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Predictability of extreme daily returns and Preference for lottery-like stocks in an emerging market

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ABSTRACT

This study investigates the presence of the MAX effect – stocks with extreme daily (positive) return in the current month perform poorly in the following month – in the Pakistani stock market (PSX). Similar to the US, Europe, and Chinese stock markets, we find a negative effect of MAX on risk-adjusted returns. Furthermore, we find that the MAX effect persists even if we extend the holding period to three- and six-month. Our results are robust for both portfolio-level and firm-level cross-sectional analyses and across subperiods, size groups, and alternative factor definitions and models. Interestingly, contrary to findings reported elsewhere, we find that the MAX effect in Pakistan exists only when the overall economy is in an expansion state. A battery of tests suggests that triviality in MAX effect during economic contraction in Pakistan is driven by the more negative subsequent performance of low-MAX stocks (short-leg), whereas, in other markets, more negative subsequent performance of high-MAX stocks (long-leg) is evident during economic downturns. Our potential explanation is partially supported by the theoretical model of Palfrey & Wang, who find that demand for speculative stocks (i.e. lottery-like stocks) is higher during 'good' economic news (expansion) than 'bad' economic news (contraction).

1. Introduction

Portfolio theory advocates that the optimal risk-return tradeoff can be attained if investors allocate their funds to just two types of assets: risk-free asset and the well-diversified portfolio (fund). However, in reality, investors are poorly diversified (Odean, 1999). Tversky and Kahneman (1992) document that investors tend to falsely believe the probability of success in gambling to be higher than it is in reality. Thus, a preference for lottery-like stocks drives the under-diversified holdings of securities. Motivated by the findings of Kumar (2009), who finds that investors exhibit a

preference for stocks with lottery-like characteristics, Bali et al. (2011) investigate the role of extreme positive returns in the cross-sectional pricing of stocks in the US. They find that monthly portfolios comprising stocks with high maximum daily return (high MAX stocks) during the preceding month significantly underperform in comparison to the portfolios of stocks experiencing low maximum daily return (low MAX stocks) during the preceding month. In other words, they report a negative return spread between portfolios with the highest and lowest maximum daily returns. The negative relationship is reported robust even after controlling for size, book-to-market, illiquidity, momentum, short-term reversal, and skewness.

Kumar (2009) further explains that a specific group of investors prefers lottery-like stocks and gambling, stocks with high idiosyncratic skewness and high idiosyncratic volatility. Such investors keep overvaluing the stocks with extreme positive returns in expectation for return persistence, reflecting the investors' lottery-like preferences (given that such stocks underperform in the future). Several theoretical studies (e.g. Brunnermeier et al., 2007) document that the lottery-like feature has a strong relationship to higher moments of the distribution of returns, where the investors prefer an asset return skewness. Barberis and Huang (2008) document that investors give more weightage to extreme events with low probabilities; therefore, a non-normal distribution will lead to a negative excess return for skewed securities, which is overpriced. More specifically, there is a preference for stocks that can generate high maximum daily returns, although the chance to achieve such high returns is very low. This preference leads to overpayment for such stocks, which ultimately results in underperformance in the succeeding month.

Empirical evidence of the Max effect and lottery-like stocks in markets other than the US is progressively increasing. For example, Annaert et al. (2013) and Walkshäusl (2014) document the existence of a MAX effect in selected European markets. They find that the MAX effect in Europe is somewhat weaker than in the US. In the context of emerging markets, the MAX effect has been examined for the Korean (Nartea et al. (2014); Cheon and Lee (2018)), Chinese (Nartea et al. (2017); Wan (2018); Hai et al. (2020)) and Brazilian (Berggrun et al., 2019) stock markets. Interestingly, Chee (2012) did not find this effect in the Japanese market, except with bivariate sorts after controlling for firm characteristics. Aboulamer and Kryzanowski (2016) document a conflicting result for the Canadian stock markets, where a positive MAX-return relationship is evident. It is also documented that the MAX effect reverses the anomalous (negative) relationship between stock returns and idiosyncratic volatility (Bali et al., 2011), first reported by Ang et al. (2006, 2009). They argue that MAX is the true effect, and the idiosyncratic volatility (IV) is a proxy that drives MAX. On the contrary, Wan (2018) finds that the IV is the true effect that subsumes the MAX effect in the Chinese stock market. More interestingly, Nartea et al. (2014) find that both MAX and IV effects co-exist independently in the Korean stock market, while Berggrun et al. (2019) find mixed results, albeit largely similar to that found in the US (Bali et al., 2011): MAX reverses the anomalous IV-return relationship in few specifications (although statistically insignificant). More recently, Ali et al. (2020) document a positive idiosyncratic volatility effect in the Singapore stock market, contrary to the findings in the US and Europe (Bali et al., 2011, Annaert et al., 2013).

These mixed results across both developed and emerging markets raise the question of the applicability of the MAX effect in other stock markets and motivate us to research this effect for markets that share different characteristics.

Andrew Karolyi (2016) expresses home- and foreign-bias in the field of empirical finance: most of the studies either examine the US or some other specific non-US markets. It is further stated that developed markets are well-connected; therefore, the same risk measures apply to these markets and produce largely similar findings. Similarly, advanced and big emerging markets (e.g. Korea, China, and Brazil) are individual investor dominated markets where gambling is a popular social activity in their culture. Thus, it is necessary to test whether emerging markets – other than those comparatively advanced and often studied emerging markets – also exhibit a negative MAX effect? In doing so, we examine the Max effect and lottery-like features in the Pakistani stock market in this study. We are not aware of other studies done in other Asian emerging markets (except for China and South Korea); however, it is the first comprehensive study investigating the MAX effect in Pakistan.[1]

Different from the developed, relatively more advanced, and big emerging markets, the Pakistani stock market is at its early development stage and offers an interesting experiment to gain insight into the possible country-specific MAX effects (Khurram et al., 2020).[2] Thus, our major contribution to the literature related to extreme daily return (MAX) is to extend Bali et al. (2011)'s work in the context of emerging markets by providing comprehensive out-of-sample tests of the MAX effect in the Pakistani stock market. In addition, we incorporate the most recent advancements in this emerging body of literature and examine the impact of extended holding periods on the persistence of the MAX effect, alternative definitions of factor models to calculate abnormal returns (alphas), comprehensive double-sorted portfolio-level analysis that controls for various cross-sectional effects, price non-synchronicity (relative idiosyncratic volatility), and economic conditions in the potential overpricing (underpricing) of high-MAX (low-MAX) stocks.

Our results exhibit a negative MAX effect in Pakistan similar to the US and European markets. This effect is stronger for risk-adjusted returns and equally-weighted portfolios than raw returns and value-weighted portfolios, respectively. The MAX effect perseveres even if we extend the holding period to 3 and 6 months. Further, we find that the MAX effect apparently does not weaken the idiosyncratic volatility effect in the Pakistani stock market. In this regard, our findings are similar to the Chinese and Korean evidence reported by Nartea et al. (2017) and Cheon and Lee (2018), respectively, but contrary to the US and European evidence by Bali et al. (2011) and Annaert et al. (2013), respectively. This highlights the significance of country-specific validation of certain anomalies initially recognized in developed markets. Our subsample analyses (pre-, post-, and ex-crisis) and robustness checks across different size groups (small, medium, and big) reveal that: the negative MAX effect is statistically significant across different subperiods and size groups, although more pronounced in the post-crisis subperiod and medium capitalization (cap) firms.

Given that the existing literature offers mixed evidence on whether the demand for speculative stocks is stronger throughout economic recessions or booms, we examine the MAX effect across two different economic conditions. Different from the findings

reported elsewhere; our results show that the negative MAX effect is only aggravated when the overall Pakistani economy, measured using GDP growth, is expanding. In search of potential explanations for this opposite trend in the PSX, we look for different characteristics and behavioural aspects of the market that are different across different economic conditions and can plausibly drive the MAX effect. A battery of tests reveals that the poor performance of the long-short MAX portfolio in Pakistan during economic slowdown periods is driven by the more negative subsequent performance of the low-MAX stocks. Our findings agree with the theoretical model of Palfrey and Wang (2012); that is, economic expansion (or good economic news) provides a demand boost for speculative assets.

The rest of this paper is organized as follows: Section 2 describes our data and discusses the estimation procedures. It also describes the construction of the risk factors and other main variables we use in this article. Section 3 presents the empirical results. Section 4 further tests the MAX effect and conducts several robustness checks and potential explanations of our major findings. Section 5 concludes the paper with a summary of our findings and future recommendations.

2. Data and methodology

Daily and monthly stock prices, index closing points, and annual accounting data (Statement of Financial Position and Income Statement) are obtained from the official website of the Pakistan Stock Exchange (PSX).[3] Cut-off yields on the Pakistani Treasury bill rate (T-bills) are obtained from the official website of the State Bank of Pakistan (SBP).[4] We use the KSE-100 index to calculate return on the market portfolio and Pakistan's 3-month T-bill cut-off yield (converted into monthly values) to calculate the risk-free rate, following recent empirical studies on the Pakistani stock market (Ali, 2021; Ali et al., 2021). The financial daily Business Recorder is used to obtain any missing information.[5] Our data span between January 2003 and December 2016 with an average (median) of 385 (397) firms. Our choice to start from 2003 is driven by the availability of data on the website of PSX. We also test different subperiods, including (i) post-crisis analysis (from January 2010 to December 2016) and (ii) ex-crisis analysis (from January 2003 to December 2016, excluding the months between December 2007 and December 2009) to eliminate the impact of the global financial crisis of 2008 and domestic market conditions between 2008 and 2009.[6] Following common practices in the existing literature, we exclude investment trusts and closed-end funds. We have also ignored daily returns on the first trading day for IPO (initial public offering) firms and deleted any observations with returns exceeding 300%.

2.1. Construction of risk factors

Given that the empirical analysis involves constructing asset-pricing factors to estimate risk-adjusted return via the model's alpha, we construct multiple risk factors. The majority of the extant literature uses the three-factor model of Fama and French (1993) to estimate the MAX effect; therefore, this study emphasizes the three-factor

model as a starting point. Later, we also add momentum factor and examine risk-adjusted returns using Carhart (1997)'s four factors model.

We construct size (SMB, small-minus-big) and value (HML, high-minus-low) factors following Fama and French (1993) and momentum (UMD, up-minus-down) factor following Carhart (1997). In addition, we take guidance from recent Pakistani asset-pricing work (Ali, 2021; Ali et al., 2018; Ali et al., 2021). Definitions of the factors and the construction methodology are given in the Appendix. While the magnitude of all the factors under study is positive, it is statistically significant at 5% level for SMB and HML only (Table A1, in the Appendix). We also examine the correlations between these factors; however, we do not note any excessively high values of the correlation coefficients that may raise a concern about any multicollinearity problem.[7]

2.2. Construction of MAX and control variables

At the beginning of each month, we construct quintile portfolios based on MAX, defined as the maximum daily return in the preceding calendar month. Portfolios are rebalanced every month. The risk-adjusted return refers to the Fama-French three-factor model's alpha. We control for several variables including size, book-to-market, short-term reversal, momentum, market beta, illiquidity, closing price, co-skewness or systematic skewness (henceforth, these terms will be used alternatively), idiosyncratic skewness, and idiosyncratic volatility using dependent 3×5 bi-variate sorts similar to that of Bali et al. (2011) and Nartea et al. (2017). All the variables under consideration are comprehensively defined in the Appendix.

In 3×5 bi-variate sorts, we first sort by the control variable (e.g. illiquidity or B/M) into tercile and then sort further into quintiles based on MAX within each tercile of the control variable. Finally, we take the average of each of the MAX categories that result in five portfolios. These portfolios have similar levels in the control variable but variation in MAX. For example, to control for book-to-market: first, we sort the stocks into tercile according to their B/M – High B/M, Medium B/M, and Low B/M. Then within each value category, stocks are sorted again into quintiles based on MAX. Consequently, fifteen B/M-MAX portfolios are generated. To illustrate, a value-neutral Low MAX portfolio is formed by averaging the returns of the three Low MAX portfolios (i.e. High B/M-Low MAX, Medium B/M- Low MAX, and Low B/M-Low MAX). So, we have a Low MAX portfolio that contains all the value (B/M) categories. We replicate the same procedure for other control variables.

Table 1 shows the descriptive statistics of our final stocks. The mean daily return over the sample period is approximately 0.91%. The standard deviation of the mean return and the difference between the minimum and maximum returns show that, on average, returns have been quite volatile. The mean value of large price jumps (MAX) is 6.83% in our sample, with a standard deviation of 10.73%. The average idiosyncratic volatility is 1.10, while systematic skewness and idiosyncratic skewness are −0.23 and 0.56, respectively. The number of firms in our sample ranges between 324 and 421.

Table 1. Summary statistics.

	Mean	St. Dev.	Median	Min	Max	SE
Return	0.914	17.239	0.035	−199.958	295.624	0.089
MAX	6.827	10.725	4.877	0.000	295.624	0.056
IV	1.099	1.177	0.832	0.000	63.822	0.006
SSKEW	−0.226	1.568	−0.304	−4.252	4.260	0.010
ISKEW	0.562	21.498	0.755	−2396.453	706.464	0.139
MOM	0.940	5.218	0.865	−55.870	79.041	0.034
STR	1.056	16.031	0.382	−199.958	136.134	0.104
Beta	0.783	7.769	0.784	−5.688	4.221	0.025
B/M	1.245	1.707	0.785	0.005	24.989	0.011
ILLIQ	0.864	0.179	0.947	0.045	1.000	0.001
CP (PKR)	92.721	332.645	26.250	5.000	12480.000	1.743
Firms	385	34.205	397	325	421	9.142

Notes: This table reports summary statistics of the variables used in this study. *Return* is the average daily return of the stocks used in the sample. *MAX* is the maximum daily return over the previous month, while idiosyncratic volatility (*IV*) is the standard deviation of the daily residuals from the CAPM. *Firms* represent the number of firms in our final sample. All the variables under study are defined in the Appendix.
Source: Authors calculation.

3. MAX effect: results and discussion

3.1. Portfolio level analysis: univariate sorts

At first, we carry out a portfolio level analysis to examine whether stocks that generate extreme returns in the preceding month perform lower in the future. Therefore, each month we categorize the stocks into five (value- and equally-weighted) portfolios based on the maximum daily return in the past month (MAX). Table 2 presents the raw and risk-adjusted returns of portfolios sorted on MAX. Portfolio 5 (High MAX) contains stocks belonging to the highest portfolio of maximum daily returns over the previous month, and portfolio 1 (Low MAX) signifies the stocks in the lowermost portfolio of maximum daily returns over the past month. The alphas of our five equally- and value-weighted portfolios monotonically decrease as we move from low-MAX portfolios to high-MAX portfolios, indicating a negative effect of the extreme positive daily returns on succeeding performance.

We also evaluate the alphas for a frequently used long-short (High-minus-Low MAX) portfolio that takes a long position in the highest MAX stocks and a short position in the lowest MAX stocks. The abnormal monthly return for equally- and value-weighted portfolios is negative (−1.74% and −1.24% respectively) and statistically significant (t= −2.93 and t= −2.09 respectively), implying a robust negative MAX effect. We further find that the negative MAX effect in Pakistan is somewhat stronger than that reported in the US (alpha= −0.66%), China (−1.14%), and Brazil (−0.8%) by Bali et al. (2011), Nartea et al. (2017), and Berggrun et al. (2019) respectively.

The mean return spread (raw returns without any risk adjustment) of the highest minus lowest MAX quintiles is negative (−1.40% per month) but statistically insignificant (*t*= −1.56). Similar findings – an insignificant spread for long-short MAX portfolio using raw returns while a negative and statistically significant spread after adjusting for risk – are reported for the European and Brazilian markets (Annaert et al., 2013, Berggrun et al., 2019). We allocate an individual stock's market capitalization as its weight in the portfolio. The results of value-weighted portfolios follow similar patterns as described for equally-weighted portfolios; however, the negative

Table 2. Returns and Fama-French (three-factor) alphas on portfolio sorted by MAX.

Quintile	EW portfolios		VW portfolios	
	Raw return	Risk-adjusted return (FF3 alpha)	Raw return	Risk-adjusted return (FF3 alpha)
Low Max	0.0071	−0.0038	0.0071	−0.0034
	(1.124)	(−0.920)	(1.158)	(−0.895)
2	0.0094	−0.0052	0.0106	−0.0034
	(1.401)	(−1.847)	(1.614)	(−1.315)
3	0.0063	−0.0081	0.0079	−0.0060
	(0.982)	(−2.448)	(1.256)	(−1.916)
4	0.0085	−0.0104	0.0097	−0.0082
	(1.198)	(−2.671)	(1.385)	(−2.144)
High Max	0.0068	−0.0212	0.0071	−0.0159
	(0.765)	(−4.050)	(1.215)	(−2.941)
High − Low	−0.0003	−0.0174	−0.00004	−0.0124
	(−0.547)	(−2.934)	(−0.002)	(−2.092)

Notes: This table estimates each portfolio's equally-weighted and value-weighted raw and risk-adjusted returns between January 2003 and December 2016. FF3 alpha is each portfolio's alpha estimated from the Fama and French (1993) three-factor model. High − Low shows the difference in monthly returns and alphas between the highest- and lowest-MAX portfolios. Newey-West t-statistics are in parenthesis.
Source: Authors calculation.

MAX effect is stronger in equally-weighted portfolios. It is logical because the tendency to hold lottery-type stocks is likely to be higher among individuals (Kumar, 2009), who largely invest in small stocks that have relatively lower weightage in value-weighted portfolios than equally-weighted portfolios.

Table 3 confirms this proposition: the high MAX stocks are generally small stocks; therefore, the MAX effect in equally-weighted portfolios is supposed to be stronger (since small stocks carry more weights in equally-weighted portfolios than the value-weighted portfolios). Further, we find that high-MAX stocks tend to have higher B/M, are winners in the preceding month as well as in the previous 11 months ($t − 2$ to $t − 12$), are more liquid, have lower market beta, are lower-priced, have more positively skewed return distributions, and have higher IV than low-MAX stocks. The stocks belonging to the high-MAX portfolio exhibit some of the lottery-type characteristics: these stocks are traded at lower prices, exhibit a high degree of idiosyncratic volatility and idiosyncratic skewness. Since these variables could possibly contribute to the existence of a negative MAX effect, we formally test this by employing bivariate sorts and cross-sectional regressions in the following sections.

3.2. Portfolio level analysis: bivariate sorts

In this section, we examine whether the apparent MAX effect in the single-sorted portfolio-level analysis is robust after controlling for size, book-to-market value of equity, short-term reversal, momentum, illiquidity, market beta, closing price, systematic skewness, idiosyncratic skewness, and idiosyncratic volatility effects. To do so, we use a battery of 3×5 bivariate sorts (as defined in the Data and Methodology Section) and report the results in Table 4. Following previous studies (e.g. Bali et al. (2011) and Nartea et al. (2017), among others), we emphasize on the alphas. In Panel A (Table 4), our results confirm that the alpha spread of 10 out of 10 portfolios that are long on high MAX stocks and short on low MAX stocks is always negative and

Table 3. Characteristics of portfolios sorted by MAX.

	Low-Max	Max 2	Max 3	Max 4	High Max	High − Low	
Size	8.418	8.474	8.115	7.151	5.603	−2.814	(−13.94)
B/M	1.091	1.267	1.306	2.659	2.873	1.783	(4.82)
STR	−0.054	−0.013	0.019	0.004	0.038	0.092	(0.08)
MOM	0.014	0.008	0.010	0.016	0.027	0.013	(4.61)
ILLIQ	0.912	0.939	0.932	0.910	0.875	−0.037	(−82.15)
Beta	2.216	0.941	0.580	0.976	1.206	−1.009	(−4.28)
CP	95.754	73.286	124.270	44.293	24.037	−71.717	(−3.29)
SSKEW	−1.064	−0.880	−0.861	−1.125	−1.299	−0.235	(−12.86)
ISKEW	0.042	0.034	0.133	0.002	0.043	0.001	(1.73)
IV	0.012	0.009	0.009	0.011	0.014	0.002	(11.52)

Notes: This table reports the average characteristics of the MAX-sorted quintile portfolios and a high-minus-low MAX portfolio. Low-MAX (Portfolio 1) comprises stocks with the lowest maximum daily returns in a month, while High-MAX (portfolio 5) includes stocks with the most extreme positive daily returns. High − Low is the difference between high- and low-MAX portfolios, and their corresponding *t*-statistics are reported in the last column (in parenthesis). For each portfolio, we report the monthly average of different characteristics of MAX-sorted portfolios over the period from January 2003 to December 2016. All variables under study are defined in the Appendix.
Source: Authors calculation.

highly significant. The results presented in Panel B (value-weighted) are largely identical to Panel A; however, the MAX effect in the equally-weighted portfolios is stronger than the value-weighted portfolios. To sum up, the negative MAX effect seems robust after controlling for stock characteristics on an individual basis. Since dependent bivariate sorts (portfolios) cannot control for multiple effects at once, we perform firm-level analysis in the next section.

3.3. Firm-level analysis: univariate cross-sectional regressions

To control for multiple effects simultaneously, we perform firm-level Fama-MacBeth regressions. It is expected that due to aggregation (in the previous section), useful information could be unexploited. Thus, we estimate the following model and its different nested versions:

$$
\begin{aligned}
R_{i,t} = {}& \beta_{i-1} + \beta_{1,t-1}MAX_{i,\ t-1} + \beta_{2,t-1}Size_{i,\ t-1} + \beta_{3,t-1}B/M_{i,\ t-1} + \beta_{4,t-1}STR_{i,\ t-1} \\
& + \beta_{5,t-1}MOM_{i,\ t-1} + \beta_{6,t-1}CP_{i,\ t-1} + \beta_{7,t-1}ILLIQ_{i,\ t-1} + \beta_{8,t-1}Beta_{i,\ t-1} \\
& + \beta_{9,t-1}SSKEW_{i,\ t-1} + \beta_{10,t-1}ISKEW_{i,\ t-1} + \beta_{11,t-1}IV_{i,\ t-1} + \varepsilon_{i,t-1}
\end{aligned}
\tag{1}
$$

Where $R_{i,t}$ is realized stock return in month t, which is regressed on one-month lagged values of the maximum daily return in the previous month (*MAX*), log of market capitalization (*Size*), book-to-market ratio (*B/M*), short-term reversal (*STR*), momentum (*MOM*), closing price (*CP*), illiquidity (*ILLIQ*), market beta (*Beta*), co-skewness (*SSKEW*), idiosyncratic skewness (*ISKEW*), and idiosyncratic volatility (*IV*).

Table 5 reports the time-series averages of the slope coefficients over the 168 months from January 2003 to December 2016. The results using two-stage Fama-MacBeth regression show a significant negative relation between MAX and the cross-section of one-month ahead stock returns. Likewise, a significant negative relation between one-month ahead stock returns and size, illiquidity, ISKEW, and IV. Given

Table 4. Alphas of double-sorted (3X5) portfolios.

Double Sorted		Panel A: Equal Weighted						Panel B: Value Weighted					
		Low MAX	2	3	4	High MAX	High − Low	Low MAX	2	3	4	High MAX	High − Low
Size	Avg	−0.004	−0.006	−0.007	−0.010	−0.021	−0.017	−0.002	−0.004	−0.005	−0.008	−0.016	−0.014
	t−stats	−0.985	−1.517	−1.679	−2.107	−3.578	−3.387	−0.614	−1.119	−1.145	−1.627	−2.727	−2.724
B/M	Avg	−0.002	−0.009	−0.008	−0.011	−0.020	−0.018	−0.001	−0.007	−0.006	−0.009	−0.015	−0.013
	t−stats	−0.444	−2.073	−1.769	−1.983	−3.198	−3.554	−0.352	−1.753	−1.388	−1.637	−2.365	−2.675
MOM	Avg	−0.004	−0.005	−0.010	−0.010	−0.021	−0.017	−0.003	−0.003	−0.008	−0.008	−0.016	−0.013
	t−stats	−0.759	−1.068	−2.241	−1.841	−3.377	−3.449	−0.664	−0.772	−1.841	−1.551	−2.669	−2.645
STR	Avg	−0.003	−0.005	−0.008	−0.013	−0.020	−0.017	−0.002	−0.003	−0.005	−0.010	−0.014	−0.012
	t−stats	−0.637	−1.342	−1.781	−2.449	−3.143	−3.455	−0.477	−0.923	−1.089	−1.911	−2.310	−2.518
CP	Avg	−0.004	−0.006	−0.009	−0.009	−0.020	−0.015	−0.003	−0.005	−0.006	−0.006	−0.014	−0.011
	t−stats	−0.960	−1.431	−2.022	−1.623	−3.470	−3.606	−0.682	−1.041	−1.474	−1.087	−2.435	−2.670
SSKEW	Avg	−0.002	−0.004	−0.008	−0.012	−0.021	−0.019	−0.002	−0.003	−0.006	−0.009	−0.016	−0.014
	t−stats	−0.719	−0.948	−1.955	−2.387	−3.415	−3.902	−0.539	−0.543	−1.323	−1.847	−2.511	−2.955
ISKEW	Avg	−0.003	−0.007	−0.007	−0.011	−0.021	−0.018	−0.002	−0.005	−0.004	−0.008	−0.016	−0.014
	t−stats	−0.581	−1.845	−1.500	−2.280	−3.292	−3.291	−0.329	−1.433	−0.809	−1.715	−2.553	−2.630
IV	Avg	−0.002	−0.006	−0.009	−0.012	−0.021	−0.019	−0.001	−0.004	−0.005	−0.009	−0.016	−0.015
	t−stats	−0.245	−1.350	−1.815	−2.368	−3.367	−4.070	−0.161	−0.909	−1.136	−1.793	−2.578	−3.074
ILLIQ	Avg	−0.001	−0.004	−0.010	−0.009	−0.024	−0.023	0.000	−0.001	−0.007	−0.005	−0.019	−0.018
	t−stats	−0.365	−0.923	−2.048	−1.921	−3.881	−4.652	−0.128	−0.333	−1.448	−1.171	−2.949	−3.639
Beta	Avg	−0.004	−0.005	−0.007	−0.012	−0.020	−0.017	−0.003	−0.004	−0.005	−0.010	−0.016	−0.013
	t−stats	−0.722	−1.062	−1.379	−2.544	−3.263	−3.372	−0.691	−0.769	−0.906	−2.215	−2.544	−2.544

Notes: This table presents the alphas (Avg.) and Newey–West *t*-statistics (*t*-stats.) of each portfolio. Alpha are estimated using Fama-French's three-factor model. At the end of each month, stocks are first sorted on a control variable (*Size, B/M, STR, MOM, ILLIQ, Beta, CP, SSKEW, ISKEW*, and *IV*) and then again by their maximum daily return in the past calendar month (*MAX*). To control for a particular factor, we average the alpha within each *MAX* category ending up with five portfolios with dispersion in *MAX* but containing all the values of the factor being controlled. *Size, B/M, STR, MOM, ILLIQ, Beta, CP, SSKEW, ISKEW*, and *IV* are defined in the Appendix. Panel A reports the results of equally-weighted portfolios, while Panel B reports the results of value-weighted portfolios. The sample period spans between January 2003 and December 2016.
Source: Authors calculation.

Table 5. Univariate Fama–MacBeth regressions.

MAX	Size	B/M	STR	MOM	CP	Illiquidity	Beta	SSKEW	ISKEW	IV
−0.058	−0.002	0.001	−0.009	−0.024	0.000	−0.03	0.002	0.001	−0.002	−0.217
(−1.95)	(−2.14)	(0.54)	(−0.86)	(−0.67)	(2.31)	(−2.41)	(1.55)	(0.90)	(−1.84)	(−1.91)

Notes: This table reports the firm-level univariate Fama–MacBeth cross-sectional regression of the return on month t with 1-month lagged $(t − 1)$ values of the MAX and other control variables. The sample period spans between January 2003 and December 2016. MAX and other control variables are defined in Table 1 and Appendix. Newey-West t-statistics are in parenthesis.
Source: Authors calculation.

that the highly correlated regressors can cause multicollinearity problems that may lead to biased estimates, we compute the variance inflation factor (VIF) to examine multicollinearity among the independent variables. In untabulated results, we note that the mean VIF value is 1.12, far lower than the threshold value of 10, indicating no serious multicollinearity problem.[8]

3.4. Firm-level analysis: Bi- and multi-variate cross-sectional regressions

In this section, we further extend our analysis and report the results of bivariate and multivariate cross-sectional regressions with MAX in Table 6. This analysis is to confirm whether the MAX effect survives after other variables have been controlled for. Our findings suggest that the negative MAX effect remains robust when we control the variables individually, except when paired with STR. Most importantly, the MAX effect persists even if we simultaneously control for all the variables we have studied in this article. In sum, the results suggest that the MAX effect exists in Pakistan in one-month holding period returns.

4. Further tests, robustness checks and discussion

4.1. Sub-sample and global financial crisis analysis

Nartea et al. (2017) find that MAX is more pronounced in big capitalization firms and recent subperiods, whilst insignificant otherwise. In this section, we divide the sample into three size groups based on the 30th and 70th percentiles (top 30% = Big, bottom 30% = Small, and middle 40% = Medium) and two equal sub-periods (2003–2009 and 2010–2016) to check robustness of our main results. Given that stock markets are immensely instable during the crisis periods, we also conduct an ex-crisis analysis, that excludes the crisis period (December 2007–December 2009). The choice to exclude such months is driven by two important reasons: (i) a combination of severe political instability in Pakistan and global financial crisis (2007–2009) (Ali et al., 2018), and (ii) the structural breaks in the time-series.

Table 7 shows that the negative MAX effect is persistent across the three size groups; however, it is more pronounced in the medium-size group than big and small size groups (Panel A). This finding suggests that the MAX effect in Pakistan is not confined to a specific size category. Similarly, our sub-period results show that the MAX effect in all three subperiods (Panel B). However, comparatively stronger in the post-crisis subperiod (2010–2016).

In an exercise where we aim to exclude crisis periods (ex-crisis analysis), our main findings largely hold: the negative MAX effect exists in the multivariate Fama-

Table 6. Bivariate and multivariate Fama-MacBeth regressions.

MAX	Size	B/M	STR	MOM	CP	Illiquidity	Beta	SSKEW	ISKEW	IV
−0.180	−0.153									
(−4.05)	(−4.13)									
−0.083		0.001								
(−1.72)		(0.31)								
−0.043			−0.002							
(−0.76)			(−0.22)							
−0.093				0.012						
(−2.07)				(0.31)						
−0.093					0.000					
(−2.05)					(0.48)					
−0.107						−0.045				
(−2.28)						(−4.18)				
−0.090							0.002			
(−1.88)							(1.95)			
−0.091								0.002		
(−1.87)								(1.61)		
−0.089									−0.001	
(−1.77)									(−1.56)	
−0.106										−0.210
(−1.97)										(−1.71)
−0.203	0.008	−0.001	−0.063	0.011	0.000	0.025	0.000	0.000	−0.001	−0.115
(−5.410)	(1.74)	(−0.68)	(−5.92)	(0.41)	(3.33)	(2.95)	(0.31)	(0.06)	(−0.75)	(−2.88)

Notes: This table reports the results of a firm-level bi- and multi-variate Fama–MacBeth cross-sectional regressions of the return on month t with 1-month lagged values of the MAX and other control variables for the period between January 2003 and December 2016. MAX and other control variables are defined in Table 1 and Appendix. Newey-West t-statistics are in parenthesis.
Source: Authors calculation.

MacBeth regression after controlling for all the variables under study. Further, we find that MAX and IV effects are probably independent of each other in the Pakistani market. Interestingly, the small firms, which are generally associated with limits to arbitrage and individual investors' dominance, generate significant negative alpha for ISKEW. This negative relationship possibly indicates investors' willingness to sacrifice mean-variance efficiency to gain skewness exposure or investors' failure to diversify (as explained by Mitton and Vorkink (2007)).

4.2. Estimation of MAX with alternative index and factor pricing model

Our results in the previous section (Table 2) pinpoint the importance of asset-pricing model we use to estimate alphas. Therefore, we extend our analysis and examine the risk-adjusted return using an alternative market portfolio – PSX-All share index, which comprises all the active stocks available – and an alternative factor model – Carhart's (1997) four-factor model – in this section. Table 8 replicates Table 2 using the above-stated alternative factor definitions. On the whole, our major findings hold: (i) increasing MAX has a negative effect on future performance and (ii) a High-minus-Low MAX portfolio generates a negative and statistically significant risk-adjusted return.

4.3. Extended holding periods

In this section, we examine the existence of a negative MAX effect for the extended holding periods of three and six months. The study follows Jegadeesh and Titman

Table 7. Fama–MacBeth cross-sectional regressions for size groups and subsample analysis.

	Panel A: Size groups			Panel B: Sub-periods		
	Small	Medium	Big	Pre-Crises	Post-Crises	Ex-Crises
MAX	−0.020	−0.298	−0.407	−0.184	−0.234	−0.211
	(−3.81)	(−7.21)	(−6.43)	(−9.33)	(−13.28)	(−14.34)
Size	−0.013	−0.016	−0.018	0.007	0.009	0.008
	(−1.01)	(−6.92)	(−5.25)	(6.82)	(10.30)	(11.01)
B/M	−0.006	0.001	0.004	−0.003	0.002	−0.000
	(−0.54)	(0.78)	(1.26)	(−1.51)	(1.27)	(−0.33)
MOM	−0.348	0.003	0.013	0.016	0.007	0.017
	(−0.70)	(0.09)	(0.43)	(0.40)	(0.18)	(0.58)
STR	−0.099	−0.064	−0.023	−0.071	−0.055	−0.058
	(−0.69)	(−5.16)	(−2.17)	(−4.02)	(−4.59)	(−5.86)
CP	0.005	0.000	0.000	0.000	0.000	0.000
	(0.61)	(4.00)	(4.08)	(3.77)	(0.01)	(3.70)
SSKEW	0.022	0.001	0.003	0.003	−0.002	−0.003
	(0.64)	(0.04)	(0.38)	(0.31)	(−0.70)	(−0.82)
ISKEW	−0.021	0.002	−0.001	0.001	−0.000	0.000
	(−1.69)	(1.50)	(−0.97)	(0.77)	(−0.20)	(0.45)
IV	0.995	−1.037	−2.097	−1.046	−1.258	−0.913
	(0.22)	(−1.92)	(−3.21)	(−1.77)	(−2.30)	(−2.27)
ILLIQ	0.061	0.024	0.041	0.030	0.020	0.022
	(0.60)	(2.16)	(3.17)	(2.00)	(2.46)	(2.61)
Beta	−0.002	0.000	0.004	−0.002	0.001	−0.000
	(−0.14)	(0.05)	(1.69)	(−0.68)	(0.63)	(−0.53)

Notes: This table reports the monthly Fama-MacBeth cross-sectional regression slope coefficients and associated Newey-West t-statistics. In panel A, we sort stocks into three portfolios based on their Size (market capitalization): small, medium, and big. In panel B, first we divide our testing period into two sub-periods, pre-crisis (2003 to 2009) and post-crisis (2010 to 2016). Then, we consider an ex-crisis sub-sample that excludes the crisis period (December 2007 to December 2009) from the full-sample (January 2003-December 2016). Each month we run a firm-level multivariate Fama-MacBeth cross-sectional regression of the return in month t with 1-month lagged values ($t-1$) of MAX and other control variables. All the variables under consideration are defined in the Appendix. Newey-West t-statistics are in parenthesis.
Source: Authors calculation.

(1993)'s procedure to construct portfolios with overlapping holding periods, as suggested by Nartea et al. (2017). More specifically, in any given month t, stocks are sorted into quintile portfolios based on MAX. We then take a long position on the highest MAX portfolio and a short position on the lowest MAX portfolio. This position is held for three and six months. Table 9 reports the alpha estimates for MAX quintiles and high-minus-low long-short portfolio (High-Low).[9] The results reported Table 9 (Panel A) are largely similar to the results reported in Table 2 (Panel A): the final row in Panel A of both tables shows that the abnormal returns are negative and statistically significant, indicating the robustness of the MAX effect across both holding periods. Panel B of Table 9 examines the six-month holding period and finds that the results are similar to those reported in Panel A. However, the magnitude of the alphas is higher for the three-month holding period, while the significance level is higher for the six-month holding period.

In sum, the overall pattern of the quintile portfolios and the statistical significance of the long-short portfolio is not dependent on the model we choose to compute risk-adjusted return. Moreover, negative and highly significant alpha spreads suggest at least a six-month lag in adjusting prices back to fundamental levels.

In addition, we estimate MAX as the mean of the five highest daily returns in a month (i.e. MAX_{5day}) and examine its average monthly cross-sectional correlation

Table 8. Estimation of alpha with alternative market index and factor pricing model.

Quintile	Panel A: Alternative index		Panel B: Alternative pricing model	
	FF3 (PSX-All) Equally-weighted	FF3 (PSX-All) Value-weighted	CH4 alpha Equally-weighted	CH4 alpha Value-weighted
Low MAX	−0.0045	−0.0042	−0.005	−0.004
	(−1.00)	(−1.02)	(−1.24)	(−1.19)
2	−0.0035	−0.0019	−0.005	−0.003
	(−1.19)	(−0.72)	(−1.83)	(−1.31)
3	−0.0073	−0.0050	−0.008	−0.006
	(−2.12)	(−1.71)	(−2.46)	(−1.93)
4	−0.0102	−0.0078	−0.010	−0.008
	(−2.48)	(−1.91)	(−2.55)	(−2.02)
High MAX	−0.0196	−0.0145	−0.020	−0.015
	(−3.71)	(−2.62)	(−3.87)	(−2.76)
High − Low	−0.0151	0.0040	−0.015	−0.010
	(−2.23)	(−1.95)	(−2.68)	(−1.81)

Notes: This table reports the alphas on equally- and value-weighted portfolios sorted by MAX from January 2003 to December 2016. In Panel A, we estimate each portfolio's alpha similar to what reported in Table 2; however, we use PSX-All index as market portfolios rather than PSX-100 in this table. Panel B of this table similarly augments the evidence reported in Table 2 using Carhart's four-factor model to compute risk-adjusted returns. The last two rows show the difference in alpha between the highest and lowest MAX portfolios and their Newey–West *t*-statistics, in parenthesis.
Source: Authors calculation.

Table 9. Alphas on equally-weighted portfolios sorted by MAX: 3- and 6-month holding periods.

Quintile	Panel A: 3-month holding period		Panel B: 6-month holding period	
	FF3	CH4	FF3	CH4
Low MAX	−0.007	−0.007	−0.008	−0.008
	(−1.89)	(−1.93)	(−2.60)	(−2.51)
2	−0.008	−0.007	−0.006	−0.005
	(−2.56)	(−2.50)	(−1.87)	(−1.74)
3	−0.004	−0.004	−0.008	−0.008
	(−1.26)	(−1.25)	(−2.59)	(−2.64)
4	−0.010	−0.010	−0.013	−0.012
	(−2.70)	(−2.62)	(−3.33)	(−3.23)
High MAX	−0.021	−0.020	−0.021	−0.020
	(−4.02)	(−3.86)	(−4.40)	(−4.24)
High − Low	−0.014	−0.013	−0.013	−0.012
	(−2.97)	(−2.77)	(−3.01)	(−2.85)

Notes: This table reports the alphas on equally-weighted portfolios sorted by MAX from January 2003 to December 2016. We use extended holding periods of three and six months. We estimate each portfolio's alpha from both FF3 (Fama & French, 1993) and CH4 (Carhart, 1997) models. The last two rows show the difference in alpha between the highest and lowest MAX portfolios and their Newey–West *t*-statistics, in parenthesis.
Source: Authors calculation.

with MAX. Our results show both (i) a strong negative MAX_{5day} effect in the Pakistani stock market and (ii) a high correlation between MAX and MAX_{5day}, indicating that the choice to choose between the two variables is inconsequential (available upon request).

4.4. The MAX effect and economic conditions

A synthesis of relevant literature reveals mixed evidence concerning the predicting power of the economic condition on the MAX effect. For example, (i) Kumar (2009) shows that investors' preference for lottery-like stocks is stronger during the

economic contraction periods, in specific, when bond default risk premium and unemployment are high; (ii) on the other hand, Palfrey and Wang (2012)'s theoretical model suggests that economic expansions (or good news) provide a high demand for speculative assets, such as the stocks in the high-MAX portfolio, and this asymmetric reaction inaugurates larger overpricing of securities that are short-sale constrained; and (iii) different from aforementioned studies, Fong and Toh (2014) document that MAX effect occurs regardless of whether the economy is contracting or expanding.

In this section, we examine whether or not the expanding or contracting economic conditions alter our main findings? Following Berggrun et al. (2019), who use Brazil's gross domestic product (GDP) as a measure of economic activity, we use Pakistan's annual GDP as our state variable of economic activity.[10] We use both GDP annual growth rate and year-on-year growth; however, our main findings hold in both cases. Each month within a year is classified as an economic-contracting month if growth during the year was below the median level. Similarly, an economic-expanding month would be recognized as if the annual GDP growth during the year was above the median of annual GDP growth. Finally, we emphasize on the equally- and value-weighted long-short (high-minus-low MAX) portfolios to observe the difference in the MAX effect across two different economic states.[11]

In Table 10 (Panel A), we observe an economically and statistically large negative MAX effect for the months in a year when it is defined as an expansion year. On the other hand, when the economy is in a contraction state, the monthly abnormal return for a high-minus-low MAX portfolio is negative but statistically insignificant. This unreliable relationship in low economic activity years implies that the negative MAX effect (i.e. propensity to overpay for speculative stocks in the Pakistani stock market that underperform in the following month) is intensified during the periods of economic expansion. The exacerbation of MAX during periods of economic expansion in this study are contrary to the findings of Cheon and Lee (2018); however, potentially support the theoretical explanation of Palfrey and Wang (2012): good economic news (i.e. when the economy is expanding) provide a high demand for speculative assets in Pakistan than bad economic news (i.e. when the economy is contracting). Additional support to this argument comes from the negative (but statistically insignificant) MAX effect during the periods of economic slowdown in the country: it shows that the subsequent underperformance of the high-MAX stocks exists irrespective of the economic condition (Fong and Toh (2014)); however, a combination of short-sale restrictions and good economic news in the PSX during periods of economic expansion plausibly contribute to more overpricing for speculative stocks than the periods during economic contraction.[12] To further understand the possible reasons that cause such anomalous relationship between MAX and different economic conditions, we examine other market characteristics in the following section.[13]

4.5. Robustness and potential explanations: the MAX effect and economic conditions

In this section, we begin by analysing alternative measures of economic conditions. We use World Bank's economic growth indicators for Pakistan and find that our results hold across two different economic growth measures.[14]

Table 10. MAX effect and economic states: Alphas on EW and VW Portfolios.

	EW portfolios		VW portfolios	
Panel A: Using Pakistan's GDP growth rate				
Expansion (above median)	−0.0250	(−4.04)	−0.0204	(−3.29)
Contraction (below median)	−0.0104	(−1.00)	−0.0055	(−0.53)
Panel B: Using World Bank's economic indicators				
Expansion (above median)	−0.0284	(−4.34)	−0.0239	(−3.56)
Contraction (below median)	−0.0009	(−0.09)	−0.0036	(−0.37)

Notes: This table shows the coefficients and *t*-statistics of the risk-adjusted high-minus-low MAX portfolios. We classify each month within a year as an economic contraction state month if the growth in Pakistan's GDP during the year was below the median level and vice versa (defined in the Appendix). Panel A uses Pakistan's GDP growth rate, while Panel B uses World Bank's economic indicators to examine whether the Pakistani economy is in expansion state or contraction state. Newey-West standard errors are reported in parenthesis. The sample period is from January 2003 to December 2016.
Source: Authors calculation.

Table 11. Examination of potential characteristics that possibly drive the MAX effect.

	Economic expansion	Economic slowdown	Pre-crisis	Post-crisis
Liquidity: Average daily trading volume (in Million) per listed firm	99.210	61.408	92.730	73.288
Liquidity: Long-Short portfolio strategy	−0.0066	−0.0014	0.0008	−0.0115
Returns: Average market returns (KSE-100)	0.0242	0.0072	0.0146	0.0205
Volatility: Standard deviation of market returns	0.0666	0.0848	0.0926	0.0539
Price non-synchronicity: Long-Short portfolio	0.0091	0.0005	0.0069	0.0053
Low MAX stocks: EW raw returns	0.0213	−0.0098	0.0010	0.0154
High MAX stocks: EW raw returns	0.0138	−0.0005	0.0009	0.0146

Notes: This table uses seven different characteristics, illustrated in each row of the first column (defined in the Appendix), to examine the drivers of the MAX effect in Pakistan. Pre- and post-crisis periods are defined in Table 7, while periods of economic expansion and contraction are defined in Table 10.
Source: Authors calculation.

Next, we re-examine our conjecture that the economic expansion state contributes to larger overpricing for speculative assets (high MAX stocks). Given that the MAX effect is stronger during the post-crisis period (see Table 7) and economic expansions (Table 10) than pre-crisis and economic slowdowns, respectively, we search for the market characteristics/drivers of such patterns. More specifically, we look for characteristics that are alike between post-crisis (pre-crisis) and economic expansion (contraction) states. To do so, we examine (i) market-wide liquidity: daily trading volume per listed firm; (ii) long-short liquidity hedge portfolio; (iii) average stock returns; (iv) volatility in returns; (v) price non-synchronicity; (vi) performance of low MAX stocks; and (vii) performance of high MAX stocks across four different periods. In Table 11, we notice that daily trading volume was higher during the economic expansion periods than economic contraction periods in Pakistan. In this case, if daily trading volume drives the MAX effect, it should be higher during the post-crisis period than the pre-crisis; however, our results are in the opposite direction. Therefore, we rule out this explanation. Similarly, our results using a long-short liquidity portfolio are inconclusive. However, average stock returns and standard deviations exhibit some interesting results: both economic expansion and post-crisis periods yield higher returns and lower standard deviations than their counterparts. While our finding contradicts with Cheon and Lee (2018), who document that the MAX effect only exists when volatility is high in the market, it supports our earlier conjecture in a sense that the MAX effect (or optimism) prevails for a longer period in Pakistan (see Table 9:

MAX effect persists for at least 6 months before prices are backed to fundamental level). Therefore, during the periods when the economy is expanding, reacting to good economic news more than bad news, and investors' expectations for a higher price equilibrium at some future date are strong (Palfrey & Wang, 2012), stock prices will consistently increase due to uniform believe. Thus, average returns are believed be higher and less volatile during the economic expansion periods than contraction periods. Subsequently, when the economy starts to shrink, investors' divergent believe and expectations will generate higher volatility in returns and lower trading volume (as shown by our results in Table 11). In this case, if our conjecture is true, weak underperformance of long-short MAX portfolio in Pakistan during the economic contraction periods should be driven by larger underperformance of low-MAX stocks (short leg) that reduces the underperformance of the high-MAX stocks (long leg), contrary to the US and other markets where strong MAX effect during the economic contraction periods is driven by larger underperformance of the high-MAX stocks.

Our results using low- and high-MAX legs support our conjecture: the MAX effect during economic slowdowns in Pakistan is driven by larger underperformance of low-MAX stocks. This finding can also be supported by the relationship between market beta and the low-MAX stocks (Table 3): since low-MAX stocks have higher beta, if market starts to slow down, low-MAX stocks generate more subsequent negative returns than high-MAX stocks. As a final robustness check, we examine price non-synchronicity (or relative idiosyncratic risk) across two different economic conditions. As per our knowledge, we are the first to construct a long-short price non-synchronicity portfolio (NS) for the Pakistani stock market.

Note that our prime aim does not include studying the performance of the long-short NS portfolio or its relationship with absolute IV. Our key interest in testing non-synchronicity is to inspect its persistence across subperiods. We calculate NS closely following Nguyen et al. (2018) and Long et al. (2020): $NS = ln\left(\frac{\sigma_{\varepsilon,i}^2}{\sigma_{r,i}^2 - \sigma_{\varepsilon,i}^2}\right)$, where $\sigma_{\varepsilon,i}^2$ is the standard deviation of the error term of stock i, and $\sigma_{r,i}^2$ is the volatility of the stock returns. We find a positive relationship between NS and future returns in Pakistan: a portfolio that takes a long (short) position on high (low) NS quintile portfolio generates a higher subsequent return. In line with the US evidence (Nguyen et al., 2018) and different from the Chinese evidence (Long et al., 2020), we find that the NS measure is possibly dominated by the link to systematic risks rather than absolute IV. In terms of its persistence across subperiods, we find that the NS measure is somewhat alike between pre- and post-crisis periods.

5. Conclusion

The literature documents both positive and negative relationship between the maximum daily return (MAX) and future stock returns. These inconsistent findings make this topic more pertinent and interesting to study; therefore, this study aims to provide an out-of-sample examination of the MAX effect. Different from developed (US and European) and relatively advanced and big emerging markets (South Korea, China, and Brazil), the Pakistani stock market (PSX) is at its early development stage,

shares different market characteristics, and offers a unique experiment to gain insight into the possible country-specific MAX effects. We find evidence of a negative and statistically significant MAX effect relatively stronger when we use equally-weighted portfolios and risk-adjusted returns instead of value-weighted portfolios and raw returns, respectively. We also find evidence of lottery-type features – high-MAX stocks are traded at a lower price and are positively (idiosyncratic) skewed than low-MAX stocks – indicating the potential to earn high returns by investing a relatively small amount, where the probability of achieving such high returns is low. Furthermore, we control for several variables (Size, B/M, STR, MOM, ILLIQ, Beta, CP, SSKEW, ISKEW, and IV) in both portfolio-level and firm-level cross-sectional analyses and find that the negative predictive ability of MAX to one-month ahead return is robust. Even when the holding period is extended to three and six months, our results remain robust. These findings indicate that it takes a relatively long lag (at least more than six months) in the price adjustment back to fundamental levels in the Pakistani stock market. A battery of robustness tests further reveals that the negative MAX effect is persistent: it significantly exists across size groups and subperiods.

Interestingly, the MAX effect in Pakistan is exacerbated only during the years when the economy is facing expansion, different from the evidence documented elsewhere. Given that the relationship between macroeconomic conditions and MAX is debatable where different studies explain this effect differently, our empirical results largely support the theoretical framework of Palfrey and Wang (2012), who document that speculative overpricing is higher when there is more good news than bad news (such as, during economic expansion periods). Searching for the drivers of this opposite effect during economic expansion states, we check several market-wide characteristics, including trading volume, pricing of liquidity and non-synchronicity factors, average returns and their volatility in the PSX, and long (high-MAX) and short (low-MAX) legs of the long-short MAX portfolio. The empirical findings support our conjecture: different from other stock markets, demand for speculative stocks (i.e. high-MAX stocks or stocks with lottery-like characteristics) is higher during periods of economic expansion, and this over-reaction (under-reaction) to good (bad) news persists for a longer period in Pakistan. More specifically, the weak MAX effect during periods of economic contraction in the Pakistani stock market is due to more negative subsequent performance of low-MAX stocks (short-leg), whereas, strong MAX effect during periods of economic contraction in other markets is due to more negative subsequent performance of high-MAX stocks (long-leg) (Fong & Toh, 2014).

Our findings suggest that investors should consider reducing their investments in low-MAX stocks when the economy is contracting since such stocks significantly underperform during economic downturn periods in Pakistan. We similarly find that low-MAX stocks have higher market beta than high-MAX stocks; therefore, they perform more poorly when the economy is facing a slowdown. In contrast, high-MAX stocks at the same time persist an expectation of a higher price equilibrium at some future date when the Pakistani economy starts to recover. However, until (i) an investor sentiment index following the guidelines of Baker and Wurgler (2006) is constructed (as suggested by Fong and Toh (2014)), (ii) a comprehensive examination of the behaviour of dominant investor type in speculative stocks (or legs) is carried

out (Ali and Ülkü (2020)), and (iii) the role of foreign investment on sentiments, stock prices and mispricing is examined (e.g. Shabbir and Muhammad (2019) and Shabbir et al. (2020)) for the Pakistani market, we leave this as a conjecture.

Moreover, given that the MAX effect in Pakistan and few other markets, including Brazil and Europe, is economically and statistically significant for risk-adjusted returns only, we recommend testing the MAX effect using alternative factor models, in specific, models that incorporate mispricing factors. For example, the choice of models to compute risk-adjusted returns could be a recently proposed misvaluation factor-augmented three-factor model (Ali & Ülkü, 2021).[15]

Notes

1. Recently, Khurram et al. (2020) study the relationship between MAX, minimum daily returns (MIN), and idiosyncratic volatility (IV) effects in Pakistan. However, their prime interest is to examine the relationship between these variables, while the robustness across firm size, sub-periods, and double-sorted portfolio-level tests that control for other important firm-level characteristics are not examined. Similarly, the existence of MAX effect across different economic conditions, pre- and post-crisis periods, and extended holding periods (or portfolio average transition probability matrix) is not examined by the authors. In sum, their findings need further testing for robustness. In this study, we not only are the first to provide a comprehensive and robust empirical evidence but also discuss the potential economic explanations and discussion. Moreover, we are also the first to inspect relative idiosyncratic volatility (price non-synchronicity) for the Pakistani stock market.
2. The Pakistani stock market (PSX) is a comparatively small market in terms of market capitalization; yet, it is important to study PSX given that its growth in the dollar-denominated capitalization (and local index) is significantly higher than most of the emerging stock markets.
3. The official website of the Pakistan stock exchange is https://www.psx.com.pk/
4. The official website of the State Bank of Pakistan is www.sbp.org.pk/
5. Source: http://www.brecorder.com/market-data/karachi-stocks/
6. Ali et al. (2018) defined crisis period in Pakistan based on a combination of domestic and global market conditions, such as the global financial crisis, severe political instability in the country, and different political reforms during this period. In addition, we have used cumulative sum (CUSUM) test to determine structural breaks in the time-series and find that the months between 2007 and 2009 represent a break.
7. These results are available upon request.
8. We re-run the regressions by winsorizing the regressors at the 99th and 95th percentiles to mitigate the problems caused by outliers, and the results are consistent.
9. Our results are based on EW portfolios. It is important to note that small stocks carry equal weight as big stocks in EW portfolios, while VW portfolios give more weight to big cap stocks.
10. Data for GPD are obtained from the official website of the SBP.
11. See appendix for more details.
12. Fong and Toh (2014) support the use of investor sentiments (by Baker and Wurgler (2006)) to examine the MAX effect. However, due to the absence of variables used by Baker and Wurgler to construct a similar sentiment index for Pakistan, we follow the guidelines of Berggrun et al. (2019) and construct economic expansion and contraction states using GDP growth rate.
13. We are thankful to the anonymous referee for this useful suggestion.
14. Note that our basic criteria to categorize the months within a year as high or low economic state months is the same as mentioned earlier in this study.

15. Ali and Ülkü (2021) test a large number of stock market anomalies, including mispricing anomalies, and find that their misvaluation factor-augmented three factor model can explain more anomalies than Fama-French's models. Similarly, examining seasonality in MAX and its long- and short-leg across periods of economic expansion and contraction would be useful to understand the pricing behavior of the MAX effect in Pakistan (Ali & Ülkü, 2019; Dailydytė & Bužienė, 2020).

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Appendix

Definitions of variables under study

We use the daily stock returns to calculate the maximum daily return over the preceding month ($MAX_{i,t}$), market beta ($Beta_{i,t}$), systematic skewness ($SSKEW_{i,t}$), idiosyncratic skewness ($ISKEW_{i,t}$), idiosyncratic volatility ($IV_{i,t}$), illiquidity ($ILLIQ_{i,t}$). The daily stock returns are calculated as the log difference of the daily closing price of the stocks. The log of the market capitalization (price times shares outstanding) at the end of month $t-1$ is defined as the size. B/M is the firm's book-to-market ratio at the end of $t-6$ (six months prior). We calculate the momentum variable ($MOM_{i,t}$) following Jegadeesh and Titman (1993)'s methodology (the cumulative return of stock i from $t-2$ to $t-12$). Following Jegadeesh (1990) and Lehmann (1990), the short-term reversal variable is calculated based on the stock's previous month's return (i.e. return in month $t-1$). The final trading price of a stock at the end of month $t-1$ is considered the closing price (Nartea et al., 2017).

Table A1. Factor construction and descriptive statistics.

Panel A: Factor Construction				
Sort	Factor breakpoints	Factors and their components		
2x3	SMB: Median capitalization (Size).	$SMB = \frac{1}{3}[SL + SM + SH] - \frac{1}{3}[BL + BM + BH]$		
	HML: 30th and 70th percentiles of book-to-market ratio.	$HML = \frac{(SH+BH)}{2} - \frac{(SL+BL)}{2}$		
Panel B: Descriptive Statistics		Rm-Rf	SMB	HML	UMD
Mean (%)		0.894	1.378	0.879	0.055
Standard Deviation		7.36	6.24	5.44	5.07
t-statistics		1.67	2.81	2.06	0.14

Notes. Panel A defines the factor construction methodology. Stocks are divided into two Size groups – Small (S) and Big (B) – and three book-to-market groups: High (H), Medium (M), and Low (L). The intersection of two size and three B/M portfolios generates six value-weighted portfolios: SL, SM, SH, BL, BM and BH. Portfolios are rebalanced at the end of December each year (*t*) to compute the monthly return for following year (*t* + 1). Last column of the table (Panel A) illustrates the formulas used to construct factors. Panel B reports descriptive statistics of the factors under study. R_m is the return on the market portfolio: KSE-100 index. R_f represents risk-free rate of return: cut-off yield on Pakistan's 3-month T-Bills rate. R_m-R_f, SMB, HML and UMD are the market, size, value and momentum factors, respectively.
Source: Authors calculation.

MAX: Maximum daily return in the previous calendar month (Bali et al., 2011):

$$MAX_{i,t} = \max(R_{i,d}) \qquad d = 1, \ldots, D_t \qquad (A1)$$

where $R_{i,d}$ is the return on stock i on day d. Dt represents the number of trading days in month t.IV: The idiosyncratic volatility of stock i at the beginning of month t is defined as the standard deviation of daily residuals from the capital asset pricing model estimated using daily returns in month t-1 (Bali et al., 2011):

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \varepsilon_{i,d} \qquad (A2)$$

$$IV_{i,t} = \sqrt{Var(\varepsilon_{i,d})}$$

SSKEW and ISKEW: Harvey and Siddique (2000) recommend decomposing total skewness into idiosyncratic- and systematic-component; therefore, we follow their methodology and use the following regression for each stock:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \gamma_i(R_{m,d} - R_{f,d})^2 + \varepsilon_{i,d} \qquad (A3)$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}-R_{f,d}$ is the daily market return in excess of daily risk-free rate ($R_{f,d}$) on day d, and $\varepsilon_{i,d}$ is the idiosyncratic return on day d. The systematic skewness (SSKEW) of stock i in month t is the estimated slope coefficient $\hat{\gamma}_i$. The idiosyncratic skewness (ISKEW) of stock i in month t is defined as the skewness of daily residuals $\varepsilon_{i,d}$ in month t.

Beta: Market beta is computed by regressing the daily stock return on daily current, lead, and lagged market returns (Bali et al., 2011; Nartea et al., 2017):

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d} \quad (A4)$$

where $R_{i,d}$ is stock i's return on day d, $R_{m,d}$ is the market return on day d, and $r_{f,d}$ is the risk-free rate on day d. Thus, the market beta (Beta) of stock i in month t is the sum of the three betas obtained from Eq. A4: $\hat{\beta}_i = \widehat{\beta_{1,i}} + \widehat{\beta_{2,i}} + \widehat{\beta_{3,i}}$

Size: The natural logarithm of the market capitalization (a stock's price in Pakistani rupee multiply by its shares outstanding) at the end of month $t-1$ is defined as the size variable at the beginning of month t.

B/M: Following the relevant/recent literature (e.g. Nartea et al., 2017), a firm's six months prior book-to-market ratio (i.e. at the end of $t-6$) is considered as the B/M for month t.

MOM: The momentum variable for each stock in month t is the cumulative return between months $t-2$ and $t-12$, following Jegadeesh and Titman (1993)

STR: The short-term reversal variable is calculated based on the stock's previous month's return (i.e. return in month $t-1$) (Jegadeesh (1990) and Lehmann (1990)).

CP: The final trading price of stock i at the end of month $t-1$ is considered the closing price for stock i (Nartea et al., 2017).

ILLIQ: Following Bekaert et al. (2007), we consider zero returns as a measure of illiquidity: the proportion of daily zero firm returns, averaged over the preceding month ($t-1$).

Asset pricing models: To calculate risk-adjusted returns, we construct three- and four-factor models following Fama and French (1993) and Carhart (1997), respectively. In addition, to adjust the local market characteristics, we take guidance from recent Pakistani asset pricing studies (e.g. Ali, 2021; Ali et al., 2021). Size (SMB) and book-to-market (HML) factors are updated annually, while momentum factor (UMD) is updated monthly.

GDP as a measure of economic states: To categorize the months within a year t as high or low economic state months, we use annual GDP growth estimated with information from the beginning of the sample to year t. For years between 2003 and 2005, we take the GDP information of at least 3 preceding years (e.g. for months in year 2003, we take the median of yearly growth rates from 2000 to 2003, and for months in year 2005, we start from 2002 and end in year 2005). For other years (2006–2016), we begin from the sample starting year (2003) and end at year t (the year for which we are estimating the overall economic condition). Our approach is similar to Berggrun et al. (2019).