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When are extreme daily returns not lottery? At earnings announcements!

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ABSTRACT

Using a sample of U.S. stocks over the period 1973–2015, 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 et al. (2011, BCW hereafter) document a significant negative relation between the maximum daily returns in the past one month (hereafter *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 explanatory power 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 warrant further analysis of the *MAX* effect. Given the rising importance of using *MAX* in studying lottery demand

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[1] This explanation is based on the premise that certain groups of investors are not well-diversified (Odean, 1999; Goetzmann and Kumar, 2008) and exhibit a preference for lottery-type stocks (Kumar, 2009).

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and asset pricing, it is important to carefully examine the reasons driving the maximum daily returns, along with their possible implications, and what may truly determine the persistence of the phenomenon.[2]

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 exhibit lower future returns. Specifically, using a large sample of all U.S. stocks between January 1973 and December 2015, 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]

In several empirical tests, we find that there is no *MAX* effect when the maximum daily returns are driven by earnings announcements.[4] First, we sort stocks in to decile *MAX* portfolios on a monthly basis. We document that earnings announcements on average account for 18.3% of the total maximum daily returns in the top *MAX* portfolio and this proportion increases over time. In the last few years of our sample period (2000–2015), earnings announcements drive up to one-third of stocks entering the top *MAX* portfolio, suggesting that many *MAX* returns are in fact due to earnings information.

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 stock 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 that 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 variations in time series settings including accounting for different investor sentiment states, different economic states, and alternative measures of the lottery features of stocks. 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

[2] Several other studies provide evidence supporting the existence of the *MAX* effect in European markets (Annaert et al., 2013; Walkshäusl, 2014), in the Australian market (Zhong and Gray, 2016), in the Chinese market (Nartea et al., 2017), and in the global markets (Cheon and Lee, 2017). Lin and Liu (2017) document that the *MAX* effect is particularly pronounced among stocks preferred by individual investors.

[3] Daniel et al. (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 that 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.

[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.

returns in a 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 predict 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* returns 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 others have assumed (Bali et al., 2011; Lin and Liu, 2017).

Bali et al. (2017) construct a new asset pricing factor, the *FMAX* factor, to capture returns that are driven by market aggregate lottery demand. They 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, they 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 examine 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 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 an 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 of explaining the abnormal returns of the betting-again-beta phenomenon than the original lottery demand factor as suggested in Bali et al. (2017a). Specifically, we document that the refined *FMAX* factor 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 and 2015, whereas the original *FMAX* factor in Bali et al. (2017a) fails to explain such alphas in several sub-sample periods.

To further investigate why *MAX* returns driven by earnings announcements attract less lottery demand, we show that earnings announcement *MAX* returns bring about a significantly higher level of uncertainty resolution than that of other *MAX* returns. This finding is consistent with several studies (e.g., Patell and Wolfson, 1979, 1981; Isakov and Perignon, 2001; Banerjee, 2011; Truong et al., 2012; Billings et al., 2015; Gallo, 2017) that document that, through fundamental information content dissemination, earnings announcements significantly resolve uncertainty and disagreement among investors that build up in the pre-announcement period. In addition, we find that among *MAX* returns that are not driven by earnings announcements, *MAX* phenomenon is significantly lower when uncertainty resolution is high. We conclude that when large stock returns reduce uncertainty in the market like in the case of earnings announcements, these stock returns are less lottery-like and lottery investors should be less attracted to these events.

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 the 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 stock 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 a 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, reduce uncertainty, and do not necessarily represent any attribute of the general stock return distribution, non-earnings announcement extreme stock returns are, however, very informative of the future probability of large price movements. Most interestingly, undiversified investors with skewness/ lottery payoff preference take different courses of actions between earnings and non-earnings announcement extreme returns, thereby resulting in contrasting effects on the expected stock returns.[8]

The remainder of the paper is organized as follows. In Section 2, we provide data and variable descriptions. In Section 3, we describe the *MAX* effect where maximum returns are driven by earnings information. In Section 4, we show the persistence of

[7] Bali et al. (2017a) 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 this effect is due to high lottery demand for high beta stocks.

[8] Lottery investors are not necessarily sophisticated enough to distinguish fundamental-driven *MAX* returns and behave more radically in these events while at the same time they are less rational in responding to other *MAX* returns. Rather, we suggest that fundamental-driven *MAX* returns like earnings announcement *MAX* returns often reduce uncertainty and investor disagreement, and hence these returns have less lottery-like characteristics to attract lottery investors.

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MAX returns when conditioned on earnings information. In Section 5, we discuss the *FMAX* factor conditioned on earnings information that does not proxy for lottery demand. In Section 6, we investigate uncertainty resolution and *MAX* returns. Concluding remarks are given in Section 7.

2. Data and variables

We obtain stock price, return data, and volume data for all U.S.-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.[9] We use daily stock returns to calculate the maximum daily stock returns for each firm in each month as proposed in Bali et al. (2011).[10] 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 follows. 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 a post-announcement delayed price response, if there is any. [11]

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 in order to compute the 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.[12] Monthly Pastor and Stambaugh (2003) liquidity factor returns are from Lubos Pastor's website.[13] The earnings momentum factor is from Chordia and Shivakumar (2006).[14] For investor sentiment measures, we use Baker and Wurgler, 2006 sentiment index, the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center, and the FEARS index from Da et al. (2015).[15] The other data we use include the Chicago Fed National Activity Index (CFNAI) from the Federal Reserve Bank of Chicago, the macroeconomic uncertainty index from Jurado et al. (2015), the economic policy uncertainty index from Baker et al. (2016), and business cycle data from NBER.[16]

The sample in this paper covers the 516 months from January 1973 through December 2015. The choice of sample period is due to data availability.[17] 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.[18]

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

Panel A of Table 1 presents the original *MAX* results as in Bali et al. (2011) for the 1973–2015 sample period. 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 and West, 1987 *t*-statistic of −3.64 (−1.96).[19] The results in Panel A show that the *MAX* phenomenon is very pronounced in our sample period, which is confirmed by the four-factor Fama-French-Carhart, the

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

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

[11] Previous works have found that earnings announcement dates are sometimes off by a day or more (e.g., DellaVigna and Pollet, 2009; DeHaan et al., 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.

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

[13] Data are available online at: http://faculty.chicagobooth.edu/lubos.pastor/research/.

[14] We thank Tarun Chordia and Lakshmanan Shivakumar for making their earnings momentum factor data available through their websites.

[15] We thank Jeffrey Wurgler and Zhi Da for making their investor sentiment data available through their websites.

[16] We thank Sydney Ludvigson and Nicholas Bloom for making their uncertainty indices available through their websites.

[17] As noted in Savor and Wilson (2016, p. 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.

[18] 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.

[19] This finding is consistent with Bali et al. (2011, p. 433), who 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.

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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 (-3.64)***	−0.61 (-1.96)**	
4-factor alpha (FFC4α)	−1.11 (-6.85)***	−0.72 (-3.23)***	
5-factor alpha (FFC4 + PS α)	−1.09 (-6.69)***	−0.72 (-3.08)***	
5-factor alpha (FF5α)	−0.81 (-6.93)***	−0.37 (-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

five-factor Fama-French-Carhart-Pastor-Stambaugh, and the five-factor Fama and French alphas from both the 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 four-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. 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.

Panel A of Table 2 presents the *MAX* analysis results 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. Note 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 four-factor or five-factor alphas, the difference in alphas between the two extreme *MAX* portfolios is also small and statistically insignificant. Here, decile 10 contains stocks with an 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.

Panel B of Table 2 presents the *MAX* analysis results 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 four-factor (five-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 four-factor alpha for the high *MAX* portfolio is −0.66% (*t*-statistic = −2.62) when value-weighted and −0.95% (*t*-statistic = −6.19) when equal-weighted.

Panel C of Table 2 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 four-factor (five-factor) alpha is −0.75% (−0.73%) per month with a *t*-statistic of −2.51 (−2.39). The differences in hedge returns and alphas are much higher for equal-weighted portfolios. A striking feature is that the difference in returns between the *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).,[20],[21]

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 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. Panel A presents the average of *EA_MAX* in each *MAX* portfolio over the whole sample period and also in two sub-sample periods. 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.

Over the entire 1973–2015 sample period, at least 8.4% of stocks in the lowest *MAX* portfolio are associated with earnings announcements; this is 13.6%, 15.1%, and 18.3% for high *MAX* portfolios 8, 9, and 10, respectively. When we split the entire sample period 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).

In Panel B of Table 3, we present the time series average of the monthly percentage of *EA_MAX* in each *MAX* portfolio. It is consistent that earnings announcements account for the largest proportion of stocks in the top *MAX* portfolio across all months. We also formally test the hypothesis that the percentage of *EA_MAX* in the top *MAX* portfolio is higher than that of the bottom *MAX* portfolio. *T*-statistics show that the difference in the percentage of *EA_MAX* between the two extreme portfolios (High-Low) is statistically significant across all months.[22]

Overall, the key findings in Table 3 are 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. These findings are consistent with the notion that large daily returns are often observed surrounding earnings announcements, and such returns can account for a significant proportion of the maximum daily returns in a month.[23]

Fig. 1 confirms that there is an increasing trend in the proportion of stocks in the high *MAX* portfolio being associated with earnings announcements over time.[24] 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 has been at least 20% since 2002.[25] 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 announcements of *MAX* stocks do not exhibit lower future returns as demonstrated in Panel A of Table 2.

[20] We conduct a number of robustness checks around our core results in Table 2. First, the results ins Table A.1 in the Appendix 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.

[21] 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. (2017a). 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*. The 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 in Table A.2 clearly show that neither the *MAX* effect nor our finding of no *MAX* effect when conditioning on earnings announcements is driven by a microstructure effect.

[22] We thank the referee for suggesting this time series approach.

[23] 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 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 abnormal stock 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.

[24] 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; Beaver et al., 2018).

[25] 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 et al., 2004). Regulation FD has also increased the quantity of corporate voluntary disclosure to the public (Bailey et al., 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.

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 (0.77)	−0.01 (-0.02)	
4-factor alpha (FFC4α)	−0.05 (-0.22)	−0.18 (-0.54)	
5-factor alpha (FFC4 + PS α)	−0.02 (-0.11)	−0.20 (-0.59)	
5-factor alpha (FF5α)	0.20 (1.18)	0.27 (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 (-4.58)***	−0.83 (-2.60)***	
4-factor alpha (FFC4 α)	−1.37 (-8.26)***	−0.93 (-4.12)***	
5-factor alpha (FFC4 + PS α)	−1.35 (-8.11)***	−0.93 (-3.90)***	
5-factor alpha (FF5 α)	−1.06 (-8.68)***	−0.59 (-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 (-8.66)***	−0.80 (-2.75)***
4-factor alpha (FFC4 α)	−1.32 (-8.06)***	−0.75 (-2.51)**
5-factor alpha (FFC4 + PS α)	−1.32 (-8.16)***	−0.73 (-2.39)**
5-factor alpha (FF5 α)	−1.27 (-8.10)***	−0.86 (-2.68)***

3.2. Bi-variate portfolio analysis

We next examine the relation between the maximum daily returns and future stock returns after controlling for firm size, book-to-market ratio, momentum, short-term reversals, illiquidity, and beta sensitivity to macroeconomic uncertainty. For each control, we first sort firms into deciles of the control variable and then within each decile we again sort stocks by *MAX*. This procedure ensures that each *MAX* portfolio, aggregated across all deciles of the control variable, then has the same distribution of each control variable.[26] The purpose of this analysis is twofold. First, we re-confirm that the *MAX* effect in our entire sample period is not driven by firm characteristics that plausibly relate to expected stock returns. Second, we show that

[26] 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.

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Table 3
Percentage of *EA_MAX* across *MAX* portfolios. Panel A. Cross-sectional averages of the monthly percentage of stocks.

	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	5761	7.37	93,534	8571	9.16
2	174,922	16,337	9.34	79,233	6844	8.64	95,689	9493	9.92
3	174,938	17,505	10.01	79,137	7218	9.12	95,801	10,287	10.74
4	175,414	18,539	10.57	79,476	7583	9.54	95,938	10,956	11.42
5	175,200	19,623	11.20	79,398	8078	10.17	95,802	11,545	12.05
6	175,506	20,584	11.73	79,548	8199	10.31	95,958	12,385	12.91
7	175,374	21,912	12.49	79,460	8503	10.70	95,914	13,409	13.98
8	175,354	23,870	13.61	79,359	8887	11.20	95,995	14,983	15.61
9	175,358	26,554	15.14	79,438	9173	11.55	95,920	17,381	18.12
High *MAX*	174,649	31,929	18.28	79,097	9700	12.26	95,552	22,229	23.26

Panel B: Time series averages of the monthly percentage of *EA_MAX* stocks

Decile/ Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Low *MAX*	11.15	10.03	3.31	17.17	7.12	1.28	16.68	7.15	1.43	16.67	6.67	1.31
2	12.03	11.58	3.45	19.01	7.83	1.62	18.88	7.63	1.80	19.27	6.98	1.90
3	12.82	12.67	4.13	20.17	8.79	1.87	19.08	8.54	1.82	19.57	8.38	2.07
4	12.16	13.79	4.71	20.40	9.56	2.50	20.15	9.78	2.27	19.50	9.30	2.62
5	11.99	15.42	5.84	20.83	10.66	2.86	19.93	10.88	2.84	19.92	10.28	2.76
6	11.94	16.20	6.70	21.11	12.18	3.07	20.48	11.44	2.93	20.20	11.13	3.24
7	12.00	17.19	7.45	21.15	13.36	3.52	20.83	13.58	3.47	20.94	12.78	3.45
8	11.95	18.93	8.75	21.95	16.26	3.85	21.75	15.14	3.87	21.89	14.71	4.10
9	13.14	21.11	10.39	23.42	18.24	4.76	23.60	17.62	4.66	22.43	17.42	4.68
High *MAX*	15.11	25.00	14.10	25.39	23.36	6.22	26.98	22.47	6.29	26.06	22.10	6.01
High - Low	3.96	14.97	10.79	8.22	16.24	4.94	10.30	15.32	4.86	9.39	15.43	4.70
	(3.14)	(6.94)	(9.51)	(5.47)	(7.36)	(13.76)	(5.20)	(6.75)	(13.12)	(5.17)	(6.82)	(13.64)

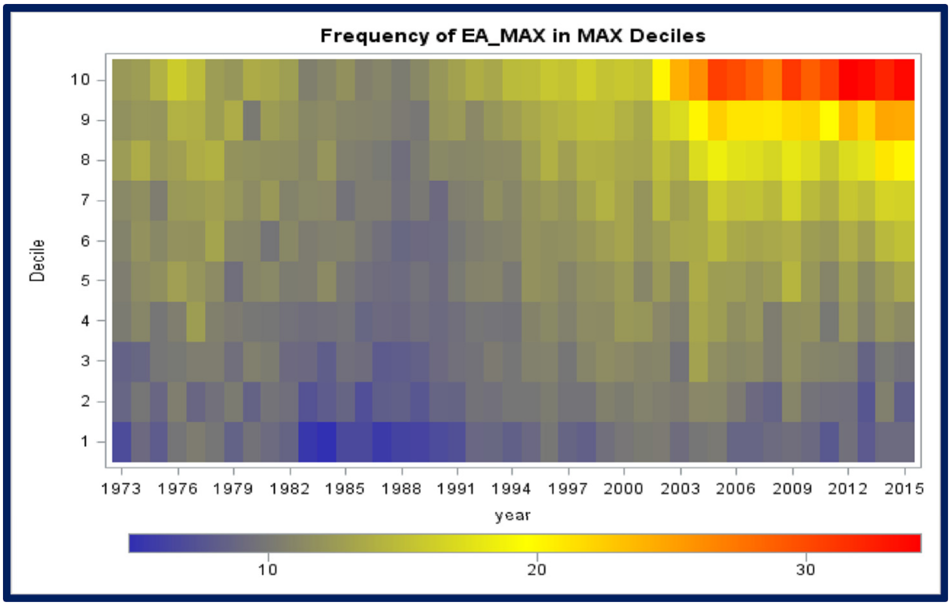

Fig. 1. Heat map of earnings announcements and *MAX*.

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

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 (t-statistic = −3.82). The corresponding difference in the four-factor alphas is −1.10% per month (t-statistic = −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-

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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*	β_{UNC}
Low *MAX*	1.08	1.02	1.12	1.07	1.06	1.07
2	1.25	1.17	1.23	1.20	1.23	1.16
3	1.24	1.14	1.19	1.13	1.16	1.17
4	1.17	1.17	1.14	1.16	1.18	1.15
5	1.14	1.18	1.10	1.05	1.10	1.16
6	1.00	1.11	1.05	1.02	1.01	1.10
7	0.86	1.02	0.91	0.92	0.96	1.01
8	0.73	0.95	0.86	0.79	0.76	0.90
9	0.51	0.72	0.62	0.60	0.56	0.69
High *MAX*	0.08	0.22	0.06	0.13	0.06	0.24
High - Low	−1.00 (-3.82)***	−0.80 (-3.17)***	−1.06 (-5.94)***	−0.94 (-4.09)***	−1.00 (-3.80)***	−0.83 (-4.32)***
FFC4 α	−1.10 (-6.90)***	−0.99 (-6.14)***	−1.22 (-10.12)***	−1.13 (-7.56)***	−1.13 (-7.20)***	−0.95 (-8.38)***

Panel B: EA_MAX and NOEA_MAX after controlling for characteristics

Decile	SIZE			BM			MOM		
	EA	Non-EA	Diff	EA	Non-EA	Diff	EA	Non-EA	Diff
Low *MAX*	0.95	1.06	0.08	0.77	1.01	0.02	0.83	1.11	0.05
2	1.12	1.26	0.26	1.01	1.16	0.00	1.20	1.24	0.12
3	1.13	1.23	−0.05	1.21	1.15	0.19	1.12	1.19	0.01
4	1.28	1.19	−0.09	1.19	1.20	0.02	1.06	1.14	0.06
5	0.99	1.12	−0.07	1.49	1.14	−0.33	1.25	1.08	−0.11
6	1.19	0.97	−0.24	1.22	1.07	−0.32	1.21	1.03	−0.25
7	1.24	0.84	−0.34	1.44	1.00	−0.33	1.17	0.92	−0.28
8	1.13	0.70	−0.55	1.21	0.95	−0.35	1.23	0.79	−0.60
9	1.04	0.40	−0.75	1.30	0.58	−0.80	1.22	0.52	−0.65
High *MAX*	0.82	−0.13	−1.24	0.99	−0.06	−1.45	0.76	−0.15	−1.31
High − Low	−0.28 (-0.93)	−1.19 (-4.51)***	−1.32 (-7.85)***	0.16 (0.57)	−1.07 (-4.13)***	−1.47 (-7.76)***	−0.08 (-0.32)	−1.26 (-7.01)***	−1.37 (-7.58)***
FFC4 α	−0.11 (-0.50)	−1.30 (-8.22)***	−1.23 (-7.02)***	0.13 (0.55)	−1.28 (-7.63)***	−1.44 (-6.74)***	−0.03 (-0.18)	−1.42 (-11.62)***	−1.28 (-6.30)***

Decile	REV			ILLIQUID			β_{UNC}		
	EA	Non-EA	Diff	EA	Non-EA	Diff	EA	Non-EA	Diff
Low *MAX*	0.68	1.06	0.12	0.85	1.06	−0.01	0.58	0.82	0.16
2	1.09	1.22	0.29	1.15	1.22	0.14	0.97	0.99	0.07
3	1.08	1.14	−0.09	1.12	1.19	0.15	0.88	0.92	0.03
4	1.16	1.15	−0.03	1.12	1.15	−0.11	1.14	0.94	0.06
5	1.25	1.04	−0.01	1.17	1.09	−0.02	1.07	0.89	−0.25
6	1.11	1.01	−0.19	1.15	1.00	−0.27	1.05	0.87	−0.10
7	1.31	0.91	−0.24	1.17	0.91	−0.33	1.04	0.72	−0.29
8	1.02	0.73	−0.48	1.38	0.72	−0.42	1.02	0.63	−0.41
9	1.22	0.52	−0.70	1.04	0.48	−0.81	0.99	0.41	−0.67
High *MAX*	1.10	−0.13	−1.46	0.97	−0.17	−1.30	1.10	−0.14	−1.26
High − Low	0.33 (1.22)	−1.19 (-5.19)***	−1.58 (-11.03)***	0.04 (0.14)	−1.23 (-4.57)***	−1.30 (-8.29)***	0.48 (1.42)	−0.96 (-3.47)***	−1.41 (-8.65)***
FFC4 α	0.43 (2.05)**	−1.37 (-9.25)***	−1.52 (-8.70)***	0.18 (0.81)	−1.38 (-8.54)***	−1.25 (-7.33)***	0.43 (1.93)*	−1.10 (-7.01)***	−1.41 (-7.77)***

market ratio (*BM*), −1.06% per month when sorted by momentum (*MOM*), −0.94% per month when sorted by short-term reversals (*REV*), −1.00% per month when sorted by illiquidity (*ILLIQUID*), and −0.83% per month when sorted by beta sensitivity to macroeconomic uncertainty (β_{UNC}), and all these returns are statistically significant at the 1% level.[27]

Panel B of Table 4 also shows 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-

[27] Following Bali et al. (2017b), for each stock and for each month in our sample, we estimate uncertainty beta from the monthly rolling regressions of excess stock returns on the macroeconomic uncertainty index from Jurado et al. (2015), over a 60-month rolling window after controlling for Fama and French, 2015 five factors and Carhart, 1997 momentum factor. In an alternative approach, we compute uncertainty beta using the economic policy uncertainty index from Baker et al. (2016) and find that our results are robust to controlling for different measures of macroeconomics uncertainty.

Table 5
Fama-Macbeth cross-sectional regressions.

	MAX	*MAX×EA*	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQUID*	β_{UNC}
(1)	−0.0719								
	(-6.10)***								
(2)		0.0305							
		(4.96)***							
(3)	−0.0856	0.0715							
	(-7.13)***	(11.76)***							
(4)	−0.0413		0.0001	−0.0008	0.0012	0.0079	−0.0367	−0.0011	−0.0040
	(-4.32)***		(0.11)	(-2.40)**	(1.41)	(4.39)***	(-8.62)***	(-0.41)	(-3.62)***
(5)	−0.0580	0.0744	0.0001	−0.0009	0.0012	0.0079	−0.0372	−0.0010	−0.0041
	(-5.86)***	(11.75)***	(0.22)	(-2.57)***	(1.37)	(4.41)***	(-8.74)***	(-0.35)	(-3.66)***

term reversals show that the top *MAX* portfolio exhibits the highest returns. In Panel B, we also examine the bi-variate portfolio, 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. We also report differences between *EA_MAX* and *NOEA_MAX* portfolios after controlling for each firm characteristic in Panel C of Table 4. [28] Consistent with the findings in Panel C of Table 2, we find that differences in returns between *NOEA_MAX* and *EA_MAX* portfolios is negligible among low *MAX* deciles (deciles 1, 2, and 3) and that a majority of the hedge returns comes from the highest *MAX* decile (decile 10) after controlling for a set of firm characteristics.

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

3.3. Fama-Macbeth regression analysis

We continue to examine the relation between *MAX*, earnings announcements, and future stock returns in a regression framework in which we control for multiple effects or factors simultaneously. Table 5 presents regression results of an examination 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.[29]

In row (1) of Table 5, the slope coefficient from the regression of realized returns on *MAX* alone is −0.07 (*t*-statistic = −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 bps (0.07×16) for the *MAX* variable in the cross-section of next month stock returns. We also document a strong momentum effect, a strong reversals effect, some value effect, and macroeconomic uncertainty exposure effect in our sample.

The key findings from these regression analyses lie in the last three rows of Table 5. 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 results are in row (3). The interaction coefficient on *MAX×EA* is 0.07 (*t*-statistic = 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* (−0.08) and *MAX×EA* (0.07) and this sum is close to zero. Thus, this is consistent with the univariate portfolio results and the bi-variate portfolio results, which show insignificant return differences between the highest and lowest *MAX* stocks when *MAX* returns are conditioned on earnings announcements. In row (4), 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. When we include *MAX*, *MAX×EA*, and all other control variables in the regression, the results in row (5) show that 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 0.01. This implies a negligible premium of 0.17 per month that *EA_MAX* places on stock returns.

[28] We thank the referee for suggesting this test.

[29] 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.

Overall, the results in Table 5 show that in a multiple regression framework where we control for several other firm characteristics, *MAX* exhibits a strong effect on future realized returns. However, this effect mostly disappears when we consider earnings announcement *MAX*.[30]

3.4. Lottery demand, institutional investor holding, and the MAX effect

It is conceivable that retail investors rather than institutional investors 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 subsection, we employ the 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 for a firm 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*.

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 shows that high *MAX* stocks, combined with low institutional ownership, exhibit much lower future returns. The return difference between the two extreme *MAX* portfolios drops monotonically across *INST* quintiles. The four-factor alpha differences are −1.93% per month in the Low *INST* quintile and −0.63% per month in the 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 four-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 four-factor alpha difference is −0.24% per month (*t*-statistic = −0.50) for *EA* column while this four-factor alpha difference is −2.12% per month (*t*-statistic = −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 and continues to be non-existent based on *EA_MAX* returns.

There are two key findings from Table 6. 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 likely do not view earnings announcement *MAX* returns as lotteries and do not exert any special demand for these stocks.[31]

3.5. Investor sentiment and the MAX effect

Investor sentiment plays an important role in understanding the overpricing of lottery-like assets (Doran et al., 2012; Fong and Toh, 2014). When sentiment is high, investors tend to be over-optimistic of the future payoffs from buying lottery-like assets, thus, they 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 profits 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: (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) the FEARS index from Da et al. (2015).[32] 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.

[30] 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.

[31] 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.

[32] 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) (e.g., Da et al., 2015).

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 (-4.81)***	−1.01 (-2.76)***	−1.09 (-3.41)***	−0.76 (-3.00)***	−0.64 (-2.55)**
FFC4 α	−1.93 (-8.48)***	−1.25 (-5.29)***	−1.28 (-5.73)***	−0.80 (-4.19)***	−0.63 (-3.26)***
FFC4 + PS α	−1.93 (-8.67)***	−1.24 (-5.32)***	−1.28 (-5.82)***	−0.77 (-4.24)***	−0.60 -(2.98)***
FF5 α	−1.43 (-6.50)***	−0.78 (-4.32)***	−0.90 (-5.22)***	−0.54 (-3.58)***	−0.43 (-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(-5.58)***	−0.28 (-0.49)	−1.37 (-3.72)***	0.15 (0.27)	−1.28 (-3.68)***	0.19 (0.40)	−0.94 (-3.60)***	0.56 (1.15)	−0.77 (-3.13)***	0.06 (0.13)
FFC4 α	−2.12 (-8.43)***	−0.24 (-0.50)	−1.68 (-6.86)***	0.17 (0.35)	−1.48 (-5.63)***	0.17 (0.36)	−0.99 (-4.86)***	0.40 (0.91)	−0.79 (-3.64)***	−0.10 (-0.20)
FFC4 + PS α	−2.13 (-8.94)***	−0.33 (-0.66)	−1.66 (-7.04)***	0.17 (0.350	−1.45 (-5.60)***	−0.01 (-0.03)	−0.96 (-4.85)***	0.39 (0.92)	−0.78 (-3.66)***	−0.12 (-0.25)
FF5 α	−1.65 (-7.30)***	−0.14 (-0.27)	−1.14 (-6.15)***	0.38 (0.77)	−1.11 (-5.01)***	0.17 (0.36)	−0.71 (-3.79)***	0.61 (1.42)	−0.54 (-2.52)**	0.12 (0.24)

Panel A (Panel B) of Table 7 reports the returns and alphas of *EA_MAX* portfolios following high (low) sentiment months for each of the sentiment measures. The last columns in each panel report the differences and abnormal returns of the High - Low *MAX* portfolios. We find that the equal-weighted average raw hedge return difference between decile 10 (highest *MAX*) and decile 1 (lowest *MAX*) is insignificant from zero. Similarly, the four-factor and five-factor alphas are also indistinguishable from zero. These findings hold across all three measures of investor sentiment. The results in Panels A and B 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 lottery-like assets (Fong and Toh, 2014), investors do not overvalue stocks with earnings-driven extreme returns, thus 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 certain stock types, such as stocks with low prices, stocks with high idiosyncratic volatility, and stocks with high idiosyncratic skewness. The findings suggest that the nature of stock returns determines whether certain large returns should not be viewed as lotteries because such returns do not appeal to lottery investors. We next examine *EA_MAX* and *NOEA_MAX* strategies conditional on the lottery characteristics of stocks. In other words, we ask if the disappearance of the *MAX* phenomenon among *EA_MAX* events depends on whether or not stocks exhibit lottery-like characteristics.

Using stock price, idiosyncratic volatility, and idiosyncratic skewness to determine lottery type of stocks, we first examine whether the lottery demand phenomenon is stronger and whether earnings announcement *MAX* may deliver lower future

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 (4.93)	1.38 (4.55)	1.26 (4.40)	1.42 (4.70)	1.34 (4.17)	1.13 (3.44)	1.23 (3.24)	1.30 (3.32)	0.88 (2.12)	0.79 (1.87)	−0.43 (-0.91)	−0.19(-0.70)	0.10 (0.39)
MCSI	1.18 (4.46)	1.13 (3.80)	1.02 (3.33)	1.10 (3.68)	1.04 (3.43)	0.95 (3.12)	1.03 (3.44)	0.94 (2.54)	0.84 (1.85)	0.69 (1.40)	−0.49 (-1.02)	−0.20 (-0.69)	0.01 (0.02)
FEARS	0.79 (1.42)	0.56 (0.75)	1.15 (1.51)	0.44 (0.73)	0.53 (0.81)	0.41 (0.49)	0.33 (0.36)	0.82 (1.31)	0.86 (1.01)	0.46 (0.41)	−0.22 (-0.32)	−0.64 (-1.26)	−0.64 (-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 (3.26)	0.90 (2.51)	1.26 (3.11)	1.19 (3.07)	1.49 (3.65)	1.52 (4.06)	1.76 (4.11)	1.59 (3.51)	1.83 (3.91)	1.85 (3.55)	0.65 (1.53)	0.20 (0.75)	0.23 (1.13)
MCSI	1.20 (3.69)	1.45 (3.84)	1.89 (5.07)	1.54 (4.15)	1.98 (5.06)	1.78 (4.39)	1.91 (3.88)	2.18 (4.62)	2.00 (4.11)	1.92 (3.50)	0.78 (1.49)	0.00 (-0.01)	0.16 (0.65)
FEARS	0.53 (0.90)	1.03 (1.46)	1.91 (3.48)	0.41 (0.48)	1.31 (1.85)	1.61 (2.17)	0.63 (0.63)	0.94 (1.13)	0.93 (1.02)	1.51 (1.55)	1.23 (1.42)	0.24 (0.37)	0.38 (0.70)

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*).[33] We consider two groups of stocks: the first (second) group includes stocks in the bottom (top) quintile of price, the top (bottom) quintile of *IVOL*, and the top (bottom) quintile of *ISKEW*. We then repeat the *MAX* analysis for each group. The results are in Table 8.

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 = −3.95) and −1.18% (t-statistic = −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 0.14% (t-statistic = 0.41) and 0.01% (t-statistic = 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 group of stocks than the second one. Consistent with prior work (Kumar, 2009; Han and Kumar, 2013; Bali et al., 2017a), we find that the lottery demand phenomenon is especially pronounced among stocks with low price, high *IVOL*, and high *ISKEW*.

We next examine whether the *MAX* phenomenon exists among these two groups of stocks when *MAX* returns are conditioned on earnings information. We repeat the *MAX* analysis for stocks that exhibit extreme daily returns as driven by earnings announcements (*EA_MAX* stocks) and report results in Panel B of Table 8. The results suggest that there is no clear *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 = 0.02) and −0.02% (t-statistic = −0.05), respectively. Again, for the group 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 we find no *MAX* effect among earnings-driven *MAX* returns and this finding is independent of whether or not the stocks are more lottery-type.,[34],[35]

[33] 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.

[34] 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 whether 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, we do not find the *MAX* effect when *MAX* returns are driven by earnings announcements.

[35] Kumar et al. (2011) and Doran et al. (2012) document that lottery demand is particularly stronger in January than in other months. If lottery demand drives the *MAX* effect, it is possible that the *MAX* effect is more pronounced in January than in non-January months. Table A.6 in the Appendix presents the results that support this prediction. The results in Panel A suggest that the abnormal returns of the High-Low *MAX* portfolios are more negative in January 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 and in other months. We find this is the case. According to Panel B of Table A.6, when *MAX* returns are driven by earnings announcements, the abnormal 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 all months when *MAX* returns are conditioned on earnings announcements.

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

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
Panel A: Returns and alphas of *MAX* portfolios													
Portfolios Using Low Price, High *IVOL*, and High *ISKEW* Stocks													
MAX	0.99 (3.49)	1.22 (3.82)	1.45 (4.42)	1.27 (3.64)	1.31 (3.68)	1.32 (3.72)	1.03 (2.72)	0.93 (2.47)	0.52 (1.34)	0.01 (0.03)	−0.98 (-3.95)	−1.18 (-7.06)	−0.94 (-6.56)
Portfolios Using High Price, Low *IVOL*, and Low *ISKEW* Stocks													
MAX	0.88 (3.31)	0.94 (3.34)	0.92 (3.16)	0.86 (2.92)	0.97 (3.14)	0.86 (2.67)	0.74 (2.17)	0.92 (2.46)	0.79 (1.94)	1.02 (2.39)	0.14 (0.41)	0.01 (0.05)	0.77 (2.81)
Panel B: Returns and alphas of *EA_MAX* portfolios													
Portfolios Using Low Price, High *IVOL*, and High *ISKEW* Stocks													
MAX	0.60 (1.32)	0.58 (1.30)	1.38 (2.68)	0.84 (1.94)	1.35 (2.66)	1.40 (3.12)	1.32 (2.91)	1.51 (3.53)	1.08 (2.52)	1.18 (2.76)	0.01 (0.02)	−0.02 (-0.05)	0.00 (0.57)
Portfolios Using High Price, Low *IVOL*, and Low *ISKEW* Stocks													
MAX	0.73 (2.40)	0.85 (2.51)	0.65 (1.91)	0.78 (2.42)	0.75 (2.13)	1.16 (2.89)	0.92 (2.29)	0.87 (1.91)	1.58 (3.43)	2.03 (3.57)	1.58 (2.79)	1.37 (2.75)	2.03 (3.55)

4. Cross-sectional predictability of *MAX*

While *MAX* is arguably a theoretically motivated variable and 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 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 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 Panel A of Table 9, the univariate regression of *MAX* on lagged *MAX*, we find a large positive coefficient that is 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.

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 in row (3) of Table 9, the coefficient on the interaction term *MAX*×*EA* is negative and also very significant. This means that the predictability of *MAX* using lagged *MAX* is substantially reduced when past *MAX* returns are associated with earnings announcements. When all lagged control variables are included, we find in row (5) that the coefficients on *MAX* and *MAX*×*EA* retain their signs and statistical significance.

There is some possibility that the negative interaction coefficient on *MAX*×*EA* reported in Panel A of Table 9 may be picking up the phenomenon that there is a lower likelihood of earnings announcements in the following month due to the earnings cycle, and hence a lower likelihood of a *MAX* event overall.[36] To get around this issue, in Panel B, we only focus on future *MAX* events that are *NOEA_MAX* and remove all future *EA_MAX* events for our dependent variable. This way, we can study the persistence of a *NOEA_MAX* event that is predicted by a past *NOEA_MAX* event or past *EA_MAX* event. Any difference in the predictability between past *NOEA_MAX* and past *EA_MAX* detected in this regression should no longer be subject to the difference in the earnings cycle. The results in Panel B are almost similar to those in Panel A. We still document that there is strong persistence in *NOEA_MAX*; however, such persistence is significantly weakened if *MAX* in the prior month is an *EA_MAX* event.

The results in Table 9 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 this phenomenon will be evident the next month. We also find that firm size, book-to-market ratio, beta, and idiosyncratic volatility are significantly related to future extreme positive returns.

[36] If lagged *MAX* is an *EA_MAX* event, it is less likely that we will see another *EA_MAX* this month. If lagged *MAX* is a *NOEA_MAX* event, the higher likelihood that this *MAX* will continue in this month could be partially due to some likelihood that there will be an earnings announcement *MAX* that occurs this month. The difference in persistence between lagged *EA_MAX* and lagged *NOEA_MAX* in explaining *MAX* this month could be, to some extent, due to the earnings cycle embedded in our setting.

Table 9
Cross sectional predictability of *MAX*. .

Panel A: Future *MAX* events can be either *NOEA_MAX* or *EA_MAX*

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

Panel B: Future *MAX* events are *NOEA_MAX*

MAX		*MAX*×*EA*	*BETA*	*SIZE*	*BM*	*MOM*	*REV*	*ILLIQUID*
(1)	0.2769 (46.92)							
(2)		0.0889 (27.46)						
(3)	0.2933 (53.05)	−0.0547 (-13.75)						
(4)	0.2392 (38.01)		0.0021 (10.12)	−0.0050 (-41.65)	−0.0041 (-10.66)	0.0024 (3.69)	−0.0494 (-24.05)	0.0068 (4.49)
(5)	0.2527 (42.68)	−0.0408 (-13.22)	0.0020 (10.06)	−0.0049 (-41.47)	−0.0041 (-10.69)	0.0024 (3.70)	−0.0492 (-24.02)	0.0065 (4.48)

5. Lottery demand factor

Bali et al. (2017a) propose a new factor, the *FMAX* factor, to capture stock returns that are driven by the aggregate lottery demand. They show that this factor offers significant explanatory power for the cross-section of expected stock returns that are incremental to that of the existing risk factors. Following this line of inquiry, we examine whether the *FMAX* factor, when constructed using earnings announcement *MAX* returns, explains the cross-section of stock returns. More importantly, we examine whether this *FMAX* factor could be improved by excluding earnings announcement *MAX* returns in the construction as we have shown that these returns do not proxy for lottery demand and do not empirically deliver lower future returns.

Following Bali et al. (2017a), the *FMAX* factor is constructed as follows. At the end of each month *t*, we 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% (*t*-statistic = −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% (*t*-statistic = −2.92). This indicates a 35% increase in the monthly lottery demand premium. At the same time, the *EA_FMAX*(*5*) factor, created using *EA_MAX*(*5*), generates an average monthly return of −0.30% (*t*-statistic = −1.32). When *MAX*(*1*) is employed to construct the lottery demand factor, the *FMAX*(*1*) factor and the *NOEA_FMAX*(*1*) factor generates an average monthly return of −0.48% (*t*-statistic = −2.03) and −0.51% (*t*-statistic = −2.50), respectively. The *EA_FMAX*(*1*) factor, constructed using *EA_MAX*(*1*), generates an insignificant lottery premium of 0.17% (*t*-statistic = 0.79). 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 whether factor models that include the *FMAX* factor help explain the betting-against-beta factor as documented in Frazzini and Pedersen (2014). Table 10 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. (2017a), 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.

Panel A of Table 10 reports the results for *FMAX*(*n*) with $n = 5$ as in Bali et al. (2017a). There are two key findings. First, consistent with the results of Frazzini and Pedersen (2014), we find that over our 1973–2015 sample period, the *BAB* factor generates an economically large and statistically significant alpha of 0.52% (0.50%) per month relative to 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 models are 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 models are 0.17% (*t*-statistic = 0.98) and 0.16% (*t*-statistic = 0.91) per month, respectively. Thus, consistent with Bali et al. (2017a), we find that the abnormal returns of the High-Low beta portfolios relative to the Fama and French (1993) three-factor model, the Carhart (1997) four-factor (FFC4) model, and the FFC4 model augmented with Pastor

Table 10
Alphas and factor sensitivities for *BAB* and *FMAX* Factors. .

Panel A. FMAX factors constructed following Bali et al. (2017a) using MAX(5). Sample 1973–2015

Specification	Alpha	MKTRF	SMB	HML	UMD	PS	FMAX	NOEA_FMAX	EA_FMAX	R^2
FFC4	0.518 (2.76)***	0.063 (1.13)	0.026 (0.34)	0.539 (5.04)***	0.217 (3.42)***					22.40%
FFC4 + PS	0.496 (2.66)***	0.065 (1.19)	0.026 (0.33)	0.538 (5.08)***	0.218 (3.43)***	0.047 (0.59)				22.49%
FFC4 + FMAX	0.225 (1.31)	0.251 (5.84)***	0.307 (5.05)***	0.274 (3.49)***	0.202 (4.74)***		−0.485 (-8.46)***			41.17%
FFC4 + PS + FMAX	0.214 (1.22)	0.252 (5.83)***	0.306 (4.94)***	0.274 (3.57)***	0.203 (4.73)***	0.024 (0.39)	−0.484 (-8.55)***			41.11%
FFC4 + NOEA_FMAX	0.174 (0.98)	0.240 (5.45)***	0.281 (4.66)***	0.310 (3.98)***	0.201 (4.58)***			−0.442 (-8.22)***		39.59%
FFC4 + PS + NOEA_FMAX	0.164 (0.91)	0.240 (5.43)***	0.280 (4.58)***	0.310 (4.07)***	0.202 (4.58)***	0.022 (0.37)		−0.440 (-8.36)***		39.53%
FFC4 + EA_FMAX	0.530 (2.80)***	0.116 (1.97)**	0.131 (1.68)*	0.465 (5.03)***	0.201 (3.64)***				−0.193 (2.60)***	26.47%
FFC4 + PS + EA_FMAX	0.495 (2.61)***	0.121 (2.14)**	0.133 (1.74)*	0.460 (5.10)***	0.202 (3.66)***	0.071 (0.88)			−0.200 (-2.84)***	26.08%

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

and Stambaugh's (2003) liquidity factor are insignificant when the *FMAX* or *NOEA_FMAX* factor is included in the factor model. Contrary to these results, the corresponding *EA_FMAX* factor, which is constructed using only *EA_MAX* stocks, cannot explain the returns associated with betting-against-beta.[37] When the *EA_FMAX* factor is included in the regressions, the alphas relative to the four-factor Fama-French-Carhart and the five-factor Fama-French-Carhart-Pastor-Stambaugh models are 0.53% (t-statistic = 2.80) and 0.50% (t-statistic = 2.61) per month, respectively.

Panel B of Table 10 reports the results for alternative measures of lottery demand factor, *FMAX*(n) with $n = 1 \dots 5$, for the whole sample period (1973–2015) and two equal subsample periods (1973–1994 and 1995–2015). 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 $n = 1 \dots 5$, and for the whole sample and both subsample periods. The results in Panel B suggest that factor models that include the *FMAX* factor constructed using non-earnings announcement *MAX* stocks provide more explanatory power for the abnormal returns of the betting-again-beta phenomenon than the original lottery demand factor suggested in Bali et al. (2017a).

6. Uncertainty resolution

What makes *EA_MAX* events economically different from *NOEA_MAX* events so that lottery investors appear to exhibit different behaviors? While we cannot further classify *NOEA MAX* events by other types of fundamental information due to strenuous data requirements and high error propensity, we cannot state that *NOEA MAX* events are exclusively driven by non-fundamentals. In this section, we explore an economic difference between *EA_MAX* events and *NO_EAMAX* events.

Earnings announcements often result in a significant resolution of uncertainty and disagreement among investors that build up in the pre-announcement period (e.g., Patell and Wolfson, 1979, 1981; Isakov and Perignon, 2001; Banerjee, 2011; Truong et al., 2012; Billings et al., 2015; Gallo, 2017). It is also expected that because earnings information typically resolves uncertainty and disagreement, there is a lower likelihood that such large return events will be repeated in the future, as

[37] We thank the referee for suggesting this test.

shown in Table 9. This is an important economic feature of *EA_MAX* that plausibly deters lottery investors from interpreting large stock returns as lotteries.

We investigate uncertainty resolution from *MAX* returns in Table 11. First, we follow Barth et al. (2017) in constructing a resolution measure that is based on stock return volatility, a commonly employed empirical measure that reflects investor disagreement and uncertainty. This measure, *RESOL*, is the ratio of stock return volatility on the day of *MAX* return to those 15 days before and 15 days after the *MAX* event. Lower ratios indicate that investor disagreement and uncertainty resolve more slowly and vice versa.

Table 11 presents the results of this analysis. In Panel A, we show the mean and median values of *RESOL* for *EA_MAX* and *NOEA_MAX* events. It is clear that *EA_MAX* events exhibit a significantly higher level of *RESOL* (mean value = 0.19), which is almost 1.4 times that of *NOEA_MAX* events (mean value = 0.139). The results for the differences in mean and median values consistently confirm that *EA_MAX* events show higher *RESOL*.

Panel B of Table 11 reports the return of the *MAX* strategy when conditioned on the level of resolution of uncertainty. When we stratify *NOEA MAX* events by the degree of uncertainty resolution, the *NOEA_MAX* hedge return is highly manifested in events of low uncertainty resolution and less so in events of high uncertainty resolution. In the group of highest uncertainty resolution, the *NOEA_MAX* hedge return is −0.80% per month. In the group of lowest uncertainty resolution, *NOEA_MAX* hedge return is −2.20% per month (almost three times higher in magnitude). There is no *MAX* effect across all *RESOL* groups for *EA_MAX* events, suggesting that earnings information plays significant roles in resolving disagreement and valuation uncertainty surrounding earnings announcements period, and as a result, there is no evidence of the *MAX* effect.

Overall, the results in Table 11 show that *EA_MAX* is associated with a high level of uncertainty resolution, which likely makes these stock returns less lottery-like. For *NOEA_MAX* events, we also find that *MAX* phenomenon is significantly reduced among high uncertainty resolution events, consistent with the idea that lottery investors are less attracted to *MAX* returns that bring about high uncertainty resolution.

7. 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 investor ownership and high lottery demand, we still do not detect any *MAX* effect when *MAX* returns are conditioned on earnings announcements. We make a simple classification between non-earnings announcement extreme positive returns and earnings-related extreme positive returns and do not find evidence of the *MAX* effect for the latter.

We show that earnings announcements account for a significant proportion of stocks entering high *MAX* portfolios and this percentage increases 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 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, provides high explanatory power for the cross-section of stock returns and correlates more strongly with economic conditions that characterize high aggregate lottery demand. This finding has a strong implication for *MAX* studies regarding the necessity of excluding earnings announcement *MAX* returns in studying the pricing of lottery demand.

Our evidence 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

Table 11
The resolution of investor disagreement and uncertainty. .

Panel A: Descriptive statistics				
Resolution of Uncertainty	(1)	(2)	Difference (1)–(2)	
RESOL	*EA_MAX*	*NOEA_MAX*	Mean (p-value)	Median (p-value)
Mean	0.190	0.139	0.00	
Median	0.140	0.100		0.00

Panel B: Resolution of uncertainty and the *MAX* effect				
	EA_MAX Sample		*NOEA_MAX* Sample	
	Hedge Return (*MAX* deciles 10-1)	*t*-stat	Hedge Return (*MAX* deciles 10-1)	*t*-stat
Low *RESOL*	−0.013	(-1.21)	−0.022	(-3.64)***
Medium *RESOL*	0.016	(2.70)***	−0.012	(-2.96)***
High *RESOL*	0.000	(0.03)	−0.008	(-2.72)***

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proportion of extreme daily returns, there are also several other corporate events that drive extreme stock returns, such as seasoned equity offerings, IPOs, M&As, among others.

8. Data availability

Data are available from the data sources identified in the paper.

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Appendix. Variable definitions

Variable	Definition and Estimation
MAX	The maximum daily return (*MAX*) within a month: $MAX_{i,t} = \max(R_{i,d}), \quad d = 1, \ldots, D_t,$ 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: $R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d},$ 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 $\widehat{\beta}_i = \widehat{\beta}_{1,i} + \widehat{\beta}_{2,i} + \widehat{\beta}_{3,i}$.
β_{UNC}	Beta sensitivity of the macroeconomic uncertainty index from Jurado et al. (2015). Following Bali et al. (2017b), 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.
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 winsorize *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*) following Ang et al. (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*.
ISKEW	Following Boyer et al. (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: $ILLIQ_{i,t} = \lvert R_{i,t} \rvert / VOLD_{i,t},$ 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.

(*continued*)

Variable	Definition and Estimation
SUE	Standardized unexpected earnings based on a rolling seasonal random walk model proposed by Livnat and Mendenhall (2006, p. 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.
RESOL	An uncertainty resolution measure. *RESOL* is the ratio of stock return volatility on the day of *MAX* return to those in 15 days before and 15 days after the *MAX* event.

Appendix C. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.finmar.2018.05.001.

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.

Decile portfolios are formed every month for the January 1973 to December 2015 period 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 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. Average raw and risk-adjusted returns, and average daily maximum returns are given in percentage terms. Newey and West, 1987 adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel B reports summary statistics for 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 month (*IVOL*), the return in the portfolio formation month (*REV*), the cumulative return over the 11 months prior to portfolio formation (*MOM*), and the standardized unexpected earnings (*SUE*).

Decile portfolios are formed every month for the January 1973 to December 2015 period 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 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. Average raw and risk-adjusted returns are given in percentage terms. Newey and West, 1987 adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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. Panel A presents the percentage of *EA_MAX* across *MAX* portfolios over the full and sub-sample periods. Panel B presents the time series average of the monthly percentage of *EA_MAX* stocks in each decile portfolio.

The last two rows in Panel B present the differences in monthly percentage of *EA_MAX* stocks between Portfolio 1 and Portfolio 10. The two-sample *t*-test results are in parentheses.

Double-sorted, equal-weighted decile portfolios are formed every month for the January 1973 to December 2015 period by sorting stocks based on the maximum daily returns after controlling for firm size, book-to-market ratio, 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 and West, 1987 adjusted *t*-statistics are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel A reports results for the original *MAX* portfolios. Panel B reports results for *EA_MAX* portfolios, *NOEA_MAX* portfolios, and differences (*DIFF*) in monthly returns between *NOEA_MAX* and *EA_MAX* portfolios across deciles. *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. *NOEA_MAX* stocks are defined as stocks of which maximum daily returns fall outside the 5-day window surrounding earnings announcements.

The table presents results of Fama-Macbeth cross-sectional regression of monthly returns on subsets of lagged predictor variables including *MAX* in the previous month and seven 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 are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 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. Average raw and risk-adjusted returns are given in percentage terms. Newey and West, 1987 adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 et al. (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 and West, 1987 adjusted *t*-statistics are in parentheses.

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 and West, 1987 adjusted *t*-statistics are in parentheses.

Each month for the January 1973 to December 2015 period 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*), and the Amihud illiquidity (*ILLIQUID*). *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. Panel A reports results when future *MAX* events can be either *NOEA_MAX* or *EA_MAX*. Panel B reports results when future *MAX* events are *NOEA_MAX*. Newey and West, 1987 adjusted *t*-statistics are in parentheses.

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 et al. (2011) and Bali et al. (2017a), 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. *EA_FMAX*(n) is the lottery demand factor created using *EA_MAX*(n). 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. (2017a). Panel B reports results for alternative measures of lottery demand factor, *FMAX*(n) with $n = 1 \ldots 5$ 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 and West, 1987 adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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Panel A presents descriptive statistics for *RESOL*, a measure for resolution of uncertainty and investor disagreement, for samples of *EA_MAX* and *NOEA_MAX* stocks. *RESOL* is the ratio of the daily return volatility on the *MAX* date, *i.e.*, a date when a stock exhibits the maximum daily returns in each month, to the sum of daily return volatility in the surrounding period, i.e., days (−15, +15). *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. *NOEA_MAX* stocks are defined as stock of which maximum daily returns fall outside the 5-day window surrounding earnings announcements. Panel B presents the hedge return from the *MAX* strategy, *i.e.*, the hedge return from *MAX* Decile 10−1, for samples of *EA_MAX* and *NOEA_MAX* stocks. Newey and West, 1987 adjusted *t*-statistics are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix for When are extreme daily returns not lottery? At earnings announcements!

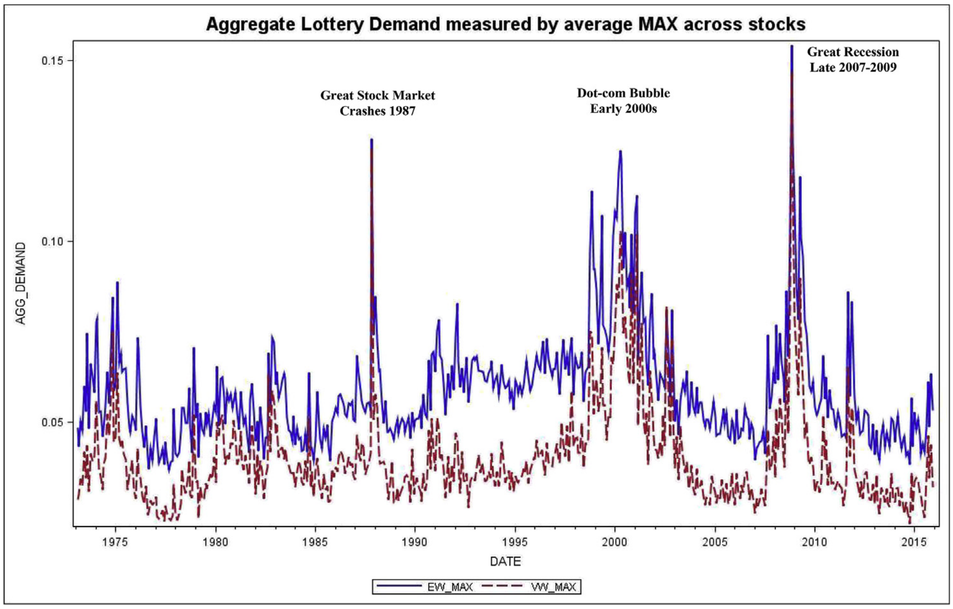

Fig. A.1. Time Series of Aggregate Lottery Demand

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 (0.18)	−1.12	−0.70	−0.02	−1.23	−0.75	−0.12	−1.33
	(-1.76)	(0.58)	(-2.69)	(-1.90)		(-3.04)	(-2.03)	(-0.05)	(-3.38)	(-2.18)	(-0.30)	(-3.76)
FFC4 + PS	−0.74	0.07	−1.12	−0.79	−0.10	−1.27	−0.87	−0.25	−1.40	−0.92	−0.38	−1.51
α	(-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 (1.35)	−0.85	−0.45	0.24 (0.88)	−0.95	−0.48	0.10 (0.37)	−1.06
	(-1.99)	(1.71)	(-3.53)	(-2.05)		(-4.01)	(-2.26)		(-4.42)	(-2.50)		(-5.14)

Decile portfolios are formed every month for the January 1973 to December 2015 period 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. Average raw and risk adjusted returns are given in percentage terms. Newey and West, 1987 adjusted *t*-statistics are in parentheses.

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 (-3.20)***	0.30 (1.06)	−1.08 (-4.14)***
4-factor alpha (FFC4 α)	−1.00 (-6.41)***	0.13 (0.67)	−1.24 (-7.94)***
5-factor alpha (FFC4 + PS α)	−0.97 (-6.30)***	0.12 (0.61)	−1.21 (-7.82)***
5-factor alpha (FF5 α)	−0.69 (-5.58)***	0.38 (2.06)**	−0.93 (-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 and West, 1987 adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 (5.90)	0.81 (6.33)	0.78 (6.45)	0.68 (6.04)	0.67 (5.46)	0.51 (4.90)	0.33 (3.21)	0.24 (2.25)	−0.13 (-1.09)	−0.65 (-3.88)	−1.49 (-5.77)
Below Median Aggregate Lottery Demand											
FFC4 α	0.16 (0.35)	0.29 (0.66)	0.35 (0.80)	0.31 (0.71)	0.31 (0.69)	0.17 (0.40)	0.01 (0.03)	−0.05 (-0.11)	−0.32 (-0.74)	−0.87 (-1.98)	−1.02 (-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

Table A4 (*continued*)

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 (3.37)	0.54 (2.44)	0.91 (4.56)	1.02 (4.78)	0.59 (2.55)	0.75 (4.99)	0.91 (3.50)	0.72 (3.92)	0.53 (2.36)	0.51 (2.32)	−0.14 (-0.43)
Below Median Aggregate Lottery Demand											
FFC4 α	0.30 (0.60)	0.24 (0.44)	0.17 (0.35)	−0.08 (-0.16)	0.61 (1.33)	0.19 (0.42)	0.28 (0.61)	0.19 (0.40)	0.24 (0.53)	0.06 (0.12)	−0.24 (-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 (5.54)	0.84 (6.37)	0.86 (6.76)	0.74 (6.09)	0.74 (5.87)	0.55 (4.78)	0.38 (3.50)	0.30 (2.63)	−0.02 (-0.16)	−0.66 (-3.96)	−1.49 (-5.49)
Below Median Aggregate Lottery Demand											
FFC4 α	0.08 (0.19)	0.19 (0.44)	0.21 (0.50)	0.20 (0.47)	0.18 (0.42)	0.11 (0.26)	−0.04 (-0.09)	−0.08 (-0.19)	−0.39 (-0.94)	−0.77 (-1.81)	−0.85 (-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 (3.30)	0.67 (2.78)	0.97 (4.27)	0.89 (3.99)	0.58 (2.52)	0.93 (5.91)	0.98 (4.04)	0.69 (3.52)	0.63 (3.12)	0.36 (1.55)	−0.36 (-1.06)
Below Median Aggregate Lottery Demand											
FFC4 α	0.20 (0.43)	−0.01 (-0.02)	−0.03 (-0.06)	−0.01 (-0.01)	0.58 (1.29)	−0.06 (-0.14)	0.19 (0.42)	0.17 (0.37)	0.13 (0.30)	0.29 (0.61)	0.08 (0.36)

Decile portfolios are formed for every month from the January 1973 to December 2015 period 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 and West, 1987 adjusted *t*-statistics are 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	High - Low FF5 α
Non-Recession	0.82 (2.88)	0.94 (3.12)	0.95 (3.10)	0.91 (2.85)	0.90 (2.74)	0.79 (2.35)	0.65 (1.85)	0.55 (1.50)	0.26 (0.65)	−0.21 (-0.48)	−0.96 (-6.71)	−0.74 (-6.49)
Recession	2.09 (2.74)	2.48 (2.48)	2.75 (2.64)	2.72 (2.44)	2.88 (2.48)	2.81 (2.29)	2.70 (2.04)	2.85 (2.17)	2.49 (1.83)	1.56 (1.23)	−1.52 (-4.32)	−1.05 (-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	High - Low FF5 α
Non-Recession	0.71(2.30)	0.79 (2.44)	0.88 (2.63)	0.85 (2.62)	0.95 (2.74)	0.87 (2.59)	1.02 (2.92)	0.86 (2.32)	0.89 (2.21)	0.89 (2.16)	0.10 (0.50)	0.29 (1.57)
Recession	2.64 (2.64)	1.99 (1.78)	2.52 (2.50)	2.86 (2.91)	3.05 (2.88)	2.89 (2.83)	3.11 (2.28)	3.77 (3.18)	3.03 (2.38)	2.86 (1.85)	−0.65 (-1.20)	−0.08 (-0.15)

Decile portfolios are formed every month by sorting stocks based on the maximum daily return (*MAX*) over the past 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* (*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 and West, 1987 adjusted t-statistics are in parentheses.

Table 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 (3.38)	0.34 (1.75)	0.38 (2.40)	0.41 (2.33)	0.69 (2.29)	−0.11 (-0.32)	0.39 (1.13)	0.71 (1.64)	0.24 (0.81)	−0.58 (-1.49)	−1.04 (-2.34)
	Non-January	0.22 (0.82)	0.14 (0.51)	0.26 (0.96)	0.09 (0.35)	0.27 (0.96)	0.24 (0.89)	0.10 (0.35)	0.03 (0.09)	−0.07 (-0.23)	−0.42 (-1.37)	−0.64 (-2.88)
FFC4 + PS α	January	0.45 (2.92)	0.32 (1.33)	0.35 (1.65)	0.49 (3.07)	0.69 (1.87)	−0.08 (-0.21)	0.34 (0.83)	0.57 (1.22)	0.09 (0.23)	−0.57 (-1.26)	−1.02 (-2.01)
	Non-January	0.21 (0.80)	0.16 (0.57)	0.26 (0.94)	0.09 (0.34)	0.27 (0.98)	0.23 (0.86)	0.09 (0.35)	0.05 (0.18)	−0.05 (-0.18)	−0.45 (-1.45)	−0.66 (-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 (-0.31)	−0.01 (-0.02)	0.61 (1.96)	0.96 (2.04)	1.15 (2.94)	0.55 (1.71)	0.27 (0.39)	1.01 (1.28)	0.76 (1.44)	−0.11 (-0.14)	−0.02 (-0.03)
	Non-January	0.50 (1.45)	0.14 (0.40)	0.08 (0.26)	0.16 (0.50)	0.28 (0.84)	0.25 (0.78)	0.28 (0.89)	0.46 (1.50)	0.46 (1.40)	0.30 (0.86)	−0.20 (-0.52)
FFC4 + PS α	January	−0.07 −0.24	−0.01 −0.03	0.52 1.23	1.25 2.50	0.89 2.37	0.61 1.70	0.20 0.31	0.92 1.10	0.37 0.62	−0.05 −0.06	0.03 (0.04)
	Non-January	0.50 (1.43)	0.12 (0.36)	0.11 (0.35)	0.15 (0.47)	0.27 (0.83)	0.28 (0.89)	0.26 (0.82)	0.45 (1.46)	0.42 (1.29)	0.27 (0.76)	−0.23 (-0.61)

Decile portfolios are formed every month for the January 1973 to December 2015 period 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 and West, 1987 adjusted t-statistics are in parentheses.

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