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Realized moments and the cross-sectional stock returns around earnings announcements

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ABSTRACT

We examine the predictability of realized measures on the cross-section of stock returns around earnings announcements. We construct realized measures (variance, skewness, kurtosis, and relative jump) using high-frequency intraday stock prices. Our results show that realized variance, skewness, and relative jumps strongly predict stock returns around earnings announcements but realized kurtosis does not. These findings are robust to various event windows, after controlling for firm characteristics, and to a range of additional tests. We further show that the predictability of realized measures is not affected by unexpected earnings. The findings also suggest that pre-announcement realized measures absorb part of the information contained in unexpected earnings.

1. Introduction

Investors are concerned about both volatility and skewness of investment returns. In general, they prefer low volatility and positive skewness (Kraus & Litzenberger, 1976). These investor preferences serve to encourage researchers to explore volatility and skewness measures in predicting stock returns from both stock and option markets. Relatedly, there is a debate about whether option prices lead stock prices or vice versa, and researchers have developed "sequential-trade" models to explore whether investors trade in the stock market or the option market (e.g., Biais & Hillion, 1994; Easley et al., 1998). Notably, there is no consensus – the evidence shows that informed traders can trade in either the stock market or the option market.

This study extends the literature regarding the predictability of realized moments on stock returns. Specifically, the purpose of this study is threefold. First, we examine whether and to what extent realized moments prior to earnings announcements predict post-event stock returns.[1] On the one hand, the availability of high-frequency intraday data allows us to estimate realized moments more accurately compared with low-frequency (e.g., daily or monthly) data. Moreover, Amaya et al. (2015) argue that realized moments from high-frequency intraday data contain different information when compared to alternatives computed from low-frequency data or those extracted from option prices. On the other hand, Savor (2012, p. 652) argues that "one would expect information-based price events to be stronger predictors of future firm performance than no-information ones". Among a number of corporate events, earnings

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[1] In this study, the "post-event" forecasting window includes the event day and its following days.

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announcements convey crucial information for stock pricing.[2] As such, we expect that realized moments have stronger predictability on stock returns around earnings announcements.

Second, we address the call made by Amaya et al. (2015) for a direct comparison of realized skewness and realized semivariances. Barndorff-Nielsen et al. (2010) decompose realized variance to realized semivariances to capture the variation of positive and negative returns. Rather than simply using the two components of realized variance, we construct a signed jump by taking the difference between the positive- and negative-signed semivariances (Bollerslev et al., 2020; Patton & Sheppard, 2015). In line with the argument of Bollerslev et al. (2020), the difference between realized positive and negative semivariances manifests in the variation that stems from price jumps. The signed jump variation might be considered as an alternative measure of skewness (Feunou et al., 2016; Feunou & Okou, 2019) and Das and Sundaram (1997) also claim that skewness should arise from the distribution of jump sizes in the jump-diffusion process, rather than driving jumps. However, the signed jump provides a measure that is much easier to estimate and interpret (Bollerslev et al., 2020). Therefore, we adopt the signed jump measure in our study.[3]

Both signed jump and realized skewness reflect the asymmetry of the intraday return distributions. Prior literature has studied the asymmetry of realized semivariances in predicting volatility (Hibbert et al., 2008; Patton & Sheppard, 2015). Choi and Lee (2017) use realized skewness as a measure of information ambiguity around analyst forecasts and recommendations. They show that only negative realized skewness predicts subsequent stock returns. We further investigate the predictive power of realized measures (variance, skewness, kurtosis, and jump) on stock returns around earnings announcements by introducing the signed jump.[4]

Finally, we investigate whether the relation between realized measures and subsequent stock returns is distinct from the market reaction to the released earnings news. Ball and Brown (1968) show that firms with unexpected earnings experience abnormal returns. In subsequent studies, Foster et al. (1984), Bernard and Thomas (1989), and Ball and Bartov (1996) show strong post-earnings announcement drift (PEAD). This suggests that post-announcement cumulative abnormal stock returns continue to drift up (down) for positive (negative) unexpected earnings, i.e., good news (bad news). Williams (2015) further documents the asymmetric effect of good news and bad news of earnings announcements. Accordingly, we examine whether the predictability of realized measures on stock returns continuously holds after incorporating the post-announcement drift effect.

Our sample includes all stocks that were constituents of the S&P 500 index at some time during the time window from January 1998 to December 2015. To construct realized measures, we collect high-frequency intraday data from the Thomson Reuters Tick History (TRTH) database. Stock prices and returns are extracted from the Center for Research in Security Prices (CRSP) database and firm characteristics are from the Compustat database. Finally, we collect data on earnings from the Institutional Brokers' Estimate System (I/B/E/S) database.

We summarize our main findings as follows. We first analyze portfolio returns by sorting pre-announcement weekly realized measures. We observe that stocks in the highest variance quintile outperform those in the lowest variance quintile for all our earnings announcement windows. However, this relation is reversed when stocks are sorted on weekly realized skewness and weekly realized jump prior to earnings announcements. We do not find any relation between portfolio returns and weekly realized kurtosis. To validate these findings, we run regression models and provide evidence that weekly realized variance, skewness and relative jump have predictive power on post-announcement cumulative abnormal stock returns (CAR).[5] For example, a unit standard deviation increase in weekly realized variance, skewness and jump estimated preceding earnings releases is significantly related to a 0.55% increase (t-statistic = 3.07), 0.29% increase (t-statistic = 2.64), and 0.24% decrease (t-statistic = -2.04) in the two-day $CAR_{(t,t+n)}$, where t is the earnings announcement date and $n = 1$, respectively. These findings are robust for different earnings announcement windows ($n = 5$, 10, and 20). Moreover, to test whether the predictability of realized measures is stronger during event periods than non-event periods, we repeat the above regressions and find that the estimated coefficients on relevant realized measures for non-announcement periods are much smaller. By employing an event dummy, we further show that the estimated coefficients in the announcement and non-announcement periods are statistically different, especially for realized skewness and jumps.

We further investigate whether the predictability of realized measures is attributable to unexpected earnings. Our results show that the magnitudes and significance levels of corresponding realized measures continue to hold after including unexpected earnings. For particular announcement windows, the estimated coefficients on standardized unexpected earnings are statistically insignificant. By further distinguishing between positive standardized unexpected earnings (good news) and negative standardized unexpected earnings (bad news), we find that while the estimated coefficients on good news are statistically significant, those on bad news are insignificant for all announcement windows. Taken together, these findings provide evidence that unexpected earnings news is partly incorporated in pre-announcement realized measures, and the predictability of these realized measures is distinct from the market reaction to unexpected earnings.

This study contributes to the relevant literature in several respects. First, it contributes to the debate on the predictive power of higher moments of stock returns on future returns. Extant literature is lacking consensus on how best to measure higher moments of the return distribution. One stream of the literature advocates option implied measures that arguably contain market forward-looking

[2] See, for example, Ball and Brown (1968), Foster et al. (1984), Sloan (1996), Kothari (2001), DellaVigna and Pollet (2009) and Hirshleifer et al. (2009).

[3] Alternative jump measures derived from different models are worth exploring in future work, see, for example, Das and Sundaram (1999), Das (2002), and Jiang and Zhu (2017).

[4] Lee (2012) provides evidence that stock price jumps tend to occur within one day before earnings news releases.

[5] Unless otherwise specified, we do not interpret realized kurtosis when we explain the estimate significance as the estimate on realized kurtosis is insignificant for almost all regression models.

information and hence should have certain advantages in predicting future returns. However, the overall empirical literature provides mixed evidence in terms of the predictive power of option implied measures of return distribution on stock future returns. For example, Bhattacharya (1987) and Anthony (1988) document that option prices lead stock prices. However, Chan et al. (1993) find no evidence that options lead stocks. In contrast, Stephan and Whaley (1990) show that stocks lead options. Previous studies also produce contradictory results on option implied measures. Xing et al. (2010) and Rehman and Vilkov (2012) find a positive relation between option implied skewness and future stock returns, but Conrad et al. (2013) show a negative relation.

Another stream of the literature proposes realized measures based on high-frequency data. Merton (1980) shows that volatility can be more accurately measured using high-frequency data. Based on this insight, daily realized volatility is computed by summing intraday squared returns (e.g., Andersen & Bollerslev, 1998; Andersen et al., 2003). Amaya et al. (2015) extend the well-established concept of realized volatility to construct realized skewness and kurtosis. Bollerslev et al. (2020) and Choi and Lee (2017) further exam the predictability of realized measures.

Second, earnings announcements are very important corporate events. Investors are actively exploring information disclosed in these announcements. If the trading activity of investors is an important driver of higher moments of stock returns, then the predictability of these moments should be more pronounced around earnings announcements. Compared to prior literature exploring option implied measures around corporate events, there are very few studies examining realized measures concerning important news announcements. For example, Diavatopoulos et al. (2012) investigate the predictability of model-free implied skewness and kurtosis prior to earnings announcements. Atilgan (2014) and Lei et al. (2020) study implied volatility spread around earnings announcements. Lin and Lu (2015) and Chan et al. (2015) examine the informational content of implied volatility spread and implied volatility skew prior to analyst news events and merger and acquisition announcements, respectively. However, only Choi and Lee (2017) investigate the predictive power of realized measures around analysts' earnings forecasts and recommendation releases. More research is needed to further explore information incorporated in realized measures around corporate events and shed light on the importance of realized measures on investment activities.

We extend the studies of Amaya et al. (2015) and Bollerslev et al. (2020) by showing that realized measures around important corporate announcements have stronger predictive power than those in non-announcement periods. Amaya et al. (2015) and Bollerslev et al. (2020) explore the unconditional relation between realized measures and future stock returns. They show that realized volatility cannot consistently predict subsequent stock returns. In contrast, we find that pre-announcement realized variance positively and significantly predicts post-event stock returns. Our findings are consistent with the results of Choi and Lee (2017) that examine realized moments around analyst forecasts and recommendations. More interestingly, we observe a negative estimated coefficient on realized skewness in the univariate regression. However, the coefficient changes from "negative" to "positive" after controlling for realized jump, while realized jump remains negatively and statistically significant in both univariate and multivariate models. This finding is in line with that of Bollerslev et al. (2020). Bollerslev et al. (2020) provide an econometric rationale and argue that there may exist a common component between realized skewness and realized jump, which accounts for the sign change.

Finally, we provide evidence in relation to the post-earnings announcement drift (PEAD) effect (Ball & Bartov, 1996; Bernard & Thomas, 1989; Foster et al., 1984). This suggests that the greater the earnings news shock, the stronger the stock market reaction. However, we show that the strong impact of unexpected earnings on subsequent stock returns does not affect the power of realized measures in predicting stock returns. In addition, we find that the PEAD effect is mostly attributable to positive unexpected earnings. Even when we distinguish between positive and negative unexpected earnings, the relation between realized measures and subsequent stock returns continues to hold.

We structure the remainder of this study as follows. Section 2 presents the econometric method used to construct realized measures and Section 3 describes the data and sample. Sections 4 and 5 detail the empirical results and additional analyses, respectively. Section 6 concludes.

2. Econometric method

This study investigates whether and the extent to which realized measures around earnings announcements predict stock returns. To address this issue, we first define the 5-min intraday log returns. On each day t, the jth 5-min return for stock i is given by:

$$r_{i,t,j} = \log P_{i,t,j+1} - \log P_{i,t,j}, \tag{1}$$

where $P_{i,t,j}$ is the jth intraday price of stock i on day t.

Following Andersen and Bollerslev (1998) and Andersen et al. (2003), the daily realized variance is computed by:

$$DailyRDvar_{i,t} = \sum_{j=1}^{N} r_{i,t,j}^2, \tag{2}$$

where N is the number of intraday return observations in a trading day.

Based on the well-established concept of realized variance, the daily realized skewness and kurtosis are computed as (Amaya et al., 2015):

$$DailyRDskew_{i,t} = \frac{\sqrt{N}\sum_{j=1}^{N} r_{i,t,j}^3}{DailyRDvar_{i,t}^{3/2}} \tag{3}$$

and

$$DailyRDkurt_{i,t} = \frac{N\sum_{j=1}^{N} r_{i,t,j}^4}{DailyRDvar_{i,t}^2}. \tag{4}$$

We further decompose the realized variance into two signed components (Barndorff-Nielsen et al., 2010):

$$DailyRDvar_{i,t}^{+} = \sum_{j=1}^{N} r_{i,t,j}^2 I\left(r_{i,t,j} > 0\right), \tag{5}$$

and

$$DailyRDvar_{i,t}^{-} = \sum_{j=1}^{N} r_{i,t,j}^2 I\left(r_{i,t,j} < 0\right). \tag{6}$$

Following Patton and Sheppard (2015), we define the difference between the above two semivariances as a signed jump:

$$DailyJ_{i,t} = DailyRDvar_{i,t}^{+} - DailyRDvar_{i,t}^{-}. \tag{7}$$

As the level of variance may vary substantially across stocks, the signed jump differs significantly. As such, we define the relative signed jump as:

$$DailyRDJ_{i,t} = \frac{DaliyJ_{i,t}}{DailyRDvar_{i,t}}. \tag{8}$$

Next, we compute weekly realized measures by averaging daily ones over the past 5 trading days:

$$RDvar_{i,t} = \frac{1}{5}\sum_{l=1}^{5} DailyRDvar_{i,t-l+1,} \tag{9}$$

$$RDskew_{i,t} = \frac{1}{5}\sum_{l=1}^{5} DailyRDskew_{i,t-l+1,} \tag{10}$$

$$RDkurt_{i,t} = \frac{1}{5}\sum_{l=1}^{5} DailyRDkurt_{i,t-l+1,} \tag{11}$$

$$RDJ_{i,t} = \frac{1}{5}\sum_{l=1}^{5} DailyRDJ_{i,t-l+1.} \tag{12}$$

3. Data

The sample used in this study includes all stocks that were constituents of the S&P 500 index over the period from January 2, 1998 to December 31, 2015.[6]

We source the high-frequency stock price tick data from the Thomson Reuters Tick History (TRTH) database. To construct realized measures, we convert the tick data into 5-min prices using the nearest tick and compute 5-min log returns for each stock (Amaya et al., 2015). The choice of 5-min sampling frequency for intraday returns is based on the balance between reducing measurement error on the one hand, and minimizing the effect of the market microstructure biases arising in very high frequencies on the other. The sampling quoted prices are between 9:30 EST and 16:00 EST. As we investigate realized measures over the trading day, overnight returns are excluded. This practice is in line with Hansen and Lunde (2006), Patton and Sheppard (2015), Amaya et al. (2015), and Bollerslev et al.

[6] As the number of earnings announcements per year is low prior to 1998, and the time-stamp of earnings announcements is more accurately recorded since 1998, our sample starts from January 1998.

(2020), among others.[7] By excluding the overnight returns, we have a total of 78 intraday returns. We also exclude the trading day if it has more than 12 consecutive 5-min returns being zero or more than 30 non-consecutive 5-min returns being zero (Chan et al., 2019).

We collect quarterly earnings announcement data including announcement dates and time, actual earnings figures, and consensus analyst forecasts from the Institutional Brokers' Estimate System (I/B/E/S) database. As the stock markets open from 9:30 EST to 16:00 EST and investors respond to earnings announcements released during trading hours immediately, we assume that news released after the trading hour window (i.e., between 16:00 EST and 9:30 EST next morning) is reflected in trading/prices on the following day (Michaely et al., 2014). We define the standardized unexpected earnings surprise (*SUE*) as the difference between the actual earnings and the consensus earnings forecast, normalized by the firm's stock price at the end of the quarter (DellaVigna & Pollet, 2009; Livnat & Mendenhall, 2006):

$$SUE_{i,t} = \frac{e_{i,t} - E_{t-1}\left[e_{i,t}\right]}{P_{i,q}}, \tag{13}$$

where $e_{i,t}$ is the earnings per share of firm i released on day t, $E_{t-1}[e_{i,t}]$ refers to the corresponding expectation of earnings per share measured by the mean estimate of analyst forecasts, and $P_{i,q}$ is the share price at the end of the corresponding quarter. Following Williams (2015), we define positive unexpected earnings (SUE^{+}) as good news, which is equal to SUE when $SUE>0$ and 0 otherwise, and negative unexpected earnings (SUE^{-}) as bad news, which is equal to SUE when $SUE<0$ and 0 otherwise.

Finally, we source the daily stock prices and returns from the Center for Research in Security Prices (CRSP) database. The corresponding accounting-related data such as book value per share is extracted from the Compustat database.

4. Empirical results

4.1. Descriptive statistics

Our main aim is to examine the predictability of the aforementioned realized measures around earnings announcements (EA), and accordingly, we refer to the sample used for earnings announcements as the EA sample. Panel A of Table 1 reports yearly descriptive statistics of the means of main variables for the EA sample over the period from January 1998 to December 2015. It shows that the number of stocks in the first several years of the sample is small, consistent with the small number of earnings announcements over this period. The unexpected earnings measures captured by *SUE* are largely dominated by negative surprises, with 14 out of 18 years being negative. The realized measures are reported with their weekly values preceding earnings announcements. Compared to the mean value of weekly realized variance (*RDvar*) over the whole sample period, 0.05%, we observe high spikes during several extreme time periods, such as the Russian and Long-Term Capital Management (LTCM) crisis in 1998, the Dot-com bubble crisis around 2000 and the Global Financial Crisis (GFC) around 2008, with values of 0.12%, 0.15%, and 0.16%, respectively. While we do not observe similar patterns for realized skewness (*RDskew*) and realized kurtosis (*RDkurt*), we notice higher values (compared to its mean value of 0.01) of relative jump (*RDJ*) in 1998, 2001, and 2009, with the value of 0.04, 0.02, and 0.02, respectively.

For purposes of comparison, we create one subsample without earnings announcements, denoted the non-EA sample. Table 1 Panel B reports the descriptive summary of weekly realized measures for both EA and non-EA samples. The last column of the table presents the difference of corresponding weekly realized measures between EA and non-EA samples. Realized variance increases and realized skewness decreases significantly before earnings news is announced, consistent with the findings of Choi and Lee (2017) on analyst forecasts and recommendations. However, realized kurtosis decreases significantly and no significant difference is observed in realized relative jump. In general, this suggests that weekly realized variance, skewness, and kurtosis are associated with corporate news releases, while stock price jump is not always related to news events (Jiang & Zhu, 2017).

Panel C of Table 1 presents correlations between weekly realized measures for the EA sample.[8] Correlations between weekly realized variance, skewness, and kurtosis, are almost insignificant, with the exception that realized skewness is related to realized kurtosis at the 10% significance level. An insignificant negative (positive) correlation exists between realized variance (kurtosis) and relative jump. More importantly, we observe a significantly positive correlation between realized skewness and relative jump, which is consistent with the finding of Bollerslev et al. (2020).

4.2. Portfolio analysis

To test the predictability of realized measures on post-event cumulative abnormal stock returns, we first estimate the abnormal

[7] Moreover, realized jump is one of the key variables in our study. Prior literature shows that a significant number of individual equity jumps arrive near the market opening (between 9:30 EST and 11:00 EST) (Bollerslev et al., 2008; Lee, 2012). Therefore, the study of jumps focusing on the day information is justified.

[8] In this study, unless otherwise specified, our results are for the sample in relation to earnings announcements (i.e., EA sample).

Table 1

Yearly descriptive summary of the earnings announcement sample. Pane A in this table reports yearly descriptive statistics (means) of variables around earnings announcements for the sample period from January 1998 to December 2015. The first column and the last column show the number of stocks and earnings announcements, respectively. RDvar, RDskew, RDkurt, and RDJ are weekly realized variance, skewness, kurtosis and relative jump, respectively, and are computed by averaging their corresponding daily values over the week prior to earnings announcements. Size represents the market capitalization calculated by using the stock closing price multiplied by total shares outstanding. BM represents the ratio of book value to market value of the firm, where book value is computed by multiplying book value per share by total shares outstanding at the most recent fiscal year end. Volume is the percentage of daily trading volume to total shares outstanding. SUE is the standardized unexpected earnings surprise calculated using Eq. (13). Panel B presents the summary statistics of weekly realized measures for earnings announcement (EA) and non-earnings announcement (non-EA) samples. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively. Panel C reports the correlation coefficients between weekly realized measures prior to earnings announcements with *p*-value in parentheses.

Panel A: Yearly descriptive statistics for the EA sample

Year	# of stocks	RDvar (%)	RDskew	RDkurt	RDJ	Size ($b)	BM	Volume (%)	SUE (%)	# of EAs
1998	178	0.117	0.142	5.702	0.037	27.07	0.259	1.587	−0.071	384
1999	241	0.095	0.006	5.821	0.002	29.59	0.247	1.522	−0.037	645
2000	270	0.149	0.050	5.865	0.013	32.95	0.288	1.668	−0.028	716
2001	361	0.081	0.078	6.500	0.020	20.54	0.373	1.447	−0.196	1045
2002	400	0.093	0.001	5.959	−0.005	15.94	0.483	1.726	−0.114	1234
2003	415	0.036	−0.050	5.987	−0.014	14.76	0.463	1.880	−0.102	1229
2004	425	0.028	0.003	6.092	−0.003	16.78	0.378	1.949	0.068	1438
2005	421	0.027	0.049	6.156	0.012	18.27	0.368	2.043	0.017	1434
2006	431	0.025	0.015	6.131	0.005	20.81	0.350	2.287	0.042	1463
2007	433	0.028	0.037	6.214	0.009	23.45	0.384	2.605	−0.089	1468
2008	441	0.161	0.028	5.724	0.009	19.84	0.586	3.241	−0.443	1497
2009	438	0.100	0.048	5.841	0.021	15.61	0.699	3.734	−1.215	1495
2010	435	0.033	0.032	5.913	0.011	19.63	0.529	3.160	0.122	1496
2011	448	0.032	0.011	6.130	0.006	22.09	0.566	2.986	−0.015	1477
2012	463	0.024	0.011	6.626	0.007	22.71	0.591	2.926	−0.093	1553
2013	468	0.018	0.013	6.726	0.009	26.40	0.467	2.511	−0.044	1586
2014	480	0.021	0.056	6.337	0.016	30.91	0.450	2.351	−0.005	1577
2015	467	0.026	−0.015	6.394	0.002	33.86	0.482	2.554	−0.030	1575

Panel B: Summary statistics of weekly realized measures

Variable	EA sample				Non-EA sample				Mean difference (EA – Non-EA)
	Mean	Std dev.	Min	Max	Mean	Std dev.	Min	Max	
RDvar (%)	0.053	0.120	0.001	9.72	0.051	0.115	0.000	19.92	0.002***
RDskew	0.023	0.482	−3.045	2.641	0.031	0.497	−5.36	4.145	−0.007**
RDkurt	6.158	2.086	2.673	22.741	6.239	2.156	2.339	45.11	−0.085***
RDJ	0.008	0.117	−0.52	0.646	0.008	0.121	0.717	0.611	0.000

Panel C: Pairwise correlation coefficients for the EA sample

	RDvar	RDskew	RDkurt	RDJ
RDvar	1			
RDskew	0.005 (0.436)	1		
RDkurt	0.004 (0.575)	0.012 (0.074)	1	
RDJ	−0.007 (0.269)	0.915 (0.000)	0.010 (0.123)	1

stock return, which is computed by adjusting the three-factor model of Fama and French (1993).[9] Specifically, for each earnings announcement day, we estimate the following regression equation (14) for 150 trading days, with the last estimation date being 5 trading days preceding the earnings announcement date:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,M} MRP_t + \beta_{i,S} SMB_t + \beta_{i,H} HML_t + \varepsilon_{i,t}, \tag{14}$$

where $r_{i,t} - r_{f,t}$ represents the daily excess return for stock *i* at day *t*. MRP_t (market risk premium), SMB_t (small minus big), and HML_t (high minus low) are the market, size, and value factors in Fama and French's (1993) three-factor model, respectively.[10] We then calculate the daily abnormal stock return as:

$$AR_{i,t} = (r_{i,t} - r_{f,t}) - \left[\widehat{\beta}_{i,M} MRP_t + \widehat{\beta}_{i,S} SMB_t + \widehat{\beta}_{i,H} HML_t\right], \tag{15}$$

[9] Fama (2014, p. 1482) argues that the Fama-French three-factor model is the most successful asset pricing model in empirical tests. We also compute abnormal returns using the Fama and French three-factor augmented by the momentum factor (Carhart, 1997), i.e., four-factor model and the five-factor model of Fama and French (2015), and reach qualitatively similar findings. The results are not reported but are available from the authors upon request.

[10] The factor returns are from Kenneth French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2
Portfolio returns based on sorting of weekly realized measures. This table presents the estimates (mean and median) of portfolio CAR from day *t* to day *t* + n, where *t* is the earnings announcement date. The sample period is from January 1998 to December 2015, including 23,312 observations. The portfolio is constructed by sorting stocks into quintiles based on weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements, shown in Panels A, B, C and D, respectively. Weekly realized measures are computed by averaging their corresponding daily values over the week prior to earnings announcements. Q1 (Q5) represents the lowest (highest) quintile of corresponding weekly realized measures. The difference of CAR between Q5 and Q1 are reported, with *t*-statistics for mean estimates and Wilcoxon *z*-statistics for median estimates in parentheses. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Panel A: Sorting by RDvar										
	Mean $CAR_{(t,t+n)}$ (%)					Median $CAR_{(t,t+n)}$ (%)				
	RDvar (%) (Mean)	n = 1	n = 5	n = 10	n = 20	RDvar (%) (Median)	n = 1	n = 5	n = 10	n = 20
Q1 (Low)	0.01	−0.02	0.06	0.16	0.29	0.01	−0.07	−0.07	0.06	0.20
Q2	0.02	0.19	0.21	0.34	0.56	0.02	0.16	0.28	0.40	0.62
Q3	0.03	0.31	0.41	0.44	0.55	0.03	0.28	0.51	0.64	0.81
Q4	0.05	0.35	0.37	0.40	0.25	0.04	0.44	0.43	0.53	0.59
Q5 (High)	0.17	0.79	1.28	1.64	2.12	0.11	0.73	1.07	1.66	1.96
High-Low		0.81***	1.22***	1.48***	1.83***		0.80***	1.15***	1.60***	1.76***
t-stat/z-stat		(5.50)	(7.03)	(7.59)	(7.73)		(6.43)	(7.28)	(8.25)	(8.06)
Panel B: Sorting by RDskew										
	Mean $CAR_{(t,t+n)}$ (%)					Median $CAR_{(t,t+n)}$ (%)				
	RDskew (Mean)	n = 1	n = 5	n = 10	n = 20	RDskew (Median)	n = 1	n = 5	n = 10	n = 20
Q1 (Low)	−0.64	0.53	0.71	0.77	0.80	−0.57	0.44	0.60	0.77	0.74
Q2	−0.21	0.45	0.55	0.76	0.89	−0.21	0.25	0.36	0.54	0.62
Q3	0.02	0.17	0.28	0.40	0.58	0.02	0.06	0.18	0.32	0.58
Q4	0.26	0.24	0.49	0.60	0.85	0.25	0.19	0.45	0.54	0.76
Q5 (High)	0.70	0.21	0.31	0.44	0.65	0.61	0.09	0.13	0.37	0.67
High-Low		−0.32**	−0.40***	−0.33*	−0.15		−0.35***	−0.47***	−0.40***	−0.07
t-stat/z-stat		(-2.47)	(-2.68)	(-1.94)	(-0.72)		(-3.78)	(-3.53)	(-2.87)	(-1.48)
Panel C: Sorting by RDkurt										
	Mean $CAR_{(t,t+n)}$ (%)					Median $CAR_{(t,t+n)}$ (%)				
	RDkurt (Mean)	n = 1	n = 5	n = 10	n = 20	RDkurt (Median)	n = 1	n = 5	n = 10	n = 20
Q1 (Low)	4.03	0.23	0.31	0.42	0.61	4.09	0.16	0.19	0.45	0.71
Q2	4.91	0.37	0.51	0.61	0.76	4.91	0.21	0.39	0.49	0.57
Q3	5.68	0.22	0.41	0.54	0.66	5.67	0.22	0.39	0.49	0.72
Q4	6.72	0.36	0.57	0.72	0.85	6.68	0.20	0.42	0.60	0.56
Q5 (High)	9.44	0.42	0.53	0.67	0.89	8.81	0.27	0.31	0.57	0.79
High-Low		0.19	0.22	0.25	0.28		0.11	0.12	0.12	0.08
t-stat/z-stat		(1.45)	(1.45)	(1.48)	(1.38)		(1.01)	(1.13)	(0.98)	(0.58)
Panel D: Sorting by RDJ										
	Mean $CAR_{(t,t+n)}$ (%)					Median $CAR_{(t,t+n)}$ (%)				
	RDJ (Mean)	n = 1	n = 5	n = 10	n = 20	RDJ (Median)	n = 1	n = 5	n = 10	n = 20
Q1 (Low)	−0.15	0.67	0.82	0.95	1.04	−0.14	0.58	0.72	0.96	0.94
Q2	−0.05	0.54	0.69	0.82	0.90	−0.05	0.27	0.45	0.47	0.67
Q3	0.01	0.11	0.26	0.41	0.60	0.01	0.06	0.15	0.36	0.58
Q4	0.07	0.17	0.36	0.48	0.68	0.07	0.09	0.40	0.47	0.63
Q5 (High)	0.17	0.12	0.21	0.30	0.56	0.16	0.03	0.04	0.26	0.53
High-Low		−0.55***	−0.61***	−0.65***	−0.48**		−0.55***	−0.68***	−0.70***	−0.41***
t-stat/z-stat		(-4.22)	(-3.96)	(3.78)	(2.39)		(-5.96)	(-5.49)	(5.45)	(-3.38)

where $\widehat{\beta}_{i,M}$, $\widehat{\beta}_{i,S}$ and $\widehat{\beta}_{i,H}$ are the estimated coefficients of Eq. (14).

We now begin sorting stocks into equally-weighted quintile portfolios based on pre-announcement weekly realized measures. Table 2 reports the mean and median estimates of portfolio cumulative abnormal return, $CAR_{i,(t,t+n)}$, sorted by weekly realized measures (*RDvar*, *RDskew*, *RDkurt*, and *RDJ*) prior to earnings announcements, where t is the earnings announcement date and n is the number of days following the earnings news release.[11] The left (right)-hand side of each panel represents the mean (median) estimates. We take mean estimates, for example, to interpret the results.

Panel A shows portfolios sorted by weekly realized variance with 0.01% in the lowest quintile (Q1) and 0.17% in the highest quintile (Q5). We observe a statistically significant mean difference of *CAR* between Q5 and Q1 (High-Low) for each earnings announcement window. It increases from 0.81% (t-statistic = 5.50) to 1.83% (t-statistic = 7.73) for the earnings announcement windows (t,t+1) to (t,t+20), indicating that the pre-announcement realized variance is positively related to subsequent stock returns. This finding is consistent with the notion that information uncertainty (proxied by realized volatility here) is a risk factor and compensated by higher stock returns. According to Merton (1987), investors who are not well-diversified demand compensation for the stock idiosyncratic risk. The positive relation between volatility and stock returns is also manifested in Brenner and Izhakian (2018).

For the portfolios sorted by weekly realized skewness shown in Panel B, we observe negative mean differences of *CAR* between Q5 and Q1 for all four event windows, but that for the event window (t,t+20) is statistically insignificant. The results of the negative mean differences of *CAR* by going long (short) in stocks at the highest (lowest) level of realized skewness are consistent with the equilibrium models that predict skewness preferences (see, e.g., Brunnermeier et al., 2007; Mitton & Vorkink, 2007; Barberis & Huang, 2008). This means that investors with skewness preferences are willing to pay a premium for stocks with positively skewed return distributions, which earn lower future returns.

Furthermore, we find that mean differences of *CAR* sorted by weekly realized kurtosis presented in Panel C are not significant for any of the four event windows. Finally, for portfolios sorted by weekly relative jump, the mean differences of *CAR* are significantly negative, with values of −0.55%, −0.61%, −0.65%, and −0.48% for n = 1, 5, 10, and 20, respectively. These results might be explained by investor overreaction to price movements preceding earnings announcements. Normally, stocks with high volatility exhibit greater information asymmetry, and accordingly this could lead to a stronger jump effect (Bollerslev et al., 2020).

For the median estimates shown in Table 2, we observe similar patterns to their corresponding mean estimates. This provides evidence that our findings are not driven by extreme observations in the sample.

In summary, our portfolio analyses show that realized variance positively predicts abnormal stock returns. Both realized skewness and relative jumps are negatively related to future abnormal stock returns. However, there is no significant relation between realized kurtosis and subsequent abnormal stock returns.

4.3. Regression results

In this section, we conduct a cross-sectional regression to investigate the predictive power of the four realized measures. The regression specification is written as:

$$CAR_{i,(t,t+n)} = \alpha + \beta_1 RDvar_{i,t-1} + \beta_2 RDskew_{i,t-1} + \beta_3 RDkurt_{i,t-1} + \beta_4 RDJ_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{i,t,k} + \varepsilon_{i,t}, \tag{16}$$

where $CAR_{i,(t,t+n)}$ is the cumulative abnormal return for stock i over the period from day t to day $t + n$, where t is the earnings announcement date. $RDvar_{i,t-1}$, $RDskew_{i,t-1}$, $RDkurt_{i,t-1}$ and $RDJ_{i,t-1}$ are the weekly realized measures preceding the earnings announcement date. We include a set of control variables, $X_{i,t,k}, k = 1,\cdots,K$. Specifically, we control for firm size ($\log(Size)_{i,t}$), book-to-market ratio ($\log(BM)_{i,t}$), firm price momentum ($MOM_{i,t}$) over the past year, trading volume ($Volume_{i,t}$) and lagged weekly abnormal return ($LagAR_{i,t-1}$).[12]

Table 3 presents the regression results of Eq. (16) for different earnings announcement windows, indicated by n = 1, 5, 10, and 20 in Panels A, B, C and D, respectively. First, we separately regress $CAR_{(t,t+n)}$ on weekly realized moments (*RDvar*, *RDskew*, *RDkurt*, and *RDJ*) prior to earnings announcements. The estimated results are shown in Model (1) - Model (4) in each panel. Model (5) reports the results including all realized measures, and Model (6) further includes control variables. The t-statistics shown in parentheses are computed by clustering both firm and calendar days to adjust for cross-sectional and serial correlation (Petersen, 2009).

For the univariate tests, we observe significantly positive estimated coefficients on weekly realized variance (*RDvar*) across all the event windows, and significantly negative estimated coefficients on weekly realized skewness (*RDskew*) and relative jump (*RDJ*). However, the estimated coefficients on realized kurtosis are insignificant for all the event windows. We take n = 1 for example to explain our results, which is for the two-day announcement window (see Panel A). The estimated coefficients on *RDvar*, *RDskew*, and *RDJ* are 3.97, −0.22, and −1.88 with t-statistic of 2.02, −2.62, and −5.37, respectively. These results are consistent for portfolios sorted by relevant realized measures, indicating that *RDvar* positively predicts but both *RDskew* and *RDJ* negatively predict the subsequent stock returns. The positive significance of *RDvar* and the negative significance of *RDskew* are in line with the univariate

[11] We also conduct portfolio analyses for the non-EA sample. We find that the mean (median) differences of *CAR* between Q5 and Q1 sorted by relevant realized measures are much smaller than those presented in Table 2. We do not report the results for the non-EA sample, but they are available upon request.

[12] Banz (1981), Fama and French (1993), and Jegadeesh and Titman (1993) study firm characteristic effects of size, value, and momentum, respectively. Volume and lagged returns are also documented as well-known variables predicting cross-sectional stock returns (Conrad et al., 1994; Lehmann, 1990).

Table 3

Realized measures and cross-sectional stock returns. This table reports the cross-sectional regression of Eq. (16). The dependent variable is CAR from day *t* to day *t* + n, where *t* is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows, shown in Panels A, B, C and D, respectively. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements. Weekly realized measures are computed by averaging their corresponding daily values over the week prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized *t*-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

	Panel A: n = 1							Panel B: n = 5						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.11	0.33***	0.35***	0.34***	0.16	1.11	0.34***	0.12	0.47***	0.52***	0.48***	0.20	4.08***	0.49***
	(1.04)	(8.12)	(2.58)	(8.32)	(0.88)	(1.05)	(8.47)	(1.16)	(10.02)	(3.29)	(10.19)	(1.01)	(3.34)	(10.31)
RDvar (%)	3.97**				3.93**	4.61***		6.44***				6.40***	6.58***	
	(2.02)				(2.01)	(3.07)		(3.28)				(3.26)	(4.06)	
RDskew		−0.22***			1.14***	0.60***	1.19***		−0.25***			1.13***	0.55**	1.22***
		(-2.62)			(5.31)	(2.64)	(5.53)		(-2.46)			(4.52)	(2.08)	(4.82)
RDkurt			−0.00		−0.00	−0.01				−0.01		−0.01	−0.01	
			(-0.21)		(-0.18)	(-0.59)				(-0.36)		(-0.33)	(-0.61)	
RDJ				−1.88***	−6.16***	−2.08**	−6.37***				−2.01***	−6.26***	−2.03*	−6.59***
				(-5.37)	(-7.03)	(-2.04)	(-7.17)				(-4.82)	(-6.08)	(1.65)	(-6.30)
Log(Size)						−0.15							−0.45***	
						(-1.33)							(-3.43)	
Log(BM)						−1.24***							−1.06***	
						(-10.60)							(-7.63)	
MOM						−0.68***							−0.78***	
						(-5.21)							(-4.56)	
Volume (%)						−0.33***							−0.32***	
						(-7.43)							(-6.60)	
LagAR						−0.71***							−0.72***	
						(-6.67)							(-5.46)	
Adj.R^2 (%)	0.54	0.03	0.00	0.13	0.78	3.72	0.26	1.04	0.02	0.00	0.10	1.23	3.14	0.20

	Panel C: n = 10							Panel D: n = 20						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.20*	0.60***	0.66***	0.61***	0.29	6.41***	0.61***	0.15	0.76***	0.76***	0.77***	0.17	10.00***	0.77***
	(1.91)	(11.43)	(3.72)	(11.58)	(1.39)	(4.76)	(11.70)	(1.56)	(12.19)	(3.68)	(12.31)	(0.79)	(6.53)	(12.42)
RDvar (%)	7.32***				7.27***	7.18***		11.44***				11.39***	11.15***	
	(3.76)				(3.75)	(4.34)		(7.04)				(7.02)	(7.56)	
RDskew		−0.24**			1.26***	0.66**	1.36***		−0.10			1.36***	0.87**	1.52***
		(-2.09)			(4.45)	(2.21)	(4.76)		(-0.76)			(4.14)	(2.51)	(4.58)
RDkurt			−0.01		−0.01	−0.02				−0.00		−0.00	−0.01	
			(-0.39)		(-0.36)	(-0.58)				(-0.05)		(-0.03)	(-0.26)	
RDJ				−2.06***	−6.80***	−2.47*	−7.18***				−1.56***	−6.69***	−3.28**	−7.28***
				(-4.40)	(-5.84)	(-1.79)	(-6.07)				(-2.91)	(-4.92)	(-2.07)	(-5.28)
Log(Size)						−0.69							−1.07***	
						(-4.80)							(-6.48)	
Log(BM)						−1.07***							−1.03***	
						(-7.03)							(-5.64)	
MOM						−0.83***							−0.73***	
						(-4.80)							(-3.34)	
Volume (%)						−0.32***							−0.40***	
						(-6.63)							(-7.34)	
LagAR						−0.73***							−0.55***	
						(-4.87)							(-3.51)	
Adj.R^2 (%)	1.09	0.02	0.00	0.08	1.26	2.89	0.20	1.90	0.00	0.00	0.03	2.00	3.41	0.12

Table 4

Regression results for testing the difference of the estimated coefficients between the EA and non-EA samples. This table presents the regression results for testing the difference of the estimated coefficients on realized measures between the EA and non-EA samples. The dependent variable is CAR from day t to day $t + n$, where t is the announcement date for the EA sample and the particular date for the non-EA sample, and n = 1, 5, 10, and 20 indicate different forecasting windows. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to date t, and their interaction terms with a dummy variable, d, which takes a value of 1 if the observation is included in the EA sample and zero otherwise. These interaction terms are presented as RDvar_d, RDskew_d, RDkurt_d, and RDJ_d. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to date t. To save space, we suppress reporting the estimates of the control variables. The sample period is from January 1998 to December 2015, including 1,511,169 observations. The parenthesized t-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	0.044***	−0.01	−0.04	−0.08**
	(2.65)	(-0.53)	(-1.47)	(-2.07)
RDvar (%)	1.12***	2.45***	4.17***	7.28***
	(8.50)	(14.52)	(22.96)	(23.56)
RDskew	0.06***	0.15***	0.13***	0.23***
	(4.81)	(7.11)	(4.74)	(6.29)
RDkurt	0.00	0.00	0.00	0.01**
	(0.49)	(0.12)	(1.37)	(2.02)
RDJ	−0.30***	−0.64***	−0.62***	−0.97***
	(-4.51)	(-6.14)	(-4.69)	(-5.51)
RDvar_d (%)	2.67	3.60**	2.69	3.71**
	(1.48)	(2.01)	(1.54)	(2.41)
RDskew_d	0.91***	0.75***	0.86***	0.84**
	(4.20)	(2.96)	(2.99)	(2.54)
RDkurt_d	0.02	0.03*	0.04***	0.03**
	(1.63)	(1.92)	(2.96)	(2.45)
RDJ_d	−4.92***	−4.15***	−4.41***	−3.94***
	(-5.58)	(-4.01)	(-3.75)	(-2.87)
Control variables	Yes	Yes	Yes	Yes
Adj.R^2 (%)	0.32	0.53	0.81	1.30

results of Amaya et al. (2015). Moreover, the negative and significant estimate on *RDJ* is consistent with the finding of Bollerslev et al. (2020).

However, when we regress $CAR_{(t,t+n)}$ on all the realized measures, we find that the sign of estimated coefficient on *RDskew* shown in Model (5) changes from "negative" to "positive", while the estimates on *RDvar*, *RDkurt*, and *RDJ* retain their signs and significance. To control for other possible variables in predicting stock returns, we further perform multivariate tests. From Model (6) in each panel of Table 3, we observe that *RDvar* is always highly significant but *RDkurt* is almost insignificant. The estimated coefficient on *RDskew* retains its positive sign and its magnitude and significance level increase from $n = 5$ to $n = 20$. Finally, the estimate on *RDJ* is always negative and significant, and also increases from $n = 5$ to $n = 20$.

Again, take $n = 1$ for example, the estimated coefficient on *RDskew* in Model (2) being −0.22 (t-statistic = -2.62), changes to 1.14 (t-statistic = 5.31) in Model (5) and 0.60 (t-statistic = 2.64) in Model (6). These results are consistent with the findings of Bollerslev et al. (2020). Based on the significantly high correlation between *RDskew* and *RDJ*, Bollerslev et al. (2020) argue that one common component exists in *RDskew* and *RSJ*. Once this common component is controlled for, the predictability of *RDskew* on stock returns reverses. Bollerslev et al. (2020) provide a formal econometric rationale to show that the sign change of the estimate on *RDskew* may arise from the data.

At the same time, these results indicate that the predictability of *RDskew* is fragile. Brenner and Izhakian (2018) report a similar situation. In their study, when ambiguity is included in the regression tests that predict excess returns, the estimated coefficient on risk (measured by volatility) changes from insignificant (negative) to significant positive. The authors argue that this change probably arises from the higher correlation between risk and ambiguity.

Regarding control variables in the regressions, the majority have estimated coefficients that are statistically significant at conventional levels. For example, larger firms, high book-to-market values, and firms that experience high stock return momentum are related to smaller stock market responses. Firms with higher stock trading volumes and pre-announcement abnormal returns are also associated with weaker stock market responses.

Here, to further investigate the sign change of the estimated coefficient on *RDskew* when including *RDJ*, we conduct one more regression by including only *RDskew* and *RDJ*. We present the results in Model (7) of Table 3. Due to the high correlation between *RDskew* and *RDJ*, the multicollinearity might drive the switch of the sign on *RDskew*, which weakens the statistical power of the regression model.[13] However, we observe that the adjusted R^2 in the regression with both *RDskew* and *RDJ* is higher than that with *RDskew* as a sole predictor. For example, in the two-day announcement window (i.e., $n = 1$), the adjusted R^2 in Model (7) including

[13] We thank the reviewer for the comment and suggestion on this point.

Table 5

Regression results including unexpected earnings. This table presents the regression results for different earnings announcement windows including unexpected earnings. The dependent variable is CAR from day t to day $t+$ n, where t is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The standardized unexpected earnings (SUE) is computed as the difference between the actual earnings and the consensus earnings forecast, normalized by the firm's stock price at the end of the quarter. The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized t-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	1.18	4.17***	6.53***	10.03***
	(1.14)	(3.45)	(4.92)	(6.56)
RDvar (%)	4.89***	6.91***	7.63***	11.26***
	(3.33)	(4.37)	(4.78)	(7.66)
RDskew	0.61***	0.57**	0.69**	0.87**
	(2.71)	(2.15)	(2.29)	(2.53)
RDkurt	−0.01	−0.01	−0.02	−0.01
	(-0.60)	(-0.63)	(-0.60)	(-0.27)
RDJ	−2.22**	−2.17*	−2.66*	−3.32**
	(-2.17)	(-1.78)	(-1.94)	(-2.10)
SUE	0.06	0.07**	0.10**	0.02
	(1.47)	(2.13)	(2.57)	(0.47)
Log(Size)	−0.16	−0.45***	−0.70***	−1.70***
	(-1.40)	(-3.52)	(-4.91)	(-6.50)
Log(BM)	−1.22***	−1.03***	−1.03***	−1.03***
	(-10.41)	(-7.40)	(-6.79)	(-5.58)
MOM	−0.70***	−0.80***	−0.87***	−0.73***
	(-5.37)	(-4.70)	(-5.01)	(-3.37)
Volume (%)	−0.32***	−0.31***	−0.32***	−0.40***
	(-7.39)	(-6.54)	(-6.56)	(-7.32)
LagAR	−0.69***	−0.70***	−0.70***	−0.54***
	(-6.58)	(-5.30)	(-4.69)	(-3.46)
Adj.R^2 (%)	3.85	3.28	3.09	3.41

both *RDskew* and *RDJ* is 0.26%, but it is only 0.03% in Model (3) which includes only *RDskew*. We also observe similar patterns for the other announcement windows (i.e., $n = 5$, 10, and 20). Therefore, we argue that the sign change of the estimate on *RDskew* is not driven by the multicollinearity but rather by omitted variable bias.

We also note that Jiang and Zhu (2017) show that jump is positively related to future returns, supporting an investor underreaction hypothesis, but our results show that realized jump is negatively related to future returns, supporting an overreaction hypothesis. To reconcile these contrasting results, we distinguish our study from Jiang and Zhu (2017) in several respects. First, the samples are different, which might generate different results (e.g., Lee, 2012). We use stock constituents of the S&P 500 from 1998 to 2015, while Jiang and Zhu (2017) use stocks traded on the NYSE and Amex between 1995 and 2012. Therefore, the size and liquidity differ between stocks in our study and that in Jiang and Zhu (2017). Da et al. (2014) claim that short-term stock reversal exists among large stocks and liquidity provision contributes to the short-term return reversal (Avramov et al., 2006). Savor (2012) shows that stock prices can overreact if investors are paying less attention. Overall, these studies provide evidence on overreaction in the short run.

Second, jumps are measured in different ways between our studies. We define jumps as the difference between positive and negative semivariances, which have been extensively adopted in the previous literature (e.g., Bollerslev et al., 2020; Patton & Sheppard, 2015). However, Jiang and Zhu (2017) identify large discontinuous changes in stock prices as jumps and define the corresponding stock return as the jump measure. To further distinguish our realized jump from Jiang and Zhu's jump measure, we follow Jiang and Zhu (2017) to identify jumps within 78 intraday stock prices and obtain intraday cumulative jump returns (CJRs) by summing the 5-min returns with the jump. Next, we construct weekly CJR (i.e., wCJR) by averaging daily CJRs over the 5 trading days prior to earnings announcements and re-run regression equation (16) in which we replace our weekly realized jump (i.e., RDJ) using wCJR. Table A in Appendix presents the results.

In general, different from the estimate on RDJ in Table 3, the regression results show that the estimated coefficients on wCJR are almost positive for the univariate regression and multivariate regressions with firm characteristics and other variables shown in Eq. (16). These results are in line with the market underreaction hypothesis of Jiang and Zhu (2017). However, except that the estimate on wCJR in the univariate regression for $n = 10$ and $n = 20$ windows is statistically significant at 10% and 1% levels, respectively, it is insignificant for all other univariate and multivariate regressions. Interestingly, when wCJR is included in the regression models, the estimate on realized skewness (i.e., RDskew) basically becomes insignificant. These findings are in contrast to those using realized jump (i.e., RDJ). As such, we argue that our realized jump measure is meaningfully different from Jiang and Zhu's jump measure. Future work might usefully examine the differences between various jump measures in different models (e.g., Das, 2002; Das & Sundaram, 1999).

Finally, concerning event analysis, we use earnings announcement days as event dates and investigate the predictability of weekly

Table 6

Regression results including good and bad unexpected earnings. This table presents the regression results for different earnings announcement windows including unexpected earnings. The dependent variable is CAR from day *t* to day *t* + n, where *t* is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The standardized unexpected earnings (SUE) is computed as the difference between the actual earnings and the consensus earnings forecast, normalized by the firm's stock price at the end of the quarter. The positive unexpected earnings (SUE^+) is equal to SUE when SUE>0 and 0 otherwise, and the negative unexpected earnings (SUE^+) is equal to SUE when SUE<0 and 0 otherwise (Williams, 2015). The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized *t*-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	0.81	3.75***	6.17***	9.47***
	(0.77)	(3.10)	(4.64)	(6.19)
RDvar (%)	4.72***	6.71***	7.46***	10.99***
	(3.14)	(4.15)	(4.58)	(7.31)
RDskew	0.60***	0.56**	0.68**	0.87**
	(2.69)	(2.13)	(2.27)	(2.50)
RDkurt	−0.01	−0.02	−0.02	−0.01
	(-0.62)	(-0.65)	(-0.62)	(-0.28)
RDJ	−2.15**	−2.10*	−2.60*	−3.23**
	(-2.10)	(-1.72)	(-1.90)	(-2.04)
SUE^+	0.37**	0.41**	0.40**	0.48***
	(2.26)	(2.12)	(2.24)	(2.68)
SUE^-	0.03	0.03	0.06*	−0.03
	(0.91)	(1.17)	(1.84)	(-1.05)
Log(Size)	−0.12	−0.41***	−0.66***	−1.02***
	(-1.08)	(-3.20)	(-4.67)	(-6.18)
Log(BM)	−1.24***	−1.06***	−1.06***	−1.07***
	(-10.67)	(-7.62)	(-6.98)	(-5.83)
MOM	−0.01***	−0.01***	−0.01***	−0.01***
	(-5.62)	(-4.85)	(-5.18)	(-3.59)
Volume (%)	−0.33***	−0.33***	−0.33***	−0.41***
	(-7.62)	(-6.78)	(-6.76)	(-7.60)
LagAR	−0.71***	−0.72***	−0.72***	−0.57***
	(-6.77)	(-5.46)	(-4.82)	(-3.66)
Adj.R^2 (%)	4.17	3.56	3.27	3.71

average jumps prior to earnings announcements, while Jiang and Zhu (2017) define a day as an event date when a stock has jumps based on cumulative jump returns. To test that their results on jumps are not driven by earnings surprises, Jiang and Zhu (2017) exclude jumps occurring within a three-day or five-day window centered on earnings announcements. Overall, we define the event date in a different way.

For purposes of comparison, we also estimate the regression for the non-EA sample. We find that the magnitudes of estimated coefficients on corresponding realized measures are much smaller than those in the EA sample. Correspondingly, the adjusted R^2 also drops significantly.[14] To further test the difference of the estimated coefficients between the EA and non-EA samples, we run the regression for the full sample using the event dummy, *d*, which takes a value of 1 if the observation is included in the EA sample and zero otherwise. Specifically, in the regression model, we include the interaction terms of realized measures and the dummy variable (i.e., *RDvar_d*, *RDskew_d*, *RDkurt_d*, and *RDJ_d*). The estimated coefficients on these interaction terms reflect the additional impact of each realized measure on subsequent stock returns around earnings announcements. Table 4 reports the results. For simplicity, we only report the results for the full regression model including all realized measures and control variables. As expected, the estimated coefficients on the interaction terms are statistically significant, with the exception that the estimates on *RDvar_d* for $n = 1$ and $n = 10$ windows are marginally insignificant. Furthermore, the magnitudes of the estimated coefficients on *RDskew_d* and *RDJ_d* are much larger than those on *RDskew* and *RDJ,* respectively. Taken together, these results are consistent with the argument of Savor (2012) that information-based variables have stronger predictive power than those absent news information.

To test whether the relation between realized measures and subsequent stock returns is distinct from the market reaction to unexpected earnings, we repeat the regression in Eq. (16) by including the standardized unexpected earnings surprise (*SUE*). Table 5 reports the regression results. For all event windows ($n = 1$, 5, 10, and 20), we observe that the estimates on *RDvar*, *RDskew*, *RDkurt,* and *RDJ* retain similar magnitudes and significance levels compared with those in Model (6) of Table 3. Moreover, we find that while the estimated coefficient on *SUE* is statistically significant for the event windows with $n = 5$ and 10, it is insignificant for the event windows with $n = 1$ and 20. On the one hand, the positive estimated coefficient on *SUE* shows the post-earnings announcement drift documented in prior literature (Ball & Bartov, 1996; Bernard & Thomas, 1989; Foster et al., 1984). On the other hand, the results

[14] The results are not reported, but are available upon request.

Table 7

Robustness test: using drift-adjusted realized measures. This table presents the regression results using drift-adjusted realized measures for different earnings announcement windows. The dependent variable is CAR from day *t* to day *t* + n, where *t* is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly drift-adjusted realized measures (AdjRDvar, AdjRDskew, AdjRDkurt, and AdjRDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized *t*-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	1.18	4.15***	6.50***	10.12***
	(1.12)	(3.39)	(4.82)	(6.60)
AdjRDvar (%)	4.63***	6.60***	7.21***	11.20***
	(3.10)	(4.10)	(4.39)	(7.66)
AdjRDskew	0.70***	0.67***	0.75***	0.97***
	(3.24)	(2.59)	(2.59)	(2.83)
AdjRDkurt	−0.01	−0.02	−0.02	−0.01
	(-0.64)	(-0.67)	(-0.64)	(-0.35)
AdjRDJ	−2.74***	−2.68**	−3.00**	−3.85**
	(-2.88)	(-2.37)	(-2.34)	(-2.48)
Log(Size)	−0.16	−0.45***	−0.70***	−1.08***
	(-1.40)	(-3.49)	(-4.86)	(-6.54)
log(BM)	−1.24***	−1.06***	−1.06***	−1.03***
	(-10.59)	(-7.61)	(-7.01)	(-5.63)
MOM	−0.69***	−0.78***	−0.84***	−0.73***
	(-5.26)	(-4.59)	(-4.83)	(-3.36)
Volume (%)	−0.33***	−0.32***	−0.32***	−0.40***
	(-7.44)	(-6.60)	(-6.64)	(-7.35)
LagAR	−0.73***	−0.74***	−0.75***	−0.59***
	(-7.87)	(-6.42)	(-5.75)	(-4.25)
Adj.R^2 (%)	3.73	3.15	2.90	3.42

Table 8

Robustness test: using drift-adjusted realized moments and controlling unexpected earnings. This table presents the regression results for different earnings announcement windows including unexpected earnings. The dependent variable is CAR from day *t* to day *t* + n, where *t* is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly drift-adjusted realized measures (AdjRDvar, AdjRDskew, AdjRDkurt, and AdjRDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The standardized unexpected earnings (SUE) is computed as the difference between the actual earnings and the consensus earnings forecast, normalized by the firm's stock price at the end of the quarter. The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized *t*-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	1.26	4.25***	6.63***	10.15***
	(1.21)	(3.51)	(4.99)	(6.64)
AdjRDvar (%)	4.92***	6.94***	7.67***	11.30***
	(3.37)	(4.42)	(4.84)	(7.77)
AdjRDskew	0.72***	0.68***	0.78***	0.97***
	(3.31)	(2.67)	(2.68)	(2.84)
AdjRDkurt	−0.01	−0.02	−0.02	−0.01
	(-0.66)	(-0.69)	(-0.67)	(-0.35)
AdjRDJ	−2.87**	−2.84**	−3.20**	−3.89**
	(-3.02)	(-2.51)	(-2.51)	(-2.51)
SUE	0.06	0.07**	0.10***	0.02
	(1.48)	(2.14)	(2.58)	(0.47)
Log(Size)	−0.16	−0.46***	−0.71***	−1.08***
	(-1.48)	(-3.58)	(-4.99)	(-6.57)
Log(BM)	−1.21***	−1.03***	−1.03***	−1.02***
	(-10.40)	(-7.38)	(-6.78)	(-5.57)
MOM	−0.71***	−0.81***	−0.87***	−0.74***
	(-5.42)	(-6.55)	(-5.04)	(-3.39)
Volume (%)	−0.32***	−0.31***	−0.32***	−0.40***
	(-7.40)	(-6.55)	(-6.57)	(-7.33)
LagAR	−0.71***	−0.72***	−0.73***	−0.58***
	(-7.78)	(-6.25)	(-5.57)	(-4.21)
Adj.R^2 (%)	3.86	3.29	3.10	3.42

Table 9

Robustness test: using realized moments and excluding major price movements. This table presents the regression results for different earnings announcement windows by removing major price movements. The dependent variable is CAR from day t to day $t+$ n, where t is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The observations with extreme abnormal return on the event date (i.e., $|AR_{i,t}|>10\%$) are removed. The sample period is from January 1998 to December 2015, including 21,640 observations. The parenthesized t-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Model	n = 1	n = 5	n = 10	n = 20
Intercept	2.01***	4.54***	6.93***	10.58***
	(2.93)	(4.88)	(6.17)	(7.66)
RDvar (%)	0.82	2.62**	3.42**	7.40**
	(1.14)	(2.35)	(2.67)	(4.66)
RDskew	0.84***	0.84***	0.88***	1.06***
	(5.01)	(3.96)	(3.52)	(3.52)
RDkurt	−0.02	−0.02	−0.02	−0.01
	(-1.27)	(-0.89)	(-0.82)	(-0.36)
RDJ	−4.07***	−4.33***	−4.49***	−5.00***
	(-5.55)	(-5.54)	(-4.04)	(-3.60)
Log(Size)	−0.20***	−0.44***	−0.67***	−1.06***
	(-2.64)	(-4.33)	(-5.57)	(-7.11)
log(BM)	−0.67***	−0.46***	−0.38***	−0.42***
	(-8.01)	(-4.06)	(-2.96)	(-2.53)
MOM	−0.60***	−0.77***	−0.75***	−0.54***
	(-6.06)	(-5.71)	(-4.87)	(-2.61)
Volume (%)	−0.22***	−0.24***	−0.27***	−0.37***
	(-7.14)	(-5.88)	(-6.11)	(-6.67)
LagAR	−0.27***	−0.24**	−0.30***	−0.17***
	(-4.22)	(-2.57)	(-2.87)	(-1.18)
Adj.R^2 (%)	1.52	1.24	1.33	1.74

indicate that while *SUE* has predictive power on stock returns for some event windows, the estimated coefficients on realized measures retain their significance. These findings suggest that the predictability of realized measures is not affected by unexpected earnings; at the same time, earnings information is partly incorporated in pre-event realized measures, which is consistent with the findings of Diavatopoulos et al. (2012) using option implied measures.

We further identify unexpected earnings as good news or bad news and report the estimation results in Table 6. Comparing the results with those reported in Table 5, we observe that the estimated coefficients on realized measures continue to hold at similar magnitudes and significance levels for all event windows.

Taking $n=1$ for example, the coefficients on *RDvar*, *RDskew*, and *RDJ* are 4.72, 0.60 and −2.15 with t-statistics of 3.14, 2.69, and −2.10, respectively. We also observe that for all event windows, the cumulative abnormal stock return has a significantly positive coefficient on good earnings news (SUE^+) and an insignificant coefficient on bad earnings news (SUE^-) (with the exception of the $n=10$ event window). This indicates that the stocks in our sample present a significant post-earnings announcement drift for good earnings news, but not for bad earnings news, which is consistent with the findings of Defond and Zhang (2014). Summarizing Tables 5 and 6, we argue that while unexpected earnings impacts abnormal returns around earnings announcements, it does not affect the predictive power of realized measures, showing that the relation between realized measures and future stock returns continuously holds.

5. Additional analyses

5.1. Drift-adjusted realized measures

The construction of daily realized measures in Eq. (2) – (8) is based on the assumption that the high-frequency mean return converges to zero. Amaya et al. (2015) and Choi and Lee (2017) argue that the findings on realized moments may be contaminated if this assumption is violated. As such, we following their work to construct drift-adjusted realized measures and repeat our analysis in Section 4.3. We define daily realized measures adjusted for the drift as follows:

$$AdjDailyRDvar_{i,t} = \sum_{j=1}^{N}\left(r_{i,t,j} - \mu_{i,w(t),j}\right)^2, \tag{17}$$

$$AdjDailyRDskew_{i,t} = \frac{\sqrt{N}\sum_{j=1}^{N}\left(r_{i,t,j} - \mu_{i,w(t),j}\right)^3}{AdjDailyRDvar_{i,t}^{3/2}}, \tag{18}$$

Table 10

Robustness test: regression results for small and large firms. This table reports the regression results for different earnings announcement windows for small firms and large firms. The dependent variable is CAR from day t to day $t+\text{n}$, where t is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt, and RDJ) prior to earnings announcements. The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The sample period is from January 1998 to December 2015. The earnings announcement (EA) sample is separated into two subsamples: small firms (Panel A) and large firms (Panel B) having below- and above-median market capitalization, respectively. Each subsample includes 11,656 observations. The parenthesized t-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Panel A: Small firms

Model	n = 1		n = 5		n = 10		n = 20	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	−1.50	−0.94	1.82	2.39	3.61	4.17*	8.69***	8.99***
	(-0.80)	(-0.53)	(0.85)	(1.18)	(1.56)	(1.88)	(3.43)	(3.59)
RDvar (%)	5.90***	5.51***	7.48***	7.09***	8.20***	7.81***	12.47***	12.26***
	(3.16)	(3.84)	(3.65)	(4.29)	(4.02)	(4.65)	(8.16)	(8.73)
RDskew	1.23***	0.60*	1.09***	0.46	1.28***	0.65	1.50***	1.16**
	(3.57)	(1.69)	(2.71)	(1.09)	(2.82)	(1.36)	(2.85)	(2.11)
RDkurt	−0.01	−0.01	−0.00	−0.00	0.02	0.02	0.03	0.03
	(-0.25)	(-0.23)	(-0.11)	(-0.90)	(0.38)	(0.39)	(0.67)	(0.68)
RDJ	−6.84***	−1.92	−6.59**	−1.69	−7.32**	−2.41	−7.48**	−4.84*
	(-4.86)	(-1.24)	(-3.99)	(-0.90)	(-3.91)	(-1.13)	(-3.46)	(-1.97)
Log(Size)	0.13	0.06	−0.23***	−0.30***	−0.43	−0.50*	−1.03***	−1.06***
	(0.59)	(-0.30)	(-0.90)	(-1.23)	(-1.59)	(-1.91)	(-3.36)	(-3.52)
log(BM)	−1.61***	−1.67***	−1.37***	−1.42***	−1.31***	−1.36***	−1.25***	−1.28***
	(-8.05)	(-8.38)	(-5.78)	(-5.98)	(-5.10)	(-5.30)	(-4.01)	(-4.12)
MOM	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(-3.83)	(-4.04)	(-4.07)	(-4.23)	(-4.10)	(-4.22)	(-3.19)	(-3.23)
Volume (%)	−0.31***	−0.31***	−0.31***	−0.32***	−0.32***	−0.32***	−0.42***	−0.42***
	(-6.04)	(-6.10)	(-5.47)	(-5.52)	(-5.56)	(-5.60)	(-6.65)	(-6.66)
LagAR		−0.72***		−0.72***		−0.72***		−0.39*
		(-5.59)		(-4.17)		(-3.60)		(-1.88)
Adj.R^2 (%)	3.57	4.25	3.02	3.51	2.81	3.20	3.99	4.06

Panel B: Large firms

	n = 1		n = 5		n = 10		n = 20	
Model	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	6.49***	6.30***	10.22***	10.02***	12.98***	12.77***	16.84***	16.60***
	(3.99)	(3.87)	(5.29)	(5.21)	(6.02)	(5.95)	(6.46)	(6.39)
RDvar (%)	3.31**	3.60**	5.86***	6.15***	6.69***	6.99***	8.12***	8.48***
	(2.23)	(2.44)	(3.01)	(3.27)	(3.24)	(3.51)	(3.36)	(3.60)
RDskew	1.16***	0.69***	1.21***	0.73***	1.20***	0.71**	1.20***	0.63
	(5.03)	(2.86)	(4.49)	(2.58)	(3.88)	(2.20)	(3.31)	(1.63)
RDkurt	−0.01	−0.01	−0.02	−0.02	−0.04	−0.04	−0.04	−0.04
	(-0.34)	(-0.49)	(-0.70)	(-0.83)	(-1.13)	(-1.25)	(1.00)	(-1.12)
RDJ	−6.55***	−3.16***	−6.63**	−3.11**	−6.68**	−3.09**	−6.31**	−2.07
	(-6.89)	(-2.81)	(-5.86)	(-2.37)	(-5.29)	(-2.14)	(-4.14)	(-1.14)
Log(Size)	−0.64***	−0.62***	−0.99***	−0.97***	−1.24***	−1.22***	−1.64***	−1.61***
	(-3.89)	(-3.77)	(-5.12)	(-5.03)	(-5.74)	(-5.67)	(-6.32)	(-6.24)
log(BM)	−0.87***	−0.87***	−0.72***	−0.73***	−0.72***	−0.73***	−0.80***	−0.81***
	(-6.60)	(-6.72)	(-4.50)	(-4.58)	(-4.26)	(-4.33)	(-3.88)	(-3.96)
MOM	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01**	−0.01**
	(-4.35)	(-4.25)	(-2.96)	(-2.89)	(-3.79)	(-3.68)	(-2.53)	(-2.42)
Volume (%)	−0.41***	−0.42***	−0.37***	−0.38***	−0.39***	−0.40***	−0.38***	−0.39***
	(-4.89)	(-4.92)	(-4.24)	(-4.30)	(-4.39)	(-4.46)	(-3.44)	(-3.62)
LagAR		−0.62***		−0.64***		−0.66***		−0.77***
		(-5.06)		(-4.41)		(-4.30)		(-3.84)
Adj.R^2 (%)	2.71	3.22	2.22	2.62	2.19	2.53	1.83	2.06

$$AdjDailyRDkurt_{i,t} = \frac{N\sum_{j=1}^{N}\left(r_{i,t,j} - \mu_{i,w(t),j}\right)^4}{AdjDailyRDvar_{i,t}^2}, \tag{19}$$

where $\mu_{i,w(t),j}$ is the average return for stock i in the week ending at day t.

Accordingly, we compute the daily drift-adjusted semivariances and relative jump as

Table 11
Double sorting stocks on RDvar and RDJ. This table reports the mean differences of CAR (%) for portfolios from day t to day $t+$ n, where t is the earnings announcement date. The sample period is from January 1998 to December 2015, including 23,312 observations. Portfolios are formed by sorting stocks into five quintiles based on RDvar as well as on RDJ. RDvar and RDJ are the weekly realized variance and jump prior to earnings announcements, respectively. The highest (lowest) values are sorted into quintile Q5 (Q1). The values of t-statistics for mean differences are reported in parentheses. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

		n = 1	n = 5	n = 10	n = 20
Q1 (Low RDvar)	RDJ Q5-Q1	−0.36**	−0.43**	−0.32	−0.30
		(-2.29)	(-2.35)	(-1.58)	(-1.26)
Q2	RDJ Q5-Q1	−0.16	−0.17	−0.29	−0.18
		(-0.75)	(-0.67)	(-1.09)	(-0.58)
Q3	RDJ Q5-Q1	−0.56**	−0.70**	−0.64**	−0.39
		(-2.19)	(-2.44)	(2.01)	(-1.09)
Q4	RDJ Q5-Q1	−1.07***	−1.26***	−1.36***	−1.38***
		(-3.62)	(-3.58)	(3.49)	(-3.06)
Q5 (High RDvar)	RDJ Q5-Q1	−0.39	−0.28	−0.31	0.11
		(-0.88)	(-0.52)	(-0.51)	(0.17)

$$AdjDailyRDvar^{+}_{i,t} = \sum_{j=1}^{N} \left(r_{i,t,j} - \mu_{i,w(t),j} \right)^2 I\left(r_{i,t,j} > 0 \right) , \tag{20}$$

$$AdjDailyRDvar^{-}_{i,t} = \sum_{j=1}^{N} \left(r_{i,t,j} - \mu_{i,w(t),j} \right)^2 I\left(r_{i,t,j} < 0 \right) , \tag{21}$$

$$AdjDailyJ_{i,t} = AdjRDvar^{+}_{i,t} - AdjRDvar^{-}_{i,t}, \tag{22}$$

$$AdjDailyRDJ_{i,t} = \frac{AdjDailyJ_{i,t}}{AdjDailyRDvar_{i,t}}. \tag{23}$$

Similarly, we compute the weekly drift-adjusted realized measures ($AdjRDvar_{i,t}$, $AdjRDskew_{i,t}$, $AdjRDkurt_{i,t}$, and $AdjRDJ_{i,t}$) by averaging their corresponding daily values over the week ending at day t.

Table 7 presents the regression results using pre-announcement weekly drift-adjusted realized measures. Compared to those estimates in Model (6) in each panel of Table 3, we find that the significance level and magnitude of each drift-adjusted realized measure remain. Therefore, we argue that the relations between realized measures and subsequent stock returns are not contaminated even without satisfying the assumption of mean return converging to zero.

To further validate our findings, we run the regression on weekly drift-adjusted realized measures by including the unexpected earnings surprise. Table 8 reports the estimated results. In comparison with those estimates presented in Table 5, we observe that their magnitude and significance are even stronger for drift-adjusted realized variance, skewness and relative jump. At the same time, *SUE* retains similar magnitude and significance to that shown in Table 5. These findings further suggest that realized variance, skewness, and jump are robustly related to subsequent stock returns.

5.2. Excluding major price movements

Ball and Kothari (1991) document a sharp increase in abnormal returns on earnings announcement days.[15] Lee (2012) suggests that extreme stock price movements are realized more frequently around earnings announcements than in non-announcement periods, and Savor (2012) shows that major price shocks strongly predict stock returns. As such, our concern is whether our findings are driven by major price movements, especially on earnings announcement days. To reduce the effect of major price shocks, we remove observations with abnormal returns greater than 10% or less than −10% on earnings announcement days. After applying this filter, we exclude 1672 observations, which represents 7.17% of our sample observations.

Table 9 reports the regression results using the original realized measures after removing observations with extreme stock prices. We observe that except for the two-day event window ($n = 1$), the estimated coefficient on *RDvar* is statistically significant for other event windows ($n = 5$, 10, and 20). For *RDskew* and *RDJ*, their estimates display larger magnitudes and higher significance levels compared with those shown in Model (6) of Table 3. In summary, this provides evidence that realized measures have strong predictive power on cross-sectional stock returns.

5.3. Small and large firms

We further test whether our main results are driven by small firms. As large firms may disclose more information relative to small

[15] Bernard and Thomas (1989) also show that abnormal returns concentrate around earnings announcements.

firms, more uncertainties in relation to small firms are probably incorporated in their stock return moments especially around corporate news releases. Thus, we split our earnings announcement (EA) sample into two subsamples, i.e., a small firm sample and a large firm sample, which include firms having below- and above-median market capitalization, respectively.

Table 10 reports the results. Panel A is for small firms and Panel B is for large firms. Model (2) in the table includes all control variables considered in this study, while Model (1) excludes the lagged abnormal return, *LagAR*. Take the two-day window (i.e., $n = 1$) for example. In Model (1), the estimated coefficients on *RDvar*, *RDskew*, and *RDJ* are statistically significant for both small and large firms. The corresponding magnitudes of estimates are larger for small firms than large firms; in particular, the estimate on *RDvar* for small firms (with a coefficient of 5.90) nearly doubles that for large firms (with a coefficient of 3.31). In general, this is consistent with the idea that large firms have better information disclosure and less information asymmetry, so the effects of realized measures are stronger among small and illiquid stocks. However, when we turn to Model (2) that controls *LagAR*, for small firms in Panel A, the estimated coefficient on *RDvar* continues to hold its significance, but it is only marginally significant for *RDskew*, and the estimate on *RDJ* is not statistically significant anymore. In contrast, the corresponding estimates on realized measures for large firms retain their significance. These results suggest that for small firms, the lagged abnormal return plays a substantial role in predicting the post-earnings announcement returns. This might be driven by investor overreaction (Bollerslev et al., 2020; Kothari et al., 2006). Interestingly, when the post-event window includes more days, say $n = 20$, the significance of estimates on *RDskew* and *RDJ* recovers for small firms, but it disappears for large firms. Summarizing the above findings, we argue that the significance of the estimated coefficients is attributable to small (large) firms for longer (shorter) event windows.

5.4. Short-term friction, reversal or liquidity

In the preceding sections, we document that realized *RDvar*, *RDskew*, and *RDJ* strongly predict stock returns. Most notably, the estimated coefficients on *RDskew* and *RDJ* in the EA sample are statistically different from those in the non-EA sample, demonstrated in Table 4.

If the stock return predictability is driven by the overreaction to skewness or jumps induced by earnings announcements, we expect to observe that the predictive power of realized measures might be reduced as the forecasting horizon becomes longer, which ranges from 2 days ($n = 1$) to 21 days ($n = 20$) in our study. For the regression model (6) in Table 3, when we move from $n = 1$ to $n = 10$, the regression adjusted R^2 gradually decreases, being 3.72%, 3.14%, and 2.89%, respectively. As such, we argue that the predictability of realized measures is probably related to market friction or news announcement effects (Guo et al., 2019).

In addition, as documented in Section 5.3, the significance of the estimates on *RDskew* and *RDJ* is more sensitive to the lagged abnormal return (*LagAR*), especially for small firms in the post-event windows. The results suggest that realized skewness and jump have no predictive power for small firms for the post-earnings windows, with 1 day, 5 days or 10 days. The significance and magnitudes of estimates on *RDskew* and *RDJ* for large firms also reduce. Taken together, these findings indicate that the predictability of realized measures is closely associated with stock return short-term reversal.

Finally, we explore whether the predictability of realized measures is related to stock liquidity. As we note that the predictability of *RDskew* might be fragile, evidenced by its sign change in the univariate and multivariate regressions, we focus on *RDJ* to test how the predictability is linked to the information environment. Specifically, we sort stocks into quintiles based on *RDvar* as well as on *RDJ*.[16] For brevity, we report the mean difference of *CAR* between the high and low levels of *RDJ* in each *RDvar* quintile in Table 11.

Generally, stocks with higher volatility exhibit greater information asymmetry, and this might help explain the predictive power of *RDJ* and portfolio strategies based on *RDJ*. The results show that with the exception of the announcement windows of $n = 1$ and $n = 5$ at the lowest level of *RDvar*, the mean differences of *CAR* are statistically significant in the quintiles Q3 and Q4 of *RDvar* for almost all announcement windows. Furthermore, the magnitudes of the mean differences of *CAR* in the quintile Q4 are nearly double compared with those in the quintile Q3. We find no significant mean difference of *CAR* in the quintiles Q2 and Q5 of *RDvar* for all four event windows. In summary, we argue that the stock liquidity effect is not clearly presented in our sample, whereas these findings suggest that investors holding stocks with moderately high variance can achieve better performance using *RDJ* portfolio strategies.

6. Conclusions

This study examines the predictability of realized variance, skewness, kurtosis, and relative jump on stock returns around earnings announcements. These realized measures are computed using high-frequency intraday stock returns. The high-frequency financial data makes it possible to estimate stock return moments more accurately than low-frequency data. We provide evidence that realized variance, skewness, and relative jump strongly predict post-earnings announcement stock returns. Generally, realized kurtosis has no predictive power on stock returns for all regression models in our sample. These findings are robust for different earnings announcement windows and also robust for mean-adjusted realized measures.

We make several extensions to the prior literature. First, we examine the predictability of realized moment measures on stock returns around important corporate events. We find that the predictive power of these realized measures is much stronger for stock

[16] Following Bollerslev et al. (2020), we also form portfolios by sorting stocks by *Size* and *Volume* as well as *RDJ*, but we do not observe a significantly monotonic increase (decrease) of the mean difference of *CAR* between highest and lowest levels of *RDJ* for the *Size* and *Volume* quintiles. We conjecture this is probably because we study stocks from the S&P 500 index, which are mostly related to larger firms. Future research could extracts all stocks included in the CRSP database.

returns around corporate events than that without event information. Second, we address the call of Amaya et al. (2015) to make a comparison between realized skewness and realized semivariances. Rather than directly employing the positive- and negative-signed semivariances, we define a relative jump. After the relative jump is included, the estimate on realized skewness changes sign. This suggests realized skewness and relative jump may have one common component, consistent with the findings of prior literature on the unconditional relation between realized measures and subsequent stock returns. We also show that the performance of realized jump based portfolios is closely related to the stock's volatility level. Finally, our results demonstrate the post-earnings announcement drift effect, but the predictability of realized measures is not affected by unexpected earnings. That is, even if we control unexpected earnings in our regression models, the relation between realized measures and subsequent stock returns continues to hold.

Author statement

Qingxia Wang: Conceptualization, Methodology, Data, software, Analysis, Writing- Original draft, Revising.
Robert Faff: Conceptualization, Methodology, Analysis, Writing-Reviewing and Editing.
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Declarations of competing interest

None.

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Appendix. Regression results using the alternative jump measure

Table A

Alternative jump measure and cross-sectional stock returns. This table reports the cross-sectional regression of Eq. (16). The dependent variable is CAR from day t to day $t+n$, where t is the earnings announcement date, and n = 1, 5, 10, and 20 indicate different event windows, shown in Panels A, B, C and D, respectively. The independent variables include weekly realized measures (RDvar, RDskew, RDkurt) and weekly jump measure (wCJR) of Jiang and Zhu (2017) prior to earnings announcements. Weekly realized and jump measures are computed by averaging their corresponding daily values over the week prior to earnings announcements. CJR is the intraday cumulative jump returns by summing the 5-min returns with the jump (Jiang & Zhu, 2017). The control variables are log of market capitalization (Log(Size)), log of book-to-market ratio (Log(BM)), momentum (MOM), volume in the percentage of daily trading volume to total shares outstanding (Volume), and lagged weekly abnormal return (LagAR), computed by averaging daily abnormal returns over the week prior to earnings announcements. The sample period is from January 1998 to December 2015, including 23,312 observations. The parenthesized t-statistics are estimated using clustered standard errors adjusted for firm and calendar day. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

	Panel A: n = 1						Panel B: n = 5					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.11	0.33***	0.35***	0.24***	0.13	1.09	0.12	0.47***	0.52***	0.33***	0.16	4.15***
	(1.04)	(8.12)	(2.58)	(2.90)	(0.69)	(1.03)	(1.16)	(10.02)	(3.29)	(3.20)	(0.77)	(3.38)
RDvar (%)	3.97**				4.04*	4.39***	6.44***				6.66***	6.59***
	(2.02)				(1.90)	(2.76)	(3.28)				(3.16)	(3.88)
RDskew		−0.22***			−0.22*	0.10		−0.25***			−0.21	0.13
		(-2.62)			(-1.90)	(0.87)		(-2.46)			(-1.51)	(0.91)
RDkurt			−0.00		−0.00	−0.02			−0.01		−0.00	−0.01
			(-0.21)		(-0.05)	(-0.88)			(-0.36)		(-0.00)	(-0.51)
wCJR				39.87	−5.45	19.42				61.17	−18.30	−1.25
				(1.07)	(-0.17)	(0.69)				(1.43)	(-0.45)	(-0.03)
Log(Size)						−0.14						−0.45***
						(-1.29)						(-3.46)
Log(BM)						−1.23***						−1.06***
						(-10.55)						(-7.61)
MOM						−0.01***						−0.01***
						(-5.15)						(-4.55)
Volume (%)						−0.33***						−0.32***
						(-7.44)						(-6.60)
LagAR						−0.77***						−0.77***
						(-8.07)						(-6.64)

(continued on next page)

Table A (*continued*)

	Panel A: n = 1						Panel B: n = 5					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Adj.R^2 (%)	0.54	0.03	0.00	0.04	0.56	3.70	1.04	0.02	0.00	0.08	1.07	3.13
	Panel C: n = 10						Panel D: n = 20					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.20*	0.60***	0.66***	0.41***	0.26	6.47***	0.15	0.76***	0.76***	0.34***	0.23	9.85***
	(1.91)	(11.43)	(3.72)	(3.70)	(1.20)	(4.78)	(1.56)	(12.19)	(3.68)	(2.73)	(0.99)	(6.41)
RDvar (%)	7.32***				7.41***	7.12***	11.44***				10.76***	10.52***
	(3.76)				(3.56)	(4.14)	(7.04)				(5.96)	(6.70)
RDskew		−0.24**			−0.23	0.13		−0.10			−0.31*	0.02
		(-2.09)			(-1.52)	(0.80)		(-0.76)			(-1.72)	(0.12)
RDkurt			−0.01		−0.01	−0.02			−0.00		−0.03	−0.03
			(-0.39)		(-0.21)	(-0.57)			(-0.05)		(-0.73)	(-0.91)
wCJR				87.13*	−6.63	4.91				195.91***	60.72	57.32
				(1.71)	(-0.15)	(0.12)				(3.39)	(1.12)	(1.18)
Log(Size)						−0.69***						−1.04***
						(-4.78)						(-6.29)
Log(BM)						−1.06***						−1.01***
						(-6.96)						(-5.57)
MOM						−0.01***						−0.01***
						(-4.76)						(-3.22)
Volume (%)						−0.32***						−0.40***
						(-6.64)						(-7.36)
LagAR						−0.78***						−0.65***
						(-6.00)						(-4.63)
Adj.R^2 (%)	1.09	0.02	0.00	0.11	1.10	2.88	1.90	0.00	0.00	0.42	1.92	3.41

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