When are Extreme Daily Returns not Lottery? At Earnings Announcements!

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Abstract

We find that quarterly earnings announcements account for more than 18% of the total maximum daily returns in the top *MAX* portfolio. Maximum daily returns as triggered by earnings announcements do not entail lower future returns. Both portfolio and regression analyses show that the *MAX* phenomenon completely disappears when conditioning *MAX* returns on earnings announcements. We further show that earnings announcement *MAX* returns do not indicate a probability of future large short-term upward returns. Excluding earnings announcement *MAX* returns in constructing the lottery demand factor results in not only a larger lottery demand premium but also superior factor model performance.

1. **Introduction**

Bali, Cakici, and Whitelaw (2011, BCW hereafter) document a significant negative relation between the maximum daily returns in the past one month (*MAX*) and expected stock returns in the immediate subsequent month. The authors attribute this phenomenon to market pressures exerted by investors preferring assets with lottery-like features.[1] According to BCW, the maximum daily returns in the past one month, or *MAX*, reliably proxy for lottery demand and lottery investors who are poorly diversified exhibit a preference for stocks as lotteries, thereby pushing up the current prices of high *MAX* stocks. As a result, high *MAX* stocks exhibit lower future returns which cannot be explained by known risk factors. Empirically, BCW show that *MAX* contains unique information regarding lottery demand that cannot be subsumed by traditional measures of idiosyncratic volatility or skewness and that *MAX* provides significant cross-sectional explanation for expected stock returns. While the *MAX* measure and the *MAX* phenomenon proposed by BCW offer influential contributions to our understanding of how lottery demand affects security prices in equilibrium, there are also other plausible interpretations of the maximum daily returns that should warrant further analysis of the *MAX* effect. Given the rising importance of using *MAX* in studying lottery demand and asset pricing, it is important to carefully examine the reasons driving the maximum daily returns, the implications, and then investigate what may truly determine the persistence of the phenomenon.[2]

[1] This explanation is based on the premise that certain groups of investors are not well-diversified (Odean, 1999; Goetzman and Kumar, 2008) and exhibit a preference for lottery-type stocks (Kumar, 2009).
[2] Several other studies provide evidence supporting the existence of the *MAX* effect in the European markets (Annaert, De Ceuster, and Verstegen, 2013; Walkshäusl, 2014), in the Australian market (Zhong and Gray, 2016), in the Chinese market (Nartea, Kong, and Wu, 2017), and in the global markets (Cheon and Lee, 2014). Lin and Liu (2017) document that the *MAX* effect is particularly pronounced among stocks preferred by individual investors.

In this paper, we argue that the maximum daily returns in the past one month, when driven by the arrival of fundamentally relevant information, do not proxy for lottery demand and that stocks with high information-driven *MAX* do not show lower future returns. Specifically, we study stocks that exhibit high maximum daily returns in the past month as triggered by earnings announcements because we can then almost exclusively attribute these *MAX* returns to an important corporate informational event. In addition, because firms routinely report earnings announcements every quarter and large positive daily earnings-response returns are widely observed, earnings announcements should account for a non-trivial proportion of maximum daily returns in any given month. In the context of earnings announcements, extreme positive daily returns indicate arrivals of new information rather than some probability of future large short-term upward moves and such extreme returns should entail little or no demand from lottery investors.[3]

We show that there is no *MAX* effect when the maximum daily returns are driven by earnings announcements in several empirical tests using a large sample of all U.S. stocks between January 1973 and December 2015.[4] First, we document that earnings announcements on average account for 18.3% of the total maximum daily returns in the top *MAX* portfolio and there is an increasing trend in this proportion among high *MAX* portfolios over time. In the last few years of our sample period, earnings announcements drive up to one-third of stocks entering the top *MAX* portfolio, suggesting that many *MAX* returns are in fact incorporations of earnings information.

[3] Daniel, Hirshleifer and Subrahmanyam (1998) propose a theoretical framework of security market under-reaction where investors overreact to private information signals and underreact to public information signals and that the under- or over-reaction is followed by long-run correction. In the context of public earnings disclosures, their theoretical framework would engender an under-reaction of stock prices to earnings information. While we cannot screen for all *MAX* returns that are exclusively driven by public information from the overall pool of *MAX* returns, we can at least reliably associate *MAX* returns which occur surrounding earnings announcements to extreme returns driven by public information disclosures.

[4] In several robustness checks, we show that when *MAX* is defined as the average of the *k* highest daily returns within a month (2, 3, 4, or 5 days) and when earnings announcements account for stock return of at least one of these days, the *MAX* effect also disappears.

We find univariate portfolio analyses do not detect any *MAX* phenomenon when earnings announcement *MAX* returns are used as the sort variable to construct *MAX* portfolios. Similarly, bivariate portfolio analyses show that the abnormal returns of zero-cost portfolios that are long high *MAX* stocks and short low *MAX* stocks after controlling for each firm characteristic completely disappear when these portfolios are constrained to *MAX* returns driven by earnings announcements. This finding, however, is in stark contrast to the finding that the original *MAX* effect as documented in BCW is not only strong in our sample period but also significantly incremented (by up to 33 *bps* per month) when stocks in *MAX* portfolios are not driven by earnings announcements. In a regression framework, while there is a significant negative relation between *MAX* and stock returns in general, there is also a significant positive relation between the interaction of *MAX*, an earnings announcement dummy, and stocks returns. Thus, the negative effect of *MAX* on stock returns is largely reversed when *MAX* is conditioned on earnings announcements. Findings from both portfolio and regression analyses point towards the conclusion that the *MAX* effect is non-existent when the maximum daily returns can be identified as responses to earnings information.

Given lottery demand is more likely driven by individual investors than institutional investors (Kumar, 2009), we examine a group of stocks with low proportions of shares held by institutional investors (where the *MAX* phenomenon is most pronounced due to the dominance of lottery investors). While we find that the *MAX* effect is particularly strong among stocks with low institutional holdings and this is consistent with the notion that lottery demand is high, we still do not detect any *MAX* effect when *MAX* returns are identified as responses to earnings announcements within this group.[5] This evidence suggests that even in an environment where lottery demand is particularly high, lottery investors do not overvalue stocks with high maximum daily returns when such returns are driven by earnings information, and hence these stocks do not exhibit lower future returns as would be predicted by BCW.[6]

We continue to find that our results, the non-existence of the *MAX* effect when *MAX* returns are conditioned on earnings announcements, are robust across variation in time-series settings including accounting for different investor sentiment states, different economic states, and alternative measures of lottery features of stocks. The results of no significant *MAX* effect when conditioning *MAX* returns on earnings announcements also hold when we control for individual stock sensitivity to macro-economic uncertainty and individual stock sensitivity to economic policy uncertainty. These results are not driven by time-variation in the aggregate lottery demand, market microstructure effect, January months versus non-January months, or the level of investor attention.

Next, we provide results from various tests that show *MAX* returns driven by earnings announcements do not relate to the probability of future large upward price moves and consequently do not proxy for lottery demand. BCW suggest that investors demand for lottery stocks can be rationalized by their expectations for the lottery probability albeit the probability is largely overweighted. Specifically, they document that stocks with extreme positive returns in a

[5] Our evidence is very similar to findings from Lin and Liu (2017) who document that the *MAX* effect is predominantly concentrated among stocks preferred by individual investors. Lottery demand is highest among individual investors who view trading as a fun gambling activity.

[6] The *MAX* effect mainly comes from the short side where the highest *MAX* portfolio exhibits negative future return because lottery demand pushes the current stock prices up while the lowest *MAX* portfolio does not exhibit high future return. We confirm this feature of the *MAX* effect in both the main sample and the sub-sample of stocks with low institutional investor holdings. The disappearance of the *MAX* effect when we condition *MAX* returns on earnings announcements is due to the disappearance of the short side. That is, the highest *MAX* portfolio no longer exhibits lower future return, supporting the notion that lottery demand does not affect the current prices of these stocks.

given month are likely to exhibit this phenomenon again in the future and lottery investors are willing to overpay for this probability. We test this hypothesis and show that while past *MAX* returns reliably predicts future *MAX* returns as shown in BCW, there is a significant reduction in the predictability of past *MAX* returns for future *MAX* returns when past *MAX* retruns are driven by earnings information. We conclude that *MAX* returns related to earnings announcements and *MAX* returns not related to earnings announcements are significantly different in nature and less likely to be predictive of each other. In other words, *MAX* returns related to earnings announcements do not indicate the probability of future large upward price moves as the extant literature would conventionally assume.

Bali, Brown, Murray, and Tang (2016) construct a new asset pricing factor, the *FMAX* factor, to capture returns that are driven by market aggregate lottery demand and show that this factor offers significant explanatory power for the cross-section of expected stock returns that is incremental to that of existing risk factors. The authors show that lottery demand is not easily diversifiable and should yield a premium on asset prices. Most importantly, the authors show that this *FMAX* factor can explain the alpha earned from the betting-again-beta strategy documented in Frazzini and Pedersen (2014).[7] Following this line of inquiry, we further our analysis by examining lottery demand at the portfolio level where *MAX* stocks entering the portfolios are driven by earnings information. We do this in a number of tests. First, we show that the *FMAX* factor, when constructed using earnings announcement *MAX* returns, does not generate any lottery demand premium over time. This *FMAX* factor is also uncorrelated to economic conditions that can likely characterize high aggregate lottery demand. These findings further confirm that *MAX* returns

[7] Bali *et al*. (2016) demonstrate that factor models that include the lottery demand factor explain the abnormal returns of the betting against beta phenomenon as documented in Frazzini and Pedersen (2014). They suggest that much of the ‘betting against beta’ effect is due to high lottery demand for high beta stocks.

driven by earnings announcements are not relating to lottery payoffs and consequently are inferior proxies for lottery demand. By contrast, the *FMAX* factor constructed using non-earnings announcement *MAX* stocks generate economically and statistically significant lottery demand premium. Second, factor models that include the *FMAX* factor constructed using non-earnings announcement *MAX* stocks do a better job in explaining the abnormal returns of the betting-again-beta phenomenon than the original lottery demand factor as suggested in Bali *et al*. (2016). Specifically, we document that the refined *FMAX* factor that we suggest in our study (which strips out *MAX* returns driven by earnings announcements) helps explain all the alphas earned from the betting-again-beta strategy in all sub-sample periods between 1973-2015 whereas the original *FMAX* factor in Bali *et al*. (2016) fails to explain such alphas in several sub-sample periods.

We contribute to the extant literature in at least two significant ways. First, while the maximum daily return is a simple and intuitive measure of large payoff and very useful in capturing lottery-like features of stock returns, we show that the sources of information that accommodate these extreme positive returns are particularly important in making the correct interpretation of such returns. Using earnings announcements to identify extreme positive stocks returns as public information arrivals, we find that large daily positive returns driven by earnings information do not indicate a persistent feature of the stock return distribution and do not proxy for lottery demand. Consequently, these stocks do not exhibit lower future returns as non-earnings announcement *MAX* stocks. Our findings indicate that considering *MAX* returns that are not driven by earnings information yields more robust and consistent *MAX* effect. We also suggest a simple but necessary refinement in research methodology where researchers should screen *MAX* returns to exclude those driven by earnings announcements in future studies examining the *MAX* effect or the *FMAX* factor so as to better explore the pricing of lottery demand.

Second, our study emphasizes the importance of understanding the sources driving extreme daily stock returns to make appropriate interpretations of these returns. Earnings and non-earnings announcement extreme daily stock returns, while seemingly identical, carry starkly different inferences about a stock's features and its future returns. While extreme daily stock returns driven by earnings information indicate arrivals of information and do not necessarily represent any attribute of the general stock return distribution, non-earnings announcement extreme stock returns are, however, very instructive of the future probability of large price movements. Most interestingly, it appears that undiversified investors with skewness/lottery payoff preference understand this dissimilarity and take different courses of actions between earnings and non-earnings announcement extreme returns, thereby resulting in contrasting effects on the expected stock returns.

The remainder of the paper is organized as follows. Section 2 provides data and variable description. Section 3 presents the *MAX* effect where maximum returns are driven by earnings information. Section 4 shows the persistence of *MAX* returns when conditioned on earnings information. Section 5 presents the *FMAX* factor conditioned on earnings information that does not proxy for lottery demand. Section 6 concludes the study.

2. Data and Variables

We obtain stock price, return data, and volume data for all US-based common stocks trading on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ from the Center for Research in Security Prices (CRSP) for the period of January 1973 to December 2015.[8] We use daily stock returns to calculate the maximum daily stock returns

[8] The U.S.-based common stocks are the CRSP securities with share code field (SHRCD) 10 or 11.

for each firm in each month as proposed in Bali *et al*. (2011).[9] Second, we use Compustat data to determine the reported quarterly earnings announcement dates and trace whether the maximum daily returns can be associated with quarterly earnings announcements.

Our classification of earnings announcements maximum daily returns and non-earnings announcement maximum daily returns is as follow. If the maximum daily returns occur within a 5-day window surrounding earnings announcements, these maximum daily returns are deemed to be associated with earnings announcements (denoted as *EA_MAX*). Those maximum daily returns falling outside the 5-day window surrounding earnings announcements are deemed not to be associated with earnings announcements (denoted as *NOEA_MAX*). The choice of a 5-day window surrounding earnings announcements allows us to capture extreme positive returns as contemporaneous responses to earnings information, pre-announcement leakage, or post-announcement delayed price response, if there is any. [10]

We also use monthly returns to calculate proxies for intermediate-term momentum and short-term reversals and trading volume data to calculate a measure of illiquidity. Equity book values and other balance sheet data are also obtained from Compustat to compute book-to-market ratio. We obtain institutional investors' shares holding from Thompson Reuters Institutional 13F. Daily and monthly market excess returns and risk factor returns are from Kenneth French's data library.[11] Monthly Pastor and Stambaugh (2003) liquidity factor returns are from Lubos Pastor's

[9] We estimate the maximum daily stock returns using firms that have at least 15 trading days each month as in Bali *et al.* (2016) and Bali *et al.* (2017). In untabulated results, we repeat our analysis using all firms and find the above filter has little impact on our findings.

[10] Previous works have found that earnings announcement dates are sometimes off by a day or more (*e.g.*, DellaVigna and Pollet, 2009; DeHaan, Shevlin, and Thornock, 2015). In untabulated results, we find that our main findings are robust to the choices of earnings announcements window. Specifically, our results remain qualitatively unchanged when we adopt a window of 3, 5, or 7 days surrounding earnings announcements to define *EA_MAX* stocks.

[11] Data are available online at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

website.[12] Earnings momentum factor is from Chordia and Shivakumar (2006).[13] For investor sentiment measures, we use Baker and Wurgler (2006)'s sentiment index, the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center, and the FEARS index from Da, Engelberg, and Gao (2015).[14] The other data we use include Chicago Fed National Activity Index (CFNAI) from the Federal Reserve Bank of Chicago, the macroeconomic uncertainty index from Jurado, Ludvigson, and Ng (2015), the economic policy uncertainty index from Baker, Bloom, and Davis (2016), and business cycle data from NBER.[15]

The sample in this paper covers the 516 months from January 1973 through December 2015. The choice of sample period is up to data availability.[16] Each month, the sample contains all common stocks on the NYSE, AMEX, and NASDAQ with a stock price at the end of formation month of $5 or more.[17]

3. Maximum Daily Returns, Earnings Announcements, and the Cross-section of Expected Returns

3.1. Univariate Portfolio Analysis

Table 1 presents the equal-weighted and value-weighted average monthly returns of decile portfolios that are formed by sorting based on the maximum daily return from the previous month

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[12] Data are available online at: http://faculty.chicagobooth.edu/lubos.pastor/research/.
[13] We thank Tarun Chordia and Lakshmanan Shivakumar for making their earnings momentum factor data available through their websites.
[14] We thank Jeffrey Wurgler and Zhi Da for making their investor sentiment data available through their websites.
[15] We thank Sydney Ludvigson and Nicholas Bloom for making their uncertainty indices available through their websites.
[16] As noted in Savor and Wilson (2016, page 93), 1973 is the first year when quarterly earnings data become fully available in Compustat and it is also the first year when NASDAQ firms are comprehensively covered by Compustat. We, therefore, choose 1973 as the starting point of our sample.
[17] Our main findings remain qualitatively unchanged when we consider all common stocks with no price restriction or with price of $1 or more at the end of the formation month.

(Panel A) and summary statistics for decile portfolios sorted by *MAX* (Panel B) for the sample period over 1973-2015.

{ENTER TABLE 1}

Panel A of Table 1 presents the original *MAX* results as in Bali *et al*. (2011) for the sample period over 1973-2015. The equal-weighted (value-weighted) average raw return difference between the highest *MAX* decile and lowest *MAX* decile is -0.96% (-0.61%) per month with a Newey-West (1987) *t*-statistic of -3.64 (-1.96).[18] The main conclusion from Panel A is that the *MAX* phenomenon is very pronounced in our sample period and this is also confirmed by the 4-factor Fama-French-Carhart, the 5-factor Fama-French-Carhart-Pastor-Stambaugh, and the 5-factor Fama and French alphas from both equal-weighted and value-weighted portfolio analyses. Similar to the finding in Bali *et al*. (2011), the *MAX* effect mainly comes from the short side where the top *MAX* portfolio exhibits lower future returns. For example, the 4-factor alpha for the top *MAX* decile is -0.70% per month if equal-weighted and -0.44% per month if value-weighted. Among low *MAX* portfolios (deciles 1, 2, 3, and 4), there is no clear pattern of returns. However, returns drop monotonically when we move from deciles 5 to 10.

To get a clear picture of the composition of high and low *MAX* portfolios, Panel B of Table 1 presents summary statistics for the stocks in each decile. Consistent with Bali *et al.* (2011), stocks entering the highest *MAX* portfolio tend to be small and illiquid stocks. They are also more exposed to market risk (showing higher values of beta), have lower book-to-market ratios, display higher volatility, and exhibit higher unexpected earnings surprises.

[18] This finding is very consistent with Bali *et al.* (2011, page 433), which show that, when excluding all stocks with prices below $5/share, the hedge return differences are higher for equal-weighted portfolios than value-weighted ones.

Panel A of Table 2 presents the *MAX* analysis where all maximum daily returns in the past month can be associated with earnings announcements (*EA_MAX*). That is the maximum daily returns occur within a 5-day window surrounding quarterly earnings announcements. Here, it is striking to see that the raw return difference between decile 10 and decile 1 is small and insignificant from zero. This is true for both equal-weighted and value-weighted portfolio analyses. Looking at the 4-factor or 5-factor alphas, we arrive at the same conclusion that the difference in alphas between the two extreme *MAX* portfolios is small and statistically insignificant. Here, decile 10 contains stocks with the average maximum daily return of 16.8%, which is not different from the average maximum daily return of decile 10 in Panel A of Table 1 for the full sample, but these stocks do not exhibit lower future returns.

{ENTER TABLE 2}

Panel B of Table 2 presents the *MAX* analysis where we only consider maximum daily returns in the past month that are not related to earnings announcements. That is the maximum daily returns occur outside the 5-day window surrounding earnings announcements. As expected, the *MAX* effect is manifested very clearly in this sample. The value-weighted average raw return difference between decile 10 (highest *MAX*) and decile 1 (lowest *MAX*) is -0.83% per month with a *t*-statistic of -2.60. The 4-factor (5-factor) alpha difference is -0.93% (-0.93%) with a *t*-statistic of -4.12 (-3.90). The return differences are much higher for equal-weighted portfolios. It is also clear that it is high *MAX* stocks that exhibit lower future returns in this sample, accounting for the majority of the extreme *MAX* portfolios return difference. The 4-factor alpha for high *MAX* portfolio is -0.66% (*t*-statistic of -2.62) when value-weighted and -0.95% (*t*-statistic of -6.19) when equal-weighted.

The last Panel of Table 2, Panel C, presents the difference in returns between *NOEA_MAX* and *EA_MAX* portfolios across *MAX* deciles. The value-weighted average raw hedge return difference between decile 10 (highest *MAX*) and decile 1 (lowest *MAX*) is -0.80% per month with a *t*-statistic of -2.75. The 4-factor and (5-factor) alphas are -0.75% (-0.73%) per month with a *t*-statistics of -2.51 (-2.39). The differences in hedge returns and alphas are much higher for equal-weighted portfolios. A striking feature in Panel C of Table 2 is that the difference in returns between *NOEA_MAX* and *EA_MAX* portfolios is negligible among low *MAX* deciles (deciles 1, 2, 3, and 4). The difference, however, increases monotonically when moving from decile 5 to 10. It also can be seen that a majority of the hedge returns comes from the highest *MAX* decile (decile 10).[19,20]

While the results in Table 2 and several robustness checks in the Appendix show that the *MAX* effect is not present within the group of stocks for which maximum daily returns in the past

[19] We conduct a number of robustness checks around our core results in Table 2 in the Appendix. First, Table A.1's results indicate that our conclusions hold when alternative measures of extreme positive returns are employed. Specifically, when *MAX* is defined as the average of the *k* highest daily returns within a month (2, 3, 4, or 5 days) and when earnings announcements account for stock return of at least one of these days, the *MAX* effect does not exist among stocks that exhibit high maximum daily returns in the past month as triggered by earnings announcements. Again, among stocks of which maximum daily returns over the past month are not related to earnings announcements, the *MAX* effect is more apparent. In unreported tests, we further examine the future performance of high *MAX* portfolios in each of the three months following the formation month. The results, which are available upon request, suggest that high *MAX* stocks continue to exhibit lower returns in each of the three months following the formation month. At the same time, there is no statistically significant relation between past extreme returns and future returns among stocks of which maximum daily returns are driven by earnings announcements.

[20] Given *MAX* portfolios are formed at the end of each month, it may be difficult to execute a trade on the last day of each month as the information may not be available until the close of the last trading day of the month. Therefore, there is a possibility that the ability of *MAX* to predict future stock returns is driven by a microstructure effect. We test this prediction using the approach proposed by Bali *et al.* (2016). Specifically, we re-estimate *MAX* using all but the last trading day of the given month and repeat portfolio analysis using this new measure of *MAX*. Results from Table A.2 in the Appendix suggest that the *MAX* effect persists when this new approach to calculate *MAX* is employed. Again, the negative relation between past extreme positive returns and future returns completely disappears when the portfolios are constrained to *MAX* returns driven by earnings announcements. By contrast, the *MAX* effect is manifested very clearly among stocks whose maximum daily returns in the past month are not related to earnings announcements. The results of Table A.2 clearly show that neither the *MAX* effect nor our finding of no *MAX* effect when conditioning on earnings announcments is driven by a microstructure effect.

month are driven by earnings announcements, it can be argued that this result should not materially change the *MAX* phenomenon if earnings announcements only account for a small proportion of stocks going into extreme *MAX* portfolios. Table 3, therefore, presents the percentage of stocks across all *MAX* portfolios of which maximum daily returns are associated with earnings announcements. There is clear evidence that earnings announcements account for a non-trivial proportion of stocks in any *MAX* portfolio and this percentage is remarkably high in high *MAX* portfolios.

{ENTER TABLE 3}

Over the entire sample period 1973-2015, at least 8.4% of stocks in the lowest *MAX* portfolio are associated with earnings announcements whereas this percentage is 13.6%, 15.1%, and 18.3% for high *MAX* portfolios 8, 9, and 10, respectively. When split into two subsample periods, we notice that this percentage for the top *MAX* portfolio is 23.3% for the later period (1995-2015) and 12.3% for the earlier period (1973-1994). The key finding in Table 3 is that earnings announcements account for a large percentage of stocks entering *MAX* portfolios and this percentage is especially large for high *MAX* portfolios. Furthermore, this pattern is increasing significantly over time.

Based on a 5-day window around quarterly earnings announcements in our classification of earnings announcements returns, in any year, there are 20 trading days where stock returns can be determined to relate to earnings announcements. Assuming that maximum daily returns are randomly distributed and therefore not driven by earnings announcements, one would expect that earnings announcements account for around 8% of any *MAX* portfolio composition (20 trading days over a total of 250 trading days in a year). This seems to be in line with the percentages between 8% and 10% observed for low *MAX* portfolios. However, in high *MAX* portfolios (deciles

8, 9, 10), the percentage of earnings announcements *MAX* returns exceeds 13%, indicating that *MAX* returns are not random in these portfolios but are highly driven by earnings announcements.[21]

Figures 1A and 1B confirm that there is an increasing trend in the proportion of stocks in the high *MAX* portfolio being associated with earnings announcements over time.[22] In the last few years of our sample period (2006-2015), about 30% of high *MAX* stocks are associated with earnings announcements and this percentage is always at least 20% since 2002.[23] Because the *MAX* effect is mainly driven by lower future returns of stocks in the top *MAX* portfolio, a high percentage of earnings announcement *MAX* stocks in the top *MAX* portfolio implies a material change in the overall *MAX* effect because earnings announcement *MAX* stocks do not exhibit lower future returns as demonstrated in Panel A of Table 2.

{ENTER FIGURE 1A}

{ENTER FIGURE 1B}

Figure 1C shows the percentage of stocks associated with earnings announcements in the high *MAX* portfolio across all calendar months. While there are four spikes corresponding to four

[21] We also employ a binomial test to formally compare the observed distribution of earnings announcement *MAX* returns in the top *MAX* decile (18.3%) to the expected distribution of 8% under the assumption that *MAX* returns in this portfolio are not driven by earnings announcements (*i.e.*, randomly distributed over time). The binomial *z*-statistic rejects the null hypothesis that the proportion of earnings announcement *MAX* returns in the top *MAX* decile is random.
[22] The increasing proportion of stocks entering high *MAX* portfolios that have earnings-driven returns over time is aligned with an increase in the informativeness of quarterly earnings announcements over time that is well-documented in the literature (*e.g.*, Landsman and Maydew, 2002).
[23] In October 2000, the SEC passed Regulation Fair Disclosure (Regulation FD) in an effort to stamp out selective disclosures of material information by public companies to market professionals and certain investors/analysts. The rule appears to have diminished the advantage of informed investors and reduced the level of information asymmetry (Eleswarapu, Thompson, and Venkataraman, 2004). Regulation FD has also increased the quantity of corporate voluntary disclosure to the public (Bailey, Li, Mao, and Zhong, 2003). With the adoption of Regulation FD, corporate official disclosures (*i.e.*, quarterly earnings announcements) should carry more important information about firm performance and, at the same time, are less subject to selective disclosure. This is expected to eventually result in a large number of high earnings-response stock returns.

seasons of earnings announcements in a year, the percentage is at least above 6% in all other non-announcement season months.

{ENTER FIGURE 1C}

Overall, Table 2 and Figures 1A, 1B, and 1C show that earnings announcements account for a significant proportion of stocks entering high *MAX* portfolios and the proportion is highest in the top *MAX* portfolio. This percentage is also increasing over time. This finding is consistent with the notion that large daily returns are often observed surrounding earnings announcements, and these returns can account for a significant proportion of the maximum daily returns in a month.[24]

3.2. Bi-variate Portfolio Analysis

In this section, we examine the relation between the maximum daily returns and future stock returns after controlling for firm size, book-to-market, momentum, short- term reversals, and illiquidity. For each control, we first sort firms into deciles of the control variable and then within each decile we again sort stocks by *MAX*. The procedure ensures that each *MAX* portfolio, aggregated across all deciles of the control variable, then has the same distribution of each control variable.[25] The purpose of this analysis is two-folds. First, we re-confirm that the *MAX* effect in our sample period is not driven by firm characteristics that plausibly relate to expected stock

[24] If earnings announcements are important sources that drive extreme daily stock returns, it is possible that the *MAX* phenomenon would significantly reduce after controlling for an earnings-related factor. We test this conjecture using Chordia and Shivakumar (2006)'s earnings momentum factor (*PMN*) along with the Fama and French (1993) three-factor (FF3) model to compute the hedge returns of the extreme *MAX* portfolios. Table A.3 reports the results for this test. Over the sample period from 1973 to 2003 for which data on *PMN* are available, we find that the inclusion of the *PMN* factor in the model reduces the hedge return from -1.12% to -0.82% (a 27% reduction in the hedge return). Given that stock abnormal returns can be driven by a variety of corporate news (Bessembinder and Zhang, 2013) and/or media coverage (Fang and Peress, 2009) and that the earnings-related factor alone significantly reduces the hedge return of the *MAX* strategy, the results further confirm that earnings announcements are one of the important sources that drive extreme daily returns.

[25] We also investigate independent bivariate sorts on each pair of the control variable and *MAX* and document very similar results to those based on dependent sorts as reported in Table 4.

returns. Second, we show that it is earnings announcements, not firm characteristics, which explain the disappearance of the *MAX* effect when *MAX* returns are conditioned on earnings announcements.

{ENTER TABLE 4}

Panel A of Table 4 shows that the *MAX* effect is consistently strong after controlling for each firm characteristic. After controlling for firm size, the equal-weighted average return difference between the highest *MAX* and lowest *MAX* portfolios is -1.00% per month with a *t*-statistic of -3.82. The corresponding difference in the four-factor alphas is -1.10% per month with a *t*-statistic of -6.90. Thus, firm size does not explain the *MAX* effect in our sample period. Bi-variate portfolio analyses using other variables confirm the same conclusion. Specifically, the 10-1 return difference is -0.80% per month when sorted by book-to-market ratio (*BM*), -1.06% per month when sorted by momentum (*MOM*), -0.94% per month when sorted by short-term reversals (*REV*), and -1.00% per month when sorted by illiquidity (*ILLIQUID*) and all these returns are statistically significant at the 1% level.

Panel B of Table 4 continues to show that when *MAX* returns are associated with earnings announcements, bi-variate portfolio sorting does not detect any *MAX* effect. The 10-1 return difference is small and statistically insignificant from zero across all bi-variate portfolio sorts. Unlike the results in Panel A where returns drop significantly moving from low and medium *MAX* portfolios to high *MAX* portfolios (8, 9, and 10), we do not observe any clear pattern in returns moving across *MAX* portfolios in Panel B where *MAX* returns are conditioned on earnings announcements. In fact, bi-variate sorts using firm size and short-term reversals show that the top *MAX* portfolio exhibits the highest returns. Panel B also re-examines the bi-variate portfolio analyses, however, using the sample that excludes *MAX* returns related to earnings announcements. Similar to prior findings of univariate portfolio analysis in Panel B of Table 2, we document that the 10-1 return difference is significantly pronounced across all bi-variate portfolio sorts. Most importantly, while we do not notice any material change in returns of low *MAX* portfolios when splitting the sample between *EA_MAX* and *NOEA_MAX*, the changes mainly reside in high *MAX* portfolios. Relative to the full sample in Panel A, returns of the top *MAX* portfolios drop substantially when *MAX* returns are not related to earnings information.

The results in Table 4 indicate that cross-sectional effects such as firm size, book-to-market, momentum, short-term reversals, and illiquidity cannot explain the low returns observed for high *MAX* stocks, but it is an exclusion of earnings announcements that chiefly determines the lower future returns of the top *MAX* portfolio and consequently the overall *MAX* effect.

3.3. Firm-level Regression Analysis

We continue to examine the relation between *MAX*, earnings announcements, and future stock returns in a regression framework which controls for multiple effects or factors simultaneously. Table 5 presents firm-level regression results of stock returns against *MAX*, other firm characteristics, and an interaction variable between *MAX* and an indicator for earnings announcements. We report Fama-MacBeth regression results where the coefficients are the time-series averages of the cross-sectional slope coefficients and the *t*-statistics are based on time-series standard errors that are also adjusted using the Newey-West procedure.[26]

{ENTER TABLE 5}

[26] In a different approach, we examine *t*-statistics based on two-way clustered robust standard errors, clustered by firm and quarter, and document qualitatively unchanged results.

In column (1), the slope coefficient from the regression of realized returns on *MAX* alone is -0.07 with a *t*-statistic of -6.10. Given the spread in the average maximum daily returns between deciles 10 and 1 is approximately 16%, this implies a monthly risk premium of 112 basis points (0.07×16) for the *MAX* variable in the cross-section of next month stock returns. Besides, we also document a strong momentum effect, a strong reversals effect, and some value effect in our sample.

The key findings from these regression analyses lie in the last three columns of Table 5. In column (9), we include an interaction variable between *MAX* and a dummy variable that takes a value of 1 if *MAX* returns are associated with earnings announcements and zero otherwise. The interaction coefficient on *MAX×EA* is 0.07 with a *t*-statistic of 11.76. It can be interpreted that the *MAX* effect on stock returns when *MAX* returns are associated with earnings announcement is equal to the sum of the coefficients on *MAX* (-0.06) and *MAX×EA* (0.07) and this sum is close to zero. Thus, this is consistent with the univariate portfolio analysis and the bi-variate portfolio analysis which show insignificant return differences between the highest and lowest *MAX* stocks when *MAX* returns are conditioned on earnings announcements. In column (10), the negative coefficient on *MAX* retains its sign and statistical significance when we include all control variables, suggesting that the *MAX* effect on the cross-section of stock returns is beyond those of other known firm characteristics. In column (11), we include *MAX*, *MAX×EA*, and all other control variables. Here, both the coefficients on *MAX* and *MAX×EA* are significant at the 1% level and the sum of the coefficients on *MAX* and *MAX×EA* is 0.010. This implies a negligible premium of 0.17 per month that *EA_MAX* places on stock returns.

Overall the results in Table 5 show that in a multiple regression framework that controls for several other firm characteristics, *MAX* exhibits a strong effect on future realized returns but this effect mostly disappears when we consider earnings announcement *MAX*. [27]

3.4. Lottery Demand, Institutional Investor Holding, and the MAX effect

It is conceivable that retail investors rather than institutional investors who are more likely to exert price pressures for lottery stocks. Thus, if lottery demand drives the *MAX* effect, we should see a more pronounced return difference between the two extreme *MAX* portfolios of stocks that are popular with retail investors. In addition, if lottery investors interpret earnings announcement maximum daily returns as lotteries instead of information arrivals, we expect to also see high earnings announcement *MAX* stocks generating lower future returns.

In this section, we rely on institutional ownership of a stock to proxy for the extent that the stock price may be affected by retail lottery investors. A stock's institutional ownership (*INST*) is computed as the fraction of its outstanding common shares owned by all 13F reporting institutions in a given quarter. We define month *t INST* to be the fraction of total shares outstanding that are owned by institutional investors as of the end of the last fiscal quarter end during or prior to month *t*.

{ENTER TABLE 6}

Table 6 shows the time-series means of the monthly equal-weighted excess returns for portfolios formed by sorting all stocks into quintiles of *INST* and then, within each quintile of *INST*, into deciles of *MAX*. Panel A of Table 6 shows that high *MAX* stocks, combined with low

[27] We also winsorize *MAX* at the 99% and 1% or perform regression analysis for only NYSE stocks (large and more liquid stocks) and document similar findings as those reported in Table 5.

institutional ownership, exhibit much lower future returns. The return difference between the two extreme *MAX* portfolios drops monotonically across *INST* quintiles. The 4-factor alpha differences are -1.93% per month in Low *INST* quintile and -0.63% per month in High *INST* quintile. These results complement those from Lin and Liu (2017) who show that the *MAX* effect is mainly driven by stocks that are preferred by retail individual investors.

Panel B of Table 6 presents the *MAX* effect across *INST* quintiles when *MAX* returns are (are not) conditioned on earnings announcements. Remarkably different from those results in Panel A, in *EA* columns of Panel B, we notice that the top *MAX* portfolios do not generate lower future returns. Across all *EA* columns, the 4-factor alphas, equal-weighted, for the top *MAX* portfolios are positive instead of being significantly negative as in Panel A. The return difference between the two extreme *MAX* portfolios is also generally insignificant for this analysis for *EA* columns. For the lowest quintile *INST1*, the 4-factor alpha difference is -0.24% per month with *t*-statistic of -0.50 for *EA* column while this 4-factor alpha difference is -2.12% per month with *t*-statistic of -8.43 for *NO_EA* column. Thus, in the group of stocks where lottery demand is highest, the *MAX* effect is especially high based on *NO_EA MAX* returns but continues to be non-existent based on *EA_MAX* returns.

The results in Table 6 can be summarized by two key findings. First, the *MAX* effect is substantially higher among stocks with low institutional ownership, mostly due to high *MAX* stocks exhibiting much lower future returns. This is consistent with the notion that lottery demand is high among these stocks, thereby pushing up current prices too high. Consequently, future returns are significantly lower for these stocks. However, despite this high lottery demand, high earnings announcement *MAX* stocks do not generate lower future returns, and the *MAX* effect continues to be non-existent when *MAX* returns are conditioned on earnings announcements. Thus, lottery investors do not view earnings announcement *MAX* returns as lotteries and do not exert any special demand for these stocks.[28]

3.5. Investor Sentiment and the MAX Effect

Investor sentiment plays an important role in understanding the overpricing of lottery-like assets (Doran, Jiang, and Peterson, 2012; Fong and Toh, 2014). When sentiment is high, investors tend to be over-optimistic of the future payoffs from buying lottery-like assets, and hence, are more likely to push up the price of lottery-like stocks (Fong and Toh, 2014) or options (Byun and Kim, 2016). As a consequence, the strategy of buying most lottery-like stocks and shorting least lottery-like stocks earns higher profit during high-sentiment periods than during low-sentiment periods. Given optimism gives rise to the preference of lottery-like assets and the *MAX* effect is more pronounced during periods of high investor sentiment (Fong and Toh, 2014), there is a possibility that lottery investors, when sentiment is high, may also overvalue stocks with earnings-driven extreme returns. We test this prediction using three different measures of investor sentiment, including: 1) investor sentiment index from Baker and Wurgler (2006, 2007), 2) the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center, and 3) FEARS index from Da, Engelberg, and Gao (2015).[29] For each sentiment measure, we define a high (low) sentiment month as one in which each sentiment index is above (below) the sample median value. The results for the sentiment tests are presented in Table 7.

[28] We also consider a number of alternatives for institutional ownership such as firm size, illiquidity and the availability of options trading. We continue to document that among smaller stocks, illiquid stocks, or stocks without options trading, earnings announcement top *MAX* stocks do not generate lower future returns. Hence, the disappearance of the *MAX* effect when conditioned on earnings announcements cannot be attributed to more efficient pricing, better liquidity, or an alleviation of short-sale constraints.

[29] Previous literature (*e.g.*, Da, Engelberg, and Gao, 2015) suggests that these three sentiment measures can be grouped into three groups: a market-based sentiment measure (Baker and Wurgler's sentiment), a survey-based sentiment measure (the MCSI index), and a search-based sentiment measure (the FEARS index).

{ENTER TABLE 7}

Panel A (Panel B) of Table 7 reports returns and alphas of *EA_MAX* portfolios following high (low) sentiment months for each of sentiment measures. The last columns in each Panel report the differences and abnormal returns of the High - Low *MAX* portfolios. According to the results in Panels A and B, the equal-weighted average raw hedge return difference between decile 10 (highest *MAX*) and decile 1 (lowest *MAX*) is insignificant from zero. Similarly, the 4-factor and (5-factor) alphas are also indistinguishable from zero. These findings hold across all three different measures of investor sentiment. The results in Panels A and B consistently indicate the non-existence of the *MAX* phenomenon when *MAX* returns are driven by earnings information. Thus, regardless of investor sentiment states which are highly correlated with investor preference for lotter-like assets (Fong and Toh, 2014), investors do not overvalue stocks with earnings-driven extreme returns, and hence, these stocks do not exhibit lower future returns.

3.6. MAX and Other Lottery Demand Measures

Kumar (2009) and Han and Kumar (2013) suggest that lottery demand is highest among stocks with features such as low price, high idiosyncratic volatility, and high idiosyncratic skewness. Using these features as alternative measures of lottery, we examine whether the lottery demand phenomenon is stronger and whether earnings announcement *MAX* may deliver lower future returns among these stocks. Specifically, for each month, stocks are sorted into quintiles based on each of the three features: stock price, idiosyncratic volatility (*IVOL*), and idiosyncratic skewness (*ISKEW*).[30] We consider two groups of stocks: the first (second) group include stocks in the bottom (top) quintile of price, the top (bottom) quintile of *IVOL*, and the top (bottom) quintile

[30] Following Boyer, Mitton, and Vorkink (2010), we measure *ISKEW* as the skewness of the residuals from a regression of excess stock returns on *MKTRF*, *SMB*, and *HML* using one month of daily return data.

of *ISKEW*. We then repeat the *MAX* analysis for each of these two groups of stocks. Table 8 reports the results for the tests.

{ENTER TABLE 8}

According to the results in Panel A of Table 8, among stocks with low prices, high *IVOL*, and high *ISKEW*, the raw return and FFC4 alpha of the High - Low *MAX* portfolios are -0.98% (*t*-statistic of -3.95) and -1.18% (*t*-statistic of -7.06), respectively. The raw return and FFC4 alpha of the High - Low *MAX* portfolios of stocks with high price, low *IVOL*, and low *ISKEW* are, in turn, 0.14% (*t*-statistic of 0.41) and 0.01% (*t*-statistic of 0.05), respectively. Thus, the differences in raw returns and alphas between the two extreme decile portfolios are more negative (and economically/statistically significant) among the first set of stocks than the second one. Consistent with prior works (Kumar, 2009; Han and Kumar, 2013; Bali *et al*., 2016), we find that the lottery demand phenomenon is especially pronounced among stocks with low price, high *IVOL*, and high *ISKEW*.

A question of interest is whether the *MAX* phenomenon exists among these two groups of stocks when *MAX* returns are conditioned on earnings information? To answer this question, we repeat the *MAX* analysis for stocks that exhibit extreme daily returns as driven by earnings announcements (*EA_MAX* stocks) and report results for the test in Panel B of Table 8. The results suggest a clear no *MAX* phenomenon. Specifically, among stocks with low price, high *IVOL*, and high *ISKEW*, the raw returns and FFC4 alpha of the High - Low *MAX* portfolios are 0.01% (*t*-statistic of 0.02) and -0.02% (*t*-statistic of -0.05), respectively. Again, for the set of stocks with high price, low *IVOL*, and low *ISKEW*, the raw returns and FFC4 alphas between the two extreme decile portfolios are statistically non-negative.

Overall, the results in Table 8 suggest that the disappearance of the *MAX* phenomenon among earnings-driven *MAX* returns are robust across different lottery features of stocks.[31, 32]

3.7. Macroeconomic Uncertainty, Economic Policy Uncertainty, and the MAX Effect

Macroeconomic uncertainty is associated with fluctuations in future consumption and investment (Bloom, 2009; Jurado *et al*., 2015; Bali *et al*., 2017) and recessions can be attributed to an increase in uncertainty (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2016). If lottery demand drives the *MAX* phenomenon and demand for lottery stocks is especially strong in recession periods, it is possible that an increase in macro uncertainty, which causes recession, can drive the *MAX* effect. We, therefore, examine whether macroeconomic uncertainty affects the persistence of the *MAX* effect. We do this in a number of tests. First, we test whether the *MAX* effect persists after controlling for macroeconomic uncertainty using bi-variate portfolio analysis. Specifically, we compute beta sensitivity of individual stock to two uncertainty indices: the macroeconomic uncertainty index from Jurado *et al*. (2015) and the economic policy uncertainty index from Baker *et al*. (2016).[33]

[31] Time-variation in lottery demand or economic states can affect the relation between lottery demand and expected stock returns (Kumar, 2009; Kumar *et al.*, 2011). Following this line of enquiry, we also test if the time-varying feature of the aggregate lottery demand or economic states drives our main results. Tables A.4 and A.5 in the Appendix present these results. Regardless of levels of the aggregate lottery demand or economic states, the *MAX* effect continues to disappear when *MAX* returns are driven by earnings announcements.

[32] Kumar, Page, and Spalt (2011) and Doran, Jiang, and Peterson (2012) document that lottery demand is particularly stronger in January months than in other months. If lottery demand drives the *MAX* effect, it is possible that the *MAX* effect is more pronounced in January months than in non-January months. Table A.6 in the Appendix presents the results that support this prediction. The results in Panel A of Table A.6 suggest that the abnormal returns of the High-Low *MAX* portfolios are more negative in January months than in other months. We then check whether our main results, the non-existence of the *MAX* effect when *MAX* returns are conditioned on earnings information, persist in both January months and in non-January months. We find this is a case. According to Panel B of Table A.6, when *MAX* returns are driven by earnings announcements, the abnornal returns of the High-Low *MAX* portfolios are insignificant from zero. The results, therefore, demonstrate that the *MAX* effect continues to be non-existent in both January months and non-January months when *MAX* returns are conditioned on earnings announcements.

[33] Jurado *et al*. (2015) develop a measure of the macroeconomic uncertainty based on macroeconomic and financial indicators. Baker *et al*. (2016) develop the economic policy uncertainty index based on newspaper coverage frequency since 1985.

Following Bali *et al*. (2017), for each stock and for each month in our sample, we estimate uncertainty beta from the monthly rolling regressions of excess stock returns on each of the two uncertainty indices over a 60-month rolling window after controlling for Fama and French (2015)'s five factors and Cahart (1997)'s momentum factor. We sort stocks into decile portfolios based on each of these two uncertainty betas and then within each decile portfolio, we again sort stocks by *MAX*. This procedure creates a set of *MAX* portfolios with similar levels of uncertainty beta, and hence these *MAX* portfolios control for differences in exposure to economic uncertainty. We then repeat the *MAX* analysis for *EA_MAX* portfolios to examine whether our main results, the disappearance of the *MAX* effect when conditioned on earnings announcements, hold after controlling for exposure to uncertainty. Second, we employ a regression framework to examine if our main findings hold after betas sensitivity of these two uncertainty indices are included as additional control variables. The results for those tests are presented in Table 9.

{ENTER TABLE 9}

The results in Panel A of Table 9 suggest that the *MAX* phenomenon persists after controlling for exposure to macroeconomic uncertainty. Specifically, the differences in monthly returns and alphas of the High - Low *MAX* portfolios are both negative and statistically (and economically) significant. This finding is robust to both exposures to macroeconomic uncertainty and economic policy uncertainty. We then repeat the *MAX* analysis for *EA_MAX* and *NOEA_MAX* portfolios separately. Among *EA_MAX* stocks, the differences in monthly returns and alphas of the High - Low *MAX* portfolios are either non-negative or weakly positive. Thus, consistent with findings in the previous sections, the *MAX* effect continues to disappear when *MAX* returns are conditioned on earnings information. For *NOEA_MAX* portfolios, the *MAX* effect is manifested very clearly, which further confirms that removing earnings-driven *MAX* returns out of the original extreme daily returns results in a more pronounced *MAX* phenomenon.

Panel B of Table 9 presents the results for the regression analysis. The results in Panel B of Table 9 can be summarized by two key findings. First, the coefficients on beta sensitivity of UNC ($\boldsymbol{\beta_{UNC}}$) are negative and statistically significant across all model specifications. Consistent with Bali *et al*. (2017), we find that exposure to economic uncertainty is negatively priced in the cross-section of individual stocks. Similarly, the coefficients on beta sensitivity to EPU, $\boldsymbol{\beta_{EPU}}$, are statistically and economically negative across all model specifications.[34] The results suggest that both exposures to macroeconomic uncertainty and economic policy uncertainty play significant roles in the cross-sectional pricing of individual stocks. Second and finally, when either $\boldsymbol{\beta_{UNC}}$ or $\boldsymbol{\beta_{EPU}}$ is included in the model as an additional control variable, the coefficients on the interaction term (*MAX*×*EA*) remain positive and statistically significant (at the 1% level), which suggests that the non-existence of the *MAX* effect among *EA_MAX* stocks is not driven by either macroeconomic uncertainty or economic policy uncertainty.[35]

4. Cross-sectional Predictability of *MAX*

While arguably *MAX* is a theoretically motivated variable and that the *MAX* effect is unquestionably persistent in our sample, our main argument is that the maximum daily returns, when driven by fundamentally relevant information such as earnings announcements, do not appeal to lottery investors because information arrivals do not necessarily relate to the stock return

[34] Our findings are aligned with Brogaard and Detzel (2015) who show that innovations in EPU earn a negative risk premium in Fama-French 25 size-momentum portfolios.
[35] UNC and EPU indices are highly correlated (correlation=0.42) (Baker *et al*., 2016, page 1604) and hence, we do not include beta sensitivity of these two indices in a single model to avoid multicollinearity.

distribution. Bali *et al*. (2011) show that high *MAX* stocks have a high likelihood of being in high *MAX* portfolios again in the future and this *MAX* persistence feature substantiates why lottery investors are more willing to pay for these stocks. Essentially, the persistence of *MAX* returns over time explains, at least partially, why *MAX* yields a premium. We examine this issue in details in this section.

We examine the persistent feature of *MAX* in a firm-level cross-sectional regression. We run regressions of the maximum daily return within a month on the maximum daily return from the previous month with the inclusion of various control variables (also lagged by one month). In column (1) of Table 10, the univariate regression of *MAX* on lagged *MAX*, we find a large positive coefficient and highly statistically significant. Thus, firms with large *MAX* in the past one month are likely to exhibit that same phenomenon again in the next month.

{ENTER TABLE 10}

In row (3), we regress future *MAX* against past *MAX* and an interaction variable between past *MAX* and *EA*, where *EA* takes a value of 1 if past *MAX* returns are driven by earnings announcements and zero otherwise. While *MAX* is significantly positive, the coefficient on the interaction coefficient *MAX*×*EA* is negative and also very significant. It means that the predictability of *MAX* using lagged *MAX* is substantially reduced when past *MAX* returns are associated with earnings announcements. In the last row when all lagged control variables are included, we find that the coefficients on *MAX* and *MAX*×*EA* retain their signs and statistical significance.

The results in Table 10 suggest that *MAX* is a persistent feature of stock returns over time, but this persistence is significantly reduced when *MAX* returns are driven by earnings information.

In other words, when past extreme positive returns come from earnings announcements, it is less likely to observe this phenomenon again in the subsequent month. We notice that firm size, book-to-market ratio, beta, and idiosyncratic volatility are also significantly related to future extreme positive returns.

5. Lottery Demand Factor

Bali, Brown, Murray, and Tang (2016) propose a new factor, the *FMAX* factor, to capture returns that are driven by the aggregate lottery demand and show that this factor offers significant explanatory power for the cross-section of expected stock returns that is incremental to that of existing risk factors. Following this line of inquiry, we examine if the *FMAX* factor, when constructed using earnings announcement *MAX* returns, explain the cross-section of stock returns. More importantly, we aim to examine whether this *FMAX* factor could be improved by excluding earnings announcement *MAX* returns in construction because we have shown that these returns do not proxy for lottery demand and do not empirically deliver lower future returns.

Following Bali *et al.* (2016), the *FMAX* factor is constructed as follows. At the end of each month t, we first sort all stocks into two groups based on market capitalization, with the breakpoint dividing the two groups being the median market capitalization of stocks traded on the NYSE. We then independently sort all stocks in our sample into three groups based on an ascending sort of *MAX*. The intersections of the two market capitalization-based groups and the three *MAX* groups generate six portfolios. The original *FMAX* factor return in month $t+1$ is taken to be the average return of the two value-weighted high-*MAX* portfolios minus the average return of the two value-weighted low-*MAX* portfolios.

In our sample, the *FMAX (5)* factor, created using *MAX*(*5*) as the measure of lottery demand, generates an average monthly return of -0.49% with a *t*-statistic of -2.23. Using the same procedure, we independently construct two other *FMAX* factors: the *EA_FMAX* factor, constructed using *EA_MAX* returns and the *NOEA_FMAX* factor, constructed using *NOEA_MAX* returns. Over the period from 1973 to 2015, the *NOEA_FMAX(5)* factor, created using *NOEA_MAX*(*5*) as the measure of lottery demand, generates an average monthly return of -0.66 % with a *t*-statistic of -2.92. This indicates a 35% increase in the monthly lottery demand permium. At the same time, the *EA_FMAX(5)* factor, created using *EA_MAX*(*5*), generates an average monthly return of -0.30 % with a *t*-statistic of -1.32. When *MAX(1)* is employed to construct the lottery demand factor, the *FMAX(1)* factor and the *NOEA_FMAX(1)* factor generate an average monthly return of -0.48% with a *t*-statistic of -2.03 and -0.51% with a *t*-statistic of -2.50, respectively. The *EA_FMAX(1)* factor, constructed using *EA_MAX*(*1*), generates an insignificant lottery premium of 0.17% with a *t*-statistic of 0.79. Here, it is clear that the *EA_FMAX* factor does not generate any lottery demand premium over time whereas the original *FMAX* and the *NOEA_FMAX* factors deliver significant lottery demand premia. It also appears that the *NOEA_FMAX* is superior because the lottery demand premium from this factor is larger than that of the original *FMAX* factor.

We then examine if factor models that include the *FMAX* factor help explain the betting-against-beta factor as documented in Frazzini and Pedersen (2014). Table 11 presents the alphas and factor sensitivities for the betting-again-beta (*BAB*) factor using different factor models. Different measures of the lottery factor are constructed following Bali *et al.* (2011) and Bali *et al.* (2016), taking *MAX*(*n*) with *n* = 1 to 5, defined as the average of the *n* highest daily returns of the given stock in the given month. The factor created using *MAX*(*n*) as the measure of lottery demand is denoted *FMAX* (*n*). The *NOEA_FMAX*(*n*) factor is the lottery demand factor created using *NOEA_MAX*(*n*) after excluding earnings announcement *MAX* returns.

{ENTER TABLE 11}

Panel A of Table 11 reports the results for *FMAX*(*n*) with n = 5 as in Bali *et al.* (2016). There are two key findings from this Panel. First, consistent with the results of Frazzini and Pedersen (2014), we find that over our sample period (1973-2015), the *BAB* factor generates an economically large and statistically significant alpha of 0.52% (0.50%) per month relative to the the four-factor Fama-French-Carhart (the five-factor Fama-French-Carhart-Pastor-Stambaugh) model. Second and most importantly, when the *FMAX* factor is included in the model, the *BAB* factor no longer generates statistically positive abnormal returns, with alphas relative to the four-factor Fama-French-Carhart and the five-factor Fama-French-Carhart-Pastor-Stambaugh of 0.23% (*t*-statistic = 1.31) and 0.21% (*t*-statistic = 1.22) per month, respectively. When the *NOEA_FMAX* factor, instead of the *FMAX* factor, is employed, the alphas relative to the four-factor Fama-French-Carhart and the five-factor Fama-French-Carhart-Pastor-Stambaugh are of 0.17% (*t*-statistic = 0.98) and 0.16% (*t*-statistic = 0.91) per month, respectively. Thus, consistent with Bali *et al.* (2016), we find that the abnormal returns of the High-Low beta portfolios relative to the Fama and French (1993) and Carhart (1997) four-factor (FFC4) model and the FFC4 model augmented with Pastor and Stambaugh's (2003) liquidity factor are insignificant when the *FMAX* or *NOEA_FMAX* factor is included in the factor model.

Panel B reports the results for alternative measures of lottery demand factor, *FMAX*(*n*) with n= 1 to 5, for the whole sample (1973-2015) and two equal subsamples. Here, we find the betting-again-beta alphas do not completely disappear when considering alternative *FMAX*(*n*) factors and/or subsample periods. Most strikingly, the *BAB*'s alpha is statistically and economically insignificant when using factor models that include the *FMAX* factor constructed using non-earnings announcement *MAX* stocks. This is true for alternative *NOEA_FMAX(n)* factors with n = 1…5, and for the whole sample and all subsample periods. The key conclusion from Panel B in Table 11 is that factor models that include the *FMAX* factor constructed using non-earnings announcement *MAX* stocks do a better job in explaining the abnormal returns of the betting-again-beta phenomenon than the original lottery demand factor as suggested in Bali *et al*. (2016).

6. Conclusion

We find that when the maximum daily returns are driven by earnings information, there is no evidence of the *MAX* effect as documented in Bali *et al*. (2011). Specifically, portfolios of high earnings announcements *MAX* returns do not generate lower future returns. This finding is not due to other firm characteristics and is in stark contrast to the finding that the usual *MAX* effect exists and is especially stronger when *MAX* returns are unrelated to earnings information. Even among a group of stocks with low institutional investors ownership and high lottery demand, we still do not detect any *MAX* effect when *MAX* returns are conditioned on earnings announcements. Our study makes a very simple classification between non-earnings announcement extreme positive returns and earnings-related extreme positive returns and documents a complete disappearance of the *MAX* effect for the latter. We suggest that extreme positive returns, when driven by fundamentally relevant information such as earnings, represent arrivals of public information rather than a feature of the stock return distribution. In such instances, extreme returns do not proxy for lottery demand, and lottery investors show no interest for these stocks.

We show that earnings announcements account for a significant proportion of stocks entering high *MAX* portfolios and this percentage is increasing over time. Because earnings announcements *MAX* returns do not proxy for lottery demand, they should not be included in the *MAX* portfolio analysis of lottery pricing. Excluding *MAX* returns driven by earnings announcements, we find that the *MAX* effect is substantially stronger and the *MAX* effect is mainly due to high *MAX* stocks exhibiting much lower future returns. In addition, the *FMAX* factor that proxies for the aggregate lottery demand, when constructed based on non-earnings announcements *MAX* returns, not only better explains the cross-section of stock returns but also correlates more strongly with economic conditions that characterize high aggregate lottery demand. This finding has a strong implication for *MAX* studies regarding the necessity to exclude earnings announcement *MAX* returns in studying the pricing of lottery demand.

Our study shows that the sources of information that drive extreme returns are very important for how these seemingly identical returns should be interpreted. While earnings announcements are frequent and account for a large proportion of extreme daily returns, there are also several other corporate events that drive extreme stock returns such as seasoned equity offerings, IPOs, M&A, among others. Future research can investigate whether the *MAX* effect manifests or disappears when extreme returns are conditioned on other types of public information disclosures. Finally, our study shows that the *MAX* effect is indeed significantly stronger than originally reported in the literature and this increment is likely because our *MAX* returns better capture lottery demand and its effect on asset prices. There is, therefore, an important avenue for future empirical research studies to derive more refined measures of *MAX* as superior proxies for lottery demand.

Appendix A: Variable definitions

Variable	Definition and Estimation
MAX	The maximum daily return (*MAX*) within a month: $$MAX_{i,t} = \max(R_{i,d}),\ \ d = 1, \ldots, D_t$$ 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*.
BETA	We follow Scholes and Williams (1977) and Dimson (1979) to use the lag and lead of the market portfolio as well as the current market when estimating beta to take into account nonsynchronous trading: $$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}\left(R_{m,d-1} - r_{f,d-1}\right) + \beta_{2,i}\left(R_{m,d} - r_{f,d}\right) + \beta_{3,i}\left(R_{m,d+1} - r_{f,d+1}\right) + \varepsilon_{i,d}$$ where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and is the risk-free rate on day d. The market beta for stock i in month t is defined as $\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i}$.
β_{UNC}	Beta sensitivity of the macroeconomic uncertainty index from Jurado *et al.* (2015). Following Bali *et al.* (2017), for each stock and for each month in our sample, we estimate the uncertainty beta from the monthly rolling regressions of excess stock returns (R) on the economic uncertainty index (UNC) over a 60-month fixed window after controlling for the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA) and profitability (RMW) factors. The model is as follows: $$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC}\, UNC_t + \beta_{i,t}^{MKT}\, MKT_t + \beta_{i,t}^{SMB}\, SMB_t + \beta_{i,t}^{HML}\, HML_t + \beta_{i,t}^{UMD}\, UMD_t + \beta_{i,t}^{CMA}\, CMA_t + \beta_{i,t}^{RMW}\, RMW_t + \varepsilon_{i,d}$$ We require at least 24 monthly observations be available for variables estimated using monthly data over the past 60 months.
β_{EPU}	Beta sensitivity of the economic policy uncertainty index from Baker *et al*. (2016). Following Bali *et al*. (2017), for each stock and for each month in our sample, we estimate the uncertainty beta from the monthly rolling regressions of excess stock returns (R) on the economic policy uncertainty (EPU) over a 60-month fixed window after controlling for the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA) and profitability (RMW) factors. The model is as follows: $$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{EPU}\, EPU_t + \beta_{i,t}^{MKT}\, MKT_t + \beta_{i,t}^{SMB}\, SMB_t + \beta_{i,t}^{HML}\, HML_t + \beta_{i,t}^{UMD}\, UMD_t + \beta_{i,t}^{CMA}\, CMA_t + \beta_{i,t}^{RMW}\, RMW_t + \varepsilon_{i,d}$$ We require at least 24 monthly observations be available for variables estimated using monthly data over the past 60 months.

SIZE	Firm size is measured by the natural logarithm of the market value of equity at the end of month *t-1* for each stock. Market value of equity is a stock's price time shares outstanding in millions dollars.
BM	Following Fama and French (1992), we compute a firm's book-to-market ratio (*BM*) 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 the prior calendar year. We also follow Fama and French (1992) to winsorise *BM* ratio at the 1% and 99% level to avoid issues with extreme observation.
MOM	To control for the medium-term momentum effect of Jegadeesh and Titman (1993), we define the momentum variable (MOM) for each stock in month t as the stock return during the 11-month period up to but not including the current month, i.e., the cumulative return from month *t-11* to month *t-1*.
REV	Following Jegadeesh (1990), we compute short-term reversal (*REV*) for each stock in month *t* as the return on the stock over the previous month, *i.e.*, the return in month *t-1*.
IVOL	We calculate idiosyncratic volatility (*IVOL_AHXZ*) following Ang, Hodrick, Xing, and Zhang (2006) as the standard deviation of the residuals from a Fama and French (1993) three-factor regression of the stock's excess return on the market excess return (*MKTRF*), size (*SMB*), and book-to-market ratio (*HML*) factors using daily return data from the month for which *IVOL* is being calculated. The regression specification is $$R_{i,d} = \alpha_i + \beta_1 MKTRF_d + \beta_2 SMB_d + \beta_3 HML_d + \varepsilon_{i,d}$$ where SMB_d and HML_d are the returns of the size and book-to-market factors of Fama and French (1993), respectively, on day *d*. We require a minimum of 15 daily return observations within the given month to calculate *IVOL_AHXZ*.
ISKEW	Following Boyer, Mitton, and Vorkink (2010), we measure *ISKEW* as the skewness of the residuals from a regression of excess stock returns on MKTRF, SMB, and HML using one month of daily return data.
ILLIQ	Following Amihud (2002) and Bali *et al*. (2011), we measure stock illiquidity for each stock in month *t* as the ratio of the absolute monthly return to its dollar trading volume: $$ILLIQ_{i,t} = \left\|R_{i,t}\right\| / VOLD_{i,t}$$ where $R_{i,t}$ is the return on stock *i* in month *t*, and $VOLD_{i,t}$ is the corresponding monthly trading volume in dollars.
EA	A dummy variable equals 1 if stocks experience maximum daily return within a 5-day window surrounding quarterly earnings announcements date, and 0 otherwise.
SUE	Standardized unexpected earnings based on a rolling seasonal random walk model proposed by Livnat and Mendenhall (2006, page 185).
INST	A stock's institutional ownership is computed as the fraction of its outstanding common shares that is owned by all 13F reporting institutions in a given quarter.

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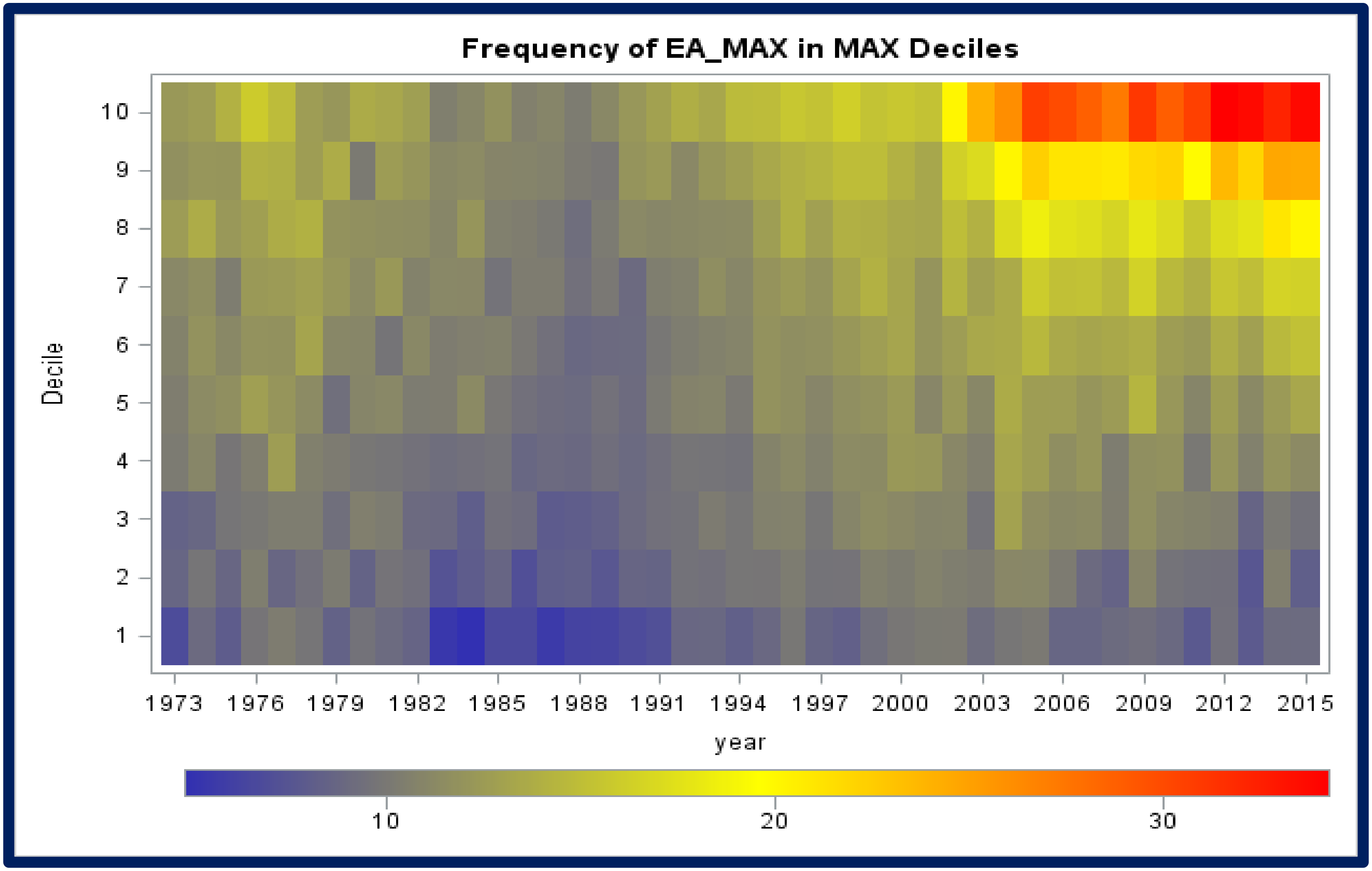
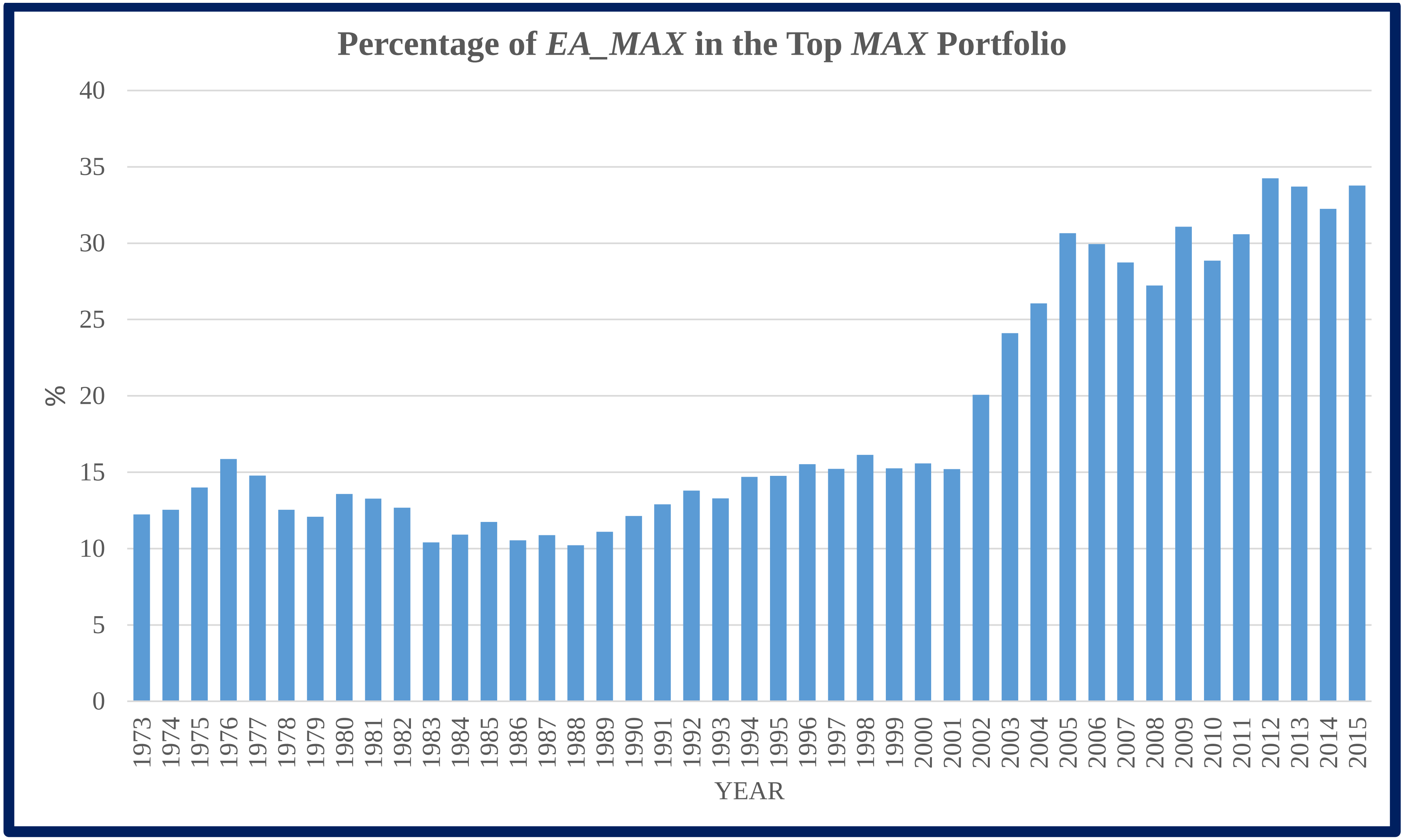
Figure 1A: Heap Map of Earnings Announcements and *MAX*



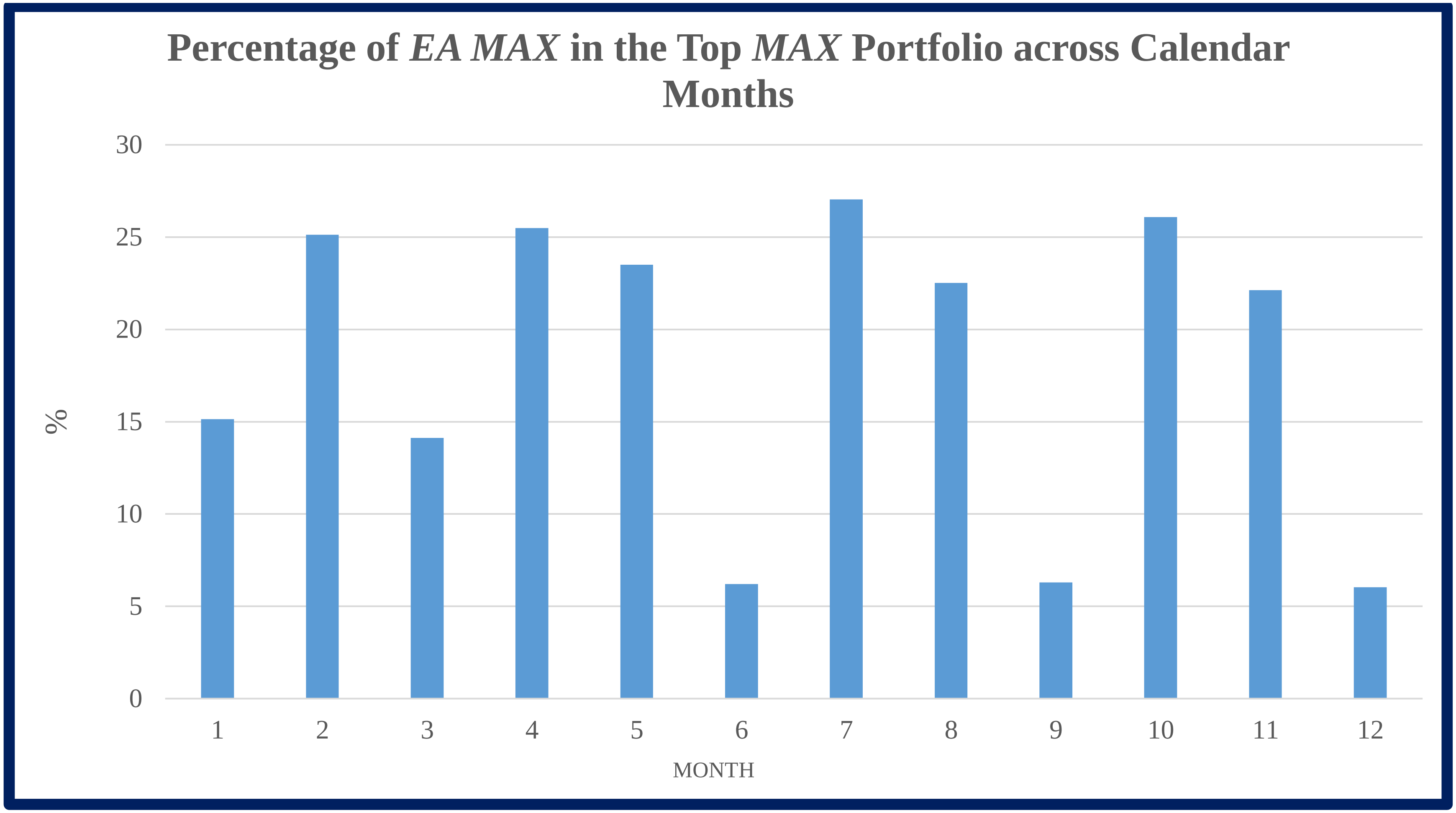
The figure shows the frequency of stocks associated with earnings announcements (*EA_MAX*) in ten *MAX* deciles over the sample period of 1973-2015. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat.

Figure 1B: Percentage of *EA_MAX* in the Top *MAX* Portfolio over Time



The figure shows the percentage of stocks associated with earnings announcements (*EA_MAX*) in the high *MAX* portfolio over the sample period of 1973-2015. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat.

Figure 1C: Percentage of *EA_MAX* in the Top *MAX* Portfolio across Calendar Months



The figure shows the percentage of stocks associated with earnings announcements (*EA_MAX*) in the high *MAX* portfolio across calendar months. The sample covers the period of 1973-2015. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat.

Table 1. Returns and Alphas on Portfolio of Stocks sorted by *MAX*

Panel A: Univariate Portfolio Sorted by *MAX*

Decile	Equal-weighted returns	Value-weighted returns	Average *MAX*
Low *MAX*	0.99	0.76	1.52
2	1.14	0.74	2.47
3	1.20	0.86	3.12
4	1.15	0.72	3.74
5	1.17	0.90	4.40
6	1.06	0.82	5.15
7	0.93	0.80	6.06
8	0.86	0.78	7.28
9	0.56	0.63	9.22
High *MAX*	0.03	0.15	16.15
High - Low	-0.96	-0.61	
	(-3.64)	**(-1.96)**	
4-factor alpha (FFC4α)	-1.11	-0.72	
	(-6.85)	**(-3.23)**	
5-factor alpha (FFC4 + PS α)	-1.09	-0.72	
	(-6.69)	**(-3.08)**	
5-factor alpha (FF5α)	-0.81	-0.37	
	(-6.93)	**(-2.10)**	

Panel B: Summary Statistics for Decile Portfolios Sorted by *MAX*

Decile	*Mkt_cap*	*Price ($)*	*BETA*	*BM*	*ILLIQ*	*IVOL*	*REV*	*MOM*	*SUE*
Low *MAX*	301.55	24.25	0.28	0.78	0.24	0.94	-1.16	10.02	0.096
2	442.41	24.38	0.52	0.69	0.19	1.26	-0.68	10.76	0.144
3	385.85	22.73	0.65	0.65	0.23	1.50	-0.13	11.00	0.159
4	318.30	20.75	0.75	0.63	0.28	1.72	0.00	11.46	0.173
5	257.39	18.77	0.83	0.62	0.35	1.96	0.50	11.57	0.187
6	216.75	17.25	0.93	0.60	0.43	2.22	1.08	12.05	0.206
7	180.19	15.63	1.02	0.59	0.53	2.52	1.80	12.10	0.217
8	150.44	14.00	1.13	0.58	0.64	2.89	2.78	12.75	0.244
9	119.48	12.31	1.25	0.56	0.83	3.43	4.65	12.96	0.261
High *MAX*	82.05	10.35	1.42	0.57	1.32	4.78	11.08	16.67	0.351

Decile portfolios are formed every month from January 1973 to December 2015 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. Panel A reports the equal-weighted (value-weighted) average monthly returns, the four-factor (five-factor) alphas on the equal-weighted (value-weighted) portfolios, and the average maximum daily return of stocks within a month. The last rows present the differences in monthly raw returns and the differences in alpha with respect to the four-factor Fama-French-Carhart (*FFC4*) model, the five-factor Fama-French-Carhart-Pastor-Stambaugh (*FFC4 + PS*), and the five-factor Fama-French (*FF5*) models between portfolio 10 and portfolio 1. Newey-West (1987) adjusted *t*-statistics are reported in parentheses. Average raw and risk-adjusted returns, and average daily maximum returns are given in percentage terms. Numbers in bold denote significance at the 5% or better. Panel B reports summary statistics for various characteristics of stocks for each decile of *MAX*: the market capitalization (in millions of dollars), the price (in dollars), the market beta, the book-to-market (*BM*) ratio, the Amihud illiquidity measure (scaled by 10^5), the idiosyncratic volatility over the past one month (*IVOL*), the return in the portfolio formation month (*REV*), and the cumulative return over the 11 months prior to portfolio formation (*MOM*). The average across months in the sample of the median values within each month of characteristics for the stocks are reported.

Table 2: Univariate Portfolios Sorted on *EA_MAX* and *NOEA_MAX*

Panel A: Univariate Portfolio Sorted by *EA_MAX*

Decile	Equal-weighted returns	Value-weighted returns	Average *MAX*
Low *MAX*	0.97	0.98	1.62
2	0.95	0.73	2.56
3	1.10	0.72	3.25
4	1.12	0.79	3.87
5	1.23	1.04	4.56
6	1.14	0.88	5.32
7	1.30	0.99	6.26
8	1.25	1.21	7.48
9	1.17	1.16	9.44
High *MAX*	1.15	0.93	16.78
High - Low	0.21	-0.01	
	(0.77)	(-0.02)	
4-factor alpha (FFC4α)	-0.05	-0.18	
	(-0.22)	(-0.54)	
5-factor alpha (FFC4 + PS α)	-0.02	-0.20	
	(-0.11)	(-0.59)	
5-factor alpha (FF5α)	0.20	0.27	
	(1.18)	(0.87)	

Panel B: Univariate Portfolio Sorted by *NOEA_MAX*

Decile	Equal-weighted returns	Value-weighted returns	Average *MAX*
Low *NOEA_MAX*	1.00	0.77	1.51
2	1.15	0.76	2.48
3	1.19	0.86	3.14
4	1.15	0.72	3.79
5	1.16	0.85	4.47
6	1.04	0.81	5.25
7	0.88	0.75	6.20
8	0.79	0.66	7.48
9	0.43	0.48	9.50
High *NOEA_MAX*	-0.22	-0.06	16.66
High - Low	-1.22	-0.83	
	(-4.58)	**(-2.60)**	
4-factor alpha (FFC4 α)	-1.37	-0.93	
	(-8.26)	**(-4.12)**	
5-factor alpha (FFC4 + PS α)	-1.35	-0.93	
	(-8.11)	**(-3.90)**	
5-factor alpha (FF5 α)	-1.06	-0.59	
	(-8.68)	**(-3.24)**	

Panel C: Return Difference (*NOEA_MAX* - *EA_MAX*)

Decile	Equal-weighted returns	Value-weighted returns
Low *DIFF*	0.04	-0.20
2	0.17	0.01
3	0.09	0.14
4	0.02	-0.07
5	-0.07	-0.19
6	-0.10	-0.08
7	-0.42	-0.24
8	-0.46	-0.55
9	-0.75	-0.68
High *DIFF*	-1.38	-0.99
High - Low	-1.42	-0.80
	(-8.66)	**(-2.75)**
4-factor alpha (FFC4 α)	-1.32	-0.75
	(-8.06)	**(-2.51)**
5-factor alpha (FFC4 + PS α)	-1.32	-0.73
	(-8.16)	**(-2.39)**
5-factor alpha (FF5 α)	-1.27	-0.86
	(-8.10)	**(-2.68)**

Decile portfolios are formed every month from January 1973 to December 2015 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. Panel A reports results for a sample of stocks of which maximum daily returns are associated with earnings announcements (*EA_MAX*). *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. Panel B reports results for a sample of stocks of which maximum daily returns fall outside the 5-day window surrounding earnings announcements (*NOEA_MAX*). Panel C reports the differences (*DIFF*) in monthly returns between *NOEA_MAX* and *EA_MAX* portfolios across deciles. The last rows in each Panel present the differences in monthly raw returns and the differences in alphas with respect to the four-factor Fama-French-Carhart model (*FFC4*), the five-factor Fama-French-Carhart-Pastor-Stambaugh (*FFC4 + PS*), and the five-factor Fama-French (*FF5*) models between portfolio 10 and portfolio 1. Newey-West (1987) adjusted *t*-statistics are reported in parentheses. Average raw and risk-adjusted returns are given in percentage terms. Numbers in bold denote significance at the 5% or better.

Table 3: Percentage of *EA_MAX* across *MAX* portfolios

	1973 - 2015			1973 - 1994			1995 - 2015		
Decile	N	*EA_MAX*	Percent	N	*EA_MAX*	Percent	N	*EA_MAX*	Percent
Low *MAX*	171,723	14,332	8.35	78,189	5,761	7.37	93,534	8,571	9.16
2	174,922	16,337	9.34	79,233	6,844	8.64	95,689	9,493	9.92
3	174,938	17,505	10.01	79,137	7,218	9.12	95,801	10,287	10.74
4	175,414	18,539	10.57	79,476	7,583	9.54	95,938	10,956	11.42
5	175,200	19,623	11.20	79,398	8,078	10.17	95,802	11,545	12.05
6	175,506	20,584	11.73	79,548	8,199	10.31	95,958	12,385	12.91
7	175,374	21,912	12.49	79,460	8,503	10.70	95,914	13,409	13.98
8	175,354	23,870	13.61	79,359	8,887	11.20	95,995	14,983	15.61
9	175,358	26,554	15.14	79,438	9,173	11.55	95,920	17,381	18.12
High *MAX*	**174,649**	**31,929**	**18.28**	**79,097**	**9,700**	**12.26**	**95,552**	**22,229**	**23.26**

The table reports the percentage of *EA_MAX* stocks across *MAX* portfolios. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) maximum daily returns over the past one month. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat.

Table 4: Bivariate Portfolios Sorted by *MAX* and Firm Characteristics

Panel A: Original *MAX* after Controlling for Firm Characteristics

Decile	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQUID*
Low *MAX*	1.08	1.02	1.12	1.07	1.06
2	1.25	1.17	1.23	1.20	1.23
3	1.24	1.14	1.19	1.13	1.16
4	1.17	1.17	1.14	1.16	1.18
5	1.14	1.18	1.10	1.05	1.10
6	1.00	1.11	1.05	1.02	1.01
7	0.86	1.02	0.91	0.92	0.96
8	0.73	0.95	0.86	0.79	0.76
9	0.51	0.72	0.62	0.60	0.56
High *MAX*	0.08	0.22	0.06	0.13	0.06
High - Low	-1.00	-0.80	-1.06	-0.94	-1.00
	(-3.82)	**(-3.17)**	**(-5.94)**	**(-4.09)**	**(-3.80)**
FFC4 α	-1.10	-0.99	-1.22	-1.13	-1.13
	(-6.90)	**(-6.14)**	**(-10.12)**	**(-7.56)**	**(-7.20)**

Panel B: *EA_MAX* and *NOEA_MAX* after Controlling for Characteristics: Equal-weighted portfolios

Decile	*SIZE*		*BM*		*MOM*		*REV*		*ILLIQUID*	
	EA	*Non-EA*	*EA*	*Non-EA*	*EA*	*Non-EA*	*EA*	*Non-EA*	*EA*	*Non-EA*
Low *MAX*	0.95	1.06	0.77	1.01	0.83	1.11	0.68	1.06	0.85	1.06
2	1.12	1.26	1.01	1.16	1.20	1.24	1.09	1.22	1.15	1.22
3	1.13	1.23	1.21	1.15	1.12	1.19	1.08	1.14	1.12	1.19
4	1.28	1.19	1.19	1.20	1.06	1.14	1.16	1.15	1.12	1.15
5	0.99	1.12	1.49	1.14	1.25	1.08	1.25	1.04	1.17	1.09
6	1.19	0.97	1.22	1.07	1.21	1.03	1.11	1.01	1.15	1.00
7	1.24	0.84	1.44	1.00	1.17	0.92	1.31	0.91	1.17	0.91
8	1.13	0.70	1.21	0.95	1.23	0.79	1.02	0.73	1.38	0.72
9	1.04	0.40	1.30	0.58	1.22	0.52	1.22	0.52	1.04	0.48
High *MAX*	0.82	-0.13	0.99	-0.06	0.76	-0.15	1.10	-0.13	0.97	-0.17
High - Low	-0.28	-1.19	0.16	-1.07	-0.08	-1.26	0.33	-1.19	0.04	-1.23
	(-0.93)	**(-4.51)**	(0.57)	**(-4.13)**	(-0.32)	**(-7.01)**	(1.22)	**(-5.19)**	(0.14)	**(-4.57)**
FFC4 α	-0.11	-1.30	0.13	-1.28	-0.03	-1.42	0.43	-1.37	0.18	-1.38
	(-0.50)	**(-8.22)**	(0.55)	**(-7.63)**	(-0.18)	**(-11.62)**	**(2.05)**	**(-9.25)**	(0.81)	**(-8.54)**

Double-sorted, equal-weighted decile portfolios are formed every month from January 1973 to December 2015 by sorting stocks based on the maximum daily returns after controlling for firm 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*. The table presents average returns across the ten control deciles to produce decile portfolios with dispersion in *MAX* but with similar levels of the control variable. ‘‘High-Low” and “FFC4 α” are the difference in average monthly returns and alpha with respect to the four-factor Fama-French-Carhart model between the High *MAX* and Low *MAX* portfolios. Newey-West (1987) adjusted *t*-statistics are reported. Panel A reports results for the original *MAX* portfolios. Panel B reports results for *EA_MAX* and *NOEA_MAX* portfolios. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat.

Table 5. Firm-level Cross-sectional Return Regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MAX	-0.0719								-0.0856	-0.0462	-0.0627
	(-6.10)								(-7.13)	(-4.80)	(-6.38)
MAX_EA		0.0305							0.0715		0.0731
		(4.96)							(11.76)		(11.52)
BETA			-0.0002							0.0001	0.0001
			(-0.44)							(0.02)	(0.13)
SIZE				-0.0003						-0.0007	-0.0008
				(-0.92)						(-2.16)	(-2.37)
BM					0.0074					0.0016	0.0016
					(2.07)					(1.74)	(1.70)
MOM						0.0064				0.0079	0.0079
						(3.48)				(4.27)	(4.28)
REV							-0.0229			-0.0356	-0.0362
							(-5.22)			(-7.67)	(-7.81)
ILLIQUID								0.0092		-0.0009	-0.0007
								(2.85)		(-0.35)	(-0.27)

Each month, we run a firm-level cross-sectional regression of the returns in that month on subsets of lagged predictor variables including *MAX* in the previous month and six control variables. Control variables are defined in Table 1. *MAX_EA* is the interaction term between *MAX* and *EA*. *EA* is a dummy variable which is equal to 1 if *MAX* returns are associated with earnings announcements and 0, otherwise. Stocks experiencing earnings announcements are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding earnings announcement date from Compustat. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey West adjusted *t*-statistics (in parentheses).

Table 6. The *MAX* effect after controlling for institutional holding

Panel A: The *MAX* effect and Institutional Ownership

Decile	*INST 1*	*INST 2*	*INST 3*	*INST 4*	*INST 5*
Low *MAX*	0.97	1.03	1.15	1.18	1.22
2	1.33	1.29	1.20	1.28	1.12
3	1.28	1.24	1.16	1.14	1.05
4	1.15	1.27	1.16	1.27	0.95
5	1.00	1.24	1.11	1.10	1.00
6	0.99	1.14	1.01	0.99	0.98
7	0.70	0.88	0.98	0.97	0.83
8	0.70	0.69	0.71	1.03	0.76
9	0.21	0.45	0.51	0.63	0.74
High *MAX*	-0.68	0.03	0.06	0.42	0.57
High - Low (10-1)	-1.66	-1.01	-1.09	-0.76	-0.64
	(-4.81)	**(-2.76)**	**(-3.41)**	**(-3.00)**	**(-2.55)**
4-factor alpha (FFC4 α)	-1.93	-1.25	-1.28	-0.80	-0.63
	(-8.48)	**(-5.29)**	**(-5.73)**	**(-4.19)**	**(-3.26)**
5-factor alpha (FFC4 + PS α)	-1.93	-1.24	-1.28	-0.77	-0.60
	(-8.67)	**(-5.32)**	**(-5.82)**	**(-4.24)**	**-(2.98)**
5-factor alpha (FF5 α)	-1.43	-0.78	-0.90	-0.54	-0.43
	(-6.50)	**(-4.32)**	**(-5.22)**	**(-3.58)**	**(-2.58)**

Panel B: The *MAX* effect for *EA_MAX* vs. *NOEA_MAX* portfolios

Decile	*INST1*		*INST 2*		*INST 3*		*INST 4*		*INST 5*	
	NO_EA	*EA*	*NO_EA*	*EA*	*NO_EA*	*EA*	*NO_EA*	*EA*	*NO_EA*	*EA*
Low MAX	0.93	0.92	1.04	0.82	1.13	0.73	1.19	1.00	1.17	0.66
2	1.35	1.12	1.36	0.66	1.24	0.97	1.28	1.20	1.27	1.10
3	1.20	1.18	1.12	1.36	1.15	1.45	1.15	1.48	1.08	1.06
4	1.12	0.96	1.24	1.33	1.09	0.53	1.08	1.36	1.06	1.11
5	1.11	1.02	1.34	1.15	1.05	1.43	1.07	0.98	0.93	0.92
6	0.96	1.19	1.11	1.62	1.05	1.36	0.92	1.16	0.86	1.15
7	0.70	1.86	0.75	1.24	0.86	1.65	0.95	1.02	0.69	1.31
8	0.57	1.05	0.63	1.46	0.70	0.77	0.93	0.85	0.72	1.02
9	0.01	1.14	0.44	1.55	0.38	0.70	0.61	1.42	0.57	1.44
High MAX	-0.88	0.91	-0.33	1.02	-0.15	0.86	0.25	1.83	0.39	1.41
High - Low (10-1)	-1.80	-0.28	-1.37	0.15	-1.28	0.19	-0.94	0.56	-0.77	0.06
	(-5.58)	(-0.49)	**(-3.72)**	(0.27)	**(-3.68)**	(0.40)	**(-3.60)**	(1.15)	**(-3.13)**	(0.13)
4-factor alpha (FFC4 α)	-2.12	-0.24	-1.68	0.17	-1.48	0.17	-0.99	0.40	-0.79	-0.10
	(-8.43)	(-0.50)	**(-6.86)**	(0.35)	**(-5.63)**	(0.36)	**(-4.86)**	(0.91)	**(-3.64)**	(-0.20)
5-factor alpha (FFC4 + PS α)	-2.13	-0.33	-1.66	0.17	-1.45	-0.01	-0.96	0.39	-0.78	-0.12
	(-8.94)	(-0.66)	**(-7.04)**	(0.350	**(-5.60)**	(-0.03)	**(-4.85)**	(0.92)	**(-3.66)**	(-0.25)
5-factor alpha (FF5 α)	-1.65	-0.14	-1.14	0.38	-1.11	0.17	-0.71	0.61	-0.54	0.12
	(-7.30)	(-0.27)	**(-6.15)**	(0.77)	**(-5.01)**	(0.36)	**(-3.79)**	(1.42)	**(-2.52)**	(0.24)

The table presents the results of dependent sort bivariate portfolio analyses of the relation between future stock returns and maximum daily return (*MAX*) over the past one month after controlling for institutional holdings (*INST*). Institutional investors' shares holding data are obtained from Thompson Reuters Institutional 13F. A stock's institutional ownership (*INST*) is computed as the fraction of its outstanding common shares that is owned by all 13F reporting institutions in a given quarter. The table shows the time-series means of the monthly equal-weighted raw returns for portfolios formed by sorting all stocks into quintiles of *INST* and then, within each quintiles of *INST*, into deciles of *MAX*. Panel A reports the *MAX* effect across *INST* quintiles. Panel B reports results for portfolios of stocks experiencing earnings announcements (*EA_MAX)* and those stocks without earnings announcements (*NOEA_MAX*). *EA_MAX* (*NOEA_MAX*) are defined as stocks that exhibit maximum daily returns within (outside) a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. The last rows in each Panel present the differences in monthly raw returns and alphas with respect to the four-factor Fama-French-Carhart (FFC4), the five-factor four-factor Fama-French-Carhart-Pastor-Stambaugh (FFC4 + PS), and the five-factor Fama-French (FF5) models between portfolio 10 and portfolio 1. Newey-West (1987) adjusted *t*-statistics are reported in parentheses. Average raw and risk-adjusted returns are given in percentage terms. Numbers in bold denote significance at the 5% or better.

Table 7. Returns and alphas of *EA_MAX* portfolios following sentiment states

Panel A: Returns and alphas of *EA_MAX* portfolios following high sentiment states

Sentiment Measure	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	High - Low		
											Ret	FFC4 α	FF5 α
Baker & Wurgler	1.29	1.38	1.26	1.42	1.34	1.13	1.23	1.30	0.88	0.79	-0.43	-0.19	0.10
	(4.93)	(4.55)	(4.40)	(4.70)	(4.17)	(3.44)	(3.24)	(3.32)	(2.12)	(1.87)	(-0.91)	(-0.70)	(0.39)
MCSI	1.18	1.13	1.02	1.10	1.04	0.95	1.03	0.94	0.84	0.69	-0.49	-0.20	0.01
	(4.46)	(3.80)	(3.33)	(3.68)	(3.43)	(3.12)	(3.44)	(2.54)	(1.85)	(1.40)	(-1.02)	(-0.69)	(0.02)
FEARS	0.79	0.56	1.15	0.44	0.53	0.41	0.33	0.82	0.86	0.46	-0.22	-0.64	-0.64
	(1.42)	(0.75)	(1.51)	(0.73)	(0.81)	(0.49)	(0.36)	(1.31)	(1.01)	(0.41)	(-0.32)	(-1.26)	(-1.11)

Panel B: Returns and alphas of *EA_MAX* portfolios following low sentiment states

Sentiment Measure	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	High - Low		
											Ret	FFC4 α	FF5 α
Baker & Wurgler	1.08	0.90	1.26	1.19	1.49	1.52	1.76	1.59	1.83	1.85	0.65	0.20	0.23
	(3.26)	(2.51)	(3.11)	(3.07)	(3.65)	(4.06)	(4.11)	(3.51)	(3.91)	(3.55)	(1.53)	(0.75)	(1.13)
MCSI	1.20	1.45	1.89	1.54	1.98	1.78	1.91	2.18	2.00	1.92	0.78	0.00	0.16
	(3.69)	(3.84)	(5.07)	(4.15)	(5.06)	(4.39)	(3.88)	(4.62)	(4.11)	(3.50)	(1.49)	(-0.01)	(0.65)
FEARS	0.53	1.03	1.91	0.41	1.31	1.61	0.63	0.94	0.93	1.51	1.23	0.24	0.38
	(0.90)	(1.46)	(3.48)	(0.48)	(1.85)	(2.17)	(0.63)	(1.13)	(1.02)	(1.55)	(1.42)	(0.37)	(0.70)

The table reports returns and alphas of *EA_MAX* portfolios following high sentiment states (Panel A) and low sentiment states (Panel B). *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. "Baker & Wurgler" refers to the Baker and Wurgler (2006)'s investor sentiment index. "MCSI" refers to the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center. "FEARS" refers to the FEARS index from Da, Engelberg, and Gao (2015). For each sentiment measure, we define a high (low) sentiment month as one in which each sentiment index is above (below) the sample median value. The last columns in each Panel present the differences in monthly raw returns (Ret) and alphas with respect to the four-factor Fama-French-Carhart (FFC4), and the five-factor Fama-French (FF5) models between portfolio 10 and portfolio 1. Average raw returns and risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table 8: Stock Price, Idiosyncratic Volatility, and Idiosyncratic Skewness

Panel A: Returns and alphas of *MAX* portfolios

Sort Variable	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low** Ret	FFC4 α	FF5 α
	Portfolios Using Low Price, High *IVOL*, and High *ISKEW* Stocks												
MAX	0.99	1.22	1.45	1.27	1.31	1.32	1.03	0.93	0.52	0.01	-0.98	-1.18	-0.94
	(3.49)	(3.82)	(4.42)	(3.64)	(3.68)	(3.72)	(2.72)	(2.47)	(1.34)	(0.03)	(-3.95)	(-7.06)	(-6.56)
	Portfolios Using High Price, Low *IVOL*, and Low *ISKEW* Stocks												
MAX	0.88	0.94	0.92	0.86	0.97	0.86	0.74	0.92	0.79	1.02	0.14	0.01	0.77
	(3.31)	(3.34)	(3.16)	(2.92)	(3.14)	(2.67)	(2.17)	(2.46)	(1.94)	(2.39)	(0.41)	(0.05)	(2.81)

Panel B: Returns and alphas of *EA_MAX* portfolios

Sort Variable	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low** Ret	FFC4 α	FF5 α
	Portfolios Using Low Price, High *IVOL*, and High *ISKEW* Stocks												
MAX	0.60	0.58	1.38	0.84	1.35	1.40	1.32	1.51	1.08	1.18	0.01	-0.02	0.00
	(1.32)	(1.30)	(2.68)	(1.94)	(2.66)	(3.12)	(2.91)	(3.53)	(2.52)	(2.76)	(0.02)	(-0.05)	(0.57)
	Portfolios Using High Price, Low *IVOL*, and Low *ISKEW* Stocks												
MAX	0.73	0.85	0.65	0.78	0.75	1.16	0.92	0.87	1.58	2.03	1.58	1.37	2.03
	(2.40)	(2.51)	(1.91)	(2.42)	(2.13)	(2.89)	(2.29)	(1.91)	(3.43)	(3.57)	(2.79)	(2.75)	(3.55)

The table reports returns and alphas of the *MAX* portfolios (Panel A) and *EA_MAX* portfolios (Panel B) using a sample of stocks with low price, high idiosyncratic volatility, and high idiosyncratic skewness and a sample of stocks with high price, low high idiosyncratic volatility, and low idiosyncratic skewness. *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. Stocks with low (high) price, high (low) idiosyncratic volatility, and high (low) idiosyncratic skewness are defined as those in the bottom (top) quintile of stock price and the top (bottom) quintile of both idiosyncratic volatility and idiosyncratic skewness. The last columns present the differences in monthly raw returns (*Ret*) and the differences in alpha with respect to the four-factor Fama-French-Carhart (*FFC4*) and Fama-French five-factor (*FF5*) models between portfolio 10 and portfolio 1. Average raw and risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table 9: Macroeconomic uncertainty, economic policy uncertainty, and the *MAX* effect

Panel A: Bivariate sort analysis

	Control for β_{UNC}			Control for β_{EPU}		
Decile	*MAX*	*EA_MAX*	*NOEA_MAX*	*MAX*	*EA_MAX*	*NOEA_MAX*
Low MAX	1.07	0.71	1.07	0.84	0.58	0.82
2	1.16	0.99	1.17	0.96	0.97	0.99
3	1.17	1.26	1.19	0.94	0.88	0.92
4	1.15	1.37	1.10	0.94	1.14	0.94
5	1.16	1.02	1.15	0.92	1.07	0.89
6	1.10	1.14	1.11	0.85	1.05	0.87
7	1.01	1.28	0.99	0.75	1.04	0.72
8	0.90	1.24	0.88	0.70	1.02	0.63
9	0.69	1.14	0.60	0.48	0.99	0.41
High MAX	0.24	1.06	0.01	0.13	1.10	-0.14
High - Low	-0.83	0.25	-1.07	-0.72	0.48	-0.96
	(-4.32)	(0.95)	(-5.49)	(-2.65)	(1.42)	(-3.47)
FFC4	-0.95	0.37	-1.18	-0.87	0.43	-1.10
	(-8.38)	(1.76)	(-10.35)	(-5.70)	(1.93)	(-7.01)

Panel B: Regression analysis after controlling for beta sensitivity to EPU and beta sensitivity to UNC

MAX	*MAX_EA*	β_{UNC}	β_{EPU}	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQUID*
-0.0719									
(-6.10)									
-0.0856	0.0715								
(-7.13)	(11.76)								
		-0.0031							
		(-2.16)							
-0.0815	0.0754	-0.0029							
(-6.90)	(9.80)	(-2.08)							
-0.0528	0.0788	-0.0030		0.0001	-0.0007	0.0018	0.0058	-0.0217	-0.0798
(-4.91)	(10.50)	(-2.61)		(0.29)	(-1.79)	(1.87)	(3.41)	(-5.27)	(-2.22)
			-0.0194						
			(-2.53)						
-0.0650	0.0752		-0.0211						
(-4.78)	(9.36)		(-2.66)						
-0.0423	0.0778		-0.0141	0.0000	-0.0005	0.0013	0.0046	-0.0178	-0.0912
(-3.49)	(10.08)		(-2.38)	(0.02)	(-1.14)	(1.14)	(2.43)	(-3.84)	(-2.09)

Panel A reports results for bivariate sort analysis. Double-sorted, equal-weighted decile portfolios are formed every month by sorting stocks based on the maximum daily returns after controlling for the beta sensitivity of the macroeconomic index (β_{UNC}) from Jurado *et al*. (2015) or the economic policy uncertainty index (β_{EPU}) from Baker *et al*. (2016). 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 presents average returns across the ten control deciles to produce decile portfolios with dispersion in *MAX* but with similar levels of the control variable. ‘‘High-Low” and “FFC4 α” are the difference in average monthly returns and alpha with respect to the four-factor Fama-French-Carhart model between the High MAX and Low MAX portfolios. Panel A reports results separately for the original *MAX* portfolios, *EA_MAX* portfolios, and *NOEA_MAX* portfolios. *EA_MAX* (*NOEA_MAX*) stocks are defined as stocks that exhibit maximum daily returns within (outside) a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. Panel B reports results for regression analysis after controlling for β_{UNC} and β_{EPU} . Each month, we run a firm-level cross-sectional regression of the returns in that month on subsets of lagged predictor variables including *MAX* in the previous month and control variables. Panel B is as per Table 5, except that β_{UNC} and β_{EPU} are included as additional control variables. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table 10. Cross sectional Predictability of *MAX*

	MAX	*MAX_EA*	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQUID*
(1)	0.2784							
	(36.83)							
(2)		0.0771						
		(17.40)						
(3)	0.2959	-0.0677						
	(42.76)	(-12.96)						
(4)	0.2393		0.0022	-0.0052	-0.0044	0.0008	-0.0550	0.0059
	(29.05)		(8.80)	(-37.97)	(-8.63)	(3.00)	(-25.36)	(4.03)
(5)	0.2552	-0.0563	0.0021	-0.0051	-0.0043	0.0024	-0.0546	0.0056
	(34.37)	(-13.29)	(8.80)	(-37.95)	(-8.65)	(3.01)	(-25.12)	(4.02)

Each month we run a firm-level cross-sectional regression of the maximum daily returns in that month (*MAX*) on subsets of seven lagged predictor variables, including 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*), the Amihud illiquidity (*ILLIQ*), and the idiosyncratic volatility (*IVOL*). *MAX_EA* is the interaction term between *MAX* and *EA*. *EA* is a dummy variable which is equal to 1 if stocks experience earnings announcements in the current month and 0, otherwise. Stocks experiencing earnings announcements are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding earnings announcement date from Compustat. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table 11. Alphas and Factor Sensitivities for *BAB* and *FMAX* Factors

Panel A. *FMAX* factors constructed following Bali *et al.* (2016) using *MAX*(5). Sample 1973-2015.

Specification	Alpha	*MKTRF*	*SMB*	*HML*	*UMD*	*PS*	*FMAX*	*NOEA_FMAX*	Adj_R2
FFC4	0.518	0.063	0.026	0.539	0.217				22.40%
	(2.76)	(1.13)	(0.34)	**(5.04)**	**(3.42)**				
FFC4 + PS	0.496	0.065	0.026	0.538	0.218	0.047			22.49%
	(2.66)	(1.19)	(0.33)	**(5.08)**	**(3.43)**	(0.59)			
FFC4 + FMAX	0.225	0.251	0.307	0.274	0.202		-0.485		41.17%
	(1.31)	**(5.84)**	**(5.05)**	**(3.49)**	**(4.74)**		**(-8.46)**		
FFC4 + PS + FMAX	0.214	0.252	0.306	0.274	0.203	0.024	-0.484		41.11%
	(1.22)	**(5.83)**	**(4.94)**	**(3.57)**	**(4.73)**	(0.39)	**(-8.55)**		
FFC4 + NOEA_FMAX	0.174	0.240	0.281	0.310	0.201			-0.442	39.59%
	(0.98)	**(5.45)**	**(4.66)**	**(3.98)**	**(4.58)**			**(-8.22)**	
FFC4 + PS + NOEA_FMAX	0.164	0.240	0.280	0.310	0.202	0.022		-0.440	39.53%
	(0.91)	**(5.43)**	**(4.58)**	**(4.07)**	**(4.58)**	(0.37)		**(-8.36)**	

Panel B. *FMAX* factor constructed by *MAX* (*n*) with *n* = 1…5

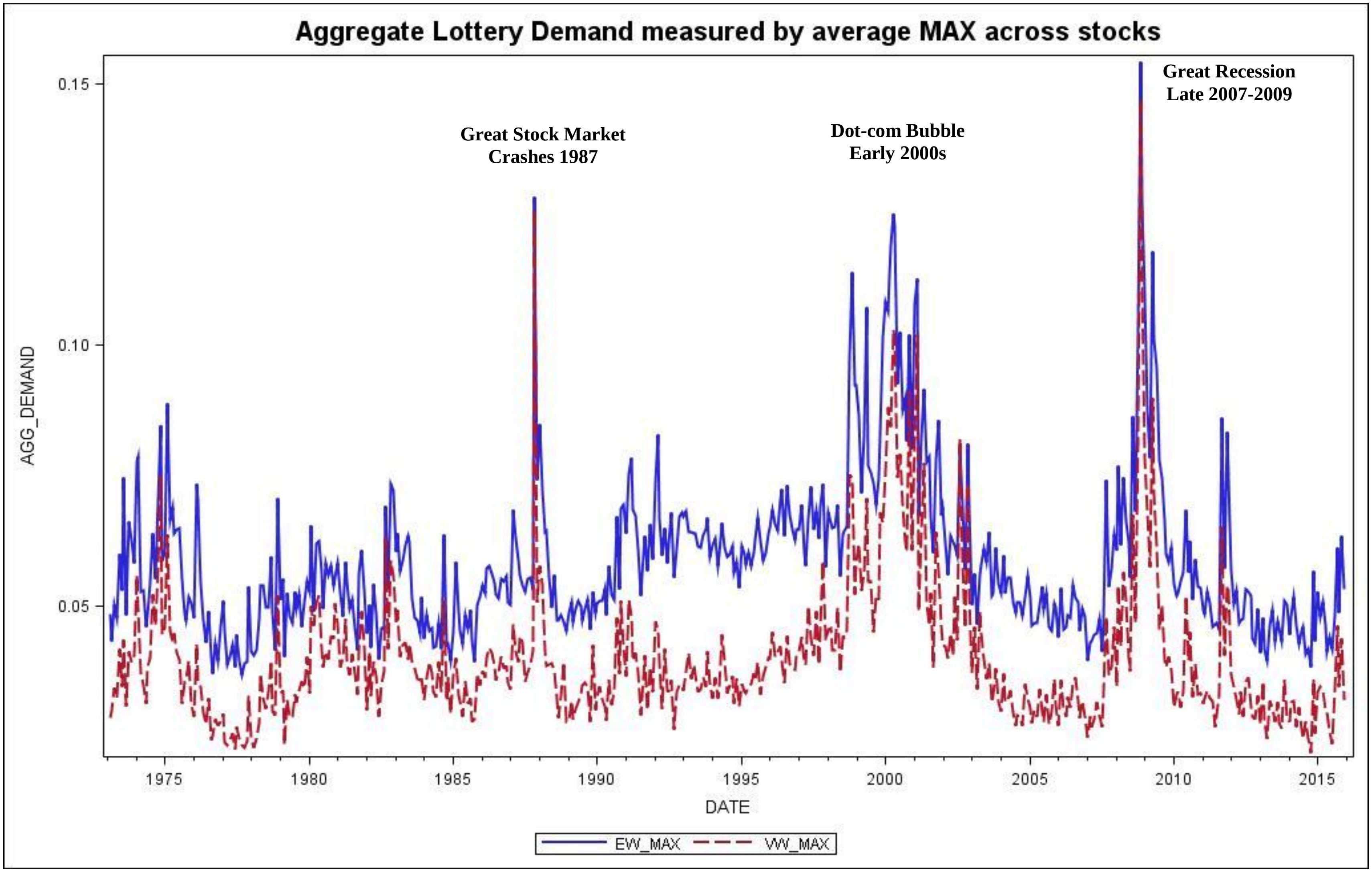
	Specification	Alpha			*FMAX/ NOEA_FMAX*		
		1973-2015	1973-1994	1995-2015	1973-2015	1973-1994	1995-2015
MAX (5)	*FFC4 + FMAX (5)*	0.225	0.342	0.228	-0.485	-0.346	-0.463
		(1.31)	**(1.75)**	(0.78)	**(-8.46)**	**(-4.59)**	**(-6.07)**
	FFC4 + NOEA_FMAX (5)	0.174	0.315	0.171	-0.442	-0.290	-0.410
		(0.98)	(1.54)	(0.55)	**(-8.22)**	**(-4.19)**	**(-6.37)**
MAX (4)	*FFC4 + FMAX (4)*	0.232	0.352	0.220	-0.489	-0.345	-0.472
		(1.36)	**(1.81)**	(0.76)	**(-8.20)**	**(-4.46)**	**(-6.25)**
	FFC4 + NOEA_FMAX (4)	0.184	0.321	0.206	-0.443	-0.298	-0.424
		(1.05)	(1.59)	(0.70)	**(-8.02)**	**(-4.30)**	**(-5.49)**
MAX (3)	*FFC4 + FMAX (3)*	0.246	0.358	0.237	-0.494	-0.352	-0.475
		(1.43)	**(1.65)**	(0.82)	**(-8.11)**	**(-3.61)**	**(-6.23)**
	FFC4 + NOEA_FMAX (3)	0.192	0.338	0.192	-0.450	-0.306	-0.430
		(1.12)	(1.56)	(0.66)	**(-8.25)**	**(-3.46)**	**(-5.98)**
MAX (2)	*FFC4 + FMAX (2)*	0.265	0.387	0.241	-0.501	-0.337	-0.494
		(1.55)	**(1.75)**	(0.84)	**(-7.83)**	**(-3.36)**	**(-6.25)**
	FFC4 + NOEA_FMAX (2)	0.204	0.350	0.194	-0.465	-0.314	-0.446
		(1.19)	(1.59)	(0.67)	**(-7.86)**	**(-3.37)**	**(-5.82)**
MAX (1)	*FFC4 + FMAX (1)*	0.259	0.341	0.249	-0.579	-0.528	-0.514
		(1.67)	**(1.75)**	(0.92)	**(-8.84)**	**(-5.77)**	**(-5.90)**
	FFC4 + NOEA_FMAX (1)	0.197	0.310	0.180	-0.546	-0.485	-0.484
		(1.25)	(1.57)	(0.65)	**(-8.79)**	**(-5.08)**	**(-5.59)**

The table presents the alphas (in percent per month) and factor sensitivities for the betting-again-beta (*BAB*) factor using different factor models. *FFC4* (*FFC4+PS*) refers to the four-factor Fama-French-Carhart (the five-factor Fama-French-Carhart-Pastor-Stambaugh) model. Different measures of the lottery factor are constructed following Bali *e al.* (2011) and Bali *et al.* (2016), taking *MAX*(*n*) with *n* = 1 to 5, defined as the average of the *n* highest daily returns of the given stock in the given month. The factor created using *MAX*(*n*) as the measure of lottery demand is denoted *FMAX* (*n*). *NOEA_FMAX*(*n*) is the lottery demand factor created using *NOEA_MAX*(n) after excluding earnings announcement *MAX* returns. The *BAB* factor is from Lasse H. Pedersen's website. Panel A reports results for *FMAX*(*n*) with *n* = 5 as in Bali *et al.* (2016). Panel B reports results for alternative measures of lottery demand factor, *FMAX*(*n*) with *n* = 1 to 5, for the whole sample (1973-2015) and for two equal subsamples. For brevity, Panel B only reports the alphas and the sensitivities of the *BAB* factor returns to lottery demand factor (*FMAX* and *NOEA_FMAX*). Newey-West (1987) adjusted *t*-statistics are reported in parentheses. Numbers in bold denote significance at 10% or better.

Appendix for
"When are Extreme Daily Returns not Lottery? At Earnings Announcements!"

Content

Figure A.1: Time-Series of Aggregate Lottery Demand



The figure shows the time-series of aggregate lottery demand over the sample period of 1973-2015. For each month *t*, aggregate lottery demand is measured as the equal-weighted (EW_MAX) or value-weighted (VW_MAX) average value of *MAX* across all stocks in the sample in month *t*.

Table A1. Alternative Measure of Lottery Demand by *MAX* (N): N = 2 to 5

	N=2			*N=3*			*N=4*			*N=5*		
Decile	*MAX*	*EA_MAX*	*NOEA_MAX*	*MAX*	*EA_MAX*	*NOEA_MAX*	*MAX*	*EA_MAX*	*NOEA_MAX*	*MAX*	*EA_MAX*	*NOEA_MAX*
Low MAX	0.77	0.76	0.80	0.80	0.81	0.84	0.79	0.82	0.85	0.81	0.80	0.92
2	0.72	0.78	0.73	0.75	0.81	0.78	0.79	0.82	0.85	0.81	0.79	0.85
3	0.87	0.74	0.91	0.90	0.85	0.90	0.84	0.82	0.86	0.81	0.76	0.86
4	0.81	0.88	0.83	0.80	0.88	0.82	0.80	0.85	0.83	0.86	0.88	0.90
5	0.78	0.71	0.74	0.79	0.67	0.78	0.80	0.74	0.81	0.73	0.67	0.77
6	0.96	0.77	0.95	0.88	0.85	0.86	0.81	0.81	0.75	0.81	0.90	0.72
7	0.72	1.00	0.66	0.81	0.89	0.82	0.84	0.85	0.85	0.83	0.82	0.84
8	0.81	0.98	0.72	0.76	0.83	0.62	0.81	0.77	0.70	0.79	0.69	0.72
9	0.49	1.00	0.32	0.40	0.78	0.25	0.41	0.77	0.24	0.45	0.69	0.33
High MAX	0.17	1.00	-0.17	0.14	0.88	-0.28	0.08	0.80	-0.37	0.06	0.71	-0.41
High - Low	-0.60	0.24	-0.96	-0.66	0.07	-1.12	-0.70	-0.02	-1.23	-0.75	-0.12	-1.33
	(-1.76)	(0.58)	**(-2.69)**	**(-1.90)**	(0.18)	**(-3.04)**	**(-2.03)**	(-0.05)	**(-3.38)**	**(-2.18)**	(-0.30)	**(-3.76)**
FFC4 + PS α	-0.74	0.07	-1.12	-0.79	-0.10	-1.27	-0.87	-0.25	-1.40	-0.92	-0.38	-1.51
	(-2.96)	(0.22)	**(-4.21)**	**(-3.10)**	(-0.33)	**(-4.73)**	**(-3.42)**	(-0.81)	**(-5.19)**	**(-3.64)**	(-1.14)	**(-5.68)**
FF5 α	-0.37	0.50	-0.73	-0.40	0.37	-0.85	-0.45	0.24	-0.95	-0.48	0.10	-1.06
	(-1.99)	**(1.71)**	**(-3.53)**	**(-2.05)**	(1.35)	**(-4.01)**	**(-2.26)**	(0.88)	**(-4.42)**	**(-2.50)**	(0.37)	**(-5.14)**

Decile portfolios are formed every month from January 1973 to December 2015 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 daily returns over the past one month. The table reports the value-weighted average monthly returns for $N = 2, 3, 4, 5$. The last rows present the differences in monthly returns and the differences in alphas with respect to the 5-factor Fama-French-Carhart-Pastor-Stambaugh (*FFC4 + PS*) and the five-factor Fama-French (*FF5*) models between portfolios 10 and 1. Newey-West (1987) adjusted t-statistics are reported in parentheses. Average raw and risk adjusted returns are given in percentage terms. Numbers in bold denote significance at the 10% or better.

Table A2. The *MAX* Effect after Controlling for a Microstructure Effect

Decile	*MAX*	*EA_MAX*	*NOEA_MAX*
Low *MAX*	0.98	0.82	0.99
2	1.10	0.96	1.11
3	1.16	1.05	1.15
4	1.11	1.00	1.11
5	1.14	1.20	1.14
6	1.07	1.09	1.05
7	0.92	1.20	0.88
8	0.86	1.20	0.79
9	0.61	1.08	0.50
High *MAX*	0.15	1.19	-0.09
High - Low	-0.83	0.30	-1.08
	(-3.20)	(1.06)	**(-4.14)**
4-factor alpha (FFC4 α)	-1.00	0.13	-1.24
	(-6.41)	(0.67)	**(-7.94)**
5-factor alpha (FFC4 + PS α)	-0.97	0.12	-1.21
	(-6.30)	(0.61)	**(-7.82)**
5-factor alpha (FF5 α)	-0.69	0.38	-0.93
	(-5.58)	**(2.06)**	**(-7.34)**

This table is as per Table 1 in the main analysis, except that decile portfolios are formed every month by sorting stocks based on the maximum daily returns over the past one month, excluding the last trading day of that month.

Table A3. The *MAX* Effect after Controlling for Earnings Momentum Factor

Decile	*FF3 α*	*FF3 α + PMN*	*FFC4 α*	*FFC4 α + PMN*
Low *MAX*	0.62	0.59	0.66	0.59
2	0.73	0.64	0.79	0.64
3	0.76	0.64	0.82	0.64
4	0.69	0.57	0.76	0.58
5	0.71	0.65	0.77	0.66
6	0.63	0.51	0.67	0.52
7	0.49	0.46	0.53	0.46
8	0.41	0.46	0.45	0.46
9	0.12	0.29	0.19	0.29
High *MAX*	-0.51	-0.23	-0.44	-0.23
High - Low	-1.12	-0.82	-1.11	-0.82
(10-1)	**(-5.60)**	**(-4.04)**	**(-6.02)**	**(-4.17)**
	Alpha reduced by 27%		Alpha reduced by 26%	

The table reports the average hedge returns from the *MAX* strategy after controlling for earnings momentum factor (*PMN*). *PMN* data is from Chordia and Shivakumar (2006). The sample covers the period of 1973-2003. Average risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted *t*-statistics are reported in parentheses. Numbers in bold denote significance at the 5% or better.

Table A4: Time-Varying Lottery Demand

Panel A: Equal-Weighted Average *MAX* as Aggregate Lottery Demand: *MAX* Portfolios

Value	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
					Above Median Aggregate Lottery Demand						
FFC4 α	0.84	0.81	0.78	0.68	0.67	0.51	0.33	0.24	-0.13	-0.65	-1.49
	(5.90)	(6.33)	(6.45)	(6.04)	(5.46)	(4.90)	(3.21)	(2.25)	(-1.09)	(-3.88)	(-5.77)
					Below Median Aggregate Lottery Demand						
FFC4 α	0.16	0.29	0.35	0.31	0.31	0.17	0.01	-0.05	-0.32	-0.87	-1.02
	(0.35)	(0.66)	(0.80)	(0.71)	(0.69)	(0.40)	(0.03)	(-0.11)	(-0.74)	(-1.98)	(-6.55)

Panel B: Equal-Weighted Average *MAX* as Aggregate Lottery Demand: *EA_MAX* portfolios

Value	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
					Above Median Aggregate Lottery Demand						
FFC4 α	0.65	0.54	0.91	1.02	0.59	0.75	0.91	0.72	0.53	0.51	-0.14
	(3.37)	(2.44)	(4.56)	(4.78)	(2.55)	(4.99)	(3.50)	(3.92)	(2.36)	(2.32)	(-0.43)
					Below Median Aggregate Lottery Demand						
FFC4 α	0.30	0.24	0.17	-0.08	0.61	0.19	0.28	0.19	0.24	0.06	-0.24
	(0.60)	(0.44)	(0.35)	(-0.16)	(1.33)	(0.42)	(0.61)	(0.40)	(0.53)	(0.12)	(-1.00)

Panel C: Value-Weighted Average *MAX* as Aggregate Lottery Demand: *MAX* Portfolios

Value	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
					Above Median Aggregate Lottery Demand						
FFC4 α	0.83	0.84	0.86	0.74	0.74	0.55	0.38	0.30	-0.02	-0.66	-1.49
	(5.54)	(6.37)	(6.76)	(6.09)	(5.87)	(4.78)	(3.50)	(2.63)	(-0.16)	(-3.96)	(-5.49)
					Below Median Aggregate Lottery Demand						
FFC4 α	0.08	0.19	0.21	0.20	0.18	0.11	-0.04	-0.08	-0.39	-0.77	-0.85
	(0.19)	(0.44)	(0.50)	(0.47)	(0.42)	(0.26)	(-0.09)	(-0.19)	(-0.94)	(-1.81)	(-6.11)

Panel D: Value-Weighted Average *MAX* as Aggregate Lottery Demand: *EA_MAX* portfolios

Value	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
					Above Median Aggregate Lottery Demand						
FFC4 α	0.72	0.67	0.97	0.89	0.58	0.93	0.98	0.69	0.63	0.36	-0.36
	(3.30)	(2.78)	(4.27)	(3.99)	(2.52)	(5.91)	(4.04)	(3.52)	(3.12)	(1.55)	(-1.06)
					Below Median Aggregate Lottery Demand						
FFC4 α	0.20	-0.01	-0.03	-0.01	0.58	-0.06	0.19	0.17	0.13	0.29	0.08
	(0.43)	(-0.02)	(-0.06)	(-0.01)	(1.29)	(-0.14)	(0.42)	(0.37)	(0.30)	(0.61)	(0.36)

Decile portfolios are formed every month from January 1973 to December 2015 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 presents the FFC4 alphas for the one-month-ahead equal-weighted portfolios for months corresponding to high aggregate demand and low aggregate lottery demand. Aggregate lottery demand in each month is calculated as the cross-sectional equal-weighted (Panel A and B) or value-weighted (Panel C and D) average value of *MAX* across all stocks in the sample. Months with above-median (below-median) aggregate lottery demand are defined as high (low) aggregate lottery demand months. Panels A and C (Panels B and D) report results for *MAX* portfolios (*EA_MAX* portfolios). *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. The column labelled High-Low presents results for the differences in alphas with respect to the four-factor Fama-French-Carhart model (*FFC4*) model between portfolio 10 and portfolio 1. Alphas are reported in percent per month. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

Table A.5: Economic States and the *MAX* effect

Panel A: Returns and alphas of *MAX* portfolios

Economic State	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low** FFC4 α	FF5 α
Non-Recession	0.82	0.94	0.95	0.91	0.90	0.79	0.65	0.55	0.26	-0.21	-0.96	-0.74
	(2.88)	(3.12)	(3.10)	(2.85)	(2.74)	(2.35)	(1.85)	(1.50)	(0.65)	(-0.48)	(-6.71)	(-6.49)
Recession	2.09	2.48	2.75	2.72	2.88	2.81	2.70	2.85	2.49	1.56	-1.52	-1.05
	(2.74)	(2.48)	(2.64)	(2.44)	(2.48)	(2.29)	(2.04)	(2.17)	(1.83)	(1.23)	(-4.32)	(-3.01)

Panel B: Returns and alphas of *EA_MAX* portfolios

Economic State	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low** FFC4 α	FF5 α
Non-Recession	0.71	0.79	0.88	0.85	0.95	0.87	1.02	0.86	0.89	0.89	0.10	0.29
	(2.30)	(2.44)	(2.63)	(2.62)	(2.74)	(2.59)	(2.92)	(2.32)	(2.21)	(2.16)	(0.50)	(1.57)
Recession	2.64	1.99	2.52	2.86	3.05	2.89	3.11	3.77	3.03	2.86	-0.65	-0.08
	(2.64)	(1.78)	(2.50)	(2.91)	(2.88)	(2.83)	(2.28)	(3.18)	(2.38)	(1.85)	(-1.20)	(-0.15)

Decile portfolios are formed every month 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 presents the monthly alphas for the one-month-ahead equal-weighted portfolios for months corresponding to different economic states. We measure economic state using the Chicago Fed National Activity Index (CFNAI). Non-recession months are defined as months $t + 1$ in which the three-month moving average CFNAI (average in months t-1, t, and $t + 1$) is greater than -0.7. Recession months are defined as months in which the three-month moving average CFNAI is less than -0.7. Panel A (Panel B) shows results for *MAX* portfolios (*EA_MAX* portfolios). *EA_MAX* stocks are defined as stocks that exhibit maximum daily returns within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. The column labelled High-Low presents results for the differences in alphas with respect to the four-factor Fama-French-Carhart model (*FFC4*) and Fama-French five-factor (FF5) models between portfolio 10 and portfolio 1. Risk-adjusted returns are reported in percent per month. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Table A.6: Univariate Portfolios Sorted on *MAX* in January and Non-January Months

Panel A: Alphas of *MAX* portfolios

Value	Month	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
FFC4 α	January	0.46	0.34	0.38	0.41	0.69	-0.11	0.39	0.71	0.24	-0.58	-1.04
		(3.38)	(1.75)	(2.40)	(2.33)	(2.29)	(-0.32)	(1.13)	(1.64)	(0.81)	(-1.49)	(-2.34)
	Non-January	0.22	0.14	0.26	0.09	0.27	0.24	0.10	0.03	-0.07	-0.42	-0.64
		(0.82)	(0.51)	(0.96)	(0.35)	(0.96)	(0.89)	(0.35)	(0.09)	(-0.23)	(-1.37)	(-2.88)
FFC4 + PS α	January	0.45	0.32	0.35	0.49	0.69	-0.08	0.34	0.57	0.09	-0.57	-1.02
		(2.92)	(1.33)	(1.65)	(3.07)	(1.87)	(-0.21)	(0.83)	(1.22)	(0.23)	(-1.26)	(-2.01)
	Non-January	0.21	0.16	0.26	0.09	0.27	0.23	0.09	0.05	-0.05	-0.45	-0.66
		(0.80)	(0.57)	(0.94)	(0.34)	(0.98)	(0.86)	(0.35)	(0.18)	(-0.18)	(-1.45)	(-2.81)

Panel B: Alphas of *EA_MAX* portfolios

Value	Month	*MAX* 1 (Low)	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX* 10 (High)	**High - Low**
FFC4 α	January	-0.09	-0.01	0.61	0.96	1.15	0.55	0.27	1.01	0.76	-0.11	-0.02
		(-0.31)	(-0.02)	(1.96)	(2.04)	(2.94)	(1.71)	(0.39)	(1.28)	(1.44)	(-0.14)	(-0.03)
	Non-January	0.50	0.14	0.08	0.16	0.28	0.25	0.28	0.46	0.46	0.30	-0.20
		(1.45)	(0.40)	(0.26)	(0.50)	(0.84)	(0.78)	(0.89)	(1.50)	(1.40)	(0.86)	(-0.52)
FFC4 + PS α	January	-0.07	-0.01	0.52	1.25	0.89	0.61	0.20	0.92	0.37	-0.05	0.03
		-0.24	-0.03	1.23	2.50	2.37	1.70	0.31	1.10	0.62	-0.06	(0.04)
	Non-January	0.50	0.12	0.11	0.15	0.27	0.28	0.26	0.45	0.42	0.27	-0.23
		(1.43)	(0.36)	(0.35)	(0.47)	(0.83)	(0.89)	(0.82)	(1.46)	(1.29)	(0.76)	(-0.61)

Decile portfolios are formed every month from January 1973 to December 2015 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 presents the risk-adjusted returns for the one-month-ahead value-weighted portfolios for portfolio holding months in January and not in January. Panel A and Panel B report results for *MAX* portfolios and *EA_MAX* portfolios, respectively. *EA_MAX* stocks are defined as stocks that exhibit maximum daily return within a 5-day window surrounding quarterly earnings announcement date obtained from Compustat. The column labelled High-Low presents results for the differences in alphas with respect to the four-factor Fama-French-Carhart model (*FFC4*), the five-factor Fama-French-Carhart-Pastor-Stambaugh (*FFC4 + PS*) models between portfolio 10 and portfolio 1. Average risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.