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A PRIMER ON BOOTSTRAP TESTING OF HYPOTHESES IN TIME SERIES MODELS: WITH AN APPLICATION TO DOUBLE AUTOREGRESSIVE MODELS*

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In this article, we discuss the bootstrap as a tool for statistical inference in econometric time series models. Importantly, in the context of testing, properties of the bootstrap under the null (size) as well as under the alternative (power) are discussed. Although properties under the alternative are crucial to ensure the consistency of bootstrap-based tests, it is often the case in the literature that only validity under the null is discussed. We provide new results on bootstrap inference for the class of double-autoregressive (DAR) models. In addition, we review key examples from the bootstrap time series literature in order to emphasize the importance of properly defining and analyzing the bootstrap generating process and associated bootstrap statistics, while also providing an up-to-date review of existing approaches. DAR models are particularly interesting for bootstrap inference: first, standard asymptotic inference is usually difficult to implement due to the presence of nuisance parameters; second, inference involves testing whether one or more parameters are on the boundary of the parameter space; third, even second-order moments may not exist. In most of these cases, the bootstrap is not considered an appropriate tool for inference. Conversely, and taking testing nonstationarity to illustrate, we show that although a standard bootstrap based on unrestricted parameter estimation is invalid, a correct implementation of the bootstrap based on restricted parameter estimation (restricted bootstrap) is first-order valid. That is, it is able to replicate, under the null hypothesis, the correct limiting distribution. Importantly, we also show that the behavior of this bootstrap under the alternative hypothesis may be more

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involved because of possible lack of finite second-order moments of the bootstrap innovations. This feature makes for some parameter configurations, the restricted bootstrap unable to replicate the null asymptotic distribution when the null is false. We show that this possible drawback can be fixed by using a novel bootstrap in this framework. For this "hybrid bootstrap," the parameter estimates used to construct the bootstrap data are obtained with the null imposed, while the bootstrap innovations are sampled with replacement from unrestricted residuals. We show that the hybrid bootstrap mimics the correct asymptotic null distribution, irrespective of the null being true or false. Monte Carlo simulations illustrate the behavior of both the restricted and the hybrid bootstrap, and we find that both perform very well even for small sample sizes.

1. INTRODUCTION

Outcomes of various bootstrap schemes applied to econometric time series models are routinely reported in the literature. This is generally done in cases where (i) the limiting distribution of the reference estimator or test statistic depends on a (possibly infinite-dimensional) vector of unknown nuisance parameters; (ii) critical values or standard errors can be obtained by simulations only; (iii) the asymptotic approximation to the distribution of the reference estimator or test statistic is poor. The increasing computational power available to researchers coupled with the fact that the implementation of bootstrap algorithms is typically straightforward, makes the bootstrap one of the most popular inference tools in the econometric analysis of time series data; see, inter alia, Davidson and MacKinnon (2006) and MacKinnon (2009).

Despite its many appealing features, the application of the bootstrap to time series models requires a detailed analysis of its asymptotic properties. This is necessary in order to establish asymptotic validity of the bootstrap, at least up to first order. Taking hypothesis testing to illustrate—as we do throughout this article—a proper statistical analysis of any bootstrap test would necessarily involve two main interconnected steps. First, it requires to determine whether, conditionally on the original data, the bootstrap correctly mimics the null asymptotic distribution of the reference test statistics under the null hypothesis. This step is generally more involved than the asymptotic analysis of the original test statistics, as the conditional distribution of the bootstrap statistic given the data are random elements in the space of distribution functions. Hence, specific probability tools are required. In general, further high-level conditions over those required for asymptotic inference are necessary and, consequently, any application of the bootstrap, which is not backed up by a proper analysis of these conditions must be taken with caution.

The second step, which is often neglected in applications of the bootstrap, is the statistical analysis of the properties of the test under the alternative hypothesis, that is, consistency of the bootstrap test. This step is more involved than assessing bootstrap validity under the null. Essentially, difficulties may arise because it requires to analyze the asymptotic behavior of the estimators used to generate the

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bootstrap data when the null is false: in particular when estimators restricted by the null hypothesis are considered.

In this article, we aim at discussing the two aforementioned steps by considering a novel application of the bootstrap to econometric time series models. Specifically, we consider bootstrap inference in the class of double-autoregressive (DAR) models, see, for example, Borkovec and Klüppelberg (2001), Ling (2004), Ling (2007*a*) and Chen et al. (2013). The DAR is a time series model with an autoregressive structure both in the conditional mean and in the conditional variance. The conditional mean has the classic autoregressive formulation, that is, it is linear in the lagged level of the process. The conditional variance is also linear in the lagged (squared) *level* of the process, which therefore contrasts classic ARCH-type or AR–ARCH type specifications where lagged innovations appear (see, e.g., Ling and Li, 1998; Ling and MacAleer, 2003; Lange, Jensen and Rahbek, 2006; Ling, 2007b; Nielsen and Rahbek, 2014). In this sense, it allows the levels of the process to affect both the conditional mean and conditional variance, as desirable in econometric modelling of interest rates,[1] see also Nielsen and Rahbek (2014). We discuss (nonstandard) bootstrap-based inference in the DAR model, with main emphasis on the likelihood-ratio (LR) test for the hypothesis that the DAR model reduces to a random walk. In essence, this can be viewed as a nonstationarity test within the DAR model. Previous studies of this testing problem are given in Ling (2004), who considers the score test, and in Klüppelberg et al. (2001), who consider a LR testing approach.

DAR models and the associated (non)stationarity testing problem are particularly interesting to illustrate implementation of the bootstrap to time series, for several reasons. First, standard asymptotic inference is usually difficult to implement due to the presence of nuisance parameters under the null hypothesis. The asymptotic distribution of the test statistics, for instance, depends on nuisance parameters (such as the kurtosis of the innovations), which makes it hard to construct tables of critical values. Second, the autoregressive parameter entering the conditional variance equation is—in order to guarantee non-negativity of the conditional variance—usually restricted to be non-negative. As a consequence, inference must deal with possible parameters on the boundary of the parameter space, a situation where the bootstrap is usually regarded as invalid (see, e.g., Andrews, 2000, Cavaliere, Nielsen and Rahbek, 2017). Third, under strict stationarity, second-order moments may not exist. Hence, understanding the properties of the bootstrap under the alternative hypothesis, which would require resampling from an infinite variance process, may be cumbersome, if not even impossible (seminal results about the possible invalidity of the bootstrap when second-order moments may not exist are given in Athreya, 1987, and Knight, 1988; for time series models, see also Cavaliere, Nielsen and Rahbek, (2020), and the references therein).

[1] The Cox–Ingersoll–Ross model is an example of a level-dependent heteroskedasticity model.

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In the following, the article shows that for the DAR model, as expected in the aforementioned cases, classic bootstrap hypothesis testing, based on generating the bootstrap data using estimators (and residuals) obtained without imposing the null hypothesis (as suggested in Hall, 1992), is invalid. Despite this fact, we also show that the problem of (non)stationarity testing in a DAR model can be successfully solved by a proper implementation of the bootstrap. More specifically, we initially show that the bootstrap based on *restricted* parameter estimation (the so-called "restricted bootstrap") is first-order valid under the null hypothesis; that is, it is able to replicate the correct limiting null distribution when the null hypothesis is true. However, we also show that the behavior of this bootstrap under the alternative hypothesis may be different because of possible lack of finite second-order moments of the bootstrap innovations. This features makes—for some parameter configurations—the restricted bootstrap unable to replicate the null asymptotic distribution when the null is false. This is a typical instance where validity of the bootstrap under the null does not imply consistency of the bootstrap test under the alternative.

We next show that this drawback can be fixed by using a new "hybrid" bootstrap, where the parameter estimates used to construct the bootstrap data are obtained with the null imposed, while the bootstrap innovations are sampled with replacement from the unrestricted residuals. This simple modification of the bootstrap algorithm, which is novel in this framework, mimics the correct asymptotic null distribution also under the alternative.

We use a Monte Carlo experiment to analyze the finite sample properties of the different bootstrap algorithms. We show substantial gains in terms of accuracy of the empirical rejection probabilities [ERPs] under the null hypothesis, while under the alternative we show that our bootstrap has power very close to the pointwise size-adjusted power of the (infeasible) asymptotic test.

Throughout the article, we use a number of examples from the bootstrap (time series) literature to illustrate the importance of properly defining the bootstrap generating process and associated bootstrap statistic, as well as the need for looking at the appropriate bootstrap statistic on the basis of a rigorous, case-by-case analysis of its theoretical properties, both under the null and under the alternative hypothesis.

1.1. Structure of the Article

The structure of the article is the following. In Section 2, we introduce the reference DAR model and the testing problem we consider throughout the article. In Section 3, we introduce the main bootstrap approaches and discuss their validity under the null hypothesis. Section 4 focuses on the behavior of the bootstrap test under the alternative hypothesis. Here, we also introduce and discuss the hybrid bootstrap scheme. Results from a small Monte Carlo study on the finite sample behavior of the asymptotic and bootstrap tests are reported in Section 5. We consider some extensions of the model and of the tests in Section 6, while Section 7 concludes. All mathematical proofs are located in the Appendix.

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1.2. Notation

The following notation is used throughout. With $x := y$ ($y =: x$), we mean that x is defined by y. For any $q \in \mathbb{R}$ ($\mathbb{R}$ denoting the set of real numbers), $q^+ := \max\{0, q\}$ and $\lfloor q \rfloor$ denotes the integer part of q. The set of non-negative real numbers is denoted by $\mathbb{R}^+$. The space of $m \times 1$ vectors of càdlàg functions on the unit interval [0, 1] is denoted by $\mathscr{D}^m$. With $X_n \to_w X$ and $X = \text{wlim} X_n$, we mean that X_n converges weakly to X. Also, $\stackrel{d}{=}$ denotes equality in distribution. We use P^*, E^* and V^*, respectively, to denote probability, expectation, and variance, conditional on the original sample. With $\stackrel{w^*}{\to}_p$, we denote weak convergence in probability; that is, $X_n^* \stackrel{w^*}{\to}_p X$ means that, as the sample size n diverges, the cumulative distribution function (cdf) of X_n^* conditional on the original data, that is, $G_n^*(x) := P^*(X_n^* \le x)$, $x \in \mathbb{R}$, converges in probability to the cdf G of X, at all continuity points of G. For a given sequence X_n^* computed from the bootstrap data, $X_n^* - X = o_p^*(1)$, in probability, or $X_n^* \stackrel{p^*}{\to}_p X$, means that for any $\epsilon > 0$, $P^*(||X_n^* - X|| > \epsilon) \to_p 0$, as $n \to \infty$. Similarly, $X_n^* = O_p^*(1)$, in probability, means that, for every $\epsilon > 0$, there exists a constant $M > 0$ such that, for all large n, $P(P^*(||X_n^*|| > M) < \epsilon)$ is arbitrarily close to one. Unless otherwise specified, integrals are between 0 and 1.

2. (NON)STATIONARITY IN A DAR MODEL

In this section, we present the leading DAR model and the associated (non)stationary testing problem which we discuss throughout the article. We introduce the main assumptions in Section 2.1, discuss estimation in Section 2.2, and the key testing procedure in Section 2.3. Bootstrap inference and hypothesis testing is discussed in Section 3.

2.1. Model and Assumptions

Consider the double-autoregressive (DAR) model (Ling, 2004), as defined through the recursion

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t, \quad \varepsilon_t := \sigma_t z_t, \quad \sigma_t^2 := \omega + \alpha x_{t-1}^2, \tag{1}$$

where the z_t's are i.i.d. random variables with zero mean and unit variance, and with a continuous, strictly positive density with respect to the Lebesgue measure.[2] The initial value, denoted by x_0, is independent of the future z_t's and will be considered fixed in the statistical analysis. As is customary for this class of models, it is also assumed that

$$\xi := Ez_t^3 = 0, \qquad \kappa := Ez_t^4 - 1 < \infty;$$

[2]The assumption of a continuous and positive density with respect to the Lebesgue measure can be relaxed.

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the case $\xi \neq 0$ is considered in Section 6. In this model, the mean of x_t conditional on the σ-field generated by $\{x_0, z_1, \ldots, z_{t-1}\}$, say $\mathcal{I}_{t-1}$, equals $(1+\pi)x_{t-1}$ while the conditional variance is given by $\sigma_t^2 := \omega + \alpha x_{t-1}^2$ and hence is level-dependent. In this respect, it differs from the standard AR-ARCH model (see, e.g., Lange, Rahbek and Jensen, 2011), where the conditional variance σ_t^2 depends on ε_{t-1}^2 rather than on x_{t-1}^2 (see also Nielsen and Rahbek, 2014, for a discussion of the multivariate DAR). Clearly, the model reduces to a standard autoregression with i.i.d. innovations when $\alpha = 0$, and to the ARCH model when $\pi = -1$, which implies $x_t = (\omega + \alpha x_{t-1}^2)^{1/2} z_t$. In the DAR model, a sufficient condition for σ_t^2 to be positive a.s. is given by the usual non-negativity constraint $\alpha \geq 0$, which we assume to hold throughout. A necessary and sufficient condition for $Ex_t^2 < \infty$ is $(1+\pi)^2 + \alpha < 1$; moreover, provided $E \log \left| 1 + \pi + \sqrt{\alpha} z_t \right| < 0$, the process can be given an initial distribution such that it is strictly stationary and geometrically ergodic if some mild regularity conditions on the density function of z_t also hold. A key feature of the model is that the classical autoregressive unit root condition, $\pi = 0$, does not imply that the process is nonstationary. More specifically, $\pi = 0$ implies nonstationarity only if $\alpha = 0$; see Fig. 1 in Ling (2004). We discuss the issue of testing for nonstationarity in Section 2.3 below.

In the following, we assume that the parameter space for the true value, denoted as θ_0 is given by $\Theta_0 := \Theta_{\mathcal{S}} \cup \Theta_{\mathcal{N}}$, where $\Theta_{\mathcal{S}} := \{\theta := (\pi, \alpha, \omega)' : E \log \left| 1 + \pi + \sqrt{\alpha} z_t \right| < 0$ with $\alpha \geq 0$ and $\omega > 0\}$ and $\Theta_{\mathcal{N}} := \{\theta := (0, 0, \omega)' : \omega > 0\}$. That is, we assume that either the process is strictly stationary (the true parameter is in $\Theta_{\mathcal{S}}$), or that the process is nonstationary and, specifically, reduces to a standard random walk with i.i.d. increments (the true parameter is in $\Theta_{\mathcal{N}}$).

2.2. Estimation

As in Ling (2004) and in Klüppelberg et al. (2002), we consider quasi maximum likelihood (QML) estimation based on the auxiliary assumption of Gaussian innovations. The results given here are employed in Sections 3 and 4 in order to establish the properties of the bootstrap test. We further assume that the user-chosen optimization set employed for maximization of the likelihood function is given by $\mathcal{T} := \{\theta := (\pi, \alpha, \omega)' : -\pi_L \leq \pi \leq \pi_U, 0 \leq \alpha \leq \alpha_U, \omega_L \leq \omega \leq \omega_U\}$, with π_L, π_U, α_U, ω_L, and ω_U positive constants and $\omega_L < \omega_U$. In practice, estimation is performed imposing the non-negativity restriction $\alpha \geq 0$ while leaving π unrestricted (and ω positive).

For a time series $\{x_1, \ldots, x_n\}$, and with x_0 fixed in the statistical analysis, the Gaussian QMLE is given by

$$\hat{\theta}_n := \arg\max_{\theta \in \mathcal{T}} L_n(\theta), \; L_n(\theta) := \sum_{t=1}^{n} l_t(\theta),$$

where, for $t = 1, \ldots, n$,

$$l_t(\theta) := -\frac{1}{2} \log \sigma_t^2(\theta) - \frac{1}{2} \left(\frac{\Delta x_t - \pi x_{t-1}}{\sigma_t(\theta)} \right)^2, \qquad \sigma_t^2(\theta) := \omega + \alpha x_{t-1}^2.$$

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Theory for the QMLE under the strict stationarity assumption, that is, when the true parameter θ_0 is in $\Theta_{\mathcal{S}}$, is provided in Ling (2004) under the assumption that α_0 is *not* on the boundary (specifically, it is required that $\alpha_0 \in [\alpha_L, \alpha_U]$ with $\alpha_L > 0$), hence not covering the case where α_0 may be zero, that is, on the boundary. By employing nonstandard arguments as, for example, in Andrews (1999, 2001), see also Cavaliere et al. (2019), we generalize Ling (2004, Thm. 1) as follows:

THEOREM 1. *Suppose that $\{x_t\}$ is generated as in (1) with $\xi = 0$ and $\kappa < \infty$, and that the true parameter vector $\theta_0 \in \Theta_{\mathcal{S}}$. Then, as $n \to \infty$, $\hat{\theta}_n = (\hat{\pi}_n, \hat{\alpha}_n, \hat{\omega}_n)'$ is consistent, that is, $\hat{\theta}_n \to_p \theta_0 = (\pi_0, \alpha_0, \omega_0)'$. The asymptotic distribution of $\hat{\theta}_n$ is given by*

$$n^{1/2}(\hat{\theta}_n - \theta_0) \to_w \zeta = \left(\zeta_\pi, \zeta_\gamma\right)',$$

with $\zeta_\pi \overset{d}{=} N\left(0, \sigma_\pi^2\right)$, $\sigma_\pi^2 := 1/E\left(x_{t-1}^2/\sigma_t^2\right)$. Moreover, ζ_π is independent of the bivariate random vector $\zeta_\gamma := (\zeta_\alpha, \zeta_\omega)'$, where

(i) *for $\alpha_0 > 0$, $\zeta_\gamma \overset{d}{=} N\left(0, \Omega_{\gamma\gamma}\right)$ with $\Omega_{\gamma\gamma}$ positive definite and given in Appendix A.2;*
(ii) *for $\alpha_0 = 0$, then, with $\varrho := Ex_t^2$,*

$$\zeta_\alpha = \max\left(0, \zeta_\alpha^0\right), \text{ and } \zeta_\omega = \zeta_\omega^0 - \varrho \max\left(0, \zeta_\alpha^0\right),$$

where $\zeta_\alpha^0 \overset{d}{=} N\left(0, \sigma_\alpha^2\right)$ and $\zeta_\omega^0 \overset{d}{=} N\left(0, \sigma_\omega^2\right)$ are independent, $\sigma_\alpha^2 = \sigma_\omega^2/\delta$, $\sigma_\omega = \sqrt{\kappa}\omega_0$, and $\delta = E\left(x_t^4\right) - \left(E\left(x_t^2\right)\right)^2$.

With respect to Ling (2004), the asymptotic distribution is no longer Gaussian when $\alpha_0 = 0$ due to the restriction that $\alpha \geq 0$. As a result, the asymptotic distribution of ($n^{1/2}$ times) $\hat{\alpha}_n$ is "half-normal," that is, of the form $\zeta^+ := \max(0, \zeta)$ with ζ Gaussian. For the case of $\alpha_0 > 0$, the asymptotic distribution of ζ is as in Thm.1 in Ling (2004). Note that asymptotic normality and consistency at the $n^{1/2}$-rate is established even in cases where $E(\Delta x_t)^2 = +\infty$, due to the structure of the score of the likelihood function, see Appendix A.2 (and Jensen and Rahbek, 2004, for similar arguments in the ARCH case).

Remark 2.1. Note that the results in Theorem 1 can be generalized to the case of $\xi \neq 0$. In this case, however, see Appendix A.2, ζ_π and ζ_γ are dependent with covariance matrix $\mathrm{Cov}\left(\zeta_\pi, \zeta_\gamma\right) = \xi\Omega_{\pi\gamma} \neq 0$, with $\Omega_{\pi\gamma}$ given in Appendix A.2, equation (A. 16).

In order to discuss the large-sample behavior of the bootstrap tests, we also need to analyze the properties of the estimator under nonstationarity. These are provided in the following theorem which, like Theorem 1, is novel.

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THEOREM 2. *Suppose that $\{x_t\}$ is generated as in (1) with $\xi = 0$ and $\kappa < \infty$ and that the true parameter vector $\theta_0 \in \Theta_{\mathcal{N}}$, that is, $\pi_0 = 0$ and $\alpha_0 = 0$. Then, as $n \to \infty$, $\hat{\theta}_n \to_p \theta_0$. Moreover,*

$$diag(n, n^{3/2}, n^{1/2})(\hat{\theta}_n - \theta_0) \to_w \lambda = (\lambda_\pi, \lambda_\alpha, \lambda_\omega)',$$

where, with B and W independent standard Brownian motions,

$$\lambda_\pi := \left(\int B_u^2 \mathrm{d}u\right)^{-1} \int B \mathrm{d}B,\ \lambda_\alpha := (\lambda_\alpha^0)^+ = \max\left(0, \lambda_\alpha^0\right),$$

for

$$\lambda_\alpha^0 := \sqrt{\kappa}\left(\int B_u^4 \mathrm{d}u - \left(\int B_u^2 \mathrm{d}u\right)^2\right)^{-1}\left(\int B^2 \mathrm{d}W - \int B_u^2 \mathrm{d}u W_1\right).$$

Moreover, $\lambda_\omega = \lambda_\omega^0 - (\int B^2 \mathrm{d}u)\lambda_\alpha$, where $\lambda_\omega^0 \overset{d}{=} \sigma_\omega W_1$ and $\sigma_\omega := \sqrt{\kappa}\omega_0$.

Remark 2.2. With respect to the (strict) stationary case, we observe that the rate of convergence of the estimator varies across parameters. In particular, $\hat{\pi}_n$ converges at the rate of n, similar to the standard autoregressive case with a unit root, while the volatility parameter, $\hat{\alpha}_n$, converges at the faster rate of $n^{3/2}$. The estimator of the intercept term in the variance equation has the usual stationary, $n^{1/2}$, rate.

Remark 2.3. Although λ in Theorem 2 clearly is non-Gaussian, and thus different from the stationary case with $\alpha_0 = 0$ in Theorem 1, one can immediately observe some similarities: (i) in the expression for λ_π, the term $(\int B_u^2 \mathrm{d}u)^{-1}$ corresponds to the variance σ_π^2 of ζ_π; (ii) in λ_α^0, the term $\sqrt{\kappa}(\int B_u^4 \mathrm{d}u - (\int B_u^2 \mathrm{d}u)^2)^{-1}$ corresponds to $\sigma_a^2 = \sigma_\omega^2/\delta$ in ζ_α^0; and (iii) finally, in the expression for λ_ω, while $\lambda_\omega^0 \overset{d}{=} \zeta_\omega^0$, the loading $\int B^2 \mathrm{d}u$ corresponds to the ϱ term in ξ_ω.

Remark 2.4. Similar to the case of Theorem 1, Theorem 2 can also be modified to the asymmetric case of $\xi \neq 0$, see the discussion in Section 6.

2.3. Testing Nonstationarity

Suppose that the econometrician is interested in testing whether $\{x_t\}$ is nonstationary, against the alternative of (strict) stationarity. In a pure AR–ARCH framework, the (unit root) null hypothesis corresponds to $\pi = 0$ in equation (1). However, the DAR process can be strictly stationary even if $\pi = 0$, provided $\alpha > 0$ and $E \log|1 + \sqrt{\alpha} z_t| < 0$; hence, testing nullity of π is not alone sufficient to assess the nonstationarity of x_t. Rather, as discussed in Ling (2004), one may test the pure random walk hypothesis, as given by $\mathsf{H}_0 : \pi = 0, \alpha = 0$, against the alternative

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$\mathsf{H}_1 : \pi \neq 0, \alpha \geq 0$. The likelihood ratio test can easily be computed in the usual way as

$$LR_n := -2(L_n(\tilde{\theta}_n) - L_n(\hat{\theta}_n)), \tag{2}$$

where $\tilde{\theta}_n := (0, 0, \tilde{\omega}_n)'$, $\tilde{\omega}_n := n^{-1} \sum_{t=1}^{n} (\Delta x_t)^2$, denotes the restricted estimator of θ, that is, $\tilde{\theta}_n := \arg\max_{\theta \in \mathcal{T}_0} L_n(\theta)$, where $\mathcal{T}_0 := \{\theta := (0, 0, \omega)' : \omega_L \leq \omega \leq \omega_U\}$. Now, the asymptotics in the previous Theorem 1 obviously break down when $\theta_0 \in \Theta_{\mathcal{N}}$, see Theorem 2. In this case, Kluppenberg et al. (2002) establish the following result for the LR test statistic in (2).

THEOREM 3. *Suppose that $\{x_t\}$ is generated as in (1) with $Ez_t^4 < \infty$ and that the true parameter vector $\theta_0 \in \Theta_{\mathcal{N}}$, that is, $\pi_0 = 0$ and $\alpha_0 = 0$. Then, as $n \to \infty$, $LR_n \to_w \mathcal{LR}_\infty(\kappa)$, where*

$$\mathcal{LR}_\infty(\kappa) = \frac{\kappa}{2} \left(\max\left(0, \frac{\int B_u^2 \mathrm{d}u W_1 - \int B_u^2 \mathrm{d}W_u}{(\int B_u^4 \mathrm{d}u - (\int B_u^2 \mathrm{d}u)^2)^{1/2}}\right)\right)^2 + \frac{(\int B_u \mathrm{d}B_u)^2}{\int B_u^2 \mathrm{d}u}, \tag{3}$$

where B and W are as in Theorem 2.

Some remarks follow.

Remark 2.5. Notice that since B and W are independent, conditionally on B, we have in particular that

$$\frac{W_1 \int B_u^2 \mathrm{d}u - \int B_u^2 \mathrm{d}W_u}{(\int B_u^4 \mathrm{d}u - (\int B_u^2 \mathrm{d}u)^2)^{1/2}} \overset{d}{=} \frac{N\left(0, \int (B_u^2 - (\int B_u^2 \mathrm{d}u))^2 \mathrm{d}u\right)}{(\int (B_u^2 - (\int B_u^2 \mathrm{d}u))^2 \mathrm{d}u)^{1/2}} \overset{d}{=} N(0, 1).$$

This implies that the first term in (3) is distributed as $\frac{\kappa}{2} (\max(0, N(0, 1)))^2$, that is, $\frac{\kappa}{2}$ times the half-χ_1^2 distribution.

Moreover, it is independent of the second term, $(\int B^2 \mathrm{d}u)^{-1} (\int B \mathrm{d}B)^2$, which is a squared Dickey–Fuller distribution. Should the condition $\xi = 0$ fail to hold, both the half χ_1^2 property and the independence of the two terms in (3) would no longer hold true; see also Section 6.

Remark 2.6. The distribution in (3) is nonpivotal, since it depends on κ. A consistent estimator of this quantity can be constructed by using the unrestricted residuals, as $\hat{\kappa}_n := n^{-1} \sum_{t=1}^{m} (1 - \hat{z}_t^2)^2$, where $\hat{z}_t := \hat{\varepsilon}_t / \hat{\sigma}_t$ for $\hat{\varepsilon}_t := \Delta x_t - \hat{\pi}_n x_{t-1}$, $\hat{\sigma}_t^2 := \hat{\omega}_n + \hat{\alpha}_n x_{t-1}^2$. An estimator $\tilde{\kappa}_n$, which imposes the null hypothesis may be constructed using the restricted residuals, $\tilde{z}_t := \tilde{\omega}_n^{-1/2} \Delta x_t$. However, this estimator overestimates κ when the null hypothesis does not hold, hence reducing the power of an asymptotic test based on $\mathcal{LR}_\infty(\tilde{\kappa}_n)$. □

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3. BOOTSTRAPPING THE ASYMPTOTIC DISTRIBUTION UNDER THE NULL HYPOTHESIS

3.1. Preliminaries and Bootstrap Algorithms

The classical requirement of any bootstrap implementation is consistent estimation of the asymptotic null distribution of the reference test statistic when the null hypothesis is true. Specifically, and taking the LR_n test statistic to illustrate, consider a bootstrap analog, say LR_n^*, which is a function of the original sample and of a vector of bootstrap innovations, say $\eta_1^*, \ldots \eta_m^*$, defined jointly with the original data on a possibly expanded probability space. With $G_n^*(\cdot) := P^*\left(LR_n^* \leq x\right)$ denoting the conditional distribution of LR_n^* given the original data, this requires that, *under the null hypothesis*, $G_n^*(\cdot) \to_p G_\infty(\cdot)$, where G_∞ denotes the cdf of $\mathcal{LR}_\infty(\kappa)$, the asymptotic distribution of LR_n under the null; see equation (3). That is, $LR_n^* \overset{w^*}{\to}_p \mathcal{LR}_\infty(\kappa)$. If, additionally, $G_\infty(\cdot)$ is continuous, then by Pólya's theorem, proximity of $G_n^*(\cdot)$ to $G_\infty(\cdot)$ holds in the sup norm,

$$\sup_{x\in\mathbb{R}} |G_n^*(x) - G_\infty(x)| \to_p 0,$$

and the bootstrap p-value, given by

$$p_n^* := 1 - G_n^*(LR_n),$$

is asymptotically uniformly distributed, that is, $p_n^* \to_w U[0,1]$. This allows to construct a bootstrap test with the correct asymptotic size at any nominal significance level. In addition, it is crucial to analyze the behavior of the bootstrap statistic under the alternative hypothesis, which is often overlooked in applications. We discuss this issue in Section 4.

Two main approaches can be given in order to define the bootstrap statistic LR_n^*. The first, the "restricted bootstrap," is based on estimation of the original model with the null hypothesis imposed; that is, with $\pi = \alpha = 0$. In this case, the bootstrap statistic mimics the original test statistic and tests the restriction $\pi = \alpha = 0$ on the bootstrap data. The second, the "unrestricted bootstrap," uses the unrestricted parameter estimates $\hat{\pi}_n, \hat{\alpha}_n$ to generate the bootstrap data, and the bootstrap statistic is based on testing $\pi = \hat{\pi}_n$ and $\alpha = \hat{\alpha}_n$ on the bootstrap data; see, for example, Hall (1992). We introduce the restricted bootstrap first.

Restricted (i.i.d.) Bootstrap:

(i) Estimate model (1) using Gaussian QML under the null hypothesis, yielding the estimates $\tilde{\theta}_n := (0, 0, \tilde{\omega}_n)'$, together with the corresponding restricted QML residuals, $\tilde{\varepsilon}_t := \Delta x_t$ and $\tilde{z}_t := \tilde{\omega}_n^{-1/2}\tilde{\varepsilon}_t$, as defined above.

(ii) Standardize the residuals as

$$\tilde{z}_{s,t} := \frac{\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t}{(n^{-1}\sum_{t=1}^n (\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t)^2)^{1/2}}$$

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and construct the bootstrap innovations using the i.i.d. bootstrap resampling scheme; that is, $z_t^* := \tilde{z}_{s,\eta_t^*}$, where η_t^*, $t = 1, \ldots, n$ is an i.i.d. sequence of discrete uniform distributions on $\{1, 2, \ldots, n\}$.

(iii) Construct the bootstrap sample $\{x_t^*\}$ from the recursion

$$\Delta x_t^* = \varepsilon_t^*, \quad \varepsilon_t^* := \sigma_t^* z_t^*, \quad \sigma_t^{*2} = \tilde{\omega}_n, t = 1, \ldots, n, \tag{4}$$

with the n bootstrap errors z_t^* generated in Step (ii) and with initial values $x_0^* = x_0$.

(iv) Using the bootstrap sample, $\{x_t^*\}$, compute the bootstrap test statistic LR_n^*. Define the corresponding p-value as $p_n^* := 1 - G_n^*(LR_n)$ with $G_n^*(\cdot)$ denoting the conditional (on the original data) cdf of LR_n^*.

(v) The restricted bootstrap test of H_0 at level ζ rejects if $p_n^* \leq \zeta$.

There are many variants of the restricted bootstrap as exemplified in the following remarks.

Remark 3.1. In the definition above, the length of the bootstrap sample equals the length of the original sample, n. A different sample size, say $m < n$, could be used in order to form the bootstrap sample. This is the so-called "m out of n" bootstrap, which (under proper conditions on m as n increases, such as $m^{-1} + mn^{-1} \to 0$) has been proved to be asymptotically valid in certain cases where bootstraps based on n observations fail; see Politis, Romano and Wolf (1999) and the references therein. However, for the "m out of n" bootstrap, while mathematically appealing in the derivations of the asymptotic theory, the choice of m is "delicate" (see Davison et al., 2003), and, moreover, in general, it does not deliver satisfactory finite sample results. As pointed out by the Editor, a further issue of the "m out of n" bootstrap (and, in general, of subsampling) is that it can lead to initialization problems in nonstationary settings, which may not be easy to address.

Remark 3.2. The bootstrap shocks in Step 2 are based on i.i.d. resampling (i.e., with replacement) from the standardized residuals. Different bootstrap schemes could in principle be used. For instance, the so-called wild bootstrap (Wu, 1986; Liu, 1988; Mammen, 1993) generates the bootstrap innovations as the (conditionally) independent sequence $z_t^* := \tilde{z}_{s,t} w_t^*$, where w_t^* is i.i.d.(0,1) with bounded fourth-order moments. Alternatively, resampling without replacement of the $\tilde{z}_{s,t}$'s could be employed, leading to the permuted bootstrap sample $z_t^* = \tilde{z}_{s,\pi^*(t)}$, $t = 1, \ldots, n$, where $\{\pi^*(1), \ldots, \pi^*(n)\}$ is a (uniformly distributed) random permutation of $\{1, \ldots, n\}$ (Cavaliere, Georgiev and Taylor, 2016; Cavaliere, Nielsen and Rahbek, 2020). Finally, a fully parametric bootstrap could be obtained by generating z_t^* as i.i.d. from any prespecified zero mean, unit variance, distribution.

Remark 3.3. In practice, the cdf G_n^* required in Step (iv) of Algorithm 1 can only be approximated through numerical simulation. As is standard, this requires generating B (conditionally) independent bootstrap statistics, $LR_{n:b}^*$, $b = 1, \ldots, B$,

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computed as above. The approximated bootstrap p-value for LR_n, is then computed as $\tilde{p}_n^* := B^{-1}\sum_{b=1}^{B}\mathbb{I}(LR_{n:b}^* > LR_n)$, and is such that $\tilde{p}_n^* \xrightarrow{a.s.} p_n^*$ as $B \to \infty$. For the choice of B, see, inter alia, Andrews and Buchinsky (2000) and Davidson and MacKinnon (2000). □

The key feature of the restricted bootstrap is that the parameter estimates used in constructing the bootstrap sample data are obtained under the restriction of the null hypothesis, H_0. As discussed, for instance in Hall (1992), in the statistics literature, it is often the case that in bootstrap implementations parameters are estimated without imposing the null hypothesis, and to subsequently calculate a bootstrap test statistic for the hypothesis $\theta = \hat{\theta}_n$, that is, the hypothesis that θ equals the unrestricted estimate. Formally, this corresponds to the unrestricted bootstrap, as defined through the following steps.

Unrestricted (i.i.d.) Bootstrap:

(i) Estimate model (1) using Gaussian QML without imposing the null hypothesis, yielding the estimates $\hat{\theta}_n := (\hat{\pi}_n, \hat{\alpha}_n, \hat{\omega}_n)'$, together with the corresponding unrestricted QML residuals, $\hat{\varepsilon}_t := \Delta x_t - \hat{\pi}_n x_{t-1}$ and $\hat{z}_t := (\hat{\omega}_n + \hat{\alpha}_n x_{t-1}^2)^{-1/2}\hat{\varepsilon}_t$, as defined above.

(ii) Standardize the residuals as

$$\hat{z}_{s,t} := \frac{\hat{z}_t - n^{-1}\sum_{t=1}^{n}\hat{z}_t}{(n^{-1}\sum_{t=1}^{n}(\hat{z}_t - n^{-1}\sum_{t=1}^{n}\hat{z}_t)^2)^{1/2}}$$

and construct the bootstrap innovations using the i.i.d. bootstrap resampling scheme; that is, $z_t^* := \hat{z}_{s,\eta_t^*}$, where η_t^*, $t = 1, \ldots, n$ is an i.i.d. sequence of discrete uniform distributions on $\{1, 2, \ldots, n\}$.

(iii) Construct the bootstrap sample $\{x_t^*\}$ from the recursion

$$\Delta x_t^* = \hat{\pi}_n x_{t-1}^* + \varepsilon_t^*, \quad \varepsilon_t^* := \sigma_t^* z_t^*, \quad \sigma_t^{*2} = \hat{\omega}_n + \hat{\alpha}_n (x_{t-1}^*)^2, \, t = 1, \ldots, n,$$

with the n bootstrap errors z_t^* generated in Step (ii) and with initial values $x_0^* = x_0$.

(iv) Using the bootstrap sample, $\{x_t^*\}$, compute the bootstrap test statistic LR_n^* for the (auxiliary) null hypothesis $\pi = \hat{\pi}_n, \alpha = \hat{\alpha}_n$. Define the corresponding p -value as $p_n^* := 1 - G_n^*(LR_n)$ with $G_n^*(\cdot)$ denoting the conditional (on the original data) cumulative distribution function (cdf) of LR_n^*.

(v) The unrestricted bootstrap test of H_0 at level ζ rejects if $p_n^* \leq \zeta$.

The logic behind the unrestricted bootstrap is to avoid potential power losses that the restricted bootstrap test may experience because of incorrectly imposing a false null hypothesis when the null does not hold. There are, however, many cases where the unrestricted bootstrap fails to mimic the asymptotic distribution, whereas the restricted bootstrap does not. Among those, two cases are extremely relevant for the testing problem considered here. The first is the case of bootstrapping when data have unit roots—as it happens in the DAR model when $\pi = 0$. The second

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is the case where a parameter lies on the boundary of the parameter space—which again appears in our testing problem as $\alpha = 0$ is a boundary point under the maintained hypothesis that $\alpha \geq 0$. We briefly discuss these two examples in the following.

Example 1. (Unit roots and unrestricted bootstrap). *Consider as in Basawa et al. (1991) the first-order autoregression with a unit root,*

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t,\ \pi = 0,$$

ε_t i.i.d. N(0, ω), $x_0 = 0$ and $t = 1, \ldots, n$. Let J_c denote an Ornstein–Uhlenbeck process with mean reversion parameter c (such that $c = 0$ corresponds to a standard Brownian motion) and set $\tau(c) := \int J_c \mathrm{d}J_c / \int J_c^2 \mathrm{d}u$. The QMLE of π is the least-squares estimator, $\hat{\pi}_n = \sum_{t=1}^n \Delta x_t x_{t-1} / \sum_{t=1}^n x_{t-1}^2$, which satisfies

$$\tau_n := n\hat{\pi}_n \to_w \tau_\infty := \tau(0), \tag{5}$$

see Phillips (1987) and the references therein. Now, consider a (fully parametric) unrestricted bootstrap, based on the recursion

$$\Delta x_t^* = \hat{\pi}_n x_{t-1}^* + \varepsilon_t^*, \tag{6}$$

for $t = 1, \ldots, n$, initialized at $x_0^* = x_0$, and with ε_t^* i.i.d. N(0, 1). With $\hat{\pi}_n^*$, the bootstrap (least-squares) estimator, $\hat{\pi}_n^* = \sum_{t=1}^n \Delta x_t^* x_{t-1}^* / \sum_{t=1}^n (x_{t-1}^*)^2$, the bootstrap analog of τ_n is defined as $\tau_n^* := n\hat{\pi}_n^*$. Unfortunately, despite $\hat{\pi}_n$ being superconsistent, τ_n^* fails to mimic the asymptotic distribution in (5). Essentially, because $n\hat{\pi}_n = O_p(1)$ rather than $o_p(1)$, the bootstrap sample (normalized by the usual rate $n^{-1/2}$) behaves, in large samples, as an Ornstein–Uhlenbeck process with random drift parameter, rather than as a Brownian motion. To see why, replace $\hat{\pi}_n$ in (6) by a sequence π_n such that $n\pi_n \to v$. Then, by extending the results in Phillips (1987) to the bootstrap case, we have that (conditionally on the original data), $\tau_n^* := n(\hat{\pi}_n^* - \hat{\pi}_n)$ is asymptotically distributed as $\tau(v)$ (see Basawa et al., 1991). In our case, $\tau_n := n\hat{\pi}_n \to_w \tau_\infty$ and, as a result, the bootstrap statistic has a random distribution function, even for $n \to \infty$, given by $\tau(\tau_\infty)$. More specifically, it can be proved that

$$\begin{aligned} P^*\left(\tau_n^* \leq x\right) &= P\left(\tau_n^* \leq x | \tau_n\right) = P\left(n(\hat{\pi}_n^* - \hat{\pi}_n) \leq x | \tau_n\right) \\ &\to_w P\left(\int J_{\tau_\infty} \mathrm{d}J_{\tau_\infty} / \int J_{\tau_\infty}^2 \mathrm{d}\, u \leq x \,\middle|\, \tau_\infty\right). \end{aligned}$$

That is, the limiting distribution can be written in terms of an Ornstein–Uhlenbeck process with a random drift, distributed as τ_∞, that is, as a Dickey–Fuller distribution. Similar arguments are applied in Cavaliere et al. (2015), see also the next section, and in terms of random bootstrap measures in Cavaliere and Georgiev (2019) and Boswijk et al. (2019).

Example 2. (Unit roots and the restricted bootstrap). *Although the unrestricted bootstrap fails to mimic the unit root distribution, the restricted bootstrap does not; see Cavaliere and Taylor (2008), Cavaliere and Taylor (2009a), and*

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Cavaliere et al. (2012) for the multivariate case. Specifically, by imposing the unit root on the bootstrap sample, that is, by setting

$$\Delta x_t^* = \varepsilon_t^*,$$

where ε_t^* *are i.i.d.* $N(0,1)$ *and* $t = 1, \ldots, n$, *it is guaranteed that* $\tau_n^* := n\hat{\pi}_n^* \xrightarrow{w^*}_p \tau\,(0)$, *in probability.*

Alternatively, it follows by standard arguments that one may use an "m out of n" version of the unrestricted bootstrap which, by considering samples of size $m = o(n)$ *ensures that* $m\hat{\pi}_n = o_p\,(1)$ *as* $m \to \infty$, *which is sufficient for* $\tau_m^* := m\hat{\pi}_m^* \xrightarrow{w^*}_p \tau\,(0)$, *in probability. However, as already emphasized, while the asymptotic arguments are mathematically appealing, in practice the "m out of n" bootstrap in this case does not have adequate finite sample properties.*

Example 3. (Boundary problems and the unrestricted bootstrap). *The standard unrestricted bootstrap is also known to fail when (some of) the parameters lie on the boundary of the parameter space. Consider, as in Cavaliere et al. (2017), see also Andrews (2000), the Gaussian ARCH model,*

$$x_t = \sqrt{\omega + \alpha x_{t-1}^2}\, z_t,$$

with z_t *i.i.d. N(0,1). Moreover, the optimization set is given by* $\mathcal{T}_\alpha = \{\alpha : \alpha \in [0, \alpha_U]\}$, $\alpha_0 \in \Theta_{\mathcal{S}_\alpha}$, *with* $\Theta_{\mathcal{S}_\alpha} = \left\{\alpha : E\log\left(\alpha z_t^2\right) < 0\right\}$, *while* ω *is kept fixed for simplicity here. We consider here testing* $\alpha_0 = 0$ *by the likelihood ratio statistic,* LR_n. *As in Theorem 3 for the DAR, the MLE* $\hat{\alpha}_n$ *satisfies for* $\alpha_0 > 0$,

$$\sqrt{n}(\hat{\alpha}_n - \alpha_0) \to_w \tfrac{\kappa}{\delta}\zeta,\ \zeta \sim N\,(0,1)\,,$$

$\delta = V\left(x_t^2\right)$, *and the associated LR statistic for* $\alpha = \alpha_0$ *is asymptotically* χ_1^2 *(times* $\frac{\kappa}{2}$*).*

In contrast, if $\alpha_0 = 0$,

$$\sqrt{n}(\hat{\alpha}_n - \alpha_0) \to_w \alpha_\infty = \max\{0, \zeta\},$$

and the associated LR statistic for $\alpha = 0$ *has an asymptotic distribution given by,*

$$LR_n \to_w \tfrac{\kappa}{2}\zeta^2 1\,(\zeta \geq 0) = \tfrac{\kappa}{2}\max\{0, \zeta\}^2.$$

Now, consider instead the (parametric) unrestricted bootstrap sample, as given by $x_t^* = \sqrt{\omega + \hat{\alpha}_n x_{t-1}^{*2}}\, z_t^*$, *with* z_t^* *i.i.d.* $N\,(0,1)$ *(independent of the original data), and the associated bootstrap statistic,* LR_n^*, *for the (bootstrap) hypothesis that* α *equals the bootstrap true value,* $\hat{\alpha}_n$. *With* $\zeta^* \sim N\,(0,1)$ *and independent of* ζ, *we conjecture from the theory in Cavaliere et al. (2019) that, conditionally on the original data, the asymptotic distribution of the* LR_n^* *statistic has a random limit,*

$$\tfrac{\kappa}{2}\left(\zeta + \alpha^*\right)^2 1\left(\zeta + \alpha^* \geq 0\right)\Big|\ \alpha^*,$$

where α^* *is a function of* α_∞ *given above. Thus, as expected, the unrestricted bootstrap fails to mimic the null asymptotic distribution.* □

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3.2. Bootstrap Validity in the DAR Model

Testing the pure random walk hypothesis in the DAR framework features the complications discussed in Examples 1 and 3. First, since the null hypothesis implies a unit root in the data, a bootstrap which does not impose the unit root on the bootstrap sample is likely to fail to be first-order valid. Second, since the null hypothesis implies a parameter (α) on the boundary of the parameter space, a bootstrap which does not account for this feature may display a random limiting distribution. The unrestricted bootstrap is neither imposing the unit root nor restricting α to be on the boundary of the parameter space; hence, it fails to be first-order valid. Conversely, under mild conditions the restricted bootstrap is able to replicate the correct null limiting distribution of the *LR* test when the null hypothesis holds true. This is proved in the next theorem.

THEOREM 4. *Under the conditions of Theorem 3, provided* $Ez_t^8 < \infty$, *as* $n \to \infty$, *the restricted bootstrap LR statistic satisfies*

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa).$$

The logic behind the proof of bootstrap validity under the null hypothesis is the following. When the restricted bootstrap is employed, the sample bootstrap is generated as

$$\Delta x_t^* = \varepsilon_t^* = \hat{\omega}_n z_t^*.$$

Conditionally on the original data, the bootstrap score, see Appendix A, depends on the vector $\left(z_t^*, z_t^{*2} - 1\right)$, which needs to satisfy a (bootstrap) functional central limit theorem of the form,

$$\mathcal{Z}_n^*(\cdot) := n^{-1/2} \sum_{t=1}^{\lfloor n\cdot \rfloor} \left(z_t^*, z_t^{*2} - 1\right) \xrightarrow{w^*}_p \left(B^*, \sqrt{\kappa} W^*\right) \tag{7}$$

with B^* and W^* two independent standard Brownian motions. It is therefore crucial to control what conditions are needed for (7) to hold, given that z_t^* is a zero-mean (conditionally) i.i.d. sample from the centered standardized residuals, $\tilde{z}_{s,t}$. This requires checking whether the (conditional) variance of $\mathcal{Z}_n^*(\cdot)$ converges to $\mathrm{diag}(1, \kappa)$ and whether the Lindeberg condition holds. As shown in the Appendix, these requirements hold provided z_t has bounded eighth-order moments. Notice that it is usually the case that in order to establish the asymptotic properties of the bootstrap, further conditions are required when compared with nonbootstrap asymptotics; the DAR case is not an exception. Notice also that the eighth-order moment condition simplifies considerably some steps of the proof using Chebychev-type and more general inequalities (for early use of this approach in time series models, see Bühlmann, 1997, Swensen, 2003, Goncalves and Kilian, 2004). It is likely that this condition can be relaxed to $4 + \delta$ moments ($\delta > 0$), for example, by using Marcinkiewicz–Zygmund-type law of large numbers, as

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done by Liu (1988) for location and regression models. The Monte Carlo results in Section 5 seems to support this conjecture.

It is worth emphasizing that for the DAR model, the limiting distribution of the LR_n test statistic for reduction to a pure random walk features a nuisance parameter, namely the constant κ. This makes the testing problem based on asymptotic inference convoluted, since the practitioner needs first to estimate κ using a proper (consistent) estimator, say $\hat{\kappa}$, and then using Monte Carlo methods to simulate the quantiles of limiting distribution $\mathcal{LR}_\infty(\hat{\kappa})$. The bootstrap allows to circumvent this problem, as it replicates the correct limiting distribution without the need of plug-in methods. This is an example of a classic application of the bootstrap to time series data, where it is used to retrieve quantiles from an asymptotic distribution which depends on a (possibly infinite dimensional) vector of nuisance parameters, see the following example.

Example 4. (Nonstationary volatility). *A classic instance of a limiting distribution depending on a nuisance parameter is the case of "nonstationary" volatility, see Boswijk et al. (2019). In this case, in the simplest form, the innovations of an econometric model can be represented as* $\varepsilon_t = \sigma_t z_t$, *where* z_t *is an i.i.d. finite variance sequence and* $\sigma_t = h(t/n)$, *where h is a bounded function satisfying some regularity conditions (e.g., it is càdlàg; see Cavaliere, 2004, and Boswijk et al., 2017 and 2019). The partial sum process associated to* ε_t *delivers the following result:*

$$S_n(\cdot) := \frac{1}{n^{1/2}} \sum_{t=1}^{\lfloor n\cdot \rfloor} \varepsilon_t \xrightarrow{w} M(\cdot) := \int_0^{\cdot} h(u)\, \mathrm{d}B(u),$$

where B is a Brownian motion and M is a continuous-time martingale with covariance kernel given by $Cov\left(M(s), M\left(s'\right)\right) = \int_0^{\min\{s,s'\}} h(u)^2\, \mathrm{d}u$. *Limit distributions of estimators and test statistics usually depend on such a covariance kernel, which is unknown in practice. Although consistent estimators could be constructed (see e.g. Cavaliere and Taylor, 2007), the bootstrap can in general automatically replicate the limiting functional M. That is, consider a vector of residuals* $\hat{\varepsilon}_t$ *satisfying* $n^{-1}\sum_{t=1}^{n}(\hat{\varepsilon}_t^2 - \varepsilon_t^2) = o_p(1)$, *and construct the bootstrap errors using the "wild" bootstrap as*

$$\varepsilon_t^* := \hat{\varepsilon}_t w_t^*,\ t = 1, \ldots, n,$$

where the w_t*'s are i.i.d.* $N(0,1)$. *Then, it holds, as* $n \to \infty$, *see Boswijk et al. (2017 and 2019),*

$$S_n^*(\cdot) := \frac{1}{n^{1/2}} \sum_{t=1}^{\lfloor n\cdot \rfloor} \varepsilon_t^* \xrightarrow{w^*}_p M(\cdot) \tag{8}$$

and hence the wild bootstrap replicates the same limiting distribution of the original functional S_n. □

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4. THE BEHAVIOR OF THE BOOTSTRAP UNDER THE ALTERNATIVE HYPOTHESIS

4.1. Preliminaries and Bootstrap Consistency

The analysis of the large sample properties of the bootstrap test statistic under the alternative hypothesis is a key requirement for a correct implementation of the bootstrap. Unfortunately, as it will be exemplified later in this section, this step is in general more involved than just proving validity under the null hypothesis.

Ideally, one would aim that, under the alternative hypothesis, LR_n^* is (asymptotically) distributed as the LR_n limit under the null. This would require that, as $n \to \infty$,

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa) \tag{9}$$

also when H_0 does not hold.

This immediately implies that the (bootstrap) test is consistent: if LR_n diverges to $+\infty$ under the alternative hypothesis then, with G_n^* denoting the cdf of LR_n^* conditional on the original data, it holds that the bootstrap p-value satisfies $p_n^* := 1 - G_n^*(LR_n) \to_p 0$. Moreover, in large samples, a test based on the (conditional) quantiles of LR_n^* would have power approximately equal to the size-adjusted power of the (asymptotic) test based on the quantiles of $\mathcal{LR}_\infty$.

In fact, a weaker result that implies bootstrap consistency can be used in case (9) does not hold. Specifically, a sufficient condition for the bootstrap p-value to shrink to zero under the alternative is (again, provided $LR_n \to \infty$ under the alternative hypothesis)

$$LR_n^* = O_p^*(1), \text{ in probability,} \tag{10}$$

or the even weaker result that

$$LR_n^* = o_p^*(LR_n), \text{ in probability.} \tag{11}$$

In the first case, the bootstrap test statistic is bounded in probability, which implies consistency of the bootstrap test at the usual rate. In the second case, both the bootstrap and the original test statistics diverge to $+\infty$. However, the fact that the conditional quantiles of LR_n^* diverge at a slower rate implies consistency of the bootstrap test. This implies that in both cases the power of the bootstrap test converges to unity as the sample size increases.

Two simple examples are now given.

Example 5. (ARCH | Boundary and restricted bootstrap). *In Example 3, unrestricted bootstrap based testing for* $\mathsf{H}_0 : \alpha = 0$ *was discussed in the ARCH model given by,*

$$x_t = \sigma_t z_t, \quad \sigma_t^2 = \omega + \alpha x_{t-1}^2, \quad \theta = (\alpha, \omega)'.$$

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Recall furthermore that the likelihood ratio statistic LR_n has the asymptotic limiting distribution as given by,

$$\mathcal{LR}_\infty(\kappa) = \frac{\kappa}{2}(\zeta^+)^2 = \frac{\kappa}{2}\max\{0,\zeta\}^2,$$

with ζ a $N(0,1)$ random variable. Consider here the restricted bootstrap based on i.i.d. resampling of the (standardized) restricted residuals proposed in Cavaliere et al. (2017), hereafter. With $\tilde{\theta}_n := (\tilde{\omega}_n, 0)'$ denoting the restricted (QML) estimator, the bootstrap data are given by

$$x_t^* := \sqrt{\tilde{\omega}_n} z_t^*, \tag{12}$$

with z_t^* sampled with replacement from the standardized residuals from restricted estimation, given by $\tilde{z}_t^s := (\tilde{z}_t - \bar{\tilde{z}}_n)/(n^{-1}\sum_{t=1}^n (\tilde{z}_t - \bar{\tilde{z}}_n)^2)^{1/2}$, $\bar{\tilde{z}}_n := n^{-1}\sum_{t=1}^n \tilde{z}_t$, with $\tilde{z}_t := x_t/\sqrt{\tilde{\omega}_n}$. The bootstrap shocks $\{z_t^* : t \le n\}$ are an i.i.d. sample from $\tilde{z}_t^s$, $t = 1,\ldots,n$, such that, conditionally on the original data, $E^*\left(z_t^*\right) = 0$ and $V^*\left(z_t^*\right) = 1$. Cavaliere et al. (2017, Thm. 1) show that under the null hypothesis, the bootstrap QLR statistic, say LR_n^*, satisfies

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa), \tag{13}$$

hence mimicking the correct asymptotic null distribution. However, if the null hypothesis does not hold, result (13) may no longer hold. Essentially, the reason is that the unrestricted estimator $\tilde{\omega}_n$ equals $n^{-1}\sum_{t=1}^n x_t^2$, which may even diverge under the stated assumptions. For instance, while under the null hypothesis $x_t = \omega^{1/2} z_t$, which implies that also $\{x_t : t \ge 1\}$ has finite fourth-order moments, under the alternative hypothesis x_t may have infinite fourth-order moments. If, additionally, it is assumed that x_t has finite fourth-order moments, such that $\kappa^\dagger := E(x_t^4)/(E(x_t^2))^2 - 1 < \infty$, by Thm. 1 in Cavaliere at al. (2017) it follows that under the alternative,

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa^\dagger),$$

such that $LR_n^* = O_p^*(1)$, in probability. Hence, while as shown in Example 3, the unrestricted bootstrap is invalid, the restricted is. Finally, note that when $\alpha_0 \neq 0$ the constant $\kappa^\ddagger > \kappa$, hence implying a potential power loss of the bootstrap test with respect to the asymptotic test.

Example 6. (Hypothesis testing on the cointegrating vectors). *Consider a p-dimensional VAR process with r cointegrating relations, as given by*

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t, \quad \pi = \alpha\beta' \quad (t = 1,\ldots,n), \tag{14}$$

with $\{\varepsilon_t\}$ independent and identically distributed (i.i.d.) with mean zero and covariance matrix Ω, and where the initial value x_0 is fixed in the statistical analysis. Furthermore, assume that the so-called "I(1, r) conditions" holds; that is, (a) the characteristic polynomial associated with (14) has $p - r$ roots equal to 1 and all other roots outside the unit circle, and (b) α and β have full column

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rank r. Under these conditions, x_t is $I(1)$ with cointegration rank r, such that the cointegrating relations $\beta' x_t$ are stationary. We want to test the null hypothesis $H_0 : \beta = \tau$, where τ a known $p \times r$ matrix of full column rank r. To this aim, it is customary to consider the LR test of Johansen (1996), which rejects H_0 when the associated LR statistic LR_n is large, with LR_n asymptotically $\chi^2_{p(p-r)}$ distributed. Now, consider a restricted bootstrap for H_0, as initially proposed in Fachin (2000), Gredenhoff and Jacobson (2001) and later discussed in Fachin and Omtzigt (2006). This bootstrap requires estimation of (14) under H_0 and then use the corresponding (restricted) estimates $\tilde{\alpha}_n$ and τ to generate the bootstrap sample as

$$\Delta x_t^* = \tilde{\alpha}_n \tau' x_{t-1}^* + \varepsilon_t^*, \tag{15}$$

where the bootstrap shocks ε_t^* are obtained by resampling (after recentering) from the restricted residuals, $\tilde{\varepsilon}_t := \Delta x_t - \tilde{\alpha}_n \tau' x_{t-1}$. Under H_0, consistency of $\tilde{\alpha}_n$ implies, along with a bootstrap (functional) CLT for $\{\varepsilon_t^*\}$, that the bootstrap LR statistic, say LR_n^*, satisfies

$$LR_n^* \xrightarrow{w^*}_p \chi^2_{p(p-r)}.$$

Hence, the bootstrap mimics the correct asymptotic distribution under the null. However, as proved in Cavaliere et al. (2015), the same result does not hold when H_0 is false. Intuitively, this is the case because when H_0 is false, $\tau' X_{t-1}$ is no longer stationary, and hence the restricted estimator $\tilde{\alpha}_n$ is based on the unbalanced regression of Δx_t (stationary) on $\tau' x_{t-1}$ (nonstationary in $p - r^*$ directions, with $r^* < r$). This implies that $\tilde{\alpha}_n \tau'$, properly normalized, does not converge to a constant but, rather, to a stochastic matrix of reduced rank r^*, see Cavaliere et al., 2015, proposition 1. As a consequence, the bootstrap estimator of β is no longer mixed Gaussian (as it is under the null hypothesis) and the statistic LR_n^* has a random limiting distribution which differs from the target χ^2 distribution. However, it still holds that $LR_n^* = O_p^*(1)$, in probability, as in (10), hence implying that the bootstrap test is consistent.

Example 7. (Bootstrap financial bubbles). *Phillips et al. (2011) consider testing for an explosive bubble regime, based on the supremum of a set of recursive right-tailed DF test statistics, τ_n. Although Harvey et al. (2016) show that the restricted (Wild) bootstrap statistic τ_n^* mimics the right limiting distribution under the null hypothesis, this result does not hold under the alternative; neither does it hold that $\tau_n^* = O_p^*(1)$, in probability. Rather, Harvey et al. (2016) show that $\tau_n^* = O_p^*\left(n^{1/2}\right)$, in probability and hence both the original and the bootstrap statistics diverge to $+\infty$. But since the bootstrap statistic diverges at a polynomial rate $n^{1/2}$ while the original statistic diverges at the exponential rate $n^{1/2}(1+\delta_1)^{n(\tau_2-\tau_1)}$, see Thm. 3 in Harvey et al. (2016), the bound in (11) applies and the bootstrap test rejects with probability tending to one as n diverges.* □

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4.2. On Consistency of the Boostrap for the DAR Model

Despite the restricted bootstrap correctly estimating the null asymptotic distribution under the null hypothesis, its performance under the alternative is not at all straightforward to establish. This is because, under the alternative hypothesis of strict stationarity, the restricted residuals $\tilde{z}_t$ are no longer close enough to the true innovations, z_t, and do not share the same properties in terms of moments. Consequently, the bootstrap score and information may have different asymptotic properties with respect to their sample analogs. Intuitively, this happens because while under the null hypothesis, $\tilde{z}_t \approx z_t$, under the alternative hypothesis $\tilde{z}_t = \tilde{\omega}_n^{-1/2}\Delta x_t$, where x_t may not possess finite fourth order moments (take, for instance, the case where $\alpha + (1+\pi)^2 = 1$ with $\pi \neq 0$, such that x_t is strictly stationary and ergodic but $Ex_t^2 = +\infty$).

More precisely, recall that a first requirement for the asymptotic result in Theorem 4 is to assess whether the bootstrap functional CLT (FCLT) in (7) holds, with z_t^* (conditionally on the original data) i.i.d. from the centered standardized residuals, $\tilde{z}_{s,t} := (n^{-1}\sum_{t=1}^n(\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t)^2)^{-1/2}(\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t)$. In terms of z_t^*, conditions for

$$n^{-1/2}\sum_{t=1}^{[n\cdot]} z_t^* \xrightarrow{w^*}_p B^*(\cdot)$$

with B^* a standard Brownian motion, are: (i) $E^* z_i^* = 0$, (ii) $E^*(z_i^*)^2 = n^{-1}\sum_{t=1}^n \tilde{z}_{s,t}^2 \to_p 1$, and (iii) a Lindeberg condition. The complication here is that under the alternative it no longer holds that $\tilde{z}_{s,t}$ is close to z_t, as it happens under the null. In contrast, $\tilde{z}_{s,t}$ is close to Δx_t (properly standardized). Although (i) and (ii) are simple to verify, the Lindeberg condition in (iii) requires further restrictions. In particular, by Lemma B.1 in Cavaliere et al. (2017) (iii) holds provided Δx_t has bounded fourth-order moments. Similarly, in order to deal with $n^{-1/2}\sum_{i=1}^{[n\cdot]}(z_t^{*2} - 1)$, the aforementioned lemma applies, provided Δx_t has bounded eighth-order moment. Under this additional assumption, the following theorem can be established.

THEOREM 5. *Let the conditions of Theorem 4 hold, and consider the restricted bootstrap test statistic, LR_n^*. Then, under H_l, if additionally $E(\Delta x_t)^8 < \infty$, then as $n \to \infty$:*

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa^\dagger)$$

where $\kappa^\dagger := \frac{E(\Delta x_t)^4}{(E(\Delta x_t)^2)^2} - 1 > \kappa$.

This theorem proves that even in the case of bounded eighth-order moments of Δx_t, under the alternative hypothesis, the bootstrap does not mimic the asymptotic distribution given in Theorem 3. Rather, it converges to $\mathcal{LR}_\infty(\kappa^\dagger)$ rather than to

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the null distribution $\mathcal{LR}_\infty(\kappa)$. However, since LR_n^* remains of order $O_p^*(1)$, in probability, the bootstrap test is consistent.

We now turn to the case where the moment condition on Δx_t fails. Establishing the limiting distribution in this case is extremely complicated, in particular because under lack of moments (in particular, second-order moments), the bootstrap CLT no longer holds. Specifically, it is well known from Athreya (1987) and Knight (1989) that in this case the bootstrap delivers a random limiting distribution, as reported in the following example.

Example 8. (Bootstrap of the sample mean under infinite variance). *Suppose that the x_t's form an i.i.d. sequence in the domain of attraction of a Stable law with tail index denoted by $\nu \in (0,2)$. In this case, it is well known that there are sequences a_n and b_n such that $S_n := a_n^{-1}\sum_{t=1}^n (x_t - b_n) \to_w S(\nu)$, a stable random variable with tail index ν. Its i.i.d. bootstrap analog is given by $S_n^* := a_n^{-1}\sum_{t=1}^n (x_t^* - E^* x_t^*)$, where the x_t^*'s are (conditionally on the original data) i.i.d. from $\{x_1, \ldots, x_n\}$. Bootstrap validity would require that, in probability, $S_n^* \xrightarrow{w^*} S(\nu)$. However, as shown by Knight (1989), because of the lack of finite second-order moments, the large extremes in the original sample do not "wash away" and, consequently, the cdf of the bootstrap statistic also depends on the original data asymptotically. Put differently, the cdf of the bootstrap statistic, conditionally on the data, is random in the limit (see eqn. (2) in Knight, 1989) and hence does not match the cdf of the $S(\nu)$. Extensions to other bootstraps in the context of (stationary and nonstationary) time series models with infinite variance are provided in Cavaliere et al. (2013, 2016, 2018) and Cavaliere, Nielsen, Rahbek (2020).* □

In particular, it is reasonable to conjecture that—similarly to the bootstrap statistic S_n^* of the previous example—the term $n^{-1/2}\sum_{t=1}^n z_t^*$, albeit not satisfying a central limit theorem (due to the randomness of its limiting distribution), is still of order $O_p^*(1)$, in probability. Put differently, the central limit theorem does not hold on z_t^*; however, its sum is still of order $n^{1/2}$. This would suggest that the bootstrap LR statistic may have a random limiting distribution which, however, is bounded in probability, hence ensuring consistency of the bootstrap test. The Monte Carlo simulations of Section 5 support this conjecture.

4.3. A Hybrid Bootstrap

We here propose a bootstrap method, which is able to mimic the null asymptotic distribution even if the null is false. This is simply a hybrid bootstrap, where we combine the use of the restricted parameter estimators (typically employed for the restricted bootstrap) with the use of the unrestricted residuals (typically employed for the unrestricted bootstrap). The hybrid bootstrap test statistic is defined through the following steps.

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Hybrid (i.i.d.) Bootstrap:

(i) Estimate model (1) using Gaussian QML under the null hypothesis, yielding the estimates $\tilde{\theta}_n := (0, 0, \tilde{\omega}_n)'$; similarly, also estimate model (1) using Gaussian QML *without* imposing the null hypothesis, yielding the estimates $\hat{\theta}_n := (\hat{\pi}_n, \hat{\alpha}_n, \hat{\omega}_n)'$, together with the corresponding unrestricted QML residuals, $\hat{\varepsilon}_t := \Delta x_t - \hat{\pi}_n x_{t-1}$ and $\hat{z}_t := (\hat{\omega}_n + \hat{\alpha}_n x_{t-1}^2)^{-1/2}\hat{\varepsilon}_t$, as defined above.

(ii) Standardize the unrestricted residuals as

$$\hat{z}_{s,t} := \frac{\hat{z}_t - n^{-1}\sum_{t=1}^n \hat{z}_t}{(n^{-1}\sum_{t=1}^n (\hat{z}_t - n^{-1}\sum_{t=1}^n \hat{z}_t)^2)^{1/2}}$$

and construct the bootstrap innovations using the i.i.d. bootstrap resampling scheme; that is, $z_t^* := \hat{z}_{s,\eta_t^*}$, where η_t^*, $t = 1, \ldots, n$ is an i.i.d. sequence of discrete uniform distributions on $\{1, 2, \ldots, n\}$.

(iii)–(v) As Steps (iii)–(v) of the restricted bootstrap.

This bootstrap is simple to implement and—with respect to the standard restricted bootstrap—it only requires unrestricted estimation of the model on the original data. Since this step is done one time only, implementation of this bootstrap is not more time consuming than the two bootstraps described earlier.

The crucial features of this bootstrap are that, due to the use of the unrestricted residuals, a bootstrap invariance principle for $(z_t^*, z_t^{*2} - 1)$ holds irrespective of the null hypothesis to be true or not. Hence, the issue of possible lack of (fourth-order) moments for z_t^* described in Section 4.2 does not arise when this bootstrap is implemented. Moreover, the use of the restricted parameter estimates in the construction of the bootstrap sample allows to avoid possible randomness of the limiting bootstrap measures due to unit roots and a parameter on the boundary under the null hypothesis. We have the following theorem.

THEOREM 6. *Let the conditions of Theorem 4 hold, and consider the hybrid bootstrap test statistic, LR_n^*. Then, both under H_0 and H_1, as $n \to \infty$:*

$$LR_n^* \xrightarrow{w^*}_p \mathcal{LR}_\infty(\kappa)$$

Remark 4.1. In principle, under the null hypothesis it is well expected that the bootstrap based on "restricted" residuals, that is, from estimation with the null imposed, delivers better size control than the hybrid bootstrap discussed here. This is a well-known property of bootstrap tests for a unit root; see, for example, Cavaliere and Taylor (2008), Cavaliere and Taylor (2009*b*), Palm et al. (2008), and the references therein. The amount of size accuracy which is lost by bootstrapping unrestricted residuals instead of plain restricted residuals is usually negligible. However, how the DAR structure affects the finite-sample properties of these two bootstrap schemes cannot be inferred from the proofs of (first-order) bootstrap

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validity. In the next section, we aim to cast some light on this issue by means of Monte Carlo simulation.

5. SIMULATIONS

In this section, we compare the finite sample properties of the LR test for the pure random walk null hypothesis with its (asymptotically valid) bootstrap analogs: the restricted bootstrap LR test and the hybrid bootstrap test of Section 4.3. By considering a detailed simulation study based on the DAR model, we aim at analyzing the finite-sample performance of the various bootstrap schemes across different choices of the bootstrap true values and different distributions of the innovations, both under the null and under the alternative hypothesis of (strict) stationarity.

The section is organized as follows. First, in Section 5.1, we describe (i) the model; (ii) the null hypothesis; and (iii) the reference LR test and associated bootstrap test statistics. Finally, we describe the design of the Monte Carlo experiment. The ERPs of the tests under the null hypothesis are investigated in Section 5.2. Section 5.3 is devoted to the analysis of the behavior of the test when the null hypothesis is false. Here, we investigate both raw and (pointwise) size-adjusted ERPs under the alternative hypothesis.

5.1. Monte Carlo Design

We consider the DAR process

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad \sigma_t^2 = \omega + \alpha x_{t-1}^2, z_t \sim \text{i.i.d.}(0,1), (t = 1, \ldots, n) \tag{16}$$

with $x_0 = 0$ and different choices of the distribution of z_t. Specifically, we consider the following three cases:

($\mathcal{E}_1$) z_t is a zero mean, unit variance Gaussian random variable;

($\mathcal{E}_2$) z_t is a standardized Student t random variable with $\nu > 4$ degrees of freedom, that is, z_t is distributed as $t(\nu)\sqrt{(\nu-2)/\nu}$, where $t(\nu)$ denotes a t random variable with $\nu \in \mathbb{R}^+$ degrees of freedom;

($\mathcal{E}_3$) z_t is a symmetric, standardized $\chi^2(1)$ random variable, that is, z_t is distributed as $S(\chi_k^2 - k)/\sqrt{2k}$, with χ_k^2 denoting a χ^2 random variable with $k \in \mathbb{N}$ degrees of freedom and S is a Rademacher random variable (i.e., a two-point distribution with $P(S = 1) = P(S = -1) = 1/2$).

For all error distributions, $\xi = 0$ and $\kappa < \infty$. Notice that for the (unimodal) distribution in $\mathcal{E}_2$, the moment of order m exists provided $\nu > m$; moreover, for $\nu > 4$, the fourth-order moment (which appears in the asymptotic distribution of the LR test of Section 2.3) is given by $\frac{3(\nu-2)}{\nu-4}$. Under $\mathcal{E}_3$, the distribution of the innovations is bimodal; moreover, all moments exist and in particular, the fourth-order moment is given by $12/k + 3$. In the simulations, we force the t and the

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symmetric χ^2 distributions to have the same fourth-order moments, which requires setting $k = 2(\nu - 4)$; specifically, we set $\nu = 5.5$ and $k = 3$, which corresponds to $\kappa = 6$.

The null hypothesis is the pure random walk hypothesis $\mathsf{H}_0 : \pi = \alpha = 0$, see Section 2.1. We focus in particular on alternatives of the form $\pi < 0$ and $\alpha = 0$ (no unit root in the mean equation and no conditional heteroskedasticity) and on alternatives of the form $\pi = 0$ and $\alpha > 0$ (conditionally heteroskedastic strictly stationary with a unit root in the mean equation). In order to investigate power, we consider these alternatives under Pitman drifts. We first consider the sequence of (near unit root) local alternatives

$$\mathsf{H}_1^{(\pi)} : \pi = c_\pi n^{-1}, \alpha = 0 \tag{17}$$

with $c_\pi < 0$ fixed. For n fixed, this alternative lies in the region of the parameter space where the process is strictly stationary, conditionally homoskedastic, and with finite fourth-order moments. Moreover, we also consider the sequence of local alternatives

$$\mathsf{H}_1^{(\alpha)} : \pi = 0, \alpha = c_\alpha n^{-3/2} \tag{18}$$

with $c_\alpha < 0$ fixed. For n fixed, this alternative with $\pi = 0$ lies in the region of the parameter space where the process displays volatility-induced strict stationarity, is conditionally heteroskedastic, but does not possess finite second-order moments.

Restricted and unrestricted estimation and associated LR tests are based on the Gaussian likelihood associated with (16), with x_0 considered fixed in the statistical analysis. Maximization of the likelihood function imposes the non-negativity constraints $\alpha \geq 0$ and $\omega > 0$.[3] The (asymptotic) LR test is based on asymptotic critical values obtained numerically by discretizing the distribution in (3) over 100, 000 steps and using 100, 000 Monte Carlo repetitions (these do not substantially differ from those reported in Table 1 of Klüppelberg et al., 2002) under the assumption that $\kappa = 2$ and $\xi = 0$; hence, the asymptotic case is not expected to be correctly sized, even in large samples, when the actual distribution of z_t departs from the Gaussian distribution.

We consider the two (asymptotically valid) bootstrap schemes introduced earlier in the article. First, the plain restricted bootstrap of Section 3.1, which is based on resampling the residuals from restricted estimation and impose the null hypothesis on the bootstrap generating process. Second, the hybrid bootstrap scheme, which employs the residuals from unrestricted parameter estimation but still imposes the null on the bootstrap sample.

Throughout, we use 10, 000 Monte Carlo replications and use $B = 399$ bootstrap repetitions. Samples of size $n \in \{50, 100, 200, 500\}$ are considered throughout. All tests are run at the nominal 1%, 5%, and 10% significance levels.

[3] All computations are performed in Matlab R2018*b* using the "fmincon" constrained optimization routine. Code is available upon request.

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TABLE 1. Size of the asymptotic and bootstrap tests

		Asymp. test			Restr. BS			Hybrid BS		
	n	1%	5%	10%	1%	5%	10%	1%	5%	10%
$z_t \sim N$	50	0.6	4.0	9.0	1.0	4.7	9.8	1.0	5.0	10.1
	100	0.5	3.9	8.8	0.9	4.7	9.6	1.0	4.9	10.0
	200	0.6	4.2	9.2	1.0	4.8	9.8	1.0	5.1	9.9
	500	0.8	4.9	10.5	1.1	5.7	10.8	1.1	5.8	10.9
$z_t \sim t$	50	2.1	6.5	11.7	0.8	4.4	9.7	1.8	5.9	10.7
	100	2.8	7.8	13.6	0.9	5.0	10.3	2.0	6.3	11.2
	200	3.2	8.1	14.1	0.9	4.9	9.8	1.8	5.8	10.5
	500	3.9	9.9	16.4	0.9	5.2	10.5	1.4	5.9	10.9
$z_t \sim \chi^2$	50	2.7	7.6	13.2	0.9	4.7	9.8	2.4	6.8	11.8
	100	3.8	9.8	15.3	0.9	5.0	10.8	2.3	7.4	11.9
	200	4.6	11.2	16.9	1.0	5.2	10.8	2.1	6.8	11.7
	500	5.5	12.5	19.2	1.2	5.6	11.0	1.8	6.5	11.5

Note: The parameter setting under the null is $\pi = 0, \alpha = 0$, and $\omega = 1$. The innovation process (z_t) is drawn, respectively, from standard normal distribution, standardized t distribution with degrees of freedom 5.5, and standardized symmetric χ^2 distribution with degrees of freedom 3. The results are obtained from 10,000 Monte Carlo simulation iterations each of which is evaluated using 399 bootstrap samples.

5.2. Empirical Rejection Probabilities Under the Null

Table 1 reports the empirical rejection probabilities (ERPs; as estimated on the 10,000 Monte Carlo replications) under the null hypothesis, $\mathsf{H}_0 : \alpha = \pi = 0$, for the three distributions for the innovations.

The following points can be made from the analysis.

For the leading case of Gaussian errors, the asymptotic LR test tends to be undersized for samples of size $n \in \{50, 100, 200\}$. For $n = 500$, the ERPs are closer to the nominal level. In contrast, both the restricted bootstrap and the hybrid bootstrap tests show excellent size control for samples of $n \in \{50, 100, 200\}$, with ERPs very close to the corresponding nominal levels. The bootstrap tests do not seem to dominate the asymptotic test in terms of size when $n = 500$.

For t-distributed errors, the asymptotic LR test is significantly oversized. This is expected, since this test is implicitly based on the (false) assumption that the errors are Gaussian. The bootstrap tests show very good size control, with the restricted bootstrap being slightly more accurate than the hybrid bootstrap (as is expected, since under the null the restricted bootstrap is based on resampling the true errors). It is interesting to notice that in this case both Theorems 4 and 6, which provide sufficient conditions for validity of the two bootstraps under the null, cannot be applied, as the errors do not possess finite eighth-order moments. Despite this fact, the performance of these bootstraps is largely satisfactory. A possible explanation for this finding, which is not uncommon in the bootstrap literature (see, e.g., the

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simulations in Gonçalves and Kilian, 2004, for stationary AR processes, or in Cavaliere, Rahbek and Taylor, 2010a, for multivariate nonstationary AR processes) is that the moment condition in Theorems 4 and 6 is indeed sufficient rather than necessary, as also conjectured in Section 3.2. In this respect, note that the t distribution employed here satisfies the conjectured $4 + \delta$ moment condition.

For the bimodal χ^2-type errors, the asymptotic tests are again substantially unreliable. For instance, when the nominal level is 1% and $n = 500$, the ERP equals 5.5%. The bootstrap seems to fix this problem very well, again with ERPs very close to the corresponding nominal levels at all the sample sizes considered. Again, the restricted bootstrap seems to marginally outperform the hybrid bootstrap.

In summary, the performance of the bootstrap tests is largely satisfactory. Not only the bootstrap allows to circumvent the nonpivotality of the asymptotic test, whose distribution depends on the unknown parameter κ, but it also delivers an excellent control of the ERP when the null hypothesis holds true.

5.3. ERPs Under Local Alternatives

We now turn to the inspection of the ERPs of the (asymptotic and bootstrap) tests when the null hypothesis does not hold. To this aim, in Section 5.3.1 we consider pure homoskedastic autoregressive alternatives in $\mathsf{H}_1^{(\pi)}$. Next, in Section 5.3.2, we consider heteroskedastic alternatives with a unit root in the mean equation, as given in $\mathsf{H}_1^{(\alpha)}$.

Throughout this section, we present both raw ERPs and (pointwise) size-adjusted rejection probabilities. To compute the latter, as suggested in Cavaliere et al. (2015) for each given point in the parameter space, we first perform the simulation under the null and record the nominal level that would have given an ERP equal to the desired significance level. Next, we use this adjusted nominal level in the simulations under the alternative hypothesis. Let, for instance, p_n^* denote the p-value of the bootstrap test, and let $p_0(\eta) := P\left(p_n^* \leq \eta | \mathsf{H}_0\right)$, with η denoting the chosen significance level. Then, the size-adjusted bootstrap test at the $100\eta\%$ level corresponds to rejecting H_0 when $p_n^* \leq \tilde{\eta}$, where $\tilde{\eta}$ is such that $p(\tilde{\eta}) := P\left(p_n^* \leq \tilde{\eta} | \mathsf{H}_0\right) = \eta$.

5.3.1. *Pure Autoregressive Alternatives.* Consider the local power of the tests under the local alternative $\mathsf{H}_1^{(\pi)}$ in (17), with samples of size $n \in \{50, 100, 200, 500\}$ and all the three error distributions described earlier. Results are reported in Table 2 for $c = -10$. For completeness, we also report the raw ERPs in Table 3. Obviously, these ERPs are affected by the deviations of the actual size of the tests from the corresponding nominal levels, see Table 1.

For Gaussian errors, the two bootstrap tests perform similarly to the (size-adjusted) asymptotic LR test for all the sample sizes considered. This is well expected from the theory.

For t-distributed errors, at nominal significance levels of 10%, the restricted bootstrap test behaves very similarly to the asymptotic test. At smaller nominal levels, however, there seems to be some power gains over the asymptotic test.

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TABLE 2. Size-adjusted power of the asymptotic and bootstrap tests under the local alternative $\pi = cn^{-1}, \alpha = 0$.

		Asymp. test			Restr. BS			Hybrid BS		
	n	1%	5%	10%	1%	5%	10%	1%	5%	10%
$z_t \sim N$	50	22.0	61.6	81.2	24.9	63.1	82.1	21.9	61.3	80.5
	100	21.9	60.3	81.0	24.2	62.3	81.0	24.6	60.8	80.3
	200	21.6	58.8	78.8	23.7	59.5	78.9	20.3	58.0	79.0
	500	20.0	55.0	77.2	20.3	54.8	76.3	20.4	54.4	76.1
$z_t \sim t$	50	7.3	45.0	72.9	17.5	53.7	72.8	9.2	41.5	67.9
	100	4.5	35.7	66.0	14.6	44.0	65.5	7.8	34.8	61.5
	200	2.9	33.0	63.7	11.3	38.6	62.3	6.1	33.1	59.9
	500	2.6	26.7	58.2	8.3	33.4	57.4	5.5	28.9	55.2
$z_t \sim \chi^2$	50	4.6	36.2	66.5	15.5	44.6	66.9	5.5	32.0	57.4
	100	4.0	26.2	55.9	11.5	36.5	57.2	7.0	25.9	50.3
	200	2.5	21.8	49.6	7.9	30.6	53.0	4.2	22.6	46.6
	500	1.8	18.5	44.7	4.4	22.7	46.8	2.7	20.4	43.2

Note: The parameter setting is $c = -10$ and $\omega = 1$. See also notes of Table 1.

TABLE 3. Raw power of the asymptotic and bootstrap tests under the local alternative $\pi = cn^{-1}, \alpha = 0$

		Asymp. test			Restr. BS			Hybrid BS		
	n	1%	5%	10%	1%	5%	10%	1%	5%	10%
$z_t \sim N$	50	16.2	54.5	78.2	21.2	60.0	80.7	21.9	59.9	80.5
	100	15.4	53.4	77.6	20.5	59.4	79.7	21.1	59.2	79.5
	200	15.7	53.6	76.8	20.3	57.9	78.2	20.3	58.0	78.2
	500	16.4	54.7	78.5	20.3	57.7	78.5	20.4	57.8	78.5
$z_t \sim t$	50	17.9	55.2	78.3	14.4	49.4	71.3	15.5	47.6	69.6
	100	18.2	54.5	78.4	11.9	42.7	66.3	12.9	42.3	65.2
	200	18.6	54.3	77.7	9.3	37.3	61.5	10.1	37.1	60.9
	500	20.0	57.7	79.7	6.5	33.4	58.2	7.4	33.5	58.0
$z_t \sim \chi^2$	50	17.4	54.0	78.3	12.8	43.4	66.0	14.8	42.0	63.4
	100	18.6	54.8	78.5	9.5	36.5	60.4	11.4	35.8	59.1
	200	19.7	56.0	79.8	6.2	30.6	55.3	7.8	30.8	54.9
	500	21.8	57.4	79.6	4.4	25.2	50.1	5.3	25.4	49.7

Note: The parameter setting is $c = -10$ and $\omega = 1$. See also notes of Table 1.

The hybrid bootstrap seems somehow less powerful than the restricted bootstrap, although the differences between the two methods seem to decrease as n increases. A similar pattern can be observed for the case of symmetrically χ^2-distributed errors. Here, again, the restricted bootstrap test seems to be slightly preferrable.

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TABLE 4. Size-adjusted power of the asymptotic and bootstrap tests under the local alternative $\pi = 0, \alpha = cn^{-3/2}$

		Asymp. test			Restr. BS			Hybrid BS		
	n	1%	5%	10%	1%	5%	10%	1%	5%	10%
$z_t \sim N$	50	24.3	39.6	50.3	21.5	38.2	50.0	24.5	40.2	50.6
	100	29.1	43.7	54.6	27.8	43.6	54.6	30.3	44.4	55.0
	200	32.4	46.9	56.9	31.9	46.6	57.0	31.4	46.6	57.4
	500	34.8	48.6	59.1	34.3	48.3	58.6	35.0	48.8	58.7
$z_t \sim t$	50	17.0	32.3	43.2	16.3	33.0	43.5	17.9	32.1	43.5
	100	18.8	34.7	45.1	20.6	35.4	45.4	20.1	34.0	45.0
	200	20.3	37.7	48.2	23.9	38.7	48.2	21.7	37.3	48.0
	500	22.7	38.2	48.7	26.1	39.7	49.0	24.7	38.5	48.5
$z_t \sim \chi^2$	50	15.8	30.6	40.5	15.6	30.8	41.1	14.6	29.9	40.2
	100	18.4	31.9	41.4	18.8	33.2	42.2	19.4	31.6	41.3
	200	19.0	34.1	43.4	20.8	35.2	44.3	19.8	33.1	42.8
	500	21.1	35.9	45.9	22.3	36.3	46.2	20.5	36.1	45.4

Note: The parameter setting is $c = 10$ and $\omega = 1$. See also notes of Table 1.

The fact that in the non-Gaussian cases ($\mathcal{E}_2$ and $\mathcal{E}_3$), the restricted bootstrap seem to experience some power gains over the asymptotic test and the hybrid bootstrap test may appear surprising. Clearly, it may depend on the chosen Monte Carlo design. However, similar evidence has already been documented in the literature: for example, Davidson and MacKinnon (2002, Fig. 14) report a case where the restricted bootstrap dominates the asymptotic test. In addition, in terms of theory, there is no result that prevents this from happening (see, e.g., Davidson and MacKinnon, 2006).

As for the size results in the previous section, in the non-Gaussian case $\mathcal{E}_2$, z_t violates the regularity condition of finite eighth-order moment. Again, this violation does not seem to affect the power of the bootstrap test.

In summary, the restricted bootstrap tests display power, which is not inferior (sometimes even superior) to the power of the corresponding asymptotic test. Moreover, implementation of the hybrid bootstrap does not seem to provide power gains (its power is in line with the power of the asymptotic test).

5.3.2. *Heteroskedastic, Unit Root Alternatives.* Results for alternatives $\mathsf{H}_1^{(\alpha)}$ in (18) are reported for $c = 10$ in Tables 4 (size-adjusted ERPs) and 5 (raw ERPs).

In terms of this local power analysis under Gaussian errors of $\mathcal{E}_1$, the hybrid bootstrap performs similarly to the asymptotic test. This is expected from our theoretical analysis (Theorem 6), which shows that the hybrid bootstrap mimics the null asymptotic distribution of the original statistic and hence, in large samples, should have the same (local) power than the asymptotic test. The same result is expected for symmetric χ^2 distributed errors. Surprisingly, also the plain, restricted bootstrap has comparable power properties. This seems to show (parallel to the

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TABLE 5. Raw power of the asymptotic and bootstrap tests under the local alternative $\pi = 0, \alpha = cn^{-3/2}$

		Asymp. test			Restr. BS			Hybrid BS		
	n	1%	5%	10%	1%	5%	10%	1%	5%	10%
$z_t \sim N$	50	21.7	36.4	48.4	19.6	36.8	49.1	24.5	39.6	50.6
	100	25.9	41.2	52.6	25.9	42.4	53.7	28.9	43.8	54.6
	200	29.4	44.6	55.9	30.1	45.8	56.5	31.4	46.6	56.8
	500	33.4	48.5	59.8	34.3	49.8	59.8	35.0	50.1	60.0
$z_t \sim t$	50	23.0	35.9	46.2	14.7	30.8	42.5	21.6	34.7	44.2
	100	27.6	40.8	50.3	18.8	34.8	45.8	24.1	37.1	46.7
	200	31.6	44.9	54.3	22.2	38.1	47.9	25.6	39.1	48.4
	500	35.6	48.5	57.8	24.4	39.7	49.4	26.6	40.6	49.7
$z_t \sim \chi^2$	50	23.5	36.1	45.2	14.1	30.3	40.6	21.9	34.0	42.3
	100	28.8	41.2	50.1	17.1	33.2	43.5	22.9	35.8	44.5
	200	33.1	45.1	53.3	19.2	35.2	45.1	23.5	36.8	45.8
	500	37.3	49.9	58.0	22.3	37.7	47.5	24.8	38.5	48.1

Note: The parameter setting is $c = 10$ and $\omega = 1$. See also notes of Table 1.

discussion of the simulations under the null) that the moment requirement in Theorem 5 is sufficient, while not necessary. Comparable results are obtained for the error distributions $\mathcal{E}_2$ and $\mathcal{E}_3$.

In summary, for both alternatives, the bootstrap tests display power, which is generally not inferior (and sometimes superior) to the power of the corresponding (size-adjusteed) asymptotic test. The implementation of the restricted bootstrap seems to provide the best performance not only in terms of size, but also in terms of size-adjusted power.

6. EXTENSION TO ASYMMETRIC INNOVATIONS

One of the assumptions in Ling (2004) and that we have assumed so far is that the third-order moment of the innovations, $\xi = Ez_t^3$, equals zero. This condition ensures that the two Brownian motions characterizing the asymptotic distribution in (3) are independent.

If this moment condition fails to hold, the limiting distribution of LR_n can no longer be expressed as the (weighted) sum of a squared Dickey–Fuller and a half-χ_1^2 independent random variables, see Remark 2.6. More precisely in Theorem 3, as shown in Klüppelberg et al. (2002, Theorem 3.1), the second term in the expression for the $\mathcal{LR}_\infty(\kappa)$ in (3) for general ξ is given by

$$\frac{1}{2}\max\left(0, \left[\xi\int B^2 dB + \sqrt{\kappa-\xi^2}\int B^2 dW - \int B^2 du\left\{\xi B_1 + \sqrt{\kappa-\xi^2}W_1\right\}\right]\right)^2 \times \left[\int B_u^4 du - \left(\int B_u^2 du\right)^2\right]^{-1} \quad (19)$$

where, as before, B and W are independent standard Brownian motions.

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Interestingly, the bootstrap may take care of this nonpivotality and we can establish the following result.

THEOREM 7. *The results of Theorems 4 and 6 hold independently of whether* $\xi = 0$ *or not.*

For the restricted bootstrap, where the z_t^*'s are based on the restricted (standardized) residuals $\tilde{z}_{s,t}$, a key insight is the following. It holds that the bootstrap (conditional) third-order moment ξ_n^*, is given by

$$\xi_n^* = E^*\left(z_t^{*3}\right) = \frac{1}{n}\sum_{t=1}^{n} \tilde{z}_{s,t}^3,$$

such that, under suitable moment restrictions on the $\{z_t\}$ sequence, $\xi_n^* \to_p \xi$. This implies, under some additional algebra, that $\mathcal{Z}_n^*(\cdot)$ of (7) satisfies in this more general setting,

$$\mathcal{Z}_n^*(\cdot) := n^{-1/2}\sum_{t=1}^{[n\cdot]}\left(z_t^*, z_t^{*2} - 1\right)' \xrightarrow{w^*}_p \begin{pmatrix} 1 & 0 \\ \xi & \sqrt{\kappa - \xi^2} \end{pmatrix} \begin{pmatrix} B_\cdot^* \\ W_\cdot^* \end{pmatrix},$$

see Appendix A.5.1, equation (A. 40). Hence, the bootstrap mimics the asymptotic distributional properties of the original statistics even if $\xi \neq 0$.

7. CONCLUSIONS

In this article, we have discussed several issues which may arise in the implementation of the bootstrap hypothesis testing to time series econometric models. Essentially, these are related to the assessment of bootstrap validity under the null hypothesis (i.e., establishing that the bootstrap mimics the correct limiting distribution of the original test statistic under the null hypothesis) as well as to the behavior of the bootstrap statistic under the alternative hypothesis.

Our discussion has focused on the DAR model, where the time series properties of the data—such as strict stationarity or the existence of moments—are determined through a very delicate balance between the parameters of conditional mean and the conditional variance equations.

Focusing on tests of the null hypothesis of nonstationarity, that is, reduction to the pure random walk, we have initially shown that—due to the possible presence of unit roots and of parameters on the boundary of the parameter space a classic—unrestricted bootstrap fails to mimic the null distribution under the null. Conversely, the restricted bootstrap works, irrespectively of a parameter of the conditional variance equation being on the boundary of the parameter space under the null hypothesis.

Next, we have discussed the possible issues which may arise under the alternative. Here, the crucial issue is that, under the alternative, the data may have infinite variance. Hence, the restricted bootstrap, based on resampling the residuals

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with the null imposed, may in fact be based on resampling an infinite variance sequence. As a consequence, the bootstrap statistic may have a *random* limiting distribution, which may lead to a lack of power over the infeasible size-adjusted asymptotic test. This observation is the basis of our next suggestion, which is a *hybrid* implementation of the bootstrap where the parameters used to generate the bootstrap sample are based on restricted estimation while the residuals used to construct the bootstrap shocks are based on unrestricted estimation.

Although most of our analysis is based on the DAR model, many of these issues are common to the great majority of econometric models. Hence, a thorough investigation of the properties of the bootstrap under the null and under the alternative is always required before its practical implementation.

There are further issues which have not been touched in this article but may as well be important to establish bootstrap validity. For instance, in our testing example, the parameters of the model are (up to an intercept) all restricted by the null hypothesis. In most cases, however, the null hypothesis restricts only a subset of the parameters. An example is testing if a parameter is on the boundary of the parameter space when the remaining parameters might be on the boundary, as in Cavaliere, Nielsen, Pedersen and Rahbek (2019). In this case, the limiting distribution of the bootstrap statistic depends on the asymptotic properties of the estimators used to generate the bootstrap data. Validity would then require (i) determination of the pseudo-true values to which the estimators converge and at what speed and (ii) the implications of this convergence on the properties of the bootstrap sample.

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A: MATHEMATICAL APPENDIX

A.1. INTRODUCTION

This appendix contains the proofs of the theory for the bootstrap implementation in the DAR model for testing the null of nonstationarity, that is $\mathsf{H}_0 : \pi = \alpha = 0$.

In Appendixes A.2 and A.3, we first establish new asymptotic (nonbootstrap) results for the QMLE $\hat{\theta}_n := \left(\hat{\pi}_n, \hat{\alpha}_n, \hat{\omega}_n\right)'$ under both stationarity as well as under the null H_0 of nonstationarity, see Theorems 1 and 2, respectively. Appendix A.3 additionally provides asymptotic theory for the LR_n statistic under H_0, see Theorem 3. The asymptotic results for the QMLE, as well as LR_n, are then applied in Appendix A.5, where asymptotic results for the (restricted and hybrid) bootstrap variants LR_n^* of LR_n are derived.

As to the general (nonstandard) likelihood theory, recall that the parameter (or, optimization) set for the DAR model is given by

$$\mathcal{T} := \{\theta = (\pi, \alpha, \omega)' : \pi \in [-\pi_L, \pi_U], \alpha \in [0, \alpha_U] \text{ and } \omega \in [\omega_L, \omega_U]\},$$

and, for estimation with the null hypothesis imposed, by $\mathcal{T}_0 := \{\theta = (\pi, \alpha, \omega)' : \pi = \alpha = 0$ and $\omega \in [\omega_L, \omega_U]\}$. As $\alpha \geq 0$, inference and testing is nonstandard and we apply theory from Andrews (1999, 2001), which treats estimation and testing under inequality constraints (and more general boundary issues), see also Vu and Zhou (1997), Kluppenberg et al. (2002) and Cavaliere et al. (2017). Thus, the asymptotic distributions of the QMLE $\hat{\theta}_n$ and the associated LR_n statistic follow by verifying regularity conditions for (i) the parameter spaces $\mathcal{T}$ and $\mathcal{T}_0$; (ii) consistency of $\hat{\theta}_n$; and (iii) convergence of the score, information, and third derivative of the log-likelihood function. For the bootstrap asymptotic theory, we verify the analogous regularity conditions for the bootstrap log-likelihood quantities, applying convergence (weakly, and in probability) conditional on the data, see, for example, Cavaliere, Nielsen and Rahbek (2015, 2017) and Cavaliere, Rahbek and Taylor (2012).

As to (i), consider first the stationary case, where the true parameter $\theta_0 \in \Theta_{\mathcal{S}}$, with $\theta_0 = (\pi_0, \alpha_0, \omega_0)'$. In this case, $\mathcal{T} - \theta_0$, in the sense of Andrews (1999, 2001), is locally equal to the cone(s),

$$\Lambda(A) = \mathbb{R} \times A \times \mathbb{R}, \tag{A.1}$$

where $A = \mathbb{R}$ if $\alpha_0 > 0$, and $A = \mathbb{R}^+$ if $\alpha_0 = 0$, such that Assumption $5^{2*(b)}$ in Andrews (1999) holds with $B_T = n^{1/2}$. For the nonstationary case, where $\theta_0 \in \Theta_{\mathcal{N}}$, then $\mathcal{T} - \theta_0$ and $\mathcal{T}_0 - \theta_0$ are locally equal to the cones $\Lambda := \Lambda\left(\mathbb{R}^+\right)$ and

$$\Lambda_0 := \{0\} \times \{0\} \times \mathbb{R}, \tag{A.2}$$

respectively. That is, with $B_T := G_n := \operatorname{diag}\left(n, n^{3/2}, n^{1/2}\right)$ in the nonstationary case, Assumption $5^{2*(b)}$ in Andrews (1999) holds.

With respect to (ii), the regularity conditions verified under (iii) imply, with probability tending to one, that $\hat{\theta}_n \to_p \theta_0$. As to (iii), note that we verify suitable bounds on the third-order log-likelihood derivative(s), rather than, as is standard, establish uniform convergence of the information (that is, the second-order log-likelihood derivative); see Jensen and Rahbek (2004*b*, Lem. 1) and Kristensen and Rahbek (2010, Lem. 11 and 12) for general asymptotic likelihood theory in the stationary and nonstationary cases, respectively.

Finally note that while the results quoted in Theorems 1 and 2, and Theorem 3, are for the case of the nuisance (asymmetry) parameter $\xi = 0$, the results are derived in the next

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subsections under the general assumption of $\xi \neq 0$ as needed for the discussion in Section 6 where we extend the asymptotic (and bootstrap) theory to address also the nuisance parameter ξ (in addition to κ).

A.2. QMLE UNDER STATIONARITY—PROOF OF THEOREM 1

In this section, we derive the asymptotic theory for the QMLE $\hat{\theta}_n = \left(\hat{\pi}_n, \hat{\alpha}_n, \hat{\omega}_n\right)'$ in Theorem 1 for the stationary case where $\theta_0 \in \Theta_{\mathcal{S}}$. We verify conditions (A.1)–(A.3) in Jensen and Rahbek (2004, Lem. 1) [JR hereafter] which imply, with probability tending to one, that $\hat{\theta}_n \to_p \theta_0$. Conditions (A.1) and (A.2), that is convergence of the score and information, are detailed below, while condition (A.3) for the third-order derivative follows as for the proof of establishing condition (C.ii) in Section A.6 for the nonstationary case.

A.2.1. Score and Observed Information

In terms of the log-likelihood function $L_n(\theta) = \sum_{t=1}^n l_t(\theta)$, define the score quantities,

$$S_n(\theta) = \sum_{t=1}^n s_t = \sum_{t=1}^n \partial l_t(\theta)/\partial\theta \text{ and } S_n = S_n(\theta)|_{\theta=\theta_0}. \tag{A.3}$$

Likewise, the observed information is given by

$$I_n(\theta) = \sum_{t=1}^n i_t = \sum_{t=1}^n (-\partial l_t(\theta)/\partial\theta\partial\theta') \text{ and } I_n = I_n(\theta)|_{\theta=\theta_0}. \tag{A.4}$$

The terms in score $S_n(\theta)$ are given by

$$\begin{aligned} s_t' &= \left(s_t^\pi, s_t^\alpha, s_t^\omega\right) \\ &= \left(\varepsilon_t x_{t-1}/\sigma_t^2, \tfrac{1}{2}\left(\varepsilon_t^2/\sigma_t^2 - 1\right) x_{t-1}^2/\sigma_t^2, \tfrac{1}{2}\left(\varepsilon_t^2/\sigma_t^2 - 1\right)/\sigma_t^2\right). \end{aligned} \tag{A.5}$$

At the true value θ_0, the score is (the sum of) a martingale differences (MGD) sequence,

$$s_{t,0}' := s_t'|_{\theta=\theta_0} = \left(z_t v_{t-1}, \tfrac{1}{2}\left(z_t^2 - 1\right) v_{t-1}^2, \tfrac{1}{2}\left(z_t^2 - 1\right)/\sigma_t^2\right), \tag{A.6}$$

with $v_{t-1} := x_{t-1}/\sigma_t$.

The terms i_t of the observed information are given by

$$\begin{aligned} i_t &= \begin{pmatrix} i_t^{\pi\pi} & i_t^{\pi\alpha} & i_t^{\pi\omega} \\ i_t^{\alpha\pi} & i_t^{\alpha\alpha} & i_t^{\alpha\omega} \\ i_t^{\pi\omega} & i_t^{\alpha\omega} & i_t^{\omega\omega} \end{pmatrix} \\ &= \begin{pmatrix} v_{t-1}^2 & (\varepsilon_t/\sigma_t) v_{t-1}^3 & \left(\varepsilon_t v_{t-1}\right)/\sigma_t^3 \\ (\varepsilon_t/\sigma_t) v_{t-1}^3 & \left(\varepsilon_t^2/\sigma_t^2 - 1/2\right) v_{t-1}^4 & \left(\varepsilon_t^2/\sigma_t^2 - 1/2\right) v_{t-1}^2/\sigma_t^2 \\ \left(\varepsilon_t v_{t-1}\right)/\sigma_t^3 & \left(\varepsilon_t^2/\sigma_t^2 - 1/2\right) v_{t-1}^2/\sigma_t^2 & \left(\varepsilon_t^2/\sigma_t^2 - 1/2\right)/\sigma_t^4 \end{pmatrix} \end{aligned} \tag{A.7}$$

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which at the true value θ_0 reduces to

$$i_{t,0} := i_t|_{\theta=\theta_0} = \begin{pmatrix} v_{t-1}^2 & z_t v_{t-1}^3 & \left(z_t v_{t-1}\right)/\sigma_t^2 \\ z_t v_{t-1}^3 & \left(z_t^2 - 1/2\right) v_{t-1}^4 & \left(z_t^2 - 1/2\right) v_{t-1}^2/\sigma_t^2 \\ \left(z_t v_{t-1}\right)/\sigma_t^2 & \left(z_t^2 - 1/2\right) v_{t-1}^2/\sigma_t^2 & \left(z_t^2 - 1/2\right)/\sigma_t^4 \end{pmatrix}. \tag{A.8}$$

A.2.2. Asymptotics for the Score and the Hessian—Proofs of Conditions (A.1) and (A.2) in JR

Note initially that, by $\kappa < \infty$, standard application of central limit theory for i.i.d. variables gives

$$n^{-1/2} \sum_{t=1}^{n} \left(z_t, z_t^2 - 1\right) \xrightarrow{w} V, \quad \mathrm{Var}\,(V) = \begin{pmatrix} 1 & \xi \\ \xi & \kappa \end{pmatrix}. \tag{A.9}$$

Next, the MGD representation of the score $s_{t,0}$,

$$s'_{t,0} = \left(z_t, z_t^2 - 1\right) \begin{pmatrix} v_{t-1} & 0 & 0 \\ 0 & \frac{1}{2} v_{t-1}^2 & \frac{1}{2\sigma_t^2} \end{pmatrix},$$

together with (A. 9), implies by standard arguments that condition (A.1) holds, that is,

$$n^{-1/2} S_n\left(\theta_0\right) = n^{-1/2} \sum_{t=1}^{n} s_{t,0} \xrightarrow{w} \mathcal{S}_\infty := \left(\mathcal{S}_\pi, \mathcal{S}'_\gamma\right)', \quad \mathcal{S}_\gamma := \left(\mathcal{S}_\alpha, \mathcal{S}_\omega\right)'.$$

Here, $\mathcal{S}_\infty$ is Gaussian with covariance matrix

$$\Omega_{\mathcal{S}} := \begin{pmatrix} \Omega_{\mathcal{S},\pi\pi} \Omega'_{\mathcal{S},\gamma\pi} \\ \Omega_{\mathcal{S},\gamma\pi} \Omega_{\mathcal{S},\gamma\gamma} \end{pmatrix}, \tag{A.10}$$

where

$$\Omega_{\mathcal{S},\pi\pi} = E\left(x_{t-1}^2/\sigma_t^2\right), \quad \Omega'_{\mathcal{S},\gamma\pi} = \left(\frac{\xi}{2} E\left(x_{t-1}^3/\sigma_t^3\right) \frac{\xi}{2} E\left(x_{t-1}/\sigma_t^3\right)\right)$$

and

$$\Omega_{\mathcal{S},\gamma\gamma} = \frac{\kappa}{4} \begin{pmatrix} E\left(x_{t-1}^4/\sigma_t^4\right) E\left(x_{t-1}^2/\sigma_t^4\right) \\ E\left(x_{t-1}^2/\sigma_t^4\right) \quad E\left(1/\sigma_t^4\right) \end{pmatrix}.$$

Note that on the one hand for $\alpha_0 > 0$, it follows that $E\left(x_{t-1}^4/\sigma_t^4\right) < \infty$ under stationarity of x_t as in JR. If, on the other hand, $\alpha_0 = 0$, then $Ex_t^4 < \infty$ is implied by $\kappa < \infty$. Moreover, for $\alpha_0 = 0$ and denoting $\Omega_{\mathcal{S}}$ under $\alpha_0 = 0$ by $\Omega_{\mathcal{S}}^0$, the covariance $\Omega_{\mathcal{S}}$ simplifies to the following

$$\Omega_{\mathcal{S},\pi\pi}^0 = \frac{1}{\omega_0} E\left(x_{t-1}^2\right), \Omega_{\mathcal{S},\gamma\pi}^{0\prime} = \left(\frac{\xi}{2\omega_0^{3/2}} E\left(x_{t-1}^3\right), 0\right) \text{ and} \tag{A.11}$$

$$\Omega_{\mathcal{S},\gamma\gamma}^0 = \frac{\kappa}{4\omega_0^2} \begin{pmatrix} E\left(x_{t-1}^4\right) E\left(x_{t-1}^2\right) \\ E\left(x_{t-1}^2\right) \quad 1 \end{pmatrix}.$$

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As to condition (A.2) for the observed information, it follows by the same arguments used for the score that by standard application of the law of large numbers,

$$n^{-1} I_n(\theta_0) = n^{-1} \sum_{t=1}^{n} i_{t,0} \xrightarrow{p} \mathcal{I}_\infty = \begin{pmatrix} \mathcal{I}_{\pi\pi} & 0 \\ 0 & \mathcal{I}_{\gamma\gamma} \end{pmatrix} = \begin{pmatrix} \Omega_{S,\pi\pi} & 0 \\ 0 & \frac{2}{\kappa}\Omega_{S,\gamma\gamma} \end{pmatrix}. \tag{A.12}$$

A.2.3. Asymptotics for the QMLE

Define first the tri-variate Gaussian variable, $\mathcal{Z} := \left(\mathcal{Z}_\pi, \mathcal{Z}_\gamma'\right)'$ with $\mathcal{Z}_\gamma := (\mathcal{Z}_a, \mathcal{Z}_\omega)'$ and

$$\mathcal{Z} := \mathcal{I}_\infty^{-1}\mathcal{S}_\infty \overset{d}{=} N\left(0, \Omega_{\mathcal{Z}}\right), \text{ where } \Omega_{\mathcal{Z}} = \mathcal{I}_\infty^{-1}\Omega_{\mathcal{S}}\mathcal{I}_\infty^{-1}. \tag{A.13}$$

For $\alpha_0 \geq 0$, $\Omega_{\mathcal{S}}$ is given by (A.10), while from (A.12), it follows that

$$\mathcal{I}_\infty^{-1} = \begin{pmatrix} \mathcal{I}_{\pi\pi}^{-1} & 0 \\ 0 & \mathcal{I}_{\gamma\gamma}^{-1} \end{pmatrix} = \begin{pmatrix} \Omega_{S,\pi\pi}^{-1} & 0 \\ 0 & \frac{\kappa}{2}\Omega_{S,\gamma\gamma}^{-1} \end{pmatrix}. \tag{A.14}$$

Hence,

$$\Omega_{\mathcal{Z}} = \mathcal{I}_\infty^{-1}\Omega_S\mathcal{I}_\infty^{-1} = \begin{pmatrix} \Omega_{\mathcal{Z},\pi\pi} & \Omega_{\mathcal{Z},\gamma\pi}' \\ \Omega_{\mathcal{Z},\gamma\pi} & \Omega_{\mathcal{Z},\gamma\gamma} \end{pmatrix}, \tag{A.15}$$

where

$$\Omega_{\mathcal{Z},\pi\pi} = \Omega_{S,\pi\pi}^{-1}, \quad \Omega_{\mathcal{Z},\gamma\gamma} = \frac{\kappa}{2}\Omega_{S,\gamma\gamma}^{-1}$$

and

$$\Omega_{\mathcal{Z},\gamma\pi} = \frac{\xi}{\delta}\Omega_{\mathcal{Z},\pi\pi} \begin{pmatrix} E\left(\frac{1}{\sigma_t^4}\right)E\left(\frac{x_{t-1}^3}{\sigma_t^3}\right) - E\left(\frac{x_{t-1}^2}{\sigma_t^4}\right)E\left(\frac{x_{t-1}}{\sigma_t^3}\right) \\ E\left(\frac{x_{t-1}^4}{\sigma_t^4}\right)E\left(\frac{x_{t-1}}{\sigma_t^3}\right) - E\left(\frac{x_{t-1}^2}{\sigma_t^4}\right)E\left(\frac{x_{t-1}^3}{\sigma_t^3}\right) \end{pmatrix}, \tag{A.16}$$

with $\delta = E\left(\frac{x_{t-1}^4}{\sigma_t^4}\right)E\left(\frac{1}{\sigma_t^3}\right) - \left(E\left(\frac{x_{t-1}^2}{\sigma_t^4}\right)\right)^2$.

Now, with $\hat{\theta}_n := \arg\max_{\theta\in\mathcal{T}} \sum l_t$ by Andrews (1999, Thm. 3),

$$n^{1/2}(\hat{\theta}_n - \theta_0) \xrightarrow{w} \arg \inf_{\lambda\in\Lambda(A)} \|\lambda - \mathcal{Z}\|_{\mathcal{I}_\infty}^2, \tag{A.17}$$

where $A = \mathbb{R}$ if $\alpha_0 > 0$ and $A = \mathbb{R}^+$ if $\alpha_0 = 0$, see (A. 1).

In the case of $\alpha_0 > 0$, it follows that for $\Lambda(\mathbb{R})$, with $\mathcal{Z}$ defined in (A. 13),

$$n^{1/2}(\hat{\theta}_n - \theta_0) \xrightarrow{w} \mathcal{Z} = \left(\mathcal{Z}_\pi, \mathcal{Z}_\gamma'\right)'.$$

Consider now the case of $\alpha_0 = 0$. For $\Lambda\left(\mathbb{R}^+\right)$, use the block-diagonality of $\mathcal{I}_\infty$ to rewrite the quadratic form on the right hand side of (A. 17) as

$$\arg \inf_{\lambda\in\Lambda(\mathbb{R}^+)} \|\lambda - \mathcal{Z}\|_{\mathcal{I}_\infty}^2 = (\mathcal{Z}_\pi, (\arg \inf_{\lambda\in\mathbb{R}^+\times\mathbb{R}} \left\|\lambda - \mathcal{Z}_\gamma\right\|_{\mathcal{I}_{\gamma\gamma}}^2)')',$$

where $\mathcal{Z}_\gamma = \mathcal{I}_{\gamma\gamma}^{-1}\mathcal{S}_\gamma$ has covariance $\Omega_{\mathcal{Z},\gamma\gamma} = \mathcal{I}_{\gamma\gamma}^{-1} = \frac{\kappa}{2}\Omega_{\mathcal{S},\gamma\gamma}^{-1}$, see (A. 15).

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Next, diagonalization of $\mathcal{I}_{\gamma\gamma}$ is obtained by using the matrix M,

$$M := \begin{pmatrix} 1 & -\varrho \\ 0 & 1 \end{pmatrix}, \quad \varrho := E x_t^2,$$

such that $\mathcal{I}_{\gamma\gamma}$ is diagonalized by postmultiplying (and premultiplying) with M (M'). That is,

$$I_{\gamma\gamma} = M \mathcal{I}_{\gamma\gamma} M' = \frac{1}{2\omega_0^2} \begin{pmatrix} \delta_0 & 0 \\ 0 & 1 \end{pmatrix}, \tag{A.18}$$

with $\delta_0 := E\left(x_{t-1}^4\right) - \left(E\left(x_{t-1}^2\right)\right)^2$. Define next,

$$Z_\gamma := (Z_\alpha, Z_\omega)' := \left(M'\right)^{-1} \mathcal{Z}_\gamma = \left(\mathcal{I}_{\gamma\gamma} M\right)^{-1} \mathcal{S}_\gamma,$$

which by definition, using the identity $\Omega_{S,\gamma\gamma} = \frac{\kappa}{2} \mathcal{I}_{\gamma\gamma}$, has covariance

$$\frac{\kappa}{2} \left(M \mathcal{I}_{\gamma\gamma} M'\right)^{-1} = \begin{pmatrix} \kappa\omega_0^2/\delta & 0 \\ 0 & \kappa\omega_0^2 \end{pmatrix}.$$

Finally, note that $\Lambda\left(\mathbb{R}^+\right)$ is invariant under transformation with the transpose of M^{-1}. That is, for any $(x, y)' \in \Lambda\left(\mathbb{R}^+\right)$,

$$\left(M'\right)^{-1} (x, y)' = (x, y - \varrho x) \in \Lambda\left(\mathbb{R}^+\right).$$

Collecting terms,

$$\begin{aligned} \inf_{\lambda \in \mathbb{R}^+ \times \mathbb{R}} \left\| \lambda - \mathcal{Z}_\gamma \right\|_{\mathcal{I}_{\gamma\gamma}}^2 &= \inf_{\eta = (\eta_\alpha, \eta_\omega)' \in \mathbb{R}^+ \times \mathbb{R}} \left\| \eta - Z_\gamma \right\|_{I_{\gamma\gamma}}^2 \\ &= \frac{1}{2\omega_0^2} \inf_{\eta \in \mathbb{R}^+ \times \mathbb{R}} \{(\eta_\alpha - Z_\alpha)^2 \delta_0 + (\eta_\omega - Z_\omega)^2\}. \end{aligned} \tag{A.19}$$

It follows that

$$\arg \inf_{\eta \in \mathbb{R}^+ \times \mathbb{R}} \{(\eta_\alpha - Z_\alpha)^2 \delta_0 + (\eta_\omega - Z_\omega)^2\} = (\max(0, Z_\alpha), Z_\omega)',$$

such that by (A. 19), and using that by definition, $\lambda = M'\eta$,

$$\begin{aligned} \arg \inf_{\lambda \in \mathbb{R}^+ \times \mathbb{R}} \left\| \lambda - \mathcal{Z}_\gamma \right\|_{\mathcal{I}_{\gamma\gamma}}^2 &= M' (\max(0, Z_\alpha), Z_\omega)' \\ &= (\max(0, Z_\alpha), Z_\omega - \varrho \max(0, Z_\alpha)). \end{aligned} \tag{A.20}$$

Here, Z_α and Z_ω are independent Gaussian distributed with

$$Z_\alpha \overset{d}{=} N\left(0, \kappa\omega_0^2/\delta\right) \text{ and } Z_\omega \overset{d}{=} N\left(0, \kappa\omega_0^2\right) \tag{A.21}$$

This establishes Theorem 1.

Remark A.1. Note that if $\xi = 0$, the covariance of $\mathcal{Z}$, see (A. 15) becomes block-diagonal,

$$\Omega_{\mathcal{Z}} = \begin{pmatrix} \Omega_{\mathcal{Z},\pi\pi} & 0 \\ 0 & \Omega_{\mathcal{Z},\gamma\gamma} \end{pmatrix}. \tag{A.22}$$

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Remark A.2. The above also reduces to Ling (2004, Thm. 1) for the case of $\alpha_0 > 0$ and $\xi = 0$.

A.3. QMLE AND LR TEST UNDER NONSTATIONARITY—THEOREMS 2 AND 3

We proceed in the following by establishing regularity conditions under which the asymptotic distribution of the QMLE and the likelihood ratio test can be derived for the nonstationary case, where $\theta_0 \in \Theta_{\mathcal{N}}$. Specifically, we verify the following regularity Conditions (C.i) and (C.ii) in terms of the log-likelihood function, $L_n(\theta)$, and its derivatives.

Condition (C.i). *With* $G_n = diag\left(g_{n,i}\right)_{i=1,2,3}$, *where*

$$\left(g_{1,n}, g_{2,n}, g_{3,n}\right) = \left(n, n^{3/2}, n^{1/2}\right),$$

it holds that

$$\left(G_n^{-1} S_n(\theta_0), G_n^{-1} I_n(\theta_0) G_n^{-1}\right) \xrightarrow{w} (\mathcal{S}_\infty, \mathcal{I}_\infty). \tag{A.23}$$

Condition (C.ii). *With* $\theta := (\theta_1, \theta_2, \theta_3)' = (\pi, \alpha, \omega)'$, *and* $i, j, k = 1, 2, 3$,

$$\sup_{\theta \in N_n(\theta_0)} \left\| n^{1/2} \left(\partial^3 L_n(\theta)\right) / \left(\partial\theta_i \partial\theta_j \partial\theta_k\right) / \left(g_{i,n} g_{j,n} g_{k,n}\right) \right\| = O_p(1), \tag{A.24}$$

where the supremum is over a the sequence of neigborhoods given by,

$$N_n(\theta_0) = \left\{\theta : g_{1,n}^2 \pi^2 + g_{2,n}^2 \alpha^2 + g_{3,n}^2 (\omega - \omega_0)^2 < \varepsilon / n\right\}.$$

Conditions (C.i) and (C.ii) are from Kristensen and Rahbek (2010, Lem. 11 and 12), where general asymptotic theory is presented for (non)stationary variables. With the parameter spaces $\mathcal{T}$ and $\mathcal{T}_0$ satisfying (i), that is, shifted they are locally equal to Λ and Λ_0, it follows as in Klüppelberg et al. (2002, Lem. B.1), see also Vu and Zhou (1997) and Andrews (2001), that with

$$\mathcal{Z} := \mathcal{I}_\infty^{-1} \mathcal{S}_\infty,$$

then the LR_n statistic converges in distribution

$$LR_n \to_w \mathcal{LR}_\infty(\kappa) = \inf_{\lambda \in \Lambda_0} \|\lambda - \mathcal{Z}\|_{\mathcal{I}_\infty}^2 - \inf_{\lambda \in \Lambda} \|\lambda - \mathcal{Z}\|_{\mathcal{I}_\infty}^2. \tag{A.25}$$

Likewise, as in Andrews (1999, Thm. 3), under (C.i) and (C.ii), it follows that

$$G_n(\hat{\theta}_n - \theta_0) \to_w \arg \inf_{\lambda \in \Lambda} \|\lambda - \mathcal{Z}\|_{\mathcal{I}_\infty}^2. \tag{A.26}$$

A.3.1. Preliminaries

Note initially, that under the null hypothesis H_0, $S_n(\theta_0) = \sum_{t=1}^n s_{t,0}$, see (A. 3), where with $\theta_0 \in \Theta_{\mathcal{N}}$,

$$s_{t,0} = \left(v_{t-1} z_t, \tfrac{1}{2} v_{t-1}^2 \left(z_t^2 - 1\right), \tfrac{1}{2\omega_0}\left(z_t^2 - 1\right)\right)', \quad \text{with } v_t := \sum_{i=1}^t z_i.$$

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Standard application of the invariance principle implies convergence to the Brownian motion V_u, $u \in (0,1)$:

$$n^{-1/2}\sum_{t=1}^{\lfloor n\cdot\rfloor}\left(z_t, z_t^2-1\right)' \xrightarrow{w} V := (V_1, V_2)',\ E(V_1 V_1') = \begin{pmatrix} 1 & \xi \\ \xi & \kappa \end{pmatrix}. \tag{A.27}$$

Define next the matrix

$$Q = \begin{pmatrix} 1 & 0 \\ -\xi/\sqrt{\kappa-\xi^2} & 1/\sqrt{\kappa-\xi^2} \end{pmatrix}, \text{ with } Q^{-1} = \begin{pmatrix} 1 & 0 \\ \xi & \sqrt{\kappa-\xi^2} \end{pmatrix}, \tag{A.28}$$

and use it to define the bivariate standard Brownian motion $(B, W)'$

$$(B, W)' := QV = (V_1, (V_2 - \xi V_1)/\sqrt{\kappa-\xi^2})'. \tag{A.29}$$

It then follows that

$$n^{-1/2}\sum_{t=1}^{\lfloor n\cdot\rfloor} Q\left(z_t, z_t^2-1\right)' \xrightarrow{w} (B_\cdot, W_\cdot)'. \tag{A.30}$$

A.3.2. Score—Condition (C.i)

Consider next the score $S_n(\theta_0)$, normalized by G_n, where

$$G_n^{-1} = \operatorname{diag}\left(n^{-1}, n^{-3/2}, n^{-1/2}\right). \tag{A.31}$$

It follows, with

$$G_n^{-1} S_n(\theta_0) = \frac{1}{n^{1/2}}\sum^{n}\left(\begin{pmatrix} n^{-1/2}\sum_{i=1}^{t-1} z_t & 0 \\ 0 & \left(n^{-1/2}\sum_{i=1}^{t-1} z_t\right)^2/2 \\ 0 & \frac{1}{2\omega_0} \end{pmatrix}\right)\left(z_t, z_t^2-1\right)',$$

that

$$\begin{aligned} G_n^{-1} S_n(\theta_0) &\xrightarrow{w} \mathcal{S}_\infty(\xi) = \left(\mathcal{S}_\pi, \mathcal{S}_\gamma'\right)' = (\mathcal{S}_\alpha, \mathcal{S}_\alpha, \mathcal{S}_\omega)' \\ &= \left(\int B\,\mathrm{d}B, \tfrac{\xi}{2}\int B^2\,\mathrm{d}B + \tfrac{\sqrt{\kappa-\xi^2}}{2}\int B^2\,\mathrm{d}W, \tfrac{\xi}{2\omega_0}B_1 + \tfrac{\sqrt{\kappa-\xi^2}}{2\omega_0}W_1\right)'. \end{aligned} \tag{A.32}$$

A.3.3. Information—Condition (C.i)

Under H_0, it follows by standard arguments that (jointly with the score) the information $I_n(\theta_0) = \sum_1^n i_{t,0}$ converges weakly

$$G_n^{-1} I_n(\theta_0) G_n^{-1} \xrightarrow{w} \mathcal{I}_\infty = \begin{pmatrix} \mathcal{I}_{\pi\pi} & 0 \\ 0 & \mathcal{I}_{\gamma\gamma} \end{pmatrix}, \tag{A.33}$$

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with

$$\mathcal{I}_{\gamma\gamma} = \frac{1}{2}\begin{pmatrix} \int B^4 \mathrm{d}u & \frac{1}{\omega_0}\int B^2 \mathrm{d}u \\ \frac{1}{\omega_0}\int B^2 \mathrm{d}u & \frac{1}{\omega_0^2} \end{pmatrix}, \text{ and } \mathcal{I}_{\pi\pi} = \int B^2 \mathrm{d}u.$$

Also observe that by definition,

$$\mathcal{I}_{\infty}^{-1} = \begin{pmatrix} \mathcal{I}_{\pi\pi}^{-1} & 0 \\ 0 & \mathcal{I}_{\gamma\gamma}^{-1} \end{pmatrix}, \quad \mathcal{I}_{\gamma\gamma}^{-1} = \frac{2}{\delta}\begin{pmatrix} 1 & -\omega_0 \int B^2 \mathrm{d}u \\ -\omega_0 \int B^2 \mathrm{d}u & \omega_0^2 \int B^4 \mathrm{d}u \end{pmatrix} \tag{A.34}$$

with $\delta = \int B^4 \mathrm{d}u - \left(\int B^2 \mathrm{d}u\right)^2$.

A.3.4. Third-order derivatives—Condition (C.ii)

It follows that (C.ii) holds by the considerations in Appendix A.6 below.

A.4. QMLE–PROOF OF THEOREM 2

By (A. 26), we have,

$$G_n(\hat{\theta}_n - \theta_0) \xrightarrow{w} \arg \inf_{\lambda \in \Lambda} \|\lambda - \mathcal{Z}\|^2_{\mathcal{I}_\infty} =: (\lambda_\pi, \lambda_\alpha, \lambda_\omega)',$$

with $\mathcal{Z}$ given by (A. 35). As before, by block-diagonality of $\mathcal{I}_\infty$ in (A. 34) and the definition of $\mathcal{Z}$ in (A. 35),

$$\lambda_\pi = \mathcal{Z}_\pi = \int B \mathrm{d}B / \int B^2 \mathrm{d}u.$$

For $\lambda_\gamma = (\lambda_\alpha, \lambda_\omega)'$, use that by definition of $Z_\gamma := (Z_\alpha, Z_\omega)'$ defined in (A. 37), we have

$$\inf_{\lambda_\gamma \in \mathbb{R}^+ \times \mathbb{R}} \left\|\lambda_\gamma - \mathcal{Z}_\gamma\right\|^2_{\mathcal{I}_{\gamma\gamma}} = \inf_{\eta \in \mathbb{R}^+ \times \mathbb{R}} \left\|\eta - Z_\gamma\right\|^2_{I_{\gamma\gamma}}.$$

In terms of $\eta = (\eta_\alpha, \eta_\omega)'$, we find

$$\begin{aligned} \arg \inf_{\eta \in \mathbb{R}^+ \times \mathbb{R}} \left\|\eta - Z_\gamma\right\|^2_{I_{\gamma\gamma}} &= \arg \inf_{\eta = (\eta_\alpha, \eta_\omega)' \in \mathbb{R}^+ \times \mathbb{R}} \left((\eta_\alpha - Z_\alpha)^2 + (\eta_\omega - Z_\omega)^2\right) \\ &= (\max(0, Z_\alpha), Z_\omega)'. \end{aligned}$$

Finally, use the identity $\lambda_\gamma = (\lambda_\alpha, \lambda_\omega)' = M'\eta$ to see that

$$\lambda_\gamma = M'(\max(0, Z_\alpha), Z_\omega)' = (\max(0, Z_\alpha), Z_\omega - (\omega_0 \int B^2 \mathrm{d}u) \max(0, Z_\alpha))'.$$

Collecting terms, and setting $\xi = 0$, ends the proof of Theorem 2.

A.4.1. LR_n Convergence—Proof of Theorem 3

From (A. 25),

$$LR_n \xrightarrow{w} \mathcal{LR}_\infty(\kappa) = \inf_{\lambda \in \Lambda_0} \|\lambda - \mathcal{Z}\|^2_{\mathcal{I}_\infty} - \inf_{\lambda \in \Lambda} \|\lambda - \mathcal{Z}\|^2_{\mathcal{I}_\infty},$$

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where $\mathcal{Z} := (\mathcal{Z}_\pi, \mathcal{Z}_\alpha, \mathcal{Z}_\omega)' = \left(\mathcal{Z}_\pi, \mathcal{Z}_\gamma'\right)' = \mathcal{I}_\infty^{-1}\mathcal{S}_\infty$ satisfies $\mathcal{Z}_\pi = \int B \mathrm{d}B / \int B^2 \mathrm{d}\, u$,

$$\mathcal{Z}_\alpha = \tfrac{1}{\delta}\left(\left(\xi \int B^2 \mathrm{d}B + \sqrt{\kappa - \xi^2}\int B^2 \mathrm{d}W\right) - \int B^2 \mathrm{d}u\left(\xi B_1 + \sqrt{\kappa - \xi^2} W_1\right)\right), \quad \textbf{(A.35)}$$

and

$$\mathcal{Z}_\omega = \tfrac{\omega_0}{\delta}\left(\int B^4 \mathrm{d}u(\xi B_1 + \sqrt{\kappa - \xi^2} W_1) - \int B^2 \mathrm{d}u\left(\xi \int B^2\ \mathrm{d}B + \sqrt{\kappa - \xi^2}\int B^2 \mathrm{d}W\right)\right).$$

By the block-diagonality of $\mathcal{I}_\infty$ in (A. 34), we may write $\mathcal{LR}_\infty(\kappa)$ as

$$\mathcal{LR}_\infty(\kappa) = \mathcal{Z}_\pi^2 \mathcal{I}_{\pi\pi} + \inf_{\lambda \in \{0\}\times\mathbb{R}} \left\|\lambda - \mathcal{Z}_\gamma\right\|_{\mathcal{I}_{\gamma\gamma}}^2 - \inf_{\lambda \in \mathbb{R}^+\times\mathbb{R}} \left\|\lambda - \mathcal{Z}_\gamma\right\|_{\mathcal{I}_{\gamma\gamma}}^2.$$

Diagonalization of $\mathcal{I}_{\gamma\gamma}$ can next be obtained by using the matrix M defined as

$$M := \begin{pmatrix} 1 & -\omega_0 \int B^2 \mathrm{d}u \\ 0 & 1 \end{pmatrix},$$

such that

$$I_{\gamma\gamma} := M \mathcal{I}_{\gamma\gamma} M' = \tfrac{1}{2}\begin{pmatrix} \delta & 0 \\ 0 & \frac{1}{\omega_0^2} \end{pmatrix}. \quad \textbf{(A.36)}$$

Next, note that $\mathcal{Z}_\gamma = \mathcal{I}_{\gamma\gamma}^{-1}\mathcal{S}_\gamma$, and hence we can define $Z_\gamma := (Z_\alpha, Z_\omega)'$, where

$$Z_\gamma = \left(M'\right)^{-1} \mathcal{Z}_\gamma = \left(\mathcal{I}_{\gamma\gamma} M'\right)^{-1} \mathcal{S}_\gamma. \quad \textbf{(A.37)}$$

By definition,

$$\mathcal{I}_{\gamma\gamma} M' = \tfrac{1}{2}\begin{pmatrix} \delta & \frac{1}{\omega_0}\int B^2 \mathrm{d}u \\ 0 & \frac{1}{\omega_0^2} \end{pmatrix}$$

and hence

$$Z_\gamma = \begin{pmatrix} \delta^{-1}\left(\left(\xi \int B^2 \mathrm{d}B + \sqrt{\kappa - \xi^2}\int B^2 \mathrm{d}W\right) - \int B^2\left(\{\mathrm{d}u \xi B_1 + \sqrt{\kappa - \xi^2} W_1\right)\right) \\ \omega_0(\xi B_1 + \sqrt{\kappa - \xi} W_1) \end{pmatrix}$$

Finally, the cones $\mathbb{R}^+ \times \mathbb{R}$ and $\{0\} \times \mathbb{R}$ are invariant to multiplication by $\left(M'\right)^{-1}$, such that we get, using the identity (A. 36),

$$\begin{aligned} \inf_{\lambda \in \mathbb{R}^+\times\mathbb{R}} \left\|\lambda - \mathcal{Z}_\gamma\right\|_{\mathcal{I}_{\gamma\gamma}}^2 &= \inf_{\lambda \in \mathbb{R}^+\times\mathbb{R}} \left(\lambda - \mathcal{Z}_\gamma\right)' \mathcal{I}_{\gamma\gamma} \left(\lambda - \mathcal{Z}_\gamma\right) \quad \textbf{(A.38)} \\ &= \inf_{\lambda \in \mathbb{R}^+\times\mathbb{R}} \left(\lambda - Z_\gamma\right)' \left(M \mathcal{I}_{\gamma\gamma} M'\right) \left(\lambda - Z_\gamma\right) \\ &= \tfrac{\delta}{2} \inf_{\lambda \in \mathbb{R}^+} (\lambda - Z_\alpha)^2 + \inf_{\lambda \in \mathbb{R}} (\lambda - Z_\omega)^2 / \left(2\omega_0^2\right) \\ &= \tfrac{\delta}{2} Z_\alpha^2 \mathbb{I}(Z_\alpha < 0). \end{aligned}$$

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Here, by definition,

$$Z_\alpha = \delta^{-1}\left(\left(\xi\int B^2\mathrm{d}B+\sqrt{\kappa-\xi^2}\int B^2\mathrm{d}W\right)-\int B^2\mathrm{d}u(\xi B_1+\sqrt{\kappa-\xi^2}W_1)\right). \tag{A.39}$$

Collecting terms, we find

$$\begin{aligned}\mathcal{LR}_\infty(\kappa) &= \mathcal{Z}_\pi^2\mathcal{I}_{\pi\pi}+\frac{\delta}{2}Z_\alpha^2 1(Z_\alpha<0)\\ &= \left(\int B\mathrm{d}B\right)^2/\int B^2\mathrm{d}u+\frac{\delta}{2}Z_\alpha^2 1(Z_\alpha<0),\end{aligned}$$

and setting $\xi = 0$ ends the proof of Theorem 3.

A.5. BOOTSTRAP—PROOF OF THEOREM 4

We verify here the equivalent of the Conditions (C.i) and (C.ii) for the bootstrap from which the bootstrap results are derived.

A.5.1. Bootstrap Score and Information

It follows that the bootstrap score is given by

$$s_{t,0}^* = \left(v_{t-1}^* z_t^*, \tfrac{1}{2}v_{t-1}^{*2}(z_t^{*2}-1), \tfrac{1}{2\tilde{\omega}_n}(z_t^{*2}-1)\right)', \text{ with } v_t^* = \sum_{i=1}^t z_i^*.$$

The bootstrap invariance principle (cf. Cavaliere, Rahbek and Taylor, 2012) implies the main result of convergence to the Brownian motion V^*, as stated in the following Lemma.

LEMMA A.1. *Assume that* $E(z_t^8)<\infty$. *Then, as* $n\to\infty$,

$$n^{-1/2}\sum_{t=1}^{\lfloor n\cdot\rfloor}\left(z_t^*, z_t^{*2}-1\right)' \xrightarrow{w^*}_p V_\cdot^* = \left(V_{1\cdot}^*, V_{2\cdot}^*\right)',\ E(V_1^* V_1^{*\prime}) = \begin{pmatrix}1 & \xi\\ \xi & \kappa\end{pmatrix}.$$

Proof. By definition, z_t^* is resampled with replacement from $\tilde{z}_{s,t}$,

$$\tilde{z}_{s,t} = \frac{\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t}{(n^{-1}\sum_{t=1}^n(\tilde{z}_t - n^{-1}\sum_{t=1}^n \tilde{z}_t)^2)^{1/2}},$$

where, under H_0,

$$\tilde{z}_t = \tilde{\omega}_n^{-1/2}\Delta x_t = \tilde{\omega}_n^{-1/2}\omega_0^{1/2} z_t.$$

With $m_t^* := \left(z_t^*, z_t^{*2}-1\right)'$ consider, for any $\lambda\in\mathbb{R}^2$, $\lambda\neq 0$,

$$\lambda' m_t^* = \lambda_1 z_t^* + \lambda_2\left(z_t^{*2}-1\right).$$

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Again, conditional on data, $\lambda' m_t^*$ is i.i.d., and hence as in Swensen (2003, eqn. (10), proof of Thm. 1), it suffices to establish

$$E^*\left(\lambda' m_t^*\right)^2 \xrightarrow{p} E\left(\lambda' m_t\right)^2, \quad \text{and} \quad E^*\left(\lambda' m_t^*\right)^4 \xrightarrow{p} E\left(\lambda' m_t\right)^4,$$

where $m_t = \left(z_t, z_t^2 - 1\right)'$, which by standard arguments holds if $Ez_t^8 < \infty$. This ends the proof of Lemma A.1. □

Next, with $Q^* = Q$ in (A. 28), construct the bivariate standard Brownian motion $\left(B^*, W^*\right)'$ as

$$\left(B^*, W^*\right)' = Q^* V^* = (V_1^*, \left(V_2^* - \xi V_1^*\right)/\sqrt{\kappa - \xi^2})',$$

such that

$$n^{-1/2} \sum_{t=1}^{\lfloor n\cdot \rfloor} Q^* \left(z_t^*, z_t^{*2} - 1\right)' \xrightarrow{w^*}_p \left(B_\cdot^*, W_\cdot^*\right)'. \tag{A.40}$$

Then, the following lemma follows.

LEMMA A.2. *If $Ez_t^8 < \infty$, and with G_n defined in (A. 31), then the bootstrap score satisfies,*

$$G_n^{-1} S_n^* \xrightarrow{w^*}_p \mathcal{S}_\infty^*,$$

where $\mathcal{S}_\infty^* = \left(\mathcal{S}_\pi^*, \mathcal{S}_\alpha^*, \mathcal{S}_\omega^*\right)'$ with,

$$\mathcal{S}_\infty^{*\prime} = \left(\int B^* dB^*, \tfrac{\xi}{2} \int B^{*2} dB^* - \tfrac{\sqrt{\kappa-\xi^2}}{2} \int B^{*2} dW^*, \tfrac{\xi}{2\omega_0} B_1^* - \tfrac{\sqrt{\kappa-\xi^2}}{2\omega_0} W_1^*\right).$$

We also have the following result on the information.

LEMMA A.3. *Under the conditions of Lemma A.2 it follows that the bootstrap information converges jointly with the score as follows:*

$$G_n^{-1} \left(\sum_1^n i_{t,0}^*\right) G_n^{-1} \xrightarrow{w^*}_p \mathcal{I}_\infty^* = \begin{pmatrix} \mathcal{I}_{\pi\pi}^* & 0 \\ 0 & \mathcal{I}_{\gamma\gamma}^* \end{pmatrix}, \text{ with}$$

$$\mathcal{I}_{\gamma\gamma}^* = \frac{1}{2} \begin{pmatrix} \int B^{*4} du & \frac{1}{\omega_0} \int B^{*2} du \\ \frac{1}{\omega_0} \int B^{*2} du & \frac{1}{\omega_0^2} \end{pmatrix},$$

and $\mathcal{I}_{\pi\pi}^* = \int B^{*2} du$.

Finally, Condition (C.ii) is shown in Appendix A.6 to hold also for the bootstrap case.

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A.5.2. Bootstrap LR_n^* statistic

Observe that by definition

$$\mathcal{I}_\infty^{*-1} = \begin{pmatrix} \mathcal{I}_{\pi\pi}^{*-1} & 0 \\ 0 & \mathcal{I}_{\gamma\gamma}^{*-1} \end{pmatrix}, \quad \mathcal{I}_{\gamma\gamma}^{*-1} = \frac{2}{\delta^*} \begin{pmatrix} 1 & -\omega_0 \int B^{*2} \mathrm{d}u \\ -\omega_0 \int B^{*2} \mathrm{d}u & \omega_0^2 \int B^{*4} \mathrm{d}u \end{pmatrix},$$

with $\delta^* = \left[\int B^{*4} \mathrm{d}u - \left(\int B^{*2} \right)^2 \right]$. We define $\mathcal{Z}^* = \left(\mathcal{Z}_\pi^*, \mathcal{Z}_\alpha^*, \mathcal{Z}_\omega^* \right)' = \mathcal{I}_\infty^{*-1} \mathcal{S}_\infty^* (\xi)$, where

$$\mathcal{Z}_\pi^* = \int B^* \mathrm{d}B^* / \int B^{*2} \mathrm{d}u \tag{A.41}$$

$$\mathcal{Z}_\pi^* = \tfrac{1}{\delta^*} \left(\left\{ \xi \int B^{*2} \mathrm{d}B^* + \sqrt{\kappa - \xi^2} \int B^{*2} \mathrm{d}W \right\} - \int B^{*2} \mathrm{d}u \{ \xi B_1^* + \sqrt{\kappa - \xi^2} W_1 \} \right)$$

$$\mathcal{Z}_\omega^* = -\tfrac{\omega_0}{\delta^*} \left(\int B^{*2} \mathrm{d}u \left\{ \xi \int B^{*2} \mathrm{d}B^* + \sqrt{\kappa - \xi^2} \int B^{*2} \mathrm{d}W \right\} + \int B^{*4} \mathrm{d}u \{ \xi B_1^* + \sqrt{\kappa - \xi^2} W_1 \} \right).$$

It follows that, as for the LR_n statistic under H_0, $LR_n^* \overset{w^*}{\to}_p \mathcal{LR}_\infty^* (\kappa)$, where,

$$\begin{aligned} \mathcal{LR}_\infty^* (\kappa) &= \left(\mathcal{Z}_\pi^* \right)^2 \mathcal{I}_{\pi\pi}^* + \frac{\delta^*}{2} Z_\alpha^{*2} 1 \left(Z_\alpha^* > 0 \right) \\ &= \left(\int B^* \mathrm{d}B^* \right)^2 / \int B^{*2} \mathrm{d}u + \frac{\delta^*}{2} Z_\alpha^{*2} 1 \left(Z_\alpha^* > 0 \right), \end{aligned}$$

with

$$Z_\alpha^* = \delta^{*-1} \left(\left\{ \xi \int B^{*2} \mathrm{d}B^* + \sqrt{\kappa - \xi^2} \int B^{*2} \mathrm{d}W^* \right\} - \int B^{*2} \mathrm{d}u \{ \xi B_1^* + \sqrt{\kappa - \xi^2} W_1^* \} \right). \tag{A.42}$$

which ends the proof of Theorem 4 using $\mathcal{LR}_\infty^* (\kappa) \overset{d}{=} \mathcal{LR}_\infty (\kappa)$.

A.5.3. Bootstrap—Proof of Theorems 6 and 7

The proof of Theorem 6 follows by replicating the proof of Theorem 4, as Lemma A.1 also applies to the case where the bootstrap innovations z_t^* are resampled from

$$\hat{z}_{s,t} = \frac{\hat{z}_t - n^{-1} \sum_{t=1}^n \hat{z}_t}{(n^{-1} \sum_{t=1}^n (\hat{z}_t - n^{-1} \sum_{t=1}^n \hat{z}_t)^2)^{1/2}}, \tag{A.43}$$

where the unrestricted residuals are given by

$$\hat{z}_t = \left(\Delta x_t - \hat{\pi}_n x_{t-1} \right) / \left(\hat{\omega}_n + \hat{\alpha}_n x_{t-1}^2 \right)^{1/2}.$$

The proof of Theorem 7 holds trivially as all arguments used to establish Theorems 4 and 6 allow $\xi \neq 0$.

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A.6. ON THE THIRD-ORDER DERIVATIVES—CONDITION (C.ii)

A.6.1. Nonbootstrap Case

With c and $(c_i)_{i=1}^3$ generic constants, it follows that (C.ii) holds as follows:

$$\partial^3 L_n(\theta)/\partial\pi^3 = 0.$$

$$g_{1,n}^{-3}\partial^3 L_n(\theta)/\partial\pi^2\partial\alpha = n^{-3}\sum_{t=1}^n \frac{x_{t-1}^4}{\sigma_t^4} \le cn^{-3}\sum_{t=1}^n x_{t-1}^4 = O_p(1).$$

$$n^{1/2}g_{1,n}^{-2}g_{3,n}^{-1}\partial^3 L_n(\theta)/\partial\pi^2\partial\omega = n^{-2}\sum_{t=1}^n \frac{x_{t-1}^2}{\sigma_t^4} \le cn^{-2}\sum_{t=1}^n x_{t-1}^2 = O_p(1).$$

$$\left|n^{1/2}g_{2,n}^{-3}\partial^3 L_n(\theta)/\partial\alpha^3\right| = \left|n^{-4}\sum_{t=1}^n\left[3\frac{\varepsilon_t^2}{\sigma_t^2}-1\right]\left(\frac{x_{t-1}^6}{\sigma_t^6}\right)\right|$$

$$\le c_1 n^{-4}\sum_{t=1}^n x_{t-1}^6\left(z_t^2-1\right) + c_2 n^{-4}\sum_{t=1}^n x_{t-1}^6 = O_p(1).$$

$$\left|n^{1/2}g_{2,n}^{-2}g_{3,n}^{-1}\partial^3 L_n(\theta)/\partial\alpha^2\partial\omega\right| = \left|n^{-3}\sum_{t=1}^n\left[3\frac{\varepsilon_t^2}{\sigma_t^2}-1\right]\left(\frac{x_{t-1}^4}{\sigma_t^6}\right)\right|$$

$$\le c_1 n^{-3}\sum_{t=1}^n x_{t-1}^4\left(z_t^2-1\right) + c_2 n^{-3}\sum_{t=1}^n x_{t-1}^4 = O_p(1).$$

$$\left|n^{1/2}g_{2,n}^{-2}g_{1,n}^{-1}\partial^3 L_n(\theta)/\partial\alpha^2\partial\pi\right| = \left|n^{-7/2}\sum_{t=1}^n 2\frac{\varepsilon_t x_{t-1}^5}{\sigma_t^6}\right|$$

$$\le c_1 n^{-7/2}\sum_{t=1}^n\left(|z_t|-E|z_t|\right)\left|x_{t-1}^5\right| + c_2 n^{-7/2}\sum_{t=1}^n\left|x_{t-1}^5\right| = O_p(1).$$

$$\left|n^{1/2}g_{3,n}^{-3}\partial^3 L_n(\theta)/\partial\omega^3\right| = \left|n^{-1}\sum_{t=1}^n\left[3\frac{\varepsilon_t^2}{\sigma_t^2}-1\right]\left(\frac{1}{\sigma_t^6}\right)\right|$$

$$\le c_1 n^{-1}\sum_{t=1}^n[z_t^2-1] + c_2 = O_p(1).$$

$$\left|n^{1/2}g_{1,n}^{-1}g_{3,n}^{-2}\partial^3 L_n(\theta)/\partial\omega^2\partial\pi\right| = \left|n^{-3/2}\sum_{t=1}^n 2\frac{\varepsilon_t x_{t-1}}{\sigma_t^6}\right|$$

$$\le c_1 n^{-3/2}\sum_{t=1}^n\left(|z_t|-E|z_t|\right)|x_{t-1}| + c_2 n^{-3/2}\sum_{t=1}^n|x_{t-1}| = O_p(1).$$

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$$\left|n^{1/2}g_{3,n}^{-2}g_{2,n}^{-1}\partial^3 L_n(\theta)/\partial\omega^2\partial\alpha\right| = \left|n^{-2}\sum_{t=1}^{n}\left[3\frac{\varepsilon_t^2 x_{t-1}^2}{\sigma_t^2}-1\right]\left(\frac{1}{\sigma_t^6}\right)\right|$$

$$\leq c_1 n^{-2}\sum_{t=1}^{n}[z_t^2-1]x_{t-1}^2 + c_2 n^{-2}\sum_{t=1}^{n}\left(x_{t-1}^2+1\right) = O_p(1).$$

$$\left|n^{1/2}g_{3,n}^{-1}g_{2,n}^{-1}g_{1,n}^{-1}\partial^3 L_n(\theta)/\partial\pi\,\partial\omega\partial\alpha\right| = \left|n^{-5/2}\sum_{t=1}^{n}2\frac{\varepsilon_t x_{t-1}^3}{\sigma_t^6}\right|$$

$$\leq c_1 n^{-5/2}\sum_{t=1}^{n}(|z_t|-E|z_t|)\left|x_{t-1}^3\right| + c_2 n^{-5/2}\sum_{t=1}^{n}\left|x_{t-1}^3\right| = O_p(1).$$

Remark A.3. Note that we here used that an invariance principle applies to the term, $\sum_{t=1}^{[n\cdot]}(|z_t|-E|z_t|)$ normalized by $n^{-1/2}$.

A.6.2. Bootstrap Case

With c and $(c_i)_{i=1}^3$ generic constants, it follows that (C.ii) holds for the bootstrap by replicating the arguments in Appendix A.6. That is, we have

$$\partial^3 L_n^*(\theta)/\partial\pi^3 = 0.$$

$$g_{1,n}^{-3}\partial^3 L_n^*(\theta)/\partial\pi^2\partial\alpha = n^{-3}\sum_{t=1}^{n}\frac{x_{t-1}^{*4}}{\sigma_t^{*4}} \leq cn^{-3}\sum_{t=1}^{n}x_{t-1}^{*4} = O_p^*(1).$$

$$n^{1/2}g_{1,n}^{-2}g_{3,n}^{-1}\partial^3 L_n^*(\theta)/\partial\pi^2\partial\omega = n^{-2}\sum_{t=1}^{n}\frac{x_{t-1}^{*2}}{\sigma_t^{*4}} \leq cn^{-2}\sum_{t=1}^{n}x_{t-1}^{*2} = O_p^*(1).$$

$$\left|n^{1/2}g_{2,n}^{-3}\partial^3 L_n^*(\theta)/\partial\alpha^3\right| = \left|n^{-4}\sum_{t=1}^{n}\left[3\frac{\varepsilon_t^{*2}}{\sigma_t^{*2}}-1\right]\left(\frac{x_{t-1}^{*6}}{\sigma_t^{*6}}\right)\right|$$

$$\leq c_1 n^{-4}\sum_{t=1}^{n}x_{t-1}^{*6}\left(z_t^{*2}-1\right) + c_2 n^{-4}\sum_{t=1}^{n}x_{t-1}^{*6} = O_p^*(1).$$

$$\left|n^{1/2}g_{2,n}^{-2}g_{3,n}^{-1}\partial^3 L_n^*(\theta)/\partial\alpha^2\partial\omega\right| = \left|n^{-3}\sum_{t=1}^{n}\left[3\frac{\varepsilon_t^{*2}}{\sigma_t^{*2}}-1\right]\left(\frac{x_{t-1}^{*4}}{\sigma_t^{6}}\right)\right|$$

$$\leq c_1 n^{-3}\sum_{t=1}^{n}x_{t-1}^{*4}\left(z_t^{*2}-1\right) + c_2 n^{-3}\sum_{t=1}^{n}x_{t-1}^{*4} = O_p^*(1).$$

$$\left|n^{1/2}g_{2,n}^{-2}g_{1,n}^{-1}\partial^3 L_n^*(\theta)/\partial\alpha^2\partial\pi\right| = \left|n^{-7/2}\sum_{t=1}^{n}2\frac{\varepsilon_t^* x_{t-1}^{*5}}{\sigma_t^{*6}}\right|$$

$$\leq c_1 n^{-7/2}\sum_{t=1}^{n}\left(\left|z_t^*\right|-E^*\left|z_t^*\right|\right)\left|x_{t-1}^{*5}\right| + c_2 n^{-7/2}\sum_{t=1}^{n}\left|x_{t-1}^{*5}\right| = O_p^*(1).$$

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$$\left|n^{1/2}g_{3,n}^{-3}\partial^3 L_n^*(\theta)/\partial\omega^3\right| = \left|n^{-1}\sum_{t=1}^{n}\left[3\frac{\varepsilon_t^{*2}}{\sigma_t^{*2}}-1\right]\left(\frac{1}{\sigma_t^{*6}}\right)\right|$$
$$\leq c_1 n^{-1}\sum_{t=1}^{n}[z_t^{*2}-1]+c_2 = O_p^*(1).$$
$$\left|n^{1/2}g_{1,n}^{-1}g_{3,n}^{-2}\partial^3 L_n^*(\theta)/\partial\omega^2\partial\pi\right| = \left|n^{-3/2}\sum_{t=1}^{n}2\frac{\varepsilon_t^* x_{t-1}^*}{\sigma_t^{*6}}\right|$$
$$\leq c_1 n^{-3/2}\sum_{t=1}^{n}\left(\left|z_t^*\right|-E^*\left|z_t^*\right|\right)\left|x_{t-1}^*\right|+c_2 n^{-3/2}\sum_{t=1}^{n}\left|x_{t-1}^*\right| = O_p^*(1).$$
$$\left|n^{1/2}g_{3,n}^{-2}g_{2,n}^{-1}\partial^3 L_n^*(\theta)/\partial\omega^2\partial\alpha\right| = \left|n^{-2}\sum_{t=1}^{n}\left[3\frac{\varepsilon_t^{*2}x_{t-1}^{*2}}{\sigma_t^{*2}}-1\right]\left(\frac{1}{\sigma_t^{*6}}\right)\right|.$$
$$\leq c_1 n^{-2}\sum_{t=1}^{n}[z_t^{*2}-1]x_{t-1}^{*2}+c_2 n^{-2}\sum_{t=1}^{n}x_{t-1}^{*2}+c_3 = O_p^*(1).$$
$$\left|n^{1/2}g_{3,n}^{-1}g_{2,n}^{-1}g_{1,n}^{-1}\partial^3 L_n^*(\theta)/\partial\pi\,\partial\omega\partial\alpha\right| = \left|n^{-5/2}\sum_{t=1}^{n}2\frac{\varepsilon_t^* x_{t-1}^{*3}}{\sigma_t^{*6}}\right|.$$
$$\leq c_1 n^{-5/2}\sum_{t=1}^{n}\left(\left|z_t^*\right|-E^*\left|z_t^*\right|\right)\left|x_{t-1}^*\right|^3+c_2 n^{-5/2}\sum_{t=1}^{n}\left|x_{t-1}^*\right|^3 = O_p^*(1).$$

Remark A.4. We have here used that a bootstrap invariance principle holds for the term, $n^{-1/2}\sum_1^{[nu]}\left(\left|z_t^*\right|-E^*\left|z_t^*\right|\right)$, under the conditions in Lemma A.1.

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