# Extreme returns and the investor's expectation for future volatility: Evidence from the Finnish stock market 


#### Abstract

We examine the significance of extreme positive returns of the previous month (MAX) as a return predictor in the Finnish stock market. We show that high fear months, i.e., months associated with the investor's high expectation for future volatility, are accompanying with low MAX effect implying that investors reluctant to gamble in high MAX stocks when they have high expectation for future volatility.


JEL Classification: G01, G21, G30, G32
Keywords: MAX effect, Extreme return, Sentiment

## 1. Introduction

Recent research in financial economics has documented a robust negative relationship between a firm's maximum daily return over the previous month (MAX) and its following month's stock return. Using a sample of the U.S. stocks, Bali et al. (2011) show that high MAX stocks produce a lower return in the following month than the low MAX stocks. Subsequently, among others, Nartea et al. (2014), Walkshausl (2014), Zhong and Gray (2016), Chan and Chui (2016), Wan (2018), Ali et al. (2019) study the MAX effects in the South Korean, European, Australian, Hong Kong, Chinese and Turkish stock markets respectively and confirms the robustness of MAX effect. In this paper, we investigate whether the MAX effect exists in a small-integrated market like Finland.

An investor can mitigate the effect of firm-specific idiosyncratic risk by holding a welldiversified portfolio, but in general individual investors are not well-diversified (Barber and Odean, 2000). Moreover, the presence of MAX effect suggests that investors are willing to pay more for stocks those exhibit extreme positive return. Hence, these stocks become overpriced and underperform in the future. This result supports the evidence of Kumar (2009) that gambling prone investors show a preference for lottery-type stocks - defined as low-priced stocks with high idiosyncratic volatility and idiosyncratic skewness.

Investors preference for lottery-like stocks is consistent with cumulative prospect theory (Tversky and Kahneman, 1992) based theoretical model of Barberis and Huang (2008) which suggests that errors in the probability weighting cause investors to overvalue stocks with positively skewed returns that have a small probability of a substantial positive return. Further, the optimal belief framework of Brunnermeier, Gollier and Parker (2007) asserts investors biased optimism on the likelihood of good states of the world cause them to under-diversify and hold stocks with a
skewed return to optimize their pay-offs. Further, Kumar (2009) show that individual investors attraction to lottery-type stocks can be linked to investors' propensity to gamble or speculate in the stock market. Therefore, individual investors cognitive biases that are related to speculative behavior can offer a plausible explanation for the MAX effect. Therefore, in this paper, we investigate the relationship between investors sentiment and MAX effect in the Finnish stock market.

Nofsinger (2005) argue that social mood of optimism and pessimism can influence financial decision-makers such as investors, corporate managers, and consumers to take similar kind of action. For example Hirshleifer and Shumway (2003) show that the sunlight has a significant effect on investor's mood. Frieder and Subrahmanyam (2004) find abnormal positive returns during Yom Kippur and St. Patrick's Day, negative returns around Rosh Hashanah (the beginning of the Jewish High Holy Days). A strong negative stock market movement to losses is observed during the time of losses of the US national soccer team is observed by Edmans, Garcia, Norli (2007).

In general, the high optimistic situation leads to extreme overconfidence, and eventually, it ends up with a market bubble. Baker and Wurgler (2006) indicate that investors sentiments can explain the cross-section of stock returns. According to them, small, volatile, and new speculative firms are more affected by sentiments. Similarly, Fong and Toh (2014) show that in the U.S. market, high negative MAX effect exists during high sentiment states. In this paper, we use the CBOE Volatility Index (VIX) as a proxy for the market sentiment to analyze the relationship between investor's expectation for future volatility and the extreme stock returns in Finnish stock market. Hence, this paper supports the current articles of financial economics in the scope of extreme return effect and sentiment in international financial markets.

Using stock returns over the period January 1999 to December 2018, we find MAX is a strong predictor of the Finnish stock returns, and the MAX effect is lower during the high fear month, i.e. the months with expected volatility. We also show that the MAX effet persists in the Finnish market even after controlling for other measures of extreme returns such as minimum daily return over the past month (MIN) and idiosyncratic volatility (IVOL), indicating MAX is the true measure of extreme return in the Finnish stock market. In general, our results of a strong MAX effect in a small integrated market like Finland supports the findings of Bali et al. (2011) for developing economies.

The remainder of the paper proceeds as follows. Section 2 describes recent literature on the MAX effect; Section 3 describes the data and the construction of the variable used in this paper. Section 4 explains the methodology of portfolio level analysis and firm-level cross-sectional regressions and reports the results. In Section 5, we discuss additional robustness test, and Section 6 , provides the concluding remarks.

## 2. Literature Review

Bali et al. (2011) study the extreme positive returns in the cross-sectional stock returns to capture the effect of investors' preference for lottery-like stocks defined as low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness. Both the portfolio-level analyses and firm-level cross-sectional regressions indicate a significant negative relationship between the MAX and expected stock returns in the U.S. equity market, which is robust to controls for size, book-to-market, momentum, short-term reversals, liquidity, and skewness. Specifically, a long position on stocks with high MAX and a short position on stocks with low MAX generates a return difference exceeding $1 \%$ per month in the US market. Interestingly, Bali et al. (2011) also report
that the inclusion of MAX in the analysis reverses the puzzling negative relation between stock returns and idiosyncratic volatility as shown in Ang, Hodrick, Xing, and Zhang (2006, 2009).

Bali et al. (2011) attribute the MAX effect to market pressures exerted by investors who prefer stocks with lottery-like features and rationalize their finding in the context of the cumulative prospect theory and optimal expectations framework. Fong and Toh (2014) find that the MAX effect in the US is mainly due to the low return of high MAX stocks rather than high returns of low MAX stocks. Supporting the behavioral explanation, they show that the MAX effect is strongly dependent on investor sentiment and shows up exclusively in the high sentiment periods due to heightened optimism among the investors.

A follow-up study by Annaert et al. (2013) shows that the US evidence also extends, albeit somewhat weakly, to a sample of 7861 companies from 13 European countries. They find that MAX stocks reflect the lottery properties and are generally small, relatively illiquid and high book-to-market stocks with high idiosyncratic volatility. Walkshäusl (2014), however, report a more robust evidence of a significantly negative relation between MAX and subsequent stock returns based on a sample of firms from 11 developed markets belong to the European Monetary Union: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The author also investigates whether the MAX effect can be traced to firm fundamentals and finds that the negative MAX-return relation is significantly stronger for firms with high cash flow volatility and significantly weaker for high profitable firms.

Zhong and Gray (2016) document a strong negative MAX effect in the Australian equities over 1991-2013 that is robust to risk adjustment and control for other common stock characteristics. They report that the effect manifests even in a partition of the largest 500 Australian stocks. They find that their documented MAX effect does not have a risk-based explanation;
instead, it reflects the degree to which the stocks are mispriced in the market. In sharp contrast to the other literature, Aboulamer and Kryzanowski (2016) find that there is a positive relationship between MAX and future returns in the Canadian market and that reversals for stocks with extreme daily returns are confined to mainly small stocks with low institutional holdings. Moreover, they report a strong positive relationship between idiosyncratic volatility and subsequent stock return, which, among other stock characteristics, is not subsumed by MAX. They argue that the Canadian market is different than the US market and has a large concentration of firms in the energy and mining industries, a high level of correlation with commodities, and the lack of evidence for the existence of sharp return reversals in monthly returns. This kind of contradictory results demands more countrywide research in this area.

A few recent papers have also shown that, like that in most well-developed markets, the MAX effect is also priced in some of the advanced emerging stock markets. Nartea et al. (2014) conduct only portfolio level analysis and report negative and significant MAX effect in South Korean stock market. They suggest that the effect is mostly due to a small-firm phenomenon, consistent with Kumar (2009) suggesting that lottery-type stocks are typically small-cap stocks. Unlike Bali et al. (2011), they find that a negative idiosyncratic volatility effect coexists with the MAX effect - a phenomenon that they attribute to the predominance of retail investors and the practice of imposing daily price limits in the South Korean market.

Nartea et al. (2017) report similar results based on both the portfolio and firm-level analyses of Chinese stocks. In addition, they find that the MAX effect in returns can last beyond the one-month holding period, suggesting that prices take a relatively longer period to revert to their fundamental levels in the Chinese stock markets. In line with the results from recent studies in the U.S. and Europe, Berggrun, Cardona, and Lizarzaburu (2017) also find the negative MAX
effect in the cross-section of Brazilian stock returns and the demand for speculative securities increases during periods of economic contraction.

Recently, Seif, Docherty, and Shamsuddin (2018) examine the return anomaly resulting from the MAX effect in a set of advanced emerging markets - Brazil, the Czech Republic, Hungary, Malaysia, Mexico, Poland, South Africa, Taiwan, and Turkey. They find strong evidence of the MAX effect in both their country-specific samples and the pooled sample of stocks across nine countries. They note that the magnitude of the effect is substantially significant compared to that reported for the U.S. and European markets. Further, their results show that the common risk factors cannot adequately explain the MAX anomaly and the MAX effect represents pervasive mispricing across emerging markets that can persist due to higher limit to arbitrage in these markets compared with developed markets.

## 3. Data and Variables

3.1 Data

We collect daily total return ${ }^{1}$ and market value data from Datastream for all available stocks listed in the Helsinki Stock Exchange for the period from January 1999 to December 2018. The starting of our sample period corresponds to the year Euro was introduced as the official currency in Finland, three years before the introduction of Euro banknotes and coins on January 1, 2002. For the entire sample period, 1999-2018, we have on average 143 stocks per year with a minimum and a maximum number of 131 and 158 stocks per year respectively. However, the construction of momentum (MOM) variable requires the past 12 months of data to produce the first observation.

[^0]Hence, we start both portfolio-level analysis and cross-sectional regressions from 2000. We also collect the CBOE Volatility Index (VIX) data for the sample period from DataStream to construct the sentiment variable.

### 3.2 Variables

Using the daily logarithmic returns, we calculate the monthly return $\left(R E T_{i, t}\right)$ as the sum of daily returns of firm $i$ in month $t$, daily maximum return over the previous month $\left(M A X_{i, t}\right)$ as the maximum daily return in month $t-1$ for the firm $i$, daily minimum return over the past month $\left(M I N_{i, t}\right)$ as the minimum daily return for firm $i$ in month $t-1$ multiplied by -1 . We calculate the multi-day maximum return $\left(M A X_{i, t}(N)\right)$ for $N=2, \ldots, 5$ days as the average of $N$ highest daily returns of firm i in the month $t-1$.Similarly, multi-day minimum return $\left(\operatorname{MIN}_{i, t}(N)\right)$ for $N=$ $2, \ldots, 5$ days is the average of $N$ lowest daily returns of firm i in the month $t-1$ multiplied by -1 . Following Jegadeesh (1990) and Lehmann (1990) the prior month return is used as the short-term reversal factor and following Jagadeesh and Titman (1993) momentum ( $M_{i, t}$ ) for stock $i$ in month $t$; is the cumulative return of stock $i$ over previous 11 months starting from $t-2$. We use the average of the daily market value of stock $i$ over the past month as the proxy for the market size $\left(S I Z E_{i, t}\right)$.

We estimate the market model of equation (1) using the daily returns of stock $i$ over the month $t-1$ to estimate the firm-specific systematic risk $\left(B E T A_{i, t}\right)$ and idiosyncratic volatility $\operatorname{IVOL}_{i, t}$ ) for stock $i$ in month $t-1$. Specifically, our estimate of $B E T A_{i, t}$ is the regression coefficient of market index retrun $\left(\beta_{i}\right)$ from equation (1) and $I V O L_{i, t}$ is the standar devaition of the residuals from monthly regressions.

$$
\begin{equation*}
R_{i, d}=\alpha_{i}+\beta_{i}\left(R_{m, d}\right)+e_{i, d} \tag{1}
\end{equation*}
$$

We use the CBOE Volatility Index (VIX) as a proxy for the market-wide sentiment and construct a dummy variable indicating one as the high sentiment months and zero as low sentiment months. We define months in which the VIX index is above the sample median as high sentiment period and otherwise, low-sentiment months.

Table 1 presents the summary statistics of the variables used in this paper where return (RET) is the monthly returns of stocks. BETA is the coefficient of the market index of the market model regression estimated using the daily stock return over a month. Momentum (MOM) is the cumulative return over past 11 months from month $\mathrm{t}-12$ to month t-2. Short-term reversal (REV) is the lagged monthly return. SIZE is the natural logarithm of the average market value of equity in a month. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the market model regression estimated with daily stock returns over the month. $\operatorname{MAX}(\mathrm{N})$ is the average of the N highest daily returns over the previous month for $\mathrm{N}=1, \ldots 5 . \operatorname{MIN}(\mathrm{N})$ is the average of the negative of the N lowest daily returns over the previous month for $\mathrm{N}=1, \ldots, 5$.
[Insert table 1 about here]

## 4. Results

### 4.1 Portfolio level Analysis

At each month, we create decile portfolios sorted by the average of the $N$ highest daily returns $(\operatorname{MAX}(N))$ over the previous month from February 2000 to December 2018 where $N=$ $1, \ldots, 5$. Portfolio $1(10)$ contains the lowest (highest) maximum multi-day returns. In table 2, we
report equal-weighted average month returns in percentage terms. The last two rows present the differences in monthly returns between portfolios 10 and 1 , and their associated $t$-statistics in parentheses based on Newey-West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors.

## [Insert table 2 about here]

Portfolio results show that the lowest return is in the highest MAX portfolios. Similarly, lowest MAX portfolio is the best performer among the other portfolios. This extreme high MAX portfolio contains lottery types stocks mentioned by Kumar (2009), which have a little probability of having a significant gain. In table 1, we see that the difference between two extreme portfolios is significant in the case of MAX to MAX5.

### 4.2 Cross-sectional regression analysis

The portfolio level analysis shows a strong relation between MAX sorted portfolios and future stock return. We now use Fama-MacBeth (1973) regressions to test if the MAX effect has non-zero premium in the cross-section of stock returns controlling for multiple effects or factors. Following Bali et al. (2011), at each month, we estimate the equation (2) and the nested version thereof. In the table (3), we report the time-series averages of the cross-sectional regression coefficients estimated at each month and their associated $t$-statistics in parentheses based on Newey-West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors.

$$
\begin{gather*}
R_{i, t}=\gamma_{0, t}+\gamma_{t, 1} \text { MAX }_{i, t}+\gamma_{t, 2} \text { BETA }_{i, t}+\gamma_{t, 3} \text { MOM }_{i, t}+\gamma_{t, 4} R E V_{i, t} \\
+\gamma_{t, 5} \text { SIZE }_{i, t}+\varepsilon_{i, t+1} \tag{2}
\end{gather*}
$$

[Insert table 3 here]

The results of table 3 indicate that a high and significant negative relation between MAX and the future return in the Finnish market. In the first model of table 3, we find a negative slope coefficient of lag MAX variable of -0.162 with a $t$-statistics of -7.231 without any control. After that from model 2 to 4 , the size of MAX coefficients is somewhat similar. However, the inclusion of all control variables the MAX coefficient is still negative and significant. Therefore, in model 5, we have the slope coefficient of MAX -0.105 when $t$ statistic related to this coefficient is -4.190 means that high MAX generating stocks have lower performance in the next month.

Model 6 to 9 shows the comparison of MAX effect during high VIX periods and low VIX periods. We see that after imposing all the controls, MAX effect is insignificant in the high VIX period indicating that people reluctant to gamble with high MAX stocks when they have a fear of high volatility in the future.

Stocks with the extreme return are likely to show high volatility as well. Ang, Hodrick, Xing, and Zhang (2006, 2009) demonstrate that high IVOL bearing stocks have a significant negative return in the subsequent month. Thus, there remains a concern if MAX is proxying for a different effect despite being theoretically motivated variable. To check if MAX is the true effect, we use two alternative measures of extreme variables: daily minimum return (MIN) and idiosyncratic volatility (IVOL). While tables B1-B5 in the appendix show the existence of MIN
effect and table C 1 in the appendix ensures the existence of IVOL effect in isolation, we estimate the following regression and the nested versions thereof to check if the MAX holds after controlling for MIN and IVOL:

$$
\begin{gather*}
R_{i, t}=\gamma_{0, t}+\gamma_{t, 1} M A X_{i, t}+\gamma_{t, 2} \text { MIN }_{i, t}+\gamma_{t, 3} I V O L_{i, t}+\gamma_{t, 4} \text { BETA }_{i, t}+\gamma_{t, 5} \text { MOM }_{i, t} \\
+\gamma_{t, 6} R E V_{i, t}+\gamma_{t, 7} S_{I Z E_{i, t}+\varepsilon_{i, t+1}} \tag{3}
\end{gather*}
$$

Table 4 shows the time-series averages of the slope coefficients $\gamma_{i, t}(\mathrm{i}=1,2, . .7)$ over the $t$ period of months from January 1999 to January 2018. We see that MAX coefficients for all four models are negetive and significant but IVOL and MIN effect cannot survives after putting all controls with MAX. MAX effect subsumes IVOL and MIN effect meaning that MAX is the only relevent effect in the Finnish market.
[Insert table 4 here]

Kumar (2009) indicates that small stocks which have high MAX and idiosyncratic volatility are the lottery like stocks from which investors have very little chance of making a big gain. Still, these stocks can create attention to the gambling prone individual investors' mindset. The results of Finnish stock market also consistent with the results of cumulative prospect theory (Tversky and Kahneman, 1992) were an incorrect or biased calculation in the probability weighting cause overvaluation of stocks that have a small chance of positive return.

## 5. Robustness tests

To check the robustness of our results, we perform a subsample analysis for the period following the global financial crisis of 2008 using the stock return data from January 2010 to December 2018. The results are presents in table 5. From the table, we observe the MAX coefficient without any control is -0.194 , where the associated $t$-statistic is -6.131 indicates that the MAX effect remains strong after 2010. After including all controls, the MAX coefficient remains significant. The MAX coefficient is -0.145 with a $t$-statistic -3.450 after inclusion of all four controls. These results indicate that the MAX effect remains very high, even within the recent ten years or post-depression years.
[Insert table 5 here]

To check the robustness of MAX effect under alternative definitions, we calculate MAX $(N)$ using the average of the $N$ highest daily returns within the month where $N=2, \ldots, 5$. We report the firms-level cross-sectional regressions in table A1-A4 in the appendix A.

## 6. Conclusion

In the Finnish Market, we find significant negative MAX effect implying that extreme returns producing stocks are showing a lower performance in the next period. This MAX effect is smaller during high VIX periods when the expectation for future volatility is high. This result is consistent with prior literature where they show that high sentiment states (low VIX periods) are associated with the very high MAX effect. By constructing a sentiment index, Baker and Wurgler
(2006) show that cross-sectional stock return is affected by sentiments as speculative investors gamble with highly volatile, small and young stocks during the time of optimism. Similarly, Stambaugh, Yu and Yuan (2012) find that greater asset pricing anomalies during high sentiments states. Consistent with the prior findings, Fong and Toh (2014) also find higher MAX effect in during high sentiment states than the other periods. Our results are indicative of the existence of some gambling prone investor's in the Finnish market who are motivated by the behavioral biases.

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Table 1: Summary Statistics

| Variables | Mean | Std. | Dev. | Min | Max |
| :---: | :---: | :---: | :---: | :---: | :---: |
| RET | 0.001 | 0.114 | -1.969 | 2.608 | 0.001 |
| BETA | 0.421 | 0.704 | -13.269 | 10.048 | 0.421 |
| SIZE | 5.028 | 2.039 | -0.968 | 12.535 | 5.028 |
| REV | 0.002 | 0.115 | -1.969 | 2.608 | 0.002 |
| MOM | 0.031 | 0.436 | -4.210 | 3.507 | 0.031 |
| MAX | 0.053 | 0.055 | 0.000 | 1.163 | 0.053 |
| MAX2 | 0.043 | 0.040 | 0.000 | 1.136 | 0.043 |
| MAX3 | 0.036 | 0.033 | 0.000 | 1.089 | 0.036 |
| MAX4 | 0.032 | 0.028 | 0.000 | 0.964 | 0.032 |
| MAX5 | 0.028 | 0.024 | -0.002 | 0.815 | 0.028 |
| MIN | -0.049 | 0.052 | -1.915 | 0.000 | -0.049 |
| MIN2 | -0.040 | 0.038 | -1.035 | 0.001 | -0.040 |
| MIN3 | -0.035 | 0.031 | -0.720 | 0.002 | -0.035 |
| MIN4 | -0.030 | 0.027 | -0.693 | 0.002 | -0.030 |
| MIN5 | -0.027 | 0.024 | -0.555 | 0.002 | -0.027 |

Note. The table shows the summary statistics of variables over the period of January 1999 to January 2018. Return (RET) is the monthly returns of stocks. BETA is the coefficient of the market index of the market model regression estimated using the daily stock return over a month. Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$. Short-term reversal (REV) is the lagged monthly return. SIZE is the natural logarithm of the average market value of equity in a month. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the market model regression estimated with daily stock returns over the month. MAX $(N)$ is the average of the $N$ highest daily returns over the previous month for $N=1, \ldots 5 . \operatorname{MIN}(N)$ is the average of the negative of the $N$ lowest daily returns over the previous month for $N=1, \ldots, 5$.

Table 2: Return on portfolios of stocks sorted by multi-day maximum returns

| Portfolios | $\mathrm{N}=1$ | $\mathrm{~N}=2$ | $\mathrm{~N}=3$ | $\mathrm{~N}=4$ | $\mathrm{~N}=5$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Low MAX $(N)$ | 0.79 | 0.77 | 0.79 | 0.73 | 0.67 |
| 2 | 0.68 | 0.85 | 0.82 | 0.78 | 0.91 |
| 3 | 0.72 | 0.55 | 0.59 | 0.71 | 0.69 |
| 4 | 0.40 | 0.53 | 0.69 | 0.55 | 0.50 |
| 5 | 0.30 | 0.43 | 0.15 | 0.20 | 0.16 |
| 6 | 0.02 | -0.20 | 0.19 | 0.39 | 0.48 |
| 7 | -0.06 | 0.31 | -0.01 | -0.01 | -0.01 |
| 8 | -0.26 | -0.33 | -0.29 | -0.37 | -0.34 |
| 9 | -0.60 | -0.71 | -0.67 | -0.75 | -0.68 |
| High MAX $(N)$ | -1.60 | -1.71 | -1.81 | -1.77 | -1.89 |
| Diff. 10-1 | $-2.39 * * *$ | $-2.48^{* * * *}$ | $-2.60 * * *$ | $-2.51^{* * * *}$ | $-2.56^{* * *}$ |
| $t$-stats | $(-5.26)$ | $(-5.34)$ | $(-5.53)$ | $(-5.23)$ | $(-5.18)$ |

Note. At each month, we form decile portfolios sorted by the average of the $N$ highest daily returns (MAX(N)) over the previous month from February 2000 to December 2018 where portfolio 1(10) contains the lowest (highest) maximum multi-day returns. This table reports the equal-weighted average monthly returns for $N=1, \ldots, 5$. The last two rows present the differences in monthly returns between portfolios 10 and 1, and their associated Newey-West (1987) adjusted t-statistics (in parentheses). The returns are in percentage terms.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table 3: Firm-level cross-sectional regression with MAX

|  | All period Sample |  |  |  |  | High VIX Period |  | Low VIX period |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| MAX | $\begin{gathered} -0.162 * * * \\ (-7.231) \end{gathered}$ | $\begin{gathered} -0.137 * * * \\ (-4.411) \end{gathered}$ | $\begin{gathered} -0.102^{* * *} \\ (-4.991) \end{gathered}$ | $\begin{gathered} -0.098^{* * *} \\ (-3.701) \end{gathered}$ | $\begin{gathered} -0.105^{* * *} \\ (-4.190) \end{gathered}$ | $\begin{gathered} -0.142^{* * *} \\ (-3.231) \end{gathered}$ | $\begin{gathered} -0.064 \\ (-1.480) \end{gathered}$ | $\begin{gathered} -0.178 * * * \\ (-4.541) \end{gathered}$ | $\begin{gathered} -0.141 * * * \\ (-3.470) \end{gathered}$ |
| BETA |  | $\begin{gathered} -0.007 \\ (-1.013) \end{gathered}$ | $\begin{gathered} -0.008 \\ (-1.429) \end{gathered}$ | $\begin{gathered} -0.008 \\ (-1.370) \end{gathered}$ | $\begin{gathered} -0.007 \\ (-1.380) \end{gathered}$ |  | $\begin{aligned} & -0.012 * \\ & (-2.230) \end{aligned}$ |  | $\begin{gathered} -0.003 \\ (-1.320) \end{gathered}$ |
| MOM |  |  | $\begin{gathered} 0.019^{* * *} \\ (4.161) \end{gathered}$ | $\begin{gathered} 0.018 * * * \\ (4.890) \end{gathered}$ | $\begin{gathered} 0.020 * * * \\ (6.201) \end{gathered}$ |  | $\begin{gathered} 0.007 \\ (1.300) \end{gathered}$ |  | $\begin{gathered} 0.031 * * * \\ (7.460) \end{gathered}$ |
| REV |  |  |  | $\begin{gathered} -0.002 \\ (-0.190) \end{gathered}$ | $\begin{gathered} -0.001 \\ (-0.060) \end{gathered}$ |  | $\begin{aligned} & -0.034 * \\ & (-2.010) \end{aligned}$ |  | $\begin{gathered} 0.029 \\ (1.620) \end{gathered}$ |
| SIZE |  |  |  |  | $\begin{gathered} -0.001 \\ (-1.310) \end{gathered}$ |  | $\begin{gathered} -0.001 \\ (-0.940) \end{gathered}$ |  | $\begin{gathered} 0.000 \\ (-0.280) \end{gathered}$ |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX and subsets of four predictor variables. The main variable of interest MAX is the maximum daily return in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. Model 1-5 are for the full sample, whereas model 6-7 are for high VIX periods, and model 8-9 are for low VIX periods. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table 4: Firm-level cross-sectional regression with MAX, MIN, and IVOL

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| :---: | :---: | :---: | :---: | :---: |
| MAX | $-0.097 * *$ | $-0.137 * * *$ | $-0.088^{* *}$ | $-0.072 * * *$ |
|  | $(-2.400)$ | $(-4.820)$ | $(-2.200)$ | $(-3.920)$ |
| IVOL | -4.081 |  | -3.236 | -3.347 |
|  | $(-2.340)$ | -0.053 | $-0.410)$ | $(-1.650)$ |
| MIN |  | $-0.1 .55)$ | $(-0.840)$ | $(1.490)$ |
|  |  |  | -0.007 |  |
| BETA |  |  | $(-1.480)$ |  |
|  |  |  | $0.019 * * *$ |  |
| MOM |  | $(6.970)$ |  |  |
| REV |  |  | 0.012 |  |
| SIZE |  |  | $(1.130)$ |  |
|  |  |  | -0.001 |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX and subsets of four predictor variables. The main variable of interest MAX is the maximum daily return in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We report the Newey-West (1987) adjusted t -statistics in parentheses.
$\begin{array}{ll}\text { *** } & P<0.01 \\ * * & P<0.05 \\ * & P<0.10\end{array}$

Table 5: Firm-level cross-sectional regression with MAX from 2010

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MAX | $-0.194^{* * *}$ | $-0.202^{* * *}$ | $-0.141^{* * *}$ | $-0.146^{* * *}$ | $-0.145^{* * *}$ |
|  | $(-6.131)$ | $(-5.290)$ | $(-5.770)$ | $(-3.890)$ | $(-3.450)$ |
| BETA |  | $0.004^{* * *}$ | $0.002^{* *}$ | $0.002^{* *}$ | 0.002 |
|  |  | $(6.600)$ | $(2.750)$ | $(2.560)$ | $(1.980)$ |
| MOM |  | $0.031^{* * *}$ | $0.029^{* * *}$ | $0.029^{* * *}$ |  |
|  |  | $(14.800)$ | $(13.190)$ | $(14.140)$ |  |
| REV |  |  | 0.007 | 0.008 |  |
|  |  |  | $(0.270)$ | $(0.290)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(0.450)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX and subsets of four predictor variables. The main variable of interest MAX is the maximum daily return in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$


## Appendix A: Firm-level cross-sectional regression with MAX( $N$ ) where $N=2, \ldots, 5$

## Table A1: Firm-level cross-sectional regression with MAX2

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MAX2 | -0.230 | $-0.198^{* * *}$ | $-0.148^{* * *}$ | $-0.145^{* * *}$ | $-0.155^{* * *}$ |
|  | $(-7.631)$ | $(-5.100)$ | $(-6.280)$ | $(-3.530)$ | $(-3.730)$ |
| BETA |  | -0.007 | -0.008 | -0.007 | -0.007 |
|  |  | $(-1.030)$ | $(-1.380)$ | $(-1.150)$ | $(-1.170)$ |
| MOM |  |  | $0.020^{* * *}$ | $0.019^{* * *}$ | $0.020^{* * *}$ |
|  |  |  | $(4.150)$ | $(4.420)$ | $(5.390)$ |
| REV |  |  |  | -0.002 | 0.001 |
|  |  |  |  | $(-0.110)$ | $(0.040)$ |
| SIZE |  |  |  | -0.001 |  |
|  |  |  |  | $(-1.240)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX2 and subsets of four predictor variables. The main variable of interest MAX2 is the average of the two highest daily returns in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table A2: Firm-level cross-sectional regression with MAX3

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MAX3 | $-0.289^{* * *}$ | $-0.251 * * *$ | $-0.187 * * *$ | $-0.183^{* * *}$ | $-0.198^{* * *}$ |
|  | $(7.490)$ | $(-5.460)$ | $(-6.790)$ | $(-4.740)$ | $(-5.300)$ |
| BETA |  | -0.006 | -0.008 | -0.006 | -0.006 |
|  |  | $(-0.990)$ | $(-1.360)$ | $(-1.270)$ | $(-1.290)$ |
| MOM |  | $0.020^{* * *}$ | 0.019 | $0.020^{* * *}$ |  |
|  |  | $(4.090)$ | $(4.960)$ | $(6.280)$ |  |
| REV |  |  | -0.001 | 0.001 |  |
|  |  |  | $(-0.110)$ | $(0.070)$ |  |
| SIZE |  |  |  | -0.001 |  |
|  |  |  |  | $(-1.400)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX3 and subsets of four predictor variables. The main variable of interest MAX3 is the average of the three highest daily returns in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table A3: Firm-level cross-sectional regression with MAX4

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MAX4 | $-0.341^{* * *}$ | $-0.298^{* * *}$ | $-0.224^{* * *}$ | $-0.220^{* * *}$ | $-0.239^{* * *}$ |
|  | $(-7.291)$ | $(-5.790)$ | $(-6.890)$ | $(-5.020)$ | $(-5.580)$ |
| BETA |  | -0.006 | -0.007 | -0.006 | -0.006 |
|  |  | $(-0.940)$ | $(-1.330)$ | $(-1.230)$ | $(-1.260)$ |
| MOM |  | $0.020^{* * *}$ | $0.019^{* * *}$ | $0.020^{* * *}$ |  |
|  |  | $(4.030)$ | $(4.850)$ | $(6.170)$ |  |
| REV |  |  | -0.001 | 0.002 |  |
|  |  |  | $(-0.040)$ | $(0.170)$ |  |
| SIZE |  |  |  | -0.001 |  |
|  |  |  |  | $(-1.370)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX4 and subsets of four predictor variables. The main variable of interest MAX4 is the average of the four highest daily returns in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted $t$-statistics in parentheses. ${ }^{* * *} P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table A4: Firm-level cross-sectional regression with MAX5

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MAX5 | $-0.392 * * *$ | $-0.346^{* * *}$ | $-0.262^{* * *}$ | $-0.257 * * *$ | $-0.278^{* * *}$ |
|  | $(-7.361)$ | $(-6.250)$ | $(-7.300)$ | $(-5.400)$ | $(-5.990)$ |
| BETA |  | -0.005 | -0.007 | -0.006 | -0.005 |
|  |  | $(-0.910)$ | $(-1.310)$ | $(-1.210)$ | $(-1.240)$ |
| MOM |  | $0.020^{* * *}$ | $0.019^{* * *}$ | $0.020^{* * *}$ |  |
|  |  | $(3.990)$ | $(4.790)$ | $(6.130)$ |  |
| REV |  |  | 0.000 | 0.003 |  |
|  |  |  | $(0.020)$ | $(0.250)$ |  |
| SIZE |  |  |  | -0.001 |  |
|  |  |  |  | $(-1.310)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MAX5 and subsets of four predictor variables. The main variable of interest MAX5 is the average of the five highest daily returns in a month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted $t$-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Appendix B: Firm-level cross-sectional regression with $\operatorname{MIN}(N)$ where $N=1, \ldots, 5$
Table B1: Firm-level cross-sectional regression with MIN

|  | All period Sample |  |  |  |  | High VIX Period Sample |  | Low VIX period Sample |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| MIN | $\begin{gathered} -0.138 * * * \\ (-4.808) \end{gathered}$ | $\begin{gathered} -0.116^{* *} \\ (-2.812) \end{gathered}$ | $\begin{gathered} -0.064 * * \\ (-2.161) \end{gathered}$ | $\begin{gathered} -0.055^{*} * \\ (-2.791) \end{gathered}$ | $\begin{gathered} -0.061 * * * \\ (-4.200) \end{gathered}$ | $\begin{aligned} & -0.067 \\ & (-1.443) \end{aligned}$ | $\begin{gathered} -0.033 \\ (-0.780) \end{gathered}$ | $\begin{gathered} -0.202 * * * \\ (-3.911) \end{gathered}$ | $\begin{gathered} -0.086 \\ (-1.820) \end{gathered}$ |
| BETA |  | $\begin{aligned} & -0.008 \\ & (-1.811) \end{aligned}$ | $\begin{aligned} & -0.009 \\ & (-1.49) \end{aligned}$ | $\begin{gathered} -0.008 \\ (-1.451) \end{gathered}$ | $\begin{gathered} -0.008 \\ (-1.560) \end{gathered}$ |  | $\begin{gathered} -0.013 \\ (-2.250) \end{gathered}$ |  | $\begin{gathered} -0.003 \\ (-1.610) \end{gathered}$ |
| MOM |  |  | $\begin{gathered} 0.022 * * * \\ (5.061) \end{gathered}$ | $\begin{gathered} 0.020 * * * \\ (4.827) \end{gathered}$ | $\begin{gathered} 0.021 * * * \\ (6.230) \end{gathered}$ |  | $\begin{gathered} 0.009 \\ (1.630) \end{gathered}$ |  | $\begin{gathered} 0.032 * * * \\ (7.960) \end{gathered}$ |
| REV |  |  |  | $\begin{gathered} -0.018 \\ (-1.842) \end{gathered}$ | $\begin{gathered} -0.019 \\ (-1.860) \end{gathered}$ |  | $\begin{gathered} -0.048 \\ (-3.090) \end{gathered}$ |  | $\begin{gathered} 0.007 \\ (0.460) \end{gathered}$ |
| SIZE |  |  |  |  | $\begin{gathered} 0.000 \\ (-0.660) \end{gathered}$ |  | $\begin{gathered} -0.001 \\ (-0.870) \end{gathered}$ |  | $\begin{gathered} 0.000 \\ (0.420) \end{gathered}$ |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN and subsets of four predictor variables. The main variable of MIN is the minimum daily return in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. Model 1-5 are for the full sample, whereas model 6-7 are for high VIX periods, and model 8-9 are for low VIX periods. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table B2: Firm-level cross-sectional regression with MIN2

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MIN2 | $-0.199^{* * *}$ | $-0.167^{* * *}$ | $-0.093^{* *}$ | $-0.091^{* * *}$ | $-0.098^{* * *}$ |
|  | $(-4.181)$ | $(-2.770)$ | $(-2.100)$ | $(-2.900)$ | $(-3.650)$ |
| BETA |  | -0.008 | -0.009 | -0.008 | -0.008 |
|  |  | $(-1.180)$ | $(-1.500)$ | $(-1.440)$ | $(-1.530)$ |
| MOM |  |  | $0.021^{* * *}$ | $0.020^{* * *}$ | $0.021^{* * *}$ |
|  |  | $(5.140)$ | $(4.710)$ | $(6.040)$ |  |
| REV |  |  | $-0.023 * *$ | $-0.024^{* *}$ |  |
|  |  |  | $(-2.630)$ | $(-2.710)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(-0.770)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN2 and subsets of four predictor variables. The main variable of interest MIN2 is the average of the two lowest daily returns in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table B3: Firm-level cross-sectional regression with MIN3

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MIN3 | -0.257 | $-0.217^{* *}$ | $-0.123^{* *}$ | $-0.130^{* * *}$ | $-0.141^{* * *}$ |
|  | $(-4.724)$ | $(-2.980)$ | $(-2.240)$ | $(-3.220)$ | $(-3.880)$ |
| BETA |  | -0.008 | -0.008 | -0.007 | -0.007 |
|  |  | $(-1.150)$ | $(-1.480)$ | $(-1.390)$ | $(-1.450)$ |
| MOM |  | $0.021^{* * *}$ | $0.020^{* * *}$ | $0.021^{* * *}$ |  |
|  |  | $(5.290)$ | $(4.760)$ | $(6.130)$ |  |
| REV |  |  | $-0.026^{* * *}$ | $-0.027 * * *$ |  |
|  |  |  | $(-3.110)$ | $(-3.230)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(-0.930)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN3 and subsets of four predictor variables. The main variable of interest MIN3 is the average of the three lowest daily returns in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table B4: Firm-level cross-sectional regression with MIN4

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MIN4 | $-0.305^{* * *}$ | $-0.259^{* * *}$ | $-0.148^{* *}$ | $-0.165^{* * *}$ | $-0.183^{* * *}$ |
|  | $(5.061)$ | $(-3.220)$ | $(-2.450)$ | $(-3.710)$ | $(-4.490)$ |
| BETA |  | -0.007 | -0.008 | -0.007 | -0.007 |
|  |  | $(-1.110)$ | $(-1.450)$ | $(-1.340)$ | $(-1.380)$ |
| MOM |  |  | $0.021^{* * *}$ | $0.020^{* * *}$ | $0.021^{* * *}$ |
|  |  | $(5.320)$ | $(4.800)$ | $(6.190)$ |  |
| REV |  |  | $-0.028^{* * *}$ | $-0.029^{* * *}$ |  |
|  |  |  | $(-3.400)$ | $(-3.510)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(-0.980)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN4 and subsets of four predictor variables. The main variable of interest MIN4 is the average of four minimum daily returns in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient for market index for the previous month estimated using the market model, (ii) MOM is the cumulative return over 11 previous months from month $t-12$ to month $t-2$, (iii) REV is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify highsentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table B5: Firm-level cross-sectional regression with MIN5

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MIN5 | $-0.356^{* * *}$ | $-0.305^{* * *}$ | $-0.176^{* *}$ | $-0.211^{* * *}$ | $-0.233^{* * *}$ |
|  | $(-5.421)$ | $(-3.500)$ | $(-2.680)$ | $(-4.260)$ | $(-5.060)$ |
| BETA |  | -0.007 | -0.007 | -0.006 | -0.006 |
|  |  | $(-1.080)$ | $(-1.440)$ | $(-1.300)$ | $(-1.340)$ |
| MOM |  |  | $0.021^{* * *}$ | $0.020^{* * *}$ | $0.021^{* * *}$ |
|  |  | $(5.290)$ | $(4.770)$ | $(6.180)$ |  |
| REV |  |  | $-0.030^{* * *}$ | $-0.032 * * *$ |  |
|  |  |  | $(-3.770)$ | $(-3.890)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(-1.050)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN5 and subsets of four predictor variables. The main variable of interest MIN5 is the average of five minimum daily returns in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient for market index for the previous month estimated using the market model, (ii) MOM is the cumulative return over 11 previous months from month $t-12$ to month $t-2$, (iii) REV is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify highsentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t -statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$


## Appendix C: Firm-level cross-sectional regression with IVOL

Table C1: Firm-level cross-sectional regression with IVOL

|  | All period Sample |  |  |  |  | High VIX Period |  | Low VIX period |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| IVOL | $\begin{gathered} -4.719 * * * \\ (-4.091) \end{gathered}$ | $\begin{gathered} -4.325^{* * *} \\ (-2.900) \end{gathered}$ | $\begin{gathered} -3.147 * * \\ (-2.650) \end{gathered}$ | $\begin{gathered} -2.914 * * * \\ (-2.840) \end{gathered}$ | $\begin{gathered} -3.253 * * * \\ (-3.061) \end{gathered}$ | $\begin{aligned} & \hline-2.581^{*} \\ & (-2.021) \end{aligned}$ | $\begin{gathered} -1.080 \\ (-0.890) \end{gathered}$ | $\begin{gathered} \hline-6.636 * * * \\ (-3.811) \end{gathered}$ | $\begin{gathered} \hline-5.208 * * * \\ (-2.820) \end{gathered}$ |
| BETA |  | $\begin{gathered} -0.009 \\ (-1.200) \end{gathered}$ | $\begin{gathered} -0.009 \\ (-1.490) \end{gathered}$ | $\begin{gathered} -0.008 \\ (-1.450) \end{gathered}$ | $\begin{gathered} -0.008 \\ (-1.534) \end{gathered}$ |  | $\begin{gathered} -0.014 * * \\ (-2.400) \end{gathered}$ |  | $\begin{gathered} -0.003 \\ (-1.360) \end{gathered}$ |
| MOM |  |  | $\begin{gathered} 0.020 * * * \\ (4.910) \end{gathered}$ | $\begin{gathered} 0.019 * * * \\ (4.710) \end{gathered}$ | $\begin{gathered} 0.020 * * * \\ (6.481) \end{gathered}$ |  | $\begin{gathered} 0.008 \\ (1.460) \end{gathered}$ |  | $\begin{gathered} 0.030 \\ (7.170) \end{gathered}$ |
| REV |  |  |  | $\begin{gathered} -0.009 \\ (-0.960) \end{gathered}$ | $\begin{gathered} -0.009 \\ (-0.921) \end{gathered}$ |  | $\begin{gathered} -0.040^{* *} \\ (-2.630) \end{gathered}$ |  | $\begin{gathered} 0.019 \\ (1.250) \end{gathered}$ |
| SIZE |  |  |  |  | $\begin{gathered} 0.000 \\ (-0.881) \end{gathered}$ |  | $\begin{gathered} -0.001 \\ (-0.810) \end{gathered}$ |  | $\begin{gathered} 0.000 \\ (0.040) \end{gathered}$ |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged IVOL and subsets of four predictor variables. The main variable of interest Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the market model regression estimated with daily stock returns over the month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. Model 1-5 are for the full sample, whereas model 6-7 are for high VIX periods, and model 8-9 are for low VIX periods. We report the Newey-West (1987) adjusted t-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$


## Appendix D: Firm-level cross-sectional regression with MIN and IVOL from 2010

Table D1: Firm-level cross-sectional regression with MIN from 2010

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| MIN | $-0.179^{* * *}$ | $-0.189^{* *}$ | $-0.111^{* *}$ | $-0.088^{* *}$ | $-0.079^{* *}$ |
|  | $(2.961)$ | $(-3.000)$ | $(-2.310)$ | $(-2.880)$ | $(-2.661)$ |
| BETA |  | $0.003^{* *}$ | 0.001 | 0.001 | 0.001 |
|  |  | $(3.800)$ | $(1.310)$ | $(1.520)$ | $(0.451)$ |
| MOM |  |  | $0.033^{* * *}$ | $0.032^{* * *}$ | $0.031^{* * *}$ |
|  |  | $(16.600)$ | $(16.710)$ | $(18.513)$ |  |
| REV |  |  | -0.009 | -0.009 |  |
|  |  |  | $(-0.500)$ | $(-0.472)$ |  |
| SIZE |  |  |  | 0.001 |  |
|  |  |  |  | $(1.741)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged MIN and subsets of four predictor variables. The main variable of MIN is the minimum daily return in a month multiplied by -1 . The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-12$ to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$

Table D2: Firm-level cross-sectional regression with IVOL from 2010

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| IVOL | $-6.640^{* * *}$ | $-6.995^{* *}$ | $-5.149^{* *}$ | $-4.415^{*}$ | $-4.861^{* *}$ |
|  | $(2.998)$ | $(-2.810)$ | $(-2.390)$ | $(-2.100)$ | $(-2.300)$ |
| BETA |  | $0.003^{* * *}$ | 0.001 | 0.001 | $0.001^{* *}$ |
|  |  | $(4.160)$ | $(1.470)$ | $(1.530)$ | $(0.830)$ |
| MOM |  | $0.030^{* * *}$ | $0.029^{* * *}$ | $0.029^{* * *}$ |  |
|  |  | $(13.720)$ | $(12.670)$ | $(13.480)$ |  |
| REV |  |  | -0.003 | -0.002 |  |
|  |  |  | $(-0.190)$ | $(-0.130)$ |  |
| SIZE |  |  |  | 0.000 |  |
|  |  |  |  | $(1.240)$ |  |

Note. Following Bali et al. (2011), in this table, we report the time-series averages of the cross-sectional regression coefficients estimated at each month. We regress monthly return on lagged IVOL and subsets of four predictor variables. The main variable of interest Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the market model regression estimated with daily stock returns over the month. The control variables are defined as follows: (i) BETA is the coefficient of market index of the market model regression estimated using the daily stock return over the previous month, (ii) Momentum (MOM) is the cumulative return over past 11 months from month $t-$ 12 to month $t-2$, (iii) Short-term reversal (REV) is the previous month's stock return and (iv) SIZE is the natural logarithm of the previous month's average market value of equity. We use CBOE Volatility Index (VIX) as a proxy for the sentiment and specify high-sentiment months are those in which the VIX index is above the sample median and otherwise, low-sentiment month. We report the Newey-West (1987) adjusted t-statistics in parentheses.
*** $P<0.01$
** $P<0.05$

* $\quad P<0.10$


[^0]:    ${ }^{1}$ As the total return index is padded i.e. on workdays that are holidays, prices are repeated from the last trading date untill a new trading occurs, we drop the days from ours sample for which all the available stock prices are the same as the previous days.

