Earnings Announcements: Ex-ante Risk Premia*

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Abstract

In this paper, we provide an estimate of the ex-ante risk premia on earnings announcements based on the option market. We find that the risk premia are time-varying and have predictive power on future stock returns. With our ex-ante risk premia as a measure of uncertainty before each earnings announcement, we find that the earnings-returns relation is much weaker when the uncertainty is high. The well-documented positive post-earnings-announcement drift (PEAD) is present only when the risk premia are high. After controlling for the announcement risk premia, the PEAD factor of the literature no longer has any abnormal returns. Moreover, while trading option straddles is not profitable unconditionally, conditional on high ex-ante risk premia, it becomes profitable even net of transaction costs.

JEL Classification: G11, G14

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1 Introduction

Earnings announcements reveal the most important fundamental information to investors and have thus been studied extensively in the literature. One central question in asset pricing is to understand the risk premia. Existing studies, such as Chari et al. (1988), Ball and Kothari (1991), Cohen et al. (2007), and Lamont and Frazzini (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. However, existing studies analyze only the ex-post risk premia or the long-term average. Prior to each earnings announcement, investors form their expectation with information at that time, which is unlikely to be the same as the one of the previous announcement. But this ex-ante risk premium has not been studied in the literature.

This paper extracts the ex-ante risk premia on earnings announcements from the option market. Intuitively, investors who have high expectations on a stock can bid up the call prices prior to the announcement, and hence the option market may contain rich information about the investor's expected return on the stock. Based on the FOMC risk premium model recently developed by Liu et al. (2022), we recover the risk premia for each earnings announcement date (the EAD risk premia) from the option market. This estimate is ex-ante because it is obtained based on trading data prior to the announcement. Our EAD risk premia are the first real-time risk premia estimation in the earnings announcement literature.

We provide convincing evidence that the EAD risk premia are economically large and time-varying. Empirically, we assume a two-state jump model for the stock price around the announcement, and estimate the upward and downward drift sizes, as well as the corresponding EAD risk premia for a total of 3812 announcements for 357 S&P 500 firms during the period from 2010 to 2021. We find that, on average, the upward (downward) drift size during the announcements is 246 (351) basis points, with a volatility of 1.63% (1.58%). The average of the corresponding EAD risk premia is 15 basis points (bps). The volatility of the risk premia is as large as 16 bps, suggesting that there is significant variation of uncertainty during different earnings announcements for different firms.

We next show that our estimated EAD risk premia contain substantial predictive information on future stock returns. When we use this ex-ante measure to predict realized EAD returns, the out-of-sample R-squared is positive for 58% of the firms, and greater than 1% for 34% of them. Sorting stocks into terciles, we find a significant difference between the realized EAD returns of the low and high portfolios.

The proposed measure serves as a perfect proxy for the ex-ante uncertainty during each corresponding earnings announcement, thus, it helps understand the role of uncertainty in explaining the cross-sectional variation of stock price reaction to the announcement, i.e., the earnings-returns relation. We find that when there is higher uncertainty, the relation is weaker. Particularly, when the ex-ante EAD 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 earnings-returns relation.[1]

Our study sheds new economic insights on existing findings about the positive post-earnings-announcement drift (PEAD). As our estimate of the EAD risk premia is able to provide a direct ex-ante measure of the risk for each single announcement, we are able to examine the performance of the PEAD factor for announcements associated with higher and lower risk separately. We find that PEAD presents only when our estimated ex-ante risk premia are high, but vanishes when the risk premia are low. In particular, PEAD leads to a return spread of 6.02% (with a t-statistics of 4.98) for the subsample of earnings announcements associated with high EAD risk premia, and the same return spread is only -0.46% (with a t-statistics of -0.61) for the subsample when the EAD risk premia are low.

[1]See 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).

There are two explanations for the existence of PEAD: information delay and risk premia (Ball and Brown (1968), Fama (1970), Foster et al. (1984), Bernard and Thomas (1989), Bernard and Thomas (1990), Angrist and Krueger (2001), Richardson et al. (2010), and Hung et al. (2015)). Our findings are consistent with asset pricing theory that they are the compensation for taking the greater risk, supporting the risk premia channel explanation for the existence of PEAD.

Finally, our study identifies the economic source of profits for trading straddles. It is well-recognized that straddle returns during earnings announcements carry information of jump risk premium (Coval and Shumway (2001), Ang et al. (2006a), Cremers et al. (2015), and Dubinsky et al. (2019)). We show that our estimated EAD risk premia indeed capture the risk presented in straddles. Such findings contain important investment implications. Due to the existence of transaction costs, investors are not able to make profits with selling straddle strategies. However, our ex-ante estimates of the EAD risk premia enable us to identify announcements with higher uncertainty before the arrival of each announcement. By limiting attention to these high risk announcements, we find that, the average return of selling straddles on earnings announcement days is 0.56%, which is economically large and statistically significant.

Our paper contributes to the understanding of market reactions to EAD. 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) 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), Angrist and Krueger (2001), Richardson et al. (2010), and Hung et al. (2015) explore the lagged reaction, by looking at longer term after earnings published (i.e. PEAD). Our ex-ante risk premia measure sheds new light on these empirical findings and contribute to both lines of literature.

Our paper adds to the study of predicting stock returns around corporate events (Ederington and Lee (1996), Drake et al. (2012), Chesney et al. (2015), Gharghori et al. (2017), and Augustin et al. (2019)). In our set-up, instead of examining various behavior explanations, we measure directly the underlying expected returns before the information releases from option prices, providing critical information on risk and return. 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 high risk premium EAD from low risk premium EAD.

Our paper is closely related to the growing line of research on the information flow between stock market and derivative market. A large body of studies investigates informed trading in option market and shows that information extracted from option prices and trading volume can predict future expected returns of underlying assets (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), and 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), and Kadan et al. (2023)). The introduced methods typically do not impose specific forms of investor preferences, but they often require a large number of reliable prices of options with different strike prices for empirical implementations. 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 apply their less data-demanding method to individual earnings events and to identify the risk premium and return variation.

The rest of the paper proceeds as follows. Section 2 discusses the data and estimation methodology. Section 3 presents the empirical evidence using data with daily frequency and minute-by-minute frequency. Section 4 explores the economic implication on unresolved puzzles. Section 5 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 adopt 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 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, an asset 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 asset, which mature 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 can be recovered by:

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

and the implied state prices π_u and π_d by:

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

Under a representative agent model, where the agent follows 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 when the underlying asset S_0 is the market, 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 $\alpha = \frac{\frac{1}{\psi-\gamma}}{1-\frac{1}{\psi}} < 0$, and $\gamma \geq \psi$ and $1 \geq \frac{1}{\psi}$. While Liu et al. (2022) focus their attention to the FOMC meetings, we apply equations (1) – (3) to recover the market risk premium right before earnings announcements.

2.2 Application to EAD

Next, we consider applying the above methodology in more detail to recover the EAD premia for individual stocks. Let the asset S_0 be a stock of interest, and the event be the earnings announcement. 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 the buying and selling ends, we derive an upper bound and a lower bound on risk premium estimates using bid and ask prices. Here we specify C_1 and C_2 as the average of the bid and ask prices. Let α_1 and α_2 be the half bid-ask spread, the present values of the payoff provided by C_1 and C_2 are bounded by the bid and ask prices:

$$C_1(1-\alpha_1) < \pi_u((1+u)S_0 - K_1^C) < C_1(1+\alpha_1),$$

$$C_2(1-\alpha_2) < \pi_u((1+u)S_0 - K_2^C) < C_2(1+\alpha_2).$$

Rearranging the terms, we have:

$$((1-\alpha_1)C_1 - (1+\alpha_2)C_2)(1+u)S_0 < (1-\alpha_1)C_1K_2^C - (1+\alpha_2)C_2K_1^C,$$
$$((1-\alpha_2)C_2 - (1+\alpha_1)C_1)(1+u)S_0 < (1-\alpha_2)C_2K_1^C - (1+\alpha_1)C_1K_2^C.$$

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

$$\underline{u} = \frac{(1+\alpha_2)C_2K_1^C - (1-\alpha_1)C_1K_2^C}{((1+\alpha_2)C_2 - (1-\alpha_1)C_1)S_0} - 1 < u. \tag{4}$$

To estimate the upper bound, we define

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

As it is not always the case that $\bar{u} > u$, the condition for this inequality is $(1-\alpha_2)C_2 > (1+\alpha_1)C_1$. When it holds, $\bar{u}$ serves as an upper bound of u.[2]

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

$$\begin{aligned}\underline{d} &= 1 - \frac{(1+\theta_1)P_1K_2^P - (1-\theta_2)P_2K_1^P}{((1+\theta_1)P_1 - (1-\theta_2)P_2)S_0},\\ \bar{d} &= 1 - \frac{(1-\theta_1)P_1K_2^P - (1+\theta_2)P_21K_1^P}{((1-\theta_1)P_1 - (1+\theta_2)P_2)S_0}.\end{aligned} \tag{6}$$

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

$$\overline{\widehat{E(r)}} = \frac{\bar{d}\left(1 - \left(\frac{1+\bar{u}}{1-\bar{d}}\right)^{\alpha}\right)}{\frac{\bar{d}}{\bar{u}} + \left(\frac{1+\bar{u}}{1-\bar{d}}\right)^{\alpha}}, \tag{7}$$

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

[3]See Section3.2.2 for details.

and the lower bound is

$$\underline{\widehat{E(r)}} = \frac{\underline{d}\left(1 - \left(\frac{1+\underline{u}}{1-\underline{d}}\right)^{\alpha}\right)}{\frac{\underline{d}}{\underline{u}} + \left(\frac{1+\underline{u}}{1-\underline{d}}\right)^{\alpha}}. \tag{8}$$

Empirically, we use (1) – (3) to recover information about the EAD premia, and use (4) – (8) to bound these estimates.[4]

3 EAD Risk Premia Estimation

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

3.1 Data and sample

Our main focus is to recover the EAD 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 (RDQ) from CompuStat and announce date (ANNDATS) from I/B/E/S. We obtain daily option prices from OptionMetrics and individual stock prices from CRSP. Due to the limited trading activities of the option market in the early years, we focus on the post-2010 period after weekly options were actively traded. Thus, our sample period spans from January 2010 to December 2021 and covers 23,116 earning announcements. We also obtain minute-by-minute option quote data for some selected stocks from the CBOE exchange to explore intra-daily patterns of the EAD risk premia.

We choose options with life spans covering the 24-hour time interval right before earnings announcements. To better identify the EAD risk premia, we only consider options that mature within three days and expire after an announcement. Our sample only retains options with the shortest maturity for each announcement. To get better estimation results for the

[4]Empirically, we drop all observations that violate $\overline{\widehat{E(r)}} \geq \underline{\widehat{E(r)}}$.

EAD risk premia, we apply two major filters to ensure the contracts in our estimation are actively traded. We require the bid-ask spread to the mid-price ratio of the option to be lower than 0.2, and the trading volume to be positive. We estimate the drift sizes in (1) based on two calls and two puts with the closest strike prices to the underlying stock price.

The screening criteria described above significantly reduce our sample size. Table 1 reports summary statistics of firm characteristics of the sample before and after the filtration. After applying these filters, the number of effective earnings dates in our sample dropped from 23,116 to 3,812. However, our research scope is still representative since the firm characteristics are similar in size, value, past returns, and market beta. For example, the average, standard deviation, and median of the CAMP beta of the whole sample are 1.03, 0.38, and 1.01, respectively, compared to 1.08, 0.35, and 1.07 for the reduced sample.

3.2 Empirical issues in the estimation

Before proceeding to the estimation of the EAD risk premia, we discuss two empirical issues and how we deal with them. The first one is how to match the timeline of the theoretical model, and the second one is to determine the value of α in (3).

3.2.1 Match timeline

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

If earnings are announced on non-trading dates, we define the previous closest trading date as day 0. For earnings announced on trading days, we identify those after the market close time (4:00 pm) as post-market announcements and those before market open time (9:00 am) as pre-market announcements. For post-market announcements, as the earnings information is not already incorporated into asset prices until the market closes, the day relative to EAD is set as day 0 for the announcement day. In contrast, for the pre-market announcements, we label the trading day before the announcement day as day 0, since the closing prices on that day reflect the information from earnings. 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.

3.2.2 Determine parameter value

To estimate the EAD risk premia, we also need to determine the level of α in (3). We use the data from January 1996 to December 2010 as the training period to select 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-square:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(\tilde{r}_{it} - \widehat{E(r)}_{it} \right)^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(\tilde{r}_{it} - \bar{r}_{it} \right)^2}, \tag{9}$$

where $\tilde{r}_{it}$ is the realized return for firm i from day t to day $t+1$, $\widehat{E(r)}_{it}$ is the risk premium estimates for firm i on day t, and $\bar{r}_{it}$ is the pooling average of historical returns for firm i. The goal is to choose a level of α to best fit the realized returns.[5]

[5]In this optimization, we also carefully consider the synchronicity issues between options and stocks markets. As Cremers and Weinbaum (2010) point out, because the option market closes two minutes after the stock market in the US, option prices could contain information that is not yet incorporated in the underlying securities prices. Option data in OptionMetrics are captured by 3:59 pm after March 2008 to provide more synchronized option data with underlying securities. But for the periods between 2005 and 2008, option prices were captured by 4:02 pm. Thus, we drop EADs that are published from 4:00 to 4:02 pm between 2005 and 2008.

3.3 Drift size estimates

Our sample covers 3812 earnings announcement dates asscoicated 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, \$1.89, and \$2.55, respectively. The middle 90% of moneyness ranging from 0.9727 to 1.0287. The strike prices are very likely to fall within the drift range in our estimation, satisfying the condition required by the model. There are 880 EAD risk premia estimated by one-day maturity options, and 1,371 estimated by two-day maturity contracts, the rest are estimated by options with three days of maturity. The short maturity guarantees that our measure captures almost exclusively the risk from the earnings announcements.

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 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 EAD returns (Vuolteenaho (2002), Frazzini and Lamont (2007), and Lochstoer and Tetlock (2020)).

The mean of state prices of upside and downside drifts are 0.5104 and 0.4907, respectively. The time interval of interest is only a few days, thus, we set the interest rate to zero for expositional simplicity. When the interest rate is set to zero, the relation of $\pi_u + \pi_d = 1$ should hold. Since the state prices are estimated independently from call and put options, this relation is not guaranteed to hold empirically. To check this, 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 0.0423. This indicates that the option market is quite efficient and our estimation methodology is very accurate.

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

$$\hat{r}_i = \begin{cases} u_i \text{ if } \tilde{r}_i > 0; \\ -d_i \text{ if } \tilde{r}_i < 0, \end{cases} \tag{10}$$

where $\tilde{r}_i$ is the realized EAD return from day 0 to day 1 for a firm i. 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 can be very 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:

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

where $\bar{r}_{t,i}$ is a standard benchmark equal to the historical average of realized return of the past 252 trading days, and T_i is the sample length for stock i. In ideal cases, when the option implied drift sizes are the same as the realized ones, the OOS R-squared is 100%, i.e., the pseudo prediction has zero prediction error. We estimate the pseudo OOS R-squared to examine how close this is true. A sufficiently high OOS R-squared indicates an accurate estimation.

To better illustrate the prediction performance, we only consider firms with at least 15 announcements. There are 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 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.

3.4 EAD risk premia estimates

To continue with the EAD risk premia estimation, we next follow (9) to calibrate the parameter α in (3). According to our calibration result, $\alpha = -1.138$. If we assume the 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 EAD risk premia and corresponding upper and lower bounds are calculated following (3), (7), and (8).

Table 4 reports summary statistics of the EAD risk premia and their upper and lower bounds, as well as the corresponding realized EAD returns. The realized EAD returns are from day 0 to day 1. The average estimated EAD risk premium is 15 bps, with average upper and lower bounds to be 26 bps and 10 bps, respectively. Comparably, the average realized EAD return is 11 bps. Notice that the EAD returns are considerably higher than the non-EADs' returns, which are 4 bps on average. This pattern is consistent with the earnings premium literature (see 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 premium for the announcements in our sample. This estimate falls between the upper and lower bounds of the risk premium, which validates our estimation procedure.

To further explore the risk premia behavior around the EAD, we also estimate the risk premia for other days with a similar methodology. We present the results in Figure 1, displaying the average of the risk premia, risk premia bounds, and realized returns around the EAD. A clear pattern is that the risk premia and corresponding bounds gradually increase from 3 bps to 11 bps as the EAD approaches. The increasing risk premia incorporate forthcoming uncertainty and risk compensation required by investors. After the EAD, when the uncertainty is resolved, the risk premium crashes to about 1 bps. The realized returns match well with the same pattern.

Finally, we test the predictive power of our estimated EAD risk premia. For each year, we divide the whole sample into observations with high EAD risk premium, medium EAD risk premium, and low EAD risk premium groups, according to 33^{th} and 67^{th} percentile.[6] The summary statistics of the EAD returns among three groups are reported in Table 5. The results show that the average realized EAD return of the portfolio formed by stocks with high estimated EAD risk premia is 30 bps, while that associated with low EAD risk premia is -1 bps. The difference is 31 bps, with a t-statistic of 2.00, indicating that the estimated EAD risk premia can substantially predict EAD returns cross-sectionally.

3.5 Drift sizes and risk premium: high-frequency scenario

To better understand the pattern of the EAD risk premia before earnings announcements and its potential predictability for realized returns, we investigate at a much finer frequency in this section. We obtain minute-by-minute option quote data from the CBOE exchange. We select three representative companies, NVIDIA Corporation (NVDA), Cisco Systems Inc (CSCO), and Microsoft Corp (MSFT), which cover different levels of the EAD risk premia. Panel A of Table 6 reports summary statistics of EAD risk premia estimation for these three firms with daily option prices. From the table we can see that the mean of estimated EAD risk premia ranges from 12 bps to 51.

Our minute-by-minute sample covers 30, 28, and 33 announcements for NVDA, CSCO, and MSFT, respectively. The dataset contains option quote prices for all available option contracts for every minute during market trading hours. We estimate the drift sizes and the EAD risk premia for all available option data. Similar to daily cases, 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 minute-by-minute drift sizes, state prices, and risk premium on day 0 of each announcement, and the corresponding realized overnight return from day 0 to day 1. At a much finer frequency, the summation of

[6] We subgroup the sample first by year to control economic condition change over different years in our sample.

the state prices of upward and downward states, $\pi_u + \pi_d$, equals 0.9975, 0.9999, and 0.9997, for the three firms, respectively. This implies that our estimation method is still valid even in high-frequency situations. With high-frequency data, we are able to use close-to-open stock return to identify realized EAD returns. The overnight return from the market close time on day 0 to the market open time on day 1 could provide a cleaner and more accurate market reaction to the earnings announcements. Therefore, we use the realized overnight return to evaluate the predictability in this section.

To better illustrate the dynamics of the EAD risk premia, we plot the estimated EAD risk premia by minute from day -3 to day 1, as shown in Figure 2.[7] Consistent with our previous results shown at a daily frequency, there is a build-up in the EAD risk premia as the earnings announcement date approaches. This is consistent with the theory: as the event is right around the corner, agents face greater uncertainty and need to be compensated with a higher risk premium. After the earnings are announced and the uncertainty is resolved, the jump risk premium collapses to a much lower level as in a normal period. In addition, from the high-frequency data, we can clearly see that the volatility of the estimated EAD risk premia is much higher on day 0 compared to other days, further supporting the theory.

To examine the predictive power of drift sizes estimated by tick data, we again construct the pseudo predictor following (10), where $\tilde{r}_i$ represents the overnight realized returns for firm i. One may have a concern that option closing prices could potentially suffer from sudden increase in the trading volume, given that option prices regularly jump up or down due to the limited market depth. To mitigate this concern, for each EAD, we construct "tick average pseudo predictor", which averages available pseudo predictor of all minutes on day 0, and compare it with the daily pseudo predictors. We present the time series prediction comparison, and show the corresponding pseudo prediction OOS R-squared in Figure 3. There are two interesting facts. First, the figure shows a strong link between the realized

[7]For each minute, we average the estimates of the EAD risk premia across different announcements, and construct confidence intervals based on the standard errors.

return and the two pseudo predictors over time, suggesting the accuracy of our method at individual level. Second, "tick average pseudo predictor" has same performance with "daily pseudo predictor", which further demonstrates our the estimation accuracy using daily data.

4 Economic Implications

In this section, based on our ex-ante EAD risk premia, we explore the economic implications for the determinants of the earnings-returns relation, the economic channel of the post-earnings-announcement drift, and the trading strategies for straddles around the earnings announcements.

4.1 Earnings response coefficient

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 the earnings announcements is one of the most important topics in accounting literature. Imhoff Jr and Lobo (1992), Bhattacharya et al. (2007), 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 EAD risk premia serve as the perfect proxy for the overall uncertainty perceived by the market before each single announcement. In this subsection, we use our EAD risk premia to provide further understanding about the role of uncertainty in determining stock reactions to earnings announcements.

Our measure has three advantages compared to existing proxies in the literature. First, it is inclusive. Unlike those only focus on a certain aspect of the uncertainty of earnings, such as earnings quality, earnings patterns, corporate governance, and economic environment, our EAD 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 uncertainty. Second, our measure captures the snapshot of the market perception right before the announcement. Therefore, our measure is not contaminated by irrelevant information long before the announcement. Finally, the EAD risk premia are estimated ex-ante. This feature ensures that the analysis is not suffered from look-ahead bias.

The contemporaneous response of the stock returns to the earnings announcement is conventionally considered as stock price change during a short period (typically 2-3 days) after the announcement. The argument of uncertainty being the determinant/key factor to the cross-sectional variation of the contemporaneous response is that, if investors are uncertain about the information released during earnings, then they tend to be reluctant to trade in stock market, resulting in little reaction reflected in stock prices. Next, we use our estimated EAD risk premia as the proxy for uncertainty and provide additional understanding of the effect of annoucement uncertainty.

Empirically, the market reaction to earnings surprises (SUE) is defined as earnings response coefficient (ERC), which is estimated as the coefficient of SUE, β, in the following regression:

$$CAR_{i,t} = \alpha + \beta SUE_{i,t} + \epsilon_{i,t}, \tag{12}$$

where $CAR_{i,t}$ is the stock cumulative abnormal return (CAR) over days one, two, and three with respect to the earnings announcement date of firm i for announcement at time t. ERC is crucial to the inferences regarding the information content of earnings: a higher ERC means a stronger reaction in the CAR to unexpected earning, suggesting that the earning is more informative.[8]

To explore the effect of announcement uncertainty to ERC, we consider the following

[8]Note that the setting of ERC estimation is flexible in the literature. Equation (12) can be cross-sectional regression, time series regression, or pooling regression, to measure the informativeness within a specific financial quarter, a specific firm, or multiple firms during a time period.

regression:

$$CAR_{i,t} = \alpha + \beta_1 SUE_{i,t} + \beta_2 EAD\_RP_{i,t} + \beta_3 SUE_{i,t} \times EAR\_RP_{i,t} + \beta_m control_{i,t} + \beta_n SUE_{i,t} \times control_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}, \tag{13}$$

where $EAD\_RP_{i,t}$ is our estiamted ex-ante EAD risk premia, $control_{i,t}$ are the control variables, and δ_t and γ_i are time and industry fixed effects, respectively.[9] In regression (13), the contemporaneous response of CAR to the announcement, ERC, is measured by

$$ERC_{i,t} = \beta_1 + \beta_3 EAR\_RP_{i,t}. \tag{14}$$

Thus, β_3 captures the sensitivity of ERC to announcement uncertainty, measured by our ex-ante EAD 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 stock response is weaker.

Table 8 reports the regression results. Column (1) reports the baseline result that only includes SUE in the regression. The ERC is 1.489, significantly positive. 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, with a one-standard-deviation increase in the announcement uncertainty (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 after the announcement.

Our results provide further evidence that uncertainty plays a crucial role in the contem-

[9] We 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)).

poraneous 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 the impact of uncertainty on ERC.

4.2 Economic channel of PEAD

Post-earnings-announcement drift (PEAD) is one of the most robust anomalies that challenge the market efficiency paradigm. Ball and Brown (1968) show first that even after earnings are announced, cumulative abnormal returns (CAPM model adjusted) continue to drift up for firms with high SUE and down for firms with low SUE.[10] 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 explanations (Bernard and Thomas (1989), Angrist and Krueger (2001), Hung et al. (2015), etc). With our ex-ante estimate of the EAD risk premia, we are able to provide additional evidence for this debate.

Following the convention in the literature, we examine the PEAD by the CAR of CAPM over the 60 trading days after an announcement. We first show that the well-known pattern of PEAD also exists in our sample. The left panel of Figure 5 depicts the time series of the value-weighted CARs for quintile portfolios sorted by SUE.[11] We can clearly see a divergence in CARs of high and low SUE portfolios, consistent with what is documented in the literature.

Next, we separate the whole sample into two subsamples divided by the median of our estimated EAD risk premia. If PEAD compensates for the EAD risk premia, then the pattern should be more significant in the high EAD risk premia subsample, as observations in this sample are those during announcements of higher uncertainty. Otherwise, if PEAD is due to the price delay effect, both samples should exhibit similar patterns. The middle and

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

[11]SUE is calculated as I/B/E/S actual earnings per share minus the median analyst consensus forecast before the corresponding announcements.

right panels of Figure 5 present CARs for subsamples with higher-than-median and lower-than-median estimated EAD risk premia, respectively. We find that PEAD is substantially more pronounced for the subsample when the EAD risk premia are high, and the pattern no longer exists for the subsample when they are low. More precisely, we report the CARs from day 2 to day 60 after the announcement in Table 7.[12] For the subsample with higher-than-median EAD risk premia, the portfolio with 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%. On the contrary, the average CARs of the portfolio with the most negative SUE is -0.27%, while that of the portfolio with the most positive SUE is surprisingly lower, which is -0.73%. We can see that PEAD completely vanishes for the announcements with low uncertainty, reinforcing the risk premium explanation of the PEAD.

4.3 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), and Dubinsky et al. (2019)). Specifically, Dubinsky et al. (2019) find that returns of holding a straddle portfolio during EAD periods are more negative than during non-EAD periods, indicating a higher jump risk premium during EAD periods. However, due to the existence of transaction costs, the opposite position of selling a straddle portfolio is not on average profitable. Our estimated EAD risk premia allow us to empirically identify earnings announcements with high jump risk premia ex-ante, so we can trade only when the potential benefit is large, leading to a profitable trading strategy.

We start with exploring straddle returns around earnings announcements. The straddle returns of long positions (short positions) are calculated from purchasing (selling) ATM call

[12] Returns on day 1 is considered as immediate market reactions after the announcement.

and put options at the offer (bid) price and selling (buying) the position at the bid (offer) at the close time of the next trading day. This calculation estimates the forward return of a straddle after accounting for transaction costs. We estimate straddle returns for all announcement days (day 0) in our sample, as well as the trading day before (day -1) and after the announcement (day 1).

The average long and short straddle returns are reported in Table 9. For all days, the one-day straddle is not profitable on average regardless of the long or short position, which suggests the efficiency of the options market. Figure 4 displays the pattern of the straddle return variation around EADs. We can see that, though always being negative, the average return of selling a straddle is larger and the average return of buying a straddle is lower on day 0. This pattern of straddle returns is consistent with Dubinsky et al. (2019), who interpret this pattern as evidence of a negative, increase in magnitude, variance risk premium or jump risk premium of underlying stocks.

We next divide our sample into subsamples of higher-than-median and lower-than-median EAD risk premia. We expect that during those announcements with higher-than-median EAD risk premia, the increase in the returns of selling straddles will be large as the selling requires more compensation for the increased risk.

Panel B of Table 9 provides summary statistics of returns of selling straddles on day 0 for both subsamples. The average returns are 0.39% and -0.17% for announcements associated with higher-than-median and lower-than-median EAD risk premia estimates, respectively. This leads to an economically large and statistically significant difference, which equals 0.56%. Therefore, based on our ex-ante estimates of the EAD risk premia, we are able to profitably trade on the jump risk premia even with the existence of transaction costs.

5 Conclusion

In this paper, we study investors return expectations during earnings announcements. Using information from option markets, we find that the ex-ante risk premia are time-varying and have predictive power on future stock returns. 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 in a number of ways, and valid also with the use of intraday data.

We also provide new insights on three stylized facts. First, we show that the immediate response of stock prices to earnings announcements is less when the ex-ante uncertainty is higher. Second, we find that the well-documented positive post-earnings-announcement drift (PEAD) is present only when the risk premia are high, consistent with a risk explanation of the PEAD rather than the one due to information delay. Third, while trading option straddles is not profitable in general, we find that the performance can be improved substantially during periods of high announcement risk premia.

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

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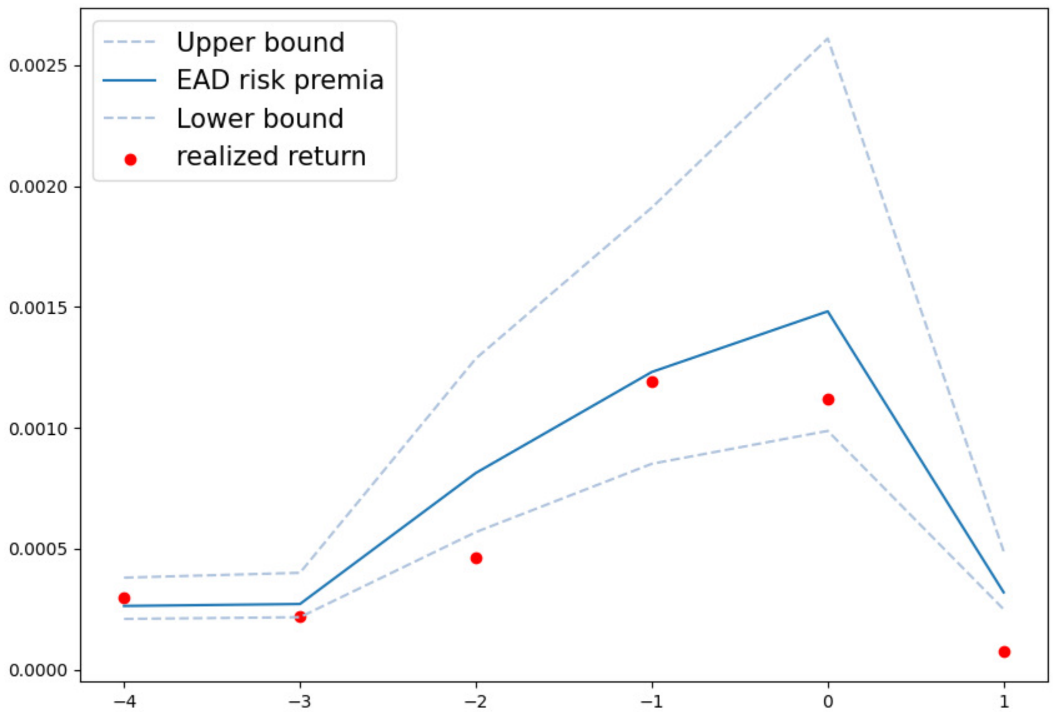

Figure 1: Risk Premium Estimates around Earnings Announcements

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

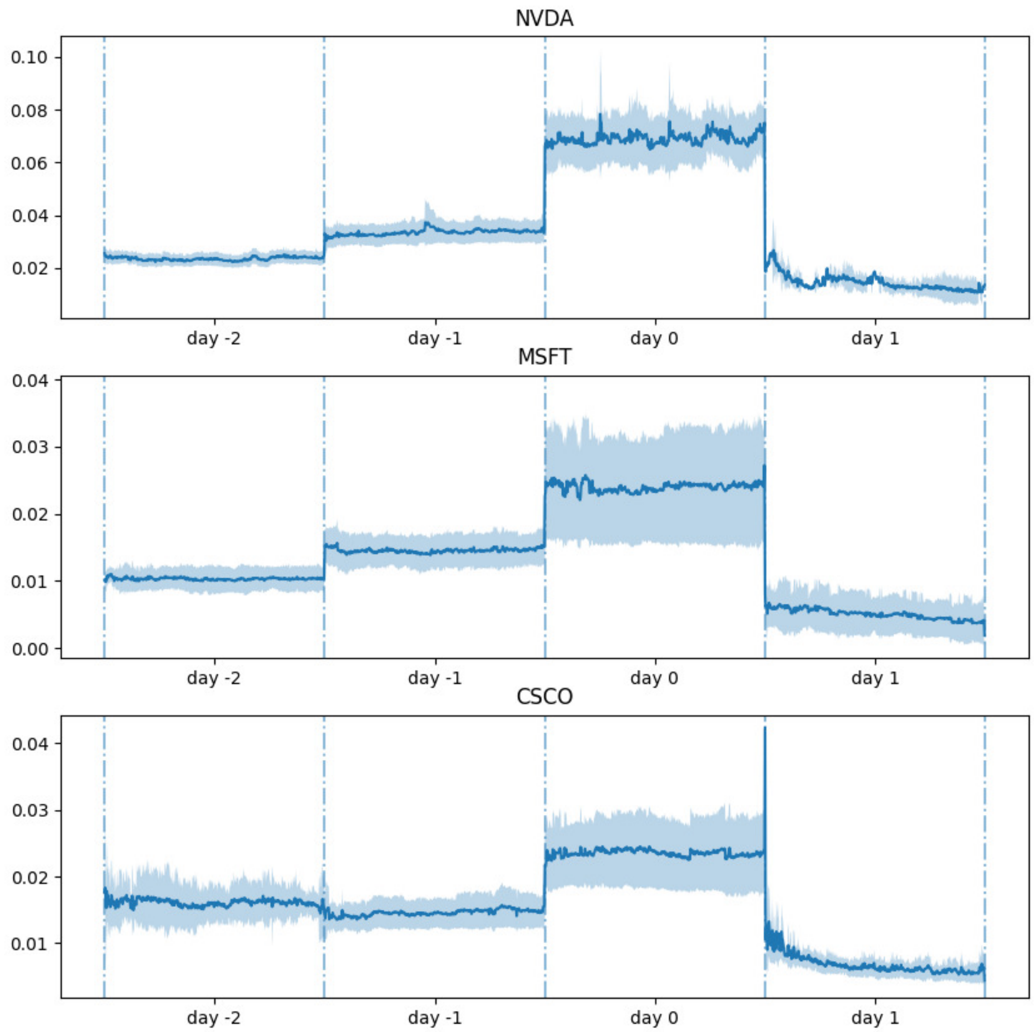

Figure 2: Minute-by-Minute Risk Premium Estimates around Earnings Announcements
Notes: The figure shows the dynamic of risk premium estimates around earnings announcements from the beginning of day -3 to the end of day 1, with day 0 being the announcement day. The risk premia are estimated by tick option price data at minute-by-minute frequency. The blue line shows the time series average across all earnings for the same firm, and the shaded area represents the 95% confidence interval. The estimated values are available from 9:30 am to 4:00 pm, covering the option market trading time of the day. The sample includes options written on the three individual firms: NVIDIA Corporation (NVDA), Microsoft Corp (MSFT), and Cisco Systems Inc (CSCO). The sample period spans from January 2010 to December 2021.

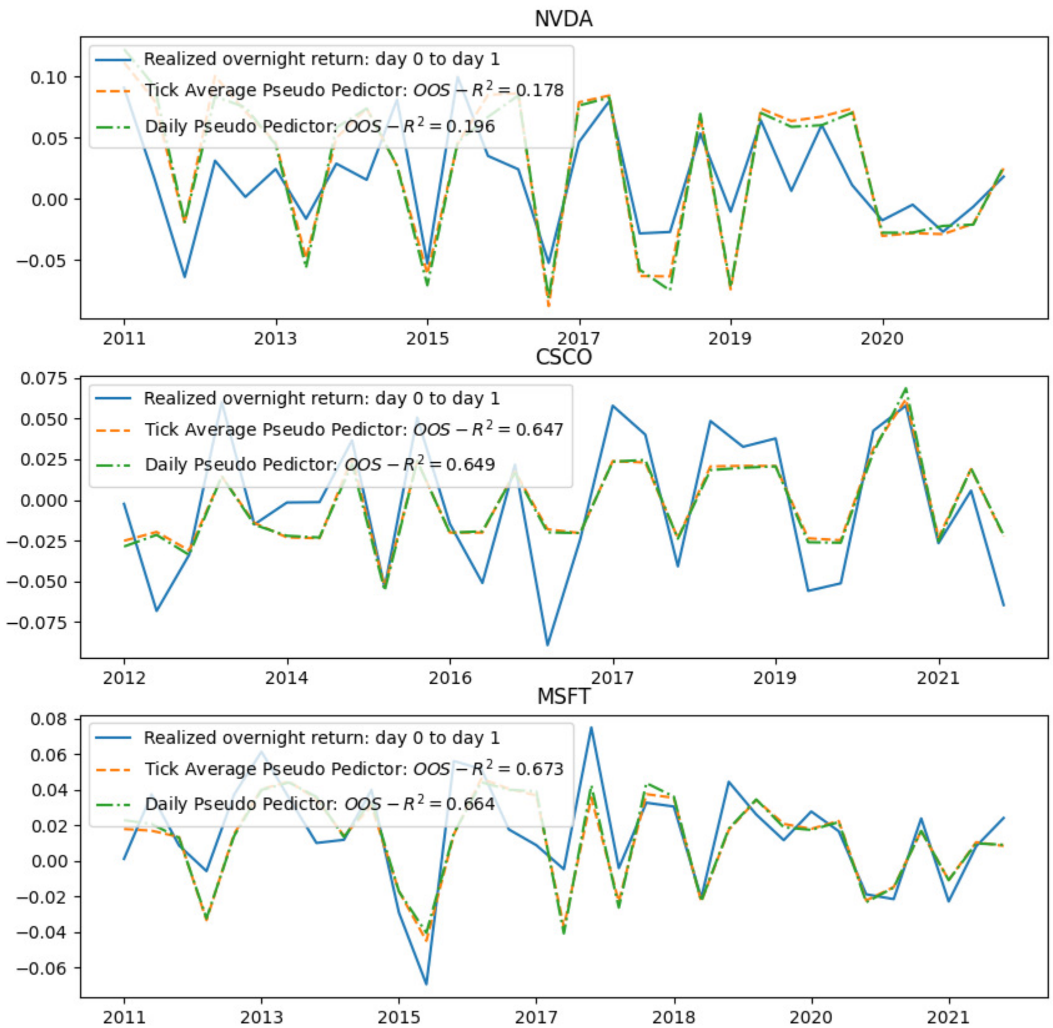

Figure 3: Pseudo Prediction

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 with minute-by-minute option prices. The sample includes options written on the three individual firms: NVIDIA Corporation (NVDA), Microsoft Corp (MSFT), and Cisco Systems Inc (CSCO). The sample period spans from January 2010 to December 2021.

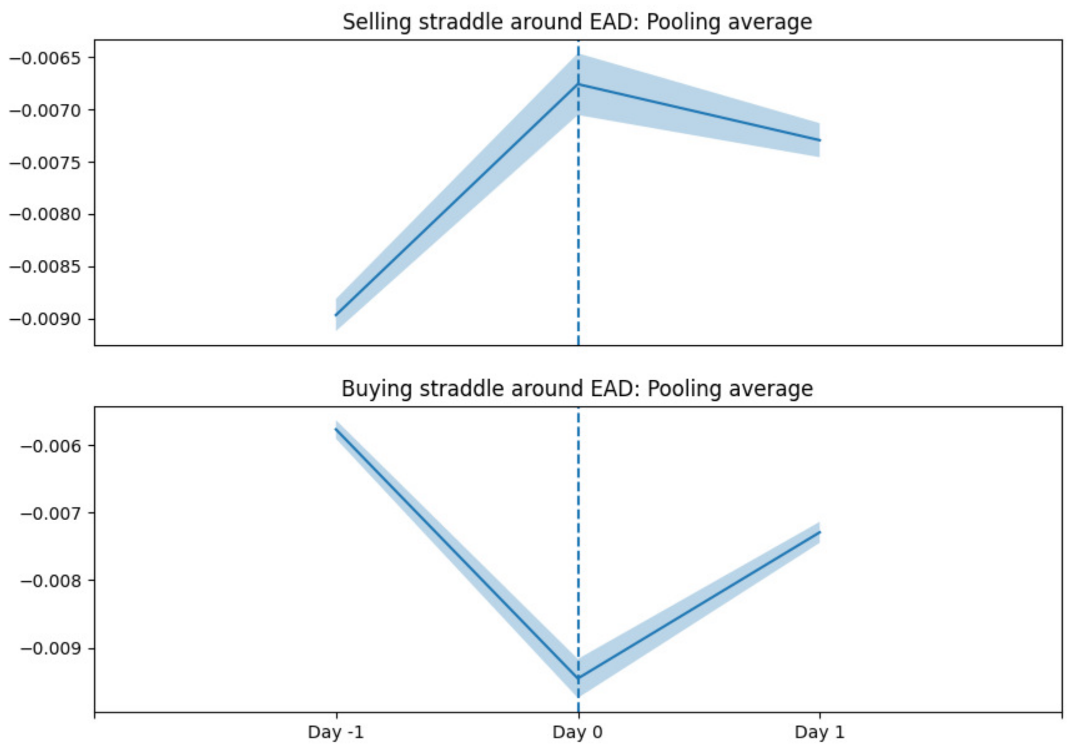

Figure 4: Straddle Returns around Earnings Announcements

Notes: The figure displays the pooling average of daily returns on 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 firms included in S&P 500 index, after applying the filters described in Section 3.1.

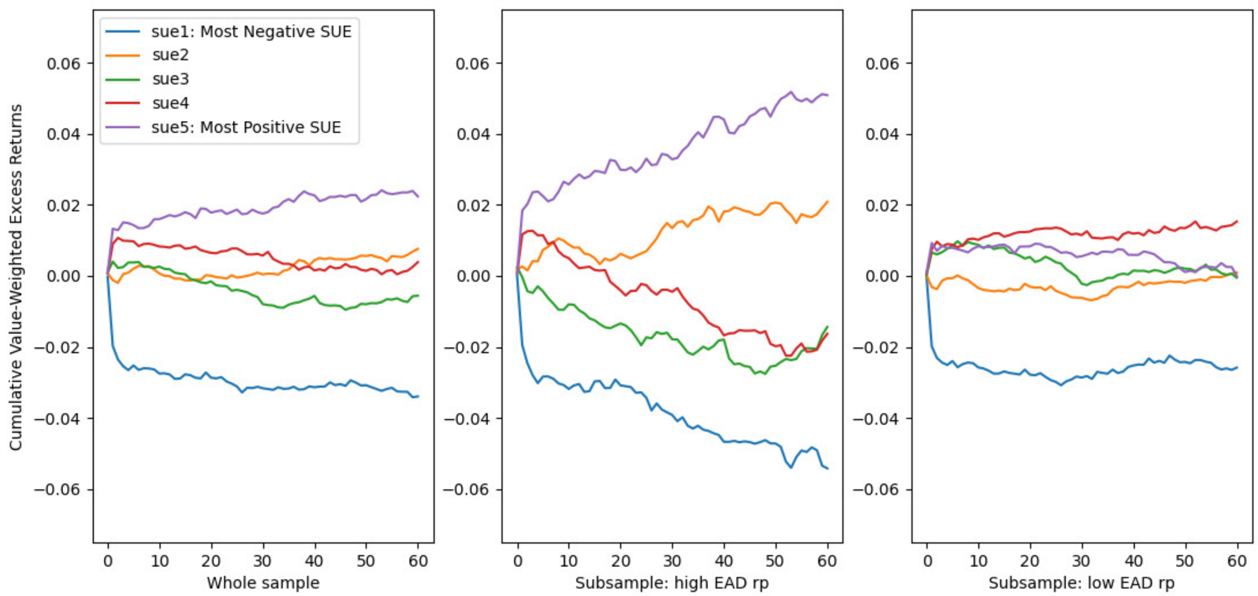

Figure 5: CARs following Earnings Announcements for Analyst-based SUE Portfolios

Notes: The left panel displays buy-and-hold value-weighted cumulative abnormal return for quintile portfolios sorted by analyst-based SUE. The middle panel and right panel present results of high risk premia group and low risk premia group, divided by the median of our estimated ex-ante EAD risk premia. The sample period spans from January 2010 to December 2021. The sample includes earnings announcements for firms included in S&P 500 index. All numbers are computed as pooling averages over quarters and over firms.

Table 1: Summary Statistics of Firm Characteristics

This table presents summary statistics of firm characteristics for the sample before and after applying the filters described in Section 3.1. The sample period spans from January 2010 to December 2021. The sample includes all S&P 500 stocks during the sample period. $MktCap$ is the log of the market capitalization; BTM is the log of book-to-market ratio; $Beta$ is the estimated CAPM beta using the past 252 trading days. Mom is the log of the gross return over the past twelve months.

	$MktCap$	BTM	$Beta$	Mom
	Full Sample (N = 23,064)			
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
	After Filtration (N = 3,812)			
Mean	17.67	0.44	1.08	0.16
Std. Dev.	1.15	0.38	0.35	0.36
Median	17.69	0.34	1.07	0.12

Table 2: Summary Statistics of Drift Sizes and State Prices Estimates

The table reports summary statistics of the variables associated with the estimation of drift sizes and state prices (Panel A) and the estimated drift sizes and state prices (Panel B). The estimation includes options written on individual firms with maturity shorter than three days and covers the earnings announcements. On each earnings announcement day in our sample, we use the prices of two call and put options that have strike prices closest to the money, and follow (1) and (2) to estimate drift sizes and state prices. The estimation uses option closing prices on day 0, defined in Section 3.2.1. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021.

Variable	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Panel A: Summary Statistics of Related Variables								
C_1	3812	1.9130	3.3330	0.2550	0.6250	1.1100	2.1213	5.6250
C_2	3812	2.6098	3.6801	0.5750	0.9900	1.6100	2.9950	7.2225
P_1	3812	1.8852	3.1769	0.2550	0.6300	1.1150	2.1113	5.5613
P_2	3812	2.5523	3.5251	0.5578	0.9850	1.5700	2.9250	6.9500
K_1^C	3812	1.0085	0.0096	1.0003	1.0027	1.0057	1.0102	1.0287
K_2^C	3812	0.9913	0.0089	0.9727	0.9894	0.9939	0.9969	0.9993
K_1^P	3812	0.9913	0.0089	0.9727	0.9894	0.9939	0.9969	0.9993
K_2^P	3812	1.0085	0.0096	1.0003	1.0027	1.0057	1.0102	1.0287
Maturity	3812	2.1288	0.7577	1.0000	2.0000	2.0000	3.0000	3.0000
Panel B: Summary Statistics of Drift Sizes and State Prices								
u	3812	0.0246	0.0163	0.0089	0.0137	0.0197	0.0296	0.0583
d	3812	0.0251	0.0158	0.0096	0.0145	0.0202	0.0303	0.0573
π_u	3812	0.5104	0.0624	0.4096	0.4700	0.5100	0.5500	0.6100
π_d	3812	0.4907	0.0612	0.4000	0.4500	0.4900	0.5250	0.5980
$\pi_u + \pi_d$	3812	1.0011	0.0423	0.9400	0.9800	1.0000	1.0200	1.0700

Table 3: OOS R-Squared of Pseudo prediction

This table reports summary statistics of the out-of-sample (OOS) R-squared of time-series pseudo prediction in (10), and the Pearson correlation coefficient between pseudo predictors and realized returns. We construct pseudo predictors on day 0, and calculate realized returns using closing prices on day 0 and day 1. The OOS R-squared calculation follows that in (11). The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021.

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
Pseudo OOS 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 EAD Risk Premia Estimates

This table reports summary statistics of the estimated EAD risk premia. We use options written on corresponding firm stockss with maturities shorter than three days and that cover the earnings announcements. On each earnings announcement, we use the prices of two call and put options that have strike prices closest to the money, and follow (3) to estimate the EAD risk premia. Also, we use the corresponding bid and ask prices to estimate the upper and lower bounds of EAD risk premia following (7) and (8). The parameter level follows calibration discussed in Section 3.2.2. Realized returns are calculated using closing prices on day 0 and day 1. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021.

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
rp	3812	0.0015	0.0016	0.0003	0.0006	0.0010	0.0018	0.0045
$\overline{rp}$	3812	0.0026	0.0026	0.0004	0.0008	0.0016	0.0037	0.0084
$\underline{rp}$	3812	0.0010	0.0011	0.0002	0.0004	0.0007	0.0012	0.0030
Realized returns	3812	0.0011	0.0386	-0.0646	-0.0260	0.0006	0.0290	0.0669

Table 5: Tercile Realized Returns Sorted by the EAD Risk Premia

This table reports average and volatility of the realized returns from day 0 to day 1 of earnings announcements for tercile portfolios sorted by our estimated ex-ante EAD risk premia. The table also reports difference and t-statistics between the high and low portfolio. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021.

	Obs	Mean	Std. Dev.
High EAD RP	1270	0.0030	0.0451
Medium EAD RP	1266	0.0005	0.0384
Low EAD RP	1276	-0.0001	0.0309
High minus Low		0.0031	
t-stat		2.00	

Table 6: Summary Statistics of the High-Frequency Estimation

This table reports summary statistics of the estimated EAD risk premium at daily frequency (Panel A) and the estimated drift sizes and state prices at minute-by-minute frequency and the corresponding realized close-to-open returns from day 0 to day 1 (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
rp	10,856	0.0050	0.0025	0.0014	0.0027	0.0052	0.0066	0.0095
$r_{overnight}$	30	0.0161	0.0432	-0.0527	-0.0149	0.0163	0.0437	0.0866
	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
rp	10,893	0.0014	0.0007	0.0007	0.0010	0.0012	0.0015	0.0026
$r_{overnight}$	28	-0.0037	0.0452	-0.0670	-0.0434	-0.0020	0.0384	0.0579
	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
rp	12,348	0.0012	0.0006	0.0004	0.0007	0.0012	0.0015	0.0022
$r_{overnight}$	33	0.0152	0.0299	-0.0253	-0.0041	0.0166	0.0354	0.0583

Table 7: Quintile Portfolios Sorted by Analyst-based SUE

This table reports cumulative abnormal returns from day 2 to day 60 of after earnings announcements of the portfolios sorted by analyst-based earnings surprises (SUE) in the previous announcement, as well as the difference with t-statistics between the high and low quintiles. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021. We report results for both the full sample and two subsamples divided by the median of our estimated ex-ante EAD risk premia.

	Whole Sample	High EAD RP	Low EAD 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 8: Pooling Regression of CAR on SUE

This table reports the coefficients and standard errors estimation of (13). We regress cumulative abnormal returns (CAR) from day 1 to day 3 on earnings surprise (SUE), EAD risk premia (RP), interactions of SUE with RP, control variables, interactions of SUE with control variables, year-quarter fixed effects, and industry fixed effects based on Fama-French 12 industry classification. 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 1% and 99& level. ***, **, * indicates significance level at 1%, 5%, and 10%, respectively. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021.

	(1)	(2)	(3)	(4)
Intercept	0.000	-0.003**	-0.002	-0.006*
	(0.001)	(0.001)	(0.003)	(0.003)
SUE	1.489***	4.337***	3.397***	3.449***
	(0.213)	(0.543)	(0.998)	(1.187)
$SUE \times RP$		-1201.449***	-584.735**	-660.149**
		(211.082)	(259.579)	(323.806)
RP		1.387*	1.064	0.504
		(0.774)	(0.848)	(0.930)
$SUE \times Controls$	No	No	Yes	Yes
Controls	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 9: Daily Straddle Returns around EADs

Panel A of this table reports average returns of at-the-money straddles around EADs and corresponding t-statistics. The sample includes all earnings announcements for S&P 500 firms from January 2010 to December 2021. The holding period for all straddles is one day. The left column presents returns of long straddles bought at the offer prices and sold at the bid prices on the next trading day. The right panel presents returns of short straddles sold at the bid prices and bought at the offer prices on the next trading day. Panel B reports return summary statistics of short straddles on the announcement day for subsamples divided by the median of our estimated ex-ante EAD risk premia.

Panel A: Daily Straddle Returns Around EADs

	Long Straddle		Short Straddle	
Days to EAD	Mean	*t*-stat	Mean	*t*-stat
-1	-0.0058	-82.11	-0.0090	-113.87
0	-0.0095	-64.19	-0.0068	-44.78
1	-0.0073	-91.73	-0.0073	-87.76

Panel B: Straddle Returns for Subsamples

	Obs	Mean	Std. Dev.	5%	25%	50%	75%	95%
High EAD RP	1214	0.0039	0.0136	-0.0215	-0.0040	0.0055	0.0136	0.0236
Low EAD RP	1215	-0.0017	0.0102	-0.0224	-0.0067	0.0006	0.0052	0.0109
High minus Low				0.0056				
t-stat				11.53				