on past returns. Third, we show the risk-adjusted momentum strategies could be used to improve the performance of momentum strategies either based on our new momentum measure or based on the traditional measure. In particular, the dynamic-volatility scaling (DVS) momentum strategy proposed by [Daniel and Moskowitz (2016)](#_ENREF_15) improves the traditional momentum strategy and the DVS version of the traditional momentum achieves a significant FF5 alpha.

The next section presents our data. We examine the traditional momentum effect of China in Section 3. The results of the CBMOM’s momentum performance are shown in Section 4. Section 5 is our discussion part, and we conclude this paper in Section 6.

# Data

We obtain the data from CSMAR[[1]](#footnote-1) database spanning 2000-01 to 2020-12. Following [Liu *et al.* (2019)](#_ENREF_32), we use the sample from 2000 to assure uniformity in accounting data and ensure efficient observations to construct portfolios. Our sample includes all Chinese A-share stocks with data available, and stocks with ST (special treatment) or PT (particular transfer) status are excluded.

**MOM**: For month t, MOM is the summation of monthly returns from month t-J to t-1, and we skip the return at present month to avoid a short-term reversal effect, which is significant and strong anomaly in China ([Zhang *et al.* 2018](#_ENREF_44); [Liu *et al.* 2019](#_ENREF_32)). Specifically, [Zhang *et al.* (2018)](#_ENREF_44) show that reversal effects based on returns over the past month are significant from one-month to one-year holding period.

**CB**: Investor’s consistent belief. We calculate CB by

where C, O, H, and L are the close, open, highest, and lowest prices, respectively, in each month, and V is the trading volume (RMB). The highest and lowest prices are used to capture the power of buyers and sellers, respectively, and the difference between the highest and lowest prices reflects the strength of confrontation between buyers and sellers. The difference between closed and open prices captures the consequence. High means that the belief of either buyers or sellers has an advantage, which indicates the high-level consistent recognition of stock prices and price trends among all investors. The second part reflects investors’ trading activities, which have an impact on the quality of , such as potential liquidity issues. Therefore, high CB reflects investors’ consistent belief, and CB is a helpful indicator to confirm the price momentum pattern. Past returns as momentum show the basic price trend, high CB shows high-level investors’ consistent belief about subsequent price continuations, and low CB indicates uncertainty in investors’ expectations.

**CBMOM**: New momentum indicator which combines CB and MOM.

**Beta**: Daily firm CAPM Beta is estimated with past 250 daily observations, and we use the daily firm CAPM Beta on the last day of month t as monthly CAPM Beta at month t.

**Size**: Firm size, which is the circulation market value for month t.

**BM, DY, ROE,** and **INS** are a firm’s book-to-market ratio, dividend yield ratio, return on equity, and institutional shareholding ratio, respectively, which are recent data available at month t.

**RVS**: Short-term reversal, which is the return at month t.

**MAX**: MAX equals the highest daily return at month t.

**VOLA**: Volatility, which is the standard deviation of daily returns at month t.

**ABTURN**: Abnormal turnover, which is calculated as

where is the daily turnover, and is the last trading day at month t.

**ILLIQ**: Amihud’s illiquidity ([Amihud 2002](#_ENREF_2)). A firm’s ILLIQ is the average of the natural log of daily illiquidity at month t, where the daily illiquidity is the absolute daily return divided by daily RMB trading volume.

**SENT**: Firm-specific investor sentiment ([Aboody *et al.* 2018](#_ENREF_1); [Weißofner & Wessels 2019](#_ENREF_43); [Li & Li 2021](#_ENREF_30)), which we calculate as the mean of daily overnight returns at month t.

Table 1 reports descriptive statistics of variables, including panel mean, first quartile, third quartile, standard deviation, and skewness. The full sample period ranges from 2000-01 to 2020-12. By excluding stocks with ST or PT statuses, we have all 2396 stocks available and a total of 292422 panel observations. CB’s panel mean and standard deviation are 0.11 and 0.15, respectively. MOM is the summation of monthly returns from month (J=11) to . We analyze the best formation period of momentum by past returns in Section 3, where we show that the strength of momentum is strongest when J equals 11, both for MOM and CBMOM. The panel mean of MOM is 13.13%, which is greater than the mean of CBMOM measured by the product of CB and MOM.

Insert Table 1 about here

# Traditional momentum effect of China

## Momentum effect based on past performance

[Asness *et al.* (2013)](#_ENREF_5) show that the momentum effect exists in almost every stock market and asset class. Unlike international markets, the momentum effect in China’s stock market is absence ([Wang & Chin 2004](#_ENREF_42)) but a contrarian effect. [Zhang *et al.* (2018)](#_ENREF_44) show that various reversal strategies generate positive returns in China with the data from 1997-01 to 2015-12, and this counterintuitive reversal of obtaining profits cannot be explained by common factors. Moreover, this reversal phenomenon is maintained at daily, weekly, and monthly frequencies.

We re-examine the performance of momentum strategies by past returns with various formation periods by using the data from 2000-01 to 2020-12. The average monthly returns and the factor-adjusted returns of MOM strategies based on different formation periods are show in Table 2. Panel A shows the results of MOM strategies formed by unconditional sorting. Specifically, for each MOM indicator corresponding to one formation period (J), according to MOM we sort stocks and divide into deciles. A MOM zero-investment momentum strategy is conducted by buying stocks in the highest decile (high MOM) and selling that in the lowest decile (low MOM). The holding period of strategy portfolios is one month, and the return of each portfolio is a value-weighted average of individual stocks’ returns. The formation period ranges from 1 to 11 months.

Insert Table 2 about here

Panel B shows the results of MOM strategies formed by size-neutral sorting. Specifically, for each MOM with J-month formation period, we first sort stocks according to Size and divide them into a large-cap (B) group and a small-cap (S) group. Then, for stocks in the large-cap group or small-cap group, we follow the above unconditional-sorting method from the MOM strategy marked by B-MOM or S-MOM. The holding period is also one month, and the portfolio return is a value-weighted mean. The return of the size-neutral MOM strategy is the equal average of returns of B-MOM and S-MOM.

In Table 2, we also present the results of factor-adjusted returns (FF5 alpha). Specifically, we fit the following time-series model for each strategy:

where and are the monthly portfolio return and risk-free interest, respectively, and independent variables are the FF5 factors ([Fama & French 2015](#_ENREF_18), [2017](#_ENREF_19)). The intercept is the factor-adjusted return.

In Table 2, Panel A shows that unconditional-sorting momentum strategies have no significant positive returns, excluding the strategy with the formation period J of 11, where the t-statistic of the strategy’s returns is weak. The results of factor-adjusted returns show that all 11 strategies have no significant momentum abnormal returns. This finding also applies to size-neutral momentum strategies.

In short, these univariate momentum strategies based on past returns do not have significant abnormal returns that cannot be explained by the popular FF5 factor model. This motivates us to explore how to accurately capture the momentum effect in China. Based on our story, the information of investors’ consistent belief in price trends plays a key role for momentum traders, and we provide evidence in the next subsection.

Additionally, according to the performance of MOM’s momentum strategies in Table 2, we use the formation period of 11 in past returns, which corresponds to the strongest momentum effect, to conduct the following analysis of MOM or CBMOM.

## Strengthening the traditional momentum effect: The role of CB

To prove that past returns and the short-term investors’ consistent belief have a synergistic effect in capturing the momentum effect, we conduct bivariate portfolio analysis with CB and MOM. Specifically, we first divide stocks into 3 CB groups: high 30%, middle 40%, and low 30%. Then, we divide the stocks in each CB group into three MOM groups: high 30% (past winners), middle 40%, and low 30% (past losers). A zero-investment momentum strategy is conducted in each CB group. We form all 9 original portfolios by CB and MOM and 3 portfolios of the conditional momentum strategy. We refresh portfolios after holding one month. In another order between CB and MOM, we also divide stocks into three MOM groups and then divide stocks in each MOM group into three CB groups. In Table 3, Panel A presents the portfolio results sorted by CB first and then sorted by MOM. Panel B shows the portfolio results sorted by MOM first and then sorted by CB.

Insert Table 3 about here

In Panel A, we find that in the low CB group, there is no significant momentum effect based on MOM, while in the high CB group, the momentum strategy based on MOM is significant and yields monthly return of 1.02% with the t-statistic of 2.77. This result directly confirms our intuition.

The results of Panel B further illustrate that the key role of CB in MOM lies in the influence of CB on past losers. We show that for past losers, higher CB leads to significantly worse returns in the future. In China, among stocks with poor past performance, high CB is helpful to find stocks that have worse performance in the future. This indicates that the insignificance of the traditional momentum effect of China is partly attributed to the absence of capturing short-term investors’ beliefs. It also means that momentum investors trade not only based on long-run price trends but also based on the short-term information about other investors’ attitudes towards recent prices, especially price directions. The simple measure of past returns is insufficient to capture a momentum effect in China. In the next section, we further prove the advantage of our momentum indicator CBMOM for capturing the momentum effect.

# The momentum performance improvement by CBMOM

## Univariate portfolio performance

After examining the enhancement role of CB in MOM, we show the performance of CBMOM as a momentum indicator. We first start from the univariate portfolio analysis. Similarly, following the analysis of univariate portfolio based on MOM in 3.1, we explore the impact of the formation period on the CBMOM’s momentum strategies, where the formation period is utilized to calculate MOM.

Table 4 shows the results of CBMOM's univariate portfolios, where unconditional-sorted portfolios are reported in Panel A, and size-neutral portfolios are reported in Panel B. The average returns of CBMOM’s unconditional-sorted portfolios are significantly positive when the formation period J ranges from 5 to 11, and the corresponding factor-adjusted returns are also significant when J equals 8, 9, or 11. We obtain a basically consistent finding from the results of CBMOM’s size-neutral portfolios.

Insert Table 4 about here

Insert Table 5 about here

Above all, CBMOM has the strongest momentum effect when the formation period is equal to 11, and the corresponding factor-adjusted alpha by FF5 is also the highest. Table 5 reports the specific results of each decile portfolio by MOM or CBMOM with the best formation period of 11, including the monthly average return, the factor-adjusted return, and the factor loadings of the long-short momentum strategy. We show that CBMOM has greater accuracy in capturing price continuations of past losers, which is consistent with the finding in the last section. The average monthly return and the FF5-adjusted alpha of the MOM’s lowest decile (past losers) portfolio are 1.45% and 0.72%, respectively, while the corresponding results for CBMOM’s lowest decile portfolio are 0.98% and 0.16%. From the coefficients of the FF5 factor model, the significantly positive intercept shows the excellent advantage of CBMOM as a momentum indicator. Compared with the MOM's momentum strategy, the CBMOM's momentum strategy has a significant positive system risk exposure of 0.21, while the MOM’s strategy has no significant system risk.

Insert Figure 1 about here

Figure 1 plots the cumulative returns of momentum factors of MOM and CBMOM based on unconditional-sorted decile portfolios. The CBMOM momentum factor had excellent cumulative returns from 2000-01 to 2020-12, exceeding 1400%, and performed better in the past five years. It should be pointed out that the CBMOM momentum factor also suffers the momentum crashes mentioned in [Daniel and Moskowitz (2016)](#_ENREF_15) during the two financial crisis periods of 2007–2010 and 2015–2016. This is also reflected by the significant system-risk exposure of the CBMOM momentum factor, where the market beta is 0.21. We also divide the sample period into four subperiods: 2000-01 to 2005-12, 2006-01 to 2010-12, 2011-01 to 2015-12, and 2016-01 to 2020-12. Then, we calculate the mean of monthly CBMOM momentum factor and five factors of [Fama and French (2015)](#_ENREF_18) for each subperiod, respectively. In Figure 2, we can see that the CBMOM momentum factor is the only one that has positive returns in all four subperiods among all factors, and the average return of the CBMOM momentum factor far exceeds the other five factors from 2016-01 to 2020-12.

Insert Figure 2 about here

In addition, we also give the results of CB’s univariate portfolios to illustrate that CB itself does not result in significant return spread, and CBMOM’s powerful capability in capturing the momentum effect should be attributed to the synergy between long-term past returns and the short-term investors’ consistent beliefs.

## Bivariate portfolio performance considering a set of firm characteristics

Considering a set of firm characteristics, we examine the performance of CBMOM’s and MOM’s strategies to show the advantage of CBMOM. For each characteristic, we use bivariate portfolio analysis to conduct CBMOM’s long-short momentum strategy and MOM’s long-short momentum strategy. Specifically, we first divide stocks into 3 groups according to each firm’s characteristic: high 30%, middle 40%, and low 30%. Then, we divide the stocks in each characteristic group into three CBMOM or MOM groups: high 30% (past winners), middle 40%, and low 30% (past losers), and we form the corresponding zero-investment momentum strategy. We refresh portfolios at the end of each month, and portfolio returns are aggregated by the value-weighted method. The firm characteristics include Size, CAPM beta (Beta), BM, DY, ROE, INS, RVS, VOLA, MAX, ABTURN, ILLIQ, and SENT.

Insert Table 6 about here

We report the results of the conditional momentum strategies, including average returns in Table 6 and factor-adjusted returns in Table 7. In almost all the characteristics we considered, CBMOM’s momentum strategies have significant and positive returns, except for small-cap and highly illiquid stocks. [Amihud (2002)](#_ENREF_2" \o "Amihud, 2002 #2) finds that illiquidity is stronger on the returns of small stock portfolios. Therefore, small size and high illiquidity are highly related to each other. The profits of CBMOM’s strategies mainly come from large/middle and liquid stocks. The results are consistent with [Avramov *et al.* (2016)](#_ENREF_7). From the perspective of market illiquidity, [Avramov *et al.* (2016)](#_ENREF_7) indicate that arbitrage is easier when markets are most liquid, and they find that momentum profits are positively (negatively) related to market liquidity (illiquidity). In Table 6, compared to CBMOM’s results, MOM’s momentum strategies do not have significant returns in most characteristic groups. We further focus on the results of factor-adjusted returns. In Table 7, we find that all MOM’s strategies no longer have significant abnormal returns that cannot be explained by the five factors postulated by [Fama and French (2015)](#_ENREF_18). However, most of CBMOM’s strategies still generate significantly positive abnormal returns in characteristic groups, including stocks with large capitalization, low beta, low BM ratio, high ROE, high institutional shareholding ratio, high return in the last month (past winners for short-term reversal), high MAX, and low illiquidity. Moreover, for the characteristics of dividend yield ratio, volatility, abnormal turnover, and firm-specific investor sentiment, the abnormal returns of CBMOM’s momentum strategies are significant and positive for both the top and bottom stock groups according to each characteristic.

Insert Table 7 about here

In short, CBMOM’s momentum strategy can generate stable profits in stocks with good fundamentals (large capitalization, low BM, DY, high ROE, high institutional shareholding ratio), good short-term price performance (high RVS, high MAX) and good risk attributes (low beta, low volatility, low illiquidity). From the perspective of investor sentiment (abnormal return, firm-specific investor sentiment), CBMOM’s momentum strategies can earn significant profits for stocks with an optimistic or pessimistic sentiment.

## Fama–MacBeth regression results

Portfolio analysis can effectively analyze the interrelationship between two variables or three variables, but it is powerless or inconvenient for multiple variables. We use month-by-month Fama–MacBeth regressions to put more control variables together and then to examine the impact of CBMOM on cross-sectional stock returns.

We fit the following four cross-sectional regressions for each month t:

where is the return of stock for month , and the vector includes a set of firm characteristics.

Insert Table 8 about here

Table 8 reports the time-series average of coefficients by the above cross-sectional regressions. The t-statistics are adjusted according to [Newey and West (1987)](#_ENREF_36). The results of Model (1) show that CB does not have a significant impact on cross-sectional stock returns. The coefficient of MOM in Model (2) is weakly significant with a t-statistic of 1.87, but CBMOM has a very significant and positive coefficient in Model (3), where the t-statistic is 3.68. In Model (4), we put CB, MOM, CBMOM (the product of CB and MOM), and other control variables into one regression. The results show that CB and MOM are insignificant, and CBMOM is still maintained with high significance. These findings confirm a significant momentum effect based on CBMOM in China.

Because the synergy between CB and MOM is not fully applicable to all CB levels, as shown in Table 3, only high CB is helpful to enhance the MOM’s momentum effect. Therefore, for each month, we divide the cross-sectional firm CBs into quintiles and use dummy variable labels:,,, , . For instance, if a firm’s CB at month t is less than the 20th percentile of all cross-sectional CB, we have 5 dummy variables for this firm to distinguish its CB level:

Then, we fit the following cross-sectional regressions for each month t:

This model can evaluate the difference of MOM’s impacts on cross-sectional stock returns under the restriction of the five levels of CB. Table 9 shows model coefficients and t-statistics. As the cross-sectional CB level increases, MOM has a greater positive impact on stock returns. The significance is strong only for the product of the dummy variable of the highest-level CB and MOM. This result confirms that the short-term information of investors’ momentum effect exists when investors have consistent expectations for future price continuations.

Insert Table 9 about here

# Discussion

## Do risk-adjusted momentum strategies based on CBMOM earn more profits than the raw strategy?

We have shown that CBMOM’s momentum strategy generates positive profits in China, and outperforms the traditional momentum strategy (MOM). Previous studies also document the risk-adjusted momentum strategies perform better than the raw momentum strategy ([Barroso & Santa-Clara 2015](#_ENREF_8); [Daniel & Moskowitz 2016](#_ENREF_15); [Fan *et al.* 2018](#_ENREF_20); [Dierkes & Krupski 2022](#_ENREF_16)): the constant-volatility scaling (CVS) momentum strategy suggested by [Barroso and Santa-Clara (2015)](#_ENREF_8) and the dynamic-volatility scaling (DVS) momentum strategy first proposed by [Daniel and Moskowitz (2016)](#_ENREF_15). In this section, we investigate the improvement of these two risk-adjusted methods on CBMOM momentum and the traditional momentum to further show the strong performance of CBMOM momentum from the investment perspective.

Specifically, the return of CVS strategy is:

where is the momentum return of CBMOM strategy (based on decile portfolios) or the traditional MOM strategy for month t, is the annualized realized volatility of the underline momentum strategy calculated by using the previous 126 daily momentum returns ([Barroso & Santa-Clara 2015](#_ENREF_8); [Fan *et al.* 2018](#_ENREF_20)). is constant target volatility that is ex-post and adjusted by investor risk preference.

[Daniel and Moskowitz (2016)](#_ENREF_15) document that momentum strategies experience crashes, and bear market states and market volatility partly predict the crashes. They also propose the DVS momentum strategy from the return-variance perspective and show the DVS momentum strategy outperforms the CVS momentum strategy of [Barroso and Santa-Clara (2015)](#_ENREF_8). According to [Daniel and Moskowitz (2016)](#_ENREF_15), we first examine the impact of the bear market states, market variance and their interaction term on the future returns of CBMOM and MOM strategies, where market volatility is the standard deviation of the previous 126 daily returns of Shanghai Securities Composite Index (SSEC), the bear market indicator variable () equals one if the cumulative SSEC return in the past 24 months is negative and is zero otherwise.

Insert Table 10 about here

Table 10 presents the regression results of momentum crash, and the dependent variables are the returns of CBMOM strategy (based on univariate decile portfolios) in Panel A and the returns of MOM strategy (based on univariate decile portfolios) in Panel B. Univariate regression results of Panel A show that the market variance () has significant and negative impact on the future returns of CBMOM momentum strategy that is consistent with the finding of [Daniel and Moskowitz (2016)](#_ENREF_15). However, the bear market indicator variable has a positive coefficient instead of a negative one in [Daniel and Moskowitz (2016)](#_ENREF_15). This demonstrates that the bear market states in China do not lead to momentum crashes. And we also regress the CBMOM returns with a constant and the bull market indicator variable that equals one if the cumulative SSEC return in the past 24 months is positive and is zero otherwise. There is a negative coefficient of the bull market indicator for model (4).

Insert Figure 3 about here

In Figure 3, we further plot the time-series cumulative momentum returns both for CBMOM and MOM strategies and mark the bull market states. Most momentum crashes and momentum with poor performance occur before the market crashes (2008:01-2008:10, 2015:06-2016:02), crop up during the extreme bull market periods (2006:01-2008:01, 2014:06-2015:06). The momentum crash from early 2009 to mid-2010 is basically consistent with the theory of [Daniel and Moskowitz (2016)](#_ENREF_15) that momentum crashes occur when the market rebounds from the bear market states.

On the whole, the bull market states are more likely to lead to momentum crashes in China. One possible reason is that the prices of past losers are pushed too high compared to the prices of past winners when the market experiences bubbles. Because in these crazy bull market periods, the soars space of loser-side prices seems larger than that of winner-side prices to irrational investors, who may choose to buy more losers, even sell owned winners.

The powerful indicator of [Daniel and Moskowitz (2016)](#_ENREF_15) doesn’t predict the returns of CBMOM strategy, neither in the univariate or multivariate models. By using to replace , the two variables of and have significant and negative impacts on the future returns of CBMOM strategy in their univariate models. Nevertheless, the two and the market variance do not have significant coefficients in the multivariate model (7)[[2]](#footnote-2).

The MOM estimation results in Panel B of Table 10 also indicate the market variance is an important variable to predict momentum returns, and the bull market states are more likely to relate with momentum crashes instead of the bear market states.

According to the in-sample findings in Table 10 and following the ex-ante approach of [Daniel and Moskowitz (2016)](#_ENREF_15), the DVS strategies for CBMOM and MOM are conducted as follow:

where is the conditional expected return of the CBMOM momentum portfolio estimated by an expanding window (the initial window is 24 months) regression of CBMOM monthly returns on (i.e., the regression (1) in Panel A of Table 10), is the expected variance of the CBMOM momentum portfolio estimated by the realized variance of 126 daily CBMOM returns. Among 7 models, we choose model (1) only including the market variance to forecast the return of CBMOM strategy due to the model shows a significant coefficient and a relatively higher adjusted . is the conditional expected return of the MOM momentum portfolio estimated by an expanding window (the initial window is 24 months) regression of monthly momentum returns on , , and (i.e., the regression (7) in Panel B of Table 10). is the expected variance of the MOM momentum portfolio (calculated as the way for ). The constant 𝜆 is chosen to achieve an ex-post annualized volatility of the benchmark asset (i.e., market index).

Insert Table 11 about here

In Table 11, we report the characteristics of these risk-adjusted momentum strategies from 2002-01 to 2020-12. Our sample starts from 2000-01, and the 24 observations from 2000-01 to 2001-12 are used to calculate the first conditional expected return of momentum strategies. Panel A presents the results of the raw momentum strategies and shows that the raw CBMOM momentum strategy has the highest annualized average returns of 1.34%, the highest annualized Sharpe ratio of 0.67, and the lowest annualized volatility of 20.56%. We report the risk-adjusted momentum strategies based on CBMOM and scale the unconditional volatilities of these strategies to the annualized volatility 20.56% of the raw CBMOM momentum strategy. The two strategies perform better than the raw strategy and there is no big difference between the two strategies. The CVS momentum strategy based on CBMOM (CVS\_CBMOM) has relatively higher annualized volatility and Sharpe ratio than the DVS momentum strategy based on CBMOM (DVS\_CBMOM). However, the evidence in Panel C shows that the DVS approach for MOM momentum has large improvements in average returns, Sharpe ratio, and the FF5 alpha over the raw MOM momentum strategy, which is consistent with the finding of [Daniel and Moskowitz (2016)](#_ENREF_15). In Panel D, we scale the unconditional volatilities of all 4 risk-adjusted momentum strategies to the annualized volatility 26.28% of SSEC (market index). The CVS\_CBMOM has the best performance, and the risk-adjusted momentum strategies based on CBMOM outperform those based on the traditional measure of MOM.

We further plot the cumulative returns of the raw momentum strategies and risk-adjusted momentum strategies in Figure 4 for CBMOM and MOM, respectively. Figure 5 also shows the cumulative returns of strategies with the same unconditional volatility that is the annualized volatility of the market index. The results indicate that the DVS approach of [Daniel and Moskowitz (2016)](#_ENREF_15) effectively decreases the impact of momentum crashes on the momentum profits (i.e., the performance of DVS-based strategies during the momentum crash period 2014-2016), especially on the traditional momentum profits. On the whole, the risk-adjusted momentum strategies improve the performance of the raw momentum strategies based on either CBMOM or MOM.

Insert Figure 4 about here

Insert Figure 5 about here

## The impact of the short-term reversal on the momentum profits based on CBMOM

One could be concerned that the strong performance of CBMOM’s momentum strategy could be induced by the prices’ rebound of short-term losers which belong to the long-term winners, or by the poor performance of short-term winners which belong to the long-term losers. To examine this, we construct the sequential bivariate portfolios (3X3) sorted by CBMOM firstly and then sorted by RVS. In Table 12, the results of Panel A demonstrate that the short-term reversal effects in long-term losers and winners are absent. Furthermore, in Table 6, the results of the sequential bivariate portfolios sorted by RVS firstly and then sorted by CBMOM show that the CBMOM-based momentum effects are significant. The two-part results suggest that the CBMOM-based momentum effect is not only strong but also can be utilized to explain the short-term reversal effect.

Following [Conrad and Yavuz (2016)](#_ENREF_14), we decompose the CBMOM-based momentum profits into the short-term-loser side and the short-term-winner side. Specifically, based on the univariate decile portfolios of CBMOM, we separate the long-term loser stocks in the lowest decile into the short-term-loser side if stocks’ returns at the recent month are negative (RVS<0), and into the short-term-winner side if stocks’ returns at the recent month are positive (RVS>=0). We do the same separation for the long-term winner stocks in the highest decile. Then, we examine the performance of the CBMOM-based momentum profits in short-term loser stocks and short-term winner stocks, respectively. The results of Panel B in Table 12 show that the average return and the FF5 alpha of the CBMOM-based momentum strategies are significant and positive on the short-term-loser side and the short-term-winner side. The momentum profits on the short-term-loser side are higher than the profits on the short-term-winner side, which could be attributed to the short-term reversal effect. However, the differences between the profits of the two sides are not significant. This suggests that the impact of the short-term reversal effect on the CBMOM-based momentum effect is absent.

Furthermore, considering an extreme case that we let CBMOM measure completely skip the recent month just like the traditional MOM do. To achieve this, we construct by , where we only use to replace in the original measure. Therefore, captures momentum information by only using the information up to the end of month . In Panel D of Table 12, we report the average returns and the FF5 alphas of univariate portfolios based on the new CBMOM measure, and the momentum profits are also significant and positive. Compared to the momentum profits based on the original measure in Table 4, the momentum profits here are relatively less.

In short, the impact of the short-term reversal effect on the CBMOM-based momentum effect is basically absent.

Insert Table 12 about here

## Does CBMOM’s momentum strategy maintain significant alphas in different factor models?

As a robust check, we examine whether the effectiveness of CBMOM’s strategy is maintained in different factor models because the significant factor-adjusted return may simply be due to the absence of a more appropriate factor model in China’s stock market. [Liu *et al.* (2019)](#_ENREF_32) construct size and value factors by excluding stocks that are potential shell companies and using the earnings-to-price ratio to capture China’s value effect. Their three-factor model explains most anomalies in China, excluding two anomalies they mentioned, short-term reversal and sentiment-based anomaly measured by abnormal turnover. By adding the fourth factor of sentiment-motivated turnover, the four-factor model can explain the remaining two anomalies. [Lin *et al.* (2020)](#_ENREF_31) perform analysis between the reversal factor and the turnover factor in China, and they show that the reversal factor is a better fourth factor. Therefore, we adopt Liu’s powerful four-factor model based on the turnover factor and Lin’s factor model based on the reversal factor to test whether CBMOM's momentum strategy returns can be explained.

According to [Liu *et al.* (2019)](#_ENREF_32), we exclude the smallest 30% firms to construct factors. Additionally, net profit data excluding nonrecurrent gains/losses in the CSMAR database are available from the first quarter in 2007. Therefore, the value factor based on EP starts in July 2007, and we use the factors from July 2007 to Dec 2020 to conduct the following empirical analysis. Meanwhile, we can also re-examine the performance of CBMOM’s momentum strategy in this period, which is also a simple robustness test.

Table 13 shows the average returns, Liu’s factor-adjusted returns, and Lin’s factor-adjusted returns for the univariate decile portfolios based on MOM/CBMOM during the period from July 2007 to Dec 2020. The MOM’s momentum strategy (H-L portfolio) has a weakly significant average return, and there are no significant intercepts of Liu’s and Lin’s models. However, the CBMOM’s momentum strategy not only maintains a significant average return but also maintains significantly positive intercepts by Liu’s four-factor and Lin’s four-factor models. This result demonstrates that the abnormal momentum profits by CBMOM are robust by the potential factor models[[3]](#footnote-3).

Insert Table 13 about here

# Conclusion

For momentum effect, stock past performance is one of the sources for a momentum trader to form the buying or selling belief, and the short-term information that can reflect other investors’ beliefs may be another decision-dependence source to the momentum trader. Intuitively, momentum traders who lack private information may hope to achieve group advantage to strengthen their momentum beliefs.

In this paper, we show that the shorter-term information of investors’ consistent belief enhances the momentum effect based on the long-term price performance. We construct an indicator to reflect investors’ consistent belief (CB) and then examine the role of one-month CB on the traditional momentum effect based on long-term past returns. In China, the traditional momentum effect based on past one-year returns is significant for the 30% high-CB stocks and insignificant for the 30% low-CB stocks.

We develop a new momentum measurement of CBMOM as the product of CB and MOM, where MOM as a traditional momentum indicator is the return over the past year. We show that CBMOM has an absolute advantage in capturing the momentum effect in China than MOM. Furthermore, for the nonlinear impact of the synergy between CB and MOM on stock returns, our results show that as the cross-sectional CB level increases, MOM shows a greater coefficient on stock returns, but the significance is strong only for the highest-level CB.

From the perspective of investors’ consistent belief in price movements, our paper is helpful to understand the phenomenon of the insignificant momentum effect in China. Moreover, the new momentum indicator we construct can effectively capture the momentum effect in China. Our research has large contributions to the literature. We will continue to study the applicability of the momentum effect based on CBMOM in international markets, especially for markets in which the traditional momentum effects as documented in [Chui *et al.* (2010)](#_ENREF_13).

# References

1. Aboody, D., Even-Tov, O., Lehavy, R., Trueman, B., 2018. Overnight Returns and Firm-Specific Investor Sentiment. Journal of Financial and Quantitative Analysis 53, 485-505
2. Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56
3. Antoniou, A., Lam, H.Y.T., Paudyal, K., 2007. Profitability of momentum strategies in international markets: The role of business cycle variables and behavioural biases. Journal of Banking & Finance 31, 955-972
4. Asem, E., Tian, G.Y., 2010. Market Dynamics and Momentum Profits. Journal of Financial and Quantitative Analysis 45, 1549-1562
5. Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and Momentum Everywhere. Journal of Finance 68, 929-985
6. Atalla, T., Joutz, F., Pierru, A., 2016. Does disagreement among oil price forecasters reflect volatility? Evidence from the ECB surveys. International Journal of Forecasting 32, 1178-1192
7. Avramov, D., Cheng, S., Hameed, A., 2016. Time-Varying Liquidity and Momentum Profits. Journal of Financial and Quantitative Analysis 51, 1897-1923
8. Barroso, P., Santa-Clara, P., 2015. Momentum has its moments. Journal of Financial Economics 116, 111-120
9. Berkman, H., Dimitrov, V., Jain, P.C., Koch, P.D., Tice, S., 2009. Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92, 376–399
10. Blitz, D., Hanauer, M.X., Vidojevic, M., 2020. The idiosyncratic momentum anomaly. International Review of Economics & Finance 69, 932-957
11. Butt, H.A., Kolari, J.W., Sadaqat, M., 2021. Revisiting momentum profits in emerging markets. Pacific-Basin Finance Journal 65, 101486
12. Butt, H.A., Virk, N.S., 2017. Momentum profits and time varying illiquidity effect. Finance Research Letters 20, 253-259
13. Chui, A.C.W., Titman, S., Wei, K.C.J., 2010. Individualism and Momentum around the World. Journal of Finance 65, 361-392
14. Conrad, J., Yavuz, M., 2016. Momentum and Reversal: Does What Goes Up Always Come Down? Review of Finance, rfw006
15. Daniel, K., Moskowitz, T.J., 2016. Momentum crashes. Journal of Financial Economics 122, 221-247
16. Dierkes, M., Krupski, J., 2022. Isolating momentum crashes. Journal of Empirical Finance 66, 1-22
17. Diether, K.B., Malloy, C.J., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. The Journal of Finance 57, 2113–2141
18. Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1-22
19. Fama, E.F., French, K.R., 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics 123, 441-463
20. Fan, M., Li, Y., Liu, J., 2018. Risk adjusted momentum strategies: A comparison between constant and dynamic volatility scaling approaches. Research in International Business and Finance 46, 131-140
21. Fong, W.M., Wong, W.K., Lean, H.H., 2005. International momentum strategies: a stochastic dominance. Journal of Financial Markets 8, 89-109
22. Gao, Y., Guo, B., Xiong, X., 2021a. Signed momentum in the Chinese stock market. Pacific-Basin Finance Journal 68, 101433
23. Gao, Y., Han, X., Li, Y., Xiong, X., 2021b. Investor heterogeneity and momentum-based trading strategies in China. International Review of Financial Analysis 74, 101654
24. Hibbert, A.M., Kang, Q., Kumar, A., Mishra, S., 2020. Heterogeneous beliefs and return volatility around seasoned equity offerings. Journal of Financial Economics 137, 571-589
25. Hong, H., Lim, T., Stein, J.C., 2000. Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. The Journal of Finance 55, 265-295
26. Hong, H., Stein, J.C., 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. The Journal of Finance 54, 2143-2184
27. Hou, K., Xue, C., Zhang, L., 2015. Digesting Anomalies: An Investment Approach. The Review of Financial Studies 28, 650-705
28. Huisman, R., Van der Sar, N.L., Zwinkels, R.C.J., 2021. Volatility expectations and disagreement. Journal of Economic Behavior & Organization 188, 379-393
29. Kang, J., Liu, M.-H., Ni, S.X., 2002. Contrarian and momentum strategies in the China stock market: 1993–2000. Pacific-Basin Finance Journal 10, 243-265
30. Li, Y., Li, W., 2021. Firm-specific investor sentiment for the Chinese stock market. Economic Modelling 97, 231-246
31. Lin, H.W., Huang, J.B., Lin, K.B., Zhang, J., Chen, S.H., 2020. Which is the better fourth factor in China? Reversal or turnover? Pacific-Basin Finance Journal 62
32. Liu, J.N., Stambaugh, R.F., Yuan, Y., 2019. Size and value in China. Journal of Financial Economics 134, 48-69
33. Liu, M., Liu, Q.Q., Ma, T.S., 2011. The 52-week high momentum strategy in international stock markets. Journal of International Money and Finance 30, 180-204
34. Makarov, I., Rytchkov, O., 2012. Forecasting the forecasts of others: Implications for asset pricing. Journal of Economic Theory 147, 941-966
35. Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32, 1151–1168
36. Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-708
37. Novy-Marx, R., 2012. Is momentum really momentum? Journal of Financial Economics 103, 429-453
38. Pan, L., Tang, Y., Xu, J., 2013. Weekly momentum by return interval ranking. Pacific-Basin Finance Journal 21, 1191-1208
39. Rouwenhorst, K.G., 1998. International Momentum Strategies. The Journal of Finance 53, 267-284
40. Shalen, C., 1993. Volume, Volatility, and the Dispersion of Beliefs. The Review of Financial Studies 6, 405-434
41. Verardo, M., 2009. Heterogeneous Beliefs and Momentum Profits. Journal of Financial and Quantitative Analysis 44, 795–822
42. Wang, C., Chin, S., 2004. Profitability of return and volume-based investment strategies in China's stock market. Pacific-Basin Finance Journal 12, 541-564
43. Weißofner, F., Wessels, U., 2019. Overnight Returns: An International Sentiment Measure. Journal of Behavioral Finance 21, 205-217
44. Zhang, W., Wang, G.Y., Wang, X.C., Xiong, X., Lei, X., 2018. Profitability of reversal strategies: A modified version of the Carhart model in China. Economic Modelling 69, 26-37

**Tables and Figures**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Descriptive Statistics | | | | | |
| Variables | Mean | Q(0.25) | Q(0.75) | Std | Skew |
| Return | 1.31% | -6.45% | 7.60% | 13.70% | 1.58 |
|  |  |  |  |  |  |
| CB | 0.11 | 0.02 | 0.14 | 0.15 | 2.63 |
| MOM | 13.13% | -18.52% | 37.25% | 47.95% | 1.08 |
| CBMOM | 2.26% | -0.62% | 2.36% | 9.75% | 4.83 |
|  |  |  |  |  |  |
| Beta | 1.13 | 0.96 | 1.29 | 0.27 | 0.07 |
| LogSize | 22.04 | 21.16 | 22.80 | 1.31 | 0.52 |
| BM | 0.67 | 0.49 | 0.85 | 0.27 | 39.58 |
| DY | 1.42% | 0.50% | 1.80% | 1.58% | 6.58 |
| ROE | 4.63% | 1.48% | 7.63% | 18.68% | -84.03 |
| INS | 37.93% | 12.06% | 59.26% | 26.24% | 0.07 |
| RVS | 1.31% | -6.45% | 7.60% | 13.70% | 1.58 |
| VLOA | 2.65% | 1.74% | 3.30% | 1.29% | 2.91 |
| MAX | 5.33% | 3.08% | 7.29% | 2.93% | 5.30 |
| ABTURN | 1.01 | 0.54 | 1.28 | 0.68 | 2.13 |
| ILLIQ | -22.00 | -22.93 | -21.15 | 1.42 | 0.20 |
| SENT | -0.10% | -0.23% | 0.07% | 0.43% | 2.36 |
| Note: This table reports the panel descriptive statistics of variables during our sample period. The sample period ranges from 2000-01 to 2020-12. | | | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| MOM’s Portfolios | | | | |
| MOM Formation period | Average return (%) | t-stat | FF5 alpha  (%) | t-stat |
|  | | | | |
| Panel A. MOM portfolios by unconditional sorting | | | | |
| J=1 | -0.16 | -0.38 | -0.47 | -1.27 |
| J=2 | 0.08 | 0.19 | -0.33 | -0.82 |
| J=3 | 0.43 | 0.99 | 0.09 | 0.22 |
| J=4 | -0.02 | -0.05 | -0.27 | -0.66 |
| J=5 | 0.11 | 0.25 | -0.17 | -0.39 |
| J=6 | 0.09 | 0.22 | -0.24 | -0.59 |
| J=7 | 0.24 | 0.53 | -0.16 | -0.37 |
| J=8 | 0.56 | 1.28 | 0.07 | 0.16 |
| J=9 | 0.36 | 0.83 | -0.11 | -0.27 |
| J=10 | 0.65 | 1.46 | 0.14 | 0.33 |
| J=11 | 0.73\* | 1.67 | 0.29 | 0.67 |
|  | | | | |
| Panel B. MOM portfolios by size-neutral sorting | | | | |
| J=1 | 0.02 | 0.07 | -0.30 | -1.09 |
| J=2 | 0.12 | 0.36 | -0.26 | -0.84 |
| J=3 | 0.44 | 1.32 | 0.06 | 0.20 |
| J=4 | 0.19 | 0.59 | -0.17 | -0.54 |
| J=5 | 0.31 | 0.97 | -0.09 | -0.30 |
| J=6 | 0.47 | 1.41 | 0.03 | 0.08 |
| J=7 | 0.56 | 1.63 | 0.11 | 0.34 |
| J=8 | 0.72\*\* | 2.10 | 0.23 | 0.71 |
| J=9 | 0.58\* | 1.69 | 0.04 | 0.12 |
| J=10 | 0.65\* | 1.83 | 0.10 | 0.31 |
| J=11 | 0.77\*\* | 2.25 | 0.26 | 0.79 |
| Note: This table reports the average monthly returns and the factor-adjusted alphas of MOM portfolios. The formation period (J) of past returns ranges from 1 month to 11 months. For the end of each month t, the past return as a momentum indicator is the summation of monthly returns from month t-J to t-1, the return at month t is skipped to avoid short-term reversal effect, and month t+1 is the holding month. Panel A presents the results for unconditional-sorted portfolios, and Panel B shows the results for size-neutral-sorted portfolios. All portfolios are refreshed after one month. The asterisks \*\*\*, \*\*, and \* indicate values significantly departing from zero at the 10%, 5%, and 1% levels, respectively. The sample period ranges from 2000-01 to 2020-12. | | | | |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| The role of investors’ consistent belief on MOM | | | | | | | |
|  | | | | | | | |
| Panel A. Average returns (%) of bivariate portfolios CB-MOM | | | | | | | |
|  | | | | | | | |
| First sort  by CB | Second sort by MOM | | | | | | |
| Loser (L) | 2 | Winner (W) | W-L | t-stat | | |
|  |  |  |  |  |  | | |
| Low | 1.77 | 1.70 | 1.93 | 0.16 | 0.47 | | |
|  |  |  |  |  |  | | |
| 2 | 1.54 | 1.63 | 2.08 | 0.54\* | 1.66 | | |
|  |  |  |  |  |  | | |
| High | 0.93 | 1.78 | 1.95 | 1.02\*\*\* | 2.77 | | |
|  |  |  |  |  |  |  |  |
|  | | | | | | | |
| Panel B. Average returns (%) of bivariate portfolios MOM-CB | | | | | | | |
|  | | | | | | | |
| First sort  by MOM | Second sort by CB | | | | | | |
| Low (L) | 2 | High (H) | H-L | t-stat | | |
|  |  |  |  |  |  | | |
| Loser | 1.75 | 1.56 | 0.92 | -0.83\*\*\* | -2.95 | | |
|  |  |  |  |  |  | | |
| 2 | 1.87 | 1.58 | 1.64 | -0.23 | -0.92 | | |
|  |  |  |  |  |  | | |
| Winner | 1.95 | 2.16 | 1.91 | -0.05 | -0.20 | | |
|  |  |  |  |  |  | | |
| Note: This table reports bivariate portfolio results to demonstrate the enhancement role of CB on MOM. Bivariate portfolio analysis is conducted under the 3X3 framework. The sample period ranges from 2000-01 to 2020-12. | | | | | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| CBMOM’s portfolios | | | | |
| MOM Formation period | Average return  (%) | t-stat | FF5 alpha  (%) | t-stat |
|  | | | | |
| Panel A. CBMOM portfolios by unconditional sorting | | | | |
| J=1 | -0.17 | -0.45 | -0.40 | -1.13 |
| J=2 | 0.28 | 0.77 | 0.02 | 0.06 |
| J=3 | 0.49 | 1.39 | 0.25 | 0.68 |
| J=4 | 0.52 | 1.36 | 0.32 | 0.82 |
| J=5 | 0.74\*\* | 1.99 | 0.56 | 1.49 |
| J=6 | 0.76\* | 1.97 | 0.48 | 1.24 |
| J=7 | 0.85\*\* | 2.19 | 0.62 | 1.60 |
| J=8 | 1.03\*\*\* | 2.80 | 0.75\*\* | 2.16 |
| J=9 | 0.93\*\* | 2.55 | 0.64\* | 1.91 |
| J=10 | 0.84\*\* | 2.31 | 0.57 | 1.59 |
| J=11 | 1.26\*\*\* | 3.47 | 0.97\*\*\* | 2.66 |
|  | | | | |
| Panel B. CBMOM portfolios by size-neutral sorting | | | | |
| J=1 | -0.10 | -0.40 | -0.36 | -1.46 |
| J=2 | 0.09 | 0.36 | -0.20 | -0.82 |
| J=3 | 0.40 | 1.61 | 0.11 | 0.47 |
| J=4 | 0.39 | 1.47 | 0.14 | 0.55 |
| J=5 | 0.67\*\* | 2.56 | 0.40 | 1.56 |
| J=6 | 0.71\*\*\* | 2.75 | 0.37 | 1.53 |
| J=7 | 0.74\*\*\* | 2.82 | 0.43\*\* | 1.77 |
| J=8 | 0.75\*\*\* | 2.85 | 0.41 | 1.64 |
| J=9 | 0.68\*\* | 2.58 | 0.30 | 1.27 |
| J=10 | 0.68\*\*\* | 2.68 | 0.31 | 1.35 |
| J=11 | 0.91\*\*\* | 3.51 | 0.54\*\* | 2.16 |
| Note: All portfolios are refreshed after one month. The sample period ranges from 2000-01 to 2020-12. | | | | |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Univariate portfolios of CB, MOM, and CBMOM | | | | | | |
|  | | | | | | |
| Panel A. Univariate portfolios | | | | | | |
| Portfolio  Deciles | CB | | MOM | | CBMOM | |
| Average  return (%) | FF5 alpha  (%) | Average  return (%) | FF5 alpha  (%) | Average  return (%) | FF5 alpha  (%) |
| Low (L) | 2.01 | 1.18 | 1.45 | 0.72 | 0.98 | 0.16 |
| 2 | 1.74 | 0.89 | 1.46 | 0.66 | 1.53 | 0.65 |
| 3 | 2.07 | 1.19 | 1.53 | 0.76 | 1.46 | 0.61 |
| 4 | 2.15 | 1.19 | 1.60 | 0.63 | 1.89 | 1.06 |
| 5 | 1.99 | 1.08 | 1.81 | 0.95 | 1.86 | 0.88 |
| 6 | 1.79 | 0.86 | 1.61 | 0.69 | 1.44 | 0.50 |
| 7 | 1.59 | 0.66 | 1.84 | 1.01 | 1.94 | 1.00 |
| 8 | 1.76 | 0.90 | 1.91 | 0.90 | 2.12 | 1.24 |
| 9 | 1.76 | 0.93 | 1.95 | 1.03 | 2.00 | 1.16 |
| High (H) | 1.67 | 0.81 | 2.18 | 1.21 | 2.25 | 1.31 |
|  | | | | | | |
| Panel B. Factor loadings of univariate portfolios | | | | | | |
|  | CB’s H-L portfolio | | MOM’s H-L portfolio | | CBMOM’s H-L portfolio | |
| Intercept | -0.33% | -0.56%\* | 0.73%\* | 0.29% | 1.26%\*\*\* | 0.97%\*\*\* |
| t-stat | (-0.96) | (-1.75) | (1.67) | (0.67) | (3.47) | (2.66) |
| RMF |  | 0.18\*\*\* |  | 0.07 |  | 0.21\*\*\* |
| t-stat |  | (2.64) |  | (0.86) |  | (3.15) |
| SMB |  | -0.13 |  | 0.32 |  | -0.03 |
| t-stat |  | (-0.84) |  | (1.56) |  | (-0.18) |
| HML |  | 0.09 |  | -0.08 |  | -0.15 |
| t-stat |  | (0.63) |  | (-0.26) |  | (-0.73) |
| RMW |  | 0.55\*\* |  | 1.05\*\*\* |  | 0.88\*\*\* |
| t-stat |  | (2.49) |  | (3.35) |  | (3.26) |
| CMA |  | 0.15 |  | 0.22 |  | 0.23 |
| t-stat |  | (0.60) |  | (0.64) |  | (0.69) |
|  |  |  |  |  |  |  |
| Adjusted |  | 14.72% |  | 6.55% |  | 16.78% |
| Note: The sample period ranges from 2000-01 to 2020-12. | | | | | | |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Return spreads of MOM and CBMOM considering firm characteristics: Average returns | | | | | |
| Characteristics | | MOM | | CBMOM | |
| Average return  (%) | t-stat | Average return  (%) | t-stat |
| Size | Low | 0.38\* | 1.89 | 0.24 | 1.14 |
|  | High | 0.77\*\* | 2.45 | 0.90\*\*\* | 3.31 |
| Beta | Low | 0.79\*\* | 2.21 | 1.14\*\*\* | 4.06 |
|  | High | 0.14 | 0.39 | 0.48\* | 1.70 |
| BM | Low | 0.75\*\* | 1.99 | 1.03\*\*\* | 3.45 |
|  | High | 0.13 | 0.43 | 0.57\*\* | 2.08 |
| DY | Low | 0.13 | 0.36 | 0.79\*\*\* | 2.67 |
|  | High | 0.50\* | 1.71 | 1.00\*\*\* | 3.88 |
| ROE | Low | -0.16 | -0.46 | 0.53\*\* | 2.07 |
|  | High | 0.75\*\* | 2.26 | 1.02\*\*\* | 3.57 |
| INS | Low | 0.43 | 1.33 | 0.55\*\* | 2.16 |
|  | High | 0.77\*\* | 2.42 | 1.01\*\*\* | 3.42 |
| RVS | Low | 0.51 | 1.55 | 0.48\* | 1.70 |
|  | High | 0.51 | 1.45 | 0.96\*\*\* | 3.18 |
| VOLA | Low | 0.92\*\*\* | 3.03 | 0.73\*\*\* | 2.69 |
|  | High | 0.22 | 0.61 | 0.60\* | 1.92 |
| MAX | Low | 0.43 | 1.32 | 0.63\*\* | 2.38 |
|  | High | 0.34 | 0.92 | 0.87\*\*\* | 2.89 |
| ABTURN | Low | 0.88\*\*\* | 2.80 | 0.89\*\*\* | 3.18 |
|  | High | 0.42 | 1.33 | 0.98\*\*\* | 3.21 |
| ILLIQ | Low | 0.80\*\* | 2.48 | 0.90\*\*\* | 3.16 |
|  | High | 0.13 | 0.46 | 0.22 | 1.11 |
| SENT | Low | 0.82\*\* | 2.20 | 1.02\*\*\* | 3.19 |
|  | High | 0.34 | 1.05 | 0.69\*\* | 2.55 |
| Note: This table reports average returns of MOM and CBMOM’s strategies considering firm characteristics. Bivariate portfolio analysis is conducted under the 3X3 framework. The sample period ranges from 2000-01 to 2020-12. | | | | | |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Return spreads of MOM and CBMOM considering firm characteristics: FF5 alphas | | | | | |
| Characteristics | | MOM | | CBMOM | |
| FF5 alpha  (%) | t-stat | FF5 alpha  (%) | t-stat |
| Size | Low | -0.05 | -0.27 | -0.14 | -0.84 |
|  | High | 0.34 | 1.03 | 0.69\*\* | 2.47 |
| Beta | Low | 0.47 | 1.19 | 0.89\*\*\* | 3.14 |
|  | High | -0.08 | -0.22 | 0.24 | 0.87 |
| BM | Low | 0.51 | 1.39 | 0.76\*\* | 2.51 |
|  | High | -0.21 | -0.73 | 0.39 | 1.61 |
| DY | Low | -0.17 | -0.47 | 0.60\*\* | 2.06 |
|  | High | 0.16 | 0.50 | 0.76\*\*\* | 2.86 |
| ROE | Low | -0.54 | -1.42 | 0.24 | 0.93 |
|  | High | 0.36 | 0.98 | 0.78\*\* | 2.57 |
| INS | Low | 0.07 | 0.23 | 0.37 | 1.62 |
|  | High | 0.44 | 1.26 | 0.77\*\* | 2.47 |
| RVS | Low | 0.18 | 0.55 | 0.28 | 0.95 |
|  | High | 0.17 | 0.46 | 0.77\*\* | 2.48 |
| VOLA | Low | 0.57\* | 1.82 | 0.59\*\* | 2.12 |
|  | High | -0.03 | -0.08 | 0.51\* | 1.71 |
| MAX | Low | 0.12 | 0.35 | 0.42 | 1.53 |
|  | High | 0.04 | 0.11 | 0.75\*\* | 2.53 |
| ABTURN | Low | 0.49 | 1.63 | 0.65\*\* | 2.30 |
|  | High | 0.11 | 0.33 | 0.79\*\* | 2.56 |
| ILLIQ | Low | 0.31 | 0.90 | 0.64\*\* | 2.25 |
|  | High | -0.18 | -0.57 | -0.08 | -0.40 |
| SENT | Low | 0.57 | 1.61 | 0.76\*\* | 2.47 |
|  | High | -0.02 | -0.06 | 0.51\*\* | 1.96 |
| Note: This table reports FF5 alphas of MOM and CBMOM’s strategies considering firm characteristics. Bivariate portfolio analysis is conducted under the 3X3 framework. The sample period ranges from 2000-01 to 2020-12. | | | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Fama–MacBeth regression results | | | | |
|  | Model (1) | Model (2) | Model (3) | Model (4) |
| Intercept | 0.11\*\*\* | 0.12\*\*\* | 0.11\*\*\* | 0.12\*\*\* |
|  | (3.48) | (3.81) | (3.61) | (3.90) |
| CB | -0.45% |  |  | -0.47% |
|  | (-1.25) |  |  | (-1.00) |
| MOM |  | 0.42%\* |  | 0.13% |
|  |  | (1.87) |  | (0.60) |
| CBMOM |  |  | 3.10%\*\*\* | 3.02%\*\*\* |
|  |  |  | (3.68) | (3.51) |
| LogSize | 0.12% | 0.12% | 0.13% | 0.10% |
|  | (0.93) | (0.95) | (0.99) | (0.80) |
| Beta | 0.00% | -0.05% | 0.06% | -0.08% |
|  | (-0.01) | (-0.14) | (0.16) | (-0.23) |
| BM | 0.93%\*\*\* | 0.90%\*\*\* | 0.91%\*\*\* | 0.93%\*\*\* |
|  | (2.59) | (2.59) | (2.59) | (2.65) |
| DY | 8.11%\*\*\* | 7.86%\*\*\* | 8.30%\*\*\* | 7.90%\*\*\* |
|  | (3.26) | (3.33) | (3.39) | (3.33) |
| ROE | 3.70%\*\*\* | 3.34%\*\* | 3.36%\*\* | 3.46%\*\*\* |
|  | (2.72) | (2.50) | (2.44) | (2.60) |
| INS | 2.08% | 2.17% | 2.18% | 2.06% |
|  | (1.28) | (1.26) | (1.27) | (1.28) |
| RVS | -2.78%\*\*\* | -2.69%\*\*\* | -2.70%\*\*\* | -2.64%\*\*\* |
|  | (-3.29) | (-3.23) | (-3.24) | (-3.16) |
| VOLA | 0.11 | 0.10 | 0.09 | 0.07 |
|  | (0.99) | (0.92) | (0.85) | (0.69) |
| MAX | -5.95%\*\* | -5.95%\*\* | -5.82%\*\* | -5.52%\*\* |
|  | (-2.11) | (-2.18) | (-2.09) | (-2.01) |
| ABTURN | -0.70%\*\*\* | -0.71%\*\*\* | -0.67%\*\*\* | -0.68%\*\*\* |
|  | (-5.19) | (-5.40) | (-5.02) | (-5.10) |
| ILLIQ | 0.58%\*\*\* | 0.61%\*\*\* | 0.60%\*\*\* | 0.60%\*\*\* |
|  | (6.50) | (6.92) | (6.75) | (6.98) |
| SENT | 0.28\*\* | 0.31\*\* | 0.31\*\* | 0.29\*\* |
|  | (2.00) | (2.28) | (2.17) | (2.14) |
| Note: The sample period ranges from 2000-01 to 2020-12. | | | | |

|  |  |  |
| --- | --- | --- |
| Fama–MacBeth regression results with cross-sectional dummy variables of CB | | |
|  | Coefficient | t-stat |
| Intercept | 0.12\*\*\* | 3.84 |
|  |  |  |
|  | 0.23% | 0.92 |
|  |  |  |
|  | 0.27% | 1.08 |
|  |  |  |
|  | 0.44%\* | 1.90 |
|  |  |  |
|  | 0.44% | 1.58 |
|  |  |  |
|  | 0.85%\*\*\* | 2.69 |
|  |  |  |
| LogSize | -0.04% | -0.11 |
| Beta | 0.11% | 0.84 |
| BM | 0.90%\*\* | 2.57 |
| DY | 7.95%\*\*\* | 3.34 |
| ROE | 3.34%\*\* | 2.50 |
| INS | 1.74% | 1.25 |
| RVS | -2.51%\*\*\* | -2.96 |
| VOLA | 0.09 | 0.84 |
| MAX | -5.96%\*\* | -2.14 |
| ABTURN | -0.69%\*\*\* | -5.19 |
| ILLIQ | 0.60%\*\*\* | 6.90 |
| SENT | 0.31\*\* | 2.20 |
| Note: The sample period ranges from 2000-01 to 2020-12. | | |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Momentum crashes | | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|  | | | | | | | |
| Panel A. CBMOM estimation results | | | | | | | |
|  | | | | | | | |
| Intercept | 2.27%\*\*\* | 0.55% | 1.24%\*\*\* | 1.82%\*\*\* | 1.75%\*\*\* | 1.54%\* | 2.63%\*\*\* |
| t-stat | 4.02 | 1.00 | 2.76 | 3.76 | 4.16 | 1.76 | 3.41 |
|  | -42.08\*\* |  |  |  |  | -34.26 | -40.82 |
| t-stat | -2.31 |  |  |  |  | -1.44 | -1.34 |
|  |  | 1.27%\* |  |  |  | 1.09% |  |
| t-stat |  | 1.74 |  |  |  | 0.93 |  |
|  |  |  | 1.81 |  |  | -6.56 |  |
| t-stat |  |  | 0.08 |  |  | -0.17 |  |
|  |  |  |  | -1.27%\* |  |  | -1.09% |
| t-stat |  |  |  | -1.74 |  |  | -0.93 |
|  |  |  |  |  | -38.76\*\* |  | 6.56 |
| t-stat |  |  |  |  | -2.25 |  | 0.17 |
|  |  |  |  |  |  |  |  |
| Adjusted | 1.71% | 0.80% | -0.40% | 0.80% | 1.59% | 1.55% | 1.55% |
|  | | | | | | | |
| Panel B. MOM estimation results | | | | | | | |
|  | | | | | | | |
| Intercept | 2.42%\*\*\* | -0.04% | 1.18%\*\* | 1.33%\*\* | 1.26%\*\* | 1.02% | 3.62%\*\*\* |
| t-stat | 3.63 | -0.07 | 2.20 | 2.30 | 2.49 | 0.99 | 4.00 |
|  | -71.07\*\*\* |  |  |  |  | -36.81 | -115.66\*\*\* |
| t-stat | -3.31 |  |  |  |  | -1.32 | -3.24 |
|  |  | 1.37% |  |  |  | 2.60%\* |  |
| t-stat |  | 1.57 |  |  |  | 1.89 |  |
|  |  |  | -40.44 |  |  | -78.85\* |  |
| t-stat |  |  | -1.44 |  |  | -1.74 |  |
|  |  |  |  | -1.37% |  |  | -2.60%\* |
| t-stat |  |  |  | -1.57 |  |  | -1.89 |
|  |  |  |  |  | -41.79\*\* |  | 78.85\* |
| t-stat |  |  |  |  | -2.03 |  | 1.74 |
|  |  |  |  |  |  |  |  |
| Adjusted | 3.83% | 0.59% | 0.43% | 0.59% | 1.23% | 4.51% | 4.51% |
| Note: The sample period ranges from 2000-01 to 2020-12. | | | | | | | |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Risk-adjusted momentum strategies (2002:01-2020:12) | | | | | | |
| Strategies | Cumulative  returns | Annualized  average  returns | Annualized  Volatility | Annualized  SR | FF5  alpha | t-stat |
|  | | | | | | |
| Panel A. Market index and the raw momentum strategies | | | | | | |
|  | | | | | | |
| SSEC | 1.11 | 0.62% | 26.28% | 0.19 | --- | --- |
| CBMOM | 12.97 | 1.34% | 20.56% | 0.67 | 0.98%\*\* | 2.56 |
| MOM | 2.99 | 0.86% | 24.41% | 0.33 | 0.37% | 0.80 |
|  | | | | | | |
| Panel B. Scaled to an annualized volatility 20.56% of CBMOM | | | | | | |
|  | | | | | | |
| CVS\_CBMOM | 25.22 | 1.61% | 20.56% | 0.83 | 1.25%\*\*\* | 3.30 |
| DVS\_CBMOM | 23.38 | 1.57% | 20.56% | 0.80 | 1.18%\*\*\* | 3.26 |
|  | | | | | | |
| Panel C. Scaled to an annualized volatility 24.41% of MOM | | | | | | |
|  | | | | | | |
| CVS\_MOM | 6.50 | 1.14% | 24.41% | 0.46 | 0.68% | 1.47 |
| DVS\_MOM | 13.22 | 1.41% | 24.41% | 0.60 | 1.07%\*\* | 2.37 |
|  | | | | | | |
| Panel D. Scaled to an annualized volatility 26.28% of SSEC | | | | | | |
|  | | | | | | |
| CVS\_CBMOM | 55.57 | 2.06% | 26.28% | 0.85 | 1.65%\*\*\* | 3.41 |
| DVS\_CBMOM | 51.54 | 2.00% | 26.28% | 0.83 | 1.57%\*\*\* | 3.38 |
| CVS\_MOM | 7.34 | 1.23% | 26.28% | 0.47 | 0.74% | 1.50 |
| DVS\_MOM | 15.63 | 1.52% | 26.28% | 0.61 | 1.17%\*\* | 2.40 |
| Note: The sample period ranges from 2002-01 to 2020-12. | | | | | | |

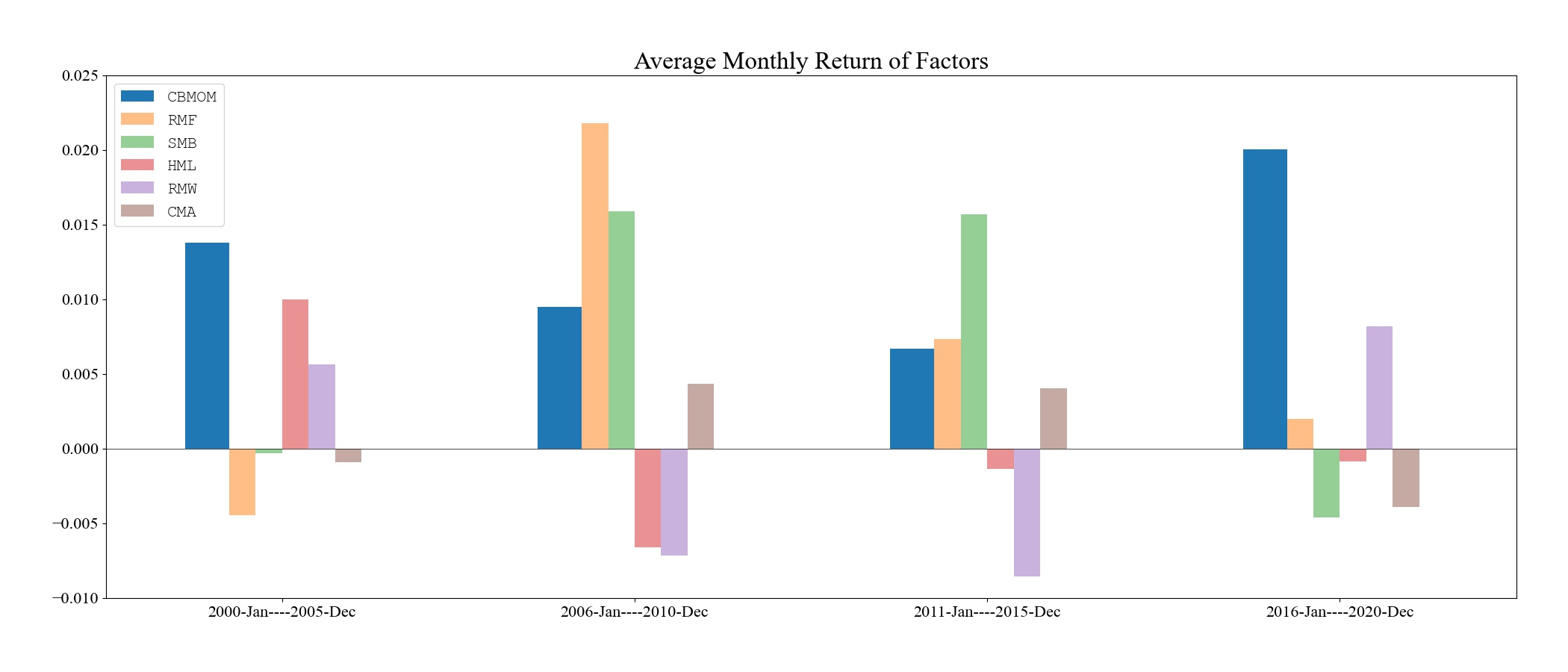
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| The impact of short-term reversal on the momentum profits based on CBMOM | | | | | |
|  | | | | | |
| Panel A. The average returns (%) of sequential bivariate portfolios by CBMOM and RVS (3X3) | | | | | |
|  | | | | | |
| First sort  by  CBMOM | Second sort by RVS | | | | |
| Short-term  loser (SL) | 2 | Short-term  winner (SW) | SW-SL | t-stat |
|  |  |  |  |  |  |
| Long-term loser (L) | 1.53 | 1.44 | 1.22 | -0.31 | -0.93 |
| 2 | 1.80 | 1.94 | 1.80 | 0.00 | 0.01 |
| Long-term winner (W) | 1.95 | 2.39 | 2.29 | 0.34 | 0.90 |
|  | | | | | |
| Panel B. Decomposing the momentum profits of CBMOM by distinguishing the short-term winners and losers | | | | | |
|  | | | | | |
| Momentum profits of CBMOM | Short-term loser  (SL, RVS<0) | | Short-term winner  (SW, RVS>=0) | | SL-SW |
|  |  | |  | |  |
| Average return (%) | 1.57\*\*\* | | 1.30\*\*\* | | 0.27 |
| t-stat | 3.56 | | 2.91 | | 0.48 |
|  |  | |  | |  |
| FF5 alpha (%) | 1.26\*\*\* | | 1.22\*\* | | -0.14 |
| t-stat | 2.87 | | 2.53 | | -0.24 |
|  | | | | | |
| Panel C. Momentum profits of CBMOM by using a measure, , that completely skips the recent month | | | | | |
|  | | | | | |
| Univariate portfolio  deciles | Average return  (%) | | FF5 alpha | |  |
| Low (L) | 1.30 | | 0.49 | |  |
| 2 | 1.56 | | 0.76 | |  |
| 3 | 1.50 | | 0.71 | |  |
| 4 | 1.78 | | 0.84 | |  |
| 5 | 1.69 | | 0.66 | |  |
| 6 | 1.75 | | 0.91 | |  |
| 7 | 1.76 | | 0.85 | |  |
| 8 | 1.74 | | 0.80 | |  |
| 9 | 2.30 | | 1.41 | |  |
| High (H) | 2.30 | | 1.34 | |  |
|  |  | |  | |  |
| H-L | 0.99\*\*\* | | 0.66\* | |  |
| t-stat | 2.79 | | 1.83 | |  |
| Note: The sample period ranges from 2000-01 to 2020-12. | | | | | |

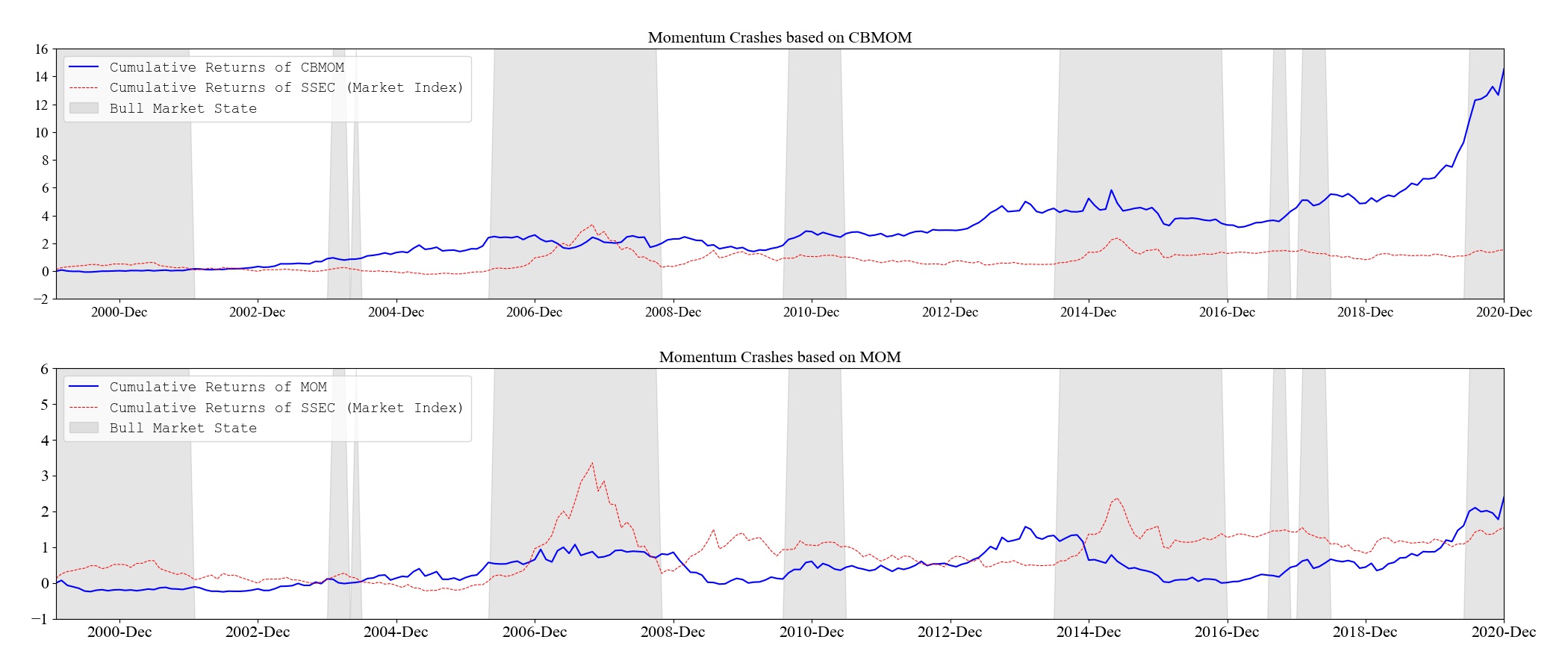
|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Robustness check: Adjusted return of momentum portfolios by Liu’s 4-factor model and Lin’s 4-factor model | | | | | | |
| Univariate  portfolio  deciles | MOM (2007–07—2020–12) | | | CBMOM (2007–07—2020–12) | | |
| Average return  (%) | Liu’s  alpha  (%) | Lin’s  alpha  (%) | Average return  (%) | Liu’s  alpha  (%) | Lin’s  alpha  (%) |
| Low (L) | 1.45 | 0.31 | 0.30 | 0.98 | -0.06 | -0.08 |
| 2 | 1.46 | 0.47 | 0.38 | 1.53 | 0.49 | 0.46 |
| 3 | 1.53 | 0.54 | 0.52 | 1.46 | 0.28 | 0.28 |
| 4 | 1.60 | 0.46 | 0.47 | 1.89 | 1.16 | 1.04 |
| 5 | 1.81 | 0.98 | 0.79 | 1.86 | 0.74 | 0.67 |
| 6 | 1.61 | 0.50 | 0.51 | 1.44 | 0.35 | 0.38 |
| 7 | 1.84 | 1.10 | 1.09 | 1.94 | 1.06 | 1.02 |
| 8 | 1.91 | 0.82 | 0.86 | 2.12 | 1.66 | 1.55 |
| 9 | 1.95 | 1.21 | 1.23 | 2.00 | 1.45 | 1.33 |
| High (H) | 2.18 | 1.30 | 1.36 | 2.25 | 1.73 | 1.58 |
|  |  |  |  |  |  |  |
| H-L | 0.73\* | 0.79 | 0.87 | 1.26\*\*\* | 1.59\*\*\* | 1.47\*\*\* |
| t-stat | (1.67) | (1.27) | (1.35) | (3.47) | (3.36) | (2.86) |
| Note: The sample period ranges from 2007-07 to 2020-12. | | | | | | |

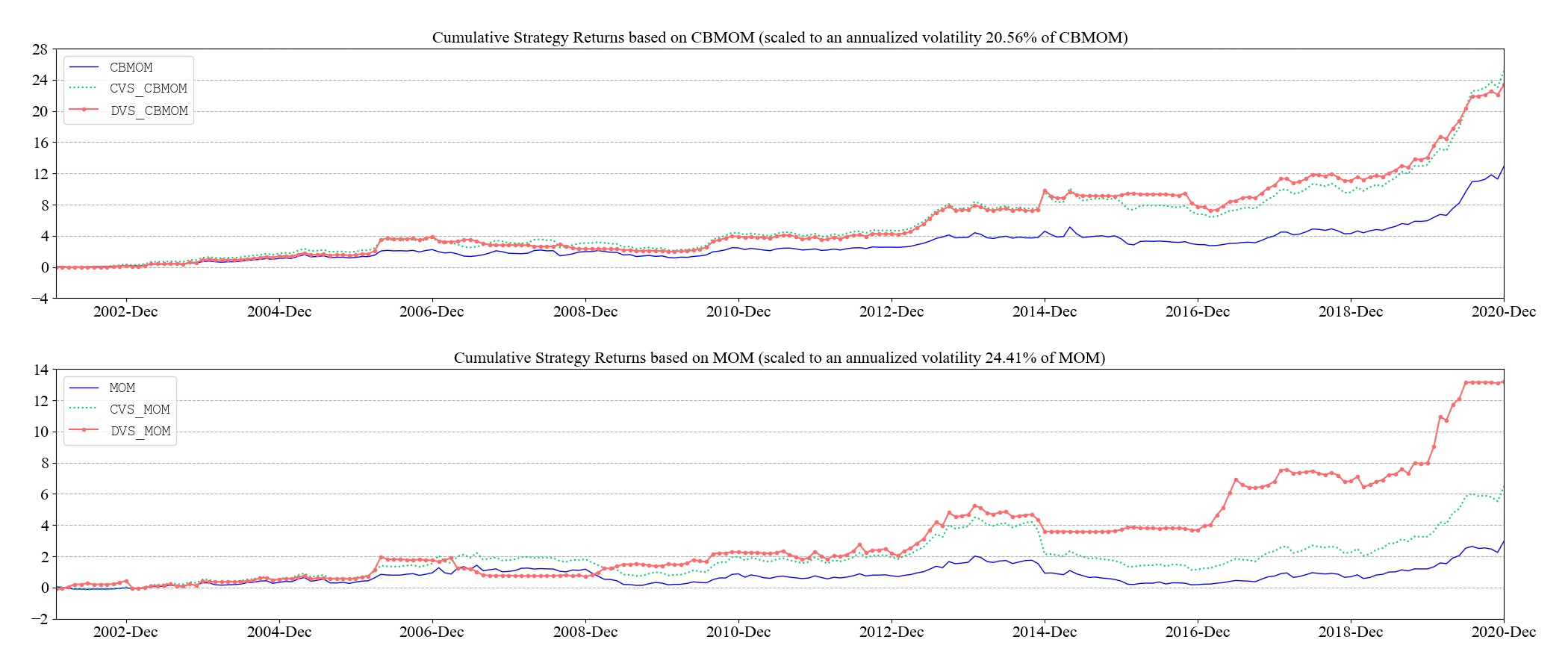


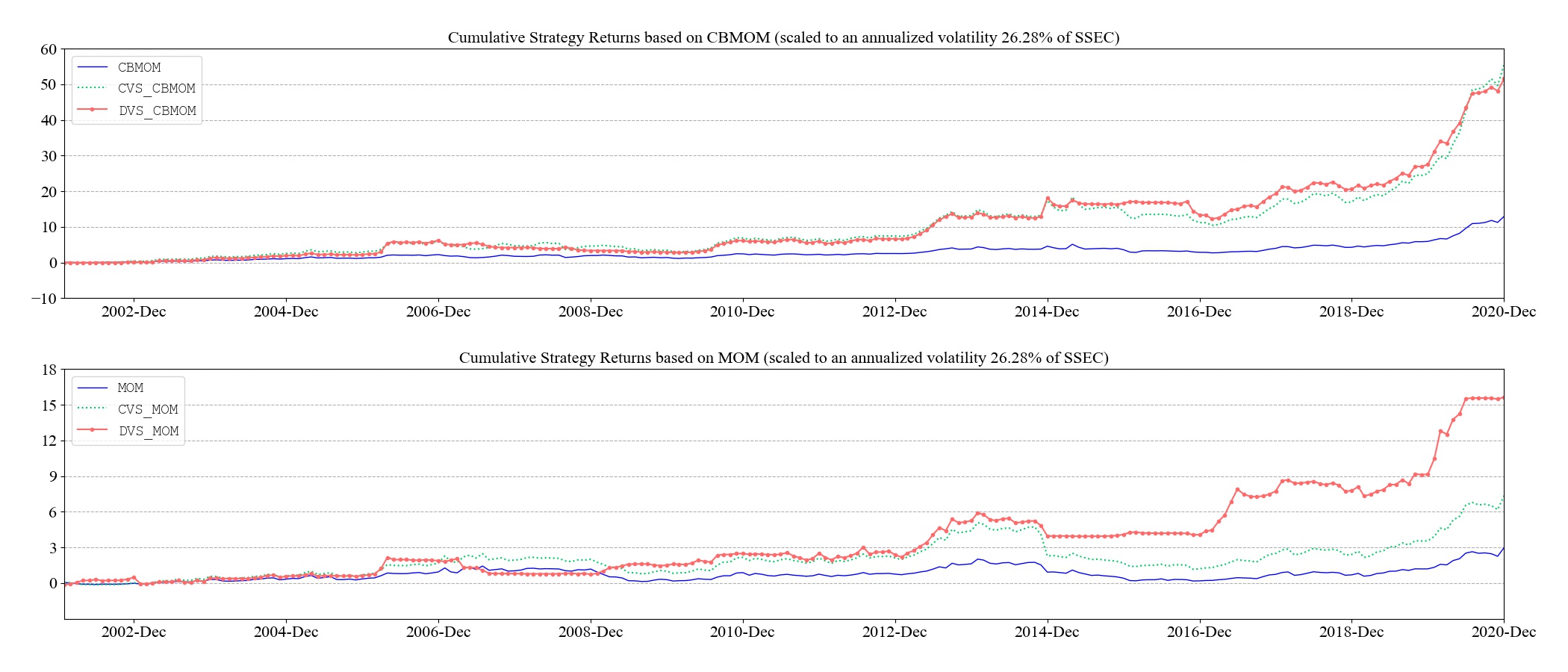












1. China Stock Market & Accounting Research. [↑](#footnote-ref-1)
2. These multivariate regression results also involve multicollinearity issues, and the data period is shorter for the Chinese stock market compared with the US market. Therefore, the results of the regressions with the bear or bull market indicators, especially the multivariate regressions, should be treated with vigilance. [↑](#footnote-ref-2)
3. We also consider the *q*-factor model proposed by [Hou *et al.* (2015)](#_ENREF_27). However, there is still a significant intercept of 0.98% with a t-stat of 2.82 for the CBMOM-based momentum profits using the 4 factor model of [Hou *et al.* (2015)](#_ENREF_27), where the sample period is 2000:01-2020:12. For the Chinese stock market, [Liu *et al.* (2019)](#_ENREF_32) find that the investment and profitability effects do not survive their factor model which is better to explain Chinese anomalies than the FF5 model of [Fama and French (2015)](#_ENREF_18) and the *q*-factor model of [Hou *et al.* (2015)](#_ENREF_27). [↑](#footnote-ref-3)