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Price behavior of small-cap stocks and momentum: A study using principal component momentum

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ABSTRACT

This study analyzes why the negative momentum effect appears in Asian (China, Japan, Korea) stock markets, contrary to the U.S. market. We use principal component momentum (PMOM), a newly devised momentum measure. The PMOM is constructed by extracting commonalities from traditional momentum measures using principal component analysis. The results show evidence of positive and negative momentum profits in the U.S. and Asian markets, respectively. Negative momentum profits in Asian markets are attributable to the strong performance reversal of small stocks in the loser portfolio. Conversely, the positive momentum profits of the U.S. market are driven by the performance continuity of small stocks in the winner portfolio. The PMOM strategy is significantly more advantageous than traditional momentum strategies, based on the economic and statistical perspectives of momentum profits. These results are robust to changes in empirical designs.

1. Introduction

Momentum in stock markets refers to a characteristic wherein stocks with past high performance continue to perform better in the future than those with poor past performance. Jegadeesh and Titman (1993) demonstrate that an investment strategy of buying a winner portfolio (stocks that performed well previously) and selling a loser portfolio (stocks that performed poorly previously) can achieve significant positive excess performance in the future. Since then, studies on developed markets in the U.S. and Europe have generally shown that a momentum strategy achieves significant positive profits (Rowenhorst, 1998). These results have been verified in more than 40 countries worldwide, based on more than 12 types of assets (Asness et al., 2013, 2014; Geczy and Samonov, 2016).[1]

However, unlike studies on developed markets, studies on the momentum effect in Asian stock markets report negative rather than

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[1] In addition, Jia, Goodell, and Shen (2022) suggest that momentum instead of reversal is a crucial factor along with market and size factors in the cryptocurrency markets. In the end, empirical evidence supporting the existence of momentum is confirmed even in alternative assets other than traditional financial instruments.

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positive momentum profits. Hameed and Kusnadi (2002) indicate that six Asian countries (Hong Kong, Singapore, Korea, Taiwan, Thailand, and Malaysia) do not yield significant positive momentum profits. Chui et al. (2000, 2010) report difficulties finding evidence of the widely recognized positive momentum in Western markets. Cheema and Nartea (2017) show evidence of significant positive momentum profits in the Shanghai and Hong Kong stock markets, rather than in the Shenzhen stock market, and significant negative momentum profits in the three Chinese stock markets during the 2008–2009 global financial crisis.[2] Chae and Eom (2009), Lee and Cho (2014), Park and Kim (2014), and Eom et al. (2020) investigate Korean stock markets and present evidence of significant negative momentum profits. In studies of Japanese stock markets, Chaves (2016) and Chang et al. (2018) report that the traditional momentum strategy fails to achieve significant momentum profits.

The momentum strategy uses momentum measures based on past price changes to classify stocks into winner and loser portfolios and then buys winners and sells losers to achieve significant excess performance in the future. Jegadeesh and Titman (1993), who first report the momentum effect, suggest cross-sectional momentum (CMOM). This momentum measure, widely employed by studies until recently, shows that stocks that performed well (or poorly) previously tend to continue to perform well (or poorly) in the future. Thus, this measure classifies all stocks based on their past periodic performance. Moskowitz et al. (2012) and He and Li (2015) suggest time-series momentum (TMOM) from the perspective of time-series price changes, such as technical indicators. This momentum measure reflects the fact that stocks with a high frequency of rising (falling) signals tend to rise (fall) in the future. Thus, this measure classifies all stocks based on long- and short-position signals. Han et al. (2013) employ moving-average momentum (MMOM), a representative technical indicator, to conduct portfolio analysis.[3] This measure reflects the characteristics of rising or falling signals based on the difference between near-past performance and distant-past performance. Thus, this measure classifies all stocks based on long- and short-position signals. Eom and Park (2021) propose principal component momentum (PMOM) as a new cross-sectional momentum measure that extracts common information about the momentum effect from the momentum measures of CMOM, TMOM, and MMOM. Their motivation to devise the PMOM is based on Neely et al. (2014), who suggest that the principal components combining indicators of technical analysis with macroeconomic variables of fundamental analysis through principal components analysis (PCA) improve the prediction power for economic situations. Eom and Park (2021) empirically verify that the devised PMOM may improve the performance of CMOM by combining TMOM and MMOM, which have properties similar to the technical analysis indicators in the Korean stock markets. Accordingly, this study empirically investigates the expandability of PMOM by applying it to the U.S. and Asian stock markets (Korea, Japan, and China). We devise a new momentum measure that directly combines CMOM with the representative indicators of technical analysis under the same methodology devising PMOM.

The main differences between the designs of this study and previous studies are summarized as follows. First, it provides evidence of the applicability and expandability of PMOM in international stock markets. PMOM is a cross-sectional measure of the factor scores with properties of the largest eigenvalue extracted by PCA using the three momentum measures of CMOM, TMOM, and MMOM for stocks. In both the U.S. stock markets, which reported positive momentum profits, and the Asian stock markets, which reported negative momentum profits, we empirically verify whether the PMOM has a comparative advantage over the other three momentum measures (CMOM, TMOM, and MMOM). The literature on technical analysis, focusing on change patterns of past stock prices, has reported the profitability and predictability of various technical indicators.[4] Accordingly, this study devises a new measure of PMOM by combining CMOM with the representative technical indicators under the same methodology devising the PMOM. It verifies its expandability from the perspective of comparative advantage. We employ four technical indicators: moving average, trading range breakout, channel trade breakout, and the Bollinger bands. These designs may provide evidence for the applicability and expandability of the PMOM methodology from different viewpoints in previous studies.

Second, this study applies the weighting method of Lo and MacKinlay (1990) to the momentum factor premium and its relationship with market capitalization for stocks, along with the construction of momentum portfolios. We refer to this method as the arbitrage-weighting method. This method differs from equal-weighting and value-weighting methods. In portfolio construction, the arbitrage-weighting method determines the investment weight as the degree to which the momentum measure of each stock deviates from the average value of the momentum measure of all stocks. On the one hand, unlike the value-weighting method based on the market capitalization of stocks, the arbitrage-weighting method allocates much higher weights to stocks that achieve extreme performance based on the magnitude of past performance. On the other hand, unlike equal- and value-weighting methods that focus on the winner and loser portfolios constructed from stocks with the highest and lowest performance, the arbitrage-weighting method investigates the momentum effect from the perspective of the overall market by including all stocks when constructing the winner and loser portfolios. This study reports the results on momentum effects, focusing on the arbitrage-weighting method. In particular, as a

[2] Some studies suggest new perspectives for negative evidence of momentum in the Chinese stock markets. Yao et al. (2022) devise an individual investor preference index on the influence degree of individual investors and show evidence that momentum does not exist within a stock group with a high index. Li et al. (2023), Li et al. (2023) show that conditional past return indicators, which combine past returns and the direction information of the short-term investors' consistent belief, have superior predictive power for future returns. Meanwhile, through functional data analysis, Li et al. (2023), Li et al. (2023) show evidence supporting the reversal rather than the momentum phenomenon.

[3] Compared with cross-sectional or time series momentum, the term "moving average momentum" is not sufficiently established. This study uses this term to mean a measure of momentum constructed using a moving-average method for long- and short-term returns.

[4] In studies on the profitability and predictability of technical indicators, Brock et al. (1992) employ technical indicators for moving averages and trading range breakouts. Sullivan et al. (1999) investigate the effect of snooping bias on performance from technical indicators, selecting moving averages, support and resistance, channel breakout, and on-balance volume averages. Neely et al. (2014) formulate a design to integrate technical indicators in economic variables using PCA, select moving averages, simple momentum, and on-balance volume.

differential design, we apply this weighting method to both the generation of momentum factor premiums and the examination of the relationship between momentum and market capitalization for stocks. Momentum factor premiums are generated based on the HML-like generation process of Fama and French (1993) using two stock groups classified by the arbitrage-weighting method instead of three stock groups classified by the value-weighting method. The bivariate size-momentum portfolio under the arbitrage-weighting method is constructed to investigate the effect of market capitalization on momentum based on the literature in which the momentum effect is significantly influenced by small-cap stocks showing characteristics of gradual information diffusion for news.[5] In particular, as a new aspect, we verify the relationship between investment weights of stocks from the arbitrage-weighting method and market capitalization of stocks, compared to the cases using the value-weighting method, to investigate the dependence of the momentum effect in the context of small-cap stocks. Through this design, which is contrary to previous studies, we expect to empirically verify whether changes in investment weights for stocks from the perspectives of past performance and market capitalization influence the momentum effect.

The main results of this study are summarized as follows. First, PMOM successfully extracts common information on the momentum effects of the three momentum measures (CMOM, TMOM, and MMOM). It has a comparative advantage in the magnitude and significance of investment performance in the U.S. and Asian stock markets. When using the PMOM, positive momentum profits in the U.S. stock markets and negative momentum profits in the Asian stock markets are more evident. Negative momentum profits in Asian stock markets are attributed mainly to the performance reversals of loser stocks. Conversely, positive momentum profits in U.S. stock markets depend on the persistence of winner stocks. These results are robust regardless of return seasonality, market crashes, and changes in empirical designs. Second, the results show that the arbitrage-weighting method is more suitable than the equal- and value-weighting methods for investigating momentum effects. Comparing the arbitrage- and value-weighting methods, the magnitude of the investment weights allocated to small-cap stocks significantly influences the momentum effect in each country. Third, according to the empirical results of size-momentum portfolios, the performance reversals of a loser portfolio with small-cap stocks in the Korean and Chinese stock markets result in negative momentum profits. The Japanese stock market shows that performance reversals in a loser portfolio with both large- and small-cap stocks result in negative momentum profit. Meanwhile, the U.S. stock market shows that strong performance persistence in a winner portfolio with small-cap stocks results in positive momentum profits. Fourth, the four-factor model, including the momentum factor premiums of PMOM in the three-factor model of Fama and French (1993), better explains variations in portfolio returns than CMOM. This result indicates that the PMOM is an enhanced momentum factor. Additionally, a newly devised momentum measure (PMOM^{NEW}), generated by combining various technical indicators with CMOM, improves the magnitude and significance of momentum profits. This means that the PMOM methodology can be practically employed as a useful tool that reflects the properties of technical indicators in cross-sectional measures of the momentum effect.

The remainder of this paper is organized as follows. Section 2 describes the data and the methodologies employed in the testing process. Section 3 presents the results of the analysis of the momentum effect using the CMOM, TMOM, MMOM, and PMOM. Subsequently, Section 4 analyzes the relationship between market capitalization and investment weight using bivariate size-momentum portfolios. Further, Section 5 presents the applicability and expandability of the PMOM. Finally, Section 6 concludes the study.

2. Data and methodology

2.1. Data and sample periods

past ở đây nghĩa là historical infomation được sử dụng để xây dựng portfolio

This study examines three countries (Korea, Japan, and China) where negative momentum profits are often reported, and the U.S. stock market has reported positive momentum profits. The sample stocks (listed and delisted on each stock market) collected from Compustat Global are as follows: N = 3154 stocks traded on Korea's KOSPI and KOSDAQ since 1986; N = 5371 stocks traded on the Japanese TOKYO and JASDAQ since 1986; and N = 3928 stocks from China's Shanghai and Shenzhen stock markets traded since 2000. For the U.S. stock markets, N = 27,414 stocks traded on the NYSE, AMEX, and NASDAQ since 1980 are collected from the CRSP. The stocks included in the test are determined using the following process. First, as Fama and French (1992, 1993), stocks in the financial sector and those without data on market capitalization and the book-to-market equity ratio (including non-negative conditions) are excluded. Second, stocks that meet the following conditions in each subperiod are selected: 1) all return data to calculate the momentum measures in the subperiods are available; 2) all price data and the number of shares outstanding in the past period are available to calculate investment weight and market capitalization; 3) among stocks with all trading volume data during the past formation period, stocks with valid non-zero return data on 50% or more trading days are available. Third, among the stocks that meet the above conditions, those influenced by extreme values and micro-small firms are limited using a 20th quartile portfolio constructed based on past volatility and market capitalization (e.g., Ang et al., 2006; Hou et al., 2020). Stocks that belong to the highest portfolio

[5] Studies on market capitalization and momentum are as follows. Hong et al. (2000), Grinblatt and Moskowitz (2004), and Asness et al. (2014) show that the momentum effect in U.S. stock markets is more evident in small-cap stocks and on the short sides. Fama and French (2012) suggest that the momentum effect worldwide is more significant for small-cap stocks than large-cap stocks. Moreover, studies (e.g., Daniel et al., 1998) that explain the momentum effect from a behavioral perspective suggest that the overreaction or underreaction of investors integrated with a firm characteristic variable, such as market capitalization or information uncertainty, results in the momentum phenomenon. Hong et al. (2000) indicate that momentum profits are inversely proportional to market capitalization and the aggregate of the analyst coverage of stocks, where the impact of analyst coverage is more substantial on loser stocks than on winner stocks. This result indicates that the momentum effect can be more significant in neglected small-cap stocks that show gradual information diffusion (Hong and Stein, 1999).

(top 5%) constructed by volatility (standard deviation), calculated using daily returns in the past formation period, are excluded. Moreover, stocks that belong to the lowest portfolio (bottom 5%) based on market capitalization in the previous month (June) are excluded. These controls mitigate the impact of high volatility due to extreme values and the impact of micro-small firms with the smallest market capitalization.

In addition, the market returns of Korea, Japan, and China are calculated according to a value-weighting scheme using the return data of all stocks collected from each country. The market risk premium (Mkt), size premium (SMB), and value premium (HML) are calculated based on Fama and French (1993). The risk-free interest rate in the Korean markets uses the yield of monetary stabilization bonds (364 days), while the Japanese and Chinese markets use the three-month interest rate and the discount rate from the FRB of St. Louis, respectively. The U.S. market's three-month T-bill rate is collected from Kenneth R. French's website (from CRSP).

The design of the sample period is as follows. Chui et al. (2000), who examined the Asian stock market, report that obtaining evidence supporting positive momentum profits was difficult after the Asian financial crisis in 1997. This study sets July 2000 as the starting month for the test period to investigate the momentum effect on the Asian stock markets. The testing period for the Korean and Japanese stock markets is 240 months, from July 2000 to June 2020. The testing period for the Chinese stock markets is 216 months, from July 2002 to June 2020. The U.S. stock markets are represented by 414 months from July 1985 to December 2019. The subperiods are divided into past portfolio formation periods and future portfolio holding periods, starting in July, as in Fama and French (1992, 1993). The lengths of past formation periods and future holding periods are based on Jegadeesh and Titman (1993). The past formation period is 12 months. The future holding periods are one, three, six, and 12 months, focusing on one month. The previous month (t–1 or June) is excluded from the past formation period in the subperiod analyses. This can limit the influence of short-term reversals (Jegadeesh, 1990), the MAX effect (Bali et al., 2011), and the idiosyncratic volatility effect (Ang et al., 2006). The rolling of the subperiods adopts the non-overlapping holding period method.

2.2. Methodology

2.2.1. Principal component momentum

This section introduces the CMOM, TMOM, and MMOM measures and describes the PMOM as a new momentum measure. First, the CMOM of Jegadeesh and Titman (1993) is a cross-sectional comparison using the periodic performance of stocks ($j = 1, 2, \ldots, N$) in past formation periods. The CMOM is calculated using the following equation:

$$MOM_j^{(k=1)} = \prod_{i=2}^{J} \left(1 + R_{j,t-1}\right) - 1 \qquad \text{product in window - 1} \tag{1}$$

where $(k = 1)$ represents CMOM and R_j represents the monthly returns of stock j. Further, the formation period is $i = 2, 3, \ldots J$ because the previous month $(t - 1)$ of the testing month is excluded. Here, J indicates the starting month of the past formation period, that is, J= 12 months $(t - 12)$.

Second, MMOM is a momentum measure of the moving average index used by Han et al. (2013) and Neely et al. (2014) and is employed for cross-sectional comparison. The moving-average index is determined as a signal of long and short positions, depending on whether the short-term performance of stocks rises or falls more than the long-term performance of stocks. This study adjusts this method for cross-sectional comparison based on relative momentum strength for the stocks to combine it cross-sectionally with CMOM under the arbitrage-weighting method. To this end, the MMOM uses the values calculated from Eq. (2) for a cross-sectional comparison of the relative momentum strength between stocks.

$$MOM_j^{(k=2)} = SP_j - LP_j \tag{2}$$

where $(k = 2)$ represents MMOM, and SP_j and LP_j, which are calculated using the equations below, represent the short- and long-term performance of stock j, respectively:

$$\mathrm{SP} = \prod_{i=2}^{S} \left(1 + R_{t-i}\right) - 1 \tag{3a}$$

$$\mathrm{LP} = \prod_{i=2}^{L} \left(1 + R_{t-i}\right) - 1 \tag{3b}$$

The length of the short-term period (S) is one month (t–2), and that of the long-term period (L) is equal to the past formation period, that is, $L \equiv J$. Using the difference between short- and long-term performances from Eq. (3a) and Eq. (3b), the values for stocks identified in Eq. (2) are used for cross-sectional comparison as the relative strength of momentum for stocks to combine it cross-sectionally with CMOM under the arbitrage-weighting method.

Third, TMOM is a momentum measure suggested by Moskowitz et al. (2012).[6] This measure determines the signals of long and short positions based on the frequency of repeated changes of rising and falling returns over a past period. This study adjusts this method for cross-sectional comparison based on relative momentum strength for the stocks to combine it cross-sectionally with CMOM under the arbitrage-weighting method. To this end, the TMOM is calculated using the average signal of the long and short positions and the absolute value of the average performance, as shown in Eq. (4).

$$MOM_j^{(k=3)} = \left|\overline{TS_j}\right| \times \overline{S_j} \tag{4}$$

where $(k = 3)$ represents TMOM, $(\overline{S_j})$ is the average signal of the long and short positions, and $\left|\overline{TS_j}\right|$ is the absolute value of the average period performance. The average signal of the long and short positions for stocks, $\overline{S_j}$, is defined by the following equations:

trung bình signal trong window, với window_size=11

Biểu thức thể hiện tính giảm dần

$$\overline{S_j} = \frac{1}{J-1}\sum\nolimits_{i=2}^{J} S_{j,t-i} \tag{5a}$$

1

$$S_{t-m} = sign\left\{\frac{1}{M}[(M)R_{t-m} + (M-1)R_{t-m-1} + \ldots + R_{t-J}]\right\} \tag{5b}$$

where $M = J - m + 1$, $m = 2, 3, \ldots, J$.

Eq. (5b) calculates signals from the average time-weighted returns using trading months as a weight; a positive value from the equation indicates a long-position signal of $S = +1$, whereas a negative value indicates a short-position signal of $S = -1$. Eq. (5a) calculates the average value based on the long- and short-position signals from each trading month, calculated by repeatedly moving backward month by month until the starting month (J, t-12) of the past formation period in Eq. (5b). This calculation process allocates more weight to recent returns in generating signals than distant returns. A positive average value gives a long-position signal ($\overline{S} = +1$) because it means that there is a higher frequency of rising prices in the past formation period. A negative average value means that there is a higher frequency of falling prices, and a short-position signal ($\overline{S} = -1$) is given.

Meanwhile, to combine cross-sectionally with CMOM under the arbitrage-weighting method, we calculated the absolute value of the average period performance ($\overline{TS_j}$) using Equation (6).

$$\overline{TS_j} = \frac{1}{J-1}\sum\nolimits_{i=2}^{J} TS_{j,t-i} \tag{6a}$$

2

$$TS_{t-m} = \frac{1}{M}[(M)R_{t-m} + (M-1)R_{t-m-1} + \ldots + R_{t-J}] \tag{6b}$$

Eq. (6b) is similar to that in the large parentheses of Eq. (5b). However, Eq. (6b) calculates the average time-weighted return. Eq. (6a) calculates the average of all values from each trading month by repeatedly moving backward every month until the starting month (J. t-12) of the past formation period in Eq. (6b) as a method to allocate more weight to recent returns. In Eq. (4), TMOM is calculated by multiplying the absolute value of the average time-weighted returns ($\left|\overline{TS_j}\right|$) from Eq. (6a) by the average values of the long- and short-position signals ($\overline{S_j}$) from Eq. (5a). Accordingly, for a cross-sectional comparison from the perspective of CMOM, we use TMOM as the relative strength of momentum for stocks.

Fourth, PMOM is a momentum measure devised by Eom and Park (2021). PMOM is a cross-sectional factor score with properties of the largest eigenvalue generated from PCA, using the cross-sectional data of CMOM, TMOM, and MMOM for stocks. This is calculated using Eq. (7) for each subperiod.

$$MOM_j^{(k=4)} = \sum\nolimits_{k=1}^{3}\left[V_{j,k}^{E(1)} \times MOM_j^{(k)}\right] \tag{7}$$

where $(k = 4)$ represents the PMOM. The cross-sectional data of CMOM $(k = 1)$, MMOM $(k = 2)$, and TMOM $(k = 3)$ for N stocks are used as input data for PCA, that is, the input structure of $(N \times K)$, $k = 1,2,3(=K)$, and $j = 1, 2\ldots, N$. As shown in Eq. (7), this study generates the PMOM for each stock as the cross-sectional factor score obtained by multiplying the eigenvector ($V_{j,k}^{E(1)}$, $k = 1, 2, 3$) by the three momentum measures (CMOM, TMOM, MMOM). The eigenvector ($V_{j,k}^{E(1)}$) only has the properties of the largest eigenvalue extracted from the PCA. Thus, PMOM has common information (i.e., the momentum effect) included in the CMOM, MMOM, and

[6] There is a method of TMOM suggested by He and Li (2015). The TMOM suggested by Moskowitz et al. (2012) is a measure that repeatedly generates long- and short-position signals by moving backward every month until the end of the past formation period—the length of the past period gradually decreases monthly. Meanwhile, the TMOM suggested by He and Li (2015) is a measure that repeatedly generates long- and short-position signals by moving backward every month while maintaining the same length of the past formation period in each step. Eom and Park (2021) indicate that the TMOM of He and Li (2015) may achieve somewhat better investment performance than the TMOM of Moskowitz et al. (2012). However, this study employs the same length of the past period with other momentum measures (CMOM, MMOM) based on Moskowitz et al. (2012). Of course, the results are qualitatively not different from those reported in this paper when maintaining the same length of the past formation period in each step, like He and Li (2015).

paper này triển khai theo phương pháp của moskowitz nhưng hiệu suất đạt được không khác nhiều so với He and Li

TMOM for stocks.[7]

2.2.2. Arbitrage-weighting method

This study employs the arbitrage-weighting method suggested by Lo and MacKinlay (1990) to construct the momentum portfolios. When constructing portfolios, this weighting method uses the degree to which each stock's momentum measure deviates from the average values of the momentum measures of all stocks. Stocks that achieve extremely high and low performance in the past formation period have much higher investment weights than other stocks. This method is not related to market capitalization, such as the equal- and value-weighting methods. In other words, whether stocks achieve more extreme performance in the formation period directly affects the magnitude of investment weights.

$$\left\{\begin{array}{ll} w_j^{(W)} = w_j, & w_j > 0 \\ w_j^{(L)} = |w_j|, & w_j \leq 0 \end{array}\right\}, w_j = \frac{1}{N}\left(MOM_j^{(k)} - \overline{MOM^{(k)}}\right), (k = 1,2,3,4) \ (8).$$

In the equation, stocks with a higher momentum measure ($MOM_j^{(k)}$) compared with the average value ($\overline{MOM^{(k)}}$) are allocated positive weights ($w_j > 0$) and are classified into a winner portfolio (W). Meanwhile, stocks with a momentum measure lower than the average value are assigned absolute values of negative weights ($w_j \leq 0$, $|w_j|$) and included in a loser portfolio (L). This weighting method has all the stocks in the winner and loser portfolios. The arbitrage portfolio is constructed by buying the winner and selling the loser portfolio (i.e., $W - L$). In Equation (8), the investment weights for stocks are determined for each of the four-momentum measures. The momentum portfolio using the arbitrage-weighting method is designed to allocate weights according to the degree of extreme performance in the past period. Therefore, momentum profits based on the arbitrage-weighting method strongly depend on performance persistence (or reversal) in the future holding period. If there is evidence of persistent performance from the past to the future, the winner's portfolio will continuously perform better than the loser's portfolio. This is evidence of the existence of positive momentum profits. Conversely, the loser portfolio is likely to perform better than the winner portfolio in the case of performance reversals from the past to the future. This result is evidence of the existence of negative momentum profits.

3. Empirical results

3.1. Momentum measures and PMOM

This section presents the characteristics of the stocks used to construct the winner and loser portfolios based on the momentum measures (CMOM, MMOM, TMOM, and PMOM). Table 1 shows the average ratio of stocks included in the winner and loser portfolios, classified using the arbitrage-weighting method for each momentum measure. The table also presents the range of the stock numbers included in the subperiod analysis.

Regardless of the momentum measure, the number of stocks constructing a winner portfolio is smaller than that of a loser portfolio. This result means many stocks achieve lower performance than average in the market. Meanwhile, each country's representative stock market indices show upward trends during the test period.[8] Accordingly, the small number of stocks in the winner portfolios suggests that the upward movements of the markets can be attributed to winner stocks with much higher rising performance or winner stocks with larger market capitalization among stocks in the winner portfolios. This is because the representative indices of stock markets are calculated using the value-weighting method based on market capitalization for stocks. The explanation for this inference is verified by the results presented later.

Fig. 1 shows the distribution of the investment weights allocated to stocks in the winner and loser portfolios, using the arbitrage-weighting method for each momentum measure. The arbitrage-weighting method gives higher weights to stocks with a higher deviation from average performance in the past period. Higher weights are observed in the tail area in the distribution of weights. Therefore, the log-log plot method is employed to emphasize the characteristics of the distribution's tail (Fama, 1965; Eom et al., 2019). The figures show the results for the U.S. stock markets. The distributions of weights for Korea, Japan, and China are not qualitatively different from those of the U.S. stock markets.

Fig. 1 shows that regardless of the momentum measures, the weights allocated to stocks in the winner portfolios are greater than those in the loser portfolios. Moreover, stocks in winner portfolios are more skewed and fatter in weight distribution than those in loser portfolios. Skewed tails indicate that the absolute values of stock performance in a winner portfolio deviate more from the average performance than those of stocks in a loser portfolio. Fatter tails indicate that the number of stocks that achieve extreme performance is greater in the winner portfolio. These characteristics are similar to the tail properties considered in previous studies, such as those of Grinblatt and Han (2005), Barberis et al. (2016), and Eom and Park (2020). These results could explain the evidence that stock market indexes show upward trends, even though the number of stocks in the loser portfolios is greater than that in the winner portfolios of

[7] For example, Baker and Wurgler (2006) suggest the investor sentiment index with a time-series factor score that reflects only the property of the largest eigenvalue generated from PCA, using proxy variables indicating investor psychology. Neely et al. (2014) use four-factor scores that reflect each property, from the largest eigenvalue to the fourth-largest eigenvalue, generated from PCA using macroeconomic variables and technical indicators. These studies use factor scores of the largest eigenvalue from PCA as data with common properties from the input data employed.

[8] In the whole period, growth rates of the representative market indexes of each country are 289% for the KOSPI (Korean), 21% for TOPIX (Japanese), 74% for Shanghai (Chinese), and 1081% for the NYSE (U.S.).

100%

Table 1
Average ratio of stocks included in winner and loser portfolios.

Number of stocks	CMOM		MMOM		TMOM		PMOM	
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
Panel A: Korean stock markets								
347 ~ 1663	0.39	0.61	0.38	0.62	0.44	0.56	0.40	0.60
Panel B: Japanese stock markets								
2479 ~ 2978	0.43	0.57	0.42	0.58	0.47	0.53	0.44	0.56
Panel C: Chinese stock markets								
779 ~ 2792	0.42	0.58	0.42	0.58	0.47	0.53	0.43	0.57
Panel D: U.S. stock markets								
3272 ~ 5384	0.42	0.58	0.42	0.58	0.48	0.52	0.43	0.57

The table shows the average ratio of stocks in the winner and loser portfolio for the past period, classified using the arbitrage weighting method in the 12 M/1 M momentum strategy. The average ratio reports on each momentum measure of the stock market. The ratio is the average ratio of the number of individual stocks in each winner and loser portfolio to all individual stocks in the analysis for each subperiod. The stock markets include Korea (Panel A), Japan (Panel B), China (Panel C), and the U.S. (Panel D). The momentum measures are cross-sectional momentum (CMOM), moving average momentum (MMOM), time-series momentum (TMOM), and principal component momentum (PMOM). The table also presents the range of stock numbers in the subperiod analysis.

Table 1. Meanwhile, the distributions of weights allocated to the stocks of the winner and loser portfolios from each momentum measure are different. In other words, each momentum measure allocates different weights to the stocks. This indicates that the different weight information of stocks allocated according to momentum measures is the differential information on the momentum effect, reflected in the PMOM through PCA. If the PMOM successfully contains the commonality of the momentum effect from the three momentum measures, it can serve as an improved momentum measure.

Table 2 presents the results for the ratio of the same stocks in each winner and loser portfolio and the relationship between investment performance achieved in the future holding period. The percentage of the same stock confirms whether each momentum measure contains unique information regarding the momentum effect. The relationship between investment performance and future holding periods verifies whether each momentum measure has common information for the momentum effect. This study devises a similarity rate (SR) to evaluate the ratio of the same stock in the portfolios.

$$SR = \frac{A \cap B}{A \cup B} \tag{9}$$

where $A \cap B$ indicates the number of the same stocks included in two portfolios, while $A \cup B$ indicates the number of all different stocks (no overlapping) included in all portfolios. Therefore, a lower *SR* for stocks in momentum portfolios means that momentum measures use unique information when constructing a momentum portfolio. In addition, the relationship between the performance of momentum portfolios is quantified using correlations among the performance achieved in each subperiod over the entire period. The higher correlation among performance in the future holding period indicates that the momentum measures have common information in the momentum effect. In Table 2, the lower triangular part of the matrix shows the SR, and the upper triangular part presents the correlation between the performance of the momentum portfolios.

Table 2 shows that SRs in the winner and loser portfolios of COMOM, MMOM, and TMOM in the past period range between 49% and 73% and 54–77%, respectively. The correlation coefficients between the future holding period excess returns of the winner and loser portfolios range between 86% and 99% and 91–99%, respectively. These results mean that each of the three momentum measures uses unique information when constructing portfolios. However, they have common information regarding the performance achieved by the momentum portfolios. When comparing PMOM to the three momentum measures, SRs from PMOM range between 63% and 88% for winner portfolios and 68–89% for loser portfolios. Correlations with investment performance from PMOM range between 83% and 97% for winner portfolios and 84–98% for loser portfolios. This means that PMOM is a measure that successfully extracts information on momentum effects included in CMOM, MMOM, and TMOM.[9]

3.2. Existence of momentum

This section reports the performance results of the momentum portfolios constructed by each momentum measure: CMOM, MMOM, TMOM, and PMOM. Eq. (10) measures the momentum profit of the arbitrage portfolio (A) formed by buying the winner portfolio (W) and selling the loser portfolio (L) using the arbitrage-weighting method for each momentum measure.

[9] In the U.S. stock markets, the SRs between PMOM and all three momentum measures not reported in the table account for 48.67% of the winner and 54.45% of the loser portfolios. The SRs for Korea, Japan, and China accounts for 48.13%, 58.43%, and 49.07% for winners, respectively, and 55.94%, 45.84%, and 51.42% for losers, respectively. The SRs of the same stocks commonly included in winner and loser portfolios based on all momentum measures account for 50% on average. These results suggest that each momentum measure uses unique information to classify all the stocks into winner and loser portfolios.

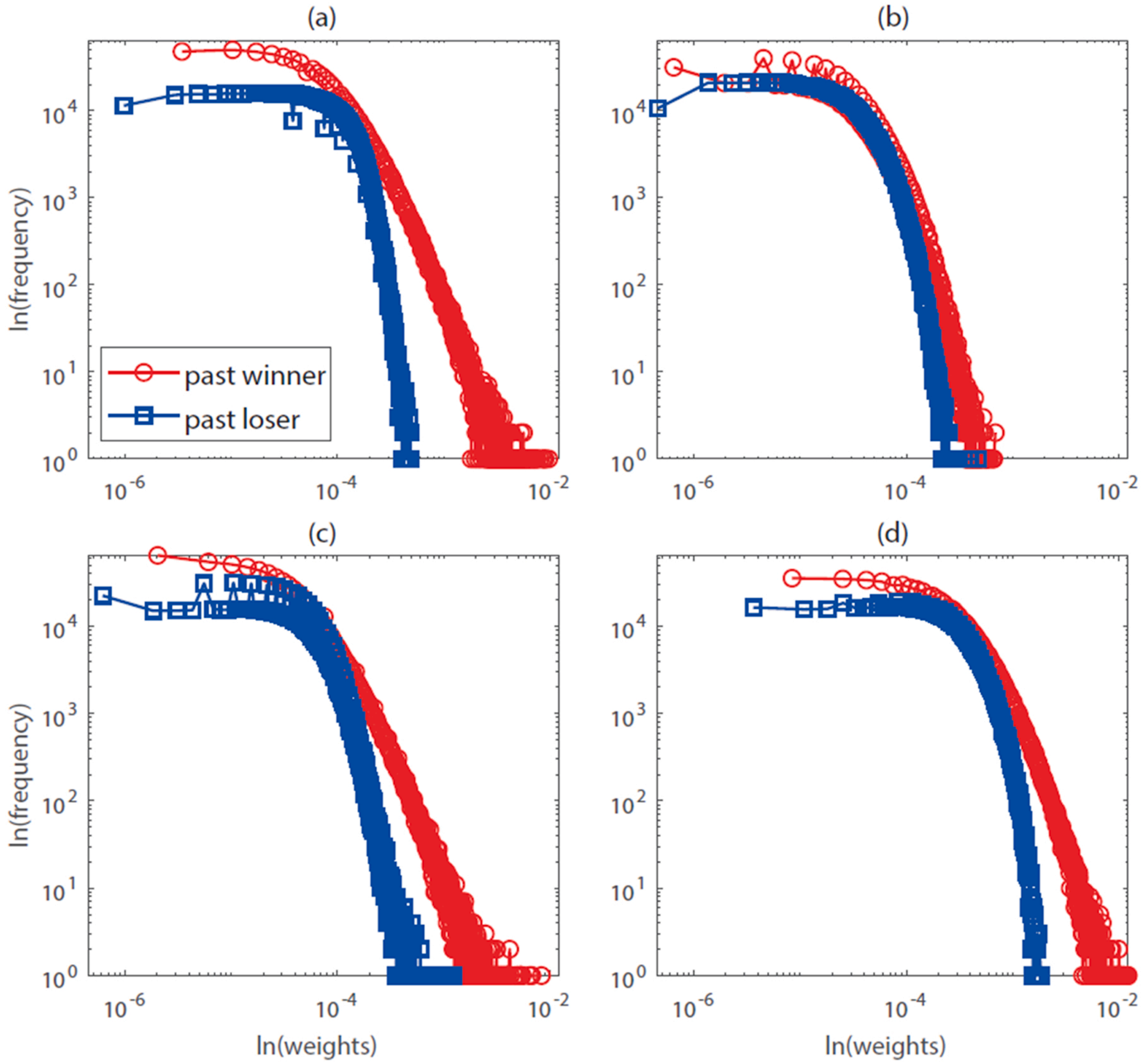


Fig. 1. Distributions of investment weights for constituent stocks of winner and loser portfolios, The figure shows the distribution of investment weights allocated to winner and loser portfolio stocks using the arbitrage-weighting method for the U.S. stock markets under each momentum measure's 12 M/1 M momentum strategy. The winner portfolios (◯, red) and loser portfolios (□, blue) are shown separately, and the momentum measures are (a) CMOM, (b) MMOM, (c) TMOM, and (d) PMOM. A log-log plot is used to investigate tails in the weight distributions. The x-axis indicates the logarithmic investment weights in each chart, and the y-axis indicates the logarithmic frequency. The legend in part (a) was applied to all the charts.

$$R_{A,t} = R_{W,t} - R_{L,t} = \sum\nolimits_{i=1}^{N_W} w_{i,t-1}^{(W)} R_{i,t}^{(W)} - \sum\nolimits_{j=1}^{N_L} w_{j,t-1}^{(L)} R_{j,t}^{(L)} \tag{10}$$

where $R_{A,t}$ denotes the momentum profit of the arbitrage portfolio. The performance of the winner and loser portfolios ($R_{W,t}$, $R_{L,t}$) in the future period is calculated by multiplying the investment weights for stocks in the past winner and loser portfolios ($w_{i,t-1}^{(W)}$, $i = 1, 2, \ldots, N_W$; $w_{j,t-1}^{(L)}$, $j = 1, 2, \ldots, N_L$) by the returns of stocks in the winner and loser portfolios ($R_{i,t}^{(W)}$, $R_{j,t}^{(L)}$) in the future period. The difference between the performances of the winner and loser portfolios is the performance of the arbitrage portfolio. A significantly positive arbitrage portfolio performance supports positive momentum profits, whereas a significantly negative arbitrage portfolio performance is evidence of negative momentum profits.

Table 3 presents the results for the Korean, Japanese, Chinese, and U.S. stock markets in Panels A, B, C, and D, respectively. For each market, performance under the 12 M/1 M momentum strategy is reported for the winner, loser, and arbitrage portfolios according to each momentum measure. The results report the momentum measures (denoted as Port) and excess returns (ExRet) relative to risk-free rates in the past formation period and excess returns and risk-adjusted returns (alphas) from the capital asset pricing model (CAPM) and the Fama and French (1993) three-factor (FF3) model in future holding periods. The statistical significance of the

Table 2
Similarity rates between portfolio constituent stocks and correlation coefficients of portfolio performances.

	Winner portfolios				Loser portfolios			
	CMOM	MMOM	TMOM	PMOM	CMOM	MMOM	TMOM	PMOM
Panel A: Korean stock markets								
CMOM		96.7%	86.0%	92.6%		97.1%	94.2%	91.4%
MMOM	0.6359		73.7%	86.3%	0.7484		89.4%	88.2%
TMOM	0.6886	0.4783		90.0%	0.7332	0.5746		93.6%
PMOM	0.8439	0.6366	0.7329		0.8503	0.7107	0.7988	
Panel B: Japanese stock markets								
CMOM		98.2%	96.0%	95.2%		98.9%	97.0%	95.9%
MMOM	0.6511		90.7%	92.6%	0.7230		94.3%	94.0%
TMOM	0.7333	0.5153		97.2%	0.7617	0.5781		98.3%
PMOM	0.8817	0.6776	0.7549		0.8900	0.7305	0.7916	
Panel C: Chinese stock markets								
CMOM		99.1%	90.5%	86.7%		99.5%	93.0%	87.0%
MMOM	0.6471		86.8%	83.0%	0.7249		90.9%	84.3%
TMOM	0.6919	0.4856		96.2%	0.7009	0.5379		95.9%
PMOM	0.8226	0.6347	0.7451		0.8119	0.6787	0.7860	
Panel D: U.S. stock markets								
CMOM		97.7%	93.4%	88.9%		97.9%	96.9%	94.2%
MMOM	0.6723		85.7%	83.0%	0.7493		93.5%	90.6%
TMOM	0.6950	0.5174		94.0%	0.7185	0.5651		97.3%
PMOM	0.8368	0.6641	0.7597		0.8453	0.7109	0.7943	

This table presents the differences and similarities between the winner and loser portfolios according to momentum measures under the 12 M/1 M momentum strategy. The results show the similarity rates (SR) of Eq. (9) and the correlation coefficients of excess returns of the winner and loser portfolios in future holding periods. The Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. stock markets (Panel D) are shown. The momentum measures presented separately are the CMOM, MMOM, TMOM, and PMOM. In the table, the lower triangular part of the matrix is the SR, and the upper triangular part is the correlation coefficient.

performance employs the t-statistic considering the standard error of Newey and West (1987, 1994), reflecting heteroscedasticity and autocorrelation from subperiods in the entire period.[10] For robust statistical evaluation, such as Harvey et al. (2015), this study interprets results as evidence robustly supporting the existence of the momentum effect when all three performance measures (ExRet, CAPM, and FF3) are significant from a conservative viewpoint.

Table 3 shows statistically significant performances of arbitrage portfolios under PMOM. Previous studies indicate that the Japanese and Chinese stock markets yield significant negative momentum profits, whereas the U.S. stock markets show significant positive momentum profits. The Korean stock market does not show noteworthy results. Results from CMOM, MMOM, and TMOM are similar. Meanwhile, all performances of winner and loser portfolios show reversal patterns in moving forward from the past to the future—in the differences between future and past performances, winner portfolios have negative values, and loser portfolios have positive values. The specified results are as follows. First, in the past formation period, winner portfolios have a higher value of momentum measures than loser portfolios, and winner portfolios have positive excess returns, while loser portfolios have negative excess returns, indicating that stocks in the winner and loser portfolios are well classified. Second, regarding the results of the future holding period in the Japanese stock markets, arbitrage portfolios show statistically significant negative momentum profits under all momentum measures. The Chinese stock markets yield significant negative momentum profits in the excess returns and risk-adjusted returns of the CAPM. However, the risk-adjusted returns of the FF3 model are insignificant. The U.S. stock markets show evidence supporting positive momentum profits under CMOM and PMOM. Nevertheless, the evidence from MMOM and TMOM is weak. These results suggest a difference in the momentum effect between Asian and U.S. stock markets, like Chui et al. (2000). Third, all countries show performance reversals in both the winner and loser portfolios when moving forward from the past formation period to the future holding period. The winner portfolios' performance shows high values reversing to low values. The loser portfolios' performance

[10] This study employs the non-overlapping holding period method in roll-sampling subperiods of the past formation period and the future four-type holding period (1 M, 3 M, 6 M, and 12 M). The lag length based on Newey and West (1994) according to changes in the holding period length is used to calculate the standard error of Newey and West (1987), and the t-statistic calculated using this standard error is reported for time-series average values of excess returns. The reasons for determining the lag length in this method are as follows. First, the fixed length of 12-lag is challenging for all countries because (for example) the U.S. stock markets have nearly twice as long test periods compared to the Chinese stock markets. Second, the changes in the future holding periods make it difficult to employ the same fixed lag length because prolonging the holding period from 1 M to 12 M makes the number of subperiods significantly smaller, especially for the Asian stock markets with shorter testing periods. Thus, this study reports results using the lag length from Newey and West (1994) when statistically evaluating the time-series average values of the excess returns by t-statistic, like Bali et al. (2016). However, performance measures of the risk-adjusted returns estimated by regression analysis based on the pricing models tend to be more affected by autocorrelation and heteroscedasticity than the average value. Thus, this study reports results employing the fixed length of 12-lag for the risk-adjusted returns. Of course, this study investigates results using the fixed length of 12-lag when calculating the time-series average values of excess returns and verifies that results are not qualitatively different from the results reported for the future 1 M holding period in this paper.

Table 3
Investment performances of the momentum portfolios.

		CMOM			MMOM			TMOM			PMOM		
		Winner	Loser	Arbitrage	Winner	Loser	Arbitrage	Winner	Loser	Arbitrage	Winner	Loser	Arbitrage
Panel A: Korean stock markets													
PAST	Port.	0.5550	-0.1791	0.7341	0.3058	-0.1022	0.4080	0.1521	-0.0653	0.2174	1.3585	-0.9427	2.3012
	ExRet.	0.2342	-0.0484	0.2825	0.1280	-0.0171	0.1451	0.0469	-0.0160	0.0629	0.5985	-0.1778	0.7763
FUTURE	ExRet.	0.0013	0.0007	0.0005	0.0005	0.0007	-0.0001	0.0004	0.0003	0.0001	0.0046^{c}	0.0039	0.0006
		(1.26)	(0.88)	(0.80)	(0.91)	(1.40)	(−0.37)	(1.54)	(1.10)	(0.71)	(1.65)	(1.38)	(0.33)
	CAPM	-0.0015^{b}	-0.0019^{a}	0.0004	-0.0010^{a}	-0.0008^{a}	-0.0002	-0.0004^{a}	-0.0006^{a}	0.0002	-0.0041^{b}	-0.0055^{a}	0.0015
		(−2.48)	(−3.92)	(0.79)	(−2.71)	(−3.18)	(−0.52)	(−3.44)	(−4.82)	(1.21)	(−2.52)	(−4.32)	(0.94)
	FF3	-0.0025^{a}	-0.0023^{a}	-0.0002	-0.0016^{a}	-0.0010^{a}	-0.0006	-0.0006^{a}	-0.0007^{a}	0.0000	-0.0065^{a}	-0.0064^{a}	-0.0001
		(−4.02)	(−8.09)	(−0.39)	(−4.04)	(−5.70)	(−1.42)	(−5.77)	(−7.95)	(0.35)	(−4.72)	(−7.31)	(−0.08)
Panel B: Japanese stock markets													
PAST	Port.	0.3320	-0.1523	0.4843	0.1824	-0.0840	0.2664	0.0962	-0.0546	0.1508	1.2433	-0.9718	2.2151
	ExRet.	0.1068	-0.0294	0.1362	0.0577	-0.0107	0.0684	0.0227	-0.0093	0.0321	0.3955	-0.1461	0.5416
FUTURE	ExRet.	0.0001	0.0007	-0.0006^{b}	-0.0001	0.0004^{c}	-0.0005^{a}	0.0001	0.0003^{c}	-0.0001^{c}	0.0005	0.0032	-0.0027^{b}
		(0.17)	(1.58)	(−2.01)	(−0.33)	(1.79)	(−2.88)	(0.74)	(1.78)	(−1.79)	(0.23)	(1.56)	(−2.21)
	CAPM	-0.0006^{c}	0.0000	-0.0006^{b}	-0.0005^{b}	0.0001	-0.0005^{a}	-0.0001	0.0000	-0.0001^{c}	-0.0027^{c}	-0.0001	-0.0026^{b}
		(−1.71)	(0.04)	(−2.05)	(−2.37)	(0.25)	(−2.81)	(−1.09)	(0.25)	(−1.81)	(−1.83)	(−0.05)	(−2.19)
	FF3	-0.0012^{a}	-0.0005^{c}	-0.0008^{b}	-0.0008^{a}	-0.0002^{c}	-0.0005^{a}	-0.0003^{a}	-0.0001	-0.0002^{b}	-0.0049^{a}	-0.0020	-0.0030^{b}
		(−4.76)	(−1.93)	(−2.43)	(−4.77)	(−1.84)	(−3.01)	(−4.36)	(−1.27)	(−2.33)	(−4.35)	(−1.54)	(−2.40)
Panel C: Chinese stock markets													
PAST	Port.	0.4128	-0.1431	0.5559	0.2357	-0.0839	0.3195	0.1091	-0.0507	0.1598	1.3424	-1.0099	2.3523
	ExRet.	0.1669	-0.0155	0.1825	0.0975	-0.0011	0.0986	0.0281	-0.0081	0.0361	0.4234	-0.1426	0.5660
FUTURE	ExRet.	0.0000	0.0017	-0.0017^{a}	-0.0001	0.0011	-0.0013^{a}	0.0002	0.0004	-0.0002^{b}	-0.0003	0.0042	-0.0044^{a}
		(0.01)	(1.37)	(−3.34)	(−0.19)	(1.45)	(−3.94)	(0.51)	(1.22)	(−2.17)	(−0.07)	(1.09)	(−2.70)
	CAPM	-0.0018^{c}	-0.0001	-0.0017^{b}	-0.0012^{c}	0.0001	-0.0012^{a}	-0.0003^{a}	-0.0001	-0.0002^{c}	-0.0064^{a}	-0.0022	-0.0041^{b}
		(−1.95)	(−0.10)	(−2.35)	(−1.89)	(0.12)	(−2.74)	(−2.61)	(−1.09)	(−1.84)	(−4.56)	(−1.53)	(−2.26)
	FF3	-0.0022^{b}	-0.0015^{b}	-0.0007	-0.0015^{b}	-0.0008	-0.0008^{b}	-0.0005^{b}	-0.0005^{a}	0.0000	-0.0071^{a}	-0.0060^{a}	-0.0012
		(−2.04)	(−2.06)	(−1.41)	(−2.02)	(−1.55)	(−2.12)	(−2.54)	(−3.05)	(0.07)	(−4.08)	(−6.50)	(−0.73)
Panel D: U.S. stock markets													
PAST	Port.	0.5594	-0.2151	0.7745	0.2939	-0.1285	0.4224	0.1510	-0.0733	0.2243	1.2405	-0.9466	2.1871
	ExRet.	0.3192	-0.0659	0.3850	0.1721	-0.0257	0.1978	0.0557	-0.0208	0.0765	0.6715	-0.2030	0.8744
FUTURE	ExRet.	0.0010	0.0000	0.0010^{c}	0.0005	0.0001	0.0004	0.0004^{c}	0.0002	0.0002	0.0035^{b}	0.0012	0.0023^{c}
		(1.27)	(0.04)	(1.66)	(1.03)	(0.26)	(1.02)	(1.83)	(0.78)	(1.31)	(2.14)	(0.63)	(1.73)
	CAPM	-0.0006	-0.0016^{a}	0.0010^{b}	-0.0004	-0.0008^{c}	0.0005^{b}	-0.0001	-0.0004^{b}	0.0002^{c}	-0.0008	-0.0037^{a}	0.0029^{a}
		(−1.02)	(−3.65)	(2.28)	(−1.05)	(−3.16)	(1.99)	(−0.90)	(−2.40)	(1.66)	(−0.71)	(−2.92)	(2.66)
	FF3	-0.0001	-0.0015^{a}	0.0014^{c}	-0.0001	-0.0007^{c}	0.0006^{a}	0.0000	-0.0003^{a}	0.0003^{b}	-0.0003	-0.0038^{a}	0.0035^{a}
		(−0.48)	(−4.52)	(3.46)	(−0.52)	(−4.34)	(3.07)	(−0.38)	(−2.92)	(2.38)	(−0.38)	(−3.99)	(3.23)

This table presents the 12 M/1 M momentum strategy performances according to momentum measures (CMOM, MMOM, TMOM, and PMOM) in each stock market in Korea (Panel A), Japan (Panel B), China (Panel C), and the U.S. (Panel D) markets. The performance of winners, losers, and arbitrage portfolios based on the arbitrage-weighting method is reported. It reports the momentum measures (ports) and excess returns (ExRet.) relative to risk-free rates for the past formation period and performance measures of excess returns and risk-adjusted returns (alpha) from the CAPM and the Fama and French three-factor (FF3) models for the future holding period. The numbers in parentheses are t-statistics adjusted for autocorrelation and heteroscedasticity based on Newey and West (1987, 1994). Further, a, b, and c indicate the significance levels at 1%, 5%, and 10%, respectively.

shows patterns of low values reversing to high values.[11] Regarding excess returns under PMOM in the Japanese markets, which yield significant negative momentum profits, winner portfolios present reversals that decrease from 3.08% in the past to 0.05% in the future (a difference of −4.36%), while loser portfolios show reversals that increase from − 3.03% in the past to 0.32% in the future (a difference of 1.75%). Meanwhile, in the U.S. stock markets with significant positive momentum profits, the excess returns from winner portfolios show reversal patterns decreasing from 4.78% to 0.35%, while the excess returns of loser portfolios show a reversal increasing from − 2.04% to –0.12%. These patterns have also been confirmed in the Korean and Chinese stock markets. Fourth, PMOM shows a comparative advantage in performance magnitude and statistical significance compared with the three momentum measures (CMOM, TMOM, MMOM). The performance of arbitrage portfolios under the PMOM in the Japanese and Chinese stock markets shows significantly larger and more significant negative momentum profits (in absolute value) than the three momentum measures. In U.S. stock markets with positive momentum profits, the magnitude of performance from PMOM is significantly greater than other momentum measures. Moreover, all the performances from PMOM are more significant, except for risk-adjusted returns under the FF3 model. These results show the comparative advantage of PMOM, providing improved performance from the perspectives of magnitude and statistical significance compared to the three momentum measures.

Additionally, the influence of the winner and loser portfolios on the momentum profits of the arbitrage portfolios differs for each country. Fig. 2 shows the trends of cumulative excess returns for each of the winner, loser, and arbitrage portfolios from the momentum measures over the entire period for each country. The figures are divided into winner (left), loser (middle), and arbitrage (right) portfolios.

According to the results, the trends in the cumulative excess returns of the winner and loser portfolios clearly differ among the U.S., Japanese, and Chinese stock markets. In the U.S. markets, the performance of winner portfolios shows evident upward trends, while loser portfolios do not reveal specific trends. Conversely, the winner portfolios of the Japanese and Chinese markets do not offer a particular trend, whereas the loser portfolios clearly show upward trends. The Korean stock markets show trends in both the winner and loser portfolios upward. Consequently, negative momentum profits in the Japanese and Chinese markets are attributed to upward performance trends in loser portfolios, whereas positive momentum profits in the U.S. markets rely on upward trends in winner portfolios. Trends in the cumulative returns of arbitrage portfolios help confirm these results. Arbitrage portfolios in the Japanese and Chinese stock markets show downward negative performance trends, whereas the U.S. stock markets show upward performance trends. This result is more clearly revealed in the case of using the PMOM than in the case of using the three momentum measures.

3.3. Robustness

This section verifies the robustness of the previous results. To this end, this study investigates the influence of January seasonality, market crashes, changes in future holding period lengths, and weighting schemes on the results. The tables associated with these robustness checks are presented in the Internet Appendix to preserve space.[12]

We investigate the effects of January on momentum profits by dividing all months of the period into January and non-January (i.e., February through December). The results show that Japan, China, and the U.S. stock markets yield significant momentum profits in non-January months, consistent with the previous results in Table 3. For all non-January momentum measures, the arbitrage portfolios of the Japanese and Chinese markets yield significant negative momentum profits, whereas those of the U.S. markets yield significant positive momentum profits. The PMOM has a higher and more significant performance (based on absolute values) than the other three momentum measures.

The effects of market crashes (Daniel and Moskowitz, 2016) on the performance of momentum portfolios are investigated by comparing the performance between the subperiods of market transitions (down→up) and other subperiods based on Asem and Tian (2010). The results show that, regardless of the momentum measures, all stock markets show that arbitrage portfolios earn significant negative performances in subperiods with market transitions (down→up). Moreover, the performance magnitude (based on absolute values) of the (down→up) periods was greater than that of the other subperiods. These results are consistent with previous studies reporting that a market crash causes negative profit on the momentum effect. However, this market crash does not affect the essential characteristics of each country's momentum profits, as shown in Table 3.

The effects of momentum profit prolonging the future holding periods (1 M→12 M) are reported for arbitrage portfolios, focusing on the PMOM. Arbitrage portfolios in the Japanese stock markets show a strong persistence of negative momentum profits. The Chinese stock markets offer overall negative performance with significant negative momentum profits for one-month and 12-month holding periods. In the U.S. stock markets, momentum profits decrease from prolonged future holding periods, as shown in previous studies (Jegadeesh and Titman, 2001). Compared with the other momentum measures, performance based on PMOM presents a greater magnitude (based on absolute values) and mostly higher significance—evidence supporting the comparative advantage of PMOM.

Next, we analyze the impact of changes in the investment weight on portfolio stocks. To this end, investment weights are assigned according to the equal- and value weighting methods to the constituent stocks of the winner and loser portfolios in <Table 3> , which

[11] To compare the performances by shifting from the past period to the future period under the 12 M/1 M momentum strategy, the performance of the past 12-month formation period (technically, 11 months due to the exclusion of the previous month to control for the effect of microstructure biases) is converted into one-month performance. For example, in the Korean stock markets, the performance of winner portfolios during the previous 12 months was 0.3955, which is converted to one-month performance at 0.0308 ($=(1+0.3955)^{1/11}-1$).

[12] An Internet Appendix for this study is available online in the "Supplementary materials" section.

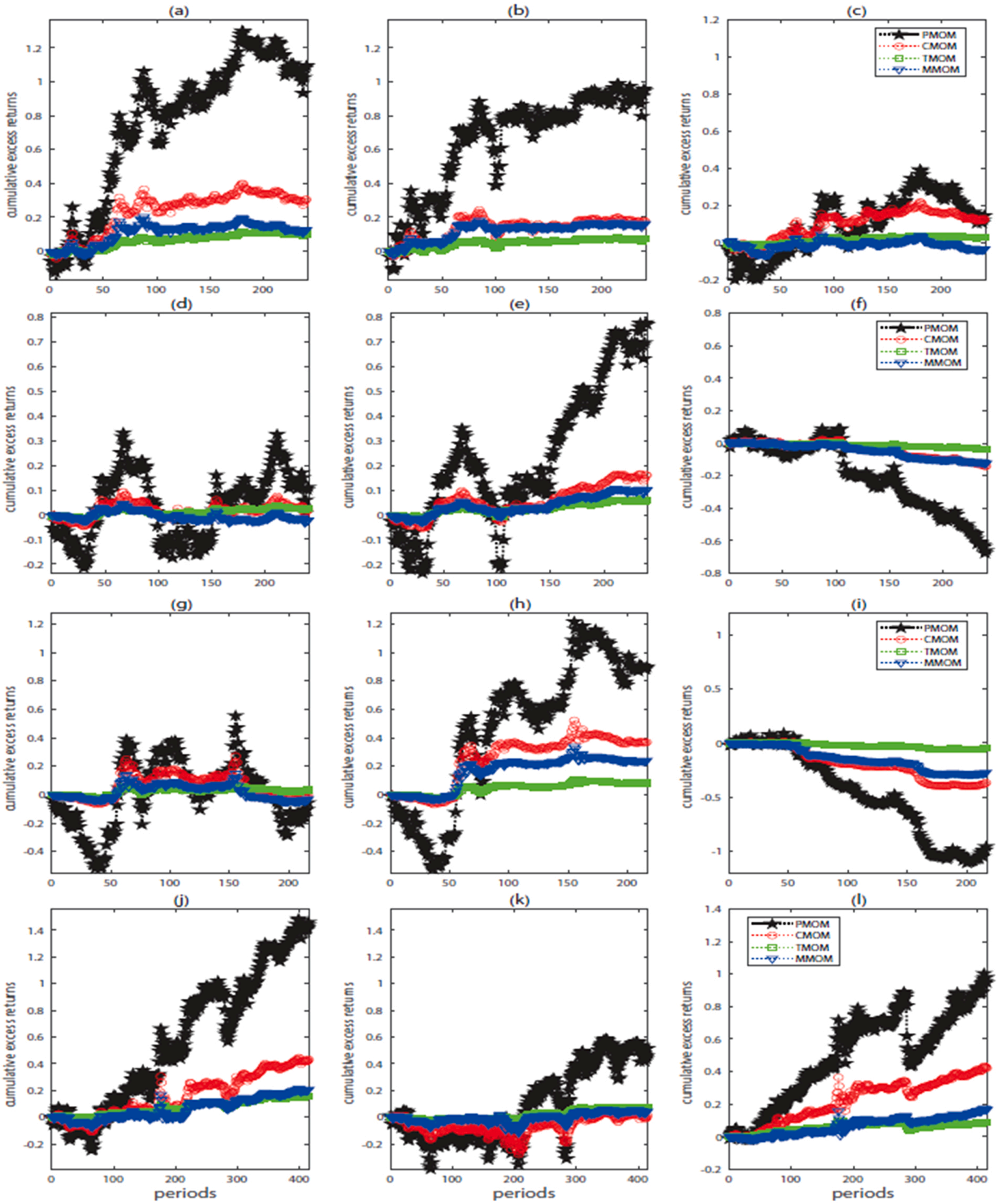


Fig. 2. Cumulative excess returns of momentum portfolios, The figures show the trends of cumulative performance from the 12 M/1 M momentum strategy according to the momentum measures over the entire period. The performance measures are excess returns. The stock markets are the Korean stock markets (figures (a), (b), (c)), the Japanese stock markets ((d), (e), (f)), the Chinese stock markets ((g), (h), (i)), and the U.S. stock markets ((j), (k), (l)). In the figures, the left side is winner portfolios, the middle is loser portfolios, and the right is arbitrage portfolios. Momentum measures are separately presented for CMOM (◯, red), MMOM (▽, blue), TMOM (□, green), and PMOM (☆, black). In the figures, the x-axis indicates the future holding periods over the entire period, and the y-axis indicates cumulative excess returns.

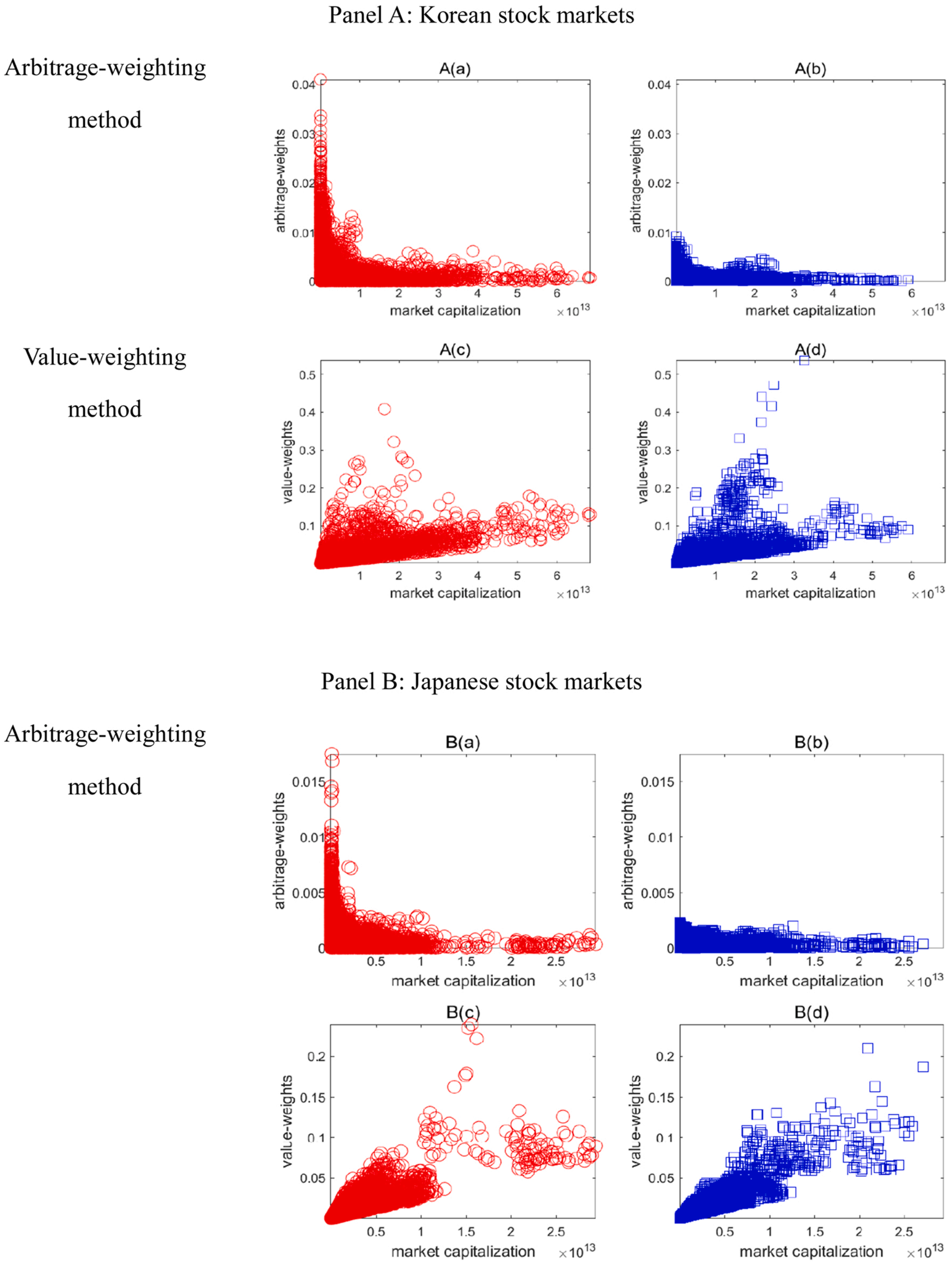


Fig. 3. Relationship between SIZE and investment weight in momentum portfoliosm, The figures show the relationship between investment weights and market capitalization for stocks in momentum portfolios under the 12 M/1 M momentum strategy using the PMOM. Momentum portfolios are constructed using the arbitrage-weighting method suggested by Lo and MacKinlay (1990). The investment weights for stocks in the portfolios are determined using the arbitrage- or value-weighting method. The markets are the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) stock markets. In each panel, the left side of the figures is the winner portfolios, denoted by (a) and (c). The right side of the figures is the loser portfolios, denoted by (b) and (d), while the upper panels present the results of the arbitrage weighting, and the lower panel shows the results

with value weighting. Scatter plots show investment weights on the y-axis and market capitalization on the x-axis for each subperiod within the entire period.

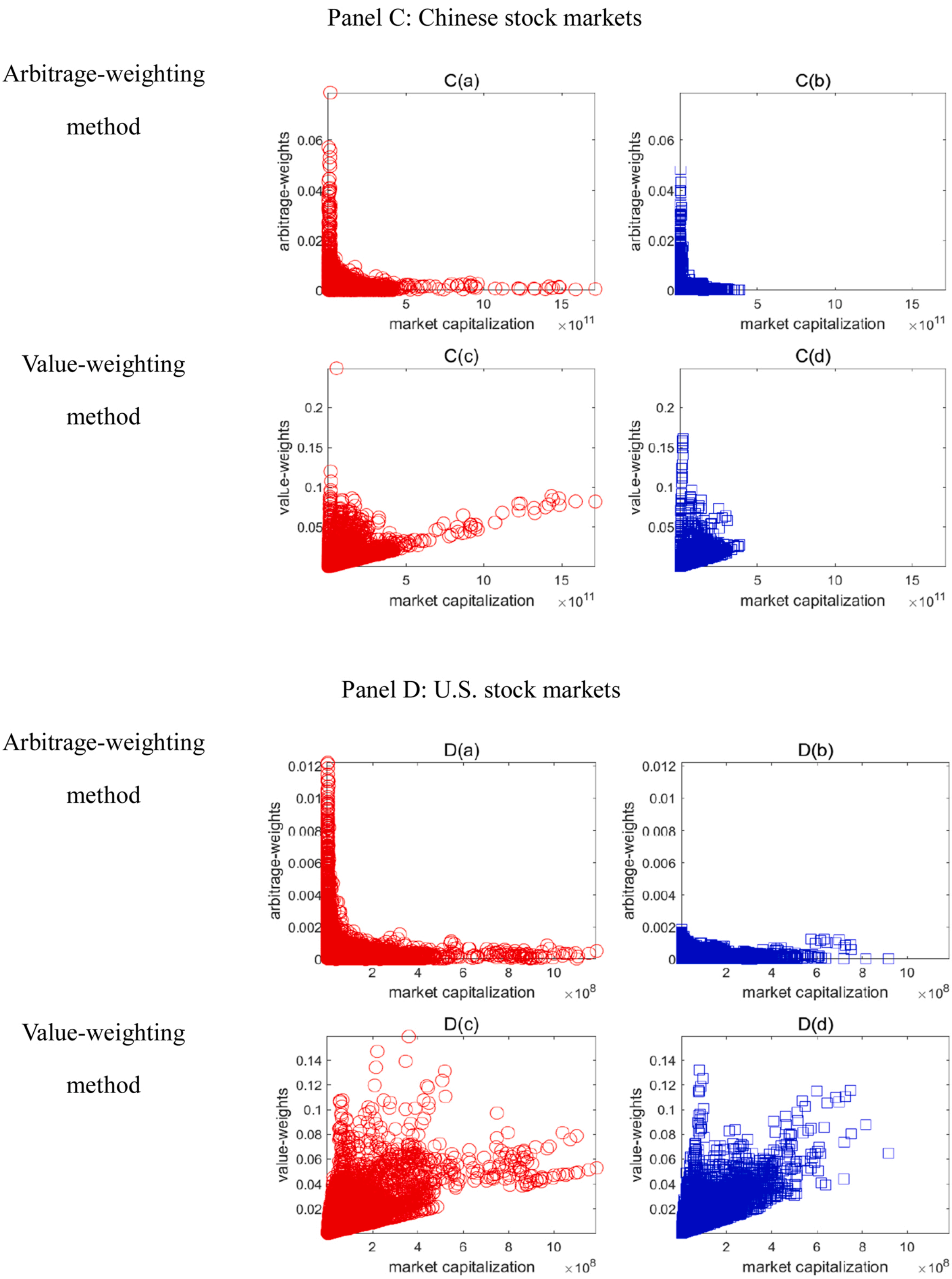


Fig. 3. (*continued*).

are classified by the arbitrage weighting method, and the performance of the momentum portfolio is analyzed.

The results of the PMOM are reported in the Internet Appendix. The results show that performance is affected by the weighting methods. Compared with the previous results (Table 3) of the Japanese and Chinese markets using the arbitrage-weighting method, the equal-weighting method weakens the statistical significance of the results, and the value-weighting method does not present significant results. In particular, the U.S. markets show contrasting results according to the weighting methods. Momentum portfolios using equal-weighting show significant positive performance, whereas those using value-weighting yield significantly negative momentum profits. These opposite results may be attributed to the difference between the performance patterns of small- and large-cap stocks in the future holding period (see size-momentum portfolio analysis in Section 4). For example, if positive momentum profits depend on small-cap stocks in winner portfolios in the U.S. stock markets, the equal-weighting method may result in positive momentum profits, whereas the value-weighting method is likely to result in negative momentum profits. Further, this study examines the effects on momentum profits by employing equal- and value-weighting methods to decile and quintile momentum portfolios, as in previous studies, without using the arbitrage-weighting method when constructing portfolios. The W-L zero-cost portfolio, built by buying the winner (W) and selling the loser (L) among the decile or quintile portfolios, evaluates the momentum effect. The results show that the W-L zero-cost portfolios from the equal-weighting method show positive evidence of the momentum effect compared with the value-weighting method. Consequently, this indicates the need for further research on the effect of the difference between investment weights for small- and large-cap stocks in constructing momentum portfolios based on momentum measures of the past period, as explained in the next section.

4. Size and momentum portfolios

4.1. Relationship between investment weights and market capitalization

This section reports the results of the relationship between investment weights and market capitalization for stocks in momentum portfolios. Two types of investment weights determined by the arbitrage-weighting method (Table 3) and value-weighting method (reported in the Internet Appendix) are applied to portfolios classified by the arbitrage-weighting method using PMOM. The arbitrage-weighting method considers the degree of extreme past performance rather than market capitalization, whereas the opposite holds for the value-weighting method. The relationships between investment weights (x-axis) and market capitalization (y-axis) over the entire period are presented as scatter plots in Fig. 3. The winner portfolios (left side) and loser portfolios (right side) from the arbitrage-weighting method (top figures) and value-weighting method (bottom figures) are presented for each country.

Fig. 3 shows that the investment weights of stocks allocated using arbitrage- and value-weighting methods evidently and differently apply in constructing momentum portfolios. The specific results are as follows. First, in Fig. 3(a) for the winner portfolio when using the arbitrage-weighting method, small-cap stocks have significantly higher weights than large-cap stocks. This result means that small-cap stocks that achieve high performance with large deviations from the past average performance influence the performance of momentum strategies significantly. This result is observed in all countries (Korea, Japan, China, and the U.S.). Meanwhile, the results of the value-weighting method (Fig. 3(c)) are considerably different from those of the arbitrage-weighting method (Fig. 3(a)). As the value-weighting method assigns investment weight according to the market capitalization of stocks, this method allocates higher weights to large-cap stocks positioned on the right side of the x-axis and allocates lower weights to small-cap stocks on the left side of the x-axis. Consequently, small-cap stocks with higher weights under the arbitrage-weighting method have extremely low weights when using the value-weighting method.

Second, the results from loser portfolios on the right-side figures (Fig. 3(b)) using the arbitrage-weighting method show that weights distributed to small-cap stocks are greater than those distributed to large-cap stocks. However, when compared with winner portfolios, there seems to be a difference in the magnitude of the investment weights for small-cap stocks and the number of large-cap stocks.[13] On the one hand, on the left side of the x-axis in the figures, the Chinese stock markets show many small-cap stocks with higher investment weights than large-cap stocks, unlike the Korean, Japanese, and U.S. stock markets. On the other hand, on the right side of the x-axis in the figures, a high frequency of large-cap stocks is verified in the Korean, Japanese, and U.S. stock markets. Nevertheless, this has not been confirmed in Chinese stock markets. This indicates that loser portfolios in the Chinese stock markets mainly comprise small-cap stocks that performed extremely poorly in the past formation period. Furthermore, the results of the value-weighting method (Fig. 3(d)) show that loser portfolios are considerably different from those of the arbitrage-weighting method (Fig. 3(b)), similar to the comparison between Fig. 3(a) and 3(c). Small-cap stocks with high weights from the arbitrage-weighting method have extremely low weights from the value-weighting method. This result is verified in all stock markets, especially in Japanese stocks with low weights for small-cap stocks. Consequently, these results suggest that the investment weights for stocks differ according to the weighting methods used. Our empirical design that combines market capitalization with the arbitrage-weighting method may help identify whether stocks with higher weights allocated by the arbitrage-weighting method belong to small- or large-cap groups more clearly. This difference may significantly affect the performance of momentum portfolios.

[13] During the whole period, when comparing the maximum (average) values of market capitalization among stocks in winner and loser portfolios, the ratios are 1.25 (1.50) in the Korean markets, 1.10 (1.51) in the Japanese markets, 5.33 (1.46) in the Chinese markets, and 1.97 (2.23) in the U.S. markets. Looking at the average market capitalization, stocks in loser portfolios have smaller values than winner portfolios. However, stocks with maximum market capitalization appear in winner portfolios for all countries. Moreover, the difference between winner and loser portfolios is highest in the Chinese stock markets.

4.2. Bivariate size-momentum portfolio

This section examines the performance of size-momentum portfolios using the arbitrage-weighting method. The results in Fig. 3 show that small-cap stocks deviate significantly from the average past performance and hence have high investment weights when constructing winner and loser portfolios through the arbitrage-weighting method. The results reported in the Internet Appendix show that momentum profits through equal- and value-weighting methods are significantly affected by the market capitalization of stocks. Accordingly, Table 4 reports momentum profits from size-momentum portfolios that combine market capitalization in the arbitrage-weighting method. The steps for constructing the size-momentum portfolios are as follows. First, all stocks are classified into three groups based on market capitalization: top 30%, medium 40%, and bottom 30%. Second, the top 30% is defined as the large-cap group, and the bottom 30% is defined as the small-cap group. Third, within each of the two stock groups, stocks are classified into winner and loser portfolios using the arbitrage-weighting method. This is a 3×2 size-momentum portfolio.[14] Fourth, we construct an arbitrage portfolio by buying a winner and selling a loser portfolio. The results present the excess and risk-adjusted returns (CAPM and FF3) of the winner, loser, and arbitrage portfolios based on the PMOM.

Table 4 shows that the market capitalization of stocks significantly influences the negative and positive momentum profits identified from previous results, particularly in the small-cap group. The specific results are as follows. In size-momentum portfolios for the Korean and Chinese markets, arbitrage portfolios from small-cap groups yield significant negative momentum profits but insignificant negative results from large-cap groups. The Japanese markets yield negative momentum profits, which are only significant for large-cap groups rather than small-cap groups. Arbitrage portfolios from the U.S. stock markets yield significant positive momentum profits from small-cap groups but show negative performance from large-cap groups. Consequently, the results show that the momentum effects in the U.S. and Asian stock markets are significantly affected by the difference in the price behavior of small- and large-cap stocks that make up the winner and loser portfolios.

To verify this evidence more robustly, Fig. 4 shows the cumulative performance trends of the winner and loser portfolios within the size-momentum portfolios based on the four-momentum measures and stock markets. The results are presented for the winner portfolios (left figures) and loser portfolios (right figures) within small-cap groups (top figures) and large-cap groups (bottom figures) for the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) stock markets, respectively. The results are described based on the PMOM. In the figures, the x-axis indicates the entire period, and the y-axis indicates the cumulative excess returns.

Fig. 4 shows visual evidence consistent with Table 4. In Panel A of Fig. 4, the Korean stock markets on both winner and loser portfolios within small-cap groups show increasing trends of cumulative excess returns. However, loser portfolios see significantly more increases than winner portfolios. This means that negative momentum profits from Table 4 for the Korean stock markets are mainly attributed to strong performance reversals of small stocks in loser portfolios in the future holding period. The Japanese stock markets in Panel B show increasing trends in loser portfolios and decreasing trends in the winner portfolios of large-cap groups. This is a possible explanation for the results showing that Japanese stock markets yield significant negative momentum profits in large-cap groups. In small-cap groups of the Japanese stock markets, both winner and loser portfolios show increasing trends in cumulative excess returns, while loser portfolios experience larger increases than winner portfolios. This means that loser portfolios drive negative momentum profits in the Japanese stock markets within small-cap groups. The Chinese stock markets in Panel C show that negative momentum profits are also attributed to loser portfolios in small-cap groups with strong reversal trends in the future holding periods. The U.S. stock markets in Panel D show evidence that positive momentum profits are attributed to the persistence of winner portfolios in small-cap groups with strong increasing trends in cumulative excess returns. Small-cap stocks that deviate significantly from past average performances achieve high performance in the future. Conversely, the loser portfolios of small-cap groups do not show a robust performance reversal pattern, unlike in the Asian stock market. Within the large-cap groups of the U.S. stock markets, winner portfolios show decreasing trends, and loser portfolios show increasing trends. This is a possible explanation for the results in Table 4, in which winner and loser portfolios have opposite trends in cumulative excess returns in large-cap groups.

In summary, the results from the performance trends (Fig. 4) show that the negative momentum profits confirmed in the Asian stock markets are attributed to the strong performance reversals of the loser portfolios in the small-cap groups. In contrast, the positive momentum profits confirmed in the U.S. market are attributed to the strong performance persistence of the winner portfolios in the small-cap groups. When comparing the results from the momentum portfolios (Table 3) and size-momentum portfolios (Table 4), arbitrage portfolios from size-momentum portfolios have an economically higher performance and a statistically more significant level. The arbitrage-weighting method that allocates weights according to the degree of deviation from the average of all performances may help identify whether the momentum effect is attributed to the performance persistence or performance reversal of stocks with high investment weights.

[14] The literature employing portfolio analysis (e.g., Ang et al., 2019) mentions that using many portfolios is better than cases where a few portfolios are used to explore the characteristics of this phenomenon. However, this study employs the two portfolios due to the research designs applying the arbitrage-weighting method, compared to equal- and value-weighting methods on quintile and decile portfolios, like the previous studies. Accordingly, when controlling for market capitalization, the matrix for the bivariate size-momentum portfolios and the matrix for the factor premium are employed in the testing process.

Làm sau cùng

Table 4
Performances of size-momentum portfolios.

	Small-cap group (bottom 30%)			Large-cap group (top 30%)		
	Winner	Loser	Arbitrage	Winner	Loser	Arbitrage
Panel A: Korean stock markets						
ExRet.	0.0059[b]	0.0095[a]	-0.0037[c]	0.0026	0.0013	0.0013
	(2.06)	(3.17)	(−1.90)	(0.88)	(0.46)	(0.66)
CAPM	-0.0016	0.0015	-0.0031[c]	-0.0061[a]	-0.0083[a]	0.0021
	(−0.61)	(0.57)	(−1.65)	(−3.34)	(−9.47)	(1.14)
FF3	-0.0041[a]	0.0005	-0.0046[b]	-0.0081[a]	-0.0091[a]	0.0010
	(−2.75)	(0.31)	(−2.10)	(−4.34)	(−8.86)	(0.52)
Panel B: Japanese stock markets						
ExRet.	0.0035	0.0054[b]	-0.0019	-0.0012	0.0015	-0.0027[c]
	(1.58)	(2.33)	(−1.30)	(−0.58)	(0.76)	(−1.89)
CAPM	0.0005	0.0022	-0.0018	-0.0045[a]	-0.0021	-0.0024[c]
	(0.23)	(1.04)	(−1.24)	(−3.16)	(−1.51)	(−1.83)
FF3	-0.0021	-0.0003	-0.0018	-0.0062[a]	-0.0028[b]	-0.0034[b]
	(−1.58)	(−0.23)	(−1.28)	(−4.72)	(−2.18)	(−2.46)
Panel C: Chinese stock markets						
ExRet.	0.0045	0.0095[b]	-0.0050[a]	-0.0022	0.0004	-0.0026
	(1.16)	(2.31)	(−3.98)	(−0.60)	(0.12)	(−1.29)
CAPM	-0.0016	0.0030	-0.0047[a]	-0.0082[a]	-0.0060[a]	-0.0022
	(−0.88)	(1.25)	(−3.35)	(−3.86)	(−3.57)	(−0.89)
FF3	-0.0060[a]	-0.0022[b]	-0.0038[a]	-0.0069[a]	-0.0079[a]	0.0010
	(−5.10)	(−2.26)	(−2.83)	(−2.87)	(−7.59)	(0.44)
Panel D: U.S. stock markets						
ExRet.	0.0066[a]	0.0013	0.0053[a]	-0.0005	0.0022	-0.0027[c]
	(4.16)	(0.57)	(3.69)	(−0.29)	(1.32)	(−1.92)
CAPM	0.0029[b]	-0.0038[b]	0.0068[a]	-0.0050[a]	-0.0025[a]	-0.0024[c]
	(2.11)	(−2.10)	(6.43)	(−4.46)	(−3.00)	(−1.88)
FF3	0.0032[a]	-0.0037[a]	0.0069[a]	-0.0042[a]	-0.0026[a]	-0.0015
	(3.50)	(−2.69)	(6.82)	(−4.96)	(−3.41)	(−1.29)

This table presents the performance of the size-momentum portfolios under the 12 M/1 M momentum strategy based on PMOM. Bivariate portfolios are constructed using the dependent double-sorting method as follows. All stocks are classified into three groups by market capitalization: the top 30%, the middle 40%, and the bottom 30%. The arbitrage-weighting method constructs winner and loser portfolios within the top 30% and the bottom 30% groups. Arbitrage weighting also determines the investment weights of stocks. The markets are the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) markets. The portfolios are winners, losers, and arbitrage portfolios. The performance measures are excess returns (ExRet.) and risk-adjusted returns (CAPM, FF3), with t-statistics adjusted by Newey and West (1987, 1994) in parentheses. Further, a, b, and c indicate significance levels of 1%, 5%, and 10%, respectively.

5. Further testing

This section investigates the applicability and expandability of the PMOM. First, we investigate the applicability of a momentum factor premium generated from the arbitrage-weighting method using the PMOM and its explanatory power for changes in stock returns. Second, the expandability of the same methodology devising PMOM is examined through a new PMOM measure generated by combining technical indicators with CMOM.

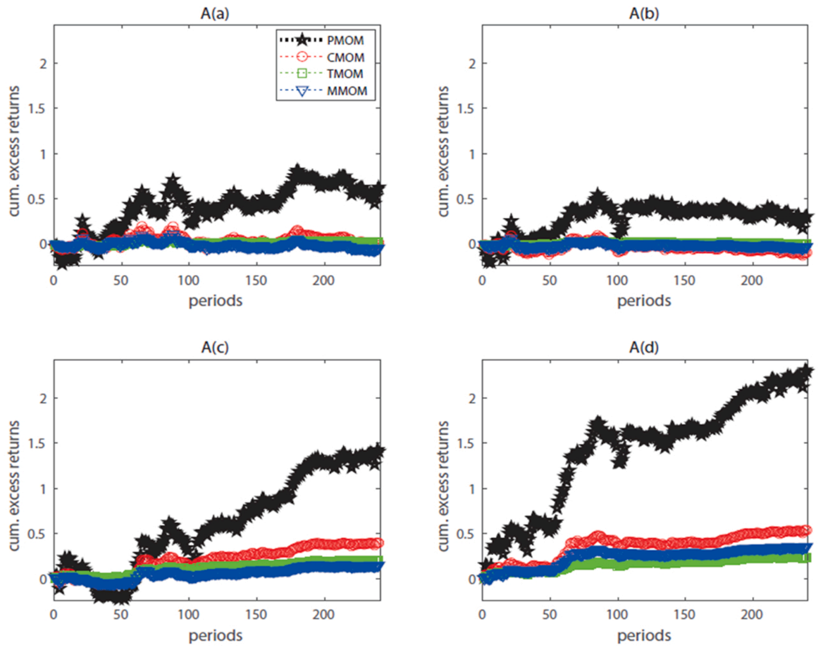
5.1. *Momentum factor premium and PMOM*

This study generates a momentum factor premium using the arbitrage-weighting method with PMOM. The momentum factor premium on the PMOM is based on the HML-like generation process of Fama and French (1993). The difference is using a 2×2 size-momentum portfolio matrix of the arbitrage-weighting method instead of a 2×3 portfolio matrix. The factor-generating process is as follows. First, according to market capitalization, stocks are divided into two groups: the top 50% (B) with large-cap stocks and the bottom 50% (S) with small-cap stocks. Second, within each stock group, a winner portfolio (W) and loser portfolio (L) are constructed by the arbitrage-weighting method using PMOM—a 2×2 size-momentum portfolio matrix. Third, the average returns from the winner and loser portfolios are calculated for the 2×2 size-momentum portfolios. The returns of the winner's portfolio constitute an average value ($\frac{BW+SW}{2}$) using a winner portfolio of large-cap stocks (BW) and a winner portfolio of small-cap stocks (SW). The returns of the loser portfolio constitute an average value ($\frac{BL+SL}{2}$) using a loser portfolio of large-cap stocks (BL) and a loser portfolio of small-cap stocks (SL). The momentum factor premium must have a positive value. To this end, the momentum factor premium for the U.S. stock markets is the positive momentum profit from the value of the winner portfolio minus the loser portfolio (winner-loser, WML= $\frac{BW+SW}{2} - \frac{BL-SL}{2}$). Conversely, the momentum factor premium for Asian stock markets with negative momentum profits is calculated from the

Panel A: Korean stock markets

Large-cap stocks group

Small-cap stocks group



Panel B: Japanese stock markets

Large-cap stocks group

Small-cap stocks group

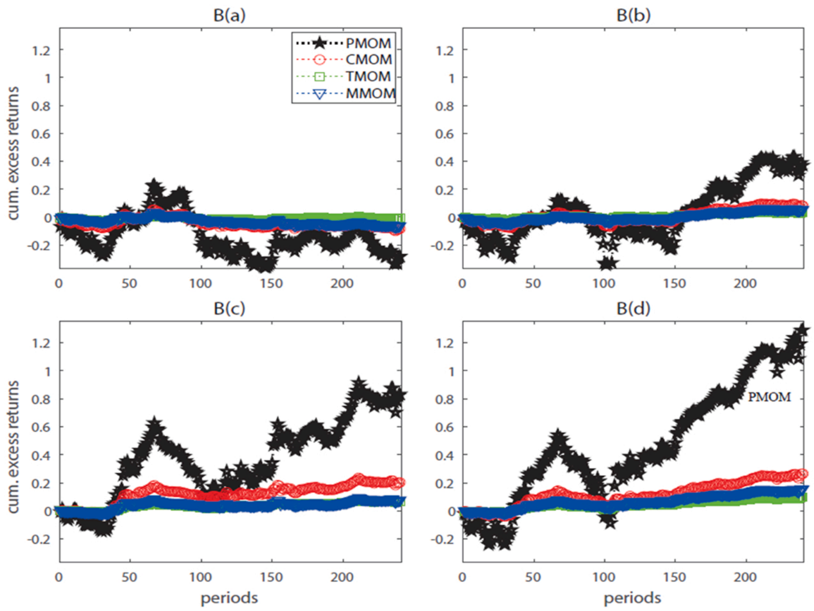


Fig. 4. Performance trends in size-momentum portfolios, The figures show the trends in the cumulative performance of a size-momentum portfolio under the 12 M/1 M momentum strategy based on PMOM. Size-momentum portfolios are constructed using a bivariate dependent double-sorting method. The markets are the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) markets. For the stock groups, the upper figures are large-cap stocks (the top 30%), labeled (a) and (b), and the lower figures are small-cap stocks (the bottom 30%), labeled (c) and (d). For the portfolios, the left side is the winner portfolio, labeled (a) and (c), and the right side is a loser portfolio, labeled (b) and (d). CMOM denotes momentum measures (◯, red), MMOM (▽, blue), TMOM (□, green), and PMOM (☆, black). The x-axis indicates future holding periods over the entire period, and the y-axis indicates cumulative excess returns. The legends in each chart labeled (a) apply to all charts in each panel.

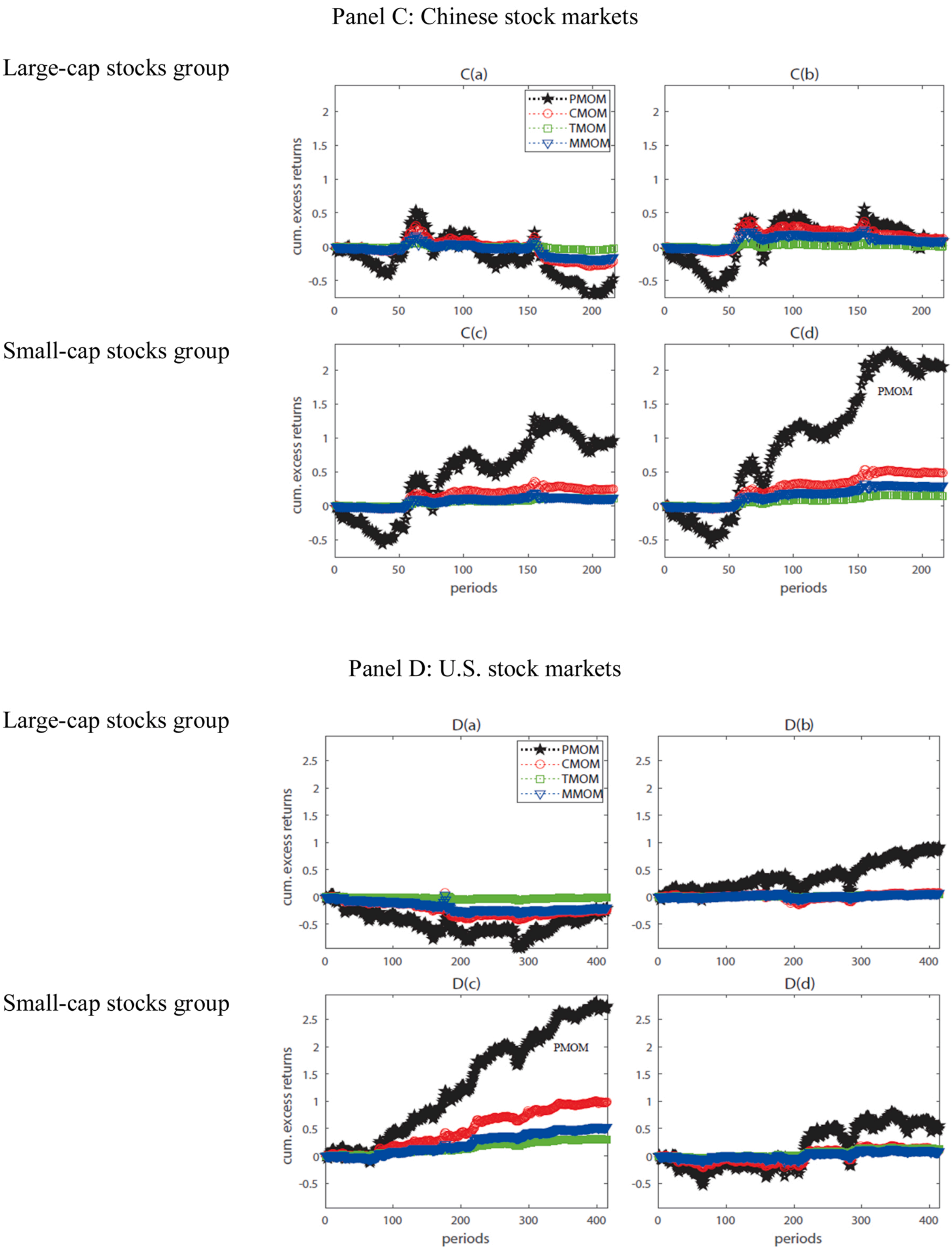


Fig. 4. (*continued*).

value of the loser portfolio minus the winner portfolio (loser–winner, LMW= $\frac{BL+SL}{2} - \frac{BW-SW}{2}$). The results are reported based on the momentum premium from PMOM (PMOM^{P}), which was verified to be comparatively advantageous over other measures, along with the momentum premium from CMOM (CMOM^{P}) as a benchmark.

Table 5
Momentum factor premiums.

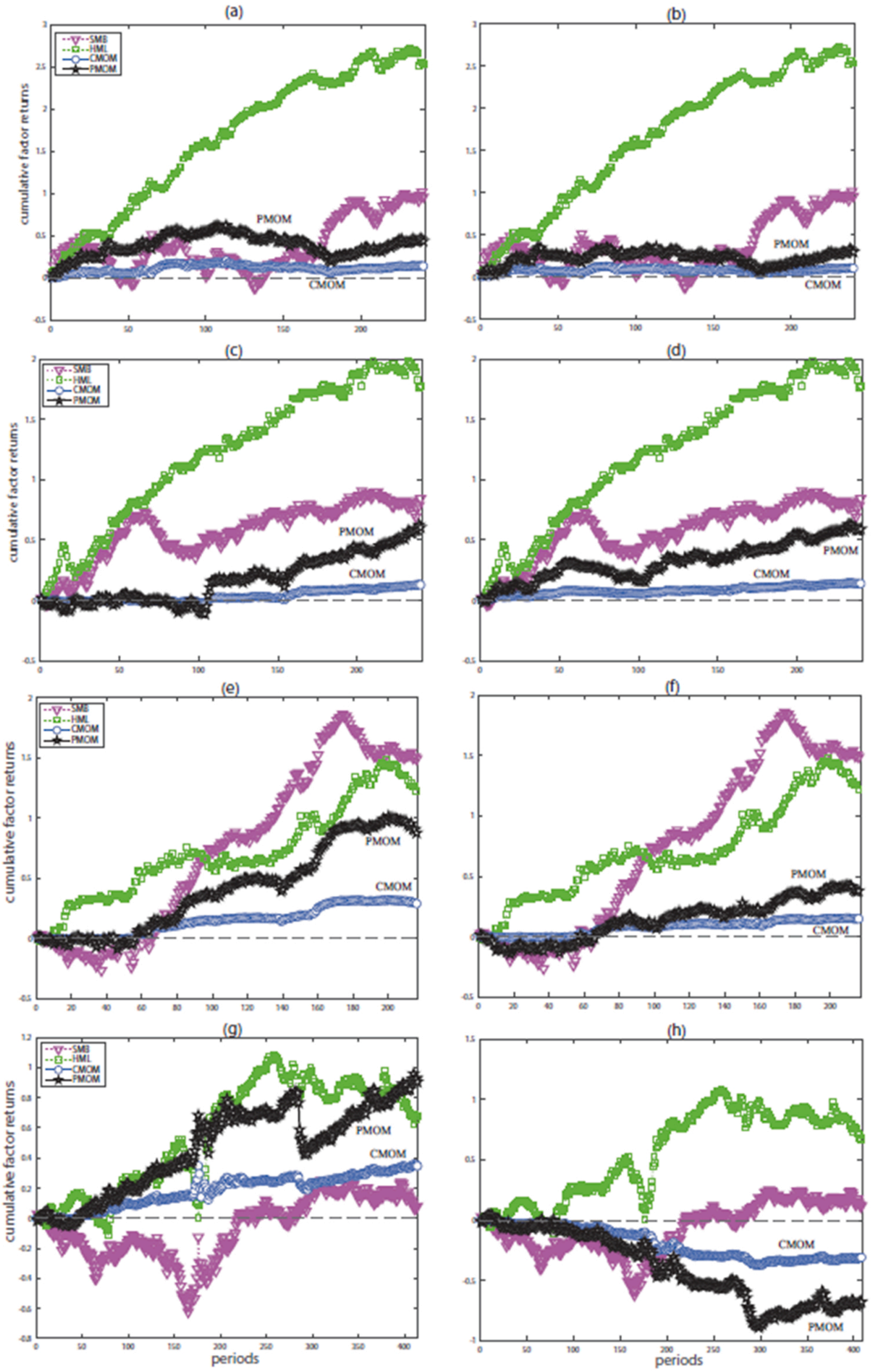
	Mkt	SMB	HML	MOM^P	1 M	6 M	12 M
Panel A: Korean Stock Markets							
Factor premiums	0.0158^{a}	0.0040	0.0106^{a}	$PMOM^P$	0.0018	0.0015	0.0033^{a}
	(3.80)	(1.13)	(4.61)		(1.27)	(1.19)	(3.23)
				$CMOM^P$	0.0006	0.0007	0.0012^{a}
					(1.10)	(1.34)	(3.06)
				P/C rate	3.10	2.16	2.82
Panel B: Japanese Stock Markets							
Factor premiums	0.0121^{b}	0.0035^{c}	0.0074^{a}	$PMOM^P$	0.0025^{b}	0.0022^{c}	0.0025^{b}
	(2.35)	(1.88)	(3.82)		(2.01)	(1.89)	(2.55)
				$CMOM^P$	0.0005^{c}	0.0005^{b}	0.0006^{a}
					(1.92)	(2.13)	(2.78)
				P/C rate	4.71	4.59	4.24
Panel C: Chinese Stock Markets							
Factor premiums	0.0099	0.0069^{b}	0.0057^{b}	$PMOM^P$	0.0041^{b}	0.0011	0.0018
	(1.37)	(2.24)	(2.46)		(2.48)	(0.88)	(1.54)
				$CMOM^P$	0.0013^{b}	0.0004	0.0007^{b}
					(2.38)	(1.30)	(2.03)
				P/C rate	3.03	2.77	2.58
Panel D: U.S. Stock Markets							
Factor premiums	0.0070^{a}	0.0002	0.0016	$PMOM^P$	0.0022^{c}	0.0001	-0.0017
	(3.23)	(0.15)	(0.91)		(1.80)	(0.12)	(−1.65)
				$CMOM^P$	0.0008^{c}	0.0000	-0.0008^{b}
					(1.97)	(−0.02)	(−2.04)
				P/C rate	2.61	-15.33	2.19

This table presents the results for the time-series average values of factor premiums. Factor premiums are the Fama and French (1993) three-factor premiums (market premium (Mkt), size premium (SMB), value premium (HML)), and $PMOM^P$ and $CMOM^P$ from a 2x2 SIZE-momentum portfolio using the arbitrage-weighting method. The momentum premiums are calculated to have positive values. For Asian stock markets with negative momentum profits, momentum premiums are measured as the average values of a loser portfolio minus a winner portfolio (LMW), and momentum premiums for U.S. stock markets with positive momentum profits are the average values of a winner portfolio minus a loser portfolio (WML). Portfolio rebalancing periods for the momentum premium are of three types: one month (1 M), six months (6 M), and 12 months (12 M). The markets are the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) stock markets. The P/C rates are the comparative ratios of $PMOM^P$ and $CMOM^P$. The numbers in parentheses are t-statistics adjusted for autocorrelation and heteroscedasticity based on Newey and West (1987, 1994). Further, a, b, and c indicate significance levels of 1%, 5%, and 10%, respectively.

Table 5 presents average values for the factor premiums in each country. The table presents $PMOM^P$ and $CMOM^P$ from the arbitrage-weighting method along with the market premium (Mkt), size premium (SMB), and value premium (HML) based on Fama and French (1992). Momentum premiums are divided into three categories, according to portfolio rebalancing periods, which are one month (1 M), six months (6 M), and 12 months (12 M). The evaluation of the statistical significance is conducted based on the t-statistic, considering the standard error of Newey and West (1987) with a 12-lag length.

The result of Table 5 shows statistically significant momentum premiums. In the one-month (1 M) rebalancing period, Japan, China, and the U.S. stock markets have significant positive momentum premiums. The Japanese markets show significant positive momentum premiums in all the rebalancing periods. The Korean markets show insignificant evidence of the momentum premiums from one- and six-month rebalancing periods; the momentum premium from the 12-month rebalancing period is positive and significant. As confirmed in previous studies (e.g., Jegadeesh and Titman, 2001), the U.S. stock markets show a significant positive momentum premium in the one-month rebalancing period and a negative momentum premium over a prolonged rebalancing period. $PMOM^P$ has a higher momentum premium than $CMOM^P$ from the magnitude viewpoint.

Fig. 5 shows the trends in the cumulative factor premiums for the entire period of each country. The figures are presented according to portfolio rebalancing periods of one month (left side) and 12 months (right side) for the four-factor premiums: SMB, HML, $PMOM^P$, and $CMOM^P$. Each market shows different time-series trends in factor premiums under the $PMOM^P$. In the figures, $PMOM^P$ mostly shows upward trends, and the strength of the upward trends appears to weaken based on changes from one-month to 12-month rebalancing periods. Regardless of the stock market, $PMOM^P$ has higher trends than $CMOM^P$, except in the 12-month rebalancing



(caption on next page)

Fig. 5. Trends in factor premiums, This figure shows the trends in the cumulative factor premiums. Factor premiums are the size premium (SMB) and the value premium (HML) based on Fama and French (1993), the PMOM premium ($PMOM^P$), and the CMOM premium ($CMOM^P$) from a 2x2 size-momentum portfolio using the arbitrage-weighting method. Momentum premiums with positive values are calculated for the Asian (Korea, Japan, and China) and U.S. stock markets. Momentum premiums for the Asian stock markets that verify negative momentum profits are the values of a loser portfolio minus a winner portfolio (LMW), and those for the U.S. stock markets that verify positive momentum profits are the values of a winner portfolio minus a loser portfolio (WML). The portfolio rebalancing periods for the momentum premium are divided into one month (left side) and 12 months (right side). The markets are the Korean stock markets labeled (a) and (b), the Japanese stock markets labeled (c) and (d), the Chinese stock markets labeled (e) and (f), and the U.S. stock markets labeled (g) and (h). In the figures, factor premiums are presented for SMB (▽, red), HML (□, green), $CMOM^P$ (◯, blue), and $PMOM^P$ (☆, black), with the x-axis indicating future holding periods over the whole period and the y-axis indicating cumulative premiums.

period for the U.S. markets. The Japanese and Chinese markets have upward trends for $PMOM^P$ in the time series, but $PMOM^P$ is lower than the other factor premiums. The Japanese markets show high trends for HML, whereas the Chinese markets show high trends for SMB and HML.[15] Meanwhile, the U.S. stock markets have contrasting trends for $PMOM^P$ based on the rebalancing period. $PMOM^P$ shows an upward trend in the one-month rebalancing period along with HML. However, when the rebalancing period was prolonged to 12 months, $PMOM^P$ showed a downward trend in contrast to the trends of the other factor premiums.

Table 6 presents results from time-series regressions of four-factor models, including $PMOM^P$ in the three-factor model of Fama and French (1993). The empirical design is based on the factor-testing processes of Fama and French (1993). A dependent variable indicates excess returns in the 2 × 2 size-momentum portfolio matrix—returns of the winner portfolio (BW) and the loser portfolio (BL) for large-cap stocks and returns of the winner portfolio (SW) and the loser portfolio (SL) for small-cap stocks. The independent variables are $PMOM^P$ and the three-factor premiums (Mkt, SMB, HML) of Fama and French (1993). As a benchmark, this study uses a four-factor model, including $CMOM^P$ instead of $PMOM^P$. Momentum premiums generated from a one-month rebalancing period are used. Results report regression coefficients and the explanatory power from the four-factor model. The statistical significance is evaluated based on the t-statistic, considering the standard error of Newey and West (1987) with a 12-lag length.

According to the results, the four-factor model explains the changes in the portfolio returns from the 2 × 2 size-momentum portfolio matrix with high explanatory power. The $PMOM^P$ in the models has significant regression coefficients. In Asian (Korean, Japanese, and Chinese) markets, regardless of market capitalization, every $PMOM^P$ in the loser portfolios has significant positive coefficients, and every $PMOM^P$ in the winner portfolios has significant negative coefficients. The U.S. markets show opposite signs in the regression coefficients of $PMOM^P$ compared to Asian markets. In other words, every $PMOM^P$ in the winner portfolios has significant positive coefficients, and every $PMOM^P$ in the loser portfolios has significant negative coefficients. This is attributed to the calculation rules for momentum premiums by subtracting a winner portfolio from a loser portfolio in Asian stock markets with negative momentum profits and subtracting a loser portfolio from a winner portfolio in the U.S. stock markets with positive momentum profits. Meanwhile, the results of the four-factor model, including $CMOM^P$ as the benchmark, show lower levels of the statistical significance of the regression coefficients and explanatory power compared with the four-factor models, including $PMOM^P$. This means that a momentum premium from the PMOM better explains the variations in stock returns than the CMOM.

5.2. A new PMOM combining technical indicators

This study generates a new PMOM measure ($PMOM^{NEW}$) that combines technical indicators in CMOM using the same methodology. The PMOM in the previous sections is combined with three momentum measures (CMOM, TMOM, and MMOM) through PCA. MMOM and TMOM are generated using the time-series characteristics of stock returns, so these measures are highly relevant to technical indicators. Technical indicators generally generate long- and short-position signals based on time-series patterns of stock prices. Regarding previous studies, Brock et al. (1992) employ moving averages and trading range breakouts to verify the profitability of technical indicators. Sullivan et al. (1999) use the moving average, support and resistance, channel breakout, and on-balance volume averages to verify the snooping bias in the predictability and profitability of technical indicators. Neely et al. (2014) analyze the improvement in predictability by combining macroeconomic variables and technical indicators (moving average, simple momentum, and on-balance volume). This study combines the technical indicators in CMOM using the methodology devising PMOM in the previous sections. To this end, four technical indicators are selected: moving average (MA), trading range breakout (TRB), channel trade breakout (CTB), and Bollinger Bands (BB).[16] Accordingly, $PMOM^{NEW}$ is generated through PCA using cross-sectional data constructed using both CMOM and signals (or values) from technical indicators for stocks.

Table 7 presents the performance of the momentum portfolios from the 12 M/1 M momentum strategy based on $PMOM^{NEW}$. The results show the excess returns (ExRet.) and risk-adjusted returns (CAPM, FF3) for each country's winner, loser, and arbitrage portfolios constructed using the arbitrage-weighting method.

[15] Momentum premiums in this study have different factor premiums based on Fama and French (1993) in some aspects, such as portfolio construction—the number of stocks in the portfolio and the weighting method. Momentum premiums in this study employ a 2×2 portfolio matrix because they employ the arbitrage-weighting method for all the stocks, whereas other factor premiums (SMB, HML) of Fama and French (1993) use a 2 × 3 portfolio matrix from the value-weighting method for stocks in the top 30% and the bottom 30%. Accordingly, it is difficult to determine the comparative advantage based on the magnitude difference between $PMOM^P$ and other factor premiums.

[16] This study presents the method to generate each of the four technical indicators in the Appendix.

Table 6
Time-series regression results of portfolio return on factor premiums.

		Mkt	SMB	HML	$PMOM^P$	R^2	$CMOM^P$	R^2
Panel A: Korean stock markets								
Large-cap stocks	Winner	0.5654[a]	0.3079[a]	-0.0357	-0.7935[a]	87.53%	-1.2384[a]	85.33%
		(30.08)	(14.12)	(−1.15)	(−16.88)		(−19.20)	
	Loser	0.5595[a]	0.2911[a]	0.0076	0.2787[a]	89.05%	0.0470	80.74%
		(37.66)	(17.70)	(0.33)	(9.12)		(0.79)	
Small-cap stocks	Winner	0.4965[a]	0.4815[a]	-0.0009	-0.4525[a]	81.81%	-0.4882[a]	71.28%
		(22.23)	(18.46)	(−0.02)	(−8.77)		(−5.23)	
	Loser	0.5024[a]	0.4983[a]	-0.0442	0.4752[a]	86.02%	0.2265[a]	77.12%
		(22.03)	(21.42)	(−1.17)	(9.46)		(3.68)	
Panel B: Japanese stock markets								
Large-cap stocks	Winner	0.2937[a]	0.3156[a]	0.0589	-0.3571[a]	52.66%	-0.7858[a]	62.05%
		(3.34)	(5.36)	(1.35)	(−3.10)		(−6.04)	
	Loser	0.2959[a]	0.2480[a]	0.0618	0.5985[a]	57.95%	0.1857	48.85%
		(3.39)	(4.64)	(1.36)	(4.72)		(1.39)	
Small-cap stocks	Winner	0.2849[a]	0.5074[a]	0.0485	-0.3921[b]	56.52%	-0.8795[a]	67.57%
		(3.29)	(8.51)	(0.75)	(−2.55)		(−5.62)	
	Loser	0.2828[a]	0.5750[a]	0.0456	0.6523[a]	60.19%	0.1490	54.70%
		(3.25)	(9.22)	(0.75)	(4.74)		(1.15)	
Panel C: Chinese stock markets								
Large-cap stocks	Winner	0.6257[a]	0.2924[a]	-0.0537	-0.8846[a]	89.50%	-1.4447[a]	67.51%
		(38.33)	(4.58)	(−0.89)	(−10.91)		(−9.49)	
	Loser	0.6164[a]	0.3200[a]	-0.0135	0.3079[a]	89.95%	0.0277	63.48%
		(43.40)	(5.01)	(−0.19)	(4.13)		(0.20)	
Small-cap stocks	Winner	0.5795[a]	0.6985[a]	0.0328	-0.4548[a]	92.19%	-0.5103[a]	67.72%
		(43.92)	(12.53)	(0.54)	(−7.38)		(−5.31)	
	Loser	0.5888[a]	0.6709[a]	-0.0074	0.3526[a]	93.73%	0.0173	69.74%
		(42.01)	(11.80)	(−0.14)	(5.68)		(0.20)	
Panel D: U.S. stock markets								
Large-cap stocks	Winner	0.6130[a]	0.4667[a]	-0.0671[a]	0.3871[a]	93.76%	0.9067[a]	89.21%
		(56.96)	(23.45)	(−2.95)	(12.78)		(6.33)	
	Loser	0.5949[a]	0.3311[a]	0.0193	-0.5713[a]	95.23%	-0.2985[a]	85.83%
		(61.49)	(15.73)	(0.58)	(−17.93)		(−4.99)	
Small-cap stocks	Winner	0.5369[a]	0.5232[a]	0.0964[a]	0.1818[a]	82.13%	0.3890[a]	74.47%
		(25.66)	(14.37)	(2.67)	(4.37)		(5.22)	
	Loser	0.5550[a]	0.6589[a]	0.0100	-0.8597[a]	85.51%	-0.4057[a]	71.87%
		(23.75)	(16.93)	(0.21)	(−14.64)		(−3.66)	

This table presents the time-series regression results of portfolio returns on factor premiums in a 2x2 size-momentum portfolio. The dependent variable is the excess returns of each large-cap stock winner (BW) and loser (BL) and each small-cap stock winner (SW) and loser (SW) from the 2x2 size-momentum portfolio using the arbitrage-weighting method. The independent variables are the factor premiums for Mkt, SMB, HML, $PMOM^P$, and $CMOM^P$. Momentum premiums for the Asian stock markets are constructed as the values of a loser portfolio minus a winner portfolio (LMW), and those for the U.S. stock markets are the values of a winner portfolio minus a loser portfolio (WML). The rebalancing period for the momentum premium is one month. The markets are the Korean (Panel A), Japanese (Panel B), Chinese (Panel C), and U.S. (Panel D) markets. The table reports the regression coefficients and explanatory power (R^2) from a four-factor model, including $PMOM^P$ and $CMOM^P$. The numbers in parentheses are t-statistics adjusted for autocorrelation and heteroscedasticity based on Newey and West (1987, 1994). Further, a, b, and c indicate significance levels of 1%, 5%, and 10%, respectively.

According to the results, $PMOM^{NEW}$ is highly similar to the results of PMOM in Table 3. In both cases, using signals and values from technical indicators, the Chinese market shows significantly negative performance, and the U.S. market shows significantly positive performance. The Korean and Japanese markets show significantly negative performance using long and short position values. Unlike in Table 3, the Korean market yields significant negative momentum profits in $PMOM^{NEW}$. Compared with the results of Table 3 using PMOM, in terms of the performance magnitude, the winner portfolios have larger values in all stock markets, and the U.S. markets show high performance of the arbitrage portfolio. Regarding statistical significance, evidence of a high significance level is confirmed in the U.S. markets. This suggests that information on technical indicators can help establish momentum strategies.

For a more evident confirmation of this improvement from $PMOM^{NEW}$, Fig. 6 compares the time-series trends in the momentum performance during the entire period. The time-series trends use excess returns for the period reported in Table 7. The figures are classified into winner (left), loser (middle), and arbitrage portfolios (right). In Fig. 6, the trends of cumulative excess returns from $PMOM^{NEW}$ show a clear difference from the trends from CMOM. They especially show evidence that $PMOM^{NEW}$ improves momentum performance in most trends compared with PMOM.

Consequently, the PMOM generated by combining CMOM with TMOM and MMOM has an improved comparative advantage

Table 7
A new PMOM combining CMOM and technical indicators.

	Using signals			Using values		
	Winner	Loser	Arbitrage	Winner	Loser	Arbitrage
Panel A: Korean stock markets						
ExRet.	0.0046	0.0050	-0.0004	0.0009	0.0047	-0.0038[b]
	(1.38)	(1.39)	(−0.22)	(0.28)	(1.58)	(−2.28)
CAPM	-0.0058[b]	-0.0060[a]	0.0002	-0.0088[a]	-0.0047[a]	-0.0041[a]
	(−2.28)	(−2.81)	(0.14)	(−4.03)	(−2.64)	(−2.69)
FF3	-0.0087[a]	-0.0072[a]	-0.0015	-0.0112[a]	-0.0060[a]	-0.0052[a]
	(−5.21)	(−4.92)	(−0.78)	(−6.05)	(−5.03)	(−2.61)
Panel B: Japanese stock markets						
ExRet.	0.0020	0.0030	-0.0010	-0.0003	0.0034	-0.0037[a]
	(0.91)	(1.22)	(−0.93)	(−0.13)	(1.50)	(−2.75)
CAPM	-0.0016	-0.0009	-0.0007	-0.0040[b]	-0.0002	-0.0038[a]
	(−0.83)	(−0.45)	(−0.58)	(−2.28)	(−0.11)	(−3.06)
FF3	-0.0040[b]	-0.0034[b]	-0.0007	-0.0065[a]	-0.0023[c]	-0.0042[a]
	(−2.53)	(−2.27)	(−0.62)	(−4.62)	(−1.67)	(−3.16)
Panel C: Chinese stock markets						
ExRet.	-0.0017	0.0037	-0.0054[a]	-0.0014	0.0055	-0.0069[a]
	(−0.45)	(0.88)	(−3.30)	(−0.34)	(1.26)	(−3.67)
CAPM	-0.0082[a]	-0.0033[c]	-0.0049[a]	-0.0084[a]	-0.0019	-0.0066[a]
	(−4.68)	(−1.83)	(−2.51)	(−4.94)	(−1.02)	(−2.99)
FF3	-0.0090[a]	-0.0062[a]	-0.0028	-0.0089[a]	-0.0058[a]	-0.0031
	(−4.93)	(−4.92)	(−1.36)	(−4.38)	(−6.02)	(−1.64)
Panel D: U.S. stock markets						
ExRet.	0.0046[b]	0.0006	0.0039[a]	0.0038[b]	0.0011	0.0027[c]
	(2.37)	(0.24)	(2.60)	(1.98)	(0.53)	(1.86)
CAPM	-0.0006	-0.0060[a]	0.0054[a]	-0.0013	-0.0044[a]	0.0031[a]
	(−0.45)	(−4.10)	(4.96)	(−0.94)	(−3.58)	(2.86)
FF3	-0.0001	-0.0059[a]	0.0057[a]	-0.0005	-0.0043[a]	0.0038[a]
	(−0.19)	(−5.79)	(5.04)	(−0.67)	(−4.90)	(3.42)

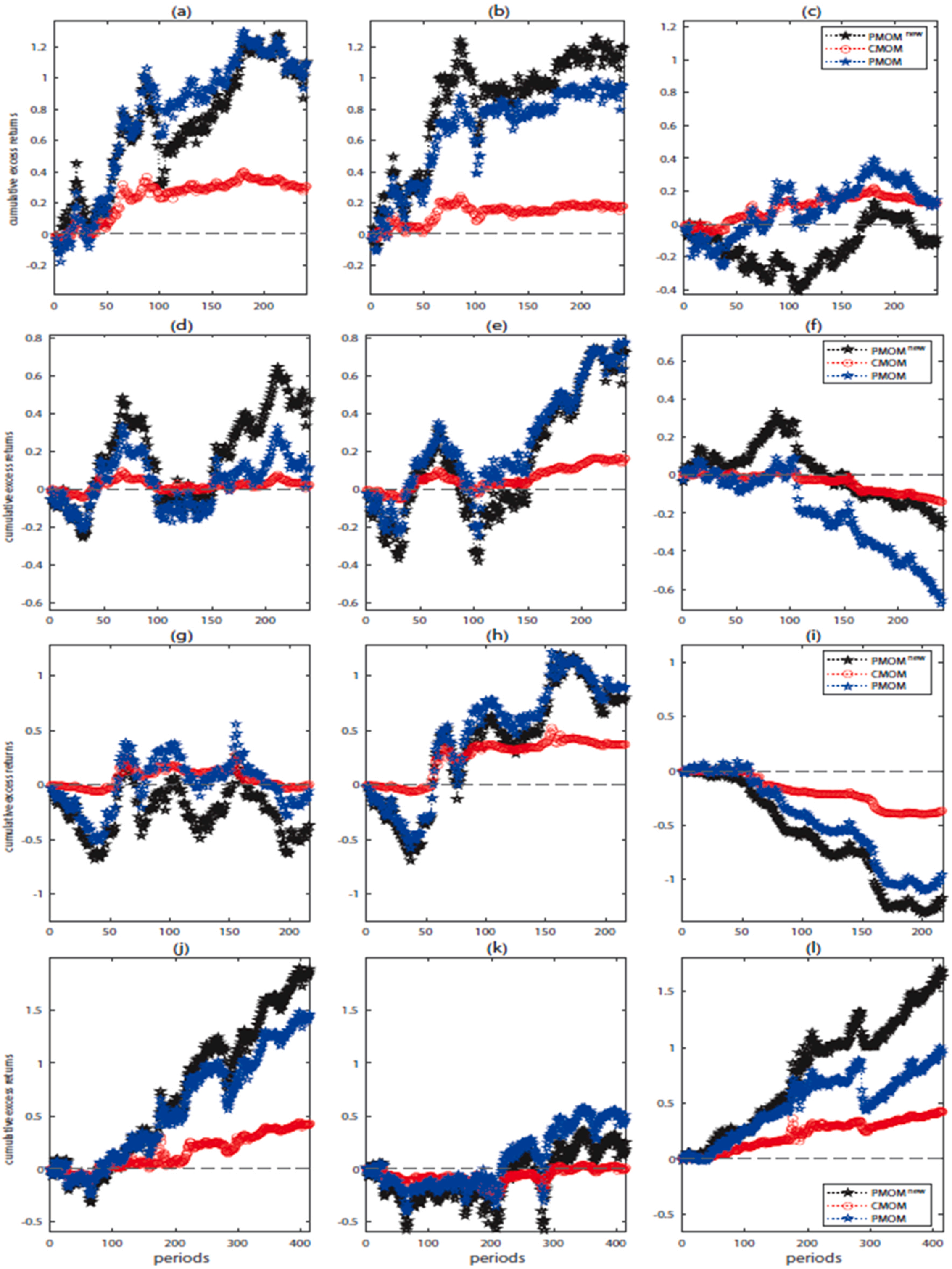
This table presents the results of the performance of momentum portfolios under the 12M/1M momentum strategy from PMOMNEW, which combines CMOM and technical indicators. There are four types of technical indicators: moving average, trading range breakout, channel trade breakout, and Bollinger Bands. Portfolios are winner, loser, and arbitrage portfolios constructed by the arbitrage-weighting method (Lo and MacKinlay, 1990). The markets are the Korean (Panel A), Japanese (PanelB), Chinese (Panel C), and U.S. (Panel D) markets. Performances are classified into cases using signals (left side) and values (right side) from technical indicators. The performance measures are excess returns (ExRet.) andrisk-adjusted returns (CAPM and FF3). The numbers in parentheses are t-statistics adjusted for autocorrelation and heteroscedasticity based on Newey and West (1987, 1994). Further, a, b, and c indicate the significance levels of 1%, 5%,and 10%, respectively.

regarding the momentum strategy's economic usefulness (magnitude) and statistical reliability (significance). Moreover, it can be easily expanded by combining CMOM and technical indicators using the same methodology devised for PMOM. Therefore, this study contributes to the literature by bridging between fundamental and technical analyses through the applicability and expandability of the methodology devising PMOM.

6. Conclusions

The momentum effect has been a long-standing research topic in finance. Since Jegadeesh and Titman (1993), many studies have reported mixed results; however, the momentum effect remains an empirical phenomenon that has not been sufficiently explained. This study empirically investigates the performance of momentum strategies in the U.S. and Asian (Korean, Japanese, and Chinese) stock markets using a newly devised PMOM measure and the momentum measures of CMOM, MMOM, and TMOM. Studies on the U.S. stock markets report significant positive momentum profits as evidence of the momentum effect. Contrary to the U.S. stock markets, studies on Asian stock markets report significant negative or insignificant momentum profits. This study investigates the difference between momentum effects in the U.S. and Asian stock markets by applying the arbitrage-weighting method to the relationship between investment weights and market capitalization for stocks and verifies the applicability and expandability of the PMOM methodology.

The main results of this study are summarized as follows. First, when comparing the PMOM momentum strategy with the other three momentum strategies (CMOM, TMOM, and MMOM), the PMOM strategy has a comparative advantage in the magnitude and statistical significance of the stock market performance. Moreover, when using the PMOM, positive momentum profits in the U.S. market and negative momentum gains in Asian markets are more clearly identified. Second, the results show that an arbitrage-weighting method is more suitable for analyzing momentum characteristics. Through the arbitrage-weighting method, this study determines that negative momentum profits in Asian stock markets are attributed to the performance reversals of loser portfolios, and



(caption on next page)

Fig. 6. Performance trends of the new PMOM combining CMOM and technical indexes, The figures show the momentum portfolios' cumulative excess return trends under the 12 M/1 M momentum strategy based on $PMOM^{NEW}$, which combines CMOM and technical indicators. There are four types of technical indicators: moving average, trading range breakout, channel trade breakout, and Bollinger Bands. The stock markets are Korean (Figures (a), (b), and (c)), Japanese ((d), (e), (f)), Chinese ((g), (h), (i)), and the U.S. ((j), (k), (l)) stock markets. In the figures, the left, middle, and right sides are the winner, loser, and arbitrage portfolios, respectively. Momentum measures presented are of three types: $PMOM^{NEW}$ (☆, black) as a benchmark, CMOM (◯, red), and PMOM (☆, blue). The x-axis indicates future holding periods over the entire period in the charts, and the y-axis indicates cumulative excess returns. The legends in the charts labeled (c) are applied to the other charts in each row.

positive momentum profits in U.S. stock markets are attributed to performance persistence in winner portfolios. Third, the performance of momentum strategies is closely related to the investment weights allocated to stocks in winner and loser portfolios. Especially, investment weights allocated to small-cap stocks that deviate significantly from the average performance of the past period have a significant impact on the momentum phenomenon. The size-momentum portfolios show that performance reversals in loser portfolios within small-cap stocks result in significant negative momentum profits in the Chinese markets, whereas performance reversals of loser portfolios drive significant negative momentum profits in the Japanese markets within both small- and large-cap stocks. Conversely, the U.S. stock markets show evidence that performance persistence in the winner portfolios of small-cap stocks results in significant positive momentum profits. Finally, this study verifies the applicability and expandability of the PMOM. The four-factor model (including the momentum premium of the PMOM) in the three-factor model of Fama and French (1993) can better explain changes in portfolio returns. Additionally, $PMOM^{NEW}$, which combines technical indicators known to have momentum properties with CMOM, may improve momentum performance from both economic and statistical perspectives.

Based on the results mentioned above, this study concludes that the PMOM is a momentum measure that can successfully extract common information on momentum effects and demonstrates how the arbitrage-weighting method is a suitable way to consider momentum characteristics better than the equal- and value-weighting methods. Moreover, empirical design using the arbitrage-weighting method for PMOM can be a useful way to link fundamental momentum and technical indicators. In addition, findings in this study motivate further exploration of whether the different momentum profits in the U.S. and Asian stock markets can be explained through the different investor behaviors, institutional holdings, or different market systems as a direction of future research.

CRediT authorship contribution statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the *Research in International Business and Finance*.

Data Availability

Data will be made available on request.

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Appendix

This study combines the technical indicators in the CMOM using the same methodology devised for the PMOM. To this end, four technical indicators are selected: moving average (MA), trading range breakout (TRB), channel trade breakout (CTB), and Bollinger Bands (BB). The long- and short-position signals (or values) from each technical indicator are determined as follows. First, the MA is the same as in Eq. (2) for the MMOM. The difference lies in using the long- and short-position signals from MA. Through MA, the long-position signal ($S = +1$) and short-position signal ($S = -1$) for each stock is determined according to the positive and negative values of the difference between short-term performance (SP) and long-term performance (LP) for stocks in the past formation period (i.e., SP–LP).

Next, TRB, CTB, and BB are described. The periodic performance of stocks from month t–12 to month t–2 in the past formation period is used as a proxy for stock prices to generate the long- and short-position signals (values) from the three technical indicators. This process is expressed as follows:

$$P_{t-12} = \sqrt{(1 + R_{t-12})} - 1$$

$$P_{t-11} = \sqrt{(1 + R_{t-12})(1 + R_{t-11})} - 1$$

....

$$P_{t-2} = \sqrt{(1+R_{t-12})(1+R_{t-11})\ldots(1+R_{t-3})(1+R_{t-2})} - 1$$

Using a periodic return series (P_t, t = −12, −11, …−3, −2) for prices, the long- and short-position signals (or values) from the three technical indicators are generated as follows. First, the TRB generates long-position signals (values) when the price of the last month (P_{t-2}) is greater than or equal to the maximum price (P_{MAX}) and short-position signals (values) when the price of the last month is less than or equal to the minimum price (P_{MIN}). This generates hold-position signals (values) for the remainder.

$$\left\{ \begin{array}{c} P_{t-2} \geq P_{MAX}, \quad S = +1 \\ P_{MIN} < P_{t-2} < P_{MAX}, \quad S = 0 \\ P_{t-2} \leq P_{MIN}, \quad S = -1 \end{array} \right\}$$

Second, the CTB considers the range calculated from the maximum and minimum prices utilized in the TRB. In other words, long- and short-position signals (values) from the CTB are generated when they satisfy the condition, whereby the channel index (CI $= \frac{P_{MAX}}{P_{MIN}}$) exceeds the upper and lower bounds of the channel breakout rate (CR=15%), in addition to the conditions for long-position and short-position decisions from the TRB.

$$\left\{ \begin{array}{c} P_{t-2} \geq P_{MAX} \text{ and } CI > CR, \quad S = +1 \\ P_{MIN} < P_{t-2} < P_{MAX}, \quad S = 0 \\ P_{t-2} \leq P_{MIN} \text{ and } CI < CR, \quad S = -1 \end{array} \right\}$$

Third, BB generates long- and short-position signals (values) by considering the average value and volatility of the price changes in the past formation period. The average value (M) is calculated using prices from the past formation period, and volatility is the range between the lower bound (LB $= M - 1.96\sigma$) and the upper bound (UB $= M + 1.96\sigma$) established using the standard deviation (σ) of stock returns based on the 95% statistical confidence interval:

$$\left\{ \begin{array}{c} P_{t-2} > LB \text{ and } P_{t-2} > M, \quad S = +1 \\ P_{t-2} < UB \text{ and } P_{t-2} < M, \quad S = -1 \\ Otherwise, \quad S = 0 \end{array} \right\}$$

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ribaf.2023.101908.

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