# Factor MAX in the Chinese Market*

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## Abstract

Using a comprehensive factor zoo, we document a notable factor MAX premium in the Chinese market. Factors with high maximum daily returns consistently outperform those with low maximum returns by 0.82% per month in the future, on a risk-adjusted basis. This premium remains robust controlling for various factor characteristics, and is not sensitive to the selection of factors. It concentrates in high-eigenvalue principal component factors, is larger in periods of elevated investor sentiment, and remains statistically significant even 12 months after formation. The factor MAX anomaly stands apart from lottery-type stock anomalies and contributes to elucidate most of these anomalies. We find factor MAX anomaly also exists in the United States.



**JEL Classification**: G12, G17

**Keywords**: Anomaly; Factor investing; Lottery preference; Big data

# 1 Introduction

China's stock market is unique, driven by its largest population of retail investors in the global capital market. These individual investors wield significant influence over stock prices, primarily due to their speculative motivation and gambling preference. The lottery preferences of retail investors contribute to the distinct "three high" phenomena in the Chinese stock market: high volatility, high price-to-earnings ratios and high turnover rates. Existing research primarily focuses on lottery preferences of retail investors in the Chinese market (Zheng and Sun, 2013; Zhu and Zhang, 2020) while overlooks institutional investors, who utilize factor investing as their mainstream trading strategy. In studies related to the U.S. market, institutional investors have also been observed to disproportionately emphasize the extreme positive return and are inclined to select lottery-like stocks to attract retail investors (Akbas and Genc, 2020; Agarwal, Jiang, and Wen, 2022). Hence, under the unique setting of Chinese market, do institutional investors intentionally prefer lottery-like factor to attract retail investors? That is, does factor investing also exhibit lottery preferences? Consequently, is there a factor MAX anomaly analogous to lottery-like stock anomalies? These are important questions that warrant investigation in this paper.

To address these questions, we compile large sample of accounting and finance data from the China Stock Market & Accounting Research (CSMAR) database and construct 142 characteristic-based non-lottery-related factors in the Chinese market following Jensen, Kelly, and Pedersen (2023). Due to the "T+1" transaction limit and price limit in the Chinese market, we choose five largest daily returns to construct the MAX proxy, which better capture the lottery characteristics of factors in the Chinese market (Zhu and Zhang, 2020). Sorting factors into quintile portfolios based on the value of MAX, we document a notable factor MAX premium: factors with higher value of MAX substantially outperform those with lower value of MAX by 0.77% per month in the future. The risk-adjusted returns relative to the Liu, Stambaugh, and Yuan (2019) 3-factor model and the Chinese Fama and French (2015) 5-factor model are 0.53% and 0.74%, respectively, both of which are significant at 1% level. Moreover, we find that the factor MAX premium differs from the stock-level MAX anomaly. Contrary to Bali, Cakici, and Whitelaw (2011) and many others, stocks with high maximum daily returns underperform those with low maximum daily returns, resulting in a low stock MAX premium, our results unveil a positive correlation between factor MAX values and future factor returns. This notable disparity underscores that the factor MAX anomaly is distinct from the stock MAX anomaly, warranting separate investigation.

According to Kumar (2009) and Bali, Cakici, and Whitelaw (2011), lottery-type stocks often exhibit elevated idiosyncratic volatility and skewness, traits that appeal to investors pursuing small probability of extreme positive returns. Thus, we proceed to investigate the portfolio characteristics for each factor MAX quintile to examine their lottery-related features. Results show that high MAX portfolio displays significantly higher volatility and skewness compared to low MAX portfolio. For instance, the idiosyncratic volatility is 0.46% for the high MAX portfolio, markedly higher than the 0.29% observed for the low MAX portfolio, reflecting a notable difference of 0.16%. Hence, lottery-like factors also exhibit lottery-related characteristics, which aligns with the findings regarding lottery-type stocks in Kumar (2009) and Bali, Cakici, and Whitelaw (2011).

As extreme returns are related to various characteristics in factor returns, we proceed to explore the performance of factor MAX strategy controlling for other factor characteristics, including momentum, idiosyncratic volatility and idiosyncratic skewness. In each case, we first sort factors into quintiles using the control variable, then within each quintile, factors are sorted into quintiles based on the value of MAX in the prior month. Bivariate portfolio analysis shows that controlling for these established cross-sectional effects does not diminish the performance of factor MAX strategy. Risk-adjusted returns consistently range from 0.44% to 0.63%, all of which are statistically significant at the 1% level. Subsequently, we reverse the sorting process to evaluate the performance of factor momentum, idiosyncratic volatility, and idiosyncratic skewness while controlling for factor MAX. Our results indicate that controlling for factor MAX significantly alters the performance of strategies based on these control variables, rendering none of the return spreads statistically significant. Hence, for both equal- and value-weight portfolios, factor MAX encompasses the return spread of well-known cross-sectional effects such as factor momentum and volatility. Further validation through Fama-MacBeth regressions confirms our findings, illustrating that none of these factor characteristics exert a significant influence on the factor MAX premium. Even when collectively included in a regression analysis, the coefficient of MAX remains stable at 0.31, supported by a $t$-statistic of 2.07. In sum, the factor MAX premium is sound and robust, which is not overshadowed by other well-known factor characteristics.

The factor MAX premium is extremely robust. It survives various factor-based risk adjustments. It withstands challenges related to the data mining of "factor zoo" and is not sensitive to the choice of factors. To illustrate, we conduct a rigorous analysis where we randomly select 100 factors to construct the MAX portfolio, repeating this process 1000 times. Remarkably, 99% of the excess returns and all risk-adjusted returns remain statistically significant at 1% level. Moreover, it is robust to the construction of the MAX proxy and decile portfolio formations.

Numerous studies have identified stock-level lottery-type anomalies in the Chinese market (Zheng and Sun, 2013; Zhu and Zhang, 2020; Nartea, Kong, and Wu, 2017). To further elucidate the robustness and distinctiveness of the factor MAX premium in this context, we investigate its relationship with these anomalies. First, from investors' perspective, factor MAX strategy consistently outperforms the stock MAX strategy without experiencing significant drawdowns over the sample period from January 2000 to December 2022. Second, spanning tests reveal that factor MAX anomaly contributes to elucidate most of the lottery-type stock anomalies, while these stock anomalies cannot significantly subsume the factor MAX premium. This suggests that the factor MAX strategy remains distinct from existing lottery anomalies and offers investors incremental investment value. Given that the factor MAX strategy is constructed based on individual factors, we explore whether the combined factor MAX premium helps explain individual anomalies. Our findings indicate that augmenting the FF5 model with the factor MAX premium substantially mitigates the absolute abnormal returns in 93 out of 142 anomalies. In essence, our results underscore that the factor MAX anomaly effectively dissects the returns of its component factors and contribute to explaining a broader spectrum of anomalies.

Despite the empirical evidence confirming significant positive expected returns from the factor MAX strategy, an essential question remains: why do factors exhibit such an anomaly? We address this issue by following the footsteps of Kozak, Nagel, and Santosh (2018, 2020), Haddad, Kozak, and Santosh (2020) and Ehsani and Linnainmaa (2022). These studies suggest that, in an economy with rational arbitrageurs and sentiment investors with distorted beliefs, arbitrageurs typically absorb any sentiment-driven demand that deviates from common factor covariances. Hence, in the absence of near-arbitrage opportunities, only factors explaining the most variation in returns should manifest pricing effects. Thus, the degree to which factors exhibit pricing effects, such as MAX, therefore depends on their exposures to undiversifiable risk. This theoretical framework directs us to explore combinations of factors that explain the most variation in returns. Building on the insights of Arnott, Kalesnik, and Linnainmaa (2023) and Ehsani and Linnainmaa (2022), we extract principal component (PC) factors from the pool of 142 factors utilized in our analysis. We sort PC factors into five groups based on their five largest daily returns in the prior month and long (short) the factors in the top (bottom) quintiles. By assessing the performance of the MAX strategy across ten different subsets of PC factors, organized by the descending order of their eigenvalues, we observe that the MAX premium concentrate in the high-eigenvalue factors, aligning with the findings of Arnott, Kalesnik, and Linnainmaa (2023) and Ehsani and Linnainmaa (2022).

Lastly, we employ several analysis to further unveil the mechanism of factor MAX premium. First, using two investor sentiment index in the Chinese market, we find that the factor MAX spread portfolio earns significantly higher returns following high sentiment periods compared to low sentiment periods. These findings align with Stambaugh, Yu, and Yuan (2012), supporting that anomalies tend to yield higher returns in periods of elevated investor sentiment. Second, the performance of factor MAX premium demonstrates robust persistence and remains statistically significant even 12 months after formation. The absence of reversal and existence of stability supports the view that the factor MAX premium is grounded in more persistent economic or behavioral factors rather than short-term market frictions. Finally, we investigate the performance of factor MAX strategy in the U.S., home to the world's largest capital market. Similar to the Chinese market, the factor MAX strategy also earns positive and significant returns in the U.S.: factors in the lowest MAX quintile outperform the factors in the highest MAX quintile by 0.35% per month in the future, on a risk-adjusted basis. This result reveals a sharp contrast with stock MAX premium in the U.S., demonstrating the our empirical analysis contributes novel evidence that enriches the existing literature.

Our study contributes to several strands of literature. First, it adds to the study on lottery preferences and lottery-type anomalies in stock market. Building on cumulative prospect theory, Barberis and Huang (2008) first theoretically establishes investors' strong preferences for lottery-type stocks. Using returns to capture the lottery preferences, Bali, Cakici, and Whitelaw (2011) reveals a negative association between maximum daily returns and future returns and Boyer, Mitton, and Vorkink (2010) finds that stocks with high expected idiosyncratic skewness underperform those with low expected idiosyncratic skewness. Regarding institutional investors, Akbas and Genc (2020) documents a positive and significant relationship between the maximum style-adjusted fund returns and future fund flows, indicating fund managers tendency to emphasize extreme positive returns to attract future fund flows. Agarwal, Jiang, and Wen (2022) demonstrate that mutual funds tend to hold lottery stocks to cater to fund investors' gambling preferences. While existing research primarily focuses on the gambling preferences of retail investors and individual stocks, our study enriches this strand of literature by exploring the lottery preferences in factor investing. Our results provide novel evidences by documenting a significant factor MAX premium, which is distinct from the stock-level factor anomaly. This enhances our understanding of the lottery preferences in Chinese market.

Second, our study adds to the burgeoning literature on factor anomalies. Ehsani and Linnainmaa (2022) uncover the presence of time series momentum in factor returns while

Arnott, Kalesnik, and Linnainmaa (2023) demonstrate strong cross-sectional factor momentum. Furthermore, Gupta and Kelly (2019) documents the widespread existence of factor momentum in markets beyond the U.S. Ma, Liao, and Jiang (2024) introduces a novel factor momentum strategy in the Chinese market, which subsumes stock momentum. While the bulk of research in this domain focuses on the U.S. market, exploring momentum effects, our study extends this discourse by documenting a novel factor MAX anomaly in the Chinese market.

Third, our study also contributes to the research on the Chinese market. Despite the performance of the Chinese economy arguably surpasses expectations, its stock market has demonstrated underwhelming performance, primarily due to the dominance of retail investors and their pronounced lottery preferences (Allen, Qian, Shan, and Zhu, 2023). Nowadays, advancements in financial technology, big data analysis as well as high frequency trading exacerbate stock market fluctuations and accentuate connections and anomalies among factors, which also caused controversy in quantitative investment. Our study enriches this strand of literature by employing a large sample of comprehensive accounting and financial data to evaluate the performance of factor investing.

This paper is organized as follows. Section 2 introduces the data used for constructing the factors in the Chinese market. Section 3 presents the results of all empirical analysis, including portfolio analysis, Fama-MacBeth regressions, digest stock anomalies and a battery of robustness tests. Section 5 concludes.

## 2 Data

We obtain data from the China Stock Market & Accounting Research (CSMAR) database covering January 2000 to December 2022, including financial statement data and monthly and daily stock returns for all A-share stocks listed on the Shanghai and Shenzhen Stock Exchanges. We restrict our focus to common stocks. To ensure the quality of the data, we exclude stocks with special and/or particular transfer status, as these tend to be under financial distress (Carpenter, Lu, and Whitelaw, 2021)

We construct 142 characteristics-based non-lottery-related factor portfolios following Jensen, Kelly, and Pedersen (2023). These factors cover a brand of anomalies in the existing literature, which can be divided into 13 groups, including accruals, debt issuance, investment, low leverage, low risk, momentum, profit growth, profitability, quality, seasonality, size, short-term reversal and others. Specifically, for each individual factor, we sort stocks into quintiles based on the corresponding characteristics. Factor return is constructed as the long minus short portfolio with the sign convention used in Jensen, Kelly, and Pedersen (2023). In particular, we sign factors so they are consistent with the literature, where long the out-performed portfolios while short the under-performed portfolios. We construct daily and monthly factor returns using both equal- and value-weighting scheme. The details of all the factors are provided in Table OA.5 in the Appendix.

# 3 Empirical Analysis

We start the empirical analysis by constructing the factor MAX strategy and investigating its performance using portfolio analysis and Fama-MacBeth regressions. We also perform a battery of tests to establish the robustness of our results.

## 3.1 Factor MAX Premium

Following Bali, Cakici, and Whitelaw (2011), we use maximum daily return to capture the lottery preferences in factor investing. Due to the "T+1" transaction limit and price limit in the Chinese market, we choose five largest daily returns to better capture the lottery characteristics of factors in Chinese market.

$$\mathrm{MAX}_{i,t} = \sum_{k=1}^{5} \mathrm{Rank}_k(\mathrm{Return}_{i,t}^{d})$$

where $\text{MAX}_{i,t}$ represents the sum of five largest daily returns for factor $i$ at month $t$, $\text{Rank}_k(\text{Return}^d_{i,t})$ represents the $k$th extreme return for factor $i$ in month $t$ in descending order.

At the beginning of each month from January 2000 to December 2022, we form quintile portfolios by sorting factors into five groups based on MAX in the preceding month, where quintile 1 (5) contains factors with the lowest (highest) value of MAX. The factor MAX spread portfolio (H–L) involves buying factors in quintile 5 and selling factors in quintile 1 and all portfolios are rebalanced monthly. We calculate the returns of MAX portfolios in month $t$+1 using equal- and value-weighting schemes. As the factors are constructed using both equal- and value-weighting schemes, we focus on two combinations of portfolios accordingly: (1) MAX is constructed using equal-weight daily factors and portfolio is formed using equal-weight monthly factor returns (EE); (2) MAX is constructed using value-weight daily factors and portfolio is formed using value-weight monthly factor returns (VV). Figure OA.1 plots the number of factors in the long and short legs of the factor MAX strategy over time. The number of factors increases from 18 at the start of 2000 to 25 approximately two years later and remains consistently above 25 thereafter. This suggests that there is a reasonable number of factors in each long and short leg throughout the analysis period, indicating that the results are not influenced by a small subset of outliers.

Table 1 presents the results of portfolio analysis. In Panel A, where MAX is constructed using equal-weight daily factor returns and portfolio is formed using equal-weight monthly factor returns, the monthly average excess returns of the factor MAX portfolios increase from –0.02% for quintile 1 to 0.74% for quintile 5, resulting in a difference of 0.77% ($t$-statistics = 3.17). Risk-adjusted returns are computed using two factor models: Liu, Stambaugh, and Yuan (2019) three-factor model (LSY3) and Chinese Fama and French (2015) five-factor model (FF5) from the CSMAR database. The rest rows of Panel A present the factor-adjusted returns and make two observations. First, although the two factor models we use represent the most recent advancements in Chinese market, they fail to fully explain the factor MAX portfolios. The abnormal return of the factor MAX spread portfolio ranges from 0.53% with LSY3 to 0.74% with FF5, suggesting that at least 50 percent of the average return of the factor MAX spread portfolio remains unexplained by existing asset pricing models. Second, unlike the well-known anomalies in Stambaugh, Yu, and Yuan (2012), the performance of the factor MAX spread portfolio is primarily derived from the long leg. The high factor MAX portfolio is undervalued, whereas the low factor MAX portfolio is generally overvalued with a much smaller magnitude.

Panel B reports the results for the most rigorous combination when MAX is constructed using value-weight daily factor returns and portfolio is formed using value-weight monthly factor returns. The results are similar to those in Panel A. For instance, the excess returns of the factor MAX spread portfolio remains 0.68% ($t$-statistics = 3.29) and risk-adjusted returns range from 0.52% to 0.82% ($t$-statistics = 2.50 and 4.30). The results in Table 1 also reveal a different return pattern between factor MAX portfolios and stock-level MAX portfolios. According to Bali, Cakici, and Whitelaw (2011) and many others, stocks with high maximum daily returns in the prior month underperform those with low maximum daily returns, resulting in a negative excess return for the stock MAX anomaly. While, our results show that factors with high maximum daily returns outperform those with low maximum daily returns, leading to a positive excess return for the factor MAX anomaly. This striking contrast demonstrates that factor MAX anomaly is distinct from stock MAX anomaly, which deserves separate investigation. For future analysis, we focus on the most rigorous case, where MAX is constructed using value weight daily factors, and the portfolio is formed using value weight monthly factor returns, for the sake of conciseness and consistency. We report the results for other combinations of portfolio construction in Appendix.

[Insert Table 1 about here]

We proceed to investigate the portfolio characteristics for each factor MAX quintile. Particularly, we sort factors into quintiles based on the value of MAX in the prior month and calculate the portfolio characteristics including mean, volatility (Vol), idiosyncratic volatility (IVol), skewness (Skew) and idiosyncratic skewness (ISkew). Idiosyncratic volatility is calculated as the standard deviation of the factor's daily idiosyncratic returns relative to the Chinese Fama-French five-factor model within a month. Idiosyncratic skewness is calculated as the skewness of daily residuals relative to first and second moments of market returns during the past three month. The results are reported in Table 2. As indicated, the high MAX portfolio exhibits significantly higher volatility and idiosyncratic volatility compared to the low MAX portfolio. For instance, in Panel A, the idiosyncratic volatility for P5 is 0.46% while 0.29 for P1, resulting in a substantial difference of 0.16% ($t$-statistics = 20.80). Additionally, the high MAX portfolio demonstrates higher skewness and idiosyncratic skewness than the low MAX portfolio. The idiosyncratic skewness for P5 is 21.50% while –1.80% for P1, with a significant difference of 23.31% ($t$-statistics = 7.93). In sum, high factor MAX portfolio generally has high idiosyncratic volatility and idiosyncratic skewness, aligning with the characteristics of lottery-type stocks documented in Kumar (2009) and Bali, Cakici, and Whitelaw (2011).

[Insert Table 2 about here]

## 3.2 Bivariate Portfolio Analysis

Previous results demonstrate that factors with high maximum daily returns significantly outperform those with low maximum daily returns, resulting in a factor MAX premium. As extreme returns are also related to momentum and volatility, we proceed to explore the performance of factor MAX strategy while controlling for factor momentum, factor minimum, factor idiosyncratic volatility and factor idiosyncratic skewness. We define factor momentum (MOM) as the sum of each factor's daily return within a month; factor minimum (MIN) as the sum of each factors five smallest daily returns within a month; factor idiosyncratic volatility (IVOL) as the standard deviation of the factor's daily idiosyncratic returns relative to the Chinese Fama-French five-factor model within a month; factor idiosyncratic skewness (ISKEW) as the skewness of daily residuals relative to the first and second moments of market returns during the past three months. In each case, we first sort factors into quintiles using the control variable, then within each quintile, factors are sorted into quintiles based on the value of MAX in the prior month. Hence, quintile 1 (5) contains factors with the lowest (highest) MAX and H–L refers to the difference in returns (alphas) between the highest MAX and lowest MAX portfolios. For brevity, we do not report returns of all 25 (5 $\times$ 5) portfolios. Instead, reported are the average excess returns and alphas across the five control quintiles to produce quintile portfolios with dispersion in MAX but with similar levels of the control variable.

The results presented in Table 3 reveal that controlling for factor momentum (MOM), factor minimum (MIN), factor idiosyncratic volatility (IVOL), and factor idiosyncratic skewness (ISKEW) does not impact the performance of the factor MAX strategy. For instance, after accounting for factor momentum, the average return difference between low MAX and high MAX portfolios is approximately 0.34% with a $t$-statistic of 2.70. The FF5-adjusted alpha is about 0.44% with a $t$-statistics of 3.66. This suggests that factor momentum does not explain the return spread between high and low factor MAX portfolios. The rest rows of Table 3 demonstrate that after controlling for factor minimum, factor idiosyncratic volatility, and factor idiosyncratic skewness, the average return differences between high MAX and low MAX portfolios are 0.53%, 0.53%, and 0.56% per month, respectively. These differences are both economically and statistically significant. And the risk-adjusted return differences are 0.64%, 0.63%, and 0.61%, which are also highly significant. These findings indicate that well-known cross-sectional effects such as factor momentum and volatility cannot explain the return spread of the factor MAX strategy.

[Insert Table 3 about here]

We continue to separate factor MAX from factor momentum and volatility by performing the reverse sort to investigate the performance of factor momentum, factor minimum, factor idiosyncratic volatility and factor idiosyncratic skewness controlling for factor MAX. In this analysis, factors are initially sorted into quintiles based on MAX, and within each quintile, we sort factors into five groups based on the control variable in the prior month. Hence, quintile 1 (5) contains factors with the lowest (highest) control variable and H-L refers to the difference in returns (alphas) between the portfolios with the highest and lowest control variable. Similar to the previous section, we report the average excess returns and alphas across the five quintiles of the control variable to produce quintile portfolios with dispersion in control variable but with similar levels of MAX.

The results presented in Table 4 highlight that controlling for factor MAX significantly impacts the performance of the strategy based on control variables. For instance, after accounting for factor MAX, the average return difference between low MOM and high MOM portfolios is about 0.22% with a $t$-statistic of 0.89. The FF5-adjusted alpha is about 0.22% with a $t$-statistics of 0.96. This suggests that the return spread between high and low MOM portfolios is subsumed by factor MAX. The rest rows of Table 4 shows that after controlling for MAX, the average return spread of MIN, IVOL, and ISKEW are 0.25%, –0.03%, –0.02% per month, respectively. None of these differences is statistically significant with $t$-statistics ranging from –0.22 to 1.11. The risk-adjusted return differences are 0.29%, –0.06%, and 0.01%, and none of them is statistically significant. These results indicate that factor MAX encompasses the return spread of well-known cross-sectional effects such as factor momentum and volatility.

[Insert Table 4 about here]

## 3.3 Fama-MacBeth Regressions

So far our analysis has focused on testing the significance of MAX as a determinant of the cross-section of future factor returns at the portfolio level. This non-parametric approach is advantageous as it does not impose a specific functional form on the relationship between MAX and future factor returns. However, it comes with two disadvantages. First, it involves a substantial loss of information in the cross-section due to aggregation. Second, it is challenging to simultaneously control for multiple effects or factors. To address these concerns, in this subsection we employ Fama–MacBeth regressions. These regressions involve running factor-specific one-month-ahead excess return regressions on MAX and various factor-specific characteristics. This allows us to assess the incremental return predictive power of MAX while accounting for other relevant factors.

In Fama-MacBeth regressions reported in Table 5, we control for a comprehensive set of factor characteristics including factor momentum (MOM), factor minimum (MIN), factor idiosyncratic volatility (IVOL), and factor idiosyncratic skewness (ISKEW). In column (1), the univariate regression reveals a significantly positive coefficient of 0.15 with $t$-statistics of 4.14. Economically, the absolute $t$-statistics is proportional to the Sharpe ratio of the MAX spread portfolios, which equals the annualized Sharpe ratio times $\sqrt{T}$, the number of years in the sample. So the 4.14 $t$-statistics suggests that an investor can earn an annualized Sharpe ratio of 0.86 (i.e., $4.87/\sqrt{23}$) if she trades for the factor MAX strategy.

Column (2) shows that controlling for factor momentum does not affect the predictive power of MAX with the coefficient remaining unchanged (0.11 with $t$-statistics = 3.55). In column (3), where we control for factor minimum (MIN), the coefficients of MAX become even larger and remain significant at the 1% level. Columns (4) and (5) demonstrate that controlling for factor idiosyncratic volatility and idiosyncratic skewness does not diminish the predictive power of MAX with coefficients of 0.17 and 0.14 ($t$-statistics of 2.87 and 4.35). In the last column, when pooling all controls in one regression, the coefficient of MAX remains 0.31 with a $t$-statistics of 2.07. In sum, the results of Fama-MacBeth regression reaffirms our previous findings that MAX possesses significant explanatory power on factor returns, and this power is not overshadowed by other well-known factor characteristics.

[Insert Table 5 about here]

## 3.4 Factor MAX vs. Lottery-related Anomalies

Previous studies have documented various lottery-related anomalies at the stock-level. For instance, Bali, Cakici, and Whitelaw (2011) shows that stocks with the highest maximum daily return over the past one month underperform those with the lowest maximum daily return return, indicating a negative relationship between maximum daily return and expected stock returns. Bali, Engle, and Murray (2016) documents a negative relationship between return skewness and future expected returns. This contrasts with the positive relationship observed at the factor level. Therefore, in this section, we further explore the relationship between the factor MAX anomaly and stock-level lottery-related anomalies.

First, from investors' perspective, we conduct a comparison between the performance of the factor MAX strategy and the stock MAX strategy over time. Specifically, stocks are sorted into quintiles based on the average of their five largest daily returns in the past one month, and the MAX spread portfolio is constructed as the top quintile minus the bottom quintile. Figure 1 depicts the log cumulative returns and log cumulative FF5 alphas of both factor MAX and stock MAX spread portfolio. As illustrated, the factor MAX strategy consistently outperforms the stock MAX strategy. Over our sample period from January 2000 to December 2022, an investor would achieve a risk-adjusted profit of $8.50 if she trades for the factor MAX strategy while $5.47 if she invests in the stock MAX strategy. Additionally, the factor MAX premium does not suffer from large drawdowns. Therefore, trading the factor MAX strategy generates significantly higher returns, especially compared with stock MAX spread portfolios.

[Insert Table 1 about here]

Moving forward, we formally investigate the relationship between factor MAX anomaly and lottery-related anomalies using spanning regressions. We consider several well-documented lottery-related anomalies, including the factor constructed based on maximum daily return (MAX1), average of largest five daily returns (MAX5), idiosyncratic volatility (IVOL), skewness

(SKEW), coskewness (COSKEW) and idiosyncratic skewness (ISKEW). To examine the ability of the factor MAX anomaly to explain the lottery-related anomalies, we run the following regression:

$$\mathrm{Ret}_t^{\mathrm{Lottery}} = \alpha + \beta \mathrm{Ret}_t^{\mathrm{FMAX}} + \varepsilon_t$$

where $\mathrm{Ret}^{\mathrm{Lottery}}$ refers to the return of lottery-related anomalies, and $\mathrm{Ret}^{\mathrm{FMAX}}$ is the return of the factor MAX anomaly. Left panel of Table 6 shows that factor MAX anomaly contributes to explaining most of the lottery-related anomalies, with insignificant alpha of 0.59% ($t$-statistics = 1.70), 0.51% ($t$-statistics = 1.39), 0.49% ($t$-statistics = 1.59), 0.12% ($t$-statistics = 0.69) of MAX1, MAX5, COSKEW, and ISKEW respectively. Subsequently, we reverse the analysis and examine whether lottery-related anomalies subsume the factor MAX anomaly. We run the following regression:

$$\mathrm{Ret}_t^{\mathrm{FMAX}} = \alpha + \beta \mathrm{Ret}_t^{\mathrm{Lottery}} + \varepsilon_t$$

The right panel of Table 6 shows that lottery-related anomalies cannot explain the factor MAX anomaly. The factor MAX strategy generates significant positive alphas of 0.72% ($t$-statistics = 2.89), 0.74% ($t$-statistics = 2.95), 0.94% ($t$-statistics = 4.36), 0.78% ($t$-statistics = 3.38), 0.54% ($t$-statistics = 2.21) for MAX1, MAX5, SKEW, COSKEW, and ISKEW respectively. In sum, results in Table 6 demonstrate that factor MAX anomaly contributes to explaining most of the lottery-related anomalies, while stock-level lottery-related anomalies cannot significantly subsume the factor MAX premium. Another observation is that factor MAX cannot explain the idiosyncratic volatility and skewness anomaly with significant alphas shown in the left panel. However, results in the right panel suggests that stock-level idiosyncratic volatility and skewness anomaly cannot explain our factor MAX, either. This suggests that the factor MAX strategy is distinct from existing lottery anomalies and provides incremental investment value for investors.

[Insert Table 6 about here]

### 3.5 Digest Stock Anomalies

The factor MAX spread portfolio, constructed based on individual factors, prompts us to explore whether the combined factor MAX premium helps explain individual anomalies. For this purpose, we include all 142 factors in our analysis and regress each of the factor's returns on the FF5 factors and FF5 factors augmented with factor MAX spread portfolio:

$$\text{Ret}_{i,t}^{\text{Factor}} = \alpha_1 + \gamma \text{FF5}_t + \varepsilon_t$$

$$\text{Ret}_{i,t}^{\text{Factor}} = \alpha_2 + \gamma \text{FF5}_t + \beta \text{Ret}_t^{\text{FMAX}} + \varepsilon_t$$

where $\text{Ret}^{\text{Factor}}$ refers to the long-short spread portfolios of the each individual factors and $\text{Ret}^{\text{FMAX}}$ refers to the return of the factor MAX spread portfolio. Then, we calculate the absolute difference between $\alpha_2$ and $\alpha_1$ to investigate whether factor MAX anomaly provides incremental explanatory power to individual stock anomalies compared with FF5 model.

The results are plotted in Figure 2, revealing that the factor MAX anomaly provides incremental explanatory power to most of the 142 anomalies, with 95 of them showing a significant reduction in the absolute value of risk-adjusted returns. Similar results are obtained when using value-weighted factors returns, where 93 out of 142 anomalies exhibit pronounced reductions in alphas. In summary, our results illustrate that the factor MAX anomaly helps decompose the returns on its component factors and contributes to explaining a larger number of anomalies.

[Insert Table 2 about here]

## 4 Economic Mechanism

Thus far, our results have demonstrated the presence of factor MAX anomaly. However, we acknowledge the need for a deeper economic explanation regarding why factors exhibit such anomalies. Although it is indisputable that factor MAX strategy earns significant positive expected returns from the empirical results, understanding the underlying reasons behind this phenomenon remains essential. Thus, in this section, we delve deeper into the economic mechanism to further understand the factor MAX premium.

## 4.1 Factor MAX Premium in High- and Low-eigenvalue PC Factors

We start addressing this issue by following the footsteps of Kozak, Nagel, and Santosh (2018, 2020), Haddad, Kozak, and Santosh (2020), and Ehsani and Linnainmaa (2022). These studies note that, in the economy with rational arbitrageurs and sentiment investors with distorted beliefs, arbitrageurs almost fully subsume any sentiment-driven demand not aligned with common factor covariances. The rationale lies in the ability of arbitrageurs to exploit profitable trades without assuming factor risk, effectively neutralizing components of sentiment-driven demand. Conversely, arbitrageurs are reluctant to engage in trades aligned with common factor covariances, as these expose them to factor risk. Consequently, in the absence of near-arbitrage opportunities, only the factors that explain the most variation in returns should carry any pricing effects. The extent to which factors can display any pricing effects, such as MAX, therefore depends on their exposures to undiversifiable risk. The theory guides us to look for those combinations of factors that explain the most variation in returns.

Following Arnott, Kalesnik, and Linnainmaa (2023) and Ehsani and Linnainmaa (2022), we extract principal component factors from the 142 factors used in our analysis. Using a rolling-window approach similar to that of Arnott, Kalesnik, and Linnainmaa (2023), we render the returns on the PC factors in month $t$+1 out of sample relative to the estimation of the eigenvectors. We use 10 years (with a minimum of 5 years) of daily returns up to the end of month $t$ and compute the first 106 eigenvectors, ordered by their eigenvalues. We compute daily returns in month $t$ and monthly returns in month $t$+1 on the PC factors from these eigenvectors and leverage the PC factors so that their variances up to month $t$ are equal to the variance of the average individual factor. The month $t$+1 returns are out of sample relative to the estimation step. Because we compute both month $t$ and $t$+1 returns using the same set of eigenvectors, the rotation of the factors is locally the same. That is, when we sort PC factors by the average of their five largest daily returns in month $t$ to create the factor MAX strategy, the month $t$+1 returns correspond to the same rotation of factors.

We sort PC factors into five groups based on their five largest daily returns in the prior month and long (short) the factors in the top (bottom) quintiles. In Table 7 we assess the performance of factor MAX strategy across ten different subsets of PC factors. The subsets are categorized by their eigenvalues, with the first subset containing the ten highest-eigenvalue PC factors; the second subset contains the ten next-highest-eigenvalue set of PC factors, and so forth. The results in the first column of Table 7 reveal that this highest-eigenvalue set of PC factors exhibits an average return of 0.71% and risk-adjusted return of 0.77% both are economically and statistically significant. Moving to the second set of PC factors, the average returns and risk-adjusted returns are statistically insignificant and economically marginal. From the third set of PC factors onwards, all average returns and risk-adjusted returns become statistically insignificant. These results align with findings in Kozak, Nagel, and Santosh (2018, 2020), indicating that factor MAX premium to concentrate in the high-eigenvalue factors.

## 4.2 Investor Sentiment

Given that factor MAX captures maximum daily returns, it is natural to investigate whether investor sentiment influences its performance. Stambaugh, Yu, and Yuan (2012) found that many anomalies generate higher returns during periods of elevated investor sentiment, particularly when short-sale constraints limit corrections to mispricing. We therefore hypothesize that factor MAX performance is stronger during periods of high investor sentiment compared to low-sentiment periods. To test this, we use the Composite Chinese Investor Sentiment Index (CICSI) and the Investor Sentiment

Indicator (ISI), defining a month as high (low) sentiment if the previous month's sentiment index is above (below) its median.

Results, shown in Table 8, confirm our hypothesis. The factor MAX spread portfolio (H-L) earns significantly higher returns following high-sentiment periods compared to low-sentiment periods. For example, in Panel A, the risk-adjusted return ($\alpha_{\text{FF5}}$) for the factor MAX spread portfolio is 1.16% (t-statistic = 4.75) after high-sentiment periods, while it is only 0.45% (t-statistic = 1.84) after low-sentiment periods. This results in a significant difference in the factor MAX premium of 0.70% (t-statistic = 2.15) between high and low sentiment conditions. This pattern is similarly evident in Panel B, which uses the Investor Sentiment Indicator as the sentiment metric. These findings align with Stambaugh, Yu, and Yuan (2012), supporting that anomalies tend to yield higher returns in periods of elevated investor sentiment.

[Insert Table 8 about here]

## 4.3 Long Term Performance

In this section, we investigate the long-term performance of the factor MAX strategy, focusing on the excess returns and risk-adjusted returns of the factor MAX spread portfolio at 3, 6, and 12 months post-formation. As shown in Table 9, the factor MAX premium demonstrates robust persistence and remains statistically significant even 12 months after formation. Specifically, at the 12-month horizon, the excess return of the factor MAX spread portfolio reaches 0.59% per month, with a t-statistic of 3.32, while the risk-adjusted return is 0.63% per month, with a t-statistic of 3.69. These outcomes align closely with the initial monthly performance documented in Table 1, reinforcing the durability of the factor MAX premium over longer periods. Additionally, the absence of a reversal pattern in returns suggests that the premium is unlikely to be a byproduct of temporary price distortions due to liquidity-driven trading. This stability supports the view that the factor MAX premium is grounded in more persistent economic or behavioral factors rather than short-term market frictions, thereby underscoring its potential as a reliable investment strategy for sustained outperformance over an extended investment horizon.

[Insert Table 9 about here]

## 4.4 Factor MAX Premium in the U.S.

Having established the significant premium of the factor MAX strategy in the Chinese market, we extend our investigation to explore whether such a premium exists in the U.S., home to the world's largest capital market. We borrow the characteristic-based factor returns from Chen and Zimmermann (2022) and define MAX as the sum of five largest daily returns. At the beginning of each month from January 1926 to December 2022, we form quintile portfolios by sorting factors into five groups based on MAX in the preceding month, where quintile 1 (5) contains factors with the lowest (highest) value of MAX. The factor MAX strategy (H-L) involves buying factors in quintile 5 and selling factors in quintile 1 and all portfolios are rebalanced monthly. We calculate the returns of MAX portfolios and factor MAX strategy in month $t$+1 using value-weighting schemes.

Table 10 presents the results of portfolio analysis for the U.S. In Panel A, the monthly average excess returns of the factor MAX portfolios increase from 0.06% for quintile 1 to 0.47% for quintile 5, resulting in a difference of 0.41% (t-statistics = 4.29). Risk-adjusted returns are computed using three factor models: Fama and French (2015) five-factor model (FF5), Hou, Xue, and Zhang (2015) q-factor model (HXZ) and Daniel, Hirshleifer, and Sun (2019) behavioral factor model (DHS). The rest rows of Panel A present the factor-adjusted returns and make two observations. First, despite employing the most recent advancements in the asset pricing, the three factor models fail to fully explain the factor MAX portfolios. The abnormal return of the factor MAX spread portfolio ranges from 0.24% with DHS and 0.35% with FF5, suggesting that at least 30 percent of the average return of the factor MAX spread portfolio remains unexplained by existing asset pricing models. Second, unlike the well-known anomalies in Stambaugh, Yu, and Yuan (2012), the performance of the factor MAX spread portfolio is primarily derived from the long leg. The high factor MAX portfolio is undervalued, whereas the low factor MAX portfolio is generally overvalued with a much smaller magnitude. Panel B reports the results for the subsample starting from 1990, showing similarities to those in Panel A.

The results in Table 10 also reveal a sharp contrast with stock MAX premium in the U.S. According to Bali, Cakici, and Whitelaw (2011) and many others, stocks with high maximum daily returns in the prior month underperform those with low maximum daily returns, resulting in a low stock MAX premium. However, our findings diverge from this pattern, revealing that factors characterized by high maximum daily returns outperform those with low maximum daily returns. Consequently, we observe a positive relationship between factor MAX and future factor returns. This disparity underscores the distinct nature of the factor MAX anomaly compared to the stock MAX anomaly, even within the U.S. market. Thus, our empirical analysis contributes novel evidence that enriches the existing literature on anomalies.

[Insert Table 10 about here]

## 4.5 Robustness

In this subsection, we conduct a series of robustness checks to demonstrate the qualitative and quantitative robustness of the factor MAX premium.

The existing literature refers to the multitude of factors as the “factor zoo”. To assess whether the factor MAX premium documented in this study is sensitive to the choice of factors, we randomly draw subsets of factors from the universe of our 142 factors. Specifically, we randomly select 50 or 100 factors and perform portfolio analysis by sorting them into five groups based on the average of their five largest returns in the prior month. This exercise is repeated 1000 times, recording the $t$-statistics of excess returns and FF5 adjusted alphas each time. The distributions of these t-statistics are plotted in Figure 3. As illustrated, the majority of both excess returns and FF5 adjusted returns are statistically significant at 5% level ($t$-statistics larger than 2). For instance, in Panel A, when randomly drawing 50 factors for 1000 times, 93% of the excess returns are significant at 1% level and 98% of the risk-adjusted returns are significant at 1% level. Turning to Panel B, when randomly drawing 100 factors for 1000 times, 99% of the excess returns are significant at 1% level and all of the risk-adjusted returns are significant at 1% level. In sum, the results in this section demonstrate that the factor MAX premium remains robust and does not depend on the specific choice of factors from the factor zoo.

[Insert Figure 3 about here]

We proceed to conduct several portfolio analysis and present the results in Table 11. First, we sort factors into quintile based on the average of their three largest daily returns (MAX3) so that P5 (P1) contains factors with the highest (lowest) MAX3 and H-L refers to the strategy that buys P5 and sells P1. Panel A of Table 11 demonstrates the continued existence of the factor MAX premium, with average excess return of 0.61% per month ($t$-statistics = 3.04). The risk-adjusted returns against LSY3 and FF5 model are 0.41% and 0.74%, respectively ($t$-statistics = 2.02 and 4.13). Second, factors are sorted into quintile based on the average of their seven largest daily returns (MAX7) so that P5 (P1) contains factors with the highest (lowest) MAX7 and H-L refers to the strategy that buys P5 and sells P1. Panel B of reveals an even larger factor MAX premium, with average excess returns of 0.70% ($t$-statistics = 3.10). The risk-adjusted returns are also larger than those in Table 1 (0.57% for LSY3 model and 0.82% for FF5 model). Finally, we form decile portfolios by sorting factors into ten groups based on the average of their five largest daily returns (MAX) in the prior month so that P10 (P1) contains the factors with the highest (lowest) MAX and H–L refers to the strategy that buys P10 and sells P1. Panel C of Table 11 displays a significantly larger factor MAX portfolio spread with average excess returns of 1.17% ($t$-statistics = 2.80). The risk-adjusted returns for LSY3 and FF5 are 0.84% and 1.28%, respectively, which are both economically and statistically significant ($t$-statistics = 2.08 and 4.18).

[Insert Table 11 about here]

## 5 Conclusion

In this paper, we unveil a novel factor MAX premium utilizing an extensive factor zoo in the Chinese market. In the cross section, factors with high maximum daily returns significantly outperform those with low maximum daily returns by 0.82% per month in the future, on a risk-adjusted basis. Importantly, the factor MAX premium stands resilient against other well-known factor characteristics and remains unaffected by the data mining of the "factor zoo". Spanning tests show that factor MAX anomaly is distinct from lottery-type stock anomalies and effectively explains a significant portion of these anomalies. Echoing the insights of Kozak, Nagel, and Santosh (2018, 2020), the factor MAX premium concentrates in high-eigenvalue principal component factors, is significantly stronger in periods of elevated investor sentiment, and remains persistent and significant up to 12 months after formation. We also document a significant factor MAX premium in the U.S.

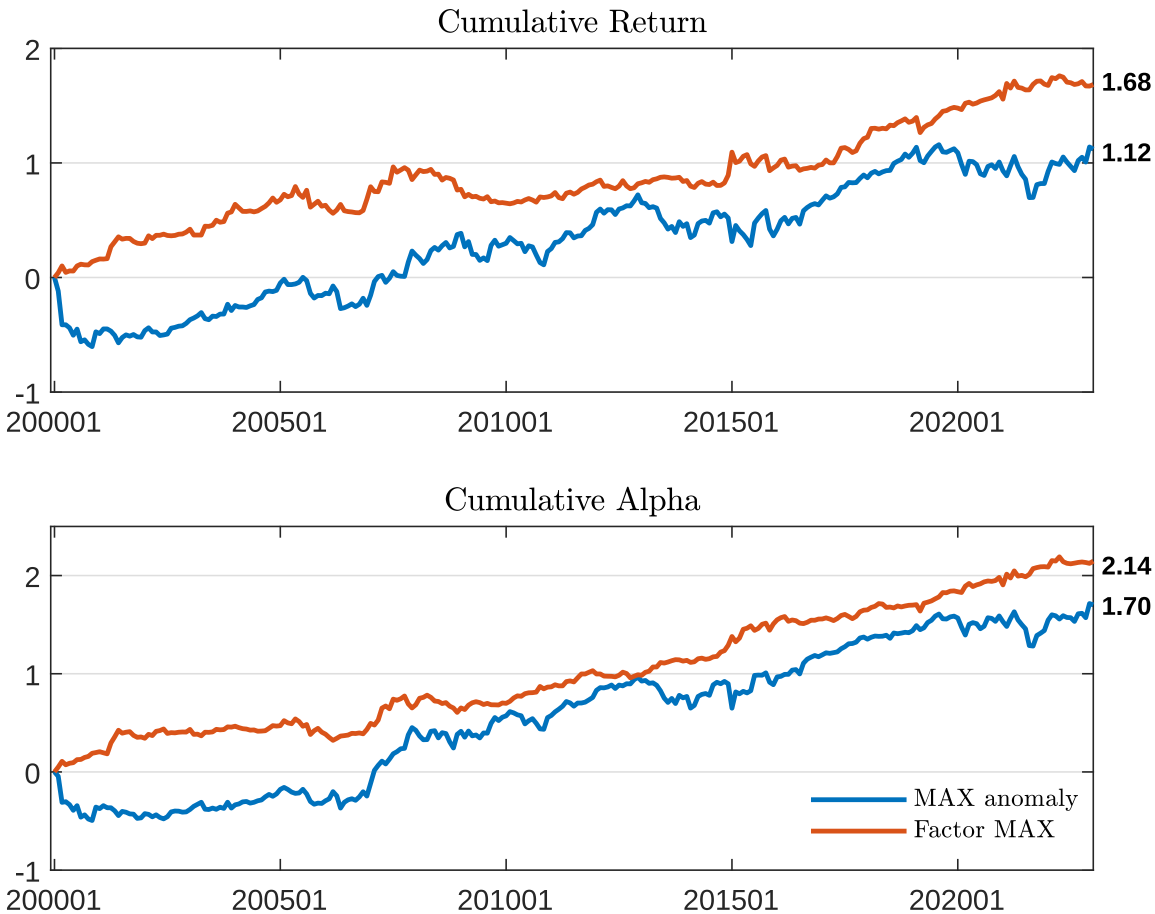


**Figure 1** Factor MAX vs. MAX anomaly: cumulative performance.

This figure plots the log cumulative returns and FF5 alphas of the factor MAX spread portfolio and stock MAX spread portfolio. We sort factors into five groups based on the average of their five largest returns (MAX) over the prior month and factor MAX spread portfolio is constructed by buying high MAX portfolio and selling low MAX portfolio. Anomalously, we sort stocks into five groups based on their maximum daily return in the prior month and MAX spread portfolio is constructed by buying (selling) the portfolio with highest (lowest) maximum daily return. The sample period is 2000:01 – 2022:12.

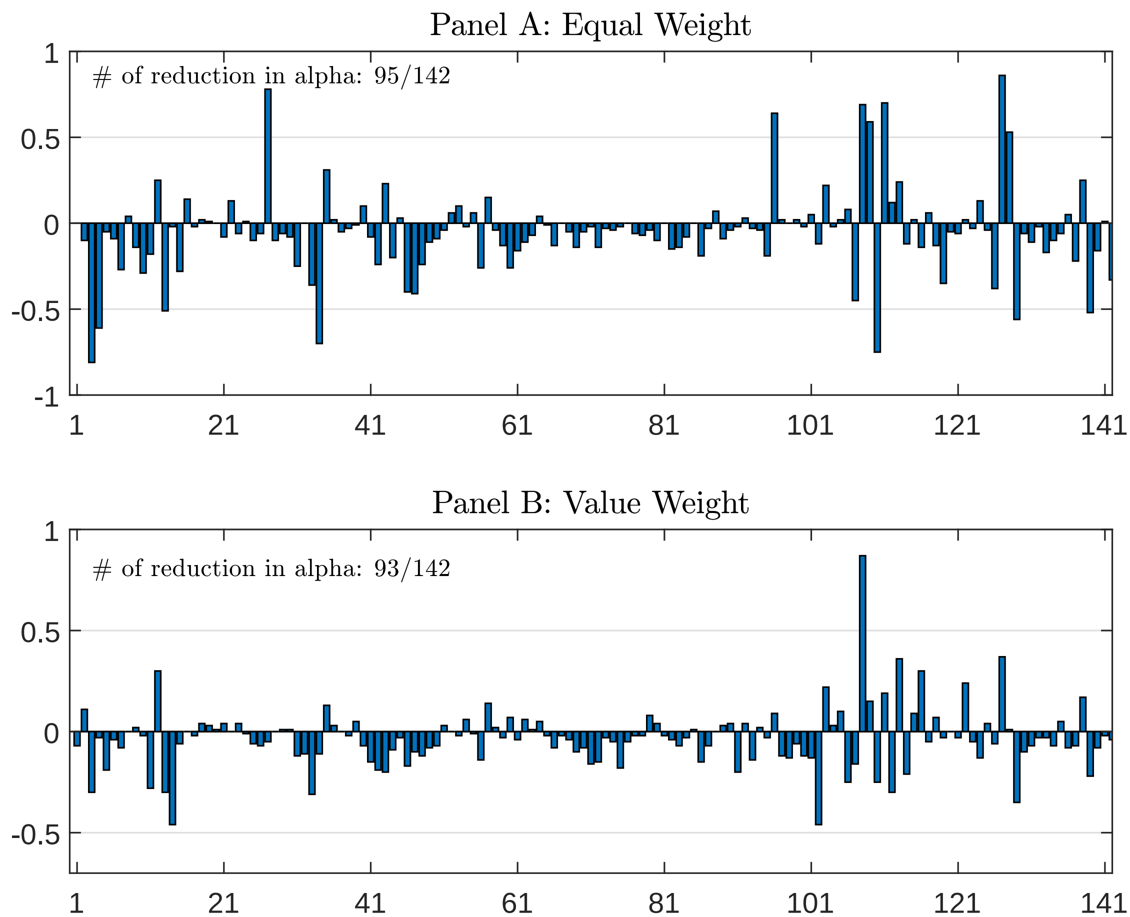


**Figure 2** Digest stock anomalies

This figure plots the absolute difference in alphas between the Chinese five-factor model (FF5) and FF5 augmented with the factor MAX spread portfolio in digesting the 142 anomalies. Panel A (B) reports the results using equal- (value-) weight anomaly returns and factor MAX spread portfolio. Negative value suggests a reduction in absolute alpha when FF5 augmented with the factor MAX spread portfolio in explaining anomaly returns. The sample period is from 2000:01–2022:12.

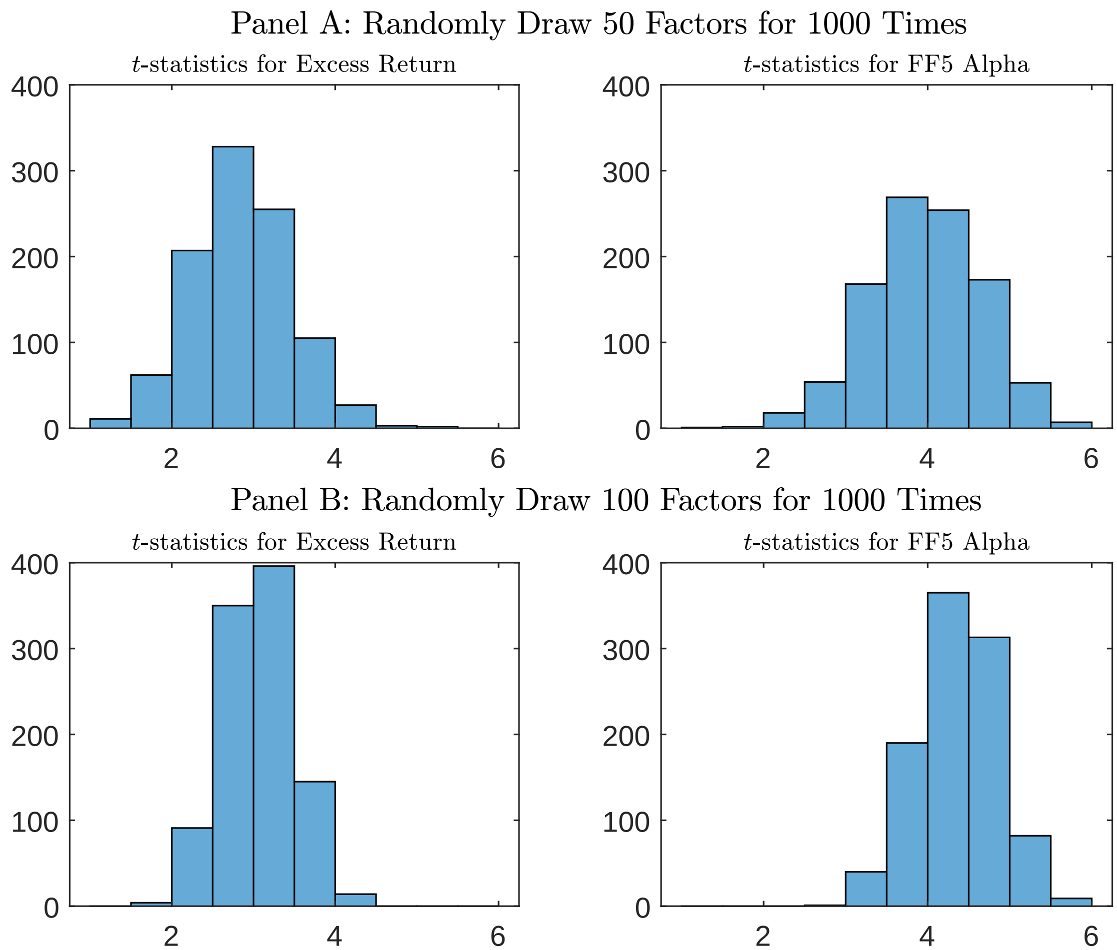


**Figure 3** Performance of the bootstrapped factor MAX spread portfolio

This figure plots the distribution of $t$-statistics of the returns and alphas for the bootstrapped factor MAX spread portfolio. Panel A (B) randomly draws 50 (100) factors from the factor zoo for 1000 times. Each time, we form the factor MAX spread portfolio and calculate the $t$-statistics for returns and FF5 alphas. The sample period is from 2000:01–2022:12.

**Table 1** Performance of factor MAX portfolios

This table reports monthly average excess returns, Sharpe ratio (SR) and alphas (in %) of factor MAX quintile portfolios, where P1 (P5) refers to the portfolio with lowest (highest) MAX, and H – L refers to the strategy that buys P5 and sells P1. Portfolios are formed by sorting factors into five groups based on the average of their five largest returns (MAX) in the prior month. All portfolios are rebalanced at a monthly frequency. Factor models include Liu, Stambaugh, and Yuan (2019) three-factor model (LSY3), and Chinese five-factor model following Fama and French (2015) (FF5). $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| Panel A: MAX is constructed using EW factors and traded on EW factors | | | | | | |
| Excess | −0.02 | 0.03 | 0.12 | 0.32 | 0.74 | 0.77 |
| | (−0.45) | (0.37) | (1.86) | (3.42) | (3.28) | (3.17) |
| SR | 0.22 | −0.03 | 0.02 | 0.12 | 0.21 | 0.22 |
| $\alpha_{\text{LSY3}}$ | −0.07 | −0.06 | 0.08 | 0.23 | 0.46 | 0.53 |
| | (−1.18) | (−0.60) | (1.38) | (2.39) | (1.96) | (2.03) |
| $\alpha_{\text{FF5}}$ | −0.01 | 0.06 | 0.15 | 0.33 | 0.73 | 0.74 |
| | (−0.12) | (1.21) | (2.59) | (4.42) | (4.88) | (4.48) |
| Panel B: MAX is constructed using VW factors and traded on VW factors | | | | | | |
| Excess | −0.04 | 0.01 | 0.18 | 0.24 | 0.64 | 0.68 |
| | (−0.61) | (0.14) | (2.21) | (2.37) | (3.52) | (3.29) |
| SR | 0.17 | −0.04 | 0.01 | 0.12 | 0.13 | 0.18 |
| $\alpha_{\text{LSY3}}$ | −0.18 | 0.00 | 0.16 | 0.18 | 0.34 | 0.52 |
| | (−2.38) | (0.01) | (2.49) | (2.28) | (1.96) | (2.50) |
| $\alpha_{\text{FF5}}$ | −0.04 | 0.04 | 0.21 | 0.31 | 0.78 | 0.82 |
| | (−0.56) | (0.53) | (4.34) | (4.73) | (5.36) | (4.30) |

**Table 2** Portfolio characteristics

This table reports the average portfolio characteristics for each factor MAX quintile, including mean, volatility (VOL), idiosyncratic volatility (IVOL), skewness (SKEW), idiosyncratic skewness (ISKEW). P1 (P5) refers to the portfolio with the lowest (highest) MAX, and H–L refers to the strategy that buys P5 and sells P1. Factor returns are value-weighted and all portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| MEAN | −0.04 | 0.07 | 0.25 | 0.22 | 0.71 | 0.75 |
| | | | | | | (2.74) |
| VOL | 0.45 | 0.53 | 0.64 | 0.79 | 1.02 | 0.57 |
| | | | | | | (27.90) |
| IVOL | 0.29 | 0.32 | 0.35 | 0.38 | 0.46 | 0.16 |
| | | | | | | (20.80) |
| SKEW | −1.61 | −0.29 | 6.03 | 16.41 | 29.47 | 31.08 |
| | | | | | | (9.96) |
| ISKEW | −1.80 | −0.24 | 3.74 | 10.72 | 21.50 | 23.31 |
| | | | | | | (7.93) |

**Table 3** Portfolios sorted by MAX after controlling for MOM, MIN, IVOL, and ISKEW

This table reports the returns and alphas (in %) of portfolios formed by sorting factors based on the MAX after controlling for factor momentum (MOM), factor minimum (MIN), factor idiosyncratic volatility (IVOL), and factor idiosyncratic skewness (ISKEW). In each case, we first sort factors into quintiles using the control variable, then within each quintile, we sort factors into quintiles based on MAX so that quintile 1 (5) contains factors with the lowest (highest) MAX and H–L refers to the difference in returns (alphas) between the highest MAX and lowest MAX portfolios. Reported are the average excess returns and alphas across the five control quintiles to produce quintile portfolios with dispersion in MAX but with similar levels of the control variable. Factor returns are value-weighted and all portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | | MAX | | | | | |
|---|---|---|---|---|---|---|---|
| | | P1 | P2 | P3 | P4 | P5 | H–L |
| MOM | Excess | 0.05 | 0.07 | 0.28 | 0.28 | 0.39 | 0.34 |
| | | (0.87) | (0.95) | (4.10) | (3.38) | (2.94) | (2.70) |
| | FF5 | 0.07 | 0.10 | 0.31 | 0.36 | 0.51 | 0.44 |
| | | (1.53) | (1.79) | (5.35) | (4.86) | (5.07) | (3.66) |
| MIN | Excess | 0.03 | 0.08 | 0.16 | 0.32 | 0.56 | 0.53 |
| | | (0.27) | (0.72) | (1.87) | (2.86) | (3.22) | (2.14) |
| | FF5 | 0.02 | 0.10 | 0.21 | 0.45 | 0.65 | 0.64 |
| | | (0.18) | (1.06) | (3.03) | (4.36) | (4.63) | (2.89) |
| IVOL | Excess | 0.02 | 0.02 | 0.21 | 0.30 | 0.55 | 0.53 |
| | | (0.21) | (0.21) | (2.61) | (2.48) | (3.16) | (2.39) |
| | FF5 | 0.03 | 0.06 | 0.25 | 0.38 | 0.66 | 0.63 |
| | | (0.31) | (0.72) | (3.41) | (5.53) | (4.52) | (3.34) |
| ISKEW | Excess | −0.07 | 0.13 | 0.21 | 0.32 | 0.49 | 0.56 |
| | | (−0.95) | (1.45) | (2.68) | (3.14) | (3.13) | (3.05) |
| | FF5 | −0.06 | 0.17 | 0.28 | 0.40 | 0.56 | 0.61 |
| | | (−0.78) | (2.18) | (4.92) | (6.66) | (4.52) | (4.10) |

**Table 4** Portfolios sorted by control variables after controlling for MAX

This table reports the returns and alphas (in %) of portfolios formed by sorting factors based on the control variables after controlling for MAX. Control variables include factor momentum (MOM), factor minimum (MIN), factor idiosyncratic volatility (IVOL), and factor idiosyncratic skewness (ISKEW). In each case, we first sort factors into quintiles using MAX, then within each quintile, we sort factors into quintiles based on the control variable so that quintile 1 (5) contains factors with the lowest (highest) control variable and H–L refers to the difference in returns (alphas) between the high control variable and low control variable portfolios. Reported are the average returns and alphas across the five control quintiles to produce quintile portfolios with dispersion in control variable but with similar levels of MAX. Factor returns are value-weighted and all portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | | Control variable | | | | | |
|---|---|---|---|---|---|---|---|
| | | P1 | P2 | P3 | P4 | P5 | H–L |
| MOM | Excess | 0.12 | 0.17 | 0.22 | 0.21 | 0.34 | 0.22 |
| | | (0.73) | (1.61) | (2.66) | (2.17) | (2.97) | (0.89) |
| | FF5 | 0.18 | 0.25 | 0.28 | 0.24 | 0.39 | 0.22 |
| | | (1.21) | (2.91) | (4.25) | (3.02) | (4.10) | (0.96) |
| MIN | Excess | 0.13 | 0.17 | 0.24 | 0.22 | 0.38 | 0.25 |
| | | (0.86) | (1.95) | (2.90) | (2.23) | (3.65) | (1.11) |
| | FF5 | 0.14 | 0.26 | 0.30 | 0.30 | 0.43 | 0.29 |
| | | (0.99) | (3.65) | (4.30) | (3.96) | (4.61) | (1.36) |
| IVOL | Excess | 0.26 | 0.22 | 0.12 | 0.18 | 0.23 | −0.03 |
| | | (3.54) | (2.74) | (1.32) | (2.22) | (2.06) | (−0.22) |
| | FF5 | 0.30 | 0.28 | 0.19 | 0.27 | 0.24 | −0.06 |
| | | (5.16) | (5.31) | (2.73) | (4.20) | (2.47) | (−0.54) |
| ISKEW | Excess | 0.21 | 0.28 | 0.22 | 0.14 | 0.19 | −0.02 |
| | | (1.93) | (3.21) | (2.69) | (1.57) | (1.85) | (−0.15) |
| | FF5 | 0.22 | 0.33 | 0.31 | 0.22 | 0.24 | 0.01 |
| | | (2.13) | (4.74) | (5.11) | (3.10) | (2.34) | (0.06) |

**Table 5** Fama-MacBeth regressions

This table reports the results of Fama-MacBeth regressions of one-month-ahead factor returns on MAX, controlling for factor momentum (MOM), factor minimum (MIN), factor idiosyncratic volatility (IVOL), and factor idiosyncratic skewness (ISKEW). Factor returns are value-weighted. Newey-West $t$-statistics are reported in parentheses. ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000:01 – 2022:12.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| MAX | 0.15*** | 0.11*** | 0.19*** | 0.17*** | 0.14*** | 0.31** |
| | (4.14) | (3.55) | (3.39) | (2.87) | (4.35) | (2.07) |
| MOM | | 0.03 | | | | −0.02 |
| | | (0.97) | | | | (−0.43) |
| MIN | | | 0.26 | | | 0.30 |
| | | | (1.42) | | | (1.38) |
| IVOL | | | | −0.10 | | 0.01 |
| | | | | (−1.84) | | (0.01) |
| ISKEW | | | | | −0.01 | −0.01 |
| | | | | | (−0.74) | (−2.46) |
| R2 | 0.09 | 0.21 | 0.13 | 0.18 | 0.14 | 0.31 |

**Table 6** Factor MAX vs. lottery-related anomaly

This table reports the results of spanning test between factor MAX spread portfolio and lottery-related anomalies. Panel A reports the results of regressing lottery-related anomalies on factor MAX spread portfolio, where lottery anomalies include factors constructed based on maximum daily return (MAX1), average of largest five daily returns (MAX5), idiosyncratic volatility (IVOL), skewness (SKEW), coskewness (COSKEW) and idiosyncratic skewness (ISKEW). Panle B reports the results of regressing factor MAX spread portfolio on lottery-related anomalies. Factor returns are value-weighted. $t$-statistics are reported in parentheses. ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000:01 – 2022:12.

| DepVar: Lottery-related anomalies | | | | DepVar: Factor MAX spread portfolio | | | |
|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $R^2$ | | $\alpha$ | $\beta$ | $R^2$ |
| MAX1 | 0.59$^{*}$ | 5.39 | −0.01 | MAX1 | 0.72$^{***}$ | 3.22 | −0.01 |
| | (1.70) | (0.67) | | | (2.89) | (0.67) | |
| MAX5 | 0.51 | 2.51 | −0.01 | MAX5 | 0.74$^{***}$ | 1.19 | −0.01 |
| | (1.39) | (0.28) | | | (2.95) | (0.28) | |
| IVOL | 0.78$^{**}$ | 42.02 | 0.10 | IVOL | 0.40$^{*}$ | 23.62 | 0.10 |
| | (2.36) | (5.12) | | | (1.72) | (5.12) | |
| SKEW | 0.72$^{**}$ | −48.76 | 0.26 | SKEW | 0.94$^{***}$ | −53.81$^{***}$ | 0.26 |
| | (3.47) | (−9.56) | | | (4.36) | (−9.56) | |
| COSKEW | 0.49 | −52.19 | 0.15 | COSKEW | 0.78$^{***}$ | −29.83$^{**}$ | 0.15 |
| | (1.59) | (−6.88) | | | (3.38) | (−6.88) | |
| ISKEW | 0.12 | 21.20 | 0.08 | ISKEW | 0.54$^{**}$ | 40.46$^{***}$ | 0.08 |
| | (0.69) | (4.73) | | | (2.21) | (4.73) | |

**Table 7** Factor MAX in high- and low-eigenvalue PC factors

This table reports monthly returns and alphas for factor MAX strategies that trade subset of PC factors ordered by their eigenvalues. We use 10 years (with a minimum of 5 years) of daily returns up to the end of month $t$ to compute the eigenvectors, compute daily PC factor returns to form the MAX strategy and compute month $t$ and $t$+1 returns on the PC factors from these eigenvalues. We order PC factors by their eigenvalues and assign them into groups. A PC factor strategy sort the factors by the average of their largest five PC factor returns and longs (shorts) the factors in the top (bottom) quintiles. Factor returns are value-weighted. Newey-West $t$-statistics are reported in parentheses. ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000:01 – 2022:12.

| | PC1 – PC10 | PC11 – PC20 | PC21 – PC30 | PC31 – PC40 | PC41 – PC50 |
|---|---|---|---|---|---|
| Returns | 0.71** | 0.05 | 0.23 | 0.22 | −0.44 |
| | (2.09) | (0.15) | (0.81) | (0.61) | (−1.18) |
| Adj. $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| $\alpha_{\text{FF5}}$ | 0.77*** | 0.12 | 0.41*** | 0.29 | −0.52 |
| | (2.43) | (0.36) | (2.65) | (0.91) | (−1.35) |
| Adj. $R^2$ | 0.06 | 0.01 | 0.10 | 0.05 | 0.01 |
| | PC51 – PC60 | PC61 – PC70 | PC71 – PC80 | PC81 – PC90 | PC91 – PC106 |
| Returns | 0.22 | 0.60 | 0.24 | 0.23 | 0.30 |
| | (0.55) | (1.59) | (0.56) | (0.59) | (0.83) |
| Adj. $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| $\alpha_{\text{FF5}}$ | 0.26 | 0.66 | 0.33 | 0.46 | 0.36 |
| | (0.72) | (1.80) | (0.85) | (1.16) | (0.90) |
| Adj. $R^2$ | 0.07 | 0.03 | −0.01 | 0.06 | 0.03 |

**Table 8** Factor MAX premium: High vs. low sentiment periods

This table reports the monthly risk-adjusted returns of factor MAX portfolios in high and low sentiment periods. We consider two indexes as the proxy for investor sentiment, including Composite Chinese Investor Sentiment Index (CICSI) and Investor Sentiment Indicator (ISI). A month is defined as a high sentiment month if the sentiment index in the previous month is above its median. P1 and P5 refer to the portfolios with the lowest and highest MAX, and H–L refers to their difference. Factor returns are value-weighted and all portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | Low sentiment | High sentiment | Difference |
|---|---|---|---|
| Panel A: Composite Chinese Investor Sentiment Index (CICSI) | | | |
| Chinese five-factor model ($\alpha_{\text{FF5}}$) | | | |
| P1 | 0.02 | −0.05 | −0.07 |
| | (0.31) | (−0.43) | (−0.54) |
| P5 | 0.48 | 1.11 | 0.63 |
| | (2.31) | (5.71) | (2.42) |
| H–L | 0.45 | 1.16 | 0.70 |
| | (1.84) | (4.75) | (2.15) |
| Liu, Stambaugh, and Yuan (2019) three-factor model ($\alpha_{\text{LSY3}}$) | | | |
| P1 | −0.10 | −0.23 | −0.13 |
| | (−1.09) | (−1.94) | (−0.95) |
| P5 | −0.08 | 0.49 | 0.56 |
| | (−0.35) | (2.04) | (1.73) |
| H–L | 0.03 | 0.72 | 0.69 |
| | (0.11) | (2.55) | (1.91) |
| Panel B: Investor Sentiment Indicator (ISI) | | | |
| Chinese five-factor model ($\alpha_{\text{FF5}}$) | | | |
| P1 | 0.03 | −0.05 | −0.08 |
| | (0.34) | (−0.49) | (−0.60) |
| P5 | 0.60 | 0.99 | 0.40 |
| | (2.81) | (4.81) | (1.40) |
| H–L | 0.57 | 1.05 | 0.48 |
| | (2.28) | (4.42) | (1.74) |
| Liu, Stambaugh, and Yuan (2019) three-factor model ($\alpha_{\text{LSY3}}$) | | | |
| P1 | −0.12 | −0.21 | −0.09 |
| | (−1.27) | (−1.73) | (−0.64) |
| P5 | −0.06 | 0.48 | 0.53 |
| | (−0.25) | (2.05) | (1.62) |
| H–L | 0.07 | 0.69 | 0.62 |
| | (0.24) | (2.62) | (1.90) |

**Table 9** Long term performance

This table reports monthly average excess returns, Sharpe ratio (SR) and alphas (in %) of factor MAX quintile portfolios $h$ months after formation, where P1 (P5) refers to the portfolio with lowest (highest) MAX, and H – L refers to the strategy that buys P5 and sells P1. Portfolios are formed by sorting factors into five groups based on the average of their five largest returns (MAX) in the prior month. Factor returns are value-weighted. All portfolios are rebalanced at a monthly frequency. Factor models include Liu, Stambaugh, and Yuan (2019) three-factor model (LSY3), and Chinese five-factor model following Fama and French (2015) (FF5). $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| Panel A: $h = 3$ | | | | | | |
| Excess | 0.01 | 0.01 | 0.13 | 0.23 | 0.63 | 0.62 |
| | (0.12) | (0.09) | (1.46) | (2.01) | (3.39) | (2.88) |
| SR | 0.17 | 0.01 | 0.01 | 0.09 | 0.12 | 0.20 |
| $\alpha_{\mathrm{LSY3}}$ | −0.05 | −0.09 | 0.06 | 0.15 | 0.39 | 0.44 |
| | (−0.68) | (−1.37) | (0.86) | (1.40) | (2.34) | (2.34) |
| $\alpha_{\mathrm{FF5}}$ | 0.03 | 0.06 | 0.22 | 0.33 | 0.64 | 0.60 |
| | (0.51) | (0.90) | (3.24) | (3.42) | (4.41) | (3.30) |
| Panel B: $h = 6$ | | | | | | |
| Excess | 0.01 | 0.01 | 0.26 | 0.22 | 0.51 | 0.51 |
| | (0.01) | (0.18) | (3.39) | (1.99) | (2.79) | (2.29) |
| SR | 0.15 | 0.01 | 0.01 | 0.19 | 0.11 | 0.17 |
| $\alpha_{\mathrm{LSY3}}$ | −0.11 | −0.12 | 0.22 | 0.14 | 0.37 | 0.48 |
| | (−0.92) | (−1.37) | (2.40) | (1.49) | (2.00) | (1.85) |
| $\alpha_{\mathrm{FF5}}$ | 0.05 | 0.06 | 0.28 | 0.28 | 0.61 | 0.56 |
| | (0.55) | (0.71) | (4.05) | (3.26) | (3.92) | (2.63) |
| Panel C: $h = 12$ | | | | | | |
| Excess | 0.02 | −0.01 | 0.03 | 0.32 | 0.61 | 0.59 |
| | (0.23) | (−0.11) | (0.33) | (3.16) | (4.47) | (3.32) |
| SR | 0.18 | 0.01 | −0.01 | 0.02 | 0.17 | 0.21 |
| $\alpha_{\mathrm{LSY3}}$ | −0.10 | −0.09 | 0.02 | 0.24 | 0.34 | 0.44 |
| | (−0.92) | (−1.25) | (0.16) | (3.54) | (2.79) | (2.42) |
| $\alpha_{\mathrm{FF5}}$ | 0.05 | 0.01 | 0.12 | 0.37 | 0.68 | 0.63 |
| | (0.55) | (0.16) | (1.46) | (4.95) | (5.46) | (3.69) |

**Table 10** Performance of factor MAX portfolios in the U.S.

This table reports monthly average excess returns, Sharpe ratio (SR) and alphas (in %) of factor MAX quintile portfolios in the U.S. market, where P1 (P5) refers to the portfolio with lowest (highest) MAX, and H – L refers to the strategy that buys P5 and sells P1. Portfolios are formed by sorting factors into five groups based on the average of their five largest returns (MAX) in the prior month. All portfolios are rebalanced at a monthly frequency. Factor models include Fama and French (2015) five-factor model (FF5), the Hou, Xue, and Zhang (2015) q-factor model (HXZ) and Daniel, Hirshleifer, and Sun (2019) behavioral factor model. $t$-statistics are reported in parentheses. The sample period is 1926:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| Panel A: 1926 – 2022 | | | | | | |
| Excess | 0.06 | 0.22 | 0.33 | 0.40 | 0.47 | 0.41 |
| | (1.21) | (5.17) | (7.51) | (7.43) | (5.54) | (4.29) |
| SR | 0.14 | 0.04 | 0.15 | 0.17 | 0.20 | 0.19 |
| $\alpha_{FF5}$ | 0.03 | 0.15 | 0.20 | 0.29 | 0.38 | 0.35 |
| | (1.07) | (4.90) | (5.76) | (6.02) | (7.16) | (5.74) |
| $\alpha_{HXZ}$ | −0.03 | 0.03 | 0.06 | 0.17 | 0.36 | 0.39 |
| | (−0.87) | (0.99) | (1.86) | (3.05) | (4.93) | (4.26) |
| $\alpha_{DHS}$ | 0.05 | 0.12 | 0.15 | 0.18 | 0.28 | 0.24 |
| | (1.65) | (3.18) | (3.57) | (3.82) | (4.17) | (3.66) |
| Panel B: 1990 – 2022 | | | | | | |
| Excess | 0.11 | 0.22 | 0.29 | 0.29 | 0.37 | 0.26 |
| | (2.77) | (3.29) | (3.79) | (3.77) | (4.81) | (3.60) |
| SR | 0.14 | 0.15 | 0.25 | 0.27 | 0.20 | 0.22 |
| $\alpha_{FF5}$ | 0.07 | 0.17 | 0.23 | 0.23 | 0.37 | 0.30 |
| | (2.01) | (3.51) | (5.40) | (3.44) | (5.03) | (3.48) |
| $\alpha_{HXZ}$ | 0.03 | 0.07 | 0.13 | 0.09 | 0.35 | 0.31 |
| | (0.79) | (1.52) | (3.36) | (1.54) | (3.97) | (3.01) |
| $\alpha_{DHS}$ | 0.08 | 0.14 | 0.17 | 0.12 | 0.26 | 0.17 |
| | (2.39) | (2.84) | (3.34) | (2.20) | (3.44) | (2.41) |

**Table 11** Robustness tests

This table presents the results of various robustness tests. Panel A reports the results of portfolio analysis when MAX is constructed using three largest daily factor returns over the prior month. Panel B reports the results of portfolio analysis when MAX is constructed using seven largest daily factor returns over the prior month. Panel C presents the results of sorting factors into ten groups based on the average of five largest daily factor returns over the prior month. The sample period is 2000:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| Panel A: MAX is constructed using three largest daily factor returns | | | | | | |
| Excess | 0.01 | 0.01 | 0.11 | 0.30 | 0.61 | 0.61 |
| | (0.04) | (0.05) | (1.25) | (2.90) | (3.32) | (3.04) |
| SR | 0.16 | 0.01 | 0.01 | 0.08 | 0.16 | 0.17 |
| $\alpha_{\text{LSY3}}$ | −0.11 | −0.02 | 0.09 | 0.23 | 0.30 | 0.41 |
| | (−1.54) | (−0.22) | (1.45) | (2.48) | (1.72) | (2.02) |
| $\alpha_{\text{FF5}}$ | 0.02 | 0.02 | 0.13 | 0.37 | 0.76 | 0.74 |
| | (0.27) | (0.23) | (2.28) | (5.73) | (5.22) | (4.13) |
| Panel B: MAX is constructed using seven largest daily factor returns | | | | | | |
| Excess | −0.06 | 0.03 | 0.20 | 0.23 | 0.63 | 0.70 |
| | (−0.87) | (0.30) | (2.46) | (2.40) | (3.40) | (3.10) |
| SR | 0.17 | −0.05 | 0.02 | 0.14 | 0.13 | 0.18 |
| $\alpha_{\text{LSY3}}$ | −0.19 | −0.01 | 0.15 | 0.17 | 0.38 | 0.57 |
| | (−2.29) | (−0.01) | (2.76) | (1.98) | (2.13) | (2.56) |
| $\alpha_{\text{FF5}}$ | −0.06 | 0.05 | 0.23 | 0.31 | 0.76 | 0.82 |
| | (−0.82) | (0.68) | (4.42) | (4.25) | (5.07) | (4.59) |

Panel C: Decile portfolios

| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | H–L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess | −0.27 | −0.06 | 0.10 | 0.07 | 0.05 | 0.17 | 0.27 | 0.30 | 0.55 | 0.90 | 1.17 |
| | (−1.61) | (−0.47) | (1.10) | (0.58) | (0.30) | (1.01) | (2.16) | (1.58) | (3.20) | (2.94) | (2.80) |
| SR | 0.18 | −0.11 | 0.17 | −0.03 | 0.07 | 0.03 | 0.02 | 0.07 | 0.11 | 0.09 | 0.16 |
| $\alpha_{\text{LSY3}}$ | −0.35 | −0.17 | −0.01 | 0.01 | −0.03 | 0.15 | 0.37 | 0.30 | 0.40 | 0.50 | 0.84 |
| | (−2.74) | (−1.32) | (−0.14) | (0.11) | (−0.17) | (1.08) | (2.59) | (2.06) | (2.12) | (1.51) | (2.08) |
| $\alpha_{\text{FF5}}$ | −0.23 | −0.01 | 0.09 | 0.09 | 0.15 | 0.27 | 0.34 | 0.44 | 0.77 | 1.05 | 1.28 |
| | (−1.96) | (−0.08) | (1.08) | (0.76) | (1.15) | (2.22) | (4.35) | (3.23) | (4.31) | (4.21) | (4.18) |

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# Online Appendix to "Lottery Preference for Factor Investing in China's A-Share Market"

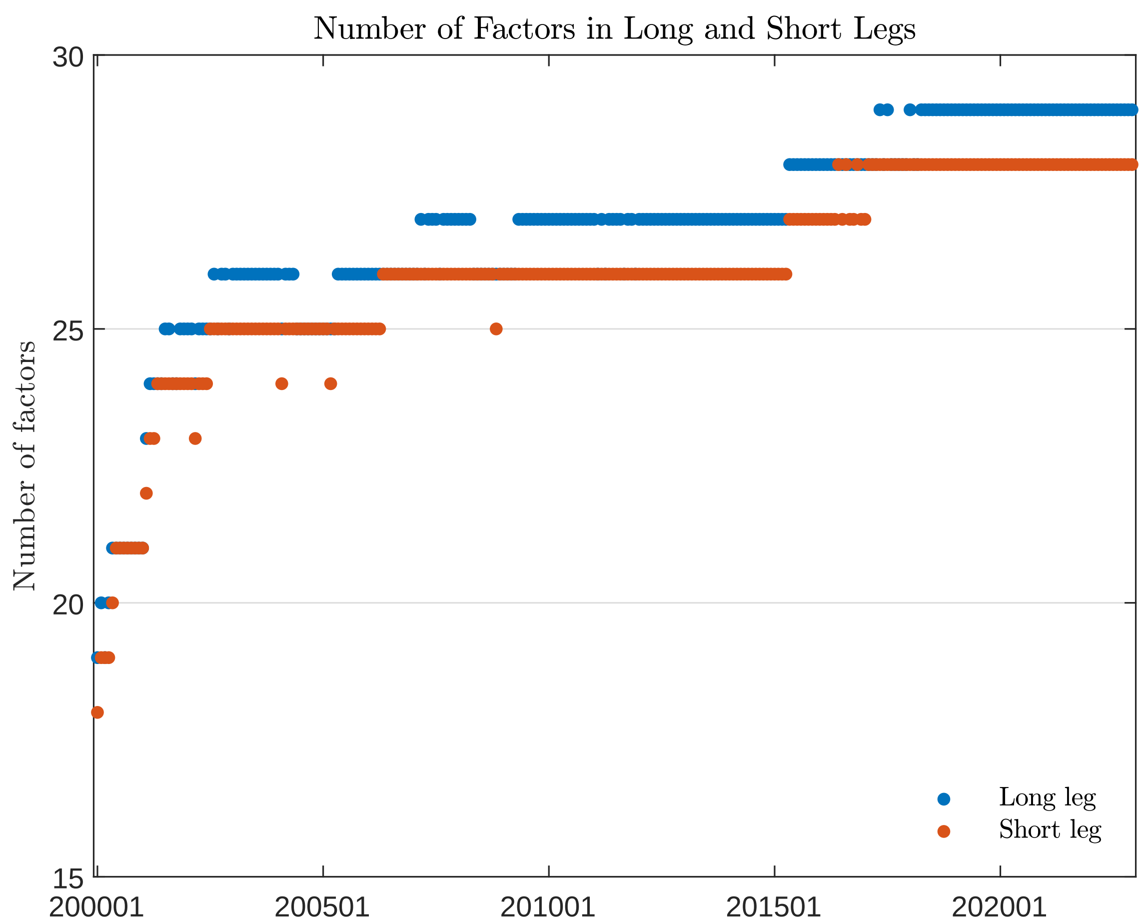


**Figure OA.1** Number of factors in long and short legs

This figure plots number of factors in the long and short legs of the factor MAX strategy. The portfolio is formed by sorting factors into quintiles based on the average of their five largest returns (MAX) in the prior month. Long (Short) leg contains the factors with the highest (lowest) MAX over the past one month. The sample period is 2000:01–2022:12.

**Table OA.1** Portfolio characteristics: Equal weighted

This table reports the average portfolio characteristics for each factor MAX quintile, including mean, volatility (Vol), idiosyncratic volatility (IVol), skewness (Skew), idiosyncratic skewness (ISkew). P1 (P5) refers to the portfolio with the lowest (highest) MAX, and H–L refers to the strategy that buys P5 and sells P1. Factor returns are value-weighted and all portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | P1 | P2 | P3 | P4 | P5 | H–L |
|---|---|---|---|---|---|---|
| Mean | −0.01 | 0.05 | 0.15 | 0.43 | 0.79 | 0.81 |
| | | | | | | (3.38) |
| Vol | 0.29 | 0.36 | 0.44 | 0.57 | 0.80 | 0.51 |
| | | | | | | (32.72) |
| IVol | 0.19 | 0.23 | 0.26 | 0.31 | 0.41 | 0.22 |
| | | | | | | (20.01) |
| Skew | 0.74 | 3.01 | 5.31 | 13.55 | 25.22 | 24.48 |
| | | | | | | (8.35) |
| ISkew | −0.33 | 1.49 | 3.05 | 9.40 | 20.70 | 21.02 |
| | | | | | | (7.05) |

**Table OA.2** Portfolios sorted by MAX after controlling for MOM, VOL, IVOL, and ISKEW: Equal-weighted

This table reports the returns and alphas (in %) of portfolios formed by sorting factors based on the MAX after controlling for momentum (MOM), volatility (VOL), idiosyncratic volatility (IVOL), and idiosyncratic skewness (ISKEW). In each case, we first sort factors into quintiles using the control variable, then within each quintile, we sort factors into quintiles based on MAX so that quintile 1 (5) contains factors with the lowest (highest) MAX and H–L refers to the difference in returns (alphas) between the highest MAX and lowest MAX portfolios. Reported are the average excess returns and alphas across the five control quintiles to produce quintile portfolios with dispersion in MAX but with similar levels of the control variable. Factor returns are equal-weighted. All portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | | MAX | | | | | |
|---|---|---|---|---|---|---|---|
| | | P1 | P2 | P3 | P4 | P5 | H–L |
| MOM | Excess | 0.09 | 0.14 | 0.17 | 0.37 | 0.48 | 0.39 |
| | | (1.99) | (2.46) | (3.05) | (3.86) | (3.67) | (3.10) |
| | FF5 | 0.10 | 0.18 | 0.19 | 0.36 | 0.49 | 0.39 |
| | | (2.76) | (3.62) | (3.90) | (5.24) | (4.86) | (3.64) |
| MIN | Excess | −0.05 | 0.01 | 0.20 | 0.40 | 0.72 | 0.77 |
| | | (−0.60) | (0.18) | (4.57) | (4.66) | (3.12) | (2.59) |
| | FF5 | −0.03 | 0.04 | 0.25 | 0.44 | 0.69 | 0.73 |
| | | (−0.48) | (0.69) | (4.69) | (5.67) | (4.97) | (3.64) |
| IVOL | Excess | −0.02 | 0.07 | 0.21 | 0.39 | 0.60 | 0.62 |
| | | (−0.26) | (0.96) | (3.15) | (3.16) | (3.41) | (2.66) |
| | FF5 | 0.01 | 0.10 | 0.22 | 0.39 | 0.60 | 0.59 |
| | | (0.22) | (1.56) | (3.57) | (4.23) | (4.35) | (3.35) |
| ISKEW | Excess | −0.00 | 0.09 | 0.14 | 0.38 | 0.62 | 0.62 |
| | | (−0.02) | (1.82) | (2.42) | (3.93) | (4.04) | (3.56) |
| | FF5 | 0.02 | 0.13 | 0.16 | 0.40 | 0.59 | 0.57 |
| | | (0.43) | (2.71) | (3.09) | (5.57) | (5.21) | (4.38) |

**Table OA.3** Portfolios sorted by control variables after controlling for MAX: Equal-weighted

This table reports the returns and alphas (in %) of portfolios formed by sorting factors based on the control variables after controlling for MAX. Control variables include momentum (MOM), volatility (VOL), idiosyncratic volatility (IVOL), and idiosyncratic skewness (ISKEW). In each case, we first sort factors into quintiles using MAX, then within each quintile, we sort factors into quintiles based on the control variable so that quintile 1 (5) contains factors with the lowest (highest) control variable and H–L refers to the difference in returns (alphas) between the high control variable and low control variable portfolios. Reported are the average returns and alphas across the five control quintiles to produce quintile portfolios with dispersion in control variable but with similar levels of MAX. Factor returns are equal-weighted. All portfolios are rebalanced at a monthly frequency. $t$-statistics are reported in parentheses. The sample period is 2000:01 – 2022:12.

| | | Control variable | | | | | |
|---|---|---|---|---|---|---|---|
| | | P1 | P2 | P3 | P4 | P5 | H–L |
| MOM | Excess | 0.09 | 0.12 | 0.28 | 0.30 | 0.43 | 0.34 |
| | | (0.70) | (1.78) | (3.29) | (2.45) | (3.25) | (1.52) |
| | FF5 | 0.12 | 0.16 | 0.31 | 0.32 | 0.40 | 0.28 |
| | | (0.98) | (3.39) | (4.90) | (3.57) | (4.15) | (1.47) |
| MIM | Excess | 0.13 | 0.17 | 0.20 | 0.31 | 0.45 | 0.32 |
| | | (1.05) | (3.71) | (2.81) | (3.11) | (4.21) | (1.58) |
| | FF5 | 0.14 | 0.21 | 0.25 | 0.32 | 0.44 | 0.31 |
| | | (1.19) | (3.78) | (4.27) | (4.38) | (5.20) | (1.80) |
| IVOL | Excess | 0.33 | 0.28 | 0.18 | 0.17 | 0.22 | −0.12 |
| | | (4.84) | (3.33) | (2.11) | (1.95) | (1.90) | (−0.92) |
| | FF5 | 0.36 | 0.30 | 0.19 | 0.19 | 0.22 | −0.13 |
| | | (6.43) | (4.24) | (3.20) | (2.61) | (2.46) | (−1.14) |
| ISKEW | Excess | 0.25 | 0.18 | 0.25 | 0.27 | 0.25 | 0.00 |
| | | (2.75) | (3.12) | (2.90) | (2.45) | (2.03) | (0.02) |
| | FF5 | 0.26 | 0.21 | 0.28 | 0.27 | 0.26 | −0.00 |
| | | (3.08) | (4.02) | (4.19) | (2.94) | (2.56) | (−0.03) |

**Table OA.4** Fama-MacBeth regressions: Equal-weighted

This table reports the results of Fama-MacBeth regressions of one-month-ahead factor returns on MAX, controlling for factor momentum (MOM), factor volatility (VOL), factor idiosyncratic volatility (IVOL), factor minimum (MIN), and factor idiosyncratic skewness (ISKEW). Factor returns are equal-weighted. Newey-West $t$-statistics are reported in parentheses. ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000:01 – 2022:12.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| MAX | 0.12*** | 0.12*** | 0.29*** | 0.20*** | 0.18*** | 0.33** |
| | (4.87) | (4.22) | (4.23) | (3.00) | (4.89) | (1.96) |
| MOM | | 0.06 | | | | 0.03 |
| | | (1.78) | | | | (0.54) |
| MIN | | | 0.21 | | | 0.01 |
| | | | (1.10) | | | (0.04) |
| IVOL | | | | −1.45 | | −0.30 |
| | | | | (−2.36) | | (−0.81) |
| ISKEW | | | | | −0.01 | −0.01 |
| | | | | | (−0.71) | (−1.61) |
| R2 | 0.09 | 0.25 | 0.16 | 0.20 | 0.12 | 0.34 |

**Table OA.5** Factor details and citations

| Description | Variable | Citation | Sign |
|---|---|---|---|
| | | **Accruals** | |
| Change in current operating working capital | cowc_gr1a | Richardson, Sloan, Soliman, and Tuna (2005) | -1 |
| Operating accruals | oaccruals_at | Sloan (1996) | -1 |
| Percent operating accruals | oaccruals_ni | Hafzalla, Lundholm, and Matthew Van Winkle (2011) | -1 |
| Years 16-20 lagged returns, non-annual | seas_16_20na | Heston and Sadka (2008) | 1 |
| Total accruals | taccruals_at | Richardson et al. (2005) | -1 |
| Percent total accruals | taccruals_ni | Hafzalla et al. (2011) | -1 |
| | | **Debt Issuance** | |
| Abnormal corporate investment | capex_abn | Titman, Wei, and Xie (2004) | -1 |
| Growth in book debt (3 years) | debt_gr3 | Lyandres, Sun, and Zhang (2008) | -1 |
| Change in financial liabilities | fnl_gr1a | Richardson et al. (2005) | -1 |
| Change in noncurrent operating liabilities | ncol_gr1a | Richardson et al. (2005) | -1 |
| Change in net financial assets | nfna_gr1a | Richardson et al. (2005) | 1 |
| Earnings persistence | ni_ar1 | Francis, LaFond, Olsson, and Schipper (2004) | 1 |
| Net operating assets | noa_at | Hirshleifer, Hou, Teoh, and Zhang (2004) | -1 |
| | | **Investment** | |
| Liquidity of book assets | aliq_at | Ortiz-Molina and Phillips (2014) | -1 |
| Asset Growth | at_gr1 | Cooper, Gulen, and Schill (2008) | -1 |
| Change in common equity | be_gr1a | Richardson et al. (2005) | -1 |
| CAPEX growth (1 year) | capx_gr1 | Xie (2001) | -1 |
| CAPEX growth (2 years) | capx_gr2 | Anderson and Garcia-Feijoo (2006) | -1 |
| CAPEX growth (3 years) | capx_gr3 | Anderson and Garcia-Feijoo (2006) | -1 |
| Change in current operating assets | coa_gr1a | Richardson et al. (2005) | -1 |
| Change in current operating liabilities | col_gr1a | Richardson et al. (2005) | -1 |
| Hiring rate | emp_gr1 | Belo, Lin, and Bazdresch (2014) | -1 |
| Inventory growth | inv_gr1 | Belo and Lin (2012) | -1 |
| Inventory change | inv_gr1a | J. K. Thomas and Zhang (2002) | -1 |
| Change in long-term net operating assets | lnoa_gr1a | Fairfield, Whisenant, and Yohn (2003) | -1 |
| Mispricing factor: Management | mispricing_mgmt | Stambaugh and Yuan (2017) | 1 |
| Change in noncurrent operating assets | ncoa_gr1a | Richardson et al. (2005) | -1 |
| Change in net noncurrent operating assets | nncoa_gr1a | Richardson et al. (2005) | -1 |
| Change in net operating assets | noa_gr1a | Hirshleifer et al. (2004) | -1 |

| Description | Variable | Citation | Sign |
|---|---|---|---|
| Change PPE and Inventory | ppeinv_gr1a | Lyandres et al. (2008) | -1 |
| Long-term reversal | ret_60_12 | De Bondt and Thaler (1985) | -1 |
| Sales Growth (1 year) | sale_gr1 | Lakonishok, Shleifer, and Vishny (1994) | -1 |
| Sales Growth (3 years) | sale_gr3 | Lakonishok et al. (1994) | -1 |
| Sales growth (1 quarter) | saleq_gr1 | | -1 |
| Years 2-5 lagged returns, non-annual | seas_2_5na | Heston and Sadka (2008) | -1 |
| | **Low Leverage** | | |
| Firm age | age | Jiang, Lee, and Zhang (2005) | -1 |
| Liquidity of market assets | aliq_mat | Ortiz-Molina and Phillips (2014) | -1 |
| Book leverage | at_be | Fama and French (1992) | -1 |
| The high-low bid-ask spread | bidaskhl_21d | Corwin and Schultz (2012) | 1 |
| Cash-to-assets | cash_at | Palazzo (2012) | 1 |
| Net debt-to-price | netdebt_me | Penman, Richardson, and Tuna (2007) | -1 |
| Earnings volatility | ni_ivol | Francis et al. (2004) | 1 |
| R&D-to-sales | rd_sale | Chan, Lakonishok, and Sougiannis (2001) | 1 |
| R&D capital-to-book assets | rd5_at | Li (2011) | 1 |
| Asset tangibility | tangibility | Hahn and Lee (2009) | 1 |
| Altman Z-score | z_score | Dichev (1998) | 1 |
| | **Low Risk** | | |
| Market Beta | beta_60m | Fama and MacBeth (1973) | -1 |
| Dimson beta | beta_dimson_21d | Dimson (1979) | -1 |
| Frazzini-Pedersen market beta | betabab_1260d | Frazzini and Pedersen (2014) | -1 |
| Downside beta | betadown_252d | Ang, Chen, and Xing (2006) | -1 |
| Earnings variability | earnings_variability | Ftyrancis et al. (2004) | -1 |
| Idiosyncratic volatility from the CAPM (21 days) | ivol_capm_21d | | -1 |
| Idiosyncratic volatility from the CAPM (252 days) | ivol_capm_252d | Ali, Hwang, and Trombley (2003) | -1 |
| Idiosyncratic volatility from the Fama-French 3-factor model | ivol_ff3_21d | Ang, Hodrick, Xing, and Zhang (2006) | -1 |
| Idiosyncratic volatility from the q-factor model | ivol_hxz4_21d | | -1 |
| Cash flow volatility | ocfq_saleq_std | Huang (2009) | -1 |
| Maximum daily return | rmax1_21d | Bali, Cakici, and Whitelaw (2011) | -1 |
| Highest 5 days of return | rmax5_21d | Bali, Brown, and Tang (2017) | -1 |
| Return volatility | rvol_21d | Ang, Hodrick, et al. (2006) | -1 |
| Years 6-10 lagged returns, non-annual | seas_6_10na | Heston and Sadka (2008) | -1 |
| Share turnover | turnover_126d | Datar, Naik, and Radcliffe (1998) | -1 |

| Description | Variable | Citation | Sign |
|---|---|---|---|
| Number of zero trades with turnover as tiebreaker (1 month) | zero_trades_21d | Liu (2006) | 1 |
| Number of zero trades with turnover as tiebreaker (6 months) | zero_trades_126d | Liu (2006) | 1 |
| Number of zero trades with turnover as tiebreaker (12 months) | zero_trades_252d | Liu (2006) | 1 |
| | **Momentum** | | |
| Current price to high price over last year | prc_highprc_252d | George and Hwang (2004) | 1 |
| Residual momentum t-6 to t-1 | resff3_6_1 | Blitz, Huij, and Martens (2011) | 1 |
| Residual momentum t-12 to t-1 | resff3_12_1 | Blitz et al. (2011) | 1 |
| Price momentum t-3 to t-1 | ret_3_1 | Jegadeesh and Titman (1993) | 1 |
| Price momentum t-6 to t-1 | ret_6_1 | Jegadeesh and Titman (1993) | 1 |
| Price momentum t-9 to t-1 | ret_9_1 | Jegadeesh and Titman (1993) | 1 |
| Price momentum t-12 to t-1 | ret_12_1 | Jegadeesh and Titman (1993) | 1 |
| Year 1-lagged return, non-annual | seas_1_1na | Heston and Sadka (2008) | 1 |
| | **Profit Growth** | | |
| Change sales minus change Inventory | dsale_dinv | Abarbanell and Bushee (1998) | 1 |
| Change sales minus change receivables | dsale_drec | Abarbanell and Bushee (1998) | -1 |
| Change sales minus change SG&A | dsale_dsga | Abarbanell and Bushee (1998) | 1 |
| Change in quarterly return on assets | niq_at_chg1 | | 1 |
| Change in quarterly return on equity | niq_be_chg1 | | 1 |
| Standardized earnings surprise | niq_su | Foster, Olsen, and Shevlin (1984) | 1 |
| Change in operating cash flow to assets | ocf_at_chg1 | Bouchaud, Krueger, Landier, and Thesmar (2019) | 1 |
| Price momentum t-12 to t-7 | ret_12_7 | Novy-Marx (2012) | 1 |
| Labor force efficiency | sale_emp_gr1 | Abarbanell and Bushee (1998) | 1 |
| Standardized Revenue surprise | saleq_su | Jegadeesh and Livnat (2006) | 1 |
| Year 1-lagged return, annual | seas_1_1an | Heston and Sadka (2008) | 1 |
| Tax expense surprise | tax_gr1a | J. Thomas and Zhang (2011) | 1 |
| | **Profitability** | | |
| Coefficient of variation for dollar trading volume | dolvol_var_126d | Chordia, Subrahmanyam, and Anshuman (2001) | -1 |
| Return on net operating assets | ebit_bev | Soliman (2008) | 1 |
| Profit margin | ebit_sale | Soliman (2008) | 1 |
| Pitroski F-score | f_score | Piotroski (2000) | 1 |
| Return on equity | ni_be | Haugen and Baker (1996) | 1 |
| Quarterly return on equity | niq_be | Hou, Xue, and Zhang (2015) | 1 |
| Ohlson O-score | o_score | Dichev (1998) | -1 |
| Operating cash flow to assets | ocfat | Bouchaud et al. (2019) | 1 |
| Operating profits-to-book equity | ope_be | Fama and French (2015) | 1 |

| Description | Variable | Citation | Sign |
|---|---|---|---|
| Operating profits-to-lagged book equity | ope_bel1 | | 1 |
| Coefficient of variation for share turnover | turnover_var_126d | Chordia et al. (2001) | -1 |
| | **Quality** | | |
| Capital turnover | at_turnover | Haugen and Baker (1996) | 1 |
| Cash-based operating profits-to-book assets | cop_at | | 1 |
| Cash-based operating profits-to-lagged book assets | cop_atl1 | Ball, Gerakos, Linnainmaa, and Nikolaev (2016) | 1 |
| Change gross margin minus change sales | dgp_dsale | Abarbanell and Bushee (1998) | 1 |
| Gross profits-to-assets | gp_at | Novy-Marx (2013) | 1 |
| Gross profits-to-lagged assets | gp_atl1 | | 1 |
| Mispricing factor: Performance | mispricing_perf | Stambaugh and Yuan (2017) | 1 |
| Number of consecutive quarters with earnings increases | ni_inc8q | Barth, Elliott, and Finn (1999) | 1 |
| Quarterly return on assets | niq_at | Balakrishnan, Bartov, and Faurel (2010) | 1 |
| Operating profits-to-book assets | op_at | | 1 |
| Operating profits-to-lagged book assets | op_atl1 | Ball et al. (2016) | 1 |
| Operating leverage | opex_at | Novy-Marx (2011) | 1 |
| Quality minus Junk: Composite | qmj | Asness, Frazzini, and Pedersen (2019) | 1 |
| Quality minus Junk: Growth | qmj_growth | Asness et al. (2019) | 1 |
| Quality minus Junk: Profitability | qmj_prof | Asness et al. (2019) | 1 |
| Quality minus Junk: Safety | qmj_safety | Asness et al. (2019) | 1 |
| Assets turnover | sale_bev | Soliman (2008) | 1 |
| | **Seasonality** | | |
| Market correlation | corr_1260d | Asness, Frazzini, Gormsen, and Pedersen (2020) | -1 |
| Coskewness | coskew_21d | Harvey and Siddique (2000) | -1 |
| Net debt issuance | dbnetis_at | Bradshaw, Richardson, and Sloan (2006) | -1 |
| Kaplan-Zingales index | kz_index | Lamont, Polk, and Saaa-Requejo (2001) | 1 |
| Change in long-term investments | lti_gr1a | Richardson et al. (2005) | -1 |
| Taxable income-to-book income | pi_nix | Lev and Nissim (2004) | 1 |
| Years 2-5 lagged returns, annual | seas_2_5an | Heston and Sadka (2008) | 1 |
| Years 6-10 lagged returns, annual | seas_6_10an | Heston and Sadka (2008) | 1 |
| Years 11-15 lagged returns, annual | seas_11_15an | Heston and Sadka (2008) | 1 |
| Years 11-15 lagged returns, non-annual | seas_11_15na | Heston and Sadka (2008) | -1 |

| Description | Variable | Citation | Sign |
|---|---|---|---|
| Years 16-20 lagged returns, annual | seas_16_20an | Heston and Sadka (2008) | -1 |
| Change in short-term investments | sti_gr1a | Richardson et al. (2005) | 1 |
| | **Size** | | |
| Amihud Measure | ami_126d | Amihud (2002) | 1 |
| Dollar trading volume | dolvol_126d | Brennan, Chordia, and Subrahmanyam (1998) | -1 |
| Market Equity | market_equity | Banz (1981) | -1 |
| Price per share | prc | Miller and Scholes (1982) | -1 |
| R&D-to-market | rd_me | Chan et al. (2001) | 1 |
| | **Short-Term Reversal** | | |
| Idiosyncratic skewness from the CAPM | iskew_capm_21d | | -1 |
| Idiosyncratic skewness from the Fama-French 3-factor model | iskew_ff3_21d | Bali, Engle, and Murray (2016) | -1 |
| Idiosyncratic skewness from the q-factor model | iskew_hxz4_21d | | -1 |
| Short-term reversal | ret_1_0 | Jegadeesh (1990) | -1 |
| Highest 5 days of return scaled by volatility | rmax5_rvol_21d | Asness et al. (2020) | -1 |
| Total skewness | rskew_21d | Bali et al. (2016) | -1 |
| | **Value** | | |
| Assets-to-market | at_me | Fama and French (1992) | 1 |
| Book-to-market equity | be_me | Rosenberg, Reid, and Lanstein (1985) | 1 |
| Book-to-market enterprise value | bev_mev | Penman et al. (2007) | 1 |
| Net stock issues | chcsho_12m | Pontiff and Woodgate (2008) | -1 |
| Debt-to-market | debt_me | Bhandari (1988) | 1 |
| Dividend yield | div12m_me | Litzenberger and Ramaswamy (1979) | 1 |
| Ebitda-to-market enterprise value | ebitda_mev | Loughran and Wellman (2011) | 1 |
| Equity duration | eq_dur | Dechow, Sloan, and Soliman (2004) | -1 |
| Net equity issuance | eqnetis_at | Bradshaw et al. (2006) | -1 |
| Equity net payout | eqnpo_12m | Daniel and Titman (2006) | 1 |
| Net payout yield | eqnpo_me | Boudoukh, Michaely, Richardson, and Roberts (2007) | 1 |
| Payout yield | eqpo_me | Boudoukh et al. (2007) | 1 |
| Free cash flow-to-price | fcf_me | Lakonishok et al. (1994) | 1 |
| Intrinsic value-to-market | ival_me | Frankel and Lee (1998) | 1 |
| Net total issuance | netis_at | Bradshaw et al. (2006) | -1 |
| Earnings-to-price | ni_me | Basu (1983) | 1 |
| Operating cash flow-to-market | ocf_me | Desai, Rajgopal, and Venkatachalam (2004) | 1 |
| Sales-to-market | sale_me | Barbee Jr, Mukherji, and Raines (1996) | 1 |