Factor MAX and Predictable Factor Returns*

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Abstract

Extreme factor returns contain valuable information about future factor performance. Factors with the highest maximum daily returns in the past month outperform those with the lowest maximum returns by 0.32% per month (t = 5.89). The profitability of this factor MAX strategy is not subsumed by factor momentum or by a range of lottery or momentum-related anomalies at the stock-level. Our evidence suggests that investors' limited attention and resulting underreaction to extreme factor-level news drive the predictive power of factor MAX. Consistent with this mechanism, the MAX strategy is more profitable for factors that receive low investor attention or whose extreme-return dates do not coincide with salient macroeconomic or firm-specific announcements. Further evidence shows that investors appear to overreact to stock-level MAX events yet underreact to factor-level MAX events, which helps reconcile why factor MAX predicts returns in the opposite direction of stock MAX.

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1 Introduction

Factor investing has become an important pillar of modern asset pricing and a key benchmark for strategic asset allocation. A large body of research shows that equity factors, such as value and momentum, deliver sizable returns beyond the aggregate stock market. As a result, these factors have effectively become investment vehicles and asset classes in their own right. Their prominence highlights the importance of understanding not only average performance but also the extent to which factor returns are predictable.

In this paper, we propose a new predictor, factor MAX, defined as the maximum daily return of a factor within a given month. In contrast to conventional predictors, most notably factor momentum, which condition on cumulative performance over recent horizons, factor MAX isolates information embedded in within-month extreme daily realizations. Each month, we form quintile portfolios by sorting factors into five groups based on the maximum daily return (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. We find that over the sample period from 1963 to 2023, the monthly average returns of the factor MAX portfolios increase from 0.09% for quintile 1 to 0.41% for quintile 5, resulting in a difference of 0.32% (t-statistics = 4.49). These return differences are not fully absorbed by leading asset-pricing models: risk-adjusted alphas for the MAX spread range from 0.24% to 0.37% per month, implying that at least one-half of the average spread remains unexplained.

By construction, factor MAX correlates with factor momentum because factors exhibiting high maximum daily returns within a month may also display strong average returns over the same window. We therefore evaluate whether factor MAX is subsumed by factor momentum. We consider both time-series and cross-sectional factor momentum strategies discussed in Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023). Spanning regressions indicate that both momentum strategies load significantly on MAX. Crucially, however, the factor MAX strategy continues to earn positive and statistically significant alphas after controlling for exposures to both forms of momentum. The results suggest that, although factor MAX and factor momentum are positively correlated, they capture distinct sources of predictability: average past performance (momentum) versus information contained in within-month extreme returns (MAX).

Extreme returns have long been viewed as informative for future returns at the individual stock level (see, e.g., Bali, Cakici, and Whitelaw, 2011). While the literature has not examined factor-level extremes, a natural question is whether factor MAX merely repackages information embedded in stock-level MAX, given that factors are portfolios of underlying equities. We find that it does not. Specifically, factor MAX contains information distinct from a range of stock-level anomalies that are explicitly constructed from extreme returns. Spanning regressions of the factor MAX spread portfolio on these stock-level "lottery-like" proxies show that the alphas of the MAX strategy remain highly significant after controlling for lottery-related anomalies. Thus, the factor MAX premium is not explained by exposures to lottery-related characteristics.

We further ask whether stock-level momentum-related anomalies subsume the returns to factor MAX strategy. Considering momentum, industry momentum, long-run reversal, and short-term reversal, we document that factor MAX loads positively and significantly on stock-level momentum and on long-run reversal, and negatively on short-term reversal. Crucially, across all specifications, the alphas of factor MAX remain statistically and economically significant, implying that the returns to factor MAX strategy is not subsumed by stock-level return-based anomalies.

The profitability of factor MAX strategy is also highly robust. First, redefining the signal as MAX5 — the sum of the five largest daily returns within a month — yields economically large and statistically significant returns. Second, the profitability persists under alternative factor construction schemes: (i) portfolios formed following the original source papers; (ii) value-weighted deciles; and (iii) capped value-weighted terciles as in Jensen, Kelly, and Pedersen (2023). Third, the results are insensitive to portfolio formation granularity: quintiles, deciles, and terciles all deliver comparable or larger spread returns. We also assess sensitivity to the breadth of the factor universe and potential data-mining concerns in the "factor zoo". In a resampling experiment, we repeatedly draw 100 factors at random and form the MAX portfolio, iterating this procedure 1,000 times. The profitability of factor MAX strategy proves remarkably stable: 99% of excess-return spreads and 100% of risk-adjusted alphas remain statistically significant at the 1% level. Collectively, these findings indicate that factor MAX adds incremental predictive content beyond stock-level lottery traits and return-based anomalies, and that the profitability is robust to alternative signal definitions, portfolio constructions, and universe selection.

What explains the predictive power of factor MAX? Although a realized extreme daily factor return may appear as a random draw from a return distribution, it can also embed salient, factor-level news. For instance, a large realization for the value factor may arise from clustered earnings announcements, e.g., when value firms collectively report positive earnings surprises on the same day. It can also come from macroeconomic shocks, such as an unexpected monetary tightening following an FOMC announcement, since rate hikes typically depress valuations of growth firms relative to value firms (e.g., Offner, 2025). Regardless of the source, these news events load at the factor level, and factor MAX provides a parsimonious statistic that captures their arrival.

If investors underreact to such factor-level news, we should observe positive return continuation following high MAX realizations. In particular, favorable news that raises expected cash flows or lowers discount rates for a factor may not be fully impounded contemporaneously, yielding higher subsequent returns. We posit that time-varying investor attention is a plausible mechanism for this underreaction. We formally evaluate this channel by constructing a composite firm-level attention index, which combines standard proxies and aggregate to the factor-level as the cross-sectional average across the long and short legs. We then perform independent double sorts on prior-month MAX and factor-level attention. The results indicate that the return to factor MAX strategy is concentrated among low-attention factors: the high–minus–low MAX spread equals 0.42% per month (t-statistics = 2.93) in the low-attention group, while it is statistically insignificant in the high-attention group. These patterns are consistent with an attention-based underreaction mechanism in which limited investor attention slows the incorporation of factor-level news into factor prices.

Interestingly, We find no evidence that factor momentum is attention-driven. Independent double sorts on factor momentum and factor-level attention reveal no statistically significant differences in the momentum high–minus–low spread between low- and high-attention groups. On the one hand, this pattern suggests that factor momentum, which often interpreted as a manifestation of underreaction, is unlikely to be driven by time-varying attention, consistent with Hou et al. (2025). On the other hand, it implies that factor MAX may be underpinned by an economic mechanism distinct from that underlying factor momentum.

We further evaluate the attention-based interpretation by conditioning the factor MAX strategy on periods of salient macroeconomic news. A growing literature indicates that such episodes increase investor attention, potentially improving the speed with which information is processed on those days. If so, the predictive content of factor MAX should weaken when macro news is extreme. To test this implication, we partition the sample into "extreme" and "non-extreme" macro-news environments using multiple proxies: aggregate market returns, the Economic Policy Uncertainty (EPU) index, and the VIX. For each proxy, months in the highest (or lowest) tail are classified as extreme; all others are non-extreme. We then evaluate the factor MAX strategy within each subsample. Consistent with the attention-based interpretation, returns to factor MAX strategy are statistically insignificant during extreme macro-news months, whereas the profitability is significant and of similar magnitude to our baseline during non-extreme months.

We conduct an analogous test at the firm level by exploiting earnings announcements. Earnings releases are salient events that draw investor attention. We classify a factor-month as having earnings news if any stocks in either the long or short leg report earnings that month; otherwise, it is designated as having no earnings news. Re-estimating performance within these subsamples yields the following: the returns to factor MAX strategy are insignificant when earnings announcements are present but significant when they are absent. This mirrors the macro conditioning and further supports an attention-based mechanism in which salient news increases investor attention and leads to weaker factor MAX effect.

We next examine whether the MAX effect is concentrated among more systematic factors, in line with recent advances in factor modeling. Kozak, Nagel, and Santosh (2018) argue that the absence of near-arbitrage opportunities implies that only factors capturing systematic comovements in returns should exert pricing power. If our attention-based mechanism indeed underlies the factor MAX returns, its effect should be more pronounced among more systematic principal components. Following Arnott, Kalesnik, and Linnainmaa (2023) and Ehsani and Linnainmaa (2022), we extract principal component factors from the factors used in our analysis. We rank PC factors by their associated eigenvalues and partition them into subsets reflecting the degree of systematicity (higher eigenvalues indicating greater common variation). Within each subset, we form quintile portfolios by sorting PC factors on the prior month's maximal daily return (MAX), and we construct a MAX spread that is long the top quintile and short the bottom quintile. The results show that the factor MAX effect is concentrated among high-eigenvalue PCs, with economically and statistically significant spreads, while the effect attenuates for lower-eigenvalue components. This pattern is consistent with the view that attention-driven mispricing operates more strongly where factor-level news is more systematic.

Finally, we explain why our factor MAX effect differs from the stock-level MAX documented by Bali, Cakici, and Whitelaw (2011). Using an event-study approach, we find that investors overreact to stock-level MAX events, consistent with Baars and Mohrschladt (2021); Gorman et al. (2022); Bali et al. (2025). Stock returns begin to decline immediately after such events, leading to subsequent return reversals. In contrast, we show that after a factor realizes its MAX, its returns continue to drift upward for at least the next 30 days. This evidence suggests that investors react differently to stock-level versus factor-level MAX events, and this reconciles why stock-level MAX negatively predicts stock returns, whereas factor MAX positively predicts factor returns.

2 Methodology

2.1 Background and motivation

The growing prevalence of factor investing has created strong interest in the search for predictors of factor returns. A well-known predictor in this literature is factor momentum, which shows that factors with strong recent performance often continue to perform well in the future. Prior research shows that factor momentum helps explain long-standing anomalies such as the stock- and industry-level momentum (e.g., Lewellen, 2002; Ehsani and Linnainmaa, 2022; Arnott, Kalesnik, and Linnainmaa, 2023), which highlights its importance in financial economics. However, with the rise of factor investing, the predictability of factor returns has its own value for the management of factor portfolios. This has motivated the development of new predictors of factor returns in addition to factor momentum (e.g., Haddad, Kozak, and Santosh, 2020; Dong, Kang, and Peress, 2025), as well as new econometric methods that help forecast factor returns (e.g., Neuhierl et al., 2023; Kagkadis et al., 2024; Lehnherr, Mehta, and Nagel, 2025).

We build on these efforts and take a new perspective. Instead of focusing on the performance of a factor over a recent period, such as the past month or the past year, we study the information that appears in the factor MAX, which is the largest daily return of a factor within a month. Extreme returns have long been viewed as a source of useful information at the individual stock level. The seminal study of Bali, Cakici, and Whitelaw (2011) shows that the maximum daily return in the past month contains important information about future stock performance. Yet, to the best of our knowledge, no study examines whether extreme factor returns also contain useful information about future factor returns. Our paper attempts to fill this gap.

A further question is how this information leads to predictable factor returns. Information arrival can move prices, but it does not necessarily imply return predictability over longer horizons. At the stock level, while some studies attribute the predictive power of MAX to investors' tendencies to chase assets with lottery-like payoffs (e.g., Bali, Cakici, and Whitelaw, 2011), recent literature shows that it can also reflect investor overreaction to salient extreme events among individual stocks (e.g., Baars and Mohrschladt, 2021; Gorman et al., 2022). In contrast, our paper evaluates how investors react to extreme factor-level news, which may offer a new and complementary view of how the market responds to extreme events in different asset classes.

2.2 Data

We obtain monthly and daily factors from "Open Source Asset Pricing" (Chen and Zimmermann, 2022), which aggregates and standardizes a comprehensive set of cross-sectional stock return predictors synthesized in prior meta-studies. To align with realistic implementation and to reduce sensitivity to microcaps, we restrict attention to factors constructed from continuous signals and formed as value-weighted quintiles. This portfolio formation mirrors common practice in the literature. The use of value-weighted portfolios enhances investability and mitigates distortions from illiquid or small stocks.[1]

[1]Our results are robust when using portfolios constructed following the original papers surveyed in Chen and Zimmermann (2022), implemented as value-weighted deciles, or the tercile-sorted capped value-weighted portfolios constructed by Jensen, Kelly, and Pedersen (2023). These results are reported in

To ensure that our findings are not mechanically driven by "lottery-like" anomalies, we exclude seven lottery-related anomalies: Maximum Returns (MaxRet), Idiosyncratic Volatility (IdioVol3F; IdioVolAHT), Return Skewness (ReturnSkew), Idiosyncratic Skewness (ReturnSkew3F), and Coskewness (CoskewACX; Coskewness). The resulting universe comprises 172 factors with continuous coverage from January 1963 through December 2023. For each factor, we utilize both monthly and daily return series to construct the MAX signal and to compute subsequent portfolio performance.

Monthly and daily stock returns (including delisting returns when available) come from CRSP, and quarterly and annual accounting variables come from Compustat. Our equity sample includes all U.S. common stocks listed on the NYSE, Amex, and Nasdaq with CRSP share codes 10 or 11. For macro and firm-level news measures, we use the Economic Policy Uncertainty (EPU) index from Baker, Bloom, and Davis (2016), the CBOE implied volatility index (VIX), and quarterly earnings announcement dates (RDQ) from Compustat.

3 Empirical Analysis

We start the empirical analysis by constructing the factor MAX strategy and evaluating its performance using portfolio analysis and spanning tests. We also perform a battery of tests to establish the robustness of our results.

3.1 Factor MAX Strategy

Following Bali, Cakici, and Whitelaw (2011), at the beginning of each month from January 1963 to December 2023, we form quintile portfolios by sorting factors into five groups based on the maximum daily return (MAX) in the preceding month, where quintile 1 (5) contains factors with the lowest (highest) value of MAX. The factor MAX spread

Section 3.4.

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 the MAX portfolios in month $t + 1$ as the equal-weighted average of the factor returns.

Table 1 presents the results of portfolio analysis. Over the sample period from 1963 to 2023, the monthly average returns of the factor MAX portfolios increase from 0.09% for quintile 1 to 0.41% for quintile 5, resulting in a difference of 0.32% per month (t-statistics = 4.49). Risk-adjusted returns are computed using five factor models: market factor model (CAPM), Fama and French (2015) five-factor model (FF5), Fama and French (2015) five-factor and momentum model (FF5+MOM), Hou, Xue, and Zhang (2015) q-factor model (HXZ), and Daniel, Hirshleifer, and Sun (2019) behavioral factor model (DHS). The remaining rows of Panel A present the risk-adjusted returns. We find that those common risk factor models cannot account for the profitability of the factor MAX strategy. The abnormal return of the factor MAX spread portfolio ranges from 0.24% with DHS to 0.37% with HXZ, and the alphas across all models are statistically significant.

[Insert Table 1 about here]

To better visualize the performance of factor MAX strategy, Figure 1 depicts the log cumulative returns and log cumulative alphas (based on Fama and French (2015) five-factor model) of factor MAX spread portfolio. As illustrated, in our sample period from January 1963 to December 2023, the strategy delivers sizable risk-adjusted gains: an investor would earn a cumulative alpha of $9.58 per dollar invested. The strategy also displays limited drawdowns, suggesting that factor MAX returns are not concentrated in some specific historical periods.

[Insert Figure 1 about here]

One potential concern is that the performance may be driven by extreme returns from some specific factors. Figure 2 plots the number of factors in the long and short legs of the factor MAX strategy over time. The number of factors increases from 22 at the start of 1963 to approximately 34 in 1990 and remains consistently above 34 thereafter. This breadth indicates that both the long and short sides of our factor strategy invest in a reasonably large number of factors throughout the sample, which alleviates concerns that the results are driven by a small number of extreme factors.

[Insert Figure 2 about here]

3.2 Relation with factor momentum

Our factor MAX strategy relates to the factor momentum, which is one of the most powerful predictors for factor returns. Specifically, Ehsani and Linnainmaa (2022) show that factor's past-year performance predicts subsequent time-series returns. Arnott, Kalesnik, and Linnainmaa (2023) find that one-month factor return predict future returns in the cross-section. By construction, the factor MAX signal is correlated with these momentum measures: factors exhibiting high maximum daily returns in the prior month are likely to have high average returns over the same month. We therefore assess whether the predictive power of factor MAX is simply a manifestation of factor momentum.

Panel A in Table 2 replicates the main findings in Ehsani and Linnainmaa (2022); Arnott, Kalesnik, and Linnainmaa (2023) over our sample period. Both time-series (TSMOM) and cross-sectional factor momentum (CSMOM) continue to perform well even accounting for recent sample periods. We then explore how factor MAX effect relates to factor momentum by running spanning regressions. Specifically, we regress monthly returns on the factor MAX strategy against monthly returns on two factor momentum strategies: one based on past one-year performance as in Ehsani and Linnainmaa (2022), and the other based on the prior month performance as in Arnott, Kalesnik, and Linnainmaa (2023). As reported in Panel B of Table 2, both momentum strategies load significantly on MAX, which is unsurprising given that all three signals condition on past returns. Crucially, however, the intercepts from these regressions remain highly significant, indicating that the factor MAX strategy continues to earn positive abnormal returns after controlling for exposures to both forms of momentum. The R^2 are modest to moderate, with approximately 5% to 26%, which suggests that factor MAX cannot be spanned by factor momentum.

We also reverse the exercise by regressing the returns of each momentum strategy on returns of factor MAX strategy. The last two columns of Panel B show that both time-series and cross-sectional momentum continue to deliver significant alphas in this specification. Taken together, the evidence indicates that, although factor MAX and factor momentum are positively correlated, they capture distinct sources of factor return predictability.

[Insert Table 2 about here]

3.3 Relation with stock-level anomalies

Although the factor MAX effect is unlikely driven by common risk factors or factor momentum, it could be related to stock-level "lottery-like" anomalies. Because extreme factor returns are aggregates of underlying extreme stock returns, one concern is that the returns to our factor MAX strategy merely reflect exposure to these stock-level effects. We therefore examine whether our results are subsumed by canonical lottery-related anomalies.

Following a large literature on lottery-related anomalies, we consider Idiosyncratic volatility (Ang et al., 2006, IdioVol3F; Ali, Hwang, and Trombley, 2003, IdioVolAHT), Maximum return (Bali, Cakici, and Whitelaw, 2011, MaxRet), Return skewness (Bali and Murray, 2015, ReturnSkew), Idiosyncratic skewness (Bali and Murray, 2015, IdioSkew), and Coskewness (Harvey and Siddique, 2000, Coskew; Ang, Chen, and Xing, 2006, CoskewACX). We run spanning regressions by projecting the return of factor MAX strategy on these stock-level anomaly returns. Panel A of Table 3 shows that the alphas of factor MAX strategy remain highly significant after controlling for all lottery-related anomalies, indicating that the factor MAX return is not explained by exposures to these anomalies. Interestingly, the loadings on most lottery anomalies are negative, meaning that returns to the factor MAX strategy are negatively correlated with typical strategies built on lottery-like payoffs among individual stocks. In Section 4, we discuss potential explanations for this pattern. One possibility is an asymmetry in investor response: investors may overreact to extreme stock-level news (generating lottery anomalies), but underreact to information embedded in extreme factor returns, leading to distinct performance from the MAX strategy at the factor level.

[Insert Table 3 about here]

Similar to our comparison with factor momentum, we further evaluate whether factor MAX effect is driven by stock-level anomalies that built on past stock returns. We consider Momentum (Jegadeesh and Titman, 1993, Mom6m, Mom12m), Industry momentum (Moskowitz and Grinblatt, 1999, IndMom), Long-run revesal (De Bondt and Thaler, 1985, LRreversal) and Short-term reversal (Jegadeesh, 1990, STreversal). We similarly run the spanning regressions and results are in Panel B of Table 3. We find that factor MAX returns load positively and significantly on stock-level momentum and on long-run reversal, whereas the loading on short-term reversal is negative. Importantly, the alphas remain statistically and economically significant across all specifications, implying that the factor MAX is not subsumed by these momentum-related anomalies from individual stocks. Overall, the evidence suggests that factor momentum, stock-level lottery characteristics, and momentum-related anomalies, cannot explain the predictive power of factor MAX for future returns.

3.4 Robustness tests

In this section, we conduct a series of robustness checks for the factor MAX strategy. First, we redefine the signal as MAX5, which is the sum of five largest daily returns in a given month, and reconstruct the factor MAX strategy based on the value of MAX5 in the preceding month. We calculate the returns of MAX portfolios in month t+1. Panel A of Table 4 shows that the monthly average returns of the factor MAX portfolio increase from 0.02% for quintile 1 to 0.49% for quintile 5, resulting in a difference of 0.47% (t-statistics = 6.72). The corresponding risk-adjusted spread is also highly significant (t-statistics = 5.88). In Panel B, we implement the strategy following the factor definitions in the original papers; the MAX spread remains economically large and statistically significant.

In Panel C, we repeat the analysis using factors formed as value-weighted deciles. We sort factors into ten groups based on MAX in the preceding month, where decile 1 (10) contains factors with the lowest (highest) value of MAX. The factor MAX spread portfolio (H–L) involves buying factors in decile 10 and selling factors in decile 1 and all portfolios are rebalanced monthly. The resulting returns of factor MAX spread portfolio is larger compared with our main results in Table 1. Finally, we repeat the factor MAX strategy using the factor set from Jensen, Kelly, and Pedersen (2023), which is constructed as capped value-weighted terciles; the factor MAX returns remain statistically significant in this alternative universe. Collectively, these tests confirm that the factor MAX results are robust to alternative definitions (MAX5), portfolio formation schemes (quintiles, deciles, terciles), and factor constructions.

[Insert Table 4 about here]

The existing literature refers to the multitude of factors as the "factor zoo". To assess whether the returns to factor MAX strategy are sensitive to the choice of factors, we randomly draw subsets of factors from the universe of our 172 factors. Specifically, we randomly select 50 or 100 factors and perform portfolio analysis by sorting them into five groups based on their largest returns in the prior month. This exercise is repeated 1000 times, recording the t-statistics of returns and FF5 adjusted alphas each time. The distributions of these t-statistics are plotted in Figure 3. As illustrated, the majority of both returns and FF5 adjusted returns are statistically significant at 1% level (t-statistics larger than 3). For instance, in Panel A, when randomly drawing 50 factors for 1000 times, 93% of the 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 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 effect remains robust and does not depend on the specific choice of factors from the factor zoo.

[Insert Figure 3 about here]

4 Inspecting the Mechanism

While an extreme factor return may appear to be a random draw from a distribution, it can also reflect important factor-specific news. In particular, the maximum within-month factor return likely captures salient and favorable factor-specific information released during the month. Under efficient information processing, such news should be incorporated into prices immediately, leaving no predictable returns in the subsequent month. Our finding of strong and positive predictability due to factor MAX therefore points to underreaction to factor-level news, which we will test in this section.

4.1 Attention and underreaction to factor MAX

In a frictionless setting with fully rational agents, factor-level news is rapidly incorporated into equilibrium prices, which immediately reflect investors' revised beliefs. In practice, however, agents are at best boundedly rational, and the speed at which news is incorporated depends critically on how attentive they are to the information (see the recent review by Loewenstein and Wojtowicz, 2025). Consistent with this view, prior research shows that low investor attention amplifies underreaction-related stock market anomalies (e.g., Chen et al., 2023).[2]

We test whether this attention-based channel can explain predictable factor returns induced by factor MAX. To measure factor-level investor attention, we first follow Chen et al. (2023) and build a firm-level composite attention index as the average z-score of five attention proxies: abnormal trading volume, past 12-month returns, analyst coverage, absolute value of earnings surprise, and 52-week high. Then for each factor, we calculate its attention measure as the average of this composite across the stocks in the factor's long and short legs. This factor-level attention proxy effectively captures investor attention to all stocks included in the factor.

If the predictive power of factor MAX arises from limited attention, we should expect its effect to be more pronounced among lower-attention factors. To test this, each month we independently sort factors into 5×5 portfolios based on prior-month MAX and prior-month factor-level attention. We then calculate average return to each of the 25 factor portfolios, and results are reported in Panel A of Table 5. Consistent with our conjecture, we find that the factor MAX effect increases monotonically as factor-level attention decreases. In the lowest attention group, the factor MAX sorted spread portfolio earns 0.42% per month (t-statistics = 2.93). In contrast, in the highest-attention group, the spread is even negative. The magnitude is economically small and statistically insignificant. Finally, the difference in the factor MAX strategy performance between low- and high-attention groups is significant. These findings support the conjecture that limited

[2] A large and related literature documents that firm-level earnings news is incorporated only gradually into prices due to limited investor attention (e.g., DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009; Ben-Rephael, Da, and Israelsen, 2017). Time-varying attention also generates predictable variation in aggregate market returns (e.g., Da, Engelberg, and Gao, 2011; Chen et al., 2022) and volatility (e.g., Andrei and Hasler, 2015; Liang, Wang, and Duong, 2024).

investor attention drives the factor MAX effect.

[Insert Table 5 about here]

Although we have shown that factor MAX is not subsumed by factor momentum in Section 3.2, the attention-based evidence for factor MAX may also help distinguish it with factor momentum. Hou et al. (2025) show that stock-level momentum effect is unlikely explained by investor attention. If we expect similar implications for factor momentum, then factor momentum should not exhibit the attention dependence we document for MAX. We therefore repeat the double sorting analysis, replacing MAX with factor momentum (measured over the prior month). Panel B of Table 5 shows no significant difference in factor momentum returns between low- and high-attention groups. Hence, the attention-driven factor MAX likely reflects a different economic mechanism than factor momentum.

Recent literature finds that investor attention increases when there is important macroeconomic or firm-level news (see, e.g., Hirshleifer and Sheng, 2022; Kroner, 2025). We thus conjecture that the factor MAX effect should concentrate in periods or firms without salient macroeconomic or firm-specific news. To test this, we partition the sample into "extreme" and "non-extreme" news environments using multiple proxies for macroeconomic and firm-level news. For macro news, we rely on aggregate market returns, the EPU index, and the VIX. Within each month, we label the highest and lowest observations in these series as days with extreme macro news and treat all other days as non-extreme. We then evaluate factor MAX strategies formed separately based on whether a factor's maximal intra-month daily return occurs on the same dates as extreme macro news. Panels A to C of Table 6 show that when the factor MAX strategy is restricted to factors whose MAX occurs on extreme macro-news dates, the strategy is no longer profitable. In contrast, the factor MAX effect becomes stronger and statistically significant when the strategy invests in factors whose MAX does not coincide with extreme macro news.

We also examine the importance of firm-level salient news. A natural approach is to compare factors whose constituent stocks do or do not have earnings announcements. In each month, we classify a factor as having earnings announcements if any stock in its long or short leg reports earnings; otherwise, it is categorized as having no earnings news. Panel D of Table 6 shows that the factor MAX strategy formed using factors with announcements does not yield significant returns. In contrast, when we focus on factors without earnings announcements, the factor MAX effect remains strong and statistically significant. Overall, this evidence supports an attention-based mechanism: salient news increases investor attention and attenuates the factor MAX effect.

[Insert Table 6 about here]

4.2 Factor MAX and mispricing in systematic components of factor returns

Kozak, Nagel, and Santosh (2018) show that in the absence of near-arbitrage opportunities, only factors that explain systematic variation in factor returns can exhibit pricing effects. If the attention-based channel indeed underlies the factor MAX effect, we should expect the factor MAX effect to be more pronounced among the more systematic principal components of factor returns.

Following Arnott, Kalesnik, and Linnainmaa (2023) and Ehsani and Linnainmaa (2022), we extract principal components from the factors used in our analysis. Due to data availability, we focus on the 122 factors with data available before 1970. 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 122 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 categorize PC factors by their eigenvalues, with the first subset containing the twenty highest-eigenvalue PC factors; the second subset contains the twenty next-highest-eigenvalue set of PC factors, and so forth. Within each subset of PC factors, we sort PC factors into five groups based on their largest daily returns in the prior month and long (short) the factors in the top (bottom) quintile. In Table 7 we assess the performance of factor MAX strategy across six different subsets of PC factors. The results in the first column of Table 7 reveal that this highest-eigenvalue set of PC factors exhibits an average return of 0.39% and risk-adjusted return of 0.48% 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 effect to concentrate in the high-eigenvalue factors.

[Insert Table 7 about here]

4.3 Reconciling with stock-level MAX effect

Finally, we discuss why factor MAX positively predicts factor returns, whereas stock-level MAX negatively predicts stock returns, as well documented by e.g., Bali, Cakici, and Whitelaw (2011). Although Bali, Cakici, and Whitelaw (2011) initially interpret the stock-level MAX effect through investors' preference for lottery-like payoffs, subsequent studies also examine whether the strong return reversals of high-MAX stocks reflect investor overreaction to extreme stock-specific payoffs (see, e.g., Baars and Mohrschladt, 2021; Gorman et al., 2022). In particular, Bali et al. (2025) show that social interactions direct investor attention toward lottery-like stocks, fostering over-optimism and thus leading to subsequent return reversals.

Overreaction to extreme stock-level returns does not necessarily imply that investors will also overreact to extreme factor returns. After all, factors are portfolios of stocks, and their MAX need not coincide with stock-level MAX. Moreover, timely trading on a factor's MAX would require investors to continuously monitor all constituent stocks in the factor zoo, which is a task that is demanding for attention-constrained investors. It is therefore reasonable to expect that while investors devote more attention to stock-specific news, they may fail to adequately process factor-level information. This asymmetry naturally leads to negative return predictability from the MAX effect at the individual-stock level, but positive return predictability at the factor level.

To more directly assess asymmetries in the reaction to extreme news, we conduct an event-study analysis at both the stock and factor levels. Instead of monthly return analysis in Bali, Cakici, and Whitelaw (2011), we analyze daily returns before and after the occurrence of high MAX events to shed better light on how investors react to the news. We define day-zero for each stock-month or factor-month event as the trading day on which a stock or a factor earns its maximum daily return for that month. We then calculate the cumulative abnormal returns for each stock or factor, starting from 10 days before day 0 and up till 50 days after the high MAX events. Event window daily abnormal stock returns are calculated with respect to the market factor (CAPM) model, and factor-level performance is computed as the cumulative sum of raw daily factor returns over the same window. Each month, we sort stocks and factors into quintiles by the prior month's MAX and calculate equal-weighted cumulative abnormal returns (for stocks) and cumulative sum returns (for factors) within each quintile, enabling a comparison of pre- and post-event adjustment dynamics across low- versus high-MAX portfolios at both aggregation levels.

Figure 4 plots how individual stocks and factors respond to high MAX news on average. Consistent with the overreaction channel discussed by Baars and Mohrschladt (2021); Gorman et al. (2022), Panel A shows that the stock returns start to decline after the news of stock-level MAX. This suggests that investors do hold overly optimistic beliefs over high MAX stocks, which leads to subsequent return reversal. In contrast, the reaction to factor-level MAX is markedly different. Panel B shows that even after a factor realizes its MAX, the following factor returns continue to drift upward for at least for the following 30 days. This pattern indicates that investors appear to underreact to factor-level extreme returns, and is consistent with the factor return predictability documented earlier.

[Insert Figure 4 about here]

5 Conclusion

This paper shows that extreme within-month factor returns, summarized by factor MAX, provide powerful and distinct predictability for future factor returns. Factors with higher MAX earn significantly higher subsequent returns, and this pattern cannot be explained by traditional factor momentum, lottery-related anomalies, or momentum-related anomalies. The effect is highly robust across alternative specifications and across multiple factor-zoo datasets. Our evidence supports a limited-attention mechanism: the MAX effect is strongest among factors that attract low investor attention. We further show that investors overreact to stock-level MAX events but underreact to factor-level MAX events, which helps to reconcile why stock-level MAX negatively predicts stock returns, whereas factor MAX positively predicts factor returns.

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Figure 1: Factor MAX: cumulative performance.
This figure plots the log cumulative returns and abnormal returns of the factor MAX spread portfolio. We sort factors into five groups based on their largest returns (MAX) over the prior month and factor MAX spread portfolio is constructed by buying high MAX portfolio and selling low MAX portfolio. Abnormal returns are adjusted by Fama and French (2015) five factor model. The sample period is 1963:01 – 2023:12.

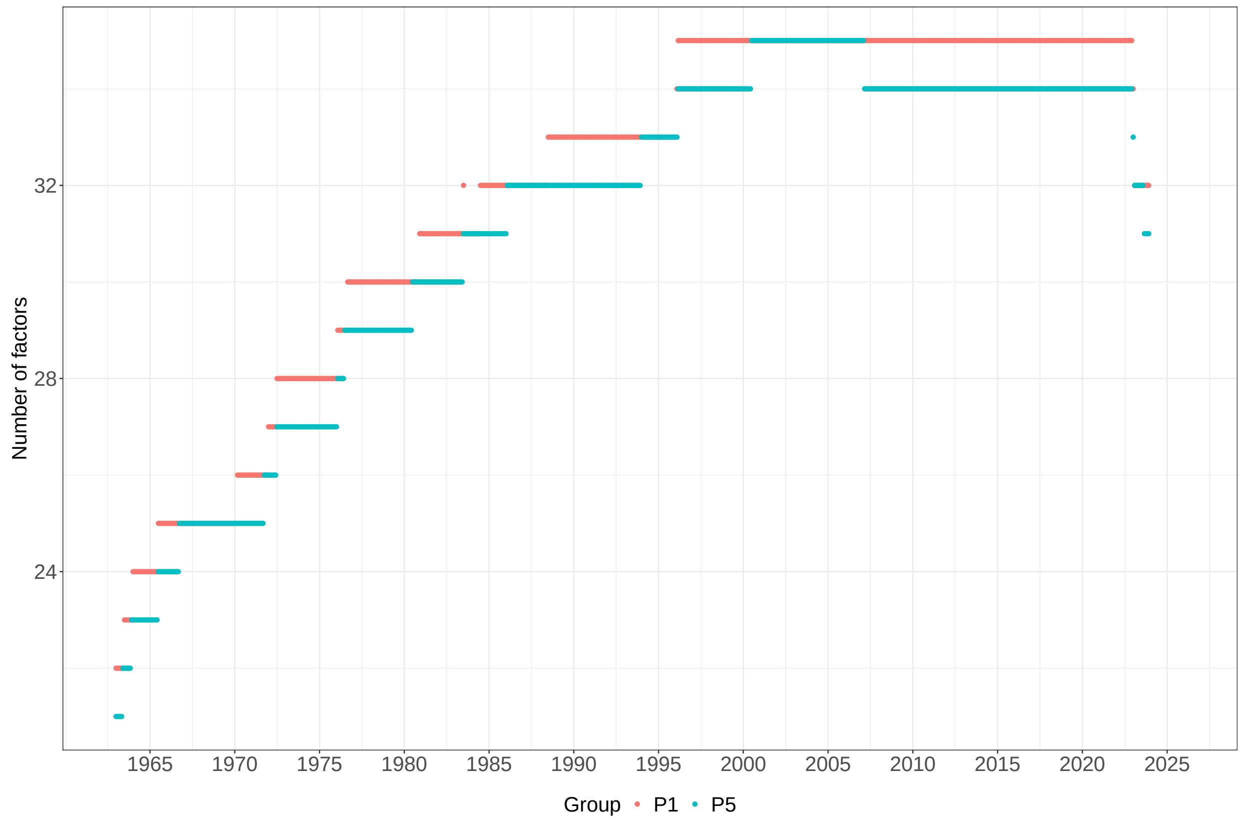

Figure 2: Number of factors in long and short legs.
This figure plots number of factors in the long and short legs of the factor MAX strategy. The portfolio is formed by sorting factors into quintiles based on their largest returns (MAX) in the prior month. Long (Short) leg contains the factors with the highest (lowest) MAX over the past one month. The sample period is 1963:01 – 2023:12.

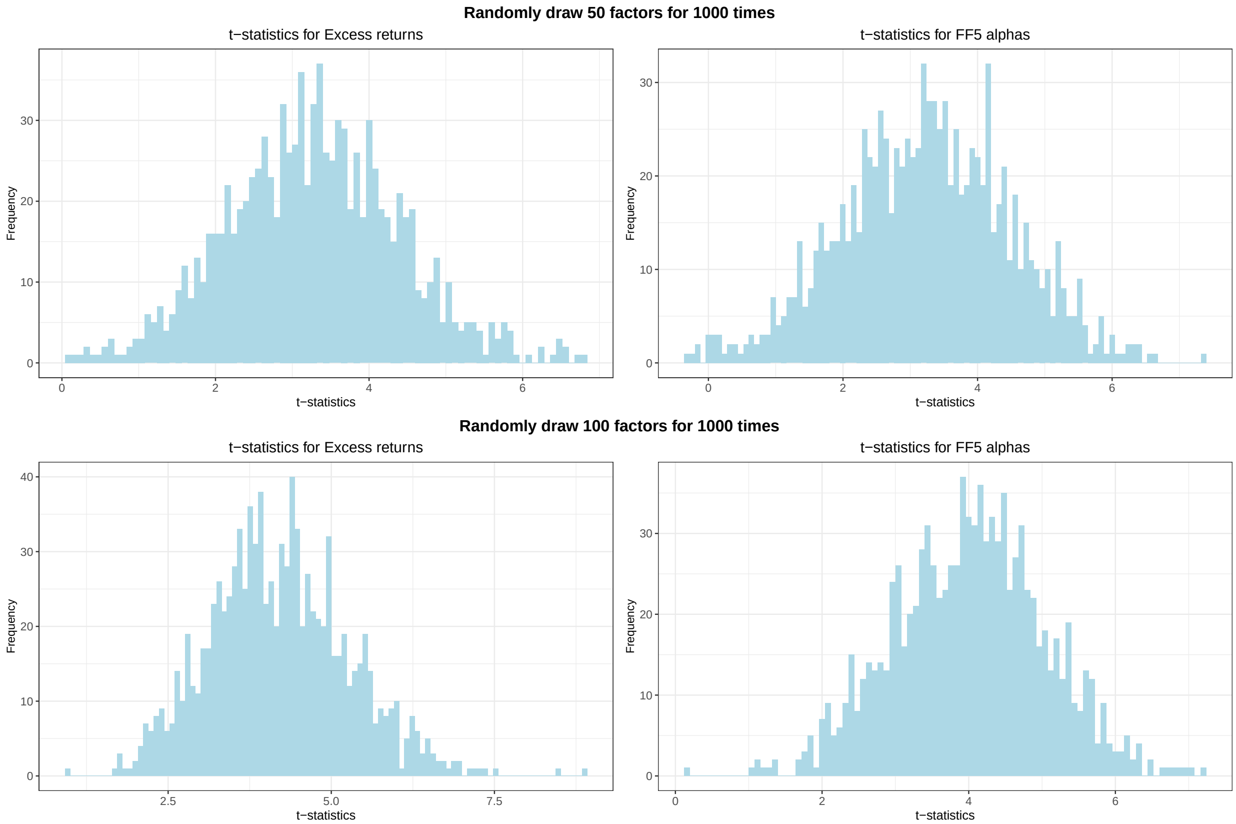

Figure 3: Performance of the bootstrapped factor MAX spread portfolio.
This figure plots the distribution of *t*-statistics of the returns and alphas for the bootstrapped factor MAX spread portfolio. Panel A (B) randomly draws 50 (100) factors from the factor zoo for 1000 times. Each time, we form the factor MAX spread portfolio and calculate the *t*-statistics for returns and abnormal returns adjusted by Fama and French (2015) five factor model. The sample period is from 1963:01–2023:12.

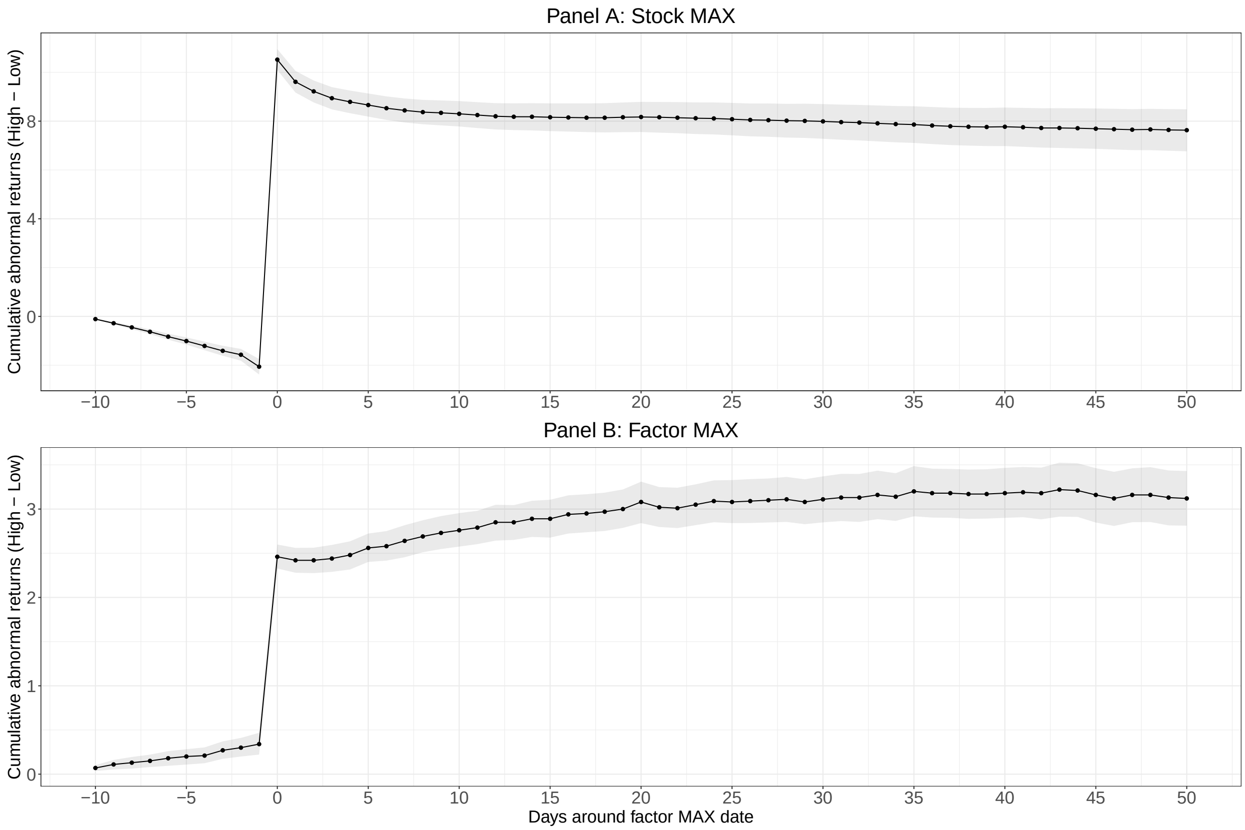

Figure 4: Cumulative abnormal returns of stock MAX and factor MAX.
This figure plots the cumulative abnormal returns at both stock and factor levels. We define day-zero for each stock-month or factor-month event as the trading day on which a stock or a factor earns its maximum daily return for that month. We then calculate the cumulative abnormal returns for each stock or factor, starting from 10 days before day 0 and up till 50 days after the high MAX events. Event window daily abnormal stock returns are calculated with respect to the market factor (CAPM) model, and factor-level performance is computed as the cumulative sum of raw daily factor returns over the same window. Shaded area indicates the 95% confidence interval. The sample period is from 1963:01–2023:12.

Table 1: Performance of factor MAX portfolios

This table reports monthly average returns, Sharpe ratio (SR) and alphas (in %) of factor MAX quintile portfolios. Portfolios are formed by sorting factors into five groups based on the largest returns (MAX) in the prior month, where P1 (P5) refers to the portfolio with lowest (highest) MAX, and H – L refers to the strategy that buys P5 and sells P1. Daily and monthly factor returns are from Chen and Zimmermann (2022). All portfolios are rebalanced at a monthly frequency. Factor models include CAPM model, Fama and French (2015) five-factor model (FF5), Fama and French (2015) five-factor and momentum model, Hou, Xue, and Zhang (2015) q-factor model and Daniel, Hirshleifer, and Sun (2019) behavioral factor model. Newey-West t-statistics are reported in parentheses. The sample period is 1963:01 – 2023:12.

	P1	P2	P3	P4	P5	H–L
Return	0.09	0.23	0.29	0.37	0.41	0.32
	(3.04)	(5.52)	(5.73)	(6.66)	(7.80)	(5.89)
SR	0.17	0.12	0.26	0.28	0.27	0.25
CAPM	0.11	0.26	0.33	0.43	0.46	0.36
	(3.62)	(5.84)	(6.57)	(7.47)	(8.13)	(4.99)
FF5	0.04	0.16	0.20	0.28	0.37	0.33
	(1.69)	(5.69)	(5.68)	(5.87)	(6.84)	(5.17)
FF5+MOM	0.03	0.13	0.16	0.21	0.30	0.27
	(1.26)	(4.96)	(5.35)	(5.53)	(5.06)	(3.52)
HXZ	-0.02	0.04	0.09	0.14	0.35	0.37
	(-0.61)	(1.13)	(2.47)	(2.74)	(4.88)	(4.18)
DHS	0.05	0.13	0.17	0.15	0.29	0.24
	(1.66)	(3.51)	(3.79)	(2.95)	(4.49)	(3.76)

Table 2: Spanning tests

This table reports the spanning tests of factor MAX portfolio, cross-sectional factor MOM (CSMOM) portfolio and time-series factor MOM (TSMOM) portfolio. Factor MAX portfolios are formed by sorting factors into five groups based on the maximum returns (MAX) in the prior month, and MAX refers to the strategy that buys P5 and sells P1. CSMOM portfolios are formed by sorting factors into five groups based on the sum of returns (MOM) in the prior month, and CSMOM refers to the strategy that buys P5 and sells P1. TSMOM is long factors with positive prior one-year returns (skipping one month) and short factors with negative returns. Daily and monthly factor returns are from Chen and Zimmermann (2022). All portfolios are rebalanced at a monthly frequency. Newey-West t-statistics are reported in parentheses. The sample period is 1963:01 – 2023:12.

Panel A: Factor momentum

	CSMOM			TSMOM		
	P1	P5	H – L	Short	Long	Long – Short
Return	-0.15	0.72	0.87	0.09	0.41	0.32
	(-1.87)	(8.47)	(5.78)	(1.56)	(7.58)	(3.34)
SR	0.18	0.31	0.27	0.12	0.28	0.06
FF5	-0.17	0.81	0.98	0.03	0.38	0.35
	(-2.22)	(9.78)	(5.83)	(0.58)	(5.40)	(2.85)

Panel B: Spanning test

	(1)	(2)	(3)	(4)	(5)
	CSMOM	MAX	TSMOM	MAX	MAX
α	0.46	0.14	0.22	0.26	0.11
	(3.35)	(2.93)	(2.51)	(4.34)	(2.34)
MAX	1.28		0.32		
	(9.75)		(3.22)		
CSMOM		0.20			0.20
		(7.47)			(7.48)
TSMOM				0.17	0.12
				(3.38)	(2.10)
N	732	732	732	732	732
Adjusted R^2	0.26	0.26	0.05	0.05	0.29

Table 3: Control for stock-level lottery-related and momentum-related anomalies

This table reports the performance of factor MAX spread portfolios controlling for stock-level lottery-related and momentum-related anomalies. Anomalies include Idiosyncratic volatility (IdioVol3F, IdioVolAHT), Maximum return (MaxRet), Return skewness (ReturnSkew), Indiosyncratic skewness(ReturnSkew3F), Coskewness (CoskewACS, Coskewness), Momentum (Mom6m, Mom12m), Industry momentum (IndMom), Long run reversal (LRreversal), Short term reversal (STreversal). Daily and monthly factor returns are from Chen and Zimmermann (2022). All portfolios are rebalanced at a monthly frequency. Newey-West t-statistics are reported in parentheses. The sample period is 1963:01 – 2023:12.

Anomaly	α	Anomaly	Adjusted R^2
Panel A: Lottery-related anomalies			
IdioVol3F	0.32	0.01	0.01
	(5.73)	(-0.16)	
IdioVolAHT	0.32	-0.01	0.01
	(6.01)	(-0.62)	
MaxRet	0.32	-0.01	0.01
	(5.92)	(-0.50)	
ReturnSkew	0.31	-0.20	0.04
	(4.84)	(-3.28)	
ReturnSkew3F	0.29	-0.16	0.02
	(4.51)	(-2.86)	
CoskewACX	0.31	0.04	0.01
	(5.14)	(1.02)	
Coskewness	0.31	0.02	0.01
	(6.04)	(0.28)	
Panel B: Momentum-related anomalies			
Mom6m	0.29	0.05	0.02
	(4.84)	(2.35)	
Mom12m	0.27	0.05	0.03
	(4.35)	(2.55)	
IndMom	0.31	0.05	0.01
	(5.37)	(1.97)	
LRreversal	0.30	0.07	0.04
	(5.09)	(2.89)	
STreversal	0.35	-0.15	0.17
	(6.45)	(-6.85)	

Table 4: Robustness tests

This table presents the results of various robustness tests. Panel A reports the results of portfolio analysis when MAX is constructed using the sum of five largest daily factor returns over the prior month. Panel B reports the results of portfolio analysis when using factors constructed following the original paper. Panel C presents the results of sorting factors into decile portfolios using value-weighted decile factors based on the largest daily factor returns over the prior month. Panel D reports the results of portfolio analysis using factor set from Jensen, Kelly, and Pedersen (2023), which is constructed as capped value-weighted terciles. Newey-West t-statistics are reported in parentheses. The sample period is 1963:01 – 2023:12.

	P1	P5	H–L		P1	P5	H–L
Panel A: Five largest daily factor returns				Panel B: Factors following original paper			
Return	0.02	0.49	0.47	Return	0.19	0.85	0.65
	(0.67)	(7.36)	(6.72)		(6.70)	(11.81)	(9.51)
SR	0.21	0.28	0.26	SR	0.31	0.55	0.42
FF5	-0.04	0.46	0.50	FF5	0.17	0.78	0.61
	(-1.47)	(6.32)	(5.88)		(7.95)	(10.22)	(8.06)
	P1	P10	H–L		P1	P3	H–L
Panel C: Decile factors and decile portfolios				Panel D: JKP tercile factors			
Return	0.11	0.71	0.61	Return	0.10	0.27	0.17
	(2.60)	(7.07)	(5.33)		(4.14)	(3.97)	(2.58)
SR	0.20	0.28	0.23	SR	0.09	0.30	0.16
FF5	0.05	0.73	0.68	FF5	0.08	0.17	0.10
	(1.29)	(6.99)	(5.72)		(3.71)	(4.67)	(2.05)

Table 5: Attention

This table reports monthly average returns of portfolios double sorted by MAX (MOM) and factor-level attention. We construct the firm-level composite attention index as the average z-score of five attention proxies (Chen et al., 2023), including abnormal trading volume, past 12-month returns, analyst coverage, absolute value of earnings surprise, and 52-week high. Factor-level attention measure is the average of firm-level attention in long and short legs. We sort factors into quintiles based on attention and MAX (MOM) independently. Reported are the average returns of the 25 (5×5) portfolios. Daily and monthly factor returns are from Chen and Zimmermann (2022). All portfolios are rebalanced at a monthly frequency. Newey-West t-statistics are reported in parentheses. Sample period is 1963:01 – 2023:12.

Panel A: Double sort on attention and factor MAX

	MAX					
Attention	P1	P2	P3	P4	P5	H–L
Low	0.24	0.32	0.29	0.42	0.65	0.42
	(2.16)	(3.99)	(2.91)	(3.39)	(5.11)	(2.93)
P2	0.12	0.26	0.19	0.24	0.48	0.36
	(2.35)	(2.96)	(2.68)	(2.70)	(3.88)	(2.83)
P3	0.09	0.22	0.30	0.38	0.38	0.28
	(2.38)	(3.14)	(4.26)	(4.26)	(2.78)	(1.98)
P4	0.13	0.17	0.30	0.40	0.25	0.12
	(2.36)	(2.64)	(3.36)	(4.77)	(1.66)	(0.78)
High	0.06	0.18	0.31	0.16	-0.01	-0.07
	(1.14)	(2.87)	(4.14)	(1.48)	(-0.04)	(-0.46)
H–L	-0.16	-0.13	0.02	-0.26	-0.67	-0.53
	(-1.47)	(-1.39)	(0.16)	(-2.41)	(-3.60)	(-2.85)

Panel B: Double sort on attention and factor MOM

	MOM					
Attention	P1	P2	P3	P4	P5	H–L
Low	0.01	0.09	0.31	0.61	0.94	0.95
	(-0.04)	(0.71)	(3.10)	(5.92)	(6.89)	(4.66)
P2	-0.15	0.05	0.24	0.38	0.70	0.84
	(-1.17)	(0.56)	(3.32)	(4.67)	(6.15)	(4.25)
P3	-0.10	0.16	0.24	0.39	0.53	0.63
	(-0.92)	(2.06)	(3.87)	(5.39)	(5.49)	(3.77)
P4	-0.15	0.16	0.24	0.36	0.60	0.75
	(-1.25)	(1.86)	(4.13)	(4.97)	(5.04)	(3.62)
High	-0.15	0.04	0.18	0.30	0.53	0.69
	(-1.37)	(0.65)	(2.64)	(3.38)	(3.76)	(3.03)
H–L	-0.15	-0.05	-0.13	-0.31	-0.41	-0.27
	(-1.05)	(-0.38)	(-1.27)	(-2.81)	(-2.95)	(-1.16)

Table 6: Macroeconomic news and firm earnings announcements

This table reports monthly average returns of portfolios sorted by MAX within subsamples partitioned by extreme versus non-extreme news environments, using multiple proxies for macroeconomic and firm-level news: aggregate stock market returns, economic policy uncertainty (EPU), the VIX index, and firm-level earnings announcements. In Panels A,B,C, each month, observations with the highest or lowest values are classified as extreme, all others are non-extreme. We then evaluate the performance of the factor MAX spread portfolio within each subsample. In Panel D, we classify a factor-month as having earnings announcements if stocks in the factor's long or short legs report earnings within the month; otherwise, they are classified as having no earnings announcements, and we evaluate the factor MAX portfolio accordingly. Daily and monthly factor returns are from Chen and Zimmermann (2022). All portfolios are rebalanced at a monthly frequency. Newey-West *t*-statistics are reported in parentheses. Sample period is 1963:01 – 2023:12.

Panel A: Market return	P1	P5	H–L	Panel B: Economic policy uncertainty	P1	P5	H–L
Extreme				Extreme			
Return	0.04	0.13	0.13	Return	-0.05	0.35	0.21
	(0.66)	(1.04)	(0.96)		(-0.45)	(1.38)	(0.80)
FF5	0.01	0.10	0.12	FF5	-0.11	0.32	0.15
	(0.13)	(0.70)	(0.78)		(-0.94)	(1.26)	(0.66)
Non-Extreme				Non-Extreme			
Return	0.11	0.54	0.44	Return	0.10	0.46	0.36
	(3.47)	(8.88)	(6.75)		(3.23)	(6.94)	(6.11)
FF5	0.06	0.45	0.40	FF5	0.05	0.40	0.35
	(0.20)	(5.80)	(4.58)		(1.96)	(6.58)	(5.11)

Panel C: VIX	P1	P5	H–L	Panel D: Firm earnings announcements	P1	P5	H–L
Extreme				Earnings announcements			
Return	-0.12	0.14	0.27	Return	0.34	0.16	-0.19
	(-1.03)	(0.31)	(0.61)		(5.58)	(2.03)	(-1.98)
FF5	-0.22	0.52	0.78	FF5	0.29	0.17	-0.12
	(-1.41)	(1.22)	(1.91)		(4.79)	(2.13)	(-1.12)
Non-Extreme				No earnings announcements			
Return	0.12	0.37	0.24	Return	0.08	0.28	0.20
	(2.99)	(5.01)	(2.81)		(2.12)	(3.69)	(2.50)
FF5	0.09	0.36	0.27	FF5	0.03	0.25	0.21
	(2.60)	(4.34)	(2.77)		(0.97)	(3.46)	(2.38)

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

This table reports monthly average 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 PC factor returns and longs (shorts) the factors in the top (bottom) quintiles. Daily and monthly factor returns are from Chen and Zimmermann (2022). Reported are the returns and Fama and French (2015) five-factor model (FF5) alpha. All portfolios are rebalanced at a monthly frequency. Newey-West t-statistics are reported in parentheses. ***, **, and * denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1963:01 – 2023:12.

	PC1 – PC20	PC21 – PC40	PC41 – PC60
Returns	0.39***	0.22*	0.21
	(3.02)	(1.91)	(1.55)
Adj. R^2	0.01	0.01	0.01
FF5	0.48***	0.18	0.33**
	(2.95)	(1.48)	(1.98)
Adj. R^2	0.01	0.03	0.01
	PC61 – PC80	PC81 – PC100	PC101 – PC122
Returns	0.02	-0.04	-0.05
	(0.10)	(-0.24)	(-0.30)
Adj. R^2	0.01	0.01	0.01
FF5	0.02	-0.14	0.05
	(0.12)	(-0.98)	(0.32)
Adj. R^2	0.01	0.01	0.01