IT COULD BE OVERREACTION, NOT LOTTERY-SEEKING, THAT IS BEHIND BALI, CAKICI AND WHITELAW'S MAX EFFECT*

Jake GORMAN+, Farida AKHTAR†, Robert B DURAND‡ and John GOULD§

January 2021

Abstract

Bali, Cakici and Whitelaw (2011) introduce the MAX effect asset pricing anomaly: high MAX stocks (being stocks with the highest 10% of maximum single-day returns during a month) subsequently underperform. We find that this post-high MAX return underperformance is a general phenomenon that is independent of stocks being identified, ex-ante, as lottery-like. With an event study approach, we also find that the average high MAX event cumulative abnormal return pattern is indicative of overreaction embedded within high MAX returns.

JEL Classification: G11, G17, G12.

Key Words: Extreme returns; Lottery-like payoffs; Gambling; Overreaction; Reversal.

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* We are grateful for comments from Ivo Welch, our referees, Yi Tang, and seminar participants at Curtin University, the 2017 FMA Annual Meeting (Boston, Massachusetts), and the 2019 West Coast Finance Colloquium (Perth, Western Australia). SAS code used to conduct the analyses reported in this paper, a sample of data, and additional analysis of a first-MAX-in-21-days effect (discussed in Section 4 of this paper) may be found via https://doi.org/10.25917/w1ve-5r50.

+ Mr Jake Gorman; Curtin University, GPO Box U1987, Perth, Australia 6845; +618 9266 7724; jake.gorman@curtin.edu.au.

† Dr Farida Akhtar; Macquarie University, Sydney, Australia 2109; +612 9850 1869; farida.akhtar@mq.edu.au.

‡ Prof Robert B Durand; Curtin University, GPO Box U1987, Perth, Australia 6845; +618 9266 9971; robert.durand@curtin.edu.au. Contact author.

§ Dr John Gould; Curtin University, GPO Box U1987, Perth, Australia 6845; +618 9266 9028; j.gould@curtin.edu.au.

Perhaps the most interesting technical stock trading anomaly since Jegadeesh and Titman's (1993) momentum effect is Bali, Cakici and Whitelaw's (2011) (henceforth BCW) MAX effect: monthly portfolios formed from stocks that had the highest (top 10% ranking) maximum single-day returns during the prior month (high MAX stocks) significantly underperform relative to portfolios of stocks with the lowest (bottom 10% ranking) maximum single-day returns (low MAX stocks). The robustness of the MAX effect is confirmed by a number of subsequent studies (e.g., see Nartea, Wu and Liu (2014), Walkshausl (2014) and Zhong and Gray (2016) for South Korean, European and Australian evidence respectively).

BCW suggest that the MAX effect anomaly is consistent with a cumulative prospect theory (Tversky and Kahneman, 1992) interpretation entailing overvaluation of stocks that exhibit lottery-like behavior. The existence and profitability of gambling and lottery enterprises is testament to the fact that many people are willing to accept a negative expected return in exchange for the chance of a large but unlikely lottery payoff. Kumar (2009) presents evidence that the propensity to gamble on lotteries is associated with an investment preference for lottery-like stocks: it is not at all contentious to accept that, in the presence of real-world impediments to arbitrage, lottery-like stocks may become over-priced relative to a mean-variance efficient asset pricing benchmark. From an ex-ante perspective, a lottery-like stock is believed to offer a highly skewed probability distribution for future returns. Boyer, Mitton and Vorkink (2010) find that the expected idiosyncratic skewness (iskew) of future stock returns is negatively related to subsequent realized one month returns: they conclude that "[i]nvestors appear to pay a premium for stocks that are expected to have more highly skewed returns" (p.200). Nevertheless, an extreme positive short-run return, such as a high MAX event, is the specific payoff materialization desired by lottery-like stock speculators. BCW argue that the MAX effect is consistent with lottery-seeking investment: "investors may be willing to pay more for stocks that exhibit extreme positive returns, and thus, these stocks exhibit lower returns in the future" (p.428).

What has not previously been considered is that, although all high expected iskew stocks might reasonably be classified as lottery-like, only a small percentage will reward speculators with an extreme positive return. And, while all high MAX stocks can be considered to have rewarded their investors with an extreme positive return, not all will have been identified by speculators, ex-ante, as lottery-like. Accordingly, our methodological contribution to unravelling the MAX effect anomaly is to investigate the performance of high MAX stocks conditional on their ex-ante identification as being lottery-like or not: specifically we consider stocks to be lottery-like if they are *expected* to yield a MAX return with a top 10% ranking. For robustness we also apply an alternative methodology of identifying lottery-like stocks as those with the highest 10% of expected iskew (in the vein of Boyer et al. (2010)): our results from this approach are qualitatively the same as those presented here and are available upon request. Kumar (2009) typifies lottery-like stock investors as "less educated" (p.1891): presumably their appreciation of probability density functions and skewness metrics is, generally, only vaguely intuitive, thus we prefer to pragmatically define lottery-like stocks as those expected to yield high MAX returns rather than those expected to offer high iskew.[1]

The key innovation of our investigation of the MAX effect is the ex-ante (pre-MAX event) identification of stocks expected to yield high MAX returns, and stocks expected conversely to not yield high MAX returns. Using an out-of-

[1] An earlier iteration of our research entails a "naïve" methodology that identifies lottery-like stocks as penny stocks (with a stock price of $5 or less): our results from this approach are qualitatively similar to those presented here.

sample logistic model we are able to predict high MAX stocks each month with success rates that are significantly better than pure luck: we define expected high MAX stocks as those for which the estimated probability of being a high MAX stock ranks in the highest 10%. On this basis we have four stock designations for each MAX event month: (i) expected and actual high MAX stocks (i.e. stocks with ex-ante expected and ex-post actual decile 10 maximum single-day returns for the month, designated *expHiMAX∩actHiMAX*); (ii) expected high MAX stocks that fail to deliver high MAX returns (*expHiMAX∩actNonHiMAX*); (iii) expected non-high MAX stocks that actually deliver high MAX returns (*expNonHiMAX∩actHiMAX*); and (iv) expected non-high MAX stocks that do not deliver high MAX returns (*expNonHiMAX∩actNonHiMAX*).

Our research aim is to determine whether we can reject the premise that the MAX effect anomaly is a consequence of lottery-seeking investment. By considering the separate performances of *expHiMAX∩actHiMAX* and *expNonHiMAX∩actHiMAX* stock portfolios we seek to test the hypothesis that post-high MAX return underperformance is *specifically* associated with stocks identified, ex-ante, to be lottery-like as indicated by the probability of achieving a high MAX return. Using a monthly portfolio approach, we find that post-high MAX return underperformance is evident for high MAX stocks *regardless* of whether they were or were not expected to yield high MAX returns: that is, on average, value-weighted portfolios of *expHiMAX∩actHiMAX* stocks, and value-weighted portfolios of *expNonHiMAX∩actHiMAX* stocks, are found to yield similar significant negative abnormal returns for the post-MAX event month. This leads us to reject the hypothesis that lottery-seeking investment is a driver of the MAX effect.

Instead of lottery-seeking, an alternative explanation for the MAX effect arises from the potential for high MAX stock returns to entail overreaction embedded within the MAX returns. In fact, if daily stock returns are subject to random investor over- or underreaction with zero average bias, BCW's method of sorting stocks into deciles by the magnitude of their MAX returns will naturally result in a high MAX decile that is over-represented/overweight with overreaction stocks and thereby overvalued on average. Fama (1998) explains that stock return overreaction is consistent with an efficient market so long as equivalent underreaction is equally likely. Being the maximum single day return across a month, a stock's MAX return will more likely be an overreaction event than an underreaction event. Then selecting stocks with the highest MAX returns will further concentrate the bias towards overreaction events. In this regard, the MAX effect anomaly becomes a "slow reversal of overreaction" anomaly. "Slow reversal of overreaction" could be attributable to short-selling costs, risks and restrictions, and elevated arbitrage risk arising from the high idiosyncratic volatility of high MAX stocks.

At a monthly time-scale, the MAX effect anomaly presents as post-high MAX return underperformance in the subsequent month. Using a stock-month cross-sectional event study approach with event-time measured in days and event day zero being the MAX event (i.e. the day on which the stock yields its highest single day return for the month), we are able to observe the cumulative average abnormal return pattern in the temporal vicinity of the MAX event for our four stock designations so as to better understand the dynamics of the MAX effect. Evidence for lottery-seeking investment as an explanation for the MAX effect might present in two ways. Firstly, a high MAX event might confirm hopeful investors' ex-ante beliefs that a stock is lottery-like, in which case we expect return outperformance in the lead-up to the hoped-for high MAX event, and then post-high MAX "cashing-out" underperformance. Secondly, a high MAX event might itself present a signal that a stock is lottery-like, sparking ex-post demand from hopeful lottery-seekers leading to post-high MAX return outperformance and anticipation, followed by (on average) disappointment and underperformance. Alternatively, an overreaction explanation for the MAX effect would simply present as post-high MAX (partial) reversal underperformance.

Our event study cumulative average abnormal return patterns are indicative of overreaction embedded within MAX returns. From event day -10 to event day +10, the only source of average return outperformance is the MAX event day itself: there is no evidence of ex-ante or ex-post lottery-seeking exuberance proximate to the MAX event. For event days +1 to +5 (i.e. the [+1,+5] event window), underperformance is ubiquitous, however, *persistent* post-high MAX underperformance across the [+6,+10] and [+11,+20] event windows in the manner of the MAX effect anomaly is only evident for unexpected high MAX events associated with $expNonHiMAX \cap actHiMAX$ stocks. Conversely, expected high MAX events associated with $expHiMAX \cap actHiMAX$ stocks actually exhibit rebound outperformance across the [+11,+20] and [+21,+40] event windows, which is contrary to the MAX effect anomaly (but perhaps suggestive of exuberance for "successful" lottery-like stocks).

We proceed by providing background on the literature about the MAX effect as well as overreaction. We introduce the data in Section 2 and then extend BCW's monthly analysis in Section 3 of the paper. We present the results of the event study using daily data in Section 4. Section 5 concludes the paper.

1. BACKGROUND

Prospect Theory and Cumulative Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1986, 1992) suggest that individuals are behaviorally inclined to place excessive emphasis on low likelihood events in their decision making, which can lead to overpayment for lottery-like investments. Cronqvist and Siegel (2014) present evidence that investors' preference for such outcomes has a genetic basis. To the extent that high MAX events are associated with lottery-like investment opportunities, lottery-seeking enthusiasm may drive overvaluation of high MAX stocks and subsequent underperformance.

Since BCW's discovery of the MAX effect, a number of studies have confirmed that it appears robust. Zhong and Gray (2016) investigate the presence of the MAX effect in Australia and its relationship with stock mispricing. Using an adaptation of the methodology of Stambaugh, Yu and Yuan (2015) to construct a stock mispricing index, Zhong and Gray find that the MAX effect is concentrated amongst overpriced stocks. Stambaugh, Yu and Yuan argue that, due to the asymmetry of barriers to arbitrage of stock mispricing, overpricing (with subsequent negative abnormal return) is more prevalent than underpricing. Zhong and Gray consider the MAX effect as a stock overpricing phenomenon associated with limits to arbitrage, but they do not specifically attribute the overpricing to lottery-seeking enthusiasm as opposed to overreaction. Therefore our study considers an aspect of MAX not envisaged by Zhong and Gray.

Fong and Toh (2014) find that the MAX effect in the US is stronger following periods of high investor sentiment. They argue that investor optimism and gambling propensity increase with sentiment, which drives lottery-seeking enthusiasm and the MAX effect. Of course, however, high sentiment could similarly drive MAX event overreaction. In keeping with Zhong and Gray, and Fong and Toh, Tah (2015) finds that the MAX effect is associated with high sentiment and high idiosyncratic volatility (where idiosyncratic volatility serves as a proxy for arbitrage costs and therefore a greater propensity for overpricing). Tah additionally finds that the MAX effect is a non-January phenomenon, in that January high MAX events do not exhibit significant underperformance in February.

High MAX stocks exhibit lottery-like characteristics (i.e. highly positively skewed or high variance return distributions). A number of studies identify the propensity for lottery-like stocks to be the province of retail traders, and there is a tendency to find that retail investors are prone to behavioral investment biases (Barber and Odean, 2000, 2008; Barberis and Huang, 2008; Han and Kumar, 2013; Kumar, 2009; Mitton and Vorkink, 2007). Dorn, Dorn and Sengmueller (2015) and Gao and Lin (2015) show that individuals connect lottery outcomes with investing in equity markets, effectively treating the funds they commit to these activities as substitutes.

A behavioral argument for investor overreaction stems from the suggestion that individuals excessively focus on new information and partially ignore previous beliefs (Grether, 1980; Kahneman and Tversky, 1972, 1973). De Bondt and Thaler (1985) attribute to overreaction their finding that separate portfolios of winner and loser stocks determined from three-year performances go on to exhibit a reversal of relative performance. A shorter run reversal anomaly is identified by Jegadeesh (1990), who finds a negative and significant relationship between monthly stock returns. Jegadeesh and Titman (1995) and Lehmann (1990) find reversal evidence in week-to-week stock returns. Chan (2003) finds stock prices reverse after extreme price movements unaccompanied by public news. Mohrschladt and Baars (2018) find immediate price reversals after high MAX observations, except when associated with earnings announcements. Nguyen and Truong (2018) find the MAX effect is absent when associated with earnings announcements. The reversal evidence is consistent with stock return overreaction due to investors overweighting the importance of new information and underweighting older information, followed by subsequent correction of the overreaction. Alternatively, transient volatility due to liquidity demand will show up as short-run reversals (Avramov, Chordia and Goyal, 2006): in this context overreaction is in fact a liquidity cost in the form of market impact.

2. DATA AND HIGH MAX PREDICTION METHODOLOGY

We obtain data for US common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ between July 1962 and December 2005, which corresponds with the data and time period analyzed by BCW. Daily and monthly stock returns, stock prices, trading volume and shares outstanding come from the Center for Research in Security Prices (CRSP) database. Stocks' book values of equity and earnings announcement dates come from COMPUSTAT. Stocks' institutional ownership data comes from the Thomson Reuters Institutional Holdings (13F) database. Daily and monthly asset pricing risk factors and risk-free rates come from Kenneth French's online data library
(http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

For stock i during month τ, the MAX event is the trading day on which the stock earns its highest single day return for the month. Our sample entails approximately 1.7 million stock-month (i, τ) MAX events from August 1964 to November 2005. To be included in the sample for month τ, we require stock i to have at least: 12 prior months of returns data; prior month trading volume and market capitalization data; and prior year book value to market value of equity ratio data. July 1962 to July 1964 data are used to "prime" our expected high MAX prediction model. August 1964 is our first MAX event month and November 2005 is the final MAX event month, and December 2005 is the final post-MAX event month.

Table 1 presents summary characteristics for stocks sorted monthly into decile portfolios according to the scale of their MAX return: of particular interest each month are the decile 10 high MAX stocks (with the highest 10% of MAX returns). Table 1 lists the time series averages of the monthly decile portfolio medians of stock characteristic variables. Table 1 indicates that, generally, the decile 10 high MAX stocks are small, low-priced stocks with high illiquidity scores and market betas, very negative prior return performance, and high idiosyncratic volatility and skewness. Table 1 also depicts BCW's MAX effect: increasing portfolio MAX decile is associated with generally decreasing return for the next month (NEXTRET), with the decile 10 high MAX stocks exhibiting an especially low average (of median) return equal to -2.08% for the post-MAX event month.

[Table 1 around here]

2.1. Expected high MAX stocks

Each month we identify, ex-ante, stocks that offer the highest chance of a high MAX outcome. For this purpose, Equation (1) is our expected high MAX stock logistic prediction model. Every six months from July 1964 to July 2005, stock-month observations (i,τ) extending back to τ equal to July 1962, are used to estimate the coefficients of the logistic model (i.e. our logistic model is re-estimated every six months through our sample period, 83 times in total, with a backwards expanding estimation window)

$$ln\left(\frac{\Pr\,(hi_{\tau}^{i,\tau}=1)}{1-\Pr\,(hi_{\tau}^{i,\tau}=1)}\right)$$

$$= a + b_1 SIZE_{(\tau-1)+}^{i,\tau} + b_2 BM_{FY}^{i,\tau} + b_3 MOM_{\tau-12,\tau-2}^{i,\tau} + b_4 REV_{\tau-1}^{i,\tau} \qquad (1)$$

$$+ b_5 ILLIQ_{\tau-1}^{i,\tau} + b_6 IVOL_{\tau-3,\tau-1}^{i,\tau} + b_7 ISKEW_{\tau-12,\tau-1}^{i,\tau} + b_8 PRICE_{(\tau-1)+}^{i,\tau}$$

where, for stock i and month τ: the binary high MAX event indicator variable, $hi_{\tau}^{i,\tau}$, equals 1 if the maximum single day return for the month is a high MAX return (i.e. ranks in the top 10% for all stocks in the month), and 0 otherwise; $SIZE_{(\tau-1)+}^{i,\tau}$ is the natural logarithm of market capitalization in millions of dollars at the end of the prior month; book-to-market, $BM_{FY}^{i,\tau}$, is the book value of equity (being the book value of common equity plus balance-sheet deferred taxes) for the latest fiscal year ending in the prior year divided by market capitalization at the end of December in the prior year; momentum, $MOM^{i,\tau}_{(\tau-12,\tau-2)}$, is the 11-month cumulative return beginning 12 months prior (i.e. up to but excluding the prior month); reversal, $REV^{i,\tau}_{\tau-1}$, is the return for the prior month; illiquidity, $ILLIQ^{i,\tau}_{\tau-1}$, is the prior month's average of, daily absolute value of stock return divided by estimated dollar trading volume, scaled by 10^5 (daily dollar trading volume is estimated as daily share trading volume multiplied by the average of the day's high, low and close stock prices); idiosyncratic volatility, $IVOL^{i,\tau}_{\tau-3,\tau-1}$, and idiosyncratic skewness, $ISKEW^{i,\tau}_{\tau-12,\tau-1}$, are, respectively, the prior three month standard deviation and prior 12 month skewness of daily Fama-French-Carhart four-factor asset pricing model regression residuals; and $PRICE^{i,\tau}_{(\tau-1)+}$ is the natural log of the closing stock price for the prior month.

For Equation (1), the *SIZE*, *BM*, *MOM*, *REV* and *ILLIQ* lagged independent variables are standard stock characteristic variables that have been shown in the literature to be significantly related to stock returns (see Fama and French, 1992; Jegadeesh and Titman, 1993; Jegadeesh, 1990; Amihud, 2002). *IVOL*, *ISKEW* and *PRICE* are included in respect of Kumar's (2009) characterization of lottery-like stocks as having high idiosyncratic volatility and skewness, and low price. Table 2 presents summary statistics for the time series of 83 sets of coefficient estimates for the Equation (1) regression. Consistent with Kumar's lottery-like stock characterization, we find that the probability of a high MAX event for a stock is, on average, positively associated with the stock's *IVOL* and *ISKEW*, and negatively associated with *PRICE*.

[Table 2 around here]

At the start of every month from August 1964 to December 2005, we use the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables to estimate the Equation (1) logistic model probability of each sample stock being a high MAX stock for the month: the top 10% of stocks ranked by estimated probability of being a high MAX stock are then designated as expected high MAX stocks for the month. Note that, by our method, each month's expected high MAX stocks are identified ex-ante with out-of-sample parameters. Figure 1 presents our high MAX stock prediction success rates: the proportion of expected high MAX stocks that become actual high MAX stocks each month. Across our sample period we achieve a monthly high MAX stock prediction success rate of 37.4% on average. The Appendix presents the formula for calculating the probability of achieving or beating a nominated prediction success rate by pure luck, which is dependent on the number of sample stocks in cross-section. For every month of our sample, our high MAX stock prediction success rate is better than pure luck with better than 5% significance; and, for every month of our sample bar two (May 1966 and July 1981), our high MAX stock prediction success rate is better than pure luck with better than 1% significance.

[Figure 1 around here]

Table 3 presents summary characteristics for stocks sorted monthly into decile portfolios according to the scale of their estimated probability of achieving a high MAX return. Table 3 lists the time series averages of the monthly decile portfolio medians of stock characteristic variables. Table 3 further confirms the success of our high MAX prediction model: increasing high MAX probability decile is associated with increasing MAX return. Of particular interest each month are the decile 10 expected high MAX stocks: comparison of the bottom rows of Table 3 and Table 1 indicates that the decile 10 expected high MAX stocks have generally lower market capitalizations and prices, and higher illiquidity scores in comparison to the actualized decile 10 high MAX stocks. Our identified expected high MAX stocks do successfully yield the highest average (of monthly median) MAX return of the Table 3 decile portfolios (with a value of 12.43%), but nevertheless yield a negative average (of monthly median) return of -1.13% for the MAX event month (the lowest for the Table 3 decile portfolios): this is consistent with ex-ante over-valuation, on average, of stocks that offer lottery-like payoff opportunities as posited by BCW. The post-MAX event month return (NEXTRET) shows persistence of underperformance for the expected high MAX decile. That is, both the decile 10 actual high MAX stocks (Table 1) and the decile 10 expected high MAX stocks (Table 3) exhibit post-MAX event month underperformance: is this due to reversal of actual high MAX overreaction, or due to ongoing price correction of overvalued lottery like stocks? We aim to shed light on this issue by investigating the post-MAX event month comparative performance of portfolios that control for investment in actual high MAX stocks and expected high MAX stocks.

[Table 3 around here]

BCW consider whether the "MAX effect" is instead a "skewness effect". Boyer et al. (2010) find that portfolios formed from stocks with the highest (lowest) expected idiosyncratic skewness significantly underperform (outperform) over the ensuing month: perhaps BCW's high MAX stock selection is proxying for high iskew stock selection. BCW find that controlling for past-year skewness (either as total skewness, systematic skewness, idiosyncratic skewness or expected total skewness) makes little difference to the firm level negative relationship between event month MAX return and post-event month return. Our results are consistent with both Boyer et al. and BCW. Our Table 1 depicts BCW's MAX effect (as shown by NEXTRET versus high MAX decile). Table 3 shows that the high MAX probability deciles are positively associated with the idiosyncratic skewness of the constituent stocks (which is reflective of our expected high MAX prediction model), which is, in turn, negatively related to stock return, as per Boyer et al.[2] A crucial distinction is that Boyer et al. classify stocks according to their potential to deliver lottery-like outcomes, whereas BCW classify stocks according to their actual delivery of lottery-like outcomes. Although all high idiosyncratic skewness stocks might reasonably be classified as lottery-like, only a small percentage will reward speculators with an extreme positive return. And, while all high MAX stocks can be considered to have rewarded their investors with an extreme positive return, not all will have been identified by speculators, ex-ante, as lottery-like. In the next section we dissect BCW's MAX effect to determine whether it is dependent on an ex-ante expectation of a high MAX return in the vein of Boyer et al.

3. DISSECTING THE MAX EFFECT

At the start of each MAX event month from August 1964 to November 2005, using the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables, we identify 10% of sample stocks as being expected high MAX stocks. These stocks are expected to yield MAX returns that will rank in decile 10 and are accordingly designated as *expHiMAX* stocks. The other 90% of stocks are expected to be non-high MAX stocks with MAX returns ranking below decile 10, hence we designate these as *expNonHiMAX* stocks. At the end of each MAX event month we are then able to identify the 10% of stocks that actually did yield decile 10 MAX returns for the month: these stocks are designated *actHiMAX*. The other 90% of stocks that

[2] In an additional analysis not presented here, we find further results consistent with Boyer et al. (2010): monthly decile portfolios formed according to ranked expected idiosyncratic skewness yield median returns that are, on average, monotonically negatively related to the portfolio decile level of expected idiosyncratic skewness.

yielded actual MAX returns ranking below decile 10 are designated *actNonHiMAX*.

We are interested in how BCW's MAX effect anomaly, which depends on ex-post (i.e. post-MAX event) identification of actual high MAX stocks (i.e. *actHiMAX* stocks), differs for stocks identified ex-ante (i.e. pre-MAX event) as expected high MAX (i.e. *expHiMAX* stocks) versus for stocks identified ex-ante as expected non-high MAX (i.e. *expNonHiMAX* stocks). To do this we compare the post-high MAX performance of portfolios formed from the intersection of *actHiMAX* stocks and *expHiMAX* stocks (*expHiMAX*∩*actHiMAX* stock portfolios) versus portfolios formed from the intersection of *actHiMAX* stocks and *expNonHiMAX* stocks (*expNonHiMAX*∩*actHiMAX* stock portfolios).

Our research aim is to determine whether we can reject the premise that the MAX effect is a consequence of lottery-seeking investment. Our null hypothesis is that the post-high MAX underperformance of stocks is not specifically associated with high MAX stocks identified, pre-MAX event, as likely to offer lottery-like high MAX returns. Our alternative hypothesis is that post-high MAX underperformance is specifically associated with high MAX stocks identified, pre-MAX event, as likely to offer a lottery-like high MAX return. The null and alternative hypotheses are:

> **H0**: Post-high MAX return underperformance of *expHiMAX*∩*actHiMAX* stock portfolios is not significantly worse than that of *expNonHiMAX*∩*actHiMAX* stock portfolios.
>
> **H1**: Post-high MAX return underperformance of *expHiMAX*∩*actHiMAX* stock portfolios is significantly worse than that of *expNonHiMAX*∩*actHiMAX* stock portfolios.

Table 4 reports the post-MAX event month Sharpe ratios and Fama-French-Carhart+reversal five-factor (FFCR5F) asset pricing alphas (i.e. abnormal returns) earned by value- and equal-weighted portfolios of stocks formed at the end of each MAX event month depending on the intersections of their designations as *expHiMAX*, *expNonHiMAX*, *actHiMAX* and *actNonHiMAX*. In respect of the potential role that reversal plays in the MAX effect anomaly, for our abnormal return analysis we augment the "standard" Fama-French-Carhart four-factor asset pricing model with the short-run reversal factor available from Kenneth French's online data library. Our conclusions are not impacted by whether or not the reversal factor is included in the asset pricing model.

[Table 4 around here]

Table 4 shows that monthly value-weighted *expHiMAX*∩*actHiMAX* stock portfolios (row (A)) and monthly value-weighted *expNonHiMAX*∩*actHiMAX* stock portfolios (row (B)) both, on average, exhibit significant underperformance in the post-MAX event month, which is in accordance with the MAX effect anomaly: notably the Sharpe ratio and alpha underperformance levels are of similar scale. Rows (A) and (C) compared to rows (B) and (D) of Table 4 show that the expected high MAX portfolios have higher volatilities than the expected non-high MAX portfolios. Nevertheless, for the value-weighted portfolios, the Sharpe ratios and alphas of the actual high MAX portfolios (rows (A) and (B)) are similar, and the Sharpe ratios and alphas of the actual non-high MAX portfolios (rows (C) and (D)) are similar. The volatilities of the equal-weighted portfolios are similar to their counterpart value-weighted portfolios, but the equal-weighted portfolio of unexpected high MAX stocks (row (B)) exhibits comparative Sharpe ratio and alpha underperformance. To summarize, post-MAX event underperformance is similarly significantly evident regardless of whether our sample is comprised of stocks that are, ex-ante, likely or not likely to yield lottery-like outcomes. In regard to our null and alternative hypotheses, H0 and H1, the alpha for the long-short difference between value-weighted *expHiMAX*∩*actHiMAX* and *expNonHiMAX*∩*actHiMAX* portfolios (row (A)-(B) in Panel B) is not significantly different from zero. This leads us to reject H1 and accept H0: that is, we reject the premise that lottery-seeking investment is a driver of the MAX effect.

The equal-weighted portfolio results in Table 4 show that post-high MAX underperformance is *not* significantly evident for equal-weighted *expHiMAX∩actHiMAX* stock portfolios (row (A)), and is only significantly evident for equal-weighted *expNonHiMAX∩actHiMAX* stock portfolios (row (B)). This further strengthens our conclusion that lottery-seeking investment is not a driver of the MAX effect.

When specifically only considering stocks identified, ex-ante, as likely to yield lottery-like outcomes (i.e. *expHiMAX* stocks), the long-short *expHiMAX∩actHiMAX* minus *expHiMAX∩actNonHiMAX* portfolio results in Table 4 (row (A)-(C) in Panel B) show the *comparative* post-high MAX underperformance associated with the MAX effect. Although the expected high MAX portfolios have the highest volatilities (compare Table 4 reported volatilities for rows (A) and (C) versus rows (B) and (D)), they actually offer the greatest long-short hedging benefit: the volatility of the expected high MAX long-short portfolio is the lowest of all the long-short portfolios (compare Table 4 Panel B reported volatilities for row (A)-(C) versus rows (A)-(B), (C)-(D) and (B)-(D)). It is also interesting to consider only stocks identified, ex-ante, as not likely to yield lottery-like outcomes (i.e. *expNonHiMAX* stocks), and compare post-MAX event performance depending on whether they happen to unexpectedly deliver a high MAX outcome or not. The long-short *expNonHiMAX∩actHiMAX* minus *expNonHiMAX∩actNonHiMAX* portfolio results in Table 4 (row (B)-(D)) show that comparative post-high MAX underperformance is significantly evident even when we control our sample to exclude stocks identified as lottery-like. This further discounts the premise that the MAX effect is a consequence of lottery-seeking investment.

Panels A and B of Table 5 respectively disaggregate the Table 4 results for portfolios of subsample stocks identified to have high institutional ownership or low institutional ownership.[3] Panels C and D of Table 5 respectively disaggregate the Table 4 results for portfolios of subsample stocks identified to have an earnings announcement in the MAX event month, or no earnings announcement in the MAX event month. Lottery-seeking noise trading might have a constrained impact on stocks with high levels of notionally informed institutional ownership, or during periods such as earnings announcement months when stocks are subject to high levels of scrutiny from informed traders. Partitioning our sample along these dimensions allows us to examine stock portfolios where noise/uninformed trading, and potentially the MAX effect, may be more, or less, pronounced; Nguyen and Truong (2018) find that high MAX returns "triggered by earnings announcements do not entail lower future returns" (p.92). We find that expected actual high MAX stocks (i.e. *expHiMAX*∩*actHiMAX* stock portfolios) do not exhibit stronger post-high MAX event underperformance than unexpected high MAX stocks (i.e. *expNonHiMAX*∩*actHiMAX* stock portfolios): in fact, post-high MAX event underperformance is much more consistently evident when the high MAX event is unexpected. That is, for the Table 5 subsample portfolios, the MAX effect is generally more notable for stocks identified ex-ante as *not* likely to deliver a lottery-like outcome, than for stocks identified as likely to deliver a lottery-like outcome. Therefore, our Table 4 inference rejecting the specific association of the MAX effect with ex-ante lottery-seeking investment is robust

[3] Institutional ownership is identified for a subsample of stocks reported in the Thomson Reuters Institutional Holdings (13F) database from March 1980 to November 2005 (entailing a reduced dataset with about 1.4 million stock-month observations). High (low) institutional ownership stocks are identified as the top (bottom) half of stocks ranked by their most recent past quarterly institutional ownership levels.

to portfolio partitioning along the dimensions of institutional ownership and earnings announcement events.

[Table 5 around here]

Table 5 shows that the post-high MAX event negative abnormal return performance of *expNonHiMAX*∩*actHiMAX* stock portfolios is particularly significantly evident for either low institutional ownership stocks (Panel B) or when the MAX-event month is not an earnings announcement month (Panel D). The association of the MAX effect anomaly with low institutional ownership stocks and with MAX events unrelated to high-scrutiny earnings announcements hints at a market inefficiency (with respect to the FFCR5F asset pricing model) that takes form when there is a reduced presence of sophisticated investors; nevertheless, our results strongly refute an ex-ante lottery-seeking investment explanation. In the next section we apply an event study approach to observe the average return pattern in the temporal vicinity of MAX events: it is possible that unexpected high MAX events actually spark ex-post lottery-seeking investment.

With regard to stocks that do not deliver a high MAX outcome, Table 5 shows that the post-MAX event performance of the *expHiMAX*∩*actNonHiMAX* stock portfolios tends to be significantly stronger than for the *expNonHiMAX*∩*actNonHiMAX* stock portfolios. Perhaps this hints at a process by which lottery-like stocks become relatively over-valued: we leave this for future investigation. In any case, we have shown that the MAX effect anomaly is almost certainly not the process by which lottery-like stocks are corrected of any relative over-valuation in comparison to non-lottery-like stocks.

4. THE MAX EFFECT IN EVENT-TIME

The evidence in the preceding section indicates that the MAX effect anomaly is associated with non-lottery-like stocks as much as (or even more so than) with lottery-like stocks. Next we are interested in observing the daily event-time pattern of MAX event related stock returns. BCW's monthly return analysis is too coarse to unequivocally identify investor reaction to high MAX events. Our analysis of daily returns allows us to focus directly on the MAX event and surrounding days using well-known event study techniques. We analyze cumulative average abnormal daily returns (CAARs) where event day-zero for each stock-month event is the trading day on which the stock earns its maximum (MAX) daily return for the month. The cross-sectional CAARs are obtained for stock-month MAX events sorted according to the monthly designations of stocks as *expHiMAX*∩*actHiMAX*, *expHiMAX*∩*actNonHiMAX*, *expNonHiMAX*∩*actHiMAX* and *expNonHiMAX*∩*actNonHiMAX* as defined in the previous section. Event window daily abnormal stock returns are calculated with respect to the Fama-French-Carhart four-factor asset pricing model. For each stock–month event, the Fama-French-Carhart four-factor asset pricing factor loadings are estimated out-of-sample for the [-275, -21] trading day pre-event window (roughly equating to a one-year estimation period).

Monthly MAX event identification occurs ex-post, after the event month has ended. Thus our event study approach suffers from the drawback that separate MAX events are identified (with certainty) at various post-event days ranging from (close of) event day zero to event day +22, depending on how many trading days there are in the event month, and whether the MAX event occurs at the end, middle or beginning of the event month. That is, in daily event time, specification of the MAX event as event day-zero entails look-ahead bias. Accordingly, our event study analysis of the MAX effect should be considered as an ex-post review of daily return dynamics. For robustness we also undertook additional analysis that avoided look-ahead bias with the alternative specification of event day-zero as the day with the highest single-day return in the past 21 trading days (that is, a first-Max-in-21 days specification). The conclusions we draw regarding MAX effect and overreaction are unchanged.[4]

Figure 2 presents the full [-10,+40] trading day MAX event window CAAR graphs, and Table 5 presents CAARs and CAAR differences for various MAX event sub-windows. We use these results to investigate the premise that high MAX events entail overvaluation by investors that "may be willing to pay more for stocks that exhibit extreme positive returns" (BCW p.428). Evidence for lottery-seeking investment as an explanation for the MAX effect might present in two ways. Firstly, a high MAX event might confirm hopeful investors' ex-ante beliefs that a stock is lottery-like, in which case we expect return outperformance in the lead-up to the hoped-for high MAX event, and then post-high MAX "cashing-out" underperformance. Secondly, a high MAX event might itself present a signal that a stock is lottery-like, sparking ex-post demand from hopeful lottery-seekers leading to post-high MAX return outperformance and anticipation, followed by (on average) disappointment and underperformance. Neither of these two possible patterns of lottery-seeking activity in relation to high MAX events is evident in our analysis. Figure 2 shows that, from event day -10 to event day +10, the only source of positive CAAR is the MAX event day zero itself: that is, regardless of expected or actual high MAX stock designation, excluding the MAX event, on average there is no evidence of overvaluation being introduced across the MAX event window from event day -10 to event day +10. Table 6 (rows (A) to (D)) shows that all four stock designation CAARs are significantly negative for the post-MAX event [+1,+5] window, which is

[4] We are grateful to an anonymous referee for emphasizing the importance of this issue. The results for this analysis are available via https://doi.org/10.25917/w1ve-5r50.

suggestive of reversal of MAX event overreaction. It is worth reiterating that, if daily stock returns are subject to random investor over- or underreaction with zero average bias, a stock's MAX return, being the maximum single day return across a month (identified ex-post), will more likely be an overreaction event than an underreaction event. By scale, the strongest [+1,+5] CAAR reversal (-4.39%) is evident for the expected high MAX stocks that deliver actual high MAX returns (i.e. the *expHiMAX∩actHiMAX* stocks): this may reflect some cashing-out by rewarded ex-ante lottery-seekers, but this reversal performance is far too short-lived to explain the MAX effect anomaly.

[Figure 2 and Table 6 around here]

For our investigation of the MAX effect, we are most interested in specifically considering actual high MAX events, both expected and unexpected (see rows (A) and (B) of Table 6). Across the [+1,+5], [+6,+10] and [+11,+20] event windows, total CAAR is similar for both the *expHiMAX∩actHiMAX* stocks and the *expNonHiMAX∩actHiMAX* stocks (-4.39-0.10+0.96 versus -2.28-0.42-0.31): this is consistent with our monthly portfolio results presented in Table 4. However, the dynamics are notably different: on average the *expNonHiMAX∩actHiMAX* stocks exhibit ongoing post-high MAX partial reversal at a reducing rate, but the *expHiMAX∩actHiMAX* stocks fall harder in the [+1,+5] window and actually rebound across the [+11,+20] window (with the rebound continuing across the [+21,+40] window).

Insofar as expected high MAX stocks proxy for lottery-like stocks, we cannot attribute the MAX effect (or, more specifically, post-high MAX return underperformance at a monthly time-scale) to reversal of lottery-seeking investor overvaluation. In fact, the actual high MAX stocks that were expected to be high MAX (i.e. the *expHiMAX∩actHiMAX* stocks) outperform strongly across the [+11,+20] and [+21,+40] event windows, which extends through the monthly MAX effect time-scale: if anything, lottery-seeking investment contributes to post-high MAX return outperformance and undermines the MAX effect anomaly. That is, BCW's (p.428) suggestion that "investors may be willing to pay more for stocks that exhibit extreme positive returns" is actually evident ex-post across the [+11,+20] and [+21,+40] windows, but only for the cohort of stocks identified as expected high MAX. That is, the event window CAAR pattern for expected high MAX stocks that actually deliver high MAX returns is consistent with MAX event overreaction and expeditious [+1,+5] reversal, followed by [+11,+20] and [+21,+40] rebound outperformance.[5] If expected high MAX stocks are the investment province of "behaviorally driven" lottery-seeking speculators, we could posit that rapid post-high MAX profit-taking reversal is consistent with the disposition effect, and that the high MAX price then serves as a pricing anchor against which the post-reversal price looks "cheap", thereby prompting a re-investment rebound (the high MAX event may also draw the attention of new speculators who also make their investment decision based on the high MAX price anchor). We leave this speculation for later investigation.

The event window CAAR pattern for unexpected high MAX stocks (*expNonHiMAX∩actHiMAX* stocks) is commensurate with return overreaction embedded within high MAX returns and slow/impeded reversal across the [+1,+5], [+6,+10] and [+11,+20] windows. It is possible that unexpected high MAX events attract buying pressure from misguided ex-post lottery-seeking investors that impedes and prolongs post-high MAX partial reversal: even so, it would still be high-MAX return overreaction, on average, that establishes the circumstances for the MAX effect to play-out. That is, high MAX overreaction and reversal is clearly the "summary" explanation for the CAAR pattern for the

[5] See also row (A)-(B) of Table 6 for the [+6,+10], [+11,+20] and [+21,+40] post-high MAX outperformance of *expHiMAX∩actHiMAX* stocks relative to *expNonHiMAX∩actHiMAX* stocks.

expNonHiMAX∩actHiMAX stocks, and the anomaly is the prolonged nature of the reversal.[6]

All four stock designation CAARs are significantly negative for the pre-MAX event [-10,-1] window, but the scale of the negative CAARs is greater for the two sets of expected high MAX stocks than for the two sets of expected non-high MAX stocks (-6.96% and -7.08% versus -3.40% and -2.81%): potentially this indicates overvaluation of expected high MAX stocks prior to the -10 event day. For the [+6,+10] and [+11,+20] event windows (beyond the immediate [+1,+5] post-MAX window), the expected high MAX stocks that fail to deliver high MAX returns (the *expHiMAX∩actNonHiMAX* stocks) also show, by scale, the strongest negative CAARs (-1.37% and -1.34%). Hence our expected high MAX stocks, serving as proxy lottery-like stocks, demonstrate pre-MAX comparative underperformance, and [+6,+10] through to [+11,+20] comparative underperformance when actual high MAX returns are not delivered. Nevertheless, the expected high MAX stocks (regardless of high MAX actualization) go on to demonstrate very strong comparative outperformance for the [+21,+40] window (with CAARs of 3.69% and 1.34%, versus -0.19% and -0.21% for the expected non-high MAX stocks). These results provide circumstantial evidence of misvaluation due to lottery-seeking investor behavior, but not commensurate with the MAX effect anomaly.

The bottom two rows of Table 6 allow us to compare the MAX event performance for controlled classifications of actual high MAX stocks and actual non-high MAX stocks. For the [+1,+5] event window, lottery-like expected high

[6] To determine if the prolonged partial reversal of unexpected high MAX returns is attributable to misguided buying support from lottery-seeking investors would seemingly require a comparative analysis of the characteristics of ex-post buyers versus ex-post sellers.

MAX stocks reverse more strongly than their non-lottery-like expected non-high MAX counterparts. However, given actual occurrence of a high MAX return (row (A)-(B)), lottery-like expected high MAX stocks exhibit comparative outperformance across the [+6,+10], [+11,+20] and [+21,+40] event windows: this suggests comparative investment exuberance for successful lottery-like stocks (after expeditious [+1,+5] post-MAX return profit-taking partial reversal), which undermines hypothesized association of prolonged post-high MAX underperformance with lottery-seeking investment. Conversely, given non-eventuation of a high MAX return (row (C)-(D)), lottery-like expected high MAX stocks exhibit ongoing comparative underperformance across the [+6,+10] and [+11,+20] windows: this suggests comparative investment despondence for failed lottery-like stocks, however their comparative performance rebounds across the [+21,+40] window.

5. CONCLUSION

Our investigation of Bali et al.'s (2011) MAX effect asset pricing anomaly finds that post-high MAX return underperformance is a general phenomenon that is independent of stocks being identified, ex-ante, as lottery-like. Our approach and results conceptually tie-together Bali et al.'s MAX effect anomaly and Boyer et al.'s (2010) expected iskew anomaly: although all high expected iskew stocks might reasonably be classified as lottery-like, only a small percentage will reward speculators with an extreme positive return; and, while all high MAX stocks can be considered to have rewarded their investors with an extreme positive return, not all will have been identified by speculators, ex-ante, as lottery-like. Additionally, with an event study approach, we find that the average high MAX event cumulative abnormal return pattern is indicative of overreaction embedded within high MAX returns.

APPENDIX

For a given month, high MAX stocks are identified as those for which the maximum single day return during the month ranks in the highest 10% for all stocks: these are *actual high MAX stocks*. For the same month, we use an out-of-sample logistic model to estimate the ex-ante probability of each stock being a high MAX stock (see Equation (1)): we define *expected high MAX stocks* as those for which the estimated probability of being a high MAX stock ranks in the highest 10% for all stocks. For all sample stocks each sample month we identified 152,100 expected high MAX stocks in total, of which 61,422 (40%) turned out to be actual high MAX stocks.

For a single month with N stocks in cross-section, there are $0.1N$ stocks that, ex-ante, are expected to be high MAX stocks. Defining $\eta \leq 0.1N$ to be a desirable minimum number of successfully predicted high MAX stocks (i.e. expected high MAX stocks that become actual high MAX stocks), and $n \leq 0.1N$ to be the actual number of successfully predicted high MAX stocks, the probability of achieving $n \geq \eta$ purely by luck (i.e. by choosing the expected high MAX stocks purely by guessing) is

$$\Pr(n \geq \eta) = \sum_{x=\eta}^{0.1N} \Pr(n = x)$$

$$= \sum_{x=\eta}^{0.1N} \binom{0.1N}{x} \frac{(0.9N)!}{N!} \frac{(0.1N)!}{(0.1N - x)!} \frac{(0.9N)!}{(0.9N - 0.1N + x)!} \,. \qquad \text{(A1)}$$

Table A1 presents pure luck high MAX stock prediction success rate probabilities for various combinations of N and η. Table A1 shows that, for samples of 500 or more stocks, there is less than 1% probability that 22% or more of the 10% of stocks guessed to be high MAX will be actual high MAX.

Table A1 – Pure luck high MAX stock prediction success rates

Description: For a notional N stocks, the probability that $\eta/(0.1N)$ or more of ex-ante "predicted" (guessed) high MAX stocks will, ex-post, be actual high MAX stocks is obtained by Equation (A1) and presented for various combinations of N and η.

Interpretation: For samples of 500 or more stocks, there is less than 1% probability that 22% or more of the 10% of stocks guessed to be high MAX will be actual high MAX. This table allows us to assess the monthly high MAX stock prediction success rate of 37.4% we achieve across the sample period (see Figure 1).

Number of stocks N	Number of "predicted" (guessed) high MAX stocks $0.1N$	Specified minimum desired high MAX stock prediction success* η	Desired prediction success rate $\geq\eta/(0.1N)$	Probability of achieving desired prediction success rate with pure luck prediction
500	50	11	≥0.220	0.0061
500	50	9	≥0.180	0.0483
1,000	100	18	≥0.180	0.0068
1,000	100	16	≥0.160	0.0320
2,000	200	31	≥0.155	0.0065
2,000	200	28	≥0.140	0.0353
10,000	1,000	122	≥0.122	0.0097
10,000	1,000	116	≥0.116	0.0445

* For the purposes of this table, η is specified so that the pure luck prediction success rate probability is ≤0.01 or ≤0.05.

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Figure 1 - Expected high MAX stock logistic prediction model success rates

Description: The figure shows the number of expected high MAX stocks each month (right axis), and the monthly high MAX stock prediction success rate (i.e. the proportion of expected high MAX stocks that become actual high MAX stocks) (left axis). Each month from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month: the top 10% of stocks ranked by estimated probability of achieving a high MAX return are then designated for the month as expected high MAX stocks.

Interpretation: Across our sample period we achieve a monthly high MAX stock prediction success rate of 37.4% on average. Our high MAX stock prediction success rate is better than pure luck with better than 5% significance; and, for every month of our sample bar two (May 1966 and July 1981), our high MAX stock prediction success rate is better than pure luck with better than 1% significance.

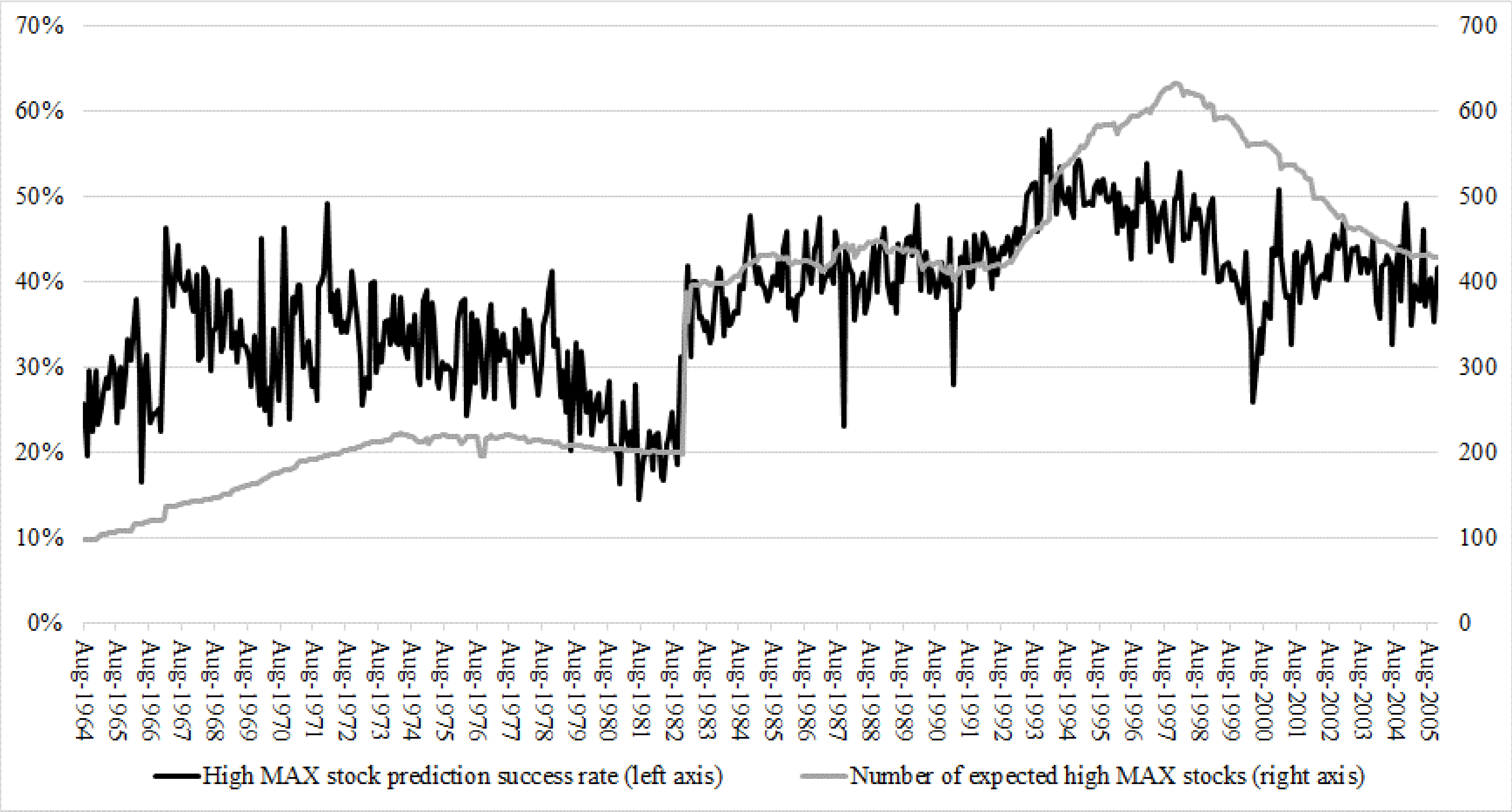

Figure 2 - MAX event CAARs for stocks sorted according to expectation and actualization of high MAX returns

Description: The figure shows the cross-sectional cumulative average abnormal returns (CAARs) with respect to the Fama-French-Carhart four-factor asset pricing model over the [-10, +40] MAX event trading day window for different stock-month MAX event expectation and actualization designations where each event day-zero is the MAX return day. Each MAX event month, from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month: the top 10% of stocks ranked by estimated probability of achieving a high MAX return are then designated expected high MAX (*expHiMAX*), and the remaining 90% of stocks are designated expected non-high MAX (*expNonHiMAX*). Additionally for each MAX event month: the top 10% of stocks ranked by realized MAX return are designated actual high MAX (*actHiMAX*), and the remaining 90% of stocks are designated actual non-high MAX (*actNonHiMAX*). From the monthly intersections of the stock designations, stock-month MAX events are designated as *expHiMAX*∩*actHiMAX*, *expHiMAX*∩*actNonHiMAX*, *expNonHiMAX*∩*actHiMAX* or *expNonHiMAX*∩*actNonHiMAX*.

Interpretation: From event day -10 to event day +10, the only source of positive CAAR is the MAX event day zero itself: that is, regardless of expected or actual high MAX stock designation, excluding the MAX event, on average there is no evidence of overvaluation being introduced across the MAX event window from event day -10 to event day +10. Beyond event day +10, the actual high MAX stocks that were expected to be high MAX exhibit outperformance on average, which is contradictory to the association of post-high MAX return underperformance with lottery-like stocks.

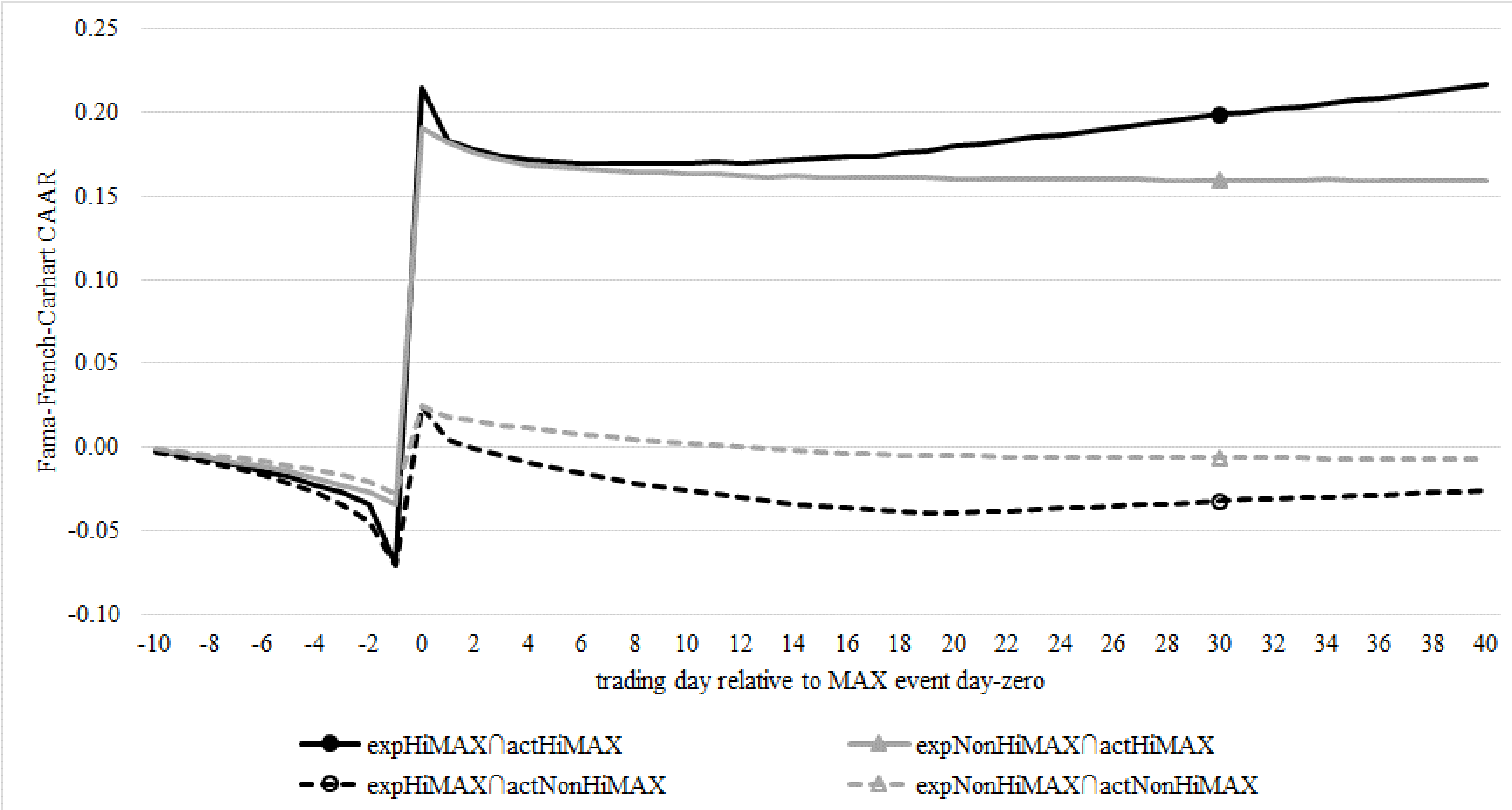
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
Fama-French-Carhart CAAR
-10 -8 -6 -4 -2 0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40
trading day relative to MAX event day-zero
expHiMAX∩actHiMAX
expNonHiMAX∩actHiMAX
expHiMAX∩actNonHiMAX
expNonHiMAX∩actNonHiMAX

Table 1 - Summary characteristics for decile portfolios sorted on actual MAX return

Description: The table presents the average across the months from August 1964 to November 2005 of the median values each month for each MAX decile stock portfolio for the following stock characteristics: MAX return; MCAP (market capitalization in millions of dollars) at the end of the month; stock PRICE at the end of the month; BETA (calculated for the month as the total of the three slope coefficients from regression of the stock's daily excess return against the lead, lag, and contemporaneous market excess return); book-value of equity to market-value of equity ratio (BM) at the start of the month; illiquidity (ILLIQ, calculated as the average for the month of the daily absolute value of return divided by estimated dollar trading volume, scaled by 10^5); momentum (MOM, the cumulative return over the prior 11 months); idiosyncratic volatility (IVOL, calculated as the standard deviation of daily Fama-French-Carhart four-factor asset pricing model regression residuals across the month and prior two months); idiosyncratic skewness (ISKEW, calculated as the skewness of daily Fama-French-Carhart four-factor asset pricing model regression residuals across the month and prior 11 months); the return for the month (RET); and the return for the next month (NEXTRET). Each month from August 1964 to November 2005, decile portfolios are formed by sorting stocks based on their maximum (MAX) single day return in the month. Decile 1 (10) contains stocks with the lowest (highest) MAX returns. There is an average of 340 stocks per MAX decile portfolio per month.

Interpretation: We replicate BCW's MAX effect: increasing portfolio MAX decile is associated with generally decreasing return for the next month (NEXTRET). Generally, high MAX stocks (decile 10) are small, low-priced stocks with high illiquidity scores and market betas, very negative prior return performance, and high idiosyncratic volatility and skewness.

MAX decile	MAX (%)	MCAP ($\$10^6$)	PRICE ($)	BETA	BM	ILLIQ (10^5)	MOM (%)	IVOL	ISKEW	RET (%)	NEXTRET (%)
1	1.67	312.9	25.17	0.32	0.863	0.015	11.59	1.21	0.315	-2.28	0.75
2	2.56	314.2	24.89	0.54	0.807	0.012	11.47	1.45	0.274	-1.00	0.88
3	3.28	236.2	22.81	0.67	0.786	0.014	11.15	1.68	0.296	-0.50	0.84
4	4.01	179.3	20.43	0.76	0.771	0.018	10.59	1.93	0.330	-0.06	0.75
5	4.82	133.9	18.21	0.87	0.767	0.024	10.20	2.20	0.369	0.36	0.62
6	5.76	101.6	15.74	0.95	0.769	0.034	8.82	2.49	0.415	0.70	0.40
7	6.95	76.1	13.29	1.03	0.769	0.050	6.88	2.85	0.464	1.26	0.15
8	8.58	55.1	10.79	1.10	0.780	0.077	4.07	3.27	0.530	2.13	-0.21
9	11.18	37.5	8.35	1.14	0.804	0.138	-0.32	3.90	0.616	3.71	-0.90
10, actual high MAX	17.64	20.4	5.36	1.19	0.853	0.351	-10.11	5.35	0.867	8.92	-2.08

Table 2 - Summary statistics for the expected high MAX stock logistic prediction model coefficients

Description: The table presents the means of 83 estimates of each of the regression coefficients and intercept for the following logistic regression model for the probability of a stock achieving a high MAX outcome, and the standard errors of those means, and, in parentheses, the T-statistics of those means. Every six months from July 1964 to July 2005, stock-month observations (i, τ) extending back to τ equal to July 1962 are used to estimate the coefficients of the following logistic model (i.e. the model is re-estimated every six months through the sample period, 83 times in total, with a backwards expanding estimation window):

$$\ln\left(\Pr\left(hi_{\tau}^{i,\tau}=1\right)/\left(1-\Pr\left(hi_{\tau}^{i,\tau}=1\right)\right)\right)=a+b_1 SIZE_{(\tau-1)+}^{i,\tau}+b_2 BM_{FY}^{i,\tau}+b_3 MOM_{\tau-12,\tau-2}^{i,\tau}+b_4 REV_{\tau-1}^{i,\tau}+b_5 ILLIQ_{\tau-1}^{i,\tau}$$
$$+b_6 IVOL_{\tau-3,\tau-1}^{i,\tau}+b_7 ISKEW_{\tau-12,\tau-1}^{i,\tau}+b_8 PRICE_{(\tau-1)+}^{i,\tau}$$

where, for stock i and month τ: the binary high MAX event indicator variable, $hi_{\tau}^{i,\tau}$, equals 1 if the maximum single day return for the month is a high MAX return (i.e. ranks in the top 10% for all stocks in the month), and 0 otherwise; $SIZE_{(\tau-1)+}^{i,\tau}$ is the natural logarithm of market capitalization in millions of dollars at the end of the prior month; book-to-market, $BM_{FY}^{i,\tau}$, is the book value of equity (being the book value of common equity plus balance-sheet deferred taxes) for the latest fiscal year ending in the prior year divided by market capitalization at the end of December in the prior year; momentum, $MOM_{(\tau-12,\tau-2)}^{i,\tau}$, is the 11-month cumulative return beginning 12 months prior (i.e. up to but excluding the prior month); reversal, $REV_{\tau-1}^{i,\tau}$, is the return for the prior month; illiquidity, $ILLIQ_{\tau-1}^{i,\tau}$, is the prior month's average of daily absolute value of stock return divided by estimated dollar trading volume, scaled by 10^5; idiosyncratic volatility, $IVOL_{\tau-3,\tau-1}^{i,\tau}$, and idiosyncratic skewness, $ISKEW_{\tau-12,\tau-1}^{i,\tau}$, are, respectively, the prior three month standard deviation and prior 12 month skewness of daily Fama-French-Carhart four-factor asset pricing model regression residuals; and $PRICE_{(\tau-1)+}^{i,\tau}$ is the natural log of the closing stock price for the prior month.

Interpretation: Consistent with Kumar's (2009) lottery-like stock characterization, we find that the probability of a high MAX event for a stock is, on average, positively associated with the stock's IVOL and ISKEW, and negatively associated with PRICE.

Statistic (for 83 estimates of each coefficient)	Intercept	Coefficient SIZE	BM	MOM	REV	ILLIQ	IVOL	ISKEW	PRICE
Minimum	-1.5656	-0.4007	-0.2766	-0.0023	-0.0081	-0.3183	0.2398	-0.0328	-0.7046
Maximum	-0.2330	-0.1624	0.0608	0.0039	0.0034	0.0104	0.9063	0.1104	-0.1862
Standard Error	0.0500	0.0056	0.0092	0.0002	0.0003	0.0092	0.0156	0.0053	0.0198
Mean	-1.0363	-0.3318	-0.1101	0.0015	-0.0048	-0.0831	0.4072	0.0206	-0.4300
	(-20.74)	(-59.04)	(-12.03)	(9.76)	(-15.62)	(-9.05)	(26.09)	(3.89)	(-21.67)

Table 3 - Summary characteristics for decile portfolios sorted on estimated probability of high MAX return

Description: The table presents the average across the months from August 1964 to November 2005 of the median values each month for each high MAX probability decile portfolio for the following stock characteristics: MAX return; MCAP (market capitalization in millions of dollars) at the end of the month; stock PRICE at the end of the month; BETA (calculated for the month as the total of the three slope coefficients from regression of the stock's daily excess return against the lead, lag, and contemporaneous market excess return); book-value of equity to market-value of equity ratio (BM) at the start of the month; illiquidity (ILLIQ, calculated as the average of the daily absolute value of return divided by estimated dollar trading volume within the month, scaled by 10^5); momentum (MOM, the cumulative return over the prior 11 months); idiosyncratic volatility (IVOL, calculated as the standard deviation of daily Fama-French-Carhart four-factor asset pricing model regression residuals across the month and prior two months); idiosyncratic skewness (ISKEW, calculated as the skewness of daily Fama-French-Carhart four-factor asset pricing model regression residuals across the month and prior 11 months); the return over the month (RET); and the return for the next month (NEXTRET). Each month from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month. Then, each month, decile portfolios are formed by sorting stocks based on their estimated probabilities of achieving a high MAX return for the month. Decile 1 (10) contains stocks with the lowest (highest) estimated probabilities of achieving high MAX returns. There is an average of 340 stocks per high MAX probability decile portfolio per month.

Interpretation: BCW consider whether the "MAX effect" is instead a "skewness effect". Boyer, Mitton and Vorkink (2010) find that portfolios formed from stocks with the highest (lowest) expected idiosyncratic skewness underperform (outperform) over the ensuing month. This table shows that the high MAX probability deciles are positively associated with the idiosyncratic skewness of the constituent stocks (which is reflective of our expected high MAX prediction model), which is, in turn, negatively related to stock return, which is consistent with Boyer et al.'s finding for idiosyncratic skewness.

High MAX probability decile	MAX (%)	MCAP ($\$10^6$)	PRICE ($)	BETA	BM	ILLIQ (10^5)	MOM (%)	IVOL	ISKEW	RET (%)	NEXTRET (%)
1	3.04	3117.6	46.54	0.87	0.639	0.001	14.31	1.25	0.176	0.82	0.85
2	3.42	772.9	32.29	0.78	0.724	0.003	13.26	1.50	0.245	0.81	0.86
3	3.85	341.0	26.24	0.73	0.746	0.008	12.81	1.73	0.297	0.79	0.85
4	4.37	186.3	21.67	0.74	0.771	0.017	11.69	1.97	0.355	0.78	0.79
5	4.88	105.2	17.63	0.73	0.810	0.032	10.60	2.22	0.425	0.59	0.58
6	5.49	65.4	13.95	0.71	0.840	0.057	8.34	2.53	0.473	0.33	0.36
7	6.30	43.6	10.54	0.70	0.868	0.101	4.53	2.92	0.535	-0.02	0.02
8	7.40	28.0	7.66	0.69	0.893	0.188	0.53	3.44	0.605	-0.38	-0.37
9	9.00	16.1	5.11	0.69	0.913	0.369	-4.93	4.22	0.683	-0.83	-0.82
10, expected high MAX	12.43	8.4	2.80	0.69	0.902	0.872	-13.54	6.00	0.822	-1.13	-1.55

Table 4 - Post-MAX event month Sharpe ratios and alphas for stock portfolios sorted according to expectation and actualization of high MAX returns

Description: The table presents the excess return means, volatilities, Sharpe ratios and Fama-French-Carhart+reversal five-factor asset pricing alphas for monthly post-MAX event portfolio returns (Panel A) and combination long-short portfolio difference returns (Panel B) for 496 months from September 1964 to December 2005. Each MAX event month, from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month: the top 10% of stocks ranked by estimated probability of achieving a high MAX return are then designated expected high MAX (*expHiMAX*), and the remaining 90% of stocks are designated expected non-high MAX (*expNonHiMAX*). Additionally for each MAX event month: the top 10% of stocks ranked by realized MAX return are designated actual high MAX (*actHiMAX*), and the remaining 90% of stocks are designated actual non-high MAX (*actNonHiMAX*). At the end of each MAX event month, value- and equal-weighted portfolios are formed from the intersections of the stock designations: *expHiMAX*∩*actHiMAX*, *expHiMAX*∩*actNonHiMAX*, *expNonHiMAX*∩*actHiMAX*, *expNonHiMAX*∩*actNonHiMAX*. The portfolios are held for the subsequent post-MAX event month. Newey-West (1987) adjusted T-statistics are reported in parentheses. Bolded alphas denote significance at the 5% level or better. Returns are presented in percentage terms.

Interpretation: This table shows that post-MAX event underperformance is similarly significantly evident regardless of whether our sample is comprised of stocks that are, ex-ante, likely or not likely to yield lottery-like outcomes. This leads us to reject the premise that lottery-seeking investment is a driver of the MAX effect.

Panel A – Stock portfolios sorted according to expectation and actualization of high MAX returns

Post-MAX event portfolio		Value-weighted excess return mean	volatility	Sharpe ratio	alpha	Equal-weighted excess return mean	volatility	Sharpe ratio	alpha
(A)	*expHiMAX*∩*actHiMAX*	-0.32	12.11	-0.03	**-1.02**	0.63	11.29	0.06	-0.07
					(-2.65)				(-0.19)
(B)	*expNonHiMAX*∩*actHiMAX*	-0.40	8.88	-0.05	**-0.89**	-0.34	8.45	-0.04	**-0.96**
					(-3.13)				(-4.98)
(C)	*expHiMAX*∩*actNonHiMAX*	0.98	10.70	0.09	0.31	1.89	10.01	0.19	**1.13**
					(0.99)				(3.50)
(D)	*expNonHiMAX*∩*actNonHiMAX*	0.48	4.43	0.11	0.03	0.84	5.49	0.15	**0.12**
					(1.80)				(2.04)

Table 4 - *Continued*

Panel B – Long-short portfolios

Post-MAX event long-short portfolio	Value-weighted excess return mean	Value-weighted volatility	Value-weighted Sharpe ratio	Value-weighted alpha	Equal-weighted excess return mean	Equal-weighted volatility	Equal-weighted Sharpe ratio	Equal-weighted alpha
(A)-(B) *expHiMAX∩actHiMAX* minus *expNonHiMAX∩actHiMAX*	0.08	7.94	0.01	-0.13 (-0.33)	0.98	5.31	0.18	**0.89** (3.38)
(C)-(D) *expHiMAX∩actNonHiMAX* minus *expNonHiMAX∩actNonHiMAX*	0.50	8.78	0.06	0.28 (0.87)	1.06	6.32	0.17	**1.01** (3.38)
(A)-(C) *expHiMAX∩actHiMAX* minus *expHiMAX∩actNonHiMAX*	-1.31	4.91	-0.27	**-1.33** (-5.67)	-1.26	3.80	-0.33	**-1.21** (-6.06)
(B)-(D) *expNonHiMAX∩actHiMAX* minus *expNonHiMAX∩actNonHiMAX*	-0.89	6.46	-0.14	**-0.92** (-3.14)	-1.18	4.32	-0.27	**-1.08** (-5.66)

Table 5 - Post-MAX event month alphas for subsample stock portfolios sorted according to expectation and actualization of high MAX returns

Description: The table presents the Fama-French-Carhart+reversal five-factor asset pricing alphas for monthly post-MAX event portfolio returns and combination long-short portfolio difference returns. Panel A (B) presents alphas for portfolios formed from a subsample of stocks reported in the Thomson Reuters Institutional Holdings (13F) database from March 1980 to November 2005 and identified as having high (low) institutional ownership, determined as the top (bottom) half of stocks ranked by their most recent past quarterly institutional ownership levels. Panel C (D) presents alphas for portfolios filtered to only include stocks for which the MAX event month was (was not) identified as an earnings announcement month. Each MAX event month, from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month: the top 10% of stocks ranked by estimated probability of achieving a high MAX return are then designated expected high MAX (*expHiMAX*), and the remaining 90% of stocks are designated expected non-high MAX (*expNonHiMAX*). Additionally for each MAX event month: the top 10% of stocks ranked by realized MAX return are designated actual high MAX (*actHiMAX*), and the remaining 90% of stocks are designated actual non-high MAX (*actNonHiMAX*). At the end of each MAX event month, value- and equal-weighted portfolios are formed from the intersections of the stock designations: *expHiMAX*∩*actHiMAX*, *expHiMAX*∩*actNonHiMAX*, *expNonHiMAX*∩*actHiMAX*, *expNonHiMAX*∩*actNonHiMAX*. The portfolios are held for the subsequent post-MAX event month. Newey-West (1987) adjusted T-statistics are reported in parentheses. Bolded figures denote significance at the 5% level or better. Returns are presented in percentage terms.

Interpretation: Partitioning our sample along the dimensions of institutional ownership, and months with and without earnings announcements, allows us to examine stock portfolios where noise/uninformed trading, and potentially the MAX effect, may be more, or less, pronounced. The MAX effect is generally more notable for stocks identified ex-ante as not likely to deliver a lottery-like outcome, than for stocks identified as likely to deliver a lottery-like outcome. Our Table 4 inference rejecting the specific association of the MAX effect with ex-ante lottery-seeking investment is robust to portfolio partitioning.

Panel A - High institutional ownership stocks

	Actual high MAX stocks			Actual non-high MAX stocks		
	Expected high MAX	Exp. non-high MAX		Expected high MAX	Exp. non-high MAX	
Post-MAX event portfolio	*expHiMAX*∩ *actHiMAX*	*expNonHiMAX*∩ *actHiMAX*	Long-short (difference)	*expHiMAX*∩ *actNonHiMAX*	*expNonHiMAX*∩ *actNonHiMAX*	Long-short (difference)
Value-weighted	-1.01	-0.56	-0.45	0.03	0.06	-0.02
	(-1.77)	(-1.09)	(-0.52)	(0.15)	(1.93)	(-0.09)
Equal-weighted	-0.66	-0.67	0.01	0.21	0.10	0.10
	(-1.56)	(-1.86)	(0.03)	(1.03)	(1.42)	(0.49)

Table 5 - *Continued*

Panel B - Low institutional ownership stocks

	Actual high MAX stocks			Actual non-high MAX stocks		
	Expected high MAX	Exp. non-high MAX		Expected high MAX	Exp. non-high MAX	
Post-MAX event portfolio	*expHiMAX∩ actHiMAX*	*expNonHiMAX∩ actHiMAX*	Long-short (difference)	*expHiMAX∩ actNonHiMAX*	*expNonHiMAX∩ actNonHiMAX*	Long-short (difference)
Value-weighted	-0.92	**-1.47**	0.54	**1.41**	-0.05	**1.46**
	(-1.61)	(-3.41)	(1.01)	(2.47)	(-0.59)	(2.65)
Equal-weighted	0.92	**-0.71**	**1.63**	**2.81**	0.31	**2.49**
	(1.54)	(-2.42)	(3.99)	(4.35)	(1.92)	(4.66)

Panel C - Stocks that announced earnings in the MAX event month

	Actual high MAX stocks			Actual non-high MAX stocks		
	Expected high MAX	Exp. non-high MAX		Expected high MAX	Exp. non-high MAX	
Post-MAX event portfolio	*expHiMAX∩ actHiMAX*	*expNonHiMAX∩ actHiMAX*	Long-short (difference)	*expHiMAX∩ actNonHiMAX*	*expNonHiMAX∩ actNonHiMAX*	Long-short (difference)
Value-weighted	0.22	0.01	0.21	0.80	0.00	0.80
	(0.40)	(0.03)	(0.36)	(1.92)	(-0.05)	(1.93)
Equal-weighted	0.42	-0.20	0.62	**1.14**	0.11	**1.04**
	(0.83)	(-0.71)	(1.36)	(2.89)	(1.15)	(2.81)

Panel D - Stocks that did not announce earnings in the MAX event month

	Actual high MAX stocks			Actual non-high MAX stocks		
	Expected high MAX	Exp. non-high MAX		Expected high MAX	Exp. non-high MAX	
Post-MAX event portfolio	*expHiMAX∩ actHiMAX*	*expNonHiMAX∩ actHiMAX*	Long-short (difference)	*expHiMAX∩ actNonHiMAX*	*expNonHiMAX∩ actNonHiMAX*	Long-short (difference)
Value-weighted	**-1.21**	**-1.51**	0.30	0.18	**0.08**	0.10
	(-3.15)	(-4.52)	(0.64)	(0.57)	(2.63)	(0.32)
Equal-weighted	-0.10	**-1.35**	**1.24**	**1.20**	0.08	**1.12**
	(-0.26)	(-7.21)	(4.48)	(3.52)	(1.35)	(3.57)

Table 6 - MAX event CAARs for stocks sorted according to expectation and actualization of high MAX returns

Description: The table presents the cross-sectional cumulative average abnormal returns (CAARs) with respect to the Fama-French-Carhart four-factor asset pricing model and CAAR differences for different stock-month MAX event expectation and actualization designations and various MAX event trading day windows where each event day-zero is the MAX return day. Each MAX event month, from August 1964 to November 2005, the most recent past Equation (1) coefficient estimates in conjunction with up-to-the-prior-month stock characteristic variables are used to estimate the Equation (1) logistic model probability of each sample stock achieving a high MAX return for the month: the top 10% of stocks ranked by estimated probability of achieving a high MAX return are then designated expected high MAX (*expHiMAX*), and the remaining 90% of stocks are designated expected non-high MAX (*expNonHiMAX*). Additionally for each MAX event month: the top 10% of stocks ranked by realized MAX return are designated actual high MAX (*actHiMAX*), and the remaining 90% of stocks are designated actual non-high MAX (*actNonHiMAX*). From the monthly intersections of the stock designations, stock-month MAX events are designated as *expHiMAX∩actHiMAX*, *expHiMAX∩actNonHiMAX*, *expNonHiMAX∩actHiMAX* or *expNonHiMAX∩actNonHiMAX*. Newey–West (1987) adjusted T-statistics are reported in parentheses. Bolded figures denote significance at the 0.5% level or better. Returns are presented in percentage terms.

Interpretation: Insofar as expected high MAX stocks proxy for lottery-like stocks, we cannot attribute the MAX effect (or, more specifically, post-high MAX return underperformance at a monthly time-scale) to reversal of lottery-seeking investor overvaluation. In fact, the actual high MAX stocks that were expected to be high MAX (i.e. the *expHiMAX∩actHiMAX* stocks) outperform strongly across the [+11,+20] and [+21,+40] event windows, which extends through the monthly MAX effect time-scale: if anything, lottery-seeking investment contributes to post-high MAX return outperformance and undermines the MAX effect anomaly.

		CAAR window				
	Stock designation	[-10,-1]	[+1,+5]	[+6,+10]	[+11,+20]	[+21,+40]
(A)	*expHiMAX∩actHiMAX*	**-6.96**	**-4.39**	-0.10	**0.96**	**3.69**
	61,422 obs.	(-61.85)	(-55.86)	(-1.52)	(10.28)	(25.50)
(B)	*expNonHiMAX∩actHiMAX*	**-3.40**	**-2.28**	**-0.42**	**-0.31**	-0.19
	67,100 obs.	(-44.52)	(-46.34)	(-10.23)	(-5.74)	(-2.38)
(C)	*expHiMAX∩actNonHiMAX*	**-7.08**	**-3.60**	**-1.37**	**-1.34**	**1.34**
	90,678 obs.	(-120.5)	(-94.91)	(-36.44)	(-22.90)	(15.10)
(D)	*expNonHiMAX∩actNonHiMAX*	**-2.81**	**-1.45**	**-0.75**	**-0.73**	**-0.21**
	1,404,584 obs.	(-312.6)	(-256.4)	(-145.4)	(-96.18)	(-17.49)
(A)-(B)	*expHiMAX∩actHiMAX* minus	**-3.56**	**-2.11**	**0.32**	**1.27**	**3.88**
	expNonHiMAX∩actHiMAX	(-26.63)	(-23.43)	(4.00)	(11.73)	(23.49)
(C)-(D)	*expHiMAX∩actNonHiMAX* minus	**-4.27**	**-2.15**	**-0.62**	**-0.61**	**1.55**
	expNonHiMAX∩actNonHiMAX	(-72.88)	(-57.41)	(-16.26)	(-10.35)	(17.23)