

Cross-Section of Expected Returns and Extreme Returns: The Role of Investor Attention and Risk Preferences

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Previous work finds a negative and significant relation between the maximum daily return over the past one month and expected future stock returns. We determine that this effect is more pronounced for stocks that achieve their maximum daily returns toward the end of the month and stocks that are associated with capital losses show greater reversals. These results suggest the effect is related to investor attention and risk preferences.

Financial economists have long been captivated with explaining the cross-section of stock returns. The rational economic models in the mold of capital asset pricing model (CAPM) and arbitrage pricing theory (APT) have helped us understand the theoretical underpinnings of the cross-section of stock returns.¹ These models rely on diversification as an important mechanism to derive the expected cross-sectional relationship between stock returns and various measures of systematic risk assuming that investors avoid idiosyncratic risk by holding diversified portfolios. However, recent empirical research finds that investors' portfolios are far from diversified and there may be rational arguments for this documented lack of diversification.² Furthermore, the last three decades of research has discovered a number of anomalies, including size, book-to-market, and momentum, that cannot be explained unambiguously in the rational framework of CAPM and APT types of models. Some financial economists have advanced alternative rationales grounded in investor irrationality emanating from behavioral biases for these anomalies. The upshot of the recent research in asset pricing suggests that beyond the diversification rationale, individual stock returns/firm attributes themselves hold the key in explaining the expected cross-section of returns. This paper is a modest attempt in that direction. We enrich the key finding of a negative and significant relation between maximum daily returns over the past month and expected stock returns in an important recent paper by Bali, Cakici, and Whitelaw (2011).³

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¹ An incomplete listing of these papers include Sharpe (1964), Lintner (1965), Mossin (1966), Kraus and Litzenberger (1976), Harvey and Siddique (2000), and Smith (2007).

² See Odean (1999), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008) for empirical evidence and Van Nieuwerburgh and Veldkamp (2010) for theoretical arguments.

³ These authors find that after controlling for MAX in the cross-sectional regressions of returns on idiosyncratic volatility, the coefficient on volatility is insignificant in some specifications or even significantly positive in others.

Specifically, we first link Bali et al.'s (2011) work on the role of extreme daily returns in future stock returns to the investor attention first mentioned in Kahneman (1973) and explored in several papers (Hong and Stein, 1999; Huberman and Regev, 2001; Dyck and Zingales, 2003; Hirshleifer and Teoh, 2003; Gabaix, Laibson, Moloche, and Weinberg, 2006; Peng and Xiong, 2006; Barber and Odean, 2008; Cohen and Frazzini, 2008; Dellavigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009). These papers argue that investors have limited attention and that plays a role in which stocks are traded by them. For instance, Barber and Odean (2008) find evidence that stocks that have recently had high returns catch the attention of investors with regard to additions to their portfolios. We extend that argument and propose that to the extent that the end of the month is a convenient time for many investors to make their portfolio rebalancing decisions, stocks that achieve maximum daily returns very close to the month end (Barone, 1990) will be far more noticeable by these inattentive investors. These stocks may be attractive to institutional investors and they window dress their portfolios to add winners toward the end of the month for reporting purposes (Thaler, 1987). The greater demand generated from these investors will exaggerate the mispricing of these stocks. When the correction takes place in the subsequent month for Bali et al. (2011) documented stocks with extreme returns, this subset of stocks that attain maximum returns close to the end of the month will demonstrate larger reversals.

We provide direct evidence as to the role of investor attention in our findings using two measures, abnormal trading volume and the Google Search Volume Index (GSVI). We find that abnormal trading volume and GSVI increase after maximum daily returns are achieved. More importantly, the increase of these two measures of investor attention is greater for stocks that achieve maximum daily returns close to the end of the month.

In addition, we contend that stocks with extreme daily returns will be especially attractive to investors sitting on paper losses in their current portfolios. This argument is motivated by the theoretical works of Barberis, Huang, and Santos (2001), Barberis, Huang, and Thaler (2003), and Grinblatt and Han (2005) who find that the psychological biases of investors influence their risk attitude. These papers argue that prospect theory and mental accounting (PTMA, hereafter)-motivated specifications of preferences have a systematic influence on the cross-section of returns. For instance, Grinblatt and Han (2005) and Frazzini (2006) use PTMA arguments to suggest that investors are risk seeking in losses. We propose that these PTMA investors sitting on paper losses are attracted toward stocks that have experienced recent high returns in the hope that they may help them recoup their losses. This phenomenon is similar to our arguments regarding investor attention above exaggerating mispricing. Consequently these stocks should experience greater reversal in the subsequent month.

First, we document the existence of Bali et al. (2011) results for our sample of stocks. We find that the reversal of returns for stocks with extreme daily returns is present for stocks with prices greater than \$5.00, unlike many anomalies present primarily in stocks with prices less than \$5.00. Our results are supportive of our two hypotheses. Our portfolio and firm-level investigations indicate that investor attention adds to the mispricing of stocks with extreme daily returns. The subsequent month reversal of stocks with extreme daily returns is largely concentrated in stocks that achieve their highest daily returns close to the end of the month. We find that stocks that attain their daily maximum returns toward the end of the month are positively related to two different proxies of investor inattention. Our results are robust to raw returns or the four-factor Fama-French-Carhart and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas.

One could argue that high *MAX* returns toward the end of the month are due to greater pressure to buy that reverses in the next few days in the following month.⁴ Papers by Nagel (2012) and Hameed and Mian (2015) point to such a possibility. We investigate this issue by excluding returns in the first five trading days in the following month and find that our results are robust to month-end buying pressures for stock with high returns as well.

Similarly, our results indicate that the risk-seeking attitude of investors with paper losses intensifies the mispricing of stocks with extreme daily returns. The reversals are larger and more significant for extreme daily returns stocks that are associated with capital losses. Our results are robust to the measurement of reversals using raw returns or four-factor Fama-French-Carhart and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas and possible illiquidity effects. To the extent that stocks with large capital losses may also be illiquid, our results may be a manifestation of the liquidity story.⁵ We examine this issue by excluding returns in the first five trading days in the following month and provide evidence that our results are beyond the illiquidity of stocks with capital losses.

The remainder of the paper is organized as follows. Section I describes the sample. Section II discusses the main results of the paper along with robustness tests. We provide our conclusions in Section III.

I. Sample

We extract data of all common stocks (with Share Code 10 and 11) on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq from Center for Research in Security Prices (CRSP) daily and monthly files from July 1962 to December 2014.⁶ We find that our results are robust for the liquidity effects that require the Pastor-Stambaugh liquidity factor in addition to the four traditional factors. Since the liquidity factor has only been available since 1968, all of Fama-French-Carhart-Pastor-Stambaugh alpha results are based on a subsample from 1968 to 2014. We use daily stock return data to compute the maximum daily stock returns for each stock in each month. We call this variable *MAX*. In addition, we also compute another variable, *DMAX*, calculated in units of days as the difference between the day the *MAX* return is observed and the last trading day of the same month.⁷ Furthermore, we use daily stock returns data to compute Scholes and William's (1977) beta (*BETA*) and capital gains overhang (*CGO*) used as control variables in the regressions. We use monthly stock return data to calculate measures of capital gains overhang (*CGO*), short-term reversal (*REV*), momentum (*PRE12RET*), liquidity (*ILLIQ*), and firm size (*SIZE*). Finally, we extract data from Compustat to compute the book-to-market ratio (*BTM*). We provide details regarding the exact computation of these variables in the Appendix. We begin the analysis with the sample without price restrictions to confirm the findings in Bali et al. (2011) and then restrict our sample to stocks worth \$5 or more to eliminate the effects of small and illiquid stocks.

⁴ We thank an anonymous referee for this insightful interpretation of our findings.

⁵ In a recent paper, Cheng, Hameed, Subrahmanyam, and Titman (2016) find results consistent with the liquidity story. We were made aware of this paper by an anonymous referee. We thank them for their input.

⁶ This essentially removes all American depository receipts (ADRs), SBIs, Units, real estate investment trusts (REITs), closed-end funds, and companies incorporated outside of the United States.

⁷ We select firms that have at least 12 trading days each month.

Table I. Returns of Portfolios Sorted on MAX

We form decile portfolios on the maximum daily return (*MAX*) each month from July 1962 to December 2014 and report value and equally weighted average monthly returns in the next month, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas. The sample period for the five-factor alpha is from January 1968 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

	No Price Restriction		Price $\geq$ \$5	
	Value-Weighted Returns	Equal-Weighted Returns	Value-Weighted Returns	Equal-Weighted Returns
Low <i>MAX</i>	0.92	1.24	0.99	1.19
2	0.97	1.37	0.98	1.35
3	0.96	1.45	0.97	1.39
4	1.00	1.45	0.92	1.39
5	1.05	1.43	1.03	1.39
6	1.05	1.40	1.08	1.32
7	0.94	1.30	0.96	1.20
8	0.83	1.29	0.89	1.05
9	0.59	1.04	0.85	0.83
High <i>MAX</i>	0.16	0.67	0.37	0.25
High – Low	–0.76*** (–2.58)	–0.58** (–2.05)	–0.62** (–2.41)	–0.93*** (–4.34)
4-Factor alpha	–0.97*** (–4.46)	–0.63** (–2.55)	–0.79*** (–4.66)	–1.13*** (–8.98)
5-Factor alpha	–0.95*** (4.01)	–0.63** (2.39)	–0.78*** (–4.27)	–1.11*** (–8.25)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

II. Results

A. Univariate Results and Persistence of Return Reversal

First, we document the existence of Bali et al.'s (2011) results for our sample of firms. Similar to Bali et al. (2011), we form decile portfolios based on maximum daily returns (*MAX*) each month from July 1962 to December 2014. The portfolios are formed with value and equal weighting schemes. To determine whether the overreaction effect is not just confined to small and illiquid stocks preferred by small investors, we examine two samples. The first sample includes all of the stocks from the CRSP files. Then, we concentrate on stocks with a minimum price of \$5.00 in the month of the portfolio construction.

Table I presents the subsequent month returns of the portfolios sorted on maximum daily returns. We also report the difference in the raw returns and factor alphas of the portfolios between the greatest and lowest daily returns. The *t*-statistics shown are adjusted for autocorrelation using the Newey-West (1987) method. We find that portfolios with the highest maximum daily return stocks underperform the portfolios with the lowest maximum daily return stocks in the subsequent months. For example, in the sample of all stocks, the equally weighted portfolios with the highest daily maximum returns yield a raw return of 0.67% per month, on average, compared to 1.24%

Table II. Firm-Level Fama-MacBeth Cross-Sectional Regressions

This table reports the time-series means of coefficient estimates from cross-sectional regressions. Each month from July 1962 to December 2014, we run firm-level Fama-MacBeth (1973) cross-sectional regressions of month t individual stock returns on the lagged explanatory variables in month $t - 1$. The explanatory variables include the maximum daily return (MAX), Scholes and William's (1977) beta ($BETA$), the log of market capitalization ($SIZE$), the book-to-market ratio (BTM), the buy and hold return over the previous 12 months (MOM), the monthly stock return (REV), and the illiquidity measure ($ILLIQ$). Detailed explanations on the variables are provided in the Appendix. The t -statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West (1987) method.

	<i>MAX</i>	<i>BETA</i>	<i>SIZE</i>	<i>BTM</i>	<i>MOM</i>	<i>REV</i>	<i>ILLIQ</i>
(1)	−0.08*** (−7.20)						
(2)	−0.06*** (−6.38)	0.01 (0.19)	−0.09*** (−3.11)	0.16*** (3.52)	0.88*** (7.64)	−0.04*** (−10.62)	0.01* (1.81)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

per month for those portfolios with the lowest daily maximum returns. The underperformance is statistically significant and found using four-factor alphas, as well. In order to eliminate the effect of month-end liquidity pressure related reversals in the following month, we also calculated a five-factor alpha that includes the Pastor-Stambaugh (2003) liquidity factor for a subsample of stocks from 1968 to 2014. Our results are similar to those for the raw returns and the four-factor alphas. We find similar underperformance in the value-weighted portfolios. When we restrict the sample to stocks whose price in the month of the portfolio formation is \$5.00 or greater, we derive results that are parallel to the entire sample though the magnitudes are slightly smaller for the value-weighted portfolios. Thus, our results are qualitatively similar to what are found in Bali et al. (2011). In fact, since we separately present our results for stocks with a price of equal to or greater than \$5.00, we find that the overreaction results indicated above are not driven by the small priced, illiquid stocks preferred by small investors, as is the case with many of the anomalies.

To check the robustness of the result that stocks with extreme daily returns in the current month demonstrate short-term reversal in the subsequent month, we conduct firm-level Fama-MacBeth (1973) cross-sectional regressions each month. The dependent variable in these regressions is the current month stock return. The primary explanatory variable of interest is the previous month's maximum daily return for the stock. In addition, we also include the lagged value of other control variables including stock beta ($BETA$), short-term reversal (REV), the buy and hold return over the previous 12 months (MOM), liquidity ($ILLIQ$), the book-to-market ratio (BTM), and firm size ($SIZE$) as described in more detail in the Appendix. We run the following regression specification:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}MAX_{i,t-1} + \lambda_{2,t}BETA_{i,t-1} + \lambda_{3,t}SIZE_{i,t-1} + \lambda_{4,t}BTM_{i,t-1} + \lambda_{5,t}MOM_{i,t-1} + \lambda_{6,t}REV_{i,t-1} + \lambda_{7,t}ILLIQ_{i,t-1} + \varepsilon_{i,t}. \quad (1)$$

Table II reports the time-series mean of the regression coefficients obtained from running the monthly Fama-MacBeth (1973) regressions above. The t -statistics shown are adjusted for

autocorrelation using the Newey-West (1987) method. In univariate regressions, the coefficient of *MAX* is negative and statistically significant. Thus, our firm-level regressions confirm the Table I results that stocks with high maximum daily returns demonstrate a reversal in returns in the subsequent month. When we include other control variables in the monthly regressions, the coefficient of our main variable of interest (i.e., prior month maximum daily returns) remains negative and statistically significant. We obtain results that are similar whether we include all stocks or restrict the sample to stocks with price of \$5.00 or more. The coefficients of the other control variables imply a statistically significant and negative size effect and a positive value effect. The sample of stocks indicates short-term reversal as captured by the *REV* variable, but medium-term momentum (*MOM*). Thus, our sample confirms reversals related to stocks that achieve their daily maximum return in the prior month consistent with the findings of Bali et al. (2011).

B. Investor Attention and Extreme Stock Returns

Motivated by Kahneman's (1973) assertion that attention is a scarce cognitive resource, several papers have examined the role of investors' inattention with respect to asset price dynamics (Hong and Stein, 1999; Huberman and Regev, 2001; Dyck and Zingales, 2003; Hirshleifer and Teoh, 2003; Gabaix et al., 2006; Peng and Xiong, 2006; Barber and Odean, 2008; Cohen and Frazzini, 2008; Hirshleifer et al., 2009; Dellavigna and Pollet, 2009). These studies generally conclude that due to cognitive constraints, investors are often distracted and/or have limited attention. Barber and Odean (2008) argue that when it comes to adding stocks to portfolios, the recent extreme winners catch the attention of investors. To the extent the end of the month is a convenient time for many investors to undertake their portfolio rebalancing decisions, stocks with maximum daily returns achieved very close to the month-end can plausibly catch the attention of these investors. Recent winners could be attractive to investors that may like to window dress their portfolios, as well. This explanation is offered by Thaler (1987) who states that institutions sell loss-making stocks and buy profit-making stocks in order to appear outstanding in the eyes of their shareholders and clients (window dressing). Barone (1990) also argues that institutional investors rebalance their portfolios in order to boost the performance indicators that are generally published at the end of the month. This excess demand from these investors may aggravate the mispricing of these stocks pushing them beyond their fundamental value. Therefore, it stands to reason that when the correction takes place in the subsequent month, these stocks are likely to show larger reversals.

To examine the impact of the proximity of extreme daily stock returns to the end of the month and their subsequent reversal, we calculate *DMAX* (distance of *MAX*) as the number of days between the day when the maximum daily return (*MAX*) is observed and the last trading day of each month. Then, we form decile portfolios on *DMAX* each month from July 1962 to December 2014 and report equally weighted and value-weighted average monthly returns in the next month, as well as four-factor Fama-French-Carhart alphas in Table III. We also compute five-factor alphas by including the Pastor-Stambaugh (2003) liquidity factor, as well, from 1968 to 2014. The *t*-statistics, as before, are adjusted for autocorrelation using the Newey-West (1987) method. We find that both equally weighted and value-weighted portfolios of stocks whose maximum daily returns are closer to the end of the month (Low *DMAX*) demonstrate systematically lower returns and four-factor and five-factor alphas in the subsequent month. The difference in the value-weighted return/four-factor alpha between the portfolios with the extreme *DMAX* (High *DMAX* – Low *DMAX*) is statistically significant at around 0.27% per month in Panel A of Table III. It is important to note that this result is not driven by the low returns of stocks with

Table III. Returns of Portfolios Sorted on DMAX

We calculate *DMAX* (distance of Max) as the number of days between the day when the maximum daily return (*MAX*) is observed and the last trading day of each month. Decile portfolios are formed on *DMAX* each month from July 1962 to December 2014 and report equally weighted and value-weighted average monthly returns in the next month, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas. The sample period for the five-factor alpha is from January 1968 to December 2014 due to the availability of Pastor-Stambaugh (2003) liquidity factor. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

Panel A. Summary Statistics of Portfolios on DMAX				
	Value-Weighted Returns	Equally Weighted Returns	DMAX	MAX
Low DMAX	0.64	0.56	0.67	5.29
2	0.84	1.03	3.57	5.59
3	0.93	1.22	6.67	5.68
4	1.01	1.14	9.89	5.77
5	1.09	1.26	12.96	5.74
6	0.91	1.24	16.01	5.72
7	1.13	1.27	18.95	5.78
8	1.07	1.26	21.79	5.75
9	0.94	1.26	24.69	5.71
High DMAX	0.95	1.22	27.49	5.60
High – Low	0.34***	0.66***		
	(2.93)	(9.05)		
4-Factor alpha	0.27**	0.61***		
	(2.18)	(7.59)		
5-Factor alpha	0.30**	0.61***		
	(2.27)	(6.94)		
Panel B. Average Cross-Sectional Correlation Coefficients				
	Return	DMAX	MAX	
Return	1.00	0.01***	−0.03***	
DMAX		1.00	0.02***	
MAX			1.00	

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

high maximum daily returns (*MAX*) as documented by Bali et al. (2011). Panel A of Table III reports that while stocks in Low *DMAX* have an average return of 5.29% of *MAX*, stocks in High *DMAX* have the corresponding average of 5.60% of *MAX*. This suggests that the negative relation between *DMAX* and future returns we find in this paper is not caused by the findings in Bali et al. (2011). We also note that *DMAX* and subsequent month's returns are positively correlated as indicated by the mean cross-sectional correlation of 0.01 in Panel B. Furthermore, the mean cross-sectional correlation between maximum daily returns (*MAX*) and *DMAX* is positive at 0.02. In untabulated results for the sample without price restrictions in the month of portfolio formation, we note similar findings. These results are consistent with our hypothesis that investor attention exacerbates the mispricing of stocks with extreme current month daily returns causing greater reversals in the subsequent month.

Table IV. Returns of Portfolios Sorted on DMAX and MAX

We calculate *DMAX* (distance of *MAX*) as the number of days between the day when the maximum daily return (*MAX*) is observed and the last trading day of each month. Quintile portfolios are formed on *DMAX* each month from July 1962 to December 2014 and then another set of quintile portfolios are formed on *MAX* within each *DMAX* quintile portfolio. Equally weighted and value-weighted average monthly returns in the next month, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas are reported. The sample period for the five-factor alpha is from January 1968 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

<i>Panel A. Value-Weighted Returns</i>								
	Low <i>MAX</i>	2	3	4	High <i>MAX</i>	H – L	4-Factor Alpha	5-Factor Alpha
Low <i>DMAX</i>	0.87	0.71	0.91	0.74	−0.01	−0.88*** (−3.81)	−1.08*** (−6.23)	−1.06*** (−5.73)
2	1.10	1.11	1.08	0.97	0.69	−0.41 (−1.62)	−0.54*** (−2.64)	−0.49** (−2.15)
3	1.02	0.92	1.05	0.78	0.74	−0.27 (−1.10)	−0.48** (−2.31)	−0.49** (−2.15)
4	0.97	1.08	1.15	1.09	0.80	−0.17 (−0.73)	−0.32* (−1.83)	−0.34* (−1.86)
High <i>DMAX</i>	0.91	1.15	0.98	0.93	0.79	−0.12 (−0.47)	−0.28 (−1.50)	−0.30 (−1.46)
<i>Panel B. Equally Weighted Returns</i>								
	Low <i>MAX</i>	2	3	4	High <i>MAX</i>	H – L	4-Factor Alpha	5-Factor Alpha
Low <i>DMAX</i>	1.09	1.26	1.12	0.73	−0.24	−1.33*** (6.60)	−1.56*** (−11.89)	−1.49*** (−10.73)
2	1.37	1.38	1.35	1.11	0.61	−0.77*** (−3.61)	−0.95*** (−7.57)	−0.94*** (6.94)
3	1.38	1.45	1.47	1.23	0.70	−0.68*** (−3.33)	−0.85*** (−6.17)	−0.83*** (−5.68)
4	1.25	1.43	1.42	1.32	0.84	−0.42** (−1.96)	−0.63*** (−4.51)	−0.60*** (−4.04)
High <i>DMAX</i>	1.25	1.44	1.40	1.24	0.87	−0.38* (−1.86)	−0.53*** (−4.73)	−0.54*** (−4.52)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

To further examine the effect of investor attention on the persistently low performance of stocks with maximum daily returns, we also make use of double-sorted portfolios. First, we make quintile portfolios by sorting stocks on *DMAX* each month from July 1962 to December 2014 and then sort stocks within each *DMAX* quintile into quintiles based on *MAX*. This helps us to understand the incremental impact of *MAX* on stocks with similar *DMAX* in the following month. We report equally weighted/value-weighted average monthly returns in the next month, as well as the four-factor Fama-French-Carhart and the five-factor Fama-French-Carhart-Pastor-Stambaugh alphas for these double sorted portfolios in Table IV. The *t*-statistics reported in parentheses are adjusted for autocorrelation using the Newey-West (1987) method. We find that the difference in returns of the portfolios sorted on *MAX* within each *DMAX* quintile indicate

Table V. Firm-Level Fama-MacBeth Cross-Sectional Regression: Tests of the Role of DMAX

This table reports the time-series means of coefficient estimates from cross-sectional regressions. Each month from July 1962 to December 2014, we run firm-level Fama-MacBeth (1973) cross-sectional regressions of month t individual stock returns on the lagged explanatory variables in month $t - 1$. The explanatory variables include the maximum daily return (MAX), Scholes and William's (1977) beta ($BETA$), the log of market capitalization ($SIZE$), the book-to-market ratio (BTM), the buy and hold return over the previous 12 months (MOM), monthly stock returns (REV), and the illiquidity measure ($ILLIQ$). The detailed explanations of the variables are provided in the Appendix. The t -statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West (1987) method.

	<i>MAX</i>	<i>DMAX</i>	<i>MAX*DMAX</i>	<i>BETA</i>	<i>SIZE</i>	<i>BTM</i>	<i>MOM</i>	<i>REV</i>	<i>ILLIQ</i>
(1)	−0.12*** (−7.89)	0.00 (0.62)	0.00*** (6.78)						
(2)	−0.09*** (−6.25)	0.00 (0.91)	0.00*** (4.03)	0.01 (0.21)	−0.10** (−2.50)	0.16*** (3.07)	0.88*** (7.48)	−0.04*** (−8.49)	0.02** (2.50)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

reversals as documented earlier and is shown in the last two columns. However, the absolute reversal monotonically increases as $DMAX$ decreases. For example, in Panel A, the difference in the monthly value-weighted returns between High MAX and Low MAX of the portfolios with high $DMAX$ is −0.12% and is statistically insignificant. The same difference in monthly value-weighted returns for portfolios with low $DMAX$ is statistically significant at −0.88% with t -statistic of −3.88. The difference between −0.88% and −0.12% is statistically significant, as well. We find similar results with the four-factor Fama-French-Carhart and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas. Our results in Panel B with the equally weighted portfolios echo our findings in Panel A. Therefore, our analysis in Table IV provides additional support to our argument that investor attention adds to the mispricing of stocks with extreme daily returns.

In order to add robustness to our analyses, we conduct monthly Fama-MacBeth (1973) cross-sectional regressions at the firm level, where the dependent variable is the current month's return. The independent variables are the lagged values of our primary variables of interest, MAX and $DMAX$. The incremental impact of $DMAX$ on MAX to explain monthly returns is captured through an interaction term, $MAX*DMAX$. We also include the lagged values of other control variables as defined in more detail in the Appendix.

Specifically, we run two specifications of the following full regression:

$$\begin{aligned}
 R_{i,t} = & \lambda_{0,t} + \lambda_{1,t}MAX_{i,t-1} + \lambda_{2,t}DMAX_{i,t-1} + \lambda_{3,t}MAX_{i,t-1} * DMAX_{i,t-1} \\
 & + \lambda_{4,t}BETA_{i,t-1} + \lambda_{5,t}SIZE_{i,t-1} + \lambda_{6,t}BTM_{i,t-1} + \lambda_{7,t}MOM_{i,t-1} + \lambda_{8,t}REV_{i,t-1} \\
 & + \lambda_{9,t}ILLIQ_{i,t-1} + \varepsilon_{i,t}.
 \end{aligned} \tag{2}$$

The results are provided in Table V. MAX is negative and statistically significant in two specifications of the regression. For example, in the full regression of Equation (2), the estimated coefficient of MAX is −0.09 with a t -statistic of −6.25. Our main variable of interest, the interaction

between *DMAX* and *MAX*, is significantly positive in both two regression specifications. In the full regression of Equation (2), the interaction term has an estimated coefficient of 0.00 (approximated from 0.0022) with a *t*-statistic of 4.03. Thus, this regression result suggests that the closer the stocks are to the end of the month, when they attain their daily maximum return in that month, the more negative their returns are in the following month.⁸

C. Relationship between Investor Attention and Daily Maximum Return

We argue in Section II.B that as institutional investors rebalance their portfolios at the end of the month toward winners to window dress their performance, they are more likely to buy stocks that have attained their daily return toward the end of the month. This occurs as attention is a limited cognitive resource that gravitates toward those stocks that attain their daily maximum return closer to the end of the month than those that hit the mark sooner. In this section, we empirically demonstrate that proxies for attention are positively related to those stocks who exhibit their maximum daily returns toward the end of the month.

Following prior literature, we use two proxies for investor attention. Barber and Odean (2008) employ abnormal trading volume as a proxy for investor attention. For each day from July 1962 to December 2014, we calculate abnormal trading volume following Barber and Odean (2008) as dollar trading volume on the day/average dollar trading volume over the previous one year. *DMAX* (distance of *MAX*) is the number of days between the day when *MAX* (maximum daily return) is observed and the last trading day of each month. Quintile portfolios are formed on *DMAX* each month from July 1962 to December 2014 and then another quintile portfolio is formed on *MAX* within each *DMAX* quintile portfolio. We compute the time-series average of the cross-sectional means of abnormal trading volume for each portfolio of stocks in days during the month before and after they attain the daily maximum return.⁹ The results are reported in Table VI.

In Panel A, we determine that the mean (median) abnormal trading volume is 1.11 (0.63) with a low of 0 and maximum of 141. More important results are reported in Panels B and C. In Panel B, we examine the abnormal trading volume before the stocks achieve their daily maximum return conditioned upon how close they are toward the end of the month. We find that abnormal trading volume is positively related to daily maximum returns in each quintile of *DMAX*. For example, it is 1.14 for those stocks in the highest quintile of daily maximum returns in Low *DMAX* compared to 0.92 for those stocks in the lowest quintile of the daily maximum return in Low *DMAX*. This result is not surprising as Barber and Odean (2008) use daily maximum returns as a proxy for investor attention. The results we document here is a manifestation of the positive association between the two proxies of investor attention. More importantly, we also see that the difference in the abnormal turnover for the highest quintile and the lowest quintile of maximum daily returns is markedly lower at 0.22 for the lowest *DMAX* portfolios versus 0.57 for the highest *DMAX* portfolios. In other words, investor attention is much lower in absolute terms for the lowest *DMAX* portfolios relative to the highest *DMAX* portfolios.

In Panel C, we display the average abnormal trading volume for *DMAX* and *MAX* sorted portfolios after the stocks achieve their daily maximum returns. Similar to Panel B, we find a positive association between abnormal trading volume and maximum daily return portfolios. Moreover, the absolute abnormal trading volume in each of the 25 portfolios is generally much

⁸ The positive coefficient of the interaction variable is due to the fact that *DMAX* is computed as the difference between the last trading day of the month and the day the stock achieved its highest return in that month.

⁹ If the maximum daily return is observed on the first trading day of the month, we compute abnormal trading volume before *MAX* for the last trading day of the previous month. Average abnormal trading volume after *MAX* includes the day when *MAX* is observed.

Table VI. Average Abnormal Trading Volume for Investor Attention

Each day, from July 1962 to December 2014, we calculate abnormal trading volume following Barber and Odean (2008) as the dollar trading volume on the day/average dollar trading volume over the previous one year. *DMAX* (distance of *MAX*) is the number of days between the day when *MAX* (maximum daily return) is observed and the last trading day of each month. Quintile portfolios are formed on *DMAX* the first of each month from July 1962 to December 2014 and then another quintile portfolio is formed on *MAX* within each *DMAX* quintile portfolio.

Panel A. Distribution of Average Abnormal Trading Volume						
Mean	Median		Minimum		Maximum	
1.11	0.63		0.00		141.39	
Panel B. Average Abnormal Trading Volume before MAX						
	Low MAX	2	3	4	High MAX	H – L
Low DMAX	0.92	0.96	0.98	1.02	1.14	0.22
2	0.95	0.98	1.01	1.06	1.21	0.25
3	0.96	1.00	1.03	1.08	1.25	0.28
4	1.00	1.03	1.07	1.15	1.33	0.33
High DMAX	1.10	1.14	1.20	1.33	1.67	0.57
Panel C. Average Abnormal Trading Volume after MAX						
	Low MAX	2	3	4	High MAX	H – L
Low DMAX	1.04	1.24	1.46	1.86	3.83	2.79
2	0.96	1.06	1.18	1.41	2.51	1.55
3	0.95	1.02	1.11	1.28	2.05	1.10
4	0.96	1.01	1.09	1.23	1.83	0.88
High DMAX	0.96	1.01	1.07	1.19	1.72	0.75
Panel D. Difference of Average Abnormal Trading Volume between after MAX and before MAX						
	Low MAX	2	3	4	High MAX	H – L
Low DMAX	0.12	0.28	0.48	0.84	2.69	2.57
2	0.01	0.08	0.17	0.35	1.30	1.30
3	−0.01	0.02	0.08	0.19	0.81	0.82
4	−0.04	−0.02	0.01	0.08	0.50	0.54
High DMAX	−0.14	−0.13	−0.12	−0.14	0.05	0.18
Low – High						2.39*** (35.13)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

higher when compared to Panel B consistent with the idea that investors' attention is heightened subsequent to stocks achieving daily returns. The higher the daily return, the more attention is devoted to them. We also note that the increase in abnormal trading volume is higher for lower *DMAX* portfolios than higher *DMAX* portfolios. Interestingly, the numbers in the last column indicating the difference in abnormal trading volume between the highest and the lowest daily stock portfolios for each *DMAX* quintile are also much higher relative to Panel B. However, more importantly and consistent with our hypotheses, the increase is much higher for lower *DMAX* portfolios than for higher *DMAX* portfolios. For example, the difference in abnormal

trading volume between the highest and lowest daily maximum returns after stocks achieve their daily maximum return is 2.79 compared to 0.22 in Panel B prior to stocks attaining their daily maximum returns for the lowest *DMAX* portfolio. The corresponding increase for the highest *DMAX* portfolio is from 0.57 to 0.75. We see a monotonic decline in the difference as we move farther away from the end of the month. Panel D examines the difference of figures between Panels B and C for the double sorted portfolios on *DMAX* and *MAX*. The difference in high minus low portfolio stocks returns decline as we move away from the end of the month, similar to the results in Panel C. The difference between high minus low portfolio stock returns between the lowest and highest *DMAX* sorts is 2.39 ($= 2.57 - 0.18$) and highly statistically significant.¹⁰ Thus, this table confirms that stocks that achieve their daily maximum returns toward the end of the month are more likely to grab the attention of investors making them candidates for addition to portfolios causing greater mispricing and leading to larger reversals in the following month.

To measure the attention for stocks with different days other than the end of the month, we also download the GSVI using ticker for our sample of stocks from 2004 to the end of 2014. We begin in 2004 as it is the first year for which GSVI data are available. The GSVI is available for some stocks on weekly basis while, for others, it is available on a monthly basis. GSVI information is also available for some stocks on both a weekly and a monthly basis. Since our analysis relates to those days between the end of the month to the day the stocks attain their maximum daily return, we restrict our analysis to the sample of stocks with weekly GSVI. The GSVI is already normalized to have a value of 0 to 100. We delete any stock that has a GSVI greater than 100. GSVI tends to increase over time for some stocks and stocks enter the GSVI database at different times. In order to compare the changes in the GSVI from one week to another across stocks that enter the sample at different stages, we standardize GSVI for each stock to have a mean of 0 and *SD* of 1. To ensure that we have a reasonable number of observations for each stock for standardization, we delete any stock with less than two years of history in GSVI. However, our results are robust to their inclusion in sample.

We measure the change in GSVI in the event week when the stocks attain their daily maximum return and the week prior to that. In untabulated results, we also compute the change in GSVI for the event week and two and three weeks prior to the event week and find similar results. In Panel A of Table VII, we report the time-series mean of the cross-sectional averages of GSVI for the entire sample. The mean GSVI is -0.012 with a much lower median of -0.153 . The average change in GSVI between the event week and the prior week are shown in Panel B for stocks sorted in 5×5 groups based on *DMAX* and the daily maximum return (*MAX*). We find that the change in GSVI is much greater in magnitude for stocks with the highest *MAX* versus those with the lowest *MAX* in all of the quintiles of the *DMAX* portfolio. For example, it is 0.021 for stocks with the lowest *MAX* return and 0.069 for those with the highest *MAX* return in the highest *DMAX* portfolios. This is consistent with the idea that stocks with higher absolute maximum returns grab the attention of investors to a greater degree than stocks with lower maximum daily returns. This finding is similar to our results above using abnormal trading volume. However, according to the last column that indicates a difference in the change of the GSVI between the highest and lowest max portfolios in each *DMAX* quintile, the average change in GSVI is much larger for the lowest *DMAX* at 0.07 relative to 0.05 for the highest *DMAX* portfolios. The difference in the change in GSVI for the lowest *DMAX* stocks of 0.07 is statistically significantly higher than 0.05 for the highest *DMAX* quintile of stocks as illustrated in the last row of Table VII. Thus, similar to our results using abnormal trading volume, these results are consistent with the idea that while investor attention increases for all stocks that reach their daily highs in a month, attention is much

¹⁰ We thank an anonymous referee for this insightful comment.

Table VII. Google Search Volume Index for Investor Attention

We download the Google Search Volume Index (GSVI) from Google Trends using tickers of stocks listed on the NYSE, AMEX, and Nasdaq from 2004 to 2014. We standardize GSVI for each firm so that it has a mean of 0 and a *SD* of 1. *DMAX* (distance of *MAX*) is the number of days between the day when *MAX* (maximum daily return) is observed and the last trading day of each month. Quintile portfolios are formed on *DMAX* the first of each month and then another quintile portfolio is formed on *MAX* within each *DMAX* quintile portfolio

Panel A. Distribution of Google Search Volume Index						
Mean	Median		Minimum		Maximum	
-0.012	-0.15		-3.26		7.51	
Panel B. Average Change of Google Search Volume Index between Event Week and Week (-1)						
	Low MAX	2	3	4	High MAX	H – L
Low DMAX	-0.03	-0.03	-0.01	-0.00	0.03	0.07
2	-0.02	-0.01	-0.02	-0.01	0.02	0.04
3	-0.02	-0.01	-0.02	-0.01	0.04	0.06
4	0.01	0.00	0.02	0.01	0.05	0.04
High DMAX	0.02	0.03	0.02	0.02	0.07	0.05
Average	-0.00	-0.01	-0.00	-0.01	0.06	
Low – High						0.02*** (4.58)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

higher for those stocks that reach their daily high closer to the end of the month. Our analysis in this section provides direct evidence to our assertion that stocks that reach their daily maximum return toward the end of the month are far more likely to grab the attention of inattentive investors than those stocks that attain their maximum daily returns earlier in the month.

D. DMAX Effect and Liquidity

In recent papers, Nagel (2012) and Hameed and Mian (2015) provide evidence regarding compensation for liquidity provisions and return reversals. In particular, one could argue that high *MAX* returns toward the end of the month are related to greater pressure to buy that reverses in the next few days in the following month. It is worth noting that our main results in Tables IV and V control for liquidity effects by using the five-factor Fama-French-Carhart-Pastor-Stambaugh in Table IV and the Amihud (2002) liquidity factor in Table V. However, we provide clearer evidence in this section to indicate that our results are beyond that of the liquidity-related buying pressure that leads to reversal in the following month.

If the results reported in Table IV with respect to the lowest *DMAX* were related to month-end buying pressure, then it is reasonable to expect the reversal for these portfolios to be concentrated in the early days of the following month. We should observe no such reversal in the later days of the following month. In Table VIII, we exclude trading days 1, 2, 3, 4, and 5 of the following month and report the average high *MAX* minus low *MAX* returns, on the raw, four-factor Fama-French-Carhart, as well as the five-factor Fama-French-Carhart-Pastor-Stambaugh alpha basis. We find that while the magnitude of reversal declines as we move further away from the beginning

Table VIII. Average Return Difference between High Max Portfolios and Low Max Portfolios across DMAX Portfolios after Excluding Returns in the Beginning Days of the Month

We calculate *DMAX* (distance of *MAX*) as the number of days between the day when the maximum daily return (*MAX*) is observed and the last trading day of each month. Quintile portfolios are formed on *DMAX* each month from July 1962 to December 2014 and another quintile portfolio is formed on *MAX* within each *DMAX* portfolio. *Ret(-j)* is the monthly return after excluding the first *j* days of the returns in the following month. Equally weighted and value-weighted average monthly returns of High *MAX* – Low *MAX* in the next month, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas are reported. The sample period for the five-factor alpha is from January 1968 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

	<i>Ret(-1)</i>	<i>Ret(-2)</i>	<i>Ret(-3)</i>	<i>Ret(-4)</i>	<i>Ret(-5)</i>
<i>Panel A. Value-Weighted Returns</i>					
Low <i>DMAX</i>	–0.91*** (–4.99)	–0.84*** (–4.88)	–0.77*** (–4.63)	–0.73*** (–4.51)	–0.62*** (–3.94)
4-Factor alpha	–1.08*** (–8.98)	–1.01*** (–8.52)	–0.96*** (–7.97)	–0.88*** (–7.66)	–0.73*** (–6.03)
5-Factor alpha	–1.02*** (–7.92)	–0.96*** (–7.51)	–0.89*** (–6.96)	–0.83*** (–6.53)	–0.71*** (–5.23)
High <i>DMAX</i>	–0.34** (–1.70)	–0.40** (–2.15)	–0.41** (–2.26)	–0.40** (–2.25)	–0.33* (–1.87)
4-Factor alpha	–0.42*** (–3.15)	–0.49*** (–4.13)	–0.50*** (–3.79)	–0.46*** (–3.37)	–0.35*** (–2.30)
5-Factor alpha	–0.42*** (–3.03)	–0.50*** (–3.85)	–0.50*** (–3.63)	–0.46*** (–3.20)	–0.34** (–2.29)
<i>Panel B. Equally Weighted Returns</i>					
Low <i>DMAX</i>	–0.92*** (–5.10)	–0.84*** (–5.00)	–0.78*** (–4.73)	–0.73*** (–4.61)	–0.62*** (–4.02)
4-Factor alpha	–1.10*** (–9.10)	–1.03*** (–8.80)	–0.97*** (–8.22)	–0.89*** (–7.95)	–0.75*** (–6.34)
5-Factor alpha	–1.02*** (–7.96)	–0.98*** (–7.58)	–0.92*** (–7.06)	–0.87*** (–6.62)	–0.69*** (–5.33)
High <i>DMAX</i>	–0.35* (–1.82)	–0.41** (–2.28)	–0.42** (–2.39)	–0.41** (–2.38)	–0.34** (–1.97)
4-Factor alpha	–0.44*** (–3.34)	–0.51*** (–4.29)	–0.52*** (–3.95)	–0.48*** (–3.49)	–0.36** (–2.42)
5-Factor alpha	–0.42*** (–3.27)	–0.50*** (–4.11)	–0.51*** (–3.89)	–0.46*** (–3.44)	–0.33** (2.29)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

of the month, the reversals are large and statistically significant for the low *DMAX* portfolios. For example, after excluding the first five trading days of the following month, in Panel A, for the value-weighted portfolios, the raw return is statistically significant at –0.62% for the low *DMAX* portfolio, while the entire month reversal for the same portfolio reported in Table IV is –0.88%. This implies that return reversal is not concentrated in the early days of the month

as would have been consistent with a buying pressure theory. Our results using the four-factor Fama-French-Carhart alpha, as well as the five-factor Fama-French-Carhart-Pastor-Stambaugh alpha, are similar as well. Our results employing equally weighted portfolios in Panel B echo our findings in Panel A. In unreported results, we also examine whether the return reversal is due more so to high *MAX* stocks or low *MAX* stocks after excluding the first five trading days of the following month. We did this with the rationale that month end buying pressure induces reversals for *MAX* stocks and should be larger for high *MAX* stocks relative to low *MAX* stocks. We found that the average return is quite stable for high *MAX* stocks, but drops significantly for low *MAX* stocks as we exclude returns in the first few days of the following month. This is also consistent with the idea that stocks that achieve their daily maximum returns closest to the month-end do not experience greater reversals in the following month due to buying pressure related liquidity effects.

E. PTMA and Extreme Stock Returns

The theoretical work of Barberis et al. (2001), Barberis et al. (2003), and Grinblatt and Han (2005) attempt to study the impact of psychological biases on the risk attitude of investors and how this influences the cross-section of returns. In particular, they find that PTMA-motivated specifications of preferences have a systematic influence on the cross-section of returns. For example, Grinblatt and Han (2005) and Frazzini (2006) use PTMA arguments to propose that investors are risk seeking in losses that lead to the disposition effect. That is, the tendency to sell winners and hold on to losers in portfolios. Their basic argument rests on the S-shaped utility curve (value function) faced by investors that encourages risk seeking in losses and risk aversion in gains. We propose that risk-seeking PTMA investors sitting on losses are attracted toward stocks with high *MAX* as they mistakenly believe that those stocks have a greater possibility to recoup their losses. This heightens the mispricing of these stocks. Thus, these stocks experience greater reversals in the subsequent month.¹¹ We use the *CGO* variable, as in Grinblatt and Han (2005), to capture differing risk-seeking attitudes among investors. It is worth noting that we use the *CGO* measure to capture differential risk attitudes of investors conditioned on past capital gains and losses. Grinblatt and Han (2005) use this measure to explain momentum in stock returns. In contrast, we believe that this measure helps us capture investors' differing risk profiles that aggravates mispricing attributed to stocks with a daily *MAX* return. Following Grinblatt and Han (2005), we compute reference price (cost basis) RP_t for each stock at the end of every month from July of 1962 to December 2014 using up to three years of previous daily data.¹² Our estimate of reference price is as follows:

$$RP_t = \frac{1}{k} \sum_{n=1}^T \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n}, \quad (3)$$

where V_t is date t 's turnover in the stock. T refers to the number of trading days in the previous three years with available daily price and volume information. The term in the parentheses multiplying

¹¹ Bhootra and Hur (2015) explain the negative relation between idiosyncratic volatility and returns using the S-shaped utility function under prospect theory and mental accounting.

¹² The use of $T = 3$ years, while somewhat arbitrary, recognizes the fact that longer time periods are not useful as distant market prices have little effect on the reference price. It also gives us an accurate measure of unrealized capital gains (losses). Moreover, Grinblatt and Han (2005) find that the ability of the capital gains overhang measure to predict future returns is insensitive to using three, five, or seven years of past returns and volume data.

Table IX. Returns of Portfolios Sorted on Capital Gains Overhang and then on MAX

We form quintile portfolios on capital gains overhang (*CGO*) and then form another quintile portfolio on *MAX* within each quintile portfolio on *CGO* from July 1962 to December 2014. Equally weighted average monthly returns in the following month after portfolio formation, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas are reported. The sample period for the five-factor alphas is from January 1968 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The detailed information on *CGO* is provided in the main text. The *CGO* is expressed as a percentage in the following table. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

	CGO	Low MAX	2	3	4	High MAX	H – L	4-Factor Alpha	5-Factor Alpha
<i>Panel A. Value-Weighted Returns</i>									
CGO1	–56.30	1.26	1.14	0.89	0.80	0.07	–1.19*** (–4.36)	–1.32*** (–5.48)	–1.36*** (–4.96)
2	–16.30	1.12	0.87	0.85	0.51	0.08	–1.04*** (–4.11)	–1.25*** (–5.99)	–1.21*** (–5.62)
3	–2.60	1.01	0.93	0.93	0.87	0.54	–0.47** (–2.12)	–0.69*** (–4.01)	–0.73*** (–3.74)
4	7.90	0.92	0.91	1.07	1.03	1.01	0.09 (0.41)	–0.04 (–0.23)	–0.05 (–0.21)
CGO5	21.40	1.08	1.13	1.23	1.43	1.42	0.34 (1.63)	0.22 (1.24)	0.26 (1.42)
<i>Panel B. Equally Weighted Returns</i>									
CGO1	–53.70	1.53	1.54	1.19	0.74	–0.33	–1.86*** (–9.91)	–1.93*** (–14.06)	–1.95*** (–13.37)
2	–16.40	1.30	1.30	1.08	0.77	–0.18	–1.49*** (–7.79)	–1.61*** (–13.55)	–1.57*** (–11.88)
3	–2.80	1.20	1.32	1.21	1.04	0.33	–0.87*** (–4.39)	–1.09*** (–9.08)	–1.08*** (–8.08)
4	7.80	1.20	1.33	1.32	1.32	0.92	–0.27 (–1.31)	–0.50*** (–3.66)	–0.47*** (–3.02)
CGO5	22.50	1.41	1.59	1.64	1.70	1.57	0.17 (0.82)	–0.07 (–0.50)	0.01 (0.06)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

P_{t-n} is weights and k is a constant that forces the entire weights sum to one. The weight on P_{t-n} reflects the probability that the shares purchased on date $t - n$ have not been traded since. Our proxy for *CGO* for each stock at the end of each month t is:

$$g_t = \frac{P_t - RP_t}{P_t}, \quad (4)$$

where P_t is the price of the stock at the end of month t . We make appropriate adjustments for stock splits and stock dividends in share turnover and share price variables, while computing RP_t and g_t . Thus, we provide *CGO* variable for each stock at the end of every month from July 1962 to December 2014.

Table X. Firm-Level Fama-MacBeth Cross-Sectional Regressions: Tests of the Role of Risk Preference

This table reports the time-series means of coefficient estimates from cross-sectional regressions. Each month, from July 1962 to December 2014, we run firm-level Fama-MacBeth(1973) cross-sectional regressions of month t individual stock returns on the lagged explanatory variables in month $t - 1$. The explanatory variables include the maximum daily return (MAX), Scholes and William's (1977) beta ($BETA$), the log of market capitalization ($SIZE$), the book-to-market ratio (BTM), the buy and hold return over the previous 12 months (MOM), monthly stock returns (REV), capital gains overhang (CGO), and the illiquidity measure ($ILLIQ$). The detailed explanations of the variables are provided in the Appendix. The t -statistics, reported in parentheses, are adjusted for autocorrelation using the Newey-West (1987) method

	<i>MAX</i>	<i>CGO</i>	<i>MAX*CGO</i>	<i>BETA</i>	<i>SIZE</i>	<i>BTM</i>	<i>MOM</i>	<i>REV</i>	<i>ILLIQ</i>
(1)	−0.08*** (−6.22)	−0.00** (−2.26)	0.15*** (9.43)						
(2)	−0.05*** (−5.17)	−0.01*** (−5.28)	0.16*** (8.12)	0.01 (0.13)	−0.09** (−2.30)	0.15*** (2.91)	0.87*** (7.80)	−0.04*** (−9.62)	0.01** (2.46)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

To test our hypothesis that investors with capital losses flock to stocks with extreme daily returns and aggravate mispricing that shows up as greater reversals in subsequent months, we adopt the following procedure. We first form quintile portfolios based on CGO and then form another set of quintile portfolios based on MAX within each quintile portfolio on CGO from July 1962 to December 2014. We compute value-weighted and equally weighted average monthly returns, as well as four-factor Fama-French-Carhart and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas in the following month after portfolio formation. The results are reported in Table IX. Consistent with our prediction, we find that portfolios of stocks with extreme daily returns that have had greater losses in the prior periods as proxied by low CGO also show greater reversals in subsequent months. For example, in Panel A, the difference in value-weighted returns between High MAX and Low MAX among stocks in the highest quintile CGO is 0.34% and it is statistically insignificant. However, the same difference in monthly value-weighted returns for stocks in the lowest quintile CGO is highly significant at −1.19% with a t -statistic of −4.36%. We find similar results with the four-factor and five-factor alphas. The results are qualitatively similar for the equally weighted returns in Panel B, as well. Thus, our results indicate that the risk-seeking attitude of investors with unrealized capital losses amplifies the mispricing of stocks with extreme daily returns.

We also conduct the above analyses controlling for other control variables at the firm level by running monthly Fama-MacBeth (1973) cross-sectional regressions where the dependent variable is the current month return. This analysis is similar to our analysis of the incremental impact of $DMAX$ on MAX at firm level for future stock returns in the previous analysis. Here, we examine the impact of CGO on MAX for future stock returns. The independent variables are lagged values of our primary variables of interest MAX and CGO . The incremental impact of CGO on MAX to explain monthly returns is captured through an interaction term, $MAX*CGO$. We also include the lagged values of other control variables as defined in more detail in the Appendix.

Table XI. Average Return Difference between High Max Portfolios and Low Max Portfolios across CGO Portfolios after Excluding Returns in the Beginning Days of the Month

Quintile portfolios are formed on *CGO* (capital gains overhang) first each month from July 1962 to December 2014 and then another quintile portfolio is formed on *MAX* within each *CGO* quintile portfolio. Low (High) *CGO* is the lowest (highest) quintile portfolio on *CGO*. *Ret(-j)* is the monthly return after excluding first *j* days of returns in the following month. This table reports value-weighted and equally weighted average monthly returns of High *MAX* – Low *MAX*, four-factor Fama-French-Carhart alphas, and five-factor Fama-French-Carhart-Pastor-Stambaugh alphas. The sample period for the five-factor alpha is from January 1968 to December 2014 due to the availability of the Pastor-Stambaugh (2003) liquidity factor. The autocorrelation adjusted *t*-statistics using the Newey-West (1987) method are reported in parentheses.

	<i>Ret(-1)</i>	<i>Ret(-2)</i>	<i>Ret(-3)</i>	<i>Ret(-4)</i>	<i>Ret(-5)</i>
<i>Panel A. Value-Weighted Returns</i>					
Low <i>CGO</i>	–1.62*** (–9.11)	–1.55*** (–8.92)	–1.49*** (–8.75)	–1.37*** (–8.56)	–1.22*** (–7.54)
4-Factor alpha	–1.63*** (–11.17)	–1.58*** (–10.12)	–1.51*** (–9.03)	–1.37*** (–8.75)	–1.19*** (–6.91)
5-Factor alpha	–1.64*** (–10.39)	–1.60*** (–9.39)	–1.52*** (–8.42)	–1.39*** (–8.13)	–1.20*** (–6.56)
High <i>CGO</i>	0.36* (1.94)	0.31* (1.81)	0.27* (1.65)	0.25 (1.55)	0.25* (1.61)
4-Factor alpha	0.15 (0.97)	0.09 (0.64)	0.04 (0.28)	0.05 (0.33)	0.08 (0.64)
5-Factor alpha	0.23 (1.37)	0.17 (1.09)	0.14 (0.89)	0.14 (0.96)	0.18 (1.28)
<i>Panel B. Equally Weighted Returns</i>					
Low <i>CGO</i>	–1.64*** (–9.42)	–1.56*** (–9.22)	–1.50*** (–9.01)	–1.38*** (–8.82)	–1.23*** (–7.75)
4-Factor alpha	–1.65*** (–11.30)	–1.60*** (–10.25)	–1.52*** (–9.15)	–1.38*** (–8.84)	–1.19*** (–6.97)
5-Factor alpha	–1.66*** (–10.58)	–1.61*** (–9.57)	–1.53*** (–8.55)	–1.39*** (–8.24)	–1.21*** (–6.64)
High <i>CGO</i>	0.33* (1.82)	0.29* (1.70)	0.25 (1.54)	0.22 (1.43)	0.22 (1.48)
4-Factor alpha	0.11 (0.77)	0.07 (0.47)	0.02 (0.11)	0.02 (0.13)	0.06 (0.42)
5-Factor alpha	0.19 (1.18)	0.15 (0.92)	0.11 (0.72)	0.11 (0.76)	0.15 (1.06)

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

Specifically, we run specifications from the following full regression:

$$\begin{aligned}
 R_{i,t} = & \lambda_{0,t} + \lambda_{1,t}MAX_{i,t-1} + \lambda_{2,t}CGO_{i,t-1} + \lambda_{3,t}CGO * MAX_{i,t-1} + \lambda_{4,t}BETA_{i,t-1} \\
 & + \lambda_{5,t}SIZE_{i,t-1} + \lambda_{6,t}BTM_{i,t-1} + \lambda_{7,t}MOM_{i,t-1} + \lambda_{8,t}REV_{i,t-1} \\
 & + \lambda_{9,t}ILLIQ_{i,t-1} + \varepsilon_{i,t}.
 \end{aligned}
 \tag{5}$$

The results can be found in Table X. *MAX* is statistically significant and negative in two specifications of Regression (1) and (2). For example, the estimated coefficient of *MAX* is -0.05 with a *t*-statistic of -5.17 after controlling for other major variables in Regression (2). Our main variable of interest, the interaction between *CGO* and *MAX*, is significantly negative in both regression specifications as well. For example, the interaction term has an estimated coefficient of 0.16 with a *t*-statistic of 8.12 in Regression (2). In summary, our results in this section establish that the risk-seeking attitude of investors with losses magnifies the mispricing of stocks with extreme daily returns.

F. CGO and Liquidity

Grinblatt and Han (2005) establish that past returns are only a noisy measure of *CGO*. *CGO* retains its predictive power for the cross-section of returns in presence past returns. However, if stocks with capital losses are positively correlated with past returns, then one may argue that our results may be alternatively explained by liquidity since loser stocks are likely be illiquid too. In order to rule out this possibility, we perform a similar analysis as in Section II.D. We exclude returns up to the five first trading days of the following month and compute value-weighted and equally weighted returns in the following month of high *MAX* – low *MAX* for portfolios sorted on *GGO*. The results reported in Table XI indicate that return reversal is largely confined to low *CGO* portfolios based on raw or four- and five-factor alphas. The reversals remain large in magnitude and statistically significant even after excluding five days of the following month. If low *CGO* portfolios' reversal had been related to the illiquidity of those portfolios, then the reversal should have taken place in the first few days of the following month. We do not see that in the results. In unreported results, we also examine when the return reversal is due more to high *MAX* stocks or low *MAX* stocks after excluding the first five trading days of the following month. We did this with the rationale that the illiquidity-induced reversal for *MAX* stocks should be larger for high *MAX* stocks relative to low *MAX* stocks. We found that the average return is quite stable for high *MAX* stocks, but drops significantly for low *MAX* stocks. Thus, it provides another piece of supporting evidence to eliminate the possibility that our results are driven by liquidity.

III. Conclusions

We extend the findings of a recent paper by Bali et al. (2011) that demonstrates the negative and significant relation between maximum daily returns over the past one month and expected stock returns. We add two new results. First, we determine that the subsequent month reversal of returns for stocks with extreme daily returns is related to investor attention and their portfolio rebalancing decisions at the end of the month. Specifically, stocks that achieved their maximum daily returns toward the end of the month and having caught the attention of investors becomes mispriced and shows greater reversals than other stocks in the following month. We find that our results are beyond that of a plausible month-end liquidity story to explain our findings. In addition, we link the subsequent month reversal of stocks with extreme daily returns to the risk preferences of investors wherein investors with unrealized capital losses become risk seeking and add stocks with daily maximum returns to their portfolios to recoup their losses. We find that stocks that are associated with capital losses show greater reversals in the following month. If stocks with capital losses suffer from illiquidity issues, then our findings may be an illiquidity driven reversal. To rule out the illiquidity driven reversal for our findings, we report returns in the following month after excluding the first five trading days and find that our results are still

valid. Our results are robust to the measurement of reversals using raw returns or four-factor Fama-French-Carhart and five-factor Fama-French-Carhart-Pastor-Stambaugh adjusted alphas.

Appendix: Definitions of Variables

MAX: *MAX* is the maximum daily return of a stock within a month:

$$MAX_{i,t} = \max(R_{i,1}, R_{i,2}, \dots, R_{i,D_t}),$$

where $R_{i,d}$ ($d = 1, 2, \dots, D_t$) is the return on stock i on day d and D_t is the number of trading days for stock i in month t .

SIZE: *SIZE* is the natural logarithm of the stock's month-end market capitalization (price $\times$ shares outstanding).

REV: *REV* is used to capture short-term reversals in stock returns and equals the return of stock i in month t ; that is, $REV_{i,t} = R_{i,t}$.

BTM: *BTM* is the firm's book-to-market ratio. Following Fama and French (1993), we compute *BTM* in month t of a year as the ratio of the book value of equity for the fiscal year ending in the prior calendar year and the market equity at the end of December of the prior calendar year. The book value of equity, computed using Compustat data, is the stockholders' equity (DATA 216), plus balance sheet deferred taxes and investment tax credits (DATA 35), minus the book value of preferred stock (DATA56 or DATA10 or DATA 130, in that order) at the fiscal year end.

CGO: Similar to Grinblatt and Han (2005), for each stock i at the end of each month t , the capital gains overhang ($CGO_{i,t}$) is obtained as:

$$CGO_{i,t} = (P_{i,t} - RP_{i,t})/P_{i,t},$$

where $P_{i,t}$ is the price of the stock i at the end of month t and $RP_{i,t}$ is the reference price for each stock i at the end of month t . The reference price, $RP_{i,t}$, is estimated as follows:

$$RP_{i,t} = \frac{1}{k} \sum_{n=1}^T \left(V_{i,t-n} \prod_{\tau=1}^{n-1} [1 - V_{i,t-n+\tau}] \right) P_{i,t-n},$$

where $V_{i,t}$ is the turnover in stock i on day t , T is the number of trading days in the previous three years with available daily price and volume information, and $P_{i,t-n}$ is price of security i on day $t-n$.

MOM: *MOM* is the momentum variable. Following Jegadeesh and Titman (1993), the momentum variable for each stock in a given month is defined as its buy and hold return over the past 12 months.

ILLIQ: *ILLIQ* is the measure of illiquidity for a stock in a given month. Following Amihud (2002), *ILLIQ* is measured as the ratio of stock's absolute monthly return to its dollar trading volume:

$$ILLIQ_{i,t} = |R_{i,t}| / VOLD_{i,t},$$

where $R_{i,t}$ and $VOLD_{i,t}$ are the return and dollar volume, respectively, of stock i in month t .

BETA: We use the daily returns within a month to estimate a stock's beta and employ the adjustment procedure of Scholes and Williams (1977) and Dimson (1979) to mitigate the impact

of nonsynchronous trading. $BETA$ is estimated using following regression model:

$$R_{i,d} - R_{f,d} = a_i + \beta_{1,i}(R_{m,d-1} - R_{f,d-1}) + \beta_{2,i}(R_{m,d} - R_{f,d}) \\ + \beta_{3,i}(R_{m,d+1} - R_{f,d+1}) + e_{i,d},$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are the return on stock i on day d , the T-Bill return on day d , and the return on the CRSP value-weighted market index on day d , respectively. The estimate of stock's beta is given by $\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i}$.

References

- Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-Section and Time Series Effects," *Journal of Financial Markets* 5, 31–56.
- Bali, T., N. Cakici, and R. Whitelaw, 2011, "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns," *Journal of Financial Economics* 99, 427–446.
- Barber, B. and T. Odean, 2008, "All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Review of Financial Studies* 21, 785–818.
- Barberis, N., M. Huang, and T. Santos, 2001, "Prospect Theory and Asset Prices," *Quarterly Journal of Economics* 116, 1–54.
- Barberis, N., M. Huang, and R. Thaler, 2003, "Individual Preferences Monetary Gambles and the Equity Premium," NBER Working paper No. W-9997, December.
- Barone, E., 1990, "The Italian Stock Market: Efficiency and Calendar Anomalies," *Journal of Banking and Finance* 14, 483–510.
- Bhootra, A. and J. Hur, 2015, "High Idiosyncratic Volatility and Low Returns: A Prospect Theory Based Explanation," *Financial Management* 44, 295–322.
- Cheng S., A. Hameed, A. Subrahmanyam, and S. Titman, 2016, "Short-Term Reversals: The Effects of Past Returns and Institutional Exits," *Journal of Financial and Quantitative Analysis* 50, 89–117.
- Cohen, L. and A. Frazzini, 2008, "Economic Links and Predictable Returns," *Journal of Finance* 63, 1977–2011.
- DellaVigna, S. and J. Pollet, 2009, "Investor Inattention and Friday Earnings Announcements," *Journal of Finance* 64, 709–749.
- Dimson, E., 1979, "Risk Measurement When Shares are Subject to Infrequent Trading," *Journal of Financial Economics* 7, 197–226.
- Dyck, A. and L. Zingales, 2003, "The Media and Asset Prices," Harvard Business School Working paper.
- Fama, E.F. and K.R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3–56.
- Fama, E.F. and J.D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* 81, 607–636.
- Frazzini, A., 2006, "The Disposition Effect and Under-Reaction to News," *Journal of Finance* 61, 2017–2046.

- Gabaix, X., D. Laibson, G. Moloche, and S. Weinberg, 2006, "The Allocation of Attention: Theory and Evidence," *American Economic Review* 96, 1043–1068.
- Goetzmann, W. and A. Kumar, 2008, "Equity Portfolio Diversification," *Review of Finance* 12, 433–463.
- Grinblatt, M. and B. Han, 2005, "Prospect Theory, Mental Accounting, and Momentum," *Journal of Financial Economics* 78, 311–339.
- Hameed, A. and G. Mian, 2015, "Industries and Stock Return Reversals," *Journal of Financial and Quantitative Analysis* 50, 89–117.
- Harvey, C. and A. Siddique, 2000, "Conditional Skewness in Asset Pricing Tests," *Journal of Finance* 55, 1263–1295.
- Hirshleifer, D., S. Lim, and S.H. Teoh, 2009, "Driven to Distraction: Extraneous Events and Underreaction to Earnings News," *Journal of Finance* 64, 2289–2325.
- Hirshleifer, D. and S.H. Teoh, 2003, "Limited Attention, Information Disclosure, and Financial Reporting," *Journal of Accounting and Economics* 36, 337–386.
- Hong, H. and J. Stein, 1999, "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *Journal of Finance* 54, 2143–2184.
- Huberman, G. and T. Regev, 2001, "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar," *Journal of Finance* 56, 387–396.
- Jegadeesh, N. and S. Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48, 65–91.
- Kahneman, D., 1973, *Attention and Effort*, Englewood Cliffs, NJ, Prentice Hall.
- Kraus, A. and R. Litzenberger, 1976, "Skewness Preference and the Valuation of Risk Assets," *Journal of Finance* 31, 1085–1100.
- Lintner, J., 1965, "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets," *Review of Economics and Statistics* 47, 13–37.
- Mitton, T. and K. Vorkink, 2007, "Equilibrium Under-diversification and the Preference for Skewness," *Review of Financial Studies* 20, 1255–1288.
- Mossin, J., 1966, "Equilibrium in Capital Asset Market," *Econometrica* 34, 768–783.
- Nagel, S., 2012, "Evaporating Liquidity," *Review of Financial Studies* 25, 2005–2039.
- Newey, W. and K. West, 1987, "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica* 55, 703–708.
- Odean, T., 1999, "Do Investors Trade Too Much?" *American Economic Review* 89, 1279–1298.
- Pastor, L. and R.F. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* 111, 642–685.
- Peng, L. and W. Xiong, 2006, "Investor Attention, Overconfidence and Category Learning," *Journal of Financial Economics* 80, 563–602.
- Scholes, M. and J. Williams, 1977, "Estimating Betas from Non-Synchronous Data," *Journal of Financial Economics* 5, 308–328.
- Sharpe, W., 1964, "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk," *Journal of Finance* 19, 425–442.

- Smith, D., 2007, "Conditional Coskewness and Asset Pricing," *Journal of Empirical Finance* 14, 91–119.
- Thaler, R., 1987, "Seasonal Movements in Security Prices II: Weekend, Holiday, Turn of the Month, and Intraday Effects," *Journal of Economic Perspectives* 1, 169–177.
- Van Nieuwerburgh, S. and L.L. Veldkamp, 2010, "Information Acquisition and Under-Diversification," *Review of Economic Studies* 77, 779–805.

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