# Stocks as Lotteries: Evidence from Corporate Earnings Announcements 

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#### Abstract

This paper analyzes the relationship between stocks' lottery-like features and abnormal returns around earnings announcements. Measuring a stock's lottery-like features by its expected return skewness, we find that earnings announcement returns are increasing in this measure. This relationship is more pronounced among firms that have superior earnings news and/or have CEOs with high gambling propensity. It reflects overpricing of lottery-like stocks, as illustrated by skewness-related return reversals in the next two years. Expected skewness is also positively associated with volume surges and the fraction of small-sized buys around earnings announcements. Further, the skewness-abnormal return relationship becomes stronger when the fraction of small-sized buys around the announcements is greater. The findings suggest that earnings announcement returns are related to investors' preference for skewness.


## JEL Classification: G11; G14

Keywords: lottery-like stocks; expected skewness; earnings announcement returns; individual investors

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#### Abstract

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## 1. Introduction

A large body of experimental evidence in economics and psychology has shown that individuals' decision-making process often deviates from that predicted by the traditional expected utility theory. One prominent example is people’s affinity for lottery-like, right-skewed payoffs, driven by their tendency to overvalue or overweight high yet unlikely gains. An early articulation of this affinity is Kahneman and Tversky (1979), who show that overweighting of small probability events favors gambling. Recent theories focus on the potential of this affinity to explain financial market phenomena that represent significant challenges for the expected utility theory. Barberis and Huang (2008) show overweighting of low probability gains by investors (under Kahneman and Tversky's (1992) cumulative prospect theory) can cause overpricing and low future returns for lottery-like securities. Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) develop optimal expectation models where agents holding rightskewed securities can improve well-being by believing big payoffs are more likely than in reality, leading to overvaluation and low future returns for these securities. ${ }^{1}$

Two strands of empirical literature have emerged to test the above implications. One examines the relationship between stocks’ lottery-like features and future returns. For example, Zhang (2006) and Boyer, Mitton, and Vorkink (2010) document that stocks with high expected idiosyncratic skewness have low subsequent returns. ${ }^{2}$ The other strand examines the market valuation of lottery-like stocks. Green and Hwang (2012) show first-day IPO returns are more positive for stocks with higher expected skewness. Schneider and Spalt (2013) show corporate executives pay higher prices for right-skewed acquisition targets. As can be seen, thus far this

[^1]literature has been confined to events that are infrequent and unusual in occurrence. Relative to these events, the inferior future returns in Zhang (2006) and Boyer et al. (2010) sustain dramatically larger samples and longer periods. As a result, the question on the primary triggers of valuations of lottery-like stocks remains open.

In this paper, we examine the relationship between the expected skewness of a firm's stock and parameters of market reactions to its earnings announcements. The rationale for focusing on earnings announcements is three-fold. First, earnings news is essential to firm value, thereby representing an ideal setting for analyzing factors driving over- or under-valuations. Second, relative to events such as acquisitions and IPOs, earnings announcements are more common among firms and happen more frequently (scheduled for every quarter), allowing us to identify the valuation effect of expected skewness, if it exists, in a more systematic manner. Third, the earnings announcement setting provides us with a rich set of data on information releases, investor and analyst behavior, and stock pricing, which can facilitate higher resolution analyses and allows us to discriminate more finely among alternative hypotheses than do existing empirical studies on valuations of lottery-like stocks.

The existing literature has examined earnings announcements in various contexts. ${ }^{3}$ Particularly related to our paper are the studies (e.g., Beaver, 1968; Chari, Jagannathan, and Ofer, 1988; Ball and Kothari, 1991; Cohen, Dey, Lys, and Sunder, 2007; Frazzini and Lamont, 2007) documenting an "earnings announcement premium:" i.e., stock returns are often high around earnings announcements, and attributing it to factors including limits of arbitrage and investor

[^2]attention. ${ }^{4}$ We do not aim to cast doubt on previous studies in this paper. Instead, in addition to examining the valuation effect of stocks' lottery-like features, another objective of our study is to explore whether investors' affinity for lottery-like payoffs constitutes an incremental source of variations in earnings announcement returns that complements the existing literature.

Skewness preference theories (Barberis and Huang, 2008; Brunnermeier and Parker, 2005; Brunnermeier, Gollier, and Parker, 2007) predict that, if a non-negligible proportion of investors prefer lottery-like stocks, a stock's abnormal returns around earnings announcements should be positively related to its expected skewness. Similar to Zhang (2006) and Green and Hwang (2012), we measure a stock's expected skewness by the intra-industry skewness computed using recent returns in its industry. As shown by Zhang (2006) and Boyer et al. (2010), the industry-level skewness predicts subsequent idiosyncratic skewness at the stock level. Consistent with the prediction of skewness preference theories, we find a positive relationship between our expected skewness measure and earnings announcement returns during the period of 1991-2010: i.e., stocks with higher expected skewness experience greater (i.e., more positive) abnormal returns in the three-day $([-1,+1])$ window relative to the announcement date. Noting the economic significance of this relationship, a one-standard deviation increase in the expected skewness measure is associated with a $0.09 \%$ ( $7.86 \%$ annualized) increase in earnings announcement returns. This finding is robust to alternative measures of stocks’ lottery-like

[^3]features and earnings announcement returns, and to the control of a large number of stock characteristics including unexpected earnings.

We further validate our finding of a positive skewness-earnings announcement return relationship by looking at two aspects related to stocks’ lottery-like features. First, skewness preference theories posit that lottery-like stocks attract investors for the potential to realize large gains. A unique feature of earnings announcements is they release information that can help investors assess a stock's upside potential. In particular, superior earnings news is likely to reaffirm their prediction of large future gains because it is representative of the right-tail events that are central to stocks' right-skewness. Consequently, skewness preferring investors purchase more lottery-like stocks with superior earnings news, leading to a stronger relation between expected skewness and earnings announcement returns. Consistent with this prediction, we find the positive skewness-earnings announcement return relationship is greater for firms with large and favorable (e.g., top quintile of the quarter) unexpected earnings. Bad earnings news (e.g., bottom quintile of the quarter), on the other hand, results in an insignificant skewness-abnormal return relationship, indicating weakened investor preference. We highlight that the latter finding shows our results are not driven by the attention-grabbing hypothesis of Lee (1992) and Barber and Odean (2008), which predicts that around earnings announcements, prices rise too much (or fall too little) due to attention of individual investors regardless of whether the news is good or bad, because we observe a strong asymmetry in the skewness-abnormal return relationship between good and bad earnings news. ${ }^{5}$

[^4]Second, we provide evidence on the link between the skewness-earnings announcement return relationship and the gambling propensity of the firm's CEO. CEOs with high gambling propensities are likely to prefer right-skewed investment projects, and we therefore expect their firms to have stronger lottery-like features and higher demand from skewness preferring investors around earnings announcements than other firms. This, in turn, can lead to a greater skewness-earnings announcement return relationship. We use two proxies for CEOs’ gambling propensity. The first one is the option-based CEO overconfidence measure (Malmendier and Tate, 2005; 2008; Campbell et al., 2011; Hirshleifer, Low, and Teoh, 2012). Overconfident individuals are characterized by the tendency to expect good outcomes or to overestimate their own efficacy in achieving success. As a result, lottery-like investment projects may be particularly appealing to overconfident CEOs. Our second gambling propensity proxy is CEO age. There is evidence that preference for right-skewed returns decreases with age (e.g., List, 2003; Goetzmann and Kumar, 2008; Kumar, 2009). Thus, younger CEOs are expected to have higher gambling propensities. Using these two proxies, we find that the positive relationship between expected skewness and earnings announcement returns becomes more pronounced when the CEO's gambling propensity is higher.

Implicit in the "overpricing" of lottery-like stocks predicted by Barberis and Huang (2008), Brunnermeier and Parker (2005), and Brunnermeier, Gollier, and Parker (2007) are longrun return reversals. We show that the price rises of lottery-like stocks around earnings announcements are transient by documenting skewness-related return reversals in the next two years. Tying these reversals directly back to the earnings announcement, we also show that they are greater for stocks with superior earnings news, which, as discussed above, reaffirms investors' prediction of large future gains and therefore is associated with a stronger skewness-
earnings announcement return relationship. There is a large literature (e.g., Bernard and Thomas, 1990) documenting a return continuation phenomenon subsequent to earnings announcements that is often attributed to investors’ underreaction to earnings news. In contrast, our evidence points to a skewness-related overreaction around the announcements, underscoring the importance of differentiating various drivers of overreaction and underreaction when analyzing returns upon and subsequent to earnings announcements.

Having documented the positive relationship between expected skewness and earnings announcement returns and the associated long-run return reversals, next, we study investors’ trading activity around the announcements to shed more light on the source of the above relationship. We do so with two sets of tests. First, skewness preference theories imply that skewness-based buying drives up both stock returns and trading volume for lottery-like stocks, suggesting that the well-documented volume surge around earnings announcements (e.g., Frazzini and Lamont, 2007) should be greater for these stocks than for other stocks. When examining stock turnover and abnormal volume around earnings announcements, we find stocks with high expected skewness indeed experience greater volume surges than other stocks. The finding that skewness is positively related to both volume and abnormal returns around earnings announcements also corroborates the evidence in the existing literature (Karpoff, 1987; among others) that return and volume tend to rise and decline together.

Our second set of tests rests on the insight of Barberis and Huang (2008) that individual investors' demand is likely to be the driver for the valuation of lottery-like securities because of their strong skewness preference (Kumar, 2005; 2009). ${ }^{6}$ We measure individual investors'

[^5]buying intensity around earnings announcements by the fraction of small-sized buys (e.g., Green and Hwang, 2012) and find that it is positively related to expected skewness. Furthermore, the positive skewness-abnormal return relationship concentrates in stocks with intense small buys. Consistent with superior earnings news reaffirming individual investors’ prediction of rightskewness, we also find that the positive relationship between expected skewness and the fraction of small buys is greater for stocks with superior earnings news than for other stocks. Overall, these findings suggest that the positive skewness-earnings announcement return relationship is related to individual investors’ skewness preference.

We also consider a number of robustness checks. Particularly worth noting are the ones related to the low future returns of stocks with high information uncertainty (IU) documented by Dechow, Sloan, and Soliman (2004), Jiang, Lee, and Zhang (2005), and Zhang (2006b). To the extent expected skewness is positively correlated with IU, our findings could be driven by return patterns of high-IU stocks. Empirical evidence, however, casts doubt on this explanation. First, Jiang et al. (2005) attribute their findings to investors overestimating the precision of private information signals about high-IU stocks and Zhang (2006a) documents a similar belief bias among financial analysts. If our findings are driven by market participants’ belief biases about high-IU stocks, there should be a systematic bias in analysts' earnings forecasts for highskewness stocks, which we show does not exist. Second, past extreme returns may coincide with greater information uncertainty but the relationship should be roughly symmetric between positive and negative returns. However, the skewness-earnings announcement return relationship we document stems from the high expected skewness related to large, positive past returns, which is consistent with investors' preference for right-skewness.

[^6]The remainder of this paper is organized as follows. Section 2 describes the data, sample, and empirical measures used in this study. We also provide evidence for the validity of our expected skewness measure in this section. Section 3 presents empirical results and robustness checks. Section 4 concludes.

## 2. Data and Sample

### 2.1. The expected skewness measure

Drawing on Zhang (2006) and Green and Hwang (2012), we measure the expected skewness (i.e., investors' expectation of how lottery-like the stock is) of stock $i$ at time $t$ as follows:

$$
\begin{equation*}
\text { Eskew }=\frac{\left(P_{99}-P_{50}\right)-\left(P_{50}-P_{1}\right)}{\left(P_{99}-P_{1}\right)} \tag{1}
\end{equation*}
$$

In equation (1), $P_{k}$ is the $k^{\text {th }}$ percentile of monthly returns in the firm's Fama-French 30-industry in the last three months. More specifically, for stock $i$ in month $t$, we pool the monthly returns of all stocks in i's FF30-industry in the past three months and compute Eskew $i_{i, t}$ using the distribution of these monthly returns. A right tail fatter than the left tail produces a positive Eskew, indicating a right-skewed stock. ${ }^{7}$ As discussed by Zhang (2006), the rationale for using estimates at the industry level for the expected skewness of individual stocks is that firms in the same industry have similar stock characteristics and experience similar economic shocks, and therefore have similar levels of expected skewness. Zhang (2006), Boyer et al. (2010), and Green and Hwang (2012) show intra-industry expected skewness measures have strong predictive power for future idiosyncratic skewness at the stock level. We will confirm this in Section 2.3

[^7]below.
Results in this paper are robust to constructing the expected skewness measure using the 5 and 95 percentiles of intra-industry return distributions or using the natural log transformations of returns (Zhang, 2006). Our findings are not driven by the choice of a three-month time series in constructing Eskew either: results (un-tabulated) are qualitatively similar when using returns in the last one, two, or six months. A longer time window increases the probability of capturing tail events while a shorter time window can be more informative about investors' current skewness expectation. Moreover, results are also consistent when using alternative industry classifications such as the FF48- or 49-industry classifications or two-digit SIC codes. Finer industry partitions increase the similarity of stocks in each industry, thereby improving the precision of the expected skewness measure. On the other hand, coarser partitions increase the number of observations for estimating the expected skewness measure, leading to a higher likelihood of capturing small probability events. Following Green and Hwang (2012), we report results from the FF30industry classification. Finally, we show in the robustness section below that our results are robust to using other proxies for stocks’ lottery-like features in the literature (e.g., Boyer et al., 2010; Bali et al., 2011).

### 2.2. Earnings announcement returns and control variables

We obtain the dates of quarterly earnings announcements from 1991 to 2010 from Compustat and merge in the returns over the $[-1,+1]$ trading day interval around each announcement date from CRSP. The market-adjusted return for this window, denoted by CAR, is used as the earnings announcement return measure throughout this study. The market is defined as the value-weighted portfolio of NYSE/AMEX/NASDAQ stocks. Adopting alternative time
windows to estimate $C A R$, including the $[-1,0],[0,+1]$, and $[-3,+3]$ intervals, leads to similar results to those reported in the paper. Our results are also robust to using raw earnings announcement returns or using the benchmark-adjusted earnings announcement returns of Baker et al. (2010). We restrict the sample period to 1991-2010 because several important datasets for this study, such as the Execucomp database for CEO option holding and age data and the Trade and Quote (TAQ) database for intraday transactions data, do not provide data for the period before the 1990s. Focusing on the period of 1991-2010 facilitates comparison across different parts of the paper, while extending the sample back to 1980 does not qualitatively change relevant results.

Following Bernard and Thomas (1990), we measure unexpected earnings news using the standardized unexpected earnings (SUE):

$$
\begin{equation*}
S U E_{i, t}=\frac{E_{i, t}-E_{i, t-4}-c_{i, t}}{\sigma_{i, t}} \tag{2}
\end{equation*}
$$

where $E_{i, t}$ is the earnings (income before extraordinary items) of firm $i$ in quarter $t, E_{i, t-4}$ is the earnings in quarter $t-4 . c_{i, t}$ and $\sigma_{i, t}$ are the time-series mean and standard deviation, respectively, of $\left(E_{i, t}-E_{i,--4}\right)$ over the last 8 quarters, with a minimum of four quarters of data required for the observation to be valid.

Additional control variables in our analyses are constructed on the premise that stock characteristics can affect investors' equity investment preferences and hence earnings announcement returns. There is a large literature on the determinants of the equity trading and ownership decisions of various types of investors (e.g., Gompers and Metrick, 2001). Drawing on this literature, we construct three groups of control variables. The first group contains variables measuring stock liquidity including a stock's market capitalization (Size), price level
(Price) and turnover rate (Turnover). The second group focuses on the stock's past performance which includes returns in the last twelve months, decomposed into returns in the last three months and the proceeding nine months ( $R E T_{-3,0}$ and $R E T_{-12,-3}$ ), and book-to-market ratio ( $B / M$ ratio). The last group measures the degree to which the stock constitutes a prudent investment. For example, older stocks (Age) and/or stocks in the S\&P 500 index (S\&P 500), and stocks with higher dividend payouts (Yield) or lower return volatility (Volatility), are more prudent. As can be seen from the tables, we used the natural log transformations of several control variables in the regressions to reduce the effects of outliers.

We extract data on stock return, age, price, number of shares outstanding, and trading volume from CRSP, and data on book value of equity, cash dividend, earnings, and S\&P 500 index from Compustat. CEO option holding and age data is from Execucomp. Trade data is from TAQ. Analyst earnings forecast data is from I/B/E/S. Earnings preannouncement data is from First Call’s Company Issued Guidance (CIG) database. Equity ownership data for institutional investors (used to estimate aggregate equity ownership of individual investors) is from the CDA/Spectrum 13F database. The main variables used in this study are described in Appendix A.

## (Insert Table 1 about here)

Table 1 presents summary statistics of the main variables. The sample includes the 278,360 observations with non-missing values for Eskew, CAR, and all control variables. The expected skewness measure, Eskew, has a mean of 0.18 and the average earnings announcement return (CAR) is $0.38 \%$. Unexpected earnings (SUE) have a mean of -0.01 . For other control variables, the liquidity measures, Size, Price, and Turnover, have means of $\$ 2,574$ million, $\$ 21.72$, and $12.27 \%$, respectively. The past performance measures, $R E T_{-3,0}, R E T_{-12,-3}$, and $B / M$ ratio, have means of $4.76 \%, 14.28 \%$, and 0.25 . Finally, the prudence measures, Age, Yield, and

Volatility, have means of 192 months, $1.76 \%$, and $13.99 \%$. These summary statistics are similar to those found in earlier studies and we omit further discussion of them for brevity.

### 2.3. The validity of the expected skewness measure

For our intra-industry expected skewness measure to be valid, it should have predicative power for future idiosyncratic skewness. Previous studies (e.g., Zhang, 2006; Boyer et al., 2010; Green and Hwang, 2012) have shown that industry-level skewness predicts subsequent idiosyncratic skewness at the stock level. In this section, we assess whether this is true in our setting using stocks with at least one earnings announcement on Compustat during the period of 1991-2010. The idiosyncratic skewness measure we use is the one in Boyer et al. (2010), estimated with residuals from the Fama and French (1993) three-factor model using daily returns through the end of months $3,6,9$, or 12 subsequent to the month for which the expected skewness measure (Eskew) is computed. ${ }^{8}$

## (Insert Table 2 about here)

In each month, we sort stocks by Eskew and form three tercile portfolios. If a stock's expected skewness is in the highest (middle, or lowest) tercile of the month, it belongs to the high- (medium-, or low-) skewness portfolio. We calculate the average idiosyncratic skewness for each portfolio in the next three, six, nine, and twelve months, respectively. Table 2 presents the time-series means of these averages, as well as those of the differences between the high- and low-skewness portfolios. This table shows our expected skewness measure has strong predictive power for future idiosyncratic skewness. For example, at the three-month horizon, stocks in the low-skewness portfolio have an average idiosyncratic skewness of 0.277 , whereas the average for stocks in the high-skewness portfolio is 0.361 . The difference between these two portfolios is

[^8]statistically significant at the $1 \%$ level. The six-, nine-, and twelve-month results are highly consistent with the three-month results.

In un-tabulated analyses, we also employ a regression framework to examine the predictive power of our expected skewness measure for future idiosyncratic skewness. The regression framework allows us to consider additional explanatory variables including those described in Section 2.2 and generates slightly stronger results than those in Table 2. We therefore present Table 2 for conservatism. Overall, results in this section confirm the findings in Zhang (2006), Boyer et al. (2010), and Green and Hwang (2012), and show that our intraindustry expected skewness measure is a valid proxy for investors' expectation of future idiosyncratic skewness.

## 3. Stocks' lottery-like features and earnings announcement returns

### 3.1. Expected skewness and earnings announcement returns

In this section, we examine the relationship between our expected skewness measure (Eskew) and market reactions to earnings announcements (CARs). As discussed in Section 1, if a non-negligible fraction of investors prefer right-skewed stocks, price reactions upon earnings announcements should be positively related to stocks’ expected skewness. We begin by comparing the earnings announcement returns of stocks with different levels of expected skewness.

## (Insert Figure 1 about here)

In each quarter, we sort stocks by their expected skewness (Eskew) at last quarter-end and form three tercile portfolios. If a stock's expected skewness is in the highest (middle, or lowest) tercile, it belongs to the high- (medium-, or low-) skewness portfolio. We then calculate the
average earnings announcement return ( $C A R$ ) for each tercile portfolio in each quarter, and present their time-series means for the 1991-1994, 1995-1998, 1999-2002, 2003-2006, and 20072010 sub periods in Figure 1. As can be seen from this figure, while there are variations over time in earnings announcement returns, stocks in the high-skewness portfolio earn greater earnings announcement returns than other stocks in all sub periods. The relationship between expected skewness and earnings announcement returns is monotonic in three out of the five sub periods, while the differences between medium- and low-skewness portfolios appear to be moderate when monotonicity is violated.

Figure 1 is suggestive of a positive relationship between expected skewness and earnings announcement returns. However, it is premature to draw such a conclusion from this figure for lack of controls of other stock characteristics that may affect price reactions to earnings announcements, which we will account for in the next test through a regression framework. Specifically, we estimate the following equation:

$$
\begin{equation*}
\operatorname{CAR}_{i t}=\alpha+\beta_{1} E^{E_{k} k e w_{i t}}+\beta_{2} S U E_{i t}+\gamma X_{i, t}+e_{i, t} . \tag{3}
\end{equation*}
$$

The dependent variable in equation (3), $C A R_{i t}$, is the market-adjusted return over the $[-1,+1]$ window relative to the earnings announcement date of firm $i$ in quarter $t$. Our main variable of interest is the expected skewness of the firm's stock measured at prior quarter-end, Eskew. ${ }^{9}$ Earnings announcement returns are known to be related to unexpected earnings (e.g., Bernard and Thomas, 1990) and we therefore include the standardized unexpected earnings measure (SUE) in the regressions to account for this relation. As indicated in the tables, additional control variables ( $X_{i, t}$ ) include the ten stock characteristics discussed in Section 2.2 (measured at prior

[^9]quarter-end) and industry fixed effects in many of the regressions, and quarter dummies in all regressions. Using year, month, or day fixed effects leads to very similar results. We estimate equation (3) using pooled ordinary least squares (OLS) regressions and cluster standard errors at the stock level. ${ }^{10}$ The coefficients and associated $t$-statistics from these regressions are reported in Table 3.

## (Insert Table 3 about here)

We start with a simple regression of earnings announcement returns on the expected skewness measure excluding all control variables except for quarter dummies. The results, reported in column 1 of Table 3, show that the coefficient on Eskew is positive and statistically significant at the $1 \%$ level. This positive relationship is consistent with the pattern observed in Figure 1, and renders support for the greater valuation of lottery-like stocks upon earnings announcements predicted by skewness preference theories. ${ }^{11}$ Further, this relationship is not driven by investors' preference or aversion to other stock characteristics because it sustains the control of unexpected earnings in column 2, additional stock characteristics described in Section 2.2 in column 3, and industry fixed effects in column 4. Noting the economic significance of the relationship, after including all control variables (column 4), a one standard deviation increase in expected skewness is associated with a $0.09 \%$ ( $7.86 \%$ annualized) increase in earnings announcement returns.

Consistent with the literature on market reactions to unexpected earnings news, we also find a positive relationship between the standardized unexpected earnings measure (SUE) and

[^10]earnings announcement returns. This relationship only moderately subdues the effect of the expected skewness measure, with the coefficient on Eskew lowered from 0.0070 in column 1 to 0.0053 in column 4, where SUE and all other control variables are included. Thus, it is not the case that more right-skewed stocks experience greater earnings announcement returns simply because they have systematically different earnings news compared to other stocks. Indeed, in un-tabulated analyses, we do not detect any significant difference in SUEs between stocks in the high-skewness portfolio constructed for Figure 1 and other stocks.

Several other stock characteristics are also related to earnings announcement returns. For example, stocks with lower past returns, market capitalizations, dividend yields, return volatility, and turnover rates tend to have higher earnings announcement returns, so do older stocks and stocks in the S\&P 500 index. Note that the finding of greater earnings announcement returns for S\&P 500 stocks is consistent with the greater investor demand for these stocks and that lack of substitutes for many of these stocks limits arbitrage with them (Wurgler and Zhuravskaya, 2002). In sum, results in this section are consistent with the idea that investors' preference for lotterylike stocks leads to higher valuations of such stocks relative to other stocks upon earnings announcements.

### 3.2. Expected skewness, unexpected earnings, and earnings announcement returns

Skewness preference theories argue that investors are attracted to lottery-like stocks because of the possibility of realizing large (albeit unlikely) future gains. Compared to many other corporate events, a unique feature of earnings announcements is they release information that helps investors assess a stock's upside potential. In particular, to the extent superior earnings news represents a right-tail event, it is likely to reaffirm investors' prediction of large future
gains. Consequently, skewness preferring investors purchase more lottery-like stocks with superior earnings news, resulting in a stronger relation between expected skewness and earnings announcement returns. We test this prediction in this section.

In each quarter, we sort stocks in ascending order into quintiles based on their unexpected earnings (SUE). ${ }^{12}$ Stocks in the top (bottom) quintile are classified into the group with best (worst) earnings news. Since superior earnings news is likely to reaffirm investors' skewness judgment, the valuation effect of the expected skewness measure is expected to be greater among stocks in the top quintile than among other stocks. We construct a dummy variable, $D^{\text {High SUE }}$, which is equal to 1 for stocks in the top quintile and 0 otherwise, and use it to decompose Eskew in equation (3) into Eskew $\times D^{\text {High SUE }}$ and Eskew $\times\left(1-D^{\text {High SUE }}\right.$ ). We then re-estimate this equation. The coefficient on the former interaction term represents the skewness-earnings announcement return relationship for stocks with superior earnings news and that on the latter interaction term represents the relationship for other stocks. The results are presented in column 5 of Table 3. Consistent with the above prediction, the coefficient on Eskew $\times D^{\text {High SUE }}$ is 0.0096 , considerably larger than the coefficient of 0.0043 on Eskew $\times\left(1-D^{\text {High SUE }}\right)$. A Wald test of the difference between these two coefficients shows it is statistically significant at the $2 \%$ level.

The unexpected earnings measure also allows us to differentiate our findings from the prediction of the attention-grabbing hypothesis of Lee (1992) and Barber and Odean (2008). According to this hypothesis, individual investors have limited attention and rarely sell short. Therefore, they buy stocks that grab their attention, regardless of whether the attention is drawn by good or bad news. Several studies, including Lee (1992), Kandel and Pearson (1995), Frazzini and Lamont (2007), and Hirshleifer et al. (2008), provide empirical support for this hypothesis.

If the positive Eskew-CAR relationship is driven by investors' attention to extreme

[^11]earnings news instead of their skewness preference, ceteris paribus, it should be roughly symmetric between good and bad earnings news because both types of news attract investor attention. To test this idea, we construct another dummy, $D^{L o w ~ S U E}$, to indicate stocks experiencing bad earnings news. This dummy is equal to 1 for stocks in the bottom quintile of quarterly distribution of SUE and 0 otherwise. We then decompose Eskew in equation (3) into Eskew $\times D^{\text {High SUE }}$, Eskew $\times D^{\text {Low SUE }}$, and Eskew $\times\left(1-D^{\text {High SUE }}-D^{\text {Low SUE }}\right)$, and re-estimate this equation. Coefficients on these three interaction terms represent the Eskew-CAR relationship for stocks with good, bad, and other earnings news, respectively. The results, presented in column 6 of Table 3, show that bad earnings news results in an insignificant Eskew-CAR relationship, judging from the negative and insignificant coefficient on Eskew $\times D^{L o w ~ S U E}$, which is in sharp contrast with the positive and significant coefficient on Eskew $\times D^{\text {High SUE }}$ ( $t=4.54$ ). To summarize, the strong asymmetry in the skewness-abnormal return relationship between high- and low-SUE stocks indicates that demand related to investors' skewness preference is enhanced (weakened) by good (bad) earnings news and our results on the greater earnings announcement returns of more right-skewed stocks are skewness-preference- instead of attention-driven.

### 3.3. Expected skewness, CEOs'gambling propensity, and earnings announcement returns

In this section, we relate the skewness-earnings announcement return relationship to the gambling propensity of the firm's CEO. The existing literature (e.g., Malmendier and Tate, 2005; 2008) has shown that CEOs' behavioral traits affect corporate decisions. In our context, CEOs with high gambling propensities are likely to prefer right-skewed investment projects. This, in turn, can be related to stronger lottery-like features of their firms and higher demand from skewness preferring investors around earnings announcements, leading to a greater skewness-
earnings announcement return relationship.
We use two proxies for CEOs' gambling propensity. The first one is a modified version of the option-based CEO overconfidence measure developed by Malmendier and Tate (2005; 2008), which is used in several recent studies including Campbell et al. (2011) and Hirshleifer, Low, and Teoh (2012). Overconfident individuals have the tendency to expect good outcomes or to overestimate their own efficacy in achieving success, especially when faced with risky tasks (Griffin and Tversky, 1992). Because lottery-like investment projects are characterized by high yet unlike payoffs, they may be particularly appealing to overconfident CEOs. The second proxy we examine is CEO age. Earlier studies show that skewness preference decreases with age (e.g., List, 2003; Goetzmann and Kumar, 2008; Kumar, 2009). We therefore conjecture that younger CEOs have higher gambling propensities.

Following Campbell et al. (2011), we measure the average moneyness of a CEO's stock options using Execucomp data. Specifically, we compute the average realizable value per option by dividing the total realizable value of the options by the number of options held by the CEO for each CEO-year. The strike price is calculated as the fiscal year-end stock price minus the average realizable value. The average moneyness of the options is then calculated as the stock price divided by the estimated strike price minus one. Only the vested options held by the CEO are included because we are only interested in options that the CEO can exercise. ${ }^{13}$ We restrict the sample to 1993-2010 in this section because prior data in Execucomp is less complete. Since other variables are on quarterly basis, lagged moneyness is used for intermediate quarters, while applying the moneyness measure to quarters of each CEO year generates similar results. This

[^12]also applies to the CEO age measure below.
Similar to Campbell et al. (2011) and Hirshleifer et al. (2012), we construct several dummies to indicate overconfident CEOs. They include $D^{\text {Confident, } 67 \%}, D^{\text {Confident, 100\% }}$, and $D^{\text {Confident, }}$ ${ }^{150 \%}$, which are equal to 1 if a CEO postpones the exercise of vested options that are more than $67 \%, 100 \%$, and $150 \%$ in the money, respectively, and 0 otherwise. Results are also consistent when using the $200 \%$ and $250 \%$ thresholds to construct these dummies. Higher moneyness of the options indicates increases in CEO overconfidence based on the premise that risk-averse, undiversified CEOs are expected to exercise in-the-money options early. We also construct two dummies for young CEOs using Execucomp data: $D^{\text {CEO age }<50}$ is equal to 1 if the CEO is less than 50 years old and 0 otherwise; $D^{\text {Young }}$ is equal to 1 if the CEO is in the lowest tercile of CEO age in the specific quarter and 0 otherwise. We observe that expected skewness is greater when CEOs have higher gambling propensity. For example, when indicating overconfident CEOs by $D^{\text {Confident, } 150 \%}$, the time-series mean of quarterly medians of Eskew is 0.20 for firms with overconfident CEOs, while it is 0.17 for other firms. This finding suggests that stocks' lotterylike features are related to CEOs’ gambling propensity.
(Insert Table 4 about here)
Next, we test the link between the positive Eskew-CAR relationship documented in Section 3.1 and CEO gambling propensity. We decompose Eskew in equation (3) into those for firms with overconfident CEOs and for other firms, denoted by Eskew $\times D^{\text {Confident, moneyness }}$ and Eskew $\times\left(1-D^{\text {Confident, moneyness }}\right)$, where moneyness $=67 \%, 100 \%$, or $150 \%$, and re-estimate this equation. The results are reported in the first three columns of Table 4. The coefficients on the interaction terms for firms with overconfident CEOs are all positive and significant in these three columns, whereas those on the interaction terms for other firms are much smaller and
insignificant. Further, the positive Eskew-CAR relationship strengthens when the CEO is more overconfident, as illustrated by the increasing difference between firms with overconfident CEOs and other firms across these three columns. In columns 4 and 5 of Table 4, we report results from re-estimating equation (3) while decomposing Eskew using the two age-based CEO gambling propensity dummies, and find they are consistent with results in the first three columns. Overall, results in this section suggest that the greater earnings announcement returns of more rightskewed stocks are related to the gambling propensity of these firms' CEOs.

### 3.4. Long-run returns

The skewness preference theories contend that lottery-like stocks tend to be overvalued because of excessive demand from skewness preferring investors. The positive skewnessearnings announcement return relationship documented in Sections 3.1-3.3 is consistent with this prediction. One step further in testing overvaluation is to examine long-run returns: if lottery-like stocks become overvalued around earnings announcements, we expect their high value to be transient in nature, followed by long-run return reversals. We test this prediction in this section.

## (Insert Table 5 about here)

We replace the dependent variable in equation (3) with stock returns in the first and second years after the announcement quarter and examine their relationship with the expected skewness measure (Eskew). ${ }^{14}$ The results are presented in Table 5 . For ease of comparison, column 1 restates results in column 4 of Table 3 where the earnings announcement return (CAR) is the dependent variable. Column 2 presents results for the cumulative return in the first subsequent year (quarters 1-4), where we observe a negative coefficient on Eskew, suggesting

[^13]return reversal in this year. ${ }^{15}$ When examining returns in the second year (quarters 5-8) in column 3, we continue to find skewness-related return reversals, based on the negative and significant coefficient on Eskew ( $t=-2.46$ ). ${ }^{16}$

Findings in columns 1-3 of Table 5 are consistent with the notion that the high valuation of lottery-like stocks around earnings announcements is transient in nature. Since overvaluation can be triggered by a variety of corporate events, our next test attempts to link the return reversals more closely to the earnings announcement itself. Specifically, we compare the relationship between expected skewness and long-run returns between firms with superior earnings news and other firms. As discussed in Section 3.2., superior earnings news can reaffirm investors' judgment that a stock is lottery-like, leading to a greater skewness-earnings announcement return relationship. We therefore expect the skewness-related return reversals to be stronger among stocks with superior earnings news.

Column 4 of Table 5 restates our results on the skewness-earnings announcement return relationship for stocks with superior earnings news vs. other stocks, as presented in column 5 of Table 3. We rerun this regression except for replacing the dependent variable with returns in the next two years and report results in the remainder of table 5 . Column 5 reports results for returns in the first subsequent year, where we find greater return reversals among stocks with superior earnings news than among other stocks: the coefficient on Eskew $\times D^{\text {High SUE }}$ is -0.0834 ( $t=-3.55$ ), whereas that on Eskew $\times\left(1-D^{\text {High SUE }}\right)$ is -0.0123 and insignificant. Further, we find skewnessrelated reversals for both stocks with superior earnings news and other stocks in the second year (column 6) and they are again stronger for the former stock group. To summarize, results in

[^14]Table 5 suggest that lottery-like stocks become overvalued around earnings announcements, as illustrated by subsequent return reversals. Furthermore, the overvaluation is directly related to earnings announcements because it is greater when investors' skewness judgment is reaffirmed by superior earnings news, leading to stronger long-run return reversals.

### 3.5. Trading volume and small-sized buys around earnings announcements

### 3.5.1. Expected skewness and trading volume around earnings announcements

We study investors' trading activity around earnings announcements in this section and Section 3.5.2, starting with comparing trading volume around the announcements between highskewness stocks and other stocks. The skewness preference theories imply that skewness-based buying drives up both stock returns and trading volume for lottery-like stocks, suggesting that the well-documented volume surge around earnings announcements (e.g., Frazzini and Lamont, 2007) should be greater for these stocks than for other stocks.

We use two volume measures: the daily stock turnover rate and the abnormal trading volume measure of Frazzini and Lamont (2007). Daily turnover rate, denoted by Daily turnover, is the share volume of the day divided by the number of shares outstanding. Frazzini and Lamont's (2007) abnormal trading volume measure, denoted by Abnormal volume, is defined as the daily scaled volume minus the average scaled volume of a portfolio of all non-announcing firms that day, where scaled volume is the ratio of daily share volume of the firm to its average daily volume over the previous one year (252 trading days). ${ }^{17}$ Non-announcing firms are defined as firms not making earnings announcements within the $[-10,10]$ window around the announcement.

[^15]
## (Insert Table 6 about here)

In each quarter, we classify stocks in the top tercile of Eskew as lottery-like stocks. Cross-sectional averages of the two trading volume measures are computed for lottery-like stocks and other stocks for each day of the $[-10,10]$ window around the announcements, and their time-series means, as well as those of the differences between the two stock groups, are reported in Table 6. The first three columns report results for Daily turnover, which show lottery-like stocks have robustly higher turnover rates than other stocks on each day of the [-10, 10] window. Moreover, while there is a clear increase in turnover rate for both stock groups in the days closely surrounding the announcement, the rise is higher for lottery-like stocks, particularly for the $[0,1]$ window: the differences between the two stock groups are $0.29 \%$ and $0.38 \%$ on days 0 and 1 , respectively, whereas they are in the $0.14 \%-0.21 \%$ range on other days.

The last three columns of Table 6 report results for Abnormal volume, which takes into account both the historical pattern of a stock's own volume and the market-wide volume variation. As can be seen, these results are consistent with those from using simple turnover rates: volume surges for both lottery-like stocks and other stocks in the few days closely surrounding the announcement date, with the rises being significantly higher for the former stock group, particularly on days 0 and 1 . For example, the average abnormal trading volume on day 0 is $94.83 \%$ for lottery-like stocks and $75.50 \%$ for other stocks, and the difference between the two groups (19.34\%) is significant with a $t$-statistic of $3.94 .{ }^{18}$ In sum, evidence in table 6 shows that lottery-like stocks experience greater volume surges than other stocks around earnings announcements, consistent with the implication of skewness preference theories that skewness-

[^16]preference-based demand for lottery-like stocks constitutes an additional volume driver for these stocks. The finding that skewness is positively related to both volume and abnormal returns around earnings announcements also corroborates the evidence in the existing literature (e.g., Karpoff, 1987) that return and volume tend to rise and decline together.

### 3.5.2. Expected skewness, small-sized buys, and earnings announcement returns

Barberis and Huang (2008) suggest that individual investors' demand is likely to be the driver for the valuation of lottery-like securities because of their strong skewness preference (Kumar, 2005; 2009). This argument rests on the idea that more sophisticated investors do not fully exploit the higher valuations of individual investors. Although we do not investigate why this is the case, which is certainly worthy of a separate research, we note a few possibilities. First, other investors may not fully realize that the valuation difference exists. Second, bounded rationality may prevent other investors from fully exploiting the valuation difference in trading. Third, as discussed in Barberis and Huang (2008), limits of arbitrage (e.g., Shleifer and Vishny, 1997) and aversion to negative skewness can make it too costly to trade on the valuation difference. Cohen et al. (2007) provide evidence that costs of arbitrage are positively related to the earnings announcement premium.

Based on the insight of Barberis and Huang (2008), we conjecture that individual investors buy stocks with higher expected skewness more actively around earnings announcements and that the skewness-earnings announcement return relationship increases in individual investors' buying intensity. We capture individual investors' trading activity using intraday transactions data from the TAQ database. The existing literature (e.g., Barber, Odean, and Zhu, 2009) shows small-sized trades signed using the Lee and Ready (1991) algorithm are
reasonable proxies for trades of individual investors before decimalization. The TAQ data is available from 1993 and we restrict the sample to prior to August 2000 because the introduction of decimalization beginning in this month shifted the distribution of trade size and made it difficult to identify trades of individual investors. Trades are classified as small if their value is below \$10,000 (e.g., Lee, 1992; Bessembinder and Kaufman, 1997) and are classified as buyeror seller-initiated using the Lee and Ready (1991) algorithm. ${ }^{19}$

Similar to Green and Hwang (2012), we measure individual investors’ buying intensity around earnings announcements by the fraction of small-sized buys, Buy, defined as the dollar value of small trades that are buyer-initiated in the $[0,1]$ window relative to the announcement date divided by the dollar value of all trades in the same window. The choice of the [0, 1] window is based on the evidence in Table 6 that volume surges are greatest for this window, indicating strong trading activities. In addition, Frazzini and Lamont (2007) show that small buys around earnings announcements rise the most for the [0, 1] window during the period of 19932000. Results are consistent when using the $[-1,1]$ window or trades on the announcement day.

## (Insert Table 7 about here)

We start with an estimation similar to equation (3) except for replacing the dependent variable with Buy and report results in column 1 of Table 7. We observe a significant coefficient of 0.0157 on Eskew in this column, suggesting that small buys around earnings announcements increase in stocks' lottery-like features. This finding complements Frazzini and Lamont (2007) by suggesting that the rise of small buys around earnings announcements documented by these authors is greater for more right-skewed stocks. Our next test relates the Eskew-CAR relationship to individual investors' buying intensity. We construct a dummy, $D^{\text {High Buy }}$, which is equal to 1 for stocks in the top tercile of Buy in the quarter and 0 otherwise, and decompose Eskew in equation

[^17](3) into those for stocks with intense small buys around earnings announcements and for other stocks, denoted by Eskew $\times D^{\text {High Buy }}$ and Eskew $\times\left(1-D^{\text {High Buy }}\right.$ ), respectively, and re-estimate this equation (reported in column 2 of Table 7). The coefficient on Eskew $\times D^{\text {High Buy }}$ is 0.0105 and significant at the $1 \%$ level, whereas that on Eskew $\times\left(1-D^{\text {High Buy }}\right)$ is negative and insignificant, suggesting that the positive Eskew-CAR relationship concentrates in stocks with intense small buys. Therefore, this relationship is at least partially driven by buying by individual investors.

We also test whether superior earnings news reaffirms individual investors’ prediction of large future gains, as implied by results in Section 3.2. Specifically, we rerun the regression in column 5 of Table 3 except for replacing the dependent variable with Buy. Recall in that regression, we decompose Eskew into those for stocks with superior earnings news and for other stocks using a dummy indicating top quintile of SUE in the quarter. Thus, the current regression differentiates the Eskew-Buy relationship between these two stock groups. The results are reported in column 3 of Table 7. The coefficients on Eskew $\times D^{\text {High SUE }}$ and Eskew $\times\left(1-D^{\text {High SUE }}\right)$ are 0.0212 and 0.0143 , respectively. Therefore, the Eskew-Buy relationship is greater for stocks with superior earnings news than for other stocks, indicating that such earnings news indeed reaffirms individual investors’ prediction of right-skewness. Taken together, findings in this section support the view that the greater earnings announcement returns experienced by more right-skewed stocks are related to individual investors’ skewness preference.

### 3.6. Robustness checks

### 3.6.1. Information uncertainty (IU)

Dechow, Sloan, and Soliman (2004), Jiang, Lee, and Zhang (2005), and Zhang (2006b) document that stocks with high information uncertainty have low future returns. To the extent
that a stock's expected skewness is positively correlated with its information uncertainty, our findings could be driven by return patterns of high-IU stocks. ${ }^{20}$ In this section, we provide two pieces of evidence that cast doubt on this alternative explanation.

## (Insert Table 8 about here)

First, Jiang et al. (2005) attribute their findings to investors overestimating the precision of private information signals about high-IU stocks and Zhang (2006a) documents a similar belief bias among financial analysts. If our findings are driven by market participants’ belief biases about certain high-IU stocks, there should be a systematic bias in analysts’ earnings forecasts for high-skewness stocks. ${ }^{21}$ To test this idea, we examine whether unexpected earnings relative to analyst forecasts, denoted by Bias, are related to Eskew. Bias is calculated as actual earnings per share minus the median consensus forecast, scaled by the stock price at the beginning of the forecast month. Using mean consensus forecasts generates almost identical results (un-tabulated). We replace the dependent variable in equation (3) with Bias and reestimate this equation. All control variables except for SUE are included in the regression while they are measured at monthly frequency to be consistent with the monthly nature of Bias. The results are presented in column 1 of Table 8, where we find a negative and insignificant coefficient on Eskew. In column 2, we replace Eskew in column 1 with a dummy indicating top tercile of Eskew in the month to directly compare unexpected earnings relative to analyst

[^18]forecasts between lottery-like stocks and other stocks, and find the coefficient on this dummy is negative and insignificant as well. In sum, we do not find any systematic bias in analysts' earnings forecasts for more right-skewed stocks. Combined with individual investors' intense buying of such stocks around earnings announcements documented in Section 3.5.2, this finding also suggests that skewness preference is less prevalent among more sophisticated market participants such as financial analysts. ${ }^{22}$ In addition, this finding shows that the positive skewness-earnings announcement return relationship is not driven by investors reacting to errors in analyst's earnings forecasts for lottery-like stocks upon announcements.

Second, past extreme returns may coincide with greater information uncertainty but the relationship should be roughly symmetric between positive and negative returns. On the other hand, the skewness-value relationship predicted by skewness preference theories is driven by large positive returns, implying an asymmetry between the left and right tails of the return distribution. Following Green and Hwang (2012), we split the expected skewness measure in equation (1) into left-skewness and right-skewness. Left-skewness is defined as (P50-P1) and right-skewness is defined as (P99-P50). When replacing Eskew in equation (3) with these two measures, we find CAR is positively related to right-skewness but unrelated to left-skewness (column 3 of Table 8). This asymmetry is also found when examining the relation between small buys around earnings announcements and these two measures (column 4), again consistent with the strong effect of right tail events on investors' investment preference predicted by the skewness preference theories. Therefore, the expected skewness measure is a suitable proxy for a stock's lottery-like features rather than for its information uncertainty.

[^19]
### 3.6.2. Other robustness checks

## (Insert Table 9 about here)

Table 9 presents further robustness checks of the relationship between expected skewness and earnings announcement returns. For ease of exposition we omit reporting coefficients on control variables but can make them available upon request. In rows 1 and 2 , we consider alternative proxies for stocks' lottery-like features. Results from the maximum daily return measure (MAX) of Bali, Cakici, and Whitelaw (2011) are in row 1 and those from the expected idiosyncratic skewness measure of Boyer, Mitton, and Vorkink (2010) are in row 2; both measures are constructed at the three-month horizon. ${ }^{23}$ As can be seen, these results are consistent with results from Eskew.

Cohen et al. (2007) show that using actual earnings announcement dates leads to an upward bias in the estimate of the announcement premium. While we use the actual announcement dates to facilitate analyses related to good or bad earnings news, we need to verify that our findings are not driven by this choice. We estimate the expected earnings announcement dates following the method of Cohen et al. (2007) and do not detect any significant difference in the timing of announcements between lottery-like stocks (those in the top tercile of quarterly distribution of Eskew) and other stocks (un-tabulated). Further, in row 3 of Table 9, we use CARs calculated from the expected announcement dates in estimating equation (3) and find consistent results to using CARs calculated from actual announcement dates. Controlling for the difference between actual and expected announcement dates does not affect results either (row 4).

We also consider whether a stock's coskewness with the market (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000) drives our results by adding the Kraus and Litzenberger (1976) coskewness measure over the previous six months to control variables in equation (3).

[^20]The results, reported in row 5 of Table 9, show the Eskew-CAR relationship is unaffected. ${ }^{24}$ Moreover, variations in Eskew can stem from either the cross-sectional differences across industries or changes in market-level skewness over time. Following Green and Hwang (2012), we construct the proxy for market-level skewness by re-calculating the skewness measure in equation (1) using returns across all stocks instead of across the FF30-industry stocks. We add the interaction between Eskew and a dummy indicating top tercile of market skewness to control variables in equation (3) and find it does not affect our results (row 6 of Table 9). In addition, the coefficient on the interaction term is small in magnitude and insignificant (omitted from reporting), indicating that the positive Eskew-CAR relationship documented in this study is driven by differences in expected skewness across industries instead of variations in market-level expected skewness over time.

Another factor that can affect earnings announcement returns is disclosure risk. Cohen et al. (2007) show voluntary disclosures through earnings preannouncements lowers the announcement premium. Following Cohen et al. (2007), we construct a dummy indicating preannouncements (denoted by Preannouncement) using data from the First Call CIG database. The sample is restricted to the period of 1998-2010 because data for prior periods are less complete (Anilowski et al., 2007). Un-tabulated results show that more right-skewed stocks (e.g., those in the top tercile of quarterly distribution of Eskew) have lower frequency of preannouncements. To gauge whether disclosure risk drives our findings, we add the preannouncement dummy to control variables in equation (3) and find the coefficient on Eskew is still positive and significant (row 7 of Table 9). Further, its magnitude is very similar to that

[^21]found in our benchmark analyses (e.g., column 4 of Table 3). Therefore, the positive Eskew-CAR relationship does not stem from disclosure risk.

In row 8 of Table 9, we use unexpected earnings relative to analyst forecasts instead of SUE as the proxy for unexpected earnings. It is calculated as the difference between actual earnings and analysts' consensus median EPS forecast, scaled by the share price at the beginning of the forecast quarter. ${ }^{25}$ As can be seen, the Eskew-CAR relationship is again unaffected. Untabulated results show it is also robust to controlling for both this measure and SUE.

Our next robustness check provides further evidence that individual investors’ preference and demand are critical for the skewness-earnings announcement return relationship. We reestimate equation (3) for stocks with high and low ownership by individual investors (top and bottom terciles at last quarter-end), calculated as one minus the fraction of shares owned by institutional investors in the CDA/Spectrum 13F database. ${ }^{26}$ These results are presented in rows 9 and 10 of Table 9 and show that the Eskew-CAR relationship is greater when individual investors own more of the stock.

Earnings announcement returns can also be affected by the clustering of announcers. For example, more announcing firms can lead to a greater ability to diversify the announcement risk, but if the correlation of return variances of announcing firms increases with increase in the concentration it would counteract the diversification effect. ${ }^{27}$ In un-tabulated analysis, we count

[^22]the number of announcers in each week of each year for lottery-like stocks (those in top tercile of quarterly distribution of Eskew) and other stocks, and calculate the time-series means of these numbers. We do not detect any significant difference in the clustering pattern between these two types of announcers. Further, when adding a dummy, $D^{\text {High Ann }}$, which is equal to 1 for firms announcing on days that are ranked in the top quintile of the quarter in terms of the number of announcers on the day and 0 otherwise, to the explanatory variables in equation (3), we find the Eskew-CAR relationship is unaffected (row 11 of Table 9). In addition, when re-estimating equation (3) while decomposing Eskew into those for firms announcing on days with large numbers of announcers and for other firms using $D^{\text {High Ann }}$, we do not find any significant difference between these two groups. Constructing $D^{\text {High Ann }}$ using the number of lottery-like announcers instead of all announcers in above tests leads to similar results as well. These results are omitted from reporting for brevity but are available upon request.

## 4. Conclusion

Experimental evidence suggests that people often deviate from the expected utility theory in decision-making. One prominent example is individuals' tendency to overvalue or overweight large yet unlikely gains. Theories by Barberis and Huang (2008), Brunnermeier and Parker (2005), and Brunnermeier, Gollier, and Parker (2007) posit that this preference for right-skewed payoffs can lead to overpricing of lottery-like securities. Individual investors are likely to be the main driver of this overvaluation because they have stronger skewness preference than institutional investors (Kumar, 2005, 2009).

We measure a stock's lottery-like features by the expected return skewness calculated from past returns in the firm's industry, and document that this skewness measure is positively
related to earnings announcement returns. This relationship is stronger when investors' prediction of large future gains is reaffirmed by superior earnings news and when the firm's CEO exhibits high gambling propensity. Moreover, this relationship reflects overpricing, as illustrated by skewness-related return reversals in the next two years. Expected skewness is also positively associated with volume surges and the fraction of small-sized buys around earnings announcements, and the skewness-abnormal return relationship becomes more pronounced when the fraction of small buys around the announcements increases. Overall, our findings suggest that earnings announcement returns are related to investors' (particularly individual investors') skewness preference.

Our results broadly fit into the research effort to understand the price formation process in response to corporate earnings announcements and that to connect investors’ trading activities to this process. Our evidence also sheds light on the negative relationship between expected idiosyncratic skewness and future stock returns documented in the existing literature by suggesting that a transient overvaluation exists for stocks with strong lottery-like features around earnings announcements. The magnitude and robustness of our results also point to potentially interesting topics for future research. For example, the role of arbitrage costs and that of investors with sophisticated arbitrage techniques (e.g., hedge funds) in the persistence and magnitude of skewness-related abnormal returns around earnings announcements can be of interest.

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## Appendix A: Variable definitions

| Skewness variables |  |
| :---: | :---: |
| Eskew | The expected skewness calculated as eskew $=\frac{\left(P_{99}-P_{50}\right)-\left(P_{50}-P_{1}\right)}{}$, where |
|  | $\left(P_{99}-P_{1}\right)$ |
|  | $P_{k}$ is the $k^{\text {th }}$ percentile of monthly stock returns in the firm's FF30-industry over the last three months. |
| RightSkew | The difference between the $99^{\text {th }}$ and $50^{\text {th }}$ percentiles of monthly stock returns in the firm's FF30-industry over the last three months. |
| LeftSkew | The difference between the $50^{\text {th }}$ and $1^{\text {st }}$ percentiles of monthly stock returns in the firm's FF30-industry over the last three months. |
| Coskew | The coskewness measure calculated over the previous six month using the method in Kraus and Litzenberger (1976). |
| Market eskew | The Eskew measure constructed using return distribution across all industries. |
| Price reaction to earnings announcements and unexpected earnings variables |  |
| CAR | The market-adjusted return for the $[-1,1]$ window relative to the earnings announcement. The market is defined as the value-weighted portfolio of NYSE/AMEX/NASDAQ stocks. |
|  | The standardized unexpected earnings defined as $S U E_{i, t}=\frac{E_{i, t}-E_{i, t-4}-c_{i, t}}{\sigma_{i, t}}$, |
| SUE | where $E_{i, t}$ is the quarterly earnings reported for quarter $t, E_{i, t-4}$ is earnings for four quarters ago. $c_{i, t}$ and $\sigma_{i, t}$ are the time series mean and standard deviation, respectively, of ( $E_{i, t}-E_{i, t-4}$ ) over the preceding 8 quarters, with a minimum of 4 quarters required for the observation to be valid. |
| Buying by individual investors around earnings announcements |  |
| Buy | The ratio of the dollar value of trades that are small (i.e., below $\$ 10,000$ ) and buyer-initiated over the $[0,1]$ window relative to the earnings announcement to the dollar value of all trades over the same window. Trades are classified as buyer- or seller-initiated using the Lee and Ready (1991) algorithm. |
| Control variables |  |
| $B / M$ ratio | Book-to-market ratio, defined as the book value of equity divided by the market capitalization. |
| Size | Market capitalization (in \$ millions), defined as the product of stock price and the number of shares outstanding. |
| $R E T_{-3,0}$ | Cumulative raw return from month -3 to month 0 . |
| $R E T_{-12,-3}$ | Cumulative raw return from month -12 to month -3. |
| Age | Number of months since the stock first appears in CRSP. |
| Price | Price per share. |
| Yield | Dividend yield calculated as dividends divided by market capitalization. |
| Volatility | The standard deviation of returns over the past 24 months. |
| Turnover | The average turnover in the past three months. |
| S\&P 500 | A dummy equal to 1 for stocks in the S\&P 500 index and 0 otherwise. |

Table 1: Summary statistics
The table reports summary statistics of main variables used in this study. All variables are described in Appendix A.

| Variable | Mean | Median | Std. | Minimum | Maximum |
| :--- | :---: | :---: | :---: | :---: | :---: |
| CAR (\%) | 0.38 | 0.11 | 9.37 | -99.23 | 337.42 |
| Eskew | 0.18 | 0.17 | 0.17 | -0.72 | 0.86 |
| SUE | -0.01 | 0.01 | 1.06 | -2.47 | 2.47 |
| B/M | 0.25 | 0.00 | 3.86 | 0.00 | 583.25 |
| Size $_{R E T_{-3,0}(\%)}$ | 2574.35 | 260.74 | 12987.28 | 0.20 | 602432.90 |
| $R E T_{-12,-3}(\%)$ | 4.76 | 2.08 | 31.97 | -94.44 | 1263.64 |
| Yield (\%) | 14.28 | 5.44 | 68.18 | -99.47 | 3584.34 |
| Volatility (\%) | 1.76 | 0.00 | 5.20 | 0.00 | 44.64 |
| Turnover (\%) | 13.99 | 11.77 | 9.45 | 0.90 | 278.42 |
| Price | 12.27 | 7.16 | 14.37 | 0.11 | 76.37 |
| Age | 21.72 | 15.88 | 29.49 | 0.03 | 2345.00 |
| S\&P 500 | 192 | 131 | 177 | 23 | 1017 |

Table 2: Predictive power of the expected skewness measure for idiosyncratic skewness
This table presents the average ex post idiosyncratic skewness sorted on the expected skewness measure, Eskew. The idiosyncratic skewness measure is the Boyer et al. (2010) measure, estimated with residuals from the Fama and French (1993) three-factor model using daily returns through the end of months 3, 6, 9, or 12 subsequent to the current month. Eskew is described in Appendix A. Stocks are sorted into terciles based on Eskew in each month and an equal-weighted portfolio is formed for each tercile. These portfolios are held for three, six, nine, and twelve months. The time-series mean of the average idiosyncratic skewness is reported for each portfolio, so are the time-series means of the differences between the portfolios with high and low expected skewness. $t$-statistics with Newey-West corrections of 12 lags are reported in parentheses.

|  | The idiosyncratic skewness |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | 3-month | 6-month | 9-month | 12-month |
| High | 0.361 | 0.448 | 0.514 | 0.566 |
| Medium | 0.314 | 0.393 | 0.467 | 0.526 |
| Low | 0.277 | 0.365 | 0.426 | 0.479 |
| High - low | 0.084 | 0.084 | 0.088 | 0.087 |
|  | $(7.00)$ | $(6.96)$ | $(7.08)$ | $(6.72)$ |

Table 3: Expected skewness and earnings announcement returns
This table reports results from pooled regressions of earnings announcement returns on the expected skewness measure. $D^{\text {High SUE }}$ is a dummy variable equal to 1 if the firm's $S U E$ is ranked in the top quintile of the quarter, and 0 otherwise. $D^{L O w S U E}$ is a dummy variable equal to 1 if the firm's SUE is ranked in the bottom quintile of the quarter, and 0 otherwise. All other variables are described in appendix A. Quarter dummies are included in all regressions and omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ${ }^{* * *},{ }^{* *}$, and ${ }^{*}$ denote significance at the $1 \%, 5 \%$, and $10 \%$ levels, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | CAR | CAR | CAR | CAR | CAR | CAR |
| Eskew | $\begin{gathered} 0.0070^{* * *} \\ (4.72) \end{gathered}$ | $\begin{gathered} 0.0051^{* * *} \\ (3.47) \end{gathered}$ | $\begin{gathered} 0.0069 * * * \\ (4.58) \end{gathered}$ | $\begin{gathered} 0.0053^{* * *} \\ (3.41) \end{gathered}$ |  |  |
| Eskew $\times D^{\text {High SUE }}$ |  |  |  |  | $\begin{gathered} 0.0096 * * * \\ (3.82) \end{gathered}$ | $\begin{gathered} 0.0115^{* * *} \\ (4.54) \end{gathered}$ |
| Eskew $\times\left(1-D^{\text {High SUE }}\right)$ |  |  |  |  | $\begin{gathered} 0.0043^{* * *} \\ (2.65) \end{gathered}$ |  |
| Eskew $\times D^{\text {Low SUE }}$ |  |  |  |  |  | $\begin{gathered} -0.0028 \\ (-1.14) \end{gathered}$ |
| Eskew $\times\left(1-D^{\text {High SUE }}-D^{\text {Low SUE }}\right)$ |  |  |  |  |  | $\begin{gathered} 0.0060^{* * *} \\ (3.60) \end{gathered}$ |
| SUE |  | $\begin{gathered} 0.0131^{* * *} \\ (60.26) \end{gathered}$ | $\begin{gathered} 0.0134^{* * *} \\ (59.87) \end{gathered}$ | $\begin{gathered} 0.0134^{* * *} \\ (59.90) \end{gathered}$ | $\begin{gathered} 0.0131^{* * *} \\ (54.02) \end{gathered}$ | $\begin{gathered} 0.0127 * * * \\ (48.08) \end{gathered}$ |
| $B / M$ |  |  | $\begin{gathered} -0.0001 \\ (-0.95) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (-0.87) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (-0.87) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (-0.88) \end{gathered}$ |
| Ln(Size) |  |  | $\begin{gathered} -0.0013^{* * *} \\ (-7.30) \end{gathered}$ | $\begin{gathered} -0.0012 * * * \\ (-6.30) \end{gathered}$ | $\begin{gathered} -0.0012 * * * \\ (-6.29) \end{gathered}$ | $\begin{gathered} -0.0012^{* * *} \\ (-6.34) \end{gathered}$ |
| $R E T_{-3,0}$ |  |  | $\begin{gathered} -0.0043^{* * *} \\ (-4.69) \end{gathered}$ | $\begin{gathered} -0.0041^{* * *} \\ (-4.48) \end{gathered}$ | $\begin{gathered} -0.0041^{* * *} \\ (-4.49) \end{gathered}$ | $\begin{gathered} -0.0042^{* * *} \\ (-4.56) \end{gathered}$ |
| $R E T_{-12,-3}$ |  |  | $\begin{gathered} -0.0015^{* * *} \\ (-3.17) \end{gathered}$ | $\begin{gathered} -0.0013^{* * *} \\ (-2.86) \end{gathered}$ | $\begin{gathered} -0.0013 * * * \\ (-2.85) \end{gathered}$ | $\begin{gathered} -0.0013^{* * *} \\ (-2.87) \end{gathered}$ |
| Yield |  |  | $\begin{gathered} -0.0101^{* *} \\ (-2.54) \end{gathered}$ | $\begin{gathered} -0.0067 * \\ (-1.65) \end{gathered}$ | $\begin{gathered} -0.0067 * \\ (-1.65) \end{gathered}$ | $\begin{gathered} -0.0069^{*} \\ (-1.69) \end{gathered}$ |
| Ln(Volatility) |  |  | $\begin{gathered} -0.0004 \\ (-0.78) \end{gathered}$ | $\begin{gathered} -0.0013^{* *} \\ (-2.28) \end{gathered}$ | $\begin{gathered} -0.0013^{* *} \\ (-2.31) \end{gathered}$ | $\begin{gathered} -0.0014^{* *} \\ (-2.33) \end{gathered}$ |
| Ln(Turnover) |  |  | $\begin{gathered} -0.0012 * * * \\ (-5.87) \end{gathered}$ | $\begin{gathered} -0.0014^{* * *} \\ (-6.51) \end{gathered}$ | $\begin{gathered} -0.0014^{* * *} \\ (-6.54) \end{gathered}$ | $\begin{gathered} -0.0014^{* * *} \\ (-6.49) \end{gathered}$ |
| Ln(Price) |  |  | $\begin{gathered} 0.0001 \\ (0.25) \end{gathered}$ | $\begin{gathered} -0.0001 \\ (-0.34) \end{gathered}$ | $\begin{gathered} -0.0001 \\ (-0.36) \end{gathered}$ | $\begin{gathered} -0.0001 \\ (-0.30) \end{gathered}$ |
| Ln(Age) |  |  | $\begin{gathered} 0.0004^{*} \\ (1.82) \end{gathered}$ | $\begin{gathered} 0.0005^{* *} \\ (1.98) \end{gathered}$ | $\begin{gathered} 0.0005^{* *} \\ (2.01) \end{gathered}$ | $\begin{gathered} 0.0005^{*} \\ (1.96) \end{gathered}$ |
| S\&P 500 |  |  | $\begin{gathered} 0.0038^{* * *} \\ (5.99) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (5.32) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (5.33) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (5.30) \end{gathered}$ |
| Intercept | $\begin{gathered} 0.0025^{* * *} \\ (8.52) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0030^{* * *} \\ (10.39) \end{gathered}$ | $\begin{gathered} 0.0095^{* * *} \\ (4.77) \end{gathered}$ | $\begin{gathered} 0.0094^{* * *} \\ (3.69) \end{gathered}$ | $\begin{gathered} 0.0094^{* * *} \\ (3.66) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0095^{* * *} \\ (3.72) \\ \hline \end{gathered}$ |
| Industry fixed effects | No | No | No | Yes | Yes | Yes |
| \# of obs. | 278,360 | 278,360 | 278,360 | 278,360 | 278,360 | 278,360 |
| Adj. R ${ }^{2}$ | 0.003 | 0.025 | 0.026 | 0.027 | 0.027 | 0.027 |

Table 4: Expected skewness, CEOs' gambling propensity, and earnings announcement returns
This table reports results from pooled regressions of earnings announcement returns on the expected skewness measure for firms that have CEOs with high gambling propensity and other firms. $D^{\text {Confident, } 67 \%}$ ( $D^{\text {Confident, } 100 \%}$ and $D^{\text {Confident, }}{ }^{150 \%}$ ) is a dummy variable equal to 1 if the firm's CEO postpones the exercise of vested options that are more than $67 \%(100 \%$ and $150 \%)$ in the money, and 0 otherwise. $D^{\text {CEO age<50 }}$ is a dummy variable equal to 1 if the firm's CEO is less than 50 years old and 0 otherwise. $D^{\text {Young }}$ is a dummy variable equal to 1 if the CEO's age is in the lowest tercile of the quarter and 0 otherwise. All other variables are described in appendix A. Quarter dummies are included in all regressions and omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ${ }^{* * *}$, ${ }^{* *}$, and * denote significance at the $1 \%, 5 \%$, and $10 \%$ levels, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | CAR | CAR | CAR | CAR | CAR |
| Eskew $\times D^{\text {Confident, } 67 \%}$ | $\begin{gathered} 0.0073 * * \\ (2.38) \end{gathered}$ |  |  |  |  |
| Eskew $\times\left(1-D^{\text {Confident, 67\% }}\right.$ ) | $\begin{aligned} & 0.0040 \\ & (1.52) \end{aligned}$ |  |  |  |  |
| Eskew $\times D^{\text {Confident, 100\% }}$ |  | $\begin{gathered} 0.0084 * * \\ (2.38) \end{gathered}$ |  |  |  |
| Eskew $\times\left(1-D^{\text {Confident, } 100 \%}\right)$ |  | $\begin{aligned} & 0.0042 \\ & (1.63) \end{aligned}$ |  |  |  |
| Eskew $\times D^{\text {Confident, } 150 \%}$ |  |  | $\begin{gathered} 0.0113^{* * *} \\ (2.75) \end{gathered}$ |  |  |
| Eskew $\times\left(1-D^{\text {Confident, } 150 \%}\right)$ |  |  | $\begin{aligned} & 0.0041 \\ & (1.62) \end{aligned}$ |  |  |
| Eskew $\times D^{\text {CEO age<50 }}$ |  |  |  | $\begin{gathered} 0.0091 * * \\ (2.37) \end{gathered}$ |  |
| Eskew $\times\left(1-D^{\text {CEO age<50 }}\right.$ ) |  |  |  | $\begin{gathered} 0.0041 * \\ (1.65) \end{gathered}$ |  |
| Eskew $\times D^{\text {Young }}$ |  |  |  |  | $\begin{gathered} 0.0080 * * \\ (2.34) \end{gathered}$ |
| Eskew $\times\left(1-D^{\text {Young }}\right)$ |  |  |  |  | $\begin{aligned} & 0.0040 \\ & (1.59) \end{aligned}$ |
| SUE | $\begin{gathered} 0.0091^{* * *} \\ (28.45) \end{gathered}$ | $\begin{gathered} 0.0091^{* * *} \\ (28.45) \end{gathered}$ | $\begin{gathered} 0.0091^{* * *} \\ (28.46) \end{gathered}$ | $\begin{gathered} 0.0092^{* * *} \\ (28.06) \end{gathered}$ | $\begin{gathered} 0.0092^{* * *} \\ (28.05) \end{gathered}$ |
| B/M | $\begin{aligned} & 0.0063 \\ & (1.57) \end{aligned}$ | $\begin{aligned} & 0.0063 \\ & (1.57) \end{aligned}$ | $\begin{aligned} & 0.0062 \\ & (1.57) \end{aligned}$ | $\begin{aligned} & 0.0063 \\ & (1.58) \end{aligned}$ | $\begin{aligned} & 0.0063 \\ & (1.57) \end{aligned}$ |
| Ln(Size) | $\begin{gathered} -0.0004 \\ (-1.22) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (-1.25) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (-1.30) \end{gathered}$ | $\begin{gathered} -0.0003 \\ (-0.95) \end{gathered}$ | $\begin{gathered} -0.0003 \\ (-0.94) \end{gathered}$ |
| RET ${ }_{-3,0}$ | $\begin{gathered} -0.0082^{* * *} \\ (-3.84) \end{gathered}$ | $\begin{gathered} -0.0083^{* * *} \\ (-3.85) \end{gathered}$ | $\begin{gathered} -0.0083 * * * \\ (-3.85) \end{gathered}$ | $\begin{gathered} -0.0080^{* * *} \\ (-3.73) \end{gathered}$ | $\begin{gathered} -0.0080^{* * *} \\ (-3.73) \end{gathered}$ |
| $R E T_{-12,3}$ | $\begin{gathered} -0.0029 * * * \\ (-3.17) \end{gathered}$ | $\begin{gathered} -0.0030^{* * *} \\ (-3.18) \end{gathered}$ | $\begin{gathered} -0.0030 * * * \\ (-3.22) \end{gathered}$ | $\begin{gathered} -0.0029 * * * \\ (-3.08) \end{gathered}$ | $\begin{gathered} -0.0029 * * * \\ (-3.08) \end{gathered}$ |
| Yield | $\begin{gathered} -0.0050 \\ (-0.25) \end{gathered}$ | $\begin{gathered} -0.0051 \\ (-0.26) \end{gathered}$ | $\begin{gathered} -0.0052 \\ (-0.26) \end{gathered}$ | $\begin{gathered} -0.0064 \\ (-0.32) \end{gathered}$ | $\begin{gathered} -0.0063 \\ (-0.32) \end{gathered}$ |
| Ln(Volatility) | $\begin{aligned} & 0.0011 \\ & (0.91) \end{aligned}$ | $\begin{gathered} 0.0010 \\ (0.87) \end{gathered}$ | $\begin{aligned} & 0.0009 \\ & (0.81) \end{aligned}$ | $\begin{gathered} 0.0008 \\ (0.67) \end{gathered}$ | $\begin{aligned} & 0.0008 \\ & (0.68) \end{aligned}$ |
| Ln(Turnover) | $\begin{gathered} -0.0004 \\ (-0.73) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (-0.74) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (-0.77) \end{gathered}$ | $\begin{gathered} -0.0002 \\ (-0.46) \end{gathered}$ | $\begin{gathered} -0.0002 \\ (-0.46) \end{gathered}$ |
| Ln(Price) | $\begin{gathered} 0.0014 * \\ (1.90) \end{gathered}$ | $\begin{gathered} 0.0014 * \\ (1.90) \end{gathered}$ | $\begin{gathered} 0.0014 * \\ (1.87) \end{gathered}$ | $\begin{gathered} 0.0014 * \\ (1.87) \end{gathered}$ | $\begin{gathered} 0.0014^{*} \\ (1.87) \end{gathered}$ |
| Ln(Age) | $\begin{gathered} -0.0005 \\ (-1.13) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (-1.11) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (-1.06) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (-0.93) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (-0.94) \end{gathered}$ |
| S\&P 500 | $\begin{gathered} -0.0006 \\ (-0.67) \end{gathered}$ | $\begin{gathered} -0.0006 \\ (-0.66) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (-0.62) \end{gathered}$ | $\begin{gathered} -0.0009 \\ (-1.03) \end{gathered}$ | $\begin{gathered} -0.0009 \\ (-1.03) \end{gathered}$ |
| Intercept | $\begin{gathered} 0.0192^{* * *} \\ (4.21) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0192^{* * *} \\ (4.21) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0191^{* * *} \\ (4.19) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0181^{* * *} \\ (3.93) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0181^{* * *} \\ (3.94) \\ \hline \end{gathered}$ |
| Industry fixed effects \# of obs. <br> Adj. R ${ }^{2}$ | $\begin{gathered} \text { Yes } \\ 78,413 \\ 0.019 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 78,413 \\ 0.019 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 78,413 \\ 0.019 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 75,703 \\ 0.019 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 75,703 \\ 0.019 \end{gathered}$ |

Table 5: Long-run returns
This table reports results from pooled regressions of earnings announcement returns and subsequent long-run returns on the expected skewness measure. $R E T_{Q 1-4}\left(R E T_{Q 5-8}\right)$ is the cumulative stock return in quarters 1-4 (5-8) subsequent to the earnings announcement quarter. $D^{\text {High SUE }}$ is a dummy variable equal to 1 if the firm's SUE is ranked in the top quintile of the quarter, and 0 otherwise. All other variables are described in appendix A. Quarter dummies are included in all regressions and omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ${ }^{* * *}$, **, and * denote significance at the $1 \%$, $5 \%$, and $10 \%$ levels, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | CAR | $R E T_{\text {Q1-4 }}$ | $R E T_{Q 5-8}$ | CAR | $R E T_{\text {Q1-4 }}$ | $R E T_{\text {Q5-8 }}$ |
| Eskew | $\begin{gathered} 0.0053^{* * *} \\ (3.41) \end{gathered}$ | $\begin{gathered} -0.0264^{*} \\ (-1.86) \end{gathered}$ | $\begin{gathered} -0.0327 * * \\ (-2.46) \end{gathered}$ |  |  |  |
| Eskew $\times D^{\text {High SUE }}$ |  |  |  | $\begin{gathered} 0.0096^{* * *} \\ (3.82) \end{gathered}$ | $\begin{gathered} -0.0834^{* * *} \\ (-3.55) \end{gathered}$ | $\begin{gathered} -0.0486^{* * *} \\ (-2.78) \end{gathered}$ |
| Eskew $\times\left(1-D^{\text {High SUE }}\right)$ |  |  |  | $\begin{gathered} 0.0043^{* * *} \\ (2.65) \end{gathered}$ | $\begin{gathered} -0.0123 \\ (-0.87) \end{gathered}$ | $\begin{gathered} -0.0287 * * \\ (-2.04) \end{gathered}$ |
| SUE | $\begin{gathered} 0.0134^{* * *} \\ (59.90) \end{gathered}$ | $\begin{gathered} 0.0198 * * * \\ (10.66) \end{gathered}$ | $\begin{gathered} 0.0031^{*} \\ (1.70) \end{gathered}$ | $\begin{gathered} 0.0131^{* * *} \\ (54.02) \end{gathered}$ | $\begin{gathered} 0.0233 * * * \\ (11.04) \end{gathered}$ | $\begin{gathered} 0.0041^{* *} \\ (2.04) \end{gathered}$ |
| B/M | $\begin{gathered} -0.0000 \\ (-0.87) \end{gathered}$ | $\begin{gathered} 0.0012^{*} \\ (1.79) \end{gathered}$ | $\begin{gathered} 0.0010^{* *} \\ (2.11) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (-0.87) \end{gathered}$ | $\begin{gathered} 0.0012 * \\ (1.78) \end{gathered}$ | $\begin{gathered} 0.0010^{* *} \\ (2.12) \end{gathered}$ |
| Ln(Size) | $\begin{gathered} -0.0012^{* * *} \\ (-6.30) \end{gathered}$ | $\begin{gathered} 0.0076 * * * \\ (3.21) \end{gathered}$ | $\begin{gathered} 0.0027 \\ (1.33) \end{gathered}$ | $\begin{gathered} -0.0012^{* * *} \\ (-6.29) \end{gathered}$ | $\begin{gathered} 0.0076^{* * *} \\ (3.21) \end{gathered}$ | $\begin{gathered} 0.0027 \\ (1.33) \end{gathered}$ |
| $R E T_{-3,0}$ | $\begin{gathered} -0.0041^{* * *} \\ (-4.48) \end{gathered}$ | $\begin{gathered} -0.0364 * * * \\ (-5.19) \end{gathered}$ | $\begin{gathered} -0.0710^{* * *} \\ (-10.98) \end{gathered}$ | $\begin{gathered} -0.0041^{* * *} \\ (-4.49) \end{gathered}$ | $\begin{gathered} -0.0364 * * * \\ (-5.18) \end{gathered}$ | $\begin{gathered} -0.0710^{* * *} \\ (-10.98) \end{gathered}$ |
| $R E T_{-12,-3}$ | $\begin{gathered} -0.0013 * * * \\ (-2.86) \end{gathered}$ | $\begin{gathered} -0.0472 * * * \\ (-14.09) \end{gathered}$ | $\begin{gathered} -0.0528^{* * *} \\ (-14.08) \end{gathered}$ | $\begin{gathered} -0.0013^{* * *} \\ (-2.85) \end{gathered}$ | $\begin{gathered} -0.0472 * * * \\ (-14.10) \end{gathered}$ | $\begin{gathered} -0.0528^{* * *} \\ (-14.08) \end{gathered}$ |
| Yield | $\begin{gathered} -0.0067 * \\ (-1.65) \end{gathered}$ | $\begin{gathered} 0.0602 \\ (1.31) \end{gathered}$ | $\begin{gathered} -0.0180 \\ (-0.55) \end{gathered}$ | $\begin{gathered} -0.0067 * \\ (-1.65) \end{gathered}$ | $\begin{gathered} 0.0602 \\ (1.31) \end{gathered}$ | $\begin{gathered} -0.0180 \\ (-0.55) \end{gathered}$ |
| Ln(Volatility) | $\begin{gathered} -0.0013^{* *} \\ (-2.28) \end{gathered}$ | $\begin{gathered} -0.0123 \\ (-1.59) \end{gathered}$ | $\begin{gathered} 0.0444^{* * *} \\ (5.91) \end{gathered}$ | $\begin{gathered} -0.0013 * * \\ (-2.31) \end{gathered}$ | $\begin{gathered} -0.0121 \\ (-1.56) \end{gathered}$ | $\begin{gathered} 0.0445 * * * \\ (5.91) \end{gathered}$ |
| Ln(Turnover) | $\begin{gathered} -0.0014^{* * *} \\ (-6.51) \end{gathered}$ | $\begin{gathered} 0.0029 \\ (1.06) \end{gathered}$ | $\begin{gathered} 0.0049^{*} \\ (1.93) \end{gathered}$ | $\begin{gathered} -0.0014^{* * *} \\ (-6.54) \end{gathered}$ | $\begin{gathered} 0.0030 \\ (1.09) \end{gathered}$ | $\begin{gathered} 0.0049 * \\ (1.94) \end{gathered}$ |
| Ln(Price) | $\begin{gathered} -0.0001 \\ (-0.34) \end{gathered}$ | $\begin{gathered} -0.1052^{* * *} \\ (-17.73) \end{gathered}$ | $\begin{gathered} -0.0481^{* * *} \\ (-10.66) \end{gathered}$ | $\begin{gathered} -0.0001 \\ (-0.36) \end{gathered}$ | $\begin{gathered} -0.1051^{* * *} \\ (-17.70) \end{gathered}$ | $\begin{gathered} -0.0481^{* * *} \\ (-10.65) \end{gathered}$ |
| Ln(Age) | $\begin{gathered} 0.0005^{* *} \\ (1.98) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (-0.13) \end{gathered}$ | $\begin{gathered} 0.0010 \\ (0.30) \end{gathered}$ | $\begin{gathered} 0.0005^{* *} \\ (2.01) \end{gathered}$ | $\begin{aligned} & -0.0005 \\ & (-0.16) \end{aligned}$ | $\begin{gathered} 0.0010 \\ (0.29) \end{gathered}$ |
| S\&P 500 | $\begin{gathered} 0.0034^{* * *} \\ (5.32) \end{gathered}$ | $\begin{gathered} 0.0266 * * * \\ (3.44) \end{gathered}$ | $\begin{gathered} 0.0041 \\ (0.59) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (5.33) \end{gathered}$ | $\begin{gathered} 0.0265 * * * \\ (3.43) \end{gathered}$ | $\begin{gathered} 0.0041 \\ (0.59) \end{gathered}$ |
| Intercept | $\begin{gathered} 0.0094^{* * *} \\ (3.69) \\ \hline \end{gathered}$ | $\begin{gathered} 1.4381^{* * *} \\ (50.29) \end{gathered}$ | $\begin{gathered} 1.5028^{* * *} \\ (51.45) \\ \hline \end{gathered}$ | $\begin{gathered} 0.0094^{* * *} \\ (3.66) \\ \hline \end{gathered}$ | $\begin{gathered} 1.4389 * * * \\ (50.29) \\ \hline \end{gathered}$ | $\begin{gathered} 1.5030 * * * \\ (51.45) \end{gathered}$ |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| \# of obs. | 278,360 | 255,473 | 234,877 | 278,360 | 255,473 | 234,877 |
| Adj. R ${ }^{2}$ | 0.027 | 0.109 | 0.103 | 0.027 | 0.109 | 0.103 |

Table 6: Expected skewness and trading volume around earnings announcements
This table presents trading volume around earnings announcements for lottery-like stocks and other stocks. Daily turnover is the stock's daily turnover rate. Abnormal volume is defined as daily scaled volume minus the average scaled volume of a portfolio of all non-announcing firms that day, where scaled volume is the ratio of daily share volume for a firm to its average daily volume over the previous 252 trading days. Non-announcing firms are the ones not announcing within the [-10, 10] window around the announcement. Daily turnover and Abnormal volume for lottery-like stocks (those with Eskew in the top tercile of the quarter) and other stocks are averaged in each quarter, and the time-series means of these averages, as well as those of the differences between the two stock groups (with associated $t$-statistics for zero difference) are reported. Eskew is described in appendix A.

| Trading day | Daily turnover |  |  |  | Abnormal volume |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Lotterylike stocks | Other stocks | Diff | t-stat | Lotterylike stocks | Other stocks | Diff | $t$-stat |
| -10 | 0.70\% | 0.56\% | 0.14\% | (4.00) | -1.28\% | -2.90\% | 1.62\% | (1.12) |
| -9 | 0.70\% | 0.55\% | 0.15\% | (4.12) | -0.01\% | -3.11\% | 3.11\% | (2.01) |
| -8 | 0.69\% | 0.54\% | 0.14\% | (4.00) | -1.99\% | -3.80\% | 1.81\% | (1.25) |
| -7 | 0.68\% | 0.54\% | 0.14\% | (4.04) | -0.10\% | -5.18\% | 5.09\% | (2.15) |
| -6 | 0.69\% | 0.54\% | 0.14\% | (4.01) | -3.08\% | -5.12\% | 2.05\% | (1.44) |
| -5 | 0.70\% | 0.55\% | 0.15\% | (3.94) | -3.01\% | -4.57\% | 1.57\% | (1.08) |
| -4 | 0.70\% | 0.55\% | 0.15\% | (4.15) | -1.34\% | -4.55\% | 3.21\% | (2.15) |
| -3 | 0.69\% | 0.55\% | 0.14\% | (3.85) | -0.71\% | -3.08\% | 2.36\% | (1.80) |
| -2 | 0.71\% | 0.57\% | 0.14\% | (3.81) | 1.43\% | -2.07\% | 3.50\% | (2.33) |
| -1 | 0.80\% | 0.65\% | 0.16\% | (4.33) | 18.02\% | 12.94\% | 5.08\% | (1.87) |
| 0 | 1.31\% | 1.02\% | 0.29\% | (3.86) | 94.83\% | 75.50\% | 19.34\% | (3.94) |
| 1 | 1.50\% | 1.12\% | 0.38\% | (4.01) | 104.10\% | 81.20\% | 22.89\% | (3.86) |
| 2 | 0.96\% | 0.75\% | 0.21\% | (3.77) | 39.01\% | 33.87\% | 5.14\% | (2.19) |
| 3 | 0.83\% | 0.67\% | 0.17\% | (3.57) | 23.28\% | 19.59\% | 3.69\% | (2.11) |
| 4 | 0.79\% | 0.63\% | 0.16\% | (3.60) | 15.64\% | 13.31\% | 2.33\% | (1.38) |
| 5 | 0.77\% | 0.61\% | 0.16\% | (3.59) | 12.46\% | 9.98\% | 2.49\% | (1.17) |
| 6 | 0.75\% | 0.59\% | 0.15\% | (3.63) | 8.97\% | 6.82\% | 2.15\% | (1.42) |
| 7 | 0.73\% | 0.59\% | 0.14\% | (3.38) | 5.42\% | 5.13\% | 0.29\% | (0.17) |
| 8 | 0.72\% | 0.58\% | 0.14\% | (3.50) | 4.57\% | 3.08\% | 1.48\% | (1.25) |
| 9 | 0.73\% | 0.57\% | 0.15\% | (3.83) | 4.38\% | 1.95\% | 2.42\% | (1.19) |
| 10 | 0.72\% | 0.57\% | 0.15\% | (3.78) | 3.34\% | 2.06\% | 1.27\% | (1.09) |

Table 7: Expected skewness, small-sized buys, and earnings announcement returns
This table presents pooled regression results on the relationship between small buys around earnings announcements, the expected skewness measure, and earnings announcement returns. $D^{\text {High Buy }}$ is a dummy variable equal to 1 if Buy is in the top tercile of the quarter and 0 otherwise. $D^{\text {High SUE }}$ is a dummy variable equal to 1 if the firm's SUE is in the top quintile of the quarter and 0 otherwise. All other variables are described in appendix A. Quarter dummies are included in all regressions and omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ${ }^{* * *}$, ${ }^{* *}$, and * denote significance at the $1 \%, 5 \%$, and $10 \%$ levels, respectively.

| Dependent variable: | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | Buy | CAR | Buy |
| Eskew | $\begin{gathered} 0.0157^{* * *} \\ (2.93) \end{gathered}$ |  |  |
| Eskew $\times D^{\text {High Buy }}$ |  | $\begin{gathered} 0.0105^{* * *} \\ (2.73) \end{gathered}$ |  |
| Eskew $\times\left(1-D^{\text {High Buy }}\right.$ ) |  | $\begin{gathered} -0.0004 \\ (-0.12) \end{gathered}$ |  |
| Eskew $\times D^{\text {High SUE }}$ |  |  | $\begin{gathered} 0.0212 * * * \\ (2.79) \end{gathered}$ |
| Eskew $\times\left(1-D^{\text {High SUE }}\right)$ |  |  | $\begin{gathered} 0.0143^{* * *} \\ (2.60) \end{gathered}$ |
| SUE | $\begin{gathered} 0.0037 * * * \\ (6.88) \end{gathered}$ | $\begin{gathered} 0.0119 * * * \\ (31.52) \end{gathered}$ | $\begin{gathered} 0.0033^{* * *} \\ (5.24) \end{gathered}$ |
| B/M | $\begin{aligned} & 0.0001 \\ & (0.08) \end{aligned}$ | $\begin{gathered} -0.0000 \\ (-0.06) \end{gathered}$ | $\begin{aligned} & 0.0001 \\ & (0.08) \end{aligned}$ |
| Ln(Size) | $\begin{gathered} -0.0238 * * * \\ (-24.47) \end{gathered}$ | $\begin{gathered} -0.0018 * * * \\ (-5.00) \end{gathered}$ | $\begin{gathered} -0.0238 * * * \\ (-24.48) \end{gathered}$ |
| $R E T_{-3,0}$ | $\begin{aligned} & 0.0001 \\ & (0.06) \end{aligned}$ | $\begin{gathered} -0.0005 \\ (-0.29) \end{gathered}$ | $\begin{aligned} & 0.0001 \\ & (0.05) \end{aligned}$ |
| $R E T_{-12,-3}$ | $\begin{gathered} 0.0060^{* * *} \\ (6.37) \end{gathered}$ | $\begin{gathered} -0.0014^{*} \\ (-1.86) \end{gathered}$ | $\begin{gathered} 0.0060^{* * *} \\ (6.37) \end{gathered}$ |
| Yield | $\begin{gathered} -0.0162 \\ (-0.61) \end{gathered}$ | $\begin{gathered} -0.0149^{*} \\ (-1.76) \end{gathered}$ | $\begin{gathered} -0.0164 \\ (-0.61) \end{gathered}$ |
| Ln(Volatility) | $\begin{gathered} 0.0042 \\ (1.59) \end{gathered}$ | $\begin{gathered} -0.0015 \\ (-1.26) \end{gathered}$ | $\begin{gathered} 0.0042 \\ (1.58) \end{gathered}$ |
| Ln(Turnover) | $\begin{gathered} -0.0146^{* * *} \\ (-14.68) \end{gathered}$ | $\begin{gathered} -0.0013^{* * *} \\ (-3.03) \end{gathered}$ | $\begin{gathered} -0.0146^{* * *} \\ (-14.69) \end{gathered}$ |
| Ln(Price) | $\begin{gathered} -0.0517^{* * *} \\ (-28.13) \end{gathered}$ | $\begin{gathered} 0.0006 \\ (0.69) \end{gathered}$ | $\begin{gathered} -0.0517 * * * \\ (-28.13) \end{gathered}$ |
| Ln(Age) | $\begin{gathered} 0.0043^{* * *} \\ (3.93) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.67) \end{gathered}$ | $\begin{gathered} 0.0043^{* * *} \\ (3.94) \end{gathered}$ |
| S\&P 500 | $\begin{gathered} 0.0389 * * * \\ (12.29) \end{gathered}$ | $\begin{gathered} 0.0039 * * * \\ (3.30) \end{gathered}$ | $\begin{gathered} 0.0390^{* * *} \\ (12.30) \end{gathered}$ |
| Intercept | $\begin{gathered} 0.3219 * * * \\ (35.03) \end{gathered}$ | $\begin{gathered} 0.0036 \\ (0.81) \end{gathered}$ | $\begin{gathered} 0.3218^{* * *} \\ (35.02) \\ \hline \end{gathered}$ |
| Industry fixed effects | Yes | Yes | Yes |
| \# of obs. | 64,827 | 64,827 | 64,827 |
| Adj. $\mathrm{R}^{2}$ | 0.274 | 0.028 | 0.274 |

Table 8: Expected skewness, information uncertainty, and earnings announcement returns This table reports results from pooled regressions associated with the relation between expected skewness and information uncertainty. $D^{\text {High Eskew }}$ is a dummy variable equal to 1 if the firm's Eskew is in the top tercile of the month and 0 otherwise. Bias is the actual earnings per share minus median consensus earnings forecast in $\mathrm{I} / \mathrm{B} / \mathrm{E} / \mathrm{S}$, scaled by price at the beginning of the forecast month. All other variables are described in appendix A. Month dummies are included in models (1) and (2) and quarter dummies are included in models (3) and (4), while they are omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ${ }^{* * *}$, **, and * denote significance at the $1 \%, 5 \%$, and $10 \%$ levels, respectively.

| Dependent variable: | (1) | (2) | (3) | (4) |
| :---: | :---: | :---: | :---: | :---: |
|  | Bias | Bias | CAR | Buy |
| Eskew | $\begin{gathered} -0.0029 \\ (-0.70) \end{gathered}$ |  |  |  |
| $D^{\text {High Eskew }}$ |  | $\begin{gathered} -0.0008 \\ (-0.80) \end{gathered}$ |  |  |
| RightSkew |  |  | $\begin{gathered} 0.0055^{* * *} \\ (4.52) \end{gathered}$ | $\begin{gathered} 0.0169 * * * \\ (4.75) \end{gathered}$ |
| LeftSkew |  |  | $\begin{gathered} -0.0011 \\ (-0.33) \end{gathered}$ | $\begin{gathered} -0.0164 \\ (-1.34) \end{gathered}$ |
| SUE |  |  | $\begin{gathered} 0.0134^{* * *} \\ (59.91) \end{gathered}$ | $\begin{gathered} 0.0037 * * * \\ (6.94) \end{gathered}$ |
| B/M | $\begin{gathered} -0.0034 \\ (-1.07) \end{gathered}$ | $\begin{gathered} -0.0034 \\ (-1.07) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (-0.86) \end{gathered}$ | $\begin{aligned} & 0.0001 \\ & (0.08) \end{aligned}$ |
| Ln(Size) | $\begin{gathered} -0.0010 \\ (-1.30) \end{gathered}$ | $\begin{gathered} -0.0010 \\ (-1.30) \end{gathered}$ | $\begin{gathered} -0.0012 * * * \\ (-6.28) \end{gathered}$ | $\begin{gathered} -0.0238^{* * *} \\ (-24.48) \end{gathered}$ |
| $R E T_{-3,0}$ | $\begin{aligned} & 0.0119 \\ & (1.44) \end{aligned}$ | $\begin{aligned} & 0.0119 \\ & (1.44) \end{aligned}$ | $\begin{gathered} -0.0043^{* * *} \\ (-4.65) \end{gathered}$ | $\begin{gathered} -0.0008 \\ (-0.36) \end{gathered}$ |
| $R E T_{-12,-3}$ | $\begin{gathered} 0.0047 * * * \\ (5.89) \end{gathered}$ | $\begin{gathered} 0.0047^{* * *} \\ (5.92) \end{gathered}$ | $\begin{gathered} -0.0013 * * * \\ (-2.83) \end{gathered}$ | $\begin{gathered} 0.0058^{* * *} \\ (6.14) \end{gathered}$ |
| Yield | $\begin{gathered} -0.3283 * * * \\ (-3.24) \end{gathered}$ | $\begin{gathered} -0.3282 * * * \\ (-3.24) \end{gathered}$ | $\begin{gathered} -0.0070^{*} \\ (-1.74) \end{gathered}$ | $\begin{gathered} -0.0159 \\ (-0.60) \end{gathered}$ |
| Ln(Volatility) | $\begin{gathered} -0.0070^{* *} \\ (-2.03) \end{gathered}$ | $\begin{gathered} -0.0070^{* *} \\ (-2.03) \end{gathered}$ | $\begin{gathered} -0.0014^{* *} \\ (-2.48) \end{gathered}$ | $\begin{gathered} 0.0043 \\ (1.61) \end{gathered}$ |
| Ln(Turnover) | $\begin{gathered} -0.0063^{* * *} \\ (-2.62) \end{gathered}$ | $\begin{gathered} -0.0063 * * * \\ (-2.62) \end{gathered}$ | $\begin{gathered} -0.0014^{* * *} \\ (-6.51) \end{gathered}$ | $\begin{gathered} -0.0146^{* * *} \\ (-14.68) \end{gathered}$ |
| Ln(Price) | $\begin{gathered} 0.0239 * * * \\ (4.17) \end{gathered}$ | $\begin{gathered} 0.0239 * * * \\ (4.17) \end{gathered}$ | $\begin{gathered} -0.0002 \\ (-0.39) \end{gathered}$ | $\begin{gathered} -0.0517^{* * *} \\ (-28.13) \end{gathered}$ |
| Ln(Age) | $\begin{gathered} -0.0008 \\ (-1.00) \end{gathered}$ | $\begin{gathered} -0.0008 \\ (-1.00) \end{gathered}$ | $\begin{gathered} 0.0005^{* *} \\ (1.99) \end{gathered}$ | $\begin{gathered} 0.0044^{* * *} \\ (3.95) \end{gathered}$ |
| S\&P 500 | $\begin{gathered} -0.0084^{* * *} \\ (-3.28) \end{gathered}$ | $\begin{gathered} -0.0084^{* * *} \\ (-3.28) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (5.26) \end{gathered}$ | $\begin{gathered} 0.0389 * * * \\ (12.28) \end{gathered}$ |
| Intercept | $\begin{gathered} -0.1031^{* * *} \\ (-4.67) \\ \hline \end{gathered}$ | $\begin{gathered} -0.1033 * * * \\ (-4.63) \end{gathered}$ | $\begin{gathered} 0.0076 * * * \\ (2.61) \\ \hline \end{gathered}$ | $\begin{gathered} 0.3223^{* * *} \\ (31.22) \\ \hline \end{gathered}$ |
| Industry fixed effects \# of obs. | $\begin{gathered} \text { Yes } \\ 180,705 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 180,705 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 278,360 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 64,827 \end{gathered}$ |
| Adj. $\mathrm{R}^{2}$ | 0.010 | 0.010 | 0.027 | 0.274 |

## Table 9: Robustness checks

This table presents robustness checks of the relationship between the expected skewness measure and earnings announcement returns. Model (4) in Table 3 is rerun in the following specifications: (1) using the MAX measure in Bali, Cakici, and Whitelaw (2011) as an alternative skewness measure, defined as the maximum daily return of the firm in the previous quarter; (2) using the expected skewness measure in Boyer, Mitton, and Vorkink (2010) as an alternative skewness measure; (3) using the market-adjusted return for the [-1, 1] window relative to the expected earnings announcement date as the dependent variable, where the expected announcement dates are estimated following the method of Cohen, Dey, Lys, and Sunder (2007); (4) adding the difference between the actual earnings announcement date and expected announcement date as an additional control variable; (5) adding Coskew as an additional control variable; (6) controlling for the expected skewness of the market by adding the interaction between Eskew and a dummy variable equal to 1 for the top tercile of Market eskew and 0 otherwise as an additional control variable; (7) adding a dummy variable, Preannouncement, that is equal to 1 for firms preannouncing earnings and 0 otherwise as an additional control variable; (8) using unexpected earnings relative to analyst forecasts to measure unexpected earnings news, which is calculated as the difference between the actual earnings and consensus median EPS forecast in I/B/E/S, scaled by the share price at the beginning of the quarter; (9) restricting the sample to stocks in the top tercile of equity ownership of individual investors at last quarter-end, where individual ownership is computed as one minus the fraction of shares owned by institutional investors in the CDA/Spectrum 13F database; (10) restricting the sample to stocks in the bottom tercile of individual ownership at last quarter-end; (11) adding a dummy variable, $D^{\text {High Ann }}$, that is equal to 1 for firms announcing on days that are ranked in the top quintile of the quarter in terms of the number of announcers on the day and 0 otherwise as an additional control variable. All other variables are described in appendix A. All regressions are pooled regressions with industry and quarter dummies (omitted from reporting). Control variables are the same as those in model (4) of Table 3 and are also omitted from reporting. Standard errors are clustered by stock and $t$-statistics are in parentheses. ***, $* *$, and $*$ denote significance at the $1 \%, 5 \%$, and $10 \%$ levels, respectively.

|  | Eskew | $t$-statistic | Controls | \# of obs. | Adj. $\mathrm{R}^{2}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Alternative expected skewness measures |  |  |  |  |  |
| (1) MAX measure | 0.0099** | (2.03) | Yes | 278,119 | 0.027 |
| (2) BMV measure | 0.0127*** | (5.54) | Yes | 277,206 | 0.027 |
| Expected earnings announcement date |  |  |  |  |  |
| (3) CARs calculated with the expected announcement dates | 0.0045*** | (3.24) | Yes | 278,280 | 0.014 |
| (4) Control for the difference between the actual and expected earnings announcement dates | 0.0053*** | (3.41) | Yes | 278,360 | 0.027 |
| Other robustness checks |  |  |  |  |  |
| (5) Control for Coskew | 0.0054*** | (3.46) | Yes | 278,360 | 0.027 |
| (6) Control for Market eskew | 0.0056*** | (3.03) | Yes | 278,360 | 0.027 |
| (7) Control for Preannouncement | 0.0055** | (2.33) | Yes | 123,153 | 0.024 |
| (8) Control for unexpected earnings relative to analyst forecasts | 0.0052*** | (2.75) | Yes | 174,712 | 0.006 |
| (9) Stocks with high ownership level by individual investors | 0.0126*** | (3.57) | Yes | 79,994 | 0.039 |
| (10) Stocks with low ownership level by individual investors | 0.0035 | (1.36) | Yes | 80,888 | 0.019 |
| (11) Control for $D^{\text {High Ann }}$ | 0.0053*** | (3.41) | Yes | 278,360 | 0.027 |



Figure 1: Expected skewness and earnings announcement returns across subperiods
This figure shows the average earnings announcement returns of stocks with different levels of expected skewness across different sub-periods of the sample. In each quarter, stocks are divided into terciles based on the expected skewness measure (Eskew). The high- (medium- and low-) skewness portfolio contains stocks ranked in the top (medium and bottom) tercile. Earnings announcement returns are averaged for each portfolio in each quarter and then across quarters in each sub-period. CAR and Eskew are described in Appendix A.


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[^1]:    ${ }^{1}$ Though not the focus of the current study, these theories (see also, Mitton and Vorkink, 2007) also imply investors are inclined to overweight right-skewed securities. Goetzmann and Kumar (2008) and Mitton and Vorkink (2007) show undiversified investors overweight right-skewed stocks.
    ${ }^{2}$ See also, Bali et al. (2011) and Kapadia (2006).

[^2]:    ${ }^{3}$ For example, Kim and Verrecchia (1994) argue that trading volume should rise around earnings announcements, a prediction borne out by empirical evidence in Lee, Mucklow, and Ready (1993). Several recent studies analyze investor attention around earnings announcements: see, e.g., Aboody, Lehavy, and Trueman (2010) and Hirshleifer, Lim, and Teoh, (2009).

[^3]:    ${ }^{4}$ Another possibility is differences of opinion increase around earnings announcements, leading to a rise in price. Many theories (e.g., Miller, 1977; Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; Mei, Scheinkman, and Xiong, 2009) show that short-sale constraints combined with differences of opinion lead to overpricing. The skewness preference theories complement these theories. In the context of earnings announcements, skewness preferring investors place higher value on lottery-like stocks than other investors, implying greater valuation divergence for these stocks than for other stocks around the announcements. Barberis and Huang (2008) argue that other investors cannot short lottery-like securities aggressively because of aversion to negative skewness. Meanwhile, a higher level of differences of opinion indicates more heterogeneity in skewness preference among investors, and the high valuation of skewness preferring investors is more likely to be reflected in stock prices when short-sale constraints bind more tightly. While these two strands of theories complement each other, only the skewness preference theories provide an explanation for why some investors place high value on lottery-like stocks.

[^4]:    ${ }^{5}$ The attention-grabbing hypothesis contends that individual investors have limited attention and rarely sell short so they buy stocks that grab their attention, regardless of whether the attention is drawn by good or bad news. Lee (1992) and Hirshleifer, Myers, Myers, and Teoh (2008) show individual investors trade heavily and are net buyers on earnings announcements regardless of whether the news is good or bad. Kandel and Pearson (1995) show volume increases on earnings announcements for good news, bad news, and no earnings announcement premium news. Frazzini and Lamont (2007) show small investors' buys soar upon earnings announcements.

[^5]:    ${ }^{6}$ The underlying assumption for this argument is that the higher valuations of individual investors for lottery-like securities are not fully corrected by arbitrage right away. This can arise in several ways. First, other investors may not fully realize that the valuation difference exists. Second, bounded rationality may prevent other investors from fully exploiting the valuation difference in trading. Third, as discussed in Barberis and Huang (2008), limits of

[^6]:    arbitrage (e.g., Shleifer and Vishny, 1997) and aversion to negative skewness can make it too costly to trade on the valuation difference. Cohen et al. (2007) provide evidence that costs of arbitrage are positively related to the earnings announcement premium.

[^7]:    ${ }^{7}$ Compared to the traditional third-moment measure of skewness, this estimator captures stocks' lottery-like features better because of its focus on tail events, which are what the skewness preferring investors care primarily about when judging how lottery-like a stock is (e.g., Zhang, 2006; Barberis and Huang, 2008; Bali et al., 2011).

[^8]:    ${ }^{8}$ See Boyer et al. (2010) for details.

[^9]:    ${ }^{9}$ Results are consistent when using a dummy for the top tercile of cross-sectional distribution of Eskew to indicate lottery-like stocks and using it to replace Eskew in the regressions. Classifying stocks in the top quartile or quintile of Eskew as lottery-like stocks leads to similar results as well. This also applies to other tests that separate highskewness stocks from other stocks.

[^10]:    ${ }^{10}$ Results are consistent when using Fama-MacBeth regressions with Newey-West corrections and when calculating standard errors using various methods including clustering them by time, industry, time and industry, and time and stock (Petersen, 2009).
    ${ }^{11}$ The relationship between expected skewness and earnings announcement returns is not always monotonic in Figure 1 with the medium-skewness portfolio sometimes having lower CARs than the low-skewness portfolio, though the differences appear to be moderate. When running a quadratic regression of CAR on Eskew and all control variables in equation (3), we do not detect any evidence for a non-monotonic relationship (un-tabulated).

[^11]:    ${ }^{12}$ Results are similar when dividing stocks into terciles or quartiles based on SUE.

[^12]:    ${ }^{13}$ Campbell et al. (2011) show this measure generates results similar to those in Malmendier and Tate (2005). Malmendier, Tate, and Yan (2011) show this measure works well after controlling for stock returns in the past five years. Results related to this measure are robustness to controlling for stock returns over the past five years instead of over the past one year.

[^13]:    ${ }^{14}$ We use stock returns subsequent to the announcement quarter to mitigate the effects of the days right after the announcement date. Results are similar when using returns after 10 days subsequent to the announcement.

[^14]:    ${ }^{15}$ Consistent with the large post-earnings-announcement-drift (PEAD) literature, we also observe a strong and positive relationship between the standardized unexpected earnings measure (SUE) and stock returns in the first year subsequent to the announcement quarter (column 2), which weakens afterward.
    ${ }^{16}$ Un-tabulated analysis shows that return reversals last for these two years and do not continue into the third year.

[^15]:    ${ }^{17}$ See Frazzini and Lamont (2007) for more details. Results are qualitatively the same when using the abnormal trading volume measure of Barber and Odean (2008).

[^16]:    ${ }^{18}$ The abnormal trading volumes on and in the days closely following the announcement day are greater in Table 6 than in Frazzini and Lamont (2007), indicating an increase in volume surges in response to earnings announcements over time, possibly due to declines in transaction costs. This change, though interesting, is beyond the scope of the current study.

[^17]:    ${ }^{19}$ Results are similar when using the $\$ 5,000$ threshold.

[^18]:    ${ }^{20}$ In un-tabulated analysis, we construct the four information uncertainty measures used in Jiang et al. (2005): firm age, return volatility, average daily turnover, and the duration of future cash flows (Dechow et al., 2004). Younger firms with higher return volatility, greater trading volume, and longer duration cash flows, are expected to have higher information uncertainty. We indeed find that stocks with higher expected skewness (e.g., top tercile of the quarter) have higher information uncertainty.
    ${ }^{21}$ In Jiang et al. (2005), high information uncertainty induces investors to trade aggressively on their private signals; if short-sale constraints keep some investors out of the market, prices of high-IU stocks will reflect the valuation of more optimistic investors. Note that the short-sale constraint issue does not apply to financial analysts. In Zhang (2006a), analysts' overestimation of the precision of their private signals about high-IU stocks leads to greater underreaction to public news so analyst forecasts are lower (higher) relative to actual earnings after good (bad) news. Since higher expected skewness means a fatter right tail relative to left tail in past return distribution, stocks with strong lottery-like features tend to have positive past news, and vice versa. Thus, if information uncertainty drives our findings, unexpected earnings relative to analyst forecasts should be positively related to skewness.

[^19]:    ${ }^{22}$ It is also consistent with findings in Kumar (2005; 2009) that individual investors have stronger preference for lottery-like stocks than institutional investors.

[^20]:    ${ }^{23}$ See Bali et al. (2011) and Boyer et al. (2010) for details about the construction of these measures.

[^21]:    ${ }^{24}$ Whether investors prefer stocks with positive or negative coskewness depends on the skewness level of the market portfolio, and coskewness is not expected to have different degrees of relevance across investor groups. Thus, we do not expect it to affect earnings announcement returns. The coefficient on the coskewness measure in the regression in row 5 of Table 9 (omitted from reporting) is indeed close to zero and insignificant. Results are similar when using the Harvey and Siddique (2000) measure.

[^22]:    ${ }^{25}$ We use price at the beginning of the forecast quarter in this test to be consistent with the quarterly nature of other variables. Regressions related to unexpected earnings relative to analyst forecasts in Table 8 are on monthly basis and therefore the measure is constructed using stock price at the beginning of the forecast month.
    ${ }^{26}$ The 13F database contains equity ownership data for institutional investors with at least $\$ 100$ million under management. Therefore, our measure of individual investors' ownership may include the ownership of some small institutional investors (those with less than $\$ 100$ million under management). However, this is not a significant concern for our analyses because Kumar (2005) shows that small institutional investors and individual investors exhibit similar skewness preferences.
    ${ }^{27}$ Un-tabulated results show that covariance of announcement returns increases in the number of announcers on the day and announcement returns are greater for firms announcing on days with larger numbers of announcers (e.g., top quintile of the quarter), rendering support for the latter argument.

