# Barra Risk Model Based Idiosyncratic Momentum for the Chinese Equity Market

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A new approach of constructing an idiosyncratic momentum using common style factors from the Barra risk model has been proposed. The method removes the limitation in the conventional approach of constructing idiosyncratic momentum using Fama-French factors, and allows to build more effective idiosyncratic momentum factor for a wide variety of international markets where the Fama-French model is not available. The performance results indicate that the idiosyncratic momentum factor carries a resemblance to the conventional price momentum, but with much lower variance and exposure to the common market factors, such as value, size, and volatility. The long-short portfolio test for both China's A-Share IMI and CSI 500 indices in the Chinese equity market demonstrates the significant improvement of this factor's return over the conventional momentum. The results strongly suggest the idiosyncratic momentum factor could be used as an effective momentum strategy for investing in China's stock market.

**Keywords:** stocks; price momentum; idiosyncratic momentum; risk model; regression

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# I. Introduction

Momentum effect, which is a tendency of recent winner stocks to continue to rise and the recent loser stocks to continue to fall, is one of the strongest and most pervasive asset pricing anomalies documented in the financial literature by numerous authors. The fundamental feature of the momentum strategy as well as its predictive power has been constantly discussed and well documented in the work of Jegadeesh and Titman (1993). During the last 2 decades, the discussion of momentum strategy and its practical application has remained active topics. Also, several momentum strategies have been proposed, and the effectiveness of these strategies has been investigated extensively in different equity markets as well as for various asset classes (Fama and French (2008), (2012), Moskowitz and Grinblatt (1999), Lewellen (2002), Rouwenhorst (1998), Griffin et al. (2003), Chui et al. (2003)).

Of all the momentum strategies, there has been wide discussion on idiosyncratic momentum during the recent decade following the pioneer work done by Grundy and Martin (2001), Gutierrez and Prinsky (2007), and Blitz et al. (2011). In their article, Grundy and Martin discussed the possibility of reducing the exposure of momentum signals to systematic risk factors, such as market and style factors, so that the low volatility of the strategy could be obtained when the fluctuations of these systematic factors were singled out. Following this idea, Gutierrez and Prinsky proposed a method of constructing an idiosyncratic momentum signal to reduce the systematic style tilts by making individual stock returns in the ranking period orthogonal to 3 fundamental factors that explain a major part of the variation in the average return: the market, size, and value factors. Furthermore, Blitz et al. (2017) provided strong evidence that idiosyncratic momentum is a distinct phenomenon by showing that it cannot be explained by any of the established asset pricing factors, such as the market, size, value, operating profitability, and investment. Recently, Chaves (2016) proposed a simple way of constructing the idiosyncratic momentum factor and demonstrated its robust performance using several samples of securities from the international equity markets, including the Japanese equity market, where conventional momentum is known to be ineffective.

Inspired by the work of Blitz et al. (2017) and Chaves (2016), we want to further investigate the idiosyncratic momentum factor and explore the possibility of using this signal to build a practical momentum strategy of investment for different equity markets.

Although various authors have engaged in extensive discussions and theoretical analysis of the performance of the idiosyncratic momentum, most of the research focuses on the idiosyncratic momentum signal constructed using the Fama-French model factors, and performance analysis is done in the US or other developed country markets. When building an idiosyncratic momentum signal for emerging markets (including Chinese equity markets), an issue arises with the traditional approach of using Fama-French factors simply because of the lack of a Fama-French model for these markets. One might argue that the Fama-French global model can be used as a proxy to construct an idiosyncratic momentum factor. However, because of the nature of the construction and specific market focus in the Fama-French global model, it is not clear whether an approach using Fama-French global model factors is the best way to generate effective idiosyncratic momentum. Also, it is not intuitive whether such an idiosyncratic momentum signal maintains desirable and optimal predictive power. Therefore, we believe a thorough understanding of the idiosyncratic momentum signal is still lacking, from the construction methodologies as well as the full performance results, when it is applied to China's stock market.

The main purpose of this paper is to fill the gap by focusing on the following 2 major tasks. First, a new way of constructing the idiosyncratic momentum factor has been proposed. This new construction method mainly follows traditional regression approach in the empirical literature (Blitz et al. (2011), Chaves (2016)), but with a modification in selecting the systematic factors for the regression process. Instead of using the Fama-French model factors, the style factors from the Barra global multifactor risk model are employed. Second, the predictive power and effectiveness of the idiosyncratic momentum signal are analyzed for the securities in the Chinese equity market, where there is no evidence of profitability with a traditional momentum strategy (Li et al. (2010), Cheung et al. (2015)).

The remainder of the paper is organized as follows. Section II introduces the Barra global multifactor risk model and describes the detailed construction method for our idiosyncratic momentum signal by using the common style factors from the Barra risk model. Section III compares several key features of the idiosyncratic momentum with the traditional momentum factor, and demonstrates the performance of the idiosyncratic momentum strategy when applied to the Chinese stock market, including the China A-Share IMI Index and CSI 500 Index.

Also in this section, the efficacy of this newly constructed signal has been compared against that of the Fama-French model based idiosyncratic momentum signal. Section IV provides the results of robustness checks, followed by a brief conclusion in Section V.

## II. Construction of the Idiosyncratic Momentum Signal

### *A. Barra Global Equity Multifactor Risk Model*

The Barra risk model is a multifactor model that originated from a series of studies of APT theory on asset pricing conducted by Ross (1976), Rosenberg and Marathe (1976). The model carries the assumption that the portfolio risk and return can be decomposed along 2 dimensions: that which is due to factors which are prevalent throughout the market and that which is due to the idiosyncratic nature of the securities in the portfolio. In fact, the Barra risk model is a powerful tool to shed light on these sources of risk and return within a portfolio. The model can be described by the equation below:

$$r_i = \sum_{k=1}^{K} x_{ik} f_k + \varepsilon_i \tag{1}$$

where $r_i$ is the total excess return over the risk-free rate of security $i$, $f_k$ is the rate of return to the Barra style factor $F_k$, $x_{ik}$ is the sensitivity of security $i$ to the style factor $F_k$, and $\varepsilon_i$ is the nonfactor or specific return of security $i$.

An equity risk model is the product of a thorough and exacting model estimation process. It is an extensive and detailed process of determining the factors that describe asset return. In the Barra risk model, factors are built using observed security attributes, such as recent trends in the stock price, dividend yield, market returns, trading activity, country membership (trends in that market), and industry membership (trends in that industry). These factors not only help to explain performance, but also anticipate future volatility. For example, industry membership factors may significantly impact assets within an industry group, whereas country membership and currency factors often dominate the global portfolios.

Barra now offers products that cover most of the traded securities all over the world. It provides a wide variety of risk models. Of these

**TABLE 1. List of common style factors in the Barra global equity model (GEM2)**

| Common Factor | Description |
|---|---|
| World | This factor captures the global market return. |
| Volatility | This factor is typically the most significant style factor. In essence, it captures market risk that cannot be explained by the "World" factor. |
| Value | This factor describes a major investment style that seeks to identify stocks that are priced low relative to fundamentals. |
| Momentum | This factor captures sustained recent relative performance. |
| Size | This factor captures the effect of large-cap stocks moving differently from small-cap stocks. |
| Size Nonlinearity(SizeNL) | This factor captures nonlinearities in the payoff to size exposure across the market-cap spectrum. |
| Growth | This factor differentiates stocks based on their prospects for sales or earnings growth. |
| Liquidity | This factor measures the relative trading activity of a security in the market. Stocks with high turnover have positive exposure to liquidity, whereas low turnover stocks have negative exposure. |
| Leverage | This factor measures the firm's financial leverage. |

**Note:** This table provides detailed descriptions of 9 common style factors in GEM2.

models, the global equity model (GEM) extends the conceptual principles of Barra's single-country counterparts to the international equity market. In this paper, we select the Barra global equity model (GEM2) simply because of its excellent coverage of the securities in the international markets, including China A-Share IMI Index and CSI 500 Index where our main research interest is. Other reasons for using the Barra GEM2 model include (a) its granular factor structure, which provides a more thorough breakdown of security returns and, therefore, a more complete analysis of decomposition and risk exposure compared to those of other methods such as single-factor approaches, and (b) its robustness in withstanding outliers.

There are 9 common style factors in the Barra GEM2 model. In the risk decomposition (1), the excess return of each security is associated with these 9 common style factors, as well as one industry, one country and one currency factor where the security originates. Table 1 provides a brief description of these common style factors. Specific details on the individual descriptor comprising each style factor can be found in Menchero et al. (2010).

The Barra equity risk model suites are built on decades of MSCI's experience in constructing both global equity indexes and risk models, and thus are recognized for their high quality data and reliable risk model research in the equity investor community. Barra publishes its risk model data monthly (at the beginning of each month) as well as daily model updates through a package of ZIP files, which are available to users through a paid subscription. The main data segments used for our idiosyncratic momentum signal construction come from the following 3 files: GEM2L_100_Factors.dat, where all factors are defined; GEM2L_100_FacRet.yyyymmdd, where the monthly returns of all factors are listed; and GEM2L_100_FacRsk.yyyymmdd, where the factor loadings for each security are provided.

*B. Barra Risk Model Based Idiosyncratic Momentum*

The idiosyncratic momentum is a residual momentum, built on the residual returns of a regression process. Using the Barra GEM2 risk model, the idiosyncratic return ($\varepsilon_{i,t}$) of stock $i$ in month $t$ is obtained as the residual of the regression:

$$r_{i,t} = \alpha_i + \sum_{k=1}^{l} \beta_{i,k} f_{k,t} + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}$ is the return of stock $i$ in month $t$, $f_{k,t}$ is the return of Barra factor $F_k$ in month $t$, $\alpha_i$ and $\beta_{i,k}$ are parameters to be estimated in the regression. In this paper, a subset of factors $\{F_1, F_2, \cdots, F_l\}$ from all Barra style factors $\{F_k, k=1, \cdots, K\}$ are selected, and their monthly returns $\{f_{k,t}\}$ are used in regression (2). More specifically, our choice of factor subset consists of 8 Barra common style factors:

$$\begin{aligned}\{F_k\} = \{&\text{World, Volatility, Value, Size,} \\ &\text{Size Nonlinearity, Growth, Liquidity, and Leverage}\}\end{aligned} \tag{3}$$

The reason for excluding Barra's "Momentum" factor from subset (3) used in regression (2) is purely based upon the consideration of preserving the momentum-like property in the resulting idiosyncratic signal, whereas the reason for excluding the "Industry" and "Country/Currency" factors from the regression is to technically avoid possible multicollinearity in the regression because of the symbolic representations of industry, country, and currency factors in the Barra risk model.

Consistent with most of the literature, regressions (2) is estimated over a 36-month rolling window for month $t$ (i.e., over the period from $t-36$ to $t$), so that it contains a sufficient number of return observations to obtain accurate estimates for stock exposures to the Barra common factor returns. For each security $i$ at month $t$, regression over the 36-month rolling window produces a set of idiosyncratic returns $\{\varepsilon_{i,t-j}, j=35,\cdots,0\}$. Then the idiosyncratic momentum (*IMOM*) factor is constructed as the cumulative compound return of the idiosyncratic returns ($\varepsilon_{i,t}$) over the months $t-12$ and $t-2$:

$$IMOM_{i,t} = \prod_{j=2}^{12}\left(1+\varepsilon_{i,t-j}\right)-1, \tag{4}$$

which carries a definition similar to that of the conventional price momentum (*MOM*)

$$MOM_{i,t} = \prod_{j=2}^{12}\left(1+r_{i,t-j}\right)-1, \tag{5}$$

In both (4) and (5), the most recent month is skipped in the signal construction to avoid the reversal, or contrarian, effect usually present in stock returns (e.g., Jegadeesh (1990) and Lo and MacKinlay (1990)).

## III. Empirical Results

In this section, the properties of the *IMOM* factor constructed in the previous section are analyzed and the performance test results for this factor in the Chinese equity market are presented. During the performance test, traditional price momentum (*MOM*) and Fama-French model factor based idiosyncratic momentum signal ($IMOM^{FF}$) are also constructed and evaluated, so that the performance results of all three signals can easily compared and their differences can be illustrated. Because multiple Fama-French models exist and each of them could be used to construct an idiosyncratic momentum signal, only the Fama-French global 3-factor mode is selected and used in this paper. Although this model mainly targets for the markets of developed countries, it is still the best choice of all available Fama-French models in capturing certain representation of underlying systematic effects of the Chinese equity market.

### *A. Test Data*

All analysis and tests are conducted using security data from 2 major indices in the Chinese equity market: the China A-Share IMI Index and CSI 500 Index. The China A-Share IMI Index represents all the sectors and more than 2,800 stocks listed on China's 2 main exchanges in Shanghai and Shenzhen, whereas the CSI 500 Index aims to comprehensively reflect the price fluctuations and performance of the mid- and small-cap companies in the Shanghai and Shenzhen security markets. These 2 universes provide good representations of the overall Chinese equity market as well as a mid- and small-cap concentrated market, which allows us to examine the effectiveness and consistency of the idiosyncratic momentum factor under 2 different universes.

During the performance test, both *MOM* and *IMOM* factors are constructed using the monthly returns of all securities in the above investment universes downloaded from the Compustat database in the time frame between 2008 and 2018. Those securities with a monthly return value above 500% are removed from the regression process simply to reduce the noise in the regression. Because the calculation of an *IMOM* factor requires valid return data for 36 consecutive months, only securities with full 36-month returns are included in the regression for each particular month.

### *B. Summary Statistics of Barra Factor and IMOM Factor*

To gain a better understanding of *IMOM* factor constructed using the Barra common style factors, the empirical investigation starts with examining at the summary statistics of Barra common factors and the relationships between these factors and the idiosyncratic momentum factor.

First, the persistence in Barra common style factor returns is examined. Blitz et al. (2011) argued that persistence in Fama-French model factor returns can potentially contribute positively to momentum's profitability. As with Barra common style factors, their persistence can also be tested by measuring the frequency with which the signs of the factor returns are the same during the formation period

**TABLE 2. Persistence in the Barra common style factor returns (December 1997 to December 2018)**

| Holding Period | World | Volatility | Value | Size | SizeNL | Growth | Liquidity | Leverage |
|---|---|---|---|---|---|---|---|---|
| 1M | 60.1660 | 50.6224 | 72.6141 | 53.9419 | 61.4108 | 49.7925 | 51.4528 | 50.6224 |
| | (3.16) | (0.19) | (7.02) | (1.22) | (3.54) | (–0.06) | (0.45) | (0.19) |
| 3M | 62.557 | 47.7178 | 82.1577 | 53.1120 | 63.0705 | 50.2075 | 46.4730 | 50.6224 |
| | (3.93) | (–0.71) | (9.98) | (0.97) | (4.06) | (0.06) | (–1.10) | (0.19) |
| 6M | 63.0705 | 47.7178 | 86.7220 | 56.0166 | 72.1992 | 52.2822 | 50.6224 | 46.8880 |
| | (4.06) | (–0.71) | (11.4) | (1.87) | (6.89) | (0.71) | (0.19) | (–0.97) |
| 12M | 60.9959 | 44.3983 | 87.1369 | 54.3568 | 76.7635 | 46.4730 | 52.2822 | 49.7925 |
| | (3.41) | (–1.74) | (11.5) | (1.35) | (8.31) | (–1.10) | (0.71) | (–0.06) |

**Note:** This table shows the results of tests for persistence in the returns of the Barra common style factors over the period of December 1997 to December 2018. With a fixed formation period and holding period, the persistence measure is calculated as the probability that the sign of the factor returns over these periods will be the same. The results for a 12-month formation period excluding the most recent month and 1, 3, 6 and 12-month holding periods are reported. In parentheses, t-statistics resulting from the difference-in-means tests are also included, which test whether the reported frequencies are different from 50%.

and the holding period. To be consistent with the construction method for idiosyncratic momentum signal, a 12-month formation period, excluding the most recent month, and alternative holding periods of 1 month, 3 months, 6 months, and 12 months are used in the test. The persistence results are listed in table 2.

The empirical results show that the frequency of factor returns for Barra common factors vary. The traditional Barra style factors, such as world, value, and size/sizeNL, behave similarly to the Fama-French market (RMRF), size (SMB), and value (HML) factors. The persistencies of these factors tend to be consistently above 50% for all the different holding periods, ranging from 53% to 87% with high *t*-statistics values. However, other Barra common factors, such as volatility, growth, and leverage, exhibit low persistence in their returns. Using these diversified Barra common factors with different factor return persistency behaviors in our construction method could help to decompose security returns at a more granular level and dynamically reduce the systematic and risk factor exposures, thus producing more effective idiosyncratic momentum signal.

Next, to see how much systematic effects has been removed from the regression process, the correlations between Barra factors and *IMOM* are computed and compared with the correlations between Barra factors and *MOM*. Each correlation is calculated as the Pearson correlation coefficient between the values of *IMOM*/*MOM* factors and the respective Barra risk loading values for all stocks in the China A-Share IMI and CSI 500 universes. Table 3 summarizes the average monthly correlations between *IMOM*/*MOM* and Barra common style factors in both the China A-Share IMI and CSI 500 universes, while the time series of monthly correlations over the period from December 2010 to December 2018 are depicted in figure 1. Because of the similarity in the results for China A-Share IMI and CSI 500 universes, only the time series of monthly correlations between the *IMOM*/*MOM* and Barra common factors for the China A-Share IMI universe are presented in figure 1. Although the Barra momentum factor is not used in our regression process to build the *IMOM* factor, its correlations to the *IMOM*/*MOM* factors are still calculated and plotted in the same figure for reference.

The results in both table 3 and figure 1 clearly show that the correlations between the *IMOM* factor and all Barra common factors (except for momentum factor) are significantly low compared to the same results for the *MOM* factor. In fact, the correlations between the

**TABLE 3. Correlations between Barra common style factors and *IMOM*/*MOM* signals**

| Index | Signal | Volatility | Value | Size | SizeNL | Growth | Liquidity | Leverage | Momentum |
|---|---|---|---|---|---|---|---|---|---|
| A-Share IMI | *IMOM* | 0.0400 | –0.0126 | 0.0832 | 0.0113 | –0.0776 | 0.0246 | 0.0638 | 0.5007 |
| | *MOM* | 0.1642 | –0.1599 | 0.1836 | 0.1086 | 0.0341 | 0.1664 | –0.0041 | 0.7546 |
| CSI 500 | *IMOM* | 0.0219 | –0.0503 | 0.1389 | –0.0418 | –0.0275 | 0.0932 | 0.0069 | 0.5315 |
| | *MOM* | 0.1685 | –0.1385 | 0.5001 | –0.2347 | 0.0485 | 0.1824 | 0.0086 | 0.8029 |

**Note:** This table outlines the average correlations between Barra factors and *IMOM* /*MOM* signals for the China A-Share IMI and CSI 500 universes. The correlations are calculated as the monthly average of Pearson correlation coefficients between the loading values of the Barra common factor and values of the *IMOM* /*MOM* signal for all stocks in the China A-Share IMI and CSI 500 universes for the period from December 2010 to December 2018.

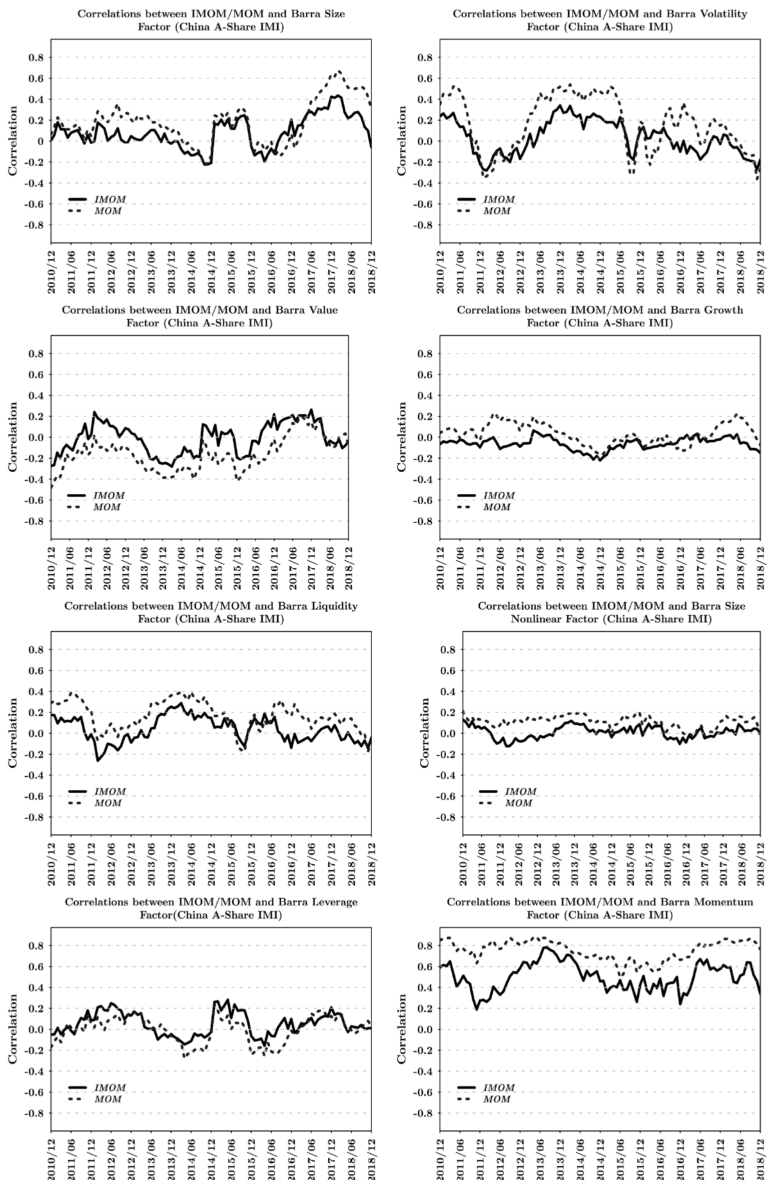


FIGURE 1.— Time series of monthly correlations between the *IMOM*/*MOM* and the Barra common factors for the period of December 2010 to December 2018

**Note:** The correlations are evaluated as the Pearson correlation coefficients between the loadings of Barra common factors and the values of *IMOM*/*MOM* factors for all stocks in the China A-Share IMI Index at the end of each month from December 2010 to December 2018.

**TABLE 4. Correlations between *IMOM* and *MOM* factors**

| | China A-Share IMI | | CSI 500 | |
|---|---|---|---|---|
| Factor | *IMOM* | *MOM* | *IMOM* | *MOM* |
| *IMOM* | 1.0000 | 0.6904 | 1.0000 | 0.7155 |
| *MOM* | ---- | 1.0000 | ---- | 1.0000 |

**Note:** This table shows the results of correlations between *IMOM* and *MOM* signals for the China A-Share IMI and CSI 500 universes. The correlations are calculated as the average of monthly Pearson correlation coefficients between the raw scores of idiosyncratic momentum and traditional price momentum signals for all stocks in the China A-Share IMI and CSI 500 universes over the entire period between December 2010 and December 2018.

*IMOM* and Barra factors are close to 0. This result is exactly what we anticipate because the *IMOM* factor, as computed by compounding monthly residual returns that are orthogonal to the Barra factors caused by the nature of the regression process, should remain nearly orthogonal to the Barra factors. From the results, one can also conclude that exposure to the Barra factors in the idiosyncratic momentum signal has been significantly reduced.

Also of note are the correlations between the *IMOM*/*MOM* and the Barra momentum factor. One might expect high correlations between these factors. Figure 1 and table 3 show, however, that these correlations reach only 50% to 75% on average. This result is reasonable because the Barra momentum factor is not the truly traditional momentum. It is weighted average of three components, 12-month relative return strength, 6-month relative return strength, and historical alpha, weighted of 0.25, 0.375, and 0.375, respectively. The correlation between the *IMOM*/*MOM* and the Barra momentum factor mainly comes from the correlated values for the 12-month and 6-month momentum components in the Barra momentum factor.

When comparing the correlation between *IMOM* and the Barra momentum factor with the correlation between *MOM* and the Barra momentum factor, it is easy to notice that the correlations between *IMOM* and Barra momentum have a large drop, from 78% to 50% on average. This raises the question about whether the *IMOM* constructed by regressing all Barra style factors still contains enough information to predict the future stock returns. It is a valid concern that the residual returns after the regressing the Barra common style factors could lose all key information, so the *IMOM* built on the residual returns would have no predictive power. To answer this question, the correlation

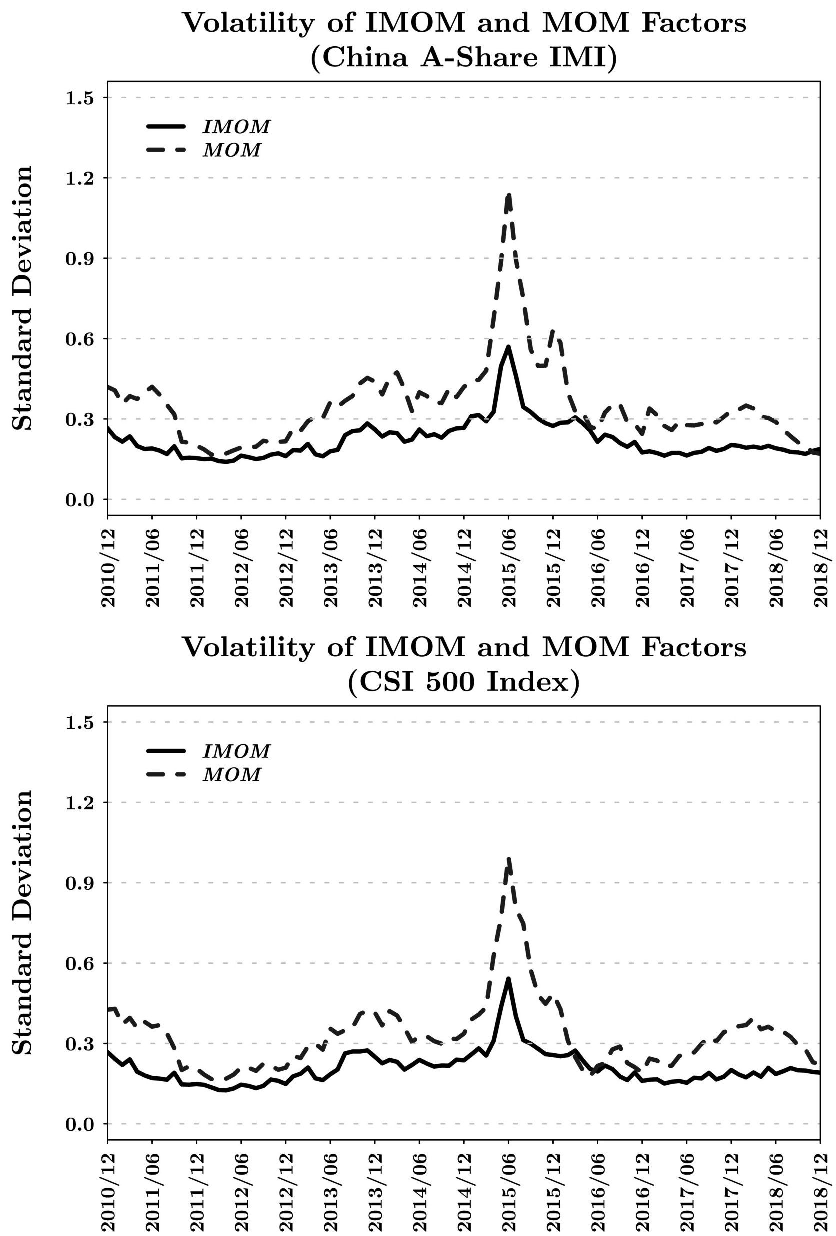


FIGURE 2.— Volatilities of *IMOM* and *MOM* factors in China A-Share IMI universe (top) and CSI 500 universe (bottom)

**Note:** The volatility is calculated monthly as the standard deviation of raw values of *IMOM* and *MOM* for all stocks within the target universe from December 2010 to December 2018.

between the *IMOM* and traditional momentum factor is computed and reported in table 4. The results in table 4 clearly indicate that the *IMOM* factor still has a fairly high correlation with the *MOM*. Thus, the *IMOM* constructed after regressing out the Barra common factors resembles *MOM*, and is still a momentum-like signal.

As various authors pointed out in their research articles, one of the most important properties of the *IMOM* factor is that it typically has significant low volatility compared to the *MOM* factor. The *IMOM* factor constructed using our approach also exhibits such a property. For verification, the monthly volatilities of both *IMOM* and *MOM* factor values for all stocks in the China A-Share IMI and CSI 500 universes are calculated and plotted the results in figure 2. As expected, the results in figure 2 clearly show that the *IMOM* signal has much lower volatility than the *MOM* factor in each month during the entire testing period from December 2010 to December 2018. The signal remains fairly stable in the 2015 Chinese market collapse, whereas the *MOM* factor experiences significant high dispersion and volatility.

### *C. Performance of IMOM and MOM Signals*

The performance of the *IMOM* signal for both the China A-Share IMI and CSI 500 universes is evaluated, and the main results are presented in this section. All performance results reported here are based on the standard alpha factor test procedure without considering other effects, such as market availability, liquidity, trading cost, and so on. During the performance test, both *MOM* and $IMOM^{FF}$ using the Fama-French global model factors are also calculated so that the efficacies of all 3 signals can be easily compared, from which the superior performance of our Barra factor based idiosyncratic momentum signal can be identified.

#### *Signal Coverage*

The first step in the performance test is to examine the coverage of the *MOM* and *IMOM* signals in both the China A-Share IMI and CSI 500 universes. For each signal, the coverage in number counts is calculated as the monthly average of the number of securities with a valid signal value. The coverage in percentage is estimated as the monthly average of the percentage of securities with valid signal values. Coverage in both number counts and percentage are reported in table 5.

**TABLE 5. Coverage of *IMOM* and *MOM* factors**

| | China A-Share IMI | | CSI 500 | |
|---|---|---|---|---|
| Factor | Number Counts | Percentage | Number Counts | Percentage |
| Constituents | 1863 | - | 494 | - |
| *IMOM* | 1339 | 71.7933 | 368 | 74.3429 |
| *MOM* | 1671 | 89.6940 | 428 | 86.7231 |

**Note:** This table shows the coverage of the *IMOM* and *MOM* signals for both the China A-Share IMI and CSI 500 universes. For each signal, coverage in both number counts and percentage is provided. The signal coverage in number counts is calculated as the monthly average of the number of securities with valid signal values, whereas the signal coverage in percentage is estimated as the monthly average of the percentage of securities with valid signal values. Also, the number count of constituents for each universe, which is the monthly average of total number of securities in that universe, is provided. All coverage data are estimated over the entire period between December 2010 and December 2018. Because of the construction method, the coverage of $IMOM^{FF}$ is the same as that of *IMOM* and is omitted from the table.

As expected, the results in table 5 show that the *MOM* signal has excellent coverage, reaching almost 90% on average for both indices. The *IMOM* signal coverage is slightly lower than the coverage of the *MOM* signal, simply because of the restrictions in the *IMOM* signal construction, which requires both the existence of historical return data and presence in the index constituent list for the entire 36 months. Even with this restriction, however, the coverage of *IMOM* for both universes is still very good, reaching above 70% on average.

*Signal Returns and Performance Comparison*

The performance test for both *IMOM* and *MOM* factors is conducted by forming sector-neutral equal-weighted quintile portfolios with a monthly rebalance frequency. The detailed steps are as follows. For each month, the securities in each universe are divided into equal-sized quintiles (labeled Q1 to Q5) based on the rankings of the *IMOM* and *MOM* factor values, respectively, in a sector-neutral manner. This ensures that there is no strong structural biases toward any given sector. Then an equal-weighted winner (long)-minus-loser (short) portfolio is formed and used to examine the returns of the *IMOM* and *MOM* factors. The equal-weighted winner (long) portfolio consists of stocks with the highest factor values from the top quintile (Q1), and the equal-weighted loser (short) portfolio consists of stocks with the lowest factor values in the bottom quintile (Q5). The winner (long)-minus-loser (short)

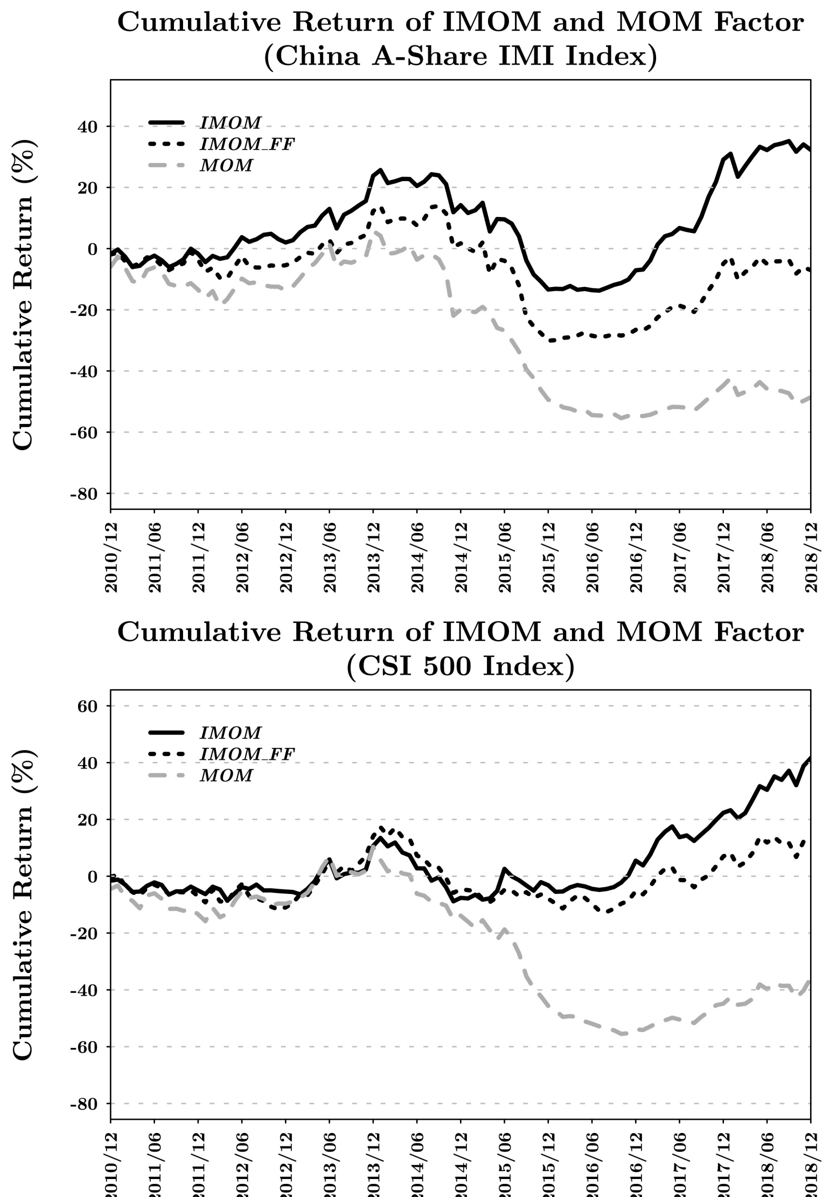


FIGURE 3.— Cumulative returns of *MOM*, *IMOM*, and $IMOM^{FF}$ factors for the China A-Share IMI and CSI 500 universes from December 2010 to December 2018

**Note:** The cumulative return for each factor is calculated as the monthly compound return of the winner-minus-loser portfolio's return constructed using the top and bottom quintile portfolios based on the sector-neutral ranking values of the respective factors.

**TABLE 6. Performance summary of *IMOM* and *MOM* factors**

| Factor | China A-Share IMI Cumu. Return | China A-Share IMI Max Drawdown | China A-Share IMI Avg. Return | China A-Share IMI Std. Dev. | CSI 500 Cumu. Return | CSI 500 Max Drawdown | CSI 500 Avg. Return | CSI 500 Std. Dev. |
|---|---|---|---|---|---|---|---|---|
| A. Overall Performance Summary | | | | | | | | |
| *IMOM* | 35.5114 | 34.3125 | 4.2558 | 2.8599 | 41.6146 | 22.3113 | 4.7201 | 2.6298 |
| *IMOM*$^{FF}$ | –6.5311 | 45.2941 | –0.1168 | 3.2627 | 14.0940 | 29.8927 | 2.0508 | 2.6788 |
| *MOM* | –49.0966 | 61.2016 | –7.4942 | 3.6863 | –35.7053 | 65.8561 | –4.6561 | 3.6536 |

| Factor | China A-Share IMI IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) | CSI 500 IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B. Detailed Performance Measurements | | | | | | | | | | | | |
| *IMOM* | 0.0201 | 0.4302 | 0.6731 | 0.6984 | 266 | 262 | 0.0215 | 0.5182 | 0.6610 | 0.6543 | 53 | 51 |
| *IMOM*$^{FF}$ | 0.0143 | –0.0101 | 0.6762 | 0.7001 | 266 | 262 | 0.0133 | 0.2214 | 0.6422 | 0.6685 | 53 | 51 |
| *MOM* | –0.0154 | –0.5878 | 0.7449 | 0.7012 | 332 | 330 | –0.0113 | –0.3679 | 0.7261 | 0.6778 | 79 | 77 |

( *Continued* )

**TABLE 6. (Continued)**

**Note:** This table shows cumulative return, max drawdown, average return, volatility, IC mean, IR, retention rate, and number of security holdings in the top and bottom quintiles of three *MOM*, *IMOM*, and $IMOM^{FF}$ strategies for the China A-Share IMI and CSI 500 universes between December 2010 and December 2018. Each strategy is defined as a winner-minus-loser portfolio constructed using the top and bottom quintile portfolios based on sector-neutral ranking of the respective factor values for all stocks in the universe. Cumulative return is the monthly compound return of the winner-minus-loser portfolio's return. Average return is the annualized monthly average of the equal-weighted returns of a winner-minus-loser portfolio. IR is the annualized risk-adjusted average return of a winner-minus-loser portfolio during the entire test period. Volatility is measured as the standard deviation of monthly returns of the winner-minus-loser portfolio during the entire test period. IC mean is the monthly average of correlation coefficients between the factor values and forward one-month return of all securities in the respective universe. Retention rate (RetR) in the top (or bottom) quintile is calculated as the monthly average of the percentage of securities remaining in top (or bottom) quintile in 2 consecutive months. Number of securities (No.) in top (or bottom) quintile is the monthly average of the number of securities in the top (or bottom) quintile within each 1-month rebalance cycle. Panel A shows the overall performance summary, and Panel B shows the detailed performance measurements.

portfolio's return is the difference between the winner and loser portfolios' returns (using 1-month holding period). Figure 3 plots the overall cumulative returns of the winner-minus-loser portfolios for all 3 factors, namely, *MOM*, *IMOM*, and $IMOM^{FF}$, throughout our entire testing period from December 2010 to December 2018 for both the China A-Share IMI and CSI 500 universes.

Besides the overall cumulative returns plotted in figure 3, several key performance measurements for the *MOM*, *IMOM*, and $IMOM^{FF}$ factors are also listed in table 6. These key performance measurements include max drawdown; average return (annualized monthly average of equal-weighted returns of winner-minus-loser portfolios over the entire test period); standard deviation (the standard deviation of monthly equal-weighed returns of winner-minus-loser portfolios over the entire test period); IC mean (or the information coefficient: monthly average of correlation coefficients between the factor values and forward 1-month return of all securities in the universe); IR (or information ratio: the risk-adjusted average returns of winner-minus-loser portfolios); retention rates in the top quintile and bottom quintile (percentage of securities remaining in the top or bottom quintile in 2 consecutive months); and the number of securities in the top and bottom quintile (monthly average of the number of securities held in the top or bottom quintile).

For the cumulative performance, figure 3 and table 6 clearly show that the *MOM* factor suffers an annual loss of 7.49% and 4.66% in the China A-Share IMI and CSI 500 universe, respectively. In contrast, both *IMOM* and $IMOM^{FF}$signals perform much better. The Fama-French global model based $IMOM^{FF}$ signal has a small loss of 0.12% in the A-Share IMI universe, whereas it generates a return of 2.06% per year in the CSI 500 market. Barra risk model based *IMOM* signal performs even better. It delivers an average return of 4.26% and 4.72% per year in both markets with a significant reduction in the max drawdown and offers decent risk-adjusted returns for both the A-Share IMI and CSI 500 universes. Judging from the overall cumulative returns, the Barra risk model based *IMOM* signal beats both $IMOM^{FF}$ and *MOM*, achieving the best performance of all three factors tested here.

In addition to cumulative return, table 6 shows the great improvements in all other performance indicators for *IMOM* and $IMOM^{FF}$ over the *MOM* signal. For the China A-Share IMI and CSI 500 universes, the IC mean of both *IMOM* and $IMOM^{FF}$ signals reaches 2.01% and 1.43%, respectively, as compared to the negative IC of *MOM*

(–1.54%). The risk-adjusted returns (IRs) of *IMOM* and $IMOM^{FF}$ increase from the negative IR of *MOM* (–0.5878) to 0.4302 and –0.0101, respectively. For the CSI 500 universe, improvements of similar magnitude in the IC and IR of both *IMOM* and $IMOM^{FF}$ signal also occur. Moreover, the performance results clearly demonstrate that the Barra model based *IMOM* strategy is far superior compared to the Fama-French model based $IMOM^{FF}$ for China's equity market.

Furthermore, the performance measurements of all three *IMOM*, $IMOM^{FF}$ and *MOM* factors on a yearly basis are evaluated and reported in table 7 in order to provide more detailed comparison of the performance among all these factors. The results in this table show that, in the China A-Share IMI and CSI 500 universes, the improvements of the IC and IR of both *IMOM* and $IMOM^{FF}$ are consistent and steady in every year. Although the ICs and IRs for *IMOM* and $IMOM^{FF}$ factors are still negative during 2014 and 2015, the improvements are significant compared to the IC and IR values of the *MOM* signal during the same period. Again, the *IMOM* factor outperforms the $IMOM^{FF}$ factor in almost every year.

The year-by-year results in table 7 further indicate that the performance improvement of *IMOM* over the *MOM* factor is stable and persistent. In fact, it is easy to notice that during the eight-year period from 2011 to 2018, *MOM* underperforms most of the time, whereas *IMOM* strategy retains the positive gain for most of years, in 6 out of 8 years for China A-Share IMI and 5 out of 8 years for CSI 500, respectively. Such results suggest that the *IMOM* strategy has much stronger performance persistency.

The performance results presented so far are mainly based on the analysis of the long-short return in quintiles. In order to see whether the performance results are sensitive to the choice of the quantiles or not, additional performance tests using different quantiles are conducted and some of the results are summarized in table 8.

The results in table 8 (as well as the results in table 6) show that the magnitudes of the L-S returns, average returns and IRs of *IMOM* and *MOM* factors are slightly degraded as the number of quantiles increases, while the max drawdown and volatilities increase. However, the results also indicate that there is no significant change in the overall pattern of the performance with different choices of quantiles. Both *IMOM* and $IMOM^{FF}$ factors still significantly outperform the *MOM* in each quantile selection, and the *IMOM* always retains stronger efficacy than the $IMOM^{FF}$.

**TABLE 7. Performance summary of *MOM* and *IMOM* factors on a yearly basis**

| | | China A-Share IMI | | | | | | CSI 500 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Year | IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) | IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) |
| *IMOM* | 2011 | 0.0031 | 0.0817 | 0.6664 | 0.6822 | 201 | 198 | –0.0002 | –0.3227 | 0.6471 | 0.6580 | 73 | 71 |
| | 2012 | 0.0186 | 0.7206 | 0.6674 | 0.7107 | 198 | 195 | 0.0246 | 0.112 | 0.6478 | 0.6227 | 53 | 51 |
| | 2013 | 0.0633 | 1.9749 | 0.6722 | 0.6973 | 235 | 232 | 0.0502 | 1.5077 | 0.6684 | 0.6496 | 47 | 45 |
| | 2014 | –0.0230 | –0.6224 | 0.6681 | 0.7264 | 282 | 280 | –0.0482 | –1.6616 | 0.6370 | 0.6896 | 45 | 42 |
| | 2015 | –0.0572 | –1.9783 | 0.6357 | 0.6538 | 306 | 302 | –0.0260 | –0.4313 | 0.6353 | 0.6028 | 50 | 48 |
| | 2016 | 0.0409 | 1.8463 | 0.6539 | 0.6903 | 312 | 308 | 0.0520 | 1.4657 | 0.6185 | 0.6635 | 52 | 50 |
| | 2017 | 0.0992 | 3.8668 | 0.7312 | 0.7551 | 313 | 311 | 0.0559 | 2.0282 | 0.6864 | 0.7377 | 53 | 51 |
| | 2018 | 0.0275 | 0.3163 | 0.6817 | 0.7109 | 289 | 286 | 0.0701 | 1.6704 | 0.7050 | 0.6885 | 47 | 45 |
| $IMOM^{FF}$ | 2011 | 0.0057 | –0.2013 | 0.6903 | 0.7143 | 201 | 198 | –0.0091 | –0.7361 | 0.6631 | 0.6898 | 73 | 71 |
| | 2012 | 0.0113 | –0.0555 | 0.6840 | 0.6885 | 198 | 195 | 0.0287 | 0.3435 | 0.6311 | 0.6428 | 53 | 51 |
| | 2013 | 0.0670 | 2.0712 | 0.6469 | 0.6984 | 235 | 232 | 0.0699 | 2.3942 | 0.6363 | 0.6726 | 47 | 45 |
| | 2014 | –0.0290 | –0.6729 | 0.6578 | 0.6990 | 282 | 280 | –0.0991 | –1.9321 | 0.6258 | 0.6867 | 45 | 42 |
| | 2015 | –0.0781 | –2.1150 | 0.6478 | 0.6643 | 306 | 302 | –0.0425 | –0.7421 | 0.5973 | 0.6495 | 50 | 48 |
| | 2016 | 0.0303 | 1.4442 | 0.6513 | 0.6914 | 312 | 308 | 0.0268 | 0.0949 | 0.6453 | 0.6471 | 52 | 50 |
| | 2017 | 0.0907 | 3.2580 | 0.7232 | 0.7510 | 313 | 311 | 0.0519 | 1.6278 | 0.6729 | 0.7213 | 53 | 51 |
| | 2018 | 0.0244 | –0.1447 | 0.6971 | 0.7021 | 289 | 286 | 0.0496 | 0.6616 | 0.6735 | 0.7022 | 47 | 45 |

( *Continued* )

**TABLE 7. (Continued)**

| | | China A-Share IMI | | | | | | CSI 500 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Year | IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) | IC Mean | IR | RetR (Q1) | RetR (Q5) | No (Q1) | No (Q5) |
| *MOM* | 2011 | –0.0301 | –0.8236 | 0.7442 | 0.6801 | 242 | 240 | –0.0279 | –1.0518 | 0.7187 | 0.6573 | 83 | 81 |
| | 2012 | 0.0015 | –0.0034 | 0.7449 | 0.6980 | 298 | 297 | 0.0076 | 0.4419 | 0.7293 | 0.7044 | 74 | 71 |
| | 2013 | 0.0564 | 1.6627 | 0.7834 | 0.7137 | 331 | 329 | 0.0491 | 1.5991 | 0.7518 | 0.7020 | 78 | 77 |
| | 2014 | –0.0703 | –1.4629 | 0.7314 | 0.7172 | 353 | 350 | –0.0911 | –2.9318 | 0.7164 | 0.6730 | 79 | 77 |
| | 2015 | –0.0973 | –4.2133 | 0.7135 | 0.6803 | 354 | 352 | –0.0889 | –3.0810 | 0.6942 | 0.6917 | 80 | 79 |
| | 2016 | –0.0324 | –1.5444 | 0.6854 | 0.6697 | 354 | 352 | –0.0422 | –2.3756 | 0.6610 | 0.6304 | 79 | 77 |
| | 2017 | 0.0621 | 2.5540 | 0.7698 | 0.7461 | 378 | 375 | 0.0535 | 2.4667 | 0.7503 | 0.7200 | 78 | 77 |
| | 2018 | 0.0092 | –0.4072 | 0.7903 | 0.7212 | 359 | 357 | 0.0754 | 0.9828 | 0.7645 | 0.7573 | 76 | 74 |

**Note:** This table shows the IC mean, IR, retention rate, and number of security holdings in the top and bottom quintiles of three *MOM*, *IMOM* and $IMOM^{FF}$ strategies for the China A-Share IMI and CSI 500 universes on a yearly basis between December 2010 and December 2018. Each strategy is defined as a winner-minus-loser portfolio constructed using the top and bottom quintile portfolios based on sector-neutral ranking of the corresponding factor values for all stocks in the respective universe. IC mean is the monthly average of correlation coefficients between the factor values and forward one-month return of all securities in the respective universe. IR is the annualized risk-adjusted returns of a winner-minus-loser portfolio during the entire test period. Retention rate (RetR) in the top (or bottom) quintile is calculated as the monthly average of the percentage of securities remaining in the top (or bottom) quintile in 2 consecutive months. Number of securities (No.) in the top (or bottom) quintile is the monthly average of the number of securities in the top (or bottom) quintile within each 1-month rebalance cycle.

**TABLE 8. Performance results of long-short portfolios for the *IMOM* and *MOM* factors using different quantiles**

| | China A-Share IMI | | | | | CSI 500 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR |
| A. Long-short Strategy in Terciles | | | | | | | | | | |
| *IMOM* | 37.5914 | 31.9701 | 4.4979 | 2.7862 | 0.4660 | 46.8814 | 20.4005 | 5.0643 | 2.0105 | 0.7272 |
| $IMOM^{FF}$ | 1.8968 | 41.6273 | 0.6539 | 3.1633 | 0.0698 | 23.6743 | 27.6232 | 2.8304 | 1.9705 | 0.4147 |
| *MOM* | –39.7589 | 51.9832 | –5.7342 | 3.2301 | –0.5125 | –23.6105 | 45.5754 | –2.8732 | 2.6866 | –0.3087 |
| B. Long-short Strategy in Octiles | | | | | | | | | | |
| *IMOM* | 25.3573 | 46.5851 | 3.4102 | 3.1868 | 0.3089 | 33.3902 | 28.6340 | 4.1645 | 3.1631 | 0.3801 |
| $IMOM^{FF}$ | –5.9512 | 52.9833 | –0.0901 | 3.7536 | –0.0069 | 12.1359 | 44.1131 | 1.9933 | 3.3303 | 0.1728 |
| *MOM* | –54.8710 | 71.5524 | –8.3834 | 4.7521 | –0.5093 | –44.0351 | 68.8953 | –5.9484 | 4.3476 | –0.3950 |
| C. Long-short Strategy in Deciles | | | | | | | | | | |
| *IMOM* | 33.1025 | 52.4411 | 4.2320 | 3.3797 | 0.3615 | 31.9800 | 34.2563 | 4.0122 | 3.2129 | 0.3605 |
| $IMOM^{FF}$ | 6.3723 | 59.6701 | 0.8709 | 4.1029 | 0.0613 | 14.3325 | 39.3107 | 2.4843 | 3.7337 | 0.1921 |
| *MOM* | –56.5748 | 78.7432 | –9.0408 | 5.0119 | –0.5207 | –49.8232 | 75.6007 | –7.0315 | 4.7901 | –0.4238 |

**Note:** This table reports the cumulative returns, max drawdown, annualized average returns, volatilities, and IRs of long-short traditional momentum and idiosyncratic momentum strategies in different quantiles for the China A-Share IMI and CSI 500 universes. Panel A lists the performance results for the long-short strategy in Terciles (Q1 to Q3). Panel B lists the performance results for the long-short strategy in Octiles (Q1 to Q8); and Panel C lists the performance results for the long-short strategy in Deciles (Q1 to Q10). Except for the different choices of quantiles, all other settings in the tests are the same as those used in table 6.

**TABLE 9. Returns of *IMOM* and *MOM* factors at particular calendar month**

| Factor | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A. China A-Share IMI | | | | | | | | | | | | |
| *IMOM* | 0.0885 | –0.3636 | 1.1527 | –0.2905 | 1.9579 | 0.6634 | –1.0372 | 0.2328 | 0.2498 | 0.0525 | 0.0558 | 1.0820 |
| *MOM* | 0.2800 | –2.0221 | –0.1913 | 0.4908 | 1.8296 | –0.6704 | –1.8296 | –1.2082 | –1.1065 | –1.7871 | –1.4760 | 0.2432 |
| B. China CSI 500 | | | | | | | | | | | | |
| *IMOM* | –0.2697 | 0.0530 | 0.7208 | 0.3945 | 2.0563 | 0.6848 | –0.8225 | –1.0372 | 0.5336 | –0.7072 | 1.3409 | 1.6112 |
| *MOM* | –0.6573 | –0.9306 | 0.7511 | 0.1379 | 2.5732 | 0.1709 | –1.4165 | –1.6865 | 0.2889 | –2.4399 | 0.4672 | 0.7544 |

**Note:** This table shows the returns of *MOM* and *IMOM* factors grouped by calendar month from December 2010 to December 2018. The return of each factor for a particular calendar month is calculated as the average returns of the winner-minus-loser portfolio in that month. Again, the winner-minus-loser portfolio is constructed using the top and bottom quintile portfolios based on sector-neutral ranking of the factor values for all stocks in the respective universe. Panel A shows the results of calendar month returns for the China A-Share IMI, and Panel B shows the results of calendar month returns for the CSI 500 universe.

*Seasonality Effects*

The seasonality effects for price momentum have been discussed and documented by several authors (Jegadeesh and Titman (1993), Grinblatt and Moskowitz (2004), Li et al. (2010), Blitz et al. (2011)). Blitz et al (2011) also investigated the seasonality effect of residual momentum for all stocks in the US market and found that seasonality has a smaller impact on the performance of the residual momentum than it does on the traditional price momentum. To examine whether the seasonality effect influences *IMOM*'s performance in the Chinese equity market, we calculate the average returns of the *IMOM* and *MOM* signals for each calendar month and list the results in table 9.

The results in table 9 indicate that the seasonality effect for *MOM* in the Chinese equity market is not as strong as that in the US market. This result is similar to what was found by Li et al. (2010). However, the results still show some notable seasonality patterns in the returns of the *MOM* signal between calendar months, with most of the negative returns concentrated in two periods: February to March, and July to October. *IMOM*, in contrast, is less affected by the seasonality effect. In fact, the seasonality effect on the *IMOM* grows weaker. The *IMOM* signal still generates strong positive earnings within these months when the earnings of the *MOM* signal are positive, whereas it yields less negative returns during the months when the *MOM* signal has negative earnings.

## IV. Robustness Checks

In the remainder of the paper, the results of robustness checks are discussed. The main purpose of the robustness check is to show that the performance improvements of *IMOM* are robust a) to the broad (*J*, *K*) momentum strategies; b) in a long-only and long-bench strategy; c) to the cross-sectional ranking portfolios; d) to the subset of the stocks with both *IMOM* and *MOM* values; and e) to the different lengths of the rolling window used to estimate the residual returns.

*A. (J, K) Momentum Strategies*

As mentioned before, a 12-1 month formation period is used to build the *MOM* and *IMOM* signals and 1-month holding period is employed for the performance tests. To see whether the performance improvements of the *IMOM* over *MOM* are also observed for alternative momentum definitions, we start to test the returns and risks of both signals for the alternative (*J*, *K*) momentum definitions of Jegadeesh and Titman (1993). For these alternative (*J*, *K*) momentum strategies, stock portfolios are formed based on *J*-month lagged returns and held for *K* months. The alternative (*J*, *K*) idiosyncratic momentum strategies are formed in a similar fashion using the idiosyncratic momentum factor instead of the traditional momentum signal. The formation periods used in this section include 3 months, 6 months, and 12-1 months. For each formation period, 4 different holding periods are selected: 1 month, 3 months, 6 months and 12 months. The winner-minus-loser quintile returns are calculated using overlapping portfolios while all other settings remain unchanged from the previous analysis. The performance results for the (*J*, *K*) strategies are reported in table 10.

For each (*J*, *K*) combination, the results indicate that there is no profitability in any of these traditional momentum strategies in the China A-Share IMI and CSI 500 universes. The idiosyncratic momentum strategies perform much better than their counterparts do. Although these strategies with small formation (*J*) and holding (*K*) periods still yield negative returns, the improvements of average returns and IR over the traditional momentum strategies are still significant. Also, because of the removal of time-varying exposure to the Barra common style factors, the volatilities of all idiosyncratic momentum strategies are consistently lower than those of the traditional momentum strategies.

### *B. Performance of Long-Only and Long-Bench Strategies*

Because it is relatively difficult to short a single stock in the current Chinese equity market, it also would be meaningful to examine the performance of long-only and long-bench strategies for the *IMOM* and *MOM* factors. For the long-only approach, the entire net worth of the portfolio is calculated based on the equal-weighted average return from the winner (long) side of the quintile bucket (Q1). For the long-bench approach, the results are presented in the active return space, where the active returns are the equal-weighted average returns from the winner (long) side of the quintile bucket (Q1) relative to equally weighted returns of the universes our analysis is based upon (i.e., the China A-Share IMI and CSI 500 universes). For each case, the same process

**TABLE 10. Performance summary of (*J*, *K*) *MOM* and *IMOM* strategies**

| | Formation | | China A-Share IMI | | | | CSI 500 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Period | | *K*=1 | *K*=3 | *K*=6 | *K*=12 | *K*=1 | *K*=3 | *K*=6 | *K*=12 |
| *IMOM* | *J*=3 | Return | –14.4418 | –8.2407 | –2.5205 | –0.0824 | –12.0464 | –4.5600 | –0.7864 | 0.0708 |
| | | Volatility | 3.3430 | 6.1305 | 8.4526 | 12.1637 | 3.9040 | 5.7802 | 8.6039 | 10.9381 |
| | | IR | –1.2164 | –0.6723 | –0.2124 | –0.0072 | –0.8907 | –0.3945 | –0.0654 | 0.0064 |
| | *J*=6 | Return | –9.7106 | –2.5430 | 1.1193 | 1.5942 | –6.7658 | –1.6808 | 1.0985 | 0.0945 |
| | | Volatility | 3.4427 | 5.6579 | 7.8068 | 12.0113 | 2.9364 | 4.3805 | 7.6743 | 10.8749 |
| | | IR | –0.8138 | –0.2254 | 0.1014 | 0.1332 | –0.6653 | –0.1921 | 0.1054 | 0.0095 |
| | *J*=12 | Return | 4.4138 | 3.5404 | 4.2081 | 2.2360 | 2.2871 | 4.0607 | 3.8478 | 0.8551 |
| | | Volatility | 2.9233 | 5.3616 | 7.5185 | 11.1268 | 2.7037 | 4.7228 | 6.8771 | 10.2443 |
| | | IR | 0.4362 | 0.3304 | 0.5594 | 0.2013 | 0.2144 | 0.4303 | 0.3958 | 0.0844 |
| *MOM* | *J*=3 | Return | –23.7863 | –14.6647 | –7.0119 | –3.8317 | –17.8178 | –12.1646 | –5.3171 | –3.1713 |
| | | Volatility | 4.2212 | 7.3284 | 8.7191 | 12.0014 | 4.4794 | 7.2459 | 7.9415 | 11.4840 |
| | | IR | –1.6555 | –1.0013 | –0.5690 | –0.3193 | –1.1477 | –0.8386 | –0.4734 | –0.2762 |
| | *J*=6 | Return | –18.2366 | –9.6301 | –4.3676 | –3.7042 | –17.7961 | –9.5238 | –4.6464 | –4.1124 |
| | | Volatility | 3.8530 | 6.5817 | 8.4475 | 11.2857 | 8.3876 | 6.3311 | 8.1906 | 12.1246 |
| | | IR | –1.3661 | –0.7324 | –0.3663 | –0.3279 | –1.3213 | –0.7518 | –0.4051 | –0.3386 |
| | *J*=12 | Return | –6.8836 | –4.9933 | –3.2098 | –4.5350 | –7.2416 | –3.3104 | –1.3519 | –2.3795 |
| | | Volatility | 3.5940 | 6.6397 | 8.6686 | 11.7174 | 3.3992 | 6.4840 | 8.1578 | 12.5036 |
| | | IR | –0.5534 | –0.3760 | –0.2614 | –0.3872 | –0.6154 | –0.2553 | –0.1174 | –0.1904 |

( *Continued* )

**TABLE 10. (Continued)**

**Note:** This table reports the annualized average returns, volatilities, and IRs of ($J$, $K$) price momentum and idiosyncratic momentum strategies for the China A-Share IMI and CSI 500 universes. Portfolios are formed using $J$-month formation periods and $K$-month holding periods with the overlapping approach of Jegadeesh and Titman (1993, 2001). The formation period is indicated in the rows; the holding period is indicated in the columns. As usual, each ($J$, $K$) strategy is defined as a winner-minus-loser portfolio constructed using the top and bottom quintile portfolios based on sector-neutral ranking of the respective factor values for all stocks in the universe. Average return is the annualized monthly average of the equal-weighted return of the winner-minus-loser portfolio. Volatility is measured as the standard deviation of the monthly returns of the winner-minus-loser portfolio during the entire test period. IR is the annualized risk-adjusted average returns of the winner-minus-loser portfolio. Because of different lengths of formation and holding period in the ($J$, $K$) strategy, we use a single time period from January 2011 to December 2017 to conduct the performance test for all strategies for easy comparison.

**TABLE 11. Performance results of long-only and long-bench portfolios for the *IMOM* and *MOM* factors**

| | China A-Share IMI | | | | | CSI 500 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR |
| A. Long-only | | | | | | | | | | |
| *IMOM* | 10.1844 | 99.0901 | 5.3031 | 7.8018 | 0.1962 | 4.1339 | 96.7501 | 4.3795 | 8.0483 | 0.1571 |
| *MOM* | –31.3549 | 148.2203 | –0.2375 | 8.5248 | –0.0080 | –29.1496 | 122.7842 | –0.1563 | 8.3021 | –0.0054 |
| B. Long-bench | | | | | | | | | | |
| *IMOM* | –9.2135 | 39.1504 | 4.6885 | 10.0823 | 0.1342 | –29.7079 | 57.9813 | 3.2154 | 10.0144 | 0.0927 |
| *MOM* | –41.5661 | 58.1617 | –0.3502 | 10.1542 | –0.0097 | –52.8364 | 68.6321 | –1.9135 | 11.0372 | –0.0501 |

**Note:** This table reports the cumulative return, max drawdown, annualized average returns, volatilities, and IRs of long-only and long-bench traditional momentum and idiosyncratic momentum strategies for the China A-Share IMI and CSI 500 universes. Panel A lists the performance results for the long-only strategy; Panel B lists the performance results for the long-bench strategy.

is used to form the quintile buckets (Q1 to Q5) -- in other words, dividing securities into quintile buckets based on sector-neutral ranking of the factor values of all stocks in the universe. The test results are listed in table 11.

For long-only and long-bench portfolios, the *MOM* signal has negative average returns of –0.24% and –0.35% for the China A-Share IMI and average returns of –0.16% and –1.91% for the CSI 500 universe. The *IMOM* performs much better than the *MOM* signal. It generates decent average returns of 5.30% and 4.68% for the China A-Share IMI and 4.38% and 3.22% for the CSI 500 universe, respectively. Of note is that the volatilities of monthly returns of both long-only and long-bench portfolios for the *IMOM* and *MOM* signals are more than 4 times higher than those of long-short portfolios. Because of the high volatility in the returns, the IRs and cumulative returns of *IMOM* signals are relatively low. In particular, in the long-bench portfolio for the China A-Share IMI and CSI 500 universe, the cumulative returns of *IMOM* are still negative.

*C. Without Sector Neutrality Treatment*

In previous analyses, all winner and loser portfolios are formed with sector neutrality treatment. As pointed out in the academic literature, momentum is typically not sector-neutral. It would be interesting to see whether the *IMOM* signal still achieves the desired performance under an environment without sector neutrality treatment. Therefore, the performance tests are rerun on the long-short portfolios formed using cross-sectional ranking instead of sector-neutral ranking. The results are reported in table 12.

As compared to the results in table 6, the results in table 12 indicate that both *IMOM* and *MOM* perform even better in the environment without neutrality treatment. Furthermore, the results in table 12 show that the *IMOM* still outperform *MOM* without sector neutrality treatment. In fact, without sector neutrality treatment, the *IMOM* strategy generates higher average returns and IR than the *MOM*. For the China A-Share IMI, the *IMOM* strategy yields cumulative returns of 38.36% with an IR of 0.39, compared to the cumulative returns of –46.46% and an IR of –0.47 for the *MOM*. Also, for the CSI 500 universe, the *IMOM* factor yields even higher cumulative returns of 68.44% and an IR of 0.61, compared to the cumulative returns of –19.90% and an IR of –0.14 for the *MOM*. Of note is that the volatilities of returns of both *IMOM* and *MOM* strategies without sector neutrality

**TABLE 12. Performance summary of *IMOM* and *MOM* factors without sector neutrality treatment**

| | China A-Share IMI | | | | | CSI 500 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR |
| *IMOM* | 38.3631 | 54.7713 | 4.7968 | 3.5784 | 0.3870 | 68.4402 | 35.0312 | 7.1365 | 3.3752 | 0.6104 |
| *MOM* | –46.4643 | 64.6322 | –6.6924 | 4.0775 | –0.4738 | –19.8952 | 53.7901 | –1.8421 | 3.8800 | –0.1367 |

**Note:** This table reports the cumulative returns, max drawdown, annualized average returns, volatilities, and IRs of traditional momentum and idiosyncratic momentum strategies constructed without sector neutrality treatment for the China A-Share IMI and CSI 500 universes between December 2010 and December 2018. Each strategy is defined as a winner-minus-loser portfolio constructed using the top and bottom quintile portfolios based on cross-sectional ranking of the respective factor values for all stocks in the universe.

treatment are slightly higher than the volatilities of those strategies treated with sector neutrality.

*D. Common Set of Stocks with Both IMOM and MOM Factor Scores*

As mentioned earlier in table 5, due to the nature of its construction method, *IMOM* factor requires more historical data for regression thus has less stock coverages than *MOM*. Therefore, the set of stocks used in the performance analysis for the *IMOM* factor contains less number of securities than the set for the *MOM* test in both China A-Share IMI and CSI 500 universes. In order to facilitate an apple to apple comparison, and also want to see how much impact to the performance results because of the discrepancy between the test samples, additional performance tests for *IMOM* and *MOM* are executed on a reduced subset of stocks, that is, the common set of stocks which have both *IMOM* and *MOM* factor scores. The test results are listed in table 13.

The results in table 13 clearly indicate that on the common set of stocks, there is a small, but not significant change in the performance metrics of *MOM* factor, whereas the performance metrics of *IMOM* and $IMOM^{FF}$ are unchanged. More specifically, the *MOM* still underperforms significantly compared to the *IMOM*, and the gap of cumulative returns, average returns, and IRs delivered by the *IMOM* and *MOM* strategy remain the same.

*E. Lengths of Rolling Windows*

Finally, it comes time to check whether the performance results of an idiosyncratic momentum signal are sensitive to the length of the rolling window used to estimate the residual return in regression (2). Up to this point, the 36-month rolling window is used uniquely during the construction of *IMOM* signal throughout the paper. Now we use several alternative lengths of rolling windows, 24 months, 30 months and 48 months, and check for any change in the performance of these *IMOM* factors generated using these alternatives. The performance analysis carried on these *IMOM* factors uses exactly the same settings as in the main analysis described in Section III. Although there are small differences in IR and max drawdown, the results are very similar to these presented in table 6 and 7, and are not reported in tabular form for brevity. Based on these test results, it can be concluded that the idiosyncratic momentum strategy is robust to the choice of rolling window size.

**TABLE 13. Performance summary of *IMOM* and *MOM* factors on the common set of stocks that have both *IMOM* and *MOM* factor scores**

| | China A-Share IMI | | | | | CSI 500 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR | Cumu. Return | Max Drawdown | Avg. Return | Std. Dev. | IR |
| *IMOM* | 35.51 | 34.31 | 4.26 | 2.85 | 0.43 | 41.66 | 22.31 | 4.72 | 2.62 | 0.52 |
| $IMOM^{FF}$ | –6.53 | 45.29 | –0.12 | 3.26 | –0.01 | 14.09 | 29.89 | 2.06 | 2.68 | 0.22 |
| *MOM* | –49.43 | 57.50 | –7.55 | 3.74 | –0.85 | –34.74 | 66.91 | –4.88 | 3.63 | –0.39 |

**Note:** This table reports the cumulative returns, max drawdown, annualized average returns, volatilities, and IRs of *MOM* and *IMOM* strategies constructed using the common set of securities with both *IMOM* and *MOM* factor scores for the China A-Share IMI and CSI 500 universes between December 2010 and December 2018. Each strategy is defined as a winner-minus-loser portfolio constructed using the top and bottom quintile portfolios based on cross-sectional ranking of the respective factor values for the set of stocks in each universe.

## V. Conclusions

The momentum factor plays an important role in the investment process, particularly in a financial environment where perhaps the most trustworthy information is the past price returns. For this reason, many investors incorporate price momentum indicators into their stock selection process or hire investment managers to employ momentum-based strategies. However, the traditional price momentum does not always prove to be significant in explaining the value of the future returns, especially in a volatile market, such as China's stock market (Jiang et al. (2015), Su (2011), and Wu (2011)).

This paper introduces a new way of constructing idiosyncratic momentum factor, which is based on the residuals after regressing the return against the style factors from the Barra global risk models. The effectiveness of this factor are tested in the Chinese equity market. The empirical results show that, unlike traditional momentum, the idiosyncratic momentum strategy generates higher long-term information ratio. Also, this strategy displays consistent performance in varying economic environments in the Chinese equity market, even during multiple-year periods where traditional momentum generates negative returns. Third, this strategy is substantially less affected by market dynamics, where the return in the month following a bull or bear market is taken into account. Last, the strategy is not specifically oriented toward small-cap stocks, which tend to carry higher transaction costs and higher firm-specific risk. These results indicate that the reduced time-varying exposure to systematic risk factors of idiosyncratic momentum significantly enhances the effectiveness of the momentum strategy to such an extent that it even solves the momentum puzzle in the Chinese equity market.

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