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Extreme Daily Returns, Lottery Mindset, Idiosyncratic Volatility and the Cross-Section of Stock Returns in a Comparatively Small Emerging Market

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ABSTRACT
The existing literature on developed and advanced emerging markets documents that the expected stock returns exhibit a positive-, negative-, and no-relationship with both idiosyncratic volatility (IVOL) and extreme daily returns (MAX or MIN). Different from developed and advanced emerging markets, the Pakistani market (PSX) is at its initial development stage with a comparatively little investment knowledge and scarcity of funds that may hinder to achieve a well-diversified portfolio. Such investment conditions may lead investors to suffer from under-diversification and behavioral biases, and therefore, provide an ideal situation to examine the IVOL, MAX and MIN effects and the relationship among these variables in the Pakistani stock market. We find a robust negative MAX effect, which is not subsumed by IVOL, MIN, and other control variables. Whereas, IVOL and MIN effects are weak and unreliable. The negative MAX-return relationship and positive MIN-return relationship indicate both preference for stocks with lottery-type features and risk-seeking behavior among the Pakistani investors. The results are robust to controls for various firm specific characteristics.
Keywords: extreme daily returns; idiosyncratic volatility; MAX and MIN effects; gambling behavior; lottery stocks in emerging markets.

INTRODUCTION

Traditional asset pricing models explain that stock returns should not be associated with idiosyncratic volatility (IVOL), since IVOL can be diversified away. However, it is widely reported that investors' portfolios may not essentially be completely diversified in practice, given that investors may hold under-diversified portfolios due to some exogenous reasons and the relationship between idiosyncratic volatility and stock returns may be positive (Merton, 1987). In such stance, investors would require higher returns on their investments in stocks with higher firm-specific (idiosyncratic) risk. However, existing literature documents mix findings—positive-, negative-, and no-relationship between IVOL and future stock returns. In addition to idiosyncratic volatility puzzle, recent studies have reported several other return anomalies that cannot be explained by traditional single- and multi-factor asset pricing models, such as the underperformance of stocks (in the succeeding month) that have yield extreme positive return in the preceding month (i.e., the MAX effect). Similarly, it is also documented that some investors strongly believe in contrarian investing strategy, which is defined as buying stocks that face significant large price drops in the preceding month. This investing strategy that primarily focuses on extreme negative returns turns the relation between lagged extreme negative return and expected stock returns into negative (i.e., the MIN effect). Some more recent relevant studies explain that investors' sturdy priority for a specific category of stocks—such as the idiosyncratic skewness (Boyer, Mitton, & Vorkink, 2009), the MAX effect and high IVOL (Bali, Cakici, & Whitelaw, 2011), and the MIN effect (Wan, 2018)—is linked with lottery mindset.

In this respect, it is documented that investors show a preference for stocks with lottery-like characteristics (Kumar, 2009), such as stocks with high idiosyncratic volatility and low price. In line with Cumulative Prospect Theory (CPT), Tversky & Kahneman (1992) document that some investors prefer lottery-like assets and tend to falsely believe the chance of success in gambling to be higher than

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it is actually. Similarly, Barberis & Huang (2001) illustrate that high idiosyncratic volatility (IVOL) stocks earn high expected returns. It is further documented that overwhelming errors lead investors to misjudge (i.e., overvalue) stocks with a little chance of generating extreme (positive) return. In a theatrical framework, Brunnermeier, Gollier, & Parker (2007) explain that the lottery-like characteristics have a strong relationship with higher moments of return distribution. Therefore, an asset return skewness is preferred by the investors. Barberis & Huang (2008) further document that investors pay more attention to extreme events that have low probabilities to occur, and this non-normal distribution leads to a negative excess return for skewed securities, which are overpriced.

Ang, Hodrick, Xing, & Zhang (2006) comprehensively examine the IVOL-return relation in the U.S. market and document that on average stocks with high idiosyncratic volatility generate low future returns, the IVOL anomaly. This relation is documented robust after controlling for a number of stock characteristics. There exists various explanations, including the effect of short-sale restrictions on stock prices and the difference of investor opinion (Boehme, Danielsen, Kumar, & Sorescu, 2009), short-term reversal (Huang, Liu, Rhee, & Zhang, 2009), and limits-to-arbitrage (Stambaugh, Yu, & Yuan, 2015). In particular, motivated by the findings of Kumar (2009) who document a propensity for stocks with lottery-like features among investors, Bali, Cakici, & Whitelaw (2011) examine the role of extreme positive returns (MAX) in the U.S. market. They find that high-MAX stocks significantly underperform in comparison to the portfolio of stocks with low MAX: this difference is as much as 1.03% per month, indicating a negative return spread between portfolios with the highest and lowest MAX. This relationship is reported robust even after controlling for various cross-sectional effects including size, book-to-market, illiquidity, short-term reversal, momentum, and skewness. More importantly, they report that the MAX effect reverses the anomalous negative IVOL-return relationship. In other words, they report that the IVOL anomaly is comprehended by the MAX effect, indicating that the (negative) MAX effect is the actual effect. To sum up, their findings suggest that IVOL is the proxy that drives the MAX effect where MAX—a signal of lottery-like features—is the true effect.

Empirical evidence on the relationship between extreme positive (or negative) returns and IVOL in other markets is still very scarce, although Annaert, De Ceuster, & Verstegen (2013) and Walkshäusl (2014) confirm a similar effect—MAX subsumes the IVOL—in the European stock markets. Nevertheless, Nartea, Wu, & Liu (2014) and Nartea, Kong, & Wu (2017) document that the IVOL and MAX effects are independent effects and do not subsume each other or reverse the sign (i.e., from negative to positive) in both South Korean and Chinese stock markets, respectively. On the contrary, Wan (2018) confirms that the IVOL effect is the true effect and it also subsumes the MAX effect in the Chinese stock market. Since the study also confirms a strong MAX effect, it can be taken as the IVOL anomaly in China is further than the effect of distinctive investor behavioral biases. Interestingly, Berggrun, Cardona, & Lizarzaburu (2019) document a contradictory result than other emerging markets (China and South Korea) in the Brazilian stock market—they report evidence of a sign reversal (from negative to positive) of the IVOL anomaly in the presence of MAX (i.e., IVOL discount). Kaniel, Saar, & Titman (2008) document that some specific type of investors has a tendency to employ contrarian investing strategy—taking long position on stocks that face large drops in the prices. This investing behavior could lead to a negative relation between the extreme negative return and future stock returns, referred to as the MIN effect. Wan (2018) documents a similar effect (i.e., MIN) in the Chinese stock market. On the contrary, Bali et al. (2011) report a positive MIN-return relation in the U.S.

These mixed results raise the question whether there are significant IVOL, MAX, and MIN effects in other stock markets, in particular, emerging markets that are at their preliminary development stage. More importantly, we also contribute to the perseverance of a mounting disagreement on the relation between the IVOL and the MAX and MIN effects in both developed (Bali et al., 2011; Walkshäusl, 2014; Fong & Toh, 2014; Egginton & Hur, 2018) and emerging (Nartea, Wu, & Liu, 2014; Nartea, Kong, & Wu, 2017; Alkan & Guner, 2018; Berggrun, Cardona, & Lizarzaburu, 2019; Wu, Chimezie, Nartea, & Zhang, 2019) stock markets.

Different from the developed stock markets (U.S. and Europe), relatively more advanced emerging stock market (South Korea), and the biggest emerging market (China), the Pakistani stock market (PSX) remains at its initial development stage and offers a natural experiment to gain insight into the possible country-specific IVOL, MIN, and MAX effects and the relationship between these variables. In addition, since PSX is at its initial development stage, it is possible that there is a comparatively little investment knowledge and scarcity of funds that hinders to achieve a well-diversified portfolio. This situation may lead investors to suffer from under-diversification and behavioral biases, and therefore, provides an ideal situation to examine the relations between the MAX and MIN effects and IVOL in the PSX.

Moreover, it is also important to study PSX from the perspective of asset-allocation given that the market has shown a marvelous growth in recent decade[1]. The dollar-denominated growth in capitalization (reported by the World Federation of Exchanges) is also higher than most of the emerging stock markets, in specific, if we compare with south-Asian and (OBOR) One Belt One Road countries. Furthermore, the PSX is an institutional investor dominated market and different from other emerging markets that report IVOL and MAX effect. For example, the literature documents that there is a strong tendency of gambling in China, Brazil, and Africa where gambling is considered as an acceptable form of entertainment in the culture (Loo, Raylu, & Oei, 2008; Tavares et al., 2010; Wu, Chimezie, Nartea, & Zhang, 2019; Ye, Li, & Cao, 2020). However, there is no evidence of social or commercial gambling as entertainment in Pakistani society.

As per our knowledge, it is the first study that contributes to the literature by expanding the evidence on the existence and significance of IVOL, MAX and MIN effects, and the relations among these anomalies in the Pakistani stock market.

This study uses both portfolio-level analysis and firm-level cross-sectional regressions, and controls for both rational risk-based and behavioral mispricing-based cross-sectional effects including market capitalization (Size), book-to-market equity (B/M), short-term reversal (STR), illiquidity (ILQ), momentum (MoM), market beta (Beta), closing price (CP), idiosyncratic skewness (ISKEW), and co-skewness (CSKEW) to check robustness.

DATA AND METHODOLOGY

Data and Sources

The daily and monthly stock prices, index closing points, and accounting data of all the listed firms are obtained from the official website of the Pakistan stock exchange (PSX)[2]. We use the PSX-100 index as a market return (R_M). To calculate risk-free rate (R_F), we obtain cut-off yield on the Pakistani Treasury bill from the official website of the State Bank of Pakistan (SBP)[3]. The cut-off yield on the 3-month Treasury bill rate is then converted into monthly values[4]. The sample period consists of 192 months between January 2003 and December 2018. We include all the stocks traded at the PSX. However, following a common practice in the literature, this study also excludes investment trusts, ETF (exchange traded funds), and closed-end funds. In addition, we have ignored both—observations with monthly returns greater than 250% and the return on the first trading day for initial public offering (IPO) firms. We follow the methodologies of Carhart (1997) and Fama & French (1993, 2015) to construct different multifactor models. However, we also adjust for the local characteristics and special features that are important from an asset allocation perspective in the Pakistani stock market (Ali, He, & Jiang, 2018; Ali, Khurram, & Jiang, 2019)[5]. Table 1 provides the summary statistics of the factors used to construct these models.

Construction of IVOL, MAX, MIN and other key variables

We use the daily stock returns, defined as the log difference of daily stock prices, to calculate the key variables at monthly intervals. The variables are defined as follows: 1) Idiosyncratic volatility is calculated relative to Fama & French (1993)'s three-factor model; 2) MIN and MAX are the minimum and maximum daily returns over the previous month, respectively; and 3) MIN-5 and MAX-5 are similarly the average of the five lowest and highest daily returns over the previous month, respectively. The log of the market capitalization of a stock—price of the stock multiply by its total shares outstanding—at the end of previous month is defined as the "*Size*" variable. B/M is the stock's six-month prior book equity to market equity ratio. We calculate the momentum variable (MoM) following the methodology of Jegadeesh & Titman (1993).

[1] Due to this tremendous growth, PSX has begun to attract both the domestic and foreign investors.
[2] The official website of the Pakistan stock exchange is https://www.psx.com.pk/
[3] Available at: www.sbp.org.pk/
[4] Since Pakistani government does not issue one-month Treasury bills (T-bills), we use three-month T-bills rate. This is in line with other asset pricing studies that examine the PSX (e.g., Ali, Khurram, & Jiang, 2019).
[5] Ali, He, & Jiang (2018) comprehensively examine different portfolio formation strategies to construct size (SMB, small-minus-big cap) and value (HML, high-minus-low B/M) factors, and highlight pitfalls that arise in the applicability of asset pricing models to the stocks traded at the PSX. Similarly, Ali, Khurram, & Jiang (2019) further extend the evidence reported by Ali, He, & Jiang (2018) and explain the impact of different sorting procedures (for example, threshold ratios that are used as breakpoints between long and short legs of a factor) on the performance of factor premiums, which further alters the performance of underlying alternative asset pricing models that combine these factors. In addition, they examine different profitability (RMW, robust-minus-weak) and investment (CMA, conservative-minus-aggressive) variables and find that Return-on-Equity and the change in the Total Assets of a firm are the variables that best represents the profitability and investment factors, respectively

Similarly, short-term reversal (STR) is calculated as the lagged one-month return, following Jegadeesh (1990) and Lehmann (1990). The last trading price of a stock at the end of the previous month is considered as the closing price. The proportion of daily zero firm returns averaged over the previous month is considered a measure of illiquidity in this study (Bekaert, Harvey, & Lundblad, 2007). We summarize these variables in Table 2.

Next, we estimate market beta by regressing the daily firm return on daily current, lagged, and lead market returns (in Eqs. 1-2). Following Harvey & Siddique (2000), similarly we decompose total skewness into systematic and idiosyncratic components (in Eq. 3).

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

Thus, the market beta used in this study adds all the three betas (lead, lag, and current), as follows:

$$\widehat{\beta_\iota} = \widehat{\beta_\iota} + \widehat{\gamma_\iota} + \widehat{\sigma_\iota}$$

The co-skewness (also known as systematic skewness) is defined as the slope coefficient, $\hat{\gamma}_i$. Similarly, the idiosyncratic skewness is defined as the daily residuals, $\varepsilon_{i,d}$, in month t.

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

Following Bali et al. (2011), we control for a number of variables including Size, B/M, STR, MoM, Beta, ILQ, ISKEW, CSKEW, and CP. Panel A of Table 3 presents descriptive statistics of the key variables used in this article. The monthly average of IVOL, MIN and MAX is 0.011, 0.070 and 0.071, respectively. The mean value of ISKEW and CSKEW is −0.182 and 0.656, respectively. The mean STR is 0.005, MoM is 0.009, Beta is 0.812, and ILQ is 0.871. The average size of our sample is approximately 8.28 billion Pakistani rupees (PKR), B/M ratio is 1.072, and the average CP is 133.88 PKR. The number of firms in our final sample, after meeting the selection criteria, ranges between 324 and 422. The average monthly cross-sectional correlation matrix is presented in Panel B of Table 3. The correlation between IVOL and MAX (MIN) in this study is 0.64 (0.68), which is lower than that in Bali et al. (2011) 0.7533 (0.7554), but higher than that in Wan (2018) 0.45(0.27).

RESULTS AND DISCUSSION

The idiosyncratic volatility

A number of studies document that the cross-sectional variations in stock returns are positively related to IVOL (e.g., Liu, Kong, Gu, & Guo, 2019, among others). In contrast, several of the other studies report a negative relationship between lagged IVOL and future returns (e.g., Wu, Chimezie, Nartea, & Zhang, 2019, among others), and hence, it is labeled as "*idiosyncratic volatility puzzle*". This section primarily investigates whether there exists a significant IVOL anomaly in Pakistan.

To do so, we categorize stocks into quintile portfolios based on the idiosyncratic volatility. The portfolios are rebalanced on monthly basis (t−1) and held for one month (t). Table 4 reports both the average monthly raw returns and alphas (abnormal returns) for both equally- and value-weighted quintile portfolios. The risk-adjusted returns are calculated using the three-, four- and five-factor models developed by Fama & French (1993), Carhart (1997) and Fama & French (2015), respectively. Q5 (Q1) is the portfolio of stocks with the highest (lowest) idiosyncratic volatility. Our results show that the equal-weighted average raw return difference between the highest and lowest quintile is 0.976% per month with a t-statistic of 1.72. Similarly, the difference in FF3, CH4 and FF5 alphas between high and low IVOL portfolios is 0.060% (t=0.12), 0.242% (t=0.47) and 0.235% (t=0.44) per month respectively. All the differences are positive, but economically and statistically insignificant. The average raw returns generally increase, as we move from low IVOL portfolio to high IVOL portfolio. The alphas of our five equally-weighted portfolios do not monotonically increase or decrease, as we move from low IVOL portfolios to high IVOL portfolios, however, the alphas of high-IVOL quintile portfolio are higher than the alphas of low-quintile portfolio. This finding suggests a positive IVOL effect on succeeding performance.

For the value-weighted portfolios, our results are largely similar to what reported in the equal-weighted portfolio. The average raw-return difference between high- and low-IVOL portfolios is 0.995% per month with a t-statistic of 1.79. The difference in FF3, CH4, and FF5 alphas between the highest and lowest quintiles are 0.190%, 0.367%, and 0.354% per month with t-statistics of 0.37, 0.73, and 0.67 respectively. In sum, the results show a positive relation between lagged IVOL and future stock returns (raw), however, this relationship is statistically insignificant for the abnormal returns (alphas). Since there is no study that examine the idiosyncratic volatility anomaly in the PSX, we compare our findings with the evidence reported in other stock markets and find that the results reported in our study are somewhat in line with the evidence reported by Fink, Fink, & He (2012) and Fu (2009).

Next, we apply the following firm-level Fama & MacBeth (1973) regression and its subsets to control for multiple effects simultaneously:

$$R_{i,t} = \alpha_{i-1} + \gamma_{1,t-1}IVOL_{i,t-1} + \gamma_{2,t-1}Size_{i,t-1} + \gamma_{3,t-1}B/M_{i,t-1} + \gamma_{4,t-1}ILQ_{i,t-1} + \gamma_{5,t-1}MoM_{i,t-1} + \gamma_{6,t-1}STR_{i,t-1} + \gamma_{7,t-1}Beta_{i,t-1} + \gamma_{8,t-1}ISKEW_{i,t-1} + \gamma_{9,t-1}CSKEW_{i,t-1} + \gamma_{10,t-1}CP_{i,t-1} + \varepsilon_{i,t-1}$$

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

Table 5 provides the time-series averages of the slopes, *t*-statistics, and adjusted R^2 values. In the univariate regression, the average slope of IVOL is 0.191 and Newey & West (1987) adjusted *t*-statistic is 0.92 (statistically insignificant). Our results in the bivariate regressions are broadly similar—the average slope of IVOL is positive but statistically insignificant. Given that the positive IVOL-return relationship is weak in the univariate regression, insignificant IVOL in the bivariate regressions does not mean that the control variables can explain the IVOL anomaly. Interestingly, when we control for all the outlined variables in multivariate regression simultaneously, the average slope of IVOL turns to negative but statistically insignificant, indicating that the predictive ability of stock returns by IVOL is not reliable. Interpreting together, the firm-level analysis suggests that there is a statistically and economically weak and unreliable relation between IVOL and future stock returns in the Pakistani stock market, contrary to the findings reported in the U.S. (Bali at el, 2011), Korea (Nartea et al., 2014) and China (Nartea at el., 2017).

The MAX and MIN effects

Bali et al. (2011) comprehensively examine the relation between extreme (daily) positive returns over the preceding month (MAX) and expected stock returns in the U.S. market. Their findings report a negative MAX effect, an indication of investor behavioral bias and plausibly a proxy for lottery-type payoffs. On the contrary, Aboulamer & Kryzanowski (2016) report a positive relation between extreme daily (positive) returns over the preceding month and future stock returns in the Canadian market. More interestingly, Chee (2012) finds that the MAX effect does not exist in the Japanese market, except when controlling for firm characteristics in bivariate sorts. In addition, Kaniel et al. (2008) report that few investors be likely to buy stocks with significant drops in prices, where Wan (2018) further confirms a similar (extreme negative return) MIN effect in the Chinese stock market. However, Bali et al. (2011) and Aziz & Ansari (2018) find a positive MIN-return relation in the U.S and Indian stock markets respectively. Motivated by the above literature that raises the question about the applicability of the MAX and MIN effects, we examine the existence of both the MAX and MIN effects in the Pakistani stock market.

We follow the portfolio sorting procedure of Bali et al. (2011). In Panel A of Table 6, portfolio 1 (low-MAX) signifies the stocks in the lower most portfolio of maximum daily returns over the preceding month, whereas portfolio 5 (high-MAX) contains stocks belonging to the highest portfolio of maximum daily returns over the preceding month.The difference in average monthly raw-return between equal-weighted (EW) high and low MAX quintiles is −0.22% per month, but statistically insignificant.

However, the abnormal returns estimated using FF3, CH4 and FF5 models for a high-minus-low MAX (High−Low) equal-weighted portfolio are all negative and statistically significant at 5% level or better, suggesting a robust negative MAX effect. The average return on High-minus-Low MAX value-weighted portfolio is negative (−0.02%) and statistically insignificant (t=−0.10), while abnormal returns between value-weighted high and low MAX quintiles are negative and statistically significant. Similar to other studies that report the MAX effect (for example, Nartea at el., 2017; Berggrun et al., 2019), our results for the value-weighted portfolios are relatively weaker than the equally-weighted portfolios, yet economically and statistically significant[6]

In Panel B of Table 6, Portfolio 1 (Low MIN) comprises stocks with the lowest MIN over the preceding month, whereas Portfolio 5 (High MIN) covers stocks with the highest MIN over the preceding month. The equally-weighted and value-weighted differences in average monthly raw-return between high and low MIN (High−Low MIN) portfolios are −0.58% per month (t=−1.04) and −0.73% per month (t=−1.37), respectively. The corresponding equally-weighted differences in abnormal returns between high and low MIN

[6] *Kumar (2009) and Bali et al, (2011) pinpoint that the high-MAX stocks belong to small size groups; therefore, MAX is stronger in equally-weighted portfolios. In other words, value-weighted portfolio construction methodology puts more weight on the market capitalization (i.e., size), and therefore the MAX effect is weaker in value-weighted portfolios.*

portfolios are 0.74% (t=1.66), 0.62% (t=1.40) and 0.56% (t=1.27) for FF3, CH4 and FF5 models, respectively. Similarly, the differences in average monthly FF3, CH4 and FF5 alphas between value-weighted high and low MIN quintiles are 0.46% (t=1.03), 0.34% (t=0.76) and 0.28% (t=0.63), respectively. Panel B of Table 6 presents the univariate portfolio-level analysis, where results show that the relation between MIN and future stock returns is economically and statistically not reliable. Since Pakistani stock market is dominated by institutional investors, contrarian investing strategy which is more popular among individual investors (such as, a strong MIN effect is evident in China) is found absent in the Pakistani stock market.

Next, we extend our analysis and examine the relation between maximum or minimum daily return in the preceding month and future stock turns, while controlling the impact of other relevant firm level characteristics. To do so, we employ the following Fama and MacBeth (1973) regressions and its different univariate and bivariate subsets:

$$R_{i,t} = \alpha_{i-1} + \gamma_{1,t-1}MIN_{i,t-1} + \gamma_{2,t-1}Size_{i,t-1} + \gamma_{3,t-1}B/M_{i,t-1} + \gamma_{4,t-1}ILQ_{i,t-1} + \gamma_{5,t-1}MoM_{i,t-1} + \gamma_{6,t-1}STR_{i,t-1} + \gamma_{7,t-1}Beta_{i,t-1} + \gamma_{8,t-1}ISKEW_{i,t-1} + \gamma_{9,t-1}CSKEW_{i,t-1} + \gamma_{10,t-1}CP_{i,t-1} + \varepsilon_{i,t-1}$$

The average slope of MAX in the univariate regression, presented in Table 7, is −0.096 with a t-statistic of −2.17. Interestingly, controlling for other variables in specification (2) increases both the average slope of MAX (−0.22% per month) and its statistical significance (t=−5.66). Our findings indicate a strong MAX effect which is not subsumed by the MIN effect in Pakistan.

Table 7 further reports that the average coefficient of one-month ahead stock returns on MIN in the univariate regression is negative, however, statistically insignificant. Different from MAX, controlling for other variables reverses the negative MIN-return relationship in the multivariate regression, i.e. turns to positive, but statistically insignificant. This finding suggests that stocks with extreme low returns have higher (lower) future returns in the succeeding month when we (do not) control for other variables, as reported in Table 6. The opposite effects of MIN and MAX in multivariate regressions that control for all the other selected variables (shown in specifications 2 and 4) are consistent with CPT and skewness preference documented by Barberis & Huang (2008). However, these results are in contrast with the premise that extreme (positive or negative) returns are proxying for IVOL.

The positive coefficient of MIN in our analysis shows that a deteriorating value of stocks leads to a higher future return. This finding is different from Wan (2018) who finds that stocks with extreme negative returns in the Chinese stock market have lower future returns in the succeeding month. However, our results are somewhat consistent with the findings of Bali et al. (2011) who document that stocks with extreme negative returns in preceding moth generate higher future returns in the following month in the U.S. Interestingly, in the bivariate and multivariate regressions that include both MAX and MIN, the MIN-return relation turns to negative and significant at 10% level. Our results further indicate that negative MIN-return relation only exists if MAX is included in the (bivariate or multivariate) regression.

ADDITIONAL TESTS AND ROBUSTNESS CHECKS

In this section, we investigate several portfolio-level and firm-level analysis to understand the relations between IVOL and MAX and MIN effects more closely.

Do MAX, MIN and IVOL subsume each other?

Bali et al. (2011) document that when MAX, a proxy for lottery-like payoff, is controlled, the negative relation between IVOL and future stock returns turns to positive. On the contrary, evidence from a relatively advanced emerging market of South Korea confirm that the MAX and IVOL effects are not dependent on each other (Nartea et al., 2014), rather, they exist independently. More interestingly, Wan (2018) examines the relation between MAX and IVOL in the Chinese stock market and finds that both IVOL and MAX effects exist simultaneously; however, IVOL is the true effect and it subsumes the MAX effect. These mixed findings make this relationship more interesting to study further.

In previous sections of this article, our findings illustrate that there is no significant IVOL anomaly, unreliable MIN effect, and a robust (negative) MAX effect in the PSX. It is also reported that extreme positive returns have higher idiosyncratic volatility. Given that the PSX is at its initial development stage, it is possible that there is a comparatively little investment knowledge and scarcity of funds that hinders to achieve a well-diversified portfolio. This situation may lead investors to suffer from under-diversification and behavioral biases, and therefore, provides an ideal situation to examine the relations between the MAX or MIN effect and IVOL. For this reason, we construct bivariate sorts to carefully examine the relations between these effects. First, we sort stocks into tertiles by control variable (for example, IVOL), then within each tertile, we again sort stocks into quintiles based on the variable of interest (for example, MAX).

Panel A (Panel B) of Table 8 documents the average returns across the five EW and VW IVOL quintile portfolios, after controlling for MAX (MIN). The results are the risk-adjusted returns (alphas) using FF3, CH4 and FF5 models. In both (EW and VW) portfolios, results are largely similar to what reported in Table 4—the difference between high and low IVOL quintiles are economically and statistically insignificant, when we control for MAX or MIN. This finding is not surprising, since the relation between IVOL and stock returns is documented unreliable in earlier sections, therefore, controlling for MAX or MIN do not alter this weak relation either. Next, we sort the variables in opposite manners—controlling for IVOL to examine the explanatory power of MAX and MIN— and present the results in Panels C and D. The results show that once we control for IVOL, the MAX and MIN effects become more significant in terms of both the magnitude and *t*-statistics. However, the relation between MIN and future risk-adjusted stock returns remains insignificant in the VW High-Low MIN portfolio.

We further perform a firm-level analysis using the methodology of Fama & MacBeth (1973), to observe the relations between IVOL and MIN/ MAX.

$$\begin{aligned}R_{i,t} = \alpha_{i-1} &+ \gamma_{1,t-1}MAX_{i,t-1} + \gamma_{2,t-1}MIN_{i,t-1}\\ &+ \gamma_{3,t-1}IVOL_{i,t-1}\\ &+ \gamma_{4,t-1}Size_{i,t-1}\\ &+ \gamma_{5,t-1}B/M_{i,t-1}\\ &+ \gamma_{6,t-1}ILQ_{i,t-1}\\ &+ \gamma_{7,t-1}MoM_{i,t-1}\\ &+ \gamma_{8,t-1}STR_{i,t-1}\\ &+ \gamma_{9,t-1}Beta_{i,t-1}\\ &+ \gamma_{10,t-1}ISKEW_{i,t-1}\\ &+ \gamma_{11,t-1}CSKEW_{i,t-1}\\ &+ \gamma_{12,t-1}CP_{i,t-1} + \varepsilon_{i,t-1}\end{aligned}$$

The results documented in Table 9 show that once we add MAX to the regression, the average slope of IVOL remains positive and insignificant. Specification (2) of the Table 9 further confirms that adding other variables along with MAX in the regression do not change the significance or reverse the positive IVOL-return relation. Conversely, the positive IVOL-return relation is reversed (but insignificant) when MIN is added to the regressions, e.g., specifications (3) and (5). Interestingly, the positive IVOL-return relation in specification (4) also represents a change in sign of the IVOL-return relation due to MIN—since specification (11) of Table 5 reports a negative IVOL-return relationship in multivariate regression (without MIN), which is reversed after MIN is added to the regression (0.28 with a *t*-statistic of 0.33). Thus, it is noticeable that adding MIN to the regressions reverses the IVOL-return relation in both (bivariate and multivariate) regressions. More interestingly, if we compare the results between specifications (4) and (6) of Table 9, the average positive slope on IVOL and MIN is reversed (turned to negative) when MAX is included in the multivariate regression.

In summary, contrary to the findings of Wan (2018) in the Chinese stock market, we find that all three effects, i.e., IVOL, MAX and MIN, are independent and do not subsume each other in the double-sorted portfolio-level analysis. However, firm-level cross-sectional regressions reveal that the IVOL effect is reversed after we include MIN to the regressions, whereas MIN and MAX effects are not subsumed (or reversed) by adding IVOL to the regressions. Moreover, in the multivariate regression that includes all the control variables, adding MAX reverses the positive relation between MIN/IVOL and future returns.

Alternative measures of MAX and MIN

Finally, we perform robustness checks of our results using alternative measures to calculate MIN and MAX effects in the Pakistani stock market. Following recent literature, we take average of the 5 highest daily returns over the preceding month and consider it as an alternative measure of extreme positive return (MAX-5). Similarly, we calculate MIN-5 as an alternative measure of extreme negative return by averaging the 5 lowest daily returns over the preceding month. The results shown in specifications (1)–(8) of Table 10 are largely similar to the results presented in Table 9. That is, there is a strong negative MAX-5 effect, but unreliable IVOL and MIN effects, where the negative MIN-5-return relation is significant only when we add MAX-5 to the regression (specifications (5) and (8) of Table 10). More importantly, the relation between MAX-5 and future stock returns is strong and it reverses the positive MIN-5-return relation (specification (7)) to a negative significant MIN-5-return relation (specification (8)). Different from MIN which reversed the IVOL effect in Table 9 (specification (4)), the IVOL effect is not subsumed by MIN-5 (specification (7) of Table 10). Since IVOL has a weak relation with future stock returns, it remains unable to subsume the predictive power of MAX-5 or MIN-5 for stock returns.

To sum up, our results grounded on alternative measures of the maximum (minimum) daily return corroborates with our main findings on the MAX and MIN effects in Pakistan. It is noticeable that the MAX, which represents lottery-like characteristics, is the true effect and it is not subsumed by the IVOL or MIN effects. Instead, the IVOL (MIN) effect is rather subsumed (reversed) by the MIN (MAX) effect in multivariate regressions when all the outlined variables ae controlled for.

CONCLUSIONS AND IMPLICATIONS

In this paper, we argue that the Pakistani stock market remains at its pilot development stage and is different than the developed and advanced emerging markets including a lack of evidence on the existence of behavioral mispricing-based trading strategies (momentum and reversal anomalies), a comparatively inexperienced investors that may face limits-to-arbitrage and under-diversification, and a low recognition of social gambling (lottery mindset) as entertainment in the society. Given that the extent literature links the maximum daily return (MAX), the minimum daily return (MIN), and idiosyncratic volatility (IVOL) with preferences for lottery-like stocks and under-diversification among investors, the Pakistani stock market (PSX) provides a natural experiment to understand these effects and the relationship among these variables due to its unique characteristics. Thus, this study is the first to empirically examine the IVOL, MIN and MAX effects in the PSX. To do so, we employ daily and monthly stock returns between January 2003 and December 2018. In addition, this study also investigates the relationship among these variables; that is, whether IVOL, MAX and MIN coexist independently or subsume each other? The main findings are as follows.

First, we find that IVOL is positively related to future returns, but this relation becomes insignificant in risk-adjusted returns (alphas), contrary to the anomalous findings of Ang, Hodrick, Xing, & Zhang (2006, 2009). This statistically insignificant positive IVOL-return relation is persistent across different portfolio-level analysis and firm-level cross-sectional regressions, except for multivariate Fama-MacBeth regression where this relation turned to negative, but statistically insignificant. Second, we find that there is a negative and statistically significant MAX effect that is stronger when we use equal-weighted portfolios and risk-adjusted returns, similar to the findings reported by Berggrun et al. (2019) for the Brazilian stock market. The negative MAX effect is robust across portfolio-level and firm-level analyses. Third, we find statistically insignificant negative (positive) MIN effect in the average raw (risk-adjusted) returns, contrary to findings of Wan (2018) for the Chinese stock market.

Bali et al. (2011) document a significant and robust MAX effect that reverses the idiosyncratic volatility effect in the U.S. market, whereas Wan (2018) document that the IVOL effect is the true effect, which essentially subsumes MAX effect in the Chinese market. First, we conduct bivariate sorts (double sorted portfolio-level analysis) to inspect the relation between IVOL and MAX or MIN more carefully, but results are inconclusive. Then, we perform firm-level Fama-Macbeth cross-sectional regressions and find that: 1) the only significant effect is MAX, which is not subsumed by MIN or IVOL; 2) the MIN effect reverses the IVOL-return relation in all cross-sectional regression specifications, but statistically not reliable; 3) the MIN effect does not exist independently—it only exists when MAX is added to the regression; and 4) adding MAX to the multivariate regression that includes MIN and IVOL and also controls for Size, B/M, Beta, MoM, STR, ILQ, ISKEW, CSKEW, and CP effects simultaneously, reverses both the IVOL- and MIN-return relation in the Pakistani stock market.

These evidence partially corroborate the argument of Bali et al. (2011), and thus, we conclude our findings in the framework of a market with poorly diversified (or under- diversified) investors who have an inclination for lottery-type stocks (i.e., lottery mindset). Therefore, the stocks with extreme negative returns offer positive and unreliable (abnormal) future returns, because investors do not consider such stocks attractive, rather, they put more weights on high-MAX stocks with a (false) belief of generating higher returns by investing less amount.

Limitations and future agenda

Since this study is the first to examine the MAX, MIN and IVOL effects, and the relationship among these effects in Pakistan, we primarily focus on these variables (for brevity) and leave few questions for future research.

As an additional extension we would like to conduct a comprehensive portfolio-level double sorted analysis that jointly examines the idiosyncratic volatility, average skewness (recently proposed by Jondeau, Zhang, & Zhu, 2019), and MAX effect. In addition, examining the robustness of these effects which partially exhibit gambling characteristics across different economic conditions (i.e., expansion or recession states), across different size groups and other anomalies, and across different investors types (e.g., individuals, institutional investors, and Shari'ah complaint Islamic investors in Pakistan) would benefit more to both researchers and practitioners. In specific, those having research or investing interests toward small emerging economies, Islamic or Shari'ah-compliant funds, and investor-induced effects that can be neutralized by investing in an alternative intuitional framework (e.g., Ali & Ülkü, 2020).

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Tables

Table 1. **Summary statistics.**

	$R_M–R_F$	SMB	HML	UMD	RMW	CMA
Panel A. Descriptive statistics						
Mean (%)	0.703	1.142	1.011	0.138	0.496	0.487
Std. Dev. (%)	7.135	5.891	5.276	4.807	3.637	3.699
Sharpe ratio	0.099	0.194	0.192	0.029	0.136	0.132
t-statistics	1.36	2.68	2.65	0.40	1.89	1.82
Panel B. Correlation coefficients						
$R_M–R_F$	1	-0.208	0.384	-0.143	-0.176	0.145
SMB	-0.208	1	0.121	-0.088	-0.010	0.141
HML	0.384	0.121	1	-0.332	-0.217	0.125
UMD	-0.143	-0.088	-0.332	1	0.060	0.029
RMW	-0.176	-0.010	-0.217	0.060	1	-0.335
CMA	0.145	0.141	0.125	0.029	-0.335	1

Notes: Authors calculation. $R_M–R_F$, SMB, HML, UMD, RMW, and CMA are the market risk premium, size factor, value factor, momentum (up-minus-down) factor, profitability factor, and investment factor respectively.

Table 2. **Descriptions of the key variables.**

Variable	Definition/ Description
IVOL	Idiosyncratic volatility is the standard deviation (Std. Dev.) of the residuals ($\varepsilon_{i,d}$), which are obtained using the following equation: $R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + smb_i(SMB_d) + hml_i(HML_d) + \varepsilon_{i,d}$
MIN	Minimum daily return over the preceding month
MAX	Maximum daily return over the preceding s month
MIN-5	An alternative measure to examine MIN. That is, the average of the five lowest daily returns over the previous month
MAX-5	An alternative measure to examine MAX. That is, the average of the five highest daily returns over the previous month
Size	Log of the market capitalization at the end of previous month ($Price\ of\ stock\ i \times tota\ shares\ outstanding\ of\ stock\ i$)
B/M	Stock's six-month prior book equity to market equity ratio
STR	The lagged one-month return
MoM	The cumulative prior return of stock *i* from t−2 to t−12, skipping the most recent month.
CP	Closing price at the end of previous month
ILQ	The ratio of daily zero firm returns(averaged) over the previous month

Table 3. **Summary statistics and correlation matrix of IVOL, MAX, MIN, and other control variables.**

Panel A. Summary statistics

	Mean	Median	5th percentile	95th percentile	Std. Dev.
IVOL	0.0107	0.0081	0.0007	0.0274	0.0123
MIN	0.0695	0.0491	0.1408	0.0171	0.1943
MAX	0.0705	0.0487	0.0186	0.1428	0.1920
Size	8.2798	8.1444	4.5270	12.6261	2.4241
Beta	0.8117	0.8082	-1.6539	3.3954	7.6610
B/M	1.0723	0.7256	0.1042	3.4252	1.8291
STR	0.0054	0.0000	-0.2202	0.2549	0.1575
MoM	0.0088	0.0073	-0.0696	0.0899	0.0514
ILQ	0.8712	0.9500	0.4762	1.0000	0.1774
ISKEW	-0.1816	-0.2538	-2.5919	2.2821	1.5343
CSKEW	0.6560	0.7975	-0.9456	2.8005	19.4628
CP	133.8782	40.4700	6.1300	516.5700	408.3125

Panel B. Correlation matrix

	MIN	MAX	Size	Beta	B/M	STR	MOM	ILQ	ISKEW	CSKEW	CP
IVOL	0.68	0.64	-0.01	0.05	0.06	-0.06	-0.03	0.13	0.01	-0.05	-0.04
MIN		0.45	0.03	0.01	-0.02	0.05	-0.01	0.02	-0.01	0.04	0.00
MAX			-0.03	-0.04	0.04	-0.06	0.01	0.00	0.02	-0.02	-0.01
Size				0.02	-0.30	0.01	0.07	0.35	0.06	0.01	0.28
Beta					0.00	0.04	0.01	0.03	0.01	0.12	0.00
B/M						0.04	-0.10	-0.08	0.01	0.00	-0.11
STR							0.00	0.09	-0.05	0.01	0.02
MoM								0.04	-0.04	0.01	0.07
ILQ									-0.01	0.04	0.00
ISKEW										0.01	0.02
CSKEW											0.00

Notes: Panel A reports summary statistics while Panel B presents the time-series average of the cross-sectional correlations between variables. All the variables are defined in Table 2 and between Eq. 1 and Eq. 3.

Table 4. **Average raw returns and risk-adjusted returns of portfolios sorted by IVOL.**

Quintile	Panel A: Equally-weighted (EW) portfolios				Panel B: Value-weighted (VW) portfolios			
	Raw return	FF3 alpha	CH4 alpha	FF5 alpha	Raw return	FF3 alpha	CH4 alpha	FF5 alpha
Low IVOL	-0.342	-1.339	-1.455	-1.361	-0.193	-1.099	-1.220	-1.124
	(-0.53)	(-3.02)	(-3.31)	(-3.05)	(-0.31)	(-2.58)	(-2.90)	(-2.61)
2	0.521	-0.588	-0.576	-0.546	0.646	-0.347	-0.334	-0.318
	(0.97)	(-2.06)	(-2.01)	(-1.87)	(1.26)	(-1.33)	(-1.27)	(-1.19)
3	0.586	-0.612	-0.610	-0.536	0.721	-0.363	-0.360	-0.295
	(0.99)	(-2.22)	(-2.19)	(-1.90)	(1.27)	(-1.47)	(-1.44)	(-1.17)
4	0.493	-0.877	-0.822	-0.807	0.623	-0.611	-0.561	-0.530
	(0.76)	(-2.92)	(-2.74)	(-2.65)	(0.97)	(-2.21)	(-2.03)	(-1.89)
High IVOL	0.635	-1.279	-1.213	-1.126	0.802	-0.908	-0.853	-0.770
	(0.83)	(-3.04)	(-2.87)	(-2.68)	(1.09)	(-2.26)	(-2.11)	(-1.91)
High−Low	**0.976**	0.060	0.242	0.235	**0.995**	0.190	0.367	0.354
	(1.72)	(0.12)	(0.47)	(0.44)	(1.79)	(0.37)	(0.73)	(0.67)

Notes: FF3, CH4 and FF5 alphas refer to the intercepts of the regressions using Fama & French's (1993), Carhart's (1997) and Fama & French's (2015) models, respectively. West and Newey (1987) *t*-statistics are presented in parentheses, where values that are significant at the 10% or higher levels in the High−Low (last) row are bolded.

Table 5. **Firm-level cross-sectional return regressions on IVOL.**

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Intercept	0.002	0.016	0.001	-0.002	0.003	-0.001	**0.036**	0.002	0.001	0.003	**0.036**
	(0.32)	(1.20)	(0.11)	(-0.04)	(0.37)	(-0.16)	(2.99)	(0.25)	(0.12)	(0.40)	(3.09)
IVOL	0.191	0.130	0.180	0.390	0.249	0.192	0.221	0.223	0.116	0.208	-0.393
	(0.92)	(0.61)	(0.95)	(1.41)	(1.12)	(0.86)	(1.03)	(1.07)	(0.46)	(1.00)	(-1.48)
Size		**-0.002**									-0.001
		(-1.88)									(-0.97)
Beta			**0.002**								**0.003**
			(1.73)								(1.93)
B/M				-0.001							-0.001
				(-0.54)							(-0.65)
STR					-0.006						-0.005
					(-0.58)						(-0.56)
MOM						0.005					**0.069**
						(0.15)					(2.38)
ILQ							**-0.036**				-0.019
							(-2.77)				(-1.24)
ISKEW								-0.000			0.000
								(-0.09)			(0.03)
CSKEW									0.001		**0.009**
									(0.31)		(2.32)
CP										**-0.000**	-0.000
										(-2.16)	(-1.08)
Avg. R2	2.65 %	6.22 %	3.70 %	5.25 %	3.80 %	3.97 %	4.59 %	3.67 %	3.84 %	4.16 %	17.89 %

Notes: All the selected variables are defined in Table 2 and Eqs. 1-3. West and Newey (1987) *t*-statistics are in parentheses where values that are significant at the 10% or higher levels are bolded.

Table 6. **Average raw returns and risk-adjusted returns of portfolios sorted by MAX or MIN.**

Quintile	Panel A: EW Portfolios				Panel B: VW Portfolios			
	Raw return	FF3 alpha	CH4 alpha	FF5 alpha	Raw return	FF3 alpha	CH4 alpha	FF5 alpha
Panel A. Portfolios sorted by MAX								
(Low MAX)	0.458	-0.246	-0.377	-0.249	0.449	-0.228	-0.343	-0.242
	(0.81)	(-0.67)	(-1.04)	(-0.67)	(0.81)	(-0.67)	(-1.02)	(-0.70)
Q2	0.609	-0.437	-0.430	-0.431	0.719	-0.286	-0.283	-0.266
	(1.01)	(-1.70)	(-1.66)	(-1.63)	(1.21)	(-1.20)	(-1.18)	(-1.09)
Q3	0.235	-0.817	-0.837	-0.740	0.369	-0.655	-0.670	-0.574
	(0.40)	(-2.75)	(-2.80)	(-2.42)	(0.64)	(-2.32)	(-2.36)	(-1.98)
Q4	0.366	-1.127	-1.083	-1.043	0.470	-0.935	-0.891	-0.836
	(0.57)	(-3.18)	(-3.04)	(-2.92)	(0.74)	(-2.70)	(-2.56)	(-2.39)
(High MAX)	0.238	-2.055	-1.935	-1.901	0.427	-1.621	-1.500	-1.460
	(0.28)	(-4.31)	(-4.09)	(-4.05)	(0.68)	(-3.32)	(-3.09)	(-3.04)
High−Low	-0.220	**-1.809**	**-1.558**	**-1.652**	-0.022	**-1.392**	**-1.157**	**-1.218**
	(-0.33)	(-3.39)	(-3.06)	(-3.03)	(-0.10)	(-2.61)	(-2.26)	(-2.24)
Panel B. Portfolios sorted by MIN								
(Low MIN)	0.633	-1.432	-1.354	-1.269	0.874	-1.014	-0.925	-0.851
	(0.81)	(-3.2)	(-3.03)	(-2.91)	(1.16)	(-2.29)	(-2.10)	(-1.95)
Q2	0.407	-1.193	-1.137	-1.119	0.625	-0.896	-0.839	-0.815
	(0.59)	(-3.18)	(-3.02)	(-2.96)	(0.92)	(-2.47)	(-2.31)	(-2.24)
Q3	0.380	-0.742	-0.770	-0.696	0.596	-0.478	-0.498	-0.427
	(0.65)	(-2.53)	(-2.61)	(-2.33)	(1.03)	(-1.71)	(-1.77)	(-1.51)
Q4	0.418	-0.638	-0.686	-0.586	0.513	-0.514	-0.559	-0.461
	(0.72)	(-2.36)	(-2.54)	(-2.12)	(0.90)	(-2.03)	(-2.21)	(-1.78)
(High MIN)	0.052	-0.692	-0.731	-0.707	0.140	-0.557	-0.588	-0.570
	(0.10)	(-2.30)	(-2.41)	(-2.28)	(0.265)	(-1.99)	(-2.09)	(-1.98)
High−Low	-0.581	0.740	0.623	0.562	-0.734	0.458	0.337	0.281
	(-1.04)	(1.65)	(1.40)	(1.27)	(-1.37)	(1.03)	(0.76)	(0.632)

Notes: This table reports the average monthly raw returns and abnormal returns (alphas) on both equally-weighted and value-weighted portfolios. West and Newey (1987) t-statistics are presented in parentheses, where values that are significant at the 10% or higher levels in the High−Low (last) row of each panel are bolded. All the selected variables are defined in Table 2 and Eqs. 1-3.

Table 7. **Firm-level Fama-MacBeth regressions on MAX and MIN.**

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.0117**	**0.0574**	0.0027	**0.0370**	0.0048	**0.0532**
	(2.04)	(5.38)	(0.43)	(3.29)	(0.71)	(4.99)
MAX	**-0.096**	**-0.220**			**-0.179**	**-0.260**
	(-2.17)	(-5.66)			(-4.36)	(-6.10)
MIN			-0.020	0.015	**-0.165**	**-0.093**
			(-0.51)	(0.36)	(-4.19)	(-1.91)
Size		**-0.002**		-0.001		-0.001
		(-1.69)		(-0.90)		(-1.33)
Beta		0.002		0.002		0.001
		(1.38)		(1.60)		(1.28)
B/M		0.001		-0.001		0.001
		(0.35)		(-0.60)		(0.36)
STR		-0.009		-0.008		-0.011
		(-1.02)		(-0.87)		(-1.22)
MoM		**0.055**		**0.077**		**0.063**
		(1.88)		(2.67)		(2.13)
ILQ		**-0.031**		-0.022		**-0.033**
		(-2.89)		(-1.35)		(-3.05)
ISKEW		-0.001		0.001		-0.001
		(-0.86)		(0.51)		(-0.80)
CSKEW		**0.004**		**0.003**		**0.005**
		(2.11)		(1.69)		(2.66)
CP		-0.000		-0.000		-0.000
		(-0.42)		(-1.05)		(-0.43)
Avg. R2	4.16 %	18.33 %	3.27 %	18.15 %	5.58 %	19.52 %

Notes: This table presents the results of firm-level Fama-MacBeth regressions of stock returns on lagged variables, as defined in Eq. 7. Values that are significant at the 10% or higher levels, using West and Newey (1987), are bolded.

Table 8. **Alphas on portfolios sorted by MAX or MIN (IVOL) controlling for IVOL (MAX and MIN).**

	EW Portfolios						**VW Portfolios**					
	FF3		**FF4**		**FF5**		**FF3**		**FF4**		**FF5**	
	alpha	t-stat	alpha	t-stat	alpha	t-stat	alpha	t-stat	alpha	t-stat	alpha	t-stat
Panel A. Sorted by IVOL controlling for MAX												
IVOL 1 (Low)	-1.256	-2.56	-1.311	-2.66	-1.252	-2.51	-1.186	-2.36	-1.269	-2.54	-1.157	-2.26
IVOL 2	-0.957	-2.05	-0.974	-2.08	-0.922	-1.99	-0.999	-2.46	-1.022	-2.51	-0.959	-2.36
IVOL 3	-0.789	-1.87	-0.763	-1.85	-0.714	-1.66	-0.803	-1.90	-0.767	-1.81	-0.754	-1.76
IVOL 4	-0.704	-1.56	-0.657	-1.49	-0.594	-1.30	-0.708	-1.47	-0.664	-1.37	-0.622	-1.25
IVOL 5 (High)	-1.008	-2.03	-0.989	-2.00	-0.910	-1.80	-0.991	-2.31	-0.949	-2.21	-0.877	-2.02
High−Low	0.248	0.64	0.322	0.84	0.342	0.87	0.195	0.47	0.320	0.77	0.281	0.65
Panel B. Sorted by IVOL controlling for MIN												
Controlling for MIN												
IVOL 1 (Low)	-1.043	-2.20	-1.090	-2.29	-1.028	-2.13	-0.960	-2.00	-1.039	-2.18	-0.929	-1.90
IVOL 2	-0.780	-1.67	-0.790	-1.69	-0.760	-1.63	-0.734	-1.85	-0.749	-1.88	-0.696	-1.75
IVOL 3	-0.650	-1.59	-0.616	-1.55	-0.564	-1.34	-0.691	-1.67	-0.651	-1.57	-0.641	-1.52
IVOL 4	-0.512	-1.12	-0.460	-1.05	-0.397	-0.83	-0.489	-1.00	-0.454	-0.92	-0.402	-0.76
IVOL 5 (High)	-0.758	-1.54	-0.753	-1.54	-0.678	-1.33	-0.693	-1.69	-0.659	-1.61	-0.575	-1.38
High−Low	0.285	0.73	0.337	0.86	0.350	0.88	0.268	0.65	0.379	0.94	0.355	0.84
Panel C. Sorted by MAX controlling for IVOL												
MAX 1 (Low)	-0.128	-0.22	-0.216	-0.39	-0.099	-0.14	-0.107	-0.17	-0.189	-0.34	-0.078	-0.09
MAX 2	-0.540	-1.43	-0.584	-1.54	-0.480	-1.22	-0.390	-1.04	-0.434	-1.15	-0.326	-0.83
MAX 3	-0.842	-1.99	-0.817	-1.91	-0.807	-1.84	-0.576	-1.37	-0.550	-1.29	-0.526	-1.20
MAX 4	-1.128	-2.43	-1.077	-2.34	-1.071	-2.29	-0.890	-1.94	-0.830	-1.83	-0.819	-1.78
MAX 5 (High)	-2.030	-3.58	-1.956	-3.43	-1.896	-3.32	-1.626	-2.87	-1.564	-2.75	-1.502	-2.63
High−Low	**-1.903**	-4.50	**-1.739**	-4.23	**-1.797**	-4.18	**-1.518**	-3.54	**-1.375**	-3.27	**-1.423**	-3.26
Panel D. Sorted by MIN controlling for IVOL												
MIN 1 (Low)	-1.376	-2.61	-1.322	-2.50	-1.267	-2.41	-0.923	-1.94	-0.871	-1.83	-0.833	-1.75
MIN 2	-0.999	-2.06	-0.987	-2.04	-0.906	-1.85	-0.771	-1.59	-0.744	-1.55	-0.683	-1.40
MIN 3	-0.921	-2.25	-0.915	-2.24	-0.886	-2.12	-0.704	-1.74	-0.700	-1.74	-0.661	-1.60
MIN 4	-0.776	-1.81	-0.806	-1.87	-0.712	-1.59	-0.675	-1.54	-0.706	-1.60	-0.603	-1.30
MIN 5 (High)	-0.634	-1.89	-0.661	-1.92	-0.614	-1.73	-0.486	-1.55	-0.508	-1.58	-0.457	-1.38
High−Low	**0.741**	1.95	**0.661**	1.75	**0.653**	1.73	0.438	1.15	0.363	0.95	0.375	0.98

Notes: This table reports the alphas of IVOL, MAX and MIN effects, where one of them is tested after controlling for the other two variables. All the variables are defined between Tables 2 and Eqs. 1-3. The Newey and West (1987) *t*-statistics are reported under the same column, where alphas in the High−Low row that are statistically significant at the 10%, 5%, or 1% level are bolded.

Table 9. **Firm-level cross-sectional regressions on IVOL, MAX and MIN.**

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.0100**	**0.0484**	0.0010	**0.0310**	0.0074	**0.0539**
	(1.75)	(3.80)	(0.16)	(2.45)	(1.26)	(5.10)
IVOL	0.313	0.111	-0.057	0.280	-0.174	-0.124
	(1.52)	(0.36)	(-0.34)	(0.33)	(-0.62)	(-0.39)
MAX	**-0.122**	**-0.195**			**-0.212**	**-0.262**
	(-2.43)	(-4.35)			(-4.42)	(-5.46)
MIN			-0.030	0.148	**-0.196**	**-0.091**
			(-0.72)	(0.92)	(-4.12)	(-1.71)
Size		**-0.002**		-0.001		-0.001
		(-1.88)		(-0.66)		(-1.33)
Beta		**0.003**		**0.002**		0.001
		(1.94)		(1.85)		(1.27)
B/M		-0.001		-0.001		0.001
		(-0.63)		(-0.73)		(0.39)
STR		-0.011		-0.008		-0.011
		(-1.08)		(-0.84)		(-1.21)
MoM		**0.054**		**0.065**		**0.059**
		(1.83)		(2.19)		(1.92)
ILQ		-0.018		-0.008		**-0.034**
		(-1.08)		(-0.34)		(-3.30)
ISKEW		-0.001		-0.001		-0.002
		(-0.85)		(-0.50)		(-1.08)
CSKEW		**0.007**		**0.009**		0.010
		(1.73)		(2.07)		(1.55)
CP		-0.000		-0.000		-0.000
		(-0.93)		(-0.88)		(-0.44)
Avg. R2	5.52 %	19.18 %	4.86 %	18.78 %	6.95 %	20.56 %

Notes: The table reports the results of Fama-MacBeth firm-level regressions of stock returns on lagged IVOL, MIN, MAX and other control variables, defined in Table 2 and Eqs. 1-3. The sample period spans between January 2003 and December 2018. Values that are significant at the 10% or higher levels are bolded.

Table 10. **Firm-level cross-sectional return regressions on IVOL, MIN-5 and MAX-5.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**0.0176**	**0.0592**	0.0001	**0.0412**	**0.0533**	**0.0594**	**0.0380**	**0.0523**
	(2.97)	(5.53)	(0.02)	(3.65)	(4.96)	(5.55)	(3.38)	(4.80)
IVOL						0.032	-0.357	-0.048
						(0.11)	(-1.33)	(-0.16)
MIN-5			-0.117	0.103	**-0.291**		0.043	**-0.326**
			(-1.22)	(1.18)	(-2.52)		(0.44)	(-2.39)
MAX-5	**-0.294**	**-0.469**			**-0.657**	**-0.490**		**-0.692**
	(-3.68)	(-6.02)			(-6.43)	(-5.97)		(-5.75)
Size		**-0.002**		-0.002	-0.002	**-0.002**	-0.001	-0.002
		(-2.20)		(-1.14)	(-1.59)	(-2.13)	(-0.96)	(-1.63)
Beta		**0.002**		**0.002**	0.002	0.002	**0.003**	0.002
		(1.67)		(1.74)	(1.40)	(1.65)	(1.83)	(1.47)
B/M		0.001		-0.001	0.001	0.001	-0.001	0.001
		(0.34)		(-0.65)	(0.39)	(0.37)	(-0.53)	(0.30)
STR		-0.011		-0.004	-0.014	-0.010	-0.006	-0.014
		(-1.15)		(-0.38)	(-1.47)	(-1.10)	(-0.68)	(-1.47)
MoM		**0.058**		**0.085**	**0.073**	**0.058**	**0.080**	**0.070**
		(1.95)		(2.97)	(2.42)	(1.92)	(2.69)	(2.23)
ILQ		**-0.024**		-0.019	**-0.026**	**-0.026**	-0.020	**-0.026**
		(-2.28)		(-1.26)	(-2.49)	(-2.50)	(-1.29)	(-2.59)
ISKEW		-0.001		0.001	-0.001	-0.002	0.000	-0.002
		(-0.81)		(0.78)	(-0.82)	(-1.10)	(0.13)	(-1.06)
CSKEW		**0.004**		**0.003**	**0.005**	**0.008**	**0.009**	**0.010**
		(2.30)		(1.70)	(2.92)	(1.79)	(2.26)	(1.79)
CP		-0.000		-0.000	-0.000	-0.000	-0.000	-0.000
		(-0.45)		(-1.07)	(-0.41)	(-0.47)	(-1.07)	(-0.40)
Avg. R2	4.32 %	18.40 %	4.16 %	17.50 %	19.94 %	19.54 %	19.20 %	20.93 %

Notes: The table reproduces the results reported in Table 9 using alternative definitions of both MIN and MAX. That is, MIN-5 and MAX-5, as defined in Table 2. Values that are significant at the 10% or higher levels are bolded.