Essays on Corporate Earnings, Lottery-Related Anomalies, and Corporate Behavior

The Hung Nguyen
Master of Finance
Bachelor of Banking and Finance

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Abstract

There is an increase over time in the informativeness of corporate earnings announcements. However, little is known about how information content at earnings dates is associated with market anomalies, especially lottery-related anomalies that are recently documented. The purpose of this thesis is to enhance our understanding of how corporate earnings are related to the pricing of assets with lottery-like payoffs and corporate future behavior.

The thesis consists of three distinct essays. The first essay investigates the relation between extreme positive stock returns and subsequent returns when such extreme returns are driven by corporate earnings announcements. The empirical analysis reveals that quarterly earnings announcements account for more than 18% of extreme daily returns and that maximum daily returns, when driven by earnings information, do not proxy for lottery demand. As a result, stocks with information-driven maximum return do not exhibit lower future returns.

The second essay studies the relation between extreme positive stock returns around past earnings announcements and stock returns in the 10-day window before current earnings announcements. The empirical analysis suggests that the average of risk-adjusted return differences between stocks with the highest earnings announcement maximum returns and stocks with the lowest earnings announcement maximum returns is 89 basis points in the 10 days leading up to earnings announcements. This result is consistent with the argument that investors have a preference for stocks with large payoffs during earnings announcements.

The third essay examines whether the timing of scheduled earnings news is associated with future firm-specific stock price crashes. Empirical analysis suggests that firms that schedule later-than-expected earnings announcement dates are more likely to exhibit future stock price crashes. In addition, investors demand higher expected returns for firms that schedule later-than-expected earnings announcement dates. Auditors also require higher audit fees to compensate for their additional effort in auditing firms that delay earnings announcement dates.

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signature: ..[redacted]

Print Name: The Hung (Harvey) Nguyen

Date: August 16, 2018

Thesis including published works declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes 01 original paper published in a peer-reviewed journal. The core theme of the thesis is corporate earnings, lottery-related anomalies, and corporate behavior. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the Monash Business School under the supervision of Professor Cameron Truong.

The inclusion of co-authors reflects the fact that the work came from active collaboration between researchers and acknowledges input into team-based research.

In the case of Chapter 1 my contribution to the work involved the following:

Thesis Chapter	**Publication Title**	**Status**	**Nature and % of student contribution**	**Co-author name(s) Nature and % of Co-author's contribution***	**Co-author(s), Monash student Y/N***
Chapter 1	When are extreme daily returns not lottery? At earnings announcements	Accepted By *Journal of Financial Markets* (ABDC: A*)	70%. Concept and collecting data and writing the first draft	Cameron Truong, input into manuscript 30%	No

I have renumbered sections of submitted or published papers in order to generate a consistent presentation within the thesis.

Student signature: [redacted] **Date:** August 10, 2018

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author I have consulted with the responsible author to agree on the respective contributions of the authors.

Main Supervisor signature: [redacted] **Date:** August 21, 2018

To my parents, my wife, and my son

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Chapter 1. Introduction

Recent research documents that lottery-like assets, i.e., assets with some probability of large payoffs are of special interest to certain investors.[1] Using the maximum daily stock return as a proxy for lottery demand, Bali, Cakici, and Whitelaw (2011) document a significant negative relation between the maximum daily returns in the past one month and expected stock returns in the immediate subsequent month, which is then referred as the *MAX* effect. The authors suggest that investors who have a strong preference for assets with lottery-like payoffs can push up the current prices of these lottery stocks. As a result, these stocks exhibit lower future returns, which cannot be explained by known risk factors. Subsequent 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). While the *MAX* phenomenon offers influential contributions to our understanding of how lottery demand affects security prices in equilibrium, what drives the extreme daily positive returns and what may determine the persistence of the phenomenon remains under-investigated.

An important corporate event that can potentially serve as a source of extreme daily stock returns is corporate earnings announcement. Corporate earnings announcements are likely to attract

[1] For example, Kumar (2009) shows that certain individual investors exhibit a preference for lottery-type stocks that are often defined as low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness. Bali, Cakici, and Whitelaw (2011) document that investors demand for stocks that have the highest maximum daily return in the prior trading month. Bali, Brown, Murray, and Tang (2017) show that this lottery demand is priced in the cross-section of monthly stock returns.

investors' attention due to the release of high information content (Barber and Odean, 2008). Quarterly earnings announcements introduce significant movements to stock returns over a short period and repeatedly, four times, over the year, offering lottery investors opportunities to reap a significant stock price surge during earnings announcements periods.[2] Furthermore, the timing of earnings news can provide signal of a firm's subsequent behavior (DeHaan, Shevlin, Thornock, 2015; Johnson and So, 2017). Given an increase over time in the informativeness of quarterly earnings announcements (e.g., Landsman and Maydew, 2002; Beaver, McNichols, and Wang, 2018), corporate earnings can provide a fruitful avenue for research that examines market efficiency and subsequent corporate behavior.

Motivated by the literature on the pricing of lottery-like stocks and the literature on predictable abnormal stock returns surrounding earnings announcements, this thesis examines how information content at earnings dates is associated with lottery-related anomalies and corporate future behavior. The thesis consists of three distinct essays, with the first two essays concentrating on how corporate earnings are associated with lottery-related anomalies and the third essay focusing on how the timing of scheduled earnings news is associated with corporate future behavior. The first essay examines the relation between extreme positive daily returns and subsequent returns when such extreme returns are driven by corporate earnings announcements. The first essay finds that corporate announcements are important sources of extreme daily returns and that the maximum daily returns, when driven by fundamentally relevant information, do not proxy for lottery demand. As a result, stocks with earning-driven maximum returns do not exhibit

[2] Studies documenting a significant risk premium around predictable earnings announcements include Ball and Kothari (1991), Chari, Jagannathan and Ofer (1988), Kalay and Lowenstein (1985), Penman (1984). Barber, De George, Lehavy, and Trueman (2013) conduct an international study of the earnings announcement premium and document that this premium is a resilient phenomenon across the globe.

lower future returns. Furthermore, the aggregate lottery demand factor, when constructed based on maximum returns that are not driven by earnings announcements, provides high explanatory power for the cross-section of stock returns and correlates strongly with economic conditions that characterize high aggregate lottery demand.

The second chapter examines whether past earnings announcement winners exhibit a predictable return pattern around their current earnings announcements. Because large stock price changes can be triggered by their upcoming earnings announcements, stocks that exhibited extreme positive returns from prior earnings announcements can attract a high level of lottery demand, resulting in a sharp price run-up in the current pre-announcement period. Using maximum earnings announcement return measure as a proxy for earnings announcement lottery payoffs, this chapter finds that in the 10 days leading up to earnings announcements, the average of risk-adjusted return differences between stocks with the highest earnings announcement maximum returns and stocks with the lowest earnings announcement maximum returns is 89 basis points. This result is consistent with the argument that investors have a preference for stocks with large payoffs during earnings announcements.

The third essay examines whether the timing of scheduled earnings news is associated with future firm-specific stock price crash. The study utilizes the recent trend toward issuing scheduling earnings news and conjectures that managers can withhold unfavorable news by strategically revising the timing of scheduled earnings news. Accumulated bad news is eventually revealed all at once, causing a crash. Empirical analysis suggests that firms that schedule later-than-expected earnings announcement dates are more likely to exhibit future stock price crashes. In addition, investors demand higher expected returns for firms that schedule later-than-expected earnings announcement dates. Auditors also require higher audit fees to compensate for their additional effort in auditing firms that delay earnings announcement dates.

Taken together, the three essays contribute to the extant literature in three significant ways. First, the thesis makes a contribution to an emerging literature which shows a preference among investors for lottery-like assets, i.e., assets that have some probability of large payoffs.[3] While the maximum daily return is a simple and intuitive measure of the lottery-like features of stock returns, the first chapter suggests that the sources of information that accommodate these extreme positive returns are important in making the correct interpretation of such returns. Using earnings announcements to identify extreme positive stock returns as public information arrivals, the first chapter suggests 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. Also utilizing corporate earnings announcements as a setting, the second essay documents a new predictable pattern of stock returns in the pre-earnings announcement period. The second essay suggests that investors over-weight stocks with high past earnings announcement pay-offs, leading to predictable returns in the period leading up to current earnings announcements.

Second, the thesis contributes to the strand of literature that examines prior stock returns when measuring the price reaction surrounding earnings announcements (see, for example, Aboody et al. (2010) and So and Wang (2014)). Findings from the second essay suggest that that prior stock return performance, when measured in a short window surrounding past earnings announcements, attracts individual investors' attention in the period leading to current earnings announcements.

[3] See, for example, Kumar (2009), Bali et al. (2011), and Bali et al. (2017).

Finally, the thesis contributes to the burgeoning literature that explores the determinants and consequences of firm-level stock price crashes. The third essay suggests that earnings calendar revisions can provide firm’s manager opportunities to withhold bad news through revising the timing of scheduled earnings announcement dates. Accumulated bad news is eventually revealed, causing a firm’s stock price to plunge. This chapter is related to prior studies that document techniques for concealment of bad news (Kim, Li, and Zhang, 2011; Kim, Li, and Li, 2014; Chen, Kim, and Yao, 2017; and Khurana, Pereira, and Zhang, 2018).

The remainder of the thesis is organized as follows. Chapter 2 discusses the first essay. The second and the third essay are discussed in Chapter 3 and Chapter 4, respectively. Chapter 5 provides a conclusion and discusses implications for future research.

Chapter 2. When are Extreme Daily Returns not Lottery? At Earnings Announcements!

2.1. Introduction

Bali, Cakici, and Whitelaw (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.[4] 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

[4] 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).

MAX in studying lottery demand 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.[5]

In this chapter, 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.[6]

[5] 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.

[6] 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.

In several empirical tests, we find that there is no *MAX* effect when the maximum daily returns are driven by earnings announcements.[7] First, we sort stocks into 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

[7] 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.

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.[8] 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.[9]

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

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[8] 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.

[9] 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.

MAX returns driven by earnings announcements do not relate to the probability of future large upward price moves and consequently do not proxy for lottery demand. BCW suggest that investors demand for lottery stocks can be rationalized by their expectations for the lottery probability albeit the probability is largely overweighted. Specifically, they document that stocks with extreme positive returns in a 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, Brown, Murray, and Tang (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).[10] 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

[10] 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.

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.[11]

The remainder of this chapter is organized as follows. In Section 2.2, we provide data and variable descriptions. In Section 2.3, we describe the *MAX* effect where maximum returns are driven by earnings information. In Section 2.4, we show the persistence of *MAX* returns when conditioned on earnings information. In Section 2.5, we discuss the *FMAX* factor conditioned on earnings information that does not proxy for lottery demand. In Section 2.6, we investigate uncertainty resolution and *MAX* returns. Concluding remarks are given in Section 2.7.

2.2. 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.[12] 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).[13] 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.

[11] 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.

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

[13] 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).

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. [14]

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.[15] Monthly Pastor and Stambaugh (2003) liquidity factor returns are from Lubos Pastor's website.[16] The earnings momentum factor is from Chordia and Shivakumar (2006).[17] For investor sentiment measures, we use Baker and Wurgler's (2006) sentiment index, the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center, and

[14] 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.

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

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

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

the FEARS index from Da et al. (2015).[18] 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.[19]

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.[20] 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.[21]

2.3. Maximum daily returns, earnings announcements, and the cross-section of expected returns

2.3.1. Univariate portfolio analysis

Table 2.1 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.

{ENTER TABLE 2.1}

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18 We thank Jeffrey Wurgler and Zhi Da for making their investor sentiment data available through their websites.
19 We thank Sydney Ludvigson and Nicholas Bloom for making their uncertainty indices available through their websites.
20 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.
21 Our main findings remain qualitatively unchanged when we consider all common stocks with no price restriction or with price of $1 or more at the end of the formation month.

Panel A of Table 2.1 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-West (1987) *t*-statistic of -3.64 (-1.96).[22] 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 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 2.1 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 2.2 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

[22] 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.

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 2.1 for the full sample, but these stocks do not exhibit lower future returns.

{ENTER TABLE 2.2}

Panel B of Table 2.2 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 2.2 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).[23,24]

While the results in Table 2.2 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 2.3, 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

[23] We conduct a number of robustness checks around our core results in Table 2.2. First, the results in Appendix 2.3 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.

[24] 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 Appendix 2.4 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 Appendix 2.4 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.

announcements account for a non-trivial proportion of stocks in any *MAX* portfolio and this percentage is remarkably high in high *MAX* portfolios.

{ENTER TABLE 2.3}

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 2.3, 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.

Overall, the key findings in Table 2.3 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.[25]

[25] 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

Figures 2.1 and 2.2 confirm that there is an increasing trend in the proportion of stocks in the high *MAX* portfolio being associated with earnings announcements over time.[26] 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.[27] 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 2.2.

{ENTER FIGURE 2.1}

{ENTER FIGURE 2.2}

2.3.2. 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

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Chordia and Shivakumar's (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. Appendix 2.5 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.

[26] 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).

[27] 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.

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

{ENTER TABLE 2.4}

Panel A of Table 2.4 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-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.[29]

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[28] 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 2.4.

[29] 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's (2015) five factors and Cahart's

Panel B of Table 2.4 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-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 2.2, 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 2.4. Consistent with the findings in Panel C of Table 2.2, 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.

(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.

The results in Table 2.4 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.

2.3.3. 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 2.5 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.[30]

{ENTER TABLE 2.5}

In row (1) of Table 2.5, 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.

[30] 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.

The key findings from these regression analyses lie in the last three rows of Table 2.5. 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.

Overall, the results in Table 2.5 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*.[31]

2.3.4. 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

[31] 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 1.5.

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 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*.

{ENTER TABLE 2.6}

Table 2.6 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 2.6 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 2.6. 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.[32]

[32] 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.

2.3.5. 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).[33] 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 2.7.

{ENTER TABLE 2.7}

Panel A (Panel B) of Table 2.7 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

[33] 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).

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.

2.3.6. 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 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*).[34] 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 2.8.

{ENTER TABLE 2.8}

In Panel A of Table 2.8, 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 2.8. 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 = -

[34] 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.

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 2.8 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.[35,36]

2.4. 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.

[35] 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. Appendix 2.2 presents the time series of aggregate lottery demand and Appendix 2.6 and Appendix 2.7 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.

[36] 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. Appendix 2.8 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 Appendix 2.8, 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.

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 2.9, 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.

{ENTER TABLE 2.9}

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 2.9, 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 2.9 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.[37] 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,

[37] 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.

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 2.9 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.

2.5. 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 2.10 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.

{ENTER TABLE 2.10}

Panel A of Table 2.10 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 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. 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 2.10 reports the results for alternative measures of lottery demand factor, *FMAX*(*n*) with *n* = 1…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…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).

2.6. 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 shown in Table 2.9. 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 2.11. 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.

{ENTER TABLE 2.11}

Table 2.11 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 2.11 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 2.11 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.

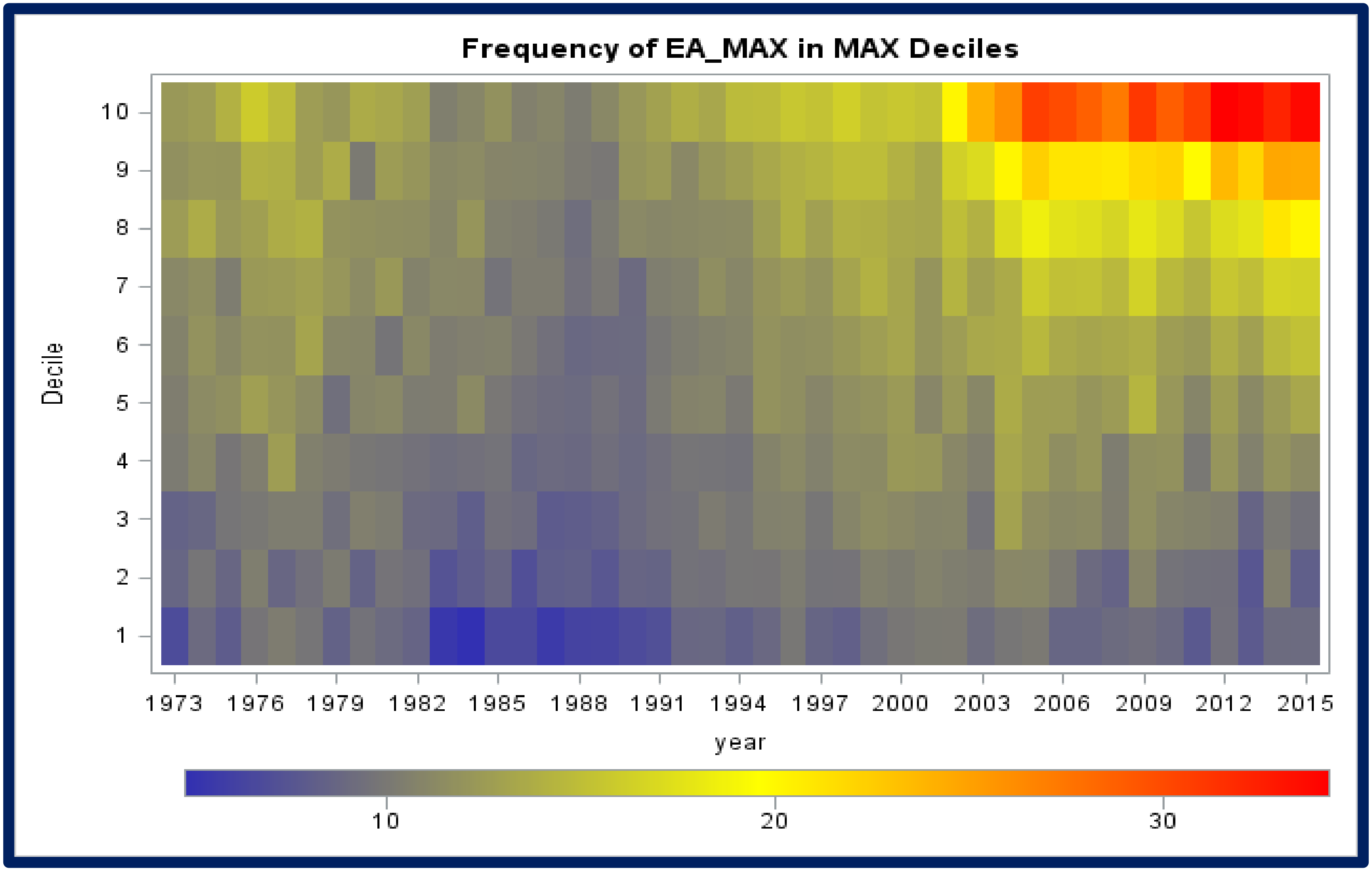
2.7. Conclusion of Chapter 2

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.

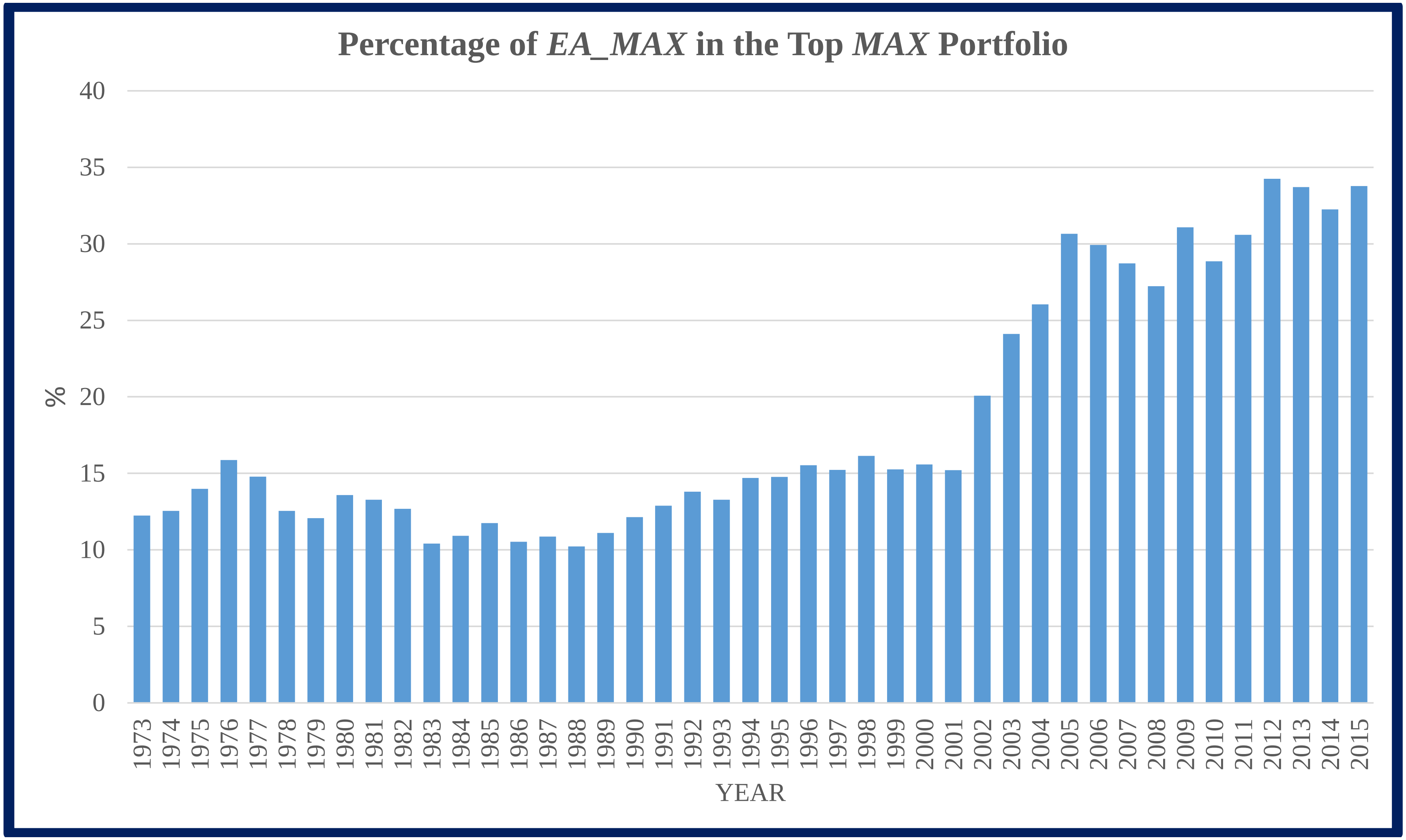
Our evidence shows that the sources of information that drive extreme returns are very important for how these seemingly identical returns should be interpreted. While earnings announcements are frequent and account for a large proportion of extreme daily returns, there are also several other corporate events that drive extreme stock returns, such as seasoned equity offerings, IPOs, M&As, among others.

Figure 2.1. Heat map of earnings announcements and MAX



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

Figure 2.2. Percentage of EA_MAX in the Top MAX Portfolio over Time



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

Table 2.1. Returns and alphas on portfolio of stocks sorted by MAX

Panel A: Univariate portfolio sorted by *MAX*

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

Panel B: Summary statistics for decile portfolios sorted by *MAX*

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

Decile portfolios are formed every month 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-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*).

Table 2.2. Univariate portfolios sorted on EA_MAX and NOEA_MAX

Panel A: Univariate portfolio sorted by *EA_MAX*

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

Panel B: Univariate portfolio sorted by *NOEA_MAX*

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

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

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

Decile portfolios are formed every month 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-West (1987) adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3. 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	5,761	7.37	93,534	8,571	9.16
2	174,922	16,337	9.34	79,233	6,844	8.64	95,689	9,493	9.92
3	174,938	17,505	10.01	79,137	7,218	9.12	95,801	10,287	10.74
4	175,414	18,539	10.57	79,476	7,583	9.54	95,938	10,956	11.42
5	175,200	19,623	11.20	79,398	8,078	10.17	95,802	11,545	12.05
6	175,506	20,584	11.73	79,548	8,199	10.31	95,958	12,385	12.91
7	175,374	21,912	12.49	79,460	8,503	10.70	95,914	13,409	13.98
8	175,354	23,870	13.61	79,359	8,887	11.20	95,995	14,983	15.61
9	175,358	26,554	15.14	79,438	9,173	11.55	95,920	17,381	18.12
High *MAX*	174,649	31,929	18.28	79,097	9,700	12.26	95,552	22,229	23.26

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)

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.

Table 2.4. 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	-0.80	-1.06	-0.94	-1.00	-0.83
	(-3.82)***	(-3.17)***	(-5.94)***	(-4.09)***	(-3.80)***	(-4.32)***
FFC4 α	-1.10	-0.99	-1.22	-1.13	-1.13	-0.95
	(-6.90)***	(-6.14)***	(-10.12)***	(-7.56)***	(-7.20)***	(-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	-1.19	-1.32	0.16	-1.07	-1.47	-0.08	-1.26	-1.37
	(-0.93)	(-4.51)***	(-7.85)***	(0.57)	(-4.13)***	(-7.76)***	(-0.32)	(-7.01)***	(-7.58)***
FFC4 α	-0.11	-1.30	-1.23	0.13	-1.28	-1.44	-0.03	-1.42	-1.28
	(-0.50)	(-8.22)***	(-7.02)***	(0.55)	(-7.63)***	(-6.74)***	(-0.18)	(-11.62)***	(-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	-1.19	-1.58	0.04	-1.23	-1.30	0.48	-0.96	-1.41
	(1.22)	(-5.19)***	(-11.03)***	(0.14)	(-4.57)***	(-8.29)***	(1.42)	(-3.47)***	(-8.65)***
FFC4 α	0.43	-1.37	-1.52	0.18	-1.38	-1.25	0.43	-1.10	-1.41
	(2.05)**	(-9.25)***	(-8.70)***	(0.81)	(-8.54)***	(-7.33)***	(1.93)*	(-7.01)***	(-7.77)***

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-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.

Table 2.5. 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)***

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.

Table 2.6. The MAX effect after controlling for institutional holding

Panel A: The *MAX* effect and institutional ownership

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

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

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

The table presents the results of dependent sort bivariate portfolio analyses of the relation between future stock returns and maximum daily return (*MAX*) over the past 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-West (1987) adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7. Returns and alphas of EA_MAX portfolios following sentiment states

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

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

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

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

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

Table 2.8. Stock Price, Idiosyncratic Volatility, and Idiosyncratic Skewness

Panel A: Returns and alphas of *MAX* portfolios

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

Panel B: Returns and alphas of *EA_MAX* portfolios

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

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

Table 2.9. 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	-0.0677						
	(42.76)	(-12.96)						
(4)	0.2393		0.0022	-0.0052	-0.0044	0.0008	-0.0550	0.0059
	(29.05)		(8.80)	(-37.97)	(-8.63)	(3.00)	(-25.36)	(4.03)
(5)	0.2552	-0.0563	0.0021	-0.0051	-0.0043	0.0024	-0.0546	0.0056
	(34.37)	(-13.29)	(8.80)	(-37.95)	(-8.65)	(3.01)	(-25.12)	(4.02)

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	-0.0547						
	(53.05)	(-13.75)						
(4)	0.2392		0.0021	-0.0050	-0.0041	0.0024	-0.0494	0.0068
	(38.01)		(10.12)	(-41.65)	(-10.66)	(3.69)	(-24.05)	(4.49)
(5)	0.2527	-0.0408	0.0020	-0.0049	-0.0041	0.0024	-0.0492	0.0065
	(42.68)	(-13.22)	(10.06)	(-41.47)	(-10.69)	(3.70)	(-24.02)	(4.48)

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-West (1987) adjusted *t*-statistics are in parentheses.

Table 2.10. 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	0.063	0.026	0.539	0.217					22.40%
	(2.76)***	(1.13)	(0.34)	(5.04)***	(3.42)***					
FFC4 + PS	0.496	0.065	0.026	0.538	0.218	0.047				22.49%
	(2.66)***	(1.19)	(0.33)	(5.08)***	(3.43)***	(0.59)				
FFC4 + FMAX	0.225	0.251	0.307	0.274	0.202		-0.485			41.17%
	(1.31)	(5.84)***	(5.05)***	(3.49)***	(4.74)***		(-8.46)***			
FFC4 + PS + FMAX	0.214	0.252	0.306	0.274	0.203	0.024	-0.484			41.11%
	(1.22)	(5.83)***	(4.94)***	(3.57)***	(4.73)***	(0.39)	(-8.55)***			
FFC4 + NOEA_FMAX	0.174	0.240	0.281	0.310	0.201			-0.442		39.59%
	(0.98)	(5.45)***	(4.66)***	(3.98)***	(4.58)***			(-8.22)***		
FFC4 + PS + NOEA_FMAX	0.164	0.240	0.280	0.310	0.202	0.022		-0.440		39.53%
	(0.91)	(5.43)***	(4.58)***	(4.07)***	(4.58)***	(0.37)		(-8.36)***		
FFC4 + EA_FMAX	0.530	0.116	0.131	0.465	0.201				-0.193	26.47%
	(2.80)***	(1.97)**	(1.68)*	(5.03)***	(3.64)***				(2.60)***	
FFC4 + PS + EA_FMAX	0.495	0.121	0.133	0.460	0.202	0.071			-0.200	26.08%
	(2.61)***	(2.14)**	(1.74)*	(5.10)***	(3.66)***	(0.88)			(-2.84)***	

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

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

The table presents the alphas (in percent per month) and factor sensitivities for the betting-again-beta (*BAB*) factor using different factor models. *FFC4* (*FFC4+PS*) refers to the four-factor Fama-French-Carhart (the five-factor Fama-French-Carhart-Pastor-Stambaugh) model. Different measures of the lottery factor are constructed following Bali 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…*5* for the whole sample (1973-2015) and for two equal subsamples. For brevity, Panel B only reports the alphas and the sensitivities of the *BAB* factor returns to lottery demand factor (*FMAX* and *NOEA_FMAX*). Newey-West (1987) adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.11. 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)***

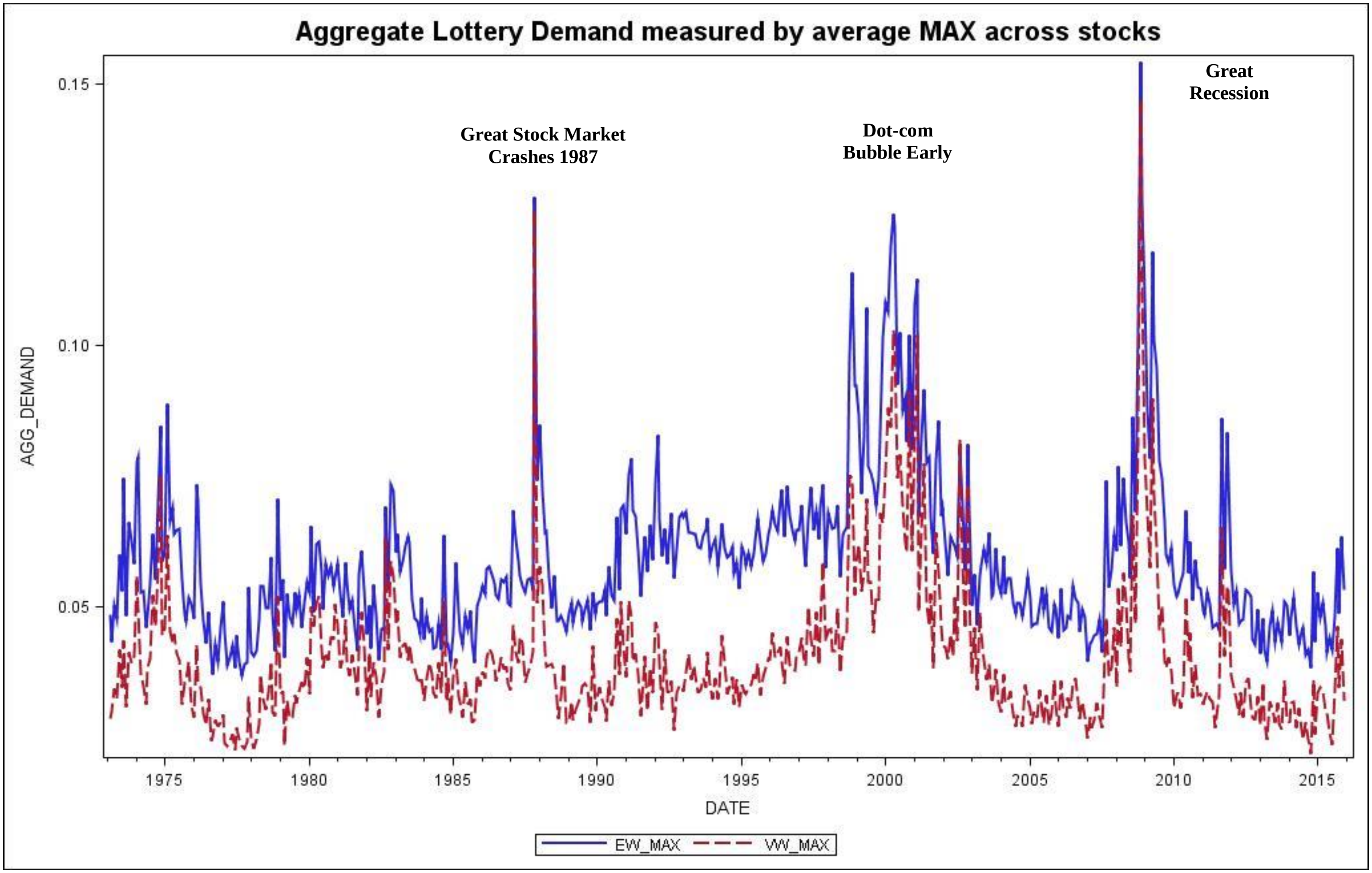
Panel A presents descriptive statistics for *RESOL*, a measure for resolution of uncertainty and investor disagreement, for samples of *EA_MAX* and *NOEA_MAX* stocks. *RESOL* is the ratio of the daily return volatility on the *MAX* date, *i.e.*, a date when a stock exhibits the maximum daily returns 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-West (1987) adjusted *t*-statistics are reported. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix 2.1. Variable definitions for Chapter 2

Variable	Definition and Estimation
MAX	The maximum daily return (*MAX*) within a month: $MAX_{i,t} = \max(R_{i,d}),\ \ d = 1, \dots, D_t,$ where $R_{i,d}$ is the return on stock *i* on day d and D_t is the number of trading days in month *t*.
BETA	We follow Scholes and Williams (1977) and Dimson (1979) to use the lag and lead of the market portfolio as well as the current market when estimating beta to take into account nonsynchronous trading: $R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}\left(R_{m,d-1} - r_{f,d-1}\right) + \beta_{2,i}\left(R_{m,d} - r_{f,d}\right) + \beta_{3,i}\left(R_{m,d+1} - r_{f,d+1}\right) + \varepsilon_{i,d},$ where $R_{i,d}$ is the return on stock *i* on day *d*, $R_{m,d}$ is the market return on day *d*, and is the risk-free rate on day *d*. The market beta for stock *i* in month *t* is defined as $\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i}$.
β_{UNC}	Beta sensitivity of the macroeconomic uncertainty index from Jurado et al. (2015). Following Bali et al. (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.
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 2.2. 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*.

Appendix 2.3. Alternative measure of lottery demand by MAX (N): N = 2 to 5

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

Decile portfolios are formed every month 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-West (1987) adjusted *t*-statistics are in parentheses.

Appendix 2.4. The MAX effect after controlling for a microstructure effect

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

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

Appendix 2.5. The MAX effect after controlling for earnings momentum factor

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

The table reports the average hedge returns from the *MAX* strategy after controlling for earnings momentum factor (*PMN*). *PMN* data is from Chordia and Shivakumar (2006). The sample covers the period of 1973-2003. Average risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix 2.6. Time-varying lottery demand

Panel A: Equal-weighted average *MAX* as aggregate lottery demand: *MAX* portfolios

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

Panel B: Equal-weighted average *MAX* as aggregate lottery demand: *EA_MAX* portfolios

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

Panel C: Value-weighted average *MAX* as aggregate lottery demand: *MAX* portfolios

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

Panel D: Value-weighted average *MAX* as aggregate lottery demand: *EA_MAX* portfolios

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

Decile portfolios are formed 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-West (1987) adjusted *t*-statistics are in parentheses.

Appendix 2.7. 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	0.94	0.95	0.91	0.90	0.79	0.65	0.55	0.26	-0.21	-0.96	-0.74
	(2.88)	(3.12)	(3.10)	(2.85)	(2.74)	(2.35)	(1.85)	(1.50)	(0.65)	(-0.48)	(-6.71)	(-6.49)
Recession	2.09	2.48	2.75	2.72	2.88	2.81	2.70	2.85	2.49	1.56	-1.52	-1.05
	(2.74)	(2.48)	(2.64)	(2.44)	(2.48)	(2.29)	(2.04)	(2.17)	(1.83)	(1.23)	(-4.32)	(-3.01)

Panel B: Returns and alphas of *EA_MAX* portfolios

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

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

Appendix 2.8. Univariate portfolios sorted on *MAX* in January and non-January months

Panel A: Alphas of *MAX* portfolios

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

Panel B: Alphas of *EA_MAX* portfolios

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

Decile portfolios are formed every month 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-West (1987) adjusted *t*-statistics are in parentheses.

Chapter 3. Earnings Announcement Lottery Payoff and the Cross Section of Stock Returns

3.1. Introduction

This chapter examines whether past earnings announcement winners exhibit a predictable return pattern around their current earnings announcements. Motivated by the literature on predictable abnormal stock returns surrounding earnings announcements (Trueman, Wong, and Zhang, 2003; Aboody, Lehavy, and Trueman, 2010; Johnson and So, 2017a) and the literature on the pricing of lottery-like stocks (Bali, Cakici, and Whitelaw, 2011; Bali, Brown, Murray, and Tang, 2017; Cheon and Lee, 2017), we examine the role of extreme positive stock returns around past earnings announcements in the cross-sectional pricing of stock returns in the 10-day window immediately before their current earnings announcements. Because large stock price changes can be triggered by their upcoming earnings announcements, stocks that exhibited extreme positive returns from prior earnings announcements should attract a high level of lottery demand, resulting in a sharp price run-up in the current pre-announcement period.[38]

[38] Quarterly earnings announcements introduce significant movements to stock returns over a short period and repeatedly, four times, over the year. On the one hand, price fluctuations around earnings announcements should be irrelevant to investors because idiosyncratic volatility is generally assumed to be diversifiable in a traditional asset pricing framework and hence expected stock returns are only determined by the covariance of stock returns with market returns (Sharpe, 1964; Lintner, 1965; Mossin, 1966). On the other hand, because investors are poorly diversified and exhibit a preference for assets with lottery-like payoffs (Kumar, 2009), stocks with extreme positive returns surrounding past earnings announcements can attract demand from lottery investors, thereby resulting in predictable price run-ups immediately before current earnings announcements.

Our empirical analysis finds evidence that is consistent with the lottery demand pricing conjecture. To identify past earnings announcement winners, we first compute the three-day excess stock return for each quarterly earnings announcement in the prior calendar year. Next, for each stock, we take the maximum value of the set of four past earnings announcement returns. We use this maximum earnings announcement return measure (denoted *EA_MAXRET*) as a proxy for earnings announcement lottery payoffs. Stocks with a high *EA_MAXRET* should appeal to investors who have a preference for lottery-type payoffs. We then sort stocks into decile portfolios every quarter based on this *EA_MAXRET* and examine abnormal stock returns in the 10 days leading to earnings announcements. For the 35-year period from January 1981 through December 2015, we find that excess stock returns from portfolios with the highest *EA_MAXRET* value are 115 bps over the 10-day period leading up to earnings announcements.

Our analysis shows that the *EA_MAXRET* phenomenon is highly consistent over time. The strategy of going long on the top *EA_MAXRET* portfolios and short on the bottom *EA_MAXRET* portfolios yields, on average, 89 bps and exhibits positive hedge returns in 109 of the 140 quarters over the 35-year sample period. We note that stocks with a high *EA_MAXRET* are not representative of the overall market. They tend to be smaller, to have higher idiosyncratic volatility, to have higher returns in the six months leading up to earnings announcements, to have a positive earnings surprise from the prior quarter, and to exhibit greater illiquidity. We conduct a battery of tests using bivariate portfolio sorts and cross-sectional regression analyses at the firm level with a comprehensive list of control variables to ensure that these firm characteristics do not drive the anomalous return differences between high- and low-earnings announcement maximum return stocks in the pre-earnings announcement period. We document that the hedge pre-earnings announcement stock returns between high- and low-*EA_MAXRET* stocks are robust to sorts on size, the book-to-market ratio, beta, idiosyncratic volatility, momentum, the Amihud illiquidity measure, and prior-quarter standardized unexpected earnings. The results from multivariate regression analyses corroborate this robustness.

Our additional robustness checks control for a comprehensive list of other variables that have been documented to predict stock returns around earnings announcements. Specifically, we find that the *EA_MAXRET* phenomenon continues to be unexplained by the *MAX* effect as documented by Bali et al. (2011); the earnings announcement returns of past stock winners as documented by Aboody et al. (2010); the price run-up caused by divergence in investor opinions documented by Berkman, Dimitrov, Jain, Koch, and Tice (2009); short-sale constraints as documented by Nagel (2005); earnings seasonality mispricing as documented by Chang, Hartzmark, Solomon, and Soltes (2016); or the return reversal ahead of earnings announcements as documented by So and Wang (2014).

Next, we make various additional risk adjustments to investigate whether the *EA_MAXRET* phenomenon is subject to risks. We find that the return differences between the two extreme *EA_MAXRET* portfolios are not affected by alternative risk adjustment procedures or alternative portfolio weightings. Furthermore, to ensure that our results are not sensitive to the period over which *EA_MAXRET* is measured, we calculate *EA_MAXRET* using several multi-quarter periods (from one rolling quarter to 16 rolling quarters in the past). We document that the return differences between the two extreme earnings announcement maximum return portfolios range between 58 and 110 bps in the 10 days leading up to earnings announcements. These return differences are all statistically significant at the 1% level and robust during the 36-year period in our study.

There is a potential measurement error in our estimates of the pre-announcement period returns. Specifically, the earnings announcements from Compustat are ex post data recorded based on the actual dates when the firms released earnings. Thus, the earnings announcement dates that investors expect in the market may not be the same as the actual earnings announcement dates, resulting in a potentially noisy measure of pre-announcement stock returns.[39] To abstract from this noise, we re-examine our *EA_MAXRET* strategy for a sample of stocks where we can establish expected earnings announcements following the methodology of Cohen et al. (2007) instead of relying on actual earnings announcements from Compustat. In this subsample, the top *EA_MAXRET* portfolios yield 142 bps in the 10-day period leading up to expected earnings announcements. A hedge *EA_MAXRET* strategy based on expected earnings announcements yields 109 bps. Furthermore, whether we use the exact earnings announcement dates from the Wall Street Horizon (WSH) database that were available to market participants ahead of earnings announcements or the earlier earnings announcement dates between the Institutional Brokers' Estimate System (I/B/E/S) and Compustat does not change our main findings.

We establish that the earnings announcement lottery payoff is a highly persistent equity characteristic. We document that the earnings announcement maximum returns from prior earnings announcements strongly predict stock excess returns surrounding current earnings announcements. In cross-sectional regressions with several control variables, maximum returns from past earnings announcements and idiosyncratic volatility are the strongest predictors of maximum returns in current earnings announcements. In other words, *EA_MAXRET* exhibits substantial persistence in firm-level cross-sectional regressions, even after we control for a variety of other firm-level variables. We interpret our findings as errors in investors' probability weighting

[39] Using expected earnings announcement dates to avoid a selection bias arising from the timing of actual earnings announcement dates, Cohen, Dey, Lys, and Sunder (2007) report significantly higher stock returns during the earnings announcement period than during the non-earnings announcement period. The authors conclude that the increased returns on earnings announcement dates are related to earnings announcement risk and this risk is non-diversifiable.

causing them to overvalue stocks that have a small probability of a large positive return during earnings announcements.[40] This interpretation is consistent with the cumulative prospect theory of Tversky and Kahneman (1992) and the optimal beliefs framework of Brunnermeier, Gollier, and Parker (2007).[41] In our final avenue of inquiry, we address the possibility that this pre-earnings announcement return is due to investors requiring a premium because idiosyncratic volatility from earnings announcements is approaching.[42] If this is simply a volatility effect, then *EA_MINRET* (the minimum past earnings announcement return), which is also highly correlated with earnings announcement volatility, should generate an effect similar to that of *EA_MAXRET*.[43] While we document an effect of *EA_MINRET* on stock returns, it is not robust. Next, controlling for earnings surprise, we document a reversal of the *EA_MAXRET* phenomenon in the post-earnings announcement period. Thus, once a lottery outcome is determined from the released earnings, the overpricing of high-*EA_MAXRET* stocks in the pre-announcement period is mostly corrected.

The findings in this study contribute three important insights to the literature. First, we document a new predictable pattern of stock returns in the pre-earnings announcement period. Our study shows that investors overweight stocks with high past earnings announcement payoffs, resulting

[40] Motivated by the idea that retail investors would be more likely to overestimate the probability of earnings announcement lottery payoffs, we test and find that the magnitude of the *EA_MAXRET* phenomenon is stronger for stocks with lower institutional ownership and for stocks with low analyst coverage. These findings indicate the importance of the investor clientele effect.

[41] Several studies, such as those of Odean (1999), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008), show that investors are not well diversified. Cohen et al. (2007) and Frazzini and Lamont (2007) argue that idiosyncratic volatility surrounding earnings announcements is not diversifiable and this could explain why investors demand a premium for earnings announcements.

[42] The literature regards earnings announcements as one short period when diversification is difficult, leading to an earnings announcement risk premium. Studies documenting a significant risk premium around predictable earnings announcements include those of Penman (1984), Kalay and Loewenstein (1985), Chari, Jagannathan, and Ofer (1988), and Ball and Kothari (1991). Barber, De George, Lehavy, and Trueman (2013) conduct an international study of the earnings announcement premium and document that this premium is a resilient phenomenon across the globe.

[43] On the other hand, much of the theoretical literature would predict that the effect of *EA_MINRET* can be the opposite. For example, under the cumulative prospect theory of Barberis and Huang (2008), investors can also overweight small probabilities of large earnings announcement losses and shun these stocks in the period leading up to current earnings announcements, resulting in predictable lower returns.

in predictable returns in the period leading up to current earnings announcements. We only find predictable pre-earnings announcement returns for stocks with high maximum past earnings announcement returns and no predictable returns for stocks with low minimum past earnings announcement returns. Hence, this pre-earnings announcement effect is not homogeneous across stocks but increases with the maximum past earnings announcement returns. We also find that the stock's maximum return from past earnings announcements strongly predicts future maximum earnings announcement returns. We conclude that earnings announcement lottery payoff momentum exists when stocks with high (low) maximum past earnings announcement returns exhibit high (low) future maximum earnings announcement returns.

Second, our study contributes to the strand of literature that examines prior stock returns when measuring price reactions surrounding earnings announcements. Aboody et al. (2010) find that past stock market winners exhibit a predictable return pattern around their earnings announcements and suggest that pre-earnings stock price performance attracts individual investors' attention.[44] So and Wang (2014) document significant reversals of pre-earnings announcement stock returns during earnings announcements and suggest that market makers demand higher expected returns prior to earnings announcements. Our study shows that prior stock return performance, when measured in a short window surrounding past earnings announcements, also attracts individual investors' attention and investment dollars in the period leading to current earnings announcements.

Finally, our study contributes to an emerging literature that shows a preference among investors for assets with lottery-like payoffs, that is, assets that have some probability of a large payoff. For

[44] Trueman et al. (2003) also find an economically large abnormal return over a five-day window before the earnings announcements of Internet stocks from 1998 to 2000 and suggest that investor attention explains this phenomenon.

example, Kumar (2009) shows that certain individual investors exhibit a preference for lottery-type stocks that are often defined as low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness. Bali et al. (2011) document investor demand for stocks that have the highest maximum daily return in the prior trading month. Bali et al. (2017a) show that this lottery demand is priced in the cross section of monthly stock returns. These studies suggest that certain investors prefer lottery-type stocks and are therefore poorly diversified, leading to predictable future returns for such stocks. In the context of earnings announcements, we find that investors prefer stocks with a probability of a large positive earnings announcement payoff and they bid up the prices of these stocks in the period leading up to earnings announcements.[45]

The remainder of this chapter is organized as follows. Section 3.2 discusses the data and methodology in constructing the earnings announcement maximum returns and other control variables. Section 3.3 presents univariate and bivariate portfolio analyses and multivariate regression analysis at the firm level. Section 3.4 provides findings from various robustness analyses. Section 3.5 draws conclusions and discusses implications for future research.

3.2. Earnings Announcement Maximum Returns

3.2.1. Data

We use stock return data from the Center for Research in Security Prices (CRSP) for common stocks (CRSP share codes 10 or 11) for firms listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ from 1980 to 2015. We use Compustat to

[45] In this study, we show that the negative relation between idiosyncratic volatility and stock returns as suggested by Ang, Hodrick, Xing, and Zhang (2006, 2009) and Jiang, Xu, and Yao (2009) does not hold in the period immediately before earnings announcements. We even document a robust reverse idiosyncratic volatility effect: stocks with high excess returns, especially excess returns measured surrounding past earnings announcements, exhibit higher returns in the pre-earnings announcement period.

determine the actual quarterly earnings announcement dates. We also define earnings announcement dates using two alternative approaches. First, we compare the earnings announcement dates reported by Compustat and I/B/E/S and follow DellaVigna and Pollet (2009) to assign the earlier date as the correct earnings announcement date. Second, we use daily snapshots of earnings calendar data provided by WSH for a subsample of firms from 2006 through 2015.[46]

For each quarter in a calendar year, we compute the value of the three-day excess stock return around the earnings announcement. Excess stock return is defined as the difference between a stock return and the CRSP value-weighted index return over the same period. Stocks with a high absolute value of the three-day excess stock return are deemed to have high earnings announcement payoffs. We then take the maximum value of this earnings announcement three-day excess stock return across all quarterly earnings announcements in the calendar year *y* - 1 and denote this measure *EA_MAXRET*. We repeat this procedure on a yearly basis. We use a portfolio sort based on *EA_MAXRET* to examine stock returns in the period leading up to earnings announcements in year *y*.

We use several variables to control for risk and other patterns in stock returns. We use the market value of common stock (*SIZE*) and the book-to-market ratio (*BM*) to control for the size effect and book-to-market effect, respectively (Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). The variables *SIZE* and *BM* are computed at the end of year *y* - 1. We compute momentum

[46] WSH provides real-time calendars of major corporate events for about 3,000 North American stocks since 2006, including scheduled and actual earnings announcement dates. The database provider updates the calendars by 4:00 a.m. EST of each trading day so that traders can track corporate events with accuracy in real time. The WSH actual earnings announcements database has an accuracy rate of over 99% (DeHaan, Shevlin, and Thornock, 2015) and is therefore a more reliable source of earnings announcements for several academic studies (e.g., DeHaan et al., 2015; Livnat and Zhang, 2015; Johnson and So, 2017b).

(*MOM*) as the stock return in the six-month period ending on day t - 11 before earnings announcements. We also compute the stock beta (*BETA*) as the factor loading on the market risk premium from the four-factor model estimated over the 200 trading days ending on day t - 11 before earnings announcements. We compute idiosyncratic volatility risk (*IVOL*) as the standard deviation of residual returns from the four-factor model that estimates beta. We follow Amihud (2002) and compute the illiquidity measure (*ILLIQ*) as the ratio of daily absolute stock returns to the dollar trading volume over the 200 trading days ending on day t - 11 before earnings announcements.[47] Finally, we compute standardized unexpected earnings from the prior quarter ($SUE_{q\text{-}1}$) as seasonally adjusted quarterly earnings per share divided by the price per share at the end of the quarter to control for post-earnings announcement drift (Bernard and Thomas, 1989, 1990).[48]

We obtain institutional investors' shares holdings from the Thomson Reuters Institutional Holdings (13F) Database. Analyst coverage is measured using data from I/B/E/S. Daily and monthly market excess returns and risk factor returns are obtained from Kenneth French's data library.[49] For investor sentiment measures, we use Baker and Wurgler's (2006) sentiment index, the Michigan Consumer Sentiment Index (MCSI) compiled by the University of Michigan Survey Research Center, and the volatility index (VIX) calculated by the Chicago Board Options Exchange (CBOE) and available from Wharton Research Data Services. The other data we use

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[47] Following Gao and Ritter (2010), we adjust for institutional features of the way volume is reported on NASDAQ. Specifically, we divide the volume reported by the CRSP for stocks that trade on NASDAQ by 2.0, 1.8, 1.6, and 1.0 for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and during or subsequent to January 2004, respectively.

[48] An advantage of the earnings surprise measure based on a seasonal random walk model over other more complex time-series model is that it can be estimated for almost every firm–quarter in the Compustat data (Livnat and Mendenhall, 2006) while performing as well as other more complex time-series models in capturing earnings news (Foster, Olsen, and Shevlin, 1984). To ensure the robustness of our findings, we repeat our analysis using standardized unexpected earnings based on analyst forecasts. The results, presented in Table 2.5, suggest that different measures of earnings surprise have little effect on our findings.

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

include the business cycle database of the National Bureau of Economic Research (NBER); the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015); and the economic policy uncertainty index of Baker, Bloom, and Davis (2016).[50]

3.2.2. Descriptive Statistics

Panel A of Table 3.1 presents summary statistics for the 599,566 firm–quarter observations in the overall sample from 1981 to 2015.[51] The mean (median) value for the three-day excess stock return around earnings announcements, *EA_MAX*, is 7.41% (5.04%). This finding highlights the high volatility in stock returns in the short window around earnings announcements. The mean value for *EXRET[-10,-1]* is 0.0044, indicating a positive premium for the stock returns in the 10-day period leading up to earnings announcements.[52] The mean (median) market value of firms in the sample is $2.249 billion ($236 million). The mean book-to-market ratio is 0.80. In the six-month period leading up to earnings announcements, the average stock return (*MOM*) is 8.5%. The average beta (*BETA*) is 0.899 and the average idiosyncratic volatility (*IVOL*) is 3.2%. The average Amihud illiquidity measure is 0.56 and the average standardized unexpected earnings from the prior quarter (SUE_{q-1}) are 0.001.

{ENTER TABLE 3.1}

Panel B of Table 3.1 presents the mean values for the variables stratified by deciles of *EA_MAXRET*. There is a striking difference in the earnings announcement maximum return

[50] We thank Sydney Ludvigson and Nicholas Bloom for making their uncertainty indexes available through their websites.
[51] Because we use *EA_MAXRET* in 1980 to form portfolios in 1981, the analysis of *EA_MAXRET* portfolio returns covers the period 1981–2015.
[52] This result is consistent with evidence from several prior studies. For example, Aboody et al. (2010) report an average pre-announcement market-adjusted return of 0.30%, while Berkman and Truong (2009) report an average of 0.34%.

between the extreme *EA_MAXRET* portfolios. On average, the three-day excess stock return surrounding past earnings announcements is -2.92% for the bottom *EA_MAXRET* portfolio and 27.94% for the top *EA_MAXRET* portfolio, for a difference of 30.90% in excess returns. The average earnings announcement maximum return of the top decile *EA_MAXRET* portfolio is also nearly four times the average earnings announcement excess return of the overall sample, as reported in Panel A (7.41%). While it may be difficult to interpret the average value for *SIZE*, since market capitalization increases over time for firms, the relative difference between the decile 1 and decile 10 *EA_MAXRET* values indicates that a high-*EA_MAXRET* portfolio tends to contain smaller stocks. There is also evidence that the book-to-market ratio is higher in the low-*EA_MAXRET* portfolio and lower in the high-*EA_MAXRET* portfolio. Stocks in the high-*EA_MAXRET* portfolio also appear to have greater price momentum, a higher beta, greater general idiosyncratic volatility, and a higher Amihud illiquidity measure. Interestingly, stocks in the high-*EA_MAXRET* portfolio exhibit a more positive earnings surprise from the prior quarter (0.011) than those in the low-*EA_MAXRET* portfolio (-0.001).

3.3. EA_MAXRET and Pre-Earnings Announcement Excess Stock Returns

3.3.1. Univariate Portfolio Analysis

Table 3.2 presents the *EXRET[-10,-1]* values for decile portfolios that are formed by sorting stocks based on *EA_MAXRET* from the prior calendar year. The results are based on actual earnings announcement dates from Compustat and pseudo-earnings announcement dates over the period 1981–2015. We construct a pseudo-earnings announcement date by subtracting a random number from a uniform distribution between 10 and 40 from the actual earnings announcement date.[53] These pseudo-earnings announcements represent random periods in which earnings are not announced. We compare the stock returns relative to actual earnings announcements (experimental group) and pseudo-earnings announcements (control group) to determine whether the stock return pattern before earnings announcements is exclusively driven by earnings announcements. Portfolio 1 (low *EA_MAXRET*) has the lowest earnings announcement maximum return and portfolio 10 (high *EA_MAXRET*) the highest.

{ENTER TABLE 3.2}

In column (1) of Table 3.2, where *EXRET[-10,-1]* is measured relative to actual earnings announcement dates, the average excess return of the top *EA_MAXRET* portfolio is 1.15% over the 10-day period leading up to earnings announcements and significant at the 1% level. The average excess return difference between decile 10 (high *EA_MAXRET*) and decile 1 (low *EA_MAXRET*) is 0.89% and also significant at the 1% level. In untabulated tests, we find that the hedge returns from going long on decile 10 of *EA_MAXRET* and short on decile 1 of *EA_MAXRET* in the 10 days leading up to earnings announcements are positive in 109 of the 140 quarters in our sample period.[54] Excess returns increase monotonically from decile 3 to decile 10. From decile 4 to decile 10, excess returns are significant at the 10% level or better and the pre-earnings announcement stock returns are especially strong in the two highest *EA_MAXRET* deciles (deciles 9 and 10). Figure 3.1 presents the annualized market-adjusted returns based on long–short

[53] We follow Lee, Ready, and Seguin (1994) and Christie, Corwin, and Harris (2002) and employ a uniform distribution between 10 and 40 days to separate actual earnings announcements from pseudo-earnings announcements when no earnings news is announced.

[54] The strategy earns positive returns in 78% of the quarters in the sample period. The *z*-score of 6.59 from a binomial distribution test rejects the null hypothesis that the proportion of positive hedge returns over the sample period of 140 quarters equals 0.5.

portfolios sorted by earnings announcement maximum returns (*EA_MAXRET*) across the 35 years of the sample period (1981–2015). The annualized hedge return is the aggregation of the four quarterly *EA_MAXRET* hedge returns in a year. The hedge portfolio earns positive abnormal returns in 33 of the 35 years of the sample period, suggesting that the spread in pre-earnings announcement stock returns is stable.

{ENTER FIGURE 3.1}

In column (2) of Table 3.2, where *EXRET[-10, -1]* is measured relative to pseudo-earnings announcement dates, the pattern of excess returns across the deciles of *EA_MAXRET* as observed in column (1) completely disappears. The excess return difference between the two extreme *EA_MAXRET* portfolios is 0.0026 and statistically insignificant, indicating no earnings announcement lottery payoff effect in the period in which no earnings news is pending. In addition, none of the excess returns across decile portfolios of *EA_MAXRET* is statistically significant, indicating no premium in stock returns if no earnings news is going to be announced. In columns (3), the differences in excess returns between actual earnings versus pseudo-earnings announcement dates confirm that the pre-earnings announcement premium is only specific to the period immediately before a pending earnings announcement and that the pre-earnings announcement premium is increasing in past earnings announcement maximum returns.

Overall, the univariate portfolio results in Table 3.2 reveal two key findings. First, there is a significant premium in the period immediately before earnings announcements. Second, pre-earnings announcement stock returns increase in past earnings announcement maximum returns. However, Panel B of Table 3.1 shows that high-*EA_MAXRET* stocks tend to have characteristics that could demand a premium and hence univariate portfolio analysis and excess return calculations may not account for all firm characteristics that could lead to the pre-earnings announcement stock return pattern. We therefore control for firm characteristics in the subsequent analyses.

3.3.2. Bivariate Portfolio Analysis

In this section, we examine the relation between *EA_MAXRET* and pre-earnings announcement excess stock returns after controlling for size, the book-to-market ratio, momentum, beta, idiosyncratic volatility, illiquidity, and prior-quarter standardized unexpected earnings. For example, in controlling for size, we first sort stocks into decile portfolios based on market capitalization. Then, within each size decile, we sort stocks into decile portfolios based on *EA_MAXRET*. We average excess returns across the 10 size deciles to produce decile portfolios of *EA_MAXRET* that contain all sizes of firms. This bivariate portfolio sort creates a set of *EA_MAXRET* decile portfolios with similar contributions from all levels of firm size and, hence, these *EA_MAXRET* decile portfolios control for differences that can be attributed to firm size. We repeat the same procedure to create decile portfolios of *EA_MAXRET* that control for other firm characteristics.

Table 3.3 presents bivariate portfolio results for *EXRET[-10,-1]* relative to actual earnings announcement dates. Panel A (Panel B) reports the results for equally weighted (value-weighted) portfolios. Column (1) of Panel A shows that, after firm size is controlled for, the average excess return difference between the high- and low-*EA_MAXRET* portfolios is 0.81% and significant at the 1% level, which is quite similar to the average hedge return of 0.89% in Table 3.2. Thus, market capitalization does not explain the earnings announcement lottery payoff effect on the pre-announcement stock returns.[55]

{ENTER TABLE 3.3}

We control for the book-to-market ratio in a similar way in column (2) of Panel A of Table 3.3 and the results show that the *EA_MAXRET* premium is also preserved. The excess return difference between the high- and low-*EA_MAXRET* portfolios is 0.95% and significant at the 1% level. In columns (3) and (4), when we control for momentum and beta, respectively, the excess return differences between the high- and low-*EA_MAXRET* portfolios are 0.82% and 0.88%, respectively, both significant at the 1% level. These returns are also economically large, since they are measured over a short period of 10 days before earnings announcements. Recall that Panel B of Table 3.1 shows that high-*EA_MAXRET* stocks tend to have strong momentum and a high beta; the correlations between *EA_MAXRET* and momentum and beta are therefore expected to reduce the variation of excess returns across *EA_MAXRET* portfolios. However, neither momentum nor beta explains the earnings announcement lottery payoff effect in the pre-announcement period.

Column (5) of Panel A in Table 3.3 controls for general stock return idiosyncratic volatility as measured by the four-factor model. Since idiosyncratic volatility and earnings announcements maximum return are highly correlated, *EA_MAXRET* could be merely an alternative measure for stock return idiosyncratic volatility (*IVOL*). However, this is not the case, as shown by the excess returns across *EA_MAXRET* portfolios in column (5). After the effect of idiosyncratic volatility is controlled for, the excess return difference between the high- and low-*EA_MAXRET* portfolios is

[55] We repeat the bivariate portfolio analyses for Standard & Poor's (S&P) 500 stocks, stocks traded on the NYSE (large and liquid stocks), and stocks with a price at the beginning of the quarter of at least $5 to minimize the impact of microcaps or microstructure bias. The results, available upon request, suggest that the earnings announcements lottery payoff effect is not chiefly driven by small or illiquid stocks.

0.60% and significant at the 1% level. Thus, the pre-earnings announcement lottery premium is not driven by the effects of general idiosyncratic volatility.

In column (6) of Panel A in Table 3.3, we control for liquidity and still document a 0.84% excess return difference between the high- and low-*EA_MAXRET* portfolios, which is also significant at the 1% level. In addition, we control for the post-earnings announcement drift phenomenon by forming portfolios based on the prior quarter's standardized unexpected earnings in column (7). The excess return difference between the high- and low-*EA_MAXRET* portfolios is 0.67% and also significant at the 1% level. Thus, liquidity and post-earnings announcement drift do not explain the positive relation between *EA_MAXRET* and excess returns in the period leading up to earnings announcements.[56]

The results in Panel B, for value-weighted portfolios, are consistent with those in Panel A, for equal-weighted portfolios, except the excess return differences between the two extreme *EA_MAXRET* portfolios in Panel B are slightly lower than in Panel A. The excess return differences between the high- and low-*EA_MAXRET* portfolios range between 60 bps and 95 bps (in Panel A) and between 28 bps and 95 bps (in Panel B) across different bivariate portfolio sorts. The hedge returns, however, are still economically and statistically significant at the 1% level.

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[56] In untabulated tests, we also examine whether the average excess return difference between the high- and low-*EA_MAXRET* portfolios persists after controlling for individual stock sensitivity to macroeconomic uncertainty. This test is motivated by recent evidence that macroeconomics uncertainty is an important risk factor for individual stocks and equity portfolios (Brogaard and Detzel, 2015; Bali, Brown, and Tang, 2017) and plays a significant role in determining the quality and timeliness of quarterly earnings forecasts (Kim, Pandit, and Wasley, 2015; Boone, Kim, and White, 2017). Specifically, we compute the beta sensitivity of individual stocks to the macroeconomic uncertainty index of Jurado et al. (2015). In the bivariate sort based on uncertainty beta and *EA_MAXRET*, the excess return difference between the high- and low-*EA_MAXRET* portfolios is 0.80% when equally weighted and 0.89% when value weighted. Thus, the pre-earnings announcement lottery effect remains robust after we control for exposure to macroeconomic uncertainty.

Overall, the results in Table 3.3 indicate that several firm characteristics well known in determining the cross section of stock returns cannot explain the earnings announcement lottery payoff effect in the pre-earnings announcement period. The effect is weaker when portfolios are formed using value weights, consistent with the notion that the pricing of *EA_MAXRET* is more pronounced among smaller stocks.

3.3.3. Firm-Level Cross-Sectional Regressions

While the bivariate portfolio analyses confirm the resilience of the earnings announcement lottery payoff, double portfolio sort analyses are not able to control for multiple effects simultaneously. In this section, we examine the cross-sectional relation between *EA_MAXRET* and excess stock returns in the pre-earnings announcement period at the firm level, using cross-sectional regressions. In all the regressions, we compute two-way cluster *t*-statistics based on standard errors clustered by firm and quarter.

Table 3.4 presents the regressions of *EXRET[-10,-1]* based on actual earnings announcement dates on several firm characteristics. In column (1), the coefficient of *EA_MAXRET* is 0.0337, with a *t*-statistic of 5.21. This confirms a significant positive relation between the earnings announcement maximum return (*EA_MAXRET*) and the excess stock return at the firm level. In columns (2), (3), and (6) to (8), we also see that excess returns in the pre-earnings announcement period are significantly and inversely related to firm size and significantly and positively related to the book-to-market ratio, idiosyncratic volatility, illiquidity, and prior-quarter standardized unexpected earnings. The results in column (8) confirm a resilient post-earnings announcement drift phenomenon leading up to the next quarterly earnings announcements. We do not find any significant relation between excess stock returns in the pre-earnings announcement period and momentum or beta. The full regression model with all the control variables in column (9) yields fairly similar results, although the inverse relation between firm size and excess return disappears. In the full regression model, we find that the excess return is significantly and positively related to *EA_MAXRET*, *IVOL*, and SUE_{q-1}.

{ENTER TABLE 3.4}

Overall, the results in Table 3.4 provide strong corroborating evidence from regression analyses of an economically and statistically significant relation between past earnings announcement maximum returns and excess stock returns in the pre-earnings announcement period. This result is consistent with the notion that earnings announcements lottery payoffs are priced in the period immediately before earnings announcements.

3.3.4. Additional Regression Analyses

We perform additional regression analyses to ensure the robustness of our results. Essentially, we control for other variables that have been documented in earlier studies that are related to stock returns around earnings announcements in the regression of *EXRET[-10,-1]* against *EA_MAXRET*.

{ENTER TABLE 3.5}

Table 3.5 presents the results from these additional regression analyses. For brevity, we only report the coefficients of *EA_MAXRET*. Controlling for none of the following has a major effect on the regression results: 1) the maximum return in the month prior to future earnings announcements (Bali et al., 2011), 2) past stock winners (Aboody et al., 2010), 3) differences in analyst opinions (Berkman et al., 2009), 4) short-sale constraints (Nagel, 2005; Berkman et al., 2009), 5) earnings seasonality (Chang, Hartzmark, Solomon, and Soltes, 2016), 6) return reversals ahead of earnings announcements (So and Wang, 2014), 7) industry fixed effects, 8) Fama–Macbeth regression with *t*-statistics adjusted following Newey and West (1987), and 9) *SUE* using analysts' forecasts (Livnat and Mendenhall, 2006). We also consider alternative measures of pre-earnings announcements returns or repeat the regression analyses for different subsamples and find these approaches/filters have little effect on our regression results.

3.3.5. Interaction Effects in Firm-Level Cross-Sectional Regressions

In this section, we examine whether the positive relation between *EA_MAXRET* and excess stock returns in the pre-earnings announcement period exhibits cross-sectional variation within each firm characteristic. While the inclusion of firm characteristics does not explain the earnings announcement lottery payoff, as shown in Table 3.4, the premium could be more pronounced among the most difficult stocks to trade in the period leading up to earnings announcements.

Table 3.6 presents an interaction regression for *EXRET[-10,-1]* based on actual earnings announcement dates. In columns (3) and (6), we find evidence that the earnings announcement lottery payoff effect is somewhat weaker among firms with a high *IVOL* (the coefficient of *EA_MAXRET *IVOL* is -0.2106, with a *t*-statistic of -3.48) and stronger among firms with a high Amihud illiquidity measure (the coefficient of *EA_MAXRET *ILLIQ* is 0.0004, with a *t*-statistic of 4.96). The positive coefficient of *EA_MAXRET *ILLIQ* is not surprising, since we expect the earnings announcement lottery payoff effect to be more pronounced among illiquid stocks. However, this interaction effect is rather small and disappears when all the control variables are included in column (8). In column (8), where all the variables and interaction effects are included, we find that the positive relation between *EA_MAXRET* and excess return is reduced among firms with a high *IVOL* measure.

Overall, the interaction analyses in Table 3.6 suggest that the positive relation between *EA_MAXRET* and excess stock returns in the pre-announcement period is robust to various interaction effects. There is evidence that the relation between *EA_MAXRET* and excess stock return is more pronounced among firms with low idiosyncratic volatility.

{ENTER TABLE 3.6}

3.4. Robustness Checks

3.4.1. Alternative Portfolio Weightings and Risk Adjustments

In this section, we examine whether the results of our main analyses are robust to different methods of portfolio weightings and different risk adjustment techniques. Panel A of Table 3.7 presents the results of the earnings announcement lottery payoff effect using alternative portfolio weighting methods. Panel B provides the results of the earnings announcement lottery payoff effect using alternative risk adjustment techniques.

{ENTER TABLE 3.7}

Column (1) of Panel A of Table 3.7 shows that the excess return difference between the high- and low-*EA_MAXRET* value-weighted portfolios is 0.90%. This value-weighted portfolio excess return difference is similar to the equal-weighted portfolio difference presented in Table 3.2 and is significant at the 1% level and also economically large over a short period of 10 days. In column (2), the excess return difference between the high- and low-*EA_MAXRET* share volume-weighted portfolios is 0.88%.[57] In column (3), the excess return difference between the high- and low-*EA_MAXRET* dollar volume-weighted portfolios is 0.84%. Overall, the earnings announcement lottery payoff effect in the pre-earnings announcement period is almost unchanged across various portfolio weighting methods.

Column (1) of Panel B of Table 3.7 presents size-adjusted returns across *EA_MAXRET* portfolios, defined as the differences between the stock returns and the portfolio returns of the size decile to which the stock belongs. We find that the size-adjusted return difference between the high- and low-*EA_MAXRET* portfolios is 0.86%. Column (2) of Panel B presents the capital asset pricing model (CAPM) alphas across the *EA_MAXRET* portfolios, where the CAPM model is calibrated using a period of 200 trading days ending on day *t* - 11 before earnings announcements. The CAPM alpha difference between the high- and low-*EA_MAXRET* portfolios is 0.84%. Column (3) presents the four-factor alphas across the *EA_MAXRET* portfolios, where the four-factor model factor loadings are also estimated using a period of 200 trading days ending on day *t* - 11 before earnings announcements. The four-factor alpha difference between the high- and low-*EA_MAXRET* portfolios is 0.85%. Hence, various risk adjustments in Panel B also confirm the presence of an earnings announcement lottery payoff in the pre-earnings announcement period.

[57] Several papers recommend the use of value-weighted returns for portfolio analyses. For example, Fama and French (2008) and Hou, Xue, Zhang (2017) suggest that microcaps, which comprise, on average, only 3% of the market value but account for about 60% of the total number of stocks, are highly influential in equal-weighted returns. Blume and Stambaugh (1983) and Asparouhova, Bessembinder, and Kalcheva (2013) find that microstructure frictions can bias upward cross-sectional monthly mean equal-weighted returns. These authors suggest that these biases are minimal in value-weighted returns. For our documented earnings announcement lottery payoff effect, the returns from the value- and equal-weighted portfolios are almost identical (0.90% vs. 0.89%), which further confirms that the documented pre-earnings announcement premium is not driven by small, illiquid stocks or market microstructure bias.

3.4.2. Alternative Measures

While our *EA_MAXRET* measure estimated from all earnings announcements in the prior calendar year is a simple and intuitive measure of the lottery feature specific to earnings announcements, the choice of the one-year period over which the four *EA_MAXRET* values are obtained for the four quarterly earnings announcements is somewhat arbitrary. Hence, alternatively, we can measure earnings announcement maximum returns over the past *N* rolling quarters, where *N* = 1, 2, …, 16 quarters. Panel A in Table 3.8 presents the results of this analysis. As before, we present the equal-weighted excess returns across the decile portfolios of *EA_MAXRET*.

{ENTER TABLE 3.8}

The results in Panel A of Table 3.8 show that the earnings announcement lottery payoff effect is robust to several alternative measures of *EA_MAXRET*. The excess return difference between the high- and low-*EA_MAXRET* portfolios when *EA_MAXRET* is measured over only one prior earnings announcement (*N* = 1) is 0.58% and significant at the 1% level. This excess return difference is 0.83% for *N* = 2, 0.77% for *N* = 3, 0.98% for *N* = 4, 0.96% for *N* = 8, and 1.10% for *N* = 16. Since the earnings announcement lottery payoff effect is robust to *EA_MAXRET* measured over different multi-quarter periods, the earnings announcement lottery payoff is likely to be highly persistent over time.

Panel B of Table 3.8 presents the earnings announcement lottery payoff effect when *EA_MAXRET* is realized in the first, second, third, and fourth quarters of the prior calendar year. The effect is strongest when *EA_MAXRET* is realized in the fourth quarter, with the top decile of *EA_MAXRET* stocks yielding 1.41% and the hedge *EA_MAXRET* strategy delivering 1.49%. A plausible explanation is that investors pay a great deal more attention to fourth-quarter earnings announcements (generally annual earnings announcements) and, therefore, large payoffs from these announcements attract a higher level of demand from lottery investors.[58] When *EX_MAXRET* is realized in the first, second, or third quarter of the prior year, the average return differences between the two extreme deciles are, in turn, 0.97%, 0.44%, and 0.87%, all significant at the 1% level. Thus, the results in Panel B of Table 3.8 suggest that the earnings announcement lottery payoff effect is robust to controlling for the timing of *EA_MAXRET*.

3.4.3. Expected and Precise Earnings Announcement Dates

Our main results are based on exact knowledge of the actual earnings announcement dates whereas, in practice, firms can deviate from their scheduled announcement dates. The actual earnings announcement dates in Compustat can therefore incur a look-ahead bias in our *EA_MAXRET* strategy, because not knowing the exact time of the earnings release leaves doubt in the measurement of *EXRET[-10,-1]*.[59]

In this section, we examine the relation between *EA_MAXRET* and excess stock returns in the period leading up to alternative sources of earnings announcement dates. First, we derive expected earnings announcement dates instead of relying on actual earnings announcements from Compustat. We form expected earnings announcement dates for a firm using the approach developed by Cohen et al. (2007) that is based on the distributions of the firm's earnings

[58] DeHaan et al. (2015) find that abnormal Google search volumes and Electronic Data Gathering, Analysis, and Retrieval 8-K downloads surrounding earnings announcement dates are particularly strong for the fourth quarter, suggesting that fourth-quarter earnings announcements especially catch investor attention and hence motivate their action (e.g., trading behavior).

[59] Implementing a trading strategy based on earnings announcement maximum returns requires knowing the actual earnings announcement dates. It could be more practical to investigate this strategy using expected earnings announcement dates. If late-announcing firms are more likely to disclose bad news and the market anticipates this bad news on the expected announcement dates when these firms did make such an announcement, computing stock returns in the period leading up to the actual earnings announcement dates could introduce a downward bias to the earnings announcement maximum return premium because expected announcement dates will likely fall in the period immediately before the actual earnings announcement dates for late announcers.

announcement dates in prior quarters. Specifically, we identify a firm's actual earnings announcement date as one of the 63 days in the quarter. We then use the median quarterly earnings announcement dates as identified using earnings announcements from the prior rolling five years as the expected earnings announcement date for the current quarterly earnings announcement.

Second, to mitigate potential ambiguities that investors may not know the actual earnings announcement dates ahead of time, we turn to the WSH database to obtain the earnings announcement dates that are available to investors ahead of the announcement time. Because WSH provides real-time corporate events, it updates its earnings calendars by 4:00 a.m. EST of each trading day so that their users are aware of all forthcoming earnings announcements together with the exact timing in the trading day. The WSH data allow us to examine the *EA_MAXRET* strategy over the WSH coverage period from 2006 to 2015.

Third, to reduce measurement error in the identification of earnings announcement dates, we follow DellaVigna and Pollet (2009) and compare the earnings announcement dates reported by Compustat and I/B/E/S and assign the earlier date as the correct earnings announcement date.

Table 3.9 presents the results of this analysis. Column (1) presents the excess returns across *EA_MAXRET* decile portfolios, where *EXRET[-10,-1]* is measured relative to expected earnings announcement dates instead of actual earnings announcement dates. The results are even stronger than those reported in Table 3.2. The excess return difference between the two extreme portfolios of earnings announcement maximum return is 109 bps in the 10 days leading to expected earnings announcements.[60]

[60] In untabulated tests, we also construct bivariate portfolio results based on *EXRET[-10,-1]* relative to expected earnings announcement dates. After controlling for size, the book-to-market ratio, momentum, beta, idiosyncratic volatility, illiquidity, and prior quarter standardized unexpected earnings, we find the excess return differences between the high and low *EA_MAXRET* portfolios to be 0.73%, 0.96%, 0.73%, 0.94%, 0.43%, 0.83%, and 0.58%,

{ENTER TABLE 3.9}

Column (2) in Table 3.9 presents excess returns across *EA_MAXRET* decile portfolios, where *EXRET[-10,-1]* is measured relative to WSH earnings announcement dates. Here, the hedge return exhibits 63 bps in the 10 days leading to precise earnings announcement dates. Column (3) repeats our main analysis using the earlier earnings announcement dates recorded between I/B/E/S and Compustat. We also document the hedge *EA_MAXRET* strategy as delivering 89 bps.

Overall, the results in Table 3.9 confirm that the earnings announcement lottery payoff effect is still present when we measure excess stock returns in the pre-earnings announcement period relative to expected earnings announcement dates instead of actual earnings announcement dates. The results, albeit smaller in magnitude, also show a significant spread for the WSH sample where the earnings announcement dates are known to the market participants ahead of time. Finally, the results are similar when we use the earlier earnings announcement dates recorded between I/B/E/S and Compustat.

3.4.4. Cross-Sectional Predictability of Earnings Announcement Maximum Returns

So far we have documented the striking phenomenon that stocks with high earnings announcement maximum returns as measured surrounding past earnings announcements exhibit high excess returns in the period immediately before current earnings announcements. This result is consistent with the idea that investors interpret stocks with high past earnings announcement maximum returns as likely to exhibit high earnings announcement maximum returns in the future. In this section, we examine the persistence of earnings announcement maximum returns, which serves as

respectively, in the 10-day period leading up to an expected earnings announcement date. These excess returns are both economically and statistically significant at the 1% level.

a basis for how investors could perceive high- versus low-lottery payoff stocks when it comes to the earnings announcement period. Table 3.10 presents the analyses of earnings announcement maximum return persistence from a cross-sectional regression framework.[61]

{ENTER TABLE 3.10}

In column (1), the relation between future earnings announcement maximum returns and *EA_MAXRET* is 0.1371, with a *t*-statistic of 14.16. Columns (2) to (8) show that earnings announcement maximum returns are negatively related to firm size but positively related to the book-to-market ratio, beta, momentum, idiosyncratic volatility, Amihud illiquidity, and prior-quarter standardized unexpected earnings. In the full model in column (9), we find that the coefficient of *EA_MAXRET* remains very large and significant. We also note that idiosyncratic volatility is strongly predictive of future earnings announcement maximum returns. The adjusted *R*-squared value of the full model is 11%, which indicates substantial cross-sectional explanatory power for future earnings announcement maximum returns.

Overall, the results in Table 3.10 show that earnings announcement maximum returns are highly persistent over time and investors can conveniently identify stocks with high versus low future earnings announcement maximum returns by observing how the stock returns behave surrounding past earnings announcements. In other words, stocks with extreme earnings announcement maximum returns in the past are likely to exhibit this feature in the future.

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[61] An alternative way to assess earnings announcement maximum return persistence is to examine the average probability that a stock in decile *i* in year *y* - 1 will be in decile *j* in year *y*. If the earnings announcement maximum returns are purely random, the probability would be 10%, since the earnings announcement maximum returns in year *y* - 1 are not informative about those in year *y*. In an unreported test, we find that the probability of the stocks in decile 10 of *EA_MAXRET* being in decile 10 again in year *y* is 17%. Moreover, the stocks in decile 10 of *EA_MAXRET* have a 36% probability of being in deciles 8 to 10 of *EA_MAXRET* again in year *y*. This finding indicates that lottery payoffs surrounding earnings announcements are not random but persist over time.

3.4.5. Earnings Announcement Minimum Returns and Pre-Earnings Announcement Excess Stock Returns

Recent developments in the literature on the pricing of idiosyncratic volatility examine the pricing of extreme stock returns as an alternative to stock return idiosyncratic volatility. While extreme stock returns and idiosyncratic volatility are highly correlated when measured over the same time period, Bali et al. (2011) show that only extreme positive returns are priced while the effect of idiosyncratic volatility either disappears or reverses in asset pricing tests. The authors interpret their findings as stocks with extreme positive stock returns exhibiting a lottery-like payoff characteristic that is preferred by investors.

In the context of earnings announcements, it is conceivable that investors also prefer stocks with large upside idiosyncratic volatility and hence insert demand for these stocks in the period leading up to earnings announcements. However, if the results in our study are purely an idiosyncratic volatility effect, we should also observe a similar pattern for stocks with large downside idiosyncratic volatility. Alternatively, if investors dislike negative extreme returns, they can shun stocks with large negative returns around past earnings announcements, resulting in a downward pressure in the prices of these stocks in the 10-day period leading to earnings announcements.

To investigate this hypothesis, we revisit the earnings announcement lottery payoff effect by using past earnings announcement minimum returns. Specifically, we compute the minimum three-day excess returns around earnings announcements in the past calendar year (denoted *EA_MINRET*) and re-examine the relation of these extreme return measures with pre-earnings announcement excess returns. Table 3.11 presents the results of earnings announcement minimum returns and *EXRET[-10,-1]*.

{ENTER TABLE 3.11}

In column (1), the coefficient on *EA_MINRET* is -0.0315, with a *t*-statistic of -4.04, which indicates a negative relation between the minimum excess stock returns around past earnings announcements and excess stock returns in the period leading up to future earnings announcements. In column (2), when control variables are included in the model, the coefficient of *EA_MINRET*, however, becomes insignificant, suggesting no relation between minimum excess stock returns around past earnings announcements and excess stock returns in the period leading up to future earnings announcements. In column (4), where both *EA_MAXRET* and *EA_MINRET* are included in the full regression model, we observe the same findings that *EA_MAXRET* is positively related to excess returns but there is an insignificant relation between *EA_MINRET* and excess returns.

The results of Table 3.11 suggest that investors value stocks with large positive payoffs surrounding past earnings announcements but are indifferent to stocks with large negative payoffs surrounding past earnings announcements. This finding is in line with the literature that shows investors could exhibit a preference for stocks with large positive payoffs while being indifferent to stocks with large negative payoffs (Thaler and Ziemba, 1988; Kumar, 2009; Bali et al., 2011).

3.4.6. Earnings Announcement Stock Returns, Post-Earnings Announcement Stock Returns, and EA_MAXRET

To conduct a complete investigation of the role of *EA_MAXRET* surrounding the earnings announcement period, in this section, we examine the relation between *EA_MAXRET* and excess return in the earnings announcement and post-earnings announcement periods. Most importantly, the prior literature on abnormal stock returns around earnings announcements shows that the earnings announcement premium is most pronounced in a short window surrounding earnings announcements. Table 3.12 presents the results of this analysis. In the regression models, we replace SUE_{q-1} by SUE_q (standardized unexpected earnings from the current quarter) to control for the relation between earnings announcement stock returns, post-earnings announcement stock returns, and contemporaneous earnings surprises. We also add *CAR[-1,+1]* as another control for earnings surprise and other relevant information associated with earnings announcements, as suggested by Truong, Shane, and Zhao (2016).

Columns (1) and (2) of Table 3.12 present the regression results for *EXRET[0,+1]*. In column (1), the coefficient of *EA_MAXRET* is 0.0022 and statistically insignificant. In column (2), where the full regression model is estimated, the coefficient of *EA_MAXRET* is 0.0083 and significant at the 1% level. Thus, during the earnings announcement period, we document a earnings announcement lottery payoff effect but it is much smaller than that documented in Table 3.4, where the pre-earnings announcement stock return *EXRET[-10,-1]* is examined. In addition, this earnings announcement payoff is somehow driven by several stock characteristics, since this payoff is absent in column (1).

Columns (3) and (4) of Table 3.12 report the regression results for *EXRET[+2,+5]*. Here, we find that the earnings announcement lottery payoff effect is actually reversed. The coefficient of *EA_MAXRET* is -0.0048 (*t*-statistic = -2.07) in column (3) and -0.0036 (*t*-statistic = -2.00) in column (4). Thus, similar to the pre-earnings announcement stock return pattern documented by Aboody et al. (2010) that reverses in the post-announcement period, the earnings announcement lottery payoff effect also reverses quickly after earnings are announced. This finding is further evidenced by the regression results for *EXRET[-10,+5]* in columns (5) and (6). The coefficient of *EA_MAXRET* is 0.032 (*t*-statistic = 0.34) in column (5) of the univariate regression and 0.091 (*t*-

statistic = 1.53) in column (6) of the multivariate regression. Hence, over the 16-day window surrounding earnings announcements, we document no significant relation between *EA_MAXRET* and excess stock returns.

Overall, the results in Table 3.12 confirm that the earnings announcement lottery payoff is mostly a pre-earnings announcement phenomenon and it reverses in the post-earnings announcement period.

{ENTER TABLE 3.12}

3.5. Further Discussion

3.5.1. Transaction Costs

We investigate whether our results are robust to accounting for transactions costs, mainly because the effect we find is most pronounced among smaller firms and more illiquid firms. We focus on the bid–ask spread and brokerage commissions as the two main sources of transaction costs. To assess the bid–ask spread's impact on *EXRET[-10, -1]*, we recalculate these returns under the assumption that an entry position is at the ask price on day -10 and an exit position is at the bid price on day -1.[62] We source the closing bid and ask prices from the CRSP daily files from 1993 to 2015.[63] Examination of the data reveals a number of instances of large differences between a day's closing bid or ask and the day's closing stock price. To ensure that our results are not driven by outliers, following Aboody et al. (2010), we drop from our full-sample pre-announcement return calculations any observation for which either 1) the day -10 closing ask is greater than 150%

[62] We also use the opening bid and ask prices as alternatives and find that the results after accounting for bid-ask impact are almost unchanged.

[63] As noted by Chung and Zhang (2014) and Marshall, Nguyen, Nguyen, and Visaltanachoti (2018), between February 1942 and December 1992, the CRSP ask and bids series are available only in cases missing a closing price. Our analysis therefore covers from 1993 to 2015, the period over which a continuous series of bid–ask data is available.

of that day's closing stock price or 2) the day -1 closing bid is less than 50% of that day's closing stock price.

We find that *EXRET[-10, -1]* for the top *EA_MAXRET* portfolio remains significantly different from zero, even after accounting for the impact of the bid–ask spread. For our sample where the bid–ask spread can be accounted for, the 10-day pre-announcement period excess return is 0.64%. We further impose a commission of $10 per 1,000 shares traded and find that the excess return is 0.57%.[64] Thus, the excess return for the top *EA_MAXRET* portfolio remains significantly different from zero, even after accounting for the impact of both bid–ask spreads and brokerage commissions.[65]

3.5.2. Institutional Ownership and Analyst Coverage

It is conceivable that retail investors are more likely than institutional investors to exert price pressures for lottery stocks (Kumar, 2009; Bali et al., 2017a). Thus, if lottery demand drives the earnings announcement lottery payoff effect, we should see a more pronounced return difference between the two extreme *EA_MAXRET* portfolios of stocks that are popular among retail investors. We use two ways to identify stocks that are more likely to be popular among retail investors. First, we stratify our sample into quintiles based on institutional ownership and focus on stocks in the

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[64] Assuming a commission of $10 per 1,000 shares traded, the round-trip cost of a 1,000=share trade will be $20. Given the average end-of-quarter share price (untabulated) for the firms in our sample is greater than $28, the brokerage commission does not exceed 0.071% (i.e., $20/($28*1,000) of the transaction value. Therefore, the after-commission excess return, after accounting for the bid–ask spread, is 0.64% - 0.071% = 0.57%.

[65] We repeat the portfolio analyses for subsamples of big and liquid stocks, including S&P 500 stocks, stocks traded on the NYSE, and stocks with beginning-of-quarter prices of at least $5. We find the earnings announcements lottery payoff effect also manifests itself among these stocks. The hedge returns between two extreme *EA_MAXRET* deciles from the subsamples (ranging from 0.80% to 0.99%) are higher than those from stocks with a low price and high skewness. These additional results further confirm that the earnings announcements lottery payoff effect is not limited to small or illiquid stocks.

bottom quintile.[66] Second, following Hirshleifer and Teoh (2003), Hirshleifer, Hsu, and Li (2013), and Bali, Peng, Shen, and Tang (2014), we stratify our sample into quintiles based on analyst coverage, which acts as a proxy for investor attention or the extent to which professional analysis can effectively guide investor attention. We also focus on stocks in the bottom quintile, where, in the shortage of analyst guidance, investor naiveté can further influence stock prices by over-extrapolating the probability of past *EA_MAXRET* values. Appendix 3.1 reports the results for these tests.

As expected, we find that the hedge *EA_MAXRET* return is highest among firms with low institutional ownership and among firms with a smaller analyst following. Specifically, the hedge *EA_MAXRET* return is 1.10% for the lowest quintile of institutional ownership and 1.28% for the lowest quintile of analyst coverage.[67]

3.5.3. Aggregate Lottery Payoff Demand

Time variation in lottery demand can affect the relation between lottery demand and expected stock returns (Kumar, 2009; Kumar, Page, and Spalt, 2011). Therefore, we test whether the time-varying feature of aggregate lottery demand drives our main results. Following Bali et al. (2017a) and Bali et al. (2017b), we estimate the aggregate lottery demand in each month as the cross-sectional equal- or value-weighted average value of *MAX* across all stocks in the sample. An annual

[66] Studies such as those of Fong and Toh (2014) and Bali et al. (2017a) suggest a stock's institutional ownership as a reliable proxy for the extent to which the stock price can be affected by retail lottery investors. A stock's institutional ownership (*INST*) is computed as the fraction of its outstanding common shares owned by all 13F reporting institutions in a given quarter. We also consider analyst coverage, measured as the number of analysts who have issued a forecast for the current fiscal year, using data from I/B/E/S.

[67] We also continue to find the hedge return *EA_MAXRET* is mostly driven by the long side of the top *EA_MAXRET* portfolio. The top *EA_MAXRET* portfolio yields 1.37% for the lowest quintile of institutional ownership and 0.74% for the highest. In a similar pattern, the top *EA_MAXRET* portfolio yields 1.59% for the lowest quintile of analyst coverage and 0.94% for the highest.

measure of aggregate lottery demand is measured as the average value of monthly measures across months in a year. Following the literature, we define years with above-median (below-median) aggregate lottery demand as high (low) aggregate lottery demand years. We then examine the *EXRET[-10,-1]* values of the *EA_MAXRET* portfolios following high (low) aggregate lottery demand years. Panel A of Appendix 3.2 reports the results for these tests. Overall, the average excess return difference between decile 10 (high *EA_MAXRET*) and decile 1 (low *EA_MAXRET*) remains positive and statistically (and economically) significant, regardless of the level of aggregate lottery demand, albeit there is some evidence that this hedge return is somewhat higher in high aggregate lottery demand periods.[68]

3.5.4. Economic States

We examine whether the earnings announcement lottery payoff effect varies with economic states, given prior evidence that the demand for lottery-type stocks increases during bad economic times (Kumar, 2009).[69] Following Blinder and Watson (2016), we define recession and non-recession states based on the business cycle database of the NBER. Specifically, we define a recession quarter as one in which any month is in a recession. Panel B of Appendix 3.2 reports the results for these tests.

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[68] The hedge *EA_MAXRET* strategy yields 0.93% in high aggregate lottery demand periods and 0.84% in low aggregate lottery demand periods.

[69] The literature also suggests that the level of lottery purchases can be influenced by psychological factors. Studies such as those of Doran, Jiang, and Peterson (2012) and Fong and Toh (2014) document that investor sentiment amplifies the overpricing of lottery-like assets. Following this line of inquiry, we also examine whether the *EA_MAXRET* phenomenon varies across different sentiment states. We use three different measures of investor sentiment, including 1) the investor sentiment index of Baker and Wurgler (2006, 2007), 2) the MCSI, and 3) the VIX. We document little difference in the *EA_MAXRET* phenomenon between high- and low-sentiment periods, suggesting that, overall, market sentiment does not play a significant role. This finding is in stark contrast with that from Fong and Toh (2014), who show the monthly *MAX* effect in Bali et al. (2011) is chiefly a high-sentiment period phenomenon.

We document a stronger effect during recession periods than during non-recession periods. The average excess return differences between decile 10 (high *EA_MAXRET*) and decile 1 (low *EA_MAXRET*) are 1.37% (0.81%) following recession (non-recession) periods.

3.5.5. Other Lottery Features

While our study identifies earnings announcement payoffs as a new lottery feature, a number of other long-established lottery features of stocks in the literature, such as low price, high idiosyncratic volatility, and high idiosyncratic skewness (Kumar, 2009; Han and Kumar, 2013), also attract high lottery demand. Using stock price, idiosyncratic volatility, and idiosyncratic skewness as alternative lottery dimensions, we examine whether the earnings announcements lottery payoff effect is weaker when other lottery features are also prevalent. Panel C of Appendix 3.2 reports the results for these tests.

We find that the *EA_MAXRET* hedge strategy yields 0.72% among stocks with high values of other lottery features and 0.87% among stocks with low values of other lottery features.[70] This finding suggests that earnings announcement payoffs are a distinct lottery feature.

3.6. Conclusion of Chapter 3

We find a statistically and economically significant relation between earnings announcement maximum returns from past earnings announcements and excess stock returns in the period leading up to current earnings announcements. The results are robust to controls for numerous other factors

[70] Specifically, for each quarter, we sort stocks into quintiles based on each of the following three features: stock price, idiosyncratic volatility, and idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010). Stocks with high values of other lottery features are in the top quintiles of price, idiosyncratic volatility, and idiosyncratic skewness. Stocks with low values of other lottery features are in the bottom quintiles of all three features.

that could plausibly explain the patterns of stock returns surrounding earnings announcements. The results are also robust to different portfolio weightings and risk adjustment techniques. In addition, we show that the earnings announcement lottery payoff effect is mostly present in the pre-earnings announcement period and is reversed in the post-earnings announcement period.

We interpret our findings as investor preference for holding stocks with some probability of a high earnings announcement payoff in the period immediately before earnings announcements. We also show significant asymmetry in the pricing of this earnings announcement payoff, in that only favorable earnings announcement returns are priced. We suggest that the phenomenon can be rationalized based on the notion that lottery investors overweight the probability of large upward earnings announcement payoffs and bid up the prices of these stocks before earnings announcements.

Our research also leads to several interesting implications for future research on the relation between earnings announcements, idiosyncratic volatility, and stock returns. For example, researchers can investigate the extent to which the preference for earnings lottery payoffs can explain the previously documented earnings announcement premium, where stock returns are abnormally higher during a short window surrounding earnings announcements (Ball and Kothari, 1991; Cohen et al., 2007; Barber et al., 2013). Researchers can also decompose the general idiosyncratic volatility of stock returns into favorable and unfavorable types of idiosyncratic volatility and study their pricing in the cross section of expected stock returns.

Table 3.1. Descriptive Statistics, 1981-2015

Panel A: Sample characteristics

	Mean	STD	P25	Median	P75
EA_MAXRET	0.0741	0.1041	0.0203	0.0504	0.0998
EXRET[-10,-1]	0.0044	0.1148	-0.0441	-0.0025	0.0415
SIZE	2.249	7.078	0.058	0.236	1.083
BM	0.800	0.766	0.332	0.600	0.999
MOM	0.085	0.512	-0.158	0.035	0.235
BETA	0.899	0.682	0.489	0.884	1.271
IVOL	0.032	0.024	0.017	0.026	0.040
ILLIQ ($\times 10^5$)	0.560	5.339	0.000	0.007	0.093
SUE_{q-1}	0.001	0.092	-0.007	0.001	0.008

Panel B: Sample characteristics across earnings announcement maximum return deciles

	1 (Low *EA_MAXRET*)	2	3	4	5	6	7	8	9	10 (High *EA_MAXRET*)
EA_MAXRET	-0.0292	0.0057	0.0190	0.0307	0.0432	0.0576	0.0756	0.1001	0.1402	0.2794
SIZE	1.438	2.656	3.053	3.124	3.062	2.903	2.318	1.810	1.285	0.682
BM	0.865	0.871	0.836	0.821	0.791	0.774	0.767	0.749	0.762	0.800
MOM	0.034	0.059	0.066	0.069	0.073	0.082	0.088	0.095	0.113	0.159
BETA	0.891	0.813	0.797	0.823	0.861	0.901	0.931	0.972	0.994	0.999
IVOL	0.039	0.028	0.025	0.025	0.027	0.029	0.031	0.033	0.037	0.047
ILLIQ($\times 10^5$)	0.812	0.506	0.406	0.312	0.305	0.374	0.453	0.523	0.694	1.288
SUE_{q-1}	-0.001	-0.001	-0.002	-0.001	-0.001	0.000	0.001	0.002	0.003	0.011

Panel A presents descriptive statistics of the main variables for the overall sample. The sample consists of 599,566 quarterly earnings announcements spanning 1981 to 2015. Panel B presents the mean values of the main variables for the deciles of the earnings announcement maximum returns. In this table, *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1; *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements, with excess return measured as the difference between the stock return and the CRSP value-weighted return over the same period; *SIZE* and *BM* denote market capitalization and the book-to-market ratio at the end of year *y* - 1, respectively; *MOM* is the firm's return over the six-month period ending on day *t* - 11 before the earnings announcement; *BETA* and *IVOL* are the stock beta and standard deviation of residual returns, respectively, from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200 trading days ending on day *t* - 11 before the earnings announcement; and SUE_{q-1} is standardized unexpected earnings from the prior quarter using the random walk model.

Table 3.2. EXRET[-10,-1] from Portfolios Sorted by Earnings Announcement Maximum Returns

	Actual Announcement Date	Pseudo-Announcement Date	Difference
	(1)	(2)	(3)
1 (Low *EA_MAXRET*)	0.0026	0.0007	0.0019
2	0.0021	0.0013	0.0008
3	0.0012	0.0014	-0.0002
4	0.0023*	0.0014	0.0009
5	0.0024***	0.0006	0.0018
6	0.0025**	0.0004	0.0021
7	0.0035**	0.0015	0.0020
8	0.0036*	0.0011	0.0025
9	0.0063***	0.0020	0.0043**
10 (High *EA_MAXRET)*	0.0115***	0.0033	0.0082***
10-1	0.0089***	0.0026	0.0063***

Decile portfolios are formed every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET* measured from year *y* - 1. Portfolio 1 (10) is the portfolio with the lowest (highest) earnings announcements maximum return in the previous year; *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1; and *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements, where the excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. Actual earnings announcements are based on earnings announcement dates from Compustat. Pseudo-earnings announcements are estimated by subtracting a randomly generated number (uniformly distributed between 10 to 40 trading days) from the actual earnings announcement dates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.3. *EXRET[-10,-1]* from Portfolios Sorted by Earnings Announcement Maximum Returns after Controlling for *SIZE*, *BM*, *MOM*, *BETA*, *IVOL*, *ILLIQ*, and SUE_{q-1}

Panel A: Equal-weighted portfolio

	SIZE (1)	*BM* (2)	*MOM* (3)	*BETA* (4)	*IVOL* (5)	*ILLIQ* (6)	SUE_{q-1} (7)
1 (Low *EA_MAXRET*)	0.0016	0.0017	0.0015	0.0021	0.0017	0.0019	0.0029*
2	0.0015	0.0022*	0.0019	0.0018	0.0021*	0.0015	0.0023*
3	0.0022*	0.0029**	0.0027**	0.0017	0.0030**	0.0023**	0.0024*
4	0.0025**	0.0021*	0.0022*	0.0018*	0.0023*	0.0021*	0.0019*
5	0.0019	0.0025**	0.0031***	0.0014	0.0030**	0.0027**	0.0023**
6	0.0021*	0.0022*	0.0025*	0.0038***	0.0025	0.0025**	0.0028**
7	0.0048***	0.0034**	0.0028**	0.0028**	0.0047***	0.0034**	0.0043***
8	0.0051***	0.0049***	0.0051***	0.0051***	0.0053***	0.0044***	0.0045***
9	0.0060***	0.0058***	0.0055***	0.0060***	0.0057***	0.0063***	0.0048***
10 (High *EA_MAXRET*)	0.0096***	0.0111***	0.0097***	0.0109***	0.0077***	0.0102***	0.0096***
10-1	0.0081***	0.0095***	0.0082***	0.0088***	0.0060***	0.0084***	0.0067***

Panel B: Value-weighted portfolio

	SIZE (1)	*BM* (2)	*MOM* (3)	*BETA* (4)	*IVOL* (5)	*ILLIQ* (6)	SUE_{q-1} (7)
1 (Low *EA_MAXRET*)	-0.0009	0.0002	-0.0017	-0.0009	-0.0008	-0.0008	0.0001
2	0.0011	0.0010	0.0005	0.0004	-0.0010	0.0007	0.0014
3	0.0002	0.0017	-0.0001	0.0007	0.0020*	0.0003	0.0001
4	0.0004	0.0013	0.0007	0.0002	0.0002	-0.0001	0.0009
5	0.0004	0.0002	0.0017**	0.0006	0.0018	0.0009	0.0000
6	0.0001	0.0008	-0.0005	0.0024***	0.0004	0.0008	0.0014**
7	0.0029**	0.0019*	0.0023***	0.0015	0.0023*	0.0016	0.0026***
8	0.0003	0.0043***	0.0022**	0.0020*	0.0007	0.0009	0.0019
9	0.0016	0.0060**	0.0026**	0.0034**	0.0017*	0.0013	0.0017
10 (High *EA_MAXRET*)	0.0069***	0.0095***	0.0062**	0.0086***	0.0020**	0.0079***	0.0072***
10-1	0.0077***	0.0093***	0.0079***	0.0095***	0.0028**	0.0087***	0.0071***

We form double-sorted decile portfolios every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET* measured from year *y* - 1 after controlling for size, the book to market, momentum, beta, idiosyncratic volatility, Amihud illiquidity, and standardized unexpected earnings. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1 and *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements, where the excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. In each case, stocks are first sorted into deciles using the control variable. Then, within each decile, the stocks are sorted into deciles based on *EA_MAXRET*. This table presents the average *EXRET[-10,-1]* values across the 10 control deciles to produce decile portfolios with dispersion in *EA_MAXRET* but with similar compositions of the control variable. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.4. Multivariate Analyses of EXRET[-10,-1]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0018	0.0145	0.0012	0.0045	0.0042	-0.0056	0.0042	0.0031	-0.0097
	(0.92)	(2.20)**	(0.79)	(1.90)*	(1.73)*	(-6.04)***	(1.82)*	(1.50)	(-2.32)**
EA_MAXRET	0.0337								0.0211
	(5.21)***								(5.62)***
SIZE		-0.0018							0.0003
		(-2.36)**							(0.61)
BM			0.0039						0.0017
			(1.87)*						(0.98)
MOM				-0.0013					-0.0005
				(-0.45)					(-0.16)
BETA					0.0001				0.0004
					(0.21)				(0.64)
IVOL						0.3115			0.2602
						(3.91)***			(4.33)***
ILLIQ							0.0003		-0.0006
							(2.96)***		(-2.00)**
SUE_{q-1}								0.0145	0.0112
								(1.90)*	(1.82)*
Adj. R^2	0.001	0.001	0.000	0.000	0.000	0.004	0.001	0.001	0.003

This table presents the regression results of *EXRET[-10,-1]* relative to the earnings announcement dates from Compustat. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1 and *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements, where the excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. The variables *SIZE* and *BM* denote market capitalization and the book-to-market ratio, respectively, at the end of year *y* - 1; *MOM* is the firm's return over the six-month period ending on day *t* - 11 before the earnings announcement; *BETA* and *IVOL* are, respectively, the stock beta and standard deviation of residual returns from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200 trading days ending on day *t* - 11 before the earnings announcement; and SUE_{q-1} is standardized unexpected earnings from the prior quarter using the random walk model. The sample consists of 599,566 firm–quarter observations spanning 1981 through 2015. The *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and quarter. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.5. Regression Analyses, Robustness Checks

	Independent Variable *EA_MAXRET*		
	Coeff.	t-Stat.	Adj. R^2
Panel A: Additional control variables			
Main Specification	0.0211	(5.62)***	0.003
(1) Control for *MAX* in the month prior to future earnings announcements	0.0244	(4.86)***	0.009
(2) Control for differences of opinion	0.0235	(5.76)***	0.005
(3) Control for short-sale constraints	0.0261	(8.73)***	0.005
(4) Control for earnings seasonality	0.0215	(5.86)***	0.003
(5) Control for return reversals around earnings announcements	0.0133	(7.61)***	0.247
(6) Control for earnings announcements returns by past winners	0.0198	(5.84)***	0.003
(7) Control for the industry effect	0.0173	(4.83)***	0.005
(8) Fama–Macbeth regression with *t*-statistics adjusted following Newey and West (1987)	0.0210	(2.35)**	0.003
(9) Use standardized unexpected earnings based on analyst forecasts (*SUE_AF*)	0.0228	(6.66)***	0.005
Panel B: Alternative measures of pre-earnings announcement returns			
(1) *EXRET[-5,-1]*	0.0162	(5.27)***	0.003
(2) *EXRET[-3,-1]*	0.0100	(4.13)***	0.003
(3) *EXRET[-4,-2]*	0.0111	(4.24)***	0.003
Panel C: Subsample analyses			
(1) NSYE stocks only	0.0206	(7.38)***	0.004
(2) S&P 500 stocks	0.0149	(3.44)***	0.011
(3) Stock price at the beginning of a quarter of at least $5	0.0262	(10.22)***	0.002
(4) Exclude financial and utility firms	0.0240	(6.41)***	0.005

This table reports the results of several robustness tests performed on the regressions of *EXRET[-10,-1]* relative to earnings announcement dates from Compustat. The main specification shows the estimates from the regression with all control variables included, as reported in column (9) in Table 2.4. For brevity, this table only reports the coefficients of *EA_MAXRET*, where *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year y - 1. The variable *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. To proxy for differences of opinion, we use stock return volatility measured as the standard deviation of a firm's daily excess stock returns over the 45-day period ending 11 days prior to the earnings announcement date (Berkman et al., 2009). Following Nagel (2005) and Berkman et al. (2009), we use institutional ownership to proxy for short-sale constraints. We follow Chang et al. (2016) to construct a measure of earnings seasonality in quarter t using five years of earnings data from quarters t - 23 to t - 4. We rank the 20 quarters of earnings data from largest to smallest and the earnings seasonality is the average rank of the same fiscal quarter as the upcoming announcement from the previous five years. We use *EXRET[-4,-2]* to control for return reversals ahead of earnings announcements (So and Wang, 2014). We use prior 12-month returns to control for the earnings announcement returns by past stock winners, as documented by Aboody et al. (2010). The variable *SUE_AF* is the I/B/E/S actual median minus the I/B/E/S median forecast in the 90-day period before the earnings announcement date, scaled by the price per share at quarter-end (Livnat and Mendenhall, 2006). Other control variable definitions are presented in Table 2.4. Unless otherwise stipulated, *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and quarter.

Table 3.6. Interaction Effects in EXRET[-10,-1]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0115	-0.0013	0.0019	0.0017	-0.0074	0.0017	0.0007	-0.0114
	(1.81)*	(-1.59)	(0.96)	(0.82)	(-6.86)***	(0.85)	(0.40)	(-3.05)***
EA_MAXRET	0.0271	0.0329	0.0348	0.0361	0.0313	0.0338	0.0333	0.0360
	(3.01)***	(3.55)***	(5.10)***	(4.98)***	(6.21)***	(5.36)***	(4.63)***	(3.41)***
*EA_MAXRET*SIZE*	0.0007							-0.0009
	(0.44)							(-0.60)
*EA_MAXRET*BM*		-0.0006						0.0015
		(-0.20)						(0.28)
*EA_MAXRET*MOM*			-0.0019					-0.0040
			(-1.30)					(-1.58)
*EA_MAXRET*BETA*				-0.0025				0.0003
				(-1.25)				(0.11)
*EA_MAXRET*IVOL*					-0.2106			-0.2069
					(-3.48)***			(-3.09)***
*EA_MAXRET*ILLIQ*						0.0004		0.0004
						(4.96)***		(0.69)
*EA_MAXRET*SUE*$_{q-1}$							-0.0198	-0.0154
							(-1.46)	(-1.05)
SIZE	-0.0017							0.0005
	(-2.20)**							(1.08)
BM		0.0040						0.0016
		(2.05)**						(1.24)
MOM			-0.0016					-0.0001
			(-0.49)					(-0.01)
BETA				0.0002				0.0002
				(0.26)				(0.32)
IVOL					0.3143			0.2876
					(3.81)***			(4.55)***
ILLIQ						-0.0004		-0.0006
						(-2.49)**		(-2.33)**

SUE_{q-1}							0.0150	0.0128
							(2.26)**	(1.78)*
Adj. R^2	0.002	0.002	0.001	0.001	0.005	0.001	0.001	0.003

This table presents the regression results of *EXRET[-10,-1]* relative to the earnings announcement dates from Compustat and interaction effects. The variable *EA_MAXRET* is the maximum value of the three-day excess returns around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1 and *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements. Excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. The variables *SIZE* and *BM* denote market capitalization and the book-to-market ratio at the end of year *y* - 1, respectively; *MOM* is the firm's return over the six-month period ending on day *t* - 11 before the earnings announcement; *BETA* and *IVOL* are, respectively, the stock beta and standard deviation of residual returns from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200 trading days ending on day *t* - 11 before the earnings announcement; and *SUE_{q-1}* is standardized unexpected earnings from the prior quarter using the random walk model. The sample consists of 599,566 firm–quarter observations spanning 1981 through 2015. The *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and quarter. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.7. Portfolios Sorted by Earnings Announcement Maximum Returns Using Alternative Portfolio Weightings and Risk Adjustments

Panel A: Alternative portfolio weightings

	Value Weighted	Volume Weighted	Dollar Volume Weighted
	(1)	(2)	(3)
1 (Low *EA_MAXRET*)	-0.0013	0.0021	0.0015
2	0.0000	0.0027**	0.0013
3	-0.0002	0.0020*	0.0010
4	0.0012	0.0005	0.0011
5	0.0003	0.0019**	0.0012
6	0.0011**	0.0024*	0.0024**
7	0.0016	0.0042**	0.0033*
8	0.0015	0.0053**	0.0046**
9	0.0046**	0.0086***	0.0099***
10 (High *EA_MAXRET*)	0.0077**	0.0109***	0.0099**
10-1	0.0090***	0.0088***	0.0084**

Panel B: Alternative risk adjustments

	Size-Adjusted Return	CAPM Alpha	Four-Factor Alpha
	(1)	(2)	(3)
1 (Low *EA_MAXRET*)	-0.0028***	0.0023	0.0022
2	-0.0034***	0.0022	0.0024**
3	-0.0043***	0.0014	0.0012
4	-0.0031***	0.0023*	0.0025***
5	-0.0030***	0.0026**	0.0024***
6	-0.0026**	0.0023*	0.0024***
7	-0.0022***	0.0030**	0.0032***
8	-0.0017***	0.0029*	0.0032***
9	0.0008	0.0056***	0.0060***
10 (High *EA_MAXRET*	0.0058***	0.0107***	0.0107***
10-1	0.0086***	0.0084***	0.0085***

Panel A presents the *EXRET[-10,-1]* portfolio returns weighted by market capitalization, share volume, and dollar volume, where *EXRET[-10,-1]* is the excess return measured as the difference between the stock return in the 10 days leading up to earnings announcements and the CRSP value-weighted return over the same period. Panel B presents the equal-weighted portfolio returns adjusted for size, CAPM, and the four-factor model. The size-adjusted return is the difference between the stock return in the 10 days leading up to earnings announcements and the portfolio return of the size decile that the stock belongs to over the same period. For each day, the CAPM and four-factor adjusted returns are calculated, respectively, as follows:

$$\alpha_{i,t,CAPM} = r_{i,t} - [r_{f,t} + \beta_1 (r_{m,t} - r_{f,t})]$$

$$\alpha_{i,t,4F} = r_{i,t} - [r_{f,t} + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 UMD_t]$$

where $r_{i,t}$ is the return of firm *i* on day *t*, $r_{f,t}$ is the risk-free rate, $r_{m,t}$ is the market return, and HML_t, SMB_t, and UMD_t are daily factors in the high-minus-low book-to-market strategy, small-minus-big size strategy, and high-minus-low momentum strategy, respectively. The factors are from Ken French's website. CAPM alpha and the four-factor alphas are the cumulative daily alphas in the 10 days leading up to earnings announcements (from -10 to -1). Decile portfolios are formed every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET*. Portfolio 1 (10) is the portfolio with the lowest (highest) stock excess return around earnings announcements in the previous year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.8. Portfolio Sorted by EA_MAXRET Measured over Different Multi-Quarter Periods and the Timing of EA_MAXRET

Panel A: Portfolio sorted by *EA_MAXRET* measured over different multi-quarter periods

	N = 1	N = 2	N = 3	N = 4	N = 8	N = 16
	(1)	(2)	(3)	(4)	(5)	(6)
1 (Low *EA_MAXRET*)	0.0042*	0.0033	0.0036*	0.0021	0.0015	-0.0008
2	0.0019	0.0014	0.0023*	0.0023**	0.0017	-0.0001
3	0.0036**	0.0018	0.0006	0.0018*	0.0012	0.0015
4	0.0013	0.0024**	0.0019*	0.0018	0.0015	0.0021**
5	0.0015	0.0021**	0.0024**	0.0024**	0.0024**	0.0027**
6	0.0031***	0.0030**	0.0029***	0.0028**	0.0029*	0.0032***
7	0.0034***	0.0024**	0.0033***	0.0029*	0.0045***	0.0039***
8	0.0034***	0.0048***	0.0033***	0.0046***	0.0059***	0.0049***
9	0.0050***	0.0045***	0.0062***	0.0083***	0.0068***	0.0071***
10 (High *EA_MAXRET*)	0.0100***	0.0117***	0.0113***	0.0119***	0.0111***	0.0101***
10-1	0.0058***	0.0083***	0.0077***	0.0098***	0.0096***	0.0110***

Panel B: Timing of *EA_MAXRET*

	Q1 EA_MAXRET	*Q2 EA_MAXRET*	*Q3 EA_MAXRET*	*Q4 EA_MAXRET*
	(1)	(2)	(3)	(4)
1 (Low *EA_MAXRET*)	0.0003	0.0048**	0.0048**	-0.0008
2	0.0025*	-0.0020	0.0032	0.0024
3	0.0018	0.0003	0.0030***	0.0012
4	0.0016	0.0017	0.0025*	0.0021
5	0.0021	0.0022**	0.0025**	0.0027***
6	0.0011	0.0038*	0.0032***	0.0016
7	0.0038**	0.0019	0.0036**	0.0051***
8	0.0052**	0.0031	0.0026	0.0045*
9	0.0061***	0.0044**	0.0065***	0.0086***
10 (High *EA_MAXRET)*	0.0100***	0.0092***	0.0135***	0.0141***
10-1	0.0097***	0.0044**	0.0087***	0.0149***

In Panel A, the decile portfolios are formed every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET* measured from the past *N* rolling quarter(s), where *N* = 1, …, 16. Portfolio 1 (10) is the portfolio with the lowest (highest) stock excess return around earnings announcements over the previous past rolling *N* quarter(s). The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1. The stock excess return around earnings announcements is the three-day excess return around earnings announcements (from day -1 to day +1). The variable *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. In Panel B, columns (1) to (4) report the results for the decile portfolios that are formed by sorting stocks based on *EA_MAXRET* realized in the first, second, third, and last quarters of the prior year, where *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1. The stock excess return around earnings announcements is the three-day excess return around earnings announcements (from day -1 to day +1). The variable *EXRET[-10,-1]* is the excess return in the 10 days leading up to earnings announcements. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.9. EXRET[-10,-1] Relative to Expected Announcement Dates and Precise Announcement Dates

	Expected Announcement Date	WSH Announcement Date	I/B/E/S/ Compustat Announcement Date
	(1)	(2)	(3)
1 (Low *EA_MAXRET*)	0.0033*	-0.0004	0.0022
2	0.0015*	0.0003	0.0026**
3	0.0008	0.0005	0.0020**
4	0.0006	0.0005	0.0024**
5	0.0025**	0.0008	0.0030***
6	0.0032***	0.0002	0.0032***
7	0.0021	0.0002	0.0034*
8	0.0040***	0.0011	0.0038*
9	0.0067***	0.0016**	0.0069***
10 (High *EA_MAXRET)*	0.0142***	0.0059***	0.0111***
10-1	0.0109***	0.0063***	0.0089***

This table presents the decile portfolios formed every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET* measured from year y - 1. Portfolio 1 (10) is the portfolio with the lowest (highest) earnings announcements maximum returns in the previous year; *EA_MAXRET* is the average of the absolute value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year y - 1; and *EXRET[-10,-1]* is the excess return in the 10 days leading up to expected earnings announcements ,where the excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. In column (1), expected earnings announcements are estimated using the approach of Cohen et al. (2007), where the expected earnings announcement dates are based on the distributions of firms' earnings announcement dates from the prior five years. For each firm–quarter, an earnings announcement date is identified as one of the 63 days in the quarter (day 1 to day 63 in the quarter). The median earnings announcement date from the previous rolling five years (20 quarters) is the expected earnings announcement date. In column (2), the earnings announcement dates are from the WSH database that provides corporate events to investors ahead of the announcement time. The WSH database allows examination of the *EA_MAXRET* strategy over their coverage period from 2006 to 2015. In column (3), following DellaVigna and Pollet (2009), the earnings announcement dates are the earlier dates between the earnings announcement dates reported by Compustat and I/B/E/S. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.10. Cross-Sectional Predictability of EA_MAXRET

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0677	0.1231	0.0709	0.0768	0.0728	0.0327	0.0771	0.0754	0.0156
	(25.01)***	(23.01)***	(24.01)***	(24.95)***	(25.04)***	(14.39)***	(25.81)***	(26.67)***	(3.22)***
EA_MAXRET	0.1371								0.0748
	(14.16)***								(9.84)***
SIZE		-0.0080							0.0009
		(-12.41)***							(1.60)
BM			0.0122						0.0047
			(4.03)***						(2.66)***
MOM				0.0150					0.0108
				(4.51)***					(5.14)***
BETA					0.0058				0.0034
					(4.29)***				(2.56)***
IVOL						1.419			1.4562
						(43.29)***			(19.98)***
ILLIQ							0.0018		-0.0009
							(4.99)***		(-1.19)
SUE_{q-1}								0.0523	0.0414
								(5.85)***	(6.14)***
Adj. R-square	0.017	0.023	0.008	0.005	0.001	0.093	0.007	0.002	0.110

The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. The variables *SIZE* and *BM* denote market capitalization and the book-to-market ratio, respectively, at the end of year *y* - 1; *MOM* is the firm's return over the six-month period ending on day *t* - 11 before the earnings announcement' *BETA* and *IVOL* are, respectively, the stock beta and standard deviation of residual returns from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200-day period ending on day *t* - 11 before the earnings announcement; and SUE_{q-1} is standardized unexpected earnings from the prior quarter using the random walk model. The *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.11. Earnings Announcement Minimum Return and EXRET[-10,-1]

	(1)	(2)	(3)	(4)
Intercept	0.0022	-0.0089	-0.0001	-0.0096
	(1.13)	(-2.13)**	(-0.05)	(-2.24)**
EA_MINRET	-0.0315	0.0057	-0.0294	0.0046
	(-4.04)***	(0.76)	(-3.94)***	(0.65)
EA_MAXRET			0.0327	0.0210
			(5.22)***	(5.76)***
SIZE		0.0003		0.0003
		(0.67)		(0.63)
BM		0.0016		0.0018
		(0.93)		(0.99)
MOM		-0.0003		-0.0006
		(-0.11)		(-0.17)
BETA		0.0005		0.0004
		(0.79)		(0.67)
IDIO		0.2974		0.2663
		(4.06)***		(4.06)***
ILLIQ		-0.0007		-0.0006
		(-2.20)**		(-2.10)**
SUE_{q-1}		0.0119		0.0111
		(1.98)**		(1.81)*
Adj. R-square	0.000	0.003	0.001	0.003

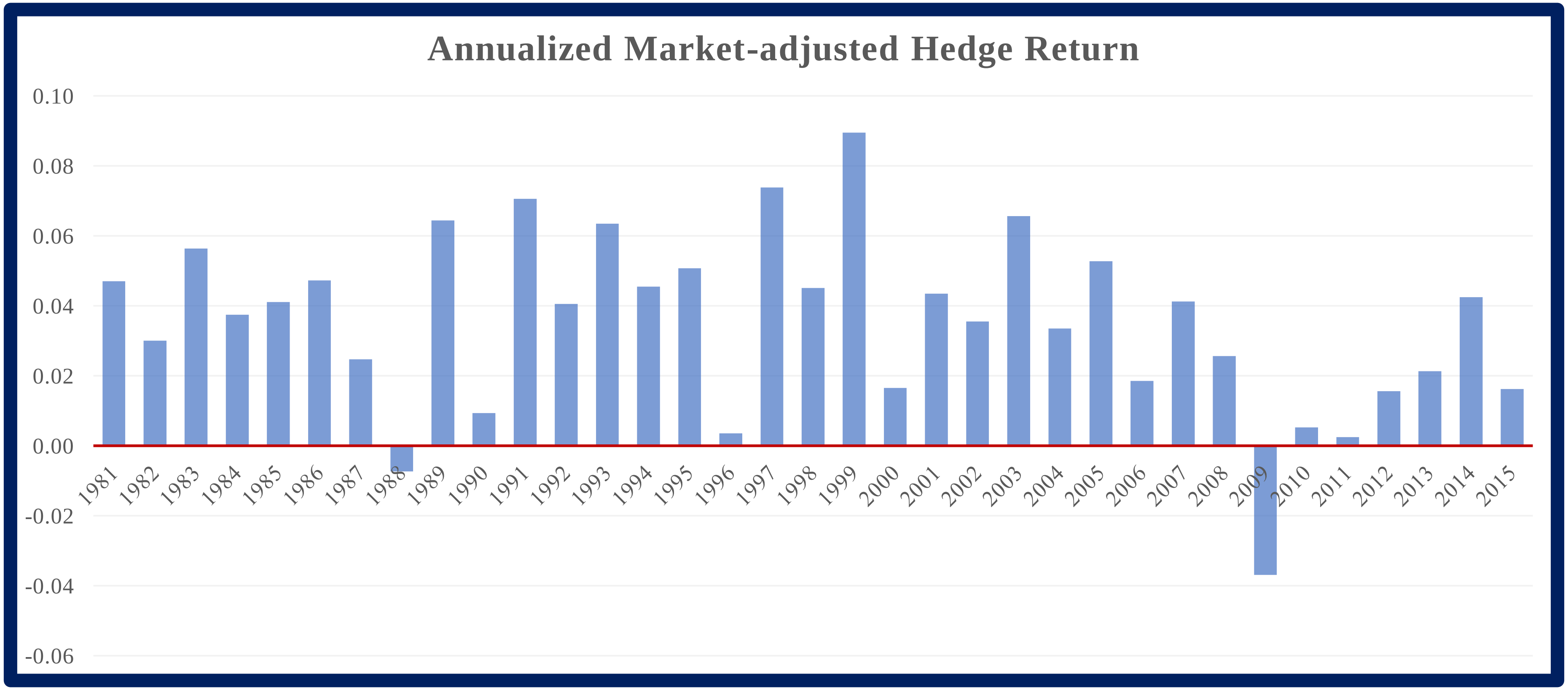
This table presents the regression results of *EXRET[-10.-1]* and the earnings announcement minimum return (*EA_MINRET*). The variable *EA_MINRET (EA_MAXRET)* is the minimum (maximum) value of the three-day stock price response to earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1; *EXRET[-10,-1]* is the excess return measured as the difference between the stock return in the 10 days leading up to earnings announcements and the CRSP value-weighted return over the same period; *SIZE* and *BM* denote, respectively, market capitalization and the book-to-market ratio at the end of year *y* - 1; *MOM* is the firm's return over the size month period ending on day *t* - 11 before the earnings announcement; *BETA* and *IVOL* are, respectively. the stock beta and standard deviation of residual returns from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200-day period ending on day *t* - 11 before the earnings announcement; and SUE_{q-1} is standardized unexpected earnings from the prior quarter using the random walk model. The *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and quarter. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.12. Multivariate Analyses of EXRET[0,+1], EXRET[+2,+5], and EXRET[-10,+5]

	EXRET[0,+1]		*EXRET[+2,+5]*		*EXRET[-10,+5]*	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0001	0.0026	-0.0003	-0.0012	0.0006	0.0002
	(0.22)	(1.71)*	(-0.93)	(-0.69)	(0.39)	(0.04)
EA_MAXRET	0.0022	0.0083	-0.0048	-0.0036	0.0032	0.0091
	(1.48)	(3.82)***	(-2.01)**	(-2.00)**	(0.34)	(1.53)
SIZE		-0.0001		0.0002		0.0003
		(-0.69)		(1.17)		(0.60)
BM		0.0030		0.0030		0.0059
		(6.98)***		(3.73)***		(1.71)*
MOM		-0.0011		-0.0029		-0.0003
		(-1.79)*		(-2.45)**		(-0.11)
BETA		-0.0010		-0.0003		-0.0019
		(-3.36)***		(-0.77)		(-1.28)
IVOL		-0.1292		-0.0832		-0.1793
		(-4.56)***		(-2.75)***		(-1.33)
ILLIQ		0.0013		0.0006		0.0010
		(4.23)**		(2.69)***		(2.14)**
SUE_q		0.0949		0.0031		
		(25.69)***		(0.96)		
CAR[-1,+1]				-0.0046		
				(-0.63)		
SUE_{q-1}						-0.0128
						(-1.61)
Adj. R-square	0.000	0.010	0.000	0.002	0.000	0.002

This table presents the regression results of *EXRET[0,+1]*, *EXRET[+2,+5]*, and *EXRET[-10,+5]* relative to the earnings announcement dates from Compustat. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1; *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements, where the excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period; *SIZE* and *BM* denote, respectively, market capitalization and the book-to-market ratio at the end of year *y* - 1; *MOM* is the firm's return over the six-month period ending on day *t* - 11 before the earnings announcement; *BETA* and *IVOL* are, respectively, the stock beta and standard deviation of residual returns from the four-factor model estimated over the 200-day period ending on day *t* - 11 before the earnings announcement; *ILLIQ* is the Amihud illiquidity ratio measured over the 200-day period ending on day *t* - 11 before the earnings announcement; SUE_q and SUE_{q-1} are standardized unexpected earnings from the current and previous quarters, respectively, using the random walk model; and *CAR[-1,+1] is* a three-day excess return around earnings announcements. The *t*-statistics, in parentheses, are based on two-way clustered robust standard errors, clustered by firm and quarter. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 3.1. Market-Adjusted Hedge Returns Based on Portfolios Sorted by Earnings Announcement Maximum Returns



This figure shows the annualized market-adjusted returns based on portfolios sorted by earnings announcement maximum returns (*EA_MAXRET*) across the 35 years of the sample period (1981–2015). The annualized hedge return is the aggregation of the four quarterly *EA_MAXRET* hedge returns in a year. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1. The decile portfolios are formed every quarter from 1981 to 2015 by sorting stocks based on *EA_MAXRET* measured from year *y* - 1. Portfolio 1 (10) is the portfolio with the lowest (highest) earnings announcements maximum return in the previous year. The variable *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements. Excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period.

Appendix 3.1. Analyst Coverage, Institutional Ownership, and Earnings Announcement Lottery Payoffs

Panel A: Institutional ownership and earnings announcement lottery payoffs

	INST 1	*INST 2*	*INST 3*	*INST 4*	*INST 5*
1 (Low *EA_MAXRET*)	0.0026	0.0087**	0.0018	0.0014	-0.0015
2	0.0011	0.0034	0.0017	0.0010	0.0002
3	0.0013	0.0061**	0.0017	0.0020	0.0000
4	0.0011	0.0057***	0.0020	-0.0013	0.0003
5	0.0025**	0.0038**	0.0014	0.0014	0.0016
6	0.0028**	0.0073***	0.0034*	0.0009	0.0002
7	0.0046***	0.0061**	0.0032	0.0039**	0.0016
8	0.0057***	0.0066**	0.0071***	0.0020	0.0033**
9	0.0071***	0.0116***	0.0069***	0.0055**	0.0025
10 (High *EA_MAXRET*)	0.0137***	0.0151***	0.0114***	0.0082***	0.0074***
10-1	0.0110***	0.0065***	0.0096***	0.0069***	0.0089***

Panel B: Analyst coverage and earnings announcement lottery payoffs

	ANAL_COV 1	*ANAL_COV 2*	*ANAL_COV 3*	*ANAL_COV 4*	*ANAL_COV 5*
1 (Low *EA_MAXRET*)	0.0031	0.0027	-0.0005	0.0003	0.0009
2	0.0039**	0.0014	-0.0013	0.0030	0.0016
3	0.0037***	0.0028*	0.0013	0.0003	-0.0008
4	0.0042***	0.0048*	0.0012	-0.0010	-0.0007
5	0.0040***	0.0013	0.0001	0.0011	0.0016
6	0.0061***	0.0027	0.0019	0.0011	0.0019**
7	0.0076***	0.0072**	0.0027	0.0021	0.0025**
8	0.0070***	0.0046*	0.0021	0.0040*	0.0022
9	0.0114***	0.0086***	0.0051**	0.0022	0.0028
10 (High *EA_MAXRET*)	0.0159***	0.0094***	0.0076***	0.0077***	0.0094***
10-1	0.0128***	0.0066***	0.0081***	0.0073***	0.0084***

We form double-sorted decile portfolios every quarter from 1980 to 2015 by sorting stocks based on *EA_MAXRET* measured from year *y* - 1 after controlling for stock institutional ownership in a prior quarter (*INST*). A stock's institutional ownership (*INST*) is computed as the fraction of its outstanding common shares owned by all 13F reporting institutions in a given quarter. Analyst coverage (*ANAL_COV*) is measured as the number of analysts who have issued a forecast for the current fiscal year in the last month of that fiscal year. Stocks are first sorted into quintiles using *INST* (Panel A) or *ANAL_COV* (Panel B). Then within each decile of control variables, the stocks are sorted into deciles based on *EA_MAXRET*. This table presents the average *EXRET[-10,-1]* values across the 10 control deciles to produce decile portfolios with dispersion in *EA_MAXRET* but with a similar control variable composition. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1 and *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix 3.2. Time-Varying Lottery Demand, Economic States, and Earnings Announcement Lottery Payoffs

Panel A: Time-varying lottery demand and earnings announcement lottery payoffs

Aggregate Lottery Demand Measure	*MAX 1* *(Low EA_MAXRET)*	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX 10* *(High EA_MAXRET)*	10 - 1
			EXRET[-10,-1] from Portfolios Sorted by *EA_MAXRET* following High Aggregate Lottery Demand								
VW_MAX	0.0070**	0.0052***	0.0027	0.0054***	0.0046***	0.0051***	0.0064***	0.0063**	0.0106***	0.0163***	0.0093***
EW_MAX	0.0086***	0.0057***	0.0038**	0.0062**	0.0053***	0.0061***	0.0073***	0.0070***	0.0116***	0.0176***	0.0090***
			EXRET[-10,-1] from Portfolios Sorted by *EA_MAXRET* following Low Aggregate Lottery Demand								
VW_MAX	-0.0019	-0.0012	-0.0004	-0.0009	0.0002	-0.0003	0.0003	0.0007	0.0017	0.0065***	0.0084***
EW_MAX	-0.0037**	-0.0017	-0.0016	-0.0018	-0.0006	-0.0014	-0.0006	-0.0001	0.0006	0.0051**	0.0088***

Panel B: Economic states and earnings announcement lottery payoffs

Economic States	*MAX 1* *(Low EA_MAXRET)*	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX 10* *(High EA_MAXRET)*	10 – 1
			EXRET[-10,-1] from Portfolios Sorted by *EA_MAXRET* following Different Economic States								
Non-recession	0.0065	0.0060**	0.0011	0.0072**	0.0000	0.0058	0.0015	0.0097***	0.0103**	0.0202***	0.0137***
Recession	0.0027	0.0017	0.0009	0.0021	0.0027*	0.0022	0.0034	0.0026	0.0054*	0.0107***	0.0081***

Panel C: EA_MAXRET and other lottery demand measures

Sort Variable	*MAX 1* *(Low EA_MAXRET)*	*MAX* 2	*MAX* 3	*MAX* 4	*MAX* 5	*MAX* 6	*MAX* 7	*MAX* 8	*MAX* 9	*MAX 10* *(High EA_MAXRET)*	10 - 1
					Portfolios Using Low-Price, High-*IVOL*, and High-*ISKEW* Stocks						
EA_MAXRET	0.0066**	0.0055**	0.0068**	0.0061**	0.0084***	0.0055**	0.0080**	0.0082***	0.0098***	0.0138***	0.0072***
					Portfolios Using High-Price, Low-*IVOL*, and Low-*ISKEW* Stocks						
EA_MAXRET	0.0003	0.0030	-0.0004	0.0008	0.0005	0.0017**	-0.0005	0.0010	0.0035*	0.0090***	0.0087***

We form decile portfolios every quarter from 1980 to 2015 by sorting stocks based on *EA_MAXRET* measured from year *y* - 1. Portfolio 1 (10) is the portfolio with the lowest (highest) earnings announcements maximum return in the previous year. The variable *EA_MAXRET* is the maximum value of the three-day excess return around earnings announcements (from day -1 to day +1) from four earnings announcements in year *y* - 1 and *EXRET[-10,-1]* is the excess return in the 10 days leading to earnings announcements. The excess return is measured as the difference between the stock return and the CRSP value-weighted return over the same period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Panel A reports the *EXRET[-10,-1]* values for the *EA_MAXRET* decile portfolios for periods corresponding to high (low) aggregate lottery demand. The aggregate lottery demand in each month is calculated as the cross-sectional equal- or value-weighted average value of the stocks' maximum daily returns across all stocks in the sample. An annual measure of aggregate lottery demand is measured as an average value of the monthly measure across the months in a year. We define years with above-median (below-median) aggregate lottery demand as high (low) aggregate lottery demand years. Panel B reports the *EXRET[-10,-1]* values for the *EA_MAXRET* decile portfolios for periods corresponding to different economic states. We define recession and non-recession states based on the business cycle database of the NBER. Specifically, we define a recession quarter as one in which any month is in a recession. Panel C reports the *EXRET[-10,-1]* values for the *EA_MAXRET* decile portfolios using samples of stocks with low (high) prices, high (low) idiosyncratic volatility, and high (low) idiosyncratic skewness. Stocks with low (high) prices, high (low) idiosyncratic volatility, and high (low) idiosyncratic skewness are defined as those in the bottom (top) quintile of stock prices and the top (bottom) quintiles of both idiosyncratic volatility and idiosyncratic skewness.

Chapter 4. The Timing of Scheduled Earnings News and Stock Price Crashes

4.1. Introduction

The link between firm's earnings news and the timing of earnings announcements has been extensively examined over decades.[71] A main challenge for prior research in this literature is that the link between announcement timing and earnings news can be driven by a combination of mutually non-exclusive endogenous and exogenous factors (Johnson and So, 2017b).[72] There is an emerging trend in which firms provide scheduling disclosures to suggest when they intend to announce earnings. These disclosures have two exciting features. First, unlike traditional measures of earnings announcements timing, scheduling disclosures are available to the public far ahead of the actual earnings announcement dates, typically weeks in advance. Second, the timing of earnings disclosures can be associated with firm's earnings surprises while being less subject to endogenous concerns that are documented in the literature (Livnat and Zhang, 2015; Johnson and So, 2017b). Scheduling disclosures, therefore, provide a fruitful avenue for research that examines market efficiency and/or subsequent corporate behavior.

[71] See, for example, Patell and Wolfson (1982), Chambers and Penman (1984), Bagnoli, Kross, and Watts (2002), Cohen, Dey, Lys, and Sunder (2007), and Berkman and Truong (2009).

[72] For example, firms can reschedule their earnings announcement dates for either unobjectionable reasons, such as scheduling conflicts of their key stakeholders (Kross and Schroeder, 1984) or intentional reasons, such as the concealment of bad news (DeHaan, Shevlin, and Thornock, 2015).

In this chapter, we study the information in the timing of scheduled earnings news utilizing a novel data set of firm scheduling disclosures. Specifically, we are interested in examining whether the timing of earnings announcement dates is associated with future firm-specific stock price crashes, that is, the likelihood of extreme drops in stock prices in a short period. The determinants and consequences of crash risk have attracted a large body of academic research, especially after a series of corporate scandals (e.g., Enron, WorldCom) in the early 2000s and recent financial turmoil.[73] Prior studies (e.g., Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Kim, Li, Zhang, 2011a, 2011b) suggest that bad news hoarding by firm management is a key driver of large share price drops. Accordingly, managers, induced by a range of incentives such as career concerns and compensation contracts, tend to conceal a firm's negative information (Ball, 2009; Kothari, Shu, Wysocki, 2009; Benmelech, Kandel, and Veronesi, 2010). Over time, the accumulation of unfavorable news reaches a threshold and is eventually released all at once, resulting in a stock price crash. We utilize the recent trend toward issuing scheduling earnings news, since earnings calendar revisions can provide firm managers the opportunities and tools for bad news hoarding. We conjecture that managers can withhold unfavorable news by strategically revising the timing of scheduled earnings news. Accumulated bad news is eventually revealed all at once, causing a crash.

Our empirical analyses rely on an earnings calendar data set provided by Wall Street Horizon (WSH) that contains a daily list of expected announcement dates for a broad cross section of U.S. firms. A key feature of this data set is that it allows us to observe how the earnings calendar changes in response to firms' scheduling disclosures.[74] Using daily snapshots of earnings

[73] See Habib, Hasan, and Jiang (2017) for a review of the literature.

[74] WSH updates the calendars by 4:00 a.m. EST of each trading day so that traders can track corporate events with accuracy in real time. The WSH actual earnings announcements database has an accuracy rate of over 99% (DeHaan, Shevlin, and Thornock, 2015) and therefore provides a more reliable source of earnings announcements for academic studies (e.g., DeHaan et al., 2015; Livnat and Zhang, 2015; Johnson and So, 2017b).

calendar data provided by WSH, we find that firms that schedule later-than-expected earnings announcement dates are more likely to exhibit future stock price crashes. In contrast, we find no evidence of a relation between the advanced scheduling of earnings announcement dates and firms' future stock price crash risk. Our results are robust to controlling for alternative definitions of the timing of earnings news, alternative measures of stock price crash risk, as well as other possible determinants of crash risk that have been documented in the literature. We further examine the impact of earnings calendar revision on crash risk when bad news hoarding is more likely. We find that the effect of earnings calendar revisions on crash risk is significant only in firms with stock prices that are sensitive to earnings, higher social responsibility ratings, higher levels of risk taking, or greater information asymmetry. In addition, we find that the association between delayed earnings and stock price crash is more pronounced when the chief executive officer (CEO) has a stronger equity incentive, when CEOs are in their early years of tenure, or firms have weaker governance monitoring mechanisms. We also document that institutional investors mitigate the impact of rescheduling earnings announcement dates on crash risk by providing external monitoring.

Since the timing of earnings news can provide signal of a firm's subsequent behavior, we consider whether the firm's stakeholders consider the timing of scheduled earnings news. We find that investors demand higher expected returns for firms that schedule later-than-expected earnings announcement dates. In addition, auditors require higher audit fees to compensate for their additional effort in auditing firms that schedule later-than-expected earnings announcement dates.

By examining how earnings calendar revisions are related to subsequent corporate behavior, we contribute to three different strands of literature. First, our paper relates to studies that measure earnings announcements timing. The literature suggests at least two ways to characterize the timing of earnings announcements: 1) tracking whether firms disclose "on schedule" by comparing ex post realizations of announcement dates and ex ante expected dates and 2) using ex ante data to examine whether firms revise what it means to be on schedule by rescheduling an announcement date that is either earlier or later compared to prior expected dates (Johnson and So, 2017b). Whereas a majority of prior studies focus on the former, our papers are among the very few studies (i.e., DeHaan et al., 2015; Livnat and Zhang, 2015; Johnson and So, 2017b) that concentrate on the latter, utilizing WSH data.

Second, our study contributes to the burgeoning literature that explores the determinants and consequences of firm-level stock price crashes. Our results suggest that earnings calendar revisions can provide firm managers opportunities to withhold bad news through revising the timing of scheduled earnings announcement dates. Accumulated bad news is eventually revealed, causing the firm's stock price to plunge. Our finding, therefore, is consistent with a bulk of studies providing empirical evidence supporting the agency conflict between managers and shareholders (manager bad news hoarding) as a key driver of stock price crashes.[75] By unmasking one technique that can be employed to facilitate bad news hoarding (i.e., strategically revising the earnings calendar), our paper is related to the work of Kim et al. (2011a), Kim et al. (2014), Chen et al. (2017), and Khurana et al. (2018), who suggest other techniques/tools for the concealment of bad news (e.g., aggressive tax strategies, corporate social responsibility disclosure, and earnings smoothing).

Third and finally, our paper contributes to the long stream of literature that studies the effect of information quality on the cost of equity (Botosan, 1997; Francis, LaFond, Olsson, and Schipper, 2004; Francis, Khurana, and Pereira, 2005; Barth, Konchitchki, and Landsman, 2013; Naiker, Navissi, and Truong, 2013) and on audit quality (Gul, Chen, and Tsui, 2003;

[75] For example, Kim et al. (2011a, 2011b), Callen and Fang (2015), Kim, Li, Lu, and Yu (2016), Kim and Zhang (2016), Chang, Chen, and Zolotoy (2017), and An, Chen, Li, and Xing (2018).

Hogan and Wilkins, 2008; Chen, Gul, Veeraraghavan, and Zolotoy, 2015). Our findings suggest that the timing of scheduled earnings news can provide signal of a firm's information quality and that the firm's stakeholders consider earnings calendar revisions when determining the firm's expected returns and the pricing of audit services.

The remainder of this chapter is organized as follows. Section 4.2 discusses the related literature and empirical predictions. Section 4.3 describes the variables and sample construction. Section 4.4 discusses the results and robustness tests. Section 4.5 presents subsample and conditioning analyses. Section 4.6 presents further discussion and Section 4.7 concludes the chapter.

4.2. Related Literature and Hypothesis Development

4.2.1. Stock Price Crash Risk: A Brief Review of Recent Research

Recent research on firm-specific stock price crash risk relies mostly on the theoretical framework proposed by Jin and Myers (2006) that attributes stock price crash to the information asymmetries between corporate insiders and external stakeholders. Specifically, under the bad news hoarding model, managers often possess higher levels of a firm's private information than outside investors do and, hence, can take advantage of information asymmetry to conceal bad news from the public. Over time, it becomes either too costly and or impossible for managers to withhold unfavorable information. Once the accumulation of negative news reaches a tipping point, it is eventually revealed to the market all at once, causing a large stock price drop, or crash.

Managers' tendency to conceal bad news can arise from various incentives, such as career-related costs, compensation schemes, promotion opportunities, or the desire to maintain the esteem of peers (Ball, 2009; Kothari et al., 2009; Benmelech et al., 2010).[76,77] Kim et al. (2011a), for example, document that the sensitivity of the value of chief financial officer (CFO) option portfolios to stock prices is positively associated with crash risk. Considering another form of compensation, He (2015) finds a negative association between CEO debt compensation incentives (i.e., debt in the form of pension and deferred compensation) and future price crash. Managerial bad news hoarding practices can also be driven by the manager's personal traits. Kim, Wang, and Zhang (2016), for example, suggest that overconfident CEOs overestimate the future prospects of their investment decisions and tend to continue negative net present value projects for extended periods. The unfavorable performance is eventually revealed to the public upon project maturity, causing a crash.

Beside incentives to withhold bad news, prior literature also documents several techniques/tools that facilitate bad news hoarding practices. Kim et al. (2011b), for instance, suggest that complex tax shelters provide tools and masks for managers to conceal negative news for extended periods and hence induce crash risk. Chen et al. (2017) and Khurana et al. (2018) find that firms with a higher degree of earnings smoothing are associated with a higher likelihood of stock price crash. Managers can use voluntary disclosures strategically to withhold bad news. Focusing on corporate social responsibility disclosures, Kim et al. (2014) find that socially responsible firms commit to a high standard of transparency and tend to engage less in bad news hoarding, resulting in lower crash risk.

Prior research also examines the impact of financial reporting quality and future crash risk. Zhu (2016), for example, finds a positive relation between total accruals and price crashes. Kim and

[76] Survey evidence from Graham, Harvey, and Rajgopal (2005) suggests that CFOs conceal negative information and gamble that the firm's future status will improve in the future, which reduces the need to disclose unfavorable news to outside investors.
[77] Chang, Chen, and Zolotoy (2017) suggest that the capital market can also provide an incentive to conceal negative information. Using stock liquidity as a proxy for such an incentive, the authors document a positive association between stock liquidity and future crash risk.

Zhang (2016) suggest that firms with a higher level of accounting conservatism tend to engage less in bad news hoarding and, hence, are less likely to experience a stock price crash. Kubick and Lockhart (2016), studying the geographic distance between a firm's managers and the U.S. Securities Exchange Commission (SEC), suggest that the closer the proximity to the SEC, the less likely managers are to influence their firm's financial report disclosures and the lower the likelihood of future stock price crashes. Ertugrul et al. (2017) show that the readability of a firm's disclosures is negatively related to managerial bad news hoarding.

4.2.2. Timing of Earnings News and Crash Risk

Our paper relates to a bulk of prior studies that examine the link between firm earnings news and the timing of earnings announcements.[78] Our study is closely related to the work of DeHaan et al. (2015), Livnat and Zhang (2015), and Johnson and So (2017b), who employ scheduling disclosures as ex ante signals to predict firm earnings news.[79] These scheduling disclosures are available to the public far ahead of the actual earnings announcements, allowing researchers to examine market efficiency and subsequent corporate behavior while being less subject to endogeneity concerns (Johnson and So, 2017b). Motivated by collective evidence that managers tend to delay disclosures of bad news to outside investors (Kothari et al., 2009 and Benmelech et al., 2010), we conjecture that managers can withhold unfavorable news by strategically revising the timing of scheduled earnings news. Accumulated bad news is

[78] See, for example, Givoly and Palmon (1982), Chambers and Penman (1984), and Bagnoli et al. (2002).
[79] Specifically, Livnat and Zhang (2015) and Johnson and So (2017b) show that, when firms advance (delay) their earnings announcements compared to prior expectations, the earnings surprises in those quarters and the abnormal returns in the month after the scheduling disclosure date tend to be positive (negative). DeHaan et al. (2015) suggest that earnings news tends to be worse (better) during periods of low (high) expected attention and that negative abnormal returns around the scheduling dates are observed when the forthcoming earnings are scheduled for a Friday.

eventually revealed all at once, causing a crash.[80] Therefore, the first and sole hypothesis in this chapter is in the null form, as follows.

Hypothesis: There is no relation between later-than-expected earnings announcement dates and future stock price crashes.

4.3. Variables and Sample Construction

In this section, we discuss the construction of our sample as well as the variables used throughout the paper.

4.3.1. Crash Risk Measures

Following previous studies (e.g., Jin and Mayer, 2006; Hutton et al., 2009; Kim et al., 2011a, 2011b; Chen et al., 2017), we measure quarterly realized crash risk using the distribution of firm-specific daily returns. Specifically, we compute firm-specific daily returns using the daily return data between each firm's earnings announcements for two adjacent quarters, as follows:

$$r_{i,d} = \beta_0 + \beta_1 r_{ind,d-1} + \beta_2 r_{mkt,d-1} + \beta_3 r_{ind,d} + \beta_4 r_{mkt,d} + \beta_5 r_{ind,d+1} + \beta_6 r_{mkt,d+1} + \varepsilon_{i,d} \quad (4.1)$$

where $r_{i,d}$ is the return on stock *i* on day *d*, $r_{ind,d}$ is the value-weighted industry return on day *d*, and $r_{mkt,d}$ is the value-weighted market return on day *d*. We include the lead and lag terms for the market index return and industry return to allow for nonsynchronous trading (Dimson, 1979). Following prior research (e.g., Chen et al., 2001, Hutton et al., 2009), we measure the firm-specific daily return for firm *i* on day *d* as the natural log of one plus the estimated residual return from Equation (3.1), that is, $R_{i,d} = \log(1 + \varepsilon_{i,d})$.[81]

[80] We also conjecture that the converse is not necessarily true for firms that advance their earnings announcements compared to prior expectations. This prediction is aligned to the results of Bagnoli et al. (2002), who find no significant association between early announcers and future earnings news.
[81] We obtain similar results (untabulated) by estimating crash risk measures using raw residual returns.

Since the focus of this chapter is on quarterly realized crash risk, consistent with prior literature (Chen et al., 2001; Kim et al., 2011b, Kim, Wang, Zhang, 2016; Chen et al., 2017), we construct two measures of firm-specific stock price crash risk for each firm *i* and quarter *t*, including $COUNT_{i,t}$ and $DUVOL_{i,t}$. The variable $COUNT_{i,t}$ is the difference between the number of $R_{i,d}$ values exceeding 3.09 standard deviations below the mean of $R_{i,d}$ and the number of $R_{i,d}$ values exceeding 3.09 standard deviations above the mean of $R_{i,d}$ over quarter *t*.[82] A higher value of *COUNT* indicates greater crash risk. The down-to-up volatility of $R_{i,d}$ during quarter *t*, $DUVOL_{i,t}$, is estimated as

$$DUVOL_{i,t} = \log[((n_{up} - 1)\sum_{down} R_{i,d}^2\ )\ /\ ((n_{down} - 1)\sum_{up} R_{i,d}^2\ )] \tag{4.2}$$

where *n* is the number of firm-specific daily returns, $R_{i,d}$, during quarter *t* and n_{up} and n_{down} are the numbers of up and down days, respectively. An up (down) day is a day whose firm-specific return is above (below) the mean of $R_{i,d}$ over the quarter.[83] A higher value of *DUVOL* indicates greater crash risk.

4.3.2. Timing of Scheduled Earnings News

We utilize daily snapshots of earnings calendar data provided by WSH that can identify so-called early and late announcers ahead of the actual earnings announcement dates. WSH provides a real-time database of upcoming earnings announcement dates that are forecasted or confirmed.[84] Since firms can issue scheduling disclosures at any time prior to earnings announcements, we follow Johnson and So's (2017b) to address look-ahead bias. Specifically,

[82] The number 3.09 is chosen to generate a 0.1% frequency in the normal distribution (Hutton et al., 2009; Kim et al., 2011a, 2011b).

[83] Section 3.5 discusses an alternative measure of crash risk: the negative conditional skewness of daily return (*NCSKEW*). Compared to *DUVOL*, *NCSKEW* involves the third moments and, hence, is more likely to be overly influenced by daily extreme returns, as suggested by Chen et al. (2001). Our results remain qualitatively the same when *NCSKEW* is employed as a measure of crash risk.

[84] The WSH codes confirmed announcement dates as V (verified) and forecasted announcement dates as T (tentative) or I (inferred).

we construct a sample of observations where the scheduling disclosure date occurs in the month (i.e., t - 31 to t - 11) ending two weeks before the scheduled announcement date, t. We measure the timing content of scheduling disclosures by computing the corresponding calendar revision, *REV*, as the difference (in days) between the unconfirmed and confirmed announcement dates. Higher (lower) values of *REV* indicate that the scheduled announcement date is earlier (later) than the unconfirmed announcement date. Following Johnson and So (2017b), for each scheduling disclosure, we define a dummy variable, *DELAYER*, that takes the value of one for firms whose scheduled announcement date is at least three days later than their unconfirmed announcement date (or $REV \leq -3$) and zero otherwise. Similarly, we define the dummy variable *ADVANCER* as equal to one for firms whose scheduled announcement date is at least three trading days earlier than their unconfirmed announcement date (or $REV \geq 3$) and zero otherwise.[85]

4.3.3. Sample Construction

Since WSH began disseminating earnings calendar data in 2006, our sample starts in 2006. We merge WSH's calendar revision sample with return data from the CRSP, financial statement information from Compustat, and analyst-based earnings surprise data from I/B/E/S. We start with a firm's quarterly earnings announcements in the intersection of the CRSP, Compustat, I/B/E/S, and WSH data. We require firms to have common shares traded on the NYSE, AMEX, or NASDAQ. The initial sample consists of 149,584 firm–quarters (6,319 firms). Following Johnson and So (2017b), we limit the sample to cases where the firm schedules its earnings announcement date within 21 trading days ahead of its scheduled announcement date (from t - 31 to t - 11) and cases where the scheduled announcement date deviates from the unconfirmed

[85] Our results do not appear sensitive to this sample requirement. We find our results are almost unchanged if we define *DELAYER* (*ADVANCER)* as equal to one for firms whose scheduled announcement date is at least four trading days later (earlier) than their unconfirmed announcement date, as suggested in Livnat and Zhang (2015). We discuss several alternative measures of the timing of scheduled earnings news in Section 4.4.2.

announcement date by at least one working day ($|REV| \geq 1$). The sample is thus reduced to 29,873 firm–quarter observations (4,253 firms). We then match these with quarterly crash risk measures and require that none of the crash risk measures or control variables is missing values. The final sample consists of 22,636 firm–quarter observations (3,308 unique firms) spanning 2006–2015. Table 4.1 presents our sample selection and the distributions of the key variables by year.

{ENTER TABLE 4.1}

Panel A of Table 4.1 shows how each of our sample requirements narrows the WSH's universe of firm–quarters to our sample. Panel B reports the number of observations by year, as well as the mean values of the crash risk measures and the measures of the timing of scheduled earnings news. The table suggests that measures of crash risk and the timing of scheduled earnings news exhibit considerable variation across the years, comparable to prior research (e.g., Kim et al., 2011a; Chen et al., 2017; Johnson and So, 2017b).

4.3.4. Control Variables

To isolate the effect of the timing of scheduled earnings news on stock price crash risk from the effects of other factors documented in the literature to be determinants of crash likelihood, we employ conventional control variables in our analysis. Specifically, we use past-year stock returns (RET_{t-1}), lagged stock turnover ($DTURN_{t-1}$), lagged stock return volatility ($SIGMA_{t-1}$), lagged firm size ($SIZE_{t-1}$), and the market-to-book ratio of the firm in the previous year (MB_{t-1}) as Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a, 2011b) find that these variables are positively associated with crash risk. We further control for lagged book leverage (LEV_{t-1}) and last year's returns on assets (ROA_{t-1}), since Hutton et al. (2009), Kim, Wang, and Zhang (2016), Kim and Zhang (2016), and Chang et al. (2017) document that these variables are negatively correlated with crash risk. We include lagged negative skewness in the returns of the firm (*$NCSKEW_{t-1}$*), since Chen et al. (2001) suggest that stock return skewness persists over time. We also include an indicator for the fourth fiscal quarter (*Q4*), since prior studies (e.g., Jacob and Jorgensen, 2007; Das, Shroff, and Zhang, 2009; Chen et al., 2017) suggest that fourth-quarter reporting differs from that of other quarters. Consistent with prior research (e.g., Chen et al., 2017), we calculate these control variables at the end of the quarter immediately before we compute our measures for crash risk. Finally, all the control variables are winsorized at the first and 99th percentiles to mitigate the impact of outliers. The descriptions of the control variables are available in Appendix 4.1.

4.3.5. Descriptive Statistics

Table 4.2 presents the summary statistics and the Pearson correlation matrix of the variables. According to Panel A, the mean value for *COUNT* is -0.07, suggesting that firms are more likely to experience extremely positive events than extremely negative events, consistent with prior findings (e.g., Hutton, Marcus, and Tehranian, 2009; Chen et al., 2017). The mean value for *DUVOL* is -0.05, slightly smaller than that reported by Chen et al. (2001).[86] Panel A shows that, on average, 38.2% of firm–quarters in our sample experience a delay when scheduling their earnings announcements, while 13.4% of firm–quarters are associated with the advanced scheduling of earnings announcement dates. These findings are generally in line with those of prior research (e.g., Livnat and Zhang, 2015; Johnson and So, 2017b), which suggests that firms are more likely to delay than advance their earnings announcements when scheduling them. In addition, these findings, together with summary statistics of the timing of scheduled earnings news in Table 4.1, Panel B, suggest that earnings calendar revisions are a fairly prevalent practice.

[86] One possible explanation is that Chen et al. (2001) construct this measure over a six-month period while we, with our focus on the timing of quarterly earnings news, measure firm-level crash risk every quarter.

Panel B of Table 4.2 reports the Spearman correlation matrix. There are two key finding from this table. First, the two crash risk measures, *COUNT* and *DUVOL*, are significantly correlated (correlation = 0.738). Second and more interestingly, both *COUNT* and *DUVOL* are positively correlated with the binary delay variable *DELAYER.*

{ENTER TABLE 4.2}

4.4. Timing of Scheduled Earnings News and Crash Risk: Main Results

4.4.1. Baseline Results

In this section, we perform regression analyses to examine the relation between the timing of scheduled earnings news and crash risk. The regression specification is as follows:

$$CRASH_{i,t} = \beta_0 + \beta_1\ DELAYER_{i,t-1} + \beta_2\ ADVANCER_{i,t-1} + \beta_3\ RET_{i,t-1} + \beta_4\ SIGMA_{i,t-1} + \beta_5\ DTURN_{i,t-1} + \beta_6\ SIZE_{i,t-1} + \beta_7\ MB_{i,t-1} + \beta_8\ LEV_{i,t-1} + \beta_9\ ROA_{i,t-1} + FEs + \varepsilon_{i,t} \quad (4.3)$$

where *i* denotes the firm, *t* denotes the quarter, *CRASH* refers to the two crash risk measures *COUNT* and *DUVOL, FEs* denotes firm fixed effects and year/quarter fixed effects, and $\varepsilon_{i,t}$ is the error term. We estimate Equation (3.3) using ordinary least squares (OLS). The *t*-statistics are computed using standard errors adjusted for heteroskedasticity and clustering at the firm level. Table 4.3 presents the baseline results.

{ENTER TABLE 4.3}

Models (1) to (3) in Table 4.3 show the results for *COUNT*, while models (4) to (6) show the results for *DUVOL*. Models (1) and (4) show the relation between the timing of scheduled earnings news and future crash risk with no control variables. In models (2), (3), (5), and (6), we include firm-level control variables. For all the models, we include firm and quarter fixed effects to control for unobservable firm-specific and time-invariant factors, respectively. We find that the coefficients of *DELAYER* are positive and statistically significant across different model specifications, suggesting that firms that schedule later-than-expected earnings announcement dates are more likely to experience a stock price crash in the future. The magnitude of these effects is also economically significant, with firms that schedule later-than-expected earnings announcement dates, on average, having about a 2.8% increase in down-to-up volatility and a 3.5% increase in the difference between the number of firm-specific daily returns below 3.09 standard deviations and the number of observation above 3.09 standard deviations around the quarter mean.

The coefficient of *ADVANCED* is statistically indistinguishable from zero across all model specifications, suggesting no significant relation between earlier-than-expected announcement dates and future stock price crash. In columns (3) and (6) of Table 4.3, where both *DELAYER* and *ADVANCED* dummies are included in the regression models, we continue to document the positive association between the delayed scheduling of earnings news and crash risk. Consistently, we find no evidence of an association between the advanced scheduling of earnings news and future stock price crash.

The results for the control variables are largely consistent with prior literature. Specifically, consistent with Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a, 2011b), we find that past returns (*RET*), firm size (*SIZE*), and the market-to-book ratio (*MB*) are significantly and positively associated with future crash risk. We also find a negative correlation between past return volatility (*SIGMA*) and future crash risk, which is consistent with the results of Chen et al. (2011). In addition, we document a significantly negative association between past returns on assets (*ROA*) and future crash risk, consistent with Hutton et al. (2009), Kim, Wang, and Zhang (2016), Kim and Zhang (2016), and Chang et al. (2017).[87]

4.4.2. Robustness Tests

In this section, we conduct additional analyses to ensure the robustness of our baseline results. Specifically, we consider three sets of additional tests. First, we consider alternative measures of crash risk. Second, we employ alternative measures of the timing of scheduled earnings news. Third and finally, we control for a set of additional control variables documented in the literature as determinants of crash risk. We report the results for these tests in Table 4.4. Firm-level control variables similar to those in the baseline regressions in Table 4.3 are included in all the models. We also include firm and year/quarter fixed effects in all the models. For brevity, we only tabulate the coefficients of *DELAYER*.[88]

We begin by considering alternative measures of stock price crash risk. First, we use alternative firm-specific thresholds to identify crash weeks. The purpose of these additional tests is to mitigate the concern that our results can be driven by a particular threshold (i.e., 3.09 standard deviations) used in defining a measure of crash risk (*COUNT*). Specifically, we define $COUNT_{i,t}$ as the difference between the number of $R_{i,d}$ values exceeding 3.2, 3.5, or four standard deviations below the mean of $R_{i,d}$ and the number of $R_{i,d}$ exceeding 3.2, 3.5, or four standard deviations above the mean of $R_{i,d}$ over quarter *t*. We report the results for these tests in rows (1) to (3) in Panel A of Table 4.4.

[87] We find that past negative return skewness (*NCSKEW)* is negatively related to future crash risk. This finding differ from the results of prior studies but is consistent with the recent work of Chen, Kim, and Yao (2017). Consistent with these authors, we find this discrepancy is due to the inclusion of firm fixed effects in the regression models.
[88] The coefficients of *ADVANCER* are consistently indistinguishable from zero in all the robustness tests.

Second, we use industry-adjusted measures of crash risk to rule out the possibility that our results are driven by more crash-prone industries. Specifically, following Kim et al. (2014), we use the following transformation to preserves the relative distance between the measures of crash risk for firms within the same industry (based on the Fama–French 12-industry classification) for each quarter:

$$\mathrm{COUNT\_IND}_{i,t} = \frac{\mathrm{COUNT}_{i,t} - \mathrm{Min.\ COUNT}_{j,t}}{\mathrm{Max.\ COUNT}_{j,t} - \mathrm{Min.\ COUNT}_{j,t}} \tag{4.4}$$

$$\mathrm{DUVOL\_IND}_{i,t} = \frac{\mathrm{DUVOL}_{i,t} - \mathrm{Min.\ DUVOL}_{j,t}}{\mathrm{Max.\ DUVOL}_{j,t} - \mathrm{Min.\ DUVOL}_{j,t}} \tag{4.5}$$

where *i* denotes the firm; *t* denotes the year/quarter; *j* denotes the Fama–French 12 industry to which firm *i* belongs*;* and *Max.* and *Min.* are the maximum and minimum values, respectively, of measures of crash risk for firm *i*'s industry in quarter *t*. We report the results for these tests in row (4) in Panel A of Table 4.4.

{ENTER TABLE 4.4}

We now consider alternative definitions of the timing of scheduled earnings news. Specifically, following Livnat and Zhang (2015), for each scheduling disclosure, we redefine the dummy *DELAYER* (*ADVANCER*) to takes the value of one if the scheduled announcement date is at least four trading days later (earlier) than the unconfirmed announcement date and zero otherwise. The results for these tests are reported in row (1) of Panel B of Table 4.4.

We also consider the industry-adjusted measure of *DELAYER* (*ADVANCER*) to mitigate the concern that earnings calendar revisions are only prevalent in certain industries. Specifically, we use the following transformation to preserves the relative distance between the measures of the timing of scheduled earnings news for firms within the same industry (based on the Fama–French 12 industry classification) for each quarter:

$$\mathrm{DELAYER\_IND}_{i,t} = \frac{\mathrm{DELAYER}_{i,t} - \mathrm{Min.\ DELAYER}_{j,t}}{\mathrm{Max.\ DELAYER}_{j,t} - \mathrm{Min.\ DELAYER}_{j,t}} \tag{4.6}$$

$$\text{ADVANCER\_IND}_{i,t} = \frac{(\text{ADVANCER}_{i,t} - \text{Min. ADVANCER}_{j,t}}{\text{Max. ADVANCER}_{j,t} - \text{Min. ADVANCER}_{j,t}} \quad (4.7)$$

where *i* denotes the firm; *t* denotes the year/quarter; *j* denotes the Fama–French 12 industry to which firm *i* belongs*;* and *Max.* and *Min.* are the maximum and minimum values, respectively, of measures of the timing of scheduled earnings news for firm *i*'s industry in quarter *t*. We report the results for these tests in row (2) of Panel B of Table 4.4.

In the last set of robustness tests, we examine whether our results remain robust after controlling for a large set of additional control variables. First, we control for discretionary accruals, since Hutton et al. (2009) suggest that firms with higher levels of discretionary accruals are more crash prone. Following these authors, we measure discretionary accruals as the three-year moving sum of the absolute value of discretionary accruals, with accruals computed using the modified Jones model of Dechow, Sloan, and Sweeney (1995).

Second, we control for stock liquidity, since Chang, Chen, and Zolotoy (2017) show that stock liquidity increases stock price crash risk. Following Lesmond (2005) and Chang et al. (2017), we measure stock liquidity using the percentage of zero returns.[89]

Third, we control for institutional ownership, since institutional investors play significant roles in governing short-term behaviors (Edmans and Manso, 2011; Callen and Fang, 2013, 2015; Chang et al., 2017), which can affect the bad news hoarding channel. Institutional ownership data is sourced from the Thomson Reuters Institutional 13F Database.

Fourth, we control for tax avoidance, since Kim et al. (2011a) document a significantly positive association between tax avoidance and future crash risk. Following Cent, Maydew, Zhang, and Zuo (2017) and Henry and Sansing (2018), we use a cash tax differential, *TA_CTD*, as a proxy

[89] We also consider alternative measures of stock liquidity, including the relative effective spread (Fang, Noe, and Tice, 2009; Fang, Tian, and Tice, 2014) and the bid–ask spread (Hasbrouck, 2009) and find our results (untabulated) remain qualitatively the same.

for tax avoidance, where *TA_CTD* is estimated as the difference between cash taxes paid and the product of the statutory tax rate and pre-tax income, scaled by lagged total assets.[90]

Fifth, we consider whether our results remain robust after controlling for accounting conservatism, since Kim et al. (2016) find a negative correlation between accounting conservatism and crash risk. We use Khan and Watts's (2009) firm-level conservatism measure *CSCORE* as a proxy for accounting conservatism.

Sixth, we control for corporate social responsibility, since Kim et al. (2014) suggest that socially responsible firms that commit to a high standard of transparency tend to engage less in bad news hoarding, resulting in lower crash risk. We follow Kim et al. to construct a firm-level measure of corporate social responsibility score, denoted as CSR, using data from the KLD database.

Seventh, we control for earnings smoothing, since Chen et al. (2017) and Khurana et al. (2017) find it to be positively associated with future crash risk. We follow Mclnnis (2010) to measure earnings smoothness as the standard deviation of net incomes divided by the standard deviation of cash flows from operations.

Finally, we control for CEO age, since Andreou, Louca, and Petrou (2017) suggest that firms headed by younger CEOs are more likely to experience stock price crashes. The CEO age data are sourced from ExecuComp. We rerun the baseline regression as in Table 4.3 and add each of the above-mentioned additional control variables and report the results for these tests in rows (1) to (8) in Panel C of Table 4.4.

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[90] We use the effective tax rate, measured as the total tax expense divided by pre-tax income, as an alternative measure of tax avoidance, following Dyreng et al. (2010) and Hasan et al. (2017), and find our results are unaffected.

Overall, the results in Table 4.4 are highly consistent with the baseline results. The coefficients of *DELAYER* are positive and statistically significant across different model specifications. Thus, after controlling for alternative definitions of the timing of schedule earnings news, alternative measures of crash risk, as well as other control variables, we consistently find a positive association between scheduling later-than-expected announcement dates and future stock price crash.

4.5. Timing of Scheduled Earnings News and Crash Risk: When Bad News Hoarding Is More Likely

Our baseline and robustness results suggest that firms that schedule later-than-expected earnings announcement dates are more likely to experience a stock price crash in the future. In this section, we further examine the impact of earnings calendar revisions on crash risk in cases when bad news hoarding is more likely. We employ two different approaches: subsample analysis and conditional analysis.

4.5.1. Earnings Response Coefficients, Corporate Social Responsibility, and Risk Taking Behavior

We partition our sample into two subsamples: one with firms that are more likely to engage in bad news hoarding and the other with firms that are less likely to conceal information through earnings manipulation. We consider four different indicators. First, we partition our sample based on the extent of abnormal stock returns in response to the unexpected component of the firm's reported earnings, that is, the earnings response coefficient *ERC*. We conjecture that the managers of firms whose stock prices are more sensitive to earnings, that is, firms with a higher *ERC*, face more pressure to hide bad news through scheduling later-than-expected earnings announcement dates. Once the accumulation of bad news reaches a certain threshold and is released all at once, stock prices will crash. We therefore expect the impact of earnings calendar revisions on crash risk to be more pronounced among firms whose stock prices are more sensitive to earnings.

We estimate *ERC* as the slope coefficient in a regression of abnormal stock returns on a measure of earnings surprise, following Teoh and Wong (1993). A higher value of *ERC* indicates a stronger market reaction to firm earnings surprises. We split our sample into two subsamples based on the sample median of *ERC*, with the first subsample including firms with above-median *ERC* values (higher *ERC* values) and the second subsample including firms with below-median *ERC* values (lower *ERC* values). We then re-estimate our baseline regression, that is, Equation (3.1), on each subsample and compare the coefficients of *DELAYER* and *ADVANCER* obtained for firms with high and low *ERC* values. We report the results for this test in Panel A of Table 4.5.

Second, we use the level of corporate social responsibility rating to split our sample. Since socially responsible firms tend to commit to a high standard of transparency, we expect these firms to engage less in scheduling later-than-expected earnings announcements for bad news hoarding. Consequently, the impact of earnings calendar revisions on crash risk could be more pronounced among firms with lower social responsibility ratings. We follow Kim et al. (2014) to construct a firm-level measure of corporate social responsibility score, *CSR_SCORE*, using data from the KLD database. Specifically, we first compute the CSR net counts as total strengths minus total concerns in five CSR categories, including community, employee relations, the environment, diversity, and products. We then use the following transformation that preserves the relative distance between CSR net counts for firms within the same industry (based on the Fama–French 12 industry classification) for each quarter:

$$\mathrm{CSR\_SCORE}_{i,t} = \frac{\mathrm{CSR}_{i,t} - \mathrm{Min.\ CSR}_{j,t}}{\mathrm{Max.\ CSR}_{j,t} - \mathrm{Min.\ CSR}_{j,t}} \tag{4.8}$$

where *i* denotes the firm; *t* denotes the year/quarter; *j* denotes the Fama–French 12 industry to which firm *i* belongs*;* and *Max.* and *Min.* are the maximum and minimum values, respectively, of the CSR net counts for firm *i*'s industry in quarter *t*. Higher values of *CSR_SCORE* indicate more socially responsible firms. We re-estimate our baseline regression on two subsamples (firms with *CSR_SCORE* values above and below the median, respectively) and report the results for this test in Panel B of Table 4.5.

Third, we partition our sample based on the riskiness of a firm. Kim et al. (2011b) and Callen and Fang (2015a) suggest that managers of firms with higher levels of risk taking are more concerned about investors' perceptions of firm riskiness and, hence, tend to conceal or delay risk-taking information. Rescheduling earnings announcement dates provide managers the tools and masks for such risk-taking behavior. We therefore conjecture that the impact of earnings calendar revisions on crash risk is more pronounced among firms with a higher level of risk taking. Following prior research (e.g., Graham et al., 2008; Hasan et al., 2014; Callen and Fang, 2015a; Chen, Gul, Veeraraghavan, and Zolotoy, 2015), we use earnings volatility as a proxy for a firm's riskiness. We measure earnings volatility (*EVOL*) as the standard deviation of quarterly earnings in the previous four years. Higher values of *EVOL* indicate a higher level of risk taking. We re-estimate our baseline regression on two subsamples (firms with *EVOL* values above and below the sample median, respectively) and report the results for this test in Panel C of Table 4.5.

Finally, we examine whether the impact of earnings calendar revisions on crash risk varies with the firm information environment. Since firms with high levels of information asymmetry tend to experience higher agency conflicts, we expect these firms to be more likely to use earnings calendar revisions to delay bad news compared to those with lower information asymmetry. Following prior studies (e.g., Callen and Fang, 2015b; Kim, Wang, Zhang, 2016), we use analyst forecast dispersion as a proxy for information asymmetry. We measure analyst forecast dispersion (*DISP*) as the standard deviation of analyst forecasts on the annual earnings of the past year. A higher value of *DISP* indicates greater information asymmetry. Similarly, we then split our sample into two subsamples based on the sample median of *DISP* and then re-estimate our baseline regression on each subsample. We report the results for this test in Panel D of Table 4.5.

{ENTER TABLE 4.5}

Overall, the results in Table 4.5 indicate that the effect of earnings calendar revisions on crash risk is significant only for firms that are sensitive to earnings stock prices or firms with a higher social responsibility rating, a higher level of risk taking, or greater information asymmetry.

4.5.2. CEO Equity Incentives, CEO Tenure, Corporate Governance, and Information Asymmetry

We further examine whether the effect of earnings calendar revisions on crash risk varies with internal performance pressure. We conjecture that managers are more likely to use earnings calendar revisions to conceal bad news when they face greater internal pressure. We use three proxies to measure internal performance pressure, including CEO equity incentives, CEO tenure, and corporate governance. We follow Bergstresser and Philippon (2006) and Kim et al. (2011a) to measure CEO equity incentive as the ratio of the CEO's equity compensation pay–performance sensitivity over the sum of the CEO's salary, bonus, and equity compensation pay–performance sensitivity. The CEO tenure data are sourced from Compustat's ExecuComp database. We use the governance index (G-Index) of Gompers, Ishii, and Metrick (2003) to measure corporate governance.

For each of the measures of internal performance pressure, we partition our sample into two subsamples based on the sample median of the measures and then re-estimate our baseline regression on each subsample. We report the results for these tests in Panels A to C of Table 4.6.

{ENTER TABLE 4.6}

The results of Table 4.6 indicate that the effect of earnings calendar revisions on crash risk is significant only when CEOs have stronger equity incentives, CEOs are in their early years of tenure, or firms have weaker governance mechanisms. These results, along with those of Table 4.5, suggest that the effect of earnings calendar revisions on crash risk is more concentrated in firms with higher agency costs.

4.5.3. Timing of Scheduled Earnings News and Crash Risk: Conditioning Analysis

We deepen our analysis by examining whether the effect of earnings calendar revisions on crash risk varies with external performance pressure. Similar to internal performance pressure, managerial incentives to reschedule earnings announcement dates to delay the release of bad news can be driven by external performance pressure. Following prior research (e.g., Kim et al., 2011a; Callen and Fang, 2013; Chang et al., 2017), we employ two proxies for external pressure, including institutional ownership and analyst coverage. Since institutional investors and analysts play significant roles in reducing information asymmetry (Easley, Hvidkjaer, and O'Hara, 2002) and in monitoring managerial risk taking behavior (Bushee and Noe, 2000; Lang, Lins, and Miller, 2004; Cohen et al., 2008; Yu, 2008), we expect that analyst following and institutional holdings can mitigate the impact of rescheduling earnings announcement dates on crash risk.

We measure the number of analysts following the firm (*ANALYST*) as the average number of analysts who provide earnings forecasts in each month during the year. We source analyst following data from I/B/E/S. We obtain institutional ownership data (*INST*) from the Thomson Reuters Institutional 13F Database. We estimate an augmented version of our baseline regression Equation (3.3) after including *INST* (or *ANALYST*) and its interaction with our variables of interest, *DELAYER* and *ADVANCER*. We report the results for these tests in Table 4.7.

{ENTER TABLE 4.7}

According to the results of Table 4.7, the effect of scheduling later-than-expected earnings announcement dates on crash risk remains positive and statistically significant at the 1% level. We find that the interaction of *DELAYER* with *INST* is negative and significant at the 5% level, suggesting that institutional investors mitigate the impact of earnings calendar revisions on crash risk. The coefficients of the interaction term *DELAYER×ANALYST* is negative but insignificant. Overall, the results of Table 4.7 suggest that external monitoring by institutional holdings plays a significant role in constraining managerial tendencies to conceal bad news through rescheduling earnings announcement dates.

4.5.4. Timing of Scheduled Earnings News and Meeting or Beating Analyst Forecasts

Thus far, our results suggest that firms that conceal bad news through scheduling later-than-expected earnings announcement dates are more likely to experience a stock price crash in the future. Since earnings calendar revisions can facilitate opportunistic managerial behavior, we expect rescheduling earnings news to be associated with another measure of earnings manipulation. Accordingly, we further examine whether the timing of scheduled earnings news is associated with the likelihood of beating analyst forecasts. Following Huang et al. (2017), we define *BEAT_1C*/*BEAT_2C*/*BEAT_3C* as a dummy variable that takes the value of one if the firm's actual earnings beat analyst forecasts by one cent/two cents/three cents and zero otherwise. We estimate an augmented version of our baseline regression Equation (3.3) after replacing crash risk measures by three dummies for beating analyst forecasts. We report the results for these tests in Table 4.8

{ENTER TABLE 4.8}

The results of Table 4.8 suggest that firms that schedule later-than-expected earnings announcement dates are less likely to beat future earnings forecasts. This evidence further confirms the consequences of managers hoarding bad news through rescheduling earnings announcement dates.

4.6. Further Discussion

In this section, we consider whether a firm's stakeholders consider the timing of scheduled earnings news. We are curious whether the timing of scheduled earnings news is associated with subsequent corporate behavior.

4.6.1. Timing of Scheduling Earnings News and the Cost of Equity Capital

We start by investigating whether there is an association between the timing of scheduled earnings and the future cost of equity capital. Since earnings calendar revisions are signals of subsequent earnings surprises (Livnat and Zhang, 2015; Johnson and So, 2017b), investors can potentially capitalize on this and demand higher expected returns for firms that schedule later-than-expected earnings announcement dates.

Following prior studies (e.g., Hail and Leuz, 2006; Li, 2010; Naiker et al., 2013; Dhaliwal et al., 2016), we measure the implied cost of equity, *ICOC*, as the equally weighted average of four implied cost of equity measures, including r_{GM}, based on the method of Gode and

Mohanram (2003); r_{CT}, based on the method of Claus and Thomas (2001); r_{GLS}, based on the method of Gebhardt et al. (2001), and r_{EAST}, based on the method of Easton (2004).[91] To study the effect of earnings calendar revisions on the implied cost of equity, we estimate the following equation:

$$ICOC_{i,t} = \alpha_0 + \gamma_1\ DELAYER\_ANN_{,t-1} + \gamma_2\ IVOL_{i,t-1} + \gamma_3\ LEV_{i,t-1} + \gamma_4\ ROA_{i,t-1} + \gamma_5\ RET_{i,t-1} + \gamma_6\ DISP_{i,t-1} + \gamma_7\ \beta MKT_{i,t-1} + \gamma_8\ \beta SMB_{i,t-1} + \gamma_9\ \beta HML_{i,t-1} + \gamma_{10}\ \beta RMW_{i,t-1} + \gamma_{11} \beta CMA_{i,t-1} + FEs + \varepsilon_{i,t} \quad (4.9)$$

where *i* denotes the firm; *t* denotes the year; *ICOC* denotes the implied cost of equity; *DELAYER_ANN* is the measure of earnings calendar revisions*; FEs* denotes firm and year fixed effects; and $\varepsilon_{i,t}$ is the error term. Given the implied cost of equity is measured for each firm–year, we construct annual measures of earnings calendar revisions based on their quarterly measures. Specifically, for each firm–year, we compute the number of quarters in which the firm schedules later-than-expected ($n_{delayer}$) or earlier-than-expected ($n_{advancer}$) earnings announcement dates.**[92]** We then take the difference between $n_{delayer}$ and $n_{advancer}$ and define a dummy variable (*DELAYER_ANN*) that takes the value of one if this difference is positive and zero otherwise. A higher value of *DELAYER_ANN* indicates a higher likelihood of scheduling later-than expected earnings announcement dates. Following prior literature (e.g., Gebhardt et al., 2001; Hall and Leuz, 2006; Dhaliwal et al., 2007; Naiker et al., 2013; Dhaliwal et al., 2016), we include in the regression model (Equation 3.8) several firm-level control variables, including firm size (*SIZE*), the book-to-market ratio (*BTM*), analyst forecast dispersion (*DISP)*, long-term growth in analyst earnings forecasts (*LTG*), leverage (*LEVERAGE*), asset tangibility (TANG), firm profitability (*ROA*), and factor loadings from the Fama–French (2015) five-

[91] We use the equally weighted average of the four measures of implied cost of equity, since there appears to be a lack of consensus on the superiority of any individual model in estimating the cost of equity capital. Our results are, however, unaffected by the use of any individual measure of the cost of equity.

[92] Later-than-scheduled (earlier-than-scheduled) quarters are defined in Section 3.3.2. Specifically, delayers (advancers) are those whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date.

factor model on risk factors (*βMKT, βSMB, βHML, βRMW,* and *βCMA*). We estimate Equation (3.9) using OLS. The *t*-statistics are computed using standard errors adjusted for heteroskedasticity and clustering at the firm level. For all models, we include firm and year fixed effects to control for unobservable firm-specific and time-invariant factors, respectively. Table 4.9 presents the results for these tests.

{ENTER TABLE 4.9}

The coefficient of *DELAER_ANN* is positive and significant at the 1% level in both model (1), which excludes all the control variables; model (2), which includes all the control variables; and models (3) to (6), which consider each individual measure of the implied cost of equity. The magnitude of these effects is also economically significant, with firms that schedule later-than-expected earnings announcement dates having, on average, an implied cost of equity capital 36 basis points (bps) higher than firms that do not delay their scheduled earnings announcement dates.[93] These results are consistent with our conjecture that investors can potentially capitalize on earnings calendar revisions and demand higher expected returns for firms that schedule later-than-expected earnings announcement dates.

4.6.2. Timing of Scheduling Earnings News and the Pricing of Audit Services

We further examine whether there is any link between the timing of scheduled earnings and firm accounting quality. If managers withhold bad news by strategically revising the timing of

[93] After accounting for the impact of the control variables, our results suggest that firms that schedule later-than-expected earnings announcement dates have a 36-bps higher implied cost of equity capital than their peers do. We estimate this difference as the coefficient of *DELAYER_ANN* divided by the average implied cost of equity across the full sample (e.g., for *ICOC*, 0.004/0.110 = 36 bps). Hail and Leuz (2006), Ben-Nasr et al. (2012), and Naiker et al. (2013) document a similar magnitude of effects on the cost of equity capital of firms and conclude such effects to be economically significant.

scheduled earnings news to allow more time to manipulate accounting information, auditors could take this into account in the pricing of their audit services.[94]

The audit fee data and other standard control variables are sourced from the Audit Analytics database. We measure audit fee, *Log(AUDIT_FEE)*, as the logarithm of audit fees (in dollars) that the firm pays its auditors over the fiscal year. We obtain firm financial information from Compustat's fundamental annual files. Follow prior studies (Simunic, 1980; Johnstone and Bedard, 2003; Gul and Goodwin, 2010; Hanlon, Krishnan, and Mills, 2012; Bentley, Omer, and Sharp, 2013; Billings et al., 2014; Chen et al., 2015), we include control variables for firm and auditor characteristics, including firm size (*SIZE*), the book-to-market ratio (*BTM*), leverage (*LEVERAGE*), asset tangibility (*TANG*), firm profitability (*ROA*), receivables and inventory ratio (*REC_INV*), special items (*SPI*), the logarithm of non-audit fees (*Log(NONAUDIT_FEE)*), operating loss (*LOSS*), auditor tenure (*AUDITOR_TENURE*), audit opinion (*OPINION*), a dummy variable (*BIG4*) that takes the value of one if the firm is audited by one of the Big 4 auditors and zero otherwise, and a dummy variable (*DEC_END*) that is equal to one if the firm's fiscal year-end is December and zero otherwise.

To study the effect of earnings calendar revisions on audit pricing, we estimate the following equation:

$$\text{Log(AUDIT\_FEE)}_{i,t} = \alpha_0 + \gamma_1\text{DELAYER\_ANN}_{,t-1} + \gamma_2\text{SIZE}_{i,t-1} + \gamma_3\text{BIG4}_{i,t-1} + \gamma_4\text{AUDITOR\_TENURE}_{i,t-1} + \gamma_5\ \text{Log(NONAUDIT\_FEE)}_{i,t-1} + \gamma_6\ \text{OPINION}_{i,t-1} + \gamma_7\ \text{DEC\_END}_{i,t-1} + \gamma_8\ \text{MB}_{i,t-1} + \gamma_9\ \text{LEV}_{i,t-1} + \gamma_{10}\ \text{ROA}_{i,t-1} + \gamma_{11}\text{TANG}_{i,t-1} + \gamma_{12}\text{REC\_INV}_{,t-1} + \gamma_{13}\ \text{LOSS}_{i,t-1} + \gamma_{14}\ \text{SPI}_{i,t-1} + \gamma_{15}\ \text{EVOL}_{i,t-1} + \text{FEs} + \varepsilon_{i,t} \tag{4.10}$$

[94] DeFond and Zhang (2014) suggest that an audit fee premium can be interpreted as compensation for extra audit effort and residual risks. Because rescheduling earnings announcement dates provides tools and masks to conceal bad news, firms that schedule later-than-expected earnings announcement dates could require a higher level of audit effort.

where *i* denotes the firm, *t* denotes the year, *Log(AUDIT_FEE)* denotes the implied cost of equity, *DELAYER_ANN* denotes a measure of earnings calendar revisions, *FEs* denotes firm and year fixed effects, and $\varepsilon_{i,t}$ is the error term. We estimate Equation (3.10) using OLS. The *t*-statistics are computed using standard errors adjusted for heteroskedasticity and clustering at the firm level. For all the models, we include firm and year fixed effects to control for unobservable firm-specific and time-invariant factors, respectively. Table 4.10 presents the results for these tests.

{ENTER TABLE 4.10}

The coefficient of *DELAER_ANN* is positive and significant at the 1% level in both model (1) in Table 4.10, which excludes all the control variables, and model (2), which includes all the control variables. These results are consistent with our prediction that auditors consider earnings calendar revisions and require higher audit fees to compensate for their additional effort in auditing firms that schedule later-than-expected earnings announcement dates.

For the control variables, we find that the audit fees are positive and significantly related to firm size, leverage, and non-audit fees but negatively and significantly related to firm profitability.[95] Overall, these findings are largely consistent with the prior literature (e.g., Johnstone and Bedard, 2003; Gul and Goodwin, 2010; Hanlon et al., 2012; Bentley et al., 2013; Billings et al., 2014; Chen et al., 2015).

[95] The coefficients on Big 4 auditors (*BIG4*) and auditors with longer tenure (*AUDITOR_TENURE*) are positive but insignificant, which is not aligned with prior studies (e.g., Billings et al., 2014; Chen et al., 2015). Our results (untabulated) suggest that this discrepancy is due to the inclusion of firm fixed effects in regression models.

4.7. Conclusion of Chapter 4

We find that firms that schedule later-than-expected earnings announcement dates are more likely to experience future stock price crashes, whereas there is no significant association between the advanced scheduling of earnings announcement dates and crash risk. The effect of earnings calendar revisions on crash risk is more concentrated among firms with higher agency costs. We also find that firm stakeholders do consider the timing of scheduled earnings news. Investors demand higher expected returns (i.e., implied cost of equity) for firms that schedule later-than-expected earnings announcement dates. Auditors also require higher audit fees to compensate for their additional effort in auditing firms that schedule later-than-expected earnings announcement dates.

Given their magnitude and robustness, our results suggest two potentially fruitful avenues for future research. First, future studies could examine the impact of earnings calendar revisions on other corporate decisions, such as mergers and acquisitions and investment decisions. Second, subsequent research could consider how other firms' key stakeholders (e.g., employees, banks, customers) respond to firm earnings calendar revisions.

Table 4.1. Sample Selection and Distribution of the Key Variables by Year

This table presents the sample distributions by year and the mean values of the crash risk measures (*COUNT* and *DUVOL*) and the measures of the timing of scheduled earnings news (*DELAYER* and *ADVANCER*). The sample consists of the firm–quarters jointly covered in the merged Compustat–CRSP database, I/B/E/S, and WSH between 2006 and 2015. The variable *COUNT* is the number of days in which the firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; and *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. The other variables definitions are in Appendix 4.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Sample selection

Sample Requirements	Observations	Firms
+ Intersection of CRSP, Compustat, I/B/E/S, and WSH	149,584	6,319
+ Scheduling disclosure date in t - 31 to t - 11	53,352	4,557
+ Calendar revision | *REV* | ≥ 1 trading days	29,873	4,253
Firm–quarter sample	29,873	4,253
+ Merge with quarterly crash risk measures	23,367	3,391
+ Include all control variables	22,636	3,308
Final sample	22,636	3,308

Panel B. Distribution by year for key variables

Fiscal year	Obs.	% Obs. with Stock Price Crash	Mean of *COUNT*	Mean of *DUVOL*	Mean of *DELAYER*	Mean of *ADVANCER*
2006	2,113	0.318	-0.065	-0.084	0.498	0.110
2007	2,462	0.333	-0.069	-0.049	0.333	0.111
2008	2,482	0.256	0.012	0.068	0.428	0.123
2009	2,347	0.323	-0.145	-0.128	0.363	0.143
2010	2,151	0.309	-0.105	-0.095	0.316	0.148
2011	2,117	0.302	-0.060	-0.043	0.344	0.130
2012	2,124	0.308	-0.052	-0.057	0.444	0.127
2013	2,213	0.323	-0.105	-0.092	0.405	0.144
2014	2,533	0.325	-0.056	-0.039	0.400	0.150
2015	2,094	0.268	-0.022	-0.005	0.331	0.183

Table 4.2. Summary Statistics and Correlation Matrix

This table presents the summary statistics and the correlation matrix. The sample consists of firm–quarters jointly covered in the merged Compustat–CRSP database, I/B/E/S, and WSH between 2006 and 2015. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter; and *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. The other variable definitions are in Appendix 4.1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary statistic

	Obs.	Mean	S.D.	P5	P25	P50	P75	P95
COUNT	22,636	-0.070	0.802	-1.000	-1.000	0.000	0.000	1.000
DUVOL	22,636	-0.050	0.648	-1.061	-0.425	-0.066	0.296	1.042
DELAY	22,636	0.382	0.486	0.000	0.000	0.000	1.000	1.000
ADVANCE	22,636	0.134	0.341	0.000	0.000	0.000	1.000	1.000
RET	22,636	0.001	0.003	-0.004	-0.001	0.001	0.002	0.005
SIGMA	22,636	0.026	0.013	0.013	0.016	0.023	0.033	0.055
NCSKEW	22,636	-0.062	1.049	-2.172	-0.614	-0.087	0.426	2.335
DTURN	22,636	0.000	0.002	-0.004	-0.001	0.000	0.001	0.004
SIZE	22,636	5.261	1.543	2.603	4.141	5.436	6.744	7.056
MB	22,636	2.541	1.833	0.519	1.218	1.963	3.415	6.594
LEV	22,636	0.180	0.169	0.000	0.014	0.145	0.295	0.527
ROA	22,636	0.002	0.033	-0.058	0.001	0.008	0.019	0.030
Q4	22,636	0.284	0.451	0.000	0.000	0.000	1.000	1.000

Panel B: Correlation matrix

	COUNT	*DUVOL*	*DELAY*	*ADVANCE*	*RET*	*SIGMA*	*NCSKEW*	*DTURN*	*SIZE*	*MB*	*LEV*	*ROA*	*Q4*
COUNT	1												
DUVOL	0.738***	1											
DELAY	0.014**	0.012*	1										
ADVANCE	0.005	-0.001	-0.309	1									
RET	0.024***	0.014**	-0.038***	0.037***	1								
SIGMA	-0.012*	0.012*	0.035***	0.042***	-0.052***	1							
NCSKEW	0.855***	0.928***	0.012*	-0.001	0.020***	0.002	1						
DTURN	0.001	0.003	-0.006	-0.004	-0.032***	0.100***	0.003	1					
SIZE	0.029***	0.016**	-0.025***	-0.052***	0.032***	-0.374***	0.023***	0.017**	1				
MB	0.015**	-0.002	-0.023***	0.027***	0.076***	-0.139***	0.007	0.041***	0.045***	1			
LEV	-0.010	-0.009	-0.033***	0.014**	0.006	-0.129***	-0.008	0.001	0.389***	-0.057***	1		
ROA	0.017**	0.004	-0.035***	-0.033***	0.082***	-0.243***	0.008	0.026***	0.290***	0.336***	-0.039***	1	
Q4	-0.003	-0.015**	0.024***	0.047***	0.043***	0.019**	-0.014**	-0.033***	-0.004	-0.002	-0.013**	0.002	1

Table 4.3. **Timing of Scheduled Earnings News and Crash Risk: Main Results**

This table presents the regression results for the relation between the timing of scheduled earnings news and crash risk. The sample consists of firm–quarters jointly covered in the merged Compustat/CRSP database, I/B/E/S, and WSH between 2006 and 2015. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; and *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. The other variable definitions are in Appendix 4.1. All continuous variables are winsorized at the first and 99th percentiles. The constant term, firm fixed effects, and year/quarter fixed effects are included in the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$COUNT_t$			$DUVOL_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
$DELAY_{t-1}$	0.033**		0.035**	0.027**		0.028**
	(2.51)		(2.49)	(2.45)		(2.49)
$ADVANCE_{t-1}$		-0.008	0.007		-0.006	0.007
		(-0.42)	(0.36)		(-0.36)	(0.39)
RET_{t-1}	0.130***	0.128***	0.130***	0.115***	0.114***	0.115***
	(4.31)	(4.22)	(4.30)	(5.05)	(4.97)	(5.04)
$SIGMA_{t-1}$	-1.815**	-1.743*	-1.816**	-1.112	-1.054	-1.113
	(-1.98)	(-1.90)	(-1.98)	(-1.51)	(-1.43)	(-1.51)
$NCSKEW_{t-1}$	-0.025***	-0.025***	-0.025***	-0.020***	-0.020***	-0.020***
	(-3.53)	(-3.54)	(-3.53)	(-3.45)	(-3.46)	(-3.45)
$DTURN_{t-1}$	1.157	1.123	1.159	-0.391	-0.418	-0.390
	(0.38)	(0.37)	(0.38)	(-0.16)	(-0.18)	(-0.16)
$SIZE_{t-1}$	0.089***	0.090***	0.089***	0.075***	0.076***	0.075***
	(3.58)	(3.61)	(3.58)	(4.00)	(4.02)	(4.00)
MB_{t-1}	0.033***	0.032***	0.033***	0.027***	0.027***	0.027***
	(4.61)	(4.58)	(4.61)	(4.32)	(4.29)	(4.32)
LEV_{t-1}	-0.328***	-0.326***	-0.328***	-0.172**	-0.171**	-0.172**
	(-3.60)	(-3.58)	(-3.60)	(-2.21)	(-2.19)	(-2.21)
ROA_{t-1}	-0.375	-0.391	-0.376	-0.240	-0.252	-0.241
	(-1.36)	(-1.41)	(-1.36)	(-1.04)	(-1.09)	(-1.04)
$Q4_{t-1}$	-0.441*	-0.456*	-0.441*	-0.405***	-0.418***	-0.406***
	(-1.67)	(-1.74)	(-1.67)	(-3.91)	(-4.06)	(-3.91)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,636	22,636	22,636	22,636	22,636	22,636
Adj. R^2	0.003	0.003	0.003	0.026	0.025	0.025

Table 4.4. Timing of Scheduled Earnings News and Crash Risk: Additional Analysis

This table presents the results of several robustness tests for the relation between the timing of scheduled earnings news and crash risk. The dependent variables are the crash risk measures *COUNT* and *DUVOL*. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where the firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; and *DELAYER* is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. For brevity, the table reports only the coefficients of *DELAYER*. Other firm-level characteristics variables are similar to those in the baseline regressions in Table 3.3. The constant term, firm fixed effects, and year/quarter fixed effects are included in all the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Coefficients of *DELAYER*	*COUNT* (1)	*DUVOL* (2)
Panel A: Alternative measures of crash risk		
(1) 3.2 standard deviations below the mean	0.030**	-
	(2.33)	
(2) 3.5 standard deviations below the mean	0.022**	-
	(2.01)	
(3) 4 standard deviations below the mean	0.019**	-
	(2.11)	
(4) Industry-adjusted crash risk measures	0.011**	0.010***
	(2.36)	(2.73)
Panel B: Alternative measures of the timing of scheduled earnings news		
(1) Alternative measure of *DELAYER* and *ADVANCER*	0.032**	0.025**
	(2.14)	(2.13)
(2) Industry-adjusted measures	0.033**	0.027**
	(2.41)	(2.45)
Panel C: Additional control variables		
(1) Control for discretionary accruals	0.062**	0.037**
	(2.32)	(2.02)
(2) Control for stock liquidity	0.041**	0.026**
	(2.31)	(2.04)
(3) Control for institutional ownership	0.037**	0.031***
	(2.53)	(2.63)
(4) Control for tax avoidance	0.035**	0.028**
	(2.47)	(2.47)
(5) Control for accounting conservatism	0.032**	0.022*
	(2.04)	(1.80)
(6) Control for earnings smoothing	0.035**	0.028**
	(2.49)	(2.49)
(7) Control for corporate social responsibility	0.035**	0.028**
	(2.51)	(2.52)
(8) Control for CEO age	0.035**	0.028**
	(2.49)	(2.49)

Table 4.5. Timing of Scheduled Earnings News and Crash Risk: Subsample Analysis

This table presents the results of the relation between the timing of scheduled earnings news and crash risk, where the full sample is partitioned by the sample median of earnings response coefficient, *ERC* (Panel A); the firm-level measure of the corporate social responsibility score, *CSR_SCORE* (Panel B); earnings volatility, *EVOL* (Panel C); and analyst forecast dispersion, *DISP* (Panel D). The dependent variables are the crash risk measures *COUNT* and *DUVOL*. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where the firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; and *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. The other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year/quarter fixed effects are included in all the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Earnings response coefficient (*ERC*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.144**	0.061	0.154***	0.016
	(2.19)	(1.57)	(3.04)	(0.54)
$ADVANCE_{t-1}$	0.034	-0.020	0.072	-0.029
	(0.37)	(-0.38)	(0.93)	(-0.65)

Panel B: Corporate social responsibility (*CSR*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.028	0.047***	-0.011	0.046***
	(0.89)	(2.68)	(-0.44)	(3.34)
$ADVANCE_{t-1}$	0.043	-0.004	0.033	-0.007
	(0.94)	(-0.16)	(0.91)	(-0.33)

Panel C: Risk taking behavior (*EVOL*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.050***	(-0.032)	0.039***	-0.025
	(3.06)	(-0.94)	(2.91)	(-0.94)
$ADVANCE_{t-1}$	0.033	-0.099**	0.021	-0.061*
	(1.32)	(-2.26)	1.03	(-1.74)

Panel D: Information asymmetry (*DISP*)				
	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.059**	0.027	0.043**	0.024
	(2.12)	(1.42)	(1.96)	(1.59)
$ADVANCE_{t-1}$	0.042	0.006	0.021	0.014
	(1.09)	(0.22)	(0.65)	(0.63)

Table 4.6. Differential Impact of the Timing of Scheduled Earnings News on Crash Risk

This table presents the results of the relation between the timing of scheduled earnings news and crash risk, where the full sample is partitioned by the sample median of CEO equity incentives, *CEO_INC* (Panel A); CEO tenure, *TENURE* (Panel B); and corporate governance, *GOV* (Panel C)**.** The dependent variables are the crash risk measures *COUNT* and *DUVOL*. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where the firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; and *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. the other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year/quarter fixed effects are included in all the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CEO equity incentives (*CEO_INC*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.037**	0.025	0.025*	0.030
	(2.20)	(0.87)	(1.87)	(1.28)
$ADVANCE_{t-1}$	0.011	0.010	0.013	-0.001
	(0.46)	(0.21)	(0.65)	(-0.04)

Panel B: CEO tenure (*TENURE*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	0.038	0.031*	0.020	0.028**
	(1.01)	(1.95)	(0.67)	(2.20)
$ADVANCE_{t-1}$	-0.022	0.012	-0.017	0.015
	(-0.34)	(0.53)	(-0.33)	(0.83)

Panel C: Corporate governance (*GOV*)

	$COUNT_t$		$DUVOL_t$	
	High	Low	High	Low
$DELAY_{t-1}$	-0.001	0.035**	0.002	0.029**
	(-0.02)	(2.25)	(0.06)	(2.32)
$ADVANCE_{t-1}$	-0.014	-0.001	-0.077	0.010
	(-0.19)	(-0.06)	(-1.42)	(0.56)

Table 4.7. Timing of Scheduled Earnings News and Crash Risk: Effect of External Performance Pressure

This table presents the cross-sectional regression results of the effect of institutional ownership (*INST*) and analyst following (*ANALYST*) on the association between the timing of scheduled earnings news and crash risk. The dependent variables are the crash risk measures *COUNT* and *DUVOL*. The variable *COUNT* is the number of days in which firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}; *DUVOL is* the down-to-up volatility of firm-specific daily returns over the quarter, where the firm-specific daily stock returns are the residual daily returns computed using Equation (3.1) in Section 3.3.1; *DELAYER* (*ADVANCER*) is a dummy variable that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise; *ANALYST* is the number of analysts following the firm, measured as the average number of analysts who provide earnings forecasts in each month during the year; and *INST* is institutional ownership, obtained from the Thomson Reuters Institutional 13F Database. The other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year/quarter fixed effects are included in all the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	INST		*ANALYST*	
	$COUNT_t$	$DUVOL_t$	$COUNT_t$	$DUVOL_t$
	(1)	(2)	(3)	(4)
$DELAY_{t-1}$	0.133***	0.087***	0.042**	0.041*
	(3.66)	(2.97)	(2.07)	(1.83)
$INST_{t-1}$	0.137**	0.079**		
	(2.78)	(1.97)		
$INST_{t-1}$ * $DELAY_{t-1}$	-0.140***	-0.082**		
	(-2.85)	(-2.04)		
$ANALYST_{t-1}$			0.010***	0.041***
			(4.91)	(4.93)
$ANALYST_{t-1}$ * $DELAY_{t-1}$			-0.001	-0.005
			(-0.40)	(-0.63)
Control Variables	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Observations	21,417	21,417	22,636	22,636
Adj. R^2	0.003	0.027	0.004	0.027

Table 4.8. Timing of Scheduled Earnings News and Meeting/Beating Analyst Forecasts

The table presents the regression results for the relation between the timing of scheduled earnings news and meeting/beating analyst forecasts. The variable *BEAT_1C/BEAT_2C/BEAT_3C* is a dummy variable that equals one if the firm's actual earnings beat analyst forecasts by one cent/two cents/three cents, and zero otherwise. The variable *DELAYER* (*ADVANCER*) is a dummy that takes the value of one for firms whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date and zero otherwise. The other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year fixed effects are included in the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroskedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$BEAT\_1C_t$	$BEAT\_2C_t$	$BEAT\_3C_t$
	(1)	(2)	(3)
$DELAYER_{t-1}$	-0.022**	-0.020**	-0.015*
	(-2.42)	(-2.21)	(-1.70)
$ADVANCER_{t-1}$	-0.003	-0.003	-0.001
	(-0.27)	(-0.21)	(-0.05)
RET_{t-1}	0.010	0.013	0.009
	(0.50)	(0.68)	(0.48)
$SIGMA_{t-1}$	1.564***	1.743***	1.825***
	(2.68)	(3.02)	(3.13)
$NCSKEW_{t-1}$	-0.006	-0.006	-0.006
	(-1.59)	(-1.57)	(-1.57)
$DTURN_{t-1}$	-0.214	-0.561	-1.227
	(-0.12)	(-0.33)	(-0.72)
$SIZE_{t-1}$	0.006	0.008	0.005
	(0.35)	(0.51)	(0.28)
MB_{t-1}	0.001	0.000	-0.002
	(0.28)	(0.05)	(-0.53)
LEV_{t-1}	-0.044	-0.017	0.015
	(-0.66)	(-0.26)	(0.24)
ROA_{t-1}	-0.255	-0.308	-0.361+
	(-1.30)	(-1.58)	(-1.84)
$Q4_{t-1}$	-0.008	-0.078	-0.063
	(-0.07)	(-0.55)	(-0.45)
Firm Fixed Effects	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Observations	19,512	19,512	1,9512
Adj. R^2	0.168	0.165	0.165

Table 4.9. Timing of Scheduled Earnings News and the Cost of Equity Capital

This table presents the regression results for the relation between the timing of scheduled earnings news and the cost of equity capital. The sample consists of firm–years jointly covered in the merged Compustat/CRSP database, I/B/E/S, and WSH between 2006 and 2015. The variable *ICOC*, the implied cost of equity, is the equally weighted average of the four implied cost of equity measures, including r_{GM}, based on the method of Gode and Mohanram (2003); r_{CT}, based on the method of Claus and Thomas (2001); r_{GLS}, based on the method of Gebhardt et al. (2001); and r_{EAST}, based on the method of Easton (2004). The variable *DELAYER_ANN* is an annual measure of earnings calendar revision. The other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year fixed effects are included in the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$ICOC_t$	$ICOC_t$	$rEAST_t$	$rGLS_t$	rOJ_t	rCT_t
$DELAYER\_ANN_{t-1}$	0.004***	0.004***	0.004**	0.003***	0.003***	0.003**
	(3.70)	(3.44)	(2.08)	(3.17)	(3.13)	(2.35)
$IVOL_{t-1}$		0.518***	0.524***	0.371***	0.524***	0.716***
		(5.38)	(4.09)	(3.92)	(4.74)	(5.28)
LEV_{t-1}		0.025***	0.019*	0.013*	0.031***	0.039***
		(3.38)	(1.65)	(1.88)	(3.92)	(3.71)
ROA_{t-1}		0.054***	0.022*	0.049***	0.081***	0.052***
		(6.23)	(1.74)	(5.24)	(6.92)	(4.93)
RET_{t-1}		-0.005***	-0.007***	-0.004**	-0.004**	-0.005***
		(-3.34)	(-3.27)	(-2.44)	(-2.31)	(-3.00)
LTG_{t-1}		-0.000	-0.000	-0.000**	-0.000	-0.000
		(-1.61)	(-1.17)	(-1.96)	(-1.40)	(-1.61)
$DISP_{t-1}$		0.014**	0.005	0.012**	0.026***	0.012*
		(2.30)	(0.54)	(2.30)	(3.95)	(1.71)
βrm_{t-1}		0.003**	0.003	0.003*	0.004**	-0.001
		(2.04)	(1.28)	(1.86)	(2.13)	(-0.43)
βsmb_{t-1}		-0.002**	-0.004***	-0.000	-0.002*	-0.001
		(-2.17)	(-2.78)	(-0.47)	(-1.76)	(-0.66)
βhml_{t-1}		0.002***	0.001	0.003***	0.002**	0.002***
		(3.43)	(1.29)	(4.54)	(2.54)	(2.75)
βrmw_{t-1}		-0.000	-0.000	-0.001	-0.000	-0.001
		(-0.82)	(-0.41)	(-1.10)	(-0.48)	(-1.41)
βcma_{t-1}		0.001	0.000	0.001*	0.001	0.000
		(1.35)	(0.49)	(1.86)	(0.94)	(0.39)
Constant	0.076***	0.057***	0.071***	0.067***	0.043***	0.061***
	(45.06)	(18.10)	(14.48)	(21.46)	(11.98)	(14.91)

Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,396	25,386	25,386	25,386	25,386	25,386
Adj. R^2	0.453	0.459	0.314	0.363	0.411	0.525

Table 4.10. Timing of Scheduled Earnings News and the Pricing of Audit Services

This table presents the regression results for the relation between the timing of scheduled earnings news and audit pricing. The sample consists of firm–years jointly covered in the merged Compustat/CRSP database, I/B/E/S, and WSH between 2006 and 2015. The term *Log(AUDIT_FEE*) is the logarithm of audit fees (in dollars) the firm pays its auditors over the fiscal year. The variable *DELAYER_ANN* is an annual measure of earnings calendar revision. The other variable definitions are in Appendix 4.1. The constant term, firm fixed effects, and year fixed effects are included in the regressions. The *t*-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and heteroscedasticity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) $Log(AUDIT\_FEE)_t$	(2) $Log(AUDIT\_FEE)_t$
$DELAYER\_ANN_{t-1}$	0.026***	0.024***
	(2.87)	(2.62)
$SIZE_{t-1}$		0.124***
		(7.89)
$BIG4_{t-1}$		0.078
		(0.70)
$AUDITOR\_TENURE_{t-1}$		0.006
		(0.77)
$Log(NONAUDIT\_FEE)_{t-1}$		0.038***
		(6.64)
$OPINION_{t-1}$		0.019
		(1.61)
DEC_END_{t-1}		-0.235
		(-1.43)
MB_{t-1}		0.000
		(0.02)
LEV_{t-1}		0.164**
		(2.52)
ROA_{t-1}		-0.186**
		(-1.99)
$TANG_{t-1}$		0.000**
		(2.25)
REC_INV_{t-1}		-0.115
		(-0.89)
$LOSS_{t-1}$		0.021
		(0.54)
SPI_{t-1}		-0.000
		(-1.63)
$EVOL_{t-1}$		0.113
		(0.66)
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	10,347	8,506
Adj. R^2	0.889	0.909

Appendix 4.1. Variable Definitions for Chapter 4

Variables	**Definition**
Crash risk measures	
COUNT	The number of days in which the firm-specific daily return is 3.09 standard deviations below the mean minus the number of days in which the firm-specific daily return is 3.09 standard deviations above the mean between the earnings announcements of Q_t and Q_{t+1}. The firm-specific daily return is the natural logarithm of one plus the estimated residual return from Equation (3.1).
DUVOL	The down-to-up volatility of firm-specific daily returns over the quarter.
NCSKEW	The negative conditional skewness of firm-specific daily returns over the quarter.
Measures of the timing of scheduling earnings news	
DELAYER	A dummy variable that takes the value of 1 for firms whose scheduled announcement date is at least three days later than their unconfirmed announcement date and 0 otherwise.
ADVANCER	A dummy variable that is equal to 1 for firms whose scheduled announcement date is at least three trading days earlier than their unconfirmed announcement date and 0 otherwise.
DELAYER_ANN	A dummy variable that takes the value of 1 for firms with more delayed earnings announcement dates than advanced earnings announcement dates in a given year and 0 otherwise. Delayers (advancers) are those whose scheduled announcement date is at least three days later (earlier) than their unconfirmed announcement date.
Firm-level variables	
DTURN	The average daily share turnover over the current quarter minus the average monthly daily share turnover over the previous quarter. The daily share turnover is calculated as the ratio of the daily trading volume to the number of shares outstanding.
SIGMA	The standard deviation of firm-specific daily returns over the quarter.
RET	The mean of firm-specific daily returns over the quarter.
SIZE	The natural logarithm of the market value of equity (*CSHOQ* × *PRCCQ*) at the end of the quarter.
MB	The ratio of the market value of equity (*CSHOQ* × *PRCCQ*) to the book value of equity (*CEQQ*).
LEV	The ratio of total liabilities (*LTQ*) to the book value of total assets (*ATQ*).
ROA	The ratio of income before extraordinary items (*IBQ*) over the book value of total assets (*ATQ*).

Q4	A dummy variable that takes the value of 1 if the current quarter is the fourth fiscal quarter and 0 otherwise.
ACCM	The moving sum of the absolute value of annual discretionary accruals over the prior three years, where annual discretionary accruals are calculated using the modified Jones model of Dechow, Sloan, and Sweeney (1995).
CSCORE	The Khan –Watts (2009) measure of accounting conservatism.
CSR_SCORE	A firm-level measure of the corporate social responsibility score, measured as the difference between the firm's raw CSR net counts and the minimum of CSR net counts across all firms in the same industry, scaled by the range of CSR net counts, following Kim et al. (2014).
ERC	The earnings response coefficient, measured as the slope coefficient in a regression of abnormal stock returns on a measure of earnings surprise, following Teoh and Wong (1993).
EVOL	Earnings volatility, measured as the standard deviation of quarterly earnings in the previous four years.
DISP	Analyst forecast dispersion, measured as the standard deviation of analyst forecasts on the annual earnings of the past year.
CEO_INC	The CEO's equity incentive, measured as the ratio of the CEO's equity compensation pay–performance sensitivity to the sum of salary, bonus, and equity compensation pay–performance sensitivity, following Bergstresser and Philippon (2006) and Kim et al. (2011a)
ANALYST	The number of analysts following the firm, measured as the average number of analysts who provide earnings forecasts in each month during the year.
INST	Institutional ownership data obtained from the Thomson Reuters Institutional 13F Database.
BEAT_1C/ BEAT_2C/ BEAT_3C	A dummy variable that takes the value of 1 if the firm's actual earnings beat analyst forecasts by 1 cent/2 cents/2 cents, and 0 otherwise, following Huang et al. (2017).
ICOC	The implied cost of equity, measured as the equally weighted average of the four measures of implied cost of equity, including $r_{GM,}$, based on the method of Gode and Mohanram (2003); r_{CT}, based on the method of Claus and Thomas (2001); r_{GLS}, based on the method of Gebhardt et al. (2001); and r_{EAST}, based on the method of Easton (2004).
IVOL	Idiosyncratic volatility, measured as the standard deviation of the residuals from regressing the daily individual stock returns of the fiscal year on contemporaneous CRSP value-weighted market returns.
Log(AUDIT_FEE)	The logarithm of audit fees (in dollars) the firm pays to its auditors over the fiscal year. The data are obtained from Audit Analytics.

Log(NONAUDIT_FEE))	The logarithm of non-audit fees (fees paid to the auditor for non-audit services). The data are obtained from Audit Analytics.
LOSS	Operating loss, a dummy variable that is equal to 1 if the firm has a negative operating income (*IB*) in the preceding three years and 0 otherwise.
REC_INV	Receivables and inventory ratio, measured as the sum of accounts receivables (*RECT*) and inventory (*INVT*) over total assets (*AT*).
SPI	Special items, a dummy that takes the value of 1 if the firm has nonzero, nonmissing special items (SPI) and 0 otherwise.
TANG	Tangibility, measured as property, plant, and equipment (*PPENT*) over total assets (*AT*).
AUDITOR_TENURE	Auditor tenure, obtained from Audit Analytics.
OPINION	Audit opinion, defined as a dummy variable equal to 1 if the audit opinion is not a standard unqualified opinion and 0 otherwise.
BIG4	A dummy variable that takes the value of 1 if the firm is audited by one of the Big 4 auditors and 0 otherwise.
DEC_END	A dummy variable that is equal to 1 if the firm's fiscal year-end is December and 0 otherwise.

Chapter 5. Conclusion

5.1. Summary of Empirical Findings

This thesis examines how the information content on earnings dates is related to the pricing of assets with lottery-like payoffs and to subsequent corporate behavior. The thesis consists of three distinct essays, with the first two essays concentrating on how corporate earnings are related to lottery-related anomalies and the third essay focusing on how the timing of scheduled earnings news is associated with future corporate behavior.

The first essay finds that, when maximum daily returns are driven by earnings information, there is no evidence of the *MAX* effect as documented by Bali et al. (2011). In addition, the *FMAX* factor that proxies for aggregate lottery demand, when constructed based on non-earnings announcements *MAX* returns, has strong explanatory power for the cross section of stock returns and correlates more strongly with economic conditions that characterize high aggregate lottery demand.

The second essay documents a statistically and economically significant relation between earnings announcement maximum returns from past earnings announcements and excess stock returns in the period leading up to current earnings announcements. This finding is consistent with the idea that investors interpret stocks with high past earnings announcement maximum returns as likely to exhibit earnings announcement maximum returns in the future.

The third essay finds that firms that schedule later-than-expected earnings announcement dates are more likely to experience future stock price crashes and that the effect of earnings calendar revisions on crash risk is more concentrated among firms with higher agency costs. In addition, firm stakeholders consider the timing of scheduled earnings news. Investors demand higher expected returns for firms that schedule later-than-expected earnings announcement dates. Auditors also require higher audit fees to compensate for their additional effort in auditing firms that delay earnings announcement dates.

Taken together, this thesis provides more insight on how an important corporate event (i.e., corporate earnings) is associated with the pricing of assets with lottery-like payoffs and corporate behavior. The thesis has implications for both investors and corporate insiders. Investors should take into account sources of information that accommodate extreme positive returns, since these drivers are useful in correctly interpreting such returns. Understanding how firm stakeholders react to earnings calendar revisions can facilitate corporate decisions.

5.2. Avenues for Future Research

Given the magnitude and robustness of the thesis's findings, several potentially fruitful avenues for future research are suggested. First, the findings of the first essay have strong implications for future studies regarding the necessity of excluding earnings announcement MAX returns in studying the pricing of lottery demand. While earnings announcements are frequent and account for a large proportion of extreme daily returns, future research could consider other corporate major events that drive extreme stock returns, such as seasoned equity offerings, initial public offering, and mergers and acquisitions. Given prior studies document the existence of the MAX effect in many international markets, subsequent research could determine international evidence of our findings for the U.S. market.

Second, the findings of the second essay have several implications for future research on the relation between earnings announcements, idiosyncratic volatility, and stock returns. For example, research could investigate the extent to which the preference for earnings lottery payoffs can explain previously documented earnings announcement premiums when stock returns are abnormally higher during a short window surrounding earnings announcements. Future research could also decompose the general idiosyncratic volatility of stock returns into favorable and unfavorable idiosyncratic volatility and study the pricing of these types of idiosyncratic volatility in the cross section of expected stock returns.

Finally, motivated by the findings of the third essay, future research could examine the impact of earnings calendar revisions on other corporate decisions, such as mergers and acquisitions and investment decisions. Subsequent studies could also consider how other key firm stakeholders (e.g., employees, banks, customers) respond to firms’ earnings calendar revisions.

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