
Lecture 5a

Testing for Jumps in a Discretely Observed Process: High Frequency

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based on joint work with Jean Jacod

References

- Testing for Jumps in a Discretely Observed Process, with Jean Jacod, forthcoming in the *Annals of Statistics*.

1. Introduction

- Different types of jumps
 - Large jumps, which are rather infrequent, are easy to pick out.
 - But **visual inspection** of most time series in finance **does not provide clear evidence** for either the presence or the absence of smaller, more frequent, jumps.

- Models with and without jumps do have quite different properties, both mathematical and financial:
 - Model calibration
 - Volatility estimation
 - Market (in)completeness
 - Option pricing and hedging
 - Risk management
 - Portfolio choice

- Detecting jumps: other approaches
 - Aït-Sahalia (2002)
 - Carr and Wu (2003)
 - BNS (2004), ABD (2004), Huang and Tauchen (2006)
 - Lee and Mykland (2005)
 - Jiang and Oomen (2006)

- This paper: we propose a **very simple** family of test statistics for jumps which converge as $\Delta_n \rightarrow 0$:
 - To **1** if there are jumps
 - To **2** if there are no jumps.
- We provide a distribution theory (hence a test) for the null hypothesis where no jumps are present, but **also one for the null where jumps are present.**

- This works as soon as the process X is an **Itô semimartingale**
 - This is a much **weaker** condition than what is usually assumed (compound Poisson processes, or jump-diffusions)
 - The limit depends **neither** on the law of the process **nor** on the coefficients of the (possibly very complicated) SDE
 - So the test does **not** require any estimation of these coefficients.

2. The Setup

- The structural assumption is that X is an **Itô semimartingale** on some filtered space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$:

$$\begin{aligned} X_t &= X_0 + A_t + M_t \\ &= X_0 + A_t^C + A_t^J + M_t^C + M_t^J \end{aligned}$$

where A_t is a finite variation and predictable mean component and M_t is a local martingale

- Each decomposable into a continuous and a pure jump part.

- The drift, volatility and jump measure are themselves **possibly stochastic** and **can possibly jump**.
- We assume that the continuous part of X is never degenerate, i.e., we have $\int_0^t |\sigma_s| ds > 0$ a.s. for all $t > 0$.

3. The Testing Problem

- X is **discretely observed** at times $i\Delta_n$ for all $i = 0, 1, \dots, n$ with $n\Delta_n = T$.
- When the jump measure is finite, there is a positive probability that the path $X(\omega)$ has no jump on $[0, T]$, although the model itself may allow for jumps: this is the **peso problem**.

3.1. Various Measures of the Variability of X

- Here are processes which measure **some kind of variability** of X and depend on the whole (unobserved) path of X :

$$A(p)_t = \int_0^t |\sigma_s|^p ds, \quad B(p)_t = \sum_{s \leq t} |\Delta X_s|^p$$

where $p > 0$ and $\Delta X_s = X_s - X_{s-}$ are the **jumps of X** .

- The quadratic variation of the process is $[X, X] = A(2) + B(2)$.

- The problem boils down to deciding whether whether $B(p)_T > 0$ for our particular observed path with any given p .
- Let the **observed discrete increments** of X (not necessarily due to jumps) be

$$\Delta_i^n X = X_{i\Delta_n} - X_{(i-1)\Delta_n}$$

and for $p > 0$ define the estimator

$$\hat{B}(p, \Delta_n)_t = \sum_{i=1}^{\lfloor t/\Delta_n \rfloor} |\Delta_i^n X|^p$$

- For $r > 0$, let

$$m_r = \mathbb{E}(|U|^r) = \pi^{-1/2} 2^{r/2} \Gamma\left(\frac{r+1}{2}\right)$$

denote the r th absolute moment of a variable $U \sim N(0, 1)$.

- We have the following convergences in probability, locally uniform in t :

$$\left\{ \begin{array}{ll} p > 2, \text{ all } X & \Rightarrow \widehat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} B(p)_t \\ p = 2, \text{ all } X & \Rightarrow \widehat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} A(2)_t + B(2)_t \\ p < 2, \text{ all } X & \Rightarrow \frac{\Delta_n^{1-p/2}}{m_p} \widehat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} A(p)_t \\ \text{all } p, X \text{ continuous} & \Rightarrow \frac{\Delta_n^{1-p/2}}{m_p} \widehat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} A(p)_t. \end{array} \right.$$

3.2. The Basic Idea

$$\bullet \left\{ \begin{array}{l} p > 2, \text{ all } X \\ \text{all } p, X \text{ continuous} \end{array} \right. \Rightarrow \begin{array}{l} \hat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} B(p)_t \\ \frac{\Delta_n^{1-p/2}}{m_p} \hat{B}(p, \Delta_n)_t \xrightarrow{\mathbb{P}} A(p)_t. \end{array}$$

- We see that when $p > 2$ the limit $B(p)_t$ of $\hat{B}(p, \Delta_n)_t$ does not depend on Δ_n , and $B(p)_t > 0$ is strictly positive if X has jumps between 0 and t .
- On the other hand when X is continuous on $[0, t]$, then the limit is $B(p)_t = 0$ but, after a normalization which does depend on Δ_n , $\hat{B}(p, \Delta_n)_t$ converges again to a limit $A(p)_t$ not depending on Δ_n .

- These considerations lead us to compare $\hat{B}(p, \Delta_n)$ on **two different Δ_n -scales**.
- Specifically, for an integer k , consider:

$$\hat{S}(p, k, \Delta_n)_t = \frac{\hat{B}(p, k\Delta_n)_t}{\hat{B}(p, \Delta_n)_t}.$$

- Theorem: For any $t > 0$ the variables $\hat{S}(p, k, \Delta_n)_t$ converge in probability to

$$\begin{cases} 1 & \text{if } X \text{ jumps} \\ k^{p/2-1} & \text{if } X \text{ is continuous} \end{cases}$$

4. Testing for Jumps

- The previous theorem provides the first step towards constructing a test for the presence or absence of jumps.
- But to construct actual tests, we need: **rates of convergence** and **asymptotic variances**.
- That are applicable under **both nulls** of jumps and no jumps.
- We also need consistent estimators of the variances.

4.1. CLT for Standardized Statistics

Theorem:

1. Let $p > 3$. The variables $(\widehat{V}_n^j)^{-1/2} \left(\widehat{S}(p, k, \Delta_n)_t - 1 \right)$ converge stably in law, in restriction to the set Ω_t^j to a variable which, conditionally on \mathcal{F} , is **centered** with **variance 1**, and which is $N(0, 1)$ if in addition the processes σ and X have no common jumps.

2. If X is continuous, then for $p \geq 2$

$$(\widehat{V}_n^c)^{-1/2} \left(\widehat{S}(p, k, \Delta_n)_t - k^{p/2-1} \right) \rightarrow N(0, 1)$$

stably in law, conditionally on \mathcal{F} .

4.2. Practical Considerations

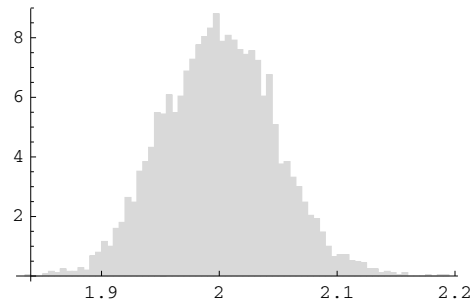
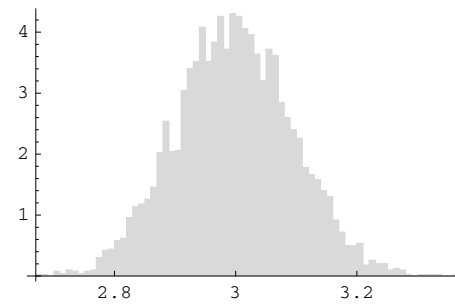
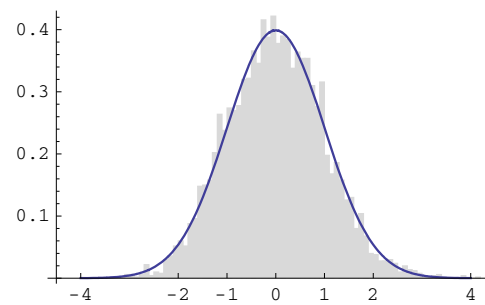
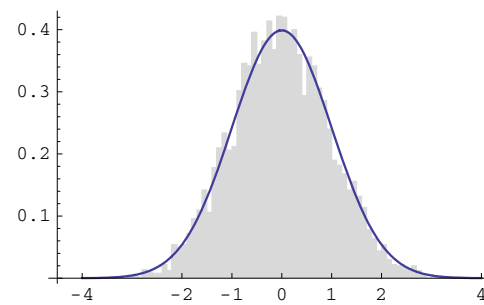
- Since we must have $p > 3$, a rather natural choice seems to be $p = 4$.
- We see that the variances are increasing with k , so it is probably wise to take $k = 2$ (although when $k > 2$ we have to separate the two points 1 and k , which are further apart than 1 and 2).

5. Simulation Results

- We calibrate the values to be realistic for a liquid stock trading on the NYSE.
- We use an observation length of $T = 1$ day, consisting of 6.5 hours of trading, that is 23,400 seconds.

Simulations: Null of No Jumps, $k = 2$ and 3

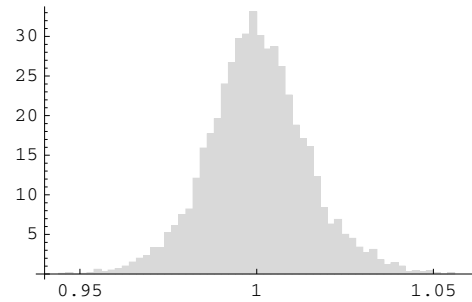
No Jumps: Distribution of the Statistic

No Jumps: $k = 2$
Non-StandardizedNo Jumps: $k = 3$
Non-StandardizedNo Jumps: $k = 2$
StandardizedNo Jumps: $k = 3$
Standardized

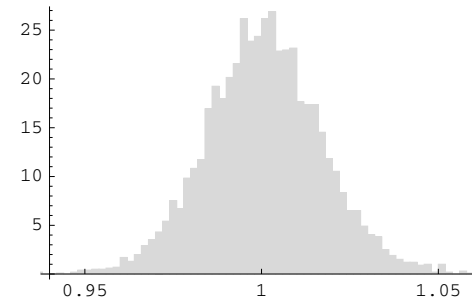
Simulations: Poisson Jumps

Poisson Jumps: Distribution of the Statistic

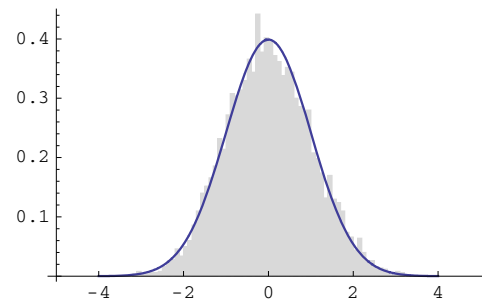
Poisson: 1 Jump per Day
Non-Standardized



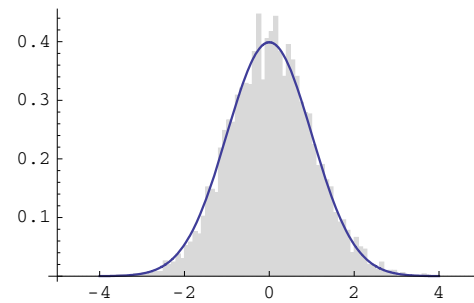
Poisson: 10 Jumps per Day
Non-Standardized



Poisson: 1 Jump per Day
Standardized



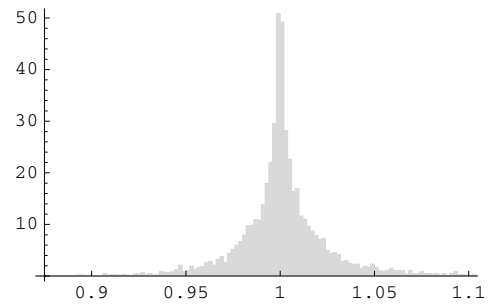
Poisson: 10 Jumps per Day
Standardized



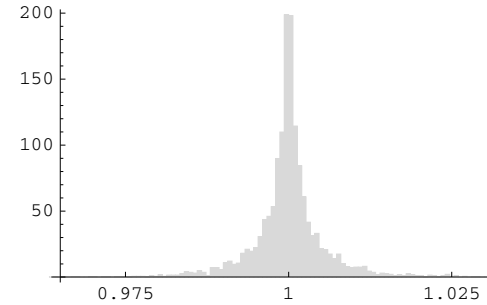
Simulations: Cauchy Jumps

Cauchy Jumps: Distribution of the Statistic

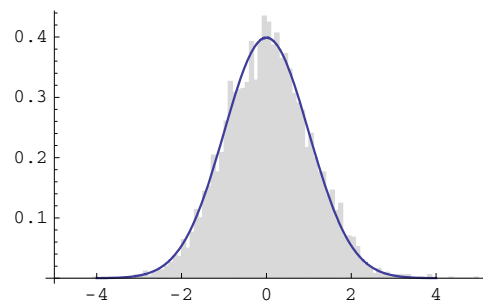
Cauchy Jumps $\theta = 10$
Non-Standardized



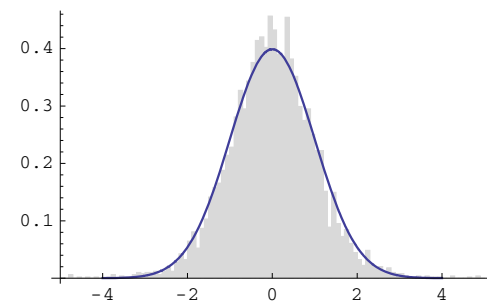
Cauchy Jumps $\theta = 50$
Non-Standardized



Cauchy Jumps $\theta = 10$
Standardized

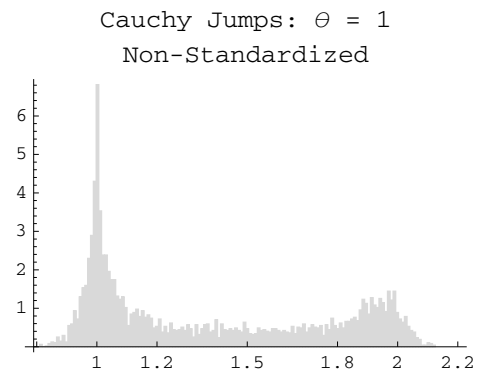
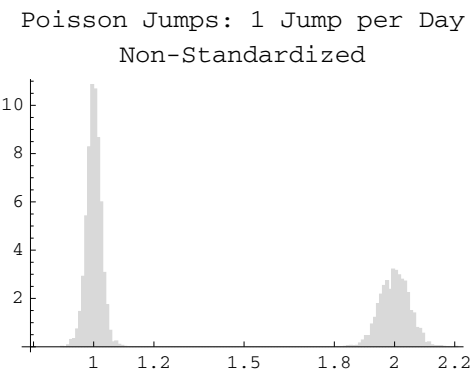


Cauchy Jumps $\theta = 50$
Standardized



Simulations: Tiny or No Jumps

Tiny Jumps or No Jumps: Distribution of the Statistic



6. Real Data Analysis

- In real data, observations of the process X are blurred by **market microstructure noise**, which messes things up at **very high frequency**.
- Assume that each observation is affected by an additive noise, that is instead of $X_{i\Delta_n}$ we really observe $Y_{i\Delta_n} = X_{i\Delta_n} + \varepsilon_i$, and the ε_i are i.i.d. with $E(\varepsilon_i^2)$ and $E(\varepsilon_i^4)$ finite.
- We show that, **in the presence of noise**, the limit of our test statistics $\widehat{S}(4, k, \Delta_n)_t$ becomes as $\Delta_n \rightarrow 0$:

$$\widehat{S}(4, k, \Delta_n)_t \xrightarrow{\mathbb{P}} \frac{1}{k}$$

Real Data Analysis: 30 DJIA Stocks, All 2005 Trading Days

Empirical Distribution of the Test Statistic: DJIA30 All 2005 Trading Days

