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Jump on the Post–Earnings Announcement Drift (corrected November 2012)

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The authors examined the potential profitability of a strategy that exploits the post–earnings announcement drifts contingent on jump dynamics identified in stock prices around earnings announcements. With long positions in positive-jump stocks and short positions in negative-jump stocks, their hedge portfolio achieved an annualized abnormal return of 15.3% and an annualized Sharpe ratio of 1.52 over the last four decades. Neither conventional risk factors nor common company characteristics explain the abnormal return.

For more than four decades—since Ball and Brown (1968) was published—the post–earnings announcement drift (PEAD), or earnings momentum, has been one of the most robust and persistent anomalies challenging the efficient market paradigm. Dubbed "the granddaddy of all underreaction events" by Fama (1998, p. 286), PEAD refers to the tendency of a stock's cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks (or even several months) following an earnings announcement. Research to date has not fully explained the reason for earnings momentum; nevertheless, the persistent phenomenon of the sluggish response of stock prices to informational shocks in earnings announcements has generated interesting implications for portfolio choices and trading strategies.[1]

Previous studies have proposed two trading signals to measure and profit from with respect to earnings announcement surprises. One signal is the standardized unexpected earnings (SUE), first proposed by Latané and Jones (1977). It measures the standardized difference between the realized earnings from earnings announcements and the expected earnings from economic models or analysts' forecasts. Chordia and Shivakumar (2006) documented that an arbitrage strategy that takes long positions in stocks with the most positive earnings surprises and short positions in stocks with the most negative earnings surprises generates a monthly return of 90 bps. The other widely used signal is the earnings announcement return (EAR), initially proposed by Chan, Jegadeesh, and Lakonishok (1996). It was recently revived by Brandt, Kishore, Santa-Clara, and Venkatachalam (2008, p. 1), who argued that EAR "captures the surprise in all aspects of the company's earnings announcement, and not just the surprises in earnings."

To exploit PEAD for profit, investors have searched for other signals around earnings announcements, including revenue surprises (Chen, Chen, Hsin, and Lee 2010; Jegadeesh and Livnat 2006), company-level liquidity (Sadka 2006), arbitrage risk measure (Mendenhall 2004), trading volume as a proxy for opinion divergence (Garfinkel and Sokobin 2006), and analyst responsiveness (Zhang 2008).

Discussion of findings. In our study, we focused on a measure of company-level informational shocks based on the realized "jump" dynamics of stock prices around earnings announcements and examined the profitability of an earnings momentum strategy that uses extreme price movements, or jumps, as trading signals. Specifically, we posited that companies' unobserved "extremely good news" is impounded in unexpectedly large and discrete price hikes, or positive jumps, around earnings announcements, whereas companies' unobserved "extremely bad news" is reflected in large and abrupt price plunges, or negative jumps, around earnings announcements. Accordingly, we considered a hedge portfolio that takes long positions in positive-jump companies and short positions in negative-jump companies. Identifying jumps by using a newly developed statistical method (Lee and Mykland 2008), we found compelling evidence of post–earnings announcement return drifts in the same direction as jumps over the subsequent three months. This strategy yielded a quarterly excess return of

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3.63%, equivalent to a 15.3% annualized return, over the sample period (1971–2009). This result suggests yet another anomaly associated with PEAD. Market participants seem largely to underreact to, or are simply unaware of, the latent "extremely good (or bad) news" signaled by the direction of jumps around earnings announcements.

Our jump-augmented PEAD strategy is motivated by the growing literature documenting the importance of accounting for the discontinuous component of (log) price processes in option hedging (Broadie, Chernov, and Johannes 2009; Kim and Kim 2005; Naik 1993), bond premium forecasting (Wright and Zhou 2009), credit risk management (Duffie and Pan 2001; Schneider, Sögner, and Veza 2010), and the evaluation of systematic risk (Todorov and Bollerslev 2010; Dunham and Friesen 2007; Yan 2011). In particular, a large strand of empirical studies that examined the causal relationship between important news events and jumps in financial markets underlies the intuition of our jump-based earnings momentum strategy.[2] For example, Maheu and McCurdy (2004) argued that normal news events induce smooth and continuous sample paths of price changes, whereas unusual news events are likely to prompt jumps—in line with our interpretation of identified jumps around earnings announcements as signals of the unobserved extremely good (or bad) news.

At first blush, our use of extreme price changes, or jumps, as a trading signal is akin to the PEAD trading strategy that uses EAR as a signal. Both jump and EAR signals attempt to extract information about stocks' future payoffs from unusual price changes around earnings announcements. However, the two signals are distinct, both theoretically and empirically. EAR measures the informational shocks through overall returns, whereas the jump signal explicitly accounts for those informational shocks that drive the discontinuous jump component of the return process. We hypothesized that the jump signal is, by construction, correlated with EAR, yet it contains information about PEAD that neither EAR nor SUE captures. Accordingly, we subjected our hypothesis to an extensive set of tests. Our results show that jump signals are not replications of EAR or SUE. Jumps occurred in all our EAR-sorted quintile portfolios, but only a small subset of stocks within each quintile portfolio experienced jumps.

We computed the historical performance of a jump-based hedge portfolio and compared it with a set of earnings momentum strategies that trade on the signals of SUE and EAR. Our jump-based strategy performed similarly to SUE-based strategies and much better than EAR-based strategies of comparable size on key evaluation criteria. We also investigated a variety of potential explanations for the excess returns from the jump-based hedge portfolio. Our results show that neither company characteristics nor common risk factors explain the abnormal returns.

Our study contributes to both the PEAD and the jump literature in several ways. First, it expands the PEAD literature by documenting yet another asset-pricing anomaly associated with the post–earnings announcement drift. Our results suggest that the discrete jump path of return processes around earnings announcements may convey unique information about the subsequent earnings momentums. Second, our study is the first to explore the asset-pricing implications of jumps in the context of PEAD and to provide evidence against the risk-based explanations for post-jump abnormal returns.[3] Finally, our results suggest that a hedge portfolio that takes long positions in positive-jump stocks and short positions in negative-jump stocks around earnings announcements generates an annualized Fama–French (1993) three-factor alpha of 15.3%.

Data, Sample, and Methodology

Before discussing our results, we present the essential elements of our study: the data, the sampling process, the jump detection method, the trading strategies, and the construction of various competing trading strategies.

Data and Sample. Our sample consisted of all companies listed on the NYSE, NASDAQ, or Amex with data available in the daily CRSP and quarterly Standard & Poor's Compustat files over October 1971–December 2009. We excluded stocks priced below $5 on the earnings announcement dates to avoid microstructure and liquidity issues associated with trading low-priced stocks.[4] To better mimic the practical trading constraints, we applied quarter-by-quarter filters to winsorize observations with the lowest (1st percentile) market value and the highest (99th percentile) illiquidity measure (Amihud 2002). We obtained the percentiles at the end of the previous year.[5] In total, our sample included 410,290 observations for 12,008 public companies, 34.1 calendar quarters for each company, and 2,735 companies in each calendar quarter.

Jump Detection Methodology. We used the nonparametric jump detection method proposed by Lee and Mykland (2008).[6] This method has been successfully applied in several empirical studies, including Lahaye, Laurent, and Neely (2011), Lee (2009), and Todorov (2010). At time t, the statistic L

can be used to test whether a jump occurs between $t-1$ and t:

$$L = \frac{R_t}{\sqrt{\sum_{j=t-K+2}^{t-1} \left(\left|R_j\right|\right)\left(\left|R_{j-1}\right|\right)}}\left(\sqrt{K-2}\right), \tag{1}$$

where R_t is the log-return over the interval $(t-1, t)$. K, the window size within which the corresponding local movements of the price process are considered, is chosen so as to eliminate the effect of jumps on the volatility estimation. Under the null hypothesis of no jumps at time t, $\sqrt{2\pi} \sim N(0,1)$. Under the alternative hypothesis of having jumps at time t, $L \to \infty$. To accommodate our return data at a daily frequency, we set K equal to 16 and specified the rejection region at the significance level of 1%, following Lee and Mykland (2008).[7]

Our Trading Strategy. We used $Jump_{(-1,1)}$ to measure the occurrences and signs of jumps over the three-day window centered on earnings announcement dates. We first applied the Lee–Mykland method to detect the occurrence of jumps on each of the three days. We called a trading day on which jumps were detected a *jump day*. We calculated $Jump_{(-1,1)}$ as the cumulative daily returns on only those jump days over the three-day window centered on earnings announcement dates. We defined positive-jump (negative-jump) stocks as companies with positive (negative) $Jump_{(-1,1)}$ and no-jump stocks as companies with no jumps on any of the three days.

After companies reported quarterly earnings on the earnings announcement date t, we took long or short positions on day $t+2$ in stocks on the basis of the sign of $Jump_{(-1,1)}$. In each calendar quarter, we formed a hedge portfolio by taking long positions in positive-jump stocks and short positions in negative-jump stocks. We maintained the positions for exactly 60 trading days, from $t+2$ to $t+61$.[8] We repeated the process for each calendar quarter over the sample period (1971–2009).

To measure the excess returns of our trading strategy, we computed CAR(2, 61), the daily cumulative abnormal returns between $t+2$ and $t+61$ for each stock. We defined the daily abnormal return as the difference between a stock's raw daily return from CRSP and the daily return of a portfolio with a similar size and book-to-market ratio (B/M).[9]

Other PEAD Trading Signals. Following the procedure laid out in Livnat and Mendenhall (2006), we constructed the standardized unexpected earnings (SUE) that measure informational shocks contained in earnings announcements:[10]

$$SUE_{h,t} = \frac{EPS_{h,t} - EPS_{h,t-4}}{P_{h,t}}, \tag{2}$$

where $EPS_{h,t}$ is primary earnings per share before extraordinary items for company h in quarter t, $EPS_{h,t-4}$ is EPS before extraordinary items four fiscal quarters prior to quarter t, and $P_{h,t}$ is the price per share for company h at the end of quarter t (all from Compustat). We defined the earnings announcement return (EAR) as the cumulative abnormal return over the three-day window centered on earnings announcement dates (see Brandt et al. 2008).

Following Brandt et al. (2008) and Chordia, Goyal, Sadka, Sadka, and Shivakumar (2009), we applied the percentiles of the previous quarter's ranking of SUE and EAR observations as the cutoff values to the current quarter's trading signals. This approach captures the immediate return accumulation after the announcement but may suffer from the potential obsoleteness of screening criteria for trading signals, especially in volatile markets.[11] We took long (short) positions in stocks within the top (bottom) percentiles and maintained the positions for the next 60 days. We then computed the cumulative post–earnings announcement abnormal returns for SUE and EAR strategies between $t+2$ and $t+61$.[12]

$Jump_{(-1,1)}$, SUE, and EAR share similarities as trading signals. They all exploit PEAD and attempt to extract information that can forecast the subsequent return drifts from publicly observable information around earnings announcements. However, the jump-based trading strategy is distinct from the SUE- and EAR-based strategies. Theoretically, the SUE-based strategy considers information in earnings surprises and the EAR-based strategy incorporates nonearnings information by capturing, from the overall return process, the intensity of market reactions to the release of earnings announcements. In reality, the jump-based trading strategy explicitly focuses on the informational shock that is represented by the discrete sample path of return processes around earnings announcements. Using the nonparametric jump detection method of Lee and Mykland (2008), we hypothesized that identified jumps in stock returns have some informational content that neither SUE nor EAR captures.[13] We then took advantage of the diverging PEAD between positive-jump stocks and negative-jump stocks around earnings announcements.[14] In summary, the jump signal does share some similarities with SUE and EAR, but it also has unique features that complement these two popular PEAD signals.

Empirical Results

In discussing our empirical results, we start with a description of the empirical frequencies of jumps in our sample period. We next examine the joint distributions of the jump signal—$Jump_{(-1,1)}$—and other trading signals, such as SUE and EAR. We then compare the portfolio performances of various trading strategies. Finally, we investigate the characteristics of jump-based portfolios and perform a factor analysis on their returns.

Jump Frequencies. To implement the jump-augmented PEAD strategy successfully, one needs a sufficient number of stocks with identified jumps in each quarter to form the hedge portfolio. However, jumps represent the discontinuous path of the return process and are, by definition, rare events. Thus, one concern is that this trading strategy may suffer from underinvestment (Wermers 2000). To alleviate this concern, we first examined the cross-sectional frequency of jump occurrences around the earnings announcements in each quarter between 1971:Q4 and 2009:Q4.

Table 1 presents the descriptive statistics of quarterly jump occurrences and frequencies over the last four decades. In a typical quarter over the entire sample period, we can see that, on average, 94 companies (3.09% of all companies) experienced negative jumps over the three-day period centered on their respective earnings announcement dates (Panel A). We also observe that, on average, 122 companies (4.07% of all companies) in each quarter experienced positive jumps over the three-day window. The frequency of jump occurrences implies that a quarterly hedge portfolio, on average, consists of 7.16% (= 3.09% + 4.07%) of all earnings-reporting companies. However, the portfolio size fluctuates substantially, ranging from 0.57% (10 companies) to 10.60% (347 companies) and from 0.78% (9 companies) to 10.92% (390 companies) for portfolios of negative and positive jumps, respectively.

Table 1. Summary Statistics of Jump Frequencies, 1971–2009

	Observations				Percentages		
	Total	Negative	Zero	Positive	Negative	Zero	Positive
A. Full sample (1971:Q4–2009:Q4)							
Mean	2,722.15	93.64	2,506.45	122.07	3.09	92.83	4.07
St. dev.	1,065.74	81.87	951.62	92.68	2.10	3.96	2.14
Min.	509	10	485	9	0.57	80.54	0.78
Max.	4,441	347	4,209	390	10.60	97.42	10.92
B. 1971:Q4–1979:Q4							
Mean	1,320.21	23.73	1,262.06	34.42	1.84	95.55	2.62
St. dev.	236.45	11.04	229.41	12.53	0.79	0.78	0.88
Min.	509	11	485	9	0.69	93.70	0.78
Max.	1,595	69	1,532	63	4.48	96.79	5.36
C. 1980:Q1–1989:Q4							
Mean	2,240.53	55.23	2,114.80	70.50	2.33	94.57	3.10
St. dev.	477.15	44.79	437.32	28.20	1.60	1.81	0.99
Min.	1,419	10	1,369	22	0.57	87.53	1.40
Max.	2,796	284	2,624	160	10.60	97.42	6.80
D. 1990:Q1–1999:Q4							
Mean	3,444.58	92.68	3,218.93	132.98	2.68	93.51	3.81
St. dev.	789.51	34.55	729.57	45.17	0.70	0.80	0.73
Min.	2,140	32	2,033	53	1.37	92.01	2.46
Max.	4,441	200	4,135	225	4.60	95.25	5.21
E. 2000:Q1–2009:Q4							
Mean	3,686.16	195.79	3,249.40	240.97	5.43	87.93	6.64
St. dev.	370.00	83.82	447.81	85.60	2.52	4.88	2.55
Min.	2,850	57	2,563	45	1.59	80.54	1.45
Max.	4,414	347	4,209	390	10.32	96.72	10.92

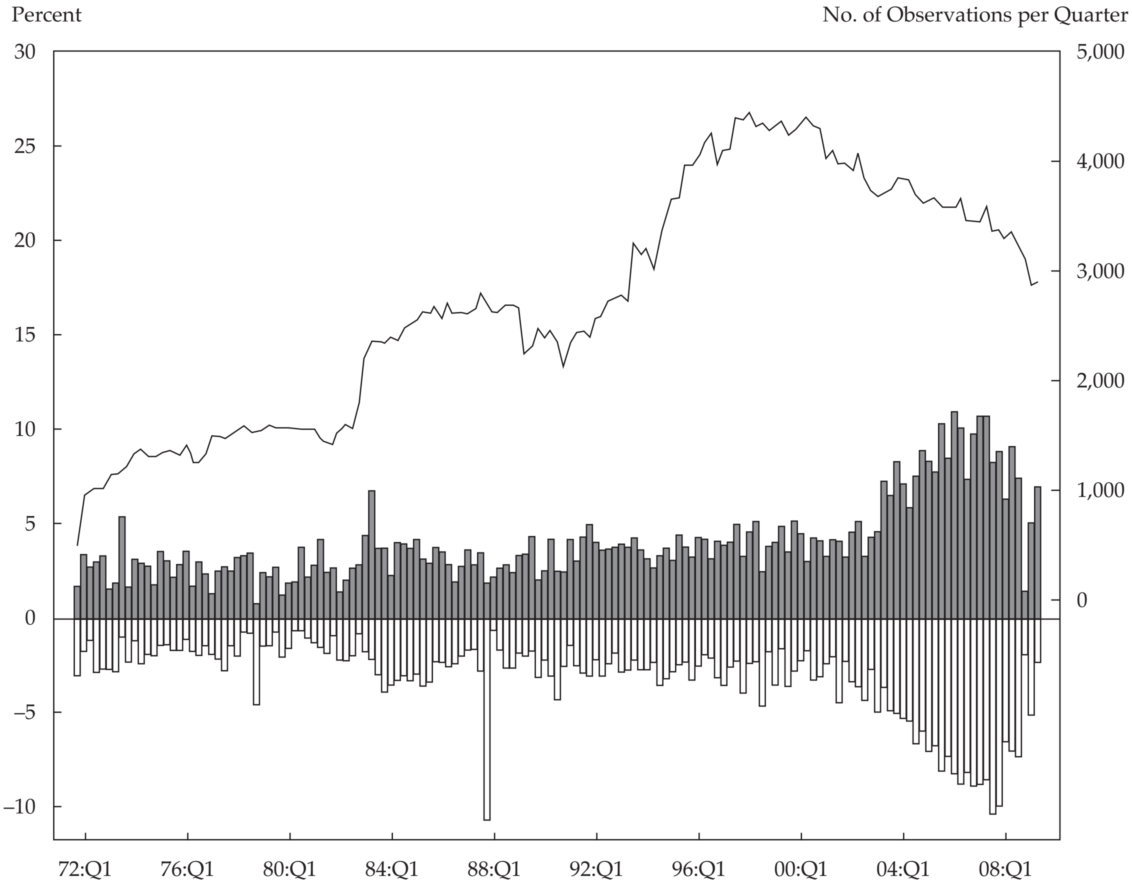
Notes: This table reports the summary statistics of quarterly observations and frequencies of negative-jump companies, no-jump companies, and positive-jump companies. We calculated the number and percentage of companies with negative, zero, and positive jumps each quarter and report their time-series quarterly averages and standard deviations over different sample periods.

Panels B through E report the descriptive statistics by decade. Overall, both the absolute number of companies and the percentage of companies with negative or positive jumps increase over time. The quarterly average percentage of companies with jumps was 4.46% (= 1.84% + 2.62%) in the 1970s, and then gradually rose to 5.43% (= 2.33% + 3.10%) and 6.49% (= 2.68% + 3.81%) in the 1980s and 1990s, before it finally surged to 12.07% (= 5.43% + 6.64%) in the last decade, consistent with the graphic illustration in **Figure 1**.

Figure 1 plots the total number of earnings-reporting companies in each quarter during the entire sample period, along the right axis, and the time-varying quarterly percentages of companies with negative jumps (downward bars) and positive jumps (upward bars), along the left axis. Not surprisingly, the upward trend in the absolute and relative numbers of companies with jumps requires today's investors to balance their portfolios with more stocks than in previous years. Even in the 1970s, however, investors could form the quarterly hedge portfolio from a pool of at least 20 stocks, thus achieving a reasonable degree of diversification. More recently, the underinvestment issue raised in Wermers (2000) is perhaps much less a concern: The minimum number of investable stocks (with identified jumps) each quarter was 85 (= 32 + 53) and 102 (= 57 + 45) in the 1990s and early 2000s, respectively.

Comparison with Other Trading Signals. The premise of our analysis is that the discontinuous sample path, or jumps, of stock return processes captures unique informational shocks that are distinct from those contained in other trading signals derived from earnings announcements, such as SUE or EAR. To test this hypothesis, we investigated the joint distributions of the jump signal—$Jump_{(-1,1)}$—and SUE (or EAR). In each calendar quarter, we first

Figure 1. Number of Earnings-Reporting Companies and Frequency of Jumps around Earnings Announcements, 1971–2009



Notes: The solid line depicts the total number of companies reporting earnings in each calendar quarter (right axis). The vertical bars plot the quarterly percentages (left axis) of companies with positive (upward bars) and negative (downward bars) jumps between 1971:Q4 and 2009:Q4. We used the statistical procedure of Lee and Mykland (2008) to detect jumps in stock prices over the three-day window centered on earnings announcements dates.

sorted stocks into quintile portfolios by their SUE (or EAR) rankings in the concurrent quarter and then divided each SUE- or EAR-sorted quintile portfolio into three jump portfolios on the basis of $Jump_{(-1,1)}$.[15] This method yielded 15 (= 5 × 3) portfolios: one positive-, one negative-, and one no-jump portfolio within each SUE- or EAR-sorted quintile portfolio.

Columns 1–3 in **Table 2** report average quarterly proportions of companies with negative, positive, or zero jump signals within each quintile portfolio sorted by SUE (Panel A) or EAR (Panel B). Across five SUE-sorted quintile portfolios, more than 90% of companies in a typical quarter experienced no jumps. Overall, stocks whose reported earnings deviate the most from market expectations are the most likely to experience discontinuous and discrete changes in stock prices. Not surprisingly, the percentages of companies with positive (negative) jumps monotonically increase (decrease) from the lowest to the highest SUE-sorted quintile portfolios. In the highest SUE-sorted quintile portfolio, 7.73% and 2.07% of companies experienced positive and negative jumps, respectively; in the lowest SUE-sorted quintile portfolio, more companies experienced negative jumps (5.41%) than positive jumps (2.92%). One concern is that the positive-jump companies tend to have higher SUEs than the negative-jump companies, giving rise to an association between jump directions and the magnitude of SUEs even within the same SUE-sorted quintile portfolio. We investigated and ruled out such a possibility. Untabulated results show that the average SUEs for positive-jump companies are not statistically different from the average SUEs for the negative-jump companies within each of the five SUE-sorted quintile portfolios.

Panel B of Table 2 reports the empirical joint distribution of $Jump_{(-1,1)}$ and EAR signals. Across five EAR-sorted quintile portfolios, we can see a pattern of jump distributions similar to that in Panel A. The three middle EAR-sorted quintile portfolios consist of a predominant number of companies, more than 97%, with no jumps. Some 15% of companies in the lowest EAR-sorted quintile portfolio experienced negative jumps, and 19% in the highest EAR-sorted quintile portfolio experienced positive jumps. By construction, EAR and $Jump_{(-1,1)}$ are highly correlated, so it is not surprising to observe high concentrations of positive (negative) jump observations in the highest (lowest) EAR-sorted quintile portfolios. Although both EAR and $Jump_{(-1,1)}$ are derived from stock returns, the latter focuses on the dynamics of the discrete path in the return process whereas the former does not differentiate the diffusion component from the discrete component in the overall returns. Therefore, it is conceivable that jump signals capture some unique and incremental information that is indistinguishable in EARs. By introducing the jump signals, we can identify a small subset of companies in each of two extreme EAR-sorted quintile portfolios and expect them to yield greater spreads so as to provide evidence on the incremental contributions of jump signals.

We next examined the return drifts of portfolios double-sorted on $Jump_{(-1,1)}$ and SUE (or EAR) to provide further evidence on the unique informational content of jump signals. Every calendar quarter, we first sorted stocks into quintile portfolios on the basis of SUE or EAR and took long positions in the quintile portfolios for 60 days between $t + 2$ and $t + 61$, where t represents the earnings announcement date. We denoted the 60-day cumulative abnormal return as CAR(2, 61).[16] We further classified stocks within each quintile into three groups on the basis of the sign of $Jump_{(-1,1)}$. We held the double-sorted portfolio for 60 days between $t + 2$ and $t + 61$. The remaining columns in Table 2 report the time-series averages of quarterly returns for each SUE- and EAR-sorted quintile portfolio and for each SUE (or EAR) and $Jump_{(-1,1)}$ double-sorted portfolio. To avoid potential bias caused by uneven distributions of investable companies (with jumps) over time, as shown in Figure 1, we calculated both equally weighted averages (columns 4–7) and portfolio-size weighted averages (columns 9–12). Columns 8 and 13 report the spreads between positive- and negative-jump groups within each SUE-sorted quintile portfolio.

Let us first focus on the findings with respect to equally weighted averages. Column 4 shows that the spread between the highest and lowest SUE-sorted (EAR-sorted) portfolios is significantly positive at 352 bps (145 bps) per quarter.[17] These findings are consistent with those in the PEAD literature showing that high-SUE (high-EAR) stocks outperform low-SUE (low-EAR) stocks.

Of particular interest are the spread between the positive- and negative-jump groups within each SUE-sorted quintile portfolio and the incremental contribution of jump signals to enhance the spread between the two extreme EAR-sorted quintile portfolios. In each of the five SUE-sorted portfolios in Panel A, on average, companies with positive jumps consistently earned higher CARs than those with negative jumps. The differences (in column 8) range from 2 bps to 457 bps and are statistically significant at the 5% level (at least) for three SUE-sorted quintile portfolios.

For the EAR-sorted portfolios in Panel B, let us focus on the highest and lowest EAR-sorted

Table 2. Distribution of Jump Signals in SUE/EAR-Sorted Quintile Portfolios, 1971–2009

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Distribution of Jumps in Each SUE/EAR-Sorted Quintile			60-Day Cumulative Abnormal Returns after Earnings Announcements, CAR(2, 61)									
				Equally Weighted Average					Portfolio-Size Weighted Average				
Portfolio	Negative (%)	Zero (%)	Positive (%)	Total (%)	Negative (%)	Zero (%)	Positive (%)	Diff. (bps)	Total (%)	Negative (%)	Zero (%)	Positive (%)	Diff. (bps)
A. SUE and Jump$_{(-1,1)}$ as sorting variable													
1 (low)	5.41	91.68	2.92	2.88***	2.59***	2.88***	2.61**	2	2.99***	1.70*	3.04***	3.81***	211*
2	4.16	92.93	2.91	2.21***	1.11	2.23***	2.66***	154	2.19***	–0.18	2.28***	2.72***	290***
3	3.16	93.28	3.57	3.03***	0.86	3.07***	3.00***	214**	2.98***	–0.08	3.08***	3.08***	315***
4	2.40	92.29	5.31	4.68***	2.78***	4.66***	5.82***	304***	4.60***	1.24*	4.63***	5.57***	432***
5 (high)	2.07	90.20	7.73	6.40***	3.99***	6.25***	8.56***	457***	6.47***	1.21	6.36***	9.24***	802***
B. EAR and Jump$_{(-1,1)}$ as sorting variable													
1 (low)	15.01	84.95	0.04	3.58***	2.13**	3.80***	1.33	—	3.53***	0.90	4.00***	11.02***	—
2	1.76	98.15	0.10	3.22***	1.09	3.25***	0.75	—	3.18***	–0.48	3.24***	2.50**	—
3	0.29	99.22	0.50	3.55***	3.17***	3.55***	2.91***	—	3.54***	1.75**	3.54***	4.25***	—
4	0.09	97.22	2.68	3.80***	0.58	3.80***	4.16***	—	3.85***	2.79	3.86***	3.50***	—
5 (high)	0.04	80.84	19.12	5.03***	0.58	4.79***	6.03***	—	5.14***	4.20**	4.88***	6.21***	—

Notes: This table reports the distribution of jump signals within SUE- and EAR-sorted quintile portfolios. Because often there are too few stocks with either positive or negative jumps in the EAR-sorted portfolios to form a reasonably sized portfolio, we do not report the spreads between positive- and negative-jump groups within each EAR-sorted quintile.

*Significant at the 10% level under untabulated Newey–West *t*-statistics.
**Significant at the 5% level under untabulated Newey–West *t*-statistics.
***Significant at the 1% level under untabulated Newey–West *t*-statistics.

quintile portfolios.[18] In the highest EAR-sorted quintile, a subset of companies with positive jumps, on average, earned a CAR 100 bps higher than the quintile average (603 bps in column 7 versus 503 bps in column 4). Similarly, a subset of negative-jump companies in the lowest EAR-sorted quintile earned an average CAR that was 145 bps lower than the quintile average (213 bps in column 5 versus 358 bps in column 4). By jointly considering signals of EAR and $Jump_{(-1,1)}$ and using the diagonal portfolios in the top-left (213 bps) and bottom-right (603 bps) corner cells (spread = 603 bps – 213 bps = 390 bps), we can more than double the spread between the two extreme EAR-sorted quintile portfolios (503 bps – 358 bps = 145 bps). The findings for the portfolio-size weighted averages (columns 9–13) are similar to, and frequently stronger than, those reported for the equally weighted averages.

In summary, jump signals are empirically related to SUEs and, by construction, are closely correlated with EARs. However, jump signals make their own distinctive and incremental contributions to predicting future stock returns. First, we can identify nontrivial proportions of companies that have the best (worst) SUEs and experience negative (positive) jumps around earnings announcement dates. Second, even though jump signals use the same intuition of "extreme returns" around earnings announcement dates, they are not simple replications of EAR signals in both theory and practice. Jump signals reinforce the performance of an EAR strategy by identifying a small subset of companies with positive jumps in the highest EAR-sorted quintile portfolio and negative jumps in the lowest EAR-sorted quintile portfolio. Finally, we have provided evidence that positive-jump portfolios consistently earn a higher average abnormal return than do negative-jump portfolios after controlling for the SUE effect.

Performances of Different Trading Strategies. Having found preliminary evidence that jump signals contain unique information that forecasts post–earnings announcement return drifts, we compared the historical performance of our proposed jump-based trading strategy with that of the SUE- and EAR-based trading strategies over the sample period 1971:Q4–2009:Q4 (157 quarterly returns).

To compare the performances of different trading strategies effectively, we constructed hedge portfolios with comparable sizes. SUE- and EAR-based trading strategies traditionally take long–short positions in the highest- and lowest-decile portfolios, thus requiring a portfolio comprising 20% of all stocks. Jump-based hedge portfolios, however, represent 7.16% of all stocks, on average. Consequently, the jump-based trading strategy may outperform other strategies simply because it is more selective with respect to portfolio construction. Therefore, to match the portfolio size of the jump-based trading strategy, we chose three sets of top- and bottom-percentile breakpoints to include, on average, 6%, 10%, and 20% of all stocks in SUE- and EAR-based hedge portfolios. The results are presented in **Table 3**.

Panel A reports the performances of three portfolios that are based on the jump signal, $Jump_{(-1,1)}$. We constructed the hedge portfolio by taking long positions in positive-jump stocks and short positions in negative-jump stocks. The hedge portfolio contained 218 stocks in a typical quarter and yielded an average quarterly abnormal return of 3.63%, equivalent to a 15.3% annualized return. The portfolio had an annualized Sharpe ratio of 1.52. Taking the time-varying portfolio size into account, we observed an even higher portfolio-size weighted average quarterly abnormal return of 3.94% and an annualized Sharpe ratio of 1.83. Over the entire sample period, the maximum quarterly loss was 12.5% and the portfolio returns exhibited negligible first-order serial correlation (–0.02), slightly negative skewness (–0.38), and fat tails (3.95).

Panels B and C line up the performances of SUE- and EAR-based hedge portfolios with various portfolio sizes. The row "p97–p3" ("p95–p5" and "p90–p10") indicates hedge portfolios consisting of stocks (in the opposite trading positions) in the upper and lower 3rd (5th and 10th) SUE or EAR percentile, as described earlier. The first row of Panel B reports the historical performance of the SUE-based hedge portfolio with the top 97th and bottom 3rd percentile breakpoints. The portfolio "p97–p3," on average, contained 174.3 stocks, or 6% of all companies, and yielded a quarterly abnormal return of 3.49%, with an annualized Sharpe ratio of 1.24. Compared with the jump-based hedge portfolio in Panel A, whose average portfolio size was slightly larger (7.14% versus 6% of all companies, or 218 versus 174), the SUE-based hedge portfolio with comparable portfolio size generated lower but more volatile abnormal returns. When we increased the number of stocks in the hedge portfolio to 10% (20%) of all companies, the average quarterly abnormal return and the annualized Sharpe ratio increased to 3.87% (4.03%) and 1.63 (2.07), respectively. Such an improvement in portfolio performance, however, comes at a hefty price. To increase the quarterly abnormal return of the SUE-based trading strategy by 24 bps (= 3.87% – 3.63%) or to raise the Sharpe

Table 3. Portfolio Performance of Different Trading Strategies, 1971–2009

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Equally Weighted				Portfolio-Size Weighted			
Portfolio	Average Portfolio Size	Maximum Quarterly Loss (%)	AR(1)[a]	Mean (%)	Sharpe Ratio	Skewness	Kurtosis	Mean (%)	Sharpe Ratio	Skewness	Kurtosis
A. Jump$_{(–1,1)}$											
Negative	94.7	–32.3	0.02	2.05**	0.41	–0.24	4.47	0.78	0.15	–0.40	4.59
Positive	123.4	–28.4	0.06	5.68***	1.16	–0.23	4.10	5.87***	1.19	–0.44	4.48
Hedge (= Pos. – Neg.)	218.2	–12.5	–0.02	3.63***	1.52	–0.38	3.95	3.94***	1.83	–0.29	4.79
B. SUE											
p97–p3	174.3	–11.4	–0.06	3.49***	1.24	0.32	4.51	2.92***	1.04	0.05	4.29
p95–p5	286.1	–11.5	–0.12	3.87***	1.63	0.17	4.13	3.39***	1.45	–0.06	4.51
p90–p10	559.3	–10.5	–0.08	4.03***	2.07	0.14	4.98	3.66***	1.92	–0.15	5.31
C. EAR											
p97–p3	183.9	–37.5	0.17	2.20***	0.63	–1.27	9.89	2.46***	0.79	–0.39	4.99
p95–p5	297.5	–34.6	0.12	1.94***	0.65	–1.51	12.52	2.03***	0.79	–0.38	5.65
p90–p10	577.0	–17.3	0.13	1.74***	0.93	–0.95	6.94	1.88***	1.02	–0.72	6.13

Note: This table compares the portfolio performances of three trading strategies: jump, SUE, and EAR.

[a]First-order autoregressive coefficient.

**Significant at the 5% level.
***Significant at the 1% level.

ratio by 7.2% (= 1.63/1.52 – 1), we would need to trade, on average, 31.2% (or 68) more stocks every quarter. By the same token, to reap a 40 bp increase (= 4.03% – 3.63%) in quarterly abnormal returns or to boost the Sharpe ratio by 36.2% (= 2.07/1.52 – 1), we would need to more than double the number of traded stocks, from 7.14% to 20% of all companies (from 218 to 559). Taking the transaction and monitoring costs into consideration, we can see that the hedge portfolio based on jump signals performs at least as well as the three SUE-based hedge portfolios in Panel B.

Panel C presents the performances of three hedge portfolios based on EAR signals. All three EAR-based hedge portfolios of different sizes perform overwhelmingly worse than the jump-based hedge portfolio. As mentioned earlier, by construction, stocks identified as experiencing either positive or negative jumps are concentrated primarily in two extreme EAR-sorted quintiles, consisting of 15% and 19% of top and bottom EAR-sorted quintiles, respectively. One concern is that the better performance of the jump-based hedge portfolio is driven entirely by the uneven distribution of EARs such that stocks with identified jumps are also those with either the highest or the lowest EARs. The first row of Panel C addresses this concern. When we constructed the hedge portfolio "p97–p3," we took long and short positions in stocks in the top and bottom three percentiles, respectively, ranked on EARs of the previous quarter. Thus, we obtained a hedge portfolio that contained approximately 6% of stocks with extreme EARs but that generated, on average, a 2.20% quarterly abnormal return with tremendously high volatility (an annualized Sharpe ratio of only 0.63). This result is in stark contrast to that from the jump-based hedge portfolio in Panel A. Stocks identified as experiencing jumps are unlikely to coincide on a large scale with those having the most extreme EARs, even though the two trading signals, by construction, share similar intuitions. If we expand the portfolio size to include more stocks, the EAR-based hedge portfolios yield even lower average abnormal returns, albeit with lower volatilities.

Characteristics of Jump-Based Portfolios. An important concern is that the excess returns of the jump-based hedge portfolio may be driven by company characteristics that are correlated with jump signals. We addressed this concern by examining the empirical correlations between jump signals and company size, Amihud's illiquidity measure, and the book-to-market ratio. We also analyzed the return differences between positive- and negative-jump stocks within each size, illiquidity, and B/M quintile portfolio. We measured company size by using market capitalization, which is the product of stock price and total number of shares outstanding (in thousands), both of which we obtained at the end of the previous quarter. Amihud's illiquidity measure is the average daily illiquidity over the 60-day period prior to the earnings announcement, where daily illiquidity is defined as 100,000 × |Return|/(Price × Volume). B/M is the ratio of a company's book value to its market capitalization measured at the end of the previous quarter.

We divided stocks into five equal-sized portfolios at the beginning of each quarter by ranking companies according to one of the following measures: market capitalization (size), illiquidity, or B/M. Within each company characteristic quintile, we further classified stocks into three jump groups (negative, zero, and positive) by $Jump_{(-1,1)}$ in the concurrent quarter.

The first three columns of **Table 4** report the empirical distributions of jump signals in each company characteristic quintile. For instance, on average, 3.17%, 91.45%, and 5.38% of companies in the smallest market-cap quintile had negative, zero, or positive jumps in each quarter. As we have already shown, the majority of companies experienced no jumps around earnings announcement dates. In all three panels, both negative- and positive-jump signals are almost evenly distributed across each company characteristic quintile. There is no evident concentration of stocks with either negative or positive jumps in the highest or lowest quintile. Except for the decreasing frequency of positive-jump signals with company size, we found no obvious monotonic pattern indicating strong correlations between jump signals and various company characteristics.

Columns 4 and 5 compare the company characteristic measures of negative- and positive-jump stocks within each characteristic quintile. If company size helps explain the different abnormal returns earned by the negative- and positive-jump portfolios, we would expect a significant difference in market capitalization between the two groups. But Panel A shows no significant difference in the average company size between negative- and positive-jump stocks within each company-size quintile. For instance, in the largest market-cap quintile, the average market value of negative-jump companies is \$5.211 billion, which is slightly larger than the average market value of positive-jump companies (\$5.064 billion). The p-value for the paired mean equality test between negative- and positive-jump groups, reported in column 6, is 0.80, which does not reject the null hypothesis of

Table 4. Company Characteristics, Jump Signals, and Portfolio Returns, 1971–2009

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
							CAR(2, 60)					
	Distribution of Jumps			Company Characteristics			Equally Weighted			Portfolio-Size Weighted		
	Negative (%)	Zero (%)	Positive (%)	Negative	Positive	*p*-Value (diff.)	Negative (%)	Positive (%)	Diff. (bps)	Negative (%)	Positive (%)	Diff. (bps)
A. Company size (current dollars in millions)												
1 (small)	3.17	91.45	5.38	25.1	24.6	0.73	5.69***	8.24***	254**	3.70***	9.33***	563***
2	3.36	92.03	4.61	76.9	77.2	0.97	1.68*	5.99***	431***	0.59	6.79***	620***
3	3.79	91.67	4.54	197.2	200.0	0.86	0.74	5.68***	494***	–0.51	5.08***	558***
4	3.83	91.67	4.50	564.2	574.9	0.82	1.14	4.03***	288***	0.19	3.27***	308***
5 (large)	3.05	93.56	3.39	5,211.1	5,063.6	0.80	1.03	3.74***	271**	0.38	3.41***	304***
B. Amihud's illiquidity measure												
1 (liquid)	3.34	93.03	3.63	0.001	0.001	0.75	0.45	4.33***	388***	0.02	3.70***	368***
2	4.13	91.19	4.69	0.004	0.004	0.82	1.14	3.85***	271**	0.14	3.39***	325***
3	3.82	91.56	4.62	0.015	0.016	0.57	0.33	5.74***	541***	0.02	5.36***	534***
4	3.24	92.26	4.50	0.063	0.061	0.77	2.72***	6.58***	386***	0.55	7.53***	698***
5 (illiquid)	2.67	92.34	4.99	0.419	0.480	0.10	6.33***	7.70***	137	4.20***	8.59***	440***
C. Book-to-market ratio												
1 (growth)	3.82	91.84	4.34	0.25	0.27	0.36	1.80	6.60***	480***	–0.02	6.69***	670***
2	3.72	91.69	4.59	0.50	0.50	0.82	2.11**	5.50***	338***	0.91	5.74***	483***
3	3.27	92.44	4.29	0.72	0.74	0.65	2.44***	5.32***	288**	1.55**	4.93***	338***
4	3.15	92.63	4.22	1.00	1.01	0.93	2.16**	5.72***	355***	0.60	5.64***	503***
5 (value)	3.24	91.78	4.98	1.80	1.80	0.95	2.24**	5.30***	306**	1.05	6.13***	508***

Note: This table presents characteristics and returns of portfolios that are double-sorted on company characteristics and jump signals.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

equal average market capitalization for the two groups of jump stocks. In other words, the jump-based hedge portfolio (reported in columns 9 and 12) in the largest (or any other) company-size quintile comprises positive- and negative-jump stocks with virtually identical market capitalizations. The equality in average company size for positive- and negative-jump stocks implies that any effect company size may have on the excess return of 271 bps (or any values in columns 9 and 12) for the jump-based hedge portfolio has been "canceled out." Therefore, we conclude that company size does not explain the abnormal return earned by the jump-based hedge portfolio.

We also examined whether illiquidity and B/M explain the excess returns for the jump-based hedge portfolio. The results, reported in Panels B and C, show that within each illiquidity (or B/M) quintile, the average illiquidity measures (or B/Ms) for stocks with positive and negative jumps are not statistically different from each other. Consequently, we conclude that the excess returns of the jump-based hedge portfolio reported in columns 9 and 12 are unlikely to be driven by the illiquidity premium or the value-versus-growth effect.

Factor Analysis. Given that the jump-based trading strategy produced an average quarterly excess return of 3.63% over the last four decades, one might wonder whether the excess returns reflect loadings on some well-known risk factors. To address this issue, we implemented the Fama–French pricing models augmented by the momentum factor (UMD) of Carhart (1997) and the liquidity factor (LIQ) of Pastor and Stambaugh (2003). The results are summarized in **Table 5**. The dependent variables in columns 1 and 2 are the negative- and positive-jump portfolio returns, respectively. The dependent variables in the remaining columns are hedge portfolio returns from different trading strategies: jump-based signals in column 3, SUE-based signals in columns 4–6, and EAR-based signals in columns 7–9.[19] To construct portfolios of comparable size, we again considered three different percentile breakpoints in the SUE- and EAR-based hedge portfolios.

Table 5. Factor Pricing Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$Jump_{(-1,1)}$			SUE			EAR		
Variable	Negative	Positive	Hedge	p97–p3	p95–p5	p90–p10	p97–p3	p95–p5	p90–p10
A. Fama–French three-factor model									
R_M	0.414***	0.474***	0.060	–0.035	–0.031	–0.049	0.082	0.074	0.032
SMB	0.157	0.289**	0.132	0.197*	0.237***	0.216***	0.180	0.193*	0.160***
HML	–0.153	–0.200	–0.047	–0.069	–0.013	–0.035	0.135	0.098	0.066
α	0.023***	0.059***	0.036***	0.035***	0.038***	0.039***	0.020***	0.017***	0.016***
R^2	0.21	0.34	0.06	0.04	0.07	0.08	0.04	0.06	0.08
B. Carhart four-factor model									
R_M	0.371***	0.465***	0.094*	–0.021	–0.018	–0.028	0.129*	0.113*	0.060
SMB	0.094	0.275**	0.181*	0.216**	0.256***	0.246***	0.248**	0.249**	0.200***
HML	–0.213	–0.213	–0.000	–0.051	0.006	–0.007	0.201	0.152	0.105
UMD	–0.179**	–0.039	0.139***	0.055	0.055	0.085	0.194***	0.161***	0.114***
α	0.028***	0.060***	0.032***	0.033***	0.036***	0.037***	0.014**	0.013**	0.013***
R^2	0.23	0.34	0.11	0.04	0.08	0.11	0.09	0.10	0.13
C. Pastor–Stambaugh five-factor model									
R_M	0.519***	0.561***	0.042	–0.087	–0.083	–0.074	0.029	0.016	–0.026
SMB	0.089	0.271**	0.182*	0.224**	0.273***	0.260***	0.251**	0.254***	0.203***
HML	–0.052	–0.085	–0.033	–0.128	–0.067	–0.073	0.118	0.075	0.021
UMD	–0.143*	–0.012	0.131**	0.053	0.079	0.104*	0.179**	0.152**	0.099***
LIQ	–0.073	–0.028	0.046	0.023	0.020	–0.000	0.070	0.068*	0.050*
α	0.017**	0.054***	0.038***	0.037***	0.038***	0.037***	0.023***	0.021***	0.019***
R^2	0.26	0.37	0.11	0.06	0.10	0.15	0.08	0.10	0.14

Note: This table reports the regression coefficients of the Fama–French three-factor (Panel A), the Carhart momentum four-factor (Panel B), and the Pastor–Stambaugh liquidity five-factor (Panel C) pricing models.

*Significant at the 10% level under untabulated Newey–West *t*-statistics.
**Significant at the 5% level under untabulated Newey–West *t*-statistics.
***Significant at the 1% level under untabulated Newey–West *t*-statistics.

Panel A of Table 5 presents the regression results of the excess hedge portfolio returns against the three Fama–French factors. R_M is the return on the market portfolio minus the risk-free rate, SMB is the size factor (small minus big), and HML is the book-to-market factor (high minus low).[20] For the negative- or positive-jump portfolio returns, the market risk factor has a significantly positive loading. However, the hedge portfolio that takes long positions in positive-jump stocks and short positions in negative-jump stocks essentially eliminates the risk exposure to the market fluctuations as well as to the SMB and HML factors. The loadings on the size, SMB, and HML factors are statistically insignificant at 0.06, 0.132, and –0.047, respectively. The factor-adjusted alpha for the jump-based hedge portfolio is 3.6% per quarter and statistically significant at the 1% level. The magnitude of alpha is similar to the 3.63% excess return reported in Panel A of Table 3. The adjusted R^2 is 0.06, indicating that the three standard risk factors have little power in explaining the variations in excess returns. Similar to jump-based hedge portfolios, SUE-based hedge portfolios with various portfolio sizes, reported in columns 4–6, yield comparable factor-adjusted excess returns and share similar features of market neutrality. However, the SUE-based hedge portfolios are exposed to the SMB risk factor with positive and significant loadings. We can see a similar pattern in columns 7–9 for the EAR-based hedge portfolios, except that the risk-adjusted excess returns are only about half those of jump-based hedge portfolios.

We then incorporated an additional risk factor, Carhart's momentum factor (UMD), into the regression. The results from the Carhart four-factor model are reported in Panel B. The jump-based hedge portfolio yields a smaller but still significantly positive factor-adjusted alpha (3.2% per quarter and significant at the 1% level) and is no longer completely immune to the market risk and SMB factors, whose loadings are both positive and weakly significant (column 3). Moreover, we can see that UMD plays an important role in explaining the variations in returns of jump-based hedge portfolios with a significantly positive loading.[21] For example, UMD almost doubles the R^2, from 0.06 in Panel A to 0.11 in Panel B. For the three SUE-based hedge portfolios, the risk-adjusted alphas decline slightly but remain highly significant. The momentum factor has little impact on the hedge portfolio returns, whereas the SMB factor continues to have significantly positive loadings. In the EAR-based hedge portfolios, both the SMB and the UMD factors have positive and significant loadings. The risk-adjusted alphas shift downward, to the range of 13–14 bps per quarter.

Finally, we incorporated the liquidity factor of Pastor and Stambaugh (2003) into the regression and present the results in Panel C. As shown in column 3, the jump-based hedge portfolio becomes market neutral with respect to the SMB and UMD factors. The liquidity factor provides little additional explanatory power for the variations in hedge portfolio returns. Nevertheless, the inclusion of the liquidity factor raises the alpha to 3.8% per quarter (significant at the 1% level). Note also that the liquidity factor has insignificant loadings for all three SUE-based hedge portfolios and weakly positive loadings for two of the EAR-based hedge portfolios (columns 8 and 9).

Conclusion

Previous studies have documented the profitability of several trading strategies that exploit PEAD, among which SUE and EAR are best known. In this article, we have proposed a novel approach to exploiting PEAD that is based on trading signals extracted from the occurrences of price discontinuities, or jumps, around earnings announcement dates. We hypothesized that these sudden and often drastic realizations of the discrete sample path of asset returns—in particular, around earnings announcement dates—capture unique information about the future asset payoff and thus predict the subsequent return drifts.

We applied the jump detection method of Lee and Mykland (2008) to identify company-specific informational shocks by the direction of jumps. Our jump-based trading strategy is to take long positions in stocks with positive-jump signals and short positions in stocks with negative-jump signals over the three-day period surrounding the earnings announcement date. We maintain the long–short positions for 60 consecutive trading days, starting from two days after the earnings announcement, and evaluate the portfolio performance on a quarterly basis. We found a time-series simple average of quarterly abnormal hedge portfolio returns of 3.63% and an annualized Sharpe ratio of 1.52.[22] The performance of the jump-based hedge portfolio is comparable to that of SUE-based portfolios and is better than that of EAR-based portfolios.

Several features of our jump-based trading strategy are worth mentioning. First, our jump signals are not replications of SUE and EAR, the two popular and well-studied trading signals in the PEAD literature. Although all three share similar motivations, they characterize distinct components of return dynamics and thus reflect disparate information. Second, the infrequent occurrences of jumps result in a relatively small hedge portfolio, which effectively reduces the transaction and monitoring costs. Third, we found little evidence that the excess returns earned on the jump-based hedge portfolio are attributable to common company characteristics, such as size, Amihud's illiquidity measure, and the book-to-market ratio. Finally, we implemented a variety of factor pricing models to examine their ability to explain variations in excess returns of jump-based hedge portfolios. The risk factors were the three Fama–French factors, Carhart's momentum factor, and Pastor and Stambaugh's liquidity factor. We found little evidence that these risk factors fully account for the average excess returns of the jump-based hedge portfolios. Alphas were significantly positive, in the range of 3.2% to 3.8% per quarter across different model specifications.

The empirical results of our study join the growing literature on the PEAD phenomenon. They lend support to a trading strategy that exploits the distinctive information in the discontinuous sample path of the return process around the information-rich period of earnings announcements.

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This article qualifies for 1 CE credit.

Appendix A. Excess Returns for a Jump-Based Trading Strategy over Various Holding Periods

The results reported in the main text are based on a jump-based trading strategy with a holding period of 60 days. To establish the robustness of our jump-based trading strategy, **Table A1** presents our findings with respect to the excess returns for our jump-based strategy over other holding periods.

Table A1. Summary Statistics of Hedge Portfolio Returns over Various Holding Periods, 1971–2009

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Equally Weighted		Portfolio-Size Weighted	
Holding Period	Evaluation Frequency	Median Portfolio Size	Max. Loss (%)	AR(1)[a]	Mean (%)	Sharpe Ratio	Mean (%)	Sharpe Ratio
One week	Quarterly	171	–5.16	0.114	0.23*	1.042	0.52***	2.50
Two weeks	Quarterly	171	–4.99	0.056	0.76***	1.564	1.07***	2.470
One month	Quarterly	171	–8.16	0.119	1.68***	1.662	2.15***	2.404
One month (1971–2009)	Monthly	45	–39.48	–0.025	1.80***	0.943	2.09***	1.486
One month (1985–2009)	Monthly	67	–20.89	0.015	2.38***	1.401	2.29***	1.704
One month (1992–2009)	Monthly	95	–12.45	0.035	2.54***	1.568	2.50***	2.014

Notes: This table reports the summary statistics of jump-based hedge portfolio returns over various holding periods. We used the cumulative abnormal returns on jump days over the three-day window centered on earnings announcement dates, $Jump_{(-1,1)}$, to determine the direction of jumps. In the top three rows, the hedge portfolio returns are computed quarterly and are defined as the average return spread between the positive- and negative-jump portfolios. The holding periods are one week, two weeks, and one month, corresponding to 5-, 10-, and 22-day holding periods starting from day $t + 2$, where t is the earnings announcement date. In the bottom three rows, the hedge portfolio returns are computed monthly over three different sample periods. Column 2 presents the median number of stocks in the hedge portfolio each quarter (top three rows) or month (bottom three rows). Column 3 records the historical maximum quarterly or monthly loss. Column 4 reports the first-order autoregressive coefficient for the hedge portfolio returns. Column 5 shows the time-series simple averages of quarterly or monthly holding-period returns. Column 7 reports the time-series portfolio-size weighted averages of quarterly or monthly holding-period returns; this weighting scheme takes into account the time-varying portfolio sizes. Columns 6 and 8 report the corresponding annualized Sharpe ratios.

[a]First-order autoregressive coefficient.

*Significant at the 10% level under untabulated Newey–West t-statistics.
***Significant at the 1% level under untabulated Newey–West t-statistics.

Notes

1. Bernard, Thomas, and Wahlen (1997) provided a comprehensive survey of the literature on the topic. The most common interpretation for PEAD is investors' underreaction to earnings surprises, as documented in Bernard and Thomas (1989), Ball and Bartov (1996), and Bartov, Radhakrishnan, and Krinsky (2000). Other interpretations include risk mismeasurement (Foster, Olsen, and Shevlin 1984) and market imperfections (Chordia, Goyal, Sadka, Sadka, and Shivakumar 2009; Mendenhall 2004).
2. For instance, Lobo (1999) traced the source of changes in jump risk in aggregate market returns to the informational surprises arising from political events; Barndorff-Nielsen and Shephard (2006) highlighted the association of jump days with identifiable macroeconomic news for the deutsche mark/U.S. dollar foreign exchange market. Andersen, Bollerslev, Diebold, and Vega (2003) and Andersen, Bollerslev, and Diebold (2007), among others, documented significant intradaily price discontinuities for both the foreign exchange and the aggregate stock markets in response to a host of macroeconomic news announcements. Bollerslev, Law, and George (2008) found that an equal-weighted index of 40 large-cap stocks exhibited significant co-jumps, with a sharp peak at the time of regularly scheduled macroeconomic news announcements over 2001–2005. Jiang and Yan (2009) documented that jumps in the short rates are associated with daily but not monthly macroeconomic informational shocks. Johannes (2004) and Lahaye, Laurent, and Neely (2011) tracked the estimated jumps in daily market returns and associated the majority of them with specific macroeconomic news events, particularly monetary policy surprises. Jiang and Yao (2010) provided evidence on a variety of informational events (including earnings announcements) that triggered jumps for a sample of stocks in the Dow Jones Industrial Average. However, Joulin, Lefevre, Grunberg, and Bouchaud (2008) found no significant pattern of clustering of jumps around either idiosyncratic company-specific or marketwide news feeds. Jiang, Lo, and Verdelhan (2011) found limited predictive power of macroeconomic news announcements for observed jumps in the U.S. Treasury market but significant impact from contemporaneous liquidity shocks. But Beber and Brandt (2010) found that the bond market absorbs macroeconomic news primarily through changes in the jump component rather than changes in the diffusive component of bond returns. Two exceptions are Lee (2009) and Lee and Mykland (2008), who studied the determinants of jump dynamics at the company level, using the same nonparametric jump detection method that we used in our study.
3. See, for example, Todorov and Bollerslev (2010); Schneider et al. (2010); Todorov (2010); Wright and Zhou (2009); Yan (2011).
4. Using the alternative cutoff value of $1 for stock price, we obtained similar results.
5. Although both cutoff values fluctuate, sometimes wildly, from year to year, our results are not sensitive to alternative choices of cutoff value, such as multiple-year moving averages or expanded/contracted percentile bands.
6. Many statistical procedures have been developed to detect the arrival, direction, and size of jumps. For instance, Aït-Sahalia (2002) derived a test for the presence of jumps from restrictions on the transition function of a continuity process. Carr and Wu (2003) relied on the differential behavior of short-dated option prices to test for the existence of jumps. Barndorff-Nielsen and Shephard (2004, 2006), Andersen et al. (2007), and Huang and Tauchen (2005) all exploited the property of multipower variations to identify jumps by assessing the proportional contributions of quadratic variations in the financial data. Jiang and Oomen (2008) proposed a detection method that uses the hedging errors of a variance swap replication strategy. Aït-Sahalia and Jacod (2009) presented a test that is valid for all Ito semimartingales and that is independent of the law of the actual stochastic process discretely sampled.
7. For more details of the procedure, see Lee and Mykland (2008).
8. The timing of the execution of trading activities is rarely synchronous across companies but depends on contingent arrivals of trading signals that occur around companies' individually prescheduled announcement dates. The overlapping of holding periods for portfolio assets complicates the calculation of portfolio abnormal returns at a quarterly frequency because the holding period of some stocks can easily cross two calendar quarters. Therefore, we treated the portfolio abnormal return in calendar quarter q as the equal-weighted average of 60-day cumulative returns across individual stocks whose trading positions were initiated in quarter q. Fully aware of the mismatch between the reported quarterly portfolio returns and their actual realizations in the next quarter, we adjusted the lead-lag term accordingly in the factor pricing tests. Under normal circumstances, however, this mismatch would not be expected to systematically distort the results of our portfolio analysis.
9. Following the methodology laid out in Kenneth French's data library, we formed 25 (the intersections of 5 size and 5 B/M) portfolios on the basis of the market value at the end of June and the B/M at the end of the fiscal year. Details of the portfolio formation are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/tw_5_ports.html. Brown and Warner (1980, 1985) documented that standard procedures for calculating excess returns are all well specified when daily returns are used. Brav, Geczy, and Gompers (2000) discussed the difficulty of identifying the "perfect" choice of benchmark return. Barber and Lyon (1997) documented that measuring long-run abnormal returns by matching sample companies with control companies of similar size and B/M yields well-specified test statistics.
10. Other studies have used different versions of SUE to measure the information in earnings announcements—see, for example, Chordia et al. (2009), Jegadeesh and Livnat (2006), and You and Zhang (2009).
11. Alternatively, investors may postpone their portfolio formation until the beginning of the next quarter, when all SUEs and EARs are observed and ranked. This approach screens the signals precisely, with the realization of all SUEs and EARs, but forgoes a large part of momentum returns owing to the delay in taking trading positions (see, e.g., Rendleman, Jones, and Latané 1982).
12. It is, however, practically infeasible to form *real-time*, trade-right-on-signal long–short portfolios if one follows the common practice of sorting companies into decile portfolios on the basis of the full realizations of SUE or EAR signals across all companies, which are observable only at the end of a given quarter.
13. In fact, we are not the first to advocate the premise that informational shocks of different natures (or of various magnitudes) have distinct impacts on the diffusion and the jump process of asset returns (see, e.g., Maheu and McCurdy 2004).

14. From a practical perspective, the jump-based trading strategy is easy to implement and allows for the progressive portfolio formation that almost instantly uses the realizations of trading signals. As Rendleman et al. (1982) showed, about half the PEAD is realized within 30 days after earnings announcements. Our trading strategy can maximize the gains of earnings momentum by responding to trading signals almost instantaneously. In contrast, the SUE- and EAR-based trading strategies construct the long–short portfolios on the basis of trading signals that are cutoff values corresponding to the top and bottom percentiles of *ex post* rankings of all companies' SUEs or EARs. It is, therefore, infeasible for investors to trade right after the earnings announcements according to signals (or cutoff values) that are unknown to them until the end of the period, which unnecessarily excludes a large part of the earnings momentum. In our study (and in practice), we used the cutoff values corresponding to various percentiles of the previous quarter's SUE or EAR to sort stocks into long–short portfolios right after the current quarter's earnings announcements (see Brandt et al. 2008; Chordia et al. 2009). Moreover, when trading stocks on jump signals, we rebalanced each period with a smaller number of stocks relative to the typical SUE- or EAR-based strategies, which often rebalance two deciles or quintiles of all sample stocks each period. We provide empirical evidence that a jump-based strategy with a relatively small portfolio size largely avoids the underinvestment problems and achieves reasonable diversification in practice.
15. This sorting method assumes the perfect foresight of a company's relative rankings of SUE (or EAR) in a given calendar quarter. Alternatively, we can more realistically form SUE- or EAR-based quintile portfolios in each quarter on the basis of the breakpoints obtained from rankings of SUEs and EARs at the end of the previous quarter. We report here the empirical results from the perfect-foresight approach. The results from the alternative approach are available upon request.
16. We also examined the excess returns for the jump-based trading strategy over other holding periods, such as one week, two weeks, and one month. The results are presented in Appendix A and are similar to those for a holding period of 60 days.
17. 352 bps = 6.40% – 2.88%, and 145 bps = 5.03% – 3.58%.
18. Because often there are too few stocks with either positive or negative jumps in the EAR-sorted quintile portfolios to form a reasonably sized portfolio, we do not report the spreads between positive- and negative-jump groups within each EAR-sorted quintile portfolio. For instance, on average, 0.04% of companies, or 0.22 stocks, have positive jumps each quarter within the lowest EAR-sorted quintile. Therefore, we interpret the average portfolio returns in Panel B with great caution and focus on the spread between the two diagonal portfolios, which are of considerable size.
19. We also ran the portfolio-size weighted regression to account for the potential bias arising from the disproportionate impact of certain quarters in which the portfolio contains too few individual stocks. The results, which remain quantitatively similar throughout, are available upon request.
20. We obtained these quarterly factors from Kenneth French's website.
21. The risk exposure of the positive- and negative-jump hedge portfolios to the momentum factor comes mostly from the negative-jump portfolio, in which the UMD factor has a negative and significant loading among negative-jump stocks. Stocks with negative jumps around earnings announcement dates have a stronger return reversal (or negative return momentum) effect on their subsequent 60-day PEADs.
22. The time-series portfolio-size weighted average of quarterly abnormal hedge portfolio returns is 3.94%, and the annualized Sharpe ratio is 1.83.

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