JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 53, No. 6, Dec. 2018, pp. 2587–2617

doi:10.1017/S0022109018000285

Anticipating Uncertainty: Straddles around Earnings Announcements

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Abstract

Straddles on individual stocks generally earn negative and significant returns. However, average at-the-money straddles from 3 days before an earnings announcement to the announcement date yield a highly significant 3.34% return. The positive returns on straddles indicate that investors underestimate the magnitude of uncertainty around earnings announcements. We find that positive straddle returns are more pronounced for smaller firms and firms with higher volatility, higher kurtosis, more volatile past earnings surprises, and less trading volume/higher transaction costs. This suggests that when firm signals are noisy, and/or when it is costlier to trade, investors underestimate the uncertainty associated with earnings announcements.

I. Introduction

A typical public firm makes quarterly earnings announcements, which are one of the most important corporate events. These announcements reveal fundamental information about the firm, and investors respond actively to this information by comparing the announced fundamentals to their ex ante expectations. Earnings announcement periods are information-dense periods, and stock trading volume can increase by as much as 50%. This is also a period of high returns. Lamont and Frazzini (2007) find that 60% of a typical stock return can be achieved if investors trade only on each quarterly earnings announcement. Another well-known fact for earnings announcements is that for both good and bad news, uncertainty builds up before the information event and plummets afterward. For instance, both Patell and Wolfson (1979) and Dubinsky and Johannes (2006) document that uncertainty dramatically increases before earnings announcements and returns to normal afterward.

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Uncertainty is of key importance for asset pricing. Nevertheless, it is difficult to measure uncertainty directly, or investors' expectation of uncertainty. Given the drastic movements in uncertainty around earnings announcements, we consider these events to be a particularly interesting venue to study how investors form their expectations of a firm's fundamental uncertainty. To our benefit, the date of a future earnings announcement is usually publicly available ex ante,[1] which facilitates separation between uncertainty about event dates and uncertainty about firm fundamentals.[2]

The challenging question we try to answer is: Can investors correctly anticipate the uncertainty dynamics around an earnings announcement? To focus directly on uncertainty rather than on the direction of the news, we adopt a straddle option trading strategy. A straddle consists of a call and put option with matching strike prices and maturity dates. In our empirical design, we focus on delta-neutral straddles, which allow an investor to trade on underlying uncertainty without any directional exposure to the underlying security.

Expected returns on straddles typically include a volatility risk premium and a jump risk premium. Absent any such premia, Coval and Shumway (2001) show that under mild assumptions, the expected return on delta-neutral straddles should be equal to the risk-free rate. Coval and Shumway further document that delta-neutral straddles on Standard & Poor's (S&P) 500 index earn approximately -3% per week, and they interpret this as consistent with market volatility carrying a negative risk premium. We confirm Coval and Shumway's finding on straddle returns at the individual stock level. In particular, equal-weighted delta-neutral at-the-money individual stock straddles have an average return of -2.12% per week with a t-statistic of -11.92. At daily and monthly frequencies, the delta-neutral straddle earns -0.19% and -17.09% on average, respectively. The negative straddle return is robust to volume weighting and open interest weighting.

If participants in the options market correctly forecast the magnitude of the uncertainty changes associated with earnings announcements, straddle holders should earn similar negative returns on average around earnings announcements. In striking contrast, delta-neutral at-the-money straddles earn positive and significant returns during earnings announcement periods. As mentioned earlier, earnings announcement dates are scheduled ex ante and are public information appearing on almost all major financial Web sites from the *Wall Street Journal* to Yahoo! Finance. We construct straddles 3 and 1 trading day(s) before the scheduled earnings announcement date and hold the straddle until the earnings announcement date or 1 day after the earnings announcement date. The straddle returns around earnings announcements are all positive and significant across all holding periods we test/consider, ranging from 2.10% to 3.34%. We further examine straddle returns for the preannouncement period and the announcement period.

[1]For instance, the *Wall Street Journal* keeps an earnings calendar for public firms, indicating the earnings announcement date. These data can be available months before the real announcement. According to Bagnoli, Kross, and Watts (2002), 80% of firms in 1998 chose to report earnings on the expected announcement dates. Dubinsky and Johannes (2006) find that all 20 of their sample firms announced earnings on expected report dates.

[2]We double-check our results using expected announcement dates, without assuming the real announcement days are known ex ante. The results are similar.

Our empirical results show that the positive straddle returns over the preannouncement period is particularly large, significant, and robust.

The contrast between positive and significant straddle returns around earnings announcements and negative and significant straddle returns over the whole sample is puzzling. Various mechanisms could be driving this result. One could argue that the positive straddle returns around earnings announcements represent compensation for risk. In this article, to reduce measurement errors in parameters estimated over extremely short periods, we work with raw returns of delta-neutral straddles without any risk adjustments. Delta-neutral straddles normally have exposure to market volatility and jump risks as they are not gamma neutral or vega neutral. Studies, such as Cremers, Halling, and Weinbaum (2015), show that both market volatility risk and market jump risk carry negative and significant risk premia. Therefore, it is unlikely that the positive straddle returns around earnings announcements represent compensation for these negatively priced risk factors.

If the positive straddle returns are not compensation for systematic risks, this would indicate that the market underestimates the uncertainties around earnings announcement days. What mechanism is behind this underestimation? We propose several nonexclusive explanations. First, we believe the noisiness of a firm's signal received by its investors can substantially affect an investor's expectation about future uncertainty associated with this firm. If there is less noise in the firm's signals, it may be easier for investors to form a more accurate expectation about future uncertainty, and vice versa.[3] That is, the underestimation of uncertainty and positive straddle returns would be more pronounced for firms with noisier signals. Second, it is possible that the straddles are too expensive to trade, and thus the option prices fail to reflect the quick changes in uncertainty around earnings announcement days. This would be consistent with the limits to arbitrage explanation in Merton (1987). Third, investors might have ambiguity aversion and be reluctant to trade before an earnings announcement, when ambiguity reaches its peak. This leads options prices to fail to reflect the most current and relevant information available to the market. In other words, because of the high ambiguity related to the distribution of earnings surprises, ambiguity-averse investors might simply avoid trading these options. If ambiguity-averse investors dominate in the options market, we are likely to observe lower trading volume around the event.

We find evidence broadly consistent with the first two explanations. Firms with noisier signals, such as firms with higher historical volatilities, larger historical earnings surprises, and more volatile past earnings surprises, all experience stronger underestimation of uncertainty and higher straddle returns around earnings announcements. Meanwhile, firms with less volume and wider bid–ask spreads, for both options and the underlying stocks, also have higher positive straddle returns. It is not surprising that straddle returns for firms with noisy signals and higher trading costs tend to overlap substantially. They tend to be smaller

[3] Investors, according to Hilbert (2012), display more behavioral biases when there is more noise in the signal. A particularly relevant behavioral bias is conservatism, meaning that investors are too slow to draw inferences from data, which leads to investors' underreaction to information in the data. In our case, when investors anticipate the uncertainty to arrive and get resolved around earnings announcements, conservatism means that they underestimate the magnitude of uncertainty the event brings to the price process.

firms with less analyst coverage, both of which are associated with less efficient information environments. We also show that option trading volume spikes around earnings announcement dates, and this makes the ambiguity aversion argument less likely.

Our article is closely related to the line of research on option returns including straddle returns (e.g., Coval and Shumway (2001)). Whereas Coval and Shumway look at option returns at the index level, both Dubinsky and Johannes (2006) and Goyal and Saretto (2009) examine equity options returns at the individual level. Dubinsky and Johannes focus on earnings announcements and find substantial price jumps on earnings announcement days. They significantly minimize the pricing errors of standard option pricing models by incorporating jumps on earnings announcement days into the models. Goyal and Saretto examine straddles and find that straddles on stocks with larger differences between historical realized volatility and implied volatility tend to have higher returns. Goyal and Saretto interpret their results to be consistent with the Barberis and Huang (2001) hypothesis that people display both loss aversion and mental accounting. A contemporaneous paper by Govindaraj, Liu, and Livnat (2012) examines whether any return differences exist between straddle portfolios with the lowest and highest past earnings surprises. Albeit with a very different focus, Govindaraj et al. also document positive and significant straddle returns using a larger window around an earnings announcement.

Our study is also related to the underreaction, overreaction, and market efficiency literature in the options market. Stein (1989) is the first to document overreaction in the long-term implied volatility on the S&P 100 index, as this implied volatility moves by the same amount as the short-term implied volatility. Poteshman (2001) examines the same issue using S&P 500 index options and finds evidence for both long-term overreaction and short-term underreaction. The rationalizations for financial market over- and underreaction are mostly based on behavioral explanations. Lemmon and Ni (2014) show that there is a significant difference between the clientele for index options and for individual stock options. Compared to index options trading, which is largely dominated by institutions, stock options trading is mainly driven by individual investors. Individual options traders are more likely to exhibit cognitive biases than are institutional traders, which is consistent with our empirical results. In terms of market efficiency as measured by transaction costs, De Fontnouvelle, Fishe, and Harris (2003), Mayhew (2002), and Battalio, Hatch, and Jennings (2003) all find that options trading is costly but that market efficiency improved (to different degrees) around the 2000s when the options market moved to a national system.

Compared to the literature, our article is one of the first to document the puzzling empirical phenomenon of positive and significant stock straddle returns around earnings announcements, which contrasts with the negative and significant stock straddle returns on nonannouncement days. Most current options pricing models fail to align with or explain the results we present. The positive straddle returns around earnings announcement periods are more pronounced for the preannouncement effect and for firms with noisier signals or higher transaction costs.

The article is organized as follows: Section II introduces the data. Section III presents the main findings of positive straddle returns around earnings announcement periods. Section IV examines straddle returns in the cross section to identify reasons for the positive straddle returns around earnings announcements. Section V concludes.

II. Data

Our sample period is Jan. 1996 to Dec. 2013. We obtain information about the underlying stocks, such as returns and security characteristics, accounting data, and earnings announcement data from the Center for Research in Security Prices (CRSP), Compustat, and Institutional Brokers' Estimate System (IBES), respectively. Our options data are from OptionMetrics, which provides end-of-day bid and ask quotes, open interest, volume, implied volatility, and option Greeks for all listed options. Unlike the stock data, the options data are vast and might be noisy because of liquidity issues and market microstructure issues. Therefore, we focus on short-term at-the-money options because these options are the most liquid. Meanwhile, to avoid the bid–ask bounce from daily closing prices, we use the closing bid–ask average value to compute option returns. Finally, to construct straddles, we pair call and put options with matching strike prices and maturity dates.

Given the above considerations, we apply the following filters to the options data: (1) The option prices are at least \$0.125; (2) the underlying stock prices are at least \$5; (3) options have positive open interest; (4) bid and ask prices must satisfy basic arbitrage bounds to filter out erroneous observations;[4] (5) options have 10 to 60 days to maturity; (6) at the time of the straddle formation, options have an absolute delta between 0.375 and 0.625 (as in Bollen and Whaley (2004)); (7) the moneyness of the option, "money," is defined as the strike price over the previous day's stock price, and to be considered at the money, options must have moneyness between 0.9 and 1.1; (8) to form straddles, only paired calls and puts with matching time to maturity and matching strike price are included; and (9) to ensure that straddles can be formed around earnings announcements, options must have price information at the beginning and end of the holding period.[5]

In Table 1, we present summary statistics for the stocks and straddles included in our sample. Panel A reports firm-level characteristics: market capitalization, book-to-market ratio (computed as the ratio of book value of equity over market value of equity), monthly stock return, annualized stock return volatility, skewness, and kurtosis (computed from the past 3-month daily stock returns). These firm characteristics are observed at the end of each calendar quarter-end, and the summary statistics are computed by pooling over all firms and all quarters.

We provide the number of observations, mean, median, and standard deviation for each firm characteristic variable. In total, our sample includes more

[4]Arbitrary boundaries include: bid $>$ 0, bid $<$ offer; for put options we require strike $\geq$ bid and offer $\geq$ max(0, strike price–stock price); for call options, we require stock price $\geq$ bid and offer $\geq$ max(0, stock price–strike price).

[5]Later, we impose an additional liquidity filter to examine the robustness of our results for the most liquid options.

TABLE 1

Summary Statistics on Options and Stocks

Table 1 reports summary statistics on stock and straddle characteristics, which are computed over a pooled sample across firms/straddles and across time. The sample period is from Jan. 1996 to Dec. 2013. We obtain data from several data sources. Data on stock returns and firm characteristics, accounting data, and earnings announcements are obtained from the Center for Research in Security Prices (CRSP), Compustat, and Institutional Brokers' Estimate System (IBES), respectively. Data on options are from OptionMetrics. We apply filters (1)–(9) to the options data. Moneyness is defined as stock price divided by strike price. We compute open interest for a straddle as the number of contracts outstanding in 100s, summing open interest from both calls and puts in the straddle. Similarly, we compute the daily volume of a straddle as the number of contracts traded in 100s, summing daily volume from both calls and puts in the straddle. Implied volatility for a straddle is the average of implied volatility of calls and puts in the straddle.

	N	Mean	Median	Std. Dev.
Panel A. Stock Characteristics				
Market capitalization (in $millions)	41,940	10,597	2,297	30,434
Book-to-market ratio	41,232	0.470	0.356	0.537
Past 12-month return	41,940	0.113	0.120	0.461
Past 3-month daily return volatility (annualized)	41,940	0.431	0.378	0.231
Past 3-month daily return skewness	41,940	0.052	0.082	1.097
Past 3-month daily return kurtosis	41,940	5.565	3.877	5.065
Panel B. Straddle Characteristics				
Moneyness	76,848	1.011	1.008	0.028
Days to maturity	76,848	38	37	13
Open interest	76,848	2,431	474	7,375
Volume	76,848	401	26	1,800
Implied volatility	76,848	0.474	0.435	0.206

than 40,000 firm-quarter observations. For each quarter, the number of sample firms ranges between 165 and 1,162.[6] Compared to earlier studies using 20 firms, such as Dubinsky and Johannes (2006), our sample covers a good amount of the cross section of stocks. The median market capitalization in our sample is about $2.297 billion. Over the same period, the median market cap for New York Stock Exchange (NYSE) firms is $1.3 billion. Therefore, our sample firms are larger than a typical NYSE firm. For book-to-market ratios, the median of our sample is 0.356. During the same period, the median book-to-market ratio for NYSE firms is 0.576. This indicates our sample includes more value firms than growth firms when compared to NYSE firms. The median past 12-month stock return is 12.0%. The median stock return volatility is 37.8%, which is lower than an average NYSE firm's volatility of about 55%. Medians for skewness and kurtosis are 0.082 and 3.877, respectively. Overall, our sample firms are larger than average with lower than average book-to-market ratios. This is consistent with our knowledge that option listing is more prevalent for larger firms.

Panel B of Table 1 reports summary statistics for individual straddles satisfying filters (1)–(9), and the summary statistics are computed by pooling over all straddles and all quarters. The mean of moneyness is 1.011, and days to maturity are on average approximately 38 days. As required by our filters, our sample includes only short-term at-the-money straddles. We compute open interest for a straddle as the number of contracts outstanding in the 100s by summing open interest from both calls and puts in the straddle. Similarly, we compute the daily volume of a straddle as the number of contracts traded in the 100s by summing the

[6]Our sample data start in 1996, during which time only very large firms had listed options. For 1996 quarter 3, after all filters, we have 165 firms. Across all quarters between 1996 and 2013, on average our sample includes 669 firms in the cross section.

daily volume from both calls and puts in the straddle. The average open interest is 2,431 round lots, and the average daily volume is 401 round lots, indicating adequate liquidity. Implied volatility for a straddle is the average of implied volatility of calls and puts in the straddle. It is on average 47.4%, which is higher than the corresponding daily return volatility in Panel A of 43.1%. The fact that implied volatility is higher than historical volatility is expected, because implied volatility contains a component of the volatility risk premium. Overall, we are confident that our sample includes only close-to-maturity, at-the-money options with reasonable trading activities.

III. Straddle Returns

There are two approaches to construct straddles: the simple straddle and the delta-neutral straddle. For the simple straddle, the investor purchases a pair of call and put options with matching strike prices and maturity dates. For the delta-neutral straddle, the investor relies on option deltas, which measure the option price's sensitivity to the underlying price movements. When puts and calls are paired for delta-neutral straddles based on strike and maturity, the weights are adjusted to make the straddle delta equal 0. For any pair of put and call options, define $\text{DELTA}_{t-1}^{\text{CALL}}$ and $\text{DELTA}_{t-1}^{\text{PUT}}$ as the deltas of the call and the put options, respectively, at the end of formation day $t-1$, and w_{t-1} as the weight on the call option. Then the straddle's delta becomes:

$$\text{(1)} \qquad \text{DELTA}_{t-1}^{\text{STRADDLE}} = w_{t-1}\text{DELTA}_{t-1}^{\text{CALL}} + (1-w_{t-1})\text{DELTA}_{t-1}^{\text{PUT}}.$$

By setting the straddle's delta at 0 to ensure that the straddle is delta neutral, the weight on the call option is determined as

$$\text{(2)} \qquad w_{t-1} = -\frac{\text{DELTA}_{t-1}^{\text{PUT}}}{\text{DELTA}_{t-1}^{\text{CALL}} - \text{DELTA}_{t-1}^{\text{PUT}}}.$$

Theoretically, the delta-neutral straddle has no exposure to price changes in the underlying asset. Given that the purpose of this article is to capture the uncertainty dynamics, independent of the direction of news on earnings announcement days, we focus on delta-neutral straddles. Results using simple straddles are quantitatively similar to those using delta-neutral straddles and are available from the authors. For the delta-neutral straddle, to observe the return dynamics around the event window, we adopt a buy-and-hold strategy. That is, we set the share numbers of calls and puts during the formation period and do not rebalance the share numbers over the event window.

It is possible that there are multiple pairs of straddles on the same stock over the same holding period. When this happens, we consider 3 weighting schemes across straddles for the same firm: equal weight, volume weight, and dollar open interest weight.[7] The volume weights are computed as the sum of the daily volumes of all calls and puts in the straddle from the previous day. The dollar open interest for one straddle is computed based on option information from the

[7]From results not shown, we also compute open-interest weighted returns, and results are similar.

previous day as follows:

$$\text{(3)} \quad \text{DOI} = (\text{CALL\_PRICE} + \text{PUT\_PRICE}) \times \min(\text{CALL\_OPEN\_INTEREST}, \text{PUT\_OPEN\_INTEREST}),$$

which is the maximum possible dollar open interest for this straddle from the previous day. We weight each straddle within the same firm according to its DOI.[8] The idea of both volume weighting and dollar open interest weighting is to focus on options with higher liquidity.

The expected return on a straddle depends on its exposure to systematic risks, such as market risk, market volatility risk, and market jump risk. Because delta-neutral straddles have zero exposure to the underlying asset, they presumably have little exposure to the market return. From results not reported, we also construct beta-neutral straddles that have zero exposure to market risk, and the results are similar to those of delta-neutral straddles. To control for exposure to market volatility risk and market jump risk, Cremers et al. (2015) construct delta-neutral, vega-neutral, and gamma-neutral index straddles by using index options with different maturity dates. However, because individual stock options tend to be much less actively traded than index options and our sample is restricted to short-term options, it is difficult to construct reasonably liquid straddles that are simultaneously vega, gamma, and delta neutral. Alternatively, we could estimate an individual straddle's exposure to market volatility and jump risk around earnings announcements. However, given our short holding period for each straddle, this estimation is not feasible. Therefore, we focus on delta-neutral straddles, rather than vega- or gamma-neutral straddles. Meanwhile, both market volatility premium and market jump premium are found to be negative in the literature, and straddles in general have positive exposures to both volatility risk and jump risk. Not adjusting for any volatility risk premium or jump risk premium would understate the returns on straddles, which biases against our findings of positive straddle returns.

In Section III.A, we examine straddles formed over all days and use them as a benchmark. Next, we examine the dynamics of uncertainty around earnings announcement days in Section III.B. We report straddle returns formed around earnings announcement days, using a pooled sample in Section III.C. To better examine day-by-day changes in the straddle returns, we apply a time-series approach with more liquidity filters on the options in Section III.D. Robustness checks are provided in the Internet Appendix (available at www.jfqa.org). Pooled samples in Sections III.A–III.C allow us to use clustered standard errors across time to be conservative, and time-series samples with stricter liquidity filters in Section III.D and the Internet Appendix allow us to follow time dynamics and offer a complementary perspective.

A. Straddle Returns over All Trading Days: A Pooled Sample

To establish the benchmark straddle returns for future comparison with straddle returns around earnings announcements, we examine daily, weekly, and

[8]From results not reported, we try a few alternative approaches, such as replacing the minimum operator with the sum of the call and put open interest, and results are similar.

monthly straddle returns over all trading days from 1996 to 2013. These straddles satisfy filters (1)–(8) in Section II. For daily straddle returns, we construct the straddle based on the midpoint of the previous day's closing ask and bid prices to identify at-the-money options and compute the straddle return over the next day using the midpoints of the closing ask and bid prices. The holding period of the at-the-money daily straddle is 1 day. For weekly straddle returns, we hold the straddle for 5 business days from Tuesday to the following Tuesday. We construct monthly straddles from month-end to the next month-end.

The average delta-neutral straddle returns are reported in Panel A of Table 2. To compute the average returns, we first use equal weight/volume weight/dollar open interest weight for different pairs of straddles for one firm at the same time. Next, we average straddle returns over time and stocks. We report t-statistic clustered by date. We start with the equal-weighted straddle returns on the left side of the table. For a 1-day holding period, the average straddle return is −0.19% (−47.50% if annualized), with a significant t-statistic of −5.11. For a 1-week holding period, the average straddle return is −2.12% (−110.24% if annualized) with a t-statistic of −11.92. For a 1-month holding period, the average straddle return is −17.09% (−205.08% if annualized) with a t-statistic of −26.82. For the

TABLE 2

Delta-Neutral Straddle Returns: Pooled Sample

Panel A of Table 2 reports daily, weekly, and monthly returns on all at-the-money delta-neutral straddles. Panels B–D report returns on at-the-money delta-neutral straddles over different windows around earnings announcements, where day 0 is the earnings announcement day. Panel B reports all straddles in our sample. Panels C and D report results on straddles with expected earnings announcement days that coincide with actual announcement days, following an approach outlined by Givoly and Palmon (1982) and extended by Cohen, Dey, Lys, and Sunder (2007), respectively. The sample period is from Jan. 1996 to Dec. 2013. Data on options are from OptionMetrics. We apply filters (1)–(8) to the options data in Panel A, and filters (1)–(9) to the remaining panels. If a stock has more than one pair of at-the-money straddles, we use equal weight, volume weight, or dollar open interest weight straddles at the stock level. The mean holding-period return is computed by pooling across firms and across time. All t-statistics are computed using standard errors clustered by date.

Holding Period	Equal-Weighted Holding Ret.	t-Stat.	Volume-Weighted Holding Ret.	t-Stat.	Dollar-Open-Weighted Holding Ret.	t-Stat.
Panel A. All Delta-Neutral Straddles						
1 day	−0.19%	−5.11	−0.14%	−3.36	−0.20%	−5.30
1 week	−2.12%	−11.92	−2.11%	−10.62	−2.12%	−11.93
1 month	−17.09%	−26.82	−16.19%	−23.35	−17.37%	−26.83
Panel B. At-the-Money Delta-Neutral Straddles around Earnings Announcements						
[−3,−1]	1.90%	16.35	2.18%	16.47	1.95%	16.74
[−3,0]	2.60%	13.92	2.36%	11.28	2.57%	13.76
[−3,1]	1.98%	8.55	1.13%	4.51	1.88%	8.00
[−1,0]	1.88%	16.36	1.55%	11.43	1.86%	15.41
[−1,1]	2.43%	13.39	1.52%	7.37	2.36%	12.22
Panel C. At-the-Money Delta-Neutral Straddles around Earnings Announcements: Givoly and Palmon's (1982) Sample						
[−3,−1]	1.90%	12.94	2.22%	12.95	1.82%	13.11
[−3,0]	2.57%	10.81	2.37%	8.58	3.11%	10.46
[−3,1]	2.03%	6.70	1.42%	4.22	2.84%	6.23
[−1,0]	1.90%	11.71	1.50%	7.89	2.55%	11.01
[−1,1]	2.54%	10.13	1.68%	5.87	3.49%	9.47
Panel D. At-the-Money Delta-Neutral Straddles around Earnings Announcements: Cohen et al.'s (2007) Sample						
[−3,−1]	2.04%	11.07	2.10%	10.24	2.10%	11.18
[−3,0]	2.58%	8.45	2.35%	6.58	2.59%	8.38
[−3,1]	1.41%	4.07	0.55%	1.51	1.44%	3.84
[−1,0]	1.44%	7.20	1.03%	4.47	1.42%	6.64
[−1,1]	1.69%	5.20	0.85%	2.25	1.68%	4.54

volume-weighted returns and dollar-open-interest-weighted returns on the right half of the table, the magnitude and significance are similar to the equal-weighted results.[9]

The strong negative returns associated with straddles are not surprising, given the findings in Coval and Shumway (2001) and Cremers et al. (2015). Meanwhile, Bollen and Whaley (2004) show that on average straddles lose money, about 3% per week, which is comparable to the magnitude of our findings.

B. Uncertainty around Earnings Announcements: A Pooled Sample

Given that straddle returns reflect investor beliefs about future uncertainty, we examine the dynamics of uncertainty around earnings announcements before discussing straddle returns around earnings announcements.

Following previous studies such as Chae (2005) and Sarkar and Schwartz (2009), we assume that earnings announcements are prescheduled events and the timing of the events are public information. In particular, Chae studies the relation between trading volume and information asymmetry around scheduled versus unscheduled announcements. Given that the literature has treated earnings announcements as scheduled events, we generally consider the abnormal straddle returns around earnings announcement as not being driven by earnings announcement dates that are not publicly available to investors. However, for robustness and completeness, later in the discussion we relax the assumption that earnings announcement dates are known ex ante. Instead, we reexamine the main results within a subsample, where the expected earnings announcement dates fall exactly on the real earnings announcement days.

We obtain the earnings announcement dates from IBES. We define day 0 as the event day, during which earnings are announced. The trading day before the announcement is day -1, and the trading day after the announcement is day 1. One complication in the real world is that some announcements are made before the market opens, and others occur after the market closes. Meanwhile, previous studies, such as deHaan, Shevlin, and Thornock (2015), also show that data on exact announcement hours can be imprecise. Therefore, we use only the announcement date and make no adjustments for announcement hour.

A natural measure of uncertainty in stock prices is realized volatility. Here we focus on daily range-based volatility (not annualized), which is computed as the difference between the daily high and low trading prices, divided by the closing price. The range-based volatility measure heuristically shows the range of price movements within a day, and higher range-based volatility means higher uncertainty. Alizadeh, Brandt, and Diebold (2002) show empirically that range-based volatility is highly efficient and robust to microstructure noise. Alternatively, a "popular" uncertainty measure is the implied volatility of an option, which is interpolated from the option price data based on a benchmark option pricing model. There are two differences between realized volatility and implied volatility. First, realized volatility measures how price reacts to new information

[9]When we compute daily, weekly, and monthly straddle returns, we maximize usable data by requiring only that the price data are available at the beginning and end of the holding period. Therefore, the straddles included in daily, weekly, and monthly holding samples can be different, which explains the difference in magnitudes across different holding periods.

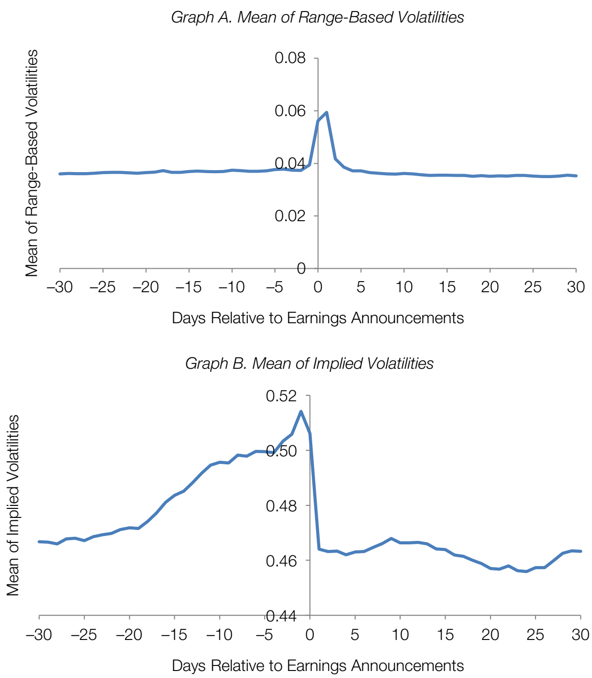
in real time, whereas implied volatility measures investors' anticipation of future volatility. Second, even though implied volatility is named "volatility," it is a price measure, reflecting information from option prices. Higher option prices mean higher implied volatility and vice versa. Thus, the implied volatility measure contains more information than just volatility as option prices also reflect volatility risk premium and/or jump risk premium. In contrast, realized volatility is a pure volatility measure.

Figure 1 plots the realized volatility and implied volatility measures from 30 days before an earnings announcement to 30 days after an earnings announcement. Given that earnings announcements occur quarterly with about 60–65 trading days in between, the horizon of the $[-30, 30]$ window roughly covers the quarterly earnings announcement cycles. In Graph A, we average range-based volatilities for all firms in our options data sample for each trading day. Starting from day -30, mean range-based volatility is 0.036. Between day -30 and day -2, range-based volatility is almost flat and increases only slightly to 0.039 on day -1. On day 0, range-based volatility jumps to 0.056 and then peaks at 0.059 on day 1. On day 2, range-based volatility collapses to 0.041 and then stays almost flat until the

FIGURE 1

Realized Volatility and Implied Volatility around Earnings Announcements: Pooled Sample

Graph A of Figure 1 displays mean range-based volatilities as the difference between the highest and lowest trading prices during the day, scaled by closing price. Graph B displays mean implied volatilities for short-term at-the-money calls and puts around earnings announcements. Day 0 is the earnings announcement day. The data are from Jan. 1996 to Dec. 2013. All numbers are computed as pooled averages, which are the averages over a pooled sample over time and over firms.



next earnings announcement. The pattern in range-based volatility clearly shows that stock prices become volatile starting from day −1, with uncertainty peaking on day 0 and day 1. The uncertainty resolves after day 2. This pattern is expected because the earnings announcement period is the most information-dense period for a typical firm, and the stock market reacts to new information in real time.

In Graph B of Figure 1, we average implied volatilities of firm-level at-the-money calls and puts for each trading day from 30 days before the earnings announcement to 30 days after the earnings announcement. The pattern of implied volatility in Graph B differs slightly from what we observe in Graph A. Starting from day −30, mean implied volatility is 0.467, and it gradually increases to 0.499 on day −4. Between day −3 and day −1, the slope for implied volatility becomes steeper, with implied volatility increasing to 0.514 on day −1, which is the highest point on the graph. On day 0, the average stays around 0.506, which is still relatively high. On day 1, implied volatility crashes to 0.464. Over the next 30 days, implied volatility remains mostly flat. For day 30, implied volatility is 0.463, which is consistent with the level observed on day −30. Implied volatility generally stays low until the next earnings announcement, unless some other important event happens unexpectedly. Unlike realized range-based volatility reported in Graph A, which reacts to news arrival in real time, implied volatility is more about anticipation of future news arrival.

The dynamics of implied volatility around earnings announcements indicate that options might become more expensive as an earnings announcement approaches. After the uncertainty resolves on day 0, implied volatility returns to a normal level. As mentioned in the introduction, this pattern has been known for more than 30 years, since Patell and Wolfson (1979). However, this does not necessarily mean option prices increase as implied volatility increases, because the effect of implied volatility might be offset by the fact that the options are moving closer to their expiration dates.

C. Straddle Returns around Earnings Announcements: A Pooled Sample

We construct straddles over different windows around earnings announcements. From the dynamics of range-based volatility and implied volatility, we focus on a spectrum of strategies that cover the running up of uncertainty until uncertainty is partially or fully resolved. To be specific, the starting dates of the straddles are chosen among days −3 and −1, and the ending dates are days −1, 0, or 1. To be included in the sample, we require all options to be short term, with expirations between 10 and 60 days, and the moneyness of the straddle to be between 0.9 and 1.1 at the beginning of the holding period. For instance, for the strategy over [−3,0], we buy the straddle on day −3 and sell the straddle on the earnings announcement day, and the holding period is 3 days. To make sure the straddle is at the money when the strategy is formed, we require moneyness (strike price divided by previous-day stock price) to be between 0.9 and 1.1 on day −3. The longest holding period is 4 trading days for strategy [−3,1], and the shortest holding period is 1 trading day for strategy [−1,0]. For completeness, we consider 5 combinations of starting and ending dates, and they are [−3,−1], [−3,0], [−3,1], [−1,0], and [−1,1].

We make two comments regarding the complexity of the straddle return construction. First, as explained in Blume and Stambaugh (1983), if investors use daily closing prices rather than bid–ask average prices, a bid–ask bounce bias is introduced into returns, which could significantly increase the returns. Blume and Stambaugh recommend using bid–ask average prices rather than daily closing prices to compute returns, and they recommend directly estimating holding-period returns rather than compounding daily returns to achieve holding-period returns. Therefore, we use bid–ask average prices to compute returns throughout this article, and we focus on holding-period returns in this section. To understand day-by-day changes in straddle returns, we compute daily returns in a later section. To minimize the Blume and Stambaugh bias in daily returns, we use daily bid–ask average prices for the return calculation and impose stricter liquidity filters to reduce potential market microstructure noise in the illiquid options. These results are discussed in Section III.D.

Second, even though the 5 buy-and-hold strategies discussed previously may have overlapping holding windows, they normally do not contain identical options and cannot be directly compounded across different holding windows. There are two possible scenarios. First, for strategies starting from different days, because of possible changes in underling prices, the moneyness of the same straddles may change from one day to another, which results in different component straddles for strategies starting from different days.[10] Second, for strategies starting on the same day but not ending on the same day, they still might not contain identical straddles. The reason is that we require component straddles to have valid closing bid–ask average prices on ending days, and some straddles might not have valid prices on different ending days. To summarize, in this section, we cannot make inferences directly from compounding returns on strategies from different windows. In Section III.D, we require valid bid–ask average prices every day within the event window, and the daily returns can be directly compounded into holding-period returns.

We consider two effects around earnings announcements: the preannouncement effect and the announcement effect. The first effect is relevant for strategies ending on day -1 or earlier, which is strictly before the announcement. The price of a straddle might increase before the announcement date because uncertainty in stock price is increasing. However, the opposite can also happen. Dubinsky and Johannes (2006) show that theoretically option prices might not increase before an earnings announcement as the effect of an increase in uncertainty might be offset by a shortened time to maturity. Empirically, this remains an open question. If the straddle returns before the earnings announcement dates are positive, this indicates that the effect of increased uncertainty dominates the effect of shortened time to maturity.

The second effect is the announcement effect. After the uncertainty is resolved, if the realized surprise is large enough, either the put or call end up being deep in the money and cover the loss from the counterpart, which leads to the

[10]For instance, strategy $[-3,0]$ might contain different sample straddles than strategy $[-1,0]$, even though the holding window of strategy $[-3,0]$ nests that of strategy $[-1,0]$. The reason is that we use only at-the-money options, and this criterion can be different on day -3 and day -1.

positive straddle returns. This is relevant for strategies ending on day 0 and day 1. According to Berkman and Truong (2009), from 1995 to 1999, more than 30% of firms announce their earnings after the market close. Thus, holding the straddles until 1 day after the earnings announcement dates guarantees that all the uncertainties associated with the earnings release are resolved.

In Panel B of Table 2, we report average short-term at-the-money delta-neutral straddle returns. The reporting format is fully compatible with Panel A. We require all straddles to have time to maturity between 10 and 60 days and the moneyness (stock price divided by strike price) to be between 0.9 and 1.1. For each firm around each earnings announcement, we might have multiple pairs of straddles, and we include results for 3 weighting schemes among straddles within the same firm: equal weighting, volume weighting, and dollar open interest weighting. For each of the 5 strategies, we pool across all stocks over all quarters to compute the mean and we cluster t-statistics on date.

The first three strategies are [−3,−1], [−3,0], and [−3,1], all of which involve buying an at-the-money straddle on day −3 before the uncertainty peaks. We first look at the equal-weighted results on the left side in Panel B of Table 2. Straddle holding-period returns over [−3,−1], [−3,0], and [−3,1] are 1.90%, 2.60%, and 1.98%, respectively. All returns have significant t-statistics, ranging from 8.55 to 16.35. The strategy of [−3,−1] mainly captures the run-up of uncertainty. The strategies [−3,0] and [−3,1] capture both the running up of uncertainty and the realized surprise. It is interesting that strategy [−3,1] has a 0.62% lower return than strategy [−3,0], indicating that over day 0 to day 1, the return on a straddle might actually be negative.

The last two strategies are [−1,0] and [−1,1]. We explain earlier that the straddles built on day −1 and day −3 are not directly comparable because the criterion for being at the money is based on the previous day's underlying stock price. Given volatile underlying price movements around earnings announcements, the moneyness for the same options on day −3 could be different from those on day −1. The holding return for strategy [−1,0] is 1.88% with a t-statistic of 16.36, and the holding return for strategy [−1,1] is 2.43% with a t-statistic of 13.39. Compared to the first 3 trading strategies, day −1 is usually the peak day for uncertainty; therefore, the significant and positive returns for both strategies' are probably driven by the realized surprise on day 0 and day 1.

When we switch to volume-weighted returns and dollar-open-interest-weighted returns on the right side in Panel B of Table 2, all straddle returns are still positive and significant with magnitudes similar to those with equal weighting. To ensure that the positive straddle returns are not driven by how we construct straddles, we conduct additional robustness checks on simple straddle returns. From results not reported, with different combinations of holding periods and weighting schemes, the simple straddle returns are between 0.80% and 2.25%, and they all have t-statistics above 6.0.

We discuss earlier that the finance and accounting literatures mostly treat earnings announcements as a prescheduled event and public information. However, it is still possible that there are firms that announce earnings on unscheduled dates. For these events, unscheduled announcements mean that investors, before the real announcements, have not incorporated any information about increasing volatility associated with earnings announcement, and the unexpected increases in volatilities lead to positive straddle returns, which could drive our findings of positive straddle returns.

We address this concern using a counterexample. If the surprise announcement is the main reason for positive straddle returns, then if there is no surprise on earnings announcement days, we should not observe positive straddle returns around earnings announcement days. In other words, if the earnings announcement dates are well expected, and if we still observe positive straddle returns on the expected announcement dates, then the main driver of the positive straddle returns is unlikely to be the surprise announcements.

Therefore, we focus on a subsample where the expected earnings announcement dates coincide with the real earnings announcement days. For observations in this subsample, we believe that the uncertainty of earnings announcement dates is minimized. If our results hold for this subsample, it supports the notion that our results are not driven by the uncertainty in earnings announcement dates.

Following the literature on expected earnings announcement dates, we take two approaches. The first is the algorithm as in Givoly and Palmon (1982), which has been widely adopted in earlier studies, such as Chambers and Penman (1984) and Begley and Fischer (1998). Givoly and Palmon use a firm's prior announcement date as a proxy for the current year's expected announcement date. In addition to Givoly and Palmon's procedure, we use the number of the day of the week in that month from last year's announcement date as a proxy for this year's expected announcement date. For instance, if last year's announcement is the third Friday of October and this year's announcement is also on the third Friday of October, we include this announcement in our sample when the expected announcement date is equal to the real announcement date. With this simple procedure, we identify 28.45% of the announcements to be exactly on the expected earnings announcement date.

Panel C of Table 2 reports the straddle returns for the subsample when announcement dates coincide with expected announcement dates following the Givoly and Palmon (1982) procedure. Again we consider 3 weighting schemes: equal weight, volume weight, and dollar open interest weight. Starting from equal-weighted results, the straddle returns over different holding periods range between 1.90% and 2.57%, with highly significant t-statistics between 6.70 and 12.94. The magnitude of results in Panel C is comparable to that in Panel B. Moreover, results on volume-weighted straddles and dollar-open-interest-weighted straddles are similar. Overall, for the restricted sample using the Givoly and Palmon algorithm, we find that straddles around earnings announcements continue to produce positive and significant returns.

The second approach we adopt for identifying the expected earnings announcement date is the algorithm in Cohen, Dey, Lys, and Sunder (2007). We divide our whole sample into 4 subperiods of 4 years and 1 subperiod of 2 years. We estimate a model for each of the 4 fiscal quarters for each firm within each subperiod. For each firm and each fiscal quarter in each subperiod, we use the median announcement date as a proxy for the expected announcement date. To be more specific, we identify each firm-quarter earnings announcement date with the day of the quarter (e.g., 3rd day of the quarter, 65th day of the quarter) and compute the median announcement date. In our sample, 29.29% of announcements dates are exactly on the expected announcement date, 53% are within 1 day of the expected announcement date, and 94.5% are within 11 days of the expected announcement date. We take only the subset of announcements that coincide with the expected announcement date and reexamine the straddle returns around these events.

In Panel D of Table 2, we report straddle returns around earnings announcements where the actual announcements fall on the expected announcement dates using the Cohen et al. (2007) algorithm. The equal-weighted straddle returns are between 1.41% and 2.58% with highly significant t-statistics. We find the magnitude of the straddle returns is in line with the magnitudes in Panels B and C and are all highly significant. Results using volume-weighted and dollar-open-interest-weighted returns share the same pattern.

With these two subsample results using expected earnings announcement dates, it is unlikely that our results are driven by unexpected earnings announcements. Even though it is still possible that in some cases the unexpected earnings news might contribute to the positive straddle returns, it is unlikely that the positive straddle returns are mainly driven by the surprise announcements.

D. Day-by-Day Straddle Returns: Time-Series Sample with Stricter Liquidity Filters

Our discussion in Sections III.A–III.C is based on pooled samples of observations across all firms and all dates, using filters (1)–(9) from Section II. The benefit of pooled samples is that they are straightforward and we can compute clustered standard errors. However, the pooled statistics do not provide information on time variations and do not allow different weighting schemes across firms. Next, we examine whether the straddle returns around earnings announcements are still positive and significant when we compute the time series of straddle returns averaged over all firms, which directly show time variation and allow for different weighting across firms.

We also compute daily straddle returns during the holding-period window to more closely track both the preannouncement effect and the announcement effect. To facilitate the comparison between holding-period straddle returns and daily straddle returns, we apply an additional liquidity filter. Given that the previous sections use filters (1)–(9), we refer to this filter as filter (10): We include only matching call and put options with daily nonmissing bid and ask price quotes, daily positive open interests, and daily positive trading volumes for every day during the holding period. This additional filter serves two purposes. First, the liquidity filter essentially excludes less liquid options, and we can potentially mitigate related market microstructure biases. Second, now the holding-period returns and the daily returns are directly comparable to the same straddle components within each holding window. With this new filter, the total number of observations decreases from 76,848 to 42,080. On average, we still have more than 310 firms each quarter, which provides decent coverage of the cross-sectional data. In Internet Appendix Table 1, we provide summary statistics for this smaller sample with filters (1)–(10), which is directly comparable to Table 1 with filters (1)–(9). It is not surprising that relative to the sample in Table 1, firms in the new sample are larger and have lower stock return volatilities, and the corresponding options have larger open interests and higher trading volumes.

Here are the specifics for computing the straddle return for the time series. First, within each firm and for each announcement, we compute average straddle returns among different pairs of straddles using either equal weights or volume weights. We drop the dollar open interest weights among straddles from the same firm because the results are similar to those for volume weights.

Second, for each quarter, we average over all firms using either equal weights or dollar open interests at the stock level from the previous month-end as weights. We define straddle dollar open interests in equation (3). For dollar open interest at the firm level, we sum the dollar open interest for all straddles for the same firm from the previous month-end.[11] We use two weighting schemes across firms for completeness. But clearly, each weighting scheme has pros and cons. The benefit of using equal weights is that it allows for all straddles to be treated equally. Given that most of our sample firms are large firms, this weighting scheme seems appropriate. But there are always potential concerns that smaller firms might have more market microstructure biases. We discuss earlier the Blume and Stambaugh (1983) bias, and we use the closing bid–ask average price and holding-period return to minimize this bias. A popular way in empirical studies to cope with the Blume and Stambaugh bias is to put more weight on firms with larger market capitalization or more trading activity. Therefore, we use dollar open interest as weights to give more weight to larger firms and firms with more liquidity.[12] One potential drawback of this approach is that if the results are more concentrated in relatively smaller but still large firms, the dollar open interest weighting scheme would bias the estimates downward.

Panel A of Table 3 reports the time-series average of the straddle returns around earnings announcements. On the left, we report time-series statistics of straddle returns using equal weights across firms, and on the right, we report the straddle returns using dollar open interest weights. All t-statistics are computed using Newey–West (1987) standard errors with 3 lags.

Using equal weights across different firms and across straddles within the same firm, the holding-period returns for our 5 straddle strategies range between 2.10% and 3.34%, all with highly significant t-statistics. If we use equal weight across different firms and volume weight across straddles within the same firm, the holding-period returns range between 1.63% and 2.93%, again all with highly significant t-statistics. Both the preannouncement effect and announcement effect are positive and strong, consistent with our results in Table 2. It is interesting that the magnitudes of the straddle returns computed using the time series are slightly higher than those computed using the pooled sample.

To facilitate a more in-depth analysis of the preannouncement effect and announcement effect, we present in Panel B of Table 3 day-by-day straddle returns for strategies [−3,1] and [−1,1]. The holding-period return is computed for a buy-and-hold strategy with no rebalancing, so we compute daily returns by

[11] We thank the referee for this suggestion.

[12] We also try to use firm market capitalization as a weight. Results are similar and available from the authors.

TABLE 3

Delta-Neutral Straddle Returns: Time-Series Sample

Panels A and B of Table 3 report time-series average returns on at-the-money delta-neutral straddles over different windows around earnings announcements, where day 0 is the earnings announcement day. The sample period is from Jan. 1996 to Dec. 2013. Data on options are from OptionMetrics. We apply filters (1)–(10) to the options data. In this table, we further require a nonmissing daily price, positive daily open interest, and positive daily volume in each strategy window so that the strategy window returns and day-by-day returns are directly comparable. In the event that a stock has more than one pair of at-the-money straddles, we use equal weight or volume weight for different straddle pairs for the same stock. To aggregate across stocks, we use either equal weights or last-month dollar open interest as weights across different firms. To compute time-series average returns, we first compute the quarterly average return across firms, and then we average over all quarters. We compute t-statistics using Newey–West (1987) standard errors with 3 lags.

Panel A. At-the-Money Delta-Neutral Straddles

	Equal Weight across Firms				Dollar Open Interest Weight across Firms			
	Equal Weight Within Firms		Volume Weight Within Firms		Equal Weight Within Firms		Volume Weight Within Firms	
Holding Period	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.
[−3,−1]	2.62%	9.67	2.59%	9.70	1.37%	3.81	1.47%	4.15
[−3,0]	3.34%	6.71	2.93%	5.84	1.10%	2.00	1.01%	1.87
[−3,1]	2.10%	2.99	1.63%	2.30	−0.67%	−1.06	−0.87%	−1.39
[−1,0]	2.59%	7.44	2.30%	6.31	0.54%	1.78	0.49%	1.51
[−1,1]	2.85%	4.60	2.34%	3.60	0.15%	0.30	0.08%	0.16

Panel B. Day by Day Returns on At-the-Money Delta-Neutral Straddles

		Equal Weight across Firms				Dollar Open Interest Weight across Firms			
		Equal Weight Within Firms		Volume Weight Within Firms		Equal Weight Within Firms		Volume Weight Within Firms	
Holding Period	Day	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.
[−3,1]	[−3,−2]	0.70%	5.36	0.65%	4.65	0.21%	1.38	0.22%	1.50
	[−2,−1]	1.62%	10.27	1.58%	9.35	1.11%	4.19	1.15%	4.46
	[−1,0]	0.63%	1.77	0.37%	1.04	−0.29%	−0.80	−0.42%	−1.17
	[0,1]	−0.33%	−1.04	−0.47%	−1.43	−1.37%	−3.07	−1.50%	−3.33
[−1,1]	[−1,0]	2.13%	6.07	1.88%	5.04	0.43%	1.39	0.40%	1.20
	[0,1]	0.84%	2.89	0.60%	1.93	−0.25%	−0.70	−0.28%	−0.71

keeping the number of shares on calls and puts constant over the holding period.[13] For instance, for strategy [−3,1], we first build the at-the-money straddles on day −3 and then hold these straddles to construct the daily returns over the next 4 days. Daily returns over each day are reported. When we use equal weights across firms and equal weights among straddles within the same firm, for preannouncement days, [−3,−2] and [−2,−1], the daily returns are 0.70% and 1.62%, respectively, both positive and significant; for announcement days, the [−1,0] return is 0.63%, positive and marginally significant. The [0,1] return is −0.33% and is insignificant. Results using volume weights across straddles within the same firm and for strategy [−1,1] (at the bottom of Panel B) are similar except that the [−1,0] return is not significant. The results suggest that the evidence for the preannouncement effect is strong when we use equal weights to average across firms.

When we use dollar open interest as weights, the return patterns are slightly different. In the right half of Panel A in Table 3, when we use dollar open interest weights across different firms and equal weights across straddles within the same

[13]We also compute alternative daily straddle returns by keeping initial value weights constant throughout the holding window. The results are in Internet Appendix Table 2. They are qualitatively similar to those in Panel B of Table 3, except that the announcement effect is much more statistically significant in Internet Appendix Table 2.

firm, strategy [−3,−1] has a holding-period return of 1.37% with a significant t-statistic of 3.81, indicating a strong preannouncement effect. When we move to strategies [−3,0] and [−1,0], which partially incorporate the announcement effect, the returns become 1.10% and 0.54%, both still positive and significant, but less so than those for strategy [−3,−1]. This indicates that the announcement effect might not be positive or significant. Results using volume weights across straddles within the same firm are similar, except that strategies [−3,0] and [−1,0] are less significant. Finally, for strategies [−3,1] and [−1,1], which nest both preannouncement effects and announcement effects, the holding-period returns are not significantly different from 0.

Panel B of Table 3 presents the daily returns using dollar open interest weights, which helps disentangle the preannouncement effect and announcement effect, as well as the difference between equal weights and dollar open interest weights. When we use dollar open interest weight across firms and equal weight within firms, the daily return over [−2,−1] is 1.11% with a t-statistic of 4.19, and the daily return over [0,1] is −1.37% with a t-statistic of −3.07, whereas the other daily returns are insignificant. Results using dollar open interest across firms and volume weight within firms are similar. When we put more weight on larger firms with more trading activities, the positive preannouncement effect is mainly driven by the return of [−2,−1], and the other daily returns before announcements are also positive but less significant. For the announcement effect over days [−1,0] and [0,1], we have mixed signs and mixed significance. Our earlier results in Panel A of Table 2 show that the daily returns of at-the-money delta-neutral straddles formed on a daily basis are negative and significant on average. In comparison with daily returns in Panel A of Table 2, the announcement effect may be reflected by the less negative or positive and insignificant returns on the event days relative to the negative and significant returns on the nonevent days.

Are the average positive returns on straddles driven by a special period or outliers in the time-series data? To answer this question, Graph A of Figure 2 plots the time-series returns for delta-neutral straddles based on the [−3,−1] and [−3,0] windows over the past 18 years, using equal weights across firms. It is evident from the plot that most of the time, delta-neutral straddle returns are positive, which implies that the positive and significant returns are not driven by any particular period. Meanwhile, we notice interesting time variation patterns in the straddle returns. For instance, straddle returns are relatively low around 2001 and 2008, which coincide with market downturns.[14] Graph B plots the time-series returns for delta-neutral straddles based on the [−3,−1] and [−3,0] windows over the past 18 years, using dollar open interest weight across firms. Strategy [−3,−1] focuses on the preannouncement effect, and the return is positive and large 74% of the time. When the announcement effect is combined with the preannouncement effect in strategy [−3,0], the returns become more volatile and are positive 55% of the time. To summarize, over the preannouncement period, the positive

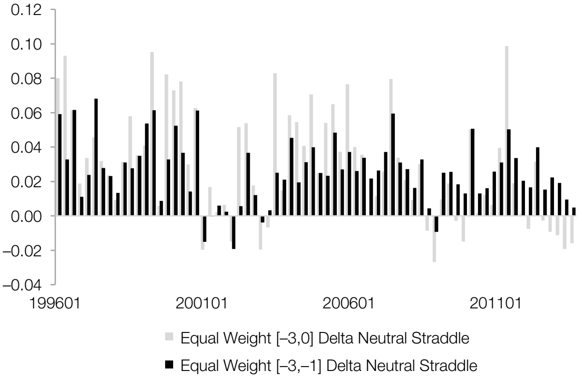
[14]The earnings calendar has become more popular in recent years. There is a concern that the positive straddle returns are correlated with the popularity of the earnings calendar, which makes information regarding earnings announcement days more accessible. The time-series results show that the positive straddle returns have not become larger in the most recent years, which fails to support the earnings calendar popularity notion.

FIGURE 2

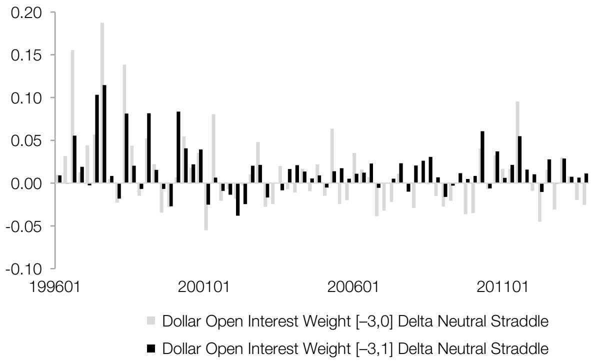
Delta-Neutral Straddle Returns over Time: Time-Series Sample

Figure 2 plots the time-series delta-neutral straddle returns over different windows around earnings announcements, where day 0 is the earnings announcement day. The sample is from Jan. 1996 to Dec. 2013. Data on options are from OptionMetrics. We apply filters (1)–(10) to the options data. We further require a nonmissing daily price, positive daily open interest, and positive daily volume in each strategy window. If a stock has more than one pair of at-the-money straddles, we use volume-weighted stock-level straddles. We report time-series straddle returns across firms using both equal weights and dollar open interest weights.

Graph A. Delta-Neutral Straddle Returns: Equal Weight across Firms



Graph B. Delta-Neutral Straddle Returns: Dollar Open Interest Weight across Firms



straddle returns are significant for both weighting schemes over the whole sample period. But for the announcement period, the straddle returns are positive and significant for the equal-weighted results but not the dollar-open-interest-weighted results. Given that neither the preannouncement effect nor the announcement effect is documented in the literature, our findings make significant contributions to this area.[15]

To summarize the empirical findings in this section, we document positive and significant straddle returns around earnings announcements. This finding is robust over time and to different ways of constructing straddle returns. Between

[15]As discussed earlier, different weighting schemes have their own pros and cons. Results based on equal weights allow us to better examine the patterns among all the firms with listed options, whereas results based on dollar open interest weights reduce concerns regarding market microstructure noise.

the preannouncement effect and announcement effect, the preannouncement effect is always positive and significant, whereas the announcement effect is mostly positive but can be negative. Our results are not driven by surprise events such as unscheduled earnings announcements. The generally positive straddle returns around earnings announcements imply that the straddle prices before earnings announcements might be too low. In other words, there is substantial underestimation of uncertainty before earnings announcements.[16]

IV. What Drives Positive Straddle Returns around Earnings Announcements?

We propose different hypotheses/explanations in Section IV.A for the positive straddle returns around earnings announcements. In Section IV.B, using selected past option and stock characteristics, we form portfolios of straddles to examine the hypotheses in Section IV.A. In Section IV.C, we predict straddle returns around earnings announcements with characteristics implied by these hypotheses, using the Fama–MacBeth (1973) regressions.

A. Our Hypothesis

The finding of positive straddle returns around earnings announcement days is in sharp contrast to the negative average straddle returns computed over all trading days. Given that straddles have positive exposure to market volatility risk and market jump risk, which are both negatively priced, it is reasonable to expect straddles to manifest the exposure through negative returns on average. However, we document the opposite effect, where straddle returns around earnings announcement days are positive. Based on the earlier reasoning, we first rule out risk as the reason for positive straddle returns around earnings announcements.

Before earnings announcements, as investors start to notice the upcoming earnings announcements, they might expect (at least based on historical evidence) both range-based volatility and implied volatility to first increase and then decrease. If participants in option markets form rational expectations of the dynamics of uncertainty around an earnings announcement based on historical patterns, buying delta-neutral straddles right before an earnings announcement should not deliver any nonzero abnormal returns. The positive straddle returns imply that the straddle prices before an earnings announcement might be too low. Stated differently, there is substantial underestimation of uncertainty before earnings announcements. It is even more intriguing that the pattern of underestimation persists year after year.

What mechanism is behind the persistent underestimation of uncertainties? We believe the existence and degree of underestimation of uncertainty could be affected by several channels: An investor's ability to estimate the uncertainty embedded in rare events or jump events depends on the noisiness of past information

[16] We conduct substantial robustness checks along the dimensions of industries, stock characteristics, and option characteristics. Portfolio-sorting results are presented in Internet Appendix Tables 3 and 4. Results using Fama–MacBeth's (1973) weighted least squares regression framework are reported in Internet Appendix Table 5. In general, our main conclusion that the preannouncement effect is positive and significant is supported by our robustness checks.

signals, the transaction costs of trading relevant information into prices, and an investor's ambiguity aversion.

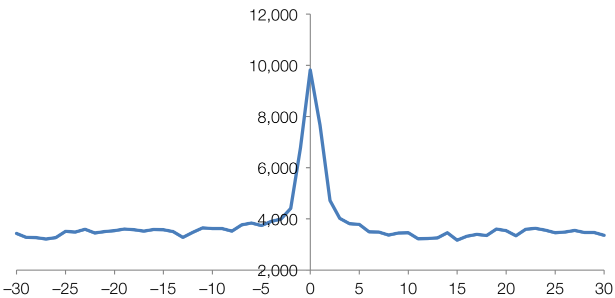
Earnings announcements do not happen on a daily basis, and often the return process experiences jumps around earnings announcement dates. To begin with, it is difficult for investors to precisely estimate uncertainty around earnings announcement periods. It is conceivable that the estimation of future uncertainty would be less precise if there are noisier firm-level signals. That is, the underestimation of uncertainty and positive straddle returns would be more pronounced for firms with noisier signals. Meanwhile, when the market is illiquid or when the transaction cost is too high, it would be challenging to incorporate "correct" information about firm-level uncertainty into option prices. That is, the underestimation of uncertainty would be greater for firms with higher transaction costs for the underlying stocks or options or both. The preceding 2 mechanisms are not mutually exclusive, and it might be that both are drivers for the positive straddle returns around earnings announcements.

Alternatively, if investors have ambiguity-averse preferences, this ambiguity aversion might cause them to stay away from trading options with upcoming earnings announcements (similar to portfolio inertia in Illeditsch (2011)). Consequently, prices fail to fully incorporate investors' expectation of uncertainty, which leads to abnormal straddle returns. In Figure 3, we plot average option trading volumes around earnings announcement dates. We first compute each stock's option trading volumes using both calls and puts, and then report the mean across all stocks over days −30 to 30. Evidently, option trading volume spikes between days −3 and 2 around earnings announcements. If the ambiguity aversion hypothesis is true, or if ambiguity-averse investors dominate in the options market, we should not observe higher option trading volumes around earnings announcements, because ambiguity-averse investors would avoid trading options during the earnings announcement period. This hypothesis contrasts our findings of higher trading volumes, as seen in Figure 3. This makes the ambiguity aversion argument less likely.

FIGURE 3

Option Trading Volumes around Earnings Announcements: Pooled Sample

Figure 3 displays the average option trading volume including all call and put options. Day 0 is the earnings announcement day. The data are from Jan. 1996 to Dec. 2013. All numbers are computed as pooled averages, which are the averages over a pooled sample over time and over firms.



B. Straddle Portfolio Returns in the Cross Section

In this section, we investigate straddle returns in the cross section to understand whether the noisiness of signals and transaction costs help explain the positive straddle returns around earnings announcements. Meanwhile, the cross-sectional study allows us to examine whether the positive straddle returns documented in the previous section are robust across different firm and option characteristics. In this section, we focus on the [−3,0] window and present 3-day holding-period returns and t-statistics on delta-neutral straddles with equal weighting across firms. To be conservative, we use volume weighting at the firm level whenever there is more than 1 at-the-money straddle.

To examine patterns in the cross section, we follow a portfolio-sorting procedure. For every quarter, we sort all firms into 4 groups, based on noisiness of signals or transaction cost measures, observed at the end of the previous quarter. We average firm-level straddle returns for the current quarter for each of the 4 groups, with equal weight within the group.[17] The means and t-statistics for straddle returns within each group are computed over 72 quarters for each of the 4 groups. All t-statistics are computed using standard errors with Newey–West (1987) adjustments with 3 lags. Our hypothesis suggests that the degree of uncertainty underestimation (positive straddle returns) is related to the noisiness of firm-level signals and/or transaction costs. If this is the case, sorting on noise measures and transaction cost measures lead to significant straddle return differences. In terms of direction, both noisier signals and higher transaction costs lead to higher straddle returns.

We collect the following measures for noisiness in the stock return process and the earnings process. For the stock return process, we compute historical higher moments, VOLATILITY, SKEWNESS, and KURTOSIS, using past 3-month daily return data. We also compute historical jump frequency, JUMP_FREQ, and historical jump size, JUMP_SIZE. We follow the Lee and Mykland (2008) procedure and use 1 year of daily returns data to extract the jump process for each firm in our sample. Presumably, it is more difficult for investors to make precise estimates of uncertainty around earnings announcements for firms with larger high moments, more frequent jumps, or larger jumps. Therefore, we expect firms with larger high moments and jumps to have higher positive straddle returns around earnings announcements.

The results are presented in Panel A of Table 4. For firms with the lowest and highest historical volatility, the straddle returns are 1.85% and 4.19%, respectively. For firms with the lowest and highest historical skewness, the straddle returns are 2.44% and 4.28%, respectively. For firms with the lowest and highest historical kurtosis, the straddle returns are 1.53% and 4.27%, respectively.

[17]In the preceding sections, we examine 5 straddle strategies over various windows around earnings announcements. When we use equal weight across firms, all results are positive and significant. For brevity, going forward, we focus on delta-neutral straddles over the [−3,0] window, using equal weighting across firms and volume weighting across straddles within the same firm. We report these results in Table 4. When we use dollar open interest weighting across firms, results over the preannouncement period [−3,−1] are positive and significant. Therefore, we examine results using dollar open interest weights across firms over the [−3,−1] window. We report these results in Internet Appendix Table 6.

TABLE 4

Noise and Transaction Costs, Delta-Neutral Straddle Returns over [−3,0]: Time-Series Sample, Equal Weight across Firms

Panels A, B, and C of Table 4 report time-series average returns on delta-neutral straddle returns sorted on high moments and jumps, past earnings surprises, and transaction costs, respectively. The sample period is from Jan. 1996 to Dec. 2013. Data on options are from OptionMetrics. We apply filters (1)–(10) to the options data. Straddles are computed over [−3,0], relative to earnings announcement days. If a stock has more than one pair of short-term at-the-money straddles, we adopt volume weighting. Each quarter, we sort all firms into 4 groups based on previous-period characteristics, and we average firm-level straddle returns for each of the 4 groups using equal weights. Historical moments are computed over the past 3-month daily returns, and historical jump statistics are computed using the past 12-month daily returns. JUMP_FREQ and JUMP_SIZE are jump frequency and jump size measures, respectively, calculated following Lee and Mykland (2008) procedure. N_ANALYSTS is the number of analysts covering the firm. The cumulative abnormal return, CAR, is computed over [−1,1] around earnings announcements and adjusted for the market return. Earnings surprises, SUE, are calculated as the difference between announced earnings and consensus forecast. The variances of SUE and CAR are computed using data from the previous 8 quarters. For transaction costs measures, we directly compute bid–ask spreads scaled by closing prices for stocks and options from the previous quarter. Volume measures are average trading volumes for stocks and options in the previous quarter. The means and t-statistics for each group are computed over 72 quarters. We compute t-statistics using the Newey–West (1987) standard errors with 3 lags.

Panel A. Sort on Past High Moments and Jumps

	VOLATILITY		SKEWNESS		KURTOSIS		JUMP_FREQ		JUMP_SIZE	
	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.
Low	1.85%	2.95	2.44%	4.48	1.53%	3.18	2.55%	4.16	3.10%	5.38
2	3.27%	4.98	2.80%	4.57	3.30%	4.72	2.45%	3.80	3.00%	4.31
3	2.89%	4.57	2.83%	4.15	3.28%	5.34	3.73%	6.21	2.82%	5.05
High	4.19%	7.24	4.28%	7.36	4.27%	5.96	3.57%	5.74	3.33%	4.66
High − Low	2.34%	4.03	1.85%	4.90	2.74%	5.39	1.02%	1.37	0.23%	0.39

Panel B. Sort on Past Earnings Surprises

	N_ANALYSTS		|SUE|		|CAR|		var(SUE)		var(CAR)	
	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.
Low	4.67%	5.70	2.49%	3.14	1.83%	2.99	2.11%	2.95	1.12%	1.46
2	3.14%	4.68	3.26%	4.27	2.45%	4.05	2.55%	4.52	2.78%	4.09
3	1.78%	3.34	2.45%	4.40	2.90%	3.86	3.05%	4.63	3.36%	5.88
High	2.12%	3.75	3.80%	5.77	4.27%	7.94	3.25%	4.69	3.95%	7.64
High − Low	−2.55%	−3.35	1.31%	1.89	2.44%	4.71	1.13%	1.37	2.84%	4.47

Panel C. Sort on Past Transaction Costs

	STOCK_SPREAD		STOCK_VOLUME		OPTION_SPREAD		OPTION_VOLUME	
	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.	Holding Ret.	t-Stat.
Low	2.21%	3.50	5.83%	7.07	1.14%	2.28	5.82%	6.11
2	2.65%	4.01	3.07%	5.31	1.82%	3.01	2.68%	4.69
3	3.75%	6.30	2.20%	3.55	3.16%	5.33	1.59%	2.97
High	3.29%	6.12	1.33%	2.05	4.93%	6.74	0.90%	2.27
High − Low	1.08%	1.84	−4.50%	−4.95	3.79%	5.33	−4.92%	−5.42

Evidently, larger historical moments do increase the difficulty of correctly estimating uncertainty around earnings announcements. The difference between the high and low is significant for all 3 moments. For the jump frequency measure, firms with the lowest and highest jump frequency have average straddle returns of 2.55% and 3.57%, respectively. The difference is 1.02% with a t-statistic of 1.37. For the jump size measure, firms with the smallest and largest jump size have average straddle returns of 3.10% and 3.33%, respectively, and the difference is not statistically significant. The evidence from using jump measures is weaker than that of historical higher moments.

Because our straddles are constructed during earnings announcement periods, an interesting question is whether investors learn from past earnings surprises about the degree of uncertainty and make correct inferences afterward. Obviously, this depends on the precision of the signal received from previous earnings announcements. If the information from previous earnings announcements contains noise, it would be difficult to correctly estimate the magnitude of uncertainty. In other words, the question we examine in Panel B of Table 4 is whether underestimation of uncertainty is more pronounced for firms with larger and noisier earnings surprises in the past.

We start by considering the number of analysts as a proxy for the overall quality of the information environment, assuming that firms with more analyst coverage tend to have more transparent information environments. We obtain the number of analysts following each firm from IBES. The average straddle returns for firms with the lowest and highest number of analysts are 4.67% and 2.12%, respectively. The difference between the 2 groups is −2.55% with a significant t-statistic of −3.35. This supports the notion that with more analysts comes a less noisy signal, and fewer options investors underestimating the uncertainty around an earnings announcement.[18]

There are many ways to measure earnings surprises. One conventional measure is the standardized difference between the announced earnings and the analyst forecast consensus scaled by analyst forecast dispersion, which is our main standardized unexpected earnings (SUE) measure.[19] A more direct surprise measure for investors is the cumulative return over the earnings announcement period, because the return responds only to "true surprises." Therefore, we compute cumulative abnormal return, CAR, over [−1,1] after adjusting for size and book-to-market characteristics using Fama–French (1993) 6-benchmark portfolio returns over the same period. To measure the magnitude of surprises, rather than the direction of surprises, we use the absolute value of SUE and CAR. For historical uncertainty in earnings surprises, we compute the SUE and CAR variances, using the previous 8 quarters.

For firms with the lowest and highest previous-quarter earnings announcement surprises, |SUE|, the average straddle returns are 2.49% and 3.80%, respectively. The difference is 1.31% with a t-statistic of 1.89. For firms with the lowest and highest |CAR| over earnings announcements, the average straddle returns are 1.83% and 4.27%, respectively. The difference is 2.44% with a significant t-statistic of 4.71. These patterns support the hypothesis that larger historical surprises result in more uncertainty underestimation. Next, we turn to the variance measure of earnings surprises. For firms with the lowest and highest variance of earnings announcement surprises, the average straddle returns are 2.11% and 3.25%, respectively. The difference is 1.13% with an insignificant t-statistic of 1.37. For firms with the lowest and highest variance of CAR, the average straddle returns are 1.12% and 3.95%, respectively. The difference is 2.84% with a highly significant t-statistic of 4.47.

Panels A and B of Table 4 present strong evidence that firms with noisier signals in past returns and earnings announcements are more likely to produce future higher straddle returns around earnings announcements.

[18] From unreported results, we also examine how institutional ownership affects straddle returns. We find that straddle returns across different levels of institutional ownership are always positive and significant, but there a clear cross-sectional pattern does not exist.

[19] From results not reported, we compute earnings surprises using a random walk model and a seasonality model. The results are similar to those using consensus forecasts.

We also examine variables related to transaction costs in the options and stock market. If transaction costs are too high or liquidity is too low, option prices might not reflect "correct" expected uncertainty in a timely way, which means higher positive straddle returns. For transaction costs measures, we directly compute bid–ask spreads scaled by closing prices for stocks and options from the previous quarter. We use average volumes for stocks and options in the previous quarter as a liquidity proxy. The results are presented in Panel C of Table 4. When we sort on stock bid–ask spread, firms with the lowest and highest spreads have straddle returns of 2.21% and 3.29%, respectively, and the difference is 1.08% with a t-statistic of 1.84. When we sort on stock trading volume, firms with the lowest and highest volumes have straddle returns of 5.83% and 1.33%, respectively, and the difference is −4.50% with a t-statistic of −4.95. Evidently, straddle returns tend to be more positive for stocks with higher spread and lower volume, which supports our hypothesis. When we turn to option bid–ask spread and option trading volume, the same pattern persists and becomes even stronger. For options with the lowest and highest bid–ask spreads, the straddle returns are 1.14% and 4.93%, respectively, and the difference is 3.79% with a t-statistic of 5.33. For options with the lowest and highest volumes, the straddle returns are 5.82% and 0.90%, respectively, and the difference is −4.92% with a t-statistic of −5.42.

The results in Panel C of Table 4 further support the hypothesis that as transaction costs increase, it becomes more difficult to incorporate information into option prices, which leads to a higher propensity to underestimate uncertainty, resulting in higher straddle returns.[20]

To summarize the findings in this section, firms with noisier signals in past returns and earnings announcements are more likely to produce higher future straddle returns before an earnings announcement. Also, when transaction costs increase and volumes decrease, there is greater uncertainty underestimation and higher straddle returns. This pattern echoes our finding in Table 3 that when we use equal weights across firms, the results are stronger, and when we use dollar open interest weights with lower weights on smaller firms, the results are weaker. This occurs mainly because the positive straddles are more pronounced for smaller firms, which tend to have lower volumes and higher spreads.

C. Fama–MacBeth (1973) Regression: What Predicts Straddle Returns around Earnings Announcements?

In the preceding sections, we compute average straddle returns at the portfolio level. We find that average straddle returns are positive and significant, and firm characteristics related to both noisiness and transaction costs help predict straddle returns. However, it is unclear from the results presented to this point which

[20]Alternative results using dollar open interest weighting across firms and over the [−3,−1] window are reported in Internet Appendix Table 6. The straddle returns are positive and statistically significant for most of the sorted portfolios, but the overall statistical significance is lower than in Table 4. In terms of high moments and jumps, we find that the kurtosis measure generates a significant return difference, similar but weaker than in Table 4. Among the past earnings surprise measures, only the number of analysts measure generates a marginally significant negative return difference, much less significant than in Table 4. For the transaction cost variables, 3 of 4 volume and spread variables generate significant return differences, similar to Table 4. We conduct many other robustness checks using different windows and different weighting schemes. The results are available from the authors.

characteristic dominates the other. It is hard to address this issue using a single-sort portfolio approach. In this section, we use the Fama–MacBeth (1973) regression approach to directly examine whether individual straddle returns can be predicted by past information and to determine which component of the past information has the strongest predictive power. In particular, for each quarter, we estimate a cross-sectional predictive regression for individual straddle returns. Then, we average all quarterly coefficients over 72 quarters to obtain mean coefficient estimates and conduct inferences. Our t-statistics are computed using standard errors with the Newey–West (1987) adjustments with 3 lags. In this section, we report results only for delta-neutral straddles during the $[-3,0]$ window.[21] Results for different windows are both qualitatively and quantitatively similar and are available from the authors.

We estimate 6 regressions. We use the first regression to set up the benchmark, in which we include the following 5 basic characteristics: days to maturity, moneyness, size, book-to-market ratio, and past 12-month returns. In the second regression, we include noisiness measures computed from historical returns: stock return kurtosis, jump frequency, and jump size. We do not include historical volatility or skewness because they are highly correlated with kurtosis. In the third regression, we use the following noisiness measures computed from earnings data: number of analysts, variance of CAR, and variance of SUE. We do not include |CAR| and |SUE| because they are highly correlated with the variances of CAR and SUE, respectively. In the fourth regression, we focus on transaction cost measures, such as historical option trading volume, option bid–ask spread, and stock bid–ask spread. These four regressions help clarify whether each information category is relevant for straddle returns. In the fifth regression, we take a "kitchen sink" approach and pool all variables together. Clearly, the kitchen sink approach might suffer from collinearity concerns. Therefore, in the final regression, we apply a model selection tool to determine which variables have the strongest predictive power among all variables, which also reduces the kitchen sink model to a parsimonious model.

Regression results are reported in Table 5. In the first regression, the coefficient on size is negative. This finding suggests that straddle returns are more positive for smaller firms. The reason could be that smaller firms have noisier signals and/or smaller firms have higher transaction costs. The coefficient on moneyness is positive and significant, suggesting that uncertainty is more pronounced for straddles relatively more in the money. The adjusted R^2 is 1.29%.

In the second regression, we examine higher historical moments and jump statistics. Consistent with Table 4, both higher historical moments and higher jump statistics carry positive signs, indicating that the positive straddle returns are larger for firms with more noise in their returns. However, the only significant coefficient in this regression is on log kurtosis. The adjusted R^2 is only 0.29%, substantially lower than the first regression.

The third regression includes only historical earnings information. The coefficient on the number of analysts is negative and significant, which suggests that

[21] We also estimate results for the $[-3,-1]$ window, and they are even stronger than those for the $[-3,0]$ window.

TABLE 5

Predicting Delta-Neutral Straddle Returns [−3,0] with Fama–MacBeth Regressions: Time-Series Sample

Table 5 reports results of the Fama–MacBeth (1973) regressions. The sample period is from Jan. 1996 to Dec. 2013. Options data are from OptionMetrics. We apply filters (1)–(10) to the options data. Delta-neutral straddles are computed over [−3,0], relative to earnings announcement days, where day 0 is the earnings announcement day. If there is more than 1 straddle for a stock over 1 period, we use volume weighting. In each quarter, we estimate a cross-sectional regression for straddle returns. Then, we average all quarterly coefficients over 72 quarters to conduct inferences. Historical moments are computed over the past 3-month daily returns, and historical jump statistics are computed using the past 12-month daily returns. JUMP_FREQ and JUMP_SIZE are jump frequency and jump size measures, respectively, calculated following Lee and Mykland (2008) procedure. N_ANALYSTS is the number of analysts covering the firm. The cumulative abnormal return, CAR, is computed over [−1,1] around earnings announcements and adjusted for the market return. Earnings surprises, SUE, are calculated as the difference between announced earnings and consensus forecast. The variances of SUE and CAR are computed using data from the previous 8 quarters. For transaction costs measures, we directly compute bid–ask spreads scaled by closing prices for stocks and options from the previous quarter. OPTION_VOLUME is average option trading volume in the previous quarter. We rely on a variable reduction technique to choose variables to include in the last regression. We compute t-statistics using the Newey–West (1987) standard errors with 3 lags.

	1		2		3		4		5		6	
	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
Intercept	−0.273	−2.20	−0.003	−0.27	0.027	2.17	0.000	0.04	−0.684	−2.16	−0.642	−2.04
DAYS_TO_MATURITY	−0.000	−0.01							0.000	1.31		
MONEYNESS	0.385	3.19							0.627	2.47	0.540	4.84
ln(SIZE)	−0.010	−5.60							−0.000	−0.04		
ln(B/M)	−0.000	−0.19							0.011	0.84		
PAST_RETURN	0.001	0.22							−0.006	−0.57		
ln(KURTOSIS)			0.018	3.37					0.010	1.33	0.014	2.85
JUMP_FREQ			0.547	1.66					2.141	0.95		
JUMP_SIZE			0.006	0.30					−0.042	−0.96		
N_ANALYSTS					−0.001	−2.88						
var(CAR)					0.208	3.16			0.107	1.16	0.192	3.22
var(SUE)					−0.204	−0.16			−0.835	−0.67		
OPTION_VOLUME							−0.000	−0.42	0.000	0.55		
OPTION_SPREAD							0.217	4.44	0.234	2.80	0.171	2.74
STOCK_SPREAD							4.299	2.29	−0.385	−0.16		
R^2	3.99%		2.12%		2.97%		2.26%		12.26%		3.77%	
Adj. R^2	1.29%		0.29%		0.42%		0.61%		2.06%		1.46%	

when there are fewer analysts following the firm, straddle returns around earnings announcements become larger. The coefficient on variance of CAR is positive and significant, suggesting that straddle returns increase with historical uncertainty. The coefficient on variance of SUE is insignificant. The adjusted R^2 is 0.42%, lower than that of the first regression but higher than that of the second regression using high historical return moments.

In the fourth regression, we include transaction cost measures such as option volumes and bid–ask spreads. We do not include stock volume because it is correlated with option volume at 76%. The option volume coefficient is negative but insignificant. Both spread variables are positive and significant, indicating that higher transaction costs lead to higher future positive straddle returns, which is consistent with our hypothesis that underestimation could be driven by higher transaction costs.

The "kitchen sink" fifth regression combines all variables from the first four regressions. All measures are insignificant except moneyness and option bid–ask spread. This is probably because, as a measure of transaction costs, option bid–ask spread is related to firm characteristics including size and historical signal noisiness. The adjusted R^2 is 2.06%.

In the final regression, to alleviate concerns regarding multicollinearity, we rely on a variable reduction technique based on Hendry and Krolzig's (2001)

PcGets algorithm. We start with a regression that includes all explanatory variables and remove the explanatory variable with the lowest absolute t-statistic. Then we reestimate the regression with the remaining variables. We repeat these steps until all variables left in the regression have a p-value above 10%.

With this procedure, we select 4 highly significant explanatory variables. The coefficient on moneyness is positive and significant. Variable kurtosis, variance of CAR, and option bid–ask spread all positively predict straddle returns, suggesting that both signal noisiness and transaction costs play a significant role in predicting straddle returns. Size is dropped in the model reduction procedure because it contains information that is jointly captured by the noisiness and transaction costs measures. The adjusted R^2 is 1.46%.

To summarize the findings in this section, moneyness, size, historical moments, variance of CAR, and transaction costs all help predict straddle returns around earnings announcement days.

V. Conclusion

How investors form their expectations of uncertainty has been one of the central themes in financial research. In this article, we use firm earnings announcements as a special event to study investors' perceptions of firms' fundamental uncertainty. We construct delta-neutral straddles 3 days or 1 day before scheduled earnings announcement dates and hold the straddles until the day of or 1 day after the earnings announcement dates. The straddle returns around earnings announcements are positive and significant, especially for the preannouncement period. This is in stark contrast to the negative and significant straddle returns on individual stocks during normal periods. We also find that the positive straddle returns around earnings announcements are higher for smaller firms, firms with higher past return volatility, firms with higher and more volatile past earnings surprises, and firms with higher transaction costs.

Positive straddle returns are inconsistent with a risk-based explanation because straddles are positively exposed to market volatility risk, which is negatively priced. Using a subsample with expected earnings announcement days, we find that it is unlikely that our results are driven by unscheduled announcements. From the cross-sectional evidence, the positive straddle returns are stronger for firms with a less transparent information environment or noisier signals, as well as for firms with higher transaction costs. That is, when it is more difficult or costly to acquire and process information about the firm, there is more underestimation of uncertainty, which leads to higher positive straddle returns.

The main focus of this article is to document investors' anticipation of uncertainty around earnings announcements rather than to search for a profitable trading strategy. As a result, we use only end-of-day bid and ask prices. For future research, it would be interesting to use intraday data and determine whether there are tradable strategies for straddles around earnings announcement days.

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