Predictability of Extreme Daily Returns in Emerging Markets

ABSTRACT: Recent evidence in the U.S. and Europe shows that stocks with extreme daily (positive) returns in the current month perform poorly in the following month. This paper examines the presence of a similar effect in the Pakistani stock market. We find a negative effect of the maximum daily return (MAX) on future performance similar to the U.S. and European markets. Other proxies for extreme returns (e.g., idiosyncratic volatility and skewness) play a weaker role as cross-sectional determinants of stock performance. However, both the MAX and idiosyncratic volatility effects seem to coexist autonomously similar to the Chinese and Korean evidence. This study is the first to examine the MAX effect and compute risk-adjusted returns using various most popular asset-pricing models for the Pakistani stock market. Our results are robust to both portfolio-level and firm-level cross-sectional analysis, across subperiods, and persistent with the US dollar-denominated returns. We document that the gambling behavior in the market only exacerbates when overall economy is in expansion state.

KEY WORDS: extreme returns, MAX effect, lottery-like stocks, idiosyncratic volatility, emerging markets

Introduction

Portfolio theory advocates that the optimal risk-return tradeoff can be attained, if investors allocate their funds in 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 have a tendency to falsely believe the probability of success in gambling to be higher than it actually is. Thus, preference for lottery-like stocks drives the under-diversified holdings of securities. Motivated by recent findings of Kumar (2009) that investors exhibit a preference for stocks with lottery-like characteristics, Bali, Cakici, and Whitelaw (2011) investigate the role of extreme positive returns in the cross-sectional pricing of stocks in the U.S. They find that monthly portfolios consisting of stocks having high maximum daily returns (high MAX stocks) during the prior month significantly underperform in comparison to the portfolios of stocks experiencing low maximum daily returns (low MAX stocks) during the preceding month. They report negative raw and risk-adjusted return spreads 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. Bali, Cakici, and Whitelaw (2011) also report that the MAX effect converses the anomalous negative relationship between stock returns and idiosyncratic volatility, first reported by Ang, Hodrick, Xing, and Zhang (2006; 2009). They argue that MAX is the true effect and the idiosyncratic volatility is a proxy that drives MAX.

Kumar (2009) documents that a specific group of investors prefer lottery-like stocks and gambling. That are stocks with high idiosyncratic skewness and high idiosyncratic volatility. It is further stated that expectedly these investors keep overvaluing the stocks with extreme positive returns in expectation for return persistence, which reflects lottery preference of the investors (because such stocks underperform in the future). Several theoretical studies (e.g., Brunnermeier, Gollier, and Parker 2007) document that lottery-like feature has a strong relationship to higher moments of the distribution of returns, and an asset return skewness is preferred by the investors. Boyer, Mitton, and Vorkink (2007) label such (skewness preferring) investors as lotto investors. Barberis and Huang (2008) document that investors give more weightage to the extreme events that have low probabilities. A non-normal distribution will lead to a negative excess return for skewed securities which is overpriced. Bali, Cakici, and Whitelaw (2011) explain that the negative MAX effect is apparently due to investor preference for stocks with lottery-like features. Specifically, stocks that have the potential to generate high maximum daily returns, although their chance of occurrence is weak (low probability). This preference leads to overpayment for these stocks which ultimately results to underperformance in the succeeding month. Based on the optimal expectations framework, Fong and Toh (2014) explain that investor optimism creates a preference for lottery-type stocks.

Empirical evidence of the Max effect in other markets is still very sparse. Though Annaert, De Ceuster, and Verstegen (2013) and Walkshausl (2014) document the existence of a MAX effect in European markets. However, the MAX effect in Europe is somewhat weaker than the U.S. market. Nartea, Wu, and Liu (2014), Cheon and Lee (2018), Nartea, Kong, and Wu (2017), Wan (2018), Berggrun, Cardona, and Lizarzaburu (2019), and Ali, Ahmed, Hasan, and Ostermark (forthcoming) confirm a negative MAX effect in the South Korean, Chinese, Brazilian, and Turkish stock markets, respectively. Interestingly, Chee (2012) did not find a MAX effect in the Japanese market, except with bivariate sorts after controlling for firm characteristics. On the other hand, Aboulamer and Kryzanowski (2016) document a conflicting result in the Canadian stock market where there exists a positive relationship between the daily maximum returns and returns in the following month. This mixed result raises the question of the applicability of the MAX effect in other stock markets and motivates us to further research on the MAX effect for other countries—especially emerging markets.

Karolyi (2016) expresses a U.S. (home) bias in the field of empirical finance because most of the studies cover U.S. markets only. Similarly, some other non-U.S. countries that are covered more often than other countries (foreign bias). Given that the developed markets are well connected, the same phenomena and risk measures apply to these markets, hence, produce similar findings. Therefore, it is vital to investigate whether emerging markets also exhibit a MAX effect like developed economies.[1] We are not aware of other studies done in Asian emerging stock markets (except for China, Korea, and Turkey), however, it is the first study that investigates the presence of the MAX effect in Pakistan, and therefore, an interesting case. If Bali, Cakici, and Whitelaw's (2011) explanation is valid, we expect to document a negative MAX effect in the Pakistani stock market. Thus, we examine whether the evidence goes for or against the relevance of extreme returns over the recent period.

For comparison we follow Bali, Cakici, and Whitelaw (2011) portfolio sorting procedure. First, stocks are sorted according to their maximum daily return in the previous month, then portfolios are formed on the basis of MAX, and finally returns are tracked for these portfolios in the following month. Portfolios are rebalanced every month, additionally,

[1] In the context of emerging markets, Max effect has been examined for very few countries, such as China, Korea and Brazil, and these emerging markets have significantly different characteristics than the Pakistani stock market (see also, Khwaja and Mian 2005 and Ali, He, and Jiang 2018 for a comprehensive overview of special characteristics of Pakistani stock market that are different than the other emerging and developed markets from the perspective of asset-pricing).

we reexamine our analysis by varying the portfolio holding period to three- and six-month. The study examines the existence of a MAX effect using univariate and bivariate sorts, and confirms the robustness of our results with a double-sort procedure to control for various cross-sectional effects, such as size, book-to-market, short-term reversal, momentum, illiquidity, market beta, closing price, systematic skewness (co-skewness), idiosyncratic skewness, and idiosyncratic volatility. In addition, we also perform firm-level Fama–MacBeth cross-sectional regressions as further robustness tests.

Our findings are easy to summarize. First, we find a negative MAX effect in Pakistan similar to the U.S. and European markets. This effect is stronger for risk-adjusted returns and equally-weighted portfolios as compared to raw returns and value-weighted portfolios, respectively. The MAX effect perseveres even if we extend the holding period to 3 and 6 months. Our results somewhat support Bali, Cakici, and Whitelaw's (2011) view that investor preference for stocks with lottery-type features drive the negative MAX effect. Second, the study finds that the MAX effect apparently does not weaken the anomalous idiosyncratic volatility effect in the Pakistani stock market. More specifically, our results suggest that both the MAX and IV effects can coexist independently and could be proxies for each other in Pakistan. In this regard, our findings are similar to the Chinese and Korean evidence reported by Nartea, Kong, and Wu (2017) and Cheon and Lee (2018), but contrary to the U.S. and European evidence reported by Bali, Cakici, and Whitelaw (2011) and Annaert, De Ceuster, and Verstegen (2013), respectively. This highlights the significance of country-specific validation of certain anomalies originally recognized in developed markets. Third, we find a puzzling idiosyncratic skewness (ISKEW) effect. There is a negative ISKEW effect in the firm-level univariate Fama-MacBeth regression, but it disappears after we control for MAX and other variables in bivariate and multivariate regressions. However, the negative ISKEW effect remains robust in the small cap firms even when we control for all the variables together including MAX and IV. It makes sense, because small cap stocks face limits to arbitrate, therefore, plausibly investors in Pakistan who invest in small cap firms either face barriers (failure) to diversify or willingly under-diversify in order to grasp the maximum upside potential.

Additionally, we perform subsample analysis (pre-, post-, and ex-crises) and robustness checks across different size groups (small, medium, and big), and find that: the negative MAX effect is statistically significant in all subperiods and across all size groups, although more pronounced in post-crises subperiod and in medium and big cap firms. We also examine the role of economic conditions in the overpricing of high MAX stocks, and the effect of using various promising asset pricing models (models that are discussed in recent empirical asset-pricing literature, such as recently developed five- and six-factor models of Fama and French (2015; 2018)) to compute risk-adjust return. Contrary to that of Kumar (2009) for the U.S market, we find a stronger negative MAX effect in periods when overall economy is expanding. With regards to asset pricing models, most of the existing literature on the MAX effect relies on the Fama and French (1993) three-factor model and few studies also use Carhart's (1997) four-factor model to estimate alpha. Given that the five- and six-factor models attained much attention in recent years by the researchers, we also use these models in addition to the three- and four-factor models. We find that the negative MAX effect, using long-short (high-minus-low MAX) hedge portfolio that takes a long position on high MAX stocks and a short position on low MAX stocks, survives against all models. Specifically, the risk-adjusted return for this high-minus-low MAX portfolio is negative and highly significant in equally-weighted portfolio, even if we hold this portfolio for 3- and 6-month periods. It shows that there is a comparatively long lag in the price adjustment back to fundamental levels.

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 reports the empirical results, and the extent and significance of the negative MAX effect using portfolio-level and firm-level analysis. This section also provides the results of univariate, bivariate, and multivariate sorts and regression analysis. Section 4 provides results of several robustness checks, such as pre-, post-, and ex-crises subperiod analysis, the existence of a MAX effect across different size groups, the impact of using various promising asset pricing models on the risk-adjusted returns (alphas), the performance of MAX effect in extended holding periods of 3- and 6-month, and finally the impact of economic conditions on the significance of

MAX effect. Section 5 concludes the paper with a summary of our findings and future recommendations.

Data and Methodology:

Daily and monthly stock prices, index closing points, and accounting data (*Balance Sheet* and *Income Statement*) of all individual firms listed at the Pakistan stock exchange (PSX) are obtained from the official website of the PSX.[2] The financial statements of financial sector and the cut-off yield on the Pakistani Treasury bill rate (T-bills) are obtained from the official website of the State Bank of Pakistan (SBP).[3] We use the PSX-100 index (value-weighted) as market return and 3-month T-bills cut-off yield (converted into monthly values) as a risk-free rate, following recent empirical studies on the Pakistani stock market (Ali, He, and Jiang 2018; Ali, Khurram, and Jiang forthcoming). The financial daily Business Recorder is used to obtain any missing information.[4] The dataset covers the period between January 2003 and December 2016 (168 months) with an overall average of 385 firms. We start our sample from 2003 because the data in digital form on the official website of the PSX is available from this period. We also conduct subsample analysis for periods from January 2010 to December 2016 (post-crises) and from January 2003 to December 2016 excluding the period between December 2007 and December 2009 (ex-crises), to eliminate the impact of the Global financial crisis of 2008 and domestic market conditions between 2008 and 2009.[5] Following common practice in the existing literature, we exclude investment trusts, exchange traded funds, and closed-end funds. We include delisted stocks till the year they are traded to avoid any survivorship bias. We have also ignored daily returns on the first trading day for IPO (initial public offering) firms and have deleted observations with returns exceeding 300%.

Construction of Risk Factors

[2] The official website of the Pakistan stock exchange is https://www.psx.com.pk/

[3] The official website of the State Bank of Pakistan is www.sbp.org.pk/

[4] Source: http://www.brecorder.com/market-data/karachi-stocks/

[5] Ali, He, and Jiang (2018) defined crises period in Pakistan based on a combination of domestic and global market conditions, such as the Global financial crises, severe political instability in the country, and different political reforms during this period).

Given that the empirical analysis involves the construction of asset-pricing factors to estimate risk-adjusted return via the model's alpha, we construct various risk factors. Most of the extant literature uses the three-factor model of Fama and French (1993) to estimate the MAX effect, therefore, as a starting point this study emphasis on the three-factor model. Later, we add momentum, profitability, and investment factors because of their relationship with the discount rate and popularity in the recent asset-pricing literature.

We construct risk factors following Fama and French (1993, 2015, 2018) and Carhart (1997). Taking guidance from recent Pakistani asset-pricing work (Ali, He, and Jiang 2018; Ali, Khurram, and Jiang forthcoming), we also adjust for the local characteristics and special features that are important from the perspective of asset allocation in the Pakistani stock market. Variables on which risk factors are constructed are defined as follows. At the end of December, we allocate stocks to two different size portfolios: a big (B) portfolio that includes the stocks with above median market capitalization in year *t*, and a small (S) portfolio that contains the remaining small stocks in year *t*. For book-to-market (B/M) value of equity of each stock, we split stocks into 3 sets (vale, neutral, and growth stocks) based on their B/M ratio in year *t*. For profitability factor, we split stocks into 3 sets based on their return on equity (ROE), defined as net profit in year *t* scaled by total shareholders' equity in year *t*-1. Finally, for investment factor, we split stocks into 3 sets based on their percentage growth in total assets, defined as the annual change in total assets between two most recent years (*t* and *t*-1) scaled by total assets in the year *t*-1. The portfolio cutoffs (other than size) are based on the 30th and 70th percentiles. The momentum variable is the cumulative return of stock *i* from $t-2$ to $t-12$, following Jegadeesh and Titman (1993) methodology. These cutoffs are used to independently sort stocks into 2×3 value-weighted portfolios, and then for the purpose of factor construction. The market risk premium is defined as the return on the market portfolio (PSX-100 index) in excess of the risk-free rate (Pakistan's 3-month T-bills cutoff yield). Finally, we have the following risk factors by using the averaging formula of Fama and French (1993, 2015, 2018): the market risk premium (MRP), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), and momentum (UMD) factors. We also examine the correlations between these factors, however, we did not notice any excessively high values of the correlation coefficients that may arise a concern about any multicollinearity problem.

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 reformed every month. The risk-adjusted return refers to the Fama-French three-factor model alpha computed using the time-series of value-weighted returns for each of the equally- and value-weighted portfolios.

We control for a number of variables including size, book-to-market, short-term reversal, momentum, market beta, illiquidity, closing price, co-skewness, idiosyncratic skewness, and idiosyncratic volatility using dependent 3×5 bi-variate sorts similar to that employed by Bali, Cakici, and Whitelaw (2011). First, we sort on the control factor (e.g., size, B/M, illiquidity, IV, and so on) into tertiles. Second, we sort further into quintiles based on MAX within each tertile. Finally, we take average of each of the MAX category 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 tertiles 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 alphas of the three Low MAX portfolios (i.e., High B/M-Low MAX, Med B/M- Low MAX, and Low B/M-Low MAX). So, we have a Low MAX portfolio which contains all value (B/M) categories. We replicate the same procedure for other control variables.

We use the daily stock returns to calculate the following variables: maximum daily return over the preceding month ($MAX_{i,t}$), market beta ($Beta_{i,t}$), systematic skewness ($SSKEW_{i,t}$), idiosyncratic skewness ($ISKEW_{i,t}$), and idiosyncratic volatility ($IVOL_{i,t}$) at monthly interval. We calculate the daily stock return as the log difference of daily stock prices. The daily stock returns for the firm *i* during the month *t* is $Return_{i,t}$ while $MAX_{i,t}$ for a given firm is the maximum daily return in the month $t-1$ for the firm *i*. Harvey and Siddique (2000) decompose total skewness into idiosyncratic and systematic components, we follow their methodology and use the following regression for each stock within each year:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \gamma_i\left(R_{m,d} - R_{f,d}\right)^2 + \varepsilon_{i,d} \qquad (1)$$

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 co-skewness or systematic skewness (henceforth, will be used alternatively) 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*. The idiosyncratic volatility (IV) of stock *i* at the beginning of month *t* is defined as the standard deviation of daily residuals from the Fama–French three-factor model estimated using daily returns in month *t*-1. Following Carpenter, Lu, and Whitelaw (2015), we compute market beta by regressing daily firm return on daily current, lead, and lagged market returns:

$$\begin{aligned} R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}\left(R_{m,d-1} - r_{f,d-1}\right) + \beta_{2,i}\left(R_{m,d} - r_{f,d}\right) + \beta_{3,i}(R_{m,d+1} \\ - r_{f,d+1}) + \varepsilon_{i,d} \end{aligned} \qquad (2)$$

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 defined as:

$$\widehat{\beta_\iota} = \widehat{\beta_{\iota,1}} + \widehat{\beta_{\iota,2}} + \widehat{\beta_{\iota,3}} \qquad (3)$$

The log of the stock's market capitalization at the end of month *t*−1 is defined as the size variable at the beginning of month *t*. B/M is the stock's book-to-market ratio 6 months prior (i.e., at the end of *t*−6). We calculate the momentum variable ($MOM_{i,t}$) following Jegadeesh and Titman (1993) methodology (the cumulative return of stock *i* from *t*−2 to *t*−12). Following Jegadeesh (1990) and Lehman (1990), the short-term reversal variable is calculated based on the stock's previous month return (i.e., return in month *t*−1). The final trading price of a stock at the end of month *t*−1 is considered as the closing price. In the context of emerging markets, zero returns as illiquidity measure is reported more reliable and robust. Thus, we follow Bekaert, Harvey, and Lundblad (2007) to define illiquidity: the proportion of daily zero firm returns averaged over the month (*t*−1).

Table 1 shows the descriptive statistics of the variables used in this article (our final stocks). The average of daily returns over the sample period is approximately 0.91%. The reported standard deviation and the difference between minimum and maximum values show that on average stocks' return 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 idiosyncratic skewness and systematic skewness are -0.23 and 0.56 respectively. The mean momentum is 0.94, short term reversal 1.06, market beta 0.78, book-to-market 1.25, and illiquidity 0.86. The average size of our sample is approximately 9.53 billion Pakistani rupees (PKR) and average closing price is 92.72 PKR. The average number of firms in our sample are 385, while the minimum and maximum number of firms are 324 and 421, respectively.

Empirical Results and Discussion

Max Effect−Portfolio Level Analysis: Univariate Sorts

At first, we perform a portfolio level analysis to show whether stocks that generate extreme returns perform lower in the future. Given the lower availability of stocks in Pakistan as compared to the U.S. or other developed markets, we sort stocks into quintiles instead of deciles. So, 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 returns and risk-adjusted returns (alphas) of portfolios sorted on MAX, for inference we use Newey West (1987) standard errors. 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 lower most portfolio of maximum daily returns over the past month. The alpha of our five equally- and value-weighted portfolios monotonically decrease, as we move from low MAX portfolios to high MAX portfolios. This finding advocates a negative effect of extreme positive daily returns on succeeding performance.

We also evaluate the alphas for often 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 return for equally- and value-weighted portfolios is negative (-1.74% and -1.24% per month respectively) and statistically significant (t=−2.93

and t=−2.09 respectively), implying a robust negative MAX effect. In sum, the negative MAX effect in Pakistan is somewhat stronger to that reported by Bali, Cakici, and Whitelaw (2011) in the U.S. (alpha=−0.66%), Nartea, Kong, and Wu (2017) in China (−1.14%), and Berggrun, Cardona, and Lizarzaburu (2019) for Brazil (−0.8%). On the other hand, the EV risk-adjusted return reported by Ali, Ahmed, Hasan, and Ostermark (2019) for the Turkish stock market is higher (−1.57%) while the VW alpha is lower (-1.09%) than the alpha we report in this study.

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 are reported by Berggrun, Cardona, and Lizarzaburu (2019) for the Brazilian market and Annaert, De Ceuster, and Verstegen (2013) for the European markets (13 countries)− they document an insignificant spread for long-short MAX portfolio using raw returns, while a negative and statistically significant spread after adjusting for risk using Carhart's four-factor model. 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. Although, the negative MAX effect on expected returns is stronger in equally-weighted portfolios. Provided that the tendency to hold lottery-type stocks is likely to be higher for individuals than for institutional investors (Kumar 2009). Moreover, institutional investors regularly inaugurate minimum market capitalization constraints on their holdings as well. Table 3 confirms this proposition: the high MAX stocks are generally small stocks, therefore, MAX effect in equally-weighted portfolios is supposed to be stronger (since small stocks carry more weight in equally-weighted portfolios, while big stocks carry more weight in the value-weighted portfolios). Table 3 further confirms that high MAX stocks tend to be smaller, have higher B/M, are comparatively 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. Further, the stocks belonging to the highest MAX portfolios exhibit lottery-type characteristics: these stocks are traded at lower prices, have a higher liquidity, exhibit a high degree of idiosyncratic volatility and idiosyncratic skewness, and a higher total skewness (untabulated result). Thus, these variables could possibly contribute in the existence of negative MAX effect.

Next, we formally test this by using bivariate sorts and cross-sectional regressions in the following sections.

Max effect − Portfolio Level Analysis: Bivariate Sorts

In this section we resort to bivariate sorts and examine whether the apparent MAX effect 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. 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, Cakici, and Whitelaw 2011; Nartea, Kong, and Wu 2017) we emphasis on the alphas because they control the standard set of systematic factors. In Panel A (Table 4), our results confirm that 10 out of 10 *t*-statistics for portfolios that are long on high MAX stocks and short on low MAX stocks (alpha spreads) are always negative and highly significant. The results reported in Panel B (value-weighted) follow the same pattern as Panel A (equal-weighted). However, the negative MAX effect is stronger in equally-weighted portfolios than the value-weighted portfolios. By and large, the negative MAX effect seems robust after controlling for stock characteristics on an individual basis. Since dependent bi-variate sorts cannot control for multiple effects at the same time, we perform firm-level analysis in the next section.

Max effect−Firm Level 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), a useful information could be unexploited. Thus, we estimate the following model and its subsets:

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

Where $R_{i,t}$ is realized stock return in month *t*, which is regressed on 1-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. We employ a two-stage Fama-MacBeth regression, results using Newey–West *t*-statistics show a significant negative relation between MAX and the cross-section of 1-month ahead stock returns. The results show significant negative coefficients for size, illiquidity, ISKEW, IV, and a slightly insignificant positive coefficient for beta. On the other hand, coefficients for B/M, MOM, STR, and SSKEW are statistically insignificant. Given that the highly correlated regressors can cause multicollinearity problems, which may lead to biased estimates, we compute the variance inflation factor (VIF) to examine multicollinearity among the independent variables. In untabulated result, we note that the mean VIF value (1.12) is far less than the threshold value of 10, which indicates that there is no serious problem of multicollinearity in our empirical analysis.

Max effect−Firm Level Bi- and Multi-variate Cross-sectional Regressions

Next, we report the results of bivariate and multivariate regressions with MAX in Table 6. This analysis is to make sure whether the MAX effect survives after we control for other variables. 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. To sum up, the results advocate that there exists a MAX effect in Pakistan in 1-month holding period returns.

Robustness Checks

Nartea, Kong, and Wu (2017) find that the MAX effect is more pronounced in big capitalization firms and in recent subperiod, whilst insignificant otherwise (i.e., small cap firms, medium cap firms, and in earlier subperiod). We divide the sample into three size groups based on the 30^{th} and 70^{th} percentiles (top 30% = Big, bottom 30% = Small, and middle 40% = Medium). Further, we split the sample into two equal sub-periods (2003-2009 and 2010-2016) and conduct the Fama-MacBeth regression to check the robustness of our results in pre- and post-crises periods. Given that the stock markets are very unstable during the crises periods, we also conduct an ex-crises analysis, which excludes the months between December 2007 and December 2009.

Panel A of Table 7 indicates that the negative MAX effect is persistent across the three size groups, however it is the most pronounced in medium size group followed by big and small size groups, respectively. This suggests that medium and big cap firms exhibit a higher MAX effect than the small firms in the Pakistani stock market. The sub-period results presented in Panel B show that the MAX effect exists in all the three subperiods, pre-, post- and ex-crises. However, between pre- and post-crises periods, it is comparatively stronger in the recent subperiod (2010-2016). In the context of ex-crises analysis, our main finding holds: the negative MAX effect exists in the multivariate Fama-MacBeth regression after controlling for all the variables. It is also interesting to know that IV effect survives in all subperiods, and it is more pronounced in medium and large firms (using multivariate settings). It implies that MAX and IV effects are probably independent of each other in the Pakistani stock market similar to the findings reported for the Chinese market (Nartea, Kong, and Wu 2017), but contrary to the suggestion of Bali, Cakici, and Whitelaw (2011) for the U.S. market.

Our results are robust across different factor asset pricing models (FF3, FF5, FF6, and CH4), across different holding periods (3- and 6-month). Kuamr (2009) finds that the MAX effect exists during the years when overall economy is in contraction state. However, we find a negative and significant MAX effect during the years when overall economy is facing expansions. Finally, we note that the MAX effect is persistent also with the US dollar-denominated returns.[6] Ali, Ahmed, Hasan, and Ostermark (forthcoming) obtained similar results, where the MAX effect was determined after introducing all the relevant control variables.

Conclusion

Using the U.S. data, Bali, Cakici, and Whitelaw (2011) find that stocks with high maximum daily return in the preceding month (MAX) underperform in the following month. Recently,

[6] Results will be provided upon request.

Nartea, Kong, and Wu (2017) document a negative MAX effect in the world's largest emerging stock market (China), while Aboulamer and Kryzanowski (2016) document a positive MAX effect in the North American developed stock market (Canada), which are contradictory to each other. These inconsistent findings make this issue even more puzzling and interesting, therefore, this study aims to provide out-of-sample tests of the MAX effect for the Pakistani stock market. We find evidence of a negative and statistically significant MAX effect that is stronger when we use equally-weighted portfolios and risk-adjusted returns instead of value-weighted portfolios and raw returns respectively, similar to the findings reported by Berggrun, Cardona, and Lizarzaburu (2019). Given that the high MAX stocks generally come from small cap, equally-weighted portfolios have higher relative weight than the value-weighted portfolios.

We also find evidence of lottery-type features: high MAX stocks are traded at lower price, so there exists a potential chance to earn huge returns by investing relatively low, and these stocks are positively skewed, which means there is a low probability of occurrence. Further, we control for several variables (size, B/M, STR, MOM, ILLIQ, beta, CP, SSKEW, ISKEW, and IV) and find negative predictive ability of MAX to one-month ahead risk-adjusted returns. Even when we extend the holding period to 3 and 6 months, our results remain robust. This finding advocates that it takes 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, exists in all size groups (small, medium and big), and is significant in both subperiods, i.e. pre-crises (2003-2009) and post-crises (2010-2016). It is interesting to note, we find a negative and significant MAX effect during the years when overall economy is facing expansions, contrary to the findings of Kuamr (2009). This important finding suggests that the gambling behavior in the Pakistani stock market takes place when economic activity expands. Moreover, we note that the MAX effect is persistent with the US dollar-denominated returns.

Additionally, bivariate and multivariate Fama-MacBeth regressions confirm that both the MAX and the IV effects survive where MAX effect does not subsume IV effect in the Pakistani stock market contrary to the findings of Bali, Cakici, and Whitelaw (2011) in the U.S. and Annaert, De-Ceuster, and Verstegen (2013) in the European markets. In sum, both the MAX effect and the anomalous IV effect are independent effects, can coexist, and can be used as proxies for each other. Our results also emphasize the importance of country-specific authentication of apparent anomalies that exist in developed stock markets to emerging stock markets. This study is the first to examine the MAX effect in Pakistan, therefore, for brevity we mainly focused on the MAX effect, leaving few questions open for future research. As an additional extension we would like to conduct a comprehensive analysis that examines the idiosyncratic volatility and idiosyncratic skewness effects, while controlling for MAX and MIN effects. More specifically, a robust analysis that examines whether MAX or MIN (minimum daily return in the previous month) drives the IV and ISKEW effects and vice-versa in the Pakistani stock market.

Reference

Aboulamer, A., and L. Kryzanowski. 2016. Are idiosyncratic volatility and MAX priced in the Canadian market? *Journal of Empirical Finance* 37:20-36.

Ali, F., R. He, and Y. Jiang. 2018. Size, Value and Business Cycle Variables. The Three-Factor Model and Future Economic Growth: Evidence from an Emerging Market. *Economies* 6 (1):14. doi: https://doi.org/10.3390/economies6010014.

Ali, F., M. Khurram, and Y. Jiang. Forthcoming. The Five-Factor Asset Pricing Model Tests and Profitability and Investment Premiums: Evidence from Pakistan. *Emerging Markets Finance and Trade*. (In press). doi: 10.1080/1540496X.2019.1650738.

Ali, S. R. M., S. Ahmed, M. N. Hasan, and R. Östermark. 2019. Predictability of Extreme Returns in the Turkish Stock Market. *Emerging Markets Finance and Trade*(In press).

Andrew Karolyi, G. 2016. Home bias, an academic puzzle. *Review of Finance* 20 (6):2049-2078.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. The Cross-Section of Volatility and Expected Returns. *The Journal of Finance* 61 (1):259-299. doi: 10.1111/j.1540-6261.2006.00836.x.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics* 91 (1):1-23. doi: https://doi.org/10.1016/j.jfineco.2007.12.005.

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

Baker, M., and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance* 61 (4):1645-1680. doi: 10.1111/j.1540-6261.2006.00885.x.

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

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

Bekaert, G., C. R. Harvey, and C. Lundblad. 2007. Liquidity and expected returns: Lessons from emerging markets. *The Review of Financial Studies* 20 (6):1783-1831.

Berggrun, L., E. Cardona, and E. Lizarzaburu. 2019. Extreme daily returns and the cross-section of expected returns: Evidence from Brazil. *Journal of Business Research* 102:201-211. doi: https://doi.org/10.1016/j.jbusres.2017.07.005.

Boyer, B., T. Mitton, and K. Vorkink. 2007. Idiosyncratic volatility and skewness: Time-series relations and thr cross-section of expected returns. Working Paper, Brigham Young University.

Brunnermeier, M. K., C. Gollier, and J. A. Parker. 2007. Optimal Beliefs, Asset Prices, and the Preference for Skewed Returns. *American Economic Review* 97 (2):159-165. doi: 10.1257/aer.97.2.159.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52 (1):57-82. doi: 10.1111/j.1540-6261.1997.tb03808.x.

Carpenter, J. N., F. Lu, and R. F. Whitelaw. 2015. The real value of China's stock market. National Bureau of Economic Research.

Chee, W. Y. 2012. "An empirical analysis of idiosyncratic volatility and extreme returns in the Japanese stock market." Lincoln University.

Cheon, Y.-H., and K.-H. Lee. 2018. Time variation of MAX-premium with market volatility: Evidence from Korean stock market. *Pacific-Basin Finance Journal* 51:32-46.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1):3-56. doi: http://dx.doi.org/10.1016/0304-405X(93)90023-5.

Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116 (1):1-22. doi: http://dx.doi.org/10.1016/j.jfineco.2014.10.010.

Fama, E. F., and K. R. French. 2018. Choosing factors. *Journal of Financial Economics* 128 (2):234-252. doi: https://doi.org/10.1016/j.jfineco.2018.02.012.

Fama, E. F., and J. D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81 (3):607-636. doi: http://doi.org/10.2307/1913811.

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

Harvey, C. R., and A. Siddique. 2000. Conditional Skewness in Asset Pricing Tests. *The Journal of Finance* 55 (3):1263-1295. doi: 10.1111/0022-1082.00247.

Jegadeesh, N. 1990. Evidence of Predictable Behavior of Security Returns. *The Journal of Finance* 45 (3):881-898. doi: 10.1111/j.1540-6261.1990.tb05110.x.

Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance* 48 (1):65-91. doi: http://dx.doi.org/10.1111/j.1540-6261.1993.tb04702.x.

Kumar, A. 2009. Who Gambles in the Stock Market? *The Journal of Finance* 64 (4):1889-1933. doi: 10.1111/j.1540-6261.2009.01483.x.

Khwaja, A. I., and A. Mian. 2005. Unchecked intermediaries: Price manipulation in an emerging stock market. *Journal of Financial Economics* 78 (1):203-241. doi: http://dx.doi.org/10.1016/j.jfineco.2004.06.014

Mitton, T., and K. Vorkink. 2007. Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies* 20 (4):1255-1288.

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

Nartea, G. V., J. Wu, and H. T. Liu. 2014. Extreme returns in emerging stock markets: evidence of a MAX effect in South Korea. *Applied financial economics* 24 (6):425-435.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55: 703–708.

Odean, T. 1999. Do Investors Trade Too Much? *American Economic Review* 89 (5):1279-1298. doi: 10.1257/aer.89.5.1279.

Palfrey, T. R., and S. W. Wang. 2012. Speculative Overpricing in Asset Markets With Information Flows. *Econometrica* 80 (5):1937-1976. doi: 10.3982/ecta8781.

Tversky, A., and D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5 (4):297-323. doi: 10.1007/bf00122574.

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

Wan, X. 2018. Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market. *International Review of Economics & Finance* 53:1-15.

Table 1. Summary statistics.

	Mean	SD	Median	Min	Max	SE
Return	0.914	17.239	0.035	-199.958	295.624	0.0894
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
ISKEW	-0.226	1.568	-0.304	-4.252	4.260	0.010
SSKEW	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
Size (PKR, mln)	9526.103	42612.54	500.004	0.296	1188604.573	0.014
CP (PKR)	92.721	332.645	26.250	5.000	12480.000	1.743
Firms	385	34.205	397	325	421	9.142

Note: This table reports summary statistics of the variables utilized in this study. *Return* is the average daily return of the stocks used in the sample. *SD* stands for standard deviation. *MAX* is the maximum daily return within a month while idiosyncratic volatility (*IV*) is the product of the standard deviation of the daily residuals of Fama and French (1993) model and the square root of the number of trading days in a month. The idiosyncratic skewness (*ISKEW*) of stock i in month t is defined as the skewness of daily residuals $\varepsilon_{i,t}$ in month t. The co-skewness or systematic skewness (*SSKEW*) of stock i in month t is the estimated slope coefficient $\hat{\gamma}_i$ (Harvey and Siddique 2000). Momentum (*MOM*) is calculated as the cumulative return over the previous 11 months (i.e., from $t-2$ to $t-12$) skipping one month (Jegadeesh and Titman 1997) while the short-term reversal variable (*STR*) is the daily average return of stock i in the month $t-1$ (Jegadeesh 1990; Lehmann 1990). *Beta* is the market beta computed following Carpenter, Lu, and Whitelaw (2015) and is obtained from regressing daily stock return on daily current, lead, and lagged market returns over the previous month and summing the three coefficients. *B/M* denotes book-to-market value of equity. Illiquidity, following Bekaert, Harvey, and Lundblad (2007), is equal to the ratio of the daily zero return over the non-zero daily returns (*ILLIQ*). We average the daily ratios in the month to get a monthly illiquidity estimate. *Size* is the market capitalization in Pakistani rupees (PKR, million) that is the product of the number of outstanding shares and share price as of the end of the month. *CP* refers to closing (monthly) share price (in PKR). *Firms* represent the total number of firms in the sample.

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

Quintile	***EW portfolios***		***VW portfolios***	
	Raw return	**FF3 alpha**	**Raw 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)

Table 2 (continued)

High-Low	-0.0003	-0.0174*		-0.00004	-0.0124**
	(-0.547)	(-2.934)		(-0.002)	(-2.092)

Note: At the beginning of every month we sort stocks into quintiles according their maximum daily return (MAX) in the past calendar month from January 2003 to December 2016. The table estimates each portfolio's equally-weighted (Panel A) and value-weighted (Panel B) raw returns and risk-adjusted returns (alphas) for the current month. FF3 alpha is each portfolio's alpha estimated from the Fama and French (1993) three-factor model for equally- and value-weighted returns of each of the MAX portfolio. High-Low shows the difference in monthly returns and differences in alpha between the highest and the lowest MAX portfolios. Newey–West *t*-statistics are in parenthesis. *, **, and *** denote significance at 1%, 5%, and 10% levels.

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)

Note: At the beginning of every month we sort stocks into quintiles according to their maximum daily return in the past calendar month. The 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, High-MAX (portfolio 5) includes stocks with the most extreme positive daily returns, and High-Low is the difference between high- and low-MAX portfolios. For each portfolio, we report the monthly averages of several characteristics of the MAX-sorted portfolios over the period from January 2003 to December 2016. *Size*, *B/M*, *STR*, *MOM*, *ILLIQ*, *Beta*, *CP*, *SSKEW*, *ISKEW*, and *IV* are defined in Table 1. *t*-statistics are reported in parenthesis in the last column of the table (High-Low), where * denotes the significance at 1% level.

Table 4. Alpha 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

Note: 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*). The alpha of each portfolio, presented with Newey–West *t*-statistics (*t*-stats.), refers to the Fama-French three-factor model alpha using the full sample of monthly returns for each portfolio, 2003-2016 period. 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 values of the factor being controlled. *Size*, *B/M*, *STR*, *MOM*, *ILLIQ*, *Beta*, *CP*, *SSKEW*, *ISKEW*, and *IV* are defined in Table 1. High−Low refers to the difference between High MAX and low MAX portfolios. Panel A reports the results of equally-weighted portfolios while Panel B reports the results of value-weighted portfolios.

Table 5. Univariate Fama-MacBeth regressions.

MAX	Size	B/M	STR	MOM	CP	ILLIQ	Beta	SSKEW	ISKEW	IV
-0.058	-0.002**	0.001	-0.009	-0.024	0.000**	-0.037**	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)

Note: The 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 for the period from January 2003 to December 2016. We report the time-series averages of the slope coefficients and associated Newey–West t-statistics (in parenthesis). Each variable is independently regressed on stock returns. MAX and other control variables are defined in Table 1. ** and *** denote statistical significance at the 5% and 10% level, respectively.

Table 6. Bivariate and multivariate Fama-MacBeth regressions.

MAX	Size	BM	STR	MOM	CP	ILLIQ	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)	

Table 6 (continued)

-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)

Note: 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 ($t-1$) values of the MAX and other control variables for the period from January 2003 to December 2016. We report the time-series averages of the slope coefficients and the associated Newey–West t-statistics (in parenthesis). MAX and other control variables are defined in Table 1. $*$, $**$, and $***$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

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)
BM	-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)

Note: The table reports the monthly Fama-MacBeth cross-sectional regression slope coefficients and associated Newey-West (1987) adjusted *t*-statistics. In panel A, we sort stocks into three portfolios by Size: small, medium, and big. In panel B, first we divide our testing period into two sub-sample periods, from 2003 to 2009 and from 2010 to 2016. Then, we consider a sub-sample (ex-crises) that excludes crises period (December 2007 to December 2009) from overall sample period (2003-2016). 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 the MAX and other control variables. MAX and the other control variables are defined in Table 1. *, **, and *** denote significance at 1%, 5%, and 10% level, respectively.