Bootstrapping high-frequency jump tests*

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Abstract

The main contribution of this paper is to propose a bootstrap test for jumps based on functions of realized volatility and bipower variation. Bootstrap intraday returns are randomly generated from a mean zero Gaussian distribution with a variance given by a local measure of integrated volatility (which we denote by $\{\hat{v}_i^n\}$). We first discuss a set of high level conditions on $\{\hat{v}_i^n\}$ such that any bootstrap test of this form has the correct asymptotic size and is alternative-consistent. We then provide a set of primitive conditions that justify the choice of a thresholding-based estimator for $\{\hat{v}_i^n\}$. Our cumulants expansions show that the bootstrap is unable to mimic the higher-order bias of the test statistic. We propose a modification of the original bootstrap test which contains an appropriate bias correction term and for which second-order asymptotic refinements are obtained.

1 Introduction

A well accepted fact in financial economics is that asset prices do not always evolve continuously over a given time interval, being instead subject to the possible occurrence of jumps (or discontinuous movements in prices). The detection of such jumps is crucial for asset pricing and risk management because their presence has important consequences for the performance of asset pricing models and hedging strategies, often introducing parameters that are hard to estimate (see e.g. Bakshi et al. (1997), Bates (1996), and Johannes (2004)). In addition, jumps contain useful market information and can be used to improve asset pricing models once detected. For instance, jumps are often associated with macro announcements (as documented by many studies, including Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007), Lee and Mykland (2008) and Lee (2012)). As shown by Savor and

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Wilson (2014), it is easier to reconcile the behavior of asset prices with the standard CAPM model on those dates. Similarly, Li et al. (2017a) show that jumps in asset prices are often associated with aggregrate market jumps, suggesting that a standard linear one-factor model is appropriate to model jump regressions.

Given the importance of jumps, many jump tests have been proposed in the literature over the years, most of the recent ones exploiting the rich information contained in high frequency data. These include tests based on bipower variation measures (such as in Barndorff-Nielsen and Shephard (2004, 2006), henceforth BN-S (2004, 2006), Huang and Tauchen (2005), Andersen et al. (2007), Jiang and Oomen (2008), and more recently Mykland et al. (2012)); tests based on power variation measures sampled at different frequencies (such as in Aït-Sahalia and Jacod (2009), Aït-Sahalia et al. (2012)), and tests based on the maximum of a standardized version of intraday returns (such as in Lee and Mykland (2008, 2012) and Lee and Hannig (2010)). In addition, tests based on thresholding or truncation-based estimators of volatility have also been proposed, as in Aït-Sahalia and Jacod (2009), Podolskij and Ziggel (2010) and Cont and Mancini (2011), based on Mancini (2001). See Aït-Sahalia and Jacod (2012, 2014) for a review of the literature on the econometrics of high frequency-based jump tests.

In this paper, we focus on the class of tests based on bipower variation originally proposed by BN-S (2004, 2006). Our main contribution is to propose a bootstrap implementation of these tests with better finite sample properties than the original tests based on the asymptotic normal distribution. Specifically, we generate the bootstrap observations under the null of no jumps, by drawing them randomly from a mean zero Gaussian distribution with a variance given by a local measure of integrated volatility (which we denote by $\{\hat{v}_i^n\}$).

Our first contribution is to give a set of high level conditions on $\{\hat{v}_i^n\}$ such that any bootstrap method of this form has the correct asymptotic size and is alternative-consistent. We then verify these conditions for a specific example of $\{\hat{v}_i^n\}$ based on a threshold-based volatility estimator constructed from blocks of intraday returns which are appropriately truncated to remove the effect of the jumps. In particular, we provide primitive assumptions on the continuous price process such that the bootstrap jump test based on the thresholding local volatility estimator is able to replicate the null distribution of the BN-S test under both the null and the alternative of jumps. Our assumptions are very general, allowing for leverage effects and general activity jumps both in prices and volatility. We show that although truncation is not needed for the bootstrap jump test to control the asymptotic size under the null of no jumps, it is important to ensure that the bootstrap jump test is consistent under the alternative of jumps. Other choices of $\{\hat{v}_i^n\}$ could be considered provided they are robust to jumps. For instance, we could rely on multipower variation volatility measures and use our high level conditions to show the first-order validity of this bootstrap method. For brevity, we focus on the thresholding-based volatility estimator, which is one of the most popular methods of obtaining jump robust test statistics.

The second contribution of this paper is to prove that an appropriate version of the bootstrap jump test based on thresholding provides a second-order asymptotic refinement under the null of no jumps[1]. To do so, we impose more restrictive assumptions on the data generating process that assume away the presence of drift and leverage effects. For this simplified model, we develop second-order asymptotic expansions of the first three cumulants of the BN-S test and of its bootstrap version. Our results show that the first-order cumulant of the BN-S test depends on the bias of bipower variation under the null of no jumps. Even though this bias does not impact the validity of the test to first-order because bipower variation is a consistent estimator of integrated volatility under the null, it has an impact on the first-order cumulant of the statistic at the second-order (i.e. at the order $O\left(n^{-1/2}\right)$). Our bootstrap test statistic is unable to capture this higher-order bias and therefore does not provide

[1] Second-order refinements are important because bootstrap tests with this property are expected to have null rejection rates that converge faster to the desired nominal level than those of the corresponding asymptotic theory-based test, hence ensuring smaller finite sample size distortions.

a second-order refinement. We propose a modification of the bootstrap statistic that is able to do so. Our simulations show that although both bootstrap versions of the test outperform the asymptotic test, the modified bootstrap test statistic has lower size distortions than the original bootstrap statistic. In the empirical application, where we apply the bootstrap jump tests to 5-minutes returns on the SPY index over the period June 15, 2004 through June 13, 2014, this version of the bootstrap test detects about half of the number of jump days detected by the asymptotic theory-based tests.

Although we focus on the BN-S test statistic, the local Gaussian bootstrap can be applied more generally to other jump tests. In particular, we provide a set of conditions under which it can be applied to the jump tests of Podolskij and Ziggel (2010) and Lee and Hannig (2010).

The rest of the paper is organized as follows. In Section 2, we provide the framework and state our assumptions. Section 3.1 contains a set of high level conditions on $\{\hat{v}_i^n\}$ such that any bootstrap method is asymptotically valid when testing for jumps using the BN-S test. Section 3.2 provides a set of primitive assumptions under which the bootstrap based on a thresholding estimator verifies these high level conditions. Section 4.1 contains the second-order expansions of the cumulants of the original statistic whereas Section 4.2 contains their bootstrap versions. Section 5 gives the Monte Carlo simulations while Section 6 provides an empirical application. Section 7 concludes. Appendix A contains a law of large numbers for smooth functions of consecutive local truncated volatility estimates. In addition, an online supplementary appendix contains the proofs of all the results in the main text. Specifically, Appendix S1 contains the proofs of the results presented in Section 3 whereas Appendix S2 contains the proofs of the results in Section 4. Appendix S3 contains formulas for the log version of our tests. Finally, Appendix S4 contains the bootstrap theory for the jump tests of Podolskij and Ziggel (2010) and Lee and Hannig (2010).

To end this section, a word on notation. We let P^* describe the probability of bootstrap random variables, conditional on the observed data. Similarly, we write E^* and Var^* to denote the expected value and the variance with respect to P^*, respectively. For any bootstrap statistic $Z_n^* \equiv Z_n^*(\cdot, \omega)$ and any (measurable) set A, we write $P^*(Z_n^* \in A) = P^*(Z_n^*(\cdot, \omega) \in A) = \Pr(Z_n^*(\cdot, \omega) \in A | \mathcal{X}_n)$, where $\omega \in \Omega$, a sample space and $\mathcal{X}_n$ denotes the observed sample. We say that $Z_n^* \to^{P^*} 0$ in prob-P (or $Z_n^* = o_{P^*}(1)$ in prob-P) if for any $\varepsilon, \delta > 0$, $P(P^*(|Z_n^*| > \varepsilon) > \delta) \to 0$ as $n \to \infty$. Similarly, we say that $Z_n^* = O_{P^*}(1)$ in prob-P if for any $\delta > 0$, there exists $0 < M < \infty$ such that $P(P^*(|Z_n^*| \geq M) > \delta) \to 0$ as $n \to \infty$. For a sequence of random variables (or vectors) Z_n^*, we also need the definition of convergence in distribution in prob-P. In particular, we write $Z_n^* \to^{d^*} Z$, in prob-P (a.s.-P), if $E^*(f(Z_n^*)) \to E(f(Z))$ in prob-P for every bounded and continuous function f (a.s.$-P$).

2 Assumptions and statistics of interest

We assume that the log-price process X_t is an Itô semimartingale defined on a probability space $(\Omega, \mathcal{F}, P)$ equipped with a filtration $(\mathcal{F}_t)_{t\geq 0}$ such that

$$X_t = Y_t + J_t, \ t \geq 0, \tag{1}$$

where Y_t is a continuous Brownian semimartingale process and J_t is a jump process. Specifically, Y_t is defined by the equation

$$Y_t = Y_0 + \int_0^t a_s ds + \int_0^t \sigma_s dW_s, \ t \geq 0, \tag{2}$$

where a and σ are two real-valued random processes and W is a standard Brownian motion. The jump process is defined as

$$J_t = \int_0^t \int_{\mathbb{R}} \left(\delta(s,x) 1_{\{|\delta(s,x)| \leq 1\}}\right)(\mu - \nu)(ds, dx) + \int_0^t \int_{\mathbb{R}} \left(\delta(s,x) 1_{\{|\delta(s,x)| > 1\}}\right) \mu(ds, dx), \tag{3}$$

where μ is a Poisson random measure on $\mathbb{R}_+ \times \mathbb{R}$ with intensity measure $\nu(ds, dx) = ds \otimes \lambda(dx)$, with λ a σ-finite measure on $\mathbb{R}$, and δ a predictable function on $\Omega \times \mathbb{R}_+ \times \mathbb{R}$.

We make the following assumptions on a, σ and J_t, where $r \in [0, 2]$.

Assumption H-r The process a is locally bounded, σ is càdlàg, and there exists a sequence of stopping times (τ_n) and a sequence of deterministic nonnegative functions γ_n on $\mathbb{R}$ such that $\int \gamma_n(x)^r \lambda(dx) < \infty$ and $|\delta(\omega, s, x)| \wedge 1 \leq \gamma_n(x)$ for all (ω, s, x) satisfying $s \leq \tau_n(\omega)$.

Assumption H-r is rather standard in this literature, implying that the r^{th} absolute power value of the jumps size is summable over any finite time interval. Since H-r for some r implies that H-r' holds for all $r' > r$, the weakest form of this assumption occurs for $r = 2$ (and essentially corresponds to the class of Itô semimartingales). As r decreases towards 0, fewer jumps of bigger size are allowed. In the limit, when $r = 0$, we get the case of finite activity jumps.

The quadratic variation process of X is given by $[X]_t = IV_t + JV_t$, where $IV_t \equiv \int_0^t \sigma_s^2 ds$ is the quadratic variation of Y_t, also known as the integrated volatility, and $JV_t \equiv \sum_{s \leq t} (\Delta J_s)^2$ is the jump quadratic variation, with $\Delta J_s = J_s - J_{s-}$ denoting the jumps in X. Without loss of generality, we let $t = 1$ and we omit the index t. For instance, we write $IV = IV_1$ and $JV = JV_1$.

We assume that prices are observed within the fixed time interval $[0, 1]$ (which we think of as a day) and that the log-prices X_t are recorded at regular time points $t_i = i/n$, for $i = 0, \ldots, n$, from which we compute n intraday returns $r_i \equiv X_{i/n} - X_{(i-1)/n}$ at frequency $1/n$; we omit the index n in r_i to simplify the notation.

Our focus is on testing for "no jumps" using the bootstrap. Specifically, following Aït-Sahalia and Jacod (2009), let $\Omega_0 = \{\omega : t \longmapsto X_t(\omega) \text{ is continuous on } [0, 1]\}$ and $\Omega_1 = \{\omega : t \longmapsto X_t(\omega) \text{ is discontinuous on } [0, 1]\}$, with $\Omega = \Omega_0 \cup \Omega_1$ and $\Omega_0 \cap \Omega_1 = \varnothing$. Our null hypothesis is defined as $H_0 : \omega \in \Omega_0$ and the alternative hypothesis is $H_1 : \omega \in \Omega_1$.

Let $RV_n = \sum_{i=1}^n r_i^2$ denote the realized volatility and let

$$BV_n = \frac{1}{k_1^2} \sum_{i=2}^n |r_{i-1}| \, |r_i|$$

be the bipower variation, where we let $k_1 = E(|Z|) = \sqrt{2}/\sqrt{\pi}$ be a special case of $k_q = E|Z|^q$, for $q > 0$, with $Z \sim N(0, 1)$.

The test statistic whose distribution we bootstrap is defined as

$$T_n = \frac{\sqrt{n}(RV_n - BV_n)}{\sqrt{\hat{V}_n}}, \tag{4}$$

where

$$\hat{V}_n \equiv \tau \cdot \widehat{IQ}_n \quad \text{with} \quad \widehat{IQ}_n = \frac{n}{(k_{4/3})^3} \sum_{i=3}^n |r_i|^{4/3} |r_{i-1}|^{4/3} |r_{i-2}|^{4/3},$$

with $\tau = \theta - 2$ and $\theta \simeq 2.6090$. The test rejects the null of "no jumps" at significance level α whenever $T_n > z_{1-\alpha}$, where $z_{1-\alpha}$ is the $100(1-\alpha)\%$ percentile of the $N(0, 1)$ distribution. This is justified by the fact that $T_n \xrightarrow{st} N(0, 1)$, in restriction to Ω_0, where $\xrightarrow{st}$ denotes stable convergence (see BN-S (2006) and Barndorff-Nielsen et al. (2006)). In particular, we can show that the test has asymptotically correct strong size, i.e. the critical region $\mathcal{C}_n = \{T_n > z_{1-\alpha}\}$ is such that for any measurable set $S \subset \Omega_0$ such that $P(S) > 0, \lim_{n \to \infty} P(\omega \in \mathcal{C}_n | S) = \alpha$. Under the alternative hypothesis, we can show that the test T_n is alternative-consistent, i.e. $\lim_{n \to \infty} P(\Omega_1 \cap \bar{\mathcal{C}}_n) = 0$, where $\bar{\mathcal{C}}_n$ is the complement of $\mathcal{C}_n$. Since the above condition implies that $P(\bar{\mathcal{C}}_n | \Omega_1) \to 0$, as $n \to \infty$, we have that $P(\mathcal{C}_n | \Omega_1) \to 1$ as $n \to \infty$, which we can interpret as saying that the test has asymptotic power equal to 1.

3 The bootstrap

We impose the null hypothesis of no jumps when generating the bootstrap intraday returns.[2] Specifically, we let

$$r_i^* = \sqrt{\hat{v}_i^n} \cdot \eta_i, \quad i = 1, \ldots, n, \tag{5}$$

for some volatility measure $\hat{v}_i^n$ based on $\{r_i : i = 1, \ldots, n\}$, and where η_i is generated independently of the data as an i.i.d. $N(0,1)$ random variable. For simplicity, we write r_i^* instead of $r_{i,n}^*$. According to (5), bootstrap intraday returns are conditionally (on the original sample) Gaussian with mean zero and volatility $\hat{v}_i^n$, and therefore do not contain jumps. This bootstrap DGP is motivated by the simplified model $X_t = \int_0^t \sigma_s dW_s$, where σ is independent of W and there is no drift nor jumps, but its consistency extends to more general models with leverage and drift, as our results in this section show.[3]

The bootstrap analogues of RV_n and BV_n are

$$RV_n^* = \sum_{i=1}^n r_i^{*2} \quad \text{and} \quad BV_n^* = \frac{1}{k_1^2} \sum_{i=2}^n \left| r_{i-1}^* \right| \left| r_i^* \right|.$$

The first class of bootstrap statistics we consider is described as

$$T_n^* = \frac{\sqrt{n} \left(RV_n^* - BV_n^* - E^* \left(RV_n^* - BV_n^* \right) \right)}{\sqrt{\hat{V}_n^*}}, \tag{6}$$

where

$$E^* \left(RV_n^* - BV_n^* \right) = \sum_{i=1}^n \hat{v}_i^n - \sum_{i=2}^n \left(\hat{v}_{i-1}^n \right)^{1/2} \left(\hat{v}_i^n \right)^{1/2},$$

and

$$\hat{V}_n^* = \tau \cdot \widehat{IQ}_n^* \quad \text{with} \quad \widehat{IQ}_n^* = \frac{n}{\left(k_{4/3} \right)^3} \sum_{i=3}^n \left| r_i^* \right|^{4/3} \left| r_{i-1}^* \right|^{4/3} \left| r_{i-2}^* \right|^{4/3}.$$

Thus, T_n^* is exactly as T_n except for the recentering of $RV_n^* - BV_n^*$ around the bootstrap expectation $E^* \left(RV_n^* - BV_n^* \right)$. This ensures that the bootstrap distribution of T_n^* is centered at zero, as is the case for T_n under the null of no jumps when n is large.

As we will study in Section 4, it turns out that T_n has a higher-order bias under the null which is not well mimicked by T_n^*, implying that this test does not yield asymptotic refinements. For this reason, we consider a second class of bootstrap statistics based on

$$\bar{T}_n^* = \frac{\sqrt{n} \left(RV_n^* - BV_n^* - E^* \left(RV_n^* - BV_n^* \right) \right)}{\sqrt{\hat{V}_n^*}} + \frac{1}{2} \frac{\sqrt{n} \left(\hat{v}_1^n + \hat{v}_n^n \right)}{\sqrt{\hat{V}_n^*}}, \tag{7}$$

where the second term accounts for the higher-order bias in T_n. This correction has an impact in finite samples, as our simulation results show. In particular, $\bar{T}_n^*$ has lower size distortions than T_n^* under the null, especially for the smaller sample sizes.

Next, we provide general conditions on $\hat{v}_i^n$ under which $T_n^* \xrightarrow{d^*} N(0,1)$, in prob-$P$ independently of whether $\omega \in \Omega_0$ or $\omega \in \Omega_1$. The consistency of the bootstrap then follows by verifying these high level conditions for a particular choice of $\hat{v}_i^n$. We verify them for a thresholding-based estimator, but other choices of $\hat{v}_i^n$ could be considered. Asymptotic refinements of the bootstrap based on $\bar{T}_n^*$ will be discussed in Section 4.

[2]This follows the recommendations of Davidson and Mackinnon (1999), who show that imposing the null in the bootstrap samples is important to minimize the probability of a type I error.

[3]However, for the second-order asymptotic refinements of the bootstrap in Section 4 we do require the absence of leverage and drift effects.

3.1 Bootstrap validity under general conditions on $\hat{v}_i^n$

The first-order asymptotic validity of the local Gaussian bootstrap can be established under Condition A below. Note that this is a high level condition that does not depend on specifying whether we are on Ω_0 or on Ω_1.

Condition A Suppose that $\{\hat{v}_i^n\}$ satisfies the following conditions:

(i) For any $K \in \mathbb{N}$ and any sequence $\{q_k \in \mathbb{R}_+ : k = 1, \ldots, K\}$ of nonnegative numbers such that $0 \leq q \equiv \sum_{k=1}^{K} q_k \leq 8$, as $n \to \infty$,

$$n^{-1+q/2} \sum_{i=K}^{n} \prod_{k=1}^{K} \left(\hat{v}_{i-k+1}^n\right)^{q_k/2} \xrightarrow{P} \int_0^1 \sigma_u^q du > 0.$$

(ii) There exists $\alpha \in [0, \frac{3}{7})$ such that $n \sum_{j=1}^{[n/(L_n+1)]} \left(\hat{v}_{j(L_n+1)}^n\right)^2 = o_P(1)$, where $L_n \propto n^{\alpha}$ and $[x]$ denotes the largest integer smaller or equal to x.

Theorem 3.1 *Under Condition A, if $n \to \infty$, $T_n^* \xrightarrow{d^*} N(0,1)$, in prob-P.*

Condition A(i) requires the multipower variations of $\hat{v}_i^n$ to converge to $\int_0^1 \sigma_u^q du$ for any $q \leq 8$. Under this condition, the probability limit of $\Sigma_n^* \equiv Var^*\left(\sqrt{n}\left(RV_n^*, BV_n^*\right)'\right)$ is equal to $\Sigma \equiv Var\left(\sqrt{n}\left(RV_n, BV_n\right)'\right)$ (for this result, $q = 4$ suffices). See Lemma S1.1 in Appendix S1 and the proof of Theorem 3.1. Together with Condition A(i), Condition A(ii) is used to show that a CLT holds for $\sqrt{n}\left(RV_n^* - E^*\left(RV_n^*\right), BV_n^* - E^*\left(BV_n^*\right)\right)'$ in the bootstrap world. In particular, since the summation terms in BV_n^* are lag-one dependent, we adopt a large-block-small-block argument, where the large blocks are made of L_n consecutive observations and the small block is made of a single element. Part (ii) ensures that the contribution of the small blocks is asymptotically negligible. The proof of Theorem 3.1 then follows by showing that $\hat{V}_n^* = \tau \cdot \widehat{IQ}_n^* \xrightarrow{P^*} V = \tau \cdot IQ$ under Condition A(i) (this follows from the convergence of the multipower variations of $\hat{v}_i^n$ of eighth order, explaining why we require $q \leq 8$).

The bootstrap test rejects $H_0 : \omega \in \Omega_0$ against $H_1 : \omega \in \Omega_1$ whenever $\omega \in \mathcal{C}_n^*$, where the bootstrap critical region is defined as $\mathcal{C}_n^* = \left\{\omega : T_n(\omega) > q_{n,1-\alpha}^*(\omega)\right\}$, where $q_{n,1-\alpha}^*(\omega)$ is such that $P^*\left(T_n^*(\cdot, \omega) \leq q_{n,1-\alpha}^*(\omega)\right) = 1 - \alpha$. Since $T_n \xrightarrow{st} N(0,1)$ on Ω_0, the fact that $T_n^* \xrightarrow{d^*} N(0,1)$, in prob-$P$, ensures that the test has correct size asymptotically. Under the alternative (i.e. on Ω_1) since T_n diverges at rate $\sqrt{n}$, but we still have that $T_n^* \xrightarrow{d^*} N(0,1)$, the test has power asymptotically. The following theorem follows from Theorem 3.1 and the asymptotic properties of T_n under H_0 and under H_1.

Theorem 3.2 *Suppose $T_n \xrightarrow{st} N(0,1)$, in restriction to Ω_0, and $T_n \xrightarrow{P} +\infty$ on Ω_1. If Condition A holds, then the bootstrap test based on T_n^* controls the asymptotic strong size and is alternative-consistent.*

3.2 Bootstrap validity when $\hat{v}_i^n$ is based on thresholding

In this section we verify Condition A for the following choice of $\hat{v}_i^n$:

$$\hat{v}_{j+(i-1)k_n}^n = \frac{1}{k_n} \sum_{m=1}^{k_n} r_{(i-1)k_n+m}^2 1_{\left\{\left|r_{(i-1)k_n+m}\right| \leq u_n\right\}},$$

where $i = 1, \ldots, \frac{n}{k_n}$ and $j = 1, \ldots, k_n$. Here, k_n is an arbitrary sequence of integers such that $k_n \to \infty$ and $k_n/n \to 0$ and u_n is a sequence of threshold values defined as $u_n = \alpha n^{-\varpi}$ for some constant $\alpha > 0$ and $0 < \varpi < 1/2$. We will maintain these assumptions on k_n and u_n throughout. The estimator $\hat{v}_i^n$ is equal to n^{-1} times a "spot volatility" estimator that is popular in the high-frequency econometrics literature under jumps (see e.g. Mancini (2001) and Aït-Sahalia and Jacod (2009)). By excluding all returns containing jumps over a given threshold when computing $\hat{v}_i^n$, we guarantee that the bootstrap distribution of T_n^* converges to a $N(0,1)$ random variable, independently of whether there are jumps or not. This is crucial for the bootstrap test to control asymptotic size and at the same time have power.

The following lemma is auxiliary in verifying Condition A.

Lemma 3.1 *Assume that X satisfies (1), (2) and (3) such that Assumption H-2 holds. Let $q = \sum_{k=1}^{K} q_k$ with $q_k \geq 0$ and $K \in \mathbb{N}$. If either of the following conditions holds: (a) $q > 0$ and X is continuous; (b) $q < 2$; or (c) $q \geq 2$, Assumption H-r holds for some $r \in [0, 2)$, and $\frac{q-1}{2q-r} \leq \varpi < \frac{1}{2}$; then*

$$n^{-1+q/2} \sum_{i=K}^{n} \prod_{k=1}^{K} \left(\hat{v}_{i-k+1}^n\right)^{q_k/2} \xrightarrow{P} \int_0^1 \sigma_u^q du > 0.$$

Lemma 3.1 follows from Theorem A.1 in Appendix A, a result that is of independent interest and can be seen as an extension of Theorem 9.4.1 of Jacod and Protter (2012) (see also Jacod and Rosenbaum (2013)). In particular, Theorem A.1 provides a law of large numbers for smooth functions of consecutive truncated local realized volatility estimators defined on non-overlapping time intervals. Instead, Theorem 9.4.1 of Jacod and Protter (2012) only allows for functions that depend on a single local realized volatility estimate even though they are possibly based on overlapping intervals. Recently, Li et al. (2017b) focus on a single local realized volatility estimate based on non-overlapping intervals and extend the limit results of Theorem 9.4.1 of Jacod and Protter (2012) to a more general class of volatility functionals that do not have polynomial growth (see also Li and Xiu (2016) for an extension to overlapping intervals). Here, we restrict our attention to functions that have at most polynomial growth, which is enough to accommodate the blocked multipower variations measures of Lemma 3.1. Our conditions on ϖ depend on the polynomial growth rate of the test function, requiring in particular a narrower range of values for ϖ as q increases (as part (c) of Lemma 3.1 shows). It would be interesting to extend the results of Li et al. (2017b) and Li and Xiu (2016) to consecutive truncated local realized volatility estimators so as to allow for more general test functions and remove the dependence of ϖ on q (even if at the cost of introducing more stringent conditions on k_n).

Given this result, we can state the following theorem.

Theorem 3.3 *Assume that X satisfies (1), (2), (3) such that Assumption H-2 holds. If in addition, either of the two following conditions holds: (a) X is continuous; or (b) Assumption H-r holds for some $r \in [0, 2)$ and $\frac{7}{16-r} \leq \varpi < \frac{1}{2}$; then the conclusion of Theorem 3.1 holds for the thresholding-based bootstrap test T_n^*.*

Theorem 3.3 shows that the thresholding-based statistic T_n^* is asymptotically distributed as $N(0,1)$ independently of whether the null of no jumps is true or not. This guarantees that the bootstrap jump test has the correct asymptotic size and is consistent under the alternative of jumps. Note that under the null, when X is continuous, the result holds for any level of truncation, including the case where $u_n = \infty$, which corresponds to no truncation. Nevertheless, to ensure that T_n^* is also asymptotically normal under the alternative hypothesis of jumps some truncation is required. Part (b) of Theorem 3.3 shows that we should choose $u_n = \alpha n^{-\varpi}$ with $\frac{7}{16-r} \leq \varpi < \frac{1}{2}$, a condition that is more stringent than the usual condition on ϖ (which is $0 < \varpi < 1/2$). The lower bound on ϖ is an increasing function of r, a number that is related to the degree of activity of jumps as specified by Assumption H-r. For finite activity jumps where $r = 0$, ϖ should be larger than or equal to 7/16 but strictly smaller than 1/2. As r increases towards 2 (allowing for an increasing number of small jumps), the range of values of ϖ becomes narrower, implying that we need to choose a smaller level of truncation in order to be able to separate the Brownian motion from the jumps contributions to returns.

The following result is a corollary to Theorem 3.3.

Corollary 3.1 *Assume that X satisfies (1), (2), (3) such that Assumption H-r holds for some $r \in [0, 2)$ and let $u_n = \alpha n^{-\varpi}$ with $\frac{7}{16-r} \leq \varpi < \frac{1}{2}$. Then, the conclusions of Theorem 3.2 are true for the thresholding-based bootstrap test T_n^*.*

4 Second-order accuracy of the bootstrap

In this section, we investigate the ability of the bootstrap test based on the thresholding local realized volatility estimator to provide asymptotic higher-order refinements under the null hypothesis of no jumps. Our analysis is based on the following simplified model for X_t,

$$X_t = \int_0^t \sigma_s dW_s, \tag{8}$$

where σ is càdlàg locally bounded away from 0 and $\int_0^t \sigma_s^2 ds < \infty$ for all $t \in [0, 1]$. In addition, we assume that σ is independent of W. Thus, we not only impose the null hypothesis of no jumps under which $J_t = 0$, but we also assume that there is no drift nor leverage effects. Under these assumptions, conditionally on the path of volatility, $r_i \sim N(0, v_i^n)$ independently across i, a result that we will use throughout this section. Allowing for the presence of drift and leverage effects would complicate substantially our analysis. In particular, we would not be able to condition on the volatility path σ when deriving our expansions if we relaxed the assumption of independence between σ and W. Allowing for the presence of a drift would require a different bootstrap method, the main reason being that the effect of the drift on the test statistic is of order $O\left(n^{-1/2}\right)$ and our bootstrap returns have mean zero by construction (see Gonçalves and Meddahi, 2009). We leave these important extensions for future research.

To study the second-order accuracy of the bootstrap, we rely on second-order Edgeworth expansions of the distribution of our test statistics T_n and T_n^*. As is well known, the coefficients of the polynomials entering a second-order Edgeworth expansion are a function of the first three cumulants of the test statistics (cf. Hall, 1992). In order to derive these higher-order cumulants, we make the following additional assumption. We rely on it to obtain the limit of the first-order cumulant of T_n (cf. $\kappa_{1,1}$ below).

Assumption V The volatility process σ_u^2 is pathwise continuous, bounded away from zero and Hölder-continuous in $L^2(P)$ on $[0, 1]$ of order $\delta > 1/2$, i.e., $E\left(\left(\sigma_u^2 - \sigma_s^2\right)^2\right) = O(|u - s|^{2\delta})$.

This assumption is useful to derive explicitly the probability limit of $nE\left(RV_n - BV_n|\mathcal{F}\right)$, which contributes to the higher order bias of the BN-S statistic. It imposes that the volatility path is continuous and, in addition, rules out stochastic volatility models driven by a Brownian motion. Examples of processes that satisfy Assumption V include the fractional Brownian motion with Hurst parameter larger than 1/2 as well as the fractional stochastic volatility model introduced by Comte and Renault (1998).

4.1 Second-order expansions of the cumulants of T_n

Next we provide asymptotic expansions for the cumulants of T_n. For any positive integer i, let $\kappa_i(T_n)$ denote the i^{th} cumulant of T_n. In particular, recall that $\kappa_1(T_n) = E(T_n)$, $\kappa_2(T_n) = Var(T_n)$ and $\kappa_3(T_n) = E(T_n - E(T_n))^3$. In addition, for any $q > 0$, we let $\overline{\sigma^q} = \int_0^1 \sigma_u^q du$.

Theorem 4.1 *Assume that X satisfies (8) and Assumption V holds, where σ is independent of W. Then, conditionally on σ, we have that*

$$\begin{aligned}
\kappa_1(T_n) &= \frac{1}{\sqrt{n}}\underbrace{\left(\frac{1}{2\sqrt{\tau}}\frac{\sigma_0^2+\sigma_1^2}{\sqrt{\overline{\sigma^4}}} - \frac{a_1}{2}\frac{\overline{\sigma^6}}{\left(\overline{\sigma^4}\right)^{3/2}}\right)}_{\equiv\kappa_1=\kappa_{1,1}+\kappa_{1,2}} + O\left(\frac{1}{n}\right); \\
\kappa_2(T_n) &= 1 + O\left(\frac{1}{n}\right); \text{ and} \\
\kappa_3(T_n) &= \frac{1}{\sqrt{n}}\underbrace{\left(a_2 + \frac{3}{2}(a_1 - a_3)\right)\frac{\overline{\sigma^6}}{\left(\overline{\sigma^4}\right)^{3/2}}}_{\equiv\kappa_3} + O\left(\frac{1}{n}\right),
\end{aligned}$$

where $\tau = \left(k_1^{-4} - 1\right) + 2\left(k_1^{-2} - 1\right) - 2$ and the constants a_1, a_2 and a_3 also depend on $k_q = E|Z|^q$, $Z \sim N(0,1)$, for certain values of $q > 0$; their specific values are given in Lemma S2.5 in the Appendix.

Theorem 4.1 shows that the first and third order cumulants of T_n are subject to a higher-order bias of order $O\left(n^{-1/2}\right)$, given by the constants κ_1 and κ_3. Since the asymptotic $N(0,1)$ approximation assumes that the values of these cumulants are zero, the error of this approximation is of the order $O\left(n^{-1/2}\right)$.

The bootstrap is asymptotically second-order accurate if the bootstrap first and third order cumulants mimic κ_1 and κ_3. As it turns out, this is not true for the bootstrap test based on T_n^*. The main reason is that it fails to capture $\kappa_{1,1}$, a bias term that is due to the fact that bipower variation is a biased (but consistent) estimator of IV. To understand how this bias impacts the first-order cumulant of T_n, note that we can write

$$T_n = \frac{\sqrt{n}(RV_n - BV_n)}{\sqrt{\hat{V}_n}} = (S_n + A_n)\left(1 + \frac{1}{\sqrt{n}}(U_n + B_n)\right)^{-1/2}, \tag{9}$$

where

$$\begin{aligned}
S_n &= \frac{\sqrt{n}(RV_n - BV_n - E(RV_n - BV_n))}{\sqrt{V_n}}; \\
A_n &= \frac{\sqrt{n}E(RV_n - BV_n)}{\sqrt{V_n}}; \; U_n = \frac{\sqrt{n}\left(\hat{V}_n - E\hat{V}_n\right)}{\sqrt{V_n}}; \\
B_n &= \frac{\sqrt{n}\left(E\hat{V}_n - V_n\right)}{\sqrt{V_n}}, \text{ and } V_n = Var\left(\sqrt{n}(RV_n - BV_n)\right).
\end{aligned}$$

By construction, conditionally on σ, $E(S_n) = 0$ and $Var(S_n) = 1$; the variable S_n drives the usual asymptotic normal approximation. The term A_n is deterministic (conditionally on σ) and reflects the fact that $E(RV_n - BV_n) \neq 0$ under the null of no jumps. In particular, we can easily see that

$E\left(RV_n - BV_n\right) = IV - E\left(BV_n\right)$. Thus, A_n reflects the bias of BV_n as an estimator of IV. We can show that $A_n = O\left(n^{-1/2}\right)$, implying that to order $O\left(n^{-1}\right)$, the first-order cumulant of T_n is

$$\kappa_1\left(T_n\right) = \frac{1}{\sqrt{n}} \underbrace{\left(\sqrt{n}A_n - \frac{1}{2}E\left(S_n U_n\right)\right)}_{\longrightarrow \kappa_{1,1}+\kappa_{1,2} \equiv \kappa_1} + O\left(\frac{1}{n}\right).$$

The limit of $\sqrt{n}A_n$ is $\kappa_{1,1}$. This follows by writing

$$\sqrt{n}A_n = \frac{nE\left(IV - BV_n\right)}{\sqrt{V_n}} = \frac{n}{\sqrt{V_n}}\left(\sum_{i=1}^{n} v_i^n - \sum_{i=2}^{n}\left|v_{i-1}^n\right|^{1/2}\left|v_i^n\right|^{1/2}\right),$$

where $IV = \sum_{i=1}^{n} v_i^n$, and noting that by Lemma S2.3 (in Appendix S2),

$$n\left(\sum_{i=1}^{n} v_i^n - \sum_{i=2}^{n}\left|v_{i-1}^n\right|^{1/2}\left|v_i^n\right|^{1/2}\right) \xrightarrow{P} \frac{1}{2}\left(\sigma_0^2 + \sigma_1^2\right), \tag{10}$$

and $V_n \xrightarrow{P} \tau\overline{\sigma^4}$, under Assumption V.

Next we show that the bootstrap test based on T_n^* does not replicate $\kappa_{1,1}$ and therefore is not second-order correct. We then propose a correction of this test and show that it matches κ_1 and κ_3.

4.2 Second-order expansions of the bootstrap cumulants

Write

$$\kappa_1^*\left(T_n^*\right) = \frac{1}{\sqrt{n}}\kappa_{1n}^* + o_P\left(\frac{1}{\sqrt{n}}\right) \text{ and } \kappa_3^*\left(T_n^*\right) = \frac{1}{\sqrt{n}}\kappa_{3n}^* + o_P\left(\frac{1}{\sqrt{n}}\right),$$

where κ_{1n}^* and κ_{3n}^* are the leading terms of the first and third order cumulants of T_n^*; they are a function of the original sample and hence depend on n. Their probability limits are denoted by κ_1^* and κ_3^* and the following theorem derives their values.

Theorem 4.2 *Assume that X satisfies (8) and Assumption V holds, where σ is independent of W. Suppose that $k_n \to \infty$ such that $k_n/n \to 0$, $\sqrt{n}/k_n$ is bounded and u_n is a sequence of threshold values defined as $u_n = \alpha n^{-\varpi}$ for some constant $\alpha > 0$ and $0 < \varpi < 1/2$. Then, conditionally on σ, we have that $\kappa_1^* = \kappa_{1,2} \neq \kappa_1$ and $\kappa_3^* = \kappa_3$, where $\kappa_{1,2}$, κ_1 and κ_3 are defined as in Theorem 4.1.*

Theorem 4.2 shows that the bootstrap test based on T_n^* only captures κ_1 partially and therefore fails to provide a second-order asymptotic refinement. The main reason is that by construction the bootstrap analogue of A_n (which we denote by A_n^*) is zero for T_n^*. Because the original test has $A_n \neq 0$, the bootstrap fails to capture this source of uncertainty. Note that the conditions on u_n used by Theorem 4.2 specify that $\varpi \in (0, 1/2)$, but the result actually follows under no restrictions on u_n since we assume that X is continuous (this explains also why we do not require strengthening the restrictions on ϖ as we did when proving Theorem 3.3).

Our solution is to add a bias correction term to T_n^* that relies on the explicit form of the limit of $\sqrt{n}A_n$. In particular, our adjusted bootstrap statistic is given by

$$\bar{T}_n^* = \frac{\sqrt{n}\left(RV_n^* - BV_n^* - E^*\left(RV_n^* - BV_n^*\right)\right)}{\sqrt{\hat{V}_n^*}} + \frac{1}{2}\frac{\sqrt{n}\left(\hat{v}_1^n + \hat{v}_n^n\right)}{\sqrt{\hat{V}_n^*}} = T_n^* + \bar{R}_n^*,$$

where $\bar{R}_n^*$ can be written as $\bar{R}_n^* = \sqrt{\frac{V_n^*}{\hat{V}_n^*}} A_n^*$. Since $n\hat{v}_i^n$ is equal to a spot volatility estimator, it follows that

$$\sqrt{n} A_n^* = \frac{1}{2} \frac{n\left(\hat{v}_1^n + \hat{v}_n^n\right)}{\sqrt{V_n^*}} \xrightarrow{P} \frac{1}{2} \frac{\left(\sigma_0^2 + \sigma_1^2\right)}{\sqrt{\tau \overline{\sigma^4}}} \equiv \kappa_{1,1}$$

under our assumptions. Hence, $\bar{T}_n^*$ is able to replicate the first and third order cumulants through order $O\left(n^{-1/2}\right)$ and therefore provides a second-order refinement. The following theorem provides the formal derivation of the cumulants of $\bar{T}_n^*$. We let $\bar{\kappa}_1^*$ and $\bar{\kappa}_3^*$ denote the probability limits of $\bar{\kappa}_{1n}^*$ and $\bar{\kappa}_{3n}^*$, the leading terms of the first-order and third-order bootstrap cumulants of $\bar{T}_n^*$.

Theorem 4.3 *Under the same assumptions as Theorem 4.2, conditionally on σ, we have that $\bar{\kappa}_1^* = \kappa_1$ and $\bar{\kappa}_3^* = \kappa_3$, where κ_1 and κ_3 are defined as in Theorem 4.1.*

5 Monte Carlo simulations

In this section, we assess by Monte Carlo simulations the performance of our bootstrap tests. Along with the asymptotic test[4] of BN-S (2006), we report bootstrap results using $\hat{v}_i^n$ based on the thresholding estimator. We follow Jacod and Rosenbaum (2013) and set $k_n = [\sqrt{n}]$. We also follow Podolskij and Ziggel (2010) and choose $\varpi = 0.4$ and $\alpha = 2.3\sqrt{BV_n}$ for the truncation parameters.

We present results for the SV2F model given by[5]

$$\begin{aligned}
dX_t &= adt + \sigma_{u,t}\sigma_{sv,t}dW_t + dJ_t, \\
\sigma_{u,t} &= C + A \cdot exp\left(-a_1 t\right) + B \cdot exp\left(-a_2\left(1-t\right)\right), \\
\sigma_{sv,t} &= s\text{-}exp\left(\beta_0 + \beta_1\tau_{1,t} + \beta_2\tau_{2,t}\right), \\
d\tau_{1,t} &= \alpha_1\tau_{1,t}dt + dB_{1,t}, \\
d\tau_{2,t} &= \alpha_2\tau_{2,t}dt + \left(1 + \phi\tau_{2,t}\right)dB_{2,t}, \\
corr\left(dW_t, dB_{1,t}\right) &= \rho_1,\ corr\left(dW_t, dB_{2,t}\right) = \rho_2.
\end{aligned}$$

The processes $\sigma_{u,t}$ and $\sigma_{sv,t}$ represent the components of the time-varying volatility in prices. We follow Huang and Tauchen (2005) and set $a = 0.03$, $\beta_0 = -1.2$, $\beta_1 = 0.04$, $\beta_2 = 1.5$, $\alpha_1 = -0.00137$, $\alpha_2 = -1.386$, $\phi = 0.25$, $\rho_1 = \rho_2 = -0.3$. At the start of each interval, we initialize the persistent factor τ_1 by $\tau_{1,0} \sim N\left(0, \frac{-1}{2\alpha_1}\right)$, its unconditional distribution. The strongly mean-reverting factor τ_2 is started at $\tau_{2,0} = 0$. The process $\sigma_{u,t}$ models the diurnal U-shaped pattern in intraday volatility. In particular, we follow Hasbrouck (1999) and Andersen et al. (2012) and set the constants $A = 0.75$, $B = 0.25$, $C = 0.88929198$, and $a_1 = a_2 = 10$. These parameters are calibrated so as to produce a strong asymmetric U-shaped pattern, with variance at the open (close) more than 3 (1.5) times that at the middle of the day. Setting $C = 1$ and $A = B = 0$ yields $\sigma_{u,t} = 1$ for $t \in [0,1]$ and rules out diurnal effects from the observed process X.

Finally, for our power analysis, we consider two alternative data generating processes. Specifically, we first generate J_t as a finite activity jump process modeled as a compound Poisson process with constant jump intensity λ and random jump size distributed as $N(0, \sigma_{jmp}^2)$. We let $\sigma_{jmp}^2 = 0$ under the null hypothesis of no jumps. Under the alternative, we let $\lambda = 0.058$, and $\sigma_{jmp}^2 = 1.7241$.

[4]Following common practice, we implement the BN-S test statistic using a version of BV_n and $\widehat{IQ}_n$ that contains a finite-sample correction of the bias introduced by boundary effects. In particular, we multiply BV_n with the factor $n/\left(n-1\right)$ and $\widehat{IQ}_n$ with $n/\left(n-2\right)$. These same corrections are used when constructing the bootstrap statistics.

[5]The function s-exp is the usual exponential function with a linear growth function splined in at high values of its argument: $s\text{-}\exp(x) = \exp(x)$ if $x \leq x_0$ and $s\text{-}\exp(x) = \frac{\exp(x_0)}{\sqrt{x_0 - x_0^2 + x^2}}$ if $x > x_0$, with $x_0 = \log(1.5)$.

These parameters are motivated by empirical studies by Huang and Tauchen (2005) and Barndorff-Nielsen, Shephard, and Winkel (2006), which suggest that the jump component accounts for 10% of the variation of the price process. Second, we consider J_t as a symmetric tempered stable process with Lévy measure $\nu(\mathrm{d}x) = c_1 \frac{e^{-d_1 x}}{x^{1+r}} \mathrm{d}x$, where $c_1 > 0$, $d_1 > 0$, and $r \in [0, 2]$ measures the degree of jump activity. We let $d_1 = 3$ and $r = 0.5$. We note that this choice of r produces an infinite-activity, finite-variation jump process. c_1 is calibrated so that J_t accounts for 10% of the quadratic variation. For a similar parameterization, see Ait-Sahalia and Xiu (2016) and Hounyo (2017). We follow Todorov et al. (2014) and generate J_t as the difference between two spectrally positive tempered stable processes, which are simulated using the acceptance-rejection algorithm of Baeumer and Meerschaert (2010).

We simulate data for the unit interval $[0, 1]$ and normalize one second to be $1/23,400$, so that $[0, 1]$ is meant to span 6.5 hours. The observed process X is generated using an Euler scheme. We then construct the $1/n$-horizon returns $r_i = X_{i/n} - X_{(i-1)/n}$ based on samples of size n. Results are presented for four different samples sizes: $n = 48$, 78, 288, and 576, corresponding approximately to "8-minute", "5-minute", "1,35-minute", and "40-second" frequencies.

Table 1 gives the 5% nominal level rejection rates. Those reported in the left part of Table 1 (under no jumps) are obtained from 10,000 Monte Carlo replications with 999 bootstrap samples for each simulated sample for the bootstrap tests. For finite activity jumps, since J_t is a compound Poisson process, even under the alternative, it is possible that no jump occurs in some sample over the interval [0,1] considered. Thus, to compute the rejection rates under the alternative of jumps we rely on the number n_0 of replications, out of 10,000, for which at least one jump has occurred. For our parameter configuration, $n_0 = 570$.

Starting with size, the results show that the linear version of the test based on the asymptotic theory of BN-S (2006) (labeled "AT" in Table 1) is substantially distorted for the smaller sample sizes. In particular, for the SV2F model without diurnal effects, the rejection rate is 15.44% for $n = 48$, decreasing to 8.45% for $n = 576$. As expected, the log version of the test has smaller size distortions: the rejection rates are now 12.66% and 7.67% for $n = 48$ and $n = 576$, respectively. The rejection rates of the bootstrap tests are always smaller than those of the asymptotic tests and therefore the bootstrap outperforms the latter under the null. This is true for both bootstrap jump tests based on (6) and (7) (denoted "Boot1" and "Boot2", respectively) and for both the linear and the log versions[6] of the test.

When X has diurnality patterns in volatility, we apply the tests to both raw returns and to transformed returns with volatility corrected for diurnal patterns. We use the nonparametric jump robust estimation of intraday periodicity in volatility suggested by Boudt et al. (2011). The results based on the raw returns appear in the middle panel of Table 1 whereas the bottom panel contains results based on the transformed returns. We can see that the test based on the asymptotic theory of BN-S has large distortions driven by the difference in volatility across blocks, even if the sample size is large. As expected, corrections for diurnal effects help reduce the distortions. The bootstrap null rejection rates are always smaller than those of the asymptotic theory-based tests. This is true even for the bootstrap test applied to the non-transformed intraday returns, which yields rejection rates that are closer to the nominal level than those obtained with the asymptotic tests based on the correction of the diurnal effects (compare "Boot2" in the middle panel with "AT" in the bottom panel). This is a very interesting finding since it implies that our bootstrap method is more robust to the presence of diurnal effects than the asymptotic theory-based tests. Of course, even better results can be obtained for the bootstrap tests by resampling the transformed intraday returns and this is confirmed by Table 1. These results also reveal that Boot2 outperforms Boot1, in particular for smaller sample sizes.

Turning now to the power analysis, for finite activity jumps, results in Table 1 (center panel) show

[6] Note that our bias correction adjustment of the bootstrap test is specific to the linear version of the statistic (as it depends on its cumulants). Since we have not developed cumulant expansions for the log version of the statistic, we do not report the analogue of "Boot2" for this test.

that the bootstrap tests have lower power than their asymptotic counterparts, especially in presence of diurnal effects. This is expected given that the latter have much larger rejections under the null than the bootstrap tests. The results also show that power is largest for tests applied to the transformed returns. For these tests, the difference in power between the bootstrap and the asymptotic tests is very small. Given that the bootstrap essentially eliminates the size distortions of the asymptotic test, these two findings strongly favor the bootstrap over the asymptotic tests.

For infinite activity jumps, the right panel of Table 1 shows that power drops significantly for all tests when there are no diurnal effects, confirming that the BN-S tests are not always the most powerful ones under infinite activity jumps. In unreported simulations, we found that the "small jumps" test by Lee and Hannig (2010) has more power in these situations, which is in line with previous results in the literature. Interestingly, the combination of stochastic volatility with diurnality and infinite activity jumps seems to restore power across all tests.

6 Empirical results

This empirical application uses trade data on the SPDR S&P 500 ETF (SPY), which is an exchange traded fund (ETF) that tracks the S&P 500 index. Our primary sample comprises 10 years of trade data on SPY starting from June 15, 2004 through June 13, 2014 as available in the New York Stock Exchange Trade and Quote (TAQ) database. After cleaning this data set using the procedure suggested by Barndorff-Nielsen et al. (2009) and removing short trading days, we are left with 2497 observations for the whole period. In addition, we consider three subperiods: '*Before crisis*', through August 29 2008 (1053 trading days); '*Crisis*', from September 2, 2008 through May 29, 2009 (185 trading days), and '*After crisis*', from June 1, 2009 through June 13, 2014 (1259 trading days).

Table 2 shows the percentage of days identified with a jump ("jump days") by the asymptotic and bootstrap tests. We consider the asymptotic version of the linear and the log test statistics as well as their bootstrap versions. For the linear bootstrap test, we rely on "Boot2", which does best in finite samples according to our simulations. For the log version of the bootstrap test, we rely on "Boot1". These tests are applied to data with and without correction for diurnal effects and are based on 5-min returns throughout. This yields 78 daily observations over the 6.5 hours of the trading session.

In line with the simulation findings, the asymptotic tests tend to substantially over detect jumps compared to the bootstrap tests, which throughout detect about half of the number of jump days detected by the asymptotic tests. More precisely, with no account for diurnal effects, the asymptotic (linear and log) tests detect 26.31% and 23.27% jump days, respectively, while the bootstrap tests detect 13.7% and 16.9% jump days. These percentages are about the same as what is obtained before and after crisis. During the crisis though, less jump days (in proportion) are detected.

We also report test results applied to returns corrected for diurnal effects. This is particularly relevant because Figure 1 suggests that these are important in our application. The U-shape of these graphs highlights the fact that the market seems to be more volatile early and late in daily trading sessions compared to the mid-day volatility. We can also see that the gap between early/late and mid-day volatilities is magnified in the crisis period. After correction for diurnal effects, less jumps days are detected by all the tests before and after crisis. However, in the crisis period, while the bootstrap still detects about the same number of jump days, the asymptotic tests detect substantially more jumps after diurnal effects correction. It is also worthwhile to point out that the gap between the bootstrap linear and log tests narrows as diurnal effects are accounted for. Overall, the bootstrap tests seem more robust to diurnality than the asymptotic tests.

Table 1: Rejection rates of asymptotic and bootstrap tests, nominal level $\alpha = 0.05$.

	Under H_0: no jumps					Under H_1: presence of jumps									
	Size					Power: with finite activity jumps					Power: with infinite activity jumps				
	Linear test			Log test		Linear test			Log test		Linear test			Log test	
n	AT	Boot1	Boot2	AT	Boot1	AT	Boot1	Boot2	AT	Boot1	AT	Boot1	Boot2	AT	Boot1
	SV2F model without diurnal effects, no jumps					SV2F model without diurnal effects, finite activity jumps					SV2F model without diurnal effects, infinite activity jumps				
48	15.44	6.97	5.92	12.66	7.04	77.52	71.58	70.68	76.26	71.94	51.48	38.95	36.49	48.33	39.00
78	13.47	6.96	5.81	11.50	7.01	81.83	77.88	76.98	80.76	77.88	58.17	49.24	47.22	56.04	49.56
288	9.64	6.24	5.64	8.84	6.11	85.61	84.35	84.17	85.61	84.35	74.10	70.25	69.70	73.20	70.12
576	8.45	5.71	5.38	7.67	5.70	88.67	88.31	87.95	88.49	88.31	79.78	77.45	77.09	79.19	77.36
	SV2F model with diurnal effects, no correction, no jumps					SV2F model with diurnal effects, no correction, finite activity jumps					SV2F model with diurnal effects, no correction, infinite activity jumps				
48	32.44	15.96	13.61	28.54	14.40	87.23	77.70	75.90	85.79	76.62	99.51	98.71	98.44	99.41	98.07
78	26.88	14.73	13.10	23.56	15.31	86.87	80.04	79.14	85.61	80.76	99.87	99.73	99.70	99.84	99.69
288	16.62	9.68	8.83	14.79	9.37	86.69	84.89	84.17	85.79	84.35	100.0	99.99	100.0	100.0	100.0
576	13.34	8.91	8.21	11.78	8.62	89.21	87.95	87.05	89.03	87.41	100.0	100.0	99.99	100.0	99.98
	SV2F model with diurnal effects, correction, no jumps					SV2F model with diurnal effects, correction, finite activity jumps					SV2F model with diurnal effects, correction, infinite activity jumps				
48	15.76	7.39	6.08	13.08	7.10	91.06	90.32	89.94	90.88	90.13	99.06	97.43	97.17	98.83	96.36
78	13.26	6.50	5.49	11.30	6.57	91.81	90.69	90.50	91.81	90.69	99.48	98.97	98.93	99.40	98.76
288	9.80	6.15	5.60	8.83	6.11	93.85	92.92	92.92	93.67	92.92	99.96	99.93	99.92	99.94	99.92
576	8.62	5.97	5.48	8.00	5.95	93.30	93.30	93.30	93.30	93.30	99.99	99.99	99.99	99.99	99.99

Notes: 'AT' is based on (4), i.e., the asymptotic theory of BN-S (2006); 'Boot1' and 'Boot2' are based on bootstrap test statistics T_n^* (cf. (6)) and $\bar{T}_n^*$ (cf. (7)), respectively. 'Boot2' takes into account the asymptotically negligible bias in T_n which may be relevant at the second-order, and under certain conditions provides the refinement for the bootstrap method. We use 10,000 Monte Carlo trials with 999 bootstrap replications each.

Table 2: Percentage of days identified as jumps day by daily statistics (nominal level $\alpha = 0.05$) using 5-min returns.

No correction for diurnal effects				With correction for diurnal effects			
AT-lin	AT-log	Boot2-lin	Boot1-log	AT-lin	AT-log	Boot2-lin	Boot1-log
Full sample: June 15, 2004 through June 13, 2014 (2497 days)							
26.31	23.27	13.70	16.90	24.23	20.54	12.66	14.46
Before crisis: June 15, 2004 through August 29, 2008 (1053 days)							
25.55	22.41	13.11	16.43	22.41	18.99	12.73	14.06
During crisis: September 2, 2008 through May 29, 2009 (185 days)							
21.62	19.46	10.81	13.51	24.32	21.62	11.35	12.97
After crisis: June 1, 2009 through June 13, 2014 (1259 days)							
27.64	24.54	14.61	17.79	25.73	21.68	12.79	15.01

Notes: 'AT-lin' and 'Boot2-lin' ('AT-log' and 'Boot1-log') stand for asymptotic and bootstrap tests using the linear (log) version of the test statistic. 'Boot2-lin' uses the second-order corrected bootstrap test statistic for asymptotic refinement.

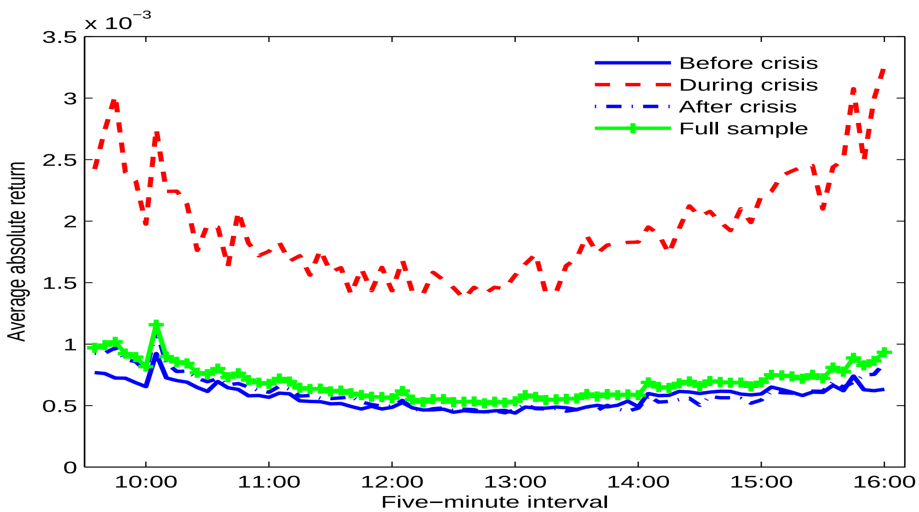

Figure 1: Diurnal pattern of SPY. The graph displays the average (over the specified samples) of absolute 5-min returns of each trading day. 'Before crisis' refers to the sample from June 15, 2004 through August 29, 2008; 'During crisis' refers to the period from September 2, 2008 through May 29, 2009, and 'After crisis' refers to the period from June 1, 2009 through June 13, 2014.

7 Conclusion

The main contribution of this paper is to propose bootstrap methods for testing the null hypothesis of "no jumps". The methods generate bootstrap returns from a Gaussian distribution with variance given by a local realized measure of integrated volatility $\{\hat{v}_i^n\}$. We first provide a set of high level conditions on $\{\hat{v}_i^n\}$ such that any bootstrap method of this form is asymptotically valid when testing for jumps using the BN-S test statistic. We then provide a detailed analysis of the bootstrap test based on a thresholding estimator for $\{\hat{v}_i^n\}$.

A second contribution of this paper is to discuss the ability of the bootstrap to provide second-order asymptotic refinements over the usual asymptotic mixed Gaussian distribution under the null of no jumps. Our results show that our bootstrap test is not second-order accurate because it is not able to match the first-order cumulant of the test statistic at higher order. We therefore propose a modification of the original bootstrap test for which an asymptotic refinement exists. The modification consists of adding a bias correction term that estimates the contribution of the bipower variation bias to the first-order cumulant of the original test. Our simulations show that this adjustment is important in finite samples, especially for the smaller sample sizes when sampling is more sparse.

We illustrate the usefulness of our bootstrap jumps test by applying it to 5-min returns on the SPY index over the period from June 15, 2004 through June 13, 2014. Overall, the main finding is that the bootstrap detects about half of the number of jump days detected by the asymptotic-theory based tests.

Appendix A: A law of large numbers for functions of non-overlapping local volatility estimates

In this section, we state and prove Theorem A.1, a result that is auxiliary in proving Lemma 3.1. As noted in the main text, Theorem A.1 has merit on its own right as it extends Theorem 9.4.1 of Jacod and Protter (2012) to the case of smooth functions of consecutive local realized volatility estimates rather than a single local estimate. Let

$$\hat{c}_{j,n} = \frac{n}{k_n} \sum_{m=1}^{k_n} r^2_{(j-1)k_n+m} 1_{\{|r_{(j-1)k_n+m}| \leq u_n\}},$$

$j = 1, \ldots, \frac{n}{k_n}$, with $r_i \equiv X_{\frac{i}{n}} - X_{\frac{i-1}{n}}$, $i = 1, \ldots, n$; $\quad u_n = \alpha n^{-\varpi}$, $\quad \varpi \in (0, \frac{1}{2})$ and k_n is a sequence of integers satisfying $k_n \to \infty$ and $\frac{k_n}{n} \to 0$ as $n \to \infty$.

Theorem A.1 *Assume that X satisfies Assumption H-2, and let g be a continuous function on $\mathbb{R}_+^\ell$ such that $|g(x_1, \ldots, x_\ell)| \leq K(1 + |x_1|^p + \cdots + |x_\ell|^p)$ for some $p \geq 0$. If either: (a) X is continuous; (b) $p < 1$; or (c) Assumption H-r holds for some $r \in [0, 2)$ and $p \geq 1$, $\quad \varpi \geq \frac{2p-1}{4p-r}$; then*

$$G_n \equiv \frac{k_n}{n} \sum_{j=\ell}^{n/k_n} g(\hat{c}_{j,n}, \hat{c}_{j-1,n}, \ldots, \hat{c}_{j-\ell+1,n}) \xrightarrow{P} \int_0^1 g(\sigma_s^2, \ldots, \sigma_s^2) ds.$$

In the proof, we will follow the standard localization argument of Jacod and Protter (2012) and assume without loss of generality that the following stronger version of Assumption H-r holds:

Assumption SH-r Assumption H-r holds, and in addition the processes a and σ are bounded, and $|\delta(\omega, t, x)| \wedge 1 \leq \gamma(x)$ with $\int |\gamma(x)|^r dx < \infty$.

Proof. We follow the proof of Theorem 9.4.1 of Jacod and Protter (2012). By localization, we assume without loss of generality that SH-r holds with $r = 2$ for $p < 1$ and that $g \geq 0$.

Step 1: We first assume that g is bounded. For all $s \in [0, 1]$ and $l = 1, \ldots, \ell$, let $\hat{c}_n^{(l)}(s) = \hat{c}_{j+l,n}$ when $(j-1)\frac{k_n}{n} \leq s < j\frac{k_n}{n}$, where $\hat{c}_{j,n} = 0$ if $j > n/k_n$. We have

$$G_n = \frac{k_n}{n} g(\hat{c}_{\ell,n}, \hat{c}_{\ell-1,n}, \ldots, \hat{c}_{1,n}) + \int_0^{1-\ell\frac{k_n}{n}} g\left(\hat{c}_n^{(\ell)}(s), \ldots, \hat{c}_n^{(1)}(s)\right) ds.$$

Thus, $E\left(\left|G_n - \int_0^1 g\left(\sigma_s^2,\ldots,\sigma_s^2\right)ds\right|\right) \leq K\frac{k_n}{n} + \int_0^{1-\ell\frac{k_n}{n}} a_n(s)ds$, with $a_n(s) = E\left|g\left(\hat{c}_n^{(\ell)}(s),\ldots,\hat{c}_n^{(1)}(s)\right) - g\left(\sigma_s^2,\ldots,\sigma_s^2\right)\right|$. Since g is bounded, we can claim that $\hat{c}_n^{(l)}(s) \xrightarrow{P} \sigma_s^2$ for all $s \in [0,1)$ by using the same argument as in the proof of Theorem 9.3.2(a) of Jacod and Protter (2012), implying that $a_n(s)$ tends to 0 as $n \to \infty$ for each s and is bounded uniformly in (n,s). The result then follows by the dominated convergence theorem.

Step 2: Let ψ be a C^∞ function: $\mathbb{R}_+ \to [0,1]$ with $1_{[0,\infty)}(x) \leq \psi(x) \leq 1_{[\frac{1}{2},\infty)}(x)$, and $\psi_\varepsilon(x) = \psi(|x|/\varepsilon)$ and $\psi'_\varepsilon = 1-\psi_\varepsilon$. For $m \geq 2$, let $g'_m(x_1,\ldots,x_\ell) = g(x_1,\ldots,x_\ell)\prod_{l=1}^{\ell}\psi'_m(x_l)$ and $g_m = g - g'_m$. Since g'_m is continuous and bounded, for any fixed m, by Step 1,

$$\frac{k_n}{n}\sum_{j=\ell}^{n/k_n} g'_m\left(\hat{c}_{j,n},\hat{c}_{j-1,n},\ldots,\hat{c}_{j-\ell+1,n}\right) \xrightarrow{P} \int_0^1 g'_m(\sigma_s^2,\ldots,\sigma_s^2)ds.$$

Note that $\int_0^1 g'_m(\sigma_s^2,\ldots,\sigma_s^2)ds = \int_0^1 g(\sigma_s^2,\ldots,\sigma_s^2)ds$ for m large enough since σ_s^2 is bounded and $\psi'_m(x) = 1$ for $|x| \leq m/2$. Thus, the result follows by showing that $\frac{k_n}{n}\sum_{j=\ell}^{n/k_n} g_m\left(\hat{c}_{j,n},\hat{c}_{j-1,n},\ldots,\hat{c}_{j-\ell+1,n}\right)$ is negligible for large n and m. By assumption,

$$g_m(x_1,\ldots,x_\ell) \leq K\left(1+\sum_{l=1}^{\ell}|x_l|^p\right)\left(1-\prod_{l=1}^{\ell}\psi'_m(x_l)\right)$$

where $1-\prod_{l=1}^{\ell}\psi'_m(x_l) \leq \sum_{l=1}^{\ell}1_{\{|x_l|\geq\frac{m}{2}\}}$, since $\psi'_m(x_l) = 1$ if $|x_l| \leq m/2$ and both sides of the inequality are nil if $|x_l| \leq m/2$ for all l. If $|x_l| > m/2$ for some l, then $\sum_{l=1}^{\ell}1_{\{|x_l|\geq\frac{m}{2}\}} \geq 1 \geq 1 - \prod_{l=1}^{\ell}\psi'_m(x_l)$. Also, if $|x_l| > m/2$ for some l, we have that $1+\sum_{l=1}^{\ell}|x_l|^p \leq 2\sum_{l=1}^{\ell}|x_l|^p$. Thus, $g_m(x_1,\ldots,x_\ell) \leq 2K\sum_{l,l'=1}^{\ell}|x_l|^p 1_{\{|x_{l'}|\geq\frac{m}{2}\}}$. Therefore, to complete the proof, it suffices to show that

$$\lim_{m\to\infty}\limsup_{n\to\infty} E\left(\frac{k_n}{n}\sum_{j=\ell}^{n/k_n}\hat{c}_{j-l+1,n}^p 1_{\{\hat{c}_{j-l'+1,n}>m\}}\right) = 0, \tag{A.1}$$

for all $l,l' = 1,\ldots,\ell$. Consider first $p<1$. Letting $\kappa = 0$ when X is continuous and $\kappa = 1$ otherwise, for $q \geq 2$, we can show that $E(|r_i|^q) \leq K_q\left(\frac{1}{n^{q/2}} + \kappa\frac{1}{n^{(q/2)\wedge 1}}\right)$ and, from the c_r-inequality, $E\left(\hat{c}_{j,n}^p\right) \leq K_q\left(1+\kappa\frac{1}{n^{q\wedge 1-q}}\right)$. By successive applications of the Hölder and Markov inequalities, for any $q>p$:

$$\begin{aligned} E\left(\hat{c}_{i,n}^p 1_{\{\hat{c}_{j,n}>m\}}\right) &\leq \left(E\left(\hat{c}_{i,n}^q\right)\right)^{\frac{p}{q}}\left(P\left(\hat{c}_{j,n}\geq m\right)\right)^{1-\frac{p}{q}} \\ &\leq \left(E\left(\hat{c}_{i,n}^q\right)\right)^{\frac{p}{q}}\left(\frac{1}{m^q}E\left(\hat{c}_{j,n}^q\right)\right)^{1-\frac{p}{q}} \leq \frac{K_q}{m^{q-p}}\left(1+\kappa\frac{1}{n^{q\wedge 1-q}}\right). \end{aligned}$$

Take $q = 2p$ if X is continuous and $q = 1 > p$ otherwise and conclude (A.1).

Next, consider $p \geq 1$. With the same alternative decomposition of X as that in Jacod and Protter (2012, Eq. (9.2.7)), we write $r_i = r_{1i} + r_{2i}$, with r_{1i} and r_{2i} the increments of the process X' and X'', respectively. We have that

$$r_i^2 1_{\{|r_i|\leq u_n\}} \leq 2\left(r_{1i}^2 + u_n^2\left(\frac{r_{2i}^2}{u_n^2}\wedge 1\right)\right) \leq K\left(r_{1i}^2 + u_n^2\left(n^{\varpi}|r_{2i}|\wedge 1\right)^2\right),$$

where we use for the last inequality the fact that $(a/b) \wedge 1 \le \max(1, 1/b)[a \wedge 1]$, with $a, b > 0$. Thus, $\hat{c}_{j,n} \le \zeta'_{j,n} + \zeta''_{j,n}$ with

$$\zeta'_{j,n} = K \frac{1}{k_n} \sum_{m=1}^{k_n} (\sqrt{n} r_{1,(j-1)k_n+m})^2, \qquad \zeta''_{j,n} = K \frac{v_n^2}{k_n} \sum_{m=1}^{k_n} \left(n^{\varpi} |r_{2,(j-1)k_n+m}| \wedge 1 \right)^2,$$

with $v_n = \sqrt{n} u_n$. Noting that

$$\hat{c}_{i,n} 1_{\{\hat{c}_{j,n} \ge m\}} \le \frac{\hat{c}_{i,n} \hat{c}_{j,n}}{m} \le \frac{1}{2m} \left(\hat{c}_{i,n}^2 + \hat{c}_{j,n}^2 \right) \le \frac{1}{m} \left(\zeta'^2_{i,n} + \zeta''^2_{i,n} + \zeta'^2_{j,n} + \zeta''^2_{j,n} \right),$$

by the c_r-inequality, $E\left(\hat{c}_{i,n}^p 1_{\{\hat{c}_{j,n} \ge m\}}\right) \le \frac{4^{p-1}}{m^p} \left(E(\zeta'^{2p}_{i,n}) + E(\zeta''^{2p}_{i,n}) + E(\zeta'^{2p}_{j,n}) + E(\zeta''^{2p}_{j,n}) \right)$. Moreover, Eqs. (9.2.12) and (9.2.13) of Jacod and Protter (2012) ensure that $E\left((\sqrt{n}|r_{1i}|)^q | \mathcal{F}_{\frac{i-1}{n}} \right) \le K_q$ and $E\left((n^{\varpi}|r_{2i}|)^2 \wedge 1 | \mathcal{F}_{\frac{i-1}{n}} \right) \le K n^{-1+r\varpi} \phi_n$,with $\phi_n \to 0$ as $n \to \infty$. Thus, by a further application of the c_r-inequality, $E(\zeta'^{2p}_{j,n}) < K$, whereas

$$\begin{aligned} E(\zeta''^{2p}_{j,n}) &\le K \frac{v_n^{4p}}{k_n} \sum_{m=1}^{k_n} E\left(\left(n^{\varpi} |r_{2,(j-1)k_n+m}| \wedge 1 \right)^{4p} \right) \le K \frac{v_n^{4p}}{k_n} \sum_{m=1}^{k_n} E\left(\left(n^{\varpi} |r_{2,(j-1)k_n+m}| \wedge 1 \right)^2 \right) \\ &\le K n^{4p(-\varpi + \frac{1}{2})} n^{-1+r\varpi} \phi_n = K n^{-w} \phi_n, \end{aligned}$$

with $w = 1 - 2p + \varpi(4p - r)$. Thus, $E\left(\hat{c}_{i,n}^p 1_{\{\hat{c}_{j,n} \ge m\}}\right) \le \frac{K}{m^p} \left(1 + n^{-w} \phi_n\right)$. Since $w \ge 0$ under the maintained assumptions, (A.1) follows.

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