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**Abstract**

The paper outlines and tests, by means of Monte-Carlo simulations, a simple strategy of using existing non-parametric tests for jumps at the daily frequency to identify jumps at higher sampling frequencies. The suggested strategy allow for identification of the number of jumps and jump times during a day, as well as, the size and direction (negative or positive) of the jumps. The method is of importance in order to facilitate detailed empirical studies concerning, for example, causes for jumps in financial price series at finer levels than the daily. The Monte Carlo study reveals that the strategy works reasonably well, particular for lower jump intensities. An application of the studied strategy on the Handelsbanken stock is provided.

**Keywords:** Financial econometrics, jumps, realized variance, bipower variation, stock price.

**JEL: C14, C15, G12.**

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# 1 Introduction

In this paper we study a simple strategy to identify price jumps at ultra-high frequency, e.g. at the second, one or five minute level. The suggested approach allow for identification of the number of jumps and jump times during a day, as well as, the size and direction (negative or positive) of these jumps. In contrast to Lee and Mykland (2008), who consider the similar questions by a new non-parametric test, the considered approach in this paper builds on repeated use of existing non-parametric tests for the presence of jumps in high frequency financial data (Barndorff-Nielsen and Shephard, 2004b, 2006).

The advent of high-frequency financial databases has opened new empirical possibilities to study the finer microstructure of financial markets. A natural question is what type of (financial) news that causes financial prices to jump. In order to draw definite conclusions regarding what type of news (e.g. firm specific, industry specific or macro news) that can cause price jumps, news have to be linked to jumps in asset prices at a finer frequency than at the daily level. A drawback with the mentioned non-parametric tests is that the realized variance and bipower variation, the measures upon which the non-parametric tests are constructed, require a sufficient number of inner intervals in finite sample calculations. This means that using the tests at finer levels than the daily will require inner intervals smaller than five minutes. It is however well known, both theoretically as well as through Monte Carlo evidence, that the tests are biased against detecting jumps due to microstructure noise (spurious serial correlation caused by various market microstructure effects including nonsynchronous trading, discrete price observations, intraday periodic volatility patterns and bid–ask bounce) when the inner intervals become smaller than five minutes. Also, since finite sample calculations of the tests require a sufficient number of inner intervals they may never be directly used at the highest sampling levels, e.g. at the minute level.

Many empirical applications in the literature (e.g. Barndorff-Nielsen and Shephard, 2004a) use an approach testing for jumps at the daily level and then conditional on finding jumps visually inspecting the "jump-day" for abnormal returns. Usually the largest absolute return is considered to be a jump - then identified at a finer frequency, e.g. at the five minute level using five minute returns. A problem with this strategy is if there are several possible potential jumps during the day and/or if they don't clearly stand out as abnormal. In this paper we build on this "visual" approach and test a simple strategy of using the non-parametric tests at the daily frequency (were they work well) in order to identify jumps at finer frequencies. The proposed strategy is evaluated by means of Monte Carlo simulation. An empirical application of the strategy on the Handelsbanken stock (one of the larger Swedish banks) is provided.

Section 2 reviews the basic model setup. Section 3 outlines the simple strategy to identify jumps at higher frequencies than the daily. Section 4 reports on the Monte Carlo experiments while Section 5 contain an empirical application of the proposed jump identification strategy.

## 2 Model setup

In this paper we follow the setup considered by Huang and Tauchen (2005). Consider the jump-diffusion specification

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + dL_J(t),$$

where $\mu(t)$ and $\sigma(t)$ are the drift and the instantaneous volatility, $w(t)$ is the standardized Brownian motion, and $L_J(t)$ is a pure jump Levy process with increments $L_J(t) - L_J(s) = \sum_{s \leq \tau \leq t} \eta(\tau)$, and $\eta(\tau)$ is the jump size. In line with Huang and Tauchen (2005) we focus on the class of Levy processes called the compound Poisson process (CPP). The CPP has constant jump intensity $\lambda$, and the jump size $k(t)$ is independently identically distributed. For a specified time period $(t, t-1)$, e.g. in daily units, the within-day geometric returns may be specified as

$$r_{t,j} = p(t - 1 + j/M) - p(t - 1 + (j-1)/M), \qquad j = 1, 2, ..., M$$

where $M$ is the sampling frequency.

Two measures of within-day price variance studied by Barndorff-Nielsen and Shepard (2004b) are the realized variance given by

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2$$

and the realized bipower variation given by

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{j=2}^{M}|r_{t,j-1}||r_{t,j}| = \frac{\pi}{2}\left(\frac{M}{M-1}\right)\sum_{j=2}^{M}|r_{t,j-1}||r_{t,j}|,$$

where $\mu_a = E(|Z|^a)$, $Z \sim N(0,1)$, $a > 0$. The $RV_t$ is a consistent estimator of the integrated variance plus the contribution from the jump component (see Andersen, Bollerslev and Diebold, 2002) while the $BV_t$ is a consistent estimator of the integrated variance unaffected by jumps (see Barndorff-Nielsen and Shepard, 2004b, 2005a). Hence, the difference $RV_t - BV_t$ is a consistent estimator of the pure jump contribution to the price variance and may be used as a basis for a test of jumps (Barndorff-Nielsen and Shepard, 2004b, 2006). To measure the scale of $RV_t - BV_t$ in units of conditional standard deviation the integrated quarticity $\int_{t-1}^{t}\sigma^4(s)ds$ may be estimated with the jump-robust realized tri-power quarticity statistic given by

$$TP_t = M\mu_{4/3}^{-3}\left(\frac{M}{M-2}\right)\sum_{j=3}^{M}|r_{t,j-2}|^{4/3}|r_{t,j-1}|^{4/3}|r_{t,j}|^{4/3}.$$

Barndorff-Nielsen and Shephard (2004b) note that $TP_t \to \int_{t-1}^{t}\sigma^4(s)ds$. Based on the results in Huang and Tauchen (2005) we use a test in ratio form in the Monte Carlo experiment. The test is given by

$$Z_{TP,rm,t} = \frac{RJ_t}{\sqrt{(\upsilon_{bb}-\upsilon_{qq})\frac{1}{M}\max(1,\frac{TP_t}{BV_t^2})}},$$

where $RJ_t = \frac{RV_t - BV_t}{RV_t}$, $\upsilon_{qq}$ and $\upsilon_{bb}$ are the variances from the asymptotic joint distribution of the $RV_t$ and $BV_t$ measures (Barndorff-Nielsen and Shepard, 2004b).

## 3 Identification strategy

The considered strategy builds on using the non-parametric ratio test in identification of jumps at the daily frequency. The sampling frequency used in the jump detection test is five minutes. The choice is motivated by that the tests are robust and are not affected by market noise at this level. The strategies builds on trying to single out the contribution of specific returns to the finite sample jump statistic by successively removing the most likely candidates (e.g. returns at the one second or one minute level) for jumps and repeatedly applying the jump test at the daily level until the finite jump statistic no longer indicated a jump.[1] The removed return observations are then the estimated jumps during that day that provide information regarding times, size and direction (negative or positive) of the jumps. The strategy is summarized in the following steps:

1. Use the test (at the daily level with e.g. 5 minutes inner intervals) to identify days with jumps.

2. Conditional on finding a jump rank the within day absolute returns at the required level of observation, e.g. at the second or 1 minute level, from the highest to the lowest.

3. Identify the highest absolute return during the day as a jump and replace the observation with a zero.

4. Redo the jump test at the daily level.

5. Repeat 3 and 4 until the finite sample test indicate that there is no jump that day.

6. Consider the replaced returns as the jumps occurring that day. These jumps (returns) provide information regarding times, sizes and the directions of the identified jumps.

# 4 Monte Carlo analysis

The setup of the Monte Carlo experiment follows Huang and Tauchen (2005).[2] The stochastic volatility jump diffusion model representing the log price process $p_t$ assumed in the experiments

[1] A possible drawback with this strategy is that the highest absolute return, the second highest absolute return and so on are singled out as jumps even though the highest absolute return need not be the one contributing most to the finite sample jump test statistic. That the highest absolute return may be contributing less is due to that in the bi-power variation measure the returns are succesivly multiplied and the contribution of a single return to the finite sample jump statistic throug the $BV$ measure will depend on the previous an the following return in the process. Hence, the finite sample contibution to the finite sample jump statistic need not be the largest for the highest absolute return observation. Due to this a second strategy was also considered where we collected the $n$ highest absolute returns in $R_n = \left\{R_{(1)}, R_{(2)}, ..., R_{(n)}\right\}$. One at a time we replaced the returns in $R_{(n)}$ with the mean return and repeated the test for each combination. In this strategy the highest absolute return need not be a jump even if the second ranked return is considered to be a jump. The simulation results did however show little difference between the two strategies so this more elaborate strategy is not reported in the paper.

[2] Details concerning the setup of the Monte Carlo experiment are reffered to their paper.

is given by

$$
\begin{aligned}
dp(t) &= \mu dt + \exp[\beta_0 + \beta_1 v(t)]dw_p(t) + dL_J(t) \\
dv(t) &= \alpha_v v(t)dt + dw_v(t),
\end{aligned}
$$

where the $w$'s are standard Brownian motions, $Corr(dw_p, dw_v) = \rho$ is the leverage correlation, $v(t)$ is a stochastic volatility factor, $L_J(t)$ is a Compound Poisson process with constant jump intensity $\lambda$ and random jump size distributed as $N(0, \sigma^2_{jmp})$. The values used in generation of the series are based on Huang and Tauchen (2005) and are given by: $\mu = 0.030$, $\beta_0 = 0.000$, $\beta_1 = 0.125$, $\alpha_v = -0.100$, $\rho = -0.620$, $\lambda = 0.118$, $2.000$, $ntick = 60$, $nstep = 390$ and $\sigma_{jmp} = 1.500$. Each experiment uses generated series of 500 days and are replicated 500 times. The test ($Z_{TP,rm,t}$) used in the strategy is evaluated at significance levels of 1 and 5 percent.[3] The analysis compares jumps identified at the five minute level (using 5 minute returns) with jumps identified at the second level (denoted ultra high frequency return in the tables) aggregated to the corresponding five minute interval. Thus, jumps are identified at the five minute level in two ways. The reason for this is that picking jumps with 5 minutes returns may potentially be misleading since a large return change, as a result of the diffusion process, i.e. with no jump, may be taken as a jump.

The considered strategy consists of two parts; the identification of jump days and the identification of number of jumps and jump times within the identified jump days. The results are therefore reported for the full strategy, i.e. identification of jumps through both these parts, as well as for the within-jump-day selection method, i.e. conditional on that the first part correctly signals a jump. Thus, the latter only considers identification of jumps by the studied strategy and ignores possible errors in the identification of jump days (studied by e.g. Huang and Tauchen, 2005).

[3] A problem encountered with the strategy is that there is no natural stop when the test falsely signals jumps and the identified jumps could potentially become very large. We solve this problem by setting the maximum number of daily jumps to 5.

## 4.1 Full strategy

Table 1 report confusion matrices for the identification of jumps for the full strategy. These figures correspond to identification of both jump days and the number of jumps within the jump days. Each matrix has four cells: the upper left cell is the percentage of no jump observations correctly classified as observations with no jump, the lower left cell is the percentage of no jump observations falsely classified as observations with jumps, the upper right cell is the percentage of jump observations falsely classified as observations with no jump and the, most interestingly, lower right cell is the percentage of jump observations correctly identified as observations with jumps.

The full strategy, using a significance level of 1 percent in the $Z_{TP,rm,t}$ tests, identifies around 63 % of the jumps correctly. For tests using the 5 percent significance level the correct identification rate is around 68 %. A notable feature is that virtually no "no jump observations" are identified as jumps using high frequency return, i.e. identifying jumps at the highest frequency. The figure based on identification through five minute returns is higher. This indicate that some of the jumps identified based of 5 minutes returns are actually normal variations false seen as jumps. As a rule of thumb then it seems reasonable to recommend identification of jumps (at ultra-high frequency or intradaily) at the highest possible frequency. With a significance level of 5 % about 0.2 % of the observations will erroneously be identified as jumps using five minutes returns. The results are similar for both levels of the jump intensity ($\lambda = 0.118$, 2.000).

## 4.2 The intradaily selection strategy

Since the main interest in this paper is on evaluating the intradaily selection strategy we condition the analysis on that the test in the first stage correctly has signalled a jump. The results are presented in Table 2 with the same interpretation of the confusion matrices as in Table 1.

With the lower jump intensity ($\lambda = 0.118$) about 96 % of the jumps are correctly identified for both significance levels of the tests ($\alpha = 0.01, 0.05$) and for using both five minutes returns as well as ultra high frequency returns. For the higher jump intensity ($\lambda = 2.000$) the figures are around 71 % for the 0.01 significance level and about 75 % for the 0.05 significance level. As in the evaluation of the full strategy the risk of using five minutes returns are shown in that

Table 1: Confusion matrix for full strategy

$\alpha = 0.01$

| | Five minute returns | | | | | Ultra high frequency return | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda = 0.118$ | | $\lambda = 2.000$ | | | $\lambda = 0.118$ | | $\lambda = 2.000$ | |
| | (NJ) | (J) | (NJ) | (J) | | (NJ) | (J) | (NJ) | (J) |
| (NJ) | 0.99972 | 0.37328 | 0.99966 | 0.37495 | (NJ) | 1.00000 | 0.37196 | 1.00000 | 0.38145 |
| (J) | 0.00028 | 0.62672 | 0.00034 | 0.62505 | (J) | 0.00000 | 0.62804 | 0.00000 | 0.61855 |

$\alpha = 0.05$

| | Five minute returns | | | | | Ultra high frequency return | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda = 0.118$ | | $\lambda = 2.000$ | | | $\lambda = 0.118$ | | $\lambda = 2.000$ | |
| | (NJ) | (J) | (NJ) | (J) | | (NJ) | (J) | (NJ) | (J) |
| (NJ) | 0.99862 | 0.32098 | 0.99859 | 0.31853 | (NJ) | 0.99999 | 0.31413 | 1.00000 | 0.32117 |
| (J) | 0.00138 | 0.67902 | 0.00141 | 0.68147 | (J) | 0.00000 | 0.68587 | 0.00000 | 0.67883 |

Table 2: Confusion matrix for intra-daily identification strategy conditional on correct signal.

$\alpha = 0.01$

| | Five minute returns | | | | | Ultra high frequency return | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda = 0.118$ | | $\lambda = 2.000$ | | | $\lambda = 0.118$ | | $\lambda = 2.000$ | |
| | (NJ) | (J) | (NJ) | (J) | | (NJ) | (J) | (NJ) | (J) |
| (NJ) | 0.99945 | 0.04085 | 0.99957 | 0.28555 | (NJ) | 1.00000 | 0.03875 | 1.00000 | 0.29362 |
| (J) | 0.00055 | 0.95915 | 0.00043 | 0.71445 | (J) | 0.00000 | 0.96125 | 0.00000 | 0.70638 |

$\alpha = 0.05$

| | Five minute returns | | | | | Ultra high frequency return | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\lambda = 0.118$ | | $\lambda = 2.000$ | | | $\lambda = 0.118$ | | $\lambda = 2.000$ | |
| | (NJ) | (J) | (NJ) | (J) | | (NJ) | (J) | (NJ) | (J) |
| (NJ) | 0.99774 | 0.04229 | 0.99833 | 0.24848 | (NJ) | 0.99999 | 0.03287 | 1.00000 | 0.25193 |
| (J) | 0.00226 | 0.95771 | 0.00167 | 0.75152 | (J) | 0.00001 | 0.96713 | 0.00000 | 0.74807 |

Table 3: Confusion matrix for intra-daily identification strategy conditional on correct signal and actual jumps =1.

| | $\alpha = 0.01$ | | | | |
|---|---|---|---|---|---|
| | Five minute returns | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99945 | 0.00372 | (NJ) | 1.00000 | 0.00036 |
| (J) | 0.00055 | 0.99628 | (J) | 0.00000 | 0.99964 |
| | $\alpha = 0.05$ | | | | |
| | Five minute returns | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99775 | 0.01232 | (NJ) | 0.99999 | 0.00100 |
| (J) | 0.00225 | 0.98768 | (J) | 0.00001 | 0.99900 |

a number of "no jump observations" are classified as jumps which is avoided using ultra-high frequency returns.

To further study the performance of the within day identification strategy of jumps we conditional on the correct signal from the test (at the daily level) as well as on the number of actual jumps during the day. The results for days with actual jumps equal to 1, 3 and 5 are presented in Table 3-5.

The results can be summarized as follows. Given that the test correctly has signalled jump almost all jumps are identified on days with one actual jump regardless of significance level of the test ($\alpha = 0.01$, 0.05) or using five minutes returns or ultra high frequency returns. For days with three actual jumps the identification rate is in the range of 68-72 percent depending on the significance level and whether five minute or ultra high frequency returns are used. The figures for five actual jumps are in the range 61-66 percent. Thus, the rate is slightly better on days with three jumps.

## 5 Empirical application

In this section we provide a small scale empirical application to illustrate potential uses of our identification strategy. Intradaily transactions data for the Swedish bank Handelsbanken

Table 4: Confusion matrix for intra-daily identification strategy conditional on correct signal and actual jumps =3.

| $\alpha = 0.01$ | | | | | |
|---|---|---|---|---|---|
| Five minute returns | | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99955 | 0.31488 | (NJ) | 1.00000 | 0.32264 |
| (J) | 0.00045 | 0.68512 | (J) | 0.00000 | 0.67736 |
| $\alpha = 0.05$ | | | | | |
| Five minute returns | | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99844 | 0.27372 | (NJ) | 1.00000 | 0.27631 |
| (J) | 0.00156 | 0.72628 | (J) | 0.00000 | 0.72369 |

Table 5: Confusion matrix for intra-daily identification strategy conditional on correct signal and actual jumps = 5.

| $\alpha = 0.01$ | | | | | |
|---|---|---|---|---|---|
| Five minute returns | | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99987 | 0.37356 | (NJ) | 1.00000 | 0.38597 |
| (J) | 0.00013 | 0.62644 | (J) | 0.00000 | 0.61403 |
| $\alpha = 0.05$ | | | | | |
| Five minute returns | | | Ultra high frequency return | | |
| | (NJ) | (J) | | (NJ) | (J) |
| (NJ) | 0.99958 | 0.33078 | (NJ) | 1.00000 | 0.34242 |
| (J) | 0.00042 | 0.66922 | (J) | 0.00000 | 0.65758 |

(SHB), covering the period 2007-01-01 to 2008-12-31, was obtained from the STORQ database[4] (a Scandinavian ultra-high frequency financial database). The data concerns trading at the Nasdaq OMX Nordic stockmarket where regular trading occur between 9 AM in the morning to 5:30 PM in the evening. Each trading day starts with a so-called morning call at 8:45 (see Nasdaq OMX for details) and ends with a closing call that starts at 5:25. Due to the morning call we did not, as is commonly done, censor the sample at the first 15 minutes of the trading day. Though we did do so at the end of the trading day. Thus, we use minute observations from 9 to 5:15. Due to technical reasons seven days contained too many missing values and were removed from the original sample. Thus, in all we have a total of 477 trading days. Since transaction prices are observed randomly over time, due to no trading activity during some parts of the day, the intradaily sub-data-sets were filled by extrapolating horizontally to obtain a price series at the minute level.

In putting the strategy to work we must first decide on what sampling frequency and significance level to use for the test. For the estimation of the realized variation measures the message from the underlying theory is to choose as high sampling frequency as possible. However, choosing a too high sampling frequency may induce market microstructure bias. We take guidance from the related study by Bollerslev, Hann Law and Tauchen (2008) and use a sample frequency of 15 minutes[5] and consider a significance level of 0.1%. In the sequel, if the test indicates that a particular day contains at least one jump we refer to the day as a jump day.

Running each day in our sample through the test indicate that 48 out of the total of 477 trading days contain at least one jump. The Figure 1 gives a plot of when in time these occur.

A visual inspection suggest that the jump days are independently spaced in time, i.e. there is no visual clustering of jump days for the current sample. The likelihood ratio based test of Christoffersen (1998) (that takes a first order Markov sequence as the alternative hypothesis) gives a far from significant value of 0.22 of the $\chi^2(1)$-distributed test statistic and confirms this suggestion.

[4] The STORQ database is organized by Lund University, Sweden, in collaboration with the Scandinavian information provider SIX.

[5] Actually, Bollerslev et al. (2008) use a sample frequency of 17,5 minutes.

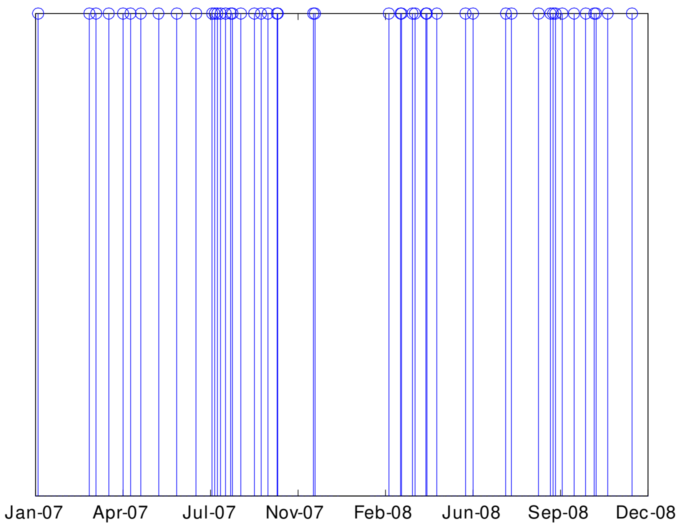


Figure 1: Jump days.

The Figure 2 gives a histogram showing when during the day the observations identified as jumps occur. Clearly, they appear to be relatively more common in the beginning and at the end of the trading day, while otherwise quite uniformly distributed.

The average (median) number of jumps on jumps days is 17.9 (4). The Figure 3 gives a histogram over the number of observations identified as jumps on jump days.

As expected the distribution of the number of jumps is highly skewed with a long right tail. Notable is that the maximum number of identified jumps on a jump day is 189. A potential explanation for this rather large number, is that trading activity is low during periods making rather "normal" price movements, of say one tick, appear large enough to be identified as price jumps. The underlying theory assumes that returns are the sum of a normal component and jump component. Hence, the proposed methodology offers no perfect identification of the size and direction of the actuals jumps. However, assuming that the normal part is small in comparison we estimate the average positive jump to 0.31% and the average negative jump to $-0.29\%$. Out of the total of 858 jumps there are 433 positive jumps and 425 negative jumps.

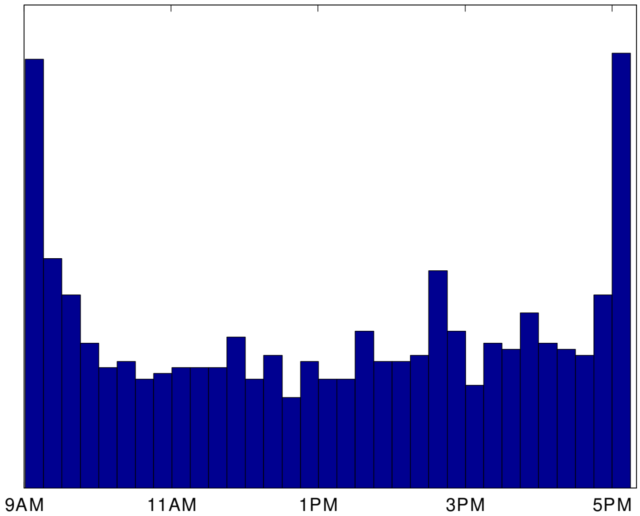


Figure 2: Histogram over when during the day jumps occur.

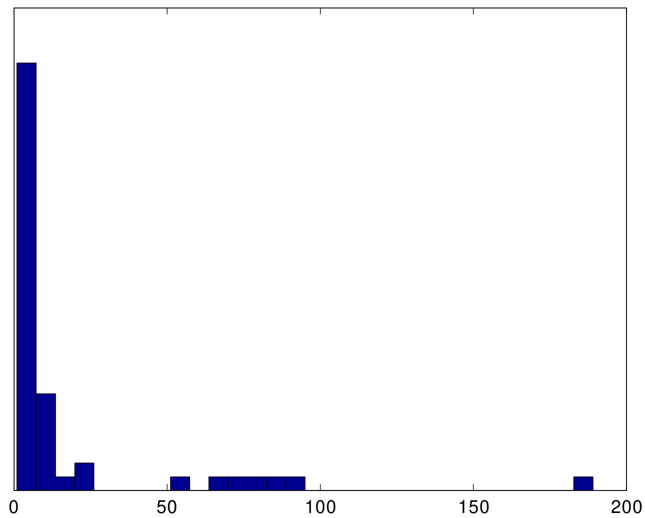


Figure 3: Histogram over the number of jumps on jump days.

# 6 Conclusion

In this paper we proposed a simple strategy of identiying jumps in financial price series. In a Monte Carlo study the suggested strategy was found to work quite well and identifies around 65 % of the jumps. In an empirical application we demonstrated some potential uses for the strategy. For example (and of obvious practical interest), some results on when during the day jumps tend to occur was provided. It was found that they are relatively more common in the beginning and at the end of the trading day.

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