International Journal of
Financial Studies

MDPI

Article

Harnessing the Power of Past Triumphs: Unleashing the MAX Effect's Potential in Emerging Market Returns

Ştefan Cristian Gherghina [1,*], Durmuş Yıldırım [2] and Mesut Dogan [3]

[1] Department of Finance, Bucharest University of Economic Studies, 6 Piata Romana, 010374 Bucharest, Romania
[2] Department of Business Administration, Ondokuz Mayıs University, Samsun 55270, Türkiye; durmus.yildirim@omu.edu.tr
[3] Department of Finance, Banking and Insurance, Bilecik Seyh Edebali University, Bilecik 11300, Türkiye; mesut.dogan@bilecik.edu.tr
* Correspondence: stefan.gherghina@fin.ase.ro

Abstract

This study investigates the presence of the MAX effect, as defined by Bali et al. (2011), in the stock market of Borsa Istanbul, aiming to validate and extend previous findings in international markets. A comprehensive analysis of 439 firms from December 2013 to November 2023 reveals that stocks with low performance in previous periods tend to show strong performance in subsequent periods. This finding indicates that the MAX effect is also applicable to Borsa Istanbul and suggests that this effect can significantly influence stock price movements in the market. Additionally, this study highlights that past maximum returns, especially those accumulated over long periods, have a distinct impact on future returns. These findings contribute to a deeper understanding of the MAX effect's presence in and impact on financial markets and offer valuable guidance for market participants.

Keywords: maximum daily return; MAX effect; portfolio management; Borsa Istanbul

check for updates

Academic Editors: Khelifa Mazouz and Zied Ftiti

Received: 3 March 2025
Revised: 5 June 2025
Accepted: 23 June 2025
Published: 8 July 2025

Citation: Gherghina, Ş. C., Yıldırım, D., & Dogan, M. (2025). Harnessing the Power of Past Triumphs: Unleashing the MAX Effect's Potential in Emerging Market Returns. *International Journal of Financial Studies*, *13*(3), 128. https://doi.org/10.3390/ijfs13030128

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Research on the factors determining the expected values in the cross-section of stock returns began with pioneering studies by Sharpe (1964), Lintner (1965), and Mossin (1966). These studies emphasized the role of the joint distribution of individual stock returns and the market portfolio in determining expected stock returns. Within the framework of the classical Capital Asset Pricing Model (CAPM), expected stock returns are generally calculated based on their covariances with the market portfolio. However, later studies have shown that factors such as preference for trends and specialization in information acquisition can also shape stock returns (Bali et al., 2011). Therefore, deeper analyses are needed to understand how investor heterogeneity and individual stock characteristics influence expected returns.

Investors in the market constantly seek new stock market anomalies that can generate abnormal returns (Sehgal et al., 2024). When making risky investment decisions, investors tend to overweight small probabilities of large gains while underweighting high probabilities of small gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Barberis & Huang, 2008). In this context, an important anomaly that has attracted considerable attention in recent years is lottery-like behavior in stock markets, driven by investors' gambling tendencies (Annaert et al., 2013; Nartea et al., 2014; Fong & Toh, 2014; Nartea et al., 2017; Berggrun et al., 2019; C. H. Lin et al., 2021; Lu et al., 2022; Byun et al., 2023).

Kumar (2009) argues that lottery-like stocks underperform due to their strong association with gambling preferences, as they attract socioeconomically similar clientele to those of actual lottery games. Other studies, such as those by Walkshäusl (2014), Zhong and Gray (2016), T. C. Lin and Liu (2018), Wang and Lien (2022), and Hai (2023), further confirm the existence of lottery-driven behavior in stock markets.

Bali et al. (2011) identified a new anomaly in their research, referred to as the maximum daily return effect (MAX effect). The MAX effect describes the tendency in which stocks with the highest maximum returns in the previous month are associated with lower risk-adjusted returns in subsequent months (Nguyen & Truong, 2018; Sehgal et al., 2024). In other words, the MAX effect reflects a significantly negative relationship between the previous month's maximum daily return and expected monthly returns (Wang & Lien, 2023; Bradrania & Gao, 2024). Studies suggest that investors perceive stocks with high MAX as similar to lottery-like investments. Investors tend to overpay for stocks with extremely positive past returns, leading to overpricing and subsequent underperformance. In this context, the MAX effect is considered a form of lottery-like behavior in financial markets, carrying significant downside risk (Gould et al., 2023; Liu et al., 2023). As a result, the MAX effect highlights the role of investor behavior, lottery preferences, and sentiment dynamics in the formation of market anomalies across global stock markets (Gao et al., 2021).

The MAX effect arises from investors' preference for stocks with lottery-like characteristics (Cheon & Lee, 2018; Ozdamar et al., 2021). This preference mirrors behaviors observed in gambling markets, where high-risk, low-probability assets with large potential payoffs are favored despite their low expected returns (Bergsma & Tayal, 2019; Ozdamar et al., 2021). Kumar (2009) argues that such stocks attract the same demographic of investors as that of lottery players. Theoretical models explain how investor preferences for skewness influence asset returns. For instance, Mitton and Vorkink (2007) show that investors with skewness preferences tend to hold poorly diversified portfolios, leading to the underperformance of stocks with high idiosyncratic skewness. Similarly, Tversky and Kahneman's (1992) prospect theory explains investors' inclination toward assets with small probabilities of large gains, influencing risk-taking behavior and contributing to mispricing, overvaluation, and negative returns.

The primary objective of this study is to investigate the existence of the MAX effect in the Borsa Istanbul (BIST) stock market. This study utilizes monthly and daily data from 448 firms traded on BIST between December 2013 and November 2023. This research contributes to the literature in multiple ways. First, most MAX effect studies focus on U.S. and European markets. Examining the MAX effect in emerging markets like Borsa Istanbul can provide new and valuable insights, helping to understand how different market conditions affect investor behavior. Second, market regulators can identify the prevalence of anomalies such as the MAX effect, enabling them to enhance market efficiency and transparency through new regulations. Third, investors can better diversify their portfolios and optimize risk management strategies based on the findings. Additionally, understanding market anomalies allows investors to identify potential investment opportunities more effectively. Finally, firms listed on BIST, financial analysts, and other market participants can gain a deeper understanding of the MAX effect, helping them refine their strategic planning and market forecasting.

This study consists of five sections. Following the Introduction, the second section highlights the significance of MAX effect and lottery-like behaviors in financial markets, summarizing previous research in this field. The third section details the methodology and variables used to measure the MAX effect. The fourth section empirically tests the existence of the MAX effect in BIST. The final section presents recommendations for investors, market

regulators, firms, and other stakeholders, along with a discussion of potential directions for future research.

2. Literature Review

Researchers have increasingly investigated the maximum daily return (MAX) effect in both developed and emerging markets. The existence of the MAX effect was first identified by Bali et al. (2011), who introduced it as a new anomaly in asset pricing. Their study suggested that extreme positive returns play a crucial role in the cross-sectional pricing of U.S. stocks. Specifically, the researchers found a statistically significant negative relationship between the previous month's maximum daily return (MAX) and the cross-section of expected stock returns in the following month. The authors argued that investors irrationally prefer assets with positively skewed returns, leading to their overvaluation. Furthermore, their findings suggest that this anomaly can be generalized across various global markets.

Following Bali et al. (2011), several studies have examined the MAX effect outside the U.S. Walkshäusl (2014) analyzed 11 European Union countries using multiple regression models and found a significant negative relationship between past MAX and future stock returns. Annaert et al. (2013), using portfolio sorting and cross-sectional regressions for 13 European markets, confirmed the presence of the MAX effect. However, Chee (2012) did not find evidence of the MAX effect in the Japanese market.

Fong and Toh (2014) found that the MAX effect is strongly linked to investor sentiment and that the underperformance of high-MAX stocks is mainly driven by lottery-like stocks. Similarly, Zhong and Gray (2016) provided evidence of a strong MAX effect in Australian stocks, attributing it to the poor performance of high-MAX stocks. Cheon and Lee (2018) found that the preference for lottery-type stocks and the degree of the MAX effect vary across countries.

In the Chinese stock market, Nartea et al. (2017) confirmed the existence of the MAX effect. Byun et al. (2023) suggested that the MAX effect is driven by investors' lottery preferences and behavioral biases. Similarly, T. C. Lin and Liu (2018) found empirical evidence supporting the existence of lottery-type investment behavior. Eraker and Ready (2015) argued that investors overpay for stocks with lottery-like returns, and the MAX effect is the most prominent among overvalued stocks. Aboulamer and Kryzanowski (2016) found that in the Canadian stock market, the relationship between extreme positive returns and future expected returns is influenced by institutional ownership. Their results indicate that reversals in extreme daily returns are more pronounced in stocks with low institutional ownership.

In recent years, empirical studies on the MAX effect have continued to be conducted. Yuan et al. (2020) examined the role of extreme positive returns in the cross-section of stock returns across seven countries. Their findings indicate that the MAX effect has weakened over time and, in some cases, even reversed. Additionally, contrary to expectations, a positive relationship between MAX and stock returns was found in Canada, the UK, and the U.S., while the MAX effect was statistically significant in China but not in Germany, France, or Japan. The authors conclude that the MAX effect is not stable over time. Gao et al. (2021) investigated the MAX effect in the Chinese financial market, finding that MAX stocks exhibit lottery-like characteristics and that the negative performance of MAX stocks is linked to investor sentiment and fluctuates over time. Furthermore, their findings suggest that the MAX effect weakened after the introduction of short-selling in 2010.

Chelikani et al. (2022) analyzed how past stock returns influence investors' demand for lottery-like stocks in the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and NASDAQ. Their study, using data from 1972 to 2018, found that the MAX

effect is primarily concentrated in stocks that previously recorded the worst returns. In contrast, stocks that had previously recorded the best returns exhibited a much weaker or even non-existent MAX effect. Khurram et al. (2022) examined the MAX effect in the Pakistan stock market, confirming that stocks with extreme daily (positive) returns tend to underperform in the following month. However, unlike previous studies, they found that the MAX effect in Pakistan is only present during periods of economic expansion, linking their findings to the theoretical model of Palfrey and Wang (2012).

Alshammari and Goto (2022) investigated how lottery-like stocks are valued in Saudi Arabia, where the majority of investors are Muslim. Their analysis revealed that lottery-like characteristics, such as high idiosyncratic volatility and/or high maximum daily returns, are generally associated with lower average returns. In other words, a significant decline in returns was observed for lottery-like stocks in Saudi Arabia. Interestingly, despite strong moral opposition to gambling and lotteries among Saudi investors, they still overpay for lottery-like stocks.

Sehgal et al. (2024) analyzed lottery behavior in the Indian stock market using data from December 2001 to March 2021. Their findings suggest that a new MAX factor, which incorporates more recent data, better captures investors' lottery behavior compared to the conventional measures suggested by Bali et al. (2011). Additionally, they highlighted that lottery stocks exhibit characteristics such as skewness, tail risk, and idiosyncratic volatility, reinforcing their attractiveness to investors despite their poor long-term performance.

3. Methodology

3.1. Data and Variable Description

The dataset used in this study comprises 680,815 daily and 35,590 monthly observations covering firms listed on Borsa Istanbul (BIST) over the period from December 2013 to November 2023. Initially, data from 439 firms were collected. However, due to data limitations, the final sample includes 377 firms. Firms with insufficient or missing stock price and financial data, as well as those affected by structural changes such as mergers or delistings, were excluded from the analysis to ensure data consistency and robustness. The data were obtained from the Eikon Datastream database and include daily and monthly stock prices, market-to-book (P/B) ratios, historical volatility, total market capitalization (size), and monthly trading volume.

The number of firms included in the sample varies over time, reflecting changes in the companies listed on BIST. Specifically, the number of firms increased from 244 in 2013 to 377 in 2023. The changes in the number of firms over years are presented in detail in Table A1 in Appendix A.

Borsa Istanbul (BIST) is selected as the empirical setting for several important reasons. First, Turkey is classified among the "Fragile Five" emerging market economies, a term coined in August of 2013 by a research analyst at Morgan Stanley (Chadwick, 2019) to describe countries with large current account deficits, heavy reliance on foreign capital inflows, and heightened vulnerability to global financial shocks. Alongside Brazil, India, Indonesia, and South Africa, Turkey exhibits significant macroeconomic fragility, which frequently results in elevated market volatility and currency depreciation. These structural vulnerabilities make BIST an ideal laboratory for testing asset pricing anomalies, such as the MAX effect, under volatile and fragile market conditions.

Second, BIST hosts a large number of listed firms across various sectors and offers relatively high liquidity compared to other regional markets, providing a rich and diverse sample for analysis. Third, the sample period from December 2013 to November 2023 is deliberately chosen to cover a decade characterized by major domestic and global financial events, including political turbulence, economic policy shifts, and external shocks. This

dynamic period allows for a comprehensive examination of the behavior of extreme returns in an emerging market setting that is sensitive to both internal and external factors.

For empirical analysis, several asset pricing factors and control variables were constructed based on standard methodologies in the literature. Specifically, the SMB (size), HML (value), and MOM (momentum) factors were computed following Fama and French (1993) and Carhart (1997), using the BIST sample. Additionally, a short-term reversal factor was calculated to capture potential mean reversion effects in stock returns.

The primary variable of interest in this study is MAX, which captures the maximum daily return of each stock within a given month. Formally, for stock i in month t, MAX is defined as follows:

$$MAX_{i,t} = max(R_{i,d}), d = 1, \ldots, D_t \quad (1)$$

where $R_{i,d}$ denotes the logarithmic return of stock i on day d. D_t represents the number of trading days in month t. Notably, while MAX typically reflects extreme positive returns, it can also take negative values in months where a stock experiences persistent declines. Consistent with Lu et al. (2022), the MAX variable inherently exhibits extreme value characteristics and is expected to follow a Fréchet distribution. Accordingly, the distributional properties of MAX, including skewness, kurtosis, and tail behavior, are carefully examined, and potential outlier effects are controlled in the analysis.

In addition to MAX, this study incorporates several control variables widely used in asset pricing research. Historical volatility is measured as the standard deviation of daily returns over the previous month. Firm size is proxied by market capitalization, while the P/B ratio reflects the firm's value characteristics. The SMB, HML, and MOM factors are included as standard risk factors.

Furthermore, a short-term reversal factor is constructed following Jegadeesh (1991) and Lehmann (1990) to examine the tendency of stock returns to reverse over short horizons. Each month, stocks are ranked based on their cumulative returns over the previous month, calculated using daily data. Two portfolios are then formed: the top 10% (winners) and the bottom 10% (losers). The reversal factor is calculated as the return difference between these portfolios:

$$\text{Reversal}_t = \overline{R}_{\text{Winners,t}} - \overline{R}_{\text{Losers,t}} \quad (2)$$

where $\overline{R}_{\text{Winners,t}}$ and $\overline{R}_{\text{Losers,t}}$ represent the average returns of the winner and loser portfolios, respectively. The reversal variable is designed to capture potential return reversals and enrich the model's explanatory power regarding stock return dynamics.

All data cleaning, processing, analysis, and result presentation were conducted using the R programming language. The dataset was carefully cleaned by removing observations with missing or erroneous values. Several R packages were utilized for data manipulation, statistical analysis, and reporting, including dplyr, tidyverse, lubridate, lmtest, sandwich, readxl, openxlsx, knitr, and kableExtra.

3.2. Data Preparation and N-Day Maximum Return Calculation

In this study, a comprehensive data preparation and preprocessing process was conducted to ensure the robustness of the analyses. In the first step, all date information was standardized. Subsequently, several filtering steps were applied to minimize the potential adverse effects of missing and outlier values, which are common in financial datasets. Observations with missing values were removed from the dataset, while economically meaningless records with negative or zero price-to-book ratios were eliminated. Additionally, the price-to-book ratio variable was winsorized at the 1st and 99th percentiles to mitigate the distorting impact of extreme values. This procedure effectively limited the influence of outliers while preserving the informational content of the dataset.

Following data preparation, the main independent variable of this study—n-day maximum returns—was systematically calculated. For each firm and each month, the highest cumulative n-day return observed within the month was computed. Specifically, the maximum returns over 1-, 2-, 3-, 4-, and 5-day periods were calculated separately, enabling a detailed analysis of the maximum return effects across different time horizons.

After calculating the n-day maximum returns, firms were ranked each calendar month based on these values and sorted into ten equally sized groups (deciles). In this classification, Decile 1 represents firms with the lowest n-day maximum returns, while Decile 10 includes those with the highest. Constructing decile portfolios on a monthly basis allows for adaptation to changing market conditions and facilitates the detection of potential anomalies over time.

Subsequently, a Generalized Extreme Value (GEV) distribution analysis was applied to examine the tail risk and extreme value characteristics of the n-day maximum returns. The GEV model captures the tail behavior and extreme value patterns of the maximum returns, revealing their potential risk implications for financial markets. The estimated shape parameter of the GEV distribution indicates the tail type, identifying whether the distribution exhibits heavy-tailed (Fréchet), bounded-tailed (Weibull), or light-tailed (Gumbel) behavior.

Finally, daily financial data were aggregated to a monthly frequency to construct the dataset required for portfolio formation and performance analysis.

3.3. Portfolio Construction and Composition

The portfolio strategies employed in this study were designed to test the cross-sectional predictive power of the n-day maximum return variable. At the end of each calendar month, all stocks in the sample were ranked based on their n-day maximum returns and sorted into ten equally sized groups (deciles). As a result of this classification, each decile group contained approximately the same number of stocks. The number of firms included in the portfolio calculation by year is presented in Table A1 in Appendix A.

Portfolio composition was determined using two different weighting methodologies. In equal-weighted portfolios, an equal amount of investment was allocated to each stock within the decile group. For example, if a decile group contained 25 stocks, 4% of the portfolio (1/25) was allocated to each stock. This approach allows for a pure assessment of the impact of the n-day maximum return, independent of stock size. In value-weighted portfolios, the weight of each stock was determined based on its market capitalization. Specifically, each stock's weight within the portfolio was calculated as the ratio of its market value to the total market value of all stocks in the decile group. The value-weighted approach better reflects market realities and allows for the testing of more practical investment strategies. Both portfolio types were rebalanced at the end of each month, ensuring that changing market conditions and firm characteristics were reflected in the portfolio composition.

Additionally, this study tested a High-Minus-Low ($10 - 1$) portfolio strategy as an arbitrage-based investment approach. This strategy involves taking a long position in stocks within the highest decile group (Decile 10) with the highest n-day maximum returns while simultaneously taking a short position in stocks within the lowest decile group (Decile 1). This forms a zero-net-investment portfolio and directly tests whether the n-day maximum return anomaly generates an economically meaningful return difference.

The performance of the constructed portfolios was evaluated using comprehensive statistical analysis methods. The average monthly return for each decile portfolio was calculated, and its statistical significance was tested using a *t*-test. The performance of the High-Minus-Low ($10 - 1$) strategy was examined in detail. The average return, t-statistic, and *p*-value of this strategy were calculated, enabling the assessment of both the statistical and economic significance of the maximum return anomaly. Performance analyses were

conducted separately for equal-weighted and value-weighted portfolios, allowing the potential impact of the weighting methodology on the results to be identified.

3.4. Fama–French–Carhart Four-Factor Model Analysis

To evaluate portfolio performance adjusted for common risk factors, the Fama–French–Carhart four-factor model was employed. The model specification is as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{m,t} - R_{f,t}\right) + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \beta_4 \cdot MOM_t + \varepsilon_{i,t} \quad (3)$$

where R_i represents the stock return; R_f denotes the risk-free rate; α is the model's intercept; $\beta_1, \beta_2, \beta_3, \beta_4$ are the factor coefficients; and $\varepsilon_{i,t}$ represents the error term. Alpha (α) measures the abnormal returns unexplained by the factors. Newey–West-adjusted standard errors were used to correct for heteroskedasticity and autocorrelation. The model was estimated for each MAX-based decile and High–Low ($10 - 1$) spread portfolios, using both equal- and value-weighted returns. The SMB, HML, and MOM factors used in this study were calculated by the authors specifically for the Turkish stock market. SMB (Small Minus Big) represents the size effect and is calculated as the return difference between small-cap and large-cap portfolios formed monthly based on market capitalization. HML (High Minus Low) captures the value effect, computed as the return difference between high-book-to-market (value) and low-book-to-market (growth) portfolios. MOM (momentum) reflects the return spread between past winners and losers, based on the top and bottom 30% of stocks ranked by their prior 12-month performance. Given this study's focus on short-term momentum, MOM is calculated using one-month daily data. The 1-year government bond yield is used as the risk-free rate in the analysis.

3.5. Cross-Sectional Regression Analyses

Cross-sectional regressions were conducted to further explore the determinants of the MAX anomaly and its relation to other known anomalies. The baseline model is specified as follows:

$$R_{i,t+1} = \alpha + \beta_1 \cdot Lag_MAX_{i,t} + \beta_2 \cdot Controls_{i,t} + \varepsilon_{i,t+1} \quad (4)$$

where the dependent variable is the stock's next-period return. Independent variables include the lagged MAX value and various control variables such as the volatility, size, book-to-market ratio, momentum, and reversal factors. Both univariate and multivariate regressions were run to isolate the individual and joint effects of MAX. The analysis was repeated for different n-day MAX definitions. Robust standard errors were used, and statistical significance was reported using standard notation.

To examine the MAX effect across return distributions, single-variable regressions were performed within each decile portfolio. Future stock returns were regressed solely on lagged MAX values to capture the marginal effect of extreme returns:

$$R_{i,t} = \alpha_i + \beta_i \cdot Lag_MAX_t^{(n)} + \varepsilon_{i,t} \quad (5)$$

This analysis allowed us to test whether the predictive power of MAX varies across low- and high-return portfolios. The results were reported for each n-day MAX version, showing how sensitivity increases across deciles.

3.6. Economic Uncertainty Interaction and Subsample Analysis

An extended model incorporating economic uncertainty was estimated to assess whether the MAX effect strengthens under higher uncertainty levels. The model is specified as follows:

$$R_{i,t+1} = \alpha + \beta \cdot Lag_MAX_{i,t} + \gamma \cdot Lag_EUI_t + \delta \cdot \left(Lag_MAX_{i,t} \times Lag_EUI_t\right) + \theta \cdot Controls_{i,t} + \varepsilon_{i,t+1} \quad (6)$$

In this specification, $R_{i,t+1}$ denotes the return of stock i in period $t+1$. The variable $Lag_MAX_{i,t}$ represents the lagged n-day maximum daily return of stock i, capturing the potential impact of extreme positive returns. Lag_EUI is the lagged economic uncertainty index, which measures the prevailing level of economic uncertainty in the market. The interaction term $Lag_MAX_{i,t} \times Lag_EUI_t$ is included to examine whether economic uncertainty moderates the effect of extreme returns (MAX) on future stock returns. $Controls_{i,t}$ refers to a set of firm-specific control variables, including the volatility, firm size, book-to-market ratio, momentum, and short-term reversal factors, which are commonly used in the asset pricing literature to account for known anomalies and risk factors. Lastly, $\varepsilon_{i,t+1}$ is the error term.

Subsample regressions were also performed by splitting the sample into high- and low-uncertainty periods based on the median value of the economic uncertainty index (EUI). Separate models were estimated within each subsample to explore potential regime-specific dynamics. Finally, difference tests were conducted to compare the MAX coefficients across the two uncertainty regimes and assess the statistical significance of any observed differences.

4. Findings

4.1. Descriptive Statistics

Table 1 presents the summary statistics of the dataset, covering a total of 35,590 observations from 439 firms listed on Borsa Istanbul.

Table 1. Descriptive statistics.

Değişkenler	*n*	Mean	Std. Dv.	Min	Max	Skew.	Kurt.	Hill	Shp.	Dist.
Max 1-Day Return	35,590	0.057	0.027	−0.038	0.100	0.216	1.796	0.002	−0.245	Wei (Bnd.)
Max 2-Day Return	35,590	0.098	0.048	−0.077	0.219	0.473	2.234	0.020	−0.070	Wei (Bnd.)
Max 3-Day Return	35,590	0.130	0.068	−0.118	0.316	0.686	2.746	0.023	−0.025	Wei (Bnd.)
Max 4-Day Return	35,590	0.155	0.085	−0.160	0.408	0.838	3.276	0.012	−0.028	Wei (Bnd.)
Max 5-Day Return	35,590	0.174	0.100	−0.268	0.496	0.930	3.798	0.006	−0.052	Wei (Bnd.)
Volatility	35,590	0.494	0.198	0.036	2.460	1.209	5.824	0.121	0.017	Fréchet (H)
Size	35,590	4264	15,415	1940	372,552	10.769	164.39	0.292	1.692	Fréchet (H)
M/B	35,590	3.801	19.922	0.090	1790.09	54.662	4220.43	0.622	0.689	Fréchet (H)
M/B (winsorized)	35,590	3.095	4.972	0.230	35.093	4.350	24.906	n.a.	0.690	Fréchet (H)
SMB	120	−0.009	0.030	−0.090	0.128	0.894	7.826	n.a.	−0.116	Wei (Bnd.)
HML	120	−0.021	0.029	−0.183	0.037	−1.470	8.240	n.a.	−0.476	Wei (Bnd.)
MOM	120	0.167	0.064	−0.041	0.471	0.539	5.757	n.a.	−0.161	Wei (Bnd.)
Reversal	120	0.499	0.124	0.306	1.177	1.677	8.995	n.a.	0.084	Fréchet (H)
EUI	120	142.453	88.361	49.903	521.295	2.455	10.283	n.a.	0.289	Fréchet (H)

Notes: This table presents descriptive statistics for all variables used in the analysis. For each variable, the number of observations, mean, standard deviation, minimum and maximum values, skewness, kurtosis, Hill index, and Sharpe ratio are reported. The last column shows the best-fitting distribution based on tail behavior, where "Wei (Bnd.)" denotes a bounded Weibull distribution, and "Fréchet (H)" refers to a heavy-tailed Fréchet distribution. The MAX n-day return variables represent the maximum daily returns within 1- to 5-day windows. Volatility is the monthly standard deviation of daily returns. Size is measured as market capitalization, and M/B represents the market-to-book ratio (both raw and winsorized versions are shown). Factor variables SMB, HML, MOM, and reversal follow Fama–French–Carhart definitions. EUI denotes the economic uncertainty index.

Table 1 presents the statistical distribution characteristics of the fundamental financial variables used in this study. This table includes the mean, standard deviation, extreme values, skewness, kurtosis, Hill estimates, shape parameters, and the appropriate distribution types for the maximum returns, volatility, firm size, market-to-book ratio, and various factor variables. Such detailed descriptive statistics are critically important for evaluating

the accuracy of distributional assumptions, especially in financial studies where extreme value analyses become significant.

Maximum returns (from Max 1-Day Return to Max 5-Day Return) are notable for their increasing mean and standard deviation values. This indicates that as the observed time period is extended, both returns and variance increase. Skewness and kurtosis values reveal that the distributions are asymmetric, with positive extreme values being influential. However, the classification of these variables as "Weibull (bounded)" suggests that while extreme values are present, they are limited in extent. The very low Hill estimate values (0.002–0.023) and negative shape parameters further confirm this limited extreme value structure.

Although MAX values typically reflect extreme positive returns, it is possible for them to be negative in certain months. This occurs when a stock experiences consistent declines throughout the entire month, making the highest observed n-day return within that month still negative. Such behavior is not a data error but rather a natural outcome in periods of persistent bearish trends, especially in fragile or volatile markets like BIST.

On the other hand, the volatility, firm size, M/B ratio, reversal, and economic uncertainty index (EUI) variables exhibit distinctly heavy-tailed distributions with strong right skewness and high kurtosis values. The Hill estimates and positive shape values for these variables are consistent with the characteristic features of the Fréchet distribution. This distribution type is frequently employed in extreme value theory (EVT) and should be considered as it can create significant deviations in analyses based on traditional normal distribution assumptions.

Particularly for the M/B ratio, extreme observations in the original (non-winsorized) values (such as maximum values of 1790) caused very high skewness and kurtosis measures; thus the winsorized version of this variable has also been separately reported. Despite winsorization, the M/B variable continues to demonstrate high extreme value effects and exhibits a structure consistent with the Fréchet distribution.

The Fama–French factors—SMB, HML, and MOM—are generally characterized by Weibull (bounded)-type distributions and appear to have relatively more limited extreme values. However, the positive Hill estimates and high skewness–kurtosis values obtained for the reversal variable and the economic uncertainty index (EUI) indicate that these variables have high potential for extreme observations, and therefore modeling them with Fréchet-type heavy-tailed distributions seems appropriate.

In conclusion, most of the variables used in this study deviate from classical statistical distributions and exhibit asymmetric, leptokurtic structures containing extreme values. The Weibull distribution assigned particularly for maximum returns methodologically diverges from the Fréchet fit documented in Lu et al. (2022).

Table 2 presents the average monthly returns of MAX portfolios formed in Borsa Istanbul during the analyzed period. This analysis provides a detailed overview of how returns vary across portfolios in terms of time frame and return levels.

As seen in the results, as the decile portfolio values increase from low to high, the average portfolio returns also rise significantly. For instance, in the one-day time frame, the average return in the lowest portfolio is 2.3%, while in the highest portfolio, this rate reaches 9.6%. This trend becomes even more pronounced in the five-day time frame, where the lowest portfolio offers a return of 6.2%, whereas the average return in the highest portfolio increases to 33.9%. The increase in returns is directly proportional to the time frame; in other words, as the time horizon is extended, stock returns also increase. This is a crucial factor for investors to consider when evaluating long-term investment strategies. The High–Low difference, which stands at 7.35% for one-day maximum returns, rises to

27.75% for five-day maximum returns, indicating that long-term investments generally have higher return potential compared to short-term investments.

Table 2. Average returns of MAX portfolios.

Portfolios	MAX(1)	MAX(2)	MAX(3)	MAX(4)	MAX(5)
Low MAX	0.023	0.040	0.053	0.060	0.062
2	0.032	0.056	0.075	0.088	0.098
3	0.039	0.067	0.089	0.105	0.117
4	0.045	0.077	0.102	0.121	0.135
5	0.052	0.088	0.116	0.137	0.153
6	0.060	0.100	0.130	0.153	0.171
7	0.067	0.113	0.147	0.173	0.193
8	0.075	0.129	0.168	0.198	0.221
9	0.084	0.146	0.195	0.233	0.262
High MAX	0.096	0.173	0.238	0.293	0.339
High–Low	0.0735 *** (349.2)	0.1326 *** (260.5)	0.1852 *** (208.1)	0.2331 *** (175.6)	0.2775 *** (156.4)

Notes: This table reports the average returns of decile portfolios sorted by the MAX variable over 1 to 5 days. "Low MAX" represents the lowest decile, while "High MAX" represents the highest decile of stocks ranked by their MAX. The "High–Low" row shows the difference in returns between the highest and lowest MAX portfolios, with the corresponding t-statistics reported in parentheses. *** denotes significance at the 1% level.

4.2. Univariate Portfolio Analysis

Table 3 presents the monthly average returns and Fama–French–Carhart (FF4) model alphas of value-weighted decile portfolios formed according to different n-day MAX definitions (from 1-day to 5-day). Portfolios are rebalanced monthly, and returns are reported with Newey–West-adjusted t-statistics.

Portfolios with low MAX values (Decile 1) consistently deliver statistically significant and positive average monthly returns across all MAX definitions (approximately 1.9–2.0%). However, after adjusting for risk factors via the FF4 model, the corresponding alpha values are generally statistically insignificant or slightly negative, suggesting that the high average returns are largely explained by exposure to systematic risk factors. For the full regression results, including alpha coefficients, factor loadings, t-statistics, and R^2 values for each decile and MAX definition, please refer to Appendix A Tables A2–A11.

In contrast, high-MAX portfolios (Decile 10) exhibit notably lower average returns, which are mostly statistically insignificant. More importantly, these portfolios generate consistently negative alphas, with some reaching statistically significant levels—for example, −6.0% under MAX(1) with a t-statistic of −2.31 (significant at the 5% level). This indicates that stocks with extreme short-term positive returns tend to underperform after risk adjustment, consistent with a mispricing hypothesis.

The High-Minus-Low (10 − 1) strategy portfolio yields negative average returns and alphas across all MAX definitions. Although the raw return differentials are not statistically significant, the risk-adjusted alpha spread becomes significant in certain specifications—most notably under MAX(1), with a differential of −5.9% ($t = -2.09$, significant at the 5% level). This finding indicates that the MAX effect is more pronounced after controlling for risk, rather than being observable through raw returns alone.

Interestingly, intermediate portfolios (e.g., Deciles 4–6) occasionally outperform the extremes, suggesting that stocks with moderate MAX values may offer more stable performance. This may reflect nonlinear investor preferences or an asymmetric pricing of extreme return profiles, possibly driven by behavioral biases.

Overall, the results from Table 3 provide evidence supporting the existence of the MAX effect in the Turkish stock market. The persistent underperformance of high-MAX

portfolios—particularly after risk adjustment—suggests that investors may irrationally overvalue "lottery-like" stocks, which subsequently disappoint. However, the lack of significance in raw return differentials highlights that this anomaly primarily emerges after accounting for systematic risk.

Table 3. Returns and alphas of value-weighted portfolios sorted by MAX values.

Portfolios	MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha
Low MAX	0.019 *** (3.02)	−0.001 (−0.12)	0.019 *** (2.81)	−0.008 (−0.87)	0.019 *** (2.87)	−0.008 (−0.94)	0.019 *** (2.99)	−0.006 (−0.70)	0.020 *** (3.03)	−0.009 (−1.00)
2	0.018 ** (2.53)	−0.004 (−0.50)	0.015 *** (2.15)	−0.007 (−1.13)	0.019 *** (2.77)	−0.002 (−0.24)	0.018 ** (2.58)	−0.001 (−0.15)	0.014 ** (2.09)	−0.008 (−0.84)
3	0.018 ** (2.56)	−0.021 ** (−2.47)	0.020 *** (2.75)	−0.018 * (−1.84)	0.018 ** (2.54)	−0.023 ** (−2.36)	0.017 ** (2.37)	−0.021 ** (−2.37)	0.017 ** (2.46)	−0.018 * (−1.71)
4	0.023 *** (3.09)	−0.005 (−0.39)	0.019 *** (2.72)	−0.014 (−1.33)	0.022 *** (3.13)	−0.006 (−0.81)	0.022 *** (3.03)	−0.013 (−1.61)	0.016 ** (2.26)	−0.024 *** (−2.79)
5	0.025 *** (3.47)	−0.011 (−1.36)	0.026 *** (3.37)	−0.008 (−0.92)	0.024 *** (3.19)	−0.005 (−0.47)	0.022 *** (3.19)	−0.008 (−0.74)	0.024 *** (3.33)	−0.001 −0.03
6	0.023 ** (2.57)	−0.011 (−0.85)	0.024 *** (3.37)	−0.019 (−1.62)	0.028 *** (3.80)	−0.027 *** (−2.69)	0.023 *** (3.16)	−0.019 (−1.65)	0.022 *** (3.03)	−0.019 ** (−2.11)
7	0.015 * (1.74)	−0.025 (−1.58)	0.019 ** (2.21)	−0.038 *** (−3.03)	0.021 *** (2.72)	−0.043 (−1.44)	0.023 ** (2.55)	−0.021 * (−1.80)	0.028 *** (3.19)	−0.015 (−1.12)
8	0.020 *** (2.64)	−0.019 (−1.45)	0.016 * (1.87)	−0.007 (−0.43)	0.016 * (1.91)	−0.034 ** (−2.12)	0.018 ** (2.17)	−0.038 *** (−2.68)	0.024 *** (2.98)	−0.023 * (−1.76)
9	0.009 (1.01)	−0.030 (−1.55)	0.021 ** (2.50)	−0.006 (−0.32)	0.020 ** (2.61)	−0.013 (−0.74)	0.015 * (1.80)	−0.015 (−0.91)	0.011 (1.37)	−0.035 ** (−2.31)
High MAX	0.014 * (1.73)	−0.060 ** (−2.31)	0.003 (0.33)	−0.049 (−1.40)	0.006 (0.62)	−0.035 (−1.09)	0.009 (0.93)	−0.031 (−0.94)	0.009 (0.92)	−0.023 (−0.68)
High–Low	−0.003 (−0.36)	−0.059 ** (−2.09)	−0.015 (−1.62)	−0.041 (−1.10)	−0.012 (−1.28)	−0.027 (−0.81)	−0.009 (−0.99)	−0.025 (−0.72)	−0.010 (−1.04)	−0.014 (−0.40)

Notes: This table reports the monthly average returns and risk-adjusted alphas of value-weighted decile portfolios sorted by different n-day MAX definitions (from MAX(1) to MAX(5)). Portfolios are rebalanced monthly based on their past maximum daily returns over the specified window. Returns and alphas are expressed in decimal form, and Newey–West-adjusted t-statistics are reported in parentheses below each coefficient. Alphas are estimated from the Fama–French–Carhart four-factor model. The bottom row presents the return and alpha differentials between the highest and lowest MAX deciles (High–Low strategy). Statistical significance is denoted by the following: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 reports the monthly average returns and FF4 model alphas of equally weighted decile portfolios sorted based on n-day MAX, using five different MAX definitions (MAX(1) to MAX(5)). Portfolios are reconstituted monthly, and all statistics are computed with Newey–West standard errors.

Portfolios in the lowest MAX decile (Decile 1) generate high and statistically significant average returns across all MAX definitions (approximately 2.0–2.4%). However, the alphas of these portfolios are consistently negative and statistically significant, typically at the 1% level. This indicates that while low-MAX stocks appear to perform well in raw terms, their performance is not abnormal after accounting for systematic risk. On the other hand, high-MAX portfolios (Decile 10) produce lower and largely insignificant average returns. Their corresponding alpha values are generally negative and in several cases statistically significant—for example, −4.8% under MAX(1) with a t-statistic of −3.74 (significant at the 1% level). These results suggest that investors may overprice stocks with extreme prior returns, leading to subsequent underperformance. The High-Minus-Low (10 − 1) strategy consistently produces negative and significant alphas in almost all MAX definitions. Under MAX(2), for instance, the alpha spread is −1.4% (t = −3.20, significant at the 1% level), with similar significance observed under MAX(1), MAX(3), and MAX(5). These results

imply that investing in high-MAX portfolios is penalized after risk adjustment and that the MAX effect does not represent an arbitrage opportunity in terms of raw return differentials. An additional observation is that middle deciles (Deciles 4–6) tend to yield more stable and relatively high returns, suggesting that moderate-MAX stocks may offer superior risk–return profiles compared to the extremes. This further supports the notion that investors may misprice extremes more severely than average-performing stocks.

Table 4. Returns and alphas of equally weighted portfolios ranked by MAX values.

Portfolios	MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha	Return	Alpha
Low MAX	0.024 *** (3.41)	−0.024 ** (−2.15)	0.022 *** (3.12)	−0.023 ** (−2.03)	0.022 *** (3.22)	−0.024 *** (−2.66)	0.020 *** (3.00)	−0.028 *** (−2.97)	0.021 *** (3.14)	−0.029 *** (−3.03)
2	0.022 *** (3.08)	−0.023 ** (−2.38)	0.025 *** (3.56)	−0.023 ** (−2.38)	0.024 *** (3.40)	−0.024 ** (−2.01)	0.026 *** (3.48)	−0.023 * (−1.87)	0.023 *** (3.12)	−0.023 * (−1.97)
3	0.025 *** (3.51)	−0.028 *** (−3.22)	0.024 *** (3.12)	−0.025 ** (−2.29)	0.024 *** (3.20)	−0.026 *** (−2.80)	0.021 *** (2.88)	−0.031 *** (−3.75)	0.022 *** (3.09)	−0.028 *** (−3.23)
4	0.025 *** (3.31)	−0.019 (−1.61)	0.025 *** (3.37)	−0.024 ** (−2.37)	0.023 *** (3.06)	−0.026 ** (−2.54)	0.025 *** (3.27)	−0.022 ** (−2.17)	0.021 *** (2.98)	−0.027 *** (−3.26)
5	0.025 *** (3.29)	−0.024 ** (−2.34)	0.021 *** (2.88)	−0.021 ** (−2.20)	0.022 *** (3.04)	−0.024 ** (−2.16)	0.021 *** (2.90)	−0.025 ** (−2.24)	0.023 *** (3.06)	−0.027 ** (−2.29)
6	0.021 *** (2.77)	−0.020 (−1.51)	0.025 *** (3.24)	−0.035 *** (−3.63)	0.023 *** (3.04)	−0.034 *** (−3.39)	0.022 *** (2.93)	−0.035 *** (−3.24)	0.023 *** (3.10)	−0.033 *** (−3.10)
7	0.020 *** (2.71)	−0.025 ** (−2.10)	0.021 *** (2.90)	−0.038 *** (−3.38)	0.021 *** (2.83)	−0.031 ** (−2.59)	0.023 *** (3.08)	0.025 * (−1.94)	0.023 *** (3.04)	−0.025 * (−1.87)
8	0.017 ** (2.50)	−0.026 ** (−2.00)	0.020 ** (2.60)	−0.021 (−1.39)	0.022 *** (2.90)	−0.024 * (−1.82)	0.023 *** (3.11)	−0.028 ** (−2.61)	0.024 *** (3.17)	−0.021 * (−1.84)
9	0.013 * (1.74)	−0.029 ** (−2.24)	0.017 ** (2.19)	−0.019 (−1.18)	0.017 ** (2.21)	−0.024 (−1.40)	0.016 ** (2.06)	−0.021 (−1.21)	0.016 ** (2.10)	−0.033 ** (−2.07)
High MAX	0.013 * (1.79)	−0.048 *** (−3.74)	0.008 (1.08)	−0.041 *** (−2.92)	0.007 (1.07)	−0.032 ** (−2.30)	0.009 (1.31)	−0.031 ** (−2.10)	0.009 (1.28)	−0.023 (−1.53)
High–Low	−0.011 ** (−2.53)	−0.023 ** (−2.27)	−0.014 *** (3.18)	−0.016 * (−1.68)	−0.014 *** (−3.20)	−0.007 (−0.69)	−0.010 ** (−2.31)	−0.003 (−0.26)	−0.012 ** (−2.57)	0.006 (−0.54)

Notes: This table reports the monthly average returns and risk-adjusted alphas of equally weighted decile portfolios sorted by different n-day MAX definitions (from MAX(1) to MAX(5)). Portfolios are rebalanced monthly based on their past maximum daily returns over the specified window. Returns and alphas are expressed in decimal form, and Newey–West-adjusted t-statistics are reported in parentheses below each coefficient. Alphas are estimated from the Fama–French–Carhart four-factor model. The bottom row presents the return and alpha differentials between the highest and lowest MAX deciles (High–Low strategy). Statistical significance is denoted by the following: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Importantly, these findings indicate that the MAX effect is stronger among smaller firms, which are overrepresented in equal-weighted portfolios. This is consistent with earlier studies (e.g., Kumar, 2009; Bali et al., 2011) documenting that lottery-like anomalies are more pronounced among small-cap stocks that attract speculative investor attention. Retail investors, influenced by extreme past returns, may irrationally overbid such stocks, leading to price corrections and underperformance. In contrast, the value-weighted portfolios presented in Table 3—more representative of large-cap firms—also exhibit the MAX anomaly but with weaker statistical strength. Although high-MAX portfolios in value-weighted form still yield negative alphas (e.g., −6.0% under MAX(1), t = −2.31), the alpha spreads (10 − 1) are generally weaker and less significant, suggesting that the anomaly is more economically relevant in the small-cap segment.

Finally, the persistence of negative alphas despite controlling for multiple risk factors supports the notion of systematic mispricing. As emphasized by Barberis and Huang (2008) and Boyer et al. (2010), such anomalies may persist due to noise trader risk, limited

arbitrage, and behavioral biases—conditions that are particularly relevant in emerging markets like Turkey.

4.3. Cross-Sectional Regression Analyses

The regression analysis results, which investigate the persistence of extreme positive daily returns, are presented in Table 5. The analysis focuses on the relationship between a stock's maximum daily return within a month (MAX) and a set of lagged predictor variables, including volatility, size, M/B ratio, SMB, HML, momentum, and reversal (short-term reversal).

Table 5. Cross-sectional predictability of MAX.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag_MAX	0.235 ***	0.390 ***							
	(45.78)	(80.35)							
Volatility	0.0284 ***		0.0484 ***						
	(41.64)		(72.71)						
Size	9.0209			5.2108 ***					
	(1.12)			(5.68)					
(M/B)	0.0001				0.0001				
	(0.29)				(1.68)				
SMB	−0.0520 ***					−0.0150 **			
	(−12.02)					(−3.13)			
HML	0.00327						−0.164 ***		
	(0.63)						(−34.35)		
MOM	−0.0148 ***							0.114 ***	
	(−3.94)							(53.49)	
Reversal	0.0576 ***								0.0756 ***
	(26.87)								(70.56)
(Intercept)	0.00283 ***	0.0348 ***	0.0329 ***	0.0567 ***	0.0569 ***	0.0567 ***	0.0535 ***	0.0378 ***	0.0192 ***
	(4.49)	(114.27)	(92.91)	(387.27)	(401.88)	(385.17)	(314.33)	(98.94)	(34.79)
adj. R^2	0.250	0.152	0.128	0.001	0.000	0.000	0.032	0.073	0.121
N	35,207	35,207	35,207	35,207	35,207	35,207	35,207	35,207	35,207

Notes: This table reports the results of the monthly firm-level cross-sectional regressions of MAX on lagged predictor variables. Each month, from December 2013 to November 2023, the maximum daily return (MAX) of each stock is regressed on lagged MAX and a set of control variables. The reported coefficients are time-series averages of the monthly estimates. T-statistics in parentheses are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation. Control variables include volatility (standard deviation of daily returns over the past month), size (log of market capitalization), market-to-book ratio (M/B), and the Fama–French–Carhart factors: SMB (size premium), HML (value premium), MOM (momentum), and reversal (short-term return reversal). Models (1) through (9) incrementally add explanatory variables to assess the robustness of the predictive power of lagged MAX. Model (1) includes only lagged MAX. Model (2) adds volatility, while Models (3) and (4) sequentially add size and M/B. Models (5) to (8) introduce SMB, HML, MOM, and reversal factors one by one. Model (9) includes all control variables and represents the full specification. Statistical significance is denoted by the following: *** $p < 0.01$, ** $p < 0.05$.

In the univariate regression, the coefficient of lagged MAX is 0.390, which is positive and highly significant (t = 80.35), with an adjusted R^2 exceeding 15%. This finding provides strong evidence for the persistence of extreme positive returns—stocks that exhibited high daily returns in the previous month tend to experience similar behavior in the current month. Among the other univariate regressions, the variables volatility, momentum, and reversal are also found to have positive and statistically significant effects on MAX, with adjusted R^2 values of 12.8%, 7.3%, and 12.1%, respectively. These results indicate that MAX values are strongly associated with risk (volatility), past momentum, and short-term return reversals, suggesting that both risk-taking and behavioral anomalies may explain the variation in extreme positive returns.

In the multivariate regressions, where all control variables are included simultaneously, the model's explanatory power improves considerably, with an adjusted R^2 reaching 25%. The lagged MAX coefficient remains significant (0.235, t = 45.78), reinforcing the evidence of return persistence. Volatility continues to exert a positive and significant effect, supporting the risk–return tradeoff hypothesis. Interestingly, the reversal variable also

remains positively significant (0.0756, t = 70.56), implying that stocks with poor short-term past performance tend to generate higher MAX subsequently—consistent with a short-term overreaction correction. On the other hand, variables such as size and the market-to-book (M/B) ratio are statistically insignificant in the full model, suggesting that these firm characteristics do not systematically influence extreme positive return behavior in this context.

Finally, Table 6 further explores this persistence effect by analyzing the coefficients of lagged MAX variables across different portfolio sorts. The progression from MAX(1) to MAX(5) illustrates the cumulative effect of past extreme returns, providing deeper insight into how the distribution of high-return days impacts future performance.

Table 6. Single-variable regression analysis results by portfolio.

Portfolios	MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
	Lag_MAX	adj. R^2	Lag_MAX	adj. R^2	Lag_MAX	adj. R^2	Lag_MAX	adj. R^2	Lag_MAX	adj. R^2
Low	0.169 ***	0.16	0.311 ***	0.162	0.419 ***	0.149	0.490 ***	0.117	0.527 ***	0.082
2	0.190 ***	0.144	0.354 ***	0.16	0.463 ***	0.153	0.564 ***	0.153	0.655 ***	0.151
3	0.228 ***	0.167	0.418 ***	0.181	0.546 ***	0.172	0.662 ***	0.172	0.771 ***	0.176
4	0.269 ***	0.182	0.449 ***	0.183	0.601 ***	0.184	0.723 ***	0.181	0.791 ***	0.159
5	0.321 ***	0.202	0.527 ***	0.203	0.699 ***	0.208	0.815 ***	0.191	0.947 ***	0.195
6	0.350 ***	0.217	0.553 ***	0.192	0.734 ***	0.189	0.873 ***	0.189	1.009 ***	0.19
7	0.302 ***	0.183	0.554 ***	0.178	0.728 ***	0.167	0.943 ***	0.183	1.117 ***	0.193
8	0.145 ***	0.13	0.472 ***	0.166	0.763 ***	0.154	1.052 ***	0.162	1.296 ***	0.168
9	0.253 ***	0.174	0.573 ***	0.19	0.822 ***	0.185	0.976 ***	0.166	1.080 ***	0.151
High	−0.00159	0.001	0.241 ***	0.089	0.597 ***	0.138	0.976 ***	0.153	1.342 ***	0.157

Notes: This table reports the results of the single-variable cross-sectional regressions of current MAX on lagged MAX values, estimated separately for each decile portfolio based on past MAX rankings. The coefficient estimates and adjusted R-squared values are shown for five alternative MAX definitions (MAX(1) to MAX(5)). The reported coefficients represent the predictive power of lagged MAX, and t-statistics are robust but not reported for brevity. Statistical significance is denoted by the following: *** $p < 0.01$.

The results reveal a clear upward trend in the Lag_MAX coefficients from MAX(1) to MAX(5) across nearly all portfolios. For example, in the lowest-MAX-decile portfolio (low), the coefficient increases from 0.169 for MAX(1) to 0.527 for MAX(5). This pattern suggests that longer cumulative measures of past extreme returns possess stronger predictive power for future extreme returns, underscoring the persistence of return extremes over time. The coefficients are consistently statistically significant at the 1% level (denoted by ***), particularly in middle- and upper-decile portfolios. In portfolios 5 through 9, the coefficients steadily increase across MAX definitions and often exceed 0.9 or even 1.0 for MAX(5), highlighting the compounding effect of consecutive high-return days. This indicates that firms with more frequent or intense past extremes tend to exhibit more persistent extreme return behavior going forward.

In contrast, the adjusted R-squared values display a more nuanced behavior. In lower-decile portfolios (e.g., low, 2, and 3), explanatory power declines from MAX(1) to MAX(5). For instance, in the low portfolio, the adjusted R^2 drops from 0.160 to 0.082, implying that while longer MAX definitions have stronger coefficients, they may explain less of the return variation in less extreme stocks. However, in middle to upper portfolios (e.g., 5, 6, and 7), adjusted R^2 values remain relatively stable or even increase with higher MAX definitions, suggesting that firms with a stronger history of extreme returns exhibit more structured and predictable return patterns.

A particularly striking result is observed in the high-MAX portfolio. For MAX(1), the Lag_MAX coefficient is nearly zero (−0.00159) and statistically insignificant, with virtually no explanatory power (adjusted $R^2 = 0.001$). However, as the cumulative measure increases to MAX(5), both the coefficient (1.342) and explanatory power (adjusted $R^2 = 0.157$) rise

substantially. This indicates that in firms already prone to extreme returns, short-term maximum returns may be noise-driven, while longer-term patterns are more informative and persistent.

In summary, these findings confirm that past extreme returns—especially when accumulated over longer horizons—play a critical role in predicting future extreme positive returns. This result is consistent with Bali et al. (2011) and Nartea et al. (2017), who document that longer-term measures of MAX exhibit stronger and more persistent predictive power. Moreover, the fact that the magnitude and explanatory power of this relationship vary significantly across portfolios supports the argument by Han and Lesmond (2011) that return predictability is not uniform across the cross-section of stocks but rather portfolio-dependent. Finally, the role of idiosyncratic volatility in amplifying extreme return behavior, as highlighted by Jiang et al. (2009), further reinforces the idea that firm-specific risk and past price extremes together shape future return dynamics. These findings contribute to the expanding literature on extreme return persistence and cross-sectional return predictability.

4.4. Economic Uncertainty Interaction and Subsample Analysis

Table 7 reports the results of regression analyses examining the interaction between economic uncertainty and the predictive power of lagged maximum daily returns (MAX) on future stock returns. Specifically, the models include interaction terms between various definitions of lagged MAX (MAX(1) through MAX(5)) and the economic uncertainty index (EUI) to assess whether uncertainty moderates the persistence of extreme positive returns.

Across all specifications, the coefficients on lagged MAX remain positive and statistically significant at the 1% level, reaffirming the strong and persistent nature of the MAX effect. For instance, the coefficient for MAX(1) is 0.2553 (t = 24.66), while that of MAX(5) is 0.3304 (t = 29.48), suggesting that both short-term and cumulative extreme returns carry meaningful information about future return behavior. These findings are consistent with Bali et al. (2011), who document that the MAX effect reflects investor demand for stocks with lottery-like payoffs, which persistently influence future returns in the cross-section of equities.

In contrast, the coefficients for the interaction terms (MAX $\times$ EUI) are statistically insignificant across all models, with t-values consistently below conventional thresholds. For example, the interaction between MAX(1) and EUI yields a coefficient of -0.0001 (t = -1.19), while the coefficient for the interaction involving MAX(5) is 0.0001 (t = 0.95). These results indicate that economic uncertainty does not significantly moderate the relationship between MAX and future stock performance. This finding aligns with Brogaard and Detzel (2015), who show that while economic policy uncertainty strongly affects aggregate-level return predictability, its influence on cross-sectional anomalies such as MAX is limited.

Control variables behave as expected: volatility is positively and significantly related to future returns, consistent with risk–return tradeoff theories, while variables such as SMB, HML, and MOM exhibit conventional signs and statistical significance in line with the asset pricing literature. The adjusted R^2 increases modestly from 0.23 (MAX(1)) to 0.30 (MAX(5)), indicating improved model fit when using cumulative MAX measures.

Overall, the findings from Table 7 suggest that the predictive ability of MAX is stable across different levels of economic uncertainty. The lack of significant interaction effects implies that investor preferences for lottery-like payoffs or speculative assets—key behavioral explanations for the MAX anomaly—may persist regardless of changes in macroeconomic uncertainty. This supports the view that the MAX effect is structural and behaviorally anchored, rather than being conditional on external economic conditions (Bonomo et al., 2015; Bali et al., 2011).

Table 7. Interaction effects between economic uncertainty and MAX on future stock returns.

Variable	EUI_MAX1	EUI_MAX2	EUI_MAX3	EUI_MAX4	EUI_MAX5
(Intercept)	0.0089 ***	0.0088 ***	0.0078 ***	0.0044 *	−0.0023
	(10.30)	(6.10)	(4.01)	(1.83)	(−0.84)
MAX(1)	0.2553 ***				
	(24.66)				
MAX(2)		0.3228 ***			
		(30.99)			
MAX(3)			0.3372 ***		
			(31.72)		
MAX(4)				0.3346 ***	
				(30.71)	
MAX(5)					0.3304 ***
					(29.48)
EUI	0.0001	0.0001	−0.0001	−0.0001	−0.0001
	(1.22)	(0.45)	(−0.57)	(−1.33)	(−1.64)
MAX(1) × EUI	−0.0001				
	(−1.19)				
MAX(2) × EUI		−0.0001			
		(−0.85)			
MAX(3) × EUI			−0.0001		
			(−0.01)		
MAX(4) × EUI				0.0001	
				(0.70)	
MAX(5) × EUI					0.0001
					(0.95)
Volatility	0.0250 ***	0.0417 ***	0.0556 ***	0.0680 ***	0.0787 ***
	(29.39)	(26.93)	(25.53)	(24.94)	(24.49)
Size	−0.0003 ***	−0.0003 **	−0.0002	0.0002	0.0008 ***
	(−4.09)	(−2.29)	(−0.90)	(0.92)	(3.33)
M/B	0.0002 ***	0.0004 ***	0.0006 ***	0.0007 ***	0.0008 ***
	(7.53)	(7.38)	(7.09)	(6.83)	(6.61)
SMB	−0.0328 ***	−0.0513 ***	−0.0651 ***	−0.0774 ***	−0.0897 ***
	(−7.32)	(−6.53)	(−5.97)	(−5.64)	(−5.47)
HML	−0.0082	−0.0270 ***	−0.0520 ***	−0.0819 ***	−0.1145 ***
	(−1.50)	(−2.81)	(−3.89)	(−4.84)	(−5.67)
MOM	−0.0095 **	−0.0155 **	−0.0214 **	−0.0295 ***	−0.0382 ***
	(−2.50)	(−2.36)	(−2.37)	(−2.62)	(−2.86)
Reversal	0.0468 ***	0.0797 ***	0.1068 ***	0.1318 ***	0.1539 ***
	(20.84)	(20.27)	(19.78)	(19.55)	(19.24)
Adj. R^2	0.23	0.284	0.3	0.302	0.301
N	35,207	35,207	35,207	35,207	35,207

Notes: This table reports the results of the monthly firm-level cross-sectional regressions of future MAX on lagged MAX variables, the economic uncertainty index (EUI), and their interaction terms. Each month from 12/2013 to 11/2023, stock-level regressions are conducted using different definitions of MAX (MAX(1) to MAX(5)), and the reported coefficients represent the time-series averages of the monthly estimates. T-statistics in parentheses are Newey and West (1987) robust standard errors, adjusted for heteroskedasticity and autocorrelation. Control variables include volatility, size, market-to-book (M/B) ratio, and the Fama–French–Carhart factors: SMB, HML, MOM, and reversal. Statistical significance is denoted by the following: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8 presents a subsample analysis that evaluates the sensitivity of MAX predictability to economic uncertainty. The sample is divided into high- and low-uncertainty periods based on the median value of the economic uncertainty index (EUI), and the predictive power of lagged MAX is estimated separately for each regime.

Across all MAX specifications (from MAX(1) to MAX(5)), the coefficients remain positive and statistically significant at the 1% level under both high- and low-uncertainty conditions, underscoring the robustness of the MAX anomaly across macroeconomic regimes. For instance, under low uncertainty, the coefficient for MAX(1) is 0.2590 (t = 31.67), compared to 0.2275 (t = 28.42) under high uncertainty. Similarly, the coefficient for MAX(5) is 0.3524 (low) versus 0.3181 (high). These findings indicate that extreme positive returns

consistently predict future returns regardless of prevailing uncertainty, a result that aligns with Bali et al. (2011), who document that the MAX effect is driven by investor demand for lottery-like assets, which tends to persist irrespective of macroeconomic risk factors.

Table 8. Sensitivity of MAX predictability to economic uncertainty.

MAX Version	Low Uncertainty	High Uncertainty	Difference (Low–High)
MAX(1)	0.2590 ***	0.2275 ***	0.0316
	(31.67)	(28.42)	(0.67)
MAX(2)	0.3297 ***	0.2958 ***	0.0338
	(39.80)	(34.65)	(0.88)
MAX(3)	0.3532 ***	0.3143 ***	0.0389
	(41.00)	(35.62)	(1.05)
MAX(4)	0.3549 ***	0.3195 ***	0.0354
	(40.01)	(35.37)	(0.94)
MAX(5)	0.3524 ***	0.3181 ***	0.0343
	(38.68)	(34.11)	(0.88)

Notes: This table presents the results of the monthly cross-sectional regressions of MAX estimated separately for periods of high and low economic uncertainty, based on the median split of the economic uncertainty index (EUI). The dependent variable is MAX, and the independent variable is lagged MAX (from MAX(1) to MAX(5)). Coefficients are time-series averages across the sample period [12/2013–11/2023]. The third column reports the difference in coefficients between low- and high-uncertainty periods. T-statistics in parentheses are Newey and West (1987)-adjusted for heteroskedasticity and autocorrelation. Statistical significance is denoted by the following: *** $p < 0.01$.

While the coefficients are slightly higher during periods of low uncertainty, suggesting a marginally stronger MAX effect in more stable environments, the differences between the two regimes are not statistically significant. The t-statistics for the differences remain below conventional significance thresholds (e.g., MAX(3) difference = 0.0389; t = 1.05), confirming that the observed variation in effect sizes is neither economically substantial nor statistically meaningful. This is in line with the findings of Brogaard and Detzel (2015), who show that economic policy uncertainty has limited influence on cross-sectional return anomalies, even though it may strongly affect market-level pricing.

These results corroborate the findings from the interaction model in Table 7, further reinforcing the conclusion that economic uncertainty does not materially alter the predictive power of past extreme returns. This interpretation is also supported by Shen et al. (2017), who demonstrate that firm-level anomalies are more strongly associated with investor sentiment than with macroeconomic variables, implying that the MAX effect is rooted in persistent behavioral patterns rather than conditional macroeconomic dynamics. The persistence of the MAX anomaly across uncertainty regimes thus supports the notion that it may be driven more by firm-level structural or behavioral characteristics than by macro-level uncertainty shocks (Bonomo et al., 2015).

5. Conclusions and Discussion

This study investigates the cross-sectional predictability of extreme positive stock returns—commonly referred to as the MAX anomaly—in the Turkish stock market between December 2013 and November 2023. Building on the prior literature (e.g., Bali et al., 2011; Nartea et al., 2017), we examine whether stocks that experienced the highest daily returns in the previous month tend to exhibit persistent return patterns and whether these patterns can be explained by traditional asset pricing factors or are driven by behavioral forces.

The empirical findings strongly confirm the presence of a robust and persistent MAX effect. Portfolio-level analyses indicate that stocks with lower past MAX values consistently outperform those with higher past extremes, a result in line with prior studies documenting

the lottery-like behavior of speculative stocks (Kumar, 2009; Han & Lesmond, 2011). While raw return differences across MAX portfolios are often modest, the Fama–French–Carhart risk-adjusted alphas reveal economically significant and consistently negative abnormal returns for high-MAX portfolios—suggesting that these stocks are systematically overvalued by investors seeking outsized payoffs.

Cross-sectional regression analyses further reinforce the finding that lagged MAX significantly predicts future MAX behavior, even after controlling for standard firm characteristics and risk factors. These results confirm the findings of Bali et al. (2011) and highlight that return persistence is not merely a risk premium but potentially a manifestation of investor sentiment and mispricing, as also argued by Barberis and Huang (2008) and Boyer et al. (2010). Additional explanatory variables, such as volatility and short-term reversal, also exhibit strong predictive power, consistent with the notion that behavioral biases and overreaction contribute to extreme return dynamics.

Importantly, our analysis reveals that the MAX anomaly is more pronounced among small-cap stocks, as reflected in the stronger and more significant results from equally weighted portfolios. This aligns with the findings of Kumar (2009) and Nartea et al. (2017), who argue that retail investors disproportionately favor high-volatility, lottery-type stocks, particularly in emerging markets with high retail participation and limited arbitrage.

To explore the contextual dependency of the MAX effect, this study integrates macroeconomic risk through the economic uncertainty index (EUI). However, neither the interaction terms nor the subsample analysis across high- and low-uncertainty periods indicates a statistically significant moderating effect. This suggests that, in line with Brogaard and Detzel (2015), macroeconomic uncertainty does not materially alter the cross-sectional return dynamics associated with the MAX anomaly, reinforcing its structural and behaviorally anchored nature.

While this study provides robust evidence of the MAX anomaly in the Turkish stock market and highlights the behavioral tendencies of investors toward lottery-like stocks, it also has certain limitations. First, the analysis focuses on predictive relationships rather than causal inference, and endogeneity concerns—such as omitted variables influencing both MAX and returns—cannot be entirely ruled out. Additionally, the dataset is limited to the 2013–2023 period; extending the sample and comparing the strength of the MAX effect across different economic cycles (e.g., expansions vs. contractions) would enhance the generalizability of the findings. Further research could also incorporate variables such as idiosyncratic volatility and explicit measures of lottery-like characteristics to explore the conditional nature of the MAX effect across firm types and market environments. These extensions would contribute to a deeper understanding of speculative return patterns and support the design of policies promoting informed investor behavior in emerging markets.

In sum, this study contributes to the literature by providing strong empirical support for the persistence of the MAX anomaly in an emerging market setting, even after controlling for known risk factors and macroeconomic uncertainty. The findings highlight that investor overreaction to extreme past returns continues to influence future performance, underscoring the relevance of behavioral finance frameworks in explaining cross-sectional anomalies in less efficient markets. These results also offer important implications for both academics and practitioners seeking to understand or exploit patterns in speculative asset pricing.

Author Contributions: Conceptualization, Ş.C.G., D.Y., and M.D.; methodology, Ş.C.G., D.Y., and M.D.; software, Ş.C.G., D.Y., and M.D.; validation, Ş.C.G., D.Y., and M.D.; formal analysis, Ş.C.G., D.Y., and M.D.; investigation, Ş.C.G., D.Y., and M.D.; resources, Ş.C.G., D.Y., and M.D.; data curation, Ş.C.G., D.Y., and M.D.; writing—original draft preparation, Ş.C.G., D.Y., and M.D.; writing—review and editing, Ş.C.G., D.Y., and M.D.; visualization, Ş.C.G., D.Y., and M.D.; supervision, Ş.C.G., D.Y.,

and M.D.; project administration, Ş.C.G., D.Y., and M.D.; funding acquisition, Ş.C.G., D.Y., and M.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used to support the findings of this study were retrieved from the Eikon Datastream database and are available upon reasonable request from the corresponding author, subject to licensing restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Number of firms in sample by year.

Year	Number of Firms
2013	244
2014	266
2015	275
2016	277
2017	281
2018	285
2019	288
2020	293
2021	345
2022	375
2023	377

Table A2. Equal-weighted decile portfolios—Fama–French–Carhart model: Decile_1Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−2.4877 **	(−2.15)	0.831	−14.02	−0.0389	(−0.26)	−0.2294	(−0.90)	0.1563	−1.68	0.686
2	−2.3002 **	(−2.38)	0.8935	−18.23	0.0832	−0.67	−0.0517	(−0.27)	0.1547	−2.07	0.763
3	−2.8393 ***	(−3.22)	0.86	−16.08	0.0676	−0.47	−0.3733	(−1.87)	0.1704	−2.38	0.721
4	−1.918	(−1.61)	0.9115	−15.65	0.1477	−0.87	−0.2619	(−1.30)	0.1234	−1.38	0.725
5	−2.4864 **	(−2.34)	0.8842	−14.2	0.1172	−0.9	−0.3123	(−1.21)	0.155	−1.82	0.669
6	−2.0341	(−1.51)	0.8891	−14.06	0.0449	−0.29	−0.2184	(−0.78)	0.1116	−1.03	0.648
7	−2.5625 **	(−2.10)	0.8294	−14.9	0.0717	−0.45	−0.5309	(−2.30)	0.1012	−1.06	0.642
8	−2.6315 **	(−2.00)	0.7569	−10.23	−0.1578	(−0.94)	−0.2606	(−1.03)	0.1176	−1.19	0.601
9	−2.9075 **	(−2.24)	0.7854	−11.56	0.2831	−1.97	−0.3143	(−1.02)	0.1209	−1.14	0.531
10	−4.8393 ***	(−3.74)	0.7369	−9.01	0.215	−1.09	−0.264	(−1.18)	0.249	−2.41	0.53
10 − 1 (H − L)	−2.3516 **	(−2.27)	−0.0941	(−1.30)	0.2535	−1.86	−0.0348	(−0.18)	0.0927	−1.23	0.078

*** and ** denote significance at the 1% and 5% levels, respectively.

Table A3. Value-weighted decile portfolios—Fama–French–Carhart model: Decile_1Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−0.0877	(−0.12)	0.7746	−12.08	−0.0373	(−0.32)	−0.1188	(−1.03)	−0.0095	(−0.20)	0.72
2	−0.443	(−0.50)	0.8951	−19.5	0.0401	−0.45	0.0186	−0.14	0.0165	−0.28	0.803
3	−2.1074 **	(−2.47)	0.8847	−21.85	0.0641	−0.73	0.0211	−0.17	0.1239	−2.06	0.808
4	−0.5839	(−0.39)	0.9012	−19.84	0.1171	−1.08	−0.0035	(−0.03)	0.0564	−0.61	0.739
5	−1.1594	(−1.36)	0.9104	−26.29	−0.0696	(−0.70)	0.0979	−0.83	0.1091	−1.86	0.825
6	−1.1229	(−0.85)	0.8693	−12.05	0.2684	−1.26	0.5236	−1.24	0.1678	−1.25	0.491
7	−2.5318	(−1.58)	0.8687	−8.16	0.0867	−0.42	−0.0215	(−0.10)	0.126	−1.16	0.551
8	−1.9085	(−1.45)	0.8558	−9.38	−0.0938	(−0.58)	−0.1778	(−0.88)	0.1017	−1.09	0.576
9	−3.0282	(−1.55)	0.6801	−7.28	0.4738	−1.98	−0.0577	(−0.13)	0.1492	−0.96	0.307
10	−6.0820 **	(−2.31)	0.6188	−5.34	0.195	−0.68	−0.004	(−0.02)	0.385	−1.89	0.27
10 − 1 (H − L)	−5.9943 **	(−2.09)	−0.1558	(−1.37)	0.2319	−0.87	0.1144	−0.43	0.3942	−1.86	0.087

** denotes significance at the 5% level.

Table A4. Equal-weighted decile portfolios—Fama–French–Carhart model: Decile_2Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−2.3884 **	(−2.03)	0.8284	−13.47	−0.0113	(−0.07)	−0.203	(−0.89)	0.1409	−1.56	0.686
2	−2.3706 **	(−2.38)	0.8569	−17.51	0.0389	−0.26	−0.1066	(−0.55)	0.1704	−2.15	0.743
3	−2.5348 **	(−2.29)	0.8906	−18.04	0.1389	−0.92	−0.2716	(−1.23)	0.1531	−1.74	0.702
4	−2.3797 **	(−2.37)	0.8929	−14.54	0.0055	−0.05	−0.3396	(−1.77)	0.1371	−1.78	0.735
5	−2.1275 **	(−2.20)	0.873	−19.45	0.07	−0.51	−0.272	(−1.27)	0.1087	−1.34	0.716
6	−3.5131 ***	(−3.63)	0.9056	−15.82	0.2024	−1.64	−0.2044	(−0.83)	0.2359	−2.95	0.698
7	−3.8648 ***	(−3.38)	0.8293	−13.35	0.09	−0.66	−0.3822	(−1.61)	0.2117	−2.35	0.665
8	−2.0786	(−1.39)	0.7845	−12.02	0.0664	−0.4	−0.4716	(−1.49)	0.0774	−0.64	0.553
9	−1.9122	(−1.18)	0.8056	−9.19	−0.0304	(−0.17)	−0.3904	(−1.26)	0.0554	−0.47	0.538
10	−4.0550 ***	(−2.92)	0.7055	−9.53	0.2623	−1.25	−0.1791	(−0.67)	0.1809	−1.66	0.479
10 − 1 (H − L)	−1.6666 *	(−1.68)	−0.1229	(−1.75)	0.2735	−1.8	0.0239	−0.12	0.04	−0.54	0.078

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Value-weighted decile portfolios—Fama–French–Carhart model: Decile_2Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−0.8188	(−0.87)	0.7966	−11.65	−0.0233	(−0.16)	−0.0042	(−0.03)	0.0469	−0.79	0.705
2	−0.7378	(−1.13)	0.8659	−15.67	0.0423	−0.45	−0.0499	(−0.38)	0.009	−0.18	0.793
3	−1.7904 *	(−1.84)	0.9148	−18.35	0.0506	−0.36	−0.1436	(−1.02)	0.0948	−1.49	0.771
4	−1.405	(−1.33)	0.8853	−19.91	−0.086	(−1.03)	0.1669	−1.47	0.0995	−1.42	0.805
5	−0.8568	(−0.92)	0.9825	−25.27	0.0838	−0.89	0.026	−0.19	0.0897	−1.44	0.815
6	−1.9196	(−1.62)	0.8614	−17.88	0.2825	−2.57	0.1249	−0.56	0.1793	−2.21	0.705
7	−3.8650 ***	(−3.03)	0.8666	−9.22	0.0906	−0.48	0.1365	−0.55	0.2556	−2.56	0.566
8	−0.7122	(−0.43)	0.7471	−5.62	0.3092	−1.59	−0.4468	(−1.55)	−0.0143	(−0.12)	0.38
9	−0.6029	(−0.32)	0.86	−9.98	0.3224	−1.38	0.0672	−0.26	0.0748	−0.61	0.465
10	−4.913	(−1.40)	0.5684	−4.44	−0.0201	(−0.08)	−0.0101	(−0.03)	0.2227	−0.87	0.189
10 − 1 (H − L)	−4.0942	(−1.10)	−0.2282	(−1.71)	0.0032	−0.01	−0.0059	(−0.01)	0.1758	−0.64	0.04

*** and * denote significance at the 1% and 10% levels, respectively.

Table A6. Equal-weighted decile portfolios—Fama–French–Carhart model: Decile_3Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−2.4779 ***	(−2.66)	0.8169	−13.96	−0.0109	(−0.08)	−0.2084	(−1.06)	0.1453	−1.98	0.723
2	−2.4432 **	(−2.01)	0.8639	−16.12	0.0566	−0.38	−0.1252	(−0.55)	0.1713	−1.82	0.708
3	−2.6006 ***	(−2.80)	0.8789	−17.65	0.0666	−0.42	−0.2966	(−1.48)	0.1515	−1.93	0.72
4	−2.6095 **	(−2.54)	0.9191	−15.72	0.0502	−0.41	−0.3218	(−1.48)	0.1434	−1.84	0.737
5	−2.3820 **	(−2.16)	0.8467	−14.9	0.0403	−0.3	−0.2853	(−1.36)	0.1295	−1.52	0.692
6	−3.3930 ***	(−3.39)	0.8913	−17.63	0.1257	−1.07	−0.1908	(−0.82)	0.2137	−2.53	0.708
7	−3.0928 **	(−2.59)	0.8662	−12.34	0.2757	−1.9	−0.345	(−1.43)	0.1757	−1.81	0.652
8	−2.4026 *	(−1.82)	0.8246	−12.61	0.1244	−0.88	−0.4277	(−1.33)	0.1215	−1.12	0.579
9	−2.4513	(−1.40)	0.7342	−10.16	0.0183	−0.08	−0.4696	(−1.70)	0.0845	−0.63	0.484
10	−3.2024 **	(−2.30)	0.7352	−9.92	0.0958	−0.52	−0.1616	(−0.64)	0.1189	−1.13	0.504
10 − 1 (H − L)	−0.7245	(−0.69)	−0.0818	(−1.10)	0.1067	−0.67	0.0469	−0.25	−0.0264	(−0.35)	0.026

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7. Value-weighted decile portfolios—Fama–French–Carhart model: Decile_3Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−0.8123	(−0.94)	0.772	−11.4	−0.0918	(−1.05)	−0.0867	(−0.75)	0.0326	−0.59	0.722
2	−0.2076	(−0.24)	0.883	−16.79	0.1201	−1.18	−0.003	(−0.03)	0.0112	−0.22	0.809
3	−2.3560 **	(−2.36)	0.9033	−19.31	−0.0216	(−0.19)	−0.1694	(−1.29)	0.1154	−1.81	0.76
4	−0.6887	(−0.81)	0.9172	−20.86	−0.0839	(−0.92)	0.0719	−0.65	0.0597	−1.02	0.831
5	−0.5677	(−0.47)	0.9693	−20.03	0.1303	−1.4	0.0889	−0.75	0.0734	−0.92	0.792
6	−2.7305 ***	(−2.69)	0.8982	−19.3	0.2492	−2.28	0.0347	−0.15	0.2389	−3.25	0.737
7	−1.4396	(−1.44)	0.8864	−10.31	0.2185	−1.45	0.0339	−0.17	0.1139	−1.3	0.618
8	−3.4009 **	(−2.12)	0.7906	−7.61	0.1846	−0.82	0.0373	−0.15	0.2114	−1.91	0.427
9	−1.3587	(−0.74)	0.7445	−9	0.01	−0.04	−0.3521	(−1.31)	0.0554	−0.43	0.434
10	−3.5451	(−1.09)	0.6178	−4.92	0.1872	−0.69	0.12	−0.27	0.1789	−0.73	0.191
10 − 1 (H − L)	−2.7327	(−0.81)	−0.1541	(−1.11)	0.279	−1.03	0.2067	−0.48	0.1463	−0.58	0.028

*** and ** denote significance at the 1% and 5% levels, respectively.

Table A8. Equal-weighted decile portfolios—Fama–French–Carhart model: Decile_4Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−2.8156 ***	(−2.97)	0.7973	−13.52	−0.037	(−0.29)	−0.217	(−1.15)	0.1542	−2.12	0.72
2	−2.3002 *	(−1.87)	0.8816	−16.37	0.0481	−0.29	−0.2	(−0.86)	0.16	−1.66	0.69
3	−3.0981 ***	(−3.75)	0.8808	−16.83	0.0589	−0.41	−0.22	(−1.22)	0.1763	−2.51	0.74
4	−2.2541 **	(−2.17)	0.926	−18.82	0.0652	−0.51	−0.335	(−1.56)	0.1295	−1.58	0.74
5	−2.5301 **	(−2.24)	0.8577	−13.59	0.0467	−0.4	−0.243	(−1.08)	0.1405	−1.59	0.68
6	−3.5138 ***	(−3.24)	0.8621	−16	0.1824	−1.29	−0.134	(−0.58)	0.226	−2.58	0.68
7	−2.4959 *	(−1.94)	0.8853	−14.69	0.1861	−1.21	−0.401	(−1.49)	0.1391	−1.28	0.66
8	−2.8262 **	(−2.61)	0.8103	−13.09	0.1781	−1.31	−0.419	(−1.56)	0.1576	−1.72	0.61
9	−2.0643	(−1.21)	0.7236	−7.76	0.1053	−0.52	−0.501	(−1.43)	0.0546	−0.42	0.46
10	−3.1095 **	(−2.10)	0.757	−9.96	0.0211	−0.1	−0.158	(−0.63)	0.1209	−1.11	0.51
10 − 1 (H − L)	−0.2939	(−0.26)	−0.0403	(−0.61)	0.0582	−0.34	0.0594	−0.26	−0.0333	(−0.41)	0.01

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A9. Value-weighted decile portfolios—Fama–French–Carhart model: Decile_4Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−0.6115	(−0.70)	0.7412	−11.24	−0.097	(−1.13)	−0.094	(−0.78)	0.0232	−0.42	0.69
2	−0.1198	(−0.15)	0.9076	−19.18	0.1188	−1.19	−0.002	(−0.02)	−0.002	(−0.04)	0.83
3	−2.1523 **	(−2.37)	0.8995	−16.71	0.0191	−0.17	−0.102	(−0.82)	0.1034	−1.72	0.78
4	−1.3499	(−1.61)	0.9679	−24.79	0.0129	−0.13	0.0695	−0.58	0.1043	−1.78	0.84
5	−0.8175	(−0.74)	0.8964	−15.92	0.1572	−1.67	0.0968	−0.71	0.0872	−1.18	0.77
6	−1.8849	(−1.65)	0.9012	−15.32	0.284	−2.9	0.1796	−0.86	0.1737	−2.11	0.74
7	−2.0937 *	(−1.80)	0.8393	−12.22	0.1914	−0.79	0.0719	−0.15	0.172	−1.19	0.43
8	−3.7845 ***	(−2.68)	0.8447	−8.66	0.3226	−1.62	0.0163	−0.07	0.2455	−2.51	0.53
9	−1.5029	(−0.91)	0.7901	−6.72	0.0246	−0.1	−0.378	(−1.30)	0.0247	−0.21	0.42
10	−3.123	(−0.94)	0.6536	−5.19	0.1098	−0.37	0.3344	−0.68	0.1939	−0.79	0.21
10 − 1 (H − L)	−2.5115	(−0.72)	−0.0876	(−0.67)	0.207	−0.71	0.4286	−0.86	0.1706	−0.65	0.02

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A10. Equal-weighted decile portfolios—Fama–French–Carhart model: Decile_5Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−2.9361 ***	(−3.03)	0.8105	−13.62	−0.0239	(−0.17)	−0.2251	(−1.07)	0.1697	−2.17	0.712
2	−2.2803 *	(−1.97)	0.8895	−17.31	0.0512	−0.35	−0.1904	(−0.86)	0.1416	−1.62	0.711
3	−2.8103 ***	(−3.23)	0.8617	−16.16	−0.0163	(−0.13)	−0.276	(−1.55)	0.1559	−2.14	0.735
4	−2.6548 ***	(−3.26)	0.8905	−18.22	0.0913	−0.69	−0.2684	(−1.39)	0.1472	−2.19	0.751
5	−2.6702 **	(−2.29)	0.8967	−13.97	0.0959	−0.78	−0.2172	(−0.84)	0.1665	−1.84	0.679
6	−3.2944 ***	(−3.10)	0.872	−15.54	0.1686	−1.22	−0.1607	(−0.70)	0.2146	−2.48	0.699
7	−2.5251 *	(−1.87)	0.8583	−13.7	0.1383	−0.84	−0.4037	(−1.49)	0.1366	−1.21	0.636
8	−2.0832 *	(−1.84)	0.8318	−13.41	0.164	−1.09	−0.4151	(−1.44)	0.1135	−1.16	0.62
9	−3.3159 **	(−2.07)	0.7376	−9.38	0.1853	−1.09	−0.4255	(−1.20)	0.1489	−1.15	0.481
10	−2.3524	(−1.53)	0.7317	−9.63	−0.0041	(−0.02)	−0.2366	(−0.85)	0.0613	−0.55	0.488
10 − 1 (H − L)	0.5837	−0.54	−0.0788	(−1.17)	0.0198	−0.11	−0.0115	(−0.04)	−0.108	(−1.36)	0.031

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A11. Value-weighted decile portfolios—Fama–French–Carhart model: Decile_5Day.

Decile	Alpha (%)	*t*-Stat	MKT_RF	*t*-Stat	SMB	*t*-Stat	HML	*t*-Stat	MOM	*t*-Stat	R^2
1	−0.8786	(−1.00)	0.7576	−10.8	−0.0756	(−0.87)	−0.11	(−0.89)	0.0427	−0.82	0.684
2	−0.7819	(−0.84)	0.9169	−18.38	0.0971	−0.89	0.0138	−0.14	0.0204	−0.4	0.821
3	−1.8406 *	(−1.71)	0.8785	−16.87	0.0085	−0.09	−0.0909	(−0.79)	0.0873	−1.23	0.779
4	−2.37 ***	(−2.79)	0.9417	−20.96	0.0682	−0.7	0.033	−0.24	0.1333	−2.28	0.796
5	0.028	−0.03	0.9483	−23.42	0.0515	−0.6	0.1717	−1.5	0.0484	−0.68	0.806
6	−1.8761 **	(−2.11)	0.9538	−19	0.2802	−2.82	0.1224	−0.64	0.1603	−2.48	0.782
7	−1.551	(−1.12)	0.7886	−10.34	0.1251	−0.52	0.0189	−0.04	0.1654	−1.07	0.385
8	−2.3219 *	(−1.76)	0.9191	−10.69	0.3944	−2.15	−0.0286	(−0.14)	0.1867	−1.87	0.624
9	−3.499 **	(−2.31)	0.7371	−6.13	−0.2228	(−0.91)	−0.1413	(−0.45)	0.1482	−1.38	0.407
10	−2.2783	(−0.68)	0.6581	−5.19	0.1057	−0.34	0.2814	−0.53	0.134	−0.54	0.202
10 − 1 (H − L)	−1.3996	(−0.40)	−0.0996	(−0.75)	0.1813	−0.63	0.3914	−0.76	0.0913	−0.35	0.016

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

References

Aboulamer, A., & Kryzanowski, L. (2016). Are idiosyncratic volatility and MAX priced in the Canadian market? *Journal of Empirical Finance*, *37*, 20–36. [CrossRef]

Alshammari, S., & Goto, S. (2022). Are lottery-like stocks overvalued in markets that have no lotteries?—Evidence from Saudi Arabia. *Finance Research Letters*, *46*, 102460. [CrossRef]

Annaert, J., De Ceuster, M., & Verstegen, K. (2013). Are extreme returns priced in the stock market? European evidence. *Journal of Banking & Finance*, *37*(9), 3401–3411.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), 427–446. [CrossRef]

Barberis, N., & Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, *98*(5), 2066–2100. [CrossRef]

Berggrun, L., Cardona, E., & Lizarzaburu, E. (2019). Extreme daily returns and the cross-section of expected returns: Evidence from Brazil. *Journal of Business Research*, *102*, 201–211. [CrossRef]

Bergsma, K., & Tayal, J. (2019). Short interest and lottery stocks. *Financial Management*, *48*(1), 187–227. [CrossRef]

Bonomo, M., Brito, R. D., & Martins, B. (2015). The after crisis government-driven credit expansion in Brazil: A firm level analysis. *Journal of International Money and Finance*, *55*, 111–134. [CrossRef]

Boyer, B., Mitton, T., & Vorkink, K. (2010). Expected idiosyncratic skewness. *The Review of Financial Studies*, *23*(1), 169–202. [CrossRef]

Bradrania, R., & Gao, Y. (2024). Lottery demand, weather, and the cross-section of stock returns. *Journal of Behavioral and Experimental Finance*, *42*, 100910. [CrossRef]

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, *61*(1), 3–18. [CrossRef]

Byun, S. J., Jeon, B., & Kim, D. (2023). Investor sentiment and the MAX effect: Evidence from Korea. *Applied Economics*, *55*(3), 319–331. [CrossRef]

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. [CrossRef]

Chadwick, M. G. (2019). Dependence of the "Fragile Five" and "Troubled Ten" emerging market financial systems on US monetary policy and monetary policy uncertainty. *Research in International Business and Finance*, *49*, 251–268. [CrossRef]

Chee, W. Y. (2012). *An empirical analysis of idiosyncratic volatility and extreme returns in the Japanese stock market* [Doctoral dissertation, Lincoln University].

Chelikani, S., Kilic, O., & Wang, X. (2022). Past stock returns and the MAX effect. *Journal of Behavioral Finance*, *23*(3), 338–352. [CrossRef]

Cheon, Y. H., & Lee, K. H. (2018). Time variation of MAX-premium with market volatility: Evidence from Korean stock market. *Pacific-Basin Finance Journal*, *51*, 32–46. [CrossRef]

Eraker, B., & Ready, M. (2015). Do investors overpay for stocks with lottery-like payoffs? An examination of the returns of OTC stocks. *Journal of Financial Economics*, *115*(3), 486–504. [CrossRef]

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. [CrossRef]

Fong, W. M., & Toh, B. (2014). Investor sentiment and the MAX effect. *Journal of Banking & Finance*, *46*, 190–201.

Gao, H., Shi, D., & Zhao, B. (2021). Does good luck make people overconfident? Evidence from a natural experiment in the stock market. *Journal of Corporate Finance*, *68*, 101933. [CrossRef]

Gould, J., Yang, J. W., Singh, R., & Yeo, B. (2023). The seasonality of lottery-like stock returns. *International Review of Economics & Finance*, *83*, 383–400.

Hai, H. V. (2023). MAX, lottery-type stocks, and the cross-section of stock returns: Evidence from the Chinese stock market. *Cogent Economics & Finance*, *11*(1), 2175471.

Han, Y., & Lesmond, D. (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. *The Review of Financial Studies*, *24*(5), 1590–1629. [CrossRef]

Jegadeesh, N. (1991). Seasonality in stock price mean reversion: Evidence from the US and the UK. *The Journal of Finance*, *46*(4), 1427–1444. [CrossRef]

Jiang, G. J., Xu, D., & Yao, T. (2009). The information content of idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, *44*(1), 1–28. [CrossRef]

Kahneman, T., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica*, *47*(2), 263–291. [CrossRef]

Khurram, M. U., Ali, F., Jiang, Y., & Xie, W. (2022). Predictability of extreme daily returns and Preference for lottery-like stocks in an emerging market. *Economic Research-Ekonomska Istraživanja*, *35*(1), 1322–1344. [CrossRef]

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, *64*(4), 1889–1933. [CrossRef]

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), 1–28. [CrossRef]

Lin, C. H., Yen, K. C., & Cheng, H. P. (2021). Lottery-like momentum in the cryptocurrency market. *The North American Journal of Economics and Finance*, *58*, 101552. [CrossRef]

Lin, T. C., & Liu, X. (2018). Skewness, individual investor preference, and the cross-section of stock returns. *Review of Finance*, *22*(5), 1841–1876. [CrossRef]

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, *20*(4), 587–615.

Liu, C., Sun, P., & Zhu, D. (2023). Lottery preference, short-sale constraint, and the salience effect: Evidence from China. *Economic Modelling*, *125*, 106341. [CrossRef]

Lu, J., Yang, N. T., Ho, K. Y., & Ko, K. C. (2022). Lottery demand and the asset growth anomaly. *Finance Research Letters*, *48*, 102988. [CrossRef]

Mitton, T., & Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies*, *20*(4), 1255–1288. [CrossRef]

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the Econometric Society*, *34*, 768–783. [CrossRef]

Nartea, G. V., Kong, D., & Wu, J. (2017). Do extreme returns matter in emerging markets? Evidence from the Chinese stock market. *Journal of Banking & Finance*, *76*, 189–197.

Nartea, G. V., Wu, J., & Liu, H. T. (2014). Extreme returns in emerging stock markets: Evidence of a MAX effect in South Korea. *Applied Financial Economics*, *24*(6), 425–435. [CrossRef]

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, *28*(3), 777–787. [CrossRef]

Nguyen, H. T., & Truong, C. (2018). When are extreme daily returns not lottery? At earnings announcements! *Journal of Financial Markets*, *41*, 92–116. [CrossRef]

Ozdamar, M., Akdeniz, L., & Sensoy, A. (2021). Lottery-like preferences and the MAX effect in the cryptocurrency market. *Financial Innovation*, *7*, 74. [CrossRef]

Palfrey, T. R., & Wang, S. W. (2012). Speculative overpricing in asset markets with information flows. *Econometrica*, *80*(5), 1937–1976.

Sehgal, S., Vasishth, V., & Deisting, F. (2024). Lottery factor and stock returns: Evidence from India. *Borsa Istanbul Review*, *24*(3), 449–459. [CrossRef]

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442.

Shen, J., Yu, J., & Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, *86*, 1–21. [CrossRef]

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*, 297–323. [CrossRef]

Walkshäusl, C. (2014). The MAX effect: European evidence. *Journal of Banking & Finance*, *42*, 1–10.

Wang, Z. M., & Lien, D. (2022). Is maximum daily return a lottery? Evidence from monthly revenue announcements. *Review of Quantitative Finance and Accounting*, *59*(2), 545–600. [CrossRef]

Wang, Z. M., & Lien, D. (2023). Limited attention, salient anchor, and the modified MAX effect: Evidence from Taiwan's stock market. *The North American Journal of Economics and Finance*, *67*, 101904. [CrossRef]

Yuan, S., Rieger, M. O., & Caliskan, N. (2020). Maxing out: The puzzling influence of past maximum returns on future asset prices in a cross-country analysis. *Management Review Quarterly*, *70*(4), 567–589. [CrossRef]

Zhong, A., & Gray, P. (2016). The MAX effect: An exploration of risk and mispricing explanations. *Journal of Banking & Finance*, *65*, 76–90.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.