

Earnings Announcements: Ex-ante Risk Premia*

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October 2023

*We thank Zachary Kaplan, Xiumin Martin, Asaf Manela, Pavel Savor, Li Wang, seminar participants at Nanjing University, Renmin University of China, Tongji University, Tsinghua University, Washington University in St. Louis, and Xian Jiaotong University, as well as participants at the 2023 European Finance Association Meetings (poster session), 2023 Financial Management Association Meetings, 2023 FMA Conference on Derivatives and Volatility, and 2023 QES Harnessing Options in Investment Management Conference for helpful comments and suggestions.

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Abstract

We provide the first estimates of the ex-ante risk premia on earnings announcements from the forward-looking information of the options market. We find that the average earnings announcement risk premium is highly significant at 15 basis points, with substantial variation across firm and across time. Sorting by the estimated ex-ante risk premium generates a daily return spread of 32 bps between high and low terciles. Moreover, the estimated ex-ante risk premia provide new insights on what drives the well documented positive post-earnings-announcement drift and offer profitable straddle strategies.

JEL Classification: G11, G14

Keywords: Earnings, risk premia, post-earning drift, options market, straddles

1 Introduction

Earnings announcements disclose crucial information about a firm to investors, pose a significant source of risk, and have thus been studied extensively in the literature. One central question is how much is the associated risk premium. Existing studies, such as Chari et al. (1988), Ball and Kothari (1991), Cohen et al. (2007), and Frazzini and Lamont (2007), find that U.S. stocks earn higher returns during earnings announcement months than during non-announcement months. Barber et al. (2013) show that this finding holds globally. These studies predominantly examine the ex-post risk premium measured by the long-term average of the realized excess returns. However, earnings announcement risk premia may vary across states and time. Yet, the ex-ante (conditional) risk premium remains largely unexplored in the existing literature.

This paper extracts the ex-ante risk premium for each individual earnings announcement from the options market. Intuitively, investors who have high (low) valuation of a stock can bid up the call (put) prices prior to the announcement, and hence the options market contains useful information about the investor's expected return on the stock. Adopting the FOMC risk premium model recently developed by Liu et al. (2022), we recover the earnings announcement (EA) risk premia from the prices of short-maturity options written on the respective stocks. This estimate is ex-ante because it is obtained based on trading data prior to the announcement. Notably, our EA risk premia are the first real-time ex-ante risk estimates in the earnings announcement literature.

We provide convincing evidence that the EA risk premia are economically large and time-varying. Theoretically, we assume a binomial-tree model for the stock price around the announcement. For each announcement, we define day 0 as the last trading day before the announcement, with no formally released information by the firm. We use the day 0 closing prices of options with the shortest maturity to compute the EA risk premia, reflecting the market view on the underlying stock prior to the announcement. We estimate the upward

and downward drift sizes, as well as the corresponding EA risk premia for a total of 3,817 announcements for 357 S&P 500 firms from 2010 to 2021.

We find that, on average, the upward (downward) drift size on the announcement day is 2.46% (2.51%), with a volatility of 1.63% (1.58%), reflecting large idiosyncratic stock price movements during earnings announcements. The average of the corresponding EA risk premia is 15 basis points (bps), closely aligned with the realized average returns of 12 bps. We also find that the EA risk premia exhibits substantial variation both across firms and across quarters. Specifically, the overall volatility of the EA risk premia is 16 bps, with the cross-sectional volatility being 14 bps and the time-series volatility being 9 bps.¹ Such large fluctuations highlight significant variations in uncertainty across different earnings announcements for various firms. This underscores the importance of our measure, which incorporates timely option information into the estimation of the EA risk premia.

Given that the ex-ante EA risk premia are derived from options before earnings announcements, it naturally prompts us to explore the extent to which these premia possess predictive information regarding future stock returns. Addressing this question becomes central to understanding the true value and implications of such premia in the financial market. Our subsequent investigations yield affirmative answers. By categorizing stocks into terciles based on their EA risk premia, we observe a significant difference of 32 bps between the realized earnings returns of the high and low portfolios. This finding highlights the potential of the EA risk premia as a forward-looking indicator in stock return predictions.

To further explore the extensive information contained in option prices during earnings announcements, we obtain minute-by-minute option trading data from CBOE for three representative firms, Nvidia Corporation, Cisco Systems Inc, and Microsoft Corp, and estimate their EA risk premia by using all the available high-frequency option data. Our analysis reveals that both intraday volatility and cross-announcement volatility intensify as the an-

¹We estimate the cross-sectional volatility by calculating the standard deviation of firm-averaged EA risk premia, while the time-series volatility is gauged by averaging the standard deviation of the EA risk premia within each firm.

nouncement approaches. This fluctuation climaxes on day 0 and diminishes sharply on day 1. Such a pattern offers intraday empirical support to the uncertainty resolution theory posited by Ball and Kothari (1991). Compared to intraday volatility, risk premia level shifts between trading days are more significant, especially over the night during which earnings are announced. This pattern supports the heightened after-hours trading around announcement days in the equity market, as documented in Jiang et al. (2012).

Our proposed measure enables us to evaluate the conditional risk premia with respect to each individual earnings call, allowing us to distinguish announcements associated with high uncertainty perceived by the market (i.e., those with high ex-ante risk premia). Therefore, it helps to understand the effect of uncertainty on the relation between unexpected returns and unexpected earnings.² We find that when there is higher (ex-ante) uncertainty perceived by the market, investors are more reluctant to react to earnings surprise immediately, especially within the first three business days following each conference call. In particular, when the ex-ante EA risk premia increase by one standard deviation, the sensitivity of stock abnormal return to the earnings surprise is reduced by 1.056, a large decrease compared to the average sensitivity of 1.489. Our result provides direct evidence supporting the conjecture that the uncertainty prior to earnings announcements is a key determinant of the initial earnings-returns relation.³

On the other hand, when we shift our attention to delayed market reactions, we find completely different results. Specifically, for unexpected returns spanning from the 4th to the 60th trading day after a conference call, a one-standard-deviation rise in our estimated EA risk premia boosts the sensitivity of these returns to unexpected earnings by 4.900. This is a striking increase from the average sensitivity of 1.717, both statistically and economically. It appears that, when our measure flags higher ex-ante uncertainty tied to an announcement,

²We follow the convention in the accounting literature to define unexpected returns as cumulative abnormal returns with respect to CAPM and unexpected earnings as the difference between actual earnings and median analyst consensus forecast.

³See Hecht and Vuolteenaho (2006), Kothari et al. (2006), Sadka and Sadka (2009), Cready and Gurun (2010), So and Wang (2014), and Savor and Wilson (2016).

investors often refrain from taking an immediate response to the newly presented information during the earnings call. Instead, they opt to a deferred reaction.

Given that our measure relates to the cross-sectional variation in the market's response speed to news released during each announcement, our study sheds new economic insights on existing findings about the post-earnings-announcement drift (PEAD). To this end, we split the announcements in our sample by the median of their ex-ante risk premia. We find that PEAD is present only when our estimated ex-ante risk premia are high, but vanishes completely when the estimated risk premia are low. In particular, PEAD leads to a return spread of 6.02% (with a t -statistic of 4.98) for the subsample of earnings announcements with high EA risk premia, and the same return spread is only -0.46% (with a t -statistic of -0.61) for the subsample when the EA risk premia are low. Therefore, the well-studied PEAD pattern is solely attributable to the earnings of firms with greater ex-ante risk premia.

There are two main explanations for the existence of PEAD in the literature: information delay and risk premia, as outlined by various studies (Ball and Brown, 1968; Fama, 1970; Foster et al., 1984; Bernard and Thomas, 1989, 1990; Richardson et al., 2010; Hung et al., 2015). Our findings show that both channels are in effect: the existence of PEAD is tied to delayed market reaction to announcements with higher ex-ante risk premia. Moreover, our EA risk premia measure offers an ex-ante approach to pinpoint announcements that are more likely to demonstrate PEAD.

Our ex-ante EA risk premia also help to understand the longstanding practical challenge of straddle unprofitability during earnings calls. Notably, several studies (e.g., Coval and Shumway, 2001; Ang et al., 2006a; Cremers et al., 2015; Dubinsky et al., 2019) suggest that straddle returns during earnings announcements carry information of jump risk premium, and this can potentially offer lucrative trading opportunities. However, the hurdle of transaction costs often renders the selling of straddles unprofitable on average. We show that our estimated EA risk premia indeed captures the risk presented in straddles. Such findings contain important investment implications. Equipped with our measure, we are able

to identify announcements with a higher jump risk premium before the arrival of each announcement. By selling straddles only on earnings announcements with high ex-ante risk premia, we find that, even after accounting for transaction costs, the average daily return on these earnings announcement days is as high as 0.23%, which is economically large and statistically significant.

Our paper contributes to the understanding of market reactions to earnings announcements. Hecht and Vuolteenaho (2006), Kothari et al. (2006), Sadka and Sadka (2009), Cready and Gurun (2010), So and Wang (2014), Truong and Corrado (2014), and Savor and Wilson (2016) investigate the contemporaneous reaction, by focusing on the return decomposition and distinguish cash flow news and discount rate news released by earnings, while Ball and Brown (1968), Fama (1970), Foster et al. (1984), Bernard and Thomas (1989), Bernard and Thomas (1990), Richardson et al. (2010), and Hung et al. (2015) explore the delayed reaction, by looking at the longer-term response after earnings announcements. Our ex-ante risk premia measure sheds new light on their empirical findings and contributes to both lines of literature, with the use of forward-looking information from the options market.

Our paper adds to the study of predicting stock returns around corporate events (Patell and Wolfson, 1981; Ederington and Lee, 1996; Drake et al., 2012; Chesney et al., 2015; Gharghori et al., 2017; Augustin et al., 2019). In our set-up, instead of examining various behavioral explanations, we measure directly the underlying expected returns from option prices before the information is released. Our measure is real-time and varies across different firms and different earnings. With our measure, one learns about the market risk-return trade-off based on the conditional information embedded in option prices, and distinguishes ex-ante high risk premium earnings calls from low ones.

Our paper is also closely related to the growing line of research on the information flow between the stock market and derivatives market. A large body of studies investigates informed trading in options market and shows that information extracted from option prices and trading volume can predict future expected returns of underlying assets (Back, 1993;

Easley et al., 1998; Ofek et al., 2004; Pan and Poteshman, 2006; Ni et al., 2008; Cremers and Weinbaum, 2010; Bollerslev et al., 2014; Ge et al., 2016; Han et al., 2020). Other studies concentrate on the recovery of the information of the underlying asset returns from option prices (Ross, 2015; Martin and Wagner, 2019; Tang, 2019; Kadan and Manela, 2019; Jensen et al., 2019; Kadan and Tang, 2020; Kadan et al., 2023). These methodologies frequently necessitate a comprehensive set of reliable option prices across diverse strike prices for empirical execution. In contrast, Liu et al. (2022) show that using only four short maturity options, much less data, can recover market risk premium around the FOMC meetings. In our paper, we adopt their method to earnings announcements to identify the associated risk premium. By using options that expire soon after announcements, we reduce the bias of the estimated risk premia being driven by other confounding events.

The rest of the paper proceeds as follows. Section 2 discusses the methodology. Section 3 presents the empirical estimations. Section 4 explores the economic implication of our measure. Section 5 includes further analysis and Section 6 concludes.

2 Methodology

In this section, we introduce the methodology we use to recover the earnings announcement date premia (EAD premia) for individual stocks. We first revisit the model developed by Liu et al. (2022), then we describe how to adapt it to individual stock options.

2.1 The Liu, Tang, and Zhou (2022) model

In this subsection, we briefly review the recovery of the Federal Open Market Committee (FOMC) risk premium under a two-state baseline case introduced by Liu et al. (2022) for an easier understanding of our applications. Assume a discrete-time model with $t = 0, 1$, and an event occurs between $t = 0-$ and $t = 0+$. Under a two-state model, a stock with price S_0

at $t = 0-$ jumps up to S_u or down to S_d immediately upon the arrival of the event, where $S_u = (1 + u)S_0$, and $S_d = (1 - d)S_0$. Assume the existence of two call and two put options written on this stock, all maturing at time $t = 0+$. Denote their prices at time $t = 0-$ as C_1, C_2, P_1 , and P_2 , and their corresponding strike prices as K_1^C, K_2^C, K_1^P , and K_2^P . Assume further that $S_u > K_1^C > K_2^C > S_d$, and that $S_u > K_2^P > K_1^P > S_d$, then the upward and downward drift sizes u and d can be recovered as:

$$\begin{aligned} u &= \frac{C_1 K_2^C - C_2 K_1^C}{S_{0-} (C_1 - C_2)} - 1, \\ d &= 1 - \frac{P_2 K_1^P - P_1 K_2^P}{S_{0-} (P_2 - P_1)}, \end{aligned} \tag{1}$$

and the implied state prices π_u and π_d as:

$$\begin{aligned} \pi_u &= \frac{C_1 - C_2}{K_2^C - K_1^C}, \\ \pi_d &= \frac{P_1 - P_2}{K_1^P - K_2^P}. \end{aligned} \tag{2}$$

Assume the marginal investor in the stock (a representative agent) has an Epstein-Zin preference in Ai and Bansal (2018) with the intertemporal elasticity of substitution parameter, ψ , and the relative risk aversion coefficient, γ , and the risk premium is further recovered by:

$$\widehat{E}(r) = \frac{d \left(1 - \left(\frac{1+u}{1-d}\right)^\alpha\right)}{\frac{d}{u} + \left(\frac{1+u}{1-d}\right)^\alpha}, \tag{3}$$

where $\alpha = \frac{1}{\frac{\psi-\gamma}{1-\psi}} < 0$, $\gamma \geq \psi$, and $1 \geq \frac{1}{\psi}$. While Liu et al. (2022) focus their attention to the FOMC meetings, we aim to apply equations (1) – (3) to recover the risk premium for earnings announcements.

2.2 Application to earnings announcements

Next, we consider applying the above methodology in more detail to recover the EA risk premia for individual stocks. Consider a stock of interest and let the event be an earnings announcement of this stock. We can directly apply (1) and (2) to recover drift sizes and state prices.

One potential concern is that individual stock options may suffer from liquidity issues such that there is a significant disparity between risk premia estimated from bid and ask prices, in contrast to the market index options used by Liu et al. (2022). To preserve information from both purchases and sales, we next derive an upper bound and a lower bound for risk premium estimates using bid and ask prices, respectively. Let C_1 and C_2 be the average of the bid and ask prices for the two call options and α_1 and α_2 be their respective half bid-ask spread. The present values of the call options are bounded by the bid and ask prices:

$$\begin{aligned} C_1(1 - \alpha_1) &< \pi_u((1 + u)S_0 - K_1^C) < C_1(1 + \alpha_1), \\ C_2(1 - \alpha_2) &< \pi_u((1 + u)S_0 - K_2^C) < C_2(1 + \alpha_2). \end{aligned}$$

Rearranging the terms, we have:

$$\begin{aligned} ((1 - \alpha_1)C_1 - (1 + \alpha_2)C_2)(1 + u)S_0 &< (1 - \alpha_1)C_1K_2^C - (1 + \alpha_2)C_2K_1^C, \\ ((1 - \alpha_2)C_2 - (1 + \alpha_1)C_1)(1 + u)S_0 &< (1 - \alpha_2)C_2K_1^C - (1 + \alpha_1)C_1K_2^C. \end{aligned} \tag{4}$$

Based on the no-arbitrage condition, $(1 + \alpha_2)C_2 > (1 - \alpha_1)C_1$, we have a lower bound on u from (4):

$$\underline{u} = \frac{(1 + \alpha_2)C_2K_1^C - (1 - \alpha_1)C_1K_2^C}{((1 + \alpha_2)C_2 - (1 - \alpha_1)C_1)S_0} - 1. \tag{5}$$

Under the assumption that $(1 - \alpha_2)C_2 > (1 + \alpha_1)C_1$, we obtain an upper bound on u :

$$\bar{u} = \frac{(1 - \alpha_2)C_2K_1^C - (1 + \alpha_1)C_1K_2^C}{((1 - \alpha_2)C_2 - (1 + \alpha_1)C_1)S_0} - 1.^4 \quad (6)$$

Similarly, for the downward state, let P_1 and P_2 be the average of the bid and ask prices for the two put options and θ_1 and θ_2 be their respective half bid-ask spread. We have that under the condition $(1 - \theta_1)P_2 > (1 + \theta_2)P_1$, the lower and upper bounds of d are respectively given by

$$\begin{aligned} \underline{d} &= 1 - \frac{(1 + \theta_1)P_1K_2^P - (1 - \theta_2)P_2K_1^P}{((1 + \theta_1)P_1 - (1 - \theta_2)P_2)S_0}, \\ \bar{d} &= 1 - \frac{(1 - \theta_1)P_1K_2^P - (1 + \theta_2)P_2K_1^P}{((1 - \theta_1)P_1 - (1 + \theta_2)P_2)S_0}. \end{aligned} \quad (7)$$

When applying (3) to individual stocks, we adopt a calibration method to determine the level of α .⁵ As $\widehat{E(r)}$ increases in both u and d , it is straightforward to show that the upper bound for $\widehat{E(r)}$ is

$$\overline{\widehat{E(r)}} = \frac{\bar{d} \left(1 - \left(\frac{1+\bar{u}}{1-\bar{d}}\right)^\alpha\right)}{\frac{\bar{d}}{\bar{u}} + \left(\frac{1+\bar{u}}{1-\bar{d}}\right)^\alpha}, \quad (8)$$

and the lower bound is

$$\underline{\widehat{E(r)}} = \frac{\underline{d} \left(1 - \left(\frac{1+\underline{u}}{1-\underline{d}}\right)^\alpha\right)}{\frac{\underline{d}}{\underline{u}} + \left(\frac{1+\underline{u}}{1-\underline{d}}\right)^\alpha}. \quad (9)$$

Empirically, we use (1) – (3) to recover information about the EA premia, and use (5) – (9) to bound these estimates.⁶

⁴Empirically, this condition is satisfied for 99.14% of our observations. We drop all the observations that violate this condition when estimating the upper bound.

⁵See Section 3.3 for details.

⁶Empirically, we make sure that the two conditions $(1 - \alpha_2)C_2 > (1 + \alpha_1)C_1$ and $(1 - \theta_1)P_2 > (1 + \theta_2)P_1$ hold, thus we always have that $\overline{\widehat{E(r)}} \geq \underline{\widehat{E(r)}}$.

3 EA Risk Premia Estimation

In this section, we estimate the EA risk premia following the methodology in Section 2. We use both daily and intraday data to show patterns of the risk premia.

3.1 Data and sample

Our main focus is to recover the EA risk premia for stocks included in the S&P 500 index. We identify the earnings announcement dates as the identical dates between the report date of quarterly earnings from CompuStat and announce date from IBES. We obtain daily option prices from OptionMetrics and individual stock prices from CRSP. Due to the limited trading activities of the options market in the early years, we focus on the post-2010 period when weekly options are actively traded. Thus, our sample period spans from January 2010 to December 2021. During this period, there are a total of 23,314 earning announcements.

Since we focus on immediate jumps in stock prices around earnings calls, it is necessary to construct an accurate timeline to separate pre-EA and post-EA periods clearly. We specify day 0 as the trading day right before each announcement, during which no information is formally released. Below are different scenarios for the definition of day 0.

If earnings are announced on non-trading dates, we define the previous closest trading day as day 0. For earnings announced on trading days, we identify those after the market close time (4:00 p.m.) as post-market announcements and those before market open time (9:00 a.m.) as pre-market announcements. For post-market announcements, because the earnings information is not already incorporated into asset prices before the market closes, the announcement day is set as day 0. In contrast, for the pre-market announcements, we label the trading day *before* the announcement day as day 0, since it is the last day before earnings are announced. Such a classification rule guarantees that the events arrive between day 0 and day 1, which corresponds to the time points $t = 0-$ and $t = 0+$ in our

model. There are 48% post-market announcements and 44% pre-market announcements. The remaining 8% are during the market time. We exclude them to cleanly identify the information arrival time.

To estimate the EA risk premia, we rely on option closing prices on day 0 for each announcement and only consider options that mature within three days. This ensures that our estimation is ex-ante and the information content is not likely to be contaminated by other events. To get better estimation results for the EA risk premia, we apply two major filters to ensure the contracts used in our estimation are actively traded. Specifically, we require the ratio of bid-ask spread to the mid-price of the option to be lower than 20% and the trading volume to be positive. We estimate the drift sizes in (1) based on two closest-to-the-money calls and two closest-to-the-money puts.

After applying these filters, we have 3,817 earnings announcements in our sample. Table 1 reports summary statistics of firm characteristics for our sample and the full universe that covers 23,314 announcements. By comparison, we can see that our research scope is representative. All firm characteristics are similar in CAPM beta, size, value, and momentum.⁷ For example, the average, standard deviation, and median of the CAPM beta of our sample are 1.08, 0.35, and 1.07, respectively, compared to 1.03, 0.38, and 1.01 for the full universe.

3.2 Drift size estimates

Our sample covers 3,817 earnings announcement dates associated with 357 firms. Panel A of Table 2 reports the summary statistics of the prices, moneyness, and maturities of options used in the estimation. The mean prices of C_1 , C_2 , P_1 , and P_2 are \$ 1.91, \$ 2.61, \$1.88, and \$2.55, respectively. The middle 90% of moneyness ranges from 0.9727 to 1.0287, all

⁷The CAPM beta is calculated with a rolling window of the past 252 trading days. Firm size is the log of market capitalization. Value is the log of the book-to-market ratio. Momentum is the log of gross return over the past twelve months.

very close to the money. There are 881 EA risk premia estimated by options maturing on day 1 and 1,564 estimated by options maturing on day 2; the rest are estimated by options maturing on day 3. The choice of options with short maturities makes it more likely that our measure captures almost exclusively the risk from the imminent earnings announcements.

The summary statistics of estimated drift sizes, state prices, and the sum of state prices are presented in Panel B. We standardize the estimates to daily horizon according to the option maturities. This helps us to match the estimated variables with the realized ones. The daily upward and downward drifts are estimated as 2.46% and 2.51% on average, with standard deviations of 1.63% and 1.58%, respectively. The estimates are consistent with the stylized fact that a large component of the annual return of a typical stock is driven by the returns during earnings announcements (Vuolteenaho, 2002; Frazzini and Lamont, 2007; Lochstoer and Tetlock, 2020).

The mean of up and down state prices are 0.5103 and 0.4908, respectively. Given that our focus is on a time interval spanning only a few days, we assume an interest rate of zero for clarity and simplicity. In this case, an efficient market indicates $\pi_u + \pi_d = 1$. Since the state prices are estimated independently from call and put options, this relation is not guaranteed to hold empirically. Along this line, we calculate $\pi_u + \pi_d$ for each estimated pair. The mean of $\pi_u + \pi_d$ equals 1.0011 with a standard deviation of 0.0424. This indicates that the options market is quite efficient and our estimation methodology appears to be accurate.

To evaluate the precision of our drift size estimates, following Liu et al. (2022), for each stock i during announcement t , we consider the pseudo predictor,

$$\hat{r}_{t,i} = \begin{cases} u_{t,i}, & \text{if } \tilde{r}_{t,i} > 0; \\ -d_{t,i}, & \text{if } \tilde{r}_{t,i} < 0, \end{cases} \quad (10)$$

where $\tilde{r}_{t,i}$ is the realized return from day 0 to day 1 for firm i during earnings announcement t . The reason that the predictor is considered as “pseudo” is that it uses the directional

information of the realized returns. However, as pointed out in Liu et al. (2022), this pseudo predictor is useful in evaluating the precision of drift size estimate. To follow their method, we estimate a “pseudo” out-of-sample (OOS) R-squared for each stock i :

$$R_{OOS,i}^2 = 1 - \frac{\sum_{t=1}^{T_i} (\tilde{r}_{t,i} - \hat{r}_{t,i})^2}{\sum_{t=1}^{T_i} (\tilde{r}_{t,i} - \bar{r}_{t,i})^2}, \quad (11)$$

where $\bar{r}_{t,i}$ is a standard benchmark, calculated as the historical average of realized returns of the past 252 trading days, and T_i is the total number of announcements in our sample for stock i . The OOS R-squared measures the percentage reduction of the squared prediction error induced by the pseudo predictor compared to the standard benchmark. In ideal cases, when the option implied drift sizes are exactly the realized ones, the OOS R-squared is 100%. Empirically, a sufficiently high OOS R-squared indicates a good estimation.

To better illustrate the prediction performance, we only consider firms with at least 15 announcements. There are a total of 100 firms considered in this analysis. Table 3 presents the summary statistics of the “pseudo” OOS R-squared and the correlation coefficient between pseudo predictors and realized EA returns. The average “pseudo” OSS R-squared is 55.76%, with the middle 90% observations ranging from 40.61% to 70.54%. This large OOS R-squared indicates that our drift size estimates are quite reasonable. The correlation coefficients range from 0.6470 to 0.8832 for the middle 90% of the distribution, with an average of 0.7841, suggesting that our drift sizes estimates are strongly correlated with realized returns.

3.3 EA risk premia estimates

Before proceeding to the estimation of the EA risk premia, we first determine the level of α in (3). We use the data from January 1996 to December 2009 as the training period to estimate this value. In this way, our estimation does not suffer from a look-ahead bias as α is

determined out-of-sample. We search for the optimal level of α to maximize the R-squared:

$$R^2 = 1 - \frac{\sum_{i=1}^N \sum_{t=1}^{T_i} \left(\tilde{r}_{t,i} - \widehat{E}(r_{t,i}) \right)^2}{\sum_{i=1}^N \sum_{t=1}^{T_i} (\tilde{r}_{t,i} - \bar{r}_{t,i})^2}, \quad (12)$$

where $\tilde{r}_{t,i}$ is the realized return for firm i from day 0 to day 1 with respect to announcement t , $\widehat{E}(r_{t,i})$ is the risk premium estimates for firm i estimated on day 0, $\bar{r}_{t,i}$ is the 252-day rolling average of historical returns for firm i , and T_i is the total number of earnings announcements for firm i during January 1996 to December 2009. The option selection criteria are the same as in our main analysis. The goal is to choose a level of α to best fit the realized returns.⁸

According to our calibration result, $\alpha = -1.138$. If we assume a conventional level of the intertemporal elasticity of substitution $\psi = 1.5$, the relative risk aversion equals 1.046, which lies in the reasonable range documented by literature. The EA risk premia and corresponding upper and lower bounds are calculated following (3), (8), and (9).

Table 4 reports summary statistics of the EA risk premia and their upper and lower bounds, as well as the corresponding realized EA returns from day 0 to day 1. The average estimated EA risk premia is 15 bps, with average upper and lower bounds to be 26 bps and 10 bps, respectively. Comparably, the average realized EA return is 12 bps. This is considerably higher than daily returns during non-EADs, which is 4 bps on average. This pattern is consistent with the earnings premia literature (Cohen et al., 2007; Frazzini and Lamont, 2007; Savor and Wilson, 2016). The average realized return can be considered as an ex-post estimate of the unconditional risk premia for the announcements in our sample. It falls between the upper and lower bounds of our ex-ante risk premia estimates, confirming the validity of our measure.

To further explore the behavior of the risk premia around the earnings calls, we also

⁸In this optimization, we also consider the synchronicity issue, as pointed out by Cremers and Weinbaum (2010), that the options market closes two minutes after the stock market in the U.S. Option data in OptionMetrics are captured by 3:59 p.m. after March 2008 synchronized with underlying securities. But for the periods between 2005 and 2008, option prices are captured by 4:02 p.m. Thus, we drop earnings announcements released from 4:00 p.m. to 4:02 p.m. between 2005 and 2008.

estimate the risk premia on days -4 to 1 with a similar methodology. We present the results in Figure 1, displaying the average of risk premia, risk premia bounds, and average realized returns for each day. A clear pattern is that the risk premia and corresponding bounds gradually increase from 3 bps to 12 bps as the earnings announcements approach. The increasing risk premia reflect forthcoming uncertainty and risk compensation required by investors. After the EAD, when the uncertainty is resolved, the risk premium crashes to about 1 bp. The realized returns display the same pattern. This pattern is consistent with the uncertainty resolution hypothesis in Ball and Kothari (1991).

Finally, we test the predictive power of our estimated EA risk premia. For each year, we divide the whole sample into observations with high, medium, and low EA risk premium groups, according to the 33th and 67th percentile.⁹ The summary statistics of the realized EA returns from day 0 to day 1 for three subsamples are reported in Table 5. The results show that the average realized return of the portfolio formed by stocks with high estimated EA risk premia is 31 bps, while that associated with low EA risk premia is -1 bp. The difference of 32 bps is economically large and statistically significant, indicating that the ex-ante estimated EA risk premia are informative of the realized EA returns cross-sectionally.

3.4 Drift sizes and risk premium: high-frequency scenario

To delve deeper into the rich information content in option prices during earnings calls, in this subsection, we examine high-frequency data to estimate the EA risk premia and obtain their dynamics over time. To this end, we obtain minute-by-minute option quote data from the CBOE for three randomly selected large-cap companies, NVIDIA Corporation (NVDA), Cisco Systems Inc (CSCO), and Microsoft Corp (MSFT). Our minute-by-minute sample covers 30, 28, and 33 announcements for NVDA, CSCO, and MSFT, respectively. The dataset contains minute-by-minute option quote prices for all available option contracts

⁹We annually subgroup the sample to control for economic condition changes over the years.

during market trading hours.

These three companies are representative as they cover different levels of the EA risk premia estimated by daily closing option prices. Panel A of Table 6 reports summary statistics of daily EA risk premia estimation for the three firms during the earnings calls that have available high-frequency data. The average EA risk premia for CSCO and MSFT are representative of typical levels among our sample of firms. In contrast, NVDA has an average EA risk premium of 51 bps, higher than the 95th percentile of the estimated EA risk premia. This allows us to explore the behavior of firms in the right tail.

To investigate the intraday behavior of the EA risk premia, we estimate the drift sizes and the EA risk premia with all available minute-by-minute option quote data. Similar to the daily case, we select two call and two put options that are closest to the money, and with the shortest maturity horizon for the estimation. Panel B of Table 6 presents the summary statistics of the high-frequency drift sizes, state prices, and risk premium on day 0 of each announcement. First, we can see that, at a much finer frequency, the average summation of the state prices, $\pi_u + \pi_d$, equals 0.9975, 0.9999, and 0.9997, for the three firms, respectively, further confirming the validity of our estimation even in high-frequency scenarios. Also, the summary statistics of estimated EA risk premia based on high-frequency align well with those based on daily data, indicating that our estimation is robust and reliable.

To illustrate the dynamics of the EA risk premia more effectively, we present a minute-by-minute plot from day -3 to day 1, as well as the 95% confidence interval, in Figure 2.¹⁰ Consistent with our previous results shown at a daily frequency, there is a build-up in the EA risk premia as the earnings announcement date approaches. More interestingly, within each day, the intraday volatility, captured by the variation of the curve, and the cross-announcement volatility, captured by the width of the confidence interval, both increase as the announcement approaches. This variation peaks throughout day 0, while drops sharply

¹⁰For each minute, we average the estimates of the EA risk premia across different announcements and construct confidence intervals based on the standard errors.

on day 1. This further supports the theory in Ball and Kothari (1991).

Another interesting observation from our analysis is the distinct difference in the behavior of the EA risk premia within a trading day compared to that between days. Specifically, the intraday volatility of the EA risk premia is relatively muted, especially when juxtaposed against the pronounced level shifts from one trading day to the next. The most pronounced change in the EA risk premia occurs between the close of day 0 and the opening of day 1, highlighting the significant information release during the announcement.¹¹ This pattern aligns with what is observed in the equity market. Jiang et al. (2012) find that after-hours trading is heightened around announcement days.

As our final analysis using the high-frequency data, we construct the pseudo predictor following (10), where \tilde{r}_i represents the overnight realized returns for firm i , which almost exclusively captures the effect of earnings announcements. For each announcement, we construct a tick-by-tick average pseudo predictor that calculates the average of all available pseudo predictors for every minute on day 0. We plot it along with the daily pseudo predictor and the overnight realized returns in Figure 3. There are two interesting facts. First, the figure shows a strong correlation between the realized return and the two pseudo predictors over time for all three firms, underscoring the precision of our approach at the individual stock level. Second, the tick average pseudo predictor is almost identical to the daily pseudo predictor, which further demonstrates the robustness of our method. This largely alleviates concerns related to synchronicity or consolidated trading (Cremers and Weinbaum, 2010; Admati and Pfleiderer, 1988; Wood et al., 1985). Therefore, in our further applications, we rely on daily option prices which allow for a much richer cross-section.

¹¹Recall that, based on our definition of day 0, the earnings call takes place between the close of day 0 and the opening of day 1.

4 Applications

In this section, we delve into various applications of our EA risk premia. First, we examine the effect of the market perceived uncertainty on the relation between unexpected returns and unexpected earnings, providing evidence on the economic channel of the post-earnings-announcement drift. Second, by identifying announcements that ex-ante present a heightened jump risk, we provide a potential strategy to profit from selling straddles net of transaction costs.

4.1 Market reaction to unexpected earnings

Since the seminal work of Collins and Kothari (1989), Kothari and Sloan (1992), and Imhoff Jr and Lobo (1992), how stock price reacts differently to earnings announcements is one of the most important topics in the accounting literature. Imhoff Jr and Lobo (1992), Bhattacharya et al. (2007), Francis et al. (2007), You and Zhang (2009), Ferri et al. (2018), Du and Huddart (2020), and Maslar et al. (2021), among others, investigate possible factors causing such variation and point out that the uncertainty prior to earnings announcements could be the main reason. Our ex-ante EA risk premia serves as a good proxy for the overall uncertainty perceived by the market before each announcement. In this subsection, we use our EA risk premia to provide further understanding of the role of uncertainty in determining stock price reactions to earnings announcements.

Our measure has three advantages compared to existing proxies in the literature. First, it is inclusive. Unlike those that only focus on a certain aspect of the uncertainty of earnings, such as earnings quality, earnings patterns, corporate governance, and economic environment, our EA risk premia aggregates all possible sources of uncertainty perceived by the market. Therefore, with a direct measure, we are able to quantitatively measure the impact of overall uncertainty. Second, our measure captures the snapshot of the market perception right before the announcement. Therefore, our measure is unlikely contaminated by irrele-

vant information long before the announcement. Finally, the EA risk premia are estimated ex-ante. This feature ensures that the analysis does not suffer from a look-ahead bias.

4.1.1 Initial market reaction

The initial response of the stock price to the earnings announcement is conventionally measured by the stock price change during a short period (typically 2-3 days) after the announcement. The argument of uncertainty being the key factor to the cross-sectional variation of the contemporaneous response is that, if investors are uncertain about the information to be released at earnings announcement, then they tend to be reluctant to immediately trade in the stock market, resulting in little initial reaction in stock prices. Along this line, we use our estimated EA risk premia as the proxy for uncertainty and provide a complementary analysis of the effect of announcement uncertainty.

Empirically, the market reactions to earnings surprises (SUE) is measured by the sensitivity of unexpected earnings to SUE. Conventionally, it is referred to as the earnings response coefficient (ERC) and estimated by the coefficient β in the following regression:

$$CAR_{i,t} = \alpha + \beta SUE_{i,t} + \epsilon_{i,t}, \quad (13)$$

where $CAR_{i,t}$ is the CAPM-adjusted cumulative abnormal return (CAR) from day 1 to day 3 of firm i for the announcement at time t .¹² ERC is crucial to the inferences regarding the information content of earnings: a higher ERC means a stronger reaction in the CAR to unexpected earnings, suggesting that the earning is more informative.¹³

To investigate the effect of announcement uncertainty on the market reactions to SUE,

¹²SUE is calculated as IBES actual earnings per share minus the median analyst consensus forecast before the corresponding announcements.

¹³Note that the setting of ERC estimation is flexible in the literature. Equation (13) can be a cross-sectional regression, a time series regression, or a pooling regression, to measure the informativeness within a specific financial quarter, a specific firm, or multiple firms during a time period.

we consider the following regression:

$$\begin{aligned}
 CAR_{i,t} = & \alpha + \beta_1 SUE_{i,t} + \beta_2 EA_RP_{i,t} + \beta_3 SUE_{i,t} \times EA_RP_{i,t} \\
 & + \beta_m controls_{i,t} + \beta_n SUE_{i,t} \times controls_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t},
 \end{aligned}
 \tag{14}$$

where $EA_RP_{i,t}$ is our estimated ex-ante EA risk premia, $controls_{i,t}$ are the control variables, and δ_t and γ_i are time and industry fixed effects, respectively.¹⁴ In this setting, ERC is determined by the combined effect of all terms that are relevant to SUE. In particular, our key parameter of interest is β_3 , which captures the sensitivity of our ERC to announcement uncertainty, measured by the ex-ante EA risk premia. Following the argument in the literature, we expect a negative value of β_3 . This would mean that following an announcement with higher uncertainty, the immediate stock response is weaker.

Table 7 reports the regression results. Column (1) reports the baseline result that only includes SUE in the regression. The baseline ERC is 1.489, significantly positive, indicating a positive relation between unexpected earnings and unexpected returns. This shows that our sample exhibits consistent results with the literature. Columns (2) to (4) show that, under different specifications, β_3 is always significantly negative. For example, with all the controls and fixed effects included, when the announcement uncertainty increases by one standard deviation (16 bps from Table 4), the ERC decreases by 1.056, which is quite considerable compared to the magnitude of the baseline ERC. This is consistent with our expectation – when the market perceives higher uncertainty before an announcement, stocks react less right after the announcement.

Our results provide further evidence that uncertainty plays a crucial role in the contemporaneous response of the stock returns to the earnings announcement. Our measure serves as an inclusive proxy for the uncertainty and delivers an informatively efficient estimate of

¹⁴We add interactions with control variables collected in Ferri et al. (2018) to rule out other factors that affect the variation in ERC: size, leverage (Collins and Kothari, 1989), book-to-market ratio (Easton and Zmijewski, 1989), earning persistence (Easton and Zmijewski, 1989), analysts' forecast dispersion (Imhoff Jr and Lobo, 1992), earnings predictability (Francis et al., 2004), idiosyncratic volatility (Ang et al., 2006b), and beta (Dimson, 1979).

the impact of uncertainty on ERC.

4.1.2 Delayed market reaction

Given the observed reluctance of investors to initially respond to SUE for announcements with high ex-ante uncertainty, a natural question emerges: are there any subsequent delayed market reactions? Notably, Ball and Brown (1968) illustrate that CAR continues to drift up for firms with high SUE and down for those with low SUE — even up to 60 trading days following the announcement, defining this trend as Post-earnings-announcement drift (PEAD).¹⁵ Recognized as one of the most robust anomalies contesting the paradigm of market efficiency, PEAD triggers exploration into the depth of its causes and implications. Based on a rational learning explanation, Francis et al. (2007) argue that PEAD can be attributed to heightened information uncertainty, wherein an initial under-reaction morphs into a gradual incorporation of information in succeeding trading days, culminating in PEAD. It is thus interesting to see if the contemporaneous under-reaction we identify correlates with PEAD. To this end, we examine the impact of the market perceived uncertainty on the relation between earnings surprise and the PEAD.

In particular, we substitute the response variable in (14) with the CAR from day 4 to 60 relative to an earnings announcement. This adjustment enables us to identify the delayed response of CAR to SUE. Considering that CAR of firms during announcements with higher ex-ante uncertainty exhibit an initial under-reaction to SUE, we anticipate a higher delayed response if the ex-ante risk, as captured by our measure, are ultimately fully absorbed by the market. This would consequently lead to a positive estimation of β_3 .

Table 8 presents our findings. When we first consider only including SUE in the regression, we find a significantly positive coefficient, confirming the existence of PEAD; specifically, the average response of CAR to SUE in the post-announcement period is 1.717 within

¹⁵Fama (1970), Foster et al. (1984), Bernard and Thomas (1989), Bernard and Thomas (1990), Richardson et al. (2010) also find consistent empirical evidence.

our sample. More interestingly, upon integrating our measure into the regression, we consistently acquire a significantly positive estimate of β_3 under various specifications. For instance, with the inclusion of all controls and fixed effects, a one-standard-deviation increase in our estimated EA risk premia amplifies the sensitivity of CAR to SUE by 4.900. This pronounced impact of our ex-ante measure underscores its pivotal role in gauging the speed at which markets assimilate information.

To sum up, our results suggest that PEAD is likely to be a result of the market's slow reaction to announcements when the corresponding ex-ante risk premia are high. When our measure indicates higher uncertainty for an announcement, investors display hesitancy in immediately reacting to new information unveiled during earnings calls, instead exhibiting a subsequent, delayed response which contributes to PEAD. Given our measure's capacity to identify conditional risk premia for each individual earnings announcement, we are able to pinpoint the ex-ante likelihood of PEAD. Next, we delve deeper to examine the relation between our measure and this anomaly.

4.1.3 Economic channel of PEAD

To better identify how the market reacts to SUE over time, we present a time-series plot of CAR for quintile portfolios sorted by SUE from day 0 to day 60 in the left panel of Figure 4. We can see that the CAR of extreme quintiles diverges swiftly during the initial few days post earnings calls, subsequently persisting in a drift, albeit at a tempered rate, for up to 60 days. This trajectory aligns coherently with the PEAD pattern documented in the literature. The first column of Table 9 displays parallel results. It reports average CARs from day 2 to day 60 after the announcement for the same quintile portfolios sorted by SUE.¹⁶ The low and high quintiles deliver average CARs of -1.08% and 0.88%, respectively, yielding a significant difference of 1.96%.

¹⁶Return on day 1 is also considered as immediate market reactions after the announcement in the literature. We repeat the analyses in this subsection with CARs from day 4 to day 60 and the results still hold.

Bernard and Thomas (1989) discuss two potential explanations of PEAD. The first is due to delayed information in the price responses. Alternatively, PEAD can be a result of risk compensation required by investors. The literature provides mixed evidence supporting either explanation (Bernard and Thomas (1989), Hung et al. (2015), Martineau (2021), etc). Our results suggest that both channels are at work: PEAD arises from delayed market response to announcements associated with higher uncertainty captured by our ex-ante risk premia. To this end, we split our sample into two subsamples by the median of our estimated EA risk premia and examine the post-earnings response in each subsample separately.

The center and right panels of Figure 4 present CARs for subsamples categorized by higher-than-median and lower-than-median estimated EA risk premia. We find that PEAD is substantially more salient for the subsample when the EA risk premia are high, and the pattern almost no longer exists for the subsample when they are low. Delving into specifics, we report average CARs for SUE-sorted quintiles from day 2 to day 60 post-announcement in Table 9. For the subsample with higher-than-median EA risk premia, the portfolio characterized by the most negative SUE has an average CAR of -3.08% , while the one with the most positive SUE has an average CAR of 2.94% , leading to a striking difference of 6.02% . In stark contrast, the average CAR of the most negative SUE portfolio is -0.27% , while that of the portfolio with the most positive SUE is even lower at -0.73% . This indicates that PEAD completely vanishes for the announcements with low uncertainty. Therefore, the existence of PEAD is almost totally driven by announcements with high ex-ante risk premia.

The results from this and the preceding subsections collectively indicate that both the information delay and risk compensation channels contribute to the existence of PEAD. Evidently, there is a delayed market response for earnings calls that are not immediately acted upon. Concurrently, the ex-ante risk premia pinpoint those earnings calls with an information delay. Thus, both channels are in effect. Our study bridges these two explanations, highlighting that price delay effects are associated with risk premia. Additionally, our

proposed EA risk premia serves as an ex-ante measure to identify announcements that are more inclined to exhibit PEAD.

One final observation is that, when comparing the left panel of Figure 4 to the original plot from Ball and Brown (1968), a somewhat diminished rate of divergence between the CARs of extreme quintiles is observed, indicating a weaker extent of PEAD. This is consistent with Martineau (2021), who argues that PEAD has ceased to exist for large firms post-2006 and has also recently vanished for microcaps, a change attributed to enhancements in market efficiency. Yet, the patterns for announcements with high risk premia displayed in the center panel of Figure 4 echo the typical PEAD trend. It appears that PEAD has not vanished; it has merely become more elusive, but discernible through our astute measures.

4.2 Differentiating straddle returns

Many studies document that straddle returns carry jump risk premium and volatility risk premium (Coval and Shumway, 2001; Ang et al., 2006a; Cremers et al., 2015; Dubinsky et al., 2019). Specifically, Dubinsky et al. (2019) observe that returns from holding a straddle portfolio during EA periods are more negative compared to non-EAD periods and claim that the difference is mainly due to the earnings jump risk premium. However, due to the existence of transaction costs, the opposite position of selling a straddle during earnings announcements is not on average profitable. One way to address this challenge requires selling a straddle portfolio only when the prospective profit, potentially determined by the associated jump risk premium, sufficiently compensates for the trading costs. Our estimated EA risk premia empower us to identify earnings announcements with elevated jump risk premium ex-ante. This allows us to engage in trades only when the potential payoff is significant, resulting in a profitable trading strategy.

We begin by analyzing straddle returns around earnings announcements. A straddle strategy involves simultaneously buying (or selling) both a call and a put option with identical

strike prices and expiration dates on the same underlying asset. Returns for long (short) straddle positions are determined by purchasing (selling) ATM call and put options at the closing ask (bid) price and subsequently selling (buying) the position at the next trading day's closing bid (ask) price. This method effectively estimates the forward return of a straddle, after accounting for transaction costs. We compute straddle returns on days -1, 0, and 1 for every earnings announcement in our sample.

In Table 10, we present the average returns for both long and short straddle positions. For all three days around earnings calls, indeed, the one-day straddle is not profitable on average regardless of a long or a short position. The only case that we have a positive average return is selling a straddle on day 0. However, the average return is only 2 bps, and not significantly different from zero. This observation is visually represented in Figure 5, which showcases the variation in straddle returns around earnings announcements. Notably, while the returns are persistently non-positive, the average returns from selling a straddle are markedly higher, whereas those from buying are correspondingly lower on day 0. Such a pattern in straddle returns aligns with the findings of Dubinsky et al. (2019), who interpret this trend as indicative of a negative, increase in magnitude, jump risk premium for the underlying stocks. The practical challenge is that, on average, the potential profit from the heightened jump risk premium during earnings is almost totally offset by the transaction costs.

Still, the sharp increase in the average return of selling a straddle on day 0 indicates potential trading opportunities. To explore such opportunities, we observe a significant positive correlation of 0.25 between our ex-ante EA risk premia and the return from selling a straddle on day 0. This association further validates our measure's ability to capture the jump risk premium around earnings calls. To uncover potential profitable trading strategies, we segment our sample into two subsets: those with above-median EA risk premia and those below. Our hypothesis is that for announcements with higher EA risk premium, the potential gains derived from selling a straddle on day 0 should adequately compensate for the

associated transaction costs. This is because, as the risk intensifies, we anticipate a notable surge in the returns from selling straddles, since traders would demand greater compensation for bearing this elevated risk.

Panel B of Table 10 provides summary statistics of returns of selling straddles on day 0 for both subsamples. The average returns are 0.23% and -0.18% for announcements associated with higher-than-median and lower-than-median ex-ante EA risk premia, respectively. Even after paying trading costs, the profit of trading that concentrates on high-risk announcements is high and significantly different from zero. Thus, utilizing our ex-ante estimates of the EA risk premia, we can effectively navigate and potentially profit from the high jump risk premia, even after accounting for transaction costs.

5 Further Analysis

In this section, we provide two further analyses to complement our main results. In the first one, we divide our sample into relatively big and small firms to evaluate the size effects. In the second one, we drop all the post-COVID announcements and assess the performance of our measure under normal economic conditions.

5.1 Size effects

Fama and French (2008) document that stock return predictability may concentrate on the microcap stocks, which are very illiquid and costly to trade. As our study focuses on the S&P 500 stocks with liquid options trading, the performance of our measure should not be driven by microcaps. Still, it is interesting to investigate whether or how our measure performs differently for firms with different market capitalizations. Along this line, we divide our sample by the median of the market capitalization and report summary statistics of the estimates for each subsample in Table 11.

Panel A and Panel B present summary statistics of the drift sizes, the EA risk premia, and bounds, as well as the realized EA returns for the larger-than-median and smaller-than-median firms, respectively. We find that smaller-than-median firms exhibit higher volatility than relatively large firms, in terms of greater mean and volatility of drift sizes, greater EA risk premia and their upper and lower bounds, as well as higher average realized EA returns. This is consistent with the notion that stocks of smaller firms are riskier, thus investors demand greater risk premia. Still, in both cases, the average realized EA returns lie between the lower and upper bounds of our ex-ante EA risk premia estimates. This indicates the robustness of our measure with respect to size effects.

5.2 Pre-COVID period

As our sample period is relatively short, there might be concerns that our results are driven by investors' abnormal behaviors during the COVID-19 pandemic (Engelhardt et al., 2020; Cooray et al., 2023). In this subsection, we focus on announcements before the stock market crash in February 2020 and evaluate the behavior of our measure under normal market conditions.

We report the summary statistics of our estimates for the sample period spanning from January 2010 to January 2020 in Table 12. This subsample includes 3,083 earnings calls. The average upward and downward drift sizes are 241 and 249 bps, respectively. The average EA risk premium is 14 bps, with lower and upper bounds being 10 and 25 bps, respectively. Again, this interval covers the average realized EA returns of 19 bps. Overall, all the statistics are qualitatively similar to what was reported before, indicating that our major conclusions are not driven by investors' abnormal behaviors during the COVID-19 pandemic.

6 Conclusion

In this paper, we study investors' ex-ante return expectations during earnings announcements. Using information from the options market, we find that the EA risk premia are time-varying and have predictive power on stock returns during conference calls. Our study provides the first time-varying risk premia estimates in the earnings announcements literature, complementing a number of studies in this area. Our estimates are robust to high-frequency data, different firm sizes, and the exclusion of the COVID-19 pandemic period.

Our measure provides new insights into the market reactions to information releases during earnings announcements. We find that when the ex-ante EA risk premia are higher, the market reacts more slowly to unexpected earnings. This offers a plausible explanation for the existence of the well-documented positive post-earnings-announcement drift. Moreover, while trading option straddles are not profitable unconditionally, we find that the performance can be improved substantially for stocks with high EA risk premia.

How investors react and how different assets (such as ETFs) perform during earnings announcements are important questions in finance. It is thus of interest to explore further the implications of the risk premia on these decision-making and performance evaluation problems. It is also intriguing to study the ex-ante EA risk premia in the global markets. All of these appear to be interesting topics for future research.

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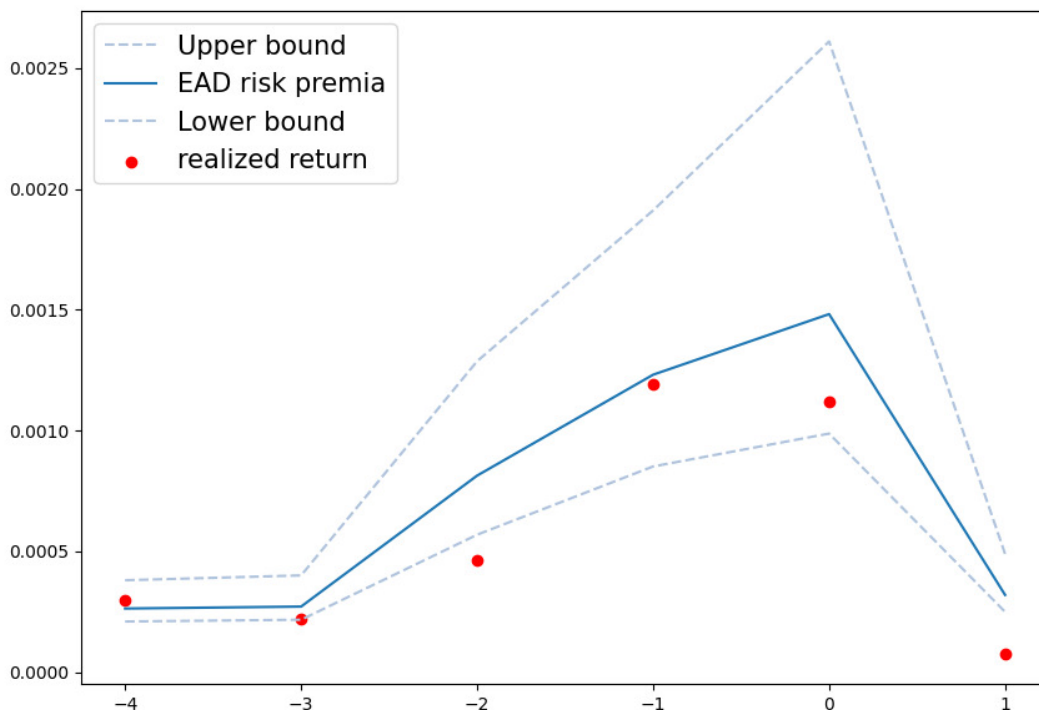


Figure 1: Risk Premia Estimates around Earnings Announcements

Notes: The figure displays the estimation of risk premia, upper bound and lower bound of risk premia, and realized forward returns around earnings announcements. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. All numbers are computed as pooling averages over quarters and over firms.

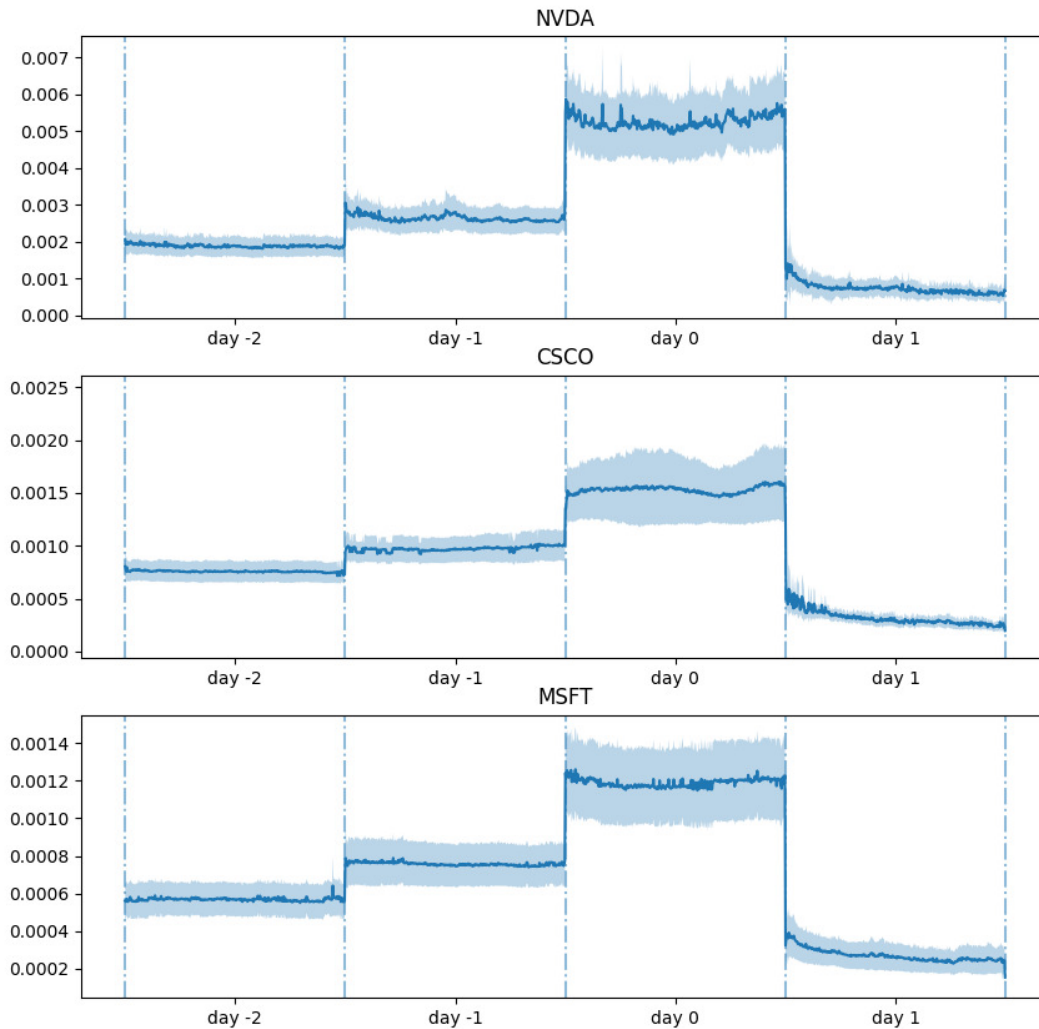


Figure 2: Minute-by-Minute Risk Premia Estimates around Earnings Announcements
 Notes: The figure shows the dynamics of risk premia estimates around earnings announcements. The risk premia are estimated by tick option pricing data at a minute-by-minute frequency. The blue line is the average across all earnings for the same firm, and the shaded area represents the 95% confidence interval. The estimated values are from 9:30 a.m. to 4:00 p.m. The sample includes options written on three firms: NVIDIA Corporation (NVDA), Microsoft Corp (MSFT), and Cisco Systems Inc (CSCO). The sample period spans from January 2010 to December 2021.

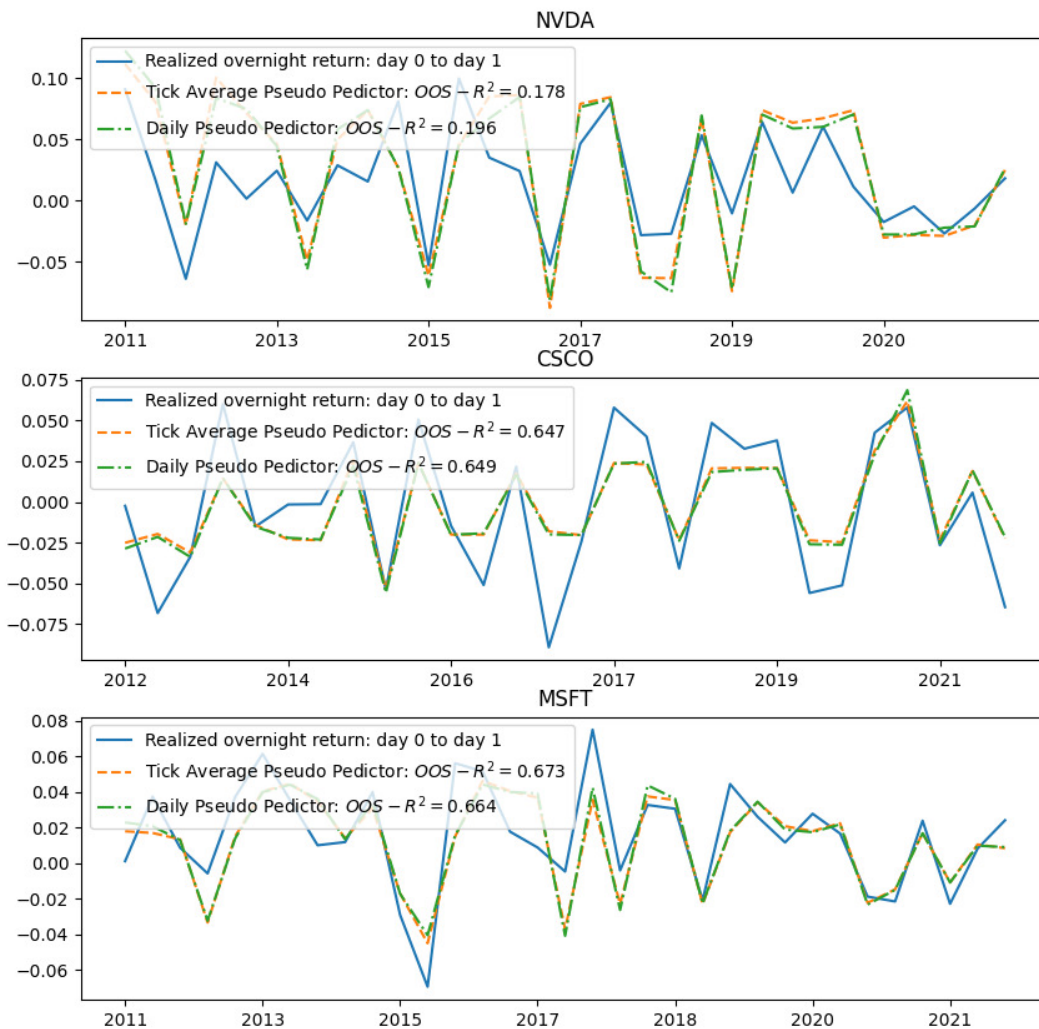


Figure 3: Pseudo Prediction by Daily and Minute-by-Minute Estimates

Notes: The figure presents the time series of the pseudo prediction on day 0, following (10), and the realized overnight announcement returns from day 0 to day 1. The pseudo prediction is estimated with both daily option prices and the daily average of drift estimates based on minute-by-minute option prices. The sample includes options written on three firms: NVIDIA Corporation (NVDA), Microsoft Corp (MSFT), and Cisco Systems Inc (CSCO). The sample period spans from January 2010 to December 2021.

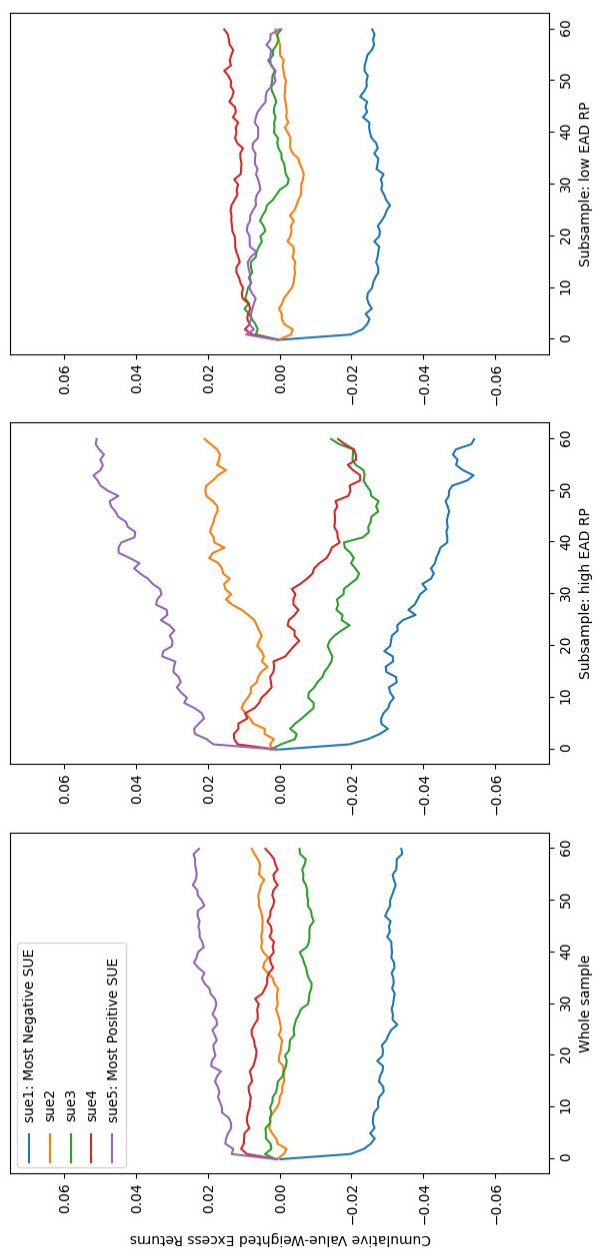


Figure 4: CARs following Earnings Announcements for SUE Sorted Portfolios

Notes: The left panel displays buy-and-hold value-weighted cumulative abnormal returns for quintile portfolios sorted by analyst-based earnings surprise (SUE). The middle and right panels present parallel results of high and low risk premia subgroups, divided by the median of our ex-ante EA risk premia. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. Abnormal returns are with respect to CAPM.

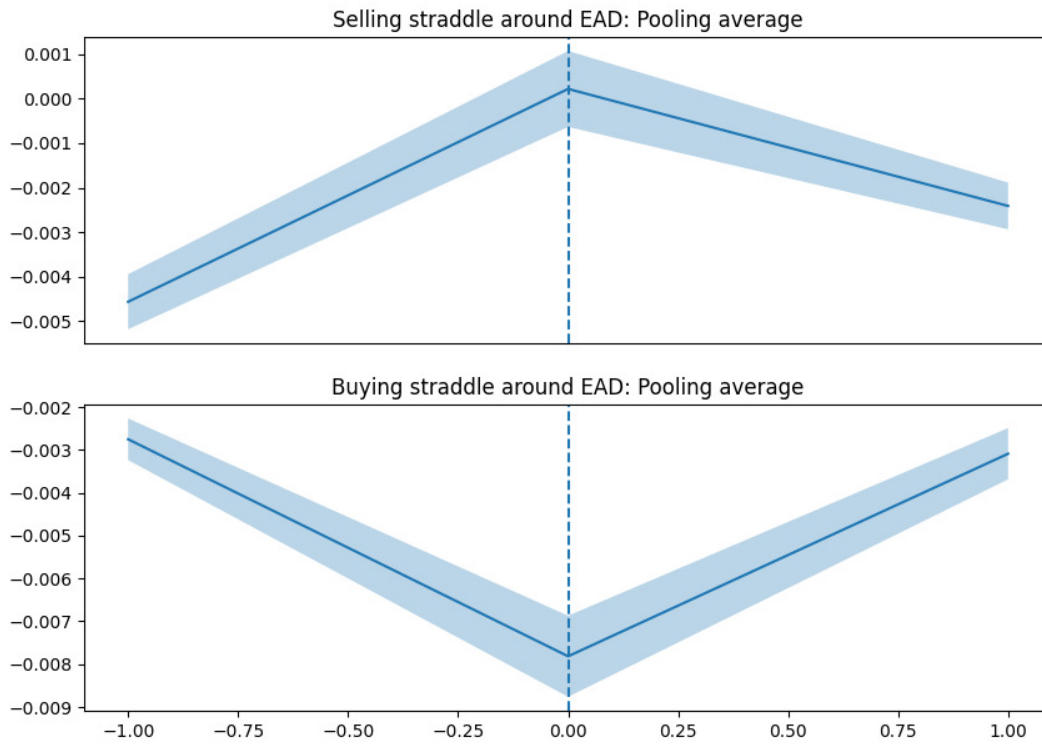


Figure 5: Straddle Returns around Earnings Announcements

Notes: The figure displays the pooling average of daily returns of at-the-money delta-neutral straddles around earnings announcements. The top panel presents returns of selling at the bid prices and buying at the offer prices. The bottom panel presents returns of buying at the offer prices and selling at the bid prices. The holding period for all straddles is one day. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1.

Table 1: Summary Statistics of Firm Characteristics

This table presents summary statistics of firm characteristics for our sample (Panel A) and the full universe of COMPUSTAT (Panel B). The sample period spans from January 2010 to December 2021. The COMPUSTAT universe includes all S&P 500 stocks during the sample period. Our sample applies the filters described in Section 3.1. *MktCap* is the log of the market capitalization; *BM* is the log of the book-to-market ratio; *Beta* is the estimated CAPM beta using return over the past 252 trading days. *Mom* is the log of the gross return over the past twelve months.

	<i>MktCap</i>	<i>BM</i>	<i>Beta</i>	<i>Mom</i>
Panel A: Our Sample (N = 3,817)				
Mean	17.67	0.44	1.08	0.16
Std. Dev.	1.15	0.38	0.35	0.36
Median	17.68	0.34	1.07	0.12
Panel B: COMPUSTAT Universe (N = 23,314)				
Mean	16.81	0.49	1.03	0.16
Std. Dev.	1.06	0.40	0.38	0.33
Median	16.69	0.39	1.01	0.13

Table 2: Summary Statistics of Drift Sizes and State Prices

The table reports summary statistics of the variables associated with the estimation (Panel A) and the estimated drift sizes and state prices (Panel B). The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. On each earnings announcement day in our sample, we use the prices of two call and two put options that have strike prices closest to the money and follow (1) and (2) to estimate drift sizes and state prices.

Variable	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Panel A: Summary Statistics of Related Variables								
C_1	3,817	1.9126	3.3310	0.255	0.625	1.11	2.125	5.625
C_2	3,817	2.6090	3.6780	0.575	0.99	1.61	2.995	7.21
P_1	3,817	1.8849	3.1751	0.255	0.63	1.115	2.115	5.555
P_2	3,817	2.5516	3.5231	0.559	0.985	1.57	2.925	6.95
K_1^C	3,817	1.0085	0.0096	1.0003	1.0027	1.0057	1.0102	1.0287
K_2^C	3,817	0.9913	0.0089	0.9728	0.9894	0.9939	0.9969	0.9993
K_1^P	3,817	0.9913	0.0089	0.9728	0.9894	0.9939	0.9969	0.9993
K_2^P	3,817	1.0085	0.0096	1.0003	1.0027	1.0057	1.0102	1.0287
Maturity	3,817	2.1286	0.7575	1	2	2	3	3
Panel B: Summary Statistics of Drift Sizes and State Prices								
u	3,817	0.0246	0.0163	0.0089	0.0137	0.0198	0.0296	0.0583
d	3,817	0.0251	0.0158	0.0096	0.0145	0.0202	0.0304	0.0573
π_u	3,817	0.5103	0.0624	0.4098	0.4700	0.5100	0.5500	0.6100
π_d	3,817	0.4908	0.0613	0.4000	0.4500	0.4900	0.5250	0.5980
$\pi_u + \pi_d$	3,817	1.0011	0.0424	0.9400	0.9800	1.0000	1.0200	1.0700

Table 3: Performance of Pseudo Prediction

This table reports summary statistics of the out-of-sample R-squared of pseudo predictions in (10) and the Pearson correlation coefficient between pseudo predictions and realized returns. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. Out-of-sample R-squared is calculated by (11).

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Out-of-Sample R^2	100	0.5576	0.0933	0.4061	0.4974	0.5551	0.6192	0.7054
Correlation Coefficient	100	0.7841	0.0742	0.6470	0.7379	0.7917	0.8331	0.8832

Table 4: Summary Statistics of the EA Risk Premia

This table reports summary statistics of the estimated EA risk premia. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. On each earnings announcement day in our sample, we follow (3) to estimate the EA risk premia $\widehat{E}(r)$. We use the corresponding bid and ask prices to estimate the upper $\overline{\widehat{E}(r)}$ and lower $\underline{\widehat{E}(r)}$ bounds of the EA risk premia following (8) and (9).

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
$\widehat{E}(r)$	3,817	0.0015	0.0016	0.0003	0.0006	0.0010	0.0018	0.0045
$\overline{\widehat{E}(r)}$	3,817	0.0026	0.0026	0.0004	0.0008	0.0016	0.0037	0.0084
$\underline{\widehat{E}(r)}$	3,817	0.0010	0.0011	0.0002	0.0004	0.0007	0.0012	0.0030
Realized returns	3,817	0.0012	0.0386	-0.0646	-0.0260	0.0007	0.0291	0.0669

Table 5: Portfolio Returns Sorted by the EA Risk Premia

This table reports the average and volatility of the realized returns during earnings announcements for tercile portfolios sorted by the EA risk premia. The table also reports the difference and t -statistic between the high and low portfolios. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1.

	Obs	Mean	Std. Dev.
High EA RP	1,272	0.0031	0.0451
Medium EA RP	1,268	0.0005	0.0384
Low EA RP	1,277	-0.0001	0.0309
High minus Low		0.0032	
t -stat		2.10	

Table 6: Summary Statistics of Estimations with Minute-by-Minute Option Prices

This table reports summary statistics of the estimated EA risk premium at a daily frequency (Panel A) and the estimated drift sizes, state prices, and the EA risk premia at the minute-by-minute frequency (Panel B) for three firms, Nvidia Corporation (NVDA), Cisco Systems Inc (CSCO), and Microsoft Corp (MSFT). At each minute on the announcement day, we choose four option contracts with a life span shorter than 3 days and strike prices closest to the money, to estimate parameters following the methodology described in Section 2. The sample includes all earnings announcements for three firms from January 2010 to December 2021.

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Panel A: Estimation with Daily Option Prices								
NVDA	30	0.0051	0.0032	0.0014	0.0028	0.0049	0.0064	0.0094
CSCO	28	0.0014	0.0009	0.0008	0.0010	0.0012	0.0016	0.0025
MSFT	33	0.0012	0.0006	0.0004	0.0007	0.0012	0.0017	0.0020
Panel B: Estimation with Minute-by-Minute Option Prices								
NVDA								
u	10,856	0.0622	0.0231	0.0242	0.0456	0.0658	0.0783	0.0989
d	10,856	0.0598	0.0215	0.0205	0.0440	0.0656	0.0758	0.0873
π_u	10,856	0.4895	0.0398	0.4200	0.4700	0.4900	0.5100	0.5500
π_d	10,856	0.5080	0.0420	0.4400	0.4800	0.5100	0.5300	0.5800
$\pi_u + \pi_d$	10,856	0.9975	0.0302	0.9500	0.9900	1.0000	1.0100	1.0400
$\widehat{E}(r)$	10,856	0.0050	0.0025	0.0014	0.0027	0.0052	0.0066	0.0095
CSCO								
u	10,893	0.0245	0.0093	0.0151	0.0197	0.0226	0.0254	0.0428
d	10,893	0.0248	0.0094	0.0161	0.0201	0.0230	0.0254	0.0547
π_u	10,893	0.5044	0.0412	0.4400	0.4800	0.5000	0.5300	0.5700
π_d	10,893	0.4956	0.0420	0.4200	0.4600	0.5000	0.5200	0.5650
$\pi_u + \pi_d$	10,893	0.9999	0.0162	0.9800	0.9900	1.0000	1.0100	1.0200
$\widehat{E}(r)$	10,893	0.0014	0.0007	0.0007	0.0010	0.0012	0.0015	0.0026
MSFT								
u	12,348	0.0259	0.0115	0.0102	0.0156	0.0227	0.0363	0.0443
d	12,348	0.0265	0.0124	0.0103	0.0153	0.0227	0.0375	0.0460
π_u	12,348	0.5043	0.0391	0.4400	0.4800	0.5070	0.5300	0.5600
π_d	12,348	0.4953	0.0391	0.4400	0.4700	0.4900	0.5160	0.5600
$\pi_u + \pi_d$	12,348	0.9997	0.0153	0.9800	0.9900	1.0000	1.0100	1.0200
$\widehat{E}(r)$	12,348	0.0012	0.0006	0.0004	0.0007	0.0012	0.0015	0.0022

Table 7: Initial Market Reaction and Ex-Ante EA Risk Premia

This table reports the coefficient estimates and standard errors in (14). We regress cumulative abnormal returns (CAR) from day 1 to day 3 with respect to an earnings announcement on analyst-based earnings surprise (SUE), EA risk premia (EA_RP), interactions of SUE and EA_RP , control variables, interactions of SUE and control variables, year-quarter fixed effects, and industry fixed effects based on Fama-French 12 industry classification. Abnormal returns are with respect to CAPM. Control variables include size, leverage, book-to-market ratio, earning persistence, analysts' forecast dispersion, earnings predictability, idiosyncratic volatility, and CAPM beta. All variables are winsorized at the 1st and 99th percentile. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1.

	Dependent Variable: $CAR[1, 3]$			
	(1)	(2)	(3)	(4)
<i>Intercept</i>	0.000 (0.001)	-0.003** (0.001)	-0.002 (0.003)	-0.006* (0.003)
<i>SUE</i>	1.489*** (0.213)	4.337*** (0.543)	3.397*** (0.998)	3.449*** (1.187)
<i>EA_RP</i>		1.387* (0.774)	1.064 (0.848)	0.504 (0.930)
<i>SUE × EA_RP</i>		-1201.449*** (211.082)	-584.735** (259.579)	-660.149** (323.806)
<i>Controls</i>	No	No	Yes	Yes
<i>SUE × Controls</i>	No	No	Yes	Yes
Year-quarter	No	No	No	Yes
Industry	No	No	No	Yes
R-squared Adj.	0.021	0.035	0.046	0.040
No. obs	2,198	2,198	2,198	2,198

Table 8: Delayed Market Reaction and Ex-Ante EA Risk Premia

This table reports the coefficient estimates and standard errors in (14). We regress cumulative abnormal returns (CAR) from day 4 to day 60 with respect to an earnings announcement on analyst-based earnings surprise (SUE), EA risk premia (EA_RP), interactions of SUE and EA_RP , control variables, interactions of SUE and control variables, year-quarter fixed effects, and industry fixed effects based on Fama-French 12 industry classification. Abnormal returns are with respect to CAPM. Control variables include size, leverage, book-to-market ratio, earning persistence, analysts' forecast dispersion, earnings predictability, idiosyncratic volatility, and CAPM beta. All variables are winsorized at the 1st and 99th percentile. Asterisks denote statistical significance at the 1% (***) , 5% (**) and 10% (*) levels. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1.

	Dependent Variable: $CAR[4, 60]$			
	(1)	(2)	(3)	(4)
<i>Intercept</i>	-0.006** (0.003)	-0.003 (0.004)	-0.037*** (0.009)	-0.030*** (0.009)
<i>SUE</i>	1.717*** (0.593)	-1.563 (1.517)	-3.751 (2.788)	-3.521 (3.104)
<i>EA_RP</i>		-1.657 (2.163)	-2.019 (2.368)	-4.036* (2.430)
<i>SUE × EA_RP</i>		1383.105** (590.084)	2583.109*** (724.968)	3062.456*** (846.534)
<i>Controls</i>	No	No	Yes	Yes
<i>SUE × Controls</i>	No	No	Yes	Yes
Year-quarter	No	No	No	Yes
Industry	No	No	No	Yes
R-squared Adj.	0.003	0.005	0.018	0.021
No. obs	2,198	2,198	2,198	2,198

Table 9: Portfolio Returns Sorted by SUE

This table reports cumulative abnormal returns from day 2 to day 60 with respect to an earnings announcement for the quintile portfolios sorted by analyst-based earnings surprises (SUE), as well as the differences with t -statistics between the high and low quintile returns. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. We report results for both the full sample and two subsamples divided by the median of the EA risk premia.

	Whole Sample	High EA RP	Low EA RP
Low	-0.0108	-0.0308	-0.0027
2	0.0088	0.0183	0.0040
3	-0.0088	-0.0125	-0.0067
4	-0.0070	-0.0287	0.0052
High	0.0088	0.0294	-0.0073
High minus Low	0.0196	0.0602	-0.0046
t -stat	2.97	4.98	-0.61

Table 10: Daily Straddle Returns around Earnings Announcements

Panel A of this table reports average returns of at-the-money straddles around earnings announcements (EA) and corresponding t -statistics. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. The holding period for all straddles is one day. Long straddles buy at the offer prices and sell at the bid prices on the next trading day. Short straddles sell at the bid prices and buy at the offer prices on the next trading day. Panel B reports average return and t -statistics of short straddles on the announcement day for subsamples divided by the median of the EA risk premia.

Panel A: Daily Straddle Returns around EADs				
Days to EA	Long Straddle		Short Straddle	
	Mean	t -stat	Mean	t -stat
-1	-0.0027	-11.0844	-0.0046	-14.4482
0	-0.0078	-16.1885	0.0002	0.5028
1	-0.0031	-10.1187	-0.0024	-9.0070

Panel B: Short Straddle Returns on Day 0		
	Mean	t -stat
High EA RP	0.0023	3.62
Low EA RP	-0.0018	-3.01

Table 11: Summary Statistics of the EA Risk Premia for Size Subsamples

This table reports summary statistics of the estimated drift sizes and the estimated EA risk premia for bigger-than-median (Panel A) and smaller-than-median (Panel B) firms. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. On each earnings announcement day in our sample, we use the prices of two call and two put options that have strike prices closest to the money, follow (1) to estimate drift sizes, and follow (3) to estimate the EA risk premia ($\widehat{E}(r)$). We use the corresponding bid and ask prices to estimate the upper ($\overline{\widehat{E}(r)}$) and lower ($\underline{\widehat{E}(r)}$) bounds of the EA risk premia following (8) and (9).

Variable	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Panel A: Bigger-Than-Median Firms								
u	1,902	0.0205	0.0128	0.0081	0.0120	0.0166	0.0249	0.0463
d	1,902	0.0213	0.0127	0.0088	0.0127	0.0174	0.0259	0.0470
$\overline{\widehat{E}(r)}$	1,902	0.0010	0.0010	0.0002	0.0004	0.0007	0.0012	0.0027
$\widehat{E}(r)$	1,902	0.0018	0.0020	0.0003	0.0006	0.0011	0.0022	0.0058
$\underline{\widehat{E}(r)}$	1,902	0.0007	0.0007	0.0002	0.0003	0.0005	0.0008	0.0019
Realized returns	1,902	0.0007	0.0352	-0.0565	-0.0236	-0.0002	0.0245	0.0595
Panel B: Smaller-Than-Median Firms								
u	1,905	0.0287	0.0181	0.0108	0.0162	0.0233	0.0351	0.0665
d	1,905	0.0288	0.0175	0.0114	0.0168	0.0233	0.0353	0.0666
$\overline{\widehat{E}(r)}$	1,905	0.0020	0.0019	0.0004	0.0008	0.0014	0.0024	0.0056
$\widehat{E}(r)$	1,905	0.0034	0.0028	0.0006	0.0013	0.0025	0.0046	0.0116
$\underline{\widehat{E}(r)}$	1,905	0.0013	0.0013	0.0003	0.0005	0.0009	0.0015	0.0036
Realized returns	1,905	0.0015	0.0417	-0.0681	-0.0288	0.0016	0.0330	0.0704

Table 12: Summary Statistics of the EA Risk Premia before COVID-19 Market Crash

This table reports summary statistics of the estimated drift sizes and the estimated EA risk premia. The sample period spans from January 2010 to January 2020. The sample includes earnings announcements for S&P 500 firms, after applying the filters described in Section 3.1. On each earnings announcement day in our sample, we use the prices of two call and two put options that have strike prices closest to the money, follow (1) to estimate drift sizes, and follow (3) to estimate the EA risk premia $\widehat{E}(r)$. We use the corresponding bid and ask prices to estimate the upper $\overline{\widehat{E}(r)}$ and lower $\underline{\widehat{E}(r)}$ bounds of the EA risk premia following (8) and (9).

Variable	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
u	3,083	0.0241	0.0161	0.0086	0.0134	0.0190	0.0291	0.0582
d	3,083	0.0249	0.0158	0.0094	0.0143	0.0199	0.0300	0.0576
$\widehat{E}(r)$	3,083	0.0014	0.0016	0.0003	0.0005	0.0009	0.0017	0.0045
$\overline{\widehat{E}(r)}$	3,083	0.0025	0.0026	0.0004	0.0008	0.0015	0.0036	0.0084
$\underline{\widehat{E}(r)}$	3,083	0.0010	0.0010	0.0002	0.0004	0.0006	0.0011	0.0029
Realized returns	3,083	0.0019	0.0383	-0.0641	-0.0247	0.0017	0.0296	0.0669