Explaining Stock Returns with Intraday Jumps*

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Abstract

The presence of jumps in stock prices is widely accepted. In this paper, we explore the impact of jumps on the pricing of stocks by extracting the average jump size of individual stock returns from high-frequency data and examining the empirical relation with subsequent stock returns. Given that jump diffusion models predict a negative relation between expected stock returns and the average jump size, our goal is to empirically confirm that negative relation. We form ten portfolios based of the average jump size and compute subsequent weekly stock returns. The raw returns of the decile of stocks with low jump size exceed those of the decile of stocks with high jump size by 74 basis points with a t-statistic of 10.89. To rule out that average jump size is not a proxy of firm characteristics, we perform additional double-sortings and regressions with proxy variables such as size, book-to-market, previous week return, volatility, skewness, kurtosis and illiquidity. The results are confirmed.

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1 Introduction

It is widely accepted that stock returns include jumps, that is, abnormal movements that are infrequent and large. The presence of jumps in stock prices makes the distribution of stock returns skewed and leptokurtotic, or "fat tailed". Ever since Press (1967) and Merton (1976), stock price dynamics have been modeled with jumps. Improvements to these models are done in Ball and Torous (1983) and Jorion (1988). Moreover, jump diffusion models have proven particularly useful when pricing options and other derivatives (See Ball and Torous (1985), Andersen, Benzoni and Lund (2002), Bakshi, Cao and Chen (1997), Eraker, Johannes, and Polson (2003), Eraker (2004) and Pan (2002) among others). In a recent study, Zhou and Zhu (2009b) document the importance of systematic jump risk when pricing daily returns.

In this paper, We explore how jump information affects the pricing of stocks. Intuitively, an extreme positive jump should have a different effect on the future price of a stock than an extreme negative jump. Given that a positive jump increases the price of the security, a risk averse investor should prefer a positive over a negative jump. Therefore, stocks with negative jumps should earn a premium compared to stocks with positive jumps. Theoretically, Yan (2010) shows that the stock return is decreasing on the average size of the jump within a stochastic discount factor framework. This means that a stock with negative jumps must be compensated with higher returns than a stock with positive jumps, confirming our intuition.

To empirically quantify the jump premium, we extract jump components from high-frequency data for the US market and test the relation between jumps and stock returns. We compute jumps from high-frequency data using the methodology proposed by Barndorff-Nielsen and Shephard (2004b) and further extended by Andersen, Bollerslev and Diebold (2007) and Tauchen and Zhou (2010).[1] The first step to get jump metrics is to decompose realized volatility into its continuous and jump components, by analysing the difference between the quadratic variation and the bipower variation. Then, using the jump component, we measure the average jump mean that we call realized jump.

We find that stock returns have a negative relation with the average jump mean. In particular, we group stocks into decile portfolios based on realized jump and explore the trading strategy that buys stocks from the decile with large positive realized jump and sells the stocks from the decile with large negative realized jump. When sorting by average realized jump, the long-short trading strategy produces an average weekly return of -73.61 basis points with a t-statistic of -10.89. We also compute the Fama-French risk adjusted alpha of the long-short portfolio, and it generates -75.04 basis points per week with a t-statistic of -11.00. Therefore, measures that hold stocks with negative jumps in the past are compensated with higher returns. The fact that a stock jump is negative translates into higher risk for the investor; hence, he is compensated for holding that

[1] This is not the only jump detection technique. Other detection methods have been proposed by Lee and Mykland (2008), Jiang and Oomen (2008) and Aït-Sahalia (2004), among others.

risk.

A set of robustness test are also performed on stock returns to ensure that the average jump size is not a proxy of existing firm characteristics known to explain stock returns. Firm characteristics to be included are size, book-to-market, previous week return, realized volatility, realized skewness, realized kurtosis and illiquidity. First, we regress stock returns on average jumps and firm characteristics using the two step Fama-MacBeth approach. The Fama-MacBeth regressions show that the average realized jump is robust to the firm characteristics previously outlined. In particular, the average realized jump measure is robust to previous week return, realized volatility, realized skewness and realized kurtosis. Hence, realized jump goes above and beyond what is explained by higher order moments of stock returns.

Second, we double sort stock returns by realized jumps and firm characteristics. The significant negative premium previously observed is still present across all quintiles when double sorting by different firm characteristics such as size, book-to-market, realized volatility, realized skewness, realized kurtosis, illiquidity, number of intraday transactions, maximum return over previous month, market beta, idiosyncratic volatility and co-skewness. To ensure that realized jump and realized skewness computed with intraday data capture different aspects of the stock return, we compare the stocks in each decile formed with these two variables. Two independent sortings are done: one by realized jumps and one by realized skewness. We find that 75% of the stocks in decile 1 and 10 move to deciles other than 1 and 10. Hence, deciles formed by realized jumps and realized skewness share at most 25 percent of the stocks. Additionally, we explore the long-short returns of double sorted portfolios. As expected, the long-short returns are significantly negative for all levels of realized jump and all levels of realized skewness. We conclude that realized jump is not explained by firm characteristics and that its explanatory power goes beyond that of realized skewness.

Third, we explore the predictability for different time periods and for different stock exchanges. The data sample is divided in two periods: 1993 to 2000 and 2001 to 2008. The cutoff date is beginning of 2001 given that the decimalization of the NYSE started in late 2000 and finished in the early 2001. The long-short portfolio returns are negative and significant for the two subperiods and are larger for the first subperiod. Fama-MacBeth regressions performed for the two subperiods confirm that realized jumps explain the cross-section of stock returns over and above firm characteristics. The data are also divided by stock exchange into NYSE and non-NYSE stocks. Once again, the long-short portfolio returns are significant for the two exchange subgroups and are larger for the NYSE subgroup.

Even though there is extensive evidence of jumps on stock prices, the relation between stock returns and jumps has received less attention. Recently, Yan (2010) finds that the average jump size is negatively related with expected stock returns in the cross section. However, jumps are not directly extracted from stock returns but from the slope of the option volatility smile. In previous studies, Zhang, Zhou and Zhu (2009) and Rehman and Vilkov (2009) find the same negative relation between the options' smirk and stock returns; however, in their case, the smirk represents the risk neutral skewness, not the jump component. This interpretation is supported by Bakshi, Kapadia and Madan (2003) who demonstrate that the slope of the option smile or option smirk is related with the risk neutral skewness. Finally, using the methodology proposed by Bakshi, Kapadia and Madan (2003), Conrad, Dittmar and Ghysels (2009) confirm the negative relation between risk-neutral skewness and stock returns.

A jump measure extracted directly from stock returns has also been used to show the relation between jumps and returns. Jiang and Yao (2007) test for the existence of jumps and find that positive (negative) jumps are followed by positive (negative) returns. Since daily data is used, they can test for jumps as far back as 1927. However, the positive relation between jumps and stock returns still remains a puzzle. On the other hand, Zhou and Zhu (2009) find a negative relation between jumps and expected stock returns for China's stock market using intraday data. To measure jumps, they use the methodology proposed by Lee and Mykland (2008) that compares intraday returns with their most recent realized volatility to test for jumps. Other methodologies to test for jumps in returns can be found in Andersen, Bollerslev, Frederiksen and Nielsen (2010) and Aït-Sahalia and Jacod (2009).

The remainder of this paper is organized as follows. In section 2, the empirical method to extract jumps is presented. Section 3 describes the data to be used in this study. Section 4 presents the results and section 5 proposes a series of robustness checks. We conclude the paper in section 6.

2 Empirical Method based on Intraday Data

In this section, we present the methodology to extract jump statistics from intraday data. The basic assumption is that jumps in stock returns are seldom and large, either positive or negative. With this assumption in mind, we plan to extract the average jump size over a given period, the jump variance and the jump intensity.

Let $s(t)$ denote the logarithmic asset price at time t, that evolves with the continuous-time jump diffusion process

$$ds(t) = \mu(t)dt + \sigma(t)dW(t) + J(t)dq(t)$$

where $\mu(t)$ is the drift, $\sigma(t)$ is the diffusion and $J(t)$ is the jump component process. $W(t)$ is a standard Brownian motion and $q(t)$ is a Poisson process with time-varying intensity $\lambda(t)$. $J(t)$ denotes the size of the correspoding jumps of the logarithmic price process with mean $\mu_J(t)$ and standard deviation $\sigma_J(t)$. To compute the jumps from high-frequency data, we first define intraday return as

$$r_{t,i} = s(t) - s(t - i\Delta)$$

where $r_{t,\Delta}$ denotes the i^{th} intraday return on day t and Δ is the sample frequency set at 5 minutes (thus, $1/\Delta = 78$).

Then, Barndorff-Nielsen and Shephard (2004b) define realized volatility and realized bipower variation as follows

$$
\begin{aligned}
RV_t &\equiv \sum_{i=1}^{1/\Delta} r_{t,i}^2 \rightarrow \int_{t-1}^{t} \sigma^2(s)ds + \sum_{i=1}^{1/\Delta} J^2(t)_{t,i}, \\
BV_t &\equiv \frac{\pi}{2} \sum_{i=3}^{1/\Delta} |r_{t,i}| \,.\, |r_{t,i-2}| \rightarrow \int_{t-1}^{t} \sigma^2(s)ds.
\end{aligned}
$$

These are two measures of the quadratic variation process. As $\Delta \rightarrow 0$, Andersen, Bollerslev and Diebold (2002) note that the realized volatility, RV_t, converges to the integrated variance plus the jump component. On the other hand, the bivariate variation, BV_t, converges to the integrated variance according to Barndorff-Nielsen and Shephard (2004b), Barndorff-Nielsen and Shephard (2005a) and Barndorff-Nielsen and Shephard (2005b). Since BV_t estimates integrated variance without jumps, the difference between $RV_t - BV_t$ provides a good estimator of the pure jump process as noted by Barndorff-Nielsen and Shephard (2004b) and Barndorff-Nielsen and Shephard (2006). To test the presence of jumps, we use the methodology used in Andersen, Bollerslev and Diebold (2007) that was first proposed by Huang and Tauchen (2005). First, the relative jump measure defined as

$$
RJ_t = \frac{RV_t - BV_t}{RV_t}
$$

indicates the contribution of jumps within a day relative to the total realized volatility. Next, we define the realized tri-power quarticity

$$
TP_t = \frac{1}{4\Delta\left[\Gamma(7/6).\Gamma(1/2)^{-1}\right]^3}.\sum_{i=5}^{1/\Delta} |r_{t,i}|^{4/3} \,.\, |r_{t,i-2}|^{4/3} \,.\, |r_{t,i-4}|^{4/3}
$$

that converges to $\int_{t-1}^{t} \sigma^4(s)ds$ as $\Delta \rightarrow 0$, even when jumps are present in the price process. To test whether a jump occurs on any given day, we construct the following test statistic of significant jump ratio

$$
z = \frac{RJ_t}{\left[((\frac{\pi}{2})^2 + \pi - 5).\Delta.\max(1, \frac{TP_t}{BV_t^2})\right]^{1/2}},
$$

that converges to $N(0,1)$. Thus, by choosing a significance level, daily jumps are detected. Following the methodology by Tauchen and Zhou (2010), the daily realized jump measure is defined in terms of the daily sign and the significant jump:

$$
\widehat{J}(t) = sign(r_t).\sqrt{RV_t - BV_t}.I(z > \Phi_a^{-1})
$$

where r_t is the daily return of the stock, $I()$ is the indicative function that takes a value of 1 if there is a jump and zero otherwise, Φ is the probability of a standard normal distribution and

α is the level of significance chosen as 0.99 as suggested by Huang and Tauchen (2005). After identifying the individual daily jump size, we can estimate the jump mean as

$$\widehat{\mu}_J = \text{Mean of } J(t),$$

over a given period of time. In this study, the average realized jump at time t for security i, $Rjump_{i,t}$, is the jump mean, $\widehat{\mu}_J$, over one week.

3 Data

Our sample uses every listed stock on the Trade and Quote (TAQ) database from January 4, 1993 to December 31, 2007. TAQ provides historical tick by tick data for all stocks listed on the New York Stock Exchange, American Stock Exchange, Nasdaq National Market System and SmallCap issues. We record prices every 5 minutes starting at 9:30 EST and construct 5-minute log-returns for the period 9:30 EST to 16:00 EST for a total of 78 daily returns. When no price is available at exactly 5 minutes, we take the last recorded price in the 5 minute period. If there is no price in a period, the return is zero for that period. The end-of-day price is the first price after 16:00 EST if any; otherwise, we take the last price available for that day.

To ensure sufficient liquidity, a stock requires at least 80 daily transactions to have a daily measure of jump.[2] The average number of intraday transactions per day for a stock is over one-thousand, which is well above the minimum number required. The weekly average realized jump estimator is the average of the available daily estimators (Wednesday to Tuesday). Only one valid day of realized jump is required to have a weekly estimator and the maximum number of daily estimators is five.

This study uses data from three additional databases. From the first database, the Center for Research and Security Prices (CRSP) database, we use daily returns of each firm to calculate weekly returns (Wednesday to Tuesday), individual historical skewness, market beta, previous week return, idiosyncratic volatility, maximum return over the previous month and illiquidity; we use daily volume to compute illiquidity; and we use outstanding shares and stock price to get the market capitalization. The second database is COMPUSTAT, which is used to extract the Standard and Poor's issuer credit ratings and book values to calculate book-to-market ratios of individual firms. From the third database, Thomson Returns Institutional Brokers Estimate System (I/B/E/S), we obtain the number of analysts that follow each individual firm.

3.1 Characteristics of Portfolios Sorted by Realized Jump

Every week, the average realized jump measure is computed for all stocks. Then, stocks are ranked according to their realized jump and grouped into decile portfolios. Table 1 displays the time

[2] Our results still hold even if the required number daily transactions is at least 100, 250 or 500.

series averages of firm characteristics for each decile portfolio from 1993 to 2007. Each week, the average of each firm characteristic is computed for all deciles; then, the average of each decile is calculated across time. Column 1 displays the portfolio of stocks with the lowest average realized jump of -2.9% and column 10 displays the portfolio of stocks with the largest average realized jump of 3.2%. Firm characteristics reported in this table are realized volatility, realized skewness, realized kurtosis, firm size, book-to-market, historical skewness, market beta, previous week return, idiosyncratic volatility (as in Ang, Hodrick, Xing and Zhang (2006),), co-skewness (as in Harvey and Siddique (2000)), maximum return over the previous month, illiquidity (as in Amihud (2002)), number of IBES analysts, S&P credit rating, stock price, number of intraday transactions, and average number of stocks per decile.

[Table 1 goes here]

Clearly, realized jump is highly correlated with realized skewness and previous week return (the return computed over the same period than the realized jump). As shown is Table 1, realized skewness monotonically increases from -0.286 for decile 1 to 0.235 for decile 10. Moreover, realized jump and realized skewness have the same sign for all portfolios. The positive relation between contemporaneous stock return and realized jump is explained by the fact that jumps on the return, either positive or negative, can drive the direction of the whole return. Previous week returns increase from -6.3% for decile 1 to 9.4%. Given that these two variables are so closely related to realized jump, we perform several tests to rule out that realized jump is just being a proxy of realized skewness or previous week return. The tests reveal that realized jump has an explanatory power of subsequent returns even in the presence these two variables.

A second feature that is observed on stocks of extreme realized jump, deciles 1 and 10, compared to stocks of other deciles is that they belong to small size firms, have high realized kurtosis, high realized volatility, high idiosyncratic volatility, high maximum return, are more illiquid, have lower number of IBES analysts following them, lower stock prices and lower number of intraday transactions. Firm size of deciles 1 and 10 is about \$1 billion while it is \$7 billion for decile 5. Realized kurtosis is about 10 for P1 and P10, and goes down to 7 for P5. Realized volatility is above 43% for P1 and P10 and is less than 20% for P5. Maximum return is 8.8% for P1 and 9.9% for P10 but it is only 5.4% for P5. Illiquidity is 23.10^{-4} for P1 and 21.10^{-4} for P10 and only 5.10^{-4} for P5. The number of analysts following the stocks with extreme jumps is about 5.0 and doubles to 10.0 for portfolios that do not jump. The stock price of P1 and P10 is around \$20 and doubles to about \$40 for P5. Finally, the average daily transactions of P1 (P10) is 780 (782) and increases to 1,286 to P5. Therefore, large positive or negative jumps occur to stocks that have similar characteristics such a size, volatility, liquidity and are followed by fewer analysts. Note that there are 212 stocks per decile portfolio each week, which translates into 2,120 stocks per week.

[Figure 1 goes here]

To better understand the realized jump measure, we present two graphs that display its historical values. Figure 1 shows the three-month moving average of the realized jump measure from 1993 to 2007 for different percentiles: 10, 25, 50, 75 and 90. Two distinctive patterns are observed for two different periods. The first one, between 1993 and 2002, displays high extreme positive and negative jumps (10th and 90th percentiles) that are always greater than ±1% and sometimes are over ±3%. However, the second one, from 2003 to 2007, shows lower absolute realized jump levels that do not exceed 1% for the 10th and 90th percentiles.

[Figure 2 goes here]

Figure 2 plots the realized jump measure for four industries: real estate, utilities, telecommunications and textiles. These industries were chosen since they display quite different patterns for the realized jump measure. Real estate and textiles industries display large positive and negative realized jumps from 1993 to 2002. Many average weekly realized jumps are above ±2.5% and some exceed ±5%. However, after 2002, realized jumps never exceed ±2.5% reflecting that the market was quiet during that time. The other two industries, utilities and telecommunications, do not have large jumps during the whole sample period and never exceed ±2.5%. Finally, realized jumps from 2003 to 2007 are much smaller than those from 1993 to 2002.

4 Realized Jumps and the Cross-Section of Stock Returns

In this section, two different tests are done to explore whether realized jumps predicts stock returns. First, portfolio returns for different levels of realized jump are analysed. Returns of equal-weighted and value-weighted are reported. In addition, the four factor Fama-French adjusted alpha is computed for all portfolios. The four factors are market return, size, book-to-market and momentum (Carhart (1997)). On Tuesday of each week, stocks are ranked according to the average realized jump level and grouped into deciles. Then, next-week stock returns of equal-weighted and value-weighted portfolios are studied. Second, cross-sectional Fama-MacBeth regressions are used to find if realized jumps explain stock returns in the presence of a wide set of control variables.

4.1 Ranking Stocks by Average Realized Jump

Table 2 reports raw returns and Fama-French adjusted alphas of equal-weighted and value-weighted decile portfolios.

[Table 2 goes here]

The most important finding is that the lower the average realized jump, the higher the stock return for the following week. As realized jumps increase, stock returns decrease. For equal-weighted portfolios, the decile with the lowest realized jump value of -2.9% reports the highest weekly return of 82 basis points. On the other hand, the decile with the highest realized jump of 3.2% has a weekly return of 8 basis points. This means that the trading strategy that buys the portfolio of high realized jump stocks and sells the portfolio with low realized jump stocks generates -74 basis points of return with a t-statistic of -10.89. Results are similar for the Fama-French adjusted alphas where the long-short portfolio reports a return of -75 basis points with a t-statistic of -11.0 for equal-weighted portfolios.

Value-weighted returns are slightly lower given that the low realized jump decile return is 59 basis points and the long-short portfolio return decreases to -55 basis points with a t-statistic of -6.09. Fama-French adjusted alphas are of similar magnitude than the raw returns. As is the case with equal-weighted returns, the long-short trading strategy is profitable due to the large return of the low-realized jump portfolio. The high-realized jump return is very close to zero, at 3 basis points. We conclude that there is a strong negative relation between realized jumps and stock returns when using the univariate sorting methodology.

4.2 Fama-Macbeth Cross-Sectional Regressions

To further gauge the predictability power of realized jumps on stock returns, we implement the cross-sectional regressions proposed by Fama and MacBeth (1973). Each week, we regress the individual stock return on previous week firm characteristics as in

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} Rjump_{i,t} + \phi_t' Z_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t+1}$ is the weekly return of stock i on week $t+1$, $Rjump_{i,t}$ is the average realized jump of stock i on week t and $Z_{i,t}$ is the vector of firm characteristics and control variables for each firm i on week t. Firm characteristics and control variables included in this regression are: realized volatility, realized skewness, realized kurtosis, previous week return, size, book-to-market, market beta, historical skewness, idiosyncratic volatility, co-skewness, maximum monthly stock return, number of IBES analysts, illiquidity and number of intraday transactions.

[Table 3 goes here]

Given that the cross-sectional regression is performed each week, a time series of regression coefficients is obtained. Table 3 reports the average values of the Fama-MacBeth coefficients γ_0, γ_1 and ϕ for four cross-sectional regressions. The t-statistics are also reported in Table 3. They are computed using the Newey-West methodology with 3 lags to account for heteroskedasticity and autocorrelation.

In the first regression, stock returns are regressed only on realized jump. The goal is to test that the realized jump measure is able to predict stock returns just by itself, without the presence of any other control variable known to predict stock returns. The coefficient of realized jump is

-0.0966 with a Newey-West t-statistic of -9.56. As expected, this regression shows that there is a negative and significant relation between stock returns and realized jumps.

The next regression, that of column 2, includes higher moments computed with intraday data. According to Amaya and Vasquez (2010), realized skewness and realized kurtosis are significantly related with stock returns. Moreover, as seen on Table 1, realized skewness and realized jumps are positively related. Hence, realized jump might just be a proxy for the third realized moment. The coefficients of realized jump, realized skewness and realized kurtosis are all significant and have the "correct" sign. The coefficient for realized jump is -0.1065 with a Newey-West t-statistic of -12.10, that of realized skewness is -0.0148 with a Newey-West t-statistic of -6.61 and that of realized kurtosis is 0.0132 with a Newey-West t-statistic of 3.80. Therefore, realized jumps and realized skewness preserve the negative relation with stock returns and realized kurtosis still has the positive relation with stock returns.

A strong predictor of weekly stock returns is its previous week return, a phenomenon known as short term return reversal (see Gutierrez and Kelley (2008)). Additionally, previous week returns, realized jumps and realized skewness are all positively related. Hence, in the third regression, previous week returns are added to the regression to assess how the interaction of these three variables (plus realized volatility and realized kurtosis) affects the predictability power of the model. As expected by the short-term return reversal, previous week return has a negative coefficient of -0.0276 with a Newey-West t-statistic of -7.86. Importantly, realized jump coefficient is still negative and significant with a value of -0.054 and a Newey-West t-statistic of -6.34. However, even if the coefficient of realized skewness is negative at -0.0025, it is not significant anymore (Newey-West t-statistic of -1.32). On the other hand, the coefficient of realized kurtosis is still positive and significant and that of realized variance is still not significant. From the third regression, we conclude that realized jump, previous week return and realized kurtosis predict stock returns but realized skewness does not. The fact that realized skewness does not predict stock returns when realized jumps are present might be due to measurement accuracy. While realized skewness is computed with returns to the third power, realized jump only uses returns to the second power.[3]

In the fourth regression, all control variables and firm characteristics are included. Importantly, the coefficient of realized jump is -0.0537 with a Newey-West t-statistic of -6.59. This means that, even in the presence of 14 control variables, realized jump predicts stock returns. Interestingly, the coefficient of realized skewness is -0.0035 with a now significant Newey-West t-statistic of -2.01. The inclusion of all control variables favored the significance of the coefficient of realized skewness. The coefficients of realized kurtosis and previous week return are 0.0070 and -0.0361 with Newey-West t-statistics of 2.42 and -11.07, respectively. The other variables that have significant coefficients are size (at -0.0016 with a Newey-West t-statistic of -5.56), historical skewness (at 0.0017 with a Newey-West t-statistic of 8.48), illiquidity (at -0.0004 with a Newey-West t-statistic

[3] Realized jump also uses the tri-power quarticity but only to compute a test statistic, not to compute the jump itself.

of -3.19) and number of intraday transactions (at 0.0011 with a Newey-West t-statistic of 4.23). Based on these coefficients, small size firms that are illiquid and with a high number of intraday transactions have higher stock returns. However, the coefficient of the number of intraday transactions and illiquidity contradict each other. If more illiquid firms have higher returns, as predicted by the positive coefficient of illiquidity, then a lower number of intraday transactions should yield a higher stock return, which is not what the negative coefficient of the number of transactions suggests. Further research must be done to uncover the impact of different measures of liquidity on weekly stock returns. Finally, the coefficients of the other firm characteristics, such as book-to-market and idiosyncratic volatility, are not significant. Therefore, realized jumps predict stock returns over and above realized skewness, previous week return, realized kurtosis and firm size.

5 Interaction between Realized Jump and Realized Skewness

In general, jumps in returns have a direct impact on higher moments. When modelling returns, a skewed distribution can be created by adding jumps to returns. However, jumps in returns might not be the only reason that a distribution is skewed. For example, Yan (2010) argues that excessive kurtosis is caused by jumps. Based on the results of the Fama-MacBeth regression presented in Table 3, both measures predict the cross-section of stock returns. In this section, we perform a detailed analysis to rule out that realized jumps and realized skewness are measuring similar things. First, the stocks of the decile portfolios formed by realized jumps and realized skewness are explored. The goal is to rule out that the stocks on each decile are different for the two sorts. This means that forming deciles based on realized jumps should be different than forming deciles based on realized skewness. Second, we analyze double sorted portfolio returns to understand how stock returns change for different levels of realized jumps and realized skewness.

[Table 4 goes here]

Each week, two independent sortings are performed, one by realized jumps and one by realized skewness. Then, stocks are assigned into two decile portfolios, one based on the realized jump ranking and another one based on the realized skewness ranking. Table 4 presents the portfolio allocation based on the two rankings. The main purpose of this double sorting is to show that stocks are not assigned to the same decile when ranked by realized jump and by realized skewness. If both variables assign stocks to the same decile, we should observe that hundred percent of the stocks are in the diagonal of Table 4. However, stocks in extreme portfolios, those of deciles 1 and 10, only share 25 and 24 percent of the stocks, respectively. That's why, independently on whether the ranking is done by realized jump or realized skewness, only one quarter of the stocks are assigned to the same extreme decile (P1 or P10) and the other 75 percent is assigned to a different decile (P2 to P9). For example, 8 percent of the stocks that belong to decile 1 when sorted by realized skewness, are in decile 10 when the sorting is done by realized jump. These stocks have the largest realized jumps over the previous week, but their skewness is actually negative. As for the other deciles, P2 to P9, they only share between 12 and 15 percent of the stocks. We conclude that the two realized measures, realized jump and realized skewness, assign stocks to different deciles. Hence, these two measures capture different aspects of the stock return behaviour.

[Table 5 goes here]

To further understand the differences between realized jumps and realized skewness, we study the portfolio returns of double sorted portfolios. As done in Table 4, two independent sortings are done, one by realized jump and one by realized skewness. Then, stocks are assigned into quintiles based on the two measures. We decide to use quintiles, instead of deciles, to keep the portfolios well populated given that 25 portfolios are analysed. We also explore the results of the long-short portfolio strategy for different levels of realized jumps and realized skewness.

Based on the results presented so far, the trading strategies that buy high realized jump stocks, or high realized skewness stocks, and sell low realized jump stocks, or low realized skewness stocks, yield negative and significant returns. Table 5 presents the long-short portolio returns for double sorted portfolios. The most notable aspect of the long-short portfolio returns is that they are all negative and significant. The long-short premium for realized jump varies from -29.5 to -47.8 basis points and the t-statistic is above -3.87 for all quintiles. Hence, when sorting by realized jumps, stock returns of the long-short portfolio are negative and significant for all levels of realized skewness. For example, when taking only stocks with the highest level of realized skewness (quintile 5) and sorting them by realized jump, the long-short portfolio has an average weekly return of -33.1 basis points with a t-statistic of -4.20. The level and significance of the long-short return is similar for all realized skewness quintiles.

On the other hand, the long-short realized skewness premium is also negative and significant for all levels of realized jump. Stocks in the lowest realized jump quintile and in the lowest realized skewness quintile have an average weekly return of 82.4 basis points while those with the highest level of realized skewness (but still in the low realized jump quintile) have a return of 34.2 basis points. Consequently, the long-short portfolio realized skewness premium for the low realized jump quintile is -48.2 basis points with a t-statistic of -6.56. Finally, out of the 25 double sorted portfolios, the portfolio with the highest return (82.4 basis points) is that of stocks with the lowest realized jump and the lowest realized skewness levels. In contrast, the one with the lowest return (1.1 basis points) is made of stocks with the highest realized jump and the highest realized skewness levels. Therefore, realized jump and realized skewness complement each other. Together, they give evidence that stocks with the lowest levels of jump and skewness are compensated with the highest future returns, while stocks with the highest level of jump and skewness earn the lowest future returns.

6 Robustness Checks

In this section, we relax the assumptions to test the robustness of the results. The first test checks that the long-short realized jump return is negative and significant for different levels of firm characteristics. In the second test, the data is divided in two periods and stock returns and Fama-MacBeth regressions results are explored. The third test looks at the results for two different stock exchange subgroups: NYSE stocks and non-NYSE stocks. In the final test, we quantify the long-term predictability of realized jumps for up to four week returns.

6.1 Double Sorting on Firm Characteristics

To gain a deeper understanding of the interaction between realized jumps and firm characteristics, we construct double sorted portfolios and analyse the average returns of the trading strategy that buys high realized jump stocks and sells low realized jump stocks. Quintile portfolios are formed based on the firm characteristic, then, within each quintile, five quintiles are constructed based on realized jumps. Table 6 reports the return of the long-short trading strategy for all firm characteristic quintiles. The main goal is to prove that realized jumps can predict subsequent stock returns for different levels of each firm characteristic. Firm characteristics included in the double sorting analysis are firm size, book-to-market, previous week return, realized volatility, realized skewness, historical skewness, illiquidity, intraday transactions, maximum return over the previous month, number of IBES analysts, market beta, idiosyncratic volatility and co-skewness. In this subsection, double sorting is conditional and not unconditional as in the previous section. First, stocks are sorted by the firm characteristic. Then, within the firm characteristic, they are once again sorted by realized jumps. In the previous section, the interaction between realized jumps and realized skewness is performed with unconditional double sortings. Nevertheless, the results of the two double sorting methodologies are similar but not identical.

[Table 6 goes here]

Three main findings can be reported by analysing the results on Table 6. 1) The long-short trading strategy is negative and statistically significant in all but three cases. 2) Those three cases occur for the same firm characteristic: previous week return. 3) The long-short realized jump premium has an increasing or decreasing pattern for the following firm characteristics: size, realized volatility, illiquidity, maximum return over previous month, number of IBES analysts and idiosyncratic volatility.

As expected, the long-short realized jump premium is negative and statistically significant for all but three cases (We address these cases further down). This means that realized jump can consistently predict future stock returns. When double sorting by co-skewness, for example, the long-short return varies from -43.7 to -58.4 basis points with a t-statistic of -6.22 and -8.15, respectively. In some cases, the negative premium is small but still negative and significant. This is the case of the long-short premium for stocks with low realized volatility that is only -6.8 basis points with a significant t-statistic of -2.0.

As previously stated, realized jump cannot predict future stock returns for all previous-week return quintiles. Those are the second, third and fourth quintiles where the long-short premium is between 0.1 and 3.1 basis points. However, for quintiles 1 and 5, the realized jump premium is negative and statistically significant. Stocks in quintile 1, those with the largest negative returns over the previous week, have a long-short realized jump premium of -65.2 with a t-statistic of -8.31 and stocks in quintile 5, those with the largest positive return, also have a negative premium of -32.8 with a t-statistic of -5.0. Therefore, realized jump predicts future returns when previous week returns are extreme, either positive or negative, but does not work when previous week returns are average.

Finally, the long-short portfolio return increases as the firm size increases, the realized volatility and idiosyncratic volatility decrease, maximum previous month returns increase and numbers of analysts decrease. Quintile 1 of firm size has a significant realized jump premium of -110.0 basis points that monotonically increases to -28.2 basis points for quintile 5. This means that the realized jump effect on stock returns is more pronounced in small firm than in big firms. The opposite happens with volatility, either realized or idiosyncratic, where the realized jump effect is stronger for highly volatile stocks. From quintile 1 to quintile 5, the long-short premium decreases from -6.8 to -126.1 for realized volatility and from -7.3 to -117.2 for idiosyncratic volatility (all premiums are statistically significant). The same pattern is observed for illiquidity: illiquid stocks have a larger negative premium. Finally, the long-short premium for stocks followed by many IBES analysts is only -29.2 and increases (in absolute value) to -84.6 basis points for companies followed by few analysts.

We conclude that, when implementing a trading strategy using realized jumps, one should focus on small illiquid firms with high volatility that are not followed by many analysts. Most important, those companies must have large positive or negative returns in the week prior to implementing the strategy.

6.2 Analysis for Different Periods

Table 7 and Table 8 present the results of the long-short trading analysis and the Fama-MacBeth regressions over two periods of the 1993-2007 range. Over the 15 year period of 1993 to 2007, the decimalisation that occurred in early 2001 is the most important event that can potentially affect the results. The decimalisation in the US stock market allows for smooth price changes of a penny, while before the decimalisation, only discrete price changes were allowed. In addition, the year 2001 divides the data sample in two equally spaced periods: from 1993 to 2000 and from 2001 to 2007.

6.2.1 Stock Returns for Different Periods

Table 7 displays the returns for deciles portfolios ranked by realized jumps. This table also reports the high-low trading strategy returns that are obtained from buying portfolio 10 (High realized jump) and selling portfolio 1 (Low realized jump). Panel A displays the results for the period 1993 to 2000 and Panel B has the ones for the period 2001 to 2007. The long-short realized jump premium is negative in the two periods, for equal- and value-weighted portfolios. The long-short premium is larger (in absolute value) for the first subsample (1993-2000) with a raw return of -109.0 basis points and a t-statistic of -10.74. The premium is also negative and significant for raw value-weighted returns at -85.43 basis points.

[Table 7 goes here]

The long-short equal-weighted return for the second period significantly decreases in absolute value to -28.52 with a t-statistic of -3.75. The Fama-French alpha for the equal-weighted return is also negative and significant. Finally, the long-short premium for value-weighted returns is negative at -15.91 basis points but is not statistically significant since its t-statistic is only -1.39. This means that realized jump predicts stock returns much better before the decimalisation. Once the decimilasation was set in place back in 2001, the realized jump effect decreases in power and is not significant for value-weighted portfolios.

6.2.2 Fama-MacBeth for Different Periods

[Table 8 goes here]

Table 8 presents the cross-sectional Fama-MacBeth regressions for the two subperiods. The coefficient for realized jump is negative and statistically significant for the four regressions in the two subperiods. Moreover, the coefficient has the same magnitude in the two subperiods. For example, in regression 4, the coefficient of realized jump is -0.0489 with a Newey-West t-statistic of -4.85 for the 1993-2000 period. In the 2001-2007 period, the coefficient of realized jumps increases to -0.0597 with a Newey-West t-statistic of -4.46.

As for the coefficients of the control variables, some of them are significant in the first subperiod but not significant in the second period. That is the case of realized skewness, illiquidity and number of intraday transactions. For the 1993-2000 period, the coefficients of realized skewness in all three regression are negative and statistically significant. For example, the coefficient of realized skewness in regression 4 is -0.0069 with a Newey-West t-statistic of -2.38. However, the coefficients of realized skewness for the 2001-2007 period are of both signs and not significant. This means that, in the presence of realized jump, realized skewness looses its power to predict future returns in the period between 2001 and 2007.

6.3 Analysis by Stock Exchange

Given that small stocks have a large negative long-short premium, we want to rule out that the results hold for large stocks trading in the NYSE and that they are not driven by small NASDAQ stocks. Hence, we divide the sample into NYSE and non-NYSE stocks to analyse the long-short portfolio returns as well as the cross-sectional Fama-MacBeth regressions.

6.3.1 Stock Returns by Stock Exchange

[Table 9 goes here]

In Table 9, the returns of equal weighted and value weighted deciles are reported. Panel A has the results for NYSE stocks. The long-short raw returns premium is -100.32 basis points with a t-statistic of -11.39. This premium is mainly driven by decile 1 (low realized jump) that has an average return of 100.87 basis points. On the other hand, decile 10 (high realized jump) has a return very close to zero with a value of 0.54 basis points. The raw return premium for value weighted portfolios is -73.98 with a t-statistic of -5.87 which is also driven by decile 1. The Fama-French alpha is of similar magnitude and statistical significance than the raw return.

Panel B shows the findings for non-NYSE stocks. All long-short realized jump premium are smaller for non-NYSE stocks than for NYSE stocks. The raw return equal weighted premium decreases from -100.32 to -26.84 basis points and the value-weighted one decreases from -73.98 to -25.50 basis points. This change is coming from a decrease in decile 1 returns and an increase in decile 10 returns. Therefore, we conclude that the results are not driven by any particular exchange subgroup.

6.3.2 Fama-MacBeth by Stock Exchange

[Table 10 goes here]

Table 10 displays the results of the cross-sectional regressions for NYSE and non-NYSE stocks. In Panel A, that of NYSE stocks, the coefficients for realized jumps and realized skewness are negative and statistically significant in all four regressions. However, in regressions 3 and 4 of Panel B, the coefficients of realized jumps and realized skewness are not statistically significant anymore for non-NYSE stocks. Further research is required to establish why realized jumps do not predict subsequent stock returns for non-NYSE stocks.

6.4 Long-Term Predictability of Stock Returns

[Table 11 goes here]

Here, we explore how long the predictability of returns lasts when stocks are sorted by realized jumps. Table 11 presents the results of the long-short realized jump return from one to four weeks. The long-short realized jump return is obtained from the trading strategy that buys stocks from decile 10 (high realized jump) and sells those of decile 1 (low realized jump). Additionally, one to four week returns are cumulative as we want to establish if there is a reversal in the negative returns observed over one week.[4] From the first week to the third week, absolute long-short returns increase from -73.61 to -82.02 basis points with a t-statistic of -10.89 and -7.17, respectively. In week four, returns slightly decrease but they are still negative and significant. More research is needed to reveal the true long-term predictability of realized jumps on returns. Our plan is to explore long-term predictability up to a year.

7 Conclusion

The presence of jumps in stock returns is accepted and has been extensively documented. In this paper, we explore whether jumps can predict future stock returns. With the increased availability of high frequency data, several methods have been developed to compute jumps. Using the Barndorff-Nielsen and Shephard (2004b) approach, intraday jumps, that we call realized jumps, are calculated on a weekly basis for the cross-section of US stocks for the period 1993-2007. Then, using univariate sorting by the realized jump measure and cross-sectional Fama-MacBeth regressions, we establish that realized jumps effectively predict stock returns. Consistent with theoretical arguments, realized jumps and stock returns have a negative relation: large positive jumps are followed by lower returns than large negative jumps. This relation holds for equal weighed and value weighted portfolios and for the Fama-French four factor alpha of these portfolios.

To gain a deeper understanding of the roots of this predictability, conditional portfolios based on a double sorting procedure are examined. First, stocks are ranked based on a firm characteristic (i.e. firm size) and assigned to a quintile portfolio. Then, within each quintile, stocks are ranked based on realized jump. Firm characteristics that are explored include firm size, book-to-market, previous week return, realized volatility, realized skewness, historical skewness, illiquidity, intraday transactions, maximum return over the previous month, number of IBES analysts, market beta, idiosyncratic volatility and co-skewness. The bivariate sorting methodology confirms the negative relation between realized jumps and stock returns. Moreover, the negative realized jump premium is larger for small illiquid firms that are not followed by many analysts, highly volatile and have large previous-week returns, either positive or negative.

The negative relation between realized jumps and stock returns survives successfully most robustness tests. First, we checked that the decile portfolios formed with realized jumps are different that the ones formed with realized skewness. Not only they are different, but also the returns of the long-short trading strategy are negative for all double sorted portfolios. This confirms that the

[4] The one week long-short returns are also found in Table 2.

realized jump and realized skewness capture different attributes of the stock return distribution. Second, we explored the returns for different subsamples as well as the long term predictability of stock returns. When looking at the long-short portfolio returns by subperiod, the 1993-2000 period has larger absolute returns than the 2001-2007 period. This might be due to the decimalisation of the stock market that occurred at the beginning of 2001. Next, the data is divided into NYSE and non-NYSE stocks. We find that both subgroups have negative and statistically significant returns. However, non-NYSE stocks have lower absolute returns than NYSE stocks. In addition, Fama-MacBeth regressions reveal that the coefficient of non-NYSE stocks is not significant when all control variables are included in the regression. Further research is needed to understand why realized jumps do not predict returns for non-NYSE stocks.

The main finding in this paper is that realized jumps predict one-week stock returns, but how long does the predictability last? To answer this question, we analyse stock return predictability for two-weeks, three-weeks and four-weeks. Not only realized jump predicts stock returns in all four windows, but the long-short trading strategy returns increase in the two-week and three-week periods. Thus, no return reversal is observed in the four-week window. We leave for future research the analysis of a larger window, up to a year, to fully explore the predictability pattern of realized jumps on stock returns. Future research should also include alternative methodologies to measure realized jumps such as the one proposed by Lee and Mykland (2008).

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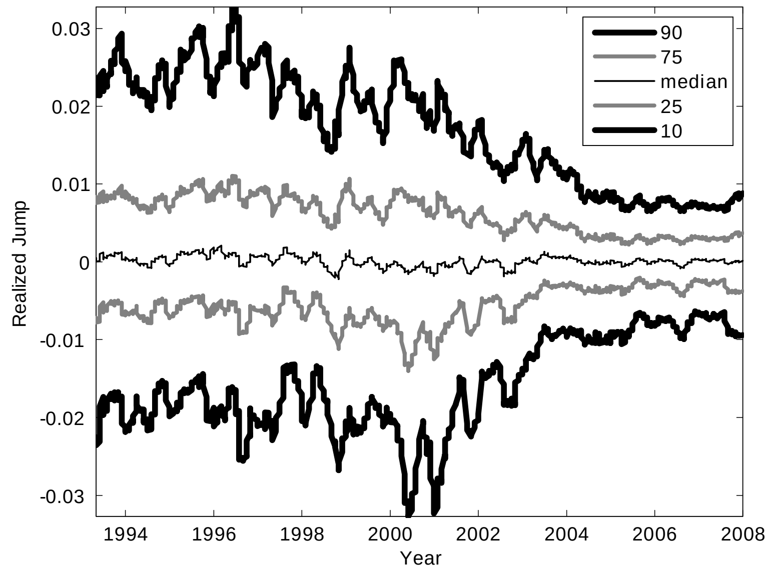
Figure 1

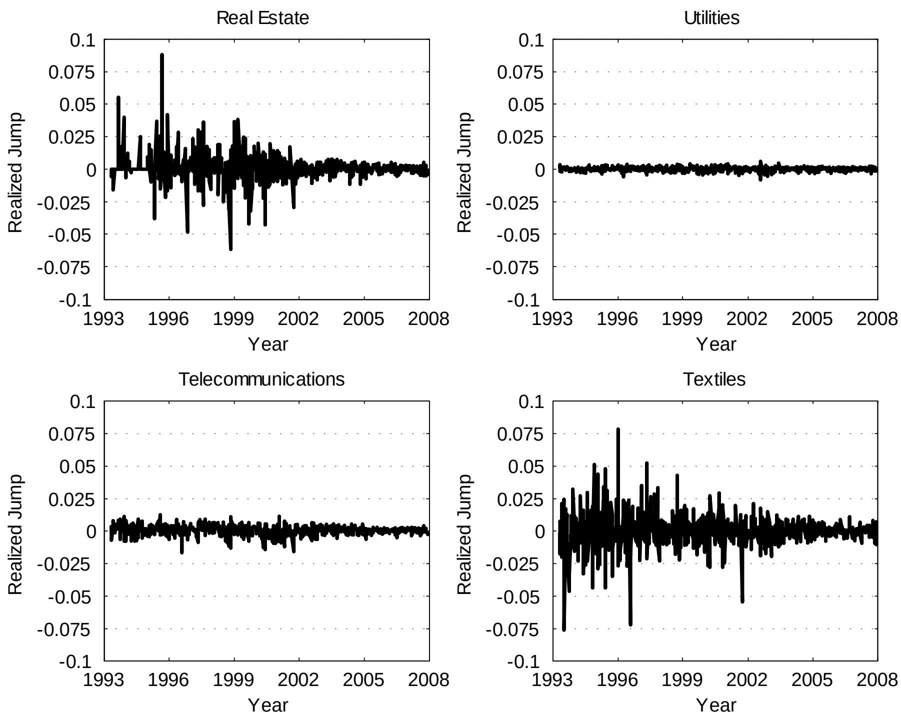
Realized Jump Three-Month Moving Average



This figure display the 10th, 25th, 50th, 75th and 90th percentiles of the three-month moving average of realized jump for the cross-section of companies listed in TAQ from January 1993 to December 2007.

Figure 2

Realized Jump of Selected Industry Groups



These figures display the weekly average of realized jump for selected industries from January 1993 to December 2007. Following Ken's French 48 industries designations, industries included in this figure are real estate, utilities, telecommunications and textiles.

Table 1

Characteristics of Portfolios Sorted by Jump Component

Deciles	1	2	3	4	5	6	7	8	9	10
Realized Jump	-0.029	-0.010	-0.005	-0.003	-0.001	0.001	0.003	0.006	0.011	0.032
Realized Volatility	0.436	0.294	0.230	0.207	0.198	0.193	0.203	0.233	0.295	0.434
Realized Skewness	-0.286	-0.194	-0.132	-0.068	-0.011	0.040	0.094	0.146	0.186	0.235
Realized Kurtosis	9.6	7.6	7.1	7.0	7.0	6.9	6.9	7.2	7.9	10.4
Size	1.10	3.08	5.40	7.14	7.93	7.92	6.93	4.92	2.79	1.01
BE/ME	0.440	0.455	0.485	0.480	0.489	0.523	0.493	0.489	0.469	0.476
Historical Skewness	0.199	0.223	0.195	0.179	0.160	0.134	0.121	0.115	0.147	0.261
Market Beta	1.26	1.21	1.10	1.05	1.02	1.02	1.04	1.09	1.13	1.13
Previous Week Return	-0.063	-0.031	-0.017	-0.006	0.003	0.009	0.018	0.031	0.049	0.094
Idiosyncratic Volatility	0.034	0.026	0.022	0.020	0.019	0.019	0.020	0.022	0.026	0.034
Co-Skewness	-0.049	-0.033	-0.022	-0.016	-0.017	-0.014	-0.017	-0.022	-0.034	-0.046
Maximum Return	0.088	0.070	0.059	0.055	0.054	0.054	0.056	0.062	0.074	0.099
Illiquidity	0.00213	0.00083	0.00057	0.00051	0.00052	0.00048	0.00047	0.00055	0.00081	0.00231
Number of Analysts	5.0	7.7	9.2	9.7	9.8	9.9	9.6	8.7	7.1	4.5
Credit Rating	8.6	8.6	8.3	8.1	8.0	7.9	8.1	8.4	8.6	8.6
Price	19.1	26.7	33.5	36.8	38.7	39.1	37.6	33.3	28.5	21.8
Number of Intraday Transactions	782	1,066	1,168	1,249	1,286	1,271	1,278	1,159	1,074	780
Number of Stocks	212	212	212	214	212	212	213	213	212	212

Each week, stocks are ranked by their realized jump measure and sorted into deciles. The equal-weighted characteristics of those deciles are computed over the same week from January 1993 to December 2007. Average characteristics of the portfolios are reported for the Realized Skewness measure, Size ($ market capitalization in $billions), BE/ME (book-to-market equity ratio), Realized volatility (weekly realized volatility computed with high-frequency data), HSkew (one month historical skewness from daily returns), Market Beta, Previous Week Return, Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000)), Maximum Return (of the previous month), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), Number of Analysts (from I/B/E/S), Credit Rating (1= AAA, 8= BBB+, 17= CCC+, 22=D), Price (stock price), Number of Transactions (intraday transactions per day) and Number of Stocks.

Table 2
Intraday Jumps and the Cross-Section of Stock Returns

	Equal weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	81.87	44.98	38.50	34.60	31.96	28.66	24.89	25.09	21.39	7.67	-73.61
	(5.59)	(3.63)	(3.76)	(3.71)	(3.61)	(3.30)	(2.83)	(2.63)	(1.97)	(0.64)	(-10.89)
Alpha, FF	81.65	45.24	38.90	35.17	32.32	29.16	25.41	25.94	21.60	7.84	-75.04
	(5.53)	(3.61)	(3.77)	(3.74)	(3.63)	(3.35)	(2.87)	(2.70)	(1.97)	(0.65)	(-11.00)

	Value weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	59.49	39.44	34.50	31.08	28.07	23.18	15.21	7.83	12.94	3.26	-55.24
	(4.17)	(3.22)	(3.49)	(3.41)	(3.14)	(2.65)	(1.73)	(0.80)	(1.14)	(0.25)	(-6.09)
Alpha, FF	61.95	40.25	35.18	32.45	29.38	25.98	17.03	10.21	15.01	4.87	-57.97
	(4.31)	(3.27)	(3.54)	(3.56)	(3.28)	(3.00)	(1.94)	(1.05)	(1.32)	(0.38)	(-6.38)

These tables report the equal-weighted and value-weighted weekly returns (in bps) of decile portfolios formed from realized jumps, their t-statistics (in parentheses) and the difference between portfolio 10 (highest realized skewness) and portfolio 1 (lowest realized skewness) over the period January 1993 to December 2007. Raw returns (in bps) are obtained from decile portfolios sorted solely from ranking stocks based on the realized jump measure. Alpha is the intercept from time-series regressions of the returns of the portfolio that buys portfolio 10 and sells portfolio 1 on the Carhart (1997) four factor model. Realized jumps are calculated using intraday data.

Table 3
Fama-MacBeth Cross-Sectional Regressions

	(1)	(2)	(3)	(4)
Intercept	0.0035	0.0025	0.0023	0.0153
	(3.65)	(2.64)	(2.50)	(4.69)
Realized Jump	-0.0966	-0.1065	-0.0540	-0.0537
	(-9.56)	(-12.10)	(-6.34)	(-6.59)
Realized Variance		-0.0472	-0.0082	-0.1518
		(-0.24)	(-0.04)	(-1.49)
Realized Skewness		-0.0148	-0.0025	-0.0035
		(-6.61)	(-1.32)	(-2.01)
Realized Kurtosis		0.0132	0.0143	0.0070
		(3.80)	(4.26)	(2.42)
Previous Week Return			-0.0276	-0.0361
			(-7.86)	(-11.07)
log (Size)				-0.0016
				(-5.56)
log (BE/ME)				0.0002
				(0.88)
Beta				-0.0011
				(-1.51)
Hskew				0.0017
				(8.48)
Idiosyncratic Volatility				-0.0244
				(-0.84)
Co-skewness				0.0011
				(0.71)
Max. Month Return				-0.0090
				(-1.19)
log (Number of Analysts+1)				0.0001
				(0.31)
log (Illiquitidy)				-0.0004
				(-3.19)
log (Number of Intraday transactions)				0.0011
				(4.23)
R^2	0.005	0.030	0.038	0.102

Results from the Fama-MacBeth cross-sectional regressions of weekly stock returns on firm characteristics are reported for the period January 1993 to December 2007. Firm characteristics are Realized Jump, Realized Volatility, Realized Skewness, Realized Kurtosis, Previous Week Return, Size (market capitalization in $billions), BE/ME (book-to-market equity ratio), Market Beta, HSkew (one month historical skewness from daily returns), Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000) with 24 months of data), Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), and Number of Intraday Transactions. This table reports the average of the coefficient estimates for the weekly regressions along with the Newey-West t-statistic (in parentheses).

Table 4
Decile Portfolio Allocation: Sorting by Realized Jump and Realized Skewness

Deciles	Deciles by Realized Skewness at t											
RJump at t	1	2	3	4	5	6	7	8	9	10	Total	%
1	25	15	12	10	8	7	6	6	5	6	154,284	10
2	17	15	13	11	10	9	8	7	6	5	154,579	10
3	12	13	13	12	11	10	9	8	7	5	154,292	10
4	9	12	12	12	11	11	10	9	8	6	155,816	10
5	7	10	11	11	12	11	11	10	9	7	154,236	10
6	6	8	10	11	11	12	12	12	11	8	154,076	10
7	5	7	9	10	11	11	12	12	12	10	155,434	10
8	5	7	8	9	10	11	12	13	14	13	154,676	10
9	5	6	7	8	9	10	11	12	15	17	154,362	10
10	8	6	6	6	7	8	9	11	14	24	154,393	10
Total	154,403	154,231	153,904	153,920	154,745	153,860	154,552	155,033	155,459	156,041	1,546,148	
%	10	10	10	10	10	10	10	10	10	10		100

Missing Stocks: 516,441

Two independent sortings are done, one by the average realized jump and one by realized skewness. Stocks are assigned a decile portfolio for the two independent sortings. This table presents the percent portfolio allocation for the realized jump and realized skewness portfolios.

Table 5
Double Sorting by Realized Jump and Realized Skewness

	Realized Skewness					
	1(low)	2	3	4	5 (high)	High-Low
1 (Low Realized Jump)	82.4	65.5	51.0	41.0	34.2	-48.2
	(6.04)	(4.65)	(3.64)	(2.84)	(2.61)	(-6.56)
2	45.8	39.6	30.0	35.1	27.3	-18.5
	(4.55)	(3.84)	(3.01)	(3.50)	(2.70)	(-3.29)
3	44.3	33.2	27.1	28.7	20.8	-23.5
	(4.47)	(3.52)	(3.05)	(3.23)	(2.45)	(-4.61)
4	32.1	24.5	24.8	24.4	20.5	-11.7
	(2.74)	(2.36)	(2.58)	(2.66)	(2.35)	(-1.45)
5 (High Realized Jump)	45.4	17.7	16.7	11.5	1.1	-44.3
	(3.58)	(1.37)	(1.34)	(0.96)	(0.10)	(-6.06)
High-Low	-37.0	-47.8	-34.3	-29.5	-33.1	
	(-4.60)	(-6.42)	(-4.98)	(-3.87)	(-4.20)	

Each week, stocks are double ranked by realized jump and realized skewness into five quintiles for the period January 1993 to December 2007. Then, the equal-weighted average weekly returns are reported for all quintile combinations along with the t-statistic (in parentheses). In addition, the long-short portfolio returns are reported for both, realized jump and realized skewness.

Table 6
Double Sorting on Firm Characteristics, then on Realized Jump

	Characteristics				
	1(low)	2	3	4	5 (high)
Across Size quintiles	-110.0	-61.1	-40.7	-20.6	-28.2
Realized Jump 5-1	(-11.70)	(-8.02)	(-6.06)	(-3.34)	(-5.26)
Across BE/ME quintiles	-54.1	-56.9	-58.3	-35.4	-34.5
Realized Jump 5-1	(-6.52)	(-7.71)	(-8.33)	(-5.34)	(-4.91)
Across Previous Week Return quintiles	-65.2	0.1	3.1	3.1	-32.8
Realized Jump 5-1	(-8.31)	(0.02)	(0.66)	(0.61)	(-5.00)
Across Realized Volatility quintiles	-6.8	-20.4	-32.1	-55.7	-126.1
Realized Jump 5-1	(-2.00)	(-5.20)	(-5.84)	(-8.02)	(-12.72)
Across Realized Skewness quintiles	-58.5	-52.0	-30.8	-32.3	-32.2
Realized Jump 5-1	(-7.36)	(-6.91)	(-4.69)	(-4.90)	(-5.11)
Across Historical Skewness quintiles	-37.1	-50.9	-57.1	-61.2	-47.4
Realized Jump 5-1	(-5.24)	(-6.22)	(-7.34)	(-8.04)	(-6.73)
Across Illiquidity quintiles	-33.6	-38.0	-41.9	-52.6	-102.7
Realized Jump 5-1	(-5.55)	(-5.81)	(-5.79)	(-6.75)	(-12.22)
Across Intraday Transactions quintiles	-41.7	-45.9	-41.4	-64.6	-60.5
Realized Jump 5-1	(-6.70)	(-6.39)	(-5.42)	(-8.02)	(-6.78)
Across Maximum Return quintiles	-15.2	-27.9	-41.4	-57.6	-97.7
Realized Jump 5-1	(-3.52)	(-5.33)	(-6.91)	(-7.74)	(-10.00)
Across Number of Analysts quintiles	-84.6	-66.0	-44.4	-29.0	-29.2
Realized Jump 5-1	(-9.40)	(-8.72)	(-6.62)	(-4.32)	(-4.44)
Across Beta quintiles	-44.3	-36.2	-44.1	-65.0	-63.2
Realized Jump 5-1	(-6.89)	(-6.67)	(-7.27)	(-9.32)	(-7.34)
Across Idiosyncratic Volatility quintiles	-7.3	-18.0	-30.4	-63.5	-117.2
Realized Jump 5-1	(-2.36)	(-4.55)	(-5.14)	(-8.60)	(-11.99)
Across Co-Skewness quintiles	-58.4	-54.6	-44.5	-43.7	-48.4
Realized Jump 5-1	(-8.15)	(-7.57)	(-6.44)	(-6.22)	(-7.24)

Each week, stocks are ranked by each firm characteristic into five quintiles. Then, within each quintile, stocks are sorted once again by the realized jump measure into five quintiles. For each firm characteristic quintile, the equal-weighted average weekly returns are reported for the realized jump quintile difference between portfolio five and one along with the t-statistic (in parentheses). Panel A displays the results for realized skewness and Panel B for realized kurtosis. Firm characteristics are Size ($ market capitalization in $billions), BE/ME (book-to-market equity ratio), Realized Volatility (weekly realized volatility computed with high-frequency data), Previous Week Return, HSkew (one month historical skewness from daily returns), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), Number of Intraday Transactions, Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Market Beta, Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)) and Coskewness (computed as in Harvey and Siddique (2000)).

Table 7
Realized Jump Portfolio Returns by Periods

Panel A: from year 1993 to 2000

	Equal weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	109.06	52.77	45.89	42.78	38.29	32.98	27.87	26.11	22.03	-0.25	-109.00
	(5.26)	(3.04)	(3.33)	(3.47)	(3.30)	(2.87)	(2.36)	(2.09)	(1.48)	(-0.02)	(-10.74)
Alpha, FF	106.68	51.02	45.07	42.56	37.74	32.76	27.58	26.72	20.72	-1.24	-109.75
	(5.07)	(2.89)	(3.21)	(3.39)	(3.20)	(2.80)	(2.30)	(2.10)	(1.37)	(-0.07)	(-10.67)

	Value weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	82.51	55.46	47.93	44.04	33.62	34.43	17.16	8.89	22.37	-3.12	-85.43
	(4.48)	(3.54)	(3.80)	(3.79)	(2.96)	(3.04)	(1.59)	(0.80)	(1.62)	(-0.20)	(-6.42)
Alpha, FF	82.92	54.62	46.88	46.25	34.69	36.48	18.78	11.64	22.13	-1.70	-86.53
	(4.43)	(3.43)	(3.64)	(3.95)	(3.03)	(3.20)	(1.72)	(1.04)	(1.58)	(-0.11)	(-6.45)

Panel B: from year 2001 to 2007

	Equal weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	46.26	34.19	29.01	23.93	22.96	23.18	22.47	21.44	20.63	17.91	-28.52
	(2.30)	(1.95)	(1.90)	(1.68)	(1.68)	(1.75)	(1.67)	(1.45)	(1.30)	(1.02)	(-3.75)
Alpha, FF	43.78	32.84	27.25	22.77	21.90	22.40	21.38	19.87	19.53	15.97	-29.29
	(2.16)	(1.86)	(1.78)	(1.59)	(1.60)	(1.69)	(1.59)	(1.35)	(1.23)	(0.91)	(-3.80)

	Value weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	27.28	19.71	17.42	14.84	19.85	9.41	9.88	7.04	1.88	11.18	-15.91
	(1.22)	(1.02)	(1.11)	(1.02)	(1.38)	(0.69)	(0.68)	(0.40)	(0.10)	(0.51)	(-1.39)
Alpha, FF	28.15	19.84	17.06	14.98	19.25	10.61	9.77	6.61	1.99	9.91	-19.40
	(1.25)	(1.02)	(1.09)	(1.03)	(1.34)	(0.79)	(0.68)	(0.38)	(0.11)	(0.45)	(-1.68)

These tables report the equal-weighted and value-weighted weekly returns (in bps) of decile portfolios formed from realized jumps, their t-statistics (in parentheses) and the difference between portfolio 10 (highest realized skewness) and portfolio 1 (lowest realized skewness) over two different periods. Panel A reports results over the period 1993 to 2000 and Panel B over the period 2001 to 2007. Raw returns (in bps) are obtained from decile portfolios sorted solely from ranking stocks based on the realized jump measure. Alpha is the intercept from time-series regressions of the returns of the portfolio that buys portfolio 10 and sells portfolio 1 on the Carhart (1997) four factor model. Realized jumps are calculated using intraday data.

Table 8
Fama-MacBeth by Periods

Panel A: from year 1993 to 2000

	(1)	(2)	(3)	(4)
Intercept	0.0042	0.0032	0.0030	0.0185
	(3.31)	(2.70)	(2.45)	(3.76)
Realized Jump	-0.1150	-0.1216	-0.0497	-0.0489
	(-9.54)	(-11.45)	(-4.77)	(-4.85)
Realized Variance		-0.1419	-0.0420	-0.1364
		(-0.76)	(-0.22)	(-1.46)
Realized Skewness		-0.0240	-0.0055	-0.0069
		(-6.90)	(-1.73)	(-2.38)
Realized Kurtosis		0.0171	0.0184	0.0105
		(3.43)	(3.72)	(2.22)
Previous Week Return			-0.0403	-0.0522
			(-8.87)	(-12.14)
log (Size)				-0.0024
				(-5.28)
log (BE/ME)				0.0001
				(0.24)
Beta				-0.0009
				(-0.99)
Hskew				0.0024
				(8.08)
Idiosyncratic Volatility				-0.0474
				(-1.07)
Co-skewness				0.0011
				(0.50)
Max. Month Return				-0.0133
				(-1.13)
log (Number of Analysts+1)				0.0004
				(1.01)
log (Illiquitidy)				-0.0006
				(-3.62)
log (Number of Intraday transactions)				0.0016
				(3.96)
R^2	0.006	0.032	0.042	0.109

Panel B: from year 2001 to 2007

	(1)	(2)	(3)	(4)
Intercept	0.0027	0.0016	0.0015	0.0112
	(1.78)	(1.06)	(1.06)	(2.86)
Realized Jump	-0.0724	-0.0868	-0.0589	-0.0597
	(-4.33)	(-5.98)	(-4.15)	(-4.46)
Realized Variance		0.0744	0.0345	-0.1707
		(0.20)	(0.09)	(-0.85)
Realized Skewness		-0.0027	0.0015	0.0010
		(-1.62)	(0.99)	(0.72)
Realized Kurtosis		0.0078	0.0089	0.0023
		(1.65)	(2.06)	(1.00)
Previous Week Return			-0.0116	-0.0154
			(-2.31)	(-3.91)
log (Size)				-0.0005
				(-2.17)
log (BE/ME)				0.0003
				(1.28)
Beta				-0.0013
				(-1.11)
Hskew				0.0009
				(3.70)
Idiosyncratic Volatility				0.0043
				(0.13)
Co-skewness				0.0012
				(0.54)
Max. Month Return				-0.0034
				(-0.41)
log (Number of Analysts+1)				-0.0003
				(-1.43)
log (Illiquitidy)				0.0000
				(-0.16)
log (Number of Intraday transactions)				0.0005
				(1.68)
R^2	0.003	0.026	0.032	0.093

Results from the Fama-MacBeth cross-sectional regressions of weekly stock returns on firm characteristics are reported for two different periods. Panel A reports results over the period 1993 to 2000 and Panel B over the period 2001 to 2007. Firm characteristics are Realized Jump, Realized Volatility, Realized Skewness, Realized Kurtosis, Previous Week Return, Size (market capitalization in $billions), BE/ME (book-to-market equity ratio), Market Beta, HSkew (one month historical skewness from daily returns), Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000) with 24 months of data), Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), and Number of Intraday Transactions. This table reports the average of the coefficient estimates for the weekly regressions along with the Newey-West t-statistic (in parentheses).

Table 9
Realized Jump Portfolio Returns by Exchange

Panel A: NYSE stocks

	Equal weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	100.87	65.25	56.47	44.49	33.96	27.24	24.79	15.96	11.09	0.54	-100.32
	(6.26)	(4.07)	(3.73)	(3.15)	(2.47)	(2.03)	(1.81)	(1.15)	(0.80)	(0.04)	(-11.39)
Alpha, FF	99.76	65.70	56.89	45.62	35.03	28.40	24.93	16.98	11.53	0.59	-100.91
	(6.13)	(4.07)	(3.72)	(3.21)	(2.53)	(2.10)	(1.81)	(1.22)	(0.82)	(0.04)	(-11.37)

	Value weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	78.89	56.40	39.49	42.57	23.92	21.92	21.31	-0.21	-1.92	4.66	-73.98
	(4.69)	(3.34)	(2.45)	(2.72)	(1.56)	(1.50)	(1.33)	(-0.01)	(-0.13)	(0.32)	(-5.87)
Alpha, FF	80.25	59.18	40.88	42.72	27.23	24.96	23.20	2.37	-1.75	6.50	-75.28
	(4.73)	(3.48)	(2.52)	(2.71)	(1.77)	(1.71)	(1.44)	(0.15)	(-0.12)	(0.44)	(-5.94)

Panel B: non-NYSE stocks

	Equal weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	51.71	38.28	34.48	30.32	30.14	29.79	23.37	25.59	22.28	24.88	-26.84
	(5.20)	(4.28)	(4.22)	(3.81)	(3.90)	(3.86)	(3.06)	(3.30)	(2.81)	(2.86)	(-5.08)
Alpha, FF	51.07	38.04	34.47	30.23	30.40	30.26	23.52	25.95	22.94	24.86	-27.97
	(5.08)	(4.22)	(4.20)	(3.78)	(3.91)	(3.90)	(3.07)	(3.33)	(2.89)	(2.84)	(-5.24)

	Value weighted										
	Low	2	3	4	5	6	7	8	9	High	High-Low
Raw Returns	40.21	30.67	37.72	26.24	30.99	24.91	19.55	12.20	14.48	14.57	-25.50
	(3.56)	(3.25)	(4.29)	(3.08)	(3.64)	(3.04)	(2.44)	(1.43)	(1.58)	(1.33)	(-2.80)
Alpha, FF	41.28	30.88	39.80	26.65	32.94	26.90	20.93	14.04	16.83	16.78	-26.15
	(3.63)	(3.25)	(4.55)	(3.12)	(3.87)	(3.29)	(2.63)	(1.66)	(1.85)	(1.53)	(-2.85)

These tables report the equal-weighted and value-weighted weekly returns (in bps) of decile portfolios formed from realized jumps, their t-statistics (in parentheses) and the difference between portfolio 10 (highest realized skewness) and portfolio 1 (lowest realized skewness) for NYSE stocks, reported on Panel A, and non-NYSE stocks, reported on Panel B. Raw returns (in bps) are obtained from decile portfolios sorted solely from ranking stocks based on the realized jump measure. Alpha is the intercept from time-series regressions of the returns of the portfolio that buys portfolio 10 and sells portfolio 1 on the Carhart (1997) four factor model. Realized jumps are calculated using intraday data.

Table 10
Fama-MacBeth Cross-Sectional Regressions by Stock Exchange

Panel A: NYSE Stocks

	(1)	(2)	(3)	(4)
Intercept	0.0040	0.0030	0.0029	0.0191
	(2.96)	(2.06)	(1.94)	(4.10)
Realized Jump	-0.1136	-0.1125	-0.0532	-0.0584
	(-11.35)	(-12.11)	(-5.39)	(-6.04)
Realized Variance		-0.0761	-0.0208	-0.1549
		(-0.48)	(-0.13)	(-1.35)
Realized Skewness		-0.0310	-0.0130	-0.0135
		(-7.01)	(-3.23)	(-3.47)
Realized Kurtosis		0.0132	0.0142	0.0071
		(2.49)	(2.71)	(1.74)
Previous Week Return			-0.0347	-0.0436
			(-9.18)	(-11.58)
log (Size)				-0.0021
				(-5.49)
log (BE/ME)				-0.0002
				(-0.67)
Beta				-0.0017
				(-2.17)
Hskew				0.0024
				(7.54)
Idiosyncratic Volatility				-0.0352
				(-1.00)
Co-skewness				0.0016
				(0.78)
Max. Month Return				-0.0157
				(-1.57)
log (Number of Analysts+1)				0.0004
				(1.19)
log (Illiquitidy)				-0.0003
				(-1.70)
log (Number of Intraday transactions)				0.0015
				(4.50)
R^2	0.006	0.031	0.040	0.110

Panel B: non-NYSE Stocks

	(1)	(2)	(3)	(4)
Intercept	0.0033	0.0027	0.0026	0.0128
	(4.24)	(3.46)	(3.36)	(3.87)
Realized Jump	-0.0363	-0.0407	-0.0046	0.0024
	(-2.02)	(-2.47)	(-0.27)	(0.15)
Realized Variance		-0.1387	-0.0887	-0.4281
		(-0.37)	(-0.24)	(-1.80)
Realized Skewness		-0.0094	-0.0042	-0.0045
		(-4.20)	(-2.00)	(-2.22)
Realized Kurtosis		0.0083	0.0090	0.0046
		(2.36)	(2.68)	(1.50)
Previous Week Return			-0.0143	-0.0213
			(-3.30)	(-5.05)
log (Size)				-0.0013
				(-4.67)
log (BE/ME)				0.0003
				(1.94)
Beta				0.0002
				(0.23)
Hskew				0.0014
				(6.54)
Idiosyncratic Volatility				0.0275
				(0.77)
Co-skewness				0.0009
				(0.70)
Max. Month Return				-0.0198
				(-1.92)
log (Number of Analysts+1)				-0.0001
				(-0.35)
log (Illiquitidy)				-0.0004
				(-3.88)
log (Number of Intraday transactions)				0.0008
				(2.65)
R^2	0.007	0.036	0.045	0.123

Results from the Fama-MacBeth cross-sectional regressions of weekly stock returns on firm characteristics are reported for NYSE stocks, reported on Panel A, and non-NYSE stocks, reported on Panel B. Firm characteristics are Realized Jump, Realized Volatility, Realized Skewness, Realized Kurtosis, Previous Week Return, Size (market capitalization in $billions), BE/ME (book-to-market equity ratio), Market Beta, HSkew (one month historical skewness from daily returns), Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000) with 24 months of data), Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), and Number of Intraday Transactions. This table reports the average of the coefficient estimates for the weekly regressions along with the Newey-West t-statistic (in parentheses).

Table 11
Long-Term Predictability of Realized Jumps

	Equal weighted - High-Low Return			
	1 Week	2 Weeks	3 Weeks	4 Weeks
Raw Returns	-73.61	-81.46	-82.02	-81.15
	(-10.89)	(-8.72)	(-7.17)	(-6.00)
Alpha, FF	-75.04	-84.20	-85.47	-84.35
	(-11.00)	(-8.92)	(-7.39)	(-6.18)

	Value weighted - High-Low Return			
	1 Week	2 Weeks	3 Weeks	4 Weeks
Raw Returns	-55.24	-63.40	-73.86	-77.24
	(-6.09)	(-4.56)	(-4.41)	(-3.85)
Alpha, FF	-57.97	-66.09	-77.94	-81.27
	(-6.38)	(-4.73)	(-4.61)	(-4.01)

This table reports cumulative returns from 1 week to 4 weeks of the the long-short realized jump return (in bps) and its t-statistics (in parentheses). The long-short realized jump premium is the difference between portfolio 10 (highest realized jump) and portfolio 1 (lowest realized jump) over the period January 1993 to December 2007. Raw returns (in bps) are obtained from decile portfolios sorted solely from ranking stocks based on the realized jump measure. Alpha is the intercept from time-series regressions of the returns of the portfolio that buys portfolio 10 and sells portfolio 1 on the Carhart (1997) four factor model. Realized jumps are calculated using intraday data.