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Information Shocks and Short-Term Market Underreaction☆

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ABSTRACT

Using jumps in stock prices as a proxy for large information shocks, we provide evidence consistent with short-term underreaction in the US equity market. Strategies long (short) stocks with positive (negative) lagged jump returns earn significantly positive returns over the next one- to three-month horizons. The results based on intraday jumps, especially overnight jumps, provide further evidence consistent with underreaction. The underreaction is robust to controlling for other firm characteristics, extends stock return momentum over intermediate to short horizons, and captures market underreaction to information shocks beyond earnings surprises. We further show that limited investor attention contributes to short-term underreaction.

1. Introduction

The literature documents evidence of investor misreaction to information shocks, with an interesting pattern of overreaction over the long run but underreaction over the short run. De Bondt and Thaler (1985) are the first to document long-term reversals in stock returns. Specifically, stocks that performed poorly over the previous three to five years achieve higher returns over the next three- to five-year holding periods than stocks that performed well over the same period. Subsequently, De Bondt and Thaler (1987) and Chopra, Lakonishok, and Ritter (1992) document further evidence of long-run reversal patterns in stock returns and attribute such patterns to investor overreaction to information.

The evidence on underreaction in the short run is mostly based on specific corporate events. One well-documented phenomenon is the post-earnings announcement drift (PEAD) of Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), and Bernard and Thomas (1989, 1990), where firms reporting positive (negative) unexpected earnings, on average, experience positive (negative) abnormal returns for up to three quarters after earnings

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announcements. Several studies also document investor underreaction to other corporate events.[1]

However, in contrast to the reversal pattern for long-run stock returns documented by De Bondt and Thaler (1985), short-term stock returns exhibit a rather mixed cross-sectional pattern. The well-known study by Jegadeesh and Titman (1993) shows that, over intermediate horizons of three to 12 months, stocks with high past returns on average continue to outperform stocks with low past returns. The pattern is referred to as stock return momentum. On the other hand, Jegadeesh (1990) and Lehmann (1990) also show clear reversals in short-term stock returns (at monthly and weekly horizons). They show that contrarian strategies based on stock returns in the previous week or month generate significant abnormal returns. While Cooper (1999) suggests overreaction as a plausible cause, most studies attribute the short-term price reversal to liquidity or market microstructure effects such as bid-ask spreads (Jegadeesh and Titman, 1995; Avramov, Chordia, and Goyal, 2006; Gutierrez and Kelley, 2008). In addition, Savor (2012), Da, Liu, and Schaumburg (2013), and Hameed and Mian (2015) provide evidence that stock returns unrelated to firm fundamentals are more likely to reverse. The implication of these findings is that stock returns over short horizons are subject to both liquidity and information effects. Thus, one challenge in examining short-term market reactions to information shocks is to disentangle the liquidity effect from the information effect in short-term stock returns.

In this paper, we identify large discontinuous changes, known as jumps, in stock prices as a proxy for information shocks and examine short-term market reactions. The approach is general and has the following advantages. First, compared to studies based on specific corporate events, our approach relaxes requirements on event dates and, more importantly, is not restricted to publicly announced events.[2] Our study thus not only has enhanced statistical power but also provides evidence on investor reaction to information shocks beyond those contained in public events. Second, in our empirical analysis, jumps are identified from both daily and intraday stock returns and used to examine market reactions. This helps mitigate concerns about the accuracy of event dates or the actual time of information arrival.[3] Finally, not all corporate events and news reports contain unexpected information with respect to stock valuation. Jumps are infrequent large changes in stock prices. As argued by Fama (1991), large changes in stock prices during short event windows are dominated by information surprises. Relying on jumps thus helps sharpen our inference on market reactions to significant information shocks. Moreover, it helps focus on misreaction instead of delayed reaction to information that investors may have previously neglected.[4]

The main data used in our study include the Center for Research in Security Prices (CRSP) stock database for daily and monthly stock returns, the Trade and Quote (TAQ) database for intraday stock returns, the Compustat database for firm characteristics, and the Institutional Brokers Estimate System (IBES) database for analyst forecasts. Jumps in daily and intraday stock prices are identified using statistical procedures similar to those of Jiang and Oomen (2008) and Jiang and Yao (2013). With identified jumps, we examine market reactions to large information shocks over short horizons based on the relation between large information shocks, as measured by cumulative jump returns, and subsequent stock returns. The sample period is from July 1975 to December 2012. The intraday analysis is limited to the period from January 1995 to December 2012.

We provide evidence consistent with the interpretation of short-term underreaction in the US stock market. Specifically, when sorted on past one-month (three-month) cumulative jump returns, stocks in the top decile with positive information shocks outperform those in the bottom decile with negative information shocks by 1.25% and 0.61% (1.17% and 0.55%) in monthly returns over the next one- and three-month investment horizons, respectively. The spreads in monthly abnormal returns are, respectively, 0.81% and 0.36% (0.79% and 0.31%) based on the DGTW alpha (Daniel, Grinblatt, Titman, and Wermers, 1997) and 1.10% and 0.39% (0.91% and 0.16%) based on the four-factor alpha (Fama and French, 1992; Carhart, 1997). That is, strategies long stocks with lagged positive jump returns and short stocks with lagged negative jump returns earn significant abnormal returns. We show that the pattern is pervasive among stocks traded on the NYSE/Amex and Nasdaq, stocks of different sizes and liquidity levels, and robust to controlling for other firm characteristics.

The results based on jumps identified from intraday stock returns provide further evidence consistent with short-term market underreaction. We show that stocks with high intraday jump returns in the past one day earn higher returns than those with low intraday jump returns over the next one- and three-day investment horizons. In particular, overnight jumps have significant predictive power for subsequent stock returns. Since corporate news often arrives during the close of market, this finding helps strengthen the interpretation of a price jump as an information event. These results, together with those based on jumps in daily stock returns, extend the stock return

[1] Examples include share repurchase announcements (Ikenberry, Lakonishok, and Vermaelen, 1995), dividend initiations and omissions (Michaely, Thaler, and Womack, 1995), and stock split announcements (Ikenberry and Ramnath, 2002).

[2] Large changes in stock prices may be driven by private information in the form of, for example, informed order flows or inside trades. Thus, not all jumps are necessarily associated with public events, such as earnings announcements, stock split announcements, and analyst revisions.

[3] Several studies document that analyst revisions are often released concurrently with important firm-specific activities, including security issues or mergers and divestitures (Asquith, Mikhail, and Au, 2005). Studies also document evidence of analysts "tipping" their own firms before making their revisions public (Irvine, Lipson, and Puckett, 2007). Thus, the information content of revisions may be reflected in stock prices prior to announcements.

[4] An example of a commonly cited news report neglected by investors is provided by Huberman and Regev (2001). News about a new cancer-curing drug by EntreMed had been published in *Nature* and some newspapers with little notice. However, an article about this new drug published in *The New York Times* more than five months later attracted great public attention and generated daily returns of more than 300% for the stock.

momentum, as documented by Jegadeesh and Titman (1993), over intermediate horizons to short horizons.

While our results show that the market underreacts to large information shocks, one question is whether the market reacts differently to positive and negative jumps. The literature documents that investors react asymmetrically to good and bad news (e.g., Chan, 2003; Ivković and Jegadeesh, 2004; Kothari, Shu, and Wysocki, 2009). We form portfolios of stocks with positive jumps and stocks with negative jumps and evaluate the predictive power of these portfolios relative to stocks with no jumps. The results suggest that, over very short horizons, there is stronger underreaction to negative jumps than to positive jumps. In addition, motivated by the argument that investors underreact to earnings surprises because they fail to understand the implications of current earnings for future earnings (Rendleman, Jones, and Latané, 1987; Bernard and Thomas, 1990), we decompose post-jump stock returns into jump and non-jump components and examine the extent to which each component contributes to underreaction. Based on an event-time analysis, our results show that positive jumps are more persistent than negative jumps. In addition, we provide evidence consistent with typical underreaction, that is, investors initially underreact to news but gradually adjust their valuation in the same direction afterward. Nevertheless, our results also suggest that there is strong persistence in positive stock price jumps and yet investors fail to fully understand the implications of positive news for future positive news.

As noted earlier, the literature documents evidence of market underreaction to earnings surprises. One interesting question is to what extent the short-term underreaction documented in this study is driven by the earnings momentum effect and vice versa. We replicate our analysis by excluding jumps associated with earnings announcements and show that the short-term underreaction remains significant. That is, jumps in stock prices capture information shocks beyond earnings surprises. Similarly, we show that the earnings momentum effect remains significant after controlling for jumps in stock prices. However, we observe a much stronger drift following earnings announcements with jumps in stock prices. For instance, when stocks are sorted into deciles according to earnings surprises over the past quarter, the drifts following earnings announcements without concurrent jumps in stock prices are 0.34% and 0.37% in the next three and six months, respectively. Following earnings announcements with concurrent jumps in stock prices, the drifts are much stronger, at 0.96% and 0.66%, respectively.

Finally, several theoretical models have been developed to explain investor misreaction. Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011) argue that underreaction may be caused by a well-established psychological constraint, that is, limited investor attention. Under the limited attention hypothesis, investors likely pay more attention to information that is presented in a salient and easily processed form but underreact to information that is presented with some degree of ambiguity. We empirically test the limited investor attention hypothesis and provide evidence that limited investor attention contributes to the short-term underreaction documented in our study. Using the magnitude of jump returns and excess trading volume as measures of investor attention, we find significantly weaker underreaction to jumps of larger magnitude and jumps with higher excess trading volume.

The rest of the paper is structured as follows. Section 2 describes the data and the jump identification procedure. Section 3 presents the main empirical results, with further analysis in Section 4. Section 5 concludes the paper.

2. Data and methodology

2.1. Data

The stock sample in our main analysis includes all common stocks (SHRCD = 10 or 11) traded on the NYSE, Amex, and Nasdaq (EXCHED = 1, 2, or 3) in the CRSP stock database. Stock returns are adjusted for delistings to avoid survivorship bias, following Shumway (1997). The information on firm characteristics and earnings announcements is obtained from Compustat. The sample period is from July 1975 to December 2012. We also use analyst earnings forecasts from IBES and the data are from January 1983 to December 2012. In addition, we compute intraday stock returns based on consolidated trades in the TAQ database and identify intraday jumps. The sample period is from January 1995 to December 2012.

Firm characteristics in our analysis include size (SIZE), the book-to-market ratio (BM), momentum (MOM), the Amihud (2002) illiquidity measure (ILLIQ), idiosyncratic volatility (IVOL), and leverage (LEV). All the variables are constructed following convention in the literature (e.g., Fama and French, 2008) and are described as follows:

- SIZE: Natural log of market capitalization at the end of June of a year.
- BM: Natural log of the book-to-market ratio. The book value of equity is stockholders' equity plus balance sheet deferred taxes and investment tax credit (TXDITC, from Compustat), if available, minus the preferred stock liquidating value (PSTKL), if available, or the redemption value (PSTKRV), if available, or the carrying value (PSTK). Depending on availability, stockholders' equity is the Compustat variable SEQ, or CEQ + PSTK, or AT − LT, in that order. All Compustat items are measured for the fiscal year ending in calendar year $t-1$. The market value of equity is computed at the end of December of year $t-1$ with data from CRSP. We exclude firms with negative book values.
- MOM: Skip-one-month lagged 11-month buy-and-hold returns.
- ILLIQ: The ratio of the absolute daily stock return to the daily dollar trading volume, averaged over a given period. Since trading volume is defined differently for Nasdaq and NYSE/Amex stocks, the trading volumes of Nasdaq stocks are adjusted by a factor of 0.7 (Boehmer, 2005).
- IVOL: Standard deviation of the residuals in the Fama-French three-factor model estimated based on daily returns over a given time period.

- LEV: Ratio of the natural log of the ratio of book assets to market equity. Book assets are total assets (from Compustat) at the end of the month of the fiscal year ending in the previous calendar year.

Panel A of Table 1 reports the cross-sectional statistics of firm characteristics for selected years in our sample period. As expected, average firm size increases over time. The negative book-to-market ratio indicates that the book value is on average lower than the market value. The level of ILLIQ suggests lower market liquidity in 1990 than in other years in Table 1. Finally, IVOL is also higher in 1990 and 2000 than in other years in Table 1.

2.2. Jump test and identification

The literature has proposed a number of approaches to identify significant information events. For example, using earnings announcements, Ball and Brown (1968) examine the relation between earnings surprises and future stock returns. Chan (2003) uses firms' headlines as information events to examine stock returns following public news. Vega (2006) uses public news combined with private information-based trading to examine the effects of public and private information on PEAD. Tetlock (2010) uses news from the Dow Jones News Archive to examine how information environment changes for publicly traded US firms during news events.

In this study, we use large discontinuous changes, known as jumps, in stock prices as a proxy for significant information events. The idea of using large price changes as proxies for information events has been used in the literature (e.g., Conrad, Cornell, Landsman, and Rountree, 2006; Savor, 2012). Jumps are infrequent large changes in stock prices typically triggered by the arrival of unexpected information. Under a very general martingale process, stock price changes can be characterized as continuous changes in the form of diffusion or discontinuous changes in the form of jumps:

$$d\ln S_t = a_t dt + \sqrt{V_t} dW_t + J_t dq_t, \tag{1}$$

where S_t is the stock price at time t, a_t is the instantaneous drift, V_t is the instantaneous variance when there are no jumps, J_t represents jumps in asset prices, W_t is standard Brownian motion, and q_t is a counting process with finite instantaneous intensity λ_t. Various statistical tests have been proposed in the recent literature to detect jumps in asset prices.[5] In this paper, we employ the variance swap jump test proposed by Jiang and Oomen (2008). Specifically, applying Itô's lemma to Eq. (1) and then integrating over time, we have

$$2\int_0^T \left[\frac{dS_t}{S_t} - d\ln S_t\right] = V_{(0,T)} + 2\int_0^T (e^{J_t} - 1 - J_t) dq_t, \tag{2}$$

where $V_{(0,T)} = \int_0^T V_t dt$ is the integrated variance. Eq. (2) forms the basis of the jump test with the following intuition. In the absence of jumps, the difference between the simple return and the log return captures one-half of the instantaneous return variance (or the variance swap). The variance swap can therefore be perfectly replicated using the log contract (Neuberger, 1994). However, in the presence of jumps, the replication strategy is imperfect and the replication error can be used for the jump test. The test does not rely on any specific stock return model, since the process in Eq. (1) imposes no functional form restriction on the drift, the diffusion, or the jump components. In addition, simulations show that the variance swap jump test has good power in detecting infrequent but large changes in stock prices. This feature particularly suits the purpose of our study since we focus on significant information shocks.

In our main analysis, we apply the jump test to daily return observations for stocks in our sample. To avoid potential look-ahead bias in our empirical analysis, jumps are identified based on a three-month rolling window. Specifically, at the beginning of each month we test whether stock prices experienced jumps over the past three months. If the null hypothesis of no jumps is rejected, we then follow a sequential procedure to determine whether the price change on a particular day represents a jump. We also perform additional analysis based on jumps in intraday stock returns. Jump tests are performed daily using intraday five-minute trading-hour returns and overnight return. If the null hypothesis of no jumps is rejected, a similar sequential procedure is followed to determine whether the price change on an intraday time interval represents a jump. In both cases, we explicitly incorporate market microstructure noise in the jump test by allowing for serial correlations in stock returns induced by non-trading effects and bid-ask spreads. Jumps are identified at the 5% critical level. Details of the jump test and the jump identification procedure are included in Appendix A.

Panel B of Table 1 reports the cross-sectional statistics of daily jump returns (JR) as well as those of positive and negative daily jump returns (JR^+ and JR^-, respectively) for selected years in our sample period. The results show that jumps represent substantial changes in stock prices. The average daily positive jump return ranges from 9% to 18% in the four selected sample years, whereas the average daily negative jump return ranges from −14% to −7%. In addition, positive jumps occur more frequently than negative jumps for individual stocks. For the whole sample period, we identify an average of 4.5 jumps per stock-year, with a ratio of almost two-to-one for positive versus negative jumps.

In Panel C of Table 1, we decompose daily returns into overnight and trading-hour components. Daily returns are normally computed as close-to-close returns, whereas overnight return is computed from previous day's close to today's open and trading-hour return is computed from open to close. The purpose is to examine the extent to which daily price jumps are driven by overnight returns (r^{ON}) or trading-hour returns (r^{TH}). We first compute r^{TH} based on the open price from the TAQ database and the

[5] For instance, Barndorff-Nielsen and Shephard (2006) propose a bipower variation (BPV) measure to separate the jump variance and diffusive variance. Lee and Mykland (2008) exploit the properties of BPV and develop a rolling-based nonparametric test of jumps. Jiang and Oomen (2008) propose a jump test based on the idea of "variance swap" and explicitly take into account market microstructure noise. Aït-Sahalia and Jacod (2009) propose a family of statistical tests of jumps using the power variations of returns.

Table 1
Summary statistics of firm characteristics and jump returns

This table reports the summary statistics of firm characteristics and jump returns for selected years in our sample period. Panel A reports the summary statistics of the natural log of market capitalization (SIZE), the natural log of the book-to-market ratio (BM), momentum (MOM), the natural log of the ratio of book assets to market equity (LEV), the Amihud (2002) illiquidity ratio pre-multiplied by 1,000,000 (ILLIQ), and idiosyncratic volatility in percentage terms (IVOL). Panel B reports the summary statistics of daily jump returns (JR), positive daily jump returns (JR+), and negative daily jump returns (JR−). Panel C reports the decomposition of total daily returns into overnight and trading-hour returns for jump days and, for comparison purposes, non-jump days.

Panel A: Summary statistics of firm characteristics

Year	Variable	*N*	5%	25%	Mean	Median	75%	95%	St. dev.
1980	*SIZE*	3855	7.52	9.03	10.42	10.26	11.68	13.82	1.92
	BM	3425	−1.80	−0.62	−0.17	0.00	0.44	0.98	0.91
	MOM	4171	−0.35	−0.07	0.26	0.13	0.43	1.22	0.59
	LEV	3425	−1.03	0.09	0.67	0.74	1.34	2.15	1.02
	ILLIQ	2003	0.01	0.04	2.02	0.20	1.02	8.26	8.18
	IVOL	4670	1.07	1.71	2.77	2.44	3.38	5.78	1.53
1990	*SIZE*	4512	7.40	9.13	10.72	10.51	12.19	14.63	2.19
	BM	4061	−2.45	−1.12	−0.61	−0.47	0.04	0.75	0.99
	MOM	5305	−0.78	−0.46	−0.16	−0.20	0.03	0.59	0.50
	LEV	4061	−1.55	−0.41	0.24	0.30	0.89	1.91	1.05
	ILLIQ	3964	0.00	0.06	11.03	0.75	5.03	45.52	50.04
	IVOL	5669	1.15	2.21	4.33	3.49	5.36	10.30	3.41
2000	*SIZE*	5359	8.98	10.57	12.14	11.97	13.56	15.81	2.11
	BM	4806	−3.08	−1.65	−0.88	−0.70	−0.01	0.85	1.26
	MOM	5726	−0.91	−0.58	−0.08	−0.14	0.24	1.05	0.67
	LEV	4806	−2.53	−1.01	−0.12	0.04	0.83	1.87	1.35
	ILLIQ	5446	0.00	0.01	3.07	0.12	1.33	15.04	11.71
	IVOL	6271	1.85	3.04	5.44	4.80	7.23	10.97	3.06
2010	*SIZE*	3243	9.67	11.46	12.85	12.78	14.18	16.24	1.99
	BM	2996	−2.14	−1.10	−0.62	−0.55	−0.07	0.70	0.92
	MOM	3763	−0.41	−0.01	0.28	0.21	0.48	1.19	0.55
	LEV	2996	−1.38	−0.50	0.11	0.09	0.68	1.62	0.93
	ILLIQ	3786	0.00	0.00	3.78	0.01	0.20	18.07	20.96
	IVOL	3931	0.94	1.56	2.69	2.26	3.33	5.76	1.77

Panel B: Summary statistics of daily jump returns

Year	Variable	*N*	5%	25%	Mean	Median	75%	95%	St. dev.
1980	*JR*	22,640	−0.10	−0.03	0.04	0.05	0.09	0.19	0.10
	JR+	16,032	0.03	0.05	0.09	0.07	0.11	0.22	0.07
	JR−	6608	−0.16	−0.09	−0.07	−0.06	−0.04	−0.02	0.05
1990	*JR*	19,126	−0.18	−0.07	0.01	0.01	0.07	0.20	0.15
	JR+	9585	0.03	0.05	0.11	0.07	0.12	0.28	0.13
	JR−	9541	−0.25	−0.11	−0.10	−0.07	−0.05	−0.03	0.08
2000	*JR*	33,269	−0.24	−0.09	0.05	0.06	0.15	0.38	0.22
	JR+	20,075	0.04	0.08	0.18	0.13	0.22	0.47	0.18
	JR−	13,194	−0.33	−0.18	−0.14	−0.12	−0.07	−0.04	0.10
2010	*JR*	19,150	−0.14	−0.05	0.04	0.04	0.09	0.23	0.15
	JR+	12,764	0.03	0.04	0.10	0.07	0.11	0.28	0.13
	JR−	6386	−0.22	−0.11	−0.09	−0.07	−0.05	−0.03	0.07

Panel C: Decomposition of daily returns (Ret): Overnight and trading-hour

	Jump days		Non-jump days	
	Overnight	Trading-hour	Overnight	Trading-hour
C1: Percentage with the same sign as daily returns				
All Ret	82.08%	95.76%	64.19%	84.85%
Positive ret	82.28%	95.79%	65.57%	84.43%
Negative ret	81.72%	95.71%	62.78%	85.28%
C2: Contribution to log daily returns				
All ret	25.84%	74.16%	19.41%	80.59%
Positive ret	27.24%	72.76%	22.55%	77.45%
Negative ret	23.22%	76.78%	15.75%	84.25%

close price from the CRSP daily stock file. The overnight return is then calculated as $r^{ON} = (1+r)/(1+r^{TH}) - 1$, where r denotes daily stock returns and is adjusted for distributions. To compute overnight returns, we require the stock to have at least one transaction before 10:00a.m. The first subpanel reports the percentage of overnight returns and trading-hour returns that have the same sign as the daily returns. The second subpanel reports average ratios of $\ln(1+r^{ON})/\ln(1+r)$ and $\ln(1+r^{TH})/\ln(1+r)$. In this calculation, we exclude stocks with daily price changes less than or equal to two ticks so that the log daily returns are not almost zero. For comparison, we report these statistics for non-jump days as well.

The results show that, on jump days, the signs of both overnight and trading-hour returns are highly consistent with those of daily returns. There is greater consistency between overnight and trading-hour returns on jump days than on non-jump days. About 82% of overnight returns and 95% of trading-hour returns have the same sign as daily returns. That is, overnight returns are less likely reversed during trading hours on jump days. The results in the second subpanel show that trading-hour returns contribute more than 70% of daily returns on jump days. Nevertheless, compared to non-jump days, overnight returns contribute to a higher portion of daily returns on jump days. On average, overnight returns contribute about 19% of daily returns on non-jump days but about 26% on jump days. The patterns are consistent for days with positive returns and days with negative returns. This is evidence that relative to non-jump days, overnight returns appear to have more information content on jump days.

3. Main empirical analysis

3.1. Information shocks and short-term market underreaction

The main research question of our study is how the market reacts to large information shocks over the short run in the US stock market. To examine this question, at the beginning of each month we sort stocks into deciles based on their lagged cumulative jump returns (CJR) over the past one month and three months. These jumps are identified using only historical information to avoid potential look-ahead bias. Stocks with no jumps have zero cumulative jump returns. To be included in the sample, a stock must have at least ten (45) daily return observations when the ranking period is one month (three months). To mitigate the market microstructure effect, we exclude jumps identified on days with zero trading volume. Similar to Jegadeesh and Titman (1993), we calculate the average monthly returns and abnormal returns of each decile portfolio with one-, three-, six-, and 12-month investment horizons. We report both characteristic-adjusted abnormal returns (DGTW alpha) and the four-factor alpha (FF4 alpha).[6]

Table 2 reports the average returns, DGTW alphas, and FF4 alphas for each decile portfolio and the spreads between the top and bottom deciles (D10–D1), together with their time series *t*-statistics based on Newey and West (1987) standard errors that are adjusted for both heteroskedasticity and serial correlation in returns. The results are based on value-weighted portfolios. If the market is efficient, we expect no significant differences in abnormal returns between stocks with positive information shocks and those with negative information shocks. On the other hand, a significantly positive (negative) spread is evidence consistent with underreaction (overreaction), that is, higher (lower) abnormal returns following positive information shocks and lower (higher) abnormal returns following negative information shocks.

The results in Table 2 show that the spreads in raw returns, DGTW alphas, and FF4 alphas between the top and bottom deciles are positive for all combinations of ranking periods and investment horizons. For example, when the ranking period is one month, the spreads in monthly returns are 1.25%, 0.61%, 0.36%, and 0.31% over one-, three-, six-, and 12-month investment horizons, respectively. When the ranking period is three months, the spreads in monthly returns are 1.17%, 0.55%, 0.34%, and 0.36% over one-, three-, six-, and 12-month investment horizons, respectively. The significance levels of the spreads are higher for combinations of shorter ranking periods and investment horizons. When the ranking period is one month, the spreads in monthly DGTW alphas and FF4 alphas are both statistically significant at the 5% level for all investment horizons. However, when the ranking period is three months, the spreads in monthly DGTW alphas and FF4 alphas are only statistically significant at the 5% level over a one-month investment horizon. The results based on equal-weighted portfolios, not reported for brevity, show consistent and slightly stronger patterns. The spreads in DGTW alphas and FF4 alphas are both statistically significant at the 5% level over all investment horizons when the ranking period is one month and over one- to three-month investment horizons when the ranking period is three months.

The abnormal returns reported in Table 2 also show which side drives the spreads between the top and bottom deciles. For most combinations of ranking periods and investment horizons, the average abnormal returns of the top decile (D10) have a larger magnitude than those of the bottom decile (D1). For example, when both the ranking period and investment horizon are one month, the average monthly abnormal returns of D10 and D1 are 0.63% and -0.18% for DGTW alphas and 0.87% and -0.23% for FF4 alphas, respectively. That is, when information shocks are measured by jump returns over the past one month and three months, there appears to be a stronger underreaction to positive information shocks.

Fig. 1 plots the monthly returns to value-weighted hedge portfolios (D10–D1) formed on past one-month cumulative jump returns (CJR) with one-month investment horizon (Panel A) and three-month investment horizon (Panel B). The two time series have a mean of 1.25% and 0.61%, respectively, for the whole sample period. Overall, the percentages of positive returns are 67% and 66%,

[6] The DGTW benchmarks are obtained from Russ Wermers' website at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.html. The monthly factor data are obtained from Kenneth R. French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2
Information shocks and short-term underreaction
Each month, stocks are sorted into deciles based on lagged cumulative jump returns (CJR) over the past one month and three months. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. This table reports the average monthly return, DGTW alpha, and Fama-French four-factor alpha (all in percentage terms) of value-weighted portfolios with one-, three-, six-, and 12-month investment horizons. The spreads in the average return, DGTW alpha, and Fama-French four-factor alpha between the top and bottom deciles as well as the absolute values of their *t*-statistics are also reported. The sample period is from July 1975 to December 2012.

Deciles	Raw return				DGTW alpha				FF4 alpha			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Sort on CJR1M												
D1	0.70	0.88	0.93	0.96	−0.18	−0.08	−0.03	−0.01	−0.23	−0.05	−0.01	−0.01
D2	0.80	0.89	0.95	0.96	−0.15	−0.07	−0.04	−0.01	−0.15	−0.09	−0.08	−0.02
D3	0.83	0.93	1.00	1.00	−0.06	−0.06	−0.01	0.00	−0.16	−0.06	0.02	0.01
D4	0.88	0.93	0.96	0.97	−0.15	−0.04	−0.04	−0.04	−0.16	−0.08	−0.05	−0.03
D5	0.81	0.91	0.96	0.97	−0.09	−0.04	−0.02	0.00	−0.19	−0.10	−0.04	−0.02
D6	0.87	0.90	0.95	0.98	−0.03	−0.07	−0.03	−0.02	−0.14	−0.09	−0.03	0.01
D7	0.86	0.93	0.99	0.98	−0.13	−0.06	−0.03	−0.01	−0.10	−0.05	0.00	−0.02
D8	0.95	0.97	0.99	0.98	0.05	0.07	0.02	0.01	−0.06	−0.05	0.00	0.00
D9	1.37	1.21	1.08	1.04	0.32	0.16	0.10	0.05	0.29	0.17	0.04	0.02
D10	1.95	1.49	1.29	1.27	0.63	0.28	0.13	0.14	0.87	0.34	0.14	0.12
D10–D1	1.25	0.61	0.36	0.31	0.81	0.36	0.17	0.15	1.10	0.39	0.15	0.13
t−Stat	[6.20]	[4.44]	[3.19]	[3.50]	[5.26]	[3.63]	[2.34]	[3.00]	[5.77]	[3.25]	[2.12]	[2.03]
Sort on CJR3M												
D1	0.53	0.85	0.92	0.95	−0.38	−0.09	−0.06	−0.05	−0.39	−0.01	−0.02	−0.03
D2	0.76	0.92	0.96	1.01	−0.16	−0.04	−0.01	0.00	−0.22	−0.06	−0.02	0.01
D3	0.81	0.93	0.95	0.98	−0.04	−0.04	−0.01	0.01	−0.18	−0.07	−0.04	−0.01
D4	0.82	0.98	0.98	0.99	−0.23	−0.10	−0.05	−0.03	−0.15	−0.01	−0.01	−0.01
D5	0.89	0.94	0.95	0.96	−0.10	−0.04	0.01	0.00	−0.11	−0.05	−0.02	−0.01
D6	0.77	0.94	0.97	0.97	−0.10	−0.04	−0.05	−0.03	−0.24	−0.08	−0.02	−0.02
D7	0.99	0.98	1.02	1.03	0.16	0.06	0.02	−0.01	−0.08	−0.04	0.01	0.03
D8	1.34	1.13	1.08	1.04	0.32	0.12	0.07	0.05	0.29	0.09	0.03	0.01
D9	1.56	1.20	1.17	1.15	0.38	0.10	0.08	0.05	0.44	0.05	0.04	0.05
D10	1.69	1.39	1.25	1.30	0.41	0.22	0.12	0.13	0.52	0.15	0.03	0.03
D10–D1	1.17	0.55	0.34	0.36	0.79	0.31	0.17	0.17	0.91	0.16	0.05	0.06
t-Stat	[5.54]	[2.82]	[2.05]	[2.26]	[4.76]	[1.94]	[1.55]	[1.85]	[4.61]	[0.97]	[0.62]	[0.06]

respectively, for the two series. That is, the hedge portfolios yield a high percentage of positive returns. The plot shows that monthly returns to hedge portfolios behave differently during the first- and second-half sub-periods. We perform further analysis separately for each of the sub-periods. During the first- and second-half sub-periods, the means of hedge portfolio returns (absolute value of *t*-stat) are, respectively, 1.18% (6.40) and 1.33% (3.89) over one-month investment horizon and 0.64% (5.11) and 0.57% (2.19) over three-month investment horizon. These numbers confirm that the results are significant in both the first- and second-half sub-periods.

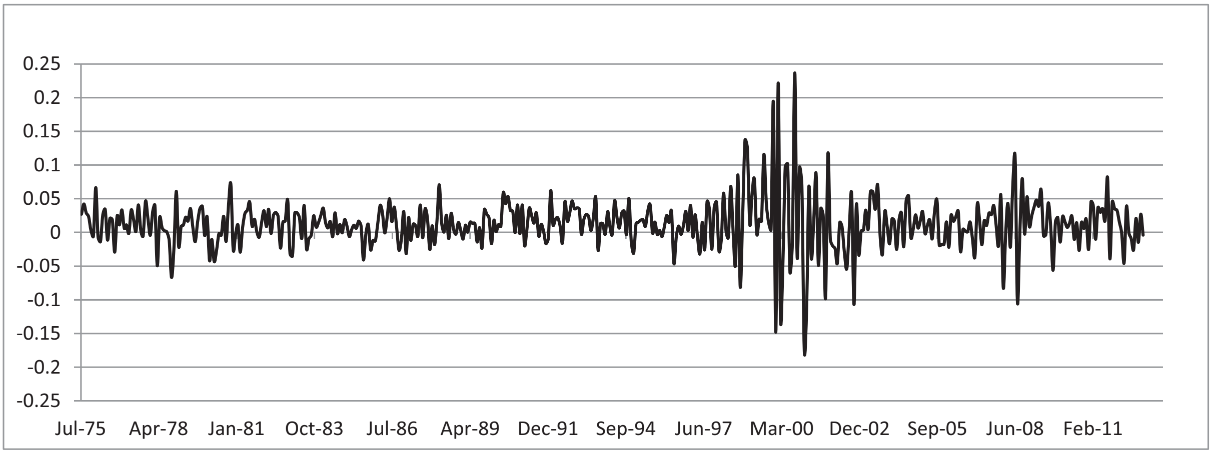
The results in Table 2 provide evidence consistent with the interpretation of short-term market underreaction to large information shocks. Since all decile portfolios are formed based on past jump returns, the results also have direct implications for trading strategies. Specifically, strategies that long stocks with lagged positive jump returns and short stocks with lagged negative jump returns earn significant abnormal returns.

3.2. Subsample results based on stock exchange, size, and illiquidity

In this section, we perform robustness checks of our main findings presented in the previous section. Since stocks traded on the NYSE/Amex are generally larger and more liquid than those traded on the Nasdaq, we perform robustness checks for stocks traded on the NYSE/Amex and Nasdaq separately. At the beginning of each month, we divide stocks into two subsamples based on whether they are traded on the NYSE/Amex or Nasdaq. Stocks in each subsample are then sorted into deciles based on their lagged cumulative jump returns (CJR) over the past one month and three months.

The results are reported in Table 3 and are based on value-weighted portfolios. Decile D1 consists of stocks with the lowest CJR, D10 consists of stocks with the highest CJR, and D2 to D9 are not reported for brevity. The results in Table 3 show that, for both the NYSE/Amex and Nasdaq subsamples, the spreads in monthly raw returns between the top and bottom deciles are positive for all combinations of ranking periods and investment horizons. For example, when the ranking period is one month, the spreads in monthly returns are 1.18%, 0.53%, 0.30%, and 0.29% for NYSE/Amex stocks and 1.32%, 0.83%, 0.44%, 0.38% for Nasdaq stocks over one-, three-, six-, and 12-month investment horizons, respectively. In comparison, the results are slightly stronger for Nasdaq stocks. When the ranking period is one month, the spreads in DGTW alphas and FF4 alphas are both significantly positive at the 5% level over one- to three-month horizons for NYSE/Amex stocks but all horizons for Nasdaq stocks. When the ranking period is three months, the spreads in DGTW alphas and FF4 alphas are both significantly positive over one-month horizon for NYSE/Amex stocks but over one- to three-month horizons

Panel A: Monthly hedge portfolio (D10–D1) returns with a one-month investment horizon



Panel B: Monthly hedge portfolio (D10–D1) returns with a three-month investment horizon

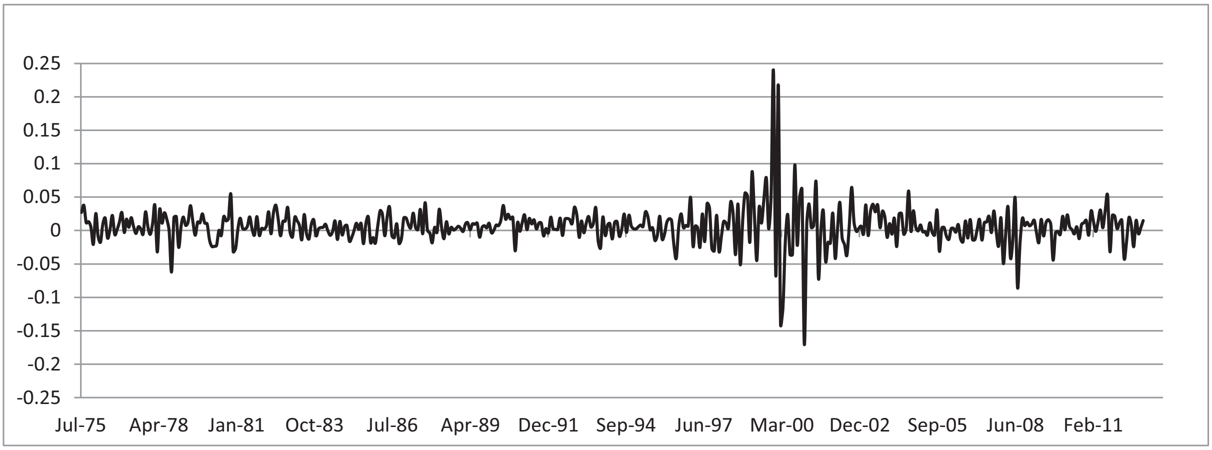


Fig. 1. Time series plots of hedge portfolio returns. Each month, stocks are sorted into deciles based on lagged cumulative jump returns (CJR) over the past one month. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. This figure plots the monthly returns of value-weighted hedge portfolios (D10–D1) with one-month investment horizon (Panel A) and three-month investment horizon (Panel B).

for Nasdaq stocks. The results in Table 3 show that, while the short-term underreaction is stronger for stocks traded on Nasdaq, the findings in Table 2 are robust for stocks traded on both the NYSE/Amex and Nasdaq.

In addition, we examine whether the results documented in Table 2 for the entire stock sample are pervasive among stocks of different size. Since jumps may be caused by liquidity shocks, we also examine whether the results are robust among stocks of different liquidity levels. At the beginning of each month, we divide stocks into three subsamples based on size and the Amihud illiquidity measure (ILLIQ), respectively. As in Fama and French (2008), we use the 20th and 50th percentiles of the market cap for NYSE stocks computed at the end of each June as the breakpoints for the size subsamples. We use the 33rd and 66th percentiles of ILLIQ for NYSE stocks computed at the end of previous quarter as the breakpoints for the ILLIQ subsamples. Stocks in each size or ILLIQ subsample are sorted into deciles based on their lagged cumulative jump returns (CJR) over the past one month and three months.

The results are reported in Table 4 for size subsamples in Panel A and ILLIQ subsamples in Panel B. The results are based on value-weighted portfolios. The results in Panel A show that, for all three size subsamples, the spreads in monthly raw returns between the top and bottom deciles are significantly positive for all combinations of ranking periods and investment horizons. For example, when the ranking period is one month, the monthly spreads in raw returns are 1.28%, 0.62%, 0.33%, and 0.27% for large-cap stocks; 1.31%, 0.82%, 0.50%, 0.36% for small stocks; and 1.39%, 0.92%, 0.64%, and 0.41% for microcaps over one-, three-, six-, and 12-month investment horizons, respectively. Overall, the results are stronger for small stocks and particularly microcaps. When the ranking period is one month, the spreads in DGTW alphas and FF4 alphas are both significantly positive at the 5% level over all horizons for all size groups. When the ranking period is three months, the spreads in DGTW alphas and FF4 alphas are both significantly positive over one-month horizon for large-cap stocks, over one- and three-month horizons for

Table 3
Robustness check: subsample results based on stock exchanges
Each month, stocks are divided into two subsamples: those traded on the NYSE/Amex and those traded on the Nasdaq. Within each subsample, stocks are sorted into deciles based on lagged cumulative jump returns (CJR) over the past one month and three months. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. This table reports the average monthly return (in percentage terms) of portfolios with one-, three-, six-, and 12-month investment horizons. The spreads in the average return, DGTW alpha, and Fama-French four-factor alpha between the top and bottom deciles as well as the absolute values of their *t*-statistics are also reported. The results are based on value-weighted portfolios. The sample period is from July 1975 to December 2012.

Deciles	NYSE/Amex				Nasdaq			
	1M	3M	6M	12M	1M	3M	6M	12M
Sort on CJR1M								
D1	0.68	0.90	0.95	0.95	0.71	0.86	0.96	1.04
D10	1.87	1.43	1.25	1.24	2.03	1.69	1.39	1.41
D10–D1	1.18	0.53	0.30	0.29	1.32	0.83	0.44	0.38
t-Stat	[6.06]	[4.56]	[3.41]	[4.34]	[5.46]	[4.87]	[3.67]	[4.17]
DGTW alpha	0.84	0.34	0.16	0.11	0.92	0.63	0.30	0.24
t-Stat	[5.36]	[3.86]	[2.64]	[2.76]	[3.52]	[3.81]	[2.44]	[2.62]
FF4 alpha	1.08	0.31	0.09	0.10	1.04	0.59	0.21	0.20
t-Stat	[5.43]	[2.93]	[1.10]	[1.85]	[4.54]	[4.20]	[2.10]	[2.80]
Sort on CJR3M								
D1	0.55	0.88	0.94	0.90	0.37	0.76	0.89	1.04
D10	1.52	1.28	1.22	1.25	1.96	1.53	1.36	1.37
D10–D1	0.97	0.39	0.27	0.35	1.58	0.77	0.47	0.34
t-Stat	[5.03]	[2.42]	[2.06]	[3.12]	[6.11]	[3.70]	[2.69]	[2.34]
DGTW alpha	0.64	0.17	0.08	0.11	1.26	0.55	0.21	0.08
t-Stat	[4.14]	[1.30]	[0.82]	[1.54]	[4.53]	[2.36]	[1.11]	[0.55]
FF4 alpha	0.71	0.00	−0.15	−0.01	1.17	0.38	0.08	0.03
t-Stat	[3.79]	[0.02]	[1.41]	[0.09]	[4.73]	[2.00]	[0.56]	[0.30]

small stocks, and over one- to six-month horizons for microcaps.

Similarly, the results in Panel B of Table 4 show that, for all three ILLIQ subsamples, the spreads in monthly raw returns between the top and bottom deciles are significantly positive for all combinations of ranking periods and investment horizons. The results are slightly stronger for illiquid stocks. When the ranking period is one month, the spreads in DGTW alphas and FF4 alphas are both significantly positive at the 5% level over all horizons for all three ILLIQ subsamples. When the ranking period is three months, the spreads in DGTW alphas and FF4 alphas are both significantly positive over one-month horizon for low and medium ILLIQ stocks and over one- and three-month horizons for high ILLIQ stocks. Overall, the results in Table 4 confirm that the evidence of short-term underreaction is pervasive among stocks of different sizes and liquidity levels.

3.3. Further evidence based on intraday stock price jumps

The results in previous subsections show that stocks with positive jump returns over the past one month and three months outperform those with negative jump returns in subsequent months. This finding extends the stock return momentum, as documented by Jegadeesh and Titman (1993), over intermediate horizons of 6 to 12 months to short horizons of one to three months. In this section, we perform further analysis based on jumps in intraday stock returns and examine market reactions to information shocks over even shorter horizons. Intraday stock returns are obtained from the TAQ database based on the consolidated trades that contain the prices of all transactions between 9:30 a.m. and 4:00 p.m. with a time stamp up to the second. To mitigate concerns related to market microstructure effects, we focus our analysis on common stocks traded on the NYSE and Amex in the CRSP database. The sample period is from January 1995 to December 2012.

We apply the standard filters used in the literature (e.g., Barndorff-Nielsen, Hansen, Lunde, and Shephard, 2009; Bollerslev, Li, and Todorov, 2016) to process the TAQ data. For instance, we exclude trades that are reported outside the normal trading hours of 9:30 a.m. to 4:00 p.m. and trades with a transaction size less than or equal to zero. To further alleviate concerns of market microstructure effects, we also exclude inactive trading days when the database contains less than one trade per hour for a given stock. Based on transaction prices, we compute five-minute returns during trading hours from 9:35 a.m. to 4:00 p.m. In our jump test, we include overnight return as one of the intraday return observations. To compute overnight returns, we require the stock to have at least one transaction before 10:00 a.m. The sample consists of 1583 firms per year, on average, in our sample period. For the whole sample period, on average, a stock has 19 trading days per year with identified intraday jumps.

Similar to the analysis based on jumps in daily returns, each day we sort stocks into deciles based on intraday cumulative jump returns (CJR) over the past one day and three days. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. Table 5 reports the average daily returns and FF4 alphas (in percentage terms) of value-weighted portfolios over the next one-, three-, five-, and ten-day horizons. The spreads in the average daily return and FF4 alpha between the top and bottom deciles as well as the absolute values of Newey-West

Table 4

Robustness check: subsample results based on size and illiquidity

Each month, stocks are divided into three subsamples based on size and Amihud illiquidity (ILLIQ). The breakpoints of size are the 20th and 50th percentiles of the market cap and the breakpoints of ILLIQ are the 33rd and 66th percentiles of ILLIQ of NYSE stocks. Within each size or ILLIQ subsample, stocks are sorted into deciles based on lagged cumulative jump returns (CJR) over the past one month and three months. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. This table reports the average monthly return (in percentage terms) of portfolios with one-, three-, six-, and 12-month investment horizons. The spreads in the average return, DGTW alpha, and Fama-French four-factor alpha between the top and bottom deciles as well as the absolute values of their *t*-statistics are also reported. The results are based on value-weighted portfolios. The sample period is from July 1975 to December 2012.

Panel A: Subsample results based on size

Deciles	Large-cap stocks				Small stocks				Microcaps			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Sort on CJR1M												
D1	0.62	0.83	0.93	0.95	0.94	0.96	1.02	1.07	1.12	0.94	0.93	1.06
D10	1.90	1.45	1.26	1.22	2.25	1.78	1.52	1.44	2.51	1.86	1.57	1.47
D10–D1	1.28	0.62	0.33	0.27	1.31	0.82	0.50	0.36	1.39	0.92	0.64	0.41
t-Stat	[6.24]	[4.41]	[3.64]	[3.88]	[6.28]	[5.14]	[4.00]	[3.42]	[6.04]	[5.31]	[4.35]	[3.60]
DGTW alpha	0.88	0.35	0.16	0.12	0.97	0.60	0.33	0.20	1.09	0.80	0.52	0.29
t-Stat	[5.57]	[3.42]	[2.69]	[2.78]	[4.19]	[3.73]	[3.70]	[2.86]	[4.51]	[4.18]	[3.47]	[2.97]
FF4 alpha	1.20	0.46	0.17	0.13	1.24	0.66	0.30	0.19	1.20	0.67	0.42	0.24
t-Stat	[6.12]	[4.08]	[2.17]	[2.49]	[6.01]	[4.86]	[3.31]	[2.75]	[5.36]	[4.54]	[3.60]	[3.08]
Sort on CJR3M												
D1	0.47	0.83	0.93	0.94	0.53	0.84	0.92	1.00	0.57	0.66	0.71	0.93
D10	1.49	1.23	1.14	1.19	1.88	1.48	1.37	1.36	1.83	1.48	1.36	1.36
D10–D1	1.02	0.40	0.21	0.25	1.35	0.64	0.45	0.37	1.26	0.82	0.65	0.43
t-Stat	[5.50]	[2.48]	[1.56]	[2.01]	[5.81]	[3.52]	[2.82]	[2.73]	[5.51]	[4.60]	[4.39]	[3.41]
DGTW alpha	0.68	0.20	0.09	0.10	1.10	0.46	0.24	0.15	1.05	0.75	0.51	0.24
t-Stat	[4.36]	[1.67]	[0.90]	[1.32]	[5.17]	[2.94]	[1.99]	[1.77]	[5.05]	[4.07]	[3.49]	[2.19]
FF4 alpha	0.80	0.09	−0.13	−0.02	1.10	0.30	0.09	0.09	0.89	0.44	0.30	0.17
t-Stat	[4.72]	[0.62]	[1.17]	[0.25]	[5.30]	[2.08]	[0.78]	[1.09]	[4.49]	[3.14]	[2.68]	[1.95]

Panel B: Subsample results based on illiquidity

Decile	Low ILLIQ				Medium ILLIQ				High ILLIQ			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Sort on CJR1M												
D1	0.64	0.84	0.89	0.92	0.89	0.95	1.03	1.05	0.95	0.90	0.90	1.01
D10	1.80	1.40	1.23	1.18	2.02	1.67	1.42	1.37	2.21	1.76	1.57	1.48
D10–D1	1.16	0.57	0.34	0.26	1.13	0.71	0.39	0.32	1.26	0.87	0.67	0.47
t-Stat	[5.93]	[5.13]	[3.37]	[2.94]	[5.89]	[5.33]	[3.70]	[3.56]	[6.12]	[5.54]	[4.63]	[3.76]
DGTW alpha	0.82	0.37	0.17	0.12	0.88	0.48	0.23	0.15	0.91	0.55	0.36	0.21
t-Stat	[5.61]	[4.63]	[2.54]	[2.48]	[4.91]	[4.39]	[3.25]	[2.86]	[4.56]	[3.89]	[3.21]	[2.80]
FF4 alpha	1.09	0.43	0.20	0.14	1.01	0.55	0.20	0.15	1.18	0.68	0.46	0.30
t-Stat	[5.94]	[4.23]	[2.27]	[2.14]	[5.95]	[4.76]	[2.60]	[2.55]	[5.89]	[5.25]	[4.39]	[3.65]
Sort on CJR3M												
D1	0.47	0.82	0.90	0.90	0.66	0.91	0.99	1.04	0.58	0.80	0.86	1.01
D10	1.54	1.22	1.15	1.18	1.68	1.38	1.31	1.32	1.79	1.51	1.40	1.40
D10–D1	1.07	0.40	0.25	0.28	1.02	0.47	0.32	0.28	1.21	0.71	0.54	0.39
t-Stat	[5.96]	[2.46]	[2.03]	[2.46]	[4.81]	[2.50]	[2.23]	[2.11]	[5.91]	[4.05]	[3.32]	[2.75]
DGTW alpha	0.70	0.22	0.12	0.12	0.80	0.23	0.09	0.06	1.04	0.63	0.38	0.19
t-Stat	[4.62]	[1.72]	[1.18]	[1.69]	[4.56]	[1.58]	[0.78]	[0.76]	[5.73]	[3.81]	[2.68]	[1.82]
FF4 alpha	0.84	0.09	0.09	0.07	0.74	0.15	0.11	0.09	0.95	0.38	0.31	0.26
t-Stat	[4.82]	[0.65]	[0.80]	[0.27]	[3.88]	[0.96]	[0.46]	[0.09]	[5.22]	[2.63]	[1.36]	[1.09]

t-statistics are also reported. The results show that intraday jump returns over the past one day have predictive power for subsequent stock returns over one-day horizon and up to three-day horizon, whereas jump returns over the past three days have predictive power for subsequent stock returns over one-day horizon. Sorted on past one-day cumulative jump returns, stocks in the top decile outperform those in the bottom decile by 0.051% and 0.012% over the next one-day and three-day horizons, respectively. Both differences are statistically significant at the 5% level. The spreads in FF4 alphas are of similar magnitude but only significant at the 5% level over one-day horizon.

As noted earlier, the information content in overnight returns may be different on jump days. The results in Panel C of Table 1 show that, compared to non-jump days, overnight returns on jump days contribute a higher proportion to total daily returns. Motivated by this observation, we further examine separately the predictive power

Table 5
Short-term underreaction: evidence based on intraday jumps

Each day, stocks are sorted into deciles based on intraday cumulative jump returns (CJR) over the previous one day and three days. Decile D1 consists of stocks with the lowest CJR and D10 consists of stocks with the highest CJR. This table reports the average daily return and Fama-French four-factor alpha (in percentage terms) of portfolios over the next one-, three-, five-, and ten-day horizons. The spreads in the average daily return and Fama-French four-factor alpha between the top and bottom deciles as well as the absolute values of their *t*-statistics are also reported. The results are based on value-weighted portfolios. The sample period is from January 1995 to December 2012.

Deciles	Raw return				FF4 alpha			
	1D	3D	5D	10D	1D	3D	5D	10D
Sort on CJR1D								
D1	0.012	0.034	0.041	0.042	−0.031	−0.010	−0.003	−0.002
D2	0.029	0.043	0.044	0.042	−0.014	0.001	0.001	0.000
D3	0.039	0.045	0.045	0.045	−0.003	0.003	0.004	0.003
D4	0.046	0.040	0.038	0.042	0.005	−0.002	−0.004	0.000
D5	0.053	0.041	0.040	0.039	0.010	−0.001	−0.001	−0.003
D6	0.047	0.048	0.045	0.044	0.005	0.006	0.003	0.001
D7	0.045	0.038	0.039	0.041	0.003	−0.004	−0.003	−0.001
D8	0.047	0.046	0.042	0.041	0.006	0.004	0.000	−0.001
D9	0.045	0.040	0.043	0.041	0.002	−0.003	0.000	−0.001
D10	0.063	0.046	0.044	0.041	0.020	0.002	0.000	−0.004
D10–D1	0.051	0.012	0.003	−0.001	0.051	0.012	0.002	−0.002
t-Stat	[4.52]	[2.05]	[0.73]	[0.37]	[4.50]	[1.88]	[0.50]	[0.64]
Sort on CJR3D								
D1	0.024	0.041	0.044	0.044	−0.021	−0.004	0.000	0.000
D2	0.048	0.046	0.046	0.044	0.006	0.004	0.004	0.002
D3	0.047	0.049	0.048	0.045	0.004	0.007	0.006	0.003
D4	0.033	0.041	0.041	0.041	−0.009	0.000	0.000	0.000
D5	0.045	0.044	0.038	0.040	0.004	0.002	−0.004	−0.002
D6	0.041	0.044	0.044	0.041	−0.001	0.003	0.002	0.000
D7	0.044	0.040	0.040	0.039	0.003	−0.001	−0.001	−0.003
D8	0.044	0.039	0.039	0.040	0.003	−0.003	−0.003	−0.002
D9	0.043	0.036	0.038	0.038	−0.001	−0.007	−0.005	−0.005
D10	0.055	0.043	0.041	0.040	0.009	−0.003	−0.006	−0.008
D10–D1	0.031	0.003	−0.003	−0.005	0.029	0.001	−0.006	−0.008
t-Stat	[4.12]	[0.30]	[0.34]	[0.64]	[3.08]	[0.11]	[0.61]	[1.13]

of overnight and trading-hour jump returns. Each day, we sort stocks into deciles separately based on overnight cumulative jump returns (ONCJR) and trading-hour cumulative jump returns (THCJR) over the past one day and three days. When portfolios are formed on overnight jump returns, the holding period starts from day $t+1$, i.e., the investment horizon skips the open-to-close window. Table 6 reports the results based on overnight jump returns (Panel A) and trading-hour jump returns (Panel B). The results show that compared to Table 5, overnight cumulative jump returns (ONCJR) have stronger predictive power for subsequent stock returns. When the ranking period is one day, stocks in the top decile outperform those in the bottom decile by 0.061%, 0.022%, and 0.010% over the next one-, three-, and five-day horizons, respectively. The spreads in both raw returns and abnormal returns are significant at the 5% level over these horizons. In contrast, the results in Panel B of Table 6 show that there are immediate return reversals, instead of return momentum, following trading-hour jumps, although these reversals are mostly insignificant. Recognizing that intraday stock returns are subject to severe market microstructure effects and many large intraday returns are quickly reversed (Christensen, Oomen, and Podolskij, 2014), we also perform analysis based on days with single jumps. The results are similar to those reported in Table 6. Overall, the results based on intraday jumps provide further evidence consistent with short-term market underreaction. In particular, overnight jumps have significant predictive power for subsequent stock returns. Given that corporate news often arrives during the close of market, this finding helps strengthen the interpretation of a price jump as an information event.

3.4. Predictive power of positive and negative jumps

The results in Tables 5 and 6 show that stocks with positive cumulative jump returns outperform those with negative cumulative jump returns. Note that a stock may have both a high magnitude of positive jumps and a high magnitude of negative jumps. Since jumps of opposite signs could offset each other when we compute cumulative jump returns, we are unable to observe the respective predictive power of positive and negative jumps. In this section, we examine separately the predictive power of positive jumps and negative jumps. The analysis also helps detect potential asymmetric reactions to good and bad news. The literature documents that investors react differently to good and bad news (e.g., Chan, 2003; Ivković and Jegadeesh, 2004; Kothari, Shu, and Wysocki, 2009).

Each day, we compute the cumulative positive jump returns, denoted by CPJR, and the cumulative negative jump returns, denoted by CNJR, of all stocks based on intraday jumps over the past one day and three days, respectively. The predictive powers of CPJR and CNJR are evaluated relative to stocks with no jumps, denoted by NJ. These stocks have no jumps (NJ) and do not appear in the subsamples

Table 6
Predictive power of overnight and trading-hour jumps
Each day, stocks are sorted into deciles based on overnight cumulative jump returns (ONCJR) and trading-hour cumulative jump returns (THCJR) over the previous one day and three days. Decile D1 consists of stocks with the lowest ONCJR or THCJR and D10 consists of stocks with the highest ONCJR or THCJR. This table reports the average daily return and Fama-French four-factor alpha (in percentage terms) of portfolios over the next one-, three-, five-, and ten-day horizons. The spreads in the average daily return and Fama-French four-factor alpha between the top and bottom deciles as well as the absolute values of their *t*-statistics are also reported. Panel A reports the results based on overnight jumps, and Panel B reports the results based on trading-hour jumps. The results are based on value-weighted portfolios. The sample period is from January 1995 to December 2012.

Panel A: Sort on overnight cumulative jump returns (ONCJR)

Deciles	Raw return				FF4 alpha			
	1D	3D	5D	10D	1D	3D	5D	10D
Sort on CJR1D								
D1	0.005	0.027	0.035	0.039	−0.038	−0.016	−0.008	−0.003
D10	0.066	0.049	0.045	0.042	0.022	0.005	0.001	−0.003
D10–D1	0.061	0.022	0.010	0.003	0.060	0.021	0.009	0.001
t-Stat	[5.63]	[3.53]	[2.20]	[0.82]	[5.56]	[3.39]	[1.97]	[0.21]
Sort on CJR3D								
D1	0.012	0.034	0.040	0.044	−0.032	−0.010	−0.003	0.001
D10	0.054	0.045	0.041	0.039	0.009	−0.002	−0.005	−0.008
D10–D1	0.043	0.010	0.001	−0.006	0.041	0.008	−0.002	−0.009
t-Stat	[2.82]	[1.67]	[0.08]	[0.80]	[3.29]	[1.45]	[0.21]	[1.44]

Panel B: Sort on trading-hour cumulative jump returns (THCJR)

Deciles	Raw return				FF4 alpha			
	1D	3D	5D	10D	1D	3D	5D	10D
Sort on CJR1D								
D1	0.046	0.046	0.042	0.042	0.003	0.003	−0.001	−0.001
D10	0.041	0.041	0.042	0.042	−0.002	−0.001	0.000	0.000
D10–D1	−0.005	−0.005	0.000	0.001	−0.004	−0.004	0.001	0.001
t-Stat	[0.56]	[0.89]	[0.02]	[0.19]	[0.49]	[0.83]	[0.19]	[0.41]
Sort on CJR3D								
D1	0.050	0.049	0.047	0.045	0.007	0.007	0.005	0.002
D10	0.039	0.035	0.039	0.042	−0.002	−0.006	−0.003	0.000
D10–D1	−0.011	−0.014	−0.009	−0.003	−0.009	−0.013	−0.008	−0.002
t-Stat	[1.64]	[1.95]	[1.80]	[0.98]	[1.21]	[1.88]	[1.66]	[0.66]

of stocks with positive or negative jumps. Table 7 reports the average returns and FF4 alphas for each subsample of stocks, as well as the spreads between the CPJR and NJ subsamples and the spreads between the CNJR and NJ subsamples, together with the absolute values of their Newey-West *t*-statistics. Panel A reports the results based on all intraday jumps and Panel B reports the results based on overnight jumps.

Consistent with the results in Table 6, overnight jumps have stronger predictive power for subsequent stock returns. The predictive power is stronger for both positive and negative jumps. For instance, as shown in Panel A, when the ranking period is one day, the average abnormal returns of stocks with negative jumps are −0.080% and −0.020% over one-day and three-day horizons, respectively; as shown in Panel B, these numbers are −0.103% and −0.041%, respectively, for stocks with negative overnight jumps. For stocks with positive jumps, the average abnormal returns are 0.045% and 0.004% over one-day and three-day horizons, respectively; the corresponding numbers for stocks with positive overnight jumps are 0.077% and 0.022%, respectively.

More importantly, consistent with the literature, the above results also highlight asymmetric reactions to negative news and positive news, that is, there is stronger underreaction to negative jumps than to positive jumps. For instance, as shown in Panel B of Table 7, based on overnight jumps, when the ranking period is one day, the average abnormal returns of stocks with positive jumps are significant up to three-day horizon, but the average abnormal returns of stocks with negative jumps are significant up to five-day horizon. When the ranking period is three days, the average abnormal returns of stocks with positive jumps are not significant over any horizon, but the average abnormal returns of stocks with negative jumps are significant over one-day horizon. Moreover, as noted above, the magnitude of abnormal returns following stocks with negative jumps is also higher than that of abnormal returns following stocks with positive jumps.

Note that, based on cumulative jump returns calculated at monthly frequency, the results in Table 2 suggest weaker underreaction to negative information shocks than to positive information shocks. These results, combined with those in Table 7 based on jump returns calculated at daily frequency, present an interesting pattern of market underreaction to positive and negative news over different horizons. The results in Table 7 suggest that investors pay more attention to negative news than to positive news over very short horizons, with abnormal returns of −0.103% over one-day horizon and −0.041% over

Table 7

Predictive power of positive and negative jumps

Each day, we compute the cumulative positive jump returns, denoted by CPJR, and the cumulative negative jump returns, denoted by CNJR, based on intraday jumps over the past one day and three days, respectively. The predictive powers of CPJR and CNJR are evaluated relative to stocks with no jumps, denoted by NJ. Panel A reports the average daily return and Fama-French four-factor alpha (in percentage terms) of the stocks in each subgroup over the next one-, three-, five-, and ten-day horizons. The spreads in the average return and Fama-French four-factor alpha between CPJR and NJ and between CNJR and NJ as well as the absolute values of their *t*-statistics are also reported. Panel B reports results based on overnight jumps. The results are based on value-weighted portfolios. The sample period is from January 1995 to December 2012.

Panel A: Based on cumulative positive and cumulative negative jump returns

	Raw return				FF4 alpha			
	1D	3D	5D	10D	1D	3D	5D	10D
Sort on CJR1D								
CNJR	−0.037	0.024	0.037	0.038	−0.080	−0.020	−0.006	−0.005
NJ	0.042	0.041	0.041	0.041	0.000	0.000	0.000	−0.001
CPJR	0.089	0.049	0.044	0.041	0.045	0.004	−0.002	−0.004
CNJR–NJ	−0.078	−0.018	−0.004	−0.003	−0.080	−0.019	−0.006	−0.005
t-Stat	[4.92]	[1.92]	[0.58]	[0.54]	[5.19]	[2.16]	[0.84]	[0.97]
CPJR–NJ	0.047	0.008	0.003	0.000	0.045	0.005	−0.001	−0.004
t-Stat	[3.17]	[0.87]	[0.38]	[0.02]	[3.01]	[0.55]	[0.17]	[0.78]
Sort on CJR3D								
CNJR	0.015	0.038	0.039	0.043	−0.029	−0.005	−0.004	−0.001
NJ	0.042	0.041	0.041	0.040	0.001	0.000	0.000	−0.001
CPJR	0.051	0.040	0.037	0.039	0.006	−0.006	−0.009	−0.008
CNJR–NJ	−0.027	−0.003	−0.002	0.003	−0.029	−0.005	−0.004	0.000
t-Stat	[2.69]	[0.39]	[0.24]	[0.44]	[3.07]	[0.67]	[0.63]	[0.02]
CPJR–NJ	0.009	−0.002	−0.004	−0.002	0.005	−0.007	−0.009	−0.007
t-Stat	[1.01]	[0.22]	[0.53]	[0.26]	[0.56]	[0.92]	[1.47]	[1.33]

Panel B: Based on overnight cumulative positive and cumulative negative jump returns

	Raw return				FF4 alpha			
	1D	3D	5D	10D	1D	3D	5D	10D
Sort on CJR1D								
CNJR	−0.062	0.002	0.024	0.035	−0.103	−0.041	−0.018	−0.008
NJ	0.042	0.042	0.041	0.041	0.000	0.000	0.000	0.000
CPJR	0.120	0.066	0.054	0.047	0.077	0.022	0.008	0.002
CNJR–NJ	−0.104	−0.040	−0.017	−0.006	−0.103	−0.041	−0.018	−0.007
t-Stat	[5.29]	[3.59]	[2.13]	[1.07]	[5.43]	[3.73]	[2.26]	[1.30]
CPJR–NJ	0.078	0.024	0.013	0.006	0.076	0.022	0.009	0.002
t-Stat	[4.32]	[2.35]	[1.66]	[1.06]	[4.19]	[2.10]	[1.16]	[0.38]
Sort on CJR3D								
CNJR	0.002	0.032	0.037	0.042	−0.041	−0.011	−0.006	−0.001
NJ	0.042	0.042	0.041	0.040	0.001	0.000	0.000	−0.001
CPJR	0.056	0.050	0.041	0.041	0.010	0.003	−0.006	−0.006
CNJR–NJ	−0.040	−0.010	−0.004	0.002	−0.042	−0.011	−0.006	0.000
t-Stat	[3.64]	[1.11]	[0.58]	[0.33]	[3.94]	[1.32]	[0.82]	[0.05]
CPJR–NJ	0.014	0.008	0.000	0.001	0.009	0.002	−0.006	−0.005
t-Stat	[1.31]	[0.91]	[0.04]	[0.11]	[0.84]	[0.29]	[0.89]	[0.87]

three-day horizon following negative overnight jumps and abnormal returns of 0.077% over one-day horizon and 0.022% over three-day horizon following positive overnight jumps. The greater attention to negative news over short horizons leads to relatively weaker underreaction to negative news over extended horizons. These findings are consistent with the conjecture of Epstein and Schneider (2008), that investors seem to react to negative news in a more timely manner, with weaker underreaction in subsequent periods.

3.5. Jump persistence and decomposition of post-jump stock returns

One of the explanations proposed in the accounting literature for PEAD or investor underreaction to earnings surprises is that investors fail to understand the implications of current earnings for future earnings. The evidence is that earnings surprises tend to be serially correlated (Rendleman, Jones, and Latané, 1987; Bernard and Thomas, 1990). For example, positive standardized unexpected earnings (SUE) are often followed by positive SUE over the next three quarters. In this section, we perform an event-time analysis to decompose post-jump stock returns into a jump component and a non-jump component and examine the extent to which each component contributes to underreaction.

Each day, we identify stocks with jumps. Day 0 denotes an event date when a stock has either positive or negative jump based on intraday cumulative jump returns. We compute the cumulative abnormal returns of stocks. Since our sample consists of stocks traded on the NYSE and Amex,

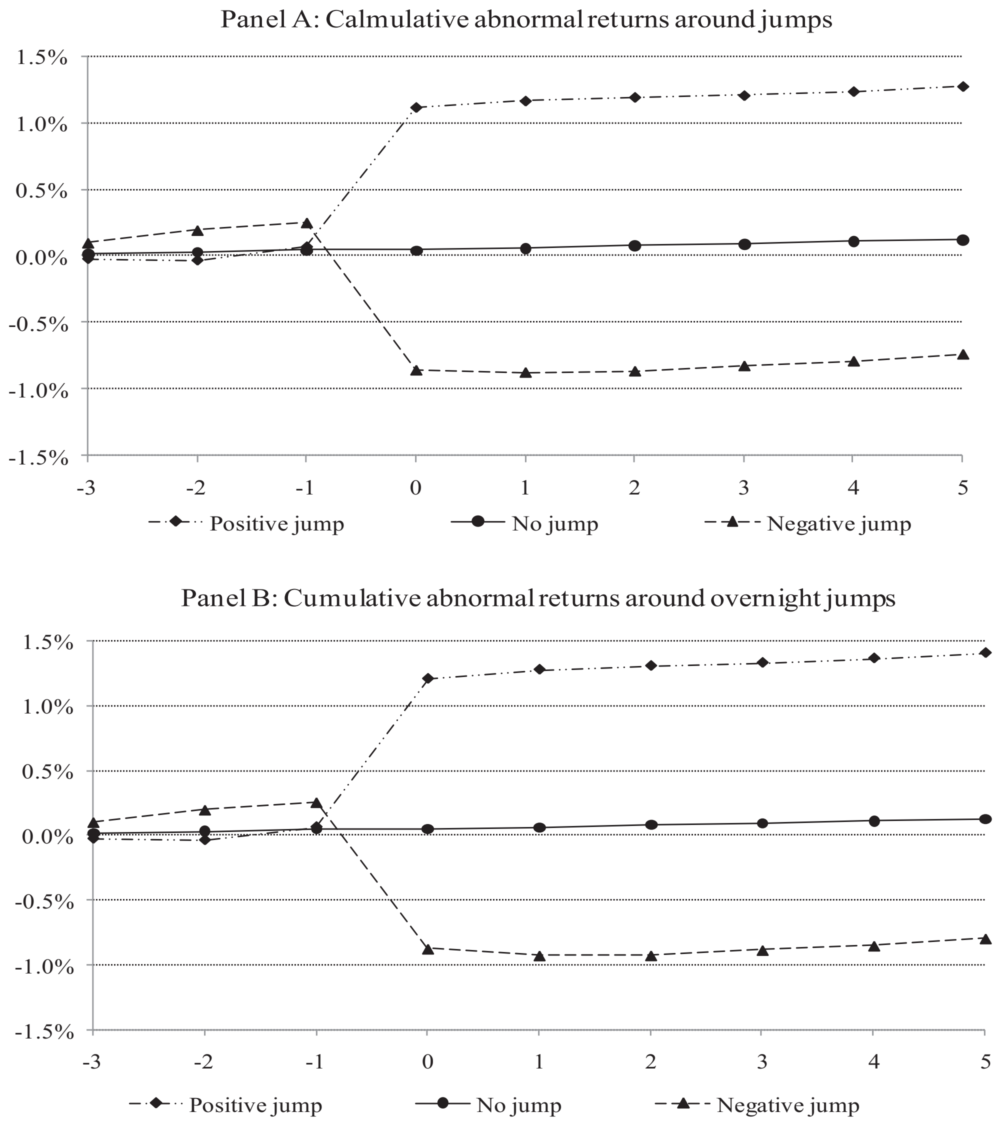


Fig. 2. Cumulative abnormal returns around stock price jumps. Each day, we identify stocks with jumps. Day 0 denotes an event date when a stock has jumps based on intraday or overnight cumulative jump returns. Panel A plots the cumulative abnormal returns starting from day −3 for stocks with positive jumps, no jumps, and negative jumps on day 0. Panel B plots cumulative abnormal returns of stocks with positive overnight jumps, no overnight jumps, and negative overnight jumps on day 0.

we use CRSP value-weighted index as benchmark in adjusting daily stock returns. Panel A of Fig. 2 plots the cumulative abnormal returns starting from day −3 for stocks with positive jumps, no jumps, and negative jumps on day 0. The results based on overnight jumps are plotted in Panel B. Consistent with earlier findings on underreaction, for stocks with positive (negative) jumps, there is a clear jump up (down) in stock prices on event date followed by gradual upward (downward) changes over very short horizons after the event. The plots in Panel B show that consistent with results in Table 6, overnight jumps have stronger predictive power for future returns. One common pattern is that the drift following positive jumps is more persistent than that following negative jumps.

To examine what contributes to underreaction, we decompose post-jump stock returns into jump and non-jump components. Again, day 0 denotes an event date when a stock has either positive or negative jump based on intraday cumulative jump returns. We decompose the stock return into a jump component and a non-jump component based on whether or not the stock price has jumps on a day. We also perform the analysis based on overnight jumps. The results are reported in Table 8 for both positive and negative jumps over the next one-, three-, five-, and ten-day horizons. Differences in cumulative jump returns (CJR) and cumulative non-jump returns (CNJR) between stocks with jumps and those with no jumps are also reported.

Table 8
Decomposition of post-jump stock returns

Each day, we identify stocks with jumps. Day 0 denotes an event date when a stock has either positive or negative jump based on intraday cumulative jump returns. Panel A reports the post-jump average cumulative jump return (CJR) and cumulative non-jump return (CNJR) over the next one-, three-, five- and ten-day horizons for both positive jumps and negative jumps. Differences in CJR and CNJR between stocks with jumps and those with no jumps as well as the absolute values of their *t*-statistics are also reported. Panel B reports the results based on overnight jumps. The sample period is from January 1995 to December 2012.

Panel A: Decomposition of stock returns following stock price jumps

	CJR				CNJR			
	[1, 1]	[1, 3]	[1, 5]	[1, 10]	[1, 1]	[1, 3]	[1, 5]	[1, 10]
Negative jumps	0.011	0.064	0.118	0.262	−0.028	−0.032	0.002	0.012
No jumps	0.015	0.045	0.074	0.147	0.002	0.005	0.007	0.015
Positive jumps	0.031	0.080	0.150	0.271	0.017	0.010	0.008	−0.005
Negative–No	−0.004	0.020	0.044	0.114	−0.030	−0.037	−0.005	−0.003
t-Stat	[0.86]	[2.69]	[3.85]	[5.43]	[4.18]	[3.05]	[0.31]	[0.13]
Positive–No	0.016	0.035	0.076	0.124	0.015	0.004	0.001	−0.020
t-Stat	[3.82]	[4.68]	[6.03]	[6.35]	[2.40]	[0.38]	[0.41]	[1.03]

Panel B: Decomposition of stock returns following overnight stock price jumps

	CJR				CNJR			
	[1, 1]	[1, 3]	[1, 5]	[1, 10]	[1, 1]	[1, 3]	[1, 5]	[1, 10]
Negative jumps	0.010	0.068	0.118	0.250	−0.062	−0.079	−0.039	−0.034
No jumps	0.012	0.035	0.059	0.117	0.001	0.004	0.005	0.011
Positive jumps	0.034	0.095	0.172	0.332	0.036	0.028	0.026	−0.029
Negative–No	−0.002	0.033	0.060	0.133	−0.063	−0.082	−0.044	−0.045
t-Stat	[0.46]	[3.32]	[4.18]	[5.89]	[5.36]	[4.71]	[2.45]	[1.82]
Positive–No	0.022	0.059	0.114	0.214	0.035	0.024	0.021	−0.040
t-Stat	[3.72]	[4.24]	[5.12]	[6.06]	[3.92]	[2.02]	[1.39]	[1.89]

The results in Panels A and B of Table 8 show a similar pattern in the respective contributions of the jump and non-jump components to underreaction. For stocks with negative jumps, the lower future returns are almost entirely realized in the form of small changes in prices, or non-jumps. Compared to stocks with no jumps, the non-jump component (CNJR) of these stocks is significantly lower over one-, three-, and five-day horizons. The jump component (CJR) is actually higher beyond one-day horizon. This pattern is consistent with typical underreaction, where investors initially underreact to news but gradually adjust their valuation in the same direction afterward.

The results based on positive jumps provide a mixed picture. In this case, the higher future returns are realized in the form of both jumps and non-jumps. Compared to stocks with no jumps, the jump component (CJR) and the non-jump component (CNJR) of these stocks are both significantly higher over one- and three-day horizons. There is clear evidence of persistence in positive jumps. That is, positive jumps are more persistent than negative jumps. Again, the higher non-jump component suggests that investors initially underreact to news but gradually adjust their valuation in the same direction afterward. We interpret the higher jump-component as evidence that there is strong persistence in positive stock price jumps, yet investors fail to fully understand the implications of positive news for future positive news. Of course, the higher jump returns imply that a higher carrying risk is also likely for arbitrageurs in exploiting anomalous returns of stocks with positive jumps (Shleifer and Vishny, 1997).

4. Further analysis

4.1. Multivariate tests: lagged jump and non-jump returns

The literature documents that a number of firm characteristics have predictive power for future stock returns. Therefore, when examining the predictive power of jump returns, we need to control for the effect of other firm characteristics. One of the variables of particular interest is the lagged short-term stock return. As noted in the introduction, the literature documents that stock returns exhibit negative serial correlations over short horizons. In the previous section, we document that jumps in stock prices are positively related to future stock returns. We perform similar analysis on the non-jump component of stock returns and show that, over short horizons, the non-jump component has a significantly negative relation with future stock returns. Each month, we compute cumulative non-jump returns (CNJR) for stocks in our sample. Sorting stocks into deciles based on CNJR over the past month, the value-weighted portfolios show that the return spread between the top and bottom CNJR deciles is −0.90%, with a Newey-West *t*-statistic of 3.39 over one-month horizon. That is, cumulative non-jump returns are negatively correlated to future stock returns over short horizons.

In the following, we examine the predictive power of both lagged cumulative jump returns (CJR) and cumulative non-jump-returns (CNJR) in a multivariate setting. Specifically, we perform the following Fama and MacBeth (1973) regressions of stock returns on lagged CJR and lagged CNJR, including other firm characteristics as control variables:

$$\mathrm{RET}_{t+1,t+h} = \alpha + \beta_1 \mathrm{CJR}_{t-k+1,t} + \beta_2 \mathrm{CNJR}_{t-k+1,t} + \varepsilon_{t+1,t+h}, \tag{3}$$

$$\begin{aligned}\mathrm{RET}_{t+1,t+h} &= \alpha + \beta_1 \mathrm{CJR}_{t-k+1,t} + \beta_2 \mathrm{CNJR}_{t-k+1,t} + \beta_3 \mathrm{LRET}_{t-5,t-1} \\ &\quad + \beta_4 \mathrm{LRET}_{t-11,t-6} + \beta_5 \mathrm{SIZE} + \beta_6 \mathrm{BM} + \beta_7 \mathrm{ILLIQ}_{t-k+1,t} \\ &\quad + \beta_8 \mathrm{IVOL}_{t-k+1,t} + \beta_9 \mathrm{LEV} + \varepsilon_{t+1,t+h},\end{aligned} \tag{4}$$

where $\mathrm{RET}_{t+1,t+h}$ denotes the holding period return over the period $[t+1,\ t+h]$, with $h=1,\ 3,\ 6,\ 12$ months; $\mathrm{CJR}_{t-k+1,t}$ and $\mathrm{CNJR}_{t-k+1,t}$ denote, respectively, lagged cumulative jump and non-jump returns over the period $[t-k+1,\ t]$, with $k=1$, 3 months; and LRET denotes lagged cumulative stock returns over various horizons. Following the literature (e.g., Grinblatt and Moskowitz, 2004), we include lagged past returns over different horizons as control variables. For example, $\mathrm{LRET}_{t-5,t-1}$ is the cumulative stock return over the period from month $t-5$ to month $t-1$. Other control variables include SIZE, BM, ILLIQ, IVOL, and LEV. For details on these variables, see Table 1.

Each month, we perform the cross-sectional regressions in Eqs. (3) and (4). Since the book-to-market ratio is included as a control variable in Eq. (4), we exclude financial firms in the regressions. Table 9 reports the average coefficient estimates and Newey-West t-statistics of the cross-sectional regressions on lagged cumulative jump and non-jump returns over the past one month (Panel A) and three months (Panel B). Consistent with the literature, stock returns are negatively related to SIZE and IVOL and positively related to BM and ILLIQ. More importantly, the results show that the coefficient estimates of lagged cumulative jump returns (CJR) are positive and statistically significant over all horizons in both Panels A and B. The coefficient estimates of lagged cumulative non-jump returns (CNJR) are significantly negative over one- and three-month horizons in Panel A and one-month horizon in Panel B and the relation becomes positive over longer horizons in both panels. These findings further confirm that the short-term market underreaction to large information shocks in Table 2 is robust to controlling for other firm characteristics. In addition, the non-jump component of stock returns has a significantly negative relation with future stock returns over short horizons.

4.2. Information shocks in jumps and earnings surprises

The literature documents evidence of short-term investor underreaction to specific corporate events and the most well-known phenomenon is PEAD. Considering the fact that earnings announcement contains important information about firm fundamentals, a natural question is the extent to which the underreaction documented in this study is driven by earnings surprises. To address this question, we replicate our analysis in Table 2 by excluding jumps that are potentially associated with earnings surprises. We classify jumps as potentially associated with earnings surprises if they occur within a three-day window centered on the earnings announcement date. We also use a five-day window and confirm that the results are consistent. For both the top and bottom CJR deciles in Table 2, we divide stocks into two sub-portfolios: an earnings-related portfolio and a non-earnings-related portfolio, the latter capturing the effect beyond earnings announcements.

Table 10 reports the spreads in raw returns, DGTW alphas, and FF4 alphas between the top and bottom CJR deciles (D10–D1) and their Newey-West t-statistics for both subsamples. The results are based on value-weighted portfolios. The results based on the non-earnings-related subsample show that even after excluding jumps associated with earnings surprises, the short-term underreaction remains significant. For all combinations of ranking periods and investment horizons, the return spreads between the top and bottom CJR deciles (D10–D1) are positive and significant at the 5% level. This suggests that jumps capture information shocks beyond earnings surprises. Not surprisingly, the drift of the earnings-related subsample is stronger. The spreads in DGTW alphas and FF4 alphas, as well as statistical significance, are generally higher following stock price jumps associated with earnings announcements. Nevertheless, when the ranking period is one month, differences in the drift between earnings-related subsample and non-earnings-related subsample are mostly insignificant.

An equally interesting question is the extent to which the short-term underreaction documented in this study explains the earnings momentum effect documented in the literature (e.g., Chan, Jegadeesh, and Lakonishok, 1996; Chordia and Shivakumar, 2005, 2006; Sadka, 2006). We perform a similar analysis as above except that we now examine the earnings momentum effect by excluding earnings announcements with concurrent stock price jumps. Following Livnat and Mendenhall (2006), we compute the SUE for each stock as follows:

$$SUE_{i,t} = \frac{(X_{i,t} - \tilde{X}_{i,t})}{P_{i,t}}, \tag{5}$$

where $X_{i,t}$ is primary earnings per share before extraordinary items for firm i in quarter t and $P_{i,t}$ is the price per share for firm i at the end of quarter t, from Compustat. The variable $\tilde{X}_{i,t}$ is the median of forecasts reported to IBES prior to the earnings announcement. Note that, in Eq. (5), earnings surprise is calculated based on market value. We confirm that our results hold when we use book value to compute earnings surprises. The data on analyst earnings forecasts are obtained from IBES and the sample period covers January 1983 to December 2012. Similarly, we use a three-day window centered on the stock price jump date to identify whether a particular earnings announcement has concurrent jumps. Again, we confirm that the results are consistent when we use a five-day window. We sort stocks into deciles based on lagged SUE and divide both the top and bottom SUE deciles into two portfolios: a jump-related portfolio and a non-jump-related portfolio. The non-jump-related portfolio captures the earnings announcement effect beyond stock price jumps.

Table 11 reports the spreads in the raw returns, DGTW alphas, and FF4 alphas between the top and bottom SUE deciles (D10–D1) and their Newey-West t-statistics for both subsamples. The results are based on value-weighted

Table 9
Multivariate tests: lagged jump and non-jump returns

Each month, we perform cross-sectional regressions of stock returns on lagged jump and non-jump returns with various control variables. Stock returns are calculated over the next one-month ($RET_{t+1,t+1}$), three-month ($RET_{t+1,t+3}$), six-month ($RET_{t+1,t+6}$), and 12-month ($RET_{t+1,t+12}$) horizons. Lagged cumulative jump returns (CJR) and cumulative non-jump returns (CNJR) are calculated over the past one month and three months. Control variables include lagged returns ($LRET_{t-5,t-1}$ and $LRET_{t-11,t-6}$), the natural log of market cap (SIZE), the natural log of the book-to-market ratio (BM), the Amihud (2002) illiquidity ratio pre-multiplied by 1,000,000 (ILLIQ), idiosyncratic volatility (IVOL), and the natural log of the ratio of the book assets to market equity (LEV). This table reports the average of the coefficient estimates of monthly regressions as well as the absolute values of Newey-West *t*-statistics. Panel A reports the results for lagged one-month cumulative jump and non-jump returns. Panel B reports the results for lagged three-month cumulative jump and non-jump returns. The sample period is from July 1975 to December 2012.

Panel A: Regressions of stock returns on lagged one-month cumulative jump and non-jump returns

	$RET_{t+1,t+1}$		$RET_{t+1,t+3}$		$RET_{t+1,t+6}$		$RET_{t+1,t+12}$	
$CJR_{t,t}$	2.19	2.55	5.51	6.67	7.38	9.33	9.95	12.60
	[5.19]	[5.78]	[6.54]	[8.27]	[4.89]	[6.38]	[4.19]	[5.55]
$CNJR_{t,t}$	−6.53	−7.46	−5.01	−6.26	−1.14	−2.42	6.45	4.50
	[7.07]	[10.21]	[5.19]	[7.87]	[0.76]	[1.86]	[2.15]	[1.74]
$LRET_{t-5,t-1}$		0.41		1.94		4.44		5.64
		[1.76]		[3.15]		[3.26]		[2.20]
$LRET_{t-11,t-6}$		0.64		1.28		1.15		−1.35
		[4.21]		[2.71]		[1.18]		[0.84]
Size		−0.12		−0.31		−0.52		−0.75
		[3.34]		[3.04]		[2.53]		[1.74]
B/M		0.28		0.75		1.41		2.53
		[4.81]		[4.63]		[3.95]		[3.05]
$ILLIQ_{t,t}$		0.01		0.02		0.03		0.06
		[3.36]		[4.20]		[2.93]		[2.22]
$IVOL_{t,t}$		−0.25		−0.59		−0.87		−1.30
		[8.71]		[7.36]		[5.27]		[4.29]
LEV		−0.05		−0.04		0.12		0.26
		[0.81]		[0.20]		[0.25]		[0.24]
Intercept	1.20	3.14	3.57	8.51	7.19	15.23	14.63	26.67
	[4.30]	[6.24]	[4.47]	[5.35]	[4.74]	[4.68]	[5.37]	[3.89]
Adj. R^2	1.23%	5.09%	0.90%	5.66%	0.69%	5.68%	0.65%	5.36%

Panel B: Regressions of stock returns on lagged three-month cumulative jump and non-jump returns

	$RET_{t+1,t+1}$		$RET_{t+1,t+3}$		$RET_{t+1,t+6}$		$RET_{t+1,t+12}$	
$CJR_{t-2,t}$	1.27	0.75	2.76	2.01	4.62	2.68	3.75	4.46
	[4.81]	[2.90]	[4.21]	[4.11]	[4.00]	[3.15]	[2.26]	[3.02]
$CNJR_{t-2,t}$	−1.93	−3.76	0.98	−2.35	4.87	−0.32	10.86	6.46
	[4.70]	[11.61]	[1.13]	[3.75]	[2.98]	[0.31]	[3.26]	[3.31]
$LRET_{t-5,t-1}$		1.36		2.52		4.57		4.21
		[6.43]		[4.70]		[4.04]		[2.13]
$LRET_{t-11,t-6}$		0.61		1.22		1.03		−1.52
		[4.16]		[2.75]		[1.12]		[1.01]
Size		−0.13		−0.36		−0.60		−0.92
		[3.98]		[4.03]		[3.33]		[2.26]
B/M		0.24		0.63		1.25		2.30
		[4.27]		[3.96]		[3.44]		[2.72]
$ILLIQ_{t-2,t}$		0.02		0.04		0.06		0.10
		[4.91]		[5.00]		[3.28]		[2.39]
$IVOL_{t-2,t}$		−0.36		−0.82		−1.22		−1.84
		[8.29]		[6.93]		[4.94]		[4.00]
LEV		−0.05		0.00		0.17		0.32
		[0.71]		[0.01]		[0.35]		[0.30]
Intercept	1.04	3.42	3.29	9.50	6.74	16.90	14.11	29.79
	[3.89]	[7.64]	[4.24]	[6.88]	[4.60]	[5.83]	[5.30]	[4.53]
Adj. R^2	1.30%	5.13%	1.13%	5.80%	1.00%	5.95%	1.11%	5.64%

portfolios. The results based on the non-jump-related subsample show that the PEAD remains significant, even after excluding earnings announcements with concurrent jumps. This is evidence that the earnings momentum effect is not subsumed by past information shocks as proxied by stock price jumps. Nevertheless, the drift of the jump-related subsample is much stronger. For example, when the stocks are sorted on lagged SUE over the past quarter, the spreads in raw returns following announcements without concurrent jumps in stock prices are 0.34% and 0.37% over the subsequent three- and six-month horizons, respectively. Following announcements with concurrent jumps, the corresponding numbers are much higher at 0.96% and 0.66%. These results are consistent with the findings of Brandt, Kishore, Santa-Clara, and Venkatachalam (2008), that large returns around an earnings announcement date have strong predictive power for future stock returns. As noted earlier, when book value is used to compute SUE, the results are similar. The findings in Table 11 show that although the short-term underreaction

Table 10
Short-term underreaction: controlling for earnings surprises

Each month, stocks are sorted into deciles based on lagged cumulative jump returns (CJR) over the past one month and three months. For both decile 1 (D1) and decile 10 (D10), we further divide stocks into two subgroups: an earnings-related portfolio and a non-earnings-related portfolio. The earnings-related portfolio includes stocks that have price jumps within a three-day window centered on the earnings announcement date. This table reports the spreads in the average monthly return, DGTW alpha, and Fama-French four-factor alpha (in percentage terms) between the top and bottom portfolios and the absolute values of their *t*-statistics for each subsample of stocks. The differences in spreads between the two stock subsamples are also reported. The results are based on value-weighted portfolios. The sample period is from July 1975 to December 2012.

Spreads	Raw return				DGTW alpha				FF4 alpha			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Sort on CJR1M												
Non-earnings related												
D10–D1	1.23	0.63	0.37	0.32	0.76	0.32	0.14	0.14	1.08	0.40	0.15	0.13
t-Stat	[6.11]	[4.29]	[3.20]	[3.31]	[4.69]	[3.05]	[2.07]	[2.59]	[4.87]	[2.69]	[1.79]	[1.83]
Earnings related												
D10–D1	1.66	0.69	0.39	0.30	1.35	0.43	0.27	0.18	1.50	0.51	0.18	0.12
t-Stat	[6.38]	[4.13]	[2.97]	[3.21]	[5.96]	[3.12]	[2.56]	[2.51]	[5.34]	[3.35]	[1.60]	[1.59]
Earnings related – non-earnings related												
Difference	0.43	0.07	0.02	−0.02	0.59	0.11	0.13	0.04	0.50	0.12	0.04	−0.01
t-Stat	[1.89]	[0.47]	[0.18]	[0.31]	[2.84]	[0.84]	[1.37]	[0.60]	[2.11]	[0.82]	[0.35]	[0.12]
Sort on CJR3M												
Non-earnings related												
D10–D1	0.92	0.40	0.30	0.32	0.53	0.14	0.11	0.12	0.64	0.01	−0.10	−0.02
t-Stat	[4.18]	[2.09]	[1.99]	[2.03]	[2.96]	[0.97]	[0.90]	[1.33]	[2.74]	[0.07]	[0.68]	[0.17]
Earnings related												
D10–D1	1.72	0.86	0.51	0.49	1.41	0.66	0.38	0.32	1.49	0.51	0.15	0.17
t-Stat	[5.84]	[3.84]	[2.70]	[2.92]	[5.20]	[3.44]	[1.87]	[1.90]	[4.89]	[2.52]	[0.90]	[1.42]
Earnings related – non-earnings related												
Difference	0.80	0.45	0.21	0.16	0.88	0.52	0.28	0.20	0.85	0.50	0.25	0.18
t-Stat	[3.19]	[3.13]	[1.98]	[1.89]	[3.49]	[3.03]	[2.32]	[1.93]	[3.18]	[2.76]	[2.16]	[1.85]

Table 11
Earnings momentum effect: controlling for past information shocks

Each month, stocks are sorted into deciles based on lagged SUE computed from analyst forecasts. For both decile 1 (D1) and decile 10 (D10), we further divide stocks into two portfolios: a jump-related portfolio and a non-jump-related portfolio. The jump-related portfolio includes stocks that have earnings announcements within a three-day window centered on the jump date. This table reports the spreads in the average monthly return, DGTW alpha, and Fama-French four-factor alpha (in percentage terms) between the top and bottom portfolios and the absolute values of their *t*-statistics for each subsample of stocks. The differences in spreads between the two stock subsamples are also reported. The results are based on value-weighted portfolios. The sample period is from January 1983 to December 2012.

Spreads	Raw return				DGTW alpha				FF4 alpha			
	1M	3M	6M	12M	1M	3M	6M	12M	1M	3M	6M	12M
Sort on SUE1M												
Non-jump related												
D10–D1	0.29	0.20	0.21	0.19	0.18	0.13	0.10	0.10	0.26	0.17	0.19	0.18
t-Stat	[2.98]	[2.69]	[2.65]	[2.57]	[2.63]	[2.46]	[2.26]	[2.36]	[2.58]	[2.30]	[2.42]	[2.55]
Jump related												
D10–D1	1.31	0.69	0.49	0.40	1.02	0.39	0.22	0.20	1.22	0.61	0.43	0.35
t-Stat	[5.66]	[4.31]	[3.97]	[3.79]	[4.40]	[2.68]	[2.01]	[2.24]	[5.21]	[3.83]	[3.52]	[3.58]
Jump related – non-jump related												
Difference	1.02	0.49	0.28	0.21	0.84	0.25	0.11	0.10	1.03	0.44	0.24	0.17
t-Stat	[4.23]	[3.10]	[2.31]	[2.25]	[3.49]	[2.02]	[1.57]	[1.69]	[3.95]	[2.67]	[1.91]	[1.77]
Sort on SUE3M												
Non-jump related												
D10–D1	0.56	0.34	0.37	0.38	0.28	0.16	0.17	0.18	0.51	0.30	0.34	0.42
t-Stat	[3.89]	[2.48]	[3.20]	[4.01]	[2.35]	[1.85]	[2.03]	[2.32]	[3.23]	[2.13]	[2.67]	[3.89]
Jump related												
D10–D1	1.68	0.96	0.66	0.52	1.26	0.74	0.42	0.32	1.57	0.94	0.60	0.50
t-Stat	[5.00]	[4.57]	[4.21]	[3.85]	[3.73]	[3.71]	[2.78]	[2.48]	[4.23]	[4.40]	[3.82]	[3.84]
Jump related – non-jump related												
Difference	1.12	0.62	0.29	0.14	0.98	0.58	0.25	0.14	1.05	0.63	0.26	0.09
t-Stat	[3.28]	[2.65]	[1.70]	[1.02]	[2.90]	[2.82]	[1.66]	[1.12]	[2.75]	[2.44]	[1.41]	[0.56]

documented in this study does not subsume the earnings momentum effect, it is much stronger than the earnings momentum effect. That is, the use of jumps as proxy for large information shocks captures more pronounced market underreactions over short horizons.

4.3. Potential explanation of short-term market underreaction: limited investor attention

The literature has proposed several explanations of investor underreaction to information shocks. The one that has received the most attention is probably the limited investor attention hypothesis proposed by Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011). Due to limited attention and information processing ability, a well-established psychological constraint, investors likely pay more attention to information that is presented in a salient and easily processed form but underreact to information shocks that carry content with some degree of ambiguity. Several models have also been developed to generate the combination of long-run overreaction and short-term underreaction (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999).

In this section, we empirically test whether the short-term underreaction documented in this study can be attributed to the limited investor attention hypothesis. Studies have examined the limited investor attention hypothesis as a potential explanation of PEAD. For example, DellaVigna and Pollet (2009) compare the responses to earnings announcements on Friday, when there is likely less investor attention, to the responses on other weekdays and find more pronounced drift following Friday earnings announcements. Hirshleifer, Lim, and Teoh (2009) find that drift to earnings surprises is greater when a larger number of related companies also announce earnings on the same day. We use two variables as a proxy of investor attention: the magnitude of the jump size and trading volume. As noted by Bamber, Barron, and Stevens (2011), both price changes and trading volume have been used in the literature to measure market responses to information events. Jumps of larger (smaller) magnitude are likely associated with more (less) salient information and indicate that more (less) information is already incorporated into stock prices. Similarly, a higher trading volume indicates greater investor attention and participation in trading in reaction to the news. Trading volume has been used as a proxy for investor attention by Hou, Peng, and Xiong (2009) and Loh (2010). We formulate and test the following two hypotheses:

H1. There is stronger (weaker) short-term market underreaction to jumps of smaller (larger) magnitude.

H2. There is stronger (weaker) short-term market underreaction to jumps with lower (higher) concurrent trading volume.

We perform the following regressions to test these hypotheses:

$$\begin{aligned}\mathrm{RET}_{t+1,t+h} &= \alpha + \beta_1 \mathrm{CJR}_{t-k+1,t} + \beta_d d_k^{JM} \mathrm{CJR}_{t-k+1,t} + \beta_2 \mathrm{CNJR}_{t-k+1,t} \\ &\quad + \beta_3 \mathrm{LRET}_{t-5,t-1} + \beta_4 \mathrm{LRET}_{t-11,t-6} + \beta_5 \mathrm{SIZE} + \beta_6 \mathrm{BM} \\ &\quad + \beta_7 \mathrm{ILLIQ}_{t-k+1,t} + \beta_8 \mathrm{IVOL}_{t-k+1,t} + \beta_9 \mathrm{LEV} + \varepsilon_{t+1,t+h},\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{RET}_{t+1,t+h} &= \alpha + \beta_1 \mathrm{CJR}_{t-k+1,t} + \beta_d d_k^{ETW} \mathrm{CJR}_{t-k+1,t} + \beta_2 \mathrm{CNJR}_{t-k+1,t} \\ &\quad + \beta_3 \mathrm{LRET}_{t-5,t-1} + \beta_4 \mathrm{LRET}_{t-11,t-6} + \beta_5 \mathrm{SIZE} + \beta_6 \mathrm{BM} \\ &\quad + \beta_7 \mathrm{ILLIQ}_{t-k+1,t} + \beta_8 \mathrm{IVOL}_{t-k+1,t} + \beta_9 \mathrm{LEV} + \varepsilon_{t+1,t+h},\end{aligned} \tag{7}$$

where $\mathrm{RET}_{t+1,t+h}$ denotes the holding period return over the period $[t+1,\ t+h]$, with $h=1$, 3, 6, 12 months, and $\mathrm{CJR}_{t-k+1,t}$ denotes lagged cumulative jump returns over the period $[t-k+1,\ t]$, with $k=1$, 3 months. The dummy variable $d_k^{JM}=1$ if the jump magnitude (JM) of a stock over the past k months is smaller than the median magnitude of the jumps for all stocks during the same time period and zero otherwise and $d_k^{ETV}=1$ if the excess trading volume (ETV) of a stock over the past k months is lower than the median excess trading volume for all stocks with jumps during the same time period and zero otherwise. The excess trading volume (ETV) of a stock is defined as the daily turnover adjusted by the average turnover over the past k months (Bamber, 1987), $k=1$, 3 months. According to both hypotheses, we expect β_d to be significantly positive. The control variables are the same as those in Eq. (4).

Each month, we perform the cross-sectional regressions in Eqs. (6) and (7). Table 12 reports the time series averages of the coefficient estimates and the Newey-West t-statistics for regressions on lagged one-month cumulative jump returns (Panel A) and lagged three-month cumulative jump returns (Panel B). The coefficient estimates of the control variables are similar to those in Table 9. More importantly, in both panels, the results show that the estimates of β_d are positive and highly significant in all model specifications. In Panel B where the cumulative jump returns are computed over past three months, the significance levels of the coefficient estimates of $\mathrm{CJR}_{t-k+1,t}$are reduced with the inclusion of the interaction term of the dummy variable and $\mathrm{CJR}_{t\text{-}k+1,t}$. This is evidence that short-term underreaction to information shocks is significantly stronger following jumps of smaller magnitude or jumps with lower concurrent trading volumes. The findings support the hypothesis that limited investor attention contributes to the short-term underreaction documented in this study.

5. Conclusion

We use jumps in stock prices as a proxy for large information shocks and examine market reactions to information shocks over the short run. We provide evidence consistent with the interpretation of short-term underreaction in the US equity market. The finding is pervasive among stocks traded on the NYSE/Amex and Nasdaq, stocks in different size and liquidity subsamples, and is robust to controlling for other firm characteristics. Based on intraday jumps in stock prices, we provide further evidence consistent with market underreaction over short horizons. In particular, overnight jumps have significant predictive power of returns over the subsequent one-week horizon. These results extend the stock return momentum, documented by Jegadeesh and Titman (1993), over intermediate horizons of six to 12 months to very short horizons. In addition, we show that the short-term underreaction documented in this study goes beyond the earnings momentum effect and market underreaction to information shocks, as proxied by jumps in stock prices, is much stronger than that to earnings surprises. Using both jump magnitude and trading volume as proxies of investor attention, we provide

Table 12

Potential explanation of short-term underreaction: limited investor attention

Each month, we perform cross-sectional regressions of stock returns on lagged jump returns and interactions with dummy variables defined based on the magnitude of jump returns or excess trading volume. Stock returns are calculated over the next one-month ($\mathrm{RET}_{t+1,t+1}$), three-month ($\mathrm{RET}_{t+1,t+3}$), six-month ($\mathrm{RET}_{t+1,t+6}$), and 12-month ($\mathrm{RET}_{t+1,t+12}$) horizons. Lagged cumulative jump returns are calculated over the past one month ($\mathrm{CJR}_{t,t}$) and three months ($\mathrm{CJR}_{t-2,t}$). The dummy variables are defined as $d^{JM}=1$ if a stock's jump magnitude is smaller than the median jump magnitude of all stocks with jumps over the same period and zero otherwise; $d^{ETV}=1$ if a stock's excess trading volume is lower than the median excess trading volume of all stocks with jumps over the same period and zero otherwise. The control variables are the same as in Table 9. This table reports the average of the coefficient estimates of monthly regressions and the absolute values of Newey-West t-statistics. Panel A reports the results for lagged one-month cumulative jump returns. Panel B reports the results for lagged three-month cumulative jump returns. The sample period is from July 1975 to December 2012.

Panel A: Results based on lagged one-month cumulative jump returns ($CJR_{t,t}$)

	$RET_{t+1,t+1}$		$RET_{t+1,t+3}$		$RET_{t+1,t+6}$		$RET_{t+1,t+12}$	
$CJR_{t,t}$	2.29	2.03	5.91	5.24	7.92	6.74	9.75	7.92
	[5.21]	[4.76]	[7.26]	[6.40]	[5.29]	[4.67]	[4.16]	[3.66]
$d^{JM}*CJR_{t,t}$	2.22		6.17		10.82		22.04	
	[3.67]		[6.23]		[6.95]		[9.13]	
$d^{ETV}*CJR_{t,t}$		2.08		6.13		10.47		18.55
		[3.52]		[6.36]		[6.06]		[6.30]
$CNJR_{t,t}$	−7.40	−7.38	−6.21	−6.13	−2.34	−2.21	4.72	4.95
	[8.42]	[8.35]	[5.43]	[5.33]	[1.79]	[1.68]	[1.81]	[1.88]
$LRET_{t-5,t-1}$	0.42	0.43	1.96	1.97	4.45	4.46	5.69	5.73
	[1.79]	[1.81]	[3.18]	[3.19]	[3.26]	[3.27]	[2.22]	[2.23]
$LRET_{t-11,t-6}$	0.64	0.64	1.26	1.26	1.12	1.13	−1.35	−1.33
	[4.16]	[4.20]	[2.66]	[2.67]	[1.15]	[1.16]	[0.83]	[0.83]
Size	−0.11	−0.12	−0.31	−0.31	−0.52	−0.53	−0.77	−0.77
	[3.28]	[3.31]	[3.17]	[3.18]	[2.58]	[2.59]	[1.80]	[1.80]
B/M	0.28	0.27	0.74	0.74	1.40	1.40	2.52	2.53
	[4.73]	[4.72]	[4.56]	[4.58]	[3.92]	[3.94]	[3.04]	[3.05]
$ILLIQ_{t,t}$	0.01	0.01	0.02	0.02	0.03	0.03	0.06	0.06
	[3.18]	[3.18]	[3.99]	[3.99]	[2.77]	[2.74]	[2.09]	[2.09]
$IVOL_{t,t}$	−0.25	−0.25	−0.58	−0.58	−0.84	−0.85	−1.24	−1.26
	[8.64]	[8.71]	[7.42]	[7.36]	[5.08]	[5.09]	[4.09]	[4.13]
LEV	−0.05	−0.05	−0.02	−0.02	0.14	0.14	0.26	0.25
	[0.69]	[0.68]	[0.12]	[0.11]	[0.29]	[0.29]	[0.24]	[0.23]
Intercept	3.05	3.07	8.46	8.49	15.18	15.24	26.80	26.90
	[6.15]	[6.20]	[5.44]	[5.47]	[4.69]	[4.71]	[3.91]	[3.92]
Adj. R^2	5.09%	5.12%	5.62%	5.65%	5.70%	5.73%	5.36%	5.37%

Panel B: Results based on lagged three-month cumulative jump returns ($CJR_{t-2,t}$)

	$RET_{t+1,t+1}$		$RET_{t+1,t+3}$		$RET_{t+1,t+6}$		$RET_{t+1,t+12}$	
$CJR_{t-2,t}$	0.46	0.63	1.35	1.86	1.48	2.51	0.82	2.95
	[1.81]	[2.49]	[2.74]	[3.77]	[1.74]	[2.95]	[0.81]	[2.72]
$d^{JM}*CJR_{t-2,t}$	2.39		5.06		9.09		16.94	
	[7.77]		[8.88]		[8.57]		[9.29]	
$d^{ETV}*CJR_{t-2,t}$		0.32		0.64		1.45		3.84
		[2.53]		[2.46]		[2.77]		[3.99]
$CNJR_{t-2,t}$	−3.71	−3.66	−2.26	−2.25	−0.20	−0.21	6.75	6.78
	[5.70]	[5.59]	[2.51]	[2.48]	[0.19]	[0.20]	[3.41]	[3.39]
$LRET_{t-5,t-1}$	1.35	1.37	2.49	2.52	4.52	4.51	4.13	4.07
	[6.37]	[6.51]	[4.66]	[4.72]	[4.01]	[3.95]	[2.11]	[2.07]
$LRET_{t-11,t-6}$	0.61	0.61	1.19	1.21	1.00	1.07	−1.54	−1.50
	[4.12]	[4.09]	[2.69]	[2.70]	[1.08]	[1.13]	[1.02]	[0.99]
Size	−0.13	−0.13	−0.36	−0.37	−0.61	−0.62	−0.94	−0.97
	[4.00]	[4.12]	[4.18]	[4.25]	[3.37]	[3.40]	[2.32]	[2.38]
B/M	0.24	0.22	0.62	0.56	1.23	1.15	2.29	2.21
	[4.21]	[3.72]	[3.90]	[3.42]	[3.43]	[3.15]	[2.72]	[2.54]
$ILLIQ_{t-2,t}$	0.02	0.02	0.04	0.04	0.06	0.06	0.09	0.10
	[4.68]	[4.89]	[4.85]	[5.07]	[3.12]	[3.36]	[2.25]	[2.41]
$IVOL_{t-2,t}$	4.68	4.89	4.85	5.07	3.12	3.36	2.25	2.41
	[8.03]	[8.25]	[6.74]	[6.97]	[4.61]	[4.98]	[3.70]	[4.06]
LEV	−0.04	−0.02	0.02	0.04	0.19	0.23	0.32	0.34
	[0.60]	[0.36]	[0.10]	[0.21]	[0.40]	[0.48]	[0.30]	[0.32]
Intercept	3.32	3.45	9.33	9.61	16.64	17.13	29.59	30.56
	[7.59]	[7.88]	[6.92]	[7.09]	[5.78]	[5.84]	[4.51]	[4.62]
Adj. R^2	5.14%	5.20%	5.77%	5.81%	5.98%	5.98%	5.65%	5.65%

evidence supporting the limited investor attention hypothesis for short-term underreaction.

Appendix A. Jump test and sequential jump identification procedure

Let $\{S_{t_0}, S_{t_1}, ..., S_{t_N}\}$be stock prices observed over the period [0, T], where $t_0 = 0$, $t_N = T$. Realized variance is defined as

$$RV_N = \sum_{i=1}^{N} r_i^2, \tag{A-1}$$

where $r_{t_i} = \ln[S_{t_i}/S_{t_{i-1}}]$ is the continuously compounded logarithmic return and the variance swap in the discretized version of the left-hand side of Eq. (2) is defined as

$$SWV_N = 2\sum_{i=1}^{N}(R_i - r_i) = 2\sum_{i=1}^{N} R_i - 2\ln(S_T/S_0), \tag{A-2}$$

where $R_{t_i} = S_{t_i}/S_{t_{i-1}} - 1$ is the simple return, both sampled with step size T/N over the interval [0, T]. Jiang and Oomen (2008) show that

$$\frac{V_{(0,T)}N}{\sqrt{\Omega_{SWV}}}\left(1 - \frac{RV_N}{SWV_N}\right) \xrightarrow{d} \mathrm{N}(0, 1), \tag{A-3}$$

where N is the number of observations sampled between zero and T, $\Omega_{SWV} = \frac{1}{9}\mu_6 X_{(0,T)}$, $X_{(0,T)} = \int_0^T V_u^3 du$, and $\mu_p = 2^{\mu/2}\Gamma[(p+1)/2]/\sqrt{\pi}$. To implement the test statistic in (A-3), we obtain consistent estimators of $V_{(0,\,T)}$ and $X_{(0,\,T)}$. Barndorff-Nielsen and Shephard (2006) show that BPV_N is a consistent estimator of $V_{(0,\,T)}$ and a consistent estimator of $V_{(0,\,T)}$ can be obtained based on the bi-power variation

$$BPV_N = \frac{1}{\mu_1^2}\sum_{i=1}^{N-1}|r_i||r_{i+1}|. \tag{A-4}$$

Furthermore, to obtain a feasible version of the test statistic in (A-3), we obtain a consistent estimator of Ω_{SWV} based on $\hat{\Omega}_{SWV} = \frac{1}{9}\mu_6 \frac{N^3\mu_{6/p}^{-p}}{N-p+1}\sum_{i=0}^{N-p}\prod_{k=1}^{p}|r_{i+k}|^{6/p}$, with $p = 6$.

The above test is performed using daily return observations over a three-month rolling window. Once the above jump test rejects the null hypothesis of no jumps in a given three-month window, we proceed to identify those days with stock price jumps following a sequential procedure. Let $\{r_{t_1}, r_{t_2}, ..., r_{t_N}\}$ be daily returns over the interval [t_1, t_N]. The sequential jump identification procedure is then described as follows:

Step 1: Assume that we have performed a jump test using return observations over a three-month window [t_1, t_N]. If the jump test does not reject the null hypothesis of no jumps, we move to the next three-month window; otherwise we record the jump test statistic JS_0 and proceed to Step 2.

Step 2: Replace each daily return by the median of the sample (denoted r_{median}) and perform the jump test on the series. For example, when day i's return is replaced, we perform the jump test on the series $\{r_{t_1}, ..., r_{t_{i-1}}, r_{median}, r_{t_{i+1}}, ..., r_{t_N}\}$ and record the test statistic JS_i for $i = 1, ..., N$.

Step 3: Construct the series JS_0–JS_i for $i = 1, ..., N$. Then, the stock price change on day j is identified as a jump if JS_0–JS_j has the highest value of all days.

Step 4: Replace the identified jump observation by r_{median} and start again from Step 1 with a new sample of stock returns.

The above procedure continues until all jumps are identified. Andersen, Bollerslev, Frederiksen, and Nielsen (2010) propose a similar procedure for identifying intraday jump returns. The main difference is that instead of using the median of the sample to replace each single return in Step 2 of the sequential procedure, they use the mean of the remaining $N - 1$ returns. To identify jumps in intraday returns, we perform the jump test each day for all stocks in our sample. Once the jump test rejects the null hypothesis of no jumps in a given day, we follow the same sequential procedure to identify intraday jumps.

Finally, daily stock returns and particularly intraday stock returns contain market microstructure noise. We take this into account in both the jump test and jump identification. Specifically, the jump test is modified with the assumption that stock prices are observed with noise, where the standard deviation of the noise is estimated from the autocovariance of observed stock returns and is used to adjust the asymptotic variance of the jump test (for details, see Jiang and Oomen, 2008). In addition, to ensure that identified jump returns are not the result of bid-ask bounce, we impose additional restrictions. That is, the absolute value of an identified jump return must be more than twice the tick size.

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