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ABSTRACT

Motivated by existing evidence of a preference among investors for assets with lottery-like payoffs and that many investors are poorly diversified, we investigate the significance of extreme positive returns in the cross-sectional pricing of stocks. Portfolio-level analyses and firm-level cross-sectional regressions indicate a negative and significant relation between the maximum daily return over the past one month (MAX) and expected stock returns. Average raw and risk-adjusted return differences between stocks in the lowest and highest MAX deciles exceed 1% per month. These results are robust to controls for size, book-to-market, momentum, short-term reversals, liquidity, and skewness. Of particular interest, including MAX reverses the puzzling negative relation between returns and idiosyncratic volatility recently documented in Ang et al. (2006, 2008).

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I. Introduction

What determines the cross-section of expected stock returns? This question has been central to modern financial economics since the path breaking work of Sharpe (1964), Lintner (1965), and Mossin (1966). Much of this work has focused on the joint distribution of individual stock returns and the market portfolio as the determinant of expected returns. In the classic CAPM setting, i.e., with either quadratic preferences or normally distributed returns, expected returns on individual stocks are determined by the covariance of their returns with the market portfolio. Introducing a preference for skewness leads to the three moment CAPM of Kraus and Litzenberger (1976), which has received empirical support in the literature as, for example, in Harvey and Siddique (2000) and Smith (2007).

Diversification plays a critical role in these models due to the desire of investors to avoid variance risk, i.e., to diversify away idiosyncratic volatility, yet a closer examination of the portfolios of individual investors suggests that these investors are, in general, not well-diversified.[1] There may be plausible explanations for this lack of diversification,[2] but nevertheless this empirical phenomenon suggests looking more closely at the distribution of individual stock returns rather than just co-moments as potential determinants of the cross-section of expected returns.

There is also evidence that investors have a preference for lottery-like assets, i.e., assets that have a relatively small probability of a large payoff. Two prominent examples are the favorite-longshot bias in horsetrack betting, i.e., the phenomenon that the expected return per dollar wagered tends to increase monotonically with the probability of the horse winning, and the popularity of lottery games despite the prevalence of negative expected returns.[3] Interestingly, in the latter case, there is increasing evidence that it is the degree of skewness in the payoffs that appeals to participants, although there are alternative explanations.[4]

Motivated by these two literatures, we examine the role of extreme positive returns in the cross-sectional pricing of stocks. Specifically, we sort stocks by their maximum daily return during the previous month and examine the monthly returns on the resulting portfolios over the period July 1962 to December 2005. For value-weighted decile portfolios, the difference between returns on the portfolios with the

[1] See, for example, Odean (1999), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008) for evidence based on the portfolios of a large sample of U.S. individual investors. Calvet, Campbell and Sodini (2007) present evidence on the underdiversification of Swedish households, which can also be substantial, although the associated welfare costs for the median household appear to be small.

[2] See, for example, Van Nieuwerburgh and Veldkamp (2008) for a model that generates under-diversification as a result of the returns to specialization in information acquisition.

[3] See Thaler and Ziemba (1988) for a survey of the literature detailing the anomalies associated with these phenomena.

[4] See, for example, Garrett and Sobel (1999) and Walker and Young (2001) on the skewness issue. As an example of an alternative explanation, Patel and Subrahmanyam (1978) provide a model based on lumpiness in the goods market.

highest and lowest maximum daily returns is –1.03%. The corresponding Fama-French-Carhart four-factor alpha is –1.18%. Both return differences are statistically significant at all standard significance levels. In addition, the results are robust to sorting stocks not only on the single maximum daily return during the month, but also the average of the two, three, four or five highest daily returns within the month. This evidence suggests that investors may be willing to pay more for stocks that exhibit extreme positive returns, and thus these stocks exhibit lower returns in the future.

This interpretation is consistent with cumulative prospect theory (Tversky and Kahneman (1992)) as modeled in Barberis and Huang (2008). Errors in the probability weighting of investors cause them to over-value stocks that have a small probability of a large positive return. It is also consistent with the optimal beliefs framework of Brunnermeier, Gollier and Parker (2007). In this model, agents optimally choose to distort their beliefs about future probabilities in order to maximize their current utility. Critical to these interpretations of the empirical evidence, stocks with extreme positive returns in a given month should also be more likely to exhibit this phenomenon in the future. We confirm this persistence, showing that stocks in the top decile in one month have a 35% probability of being in the top decile in the subsequent month and an almost 70% probability of being in one of the top three deciles. Moreover, maximum daily returns exhibit substantial persistence in firm-level cross-sectional regressions, even after controlling for a variety of other firm-level variables.

Not surprisingly, the stocks with the most extreme positive returns are not representative of the full universe of equities. For example, they tend to be small, illiquid securities with high returns in the portfolio formation month and low returns over the prior 11 months. To ensure that it is not these characteristics, rather than the extreme returns, that are driving the documented return differences, we perform a battery of bivariate sorts and re-examine the raw return and alpha differences. The results are robust to sorts on size, book-to-market ratio, momentum, short-term reversals, and illiquidity. Results from cross-sectional regressions corroborate this evidence.

Are there alternative interpretations of this apparently robust empirical phenomenon? Recent papers by Ang et al. (2006, 2008) document the anomalous finding that stocks with high idiosyncratic volatility have low subsequent returns. It is no surprise that the stocks with extreme positive returns also have high idiosyncratic (and total) volatility when measured over the same time period. This positive correlation is partially by construction, since realized monthly volatility is calculated as the sum of squared daily returns, but even excluding the day with the largest return in the volatility calculation only reduces this association slightly. Could the maximum return simply be proxying for idiosyncratic volatility? We investigate this question using two methodologies, bivariate sorts on extreme returns and idiosyncratic volatility and firm-level cross-sectional regressions. The conclusion is that not only is the effect of extreme positive returns we document robust to controls for idiosyncratic volatility, but that this effect reverses the idiosyncratic volatility effect documented in Ang et al. (2006, 2008). When sorted first on maximum returns, the equal-weighted return difference between high and low idiosyncratic portfolios is *positive* and both economically and statistically significant. In a cross-sectional regression context, when both variables are included, the coefficient on the maximum return is negative and significant while that on idiosyncratic volatility is *positive*, albeit insignificant in some specifications. These results are consistent with our preferred explanation—poorly diversified investors dislike idiosyncratic volatility, like lottery-like payoffs, and influence prices and hence future returns.

A slightly different interpretation of our evidence is that extreme positive returns proxy for skewness, and investors exhibit a preference for skewness. For example, Mitton and Vorkink (2007) develop a model of agents with heterogeneous skewness preferences and show that the result is an equilibrium in which idiosyncratic skewness is priced. However, we show that the extreme return effect is robust to controls for total and idiosyncratic skewness and to the inclusion of a measure of expected as in Boyer, Mitton and Vorkink (2008). It is also unaffected by controls for co-skewness, i.e., the contribution of an asset to the skewness of a well-diversified portfolio.

A further interesting question is whether the effect of extreme positive returns could be a result of investor over-reaction to firm-specific good news. As this over-reaction is reversed, returns in the subsequent month would be lower than justified by the operative model of risk and return. This hypothesis is difficult to reject definitively, but it does seem to be inconsistent with the existing literature. In particular, the preponderance of existing evidence indicates that stocks under-react not over-react to firm specific news.[5] One prominent and relevant example is the post-earnings announcement drift phenomenon, wherein the stock price continues to drift in the same direction as the price move at the earnings announcement.[6] Thus, if the extreme positive returns were caused by good earnings news, we should expect to see under-reaction not over-reaction. In fact, given that some of the firms in our high maximum return portfolio are undoubtedly there because of price moves on earnings announcement days, the low future returns are actually reduced in magnitude by this effect.

The paper is organized as follows. Section II provides the univariate portfolio-level analysis, and the bivariate analyses and firm-level cross-sectional regressions that examine a comprehensive list of control variables. Section III focuses more specifically on extreme returns and idiosyncratic volatility. Section IV presents results for skewness and extreme returns. Section V provides further robustness checks, and Section VI concludes.

[5] See Daniel, Hirshleifer and Subrahmanyam (1998) for a survey of some of this literature. However, Chan (2003) presents evidence that monthly returns exhibit reversals not continuation if the original price movements are not accompanied by a public release of news.

[6] See Bernard and Thomas (1989) and many subsequent papers.

II. Extreme Positive Returns and the Cross-Section of Expected Returns

A. Data

The first dataset includes all New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ financial and nonfinancial firms from the Center for Research in Security Prices (CRSP) for the period from January 1926 through December 2005. We use daily stock returns to calculate the maximum daily stock returns for each firm in each month as well as such variables as the market beta, idiosyncratic volatility, and various skewness measures; we use monthly returns to calculate proxies for intermediate-term momentum and short-term reversals; we use volume data to calculate a measure of illiquidity; and we use share prices and shares outstanding to calculate market capitalization. The second dataset is COMPUSTAT, which is used to obtain the equity book values for calculating the book-to-market ratios of individual firms. These variables are defined in detail in the Appendix and are discussed as they are used in the analysis.

B. Univariate Portfolio-Level Analysis

Table I presents the value-weighted and equal-weighted average monthly returns of decile portfolios that are formed by sorting the NYSE/AMEX/NASDAQ stocks based on the maximum daily return within the previous month (MAX). The results are reported for the sample period July 1962 to December 2005. We start the sample in July 1962 for the analysis because this starting point corresponds to that used in much of the literature on the cross-section of expected returns; however, the results are similar using the sample starting in January 1926. The results are also robust within subsamples of the 1962-2005 sample. For brevity, none of these robustness checks are reported in detail in the paper.

Portfolio 1 (low MAX) is the portfolio of stocks with the lowest maximum daily returns during the past month, and portfolio 10 (high MAX) is the portfolio of stocks with the highest maximum daily returns during the previous month. The value-weighted average raw return difference between decile 10 (high MAX) and decile 1 (low MAX) is –1.03% per month with a corresponding Newey-West (1987) t-statistic of –2.83. In addition to the average raw returns, Table I also presents the magnitude and statistical significance of the difference in intercepts (Fama-French-Carhart four factor alphas) from the regression of the value-weighted portfolio returns on a constant, the excess market return, a size factor (SMB), a book-to-market factor (HML), and a momentum factor (MOM), following Fama and French (1993) and Carhart (1997).[7] As shown in the last row of Table I, the difference in alphas between the high MAX and low MAX portfolios is –1.18% per month with a Newey-West t-statistic of –4.71. This difference is economically significant and statistically significant at all conventional levels.

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[7] SMB (small minus big), HML (high minus low), and MOM (winner minus loser) are described in and obtained from Kenneth French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Taking a closer look at the value-weighted averages returns across deciles, it is clear that the pattern is not one of a uniform decline as MAX increases. The average returns of deciles 1 to 7 are approximately the same, in the range of 1.00% to 1.16% per month, but, going from decile 7 to decile 10, average returns drop significantly, from 1.00% to 0.86%, 0.52% and then to –0.02% per month. Interestingly, the reverse of this pattern is evident across the deciles in the average across months of the average maximum daily return of the stocks within each decile. By definition, this average increases monotonically from deciles 1 to 10, but this increase is far more dramatic for deciles 8, 9 and 10. These deciles contain stocks with average maximum daily returns of 9%, 12%, and 24%, respectively. Given a preference for upside potential, investors may be willing to pay more for, and accept lower expected returns on, assets with these extremely high positive returns. In other words, it is conceivable that investors view these stocks as valuable lottery-like assets, with a small chance of a large gain.

As shown in the second column of Table I, similar, although somewhat less economically and statistically significant results, are obtained for the returns on equal-weighted portfolios. The average raw return difference between the low MAX and high MAX portfolios is –0.65% per month with a t-statistic of –1.83. The corresponding difference in alphas is –0.66% per month with a t-statistic of –2.31. As with the value-weighted returns, it is the extreme deciles, in this case deciles 9 and 10, that exhibit low future returns.

While conditioning on the single day with the maximum return is both simple and intuitive as a proxy for extreme positive returns, it is also slightly arbitrary. As an alternative we also rank stocks by the average of the N ($N=1, 2, \ldots, 5$) highest daily returns within the month, with the results reported in Table II. As before, we report the difference between the returns and alphas on the deciles of firms with the highest and lowest average daily returns over the prior month. For ease of comparison we report the results from Table I in the first column ($N=1$). For both the value-weighted returns (Panel A) and the equal-weighted returns (Panel B) the returns patterns when sorting on average returns over multiple days are similar to those when sorting on the single maximum daily return. In fact, if anything, the raw return and alpha differences are both economically and statistically more significant as we average over more days. For example, for value-weighted returns these differences increase in magnitude from –1.03 and –1.18 for $N=1$ to –1.23 and –1.32 for $N=5$. However, for simplicity we focus on the single day measures in the remainder of the paper except in cases where the multiple day averages are needed to illustrate or illuminate a point.

Of course, the maximum daily returns documented in Table I and those underlying the portfolio sorts in Table II are for the portfolio formation month, not for the subsequent month over which we measure average returns. Investors may pay high prices for stocks that have exhibited extreme positive returns in the past in the expectation that this behavior will be repeated in the future, but a natural question is whether these expectations are rational. Table III investigates this issue by presenting the average month-to-month portfolio transition matrix. Specifically, it presents the average probability that a stock in decile *i* (defined by the rows) in one month will be in decile *j* (defined by the columns) in the subsequent month. If maximum daily returns were completely random, then all the probabilities should be approximately 10%, since a high or low maximum return in one month should say nothing about the maximum return in the following month. Instead, all the diagonal elements of the transition matrix exceed 10%, illustrating that MAX is persistent. Of greater importance, this persistence is especially strong for the extreme portfolios. Stocks in decile 10 have a 35% chance of appearing in the same decile next month. Moreover, they have a 68% probability of being in deciles 8-10, all of which exhibit high maximum daily returns in the portfolio formation month and low returns in the subsequent month.

A slightly different way to examine the persistence of extreme positive daily returns is to look at firm-level cross-sectional regressions of MAX on lagged predictor variables. Specifically, for each month in the sample we run a regression across firms of the maximum daily return within that month on the maximum daily return from the previous month and six lagged control variables that are defined in the Appendix and discussed in more detail later—the market beta (BETA), the market capitalization (SIZE), the book-to-market ratio (BM), the return in the previous month (REV), the return over the 11 months prior to that month (MOM), and a measure of illiquidity (ILLIQ). Table IV reports the average cross-sectional coefficients from these regressions and the Newey-West (1987) adjusted t-statistics. In the univariate regression of MAX on lagged MAX, the coefficient is positive, quite large, and extremely statistically significant, and the R-squared of over 16% indicates substantial cross-sectional explanatory power. In other words, stocks with extreme positive daily returns in one month also tend to exhibit similar features in the following month. When the six control variables are added to the regression, the coefficient on lagged MAX remains large and significant.

As a final check on the return characteristics of stocks with extreme positive returns, we examine more closely the distribution of monthly returns on stocks in the high MAX and low MAX portfolios. Tables I and II report the mean returns on these stocks, and Tables III and IV document that the presence, or absence, of extreme positive returns is persistent, but what are the other features of the return distribution?

Table V presents descriptive statistics for the approximately 240,000 monthly returns on stocks within the two extreme deciles in the post-formation month. The mean returns are almost identical to those reported in Table I for the equal-weighted portfolio. The slight difference is attributable to the fact that Table I reports averages of returns across equal-weighted portfolios that contain slightly different numbers of stocks, whereas Table V weights all returns equally. In addition to having a lower average return, high MAX stocks display significantly higher volatility and more positive skewness. The percentiles of the return distribution illustrate the upper tail behavior. While median returns on high MAX stocks are lower, the returns at the 90th, 95th and 99th percentiles are more than twice as large as those for low MAX stocks. Clearly, high MAX stocks exhibit higher probabilities of extreme positive returns in the following month. The percentiles of the distribution are robust to outliers, but the moments are not, so in the final two columns we report statistics for returns where the 0.5% most extreme returns in both tails have been eliminated. While means, standard deviations and skewness for the trimmed distributions fall, the relative ordering remains—high MAX stocks have lower means, but higher volatilities and skewness than their low MAX counterparts in the subsequent month.

The complete distribution of returns on stocks in these portfolios is presented in Figure 1, where the numbers on the horizontal axis give the center of the return ranges, each of which spans 5%. For example, the columns above the number 5% represent the percentage of returns that fall between 2.5% and 7.5% for the high MAX and low MAX portfolios. The exceptions are the columns on the far left and far right which tabulate percentages of returns that fall within and below or above the range, respectively. It is clear from this plot that high MAX stocks provide a greater probability of a large positive return. For monthly returns in any range above 12.5%, high MAX stocks appear more frequently than low MAX stocks. Moreover, the relative probability increases as the returns become more extreme. Large negative returns are also more likely on high MAX stocks due to their higher volatility, and we will return to a closer examination of the role of volatility in Section III.

We do not measure investor expectations directly, but the results documented in Tables III, IV and V and Figure 1 are certainly consistent with the underlying theory about preferences for stocks with extreme positive returns. While MAX measures the propensity for a stock to deliver lottery-like payoffs in the portfolio formation month, these stocks continue to exhibit this behavior in the future.

To get a clearer picture of the composition of the high MAX portfolios, Table VI presents summary statistics for the stocks in the deciles. Specifically, the table reports the average across the months in the sample of the median values within each month of various characteristics for the stocks in each decile. We report values for the maximum daily return (in percent), the market beta, the market capitalization (in millions of dollars), the book-to-market (BM) ratio, a measure of illiquidity (scaled by 10^5), the price (in dollars), the return in the portfolio formation month (REV), and the return over the 11 months prior to portfolio formation (MOM).[8] Definitions of these variables are given in the Appendix.

The portfolios exhibit some striking patterns. As we move from the low MAX to the high MAX decile, the average across months of the median daily maximum return of stocks increases from 1.62% to

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[8] The qualitative results from the average statistics are very similar to those obtained from the median statistics. Since the median is a robust measure of the center of the distribution that is less sensitive to outliers than the mean, we choose to present the median statistics in Table VI.

17.77%. With the exception of decile 10, these values are similar to those reported in Table I for the average maximum daily return. For decile 10, the average maximum return exceeds the median by approximately 6%. The distribution of maximum daily returns is clearly right skewed, with some stocks exhibiting very high returns. These outliers are not a problem in the portfolio-level analysis, but we will revisit this issue in the firm-level, cross-sectional regressions.

Betas are calculated monthly using a regression of daily excess stock returns on daily excess market returns; thus, these values are clearly noisy estimates of the true betas. Nevertheless, the monotonic increase in beta as MAX increases does suggest that stocks with high maximum daily returns are more exposed to market risk. To the extent that market risk explains the cross-section of expected returns, this relation between MAX and beta serves only to emphasize the low raw returns earned by the high MAX stocks as documented in Table I. The difference in 4-factor alphas should control for this effect, which partially explains why this difference is larger than the difference in the raw returns.

As MAX and beta increase across the deciles, market capitalization decreases. The absolute numbers are difficult to interpret since market capitalizations go up over time, but the relative values indicate that the high MAX portfolios are dominated by smaller stocks. This pattern is good news for the raw return differences documented in Table I since, as with beta, the concentration of small stocks in the high MAX deciles would suggest that these portfolios should earn a return premium not the return discount observed in the data. Again, this phenomenon may partially explain why the alpha difference exceeds the difference in raw returns.

Median book-to-market ratios are similar across the portfolios, although if anything high MAX portfolios do have a slight value tilt.

In contrast, the liquidity differences are substantial. Our measure of illiquidity is the absolute return over the month divided by the monthly trading volume, which captures the notion of price impact, i.e., the extent to which trading moves prices (see Amihud (2002)). We use monthly returns over monthly trading volume, rather than a monthly average of daily values of the same quantity, because a significant fraction of stocks have days with no trade. Eliminating these stocks from the sample reduces the sample size with little apparent change in the empirical results. Based on this monthly measure, illiquidity increases quite dramatically for the high MAX deciles, consistent with these portfolios containing smaller stocks. Again, this pattern only serves to strengthen the raw return differences documented in Table I since these stocks should earn a higher return to compensate for their illiquidity. Moreover, the 4-factor alphas do not control for this effect except to the extent that the size and book-to-market factors also proxy for liquidity.

The small, relatively illiquid stocks in the high MAX portfolios also tend to have low prices, declining to a median price of $6.47 for decile 10. While this pattern is not surprising, it does suggest that there may be measurement issues with some low priced stocks in the higher MAX portfolios associated with microstructure phenomena. To eliminate the possibility that these measurement errors are driving the results, we repeat the analysis in Table I excluding all stocks with prices below $5/share. For brevity, we do not report these results in detail, but, not surprisingly, the value-weighted results are essentially unchanged because the low priced stocks also tend to be those with low market capitalizations. Of greater interest, for the equal-weighted portfolios, the raw return and alpha differences increase in magnitude to –0.71% and –0.81% per month, respectively, with a corresponding increase in the associated t-statistics.

The final 2 columns of Table VI report median returns in the portfolio formation month (REV) and the return over the previous 11 months (MOM). These two variables indicate the extent to which the portfolios are subject to short-term reversal and intermediate-term momentum effects, respectively. Jegadeesh and Titman (1993) and subsequent papers show that over intermediate horizons, stocks exhibit a continuation pattern, i.e., past winners continue to do well and past losers continue to perform badly. Over shorter horizons stocks exhibit return reversals, due partly to microstructure effects such as bid-ask bounce (Jegadeesh (1990) and Lehmann (1990)).

Given that the portfolios are sorted on maximum daily returns, it is hardly surprising that median returns in the same month are also high, i.e., stocks with a high maximum daily return also have a high return that month. More interesting is the fact that the differences in median monthly returns for the portfolios of interest are smaller than the differences in the median MAX. For example, the difference in MAX between deciles 9 and 10 is 6.8% relative to a difference in monthly returns of 5.2%. In other words, the extreme daily returns on the lottery-like stocks are offset to some extent by lower returns on other days. This phenomenon explains why these same stocks can have lower average returns in the subsequent month (Table I) even though they continue to exhibit a higher frequency of extreme positive returns (Tables III, IV and V).

This lower average return is also mirrored in the returns over the prior 11 months. The high MAX portfolios exhibit significantly lower and even negative returns over the period prior to the portfolio formation month. The strength of this relation is perhaps surprising, but it is consistent with the fact that stocks with extreme positive daily returns are small and have low prices.

Given these differing characteristics, there is some concern that the 4-factor model used in Table I to calculate alphas is not adequate to capture the true difference in risk and expected returns across the portfolios sorted on MAX. For example, the HML and SMB factors of Fama and French do not fully explain the returns of portfolios sorted by book-to-market ratios and size.[9] Moreover, the 4-factor model does not control explicitly for the differences in expected returns due to differences in illiquidity or other

[9] Daniel and Titman (1997) attribute this failure to the fact that returns are driven by characteristics not risk. We take no stand on this issue, but instead conduct a further battery of tests to demonstrate the robustness of our results.

known empirical phenomenon such as short-term reversals. With the exception of short-term reversals and intermediate-term momentum, it seems unlikely that any of these factors can explain the return differences in Table I because high MAX stocks have characteristics that are usually associated with high expected returns, while these portfolios actually exhibit low returns. Nevertheless, in the following two subsections we provide different ways of dealing with the potential interaction of the maximum daily return with firm size, book-to-market, liquidity, and past returns. Specifically, we test whether the negative relation between MAX and the cross-section of expected returns still holds once we control for size, book-to-market, momentum, short-term reversal and liquidity using bivariate portfolio sorts and Fama-MacBeth (1973) regressions.

C. Bivariate Portfolio-Level Analysis

In this section we examine the relation between maximum daily returns and future stock returns after controlling for size, book-to-market, momentum, short-term reversals, and liquidity. For example, we control for size by first forming decile portfolios ranked based on market capitalization. Then, within each size decile, we sort stocks into decile portfolios ranked based on MAX so that decile 1 (decile 10) contains stocks with the lowest (highest) MAX. For brevity, we do not report returns for all 100 (10×10) portfolios. Instead, the first column of Table VII, Panel A presents returns averaged across the 10 size deciles to produce decile portfolios with dispersion in MAX, but which contain all sizes of firms. This procedure creates a set of MAX portfolios with very similar levels of firm size, and thus these MAX portfolios control for differences in size. After controlling for size, the value-weighted average return difference between the low MAX and high MAX portfolios is about –1.22% per month with a Newey-West t-statistic of –4.49. The 10-1 difference in the 4-factor alphas is –1.19% per month with a t-statistic of –5.98. Thus, market capitalization does not explain the high (low) returns to low (high) MAX stocks.

The fact that these results are, if anything, both economically and statistically more significant than those presented for the univariate sort in Table I is perhaps not too surprising. As shown in Table VI, the high MAX stocks, which have low subsequent returns, are generally small stocks. The standard size effect would suggest that these stocks should have high returns. Thus, controlling for size should enhance the effect on raw returns and even on 4-factor alphas to the extent that the SMB factor is an imperfect proxy. However, there is a second effect of bivariate sorts that works in the opposite direction. Size and MAX are correlated; hence, variation in MAX within size-sorted portfolios is smaller than in the broader universe of stocks. That this smaller variation in MAX still generates substantial return variation is further evidence of the significance of this phenomenon.

We control for book-to-market (BM) in a similar way, with the results reported in the second column of Table VII, Panel A. Again the effect of MAX is preserved, with a value-weighted average raw return difference between the low MAX and high MAX deciles of –0.93% per month and a corresponding t-statistic of –3.23. The 10-1 difference in the 4-factor alphas is also negative, –1.06% per month, and highly significant.

When controlling for momentum in column 3, the raw return and alpha differences are smaller in magnitude, but they are still economically large and statistically significant at all conventional levels. Again, the fact that momentum and MAX are correlated reduces the dispersion in maximum daily returns across the MAX portfolios, but intermediate-term continuation does not explain the phenomenon we document.

Column 4 controls for short-term reversals. Since firms with large positive daily returns also tend to have high monthly returns, it is conceivable that MAX could be proxying for the well known reversal phenomenon at the monthly frequency, which we do not control for in the 4-factor model in Table I. However, this is not the case. After controlling for the magnitude of the monthly return in the portfolio formation month, the return and alpha differences are still 81 and 98 basis points, respectively, and both numbers exhibit strong statistical significance.

Short-term reversals are attributable, in part, to market microstructure effects such as bid-ask bounce. It is conceivable that the monthly return reversals we control for using the variable REV do not adequately capture these short-term effects. To verify that it is not daily or weekly microstructure effects that are driving our results, we subdivide the high MAX portfolio according to when in the month the maximum daily return occurs. If the effect we document is more prominent for stocks whose maximum return occurs towards the end of the month, it would cast doubt on our interpretation of the evidence. There is no evidence of this phenomenon. Moreover, the low returns associated with high MAX stocks persist beyond the first month after portfolio formation. Thus, short-term reversals at the daily, weekly or monthly frequency do not seem to explain the results.

Finally, we control for liquidity by first forming decile portfolios ranked based on the illiquidity measure of Amihud (2002), with the results reported in final column of Table VII. Again, variation in MAX is apparently priced in the cross-section, with large return differences and corresponding t-statistics. Thus, liquidity does not explain the negative relation between maximum daily returns and future stock returns.

Next, we turn to an examination of the equal-weighted average raw and risk-adjusted returns on MAX portfolios after controlling for the same cross-sectional effects as in Table VII, Panel A. Again, to save space, instead of presenting the returns of all 100 (10×10) portfolios for each control variable, we report the average returns of the MAX portfolios, averaged across the 10 control deciles to produce decile portfolios with dispersion in MAX but with similar levels of the control variable.

Table VII, Panel B shows that after controlling for size, book-to-market, momentum, short-term reversal, and liquidity, the equal-weighted average return differences between the low MAX and high MAX portfolios are –1.11%, –0.59%, –0.76%, –0.83%, and –0.81% per month, respectively. These average raw return differences are both economically and statistically significant. The corresponding values for the equal-weighted average risk-adjusted return differences are –1.06%, –0.54%, –0.88%, –0.02%, and –0.79%, which are also highly significant.

These results indicate that for both the value-weighted and the equal-weighted portfolios, the well-known cross-sectional effects such as size, book-to-market, momentum, short-term reversal, and liquidity can not explain the low returns to high MAX stocks.

D. Firm-Level Cross-Sectional Regressions

So far we have tested the significance of the maximum daily return as a determinant of the cross-section of future returns at the portfolio level. This portfolio-level analysis has the advantage of being non-parametric in the sense that we do not impose a functional form on the relation between MAX and future returns. The portfolio-level analysis also has two potentially significant disadvantages. First, it throws away a large amount of information in the cross-section via aggregation. Second, it is a difficult setting in which to control for multiple effects or factors simultaneously. Consequently, we now examine the cross-sectional relation between MAX and expected returns at the firm level using Fama and MacBeth (1973) regressions.

We present the time-series averages of the slope coefficients from the regressions of stock returns on maximum daily return (MAX), market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), and illiquidity (ILLIQ). The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have non-zero premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$\begin{aligned} R_{i,t+1} = {} & l_{0,t} + l_{1,t} MAX_{i,t} + l_{2,t} BETA_{i,t} + l_{3,t} SIZE_{i,t} + l_{4,t} BM_{i,t} + l_{5,t} MOM_{i,t} \\ & + l_{6,t} REV_{i,t} + l_{7,t} ILLIQ_{i,t} + e_{i,t+1} \end{aligned} \tag{1}$$

where $R_{i,t+1}$ is the realized return on stock *i* in month *t*+1. The predictive cross-sectional regressions are run on the one-month lagged values of MAX, BETA, SIZE, BM, REV, and ILLIQ, and MOM is calculated over the 11-month period ending 2 months prior to the return of interest.

Table VIII reports the time series averages of the slope coefficients $l_{i,t}$ (i = 1, 2, …, 7) over the 522 months from July 1962 to December 2005 for all NYSE/AMEX/NASDAQ stocks. The Newey-West adjusted t-statistics are given in parentheses. The univariate regression results show a negative and statistically significant relation between the maximum daily return and the cross-section of future stock returns. The average slope, $l_{1,t}$, from the monthly regressions of realized returns on MAX alone is –0.0434 with a t-statistic of –2.92. The economic magnitude of the associated effect is similar to that documented in Tables I and VII for the univariate and bivariate sorts. The spread in median maximum daily returns between deciles 10 and 1 is approximately 16%. Multiplying this spread by the average slope yields an estimate of the monthly risk premium of –69 basis points.

In general, the coefficients on the individual control variables are also as expected—the size effect is negative and significant, the value effect is positive and significant, stocks exhibit intermediate-term momentum and short-term reversals, and illiquidity is priced. The average slope on BETA is negative and statistically insignificant, which contradicts the implications of the CAPM but is consistent with prior empirical evidence. In any case, these results should be interpreted with caution since BETA is estimated over a month using daily data, and thus is subject to a significant amount of measurement error. The regression with all 6 control variables shows similar results, although the size effect is weaker.

Of primary interest is the last line of Table VIII, which shows the results for the full specification with MAX and the 6 control variables. In this specification the average slope coefficient on MAX is –0.0662, substantially larger than in the univariate regression, with a commensurate increase in the t-statistic to –6.62. This coefficient corresponds to a 106 basis point difference in expected monthly returns between median stocks in the high and low MAX deciles. The explanation for the increased magnitude of the estimated effect in the full specification is straightforward. Since stocks with high maximum daily returns tend to be small and illiquid, controlling for the increased expected return associated with these characteristics pushes the return premium associated with extreme positive return stocks even lower. These effects more than offset the reverse effect associated with intermediate-term momentum and short-term reversals, which partially explain the low future returns on high MAX stocks.

The strength of the results is somewhat surprising given that there are sure to be low-priced, thinly traded stocks within our sample whose daily returns will be exhibit noise due to microstructure and other effects. To confirm this intuition, we re-run the cross-sectional regressions after winsorizing MAX at the 99^{th} and 95^{th} percentiles to eliminate outliers. In the full specification, the average coefficient on MAX increases to –0.0788 and –0.0902, suggesting that the true economic effect is even larger than that documented in Table VIII. A different but related robustness check is to run the same analysis using only NYSE stocks, which tend to be larger and more actively traded and are thus likely to have less noisy daily returns. For this sample, the baseline coefficient of –0.066 in Table VIII increases to –0.077.

The regression in equation (1) imposes a linear relation between returns and MAX for simplicity rather than for theoretical reasons. However, adding a quadratic term to the regression or using a piecewise linear specification appears to add little if anything to the explanatory power. Similarly, interacting MAX with contemporaneous volume, with the idea that trading volume may be related to the informativeness of the price movements, also proved fruitless.

The clear conclusion is that cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant negative relation between extreme positive returns and future returns, consistent with models that suggest that idiosyncratic lottery-like payoffs are priced in equilibrium.

III. Idiosyncratic Volatility and Extreme Returns

While arguably MAX is a theoretically motivated variable, there is still a concern that it may be proxying for a different effect. In particular, stocks with high volatility are likely to exhibit extreme returns of both signs. Moreover, stocks with high maximum daily returns in a given month will also have high realized volatility in the same month, measured using squared daily returns, almost by construction. Ang et al. (2006, 2008) document that idiosyncratic volatility has a significant negative price in the cross-section, i.e., stocks with high idiosyncratic volatility have low subsequent returns;[10] thus, it is plausible that MAX is proxying for this effect. We examine this issue in detail in this section.

As preliminary evidence, Table IX provides the average monthly cross-sectional correlations between four variables of interest—MAX (the maximum daily return within the month), MIN (the negative of the minimum daily return within the month), TVOL (monthly realized total volatility measured using daily returns within the month), and IVOL (monthly realized idiosyncratic volatility measured using the residuals from a daily market model within the month). TVOL, IVOL and MIN are defined in the Appendix. We reverse the sign on the minimum daily returns so that high values of MIN correspond to more extreme returns. Note that idiosyncratic volatility and total volatility are essentially identical when measured within a month due to the low explanatory power of the market model regression. In our sample, the average cross-sectional correlation between these variables exceeds 0.98. We choose to work with IVOL since it corresponds to the variable used by Ang et al.[11]

The average, cross-sectional correlations between IVOL and both MAX and MIN are approximately 0.75, which is very high given that all three variables are calculated at the individual stock level. Moreover, this correlation is not driven simply by the fact that a squared extreme daily return leads to a high measured realized volatility. Even when the maximum and minimum daily returns are eliminated prior to the calculation of volatility, volatility remains highly correlated with MAX and MIN.

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[10] This idiosyncratic volatility effect may not exist for all stocks. For example, Fang and Peress (2008) show that the effect is reversed for stocks with no media coverage.

[11] Measuring idiosyncratic volatility relative to a 3-factor or 4-factor model rather than the market model has little effect on the results.

MAX and MIN are also quite closely related, with a correlation of 0.55. Clearly stocks with high volatility exhibit extreme returns and vice versa.

A second important piece of preliminary evidence is to verify the relation between idiosyncratic volatility and future returns in our sample. Table X presents the results from a univariate portfolio sort on IVOL, similar to that given in Table I for MAX. In fact, the results look very similar to those in Table I. For value-weighted returns, deciles 1 through 7 (lower idiosyncratic volatility) all exhibit average monthly returns of around 1%. These returns fall dramatically for the higher volatility stocks, all the way to 0.02% per month for decile 10. Both the return differences and the four-factor alpha differences are economically and statistically significant. These results coincide closely with the results in Ang et al. (2006), although they form quintiles rather than deciles and use a slightly shorter sample period. Of some interest, there is no evidence of an idiosyncratic volatility effect in equal-weighted portfolios. This result is documented in Bali and Cakici (2008).

Columns 3 and 4 of the table show the average across months of the average idiosyncratic volatility and MAX within the deciles. IVOL increases across the portfolios by construction, and it rises dramatically for the top deciles. Given the correlation documented above it is not surprising that average maximum daily returns also increase across the IVOL-sorted portfolios. In fact, the range is not that much smaller than in the MAX-sorted portfolios.

To examine the relation between extreme returns and volatility more closely, we first conduct four bivariate sorts. In Table XI, Panel A we sort on both the maximum daily return (MAX) and the average of the five highest daily returns (MAX(5)), controlling for idiosyncratic volatility. We first form decile portfolios ranked based on idiosyncratic volatility, and within each IVOL decile we sort stocks into decile portfolios based on MAX or MAX(5) so that decile 1 (decile 10) contains stocks with the lowest (highest) MAX(N). Panel A shows the average of the value-weighted and equal-weighted returns across the IVOL deciles and the associated Newey-West t-statistics. The key statistics are the return and 4-factor alpha differences (and Newey-West t-statistics) between the low MAX(N) and high MAX(N) portfolios, i.e., the differences between returns on portfolios that vary in MAX(N) but have approximately the same levels of idiosyncratic volatility.

The value-weighted average raw return difference between the low MAX and high MAX deciles is –0.35% per month with a t-statistic of –2.42. The 10-1 difference in the 4-factor alphas is also negative, –0.34% per month, and highly significant. These magnitudes are much smaller than we have seen previously, but this result is hardly surprising. Idiosyncratic volatility and MAX are highly correlated; thus, after controlling for idiosyncratic volatility, the spread in maximum returns is significantly reduced. Nevertheless, idiosyncratic volatility does not completely explain the high (low) returns to low (high) MAX stocks. The equal-weighted average raw and risk-adjusted return differences between the low MAX and high MAX portfolios are much more negative, greater than 90 basis points per month in absolute magnitude, and highly significant with the t-statistics of –7.86 to –7.96, respectively. However, recall that the idiosyncratic volatility effect does not exist in equal-weighted portfolios as shown in Table X.

When we sort on the average of the five highest daily returns within the month, the return and alpha differences for both value-weighted and equal-weighted portfolios exhibit substantially greater economic and statistical significance, consistent with the univariate results reported in Table II.

What happens if we perform the reverse sort, i.e., if we examine the explanatory power of idiosyncratic volatility after controlling for MAX(N)? In Table XI, Panel B we first form decile portfolios ranked based either on the maximum daily returns over the past one month (MAX) or the average of the five highest daily returns (MAX(5)). Then, within each MAX(N) decile, we sort stocks into decile portfolios ranked based on IVOL so that decile 1 (decile 10) contains stocks with the lowest (highest) IVOL. When controlling for MAX, the average value-weighted raw return difference between the low IVOL and high IVOL portfolios is –0.38% per month with a t-statistic of –1.98. The 10-1 difference in the 4-factor alphas is also negative, –0.44% per month, and statistically significant. These magnitudes are much smaller than those obtained from the univariate volatility portfolios; nevertheless, for the value-weighted portfolios, maximum daily return does not completely explain the idiosyncratic volatility puzzle in a simple bivariate sort.

There are two possible explanations for this result in combination with the results of Table XI, Panel A, and Table X. First, MAX and IVOL could be picking up separate effects, both of which exist in the data. The absence of an idiosyncratic volatility effect in equal-weighted portfolios could be due to measurement issues for smaller stocks. Alternatively, it could be that bivariate sorts are not powerful enough to disentangle the true effect. While the idea of the bivariate sort is to produce portfolios with variation in the variable of interest but similar levels of the control variable, this goal is extremely difficult to achieve for highly correlated variables. While the stocks in the portfolios whose returns are reported in the first column of Table XI, Panel B do vary in their levels of idiosyncratic volatility, they also vary in their maximum daily returns. For example, the averages of the median idiosyncratic volatilities are 1.69% and 4.57% for the low and high IVOL portfolios, respectively, but the averages of the median MAX for these portfolios are 6.03% and 8.90%. Thus, it is difficult to know which effect is actually producing the negative return and alpha differences between these portfolios.

Columns two through four of Panel B shed further light on this issue. In column two, we report the results for equal-weighted portfolios, controlling for MAX. The average return difference between the high IVOL and low IVOL portfolios is about 0.98% per month with a Newey-West t-statistic of 4.88. The 10-1 difference in the 4-factor alphas is 0.95% per month with a t-statistic of 4.76. Thus, after controlling for MAX, we find a significant and positive relation between IVOL and the cross-section of expected returns. This is the reverse of the counter-intuitive negative relation documented by Ang et al. (2006, 2008). Once we control for extreme positive returns, there appears to be a reward for holding idiosyncratic risk. This result is consistent with a world in which risk averse and poorly diversified agents set prices, yet these agents have a preference for lottery like assets, i.e., assets with extreme positive returns in some states.

First, note that measurement error in idiosyncratic volatility cannot explain this positive and significant relation between idiosyncratic volatility and returns. Measurement error in the sorting variable will push return differences toward zero, but it cannot explain a sign reversal that is statistically significant, especially at the levels we report. Second, the inability to adequately control for variation in the control variable MAX is also not a viable explanation for these results. Residual variation in MAX is generating, if anything, the opposite effect. Finally, a positive relation between idiosyncratic volatility and returns and a negative relation between MAX and returns provides an explanation for the absence of a univariate idiosyncratic volatility effect in equal-weighted portfolios. This particular weighting scheme causes the IVOL and MAX effects to cancel, generating small and insignificant return differences.

To confirm these conclusions, the last two columns of Table XI, Panel B present results for portfolios that control for our somewhat more powerful measure of extreme returns, the average of the five highest daily returns during the month (MAX(5)). Using this control variable, the differences between the raw and risk-adjusted returns on high IVOL and low IVOL portfolios are positive, albeit insignificant, and the differences for equal-weighted portfolios are positive and extremely economically and statistically significant. The evidence supports the theoretically coherent hypothesis that lottery-like stocks command a price premium and those with high idiosyncratic risk trade at a discount.

We further examine the cross-sectional relation between IVOL and expected returns at the firm level using Fama-MacBeth regressions, with the results reported in the top half of Table XII. In the univariate regression the average slope coefficient on IVOL is negative, –0.05, but it is not statistically significant (t-stat = –0.97). This lack of significance mirrors the result in Table X, where there is little or no relation between volatility and future returns in equal-weighted portfolios. The cross-sectional regressions put equal weight on each firm observation.

When we add MAX to the regression, the negative relation between idiosyncratic volatility and expected returns is reversed. Specifically, the estimated average slope coefficient on IVOL is 0.39 with a Newey-West t-statistic of 4.69. This positive relation between IVOL and expected returns remains significant even after augmenting the regression with the 6 control variables.

Based on the bivariate equal-weighted portfolios and the firm-level cross-sectional regressions with MAX and IVOL, our conclusion is that there is no idiosyncratic volatility puzzle as recently documented in Ang et al. (2006, 2008). In fact, stocks with high idiosyncratic volatility have higher future returns as would be expected in a world where poorly diversified and risk averse investors help determine prices. We conclude that the reason for the presence of a negative relation between IVOL and expected returns documented by Ang et al. is that IVOL is a proxy for MAX. Interestingly, Han and Kumar (2008) provide evidence that the idiosyncratic volatility puzzle is concentrated in stocks dominated by retail investors. This evidence complements our results, since it is retail investors who more likely to suffer from under-diversification and exhibit a preference for lottery-like assets.

A slightly different way to examine the relation between extreme returns and volatility is to look at minimum returns. If it is a volatility effect that is driving returns, then MIN (the minimum daily return over the month), which is also highly correlated with volatility, should generate a similar effect to MAX. On the other hand, much of the theoretical literature would predict that the effect of MIN should be the opposite of that of MAX. For example, if investors have a skewness preference, then stocks with negatively skewed returns should require higher returns. Similarly, under the CPT of Barberis and Huang, small probabilities or large losses are over-weighted, and thus these stocks have lower prices and higher expected returns.

To examine this issue we form portfolios of stocks sorted on MIN after controlling for MAX. For brevity the result are not reported, but the return and alpha differences are positive and statistically significant, although both the magnitudes and level of significance are lower than those for MAX. This evidence suggests that stocks with extreme low returns have higher expected returns in the subsequent month. The opposite effects of MAX and MIN are consistent with cumulative prospect theory and skewness preference, but they are not consistent with the hypothesis that extreme returns are simply proxying for idiosyncratic volatility.

In addition to the portfolio-level analyses, we run firm-level Fama-MacBeth cross-sectional regressions with MAX, MIN and IVOL. The bottom half of Table XII presents the average slope coefficients and the Newey-West adjusted t-statistics. For all econometric specifications, the average slope on MAX remains negative and significant, confirming our earlier findings from the bivariate sorts. After controlling for MIN and IVOL, as well as market beta, size, book-to-market, momentum, short-term reversals and liquidity, the average slope on MAX is –0.090 with a t-statistic of –6.22.

For specifications with MAX and MIN, but not IVOL, the average slope on MIN is positive and both economically and statistically significant. Note that the original minimum returns are multiplied by –1 in constructing the variable MIN. Therefore, the positive slope coefficient means that the more a stock fell in value the higher the future expected return. The addition of the 6 control variables clearly weakens the estimated effect. This result is not surprising since stocks with extreme negative returns have characteristics similar to those of firms with extreme positive returns, i.e., they tend to be small and illiquid. Thus, size and illiquidity both serve to explain some of the positive returns earned by these stocks.

For the full specification with MAX, MIN, and IVOL, the coefficients on MIN and IVOL are no longer statistically significant. However, this result is most likely due to the multicollinearity in the regression, i.e., the correlations between MIN and IVOL (see Table IX) and between MIN, IVOL and the control variables. The true economic effect of extreme negative returns is still an open issue, but these regressions provide further evidence that there is no idiosyncratic volatility puzzle.

IV. Skewness and MAX

Our final empirical exercise is to examine the link, if any, between extreme positive returns and skewness in terms of their ability to explain the cross-section of expected returns. The investigation of the role of higher moments in asset pricing has a long history. Arditti (1967), Kraus and Litzenberger (1976), and Kane (1982) extend the standard mean-variance portfolio theory to incorporate the effect of skewness on valuation. They present a three-moment asset pricing model in which investors hold concave preferences and like positive skewness. In this framework, assets that decrease a portfolio's skewness (i.e., that make the portfolio returns more left-skewed) are less desirable and should command higher expected returns. Similarly, assets that increase a portfolio's skewness should generate lower expected returns.[12]

From our perspective, the key implication of these models is that it is systematic skewness, not idiosyncratic skewness, that explains the cross-sectional variation in stocks returns. Investors hold the market portfolio in which idiosyncratic skewness is diversified away, and thus the appropriate measure of risk is co-skewness—the extent to which the return on an individual asset covaries with the variance of market returns. Harvey and Siddique (1999, 2000) and Smith (2007) measure conditional co-skewness and find that stocks with lower co-skewness outperform stocks with higher co-skewness, consistent with the theory, and that this premium varies significantly over time.

In contrast, the extreme daily returns measured by MAX are almost exclusively idiosyncratic in nature, at least for the high MAX stocks, which produce the anomalous, low subsequent returns. Of course, this does not mean that MAX is not proxying for the systematic skewness, or co-skewness, of stocks. Thus, the first question is whether MAX, despite its idiosyncratic nature, is robust to controls for co-skewness.

The second question is whether MAX is priced because it proxies for idiosyncratic skewness. In other words, is MAX simply a good proxy for the third moment of returns? There is some empirical

[12] Arditti (1971), Friend and Westerfield (1980), Sears and Wei (1985), Barone-Adesi (1985), and Lim (1989) provide empirical analyses of the role of skewness.

evidence for a skewness effect in returns. For example, Zhang (2005) computes a measure of cross-sectional skewness, e.g., the skewness of firm returns within an industry, that predicts future returns at the portfolio level. Boyer, Mitton and Vorkink (2008) employ a measure of expected skewness, i.e., a projection of 5-year ahead skewness on a set of pre-determined variables, including stock characteristics, to predict portfolio returns over the subsequent month. Finally, Conrad, Dittmar and Ghysels (2008) show that measures of risk-neutral skewness from option prices predict subsequent returns. In all three cases the direction of the results is consistent with our evidence, i.e., more positively skewed stocks have lower returns, but these effects are generally weaker than the economically and statistically strong evidence we document in Section II.

Of equal importance, there is no theoretical reason to prefer return skewness to extreme returns as a potential variable to explain the cross-section of expected returns. In the model of Barberis and Huang (2008), based on the cumulative prospect theory of Tversky and Kahneman (1992), it is the low probability, extreme return states that drive the results, not skewness directly. Similarly, in the optimal beliefs model of Brunnermeier, Gollier and Parker (2007), it is again low probability states that drive the relevant pricing effects. Only in the model of Mitton and Vorkink (2007), who assume a preference for positive skewness, is skewness the natural measure.

To determine whether the information content of maximum daily returns and skewness are similar, we test the significance of the cross-sectional relation between MAX and future stock returns after controlling for total skewness (TSKEW), idiosyncratic skewness (ISKEW) and systematic skewness (SSKEW). In contrast with our other control variables, we calculate these skewness measures primarily over one year using daily returns.[13] A one-year horizon provides a reasonable tradeoff between having a sufficient number of observations to estimate skewness and accommodating time-variation in skewness. Total skewness is the natural measure of the third central moment of returns; systematic skewness, or co-skewness, is the coefficient of a regression of returns on squared market returns, including the market return as a second regressor (as in Harvey and Siddique (2000)); and idiosyncratic skewness is the skewness of the residuals from this regression. These variables are defined in more detail in the Appendix. Total skewness and idiosyncratic skewness are similar for most stocks due to the low explanatory power of the regression using daily data.

We first perform bivariate sorts on MAX while controlling for skewness. We control for total skewness by forming decile portfolios ranked based on TSKEW. Then, within each TSKEW decile, we sort stocks into decile portfolios ranked based on MAX so that decile 1 (decile 10) contains stocks with the lowest (highest) MAX. The first column of Table XIII shows returns averaged across the 10 TSKEW

[13] We test the robustness of our conclusions to variation in the measurement horizon (1, 3, 6, and 12 months) and find similar results.

deciles to produce decile portfolios with dispersion in MAX, but which contain firms with all levels of total skewness. After controlling for total skewness, the value-weighted average return difference between the low MAX and high MAX portfolios is about –0.94% per month with a Newey-West t-statistic of –3.06. The 10-1 difference in the 4-factor alphas is –1.00% per month with a t-statistic of –4.34. Thus, total skewness does not explain the high (low) returns to low (high) MAX stocks.

The last two columns of Table XIII present similar results from the bivariate sorts of portfolios formed based on MAX after controlling for systematic and idiosyncratic skewness, respectively. After controlling for systematic skewness, or co-skewness, the value-weighted average raw and risk-adjusted return differences between the low MAX and high MAX portfolios are in the range of 110 to 123 basis points per month and highly significant. After controlling for idiosyncratic skewness, the value-weighted average raw and risk-adjusted return differences between the low MAX and high MAX portfolios are –0.93% to –1.01% per month with the t-statistics of –2.96 and –4.34. These results indicate that systematic and idiosyncratic skewness cannot explain the significantly negative relation between MAX and expected stock returns.

One concern with this analysis is that lagged skewness may not be a good predictor of future skewness, as argued by Boyer, Mitton and Vorkink (2008). In a rational market, it is expected future skewness that matters. This issue is addressed in Table XIV, which presents results from cross-sectional, firm-level regressions of total skewness on lagged values of total skewness and our six control variables.[14] Skewness is significantly persistent, both in a univariate and multivariate context, although the explanatory power of the regressions is not very high. One possibility is to use the fitted values from the month-by-month cross-sectional regressions as a measure of expected skewness (as in Boyer, Mitton and Vorkink (2008)), and thus we include this variable in the cross-sectional return regressions that follow.

Table XV presents the cross-sectional Fama-MacBeth regression results including TSKEW, SSKEW, ISKEW and expected total skewness (E(TSKEW)) as control variables. The table reports the time series averages of the slope coefficients over the sample period July 1962 to December 2005, with Newey-West adjusted t-statistics given in parentheses. The inclusion of any of the skewness measures has only a limited effect on MAX. The average coefficients on MAX in the different specifications are all approximately –0.54, slightly smaller in magnitude than the –0.66 reported in Table VIII, but still economically very significant and statistically significant at all conventional levels, with t-statistics above 5 in magnitude. In all the specifications the coefficients on the skewness variables are positive, the opposite of the sign one would expect if investors have a preference for positive skewness. However, in the full specifications these average coefficients are statistically insignificant. The results for systematic skewness (co-skewness) differ from the significant negative relation found in Harvey and Siddique (2000)

[14] Using idiosyncratic skewness generates similar results.

and Smith (2007), presumably due to differences in the methodology. For idiosyncratic skewness, we cannot replicate the negative and significant relation found in Zhang (2005) and Boyer, Mitton and Vorkink (2008). Again differences in methodology presumably account for the discrepancy, a key difference being that both papers predict only portfolio returns, not the returns on individual securities.

For our purposes, however, the message of Tables XIII and XV is clear. There is no evidence that the effect of extreme positive returns that we document is subsumed by available measures of skewness.

V. Conclusion

We document a statistically and economically significant relation between lagged extreme positive returns, as measured by the maximum daily return over the prior month or the average of the highest daily returns within the month, and future returns. This result is robust to controls for numerous other potential risk factors and control variables. Of particular interest, inclusion of our MAX variable reverses the anomalous negative relation between idiosyncratic volatility and returns in Ang et al. (2006, 2008). We interpret our results in the context of a market with poorly diversified yet risk averse investors who have a preference for lottery-like assets. In fact, it may be the preference for lottery-like payoffs that causes under-diversification in the first place, since well-diversified equity portfolios do not exhibit this feature. Thus the expected returns on stocks that exhibit extreme positive returns are low but, controlling for this effect, the expected returns on stocks with high idiosyncratic risk are high.

One open question is why the effect we document is not traded away by other well-diversified investors. However, exploiting this phenomenon would require shorting stocks with extreme positive returns. The inability and/or unwillingness of many investors to engage in short selling has been discussed extensively in the literature. Moreover, stocks with extreme positive returns are small and illiquid on average, suggesting that transactions costs may be a serious impediment to implementing the relevant trading strategy.

We also present some evidence that stocks with extreme negative returns exhibit the reverse effect, i.e., investors find them undesirable and hence they offer higher future returns. While this phenomenon is not robust in all our cross-sectional regression specifications, these analyses suffer from a variety of problems. Of course, since exploiting this anomaly does not require taking a short position, one might expect the effect to be smaller than for stocks with extreme positive returns due to the presence of well-diversified traders.

While the extreme daily returns we exploit are clearly idiosyncratic, we make no effort to classify them further. In other words, we do not discriminate between returns due to earnings announcements, takeovers, other corporate events, or releases of analyst recommendations. Nor do we distinguish price moves that occur in the absence of new public information. Given the magnitude and robustness of our results, this presents a potentially fruitful avenue of further research. Investigating the time series patterns in the return premia we document is also of interest.

Appendix: Variable Definitions

MAXIMUM: MAX is the maximum daily return within a month:

$$MAX_{i,t} = \max(R_{i,d}) \qquad d = 1,\ldots,D_t \tag{2}$$

where $R_{i,d}$ is the return on stock *i* on day *d* and D_t is the number of trading days in month *t*.

MINIMUM: MIN is the negative of the minimum daily return within a month:

$$MIN_{i,t} = -\min(R_{i,d}) \qquad d = 1,\ldots,D_t \tag{3}$$

where $R_{i,d}$ is the return on stock *i* on day *d* and D_t is the number of trading days in month *t*.

TOTAL VOLATILITY: The total volatility of stock *i* in month *t* is defined as the standard deviation of daily returns within month *t*:

$$TVOL_{i,t} = \sqrt{\mathrm{var}(R_{i,d})} \tag{4}$$

BETA and IDIOSYNCRATIC VOLATILITY: To estimate the monthly beta and idiosyncratic volatility of an individual stock, we assume a single factor return generating process:

$$R_{i,d} - r_{f,d} = a_i + b_i(R_{m,d} - r_{f,d}) + e_{i,d}\,, \tag{5}$$

where $R_{i,d}$ is the return on stock *i* on day *d*, $R_{m,d}$ is the market return on day *d*, $r_{f,d}$ is the risk-free rate on day *d*, and $e_{i,d}$ is the idiosyncratic return on day *d*.[15] We estimate equation (5) for each stock using daily returns within a month. The estimated slope coefficient $\hat{b}_{i,t}$ is the market beta of stock *i* in month *t*. The idiosyncratic volatility of stock *i* in month *t* is defined as the standard deviation of daily residuals in month *t*:

$$IVOL_{i,t} = \sqrt{\mathrm{var}(e_{i,d})}\;. \tag{6}$$

SIZE: Following the existing literature, firm size is measured by the natural logarithm of the market value of equity (a stock's price times shares outstanding in millions of dollars) at the end of month t-1 for each stock.

[15] In our empirical analysis, $R_{m,d}$ is measured by the CRSP daily value-weighted index and $r_{f,d}$ is the one-month T-bill return available at Kenneth French's online data library.

<u>BOOK-TO-MARKET</u>: Following Fama and French (1992), we compute a firm's book-to-market ratio in month *t* using the market value of its equity at the end of December of the previous year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in prior calendar year.[16]

<u>INTERMEDIATE-TERM MOMENTUM</u>: Following Jegadeesh and Titman (1993), the momentum variable for each stock in month *t* is defined as the cumulative return on the stock over the previous 11 months starting 2 months ago, i.e., the cumulative return from month *t*–12 to month *t*–2.

<u>SHORT-TERM REVERSAL</u>: Following Jegadeesh (1990) and Lehmann (1990), the reversal variable for each stock in month *t* is defined as the return on the stock over the previous month, i.e., the return in month *t*–1.

<u>ILLIQUIDITY</u>: Following Amihud (2002), we measure stock illiquidity for each stock in month *t* as the ratio of the absolute monthly stock return to its dollar trading volume:

$$ILLIQ_{i,t} = |R_{i,t}| / VOLD_{i,t}, \tag{7}$$

where $R_{i,t}$ is the return on stock *i* in month *t*, and $VOLD_{i,t}$ is the respective monthly trading volume in dollars.

<u>TOTAL SKEWNESS</u>: The total skewness of stock *i* for month *t* is computed using daily returns within year *t*:

$$TSKEW_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \left(\frac{R_{i,d} - m_i}{s_i} \right)^3 \tag{8}$$

where D_t is the number of trading days in year *t*, $R_{i,d}$ is the return on stock *i* on day *d*, m_i is the mean of returns of stock *i* in year *t*, and s_i is the standard deviation of returns of stock *i* in year *t*.

<u>SYSTEMATIC and IDIOSYNCRATIC SKEWNESS</u>: Following Harvey and Siddique (2000), we decompose total skewness into idiosyncratic and systematic components by estimating the following regression for each stock:

$$R_{i,d} - r_{f,d} = a_i + b_i (R_{m,d} - r_{f,d}) + g_i (R_{m,d} - r_{f,d})^2 + e_{i,d}, \tag{9}$$

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[16] To avoid issues with extreme observations, following Fama and French (1992), the book-to-market ratios are winsorized at the 0.5% and 99.5% levels, i.e., the smallest and largest 0.5% of the observations on the book-to-market ratio are set equal to the 0.5th and 99.5th percentiles, respectively.

where $R_{i,d}$ is the return on stock *i* on day *d*, $R_{m,d}$ is the market return on day *d*, $r_{f,d}$ is the risk-free rate on day *d*, and $e_{i,d}$ is the idiosyncratic return on day *d*. The idiosyncratic skewness (*ISKEW*) of stock *i* in year *t* is defined as the skewness of daily residuals $e_{i,d}$ in year *t*. The systematic skewness (*SSKEW*) or co-skewness of stock *i* in year *t* is the estimated slope coefficient $\hat{g}_{i,t}$ in equation (9).

References

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2008, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics*, forthcoming.

Arditti, Fred D., 1967, Risk and the required return on equity, *Journal of Finance* 22, 19-36.

Arditti, Fred D., 1971, Another look at mutual fund performance, *Journal of Financial and Quantitative Analysis* 6, 909-912.

Bali, Turan G., and Nusret Cakici, 2008, Idiosyncratic volatility and the cross-section of expected returns, *Journal of Financial and Quantitative Analysis* 43, 29-58.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review*, forthcoming.

Barone-Adesi, Giovanni, 1985, Arbitrage equilibrium with skewed asset returns, *Journal of Financial and Quantitative Analysis* 20, 299-313.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research, Supplement* 27, 1-48.

Boyer, Brian, Todd Mitton and Keith Vorkink, 2008, Expected idiosyncratic skewness, Working Paper, Brigham Young University.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker, 2007, Optimal beliefs, asset prices and the preference for skewed returns, *American Economic Review* 97, 159-165.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2007, Down or out: Asssessing the welfare costs of household investment mistakes, *Journal of Political Economy* 115, 707-747.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chan, Wesley S., 2003, Stock price reaction to news and no-news: Drift and reversals after headlines, *Journal of Financial Economics* 70, 223-260.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels, 2008, Skewness and the bubble, Working Paper, University of North Carolina at Chapel Hill.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839-1885.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 52, 1-33.

Fama, Eugene F., and Kenneth French, 1992, Cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk and return: Some empirical tests, *Journal of Political Economy* 81, 607-636.

Fang, Lily, and Joel Peress, 2008, Media coverage and the cross-section of stock returns, *Journal of Finance* forthcoming.

Friend, Irwin, and Randolph Westerfield, 1980, Co-skewness and capital asset pricing, *Journal of Finance* 35, 897-913.

Garrett, Thomas A., and Russell S. Sobel, 1999, Gamblers favor skewness, not risk: Further evidence from United States' lottery games, *Economics Letters* 63, 85-90.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance*, forthcoming.

Han, Bing, and Alok Kumar, 2008, Retail clienteles and the idiosyncratic volatility puzzle, Working Paper, University of Texas at Austin.

Harvey, Campbell, and Akhtar Siddique, 1999, Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis* 34, 465-487.

Harvey, Campbell, and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263-1295.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kane, Alex, 1982, Skewness preference and portfolio choice, *Journal of Financial and Quantitative Analysis* 17, 15-25.

Kraus, Alan, and Robert H., Litzenberger, 1976, Skewness preference and the valuation of risk assets, *Journal of Finance* 31, 1085-1100.

Lehmann, Bruce, 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lim, Kian-Guan, 1989, A new test of the three-moment capital asset pricing model, *Journal of Financial and Quantitative Analysis* 24, 205-216.

Lintner, John, 1965, The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255-1288.

Mossin, Jan, 1966, Equilibrium in a capital asset market, *Econometrica* 34, 768-783.

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

Odean, Terrence, 1999, Do investors trade too much? *American Economic Review* 89, 1279-1298.

Patel, Nitin R., and Marti G. Subrahmanyam, 1978, Utility theory and participation in unfair lotteries, *Journal of Economic Theory* 19, 555-557.

Sears, R. Stephen, and K. C. John Wei, 1984, Asset pricing, higher moments, an the market risk premium: A note, *Journal of Finance* 40, 1251-1253.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

Smith, Daniel R., 2007, Conditional coskewness and asset pricing, *Journal of Empirical Finance* 14, 91-119.

Thaler, Richard H., and William T. Ziemba, 1988, Parimutuel betting markets: Racetracks and lotteries, *Journal of Economic Perspectives* 2, 161-174.

Tversky, Amos, and Daniel Kahneman, 1992, Advance in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297-323.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2008, Information acquisition and under-diversification, Working Paper, NYU.

Walker, Ian, and Juliet Young, 2001, An economist's guide to lottery design, *Economic Journal* 111, F700-F722.

Zhang, Yijie, 2005, Individual skewness and the cross-section of expected returns, Working Paper, Yale University.

Table I. Returns on Portfolios of Stocks Sorted by MAX

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily return (MAX) over the past one month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) maximum daily returns over the past one month. The table reports the value-weighted and equal-weighted average monthly returns and the average maximum daily return of stocks within a month. The last two rows present the differences in monthly returns and the differences in alphas with respect to the 4-factor Fama-French-Carhart model between portfolios 10 and 1. Average raw and risk-adjusted returns, and average daily maximum returns are given in percentage terms. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Decile	**Value-Weighted Average Return**	**Equal-Weighted Average Return**	**Average MAX**
Low MAX	1.01	1.29	1.30
2	1.00	1.45	2.47
3	1.00	1.55	3.26
4	1.11	1.55	4.06
5	1.02	1.49	4.93
6	1.16	1.49	5.97
7	1.00	1.37	7.27
8	0.86	1.32	9.07
9	0.52	1.04	12.09
High MAX	-0.02	0.64	23.60
Return Difference	**-1.03** (**-2.83**)	**-0.65** (**-1.83**)	
Alpha Difference	**-1.18** (**-4.71**)	**-0.66** (**-2.31**)	

Table II. Returns on Portfolios of Stocks Sorted by Multi-Day Maximum Returns

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the average of the *N* highest daily returns (MAX(N)) over the past one month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) maximum multi-day returns over the past one month. The table reports the value-weighted (Panel A) and equal-weighted (Panel B) average monthly returns for N=1,…,5. The last two rows present the differences in monthly returns and the differences in alphas with respect to the 4-factor Fama-French-Carhart model between portfolios 10 and 1. Average raw and risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A. Value-Weighted Returns on MAX(N) Portfolios

Decile	**N=1**	**N=2**	**N=3**	**N=4**	**N=5**
Low MAX(N)	1.01	1.00	1.05	1.02	1.05
2	1.00	0.96	0.98	1.02	1.07
3	1.00	1.06	1.09	1.08	1.06
4	1.11	1.08	1.02	1.01	1.04
5	1.02	1.08	1.05	1.06	1.04
6	1.16	1.03	1.08	1.03	1.01
7	1.00	1.04	1.00	1.06	1.06
8	0.86	0.78	0.68	0.70	0.70
9	0.52	0.50	0.49	0.43	0.48
High MAX(N)	-0.02	-0.16	-0.13	-0.12	-0.18
Return Difference	**-1.03** (**-2.83**)	**-1.16** (**-2.97**)	**-1.18** (**-2.95**)	**-1.14** (**-2.74**)	**-1.23** (**-2.93**)
Alpha Difference	**-1.18** (**-4.71**)	**-1.29** (**-4.56**)	**-1.26** (**-4.12**)	**-1.21** (**-3.71**)	**-1.32** (**-4.07**)

Table II (continued)

Panel B. Equal-Weighted Returns on MAX(N) Portfolios

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX(N)	1.29	1.28	1.27	1.29	1.30
2	1.45	1.45	1.48	1.49	1.54
3	1.55	1.55	1.56	1.59	1.59
4	1.55	1.58	1.61	1.62	1.60
5	1.49	1.56	1.56	1.52	1.55
6	1.49	1.45	1.49	1.53	1.52
7	1.37	1.44	1.43	1.42	1.43
8	1.32	1.28	1.27	1.28	1.26
9	1.04	1.01	1.00	0.95	0.94
High MAX(N)	0.64	0.59	0.54	0.51	0.49
Return Difference	**-0.65** **(-1.83)**	**-0.69** **(-1.88)**	**-0.73** **(-1.99)**	**-0.78** **(-2.11)**	**-0.81** **(-2.21)**
Alpha Difference	**-0.66** **(-2.31)**	**-0.72** **(-2.36)**	**-0.78** **(-2.53)**	**-0.84** **(-2.75)**	**-0.89** **(-2.93)**

Table III. Time-Series Average of the MAX Transition Matrix

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily returns (MAX) over the past one month. The table reports the average of the month-to-month transition matrices for the stocks in these portfolios, i.e., the average probability (in percent) that a stock in decile *i* (as given by the rows of the matrix) in one month will be in decile *j* (as given by the columns of the matrix) in the subsequent month.

	Low MAX	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High MAX**
Low MAX	33.67	18.71	12.51	8.94	6.61	5.12	4.14	3.50	3.12	3.67
2	19.12	21.01	16.09	12.41	9.65	7.28	5.37	4.12	2.96	1.99
3	12.83	16.38	16.47	13.88	11.21	9.32	7.39	5.58	4.19	2.75
4	9.07	12.88	13.93	14.52	12.84	10.77	9.21	7.44	5.56	3.77
5	6.60	9.90	11.71	12.73	13.81	12.49	10.81	9.54	7.46	4.96
6	5.02	7.38	9.62	11.29	12.37	13.73	12.76	11.30	9.78	6.74
7	3.99	5.43	7.58	9.69	11.27	12.72	14.51	13.57	12.11	9.13
8	3.31	3.91	5.61	7.60	9.96	11.78	13.71	16.16	15.21	12.76
9	3.00	2.78	4.07	5.64	7.68	10.25	12.76	15.61	19.58	18.63
High MAX	3.61	1.73	2.45	3.32	4.82	6.66	9.42	13.49	19.93	34.57

Table IV. Cross-Sectional Predictability of MAX

Each month from July 1962 to December 2005 we run a firm-level cross-sectional regression of the maximum daily return in that month (MAX) on subsets of lagged predictor variables including MAX in the previous month and six control variables that are defined in the Appendix. The table reports the time series averages of the cross-sectional regression coefficients, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R-squareds.

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ	R-squared
0.4054							16.64%
(45.34)							
0.2810	0.2178	–0.8416	–0.2349	–0.5805	–0.0700	0.0397	28.41%
(31.20)	(10.65)	(–25.91)	(–7.42)	(–5.21)	(–19.58)	(6.91)	

Table V. Distribution of Monthly Returns for Stocks in the High and Low MAX Portfolios

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily returns (MAX) over the past one month. The table reports descriptive statistics for the approximately 240,000 monthly returns on the individual stocks in deciles 1 (low MAX) and 10 (high MAX) in the following month. The tails of the return distribution are trimmed by removing the 0.5% most extreme observations in each tail prior to the calculation of the statistics in the final two columns.

			Trimmed	
	Low MAX	**High MAX**	**Low MAX**	**High MAX**
Mean	1.26%	0.60%	1.04%	-0.16%
Median	0.35%	-2.50%	0.35%	-2.50%
Std Dev	12.54%	30.21%	9.70%	24.12%
Skewness	4.26	5.80	0.59	1.35
Percentiles				
1%	-29.6%	-52.1%		
5%	-14.7%	-33.8%		
10%	-9.3%	-25.9%		
25%	-3.4%	-14.3%		
50%	0.3%	-2.5%		
75%	5.1%	9.5%		
90%	11.6%	28.6%		
95%	17.7%	46.3%		
99%	40.0%	100.0%		

Table VI. Summary Statistics for Decile Portfolios of Stocks Sorted by MAX

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum (MAX) daily returns over the past one month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) maximum daily returns over the past one month. The table reports for each decile the average across the months in the sample of the median values within each month of various characteristics for the stocks—the maximum daily return (in percent), the market beta, the market capitalization (in millions of dollars), the book-to-market (BM) ratio, our measure of illiquidity (scaled by 10^5), the price (in dollars), the return in the portfolio formation month (labeled REV), and the cumulative return over the 11 months prior to portfolio formation (labeled MOM). There is an average of 309 stocks per portfolio.

Decile	**MAX**	**Market Beta**	**Size** (\$$10^6$)	**BM Ratio**	**Illiquidity** (10^5)	**Price** (\$)	**REV**	**MOM**
Low MAX	1.62	0.29	316.19	0.7259	0.2842	25.44	–2.44	10.95
2	2.51	0.49	331.47	0.6809	0.1418	25.85	–0.96	11.16
3	3.22	0.60	250.98	0.6657	0.1547	23.88	–0.42	10.90
4	3.92	0.69	188.27	0.6563	0.1935	21.47	–0.01	10.25
5	4.71	0.78	142.47	0.6605	0.2456	19.27	0.43	9.77
6	5.63	0.86	108.56	0.6636	0.3242	16.95	0.82	8.62
7	6.80	0.95	80.43	0.6738	0.4501	14.53	1.48	6.71
8	8.40	1.01	58.69	0.7013	0.7067	12.21	2.34	3.75
9	11.01	1.09	39.92	0.7487	1.3002	9.57	4.01	–0.85
High MAX	17.77	1.13	21.52	0.8890	4.0015	6.47	9.18	–11.74

Table VII. Returns on Portfolios of Stocks Sorted by MAX After Controlling for SIZE, BM, MOM, REV, and ILLIQ

Double-sorted, value-weighted (Panel A) and equal-weighted (Panel B) decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily returns after controlling for size, book-to-market, intermediate-term momentum, short-term reversals and illiquidity. In each case, we first sort the stocks into deciles using the control variable, then within each decile, we sort stocks into decile portfolios based on the maximum daily returns over the previous month so that decile 1 (10) contains stocks with the lowest (highest) MAX. This table presents average returns across the 10 control deciles to produce decile portfolios with dispersion in MAX but with similar levels of the control variable. "Return Difference" is the difference in average monthly returns between the High MAX and Low MAX portfolios. "Alpha Difference" is the difference in 4-factor alphas on the High MAX and Low MAX portfolios. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A: Value-Weighted Portfolios

Decile	SIZE	BM	MOM	REV	ILLIQ
Low MAX	1.47	1.22	1.32	1.06	1.29
2	1.60	1.19	1.14	1.18	1.31
3	1.69	1.27	1.17	1.19	1.30
4	1.65	1.19	1.07	1.18	1.23
5	1.57	1.17	1.03	1.15	1.12
6	1.49	1.23	1.03	1.15	1.06
7	1.29	1.13	0.96	1.04	0.99
8	1.20	0.99	0.93	1.07	0.88
9	0.93	0.89	0.88	0.86	0.60
High MAX	0.25	0.29	0.67	0.25	0.18
Return Difference	**-1.22 (-4.49)**	**-0.93 (3.23)**	**-0.65 (-3.18)**	**-0.81 (-2.70)**	**-1.11 (-4.07)**
Alpha Difference	**-1.19 (-5.98)**	**-1.06 (-4.87)**	**-0.70 (-5.30)**	**-0.98 (-5.37)**	**-1.12 (-5.74)**

Table VII (continued)

Panel B: Equal-Weighted Portfolios

Decile	SIZE	BM	MOM	REV	ILLIQ
Low MAX	1.52	1.37	1.47	1.36	1.40
2	1.63	1.50	1.45	1.56	1.59
3	1.73	1.53	1.38	1.60	1.60
4	1.70	1.54	1.32	1.58	1.58
5	1.62	1.48	1.29	1.59	1.52
6	1.54	1.52	1.20	1.53	1.52
7	1.38	1.45	1.15	1.44	1.40
8	1.27	1.33	1.08	1.33	1.32
9	1.04	1.19	1.03	1.15	1.05
High MAX	0.41	0.78	0.71	0.52	0.59
Return Difference	**-1.11 (-4.05)**	**-0.59 (-2.00)**	**-0.76 (-3.70)**	**-0.83 (-2.83)**	**-0.81 (-2.68)**
Alpha Difference	**-1.06 (-5.18)**	**-0.54 (-1.96)**	**-0.88 (-7.62)**	**-1.02 (-5.09)**	**-0.79 (-3.40)**

Table VIII. Firm-Level Cross-Sectional Return Regressions

Each month from July 1962 to December 2005 we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including MAX in the previous month and six control variables that are defined in the Appendix. In each row, the table reports the time series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses).

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
–0.0434						
(–2.92)						
	–0.0624					
	(–1.18)					
		–0.1988				
		(–4.08)				
			0.4651			
			(6.73)			
				0.7317		
				(4.67)		
					–0.0675	
					(–11.24)	
						0.0371
						(3.87)
	–0.0190	–0.0845	0.3321	0.7392	–0.0753	0.0225
	(–0.40)	(–1.68)	(4.81)	(5.28)	(–14.12)	(3.76)
–0.0662	0.0607	–0.1376	0.3195	0.6776	–0.0710	0.0232
(–6.62)	(1.37)	(–3.10)	(4.73)	(4.93)	(–13.53)	(3.99)

Table IX. Time-Series Average of Cross-Sectional Correlations

The table reports the average across months of the cross-sectional correlation of the maximum daily return (MAX), the minimum daily return (MIN), total volatility (TVOL), and idiosyncratic volatility (IVOL) for the period July 1962 to December 2005.

	MAX	**MIN**	**TVOL**	**IVOL**
MAX	1	0.5491	0.7591	0.7533
MIN		1	0.7603	0.7554
TVOL			1	0.9842
IVOL				1

Table X. Returns on Portfolios of Stocks Sorted by IVOL

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the idiosyncratic volatility (IVOL) over the past one month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) volatility over the past one month. The table reports the value-weighted and equal-weighted average monthly returns and the time series average of the average IVOL and MAX within a month. The last two rows present the differences in monthly returns and the differences in alphas with respect to the 4-factor Fama-French-Carhart model, between portfolios 10 and 1. Average raw and risk-adjusted returns, average daily maximum returns, and average volatilities are defined in percentage terms. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Decile	Value-Weighted Average Return	Equal-Weighted Average Return	Average IVOL	Average MAX
Low IVOL	0.95	1.06	0.82	1.95
2	1.05	1.21	1.16	2.84
3	1.01	1.34	1.43	3.51
4	1.05	1.39	1.71	4.15
5	1.20	1.47	2.00	4.87
6	0.97	1.42	2.34	5.70
7	0.94	1.37	2.75	6.72
8	0.76	1.37	3.31	8.15
9	0.54	1.25	4.20	10.51
High IVOL	0.02	1.43	6.40	17.31
Return Difference	**–0.93** **(–3.23)**	**0.37** **(1.09)**		
Alpha Difference	**–1.33** **(–5.09)**	**–0.14** **(–0.64)**		

Table XI. Returns on Portfolios of Stocks Sorted by MAX and IVOL After Controlling for IVOL and MAX

Double-sorted, value-weighted (VW) and equal-weighted (EW) decile portfolios are formed every month from July 1962 to December 2005. In Panel A we sort stocks based on the maximum daily return (MAX) or average of the 5 highest daily returns (MAX(5)) after controlling for idiosyncratic volatility (IVOL). In Panel B we sort stocks based on idiosyncratic volatility (IVOL) after controlling for the maximum daily return (MAX) or average of the 5 highest daily returns (MAX(5)). In both cases we first sort the stocks into deciles using the control variable, then within each decile, we sort stocks into decile portfolios based on the variable of interest. The columns report average returns across the 10 control deciles to produce decile portfolios with dispersion in the variable of interest but with similar levels of the control variable. "Return Difference" is the difference in average monthly returns between deciles 10 and 1. "Alpha Difference" is the difference in 4-factor alphas between deciles 10 and 1. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A. Sorted by MAX and MAX(5) Controlling for IVOL

	N=1		**N=5**	
Decile	**VW**	**EW**	**VW**	**EW**
Low MAX(N)	1.12	2.01	1.39	2.25
2	1.09	1.65	1.18	1.81
3	0.94	1.54	1.20	1.67
4	0.93	1.41	1.11	1.51
5	0.80	1.34	0.99	1.38
6	0.77	1.22	0.84	1.21
7	0.79	1.19	0.74	1.11
8	0.82	1.23	0.79	1.06
9	0.76	1.04	0.67	0.93
High MAX(N)	0.77	1.10	0.53	0.75
Return	**-0.35**	**-0.91**	**-0.86**	**-1.50**
Difference	**(-2.42)**	**(-7.86)**	**(-4.36)**	**(-9.21)**
Alpha	**-0.34**	**-0.92**	**-0.84**	**-1.58**
Difference	**(-2.48)**	**(-7.96)**	**(-4.98)**	**(-10.05)**

Table XI (continued)

Panel B. Sorted by IVOL Controlling for MAX and MAX(5)

	MAX		MAX(5)	
Decile	**VW**	**EW**	**VW**	**EW**
Low IVOL	1.03	1.18	0.89	0.84
2	0.93	1.15	0.86	1.02
3	0.90	1.10	0.78	1.03
4	0.92	1.17	0.93	1.17
5	0.95	1.27	0.97	1.20
6	0.88	1.21	0.98	1.28
7	0.94	1.37	0.99	1.40
8	0.83	1.48	1.09	1.56
9	0.73	1.52	0.96	1.69
High IVOL	0.66	2.16	0.95	2.51
Return Difference	**-0.38** (-1.98)	**0.98** (4.88)	**0.06** (0.29)	**1.67** (8.04)
Alpha Difference	**-0.44** (-3.12)	**0.95** (4.76)	**0.05** (0.34)	**1.74** (7.67)

Table XII. Firm-Level Cross-Sectional Return Regressions with MAX, MIN and IVOL

Each month from July 1962 to December 2005 we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including MAX, MIN and IVOL in the previous month and six control variables that are defined in the Appendix. In each row, the table reports the time series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses).

MAX	IVOL	MIN	BETA	SIZE	BM	MOM	REV	ILLIQ
–0.0434								
(–2.92)								
	–0.0530							
	(–0.97)							
–0.1549	0.3857							
(–10.19)	(4.69)							
–0.0988	0.1219		0.0636	–0.1065	0.3232	0.7185	–0.0715	0.0241
(–7.69)	(1.95)		(1.44)	(–2.74)	(4.88)	(5.39)	(–14.30)	(3.94)
		0.0593						
		(2.41)						
–0.0900		0.1280						
(–7.84)		(6.21)						
–0.0769		0.0350	0.0372	–0.1142	0.3294	0.7004	–0.0694	0.0234
(–8.82)		(2.43)	(0.89)	(–2.75)	(4.96)	(5.12)	(–14.30)	(5.12)
–0.1103	0.0840	0.1029						
(–6.90)	(0.94)	(5.43)						
–0.0901	0.0649	0.0174	0.0320	–0.1071	0.3261	0.7100	–0.0709	0.0238
(–6.22)	(0.83)	(1.12)	(0.71)	(–2.75)	(4.93)	(5.31)	(–14.70)	(3.92)

Table XIII. Returns on Portfolios of Stocks Sorted by MAX After Controlling for Skewness

Double-sorted, value-weighted decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily returns after controlling for total (TSKEW), systematic (SKEW), and idiosyncratic skewness (ISKEW). In each case, we first sort the stocks into deciles using the control variable, then within each decile, we sort stocks into decile portfolios based on the maximum daily returns over the previous month so that decile 1 (10) contains stocks with the lowest (highest) MAX. The table reports average returns across the 10 control deciles to produce decile portfolios with dispersion in MAX but with similar levels of the control variable. "Return Difference" is the difference in average monthly returns between high MAX and low MAX portfolios. "Alpha Difference" is the difference in 4-factor alphas between high MAX and low MAX portfolios. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Decile	TSKEW	SSKEW	ISKEW
Low MAX	1.06	1.12	1.04
2	1.11	1.06	1.14
3	1.21	1.06	1.18
4	1.07	1.10	1.08
5	1.13	1.11	1.17
6	1.14	1.10	1.10
7	0.97	0.98	0.99
8	0.87	0.89	0.91
9	0.76	0.80	0.74
High MAX	0.12	0.03	0.11
Return Difference	**-0.94** (-3.06)	**-1.10** (-3.75)	**-0.93** (-2.96)
Alpha Difference	**-1.00** (-4.34)	**-1.23** (-5.50)	**-1.01** (-4.34)

Table XIV. Cross-Sectional Predictability of Skewness

Each month from July 1962 to December 2005 we run a firm-level cross-sectional regression of the total skewness measured using daily returns over the subsequent year (TSKEW) on subsets of lagged predictor variables including TSKEW in the previous year and six control variables that are defined in the Appendix. The table reports the time series averages of the cross-sectional regression coefficients, their associated Newey-West (1987) adjusted t-statistics (in parentheses), and the regression R-squareds.

TSKEW	BETA	SIZE	BM	MOM	REV	ILLIQ	R-squared
0.1507							2.46%
(28.38)							
0.0808	0.0071	-0.1216	-0.0467	0.1475	0.0007	0.0282	9.69%
(21.70)	(2.54)	(-23.24)	(-6.24)	(12.64)	(3.60)	(2.03)	

Table XV. Firm-Level Cross-Sectional Return Regressions with MAX and Skewness

Each month from July 1962 to December 2005 we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including MAX in the previous month, skewness measured over the preceding year (TSKEW, SSKEW, ISKEW), fitted expected total skewness (E(TSKEW)) based on the regression in Table XIV, and six control variables that are defined in the Appendix. In each row, the table reports the time series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses).

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ	TSKEW	SSKEW	ISKEW	E(TSKEW)
							0.1330			
							(2.56)			
								0.2436		
								(0.84)		
									0.1324	
									(2.53)	
–0.0541	0.0521	–0.1402	0.2853	0.6805	–0.0732	0.0270	0.0274			
(–5.30)	(1.05)	(–2.92)	(3.96)	(4.60)	(–13.74)	(2.66)	(1.07)			
–0.0534	0.0494	–0.1422	0.2870	0.6891	–0.0733	0.0278		0.2255		
(–5.20)	(1.00)	(–2.92)	(3.96)	(4.63)	(–13.74)	(2.77)		(0.81)		
–0.0541	0.0522	–0.1403	0.2853	0.6801	–0.0732	0.0270			0.0274	
(–5.30)	(1.05)	(–2.93)	(3.96)	(4.60)	(–13.74)	(2.66)			(1.04)	
										1.5188
										(3.92)
–0.0540	0.0414	–0.0130	0.3261	0.5778	–0.0753	0.0056				0.5770
(–5.30)	(0.83)	(–0.11)	(3.59)	(3.39)	(–12.42)	(0.32)				(0.59)

Figure 1. Distribution of Monthly Returns for High and Low MAX Portfolios

Decile portfolios are formed every month from July 1962 to December 2005 by sorting stocks based on the maximum daily returns (MAX) over the past one month. The figure shows the frequency of the approximately 240,000 monthly returns on the individual stocks in deciles 1 (low MAX) and 10 (high MAX) in the following month. The numbers on the horizontal axis give the center of the return ranges, each of which spans 5%, e.g., the columns above the number 5% represent the percentage of returns that fall between 2.5% and 7.5%. The exceptions are the columns on the far left and far right which tabulate percentages of returns that fall within and below or above the range, respectively.