BOOTSTRAPPING NON-CAUSAL AUTOREGRESSIONS: WITH APPLICATIONS TO EXPLOSIVE BUBBLE MODELLING

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Abstract

In this paper we develop bootstrap-based inference for non-causal autoregressions with heavy tailed innovations. This class of models is widely used for modelling bubbles and explosive dynamics in economic and financial time series. In the non-causal, heavy tail framework, a major drawback of asymptotic inference is that it is not feasible in practice as the relevant limiting distributions depend crucially on the (unknown) decay rate of the tails of the distribution of the innovations. In addition, even in the unrealistic case where the tail behavior is known, asymptotic inference may suffer from small-sample issues. To overcome these difficulties, in this paper we study novel bootstrap inference procedures, using parameter estimates obtained with the null hypothesis imposed (the so-called restricted bootstrap). We discuss three different choices of bootstrap innovations: wild bootstrap, based on Rademacher errors; permutation bootstrap; a combination of the two ('permutation wild bootstrap'). Crucially, implementation of these bootstraps do not require any a priori knowledge about the distribution of

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the innovations, such as the tail index or the convergence rates of the estimators. We establish sufficient conditions ensuring that, under the null hypothesis, the bootstrap statistics estimate consistently particular *conditional* distributions of the original statistics. In particular, we show that validity of the permutation bootstrap holds without any restrictions on the distribution of the innovations, while the permutation wild and the standard wild bootstraps require further assumptions such as symmetry of the innovation distribution. Extensive Monte Carlo simulations show that the finite sample performance of the proposed bootstrap tests is exceptionally good, both in terms of size and of empirical rejection probabilities under the alternative hypothesis. We conclude by applying the proposed bootstrap inference to Bitcoin/USD exchange rates and to crude oil prices data. We find that indeed non-causal models with heavy tailed innovations are able to fit the data, also in periods of bubble dynamics.

Keywords: Non-causal Autoregressions; Heavy Tails; Bubble Dynamics; Bootstrap.
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1 Introduction

In the recent economic and statistical literature there has been an increasing interest in non-causal processes with heavy tailed innovations, see e.g. Gourieroux and Zakoïan (2017), Hecq, Lieb and Telg (2016), Lanne and Luoto (2017) and the references therein. Despite their simplicity, these models, even in their simplest form, are capable of mimicking periods of explosive, bubble-type dynamics and other types of complex, nonlinear behavior as witnessed repeatedly in financial and economic series; see Hencic and Gourieroux (2015) and Hecq et al. (2016). In economics, non-causal processes are also shown in Gourieroux, Jasiak and Monfort (2016) to be in the solution set of stationary linear rational expectations models, see also Lanne and Luoto (2013) who derive a noncausal autoregressive representation for inflation starting from a standard New Keynesian Phillips curve. Non-causal models are currently used also for forecasting time series with forward looking component, such as inflation or stock returns (Lanne and Luoto, 2013; Gourieroux and Jasiak, 2016; Lanne, Meitz and Saikkonen, 2013).

A major drawback of this class of models, which limits its application in empirical works, is that estimation and testing based on asymptotic inference is extremely hard to implement in practice. In fact, as is well-known from the seminal works by Davis and Resnick (1985a,b, 1986), the relevant limiting distributions depend crucially on nuisance parameters and on the exact distribution of the innovations. Specifically, rates of convergence of estimators and test statistics as well as the form of the corresponding limiting distributions depend on tails of the distribution of the innovations. In addition, as is well known also for causal processes, even in the unrealistic case where the relevant asymptotic distributions were known, asymptotic inference would suffer from small-sample issues in terms of size when testing hypotheses of interest and of empirical coverage when interval estimation is considered.

In contrast, we propose here to resort to bootstrap implementations of ordinary least squares [OLS] based inference. While the bootstrap in standard causal model with finite variance has been deeply explored (see e.g. Gonçalves and White, 2004), to the best our knowledge the bootstrap in non-causal autoregressions with heavy-tailed case has not been pursued in the literature. In the standard, *causal* framework, the presence of heavy tails make the standard (Efron's) bootstrap (based on i.i.d. resampling) an inconsistent estimator of the null distribution of the test statistics of interest, see Athreya (1987) and Knight (1989). Other types of bootstrap, such as the 'm out of n' bootstrap (which is based on bootstrap samples with length – 'm' – less than the length – 'n' – of the original sample) have been proposed, but their performance in finite samples is often unsatisfactory, see e.g. Cornea-Maderia and Davidson (2015) and the discussion in

Section 5 below. Importantly, these bootstraps often require to arbitrarily select the size m of the bootstrap sample or to implement data-dependent methods (as in Bickel and Sakov, 2008). Moreover, the properties of these bootstraps in the non-causal world is largely unknown.

In this paper we take a different route, based on two main ingredients. First, we rely on bootstrap algorithms to generate non-causal bootstrap data where parameter estimates obtained with the null hypothesis imposed on the bootstrap sample. This is the so-called 'restricted bootstrap' (see, *inter alia*, Davidson and MacKinnon, 2006 and Cavaliere, Nielsen and Rahbek, 2015), which we here adapt to the non-causal framework ('unrestricted bootstrap' algorithms are also considered in our analysis although – as will be demonstrated – they tend to be inferior to restricted bootstraps). Second, following a recent proposal made by Cavaliere, Georgiev and Taylor (2016) for *causal* processes, we discuss three different choices of bootstrap innovations: standard wild bootstrap based on Rademacher errors; permutation bootstrap; a combination of the two ('permutation wild bootstrap'). In contrast to (plain or 'm out of n') i.i.d. bootstrap methods, the proposed bootstraps – instead of resampling with replacement from a set of residuals, say $\tilde{\varepsilon}_t$ – work as follows. The wild bootstrap, usually implemented in the causal finite variance case to account for possible heteroskedasticity in the data (Goncalves and Kilian, 2004), generates the bootstrap errors as $\varepsilon_t^* = w_t^* \tilde{\varepsilon}_t$ with $\{w_t^*\}$ an i.i.d. sequence independent of Rademacher random variables, i.e. satisfying $P(w_t^* = 1) = P(w_t^* = -1) = \frac{1}{2}$ (in contrast to the finite variance case, due to the series representation in Lepage, Woodroofe and Zinn, 1981, other choices for the distribution of w_t^* do not work). The permutation bootstrap, proposed initially by LePage and Podgorski (1996) in the context of a regression model with infinite variance errors, generates the bootstrap innovations by simply taking a (uniformly distributed) random permutation of the residuals $\tilde{\varepsilon}_t$. Finally, the permutation-wild bootstrap, combines the two schemes and multiply the randomly permuted residuals with the random, Rademacher sequence $\{w_t^*\}$.

A crucial feature of these bootstraps is that their implementation and related computation of e.g. bootstrap p-values do not require *any* a priori knowledge about the distribution of the innovations, such as the previously mentioned tail index or the convergence rates of the estimators. Moreover, despite the complexity of the underlying statistical theory, the bootstrap algorithms are very simple to implement and do not require the practitioner to choose any tuning parameters.

Although our bootstraps do not estimate the unconditional distribution of the statistics of interest, we establish sufficient conditions ensuring that, under the null hypothesis, the bootstrap statistics estimate consistently particular *conditional* distributions of the original statistics. This is important because, even if the use of OLS inference does not take the tail behavior featured by heavy tailed processes into account, the use of the aforementioned bootstraps allow to restrict the reference population with respect to which the test statistics are compared. For instance, the wild bootstrap estimates the limit null distributions of the original test statistics conditional on the absolute values of the innovations. Similarly, the permutation bootstrap estimates the limit null distributions of the original test statistics conditional on the *order* statistics of the original innovations. Although, as pointed out by an anonymous referee, the statistical literature does not provide a full answer to whether conditional or unconditional bootstrap-based inference performs better, it is important to investigate if in the framework of noncausal autoregressions, conditional inference actually leads to an increase of power with respect to unconditional inference (as is the case for the simple location model with i.i.d. errors, see Cavaliere *et al.*, 2013). Such power increase is confirmed in our Monte Carlo simulations, see Section 5 below.

Our theoretical analysis show that validity of the permutation bootstrap holds without any restriction on the distribution of the innovations, while the permutation wild and the standard wild bootstraps require further assumptions such as symmetry. Interestingly, in the special case of first-order non-causal autoregressions we show that the wild bootstrap mimics exactly (i.e. with no estimation error) the conditional distribution of the original statistic, conditional on the absolute values of the original innovations.

Extensive Monte Carlo simulations show that the finite sample performance of the proposed bootstrap tests is exceptionally good, both in terms of size and of empirical rejection probabilities under the alternative hypothesis.

We conclude by considering two empirical applications of the proposed bootstrap inference. In the first we consider Bitcoin/USD exchange rates. These data were analyzed in a recent paper by Gourieroux and Hencic (2015) using approximate likelihood methods based on the Cauchy density. Using our proposed bootstraps, we find that a non-causal model with heavy tailed innovations fits the data well also in periods of bubble dynamics. The second application focuses on (Dubai) crude oil price data, and again confirm the finding that the non-causal dynamics is an important feature of data which exhibit periods with bubble-type behaviour. The two applications clearly illustrate that bootstrap inference in non-causal models with heavy tails is simple and feasible, despite the fact that no assumptions on the tail behaviour of the data are made.

The paper is organized as follows. Section 2 provides an introduction to non-causal autoregressive processes with heavy tailed innovations, with focus on non-causal autoregressive processes of order $k = 1$, which we denote as $AR^{+}(1)$. In Section 3 we derive validity of the three bootstrap schemes described above, with a detailed theory on both finite sample and asymptotic properties. Next, in Section 4 we extend our asymptotic results to the general case of higher order non-causal autoregressions, denoted $AR^{+}(k)$. Finite sample properties of our bootstrap schemes for $AR^{+}(k)$ inference are investigated by Monte Carlo simulation in Section 5. Additional Monte Carlo simulations are provided in the accompanying supplementary material, Cavaliere, Nielsen and Rahbek (2017). The two illustrative empirical applications are provided in Section 6. Section 7 concludes. All mathematical proofs are relegated to the Appendix, along with a short review of some standard results on heavy tailed processes.

2 Non-causal stable first-order autoregressions

Before presenting our results on general non-causal autoregressions in Section 4, we start by discussing the non-causal AR$^+$(1) process with heavy-tailed innovations. We first define the model in Section 2.1 and compare it with standard, causal processes (denoted by AR$^-$(k) in what follows) with finite variance. The time series properties are then discussed in Section 2.2. Estimation, testing and related asymptotic inference are reviewed in Section 2.3.

2.1 The AR$^+$(1) model

Consider initially the non-causal autoregressive model of order one, $AR^+(1)$, as given by the forward recursion

$$x_t = \rho x_{t+1} + \varepsilon_t,\ t \in \mathbb{Z} \tag{1}$$

where ε_t is an i.i.d. sequence of random variables with heavy tails. The presence of heavy tails, as detailed below, excludes the standard case of finite variance innovations, $E\varepsilon_t^2 < \infty$. Instead, we require that that the tails of the distribution of ε_t decay at a slow rate; more precisely,

$$P\left(|\varepsilon_t| > x\right) \sim cx^{-\alpha} L\left(x\right) \tag{2}$$

for some constant $c > 0$, $\alpha \in (0, 2)$ and $L\left(\cdot\right)$ a slowly varying function at infinity; see Definition A.1 of Appendix A.

As is clear from the definition of the evolution of x_t in (1), the process is non-causal or autoregressive forward in time. This formulation implies (see also Gourieroux and Zakoïan, 2017) that periods of explosive type behavior will occur, as often witnessed in the (exponential) build up and (sudden) decay of bubble phenomena in economic time series; classic examples include stock returns, bit-coin data and social media type (e.g. Twitter or Google search) data. It is also worth noting that under the heavy tail assumption, the standard Gaussian case is ruled out, consequently excluding that the non-causal representation is identical to a standard causal autoregression with the same parameter ρ (see e.g. Brockwell and Davis, 1991, Proposition 4.4.2 and Gourieroux and Zakoïan, 2017, Proposition 3, for the heavy tailed case).

A key example of heavy tailed innovation obtains when the ε_t's are *stable* random variables. Stable distributions (see e.g. Andrews et al., 2009, and references therein) are indexed by an exponent α (here restricted to lie in the open interval $(0, 2)$), usually labelled 'characteristic exponent' or 'tail index', a skewness parameter $|\beta| \leq 1$, a strictly positive and finite scale parameter $\sigma > 0$, and a location parameter $\mu \in \mathbb{R}$, which is set to zero in the following. If $\beta = 0$, the stable distribution is symmetric (about μ). The Cauchy distribution, which is specifically investigated in Gourieroux and Zakoïan (2017), is a special case of the stable distributions as seen by setting $\alpha = 1$ and $\beta = 0$. Also, for stable random variables (2) holds with $L(x) = 1$ and $c = c(\alpha, \beta, \gamma) > 0$ (see e.g. Nolan, 2016):

$$P(|\varepsilon_t| > x) \sim cx^{-\alpha}$$

such that ε_t exhibits the so-called Pareto-type tails. Hence, $E|\varepsilon_t|^p = +\infty$ for all $p \geq \alpha$ while $E|\varepsilon_t|^p < +\infty$ for $p < \alpha$. Consequently, for any $\alpha \in (0, 2)$, ε_t has infinite variance and, for $\alpha \in (0, 1)$, the variance is undefined and ε_t has infinite unconditional expectation.

2.2 Time series properties

As in the causal case, the non-causal $\mathrm{AR}^+(1)$ process x_t is strictly stationary provided $|\rho| < 1$. Then, the strictly stationary solution has the one-sided moving average representation

$$x_t = \sum\nolimits_{j=0}^{\infty} \rho^j \varepsilon_{t+j} \tag{3}$$

which is convergent a.s. for any $\alpha \in (0, 2)$. Notice also that x_t inherits the same tail and moment properties of ε_t (cf. Brockwell and Davis, 1991, Remark 1 of Section 13.3). In particular, x_t has Pareto-type tails and satisfies $E|x_t|^p < \infty$ for $p \in [0, \alpha)$ and $E|x_t|^p = \infty$ for $p \geq \alpha$; see Section A of the Appendix for details.

From Gourieroux and Zakoïan (2017), the $\mathrm{AR}^+(1)$ with stable errors has, for $\rho \neq 0$ and $\beta = 0$, the surprising property of being a Markov chain with expectation, conditional on the past, given by

$$E\left(x_t | x_{t-1}\right) = \operatorname{sgn}\left(\rho\right) |\rho|^{(\alpha-1)} x_{t-1}$$

For the standard Cauchy case (that is, $\beta = 0$ and $\alpha = 1$) with $\rho \in (0, 1)$, this leads to the martingale property

$$E\left(x_t | x_{t-1}\right) = x_{t-1}. \tag{4}$$

In this case the variance of x_t, conditional on the past, changes over time and is given by

$$V\left(x_t | x_{t-1}\right) = \frac{\sigma^2}{\rho\left(1-\rho\right)} + \frac{1-\rho}{\rho} x_{t-1}^2 =: \sigma_{t|t-1}^2. \tag{5}$$

Taken together, (4) and (5) implies that in the Cauchy case x_t can be given a semi-strong double autoregressive (DAR) representation (Ling, 2004, 2007; Ling and Li, 2008;

Nielsen and Rahbek, 2014; Yang and Ling, 2017)

$$x_t = x_{t-1} + \sigma_{t|t-1} z_t$$

with z_t a martingale difference sequence with unit conditional variance and a conditional density depending on x_{t-1}.

2.3 Estimation

In line with Davis and Resnick (1985, 1986a,b) and Gourieroux and Zakoïan (2017), we consider the empirical autocorrelation coefficient or equivalently the ordinary least-squares [OLS] estimator of ρ in the non-causal AR$^+$(1) model. This estimator is non-parametric, in that it does not utilize the specification of the distribution of ε_t. In the special case where the distribution of the ε_t's is known, maximum likelihood [ML] can be employed. For instance, where the ε_t's are assumed to be stable random variables, MLE can be implemented along the lines proposed in Andrews *et al.* (2009), although this is challenging due to the lack of closed-form expressions for the likelihood[1]. However, in the general case treated here where the ε_t's are only known to be in the domain of attraction of a stable distribution, MLE cannot be implemented. Other estimators, such least absolute deviation (LAD) estimators could also be considered; here we focus on OLS estimation only (for LAD estimation, see Hecq *et al.*, 2016).

The OLS estimator (which corresponds to the Gaussian QMLE conditional on x_T

[1]See also Breidt, Davis, Lii and Rosenblatt (1991), Hecq, Lieb and Telg (2016) and Lanne and Saikkonen (2011) for further applications of MLE to non-causal heavy tailed processes.

fixed), is given by[2]

$$\hat{\rho}_T = \frac{\sum_{t=1}^{T-1} x_t x_{t+1}}{\sum_{t=1}^{T-1} x_{t+1}^2} =: \frac{S_{01}}{S_{11}} \tag{6}$$

Crucially, and in contrast to the usual finite variance case, the asymptotic properties of $\hat{\rho}_T$ depend on several (unknown) features of the distribution of ε_t. Importantly, not only the speed of convergence of the estimator depend on the unknown tail index α, but also on the unknown slowly varying function $L(\cdot)$.

To illustrate, consider the special case where ε_t is symmetric about 0 and $E|\varepsilon_t|^\alpha = +\infty$, $\alpha \in (0, 2)$. Then, it follows by Theorem 4.4 in Davis and Resnick (1986a) that for some normalizing sequence $n_T \to \infty$, as $T \to \infty$

$$n_T (\hat{\rho}_T - \rho) \xrightarrow{w} Z := \frac{1-\rho^2}{(1-\rho^\alpha)^{1/\alpha}} \frac{\mathcal{S}_1}{\mathcal{S}_0} \tag{7}$$

where $\mathcal{S}_0$ and $\mathcal{S}_1$ are independent stable random variables with tail index $\alpha/2$ and α, respectively (for the general case, see Appendix A.2). In particular, when ε_t has Pareto-type tails, then (7) holds with $n_T = (T/\log(T))^{1/\alpha}$. Also, when $\alpha = 1$ and ε_t is stable (such that ε_t is Cauchy), the previous expression reduces to

$$\frac{T}{\log T} (\hat{\rho}_T - \rho) \to_w Z = (1+\rho) \frac{\mathcal{S}_1}{\mathcal{S}_0}. \tag{8}$$

In this special case, $\mathcal{S}_1$ is standard Cauchy ($C(0,1)$) and $\mathcal{S}_0$ Lèvy distributed on $(0, \infty)$, which also implies that $\mathcal{S}_0^{-1}$ is χ_1^2. Hence, Z of (8) is distributed as $(1+\rho) C(0,1) \chi_1^2$.

Studentized statistics show similar properties. For instance, consider the standard

[2]One may also consider the sample autocorrelation coefficient, as given by

$$\hat{\phi}_T := \frac{\sum_{t=2}^{T} x_t x_{t-1}}{\sum_{t=1}^{T} x_t^2} = (1 - \frac{x_1^2}{\sum_{t=1}^{T} x_t^2})\hat{\rho}_T \ ,$$

see Davis and Resnick (1986a,b). For the present purposes the two formulations are equivalent and leads to the same results.

t-ratio

$$t_T := \frac{\hat{\rho}_T - \rho_0}{\hat{\sigma}_T S_{11}^{-1/2}}$$

where $S_{11} := \sum_{t=1}^{T-1} x_{t+1}^2$ and $\hat{\sigma}_T^2$ is the residual variance, $\hat{\sigma}_T^2 := T^{-1} \sum_{t=1}^{T} \hat{\varepsilon}_t^2$, for $\hat{\varepsilon}_t := x_t - \hat{\rho}_T x_{t+1}$. In the special case considered above it is straightforward to prove, see Lemma A.5 in the Appendix, that $t_T = O_p\left(T^{1/2} n_T^{-1}\right)$; hence, in practice it is not even obvious how to normalize the Student t-statistic in order to perform asymptotic inference.

As the examples above clearly indicate, asymptotic inference based on OLS estimation is infeasible, as the related asymptotic distributions depend on α, which is unknown in practice. Moreover, even in cases where α is known, inference is not feasible in general, as the normalizing sequence n_T may depend on further unknown quantities, see the next section and Appendix A.2. Hence, we next investigate the usefulness of the bootstrap in approximating the distribution of the OLS estimator in the non-causal case. Crucially, as we will argue next, the bootstrap allows for feasible inference when the tail index α and/or the normalizing sequence n_T are not known.

3 The Bootstrap for the non-causal $\mathrm{AR}^+(1)$

In this section we discuss the bootstrap in the non-causal $\mathrm{AR}^+(1)$ model by focusing on tests of the null hypothesis $\mathsf{H}_0 : \rho = \bar{\rho}$ against the two sided alternative $\rho \neq \bar{\rho}$. We consider test statistics of the form

$$\text{(i): } r_T = \hat{\rho}_T - \bar{\rho} \qquad \text{(ii) } t_T = \frac{\hat{\rho}_T - \bar{\rho}}{\hat{\sigma}_T S_{11}^{-1/2}} \tag{9}$$

with S_{11} and $\hat{\sigma}_T^2$ as defined earlier. As discussed in the previous section, the asymptotic distributions of (appropriately normalized versions of) r_T and t_T are generally unknown and asymptotic inference is infeasible. In what follows, the true value of the AR parameter is denoted by ρ_0. Also, the unrestricted least squares residuals are denoted by $\hat{\varepsilon}_t = x_t - \hat{\rho}_T x_{t+1}$, while the restricted residuals are denoted by $\tilde{\varepsilon}_t = x_t - \bar{\rho} x_{t+1}$, such that, under the null hypothesis, $\tilde{\varepsilon}_t = \varepsilon_t$ $(t = 1, ..., T-1)$.

We initially describe in section 3.1 the two main bootstrap schemes which we propose in the paper. The first is a restricted bootstrap scheme, where the bootstrap DGP satisfies the null hypothesis, while the second is a classic unrestricted bootstrap, where the null hypothesis is not imposed on the bootstrap sample. Then, in section 3.2 we discuss finite sample and asymptotic properties of bootstrap tests based on both schemes.

3.1 Bootstrap schemes

Given the autoregressive structure of the data generating process in (1), we discuss our two recursive bootstrap schemes – the restricted and the unrestricted scheme. For the first, we are able to provide exact results while for the latter, the unrestricted bootstrap, we provide asymptotic results. As already emphasized, the bootstrap here is used to provide approximations of particular *conditional* distributions of the original statistics (where the conditioning set depends on the actual construction of the bootstrap innovations), rather than estimating the unconditional null distribution as is typically the case in the bootstrap literature.

3.1.1 Restricted bootstrap

For some bootstrap innovations ε_t^* $(t = 1, ..., T-1)$ to be described below, we define the bootstrap process x_t^*, $t = 1, ..., T$ by

$$x_t^* = \bar{\rho} x_{t+1}^* + \varepsilon_t^*, \; t = 1, ..., T-1$$

initialized at $x_T^* = x_T$. This corresponds to $x_t^* := \sum_{i=0}^{T-t-1} \bar{\rho}^i \varepsilon_{t+i}^* + \bar{\rho}^{T-t} x_T$ for $t = 1, ..., T$, see also the MA representation in (3).

The choice of the bootstrap innovations ε_t^* is crucial in the heavy tail framework. For instance, it is well known that the i.i.d. bootstrap where the ε_t^*'s are i.i.d. draws from the empirical distribution function of the residuals renders the bootstrap inconsistent, see Athreya (1987) and Knight (1989). Hence, we consider three alternative bootstrap re-sampling methods, which were also considered in Cavaliere, Georgiev and Taylor (2016) for the sieve bootstrap in classic causal AR models. The first is a *permutation* bootstrap, where $\varepsilon_t^* = \tilde{\varepsilon}_{\pi^*(t)}$, $t = 1, 2, ..., T-1$ with $\{\pi^*(i)\}_{i=1}^{T-1}$ a uniformly distributed random permutation of $\{1, 2, ..., T-1\}$. The second is a *wild* bootstrap based on Rademacher innovations[3], where $\varepsilon_t^* = w_t^* \tilde{\varepsilon}_t$, $t = 1, 2, ..., T-1$, with $\{w_t^*\}_{t=1}^{T-1}$ an i.i.d. sequence independent of the original data and satisfying $P(w_t^* = 1) = P(w_t^* = -1) = \frac{1}{2}$. The third, the *permutation-wild* bootstrap, combines the two and sets $\varepsilon_t^* = w_t^* \tilde{\varepsilon}_{\pi^*(t)}$, $t = 1, 2, ..., T-1$, with w_t^* and $\pi^*(t)$ as defined before.

We bootstrap the two statistics in (9) by considering their bootstrap analogs as given by:

$$\text{(i) } r_T^* = \hat{\rho}_T^* - \bar{\rho} \qquad \text{(ii) } t_T^* = \frac{\hat{\rho}^* - \bar{\rho}}{\hat{\sigma}_T^* S_{11}^{*-1/2}}, \tag{10}$$

with $\hat{\rho}_T^*$, $\hat{\sigma}_T^*$ and S_{11}^* the analogues of $\hat{\rho}_T$, $\hat{\sigma}_T$ and S_{11} in terms of the bootstrap sample $\{x_t^*\}$.

3.1.2 Unrestricted bootstrap

With $\hat{\rho}_T$ defined in (6), the unrestricted bootstrap process $x_t^\dagger$, $t = 1, ..., T$ satisfies

$$x_t^\dagger = \hat{\rho}_T x_{t+1}^\dagger + \varepsilon_t^\dagger,\ t = 1, ..., T-1 \tag{11}$$

[3]Notice that in a simple, static location model, the wild bootstrap based on Rademacher shocks corresponds to the sign bootstrap of LePage (1992).

with $x_t^\dagger$ initialized at $x_T^\dagger = x_T$, such that $x_t^\dagger = \sum_{i=0}^{T-t-1} \hat{\rho}_T^i \varepsilon_{t+i}^\dagger + \hat{\rho}_T^{T-t} x_T$ for $t = 1, ..., T$, as noted for the restricted bootstrap. The resampling methods are as before (wild bootstrap, permutation bootstrap and combination thereof) but with $\tilde{\varepsilon}_t$ now replaced by the unrestricted residuals, $\hat{\varepsilon}_t := x_t - \hat{\rho}_T x_{t+1}$. Notice that while for the restricted bootstrap under the null hypothesis it holds that $\tilde{\varepsilon}_t = \varepsilon_t$ (and hence resampling is from the true errors), for the unrestricted bootstrap it holds that $\hat{\varepsilon}_t = \varepsilon_t - (\hat{\rho}_T - \rho_0) x_{t+1}$. This difference is not generally crucial in the finite variance case; however, under heavy tailed innovations the asymptotic properties of the term $(\hat{\rho}_T - \rho_0) x_{t+1}$ are essential in order to assess the validity of the bootstrap.

For the unrestricted bootstrap, the reference bootstrap statistics are given by

$$\text{(i) } r_T^\dagger = \hat{\rho}_T^\dagger - \hat{\rho}_T \qquad \text{(ii) } t_T^\dagger = \frac{\hat{\rho}_T^\dagger - \hat{\rho}_T}{\hat{\sigma}_T^\dagger S_{11}^{\dagger -1/2}},$$

with $\hat{\rho}_T^\dagger$, $\hat{\sigma}_T^\dagger$ and $S_{11}^\dagger$ are the analogues of $\hat{\rho}_T$, $\hat{\sigma}_T$ and S_{11} in terms of the bootstrap sample $\{x_t^\dagger\}$.

We now turn to the finite sample and asymptotic properties of the two bootstrap schemes.

3.2 Properties of the bootstrap

In order to investigate the properties of our bootstrap schemes in the AR$^+$(1) model, we first focus on some exact, finite sample results for the restricted bootstrap. We initially show that under the null hypothesis this bootstrap replicates (with no estimation error) specific *conditional* distributions of the original statistics, irrespective of the dimension of the sample. Since the same exactness property does not hold when the unrestricted bootstrap is employed, we then proceed by establishing that the bootstrap asymptotically replicate such conditional distributions.

3.2.1 Finite sample properties (restricted bootstrap)

As observed above, under the null hypothesis $\tilde{\varepsilon}_t = \varepsilon_t$ such that for the restricted bootstrap the permutation, wild or the combined bootstraps resample from the true ε_t's. This implies that we can state the following exact finite sample result involving the distribution of the restricted bootstrap statistics, conditional on the data, and the distribution of the original statistics, conditional on suitable functions of the data, when the null hypothesis H_0: $\rho = \bar{\rho}$ holds. Here $\mathcal{D}(Y|X)$ denotes the (possibly random) cumulative distribution function of Y given X. Moreover, $\varepsilon_{(t)}$ $(t = 1, ..., T-1)$ denote the order statistics of $\{\varepsilon_t\}$ while $|\varepsilon|_{(t)}$ $(t = 1, ..., T-1)$ denote the order statistics of $\{|\varepsilon_t|\}$.

Lemma 1 (Restricted bootstrap) *With $\{x_t\}_{t=1}^T$ given by (1) with any tail index $\alpha > 0$, consider the restricted bootstrap statistics defined in (10). Then under the null hypothesis $\rho_0 = \bar{\rho}$ it holds that:*

(i) For the permutation bootstrap,

$$\mathcal{D}(r_T^*|\{x_t\}_1^T) = \mathcal{D}(r_T|\{\varepsilon_{(t)}\}_1^{T-1}, x_T);$$

(ii) For the wild bootstrap, if in addition the distribution of ε_t is symmetric about 0,

$$\mathcal{D}(r_T^*|\{x_t\}_1^T) = \mathcal{D}(r_T|\{|\varepsilon_t|\}_1^{T-1}, x_T) \ ;$$

(iii) For the combined permutation-wild bootstrap, if the distribution of ε_t is symmetric about 0,

$$\mathcal{D}(r_T^*|\{x_t\}_1^T) = \mathcal{D}(r_T|\left\{|\varepsilon|_{(t)}\right\}_1^{T-1}, x_T) \ .$$

The same results hold with r_T, r_T^* replaced by t_T, t_T^*, respectively.

Remark 3.1 Lemma 1 implies that the restricted bootstrap replicates particular conditional distributions of the original statistics. Specifically, denote (to simplify notation) by F_T^* the distribution function of r_T^* conditional on the original data, and by F_T the distribution function of the original statistic r_T, conditionally on the statistics specified in the lemma. Then, for any metric $\varrho(\cdot)$ on the space of distribution functions, such as the Lèvy metric (see below), the distance $\varrho(F_T, F_T^*)$ equals 0. As shown in the simulations of Section 5 this is reflected by the excellent size properties displayed by the restricted bootstrap in small samples.

Remark 3.2 The results in Lemma 1 do not hold for the unrestricted bootstrap, and consequently for this bootstrap we instead establish some asymptotic results. As already indicated, the reason is that the difference between unrestricted residuals and true errors, given by $\hat{\varepsilon}_t - \varepsilon_t = -(\hat{\rho}_T - \bar{\rho})\, x_{t+1}$, is not zero and instead becomes negligible only asymptotically (under suitable conditions).

Remark 3.3 The symmetry assumption in Lemma 1(ii) and (iii) is crucial for validity of the wild and permutation-wild bootstraps. This is because symmetry implies that under the null hypothesis the original innovation ε_t and its bootstrap analog ε_t^* have the same distribution conditionally on the absolute value $|\varepsilon_t|$. This distributional equality, which is crucial to the proof of Lemma 1, is clearly violated when ε_t is not symmetrically distributed. It is also worth noticing that exactness of the permutation bootstrap is not based on the symmetry assumption.

Remark 3.4 In the (causal) finite variance case, wild bootstrap validity generally requires that the bootstrap shocks w_t^*'s have zero mean, unit variance and finite fourth order moment. On the contrary, in the heavy tail case, w_t^* necessarily needs to have the two-point (Rademacher) distribution; other choices (such as the Gaussian or the much used Liu's and Mammen's two point distributions) would undermine bootstrap validity in the sense of Lemma 1, also asymptotically, because ε_t^*, conditionally on the data, would not have the same distribution as ε_t, conditionally on the absolute value $|\varepsilon_t|$.

REMARK 3.5 Importantly, Lemma 1 only requires i.i.d.-ness of the sequence $\{\varepsilon_t\}$ (and symmetry for the permutation and permutation wild schemes, see the previous remark) and hence allows for any value of the non-causal autoregressive parameter ρ as well as of the tail index α.

Finally, it is important to notice that the fact the bootstrap reproduces with no estimation error a particular conditional distribution of the original statistic is not enough for establishing that the bootstrap p-value, p_T^*, is uniformly distributed under the null hypothesis. This result is carefully discussed in Davidson and Flachaire (2014) for a regression model with regressors independent of the shocks at all leads and lags. In particular, as in their Theorem 1, we can use Lemma 1 to prove that, although the bootstrap is not exact for any arbitrary nominal level, the discrepancy between a chosen nominal level and the actual level is very small, even for samples of very small size (see Davidson and Flachaire, 2014, pp.164–165). Specifically, such discrepancy does not approximately exceed 2^{-T} for the wild bootstrap and $(T!)^{-1}$ for the permutation-based bootstraps.

3.2.2 Large sample properties

We now turn to the large sample properties of the unrestricted bootstrap. In particular, we establish that, under the null hypothesis, the permutation and the permutation-wild bootstraps behave asymptotically as the restricted bootstrap statistics. The same result does not hold for the standard wild bootstrap, as it will be clarified later.

In order to state our results below and in the next section, we make use of the following assumption, see also Davis and Resnick (1986) and the discussion therein.

Assumption 1 *With* $\{x_t\}_1^T$ *as given in (1), assume that* (i) $|\rho| < 1$*;* (ii) *the tail decay of* $\{\varepsilon_t\}$ *in (2) holds with* $\alpha \in (0,2)$ *and* $\lim_{x\to\infty} P(\varepsilon_t > x)/P(|\varepsilon_t| > x) =: p \in [0,1]$, $\lim_{x\to\infty} P(\varepsilon_t < -x)/P(|\varepsilon_t| > x) = 1 - p$*;* (iii) $E|\varepsilon_t|^\alpha = +\infty$*;* (iv) *for* $\alpha \in (1,2)$, $E(\varepsilon_t) = 0$ *while, for* $\alpha = 1$, ε_t *is symmetrically distributed.*

Assumption 1(i) is a standard stationarity condition for non-causal autoregressions, see also Section 2. Assumption 1(ii) is classic in the heavy tail literature and corresponds to assuming that $\{\varepsilon_t\}$ is in the domain of attraction of an α-stable law; see Appendix A. Assumption 1(iii) connects the tail index α to the (in)finiteness of the moments of ε_t. Finally, Assumption 1(iv) is a very mild requirement which essentially rules out some pathological cases arising at the singularity $\alpha = 1$.

The following lemma provides the asymptotic properties under the null hypothesis. Specifically, recall that Lemma 1 shows that under the null hypothesis the distribution of restricted bootstrap statistic r_T^*, conditional on the original data, is identical to the distribution of original statistic r_T, conditional on appropriate transformations of the original innovations $\{\varepsilon_t\}$. Recall, additionally, that the original statistic r_T converges weakly at the rate n_T, see (7) for the symmetric case and Lemma A.4 in Appendix for the general case. In the next lemma we show that under the null hypothesis the unrestricted bootstrap statistic $r_T^\dagger$ and restricted bootstrap statistic r_T^* are close in the sense that

$$n_T(r_T^\dagger - r_T^*) = o_p^*(1),$$

see Appendix B for notation on bootstrap stochastic orders. Importantly, this implies that (under the null hypothesis) the distribution of unrestricted bootstrap statistic $r_T^\dagger$, conditional on the original data, asymptotically coincides with the distribution of original statistic r_T, conditional on appropriate transformations of the original innovations $\{\varepsilon_t\}$. More precisely, the Lèvy metric between these two conditional distributions tends to zero, in probability (see also Remark 3.6 below).

Lemma 2 *Let $\{x_t^\dagger\}_{t=1}^T$ be the unrestricted bootstrap process defined in (11) using either permutation or permutation-wild bootstrap shocks. Then, under Assumption 1, if the null hypothesis holds then*

$$n_T(r_T^\dagger - r_T^*) = o_{p^*}(1)$$

with n_T as given in Appendix B.2. Likewise, for the studentized bootstrap statistics $t_T^\dagger, t_T^*$, it holds that

$$\frac{n_T}{T^{1/2}}(t_T^\dagger - t_T^*) = o_{p^*}(1)\,.$$

Remark 3.6 From Lemma 2 we are able to conclude that asymptotically and conditionally on the data, the unrestricted bootstrap test statistics behave as the restricted bootstrap test statistics under the null. In particular, this implies, for the permutation bootstrap, that in terms of the Levy-metric $\varrho_L(\cdot)$,[4]

$$\varrho_L\left(F_T^\dagger, F_T^*\right) \xrightarrow{p} 0$$

where F_T^* ($F_T^\dagger$) is now the distribution function of the normalized restricted bootstrap statistic $n_T r_T^*$ (unrestricted bootstrap statistic $n_T r_T^\dagger$) conditional on the original data. Hence, using also Lemma 1,

$$\varrho_L\left(F_T^\dagger, F_T\right) \xrightarrow{p} 0$$

with F_T the distribution function of the normalized original statistic $n_T r_T$, conditionally on the statistics specified in Lemma 1. Under symmetry of ε_t, an equivalent result holds for the permutation-wild bootstrap.

Remark 3.7 While the permutation and the permutation wild bootstraps are asymp-

[4]For a given $\eta > 0$, η-proximity of two cumulative distribution functions, say F and F^*, at a point x can be evaluated by means of the indicator $I_\eta^{F,F^*}(x) := \mathbb{I}\left(F^*(x-\eta) - \eta \le F(x) \le F^*(x+\eta) + \eta\right)$. Then, the Lévy metric between F and F^* is defined as follows:

$$\varrho_L(F, F^*) := \inf\{\eta > 0 : \forall x \in \mathbb{R},\ I_\eta^{F,F^*}(x) = 1\}.$$

totically valid (in the Levy metric), a similar result does not hold for the standard wild bootstrap, even under the symmetry assumption. However, we show in section 5 that this bootstrap (in the case of symmetric innovations) has good finite sample size properties.

4 Higher-order dynamics

Consider now the AR$^+(k)$ process ($k \geq 1$)

$$x_t = \rho_1 x_{t+1} + ... + \rho_k x_{t+k} + \varepsilon_t = \beta' z_{t+1} + \varepsilon_t \tag{12}$$

where $z_t := (x_t, ..., x_{t+k-1})'$, $\beta := (\rho_1, ..., \rho_k)'$ and the ε_t's as defined earlier. Interest lies in testing linear hypotheses of the form $\mathsf{H}_0 : R'\beta = r$, where R is $k \times 1$ and r scalar (extension to multiple hypotheses are considered in Remark 4.3 below). As is standard, we focus on the test statistics

$$\text{(i) } r_T = R'\hat{\beta}_T - r \quad \text{(ii) } t_T = \frac{R'\hat{\beta}_T - r}{\hat{\sigma}_T (R' S_{11}^{-1} R)^{1/2}} \tag{13}$$

where, with $S_{11} := \sum_{t=1}^{T-k} z_{t+1} z_{t+1}'$ and $S_{10} := \sum_{t=1}^{T-k} z_{t+1} x_t$, $\hat{\beta}_T := S_{11}^{-1} S_{10}$ is the OLS estimator of β and $\hat{\sigma}_T^2 := T^{-1} \sum_{t=1}^{T-k} \hat{\varepsilon}_t^2$, $\hat{\varepsilon}_t := x_t - \hat{\beta}_T' z_{t+1}$, is the residual variance.

Consider the restricted bootstrap, based on the restricted OLS estimator, $\tilde{\beta}_T$, and associated residuals, $\tilde{\varepsilon}_t := x_t - \tilde{\beta}_T' z_{t+1}$, $t = 1, ..., T-k$. The bootstrap sample is generated recursively with H_0 imposed as

$$x_t^* = \tilde{\beta}_T' z_{t+1}^* + \varepsilon_t^*, \ t = 1, ..., T-k \tag{14}$$

and initialized at $x_t^* = x_t$, $t = T-k+1, ..., T$. The ε_t^*'s are, as before, based on permutation and permutation-wild bootstrap resampling of the restricted residuals $\tilde{\varepsilon}_t$'s.

The wild bootstrap is invalid in this case and hence it is not considered further (see Remark 4.1 below). The restricted bootstrap statistics r_T^* and t_T^* are

$$\text{(i) } r_T^* = R'\hat{\beta}_T^* - r \qquad \text{(ii) } t_T^* = \frac{R'\hat{\beta}_T^* - r}{\hat{\sigma}_T^*(R' S_{11}^{*-1} R)^{1/2}}$$

where, with $S_{11}^* := \sum_{t=1}^{T-k} z_{t+1}^* z_{t+1}^{*\prime}$ and $S_{10}^* := \sum_{t=1}^{T-k} z_{t+1}^* x_t$, $\hat{\beta}_T^* := S_{11}^{*-1} S_{10}^*$ is the OLS estimator of β obtained on the bootstrap sample and $\hat{\sigma}_T^{*2} := T^{-1} \sum_{t=1}^{T-k} \hat{\varepsilon}_t^{*2}$, $\hat{\varepsilon}_t^* := x_t^* - \hat{\beta}_T^{*\prime} z_{t+1}^*$, the corresponding residual variance.

As before, and taking the r_T statistic to illustrate, let $\varrho_L(\cdot,\cdot)$ denote the Levy metric in the space of distribution functions. Moreover, let F_T be the distribution function of (normalized) original statistic, $n_T r_T$, with r_T as in (13), conditionally on $\{\varepsilon_{(t)}\}_1^{T-k}$, $\{x_T\}_{t=T-k+1}^T$ for the permutation bootstrap, and conditionally on $\{|\varepsilon|_{(t)}\}_1^{T-k}$, $\{x_T\}_{t=T-k+1}^T$ for the permutation wild bootstrap. Finally, let F_T^* denote the distribution function of the normalized bootstrap statistic $n_T r_T^*$, conditionally on the original data. The following Theorem holds under the null hypothesis H_0 as the sample size diverges.

THEOREM 1 *With $\{x_t\}_1^T$ as given in (12), assume that ε_t satisfy condition (ii)-(iv) in Assumption 1 and that all characteristic roots associated to (12) are outside the unit disk in the complex plane. Then, under the null hypothesis,*

$$\varrho_L\left(F_T^*, F_T\right) \xrightarrow{p} 0 \tag{15}$$

as $T \to \infty$.

Some remarks are in order.

REMARK 4.1 Unlike the $\mathrm{AR}^+(1)$ case, when $k > 1$ the restricted bootstrap is exact only asymptotically. This happens because, even under the null hypothesis, the restricted residuals $\tilde{\varepsilon}_t$ would differ from the true innovations, ε_t. For the permutation and the permutation wild bootstrap, however, the difference $\tilde{\varepsilon}_t - \varepsilon_t$ vanishes sufficiently fast to ensure that the convergence in (15) holds. The same property does not hold for the wild bootstrap scheme, where the difference $\tilde{\varepsilon}_t - \varepsilon_t$ is not negligible, even asymptotically (as is also the case for causal models, see Cavaliere *et al.*, 2016, Remark 4.2).

REMARK 4.2 The unrestricted bootstrap based on the permutation and permutation-wild schemes (the latter under symmetry) can be proved to be valid too. Simulation results provided in Section 5 confirm this.

REMARK 4.3 The case of multivariate (q-dimensional, $q \geq 1$) hypotheses such as $\mathsf{H}_0 : R'\beta = r$, where R is now $k \times q$ (with full column rank q) and r is $q \times 1$ can be studied by bootstrapping F-type statistics of the form $\mathcal{F}_T := \left(q\hat{\sigma}_T^2\right)^{-1} (R'\hat{\beta}_T - r)'(R'S_{11}^{-1}R)^{-1}(R'\hat{\beta}_T - r)$. With $\tilde{\beta}$ the OLS estimator restricted by H_0, the bootstrap sample is generated recursively as in (14) and the bootstrap statistic $\mathcal{F}_T^*$ corresponds to $\mathcal{F}_T$ computed on the bootstrap sample. Theorem 1 can be extended and proved to be valid in this case too. Exactness of the restricted bootstrap occur under H_0 in the special case where $k = q$ (implying that $\tilde{\varepsilon}_t = \varepsilon_t$ under the null hypothesis).

REMARK 4.4 Theorem 1 establishes for the AR$^+$ (k) model asymptotic proximity (in the Levy metric) of the distribution of the bootstrap statistics, conditionally on the original data, and the distribution of the original statistics, conditional on suitable statistics. This result, in general, does not imply that the bootstrap p-values are asymptotically uniformly distributed. For this to be the case, it would be sufficient to prove that the limiting distribution function of the bootstrap statistic (conditionally on the data) is continuous with probability one. A proof of this result seems to be very hard to obtain. However, for the simpler location model with heavy tailed, i.i.d. errors, asymptotic continuity of the bootstrap distribution can be established as done e.g. in Knight (1989, p.1173-4) for a standard i.i.d. bootstrap. We hence conjecture that continuity should carry over to the statistics considered here. This conjecture is supported by the Monte Carlo results in Section 5.

5 Finite sample simulations

To illustrate the finite sample properties of the proposed bootstrap tests in the non-causal autoregression framework, we present here results from a set of Monte Carlo simulations. As in Section 2 and Section 3, we consider the non-causal $\text{AR}^{+}(1)$ model (1). The data generating process has $\rho_0 = 0.5$, and innovations distributed according to a stable law, $\varepsilon_t \sim S(\alpha, \beta)$, for the four combinations $(\alpha, \beta) \in (1, 1.5) \times (0, 0.75)$, and $T = 100$ observations[5]. We focus on testing null hypotheses of the form

$$\mathsf{H}_0 : \rho = \bar{\rho},$$

against two-sided alternatives, $\rho \neq \bar{\rho}$. The test statistics are r_T and its studentized version, t_T, as given in Section 2.

Table 1 report results for the restricted bootstrap based on the three considered resampling schemes, i.e. the wild bootstrap, the permutation bootstrap and the permutation-wild bootstrap. All bootstrap tests are implemented with 999 bootstrap samples. Results for the corresponding unrestricted bootstraps are given in Table 2. Finally, in Table 3 we present results obtained using a fully parametric (restricted) bootstrap, where the ε_t^*'s are i.i.d. copies of the original ε_t's. Notice that this bootstrap is infeasible in practice and used here only for comparisons.

Section (A) in Table 1 focuses on the size properties and reports empirical rejection frequencies (ERFs) at nominal significance levels 2.5%, 5% and 10% under the null hypothesis (i.e. $\bar{\rho} = \rho_0 = 0.5$). We observe that the permutation bootstrap has excellent

[5] Additional Monte Carlo simulations for different choices of lag length, k, sample length T and (α, β)–indices are provided in the supplementary material, Cavaliere, Nielsen and Rahbek (2017).

				(A) ERF, Null			(B) ERF, Alternative, $\bar{\rho}$						
Bootstrap scheme	Statistic	α	β	2.5	5.0	10.0	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Wild	r_T	1.0	0.00	2.3	4.7	9.6	34.2	25.5	16.1	4.7	31.8	53.1	69.3
	t_T	1.0	0.00	2.3	4.7	9.4	61.0	46.5	26.6	4.7	26.7	46.7	64.2
	r_T	1.0	0.75	26.0	34.7	45.6	70.0	67.4	63.6	34.7	10.0	18.7	31.4
	t_T	1.0	0.75	33.8	41.8	50.9	91.1	86.2	76.9	41.8	10.1	16.1	27.3
	r_T	1.5	0.00	2.6	5.3	10.0	32.6	18.3	8.0	5.3	15.9	34.2	55.0
	t_T	1.5	0.00	2.7	5.3	9.9	44.9	27.2	12.1	5.3	12.5	28.0	47.7
	r_T	1.5	0.75	4.0	7.5	13.4	36.0	20.4	9.4	7.5	17.2	32.1	50.5
	t_T	1.5	0.75	4.5	8.0	13.8	47.2	28.8	13.9	8.0	14.4	26.9	43.8
Permutation	r_T	1.0	0.00	2.7	5.4	10.6	61.0	37.5	18.1	5.4	20.1	43.9	70.9
	t_T	1.0	0.00	2.8	5.2	10.4	65.2	41.3	20.0	5.2	19.2	40.1	66.2
	r_T	1.0	0.75	2.6	5.0	9.5	68.9	44.3	21.1	5.0	12.3	25.7	49.3
	t_T	1.0	0.75	2.5	4.9	9.4	70.7	47.0	22.7	4.9	12.2	23.1	40.2
	r_T	1.5	0.00	2.7	5.5	10.3	44.8	23.8	9.3	5.5	13.2	32.4	57.9
	t_T	1.5	0.00	2.7	5.4	10.2	49.9	27.9	11.6	5.4	11.5	28.5	52.8
	r_T	1.5	0.75	2.6	5.4	10.4	47.2	26.0	10.8	5.4	14.8	35.0	58.5
	t_T	1.5	0.75	2.7	5.2	10.4	50.9	29.3	12.4	5.2	12.5	29.8	52.7
Permutation-wild	r_T	1.0	0.00	2.7	5.3	10.4	60.9	36.9	17.7	5.3	20.6	45.0	75.6
	t_T	1.0	0.00	2.7	5.3	10.3	66.1	41.7	20.1	5.3	19.2	39.5	66.8
	r_T	1.0	0.75	4.1	9.6	21.4	90.1	71.0	37.7	9.6	13.8	24.8	43.7
	t_T	1.0	0.75	6.9	13.3	25.1	92.3	76.9	45.3	13.3	15.1	23.5	38.1
	r_T	1.5	0.00	2.7	5.3	10.2	45.3	23.2	9.2	5.3	14.2	34.2	61.2
	t_T	1.5	0.00	2.8	5.5	10.0	51.1	28.5	11.7	5.5	11.6	28.2	53.1
	r_T	1.5	0.75	2.4	5.2	11.3	47.5	26.3	11.3	5.2	13.6	33.6	57.6
	t_T	1.5	0.75	3.2	6.2	11.9	53.3	31.6	14.5	6.2	11.9	27.9	50.9

TABLE 1: Simulation results for the restricted Wild bootstrap, the Permutation bootstrap and the Permutation-wild bootstrap for the statistics r_T and t_T. Section (A) reports empirical rejection frequencies (ERF) for the bootstrap test of a true null hypothesis, $\bar{\rho} = \rho_0 = 0.5$, for significance levels 2.5%, 5%, and 10%. Section (B) reports ERF for the bootstrap tests for different values of $\bar{\rho}$, $\bar{\rho} \in \{0.35, 0.40, ..., 0.65\}$. The innovations of the DGP are drawn from a stable distribution, $S(\alpha, \beta)$, and $T = 100$. Results are based on 999 bootstrap samples and 10000 Monte Carlo replications.

				(A) ERF, Null			(B) ERF, Alternative, $\bar{\rho}$						
Bootstrap scheme	Statistic	α	β	2.5	5.0	10.0	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Wild	r_T	1.0	0.00	2.6	5.0	9.9	35.5	26.7	17.6	5.0	32.1	53.5	69.7
	t_T	1.0	0.00	2.7	5.1	9.8	61.4	47.2	27.5	5.1	27.5	47.5	64.7
	r_T	1.0	0.75	29.2	37.3	47.0	73.0	71.2	67.3	37.3	10.0	18.8	32.4
	t_T	1.0	0.75	36.7	43.9	52.2	91.3	86.9	78.3	43.9	10.4	16.2	28.1
	r_T	1.5	0.00	2.8	5.5	10.5	33.8	19.3	8.7	5.5	16.3	34.6	55.3
	t_T	1.5	0.00	2.9	5.5	10.1	45.3	28.2	12.7	5.5	13.0	28.2	48.3
	r_T	1.5	0.75	7.1	10.3	16.2	31.0	18.2	9.5	10.3	21.8	36.7	54.2
	t_T	1.5	0.75	7.4	10.8	16.6	41.9	25.4	12.8	10.8	19.6	32.2	48.4
Permutation	r_T	1.0	0.00	2.7	5.4	10.6	61.6	38.0	18.3	5.4	20.2	44.3	71.4
	t_T	1.0	0.00	2.8	5.2	10.4	66.1	42.2	20.3	5.2	19.3	40.0	66.2
	r_T	1.0	0.75	4.5	8.4	16.1	89.0	68.0	34.0	8.4	13.3	25.7	48.3
	t_T	1.0	0.75	4.7	8.6	16.1	90.2	70.3	35.9	8.6	13.1	23.2	39.4
	r_T	1.5	0.00	2.7	5.1	10.2	44.9	23.4	9.2	5.1	13.6	33.0	58.5
	t_T	1.5	0.00	2.8	5.5	10.3	51.1	28.8	12.0	5.5	11.6	28.7	53.3
	r_T	1.5	0.75	3.3	6.6	12.8	49.2	27.7	12.6	6.6	16.5	38.9	63.0
	t_T	1.5	0.75	3.3	6.4	12.3	52.5	30.9	14.6	6.4	12.0	28.6	52.0
Permutation-wild	r_T	1.0	0.00	2.7	5.3	10.5	61.1	36.8	17.8	5.3	20.5	45.0	75.5
	t_T	1.0	0.00	2.7	5.3	10.3	66.0	41.8	20.1	5.3	19.2	39.4	66.9
	r_T	1.0	0.75	4.2	9.8	21.9	90.2	71.7	38.6	9.8	13.8	24.8	43.7
	t_T	1.0	0.75	6.9	13.4	25.6	92.4	77.3	46.2	13.4	15.3	23.6	38.2
	r_T	1.5	0.00	2.8	5.3	10.2	45.1	23.2	9.1	5.3	14.2	34.2	61.3
	t_T	1.5	0.00	2.8	5.5	10.2	51.0	28.5	11.7	5.5	11.6	28.1	53.1
	r_T	1.5	0.75	2.4	5.3	11.6	47.4	26.3	11.3	5.3	13.7	33.7	57.8
	t_T	1.5	0.75	3.1	6.3	12.2	53.3	31.6	14.4	6.3	11.9	28.0	51.0

TABLE 2: Simulation results for the unrestricted Wild bootstrap, the Permutation bootstrap and the Permutation-wild bootstrap for the statistics r_T and t_T. Section (A) reports empirical rejection frequencies (ERF) for the bootstrap test of a true null hypothesis, $\rho = 0.5$, for significance levels 2.5%, 5%, and 10%. Section (B) reports ERF for the bootstrap tests for different values of ρ, $\rho \in \{0.35, 0.40, ..., 0.65\}$. The innovations of the DGP are drawn from a stable distribution, $S(\alpha, \beta)$, and $T = 100$. Results are based on 999 bootstrap samples and 10000 Monte Carlo replications.

Statistic	α	β	(A) ERF, Null 2.5	5.0	10.0	(B) ERF, Alternative, $\bar{\rho}$ 0.35	0.40	0.45	0.50	0.55	0.60	0.65
r_T	1.0	0.00	2.7	5.2	10.4	53.3	15.8	6.9	5.2	9.1	24.2	78.9
t_T	1.0	0.00	2.6	5.3	10.3	65.5	19.6	8.0	5.3	7.8	18.0	67.4
r_T	1.0	0.75	2.7	4.8	9.6	50.9	27.7	12.9	4.8	2.2	2.9	9.7
t_T	1.0	0.75	2.7	4.9	9.9	51.6	28.2	13.4	4.9	2.0	1.4	2.2
r_T	1.5	0.00	2.9	5.4	10.3	37.9	15.7	6.6	5.4	11.1	26.4	58.3
t_T	1.5	0.00	3.0	5.3	10.2	44.3	20.8	8.6	5.3	8.8	20.4	46.4
r_T	1.5	0.75	2.7	5.3	10.4	38.0	19.1	9.0	5.3	9.1	25.0	55.7
t_T	1.5	0.75	2.6	5.2	10.5	42.2	22.4	10.6	5.2	6.1	14.7	36.9

Table 3: Simulation results for the infeasible fully parametric bootstrap for the statistics r_T and t_T. Section (A) reports empirical rejection frequencies (ERF) for the bootstrap test of a true null hypothesis, $\rho = 0.5$, for significance levels 2.5%, 5%, and 10%. Section (B) reports ERF for the bootstrap tests for different values of ρ, $\rho \in \{0.35, 0.40, ..., 0.65\}$. The innovations of the DGP are drawn from a stable distribution, $S(\alpha, \beta)$, and $T = 100$. Results are based on 999 bootstrap samples and 10000 Monte Carlo replications.

size properties, with ERFs close to the nominal levels, for all combinations of (α, β). As expected, the wild bootstrap and the permutation-wild bootstrap show inflated ERFs in cases where the distribution of ε_t is asymmetric, most severe when $\alpha = 1$. The differences in terms of size between the statistic r_T and its studentized version t_T are small, although the test based on r_T is marginally preferable.

Section (B) of the table presents ERFs (for tests at the nominal 5% level) for different values of $\bar{\rho}$, $\bar{\rho} \in \{0, 35, 0.40, ..., 0.65\}$, and focuses on the power properties of the proposed tests. We observe that the permutation bootstrap test and the permutation-wild bootstrap test have good power when compared to the infeasible fully parametric bootstrap (in particular for alternatives close to the null, see Table 3), while the wild bootstrap test, as expected, performs poorly when the error distribution is asymmetric. Again, the non-studentized statistic, r_T, is generally preferable, although the difference in power is not large.

The overall conclusion from Table 1 is that, in line with the theoretical claims in Section 3.2, all restricted bootstrap tests seem to work is cases of symmetric error distributions, while only the permutation bootstrap is valid in asymmetric cases.

Turning to the unrestricted bootstrap, results in Table 2 support the overall conclusion that the restricted bootstraps are slightly preferable over the corresponding unrestricted bootstraps in terms of size, in particular in the asymmetric cases. We have also compared the results for our unrestricted bootstrap schemes with those in Tables 1–2 in Cavaliere *et al.* (2016) (notice that only unrestricted bootstrap alogorithms are covered there) on standard causal processes. Despite causal and non-causal models being highly different, we find that in both cases the wild, permulation and permutation wild bootstraps outperform in terms of power both the unfeasible parametric bootstrap and the 'm out of n' bootstrap[6].

Additionally in unreported simulations[7], we investigated possible effects of different centering schemes for the estimated residuals, in particular using centering around the median of the residuals and around their sample mean (notice that our theory does not cover the use of re-centred residuals). On the one hand, these recentering schemes tend to inflate the empirical size of the permutation bootstrap in cases of asymmetric distributions, and in general do not lead to any uniform improvement of the performance of the bootstrap tests in terms of size. On the other hand, in terms of ERFs under the alternative, we observe that – only for the special case of the wild bootstrap – centering increases the rejection probabilities. The permutation bootstrap is not affected in terms of ERFs under the alternative by the possible recentering of the residuals.

[6]The supplementary material Cavaliere, Nielsen and Rahbek (2017) reports simulations for the 'm out of n' bootstrap.

[7]Available from the authors upon request.

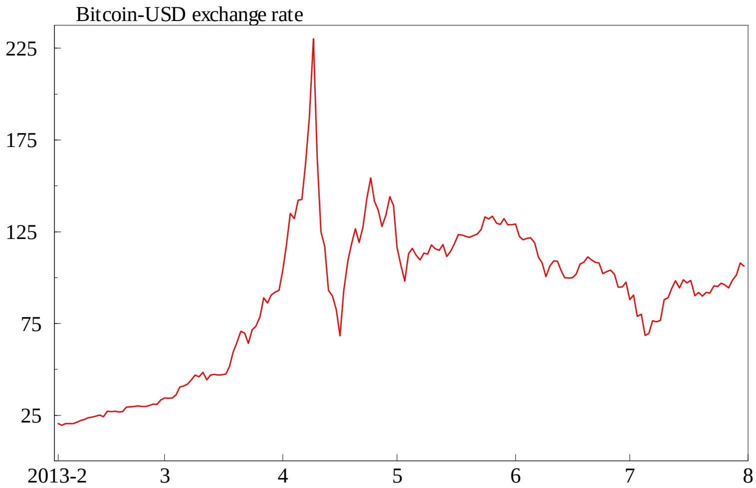

FIGURE 1: Daily Bitcoin-USD exchange rate from February 1 – July 31, 2013.

6 Empirical illustrations

6.1 Bitcoin-USD exchange rates

Consider first the Bitcoin-USD exchange rate, as recorded at the MtGox Bitcoin exchange, see Figure 1. Data are daily and cover the period February–July 2013 ($T = 181$ observations).[8] Gourieroux and Hencic (2015) provide a detailed description and discussion of the data and find that an $\text{AR}^+(k)$ model with $k = 2$ fits the data well.

We proceed by analyzing the Bitcoin data using a general to specific approach by initially estimating an $\text{AR}^+(5)$ model by OLS. The $\text{AR}^+(5)$ model is given by (12) with $k = 5$ and consequently $\beta = (\rho_1, ..., \rho_5)'$. To illustrate, we consider testing of the $\text{AR}^+(k-1)$ model against an $\text{AR}^+(k)$ model, for $k = 2, ..., 5$. In addition, we also report joint tests for the $\text{AR}^+(2)$ model against the $\text{AR}^+(k)$ model, $k = 3, ..., 5$. For instance, the joint test for $k = 2$ against $k = 5$ corresponds to testing the null hypothesis

[8] Daily closing prices were obtained from www.quandl.com/collections/markets/bitcoin-data.

	AR$^+(k)$			
k	5	4	3	2
$\hat{\rho}_1$	1.212	1.214	1.216	1.203
$\hat{\rho}_2$	−0.287	−0.285	−0.296	−0.230
$\hat{\rho}_3$	0.028	0.011	0.055	
$\hat{\rho}_4$	−0.026	0.036		
$\hat{\rho}_5$	0.051			
	p-value for stepwise test AR$^+(k-1)$ against AR$^+(k)$			
Wild	0.651	0.783	0.760	0.143
Permutation	0.453	0.591	0.406	0.000
Permutation-wild	0.457	0.572	0.392	0.000
	p-value for joint test AR$^+(2)$ against AR$^+(k)$			
Wild	0.968	0.969	0.760	
Permutation	0.877	0.860	0.406	
Permutation-wild	0.857	0.859	0.392	

TABLE 4: Empirical analysis of Bitcoin data. Bootstrap p-values are based on 999 bootstrap replications.

$\mathsf{H}_0 : R'\beta = 0$ where

$$R' = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}.$$

As is clear from the reported bootstrap p-values in Table 4, all tests support the AR$^+(2)$ model, thus confirming the findings of Hencic and Gourieroux (2015). The validity of the reduction from an AR$^+(k)$ model of order $k = 5$ to $k = 2$ holds for all variants of the bootstrap implementations, while the wild bootstrap (borderline) suggests a further reduction to an AR$^+(1)$.

The fitted AR$^+$(2) model is given by

$$x_t = \hat{\rho}_1 x_{t+1} + \hat{\rho}_2 x_{t+2} + \hat{\varepsilon}_t,$$

where x_t denote the (de-trended) Bitcoin/USD exchange rate, with parameter estimates given in Table 4.

In order to study the dependence structure of estimated residuals Gourieroux and Zakoïan (2017) propose to study the empirical correlation of the $\hat{\varepsilon}_t$'s for an AR$^+$(1) model,

$$\sum_{t=2}^{T-1} \hat{\varepsilon}_t \hat{\varepsilon}_{t-1} / \sum_{t=1}^{T-1} \hat{\varepsilon}_t^2, \tag{16}$$

whose (upon normalization) asymptotic distribution is found by simulation for the special case where the distribution of the ε_t's is known. The empirical correlation in (16) is closely related to the OLS estimator in (6) and therefore, upon an appropriate normalization, has a limiting distribution which can be represented in terms of a ratio of stable distributions, see (A.8). Our proposed strategy of estimating an AR$^+$(k) model first, and then testing by bootstrap p-values whether a reduction to an AR$^+$($k-1$) model is valid, is equivalent in the sense that the test statistic for a reduction from the AR$^+$(2) to the AR$^+$(1) has similar asymptotic properties to those of a test based on (16). Our results are more general, however, as they allow testing the AR$^+$(k) structure for any $k \geq 1$ and, importantly, it is made feasible by the proposed bootstrap inference which can be used independently of the tail properties of the innovations ε_t.

As emphasized in Gourieroux and Zakoïan (2017), the AR$^+$(1) model with Cauchy innovations has a causal recursive double autoregressive structure, hence motivating a misspecification analysis for both autocorrelation and ARCH-type effects in the causal AR$^-$(1) model. Diagnostics of 'causal vs. non-causal' can be based on the estimated non-causal residuals, $\hat{\varepsilon}_t$, and estimated causal residuals, $\hat{\varepsilon}_t^-$ say, for autocorrelation and

ARCH-type effects. However, the empirical autocorrelation coefficient between $\hat{\varepsilon}_t$ and $\hat{\varepsilon}_{t+1}$ has a non-standard, non-pivotal limiting distribution; hence, Lagrange multiplier type tests for no autocorrelation (when based on conventional asymptotic χ^2-based p-values) are not valid. Likewise, standard Lagrange multiplier statistics for ARCH effects are also invalid, as these are based on covariances between $\hat{\varepsilon}_t^2$ and its own lag(s).

To overcome these difficulties we propose to use Spearman's rank statistic. For any bivariate sequence $\{(v_t, w_t)\}_{t=1}^T$, this statistic is given by

$$S_T\left((v_t, w_t)_{t=1}^T\right) = R_T\left(\frac{T-2}{1-R_T^2}\right)^{1/2},$$

where $R_T := 1 - 6\sum_{i=1}^T d_i^2/\left(T\left(T^2-1\right)\right)$ with $d_i = \text{rk}_i(\{v_t\}_{t=1}^T) - \text{rk}_i(\{w_t\}_{t=1}^T)$ the difference between the two ranks of the observations $\{(v_t, w_t)\}_{t=1}^T$. S_T is approximately t_m-distributed with $m = T-2$ degrees of freedom, see e.g. Moran (1950). The results in Table 5 apply for the non-causal case $(v_t, w_t) = (\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1})$ (and for the causal case $(\hat{\varepsilon}_t^-, \hat{\varepsilon}_{t-1}^-)$) to test for zero autocorrelation or level dependence, and $(v_t, w_t) = (\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1}^2)$ $((\hat{\varepsilon}_t^-, (\hat{\varepsilon}_{t-1}^-)^2))$ to test for double autoregressive ARCH type dependence. We find that for both the non-causal AR$^+$(2) and causal AR$^-$(2) there is no autocorrelation, while the stronger ARCH effects for the causal AR$^-$(2) model supports further the AR$^+$(2) model.

6.2 Crude oil prices

As a second empirical application, we consider the Dubai crude oil price obtained from the FRED database of the Federal Reserve Bank of St. Louis. Figure 2 shows monthly observations for the log-transformation of the real oil price, using the consumer price index as deflator, for the period August 2004 to July 2016 ($T = 144$ observations).

For the empirical ananlysis, as for the previous example we start with an AR$^+$(5) model for the time-series corrected for a constant and apply general to specific testing.

	(v_t, w_t)	Spearman corr., R_T	Test statistic, S_T	p-value
Autocorrelation				
Non-causal	$(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1})$	0.017	0.228	0.820
Causal	$(\hat{\varepsilon}_t^-, \hat{\varepsilon}_{t-1}^-)$	-0.010	-0.127	0.899
ARCH-type				
Non-causal	$(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1}^2)$	0.023	0.309	0.758
Causal	$(\hat{\varepsilon}_t^-, (\hat{\varepsilon}_{t-1}^-)^2)$	0.130	1.747	0.082

TABLE 5: Misspecification tests for non-causal residuals, $\hat{\epsilon}_t = x_t - \hat{\rho}_1 x_{t+1} - \hat{\rho}_2 x_{t+2}$, and causal residuals, $\hat{\epsilon}_t^- = x_t - \hat{\rho}_1^- x_{t-1} - \hat{\rho}_2^- x_{t-2}$, where $\hat{\rho}_1^-$ and $\hat{\rho}_2^-$ denote the LS estimates in the causal $AR^-(2)$ model.

The bootstrap test results reported in Table 6 clearly point towards an $AR^+(2)$ model for all three different bootstrap algorithms.

We report in Table 7 the Spearman rank correlation diagnostics for residual autocorrelation and double autoregressive ARCH-type dependence in the estimated residuals from the non-causal $AR^+(2)$ model and from a causal $AR^-(2)$ model. For both the non-causal and the causal model we find that there is no evidence of autocorrelation, while the stronger ARCH effects for the causal $AR^-(2)$ model again provide more support to the $AR^+(2)$ model.

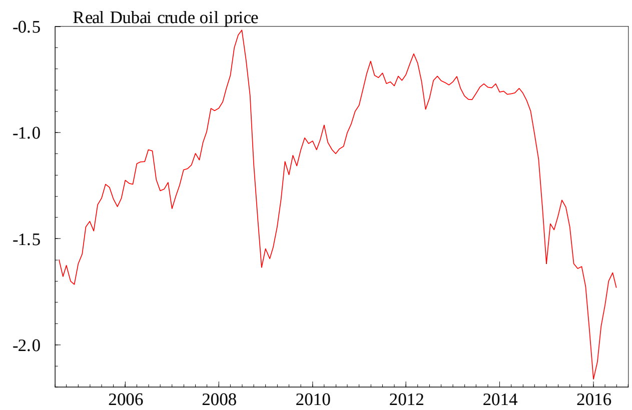

FIGURE 2: Montly data for the real Dubai crude oil price, August 2004-July 2016.

	$AR^+(k)$			
k	5	4	3	2
$\hat{\rho}_1$	1.339	1.355	1.365	1.392
$\hat{\rho}_2$	−0.281	−0.294	−0.348	−0.437
$\hat{\rho}_3$	−0.162	−0.185	−0.069	
$\hat{\rho}_4$	0.016	0.071		
$\hat{\rho}_5$	0.031			
	p-value for stepwise test $AR^+(k-1)$ against $AR^+(k)$			
Wild	0.720	0.403	0.521	0.000
Permutation	0.704	0.385	0.380	0.000
Permutation-wild	0.713	0.392	0.386	0.000
	p-value for joint test $AR^+(2)$ against $AR^+(k)$			
Wild	0.585	0.301	0.528	
Permutation	0.545	0.222	0.380	
Permutation-wild	0.532	0.223	0.386	

TABLE 6: Empirical analysis of the real Dubai crude oil prices. Bootstrap p-values are based on 999 bootstrap replications.

	(v_t, w_t)	Spearman corr., R_T	Test statistic, S_T	p-value
Autocorrelation				
Non-causal	$(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1})$	−0.048	−0.564	0.573
Causal	$(\hat{\varepsilon}_t^-, \hat{\varepsilon}_{t-1}^-)$	−0.064	−0.754	0.451
ARCH-type				
Non-causal	$(\hat{\varepsilon}_t, \hat{\varepsilon}_{t-1}^2)$	0.031	0.364	0.717
Causal	$(\hat{\varepsilon}_t^-, (\hat{\varepsilon}_{t-1}^-)^2)$	−0.144	−1.719	0.088

TABLE 7: Misspecification tests for the real Dubai crude oil price, The non-causal residuals are given by $\hat{\epsilon}_t = x_t - \hat{\rho}_1 x_{t+1} - \hat{\rho}_2 x_{t+2}$, and the causal residuals, $\hat{\epsilon}_t^- = x_t - \hat{\rho}_1^- x_{t-1} - \hat{\rho}_2^- x_{t-2}$, where $\hat{\rho}_1^-$ and $\hat{\rho}_2^-$ denote the LS estimates in the causal $AR^-(2)$ model.

7 Concluding remarks

This paper investigates validity of bootstrap-based inference for pure non-causal $\mathrm{AR}^+(k)$ processes, thereby making inference feasible, when the innovations display heavy tails. In terms of bootstrap algorithms, we propose to apply the restricted bootstrap, *i.e.* parameters estimated under the null hypothesis are used for generating the bootstrap sample, together with bootstrap innovations resampled by permutation bootstrap or wild bootstrap, and a combination thereof. The proposed bootstrap inference is simple to implement in practice and works very well in finite samples. In the empirical applications, in order to distinguish non-causal from causal processes, we apply diagnostics checking based on Spearman rank statistics in terms of both causally and non-causally estimated autoregressive residuals. As suggested by Gourieroux and Zakoïan (2017), a pure non-causal process will upon estimation have residuals which are uncorrelated in levels and squares over time, while if estimated by a causal autoregression, correlation in the squares will be detectable, as was confirmed in our included empirical analysis. Finally, as is well-known we stress that it is also of interest to consider *mixed* causal and non-causal processes. For these however, due to identification issues addressed *e.g.* in Hecq *et al.* (2016), it is required to extend our bootstrap theory to include (quasi-) maximum likelihood or LAD-type estimation and inference, which we leave for future research.

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Appendix

This Appendix is organized as follows. Appendix A lists some basic results on heavy tailed sequences, while Appendix B contains the proofs of all the theoretical results. Note that the supplementary material, Cavaliere, Rahbek and Nielsen (2017) contains tables with additional Monte Carlo simulations.

AR: sentence on suppl

A Some results on Heavy Tailed sequences

A.1 Large T results for heavy tailed sequences

We start by introducing the concept of regularly and slowly varying functions at infinity, which are useful in the characterization of distributions with heavy tails such as Pareto-type tails. These functions are defined as follows.

Definition A.1 *A (positive and measurable) function $g(x)$ is said to be* regularly varying *at infinity with index $\alpha \in \mathbb{R}$ if it satisfies*

$$\lim_{\lambda \to \infty} \frac{g(\lambda x)}{g(\lambda)} = x^{-\alpha}$$

for all $x > 0$. If $\alpha = 0$, g is said to be slowly varying *at infinity.*

Distributions with Pareto-Lèvy type tails such as Pareto and Stable (with $\alpha < 2$) distributions satisfy

$$\bar{F}(x) := P(X > x) \sim cx^{-\alpha},\ \alpha \in (0, 2)$$

This implies, in particular, that $\bar{F}(x)$ is regularly varying with index α, that is

$$\lim_{\lambda \to \infty} \frac{\bar{F}(\lambda x)}{\bar{F}(\lambda)} = x^{-\alpha}$$

From Mikosch (1999, Remark 1.1.3) it follows that any regularly varying function has representation

$$\bar{F}(x) = cx^{-\alpha} L(x),\ \alpha \in (0, 2) \tag{A.1}$$

for some slowly varying function. Thus, Pareto and Stable distributions are special cases of (A.1) where the slowly varying component $L(x)$ is constant.

An important and related concept is the domain of attraction of a stable law.

Definition A.2 *Consider an i.i.d. sequence $\{\varepsilon_t\}_{t\geq 1}$, each of them with distribution function F. Then, F is said to belong to the domain of attraction of an α-stable distribution S_α if there exist constants $a_T > 0$ and d_T such that*

$$\frac{1}{a_T}\sum\nolimits_{t=1}^{T}(\varepsilon_t - d_T) \to_d S_\alpha$$

as $T \to \infty$. If $a_T = T^{1/\alpha}$, F is said to belong to the 'normal' domain of attraction of an α-stable distribution S_α.

The relation between the property of being in the domain of attraction of a stable law and the behavior of the tails is given in the following Lemma from Chan and Tran (1989), see also Janssen (1989).

Lemma A.1 (Chan and Tran, 1989) *A random variable with distribution function $F(x) = 1 - \bar{F}(x)$ is in the domain of attraction of a stable random variable with index $\alpha \in (0,2)$* if and only if

$$\bar{F}(x) \sim px^{-\alpha}L(x)\,,\ \alpha \in (0,2)\,,\ as\ x \to \infty$$

where

$$p = \lim_{x\to\infty}\frac{\bar{F}(x)}{\bar{F}(x) + F(-x)} = \lim_{x\to\infty}\frac{P(X > x)}{P(|X| > x)} \in [0,1]$$

In order to characterize the asymptotic behavior of sample mean, variances and autocovariances of heavy tailed, i.i.d. sequence $\{\varepsilon_t\}_{t\geq 1}$ (see the next section), as well as to prove the main theory provided in this paper, it is necessary to define the following two normalizing sequences:

$$a_T := \inf_{x\in\mathbb{R}^+}\left(P(|\varepsilon_t| > x) \leq T^{-1}\right),\ \tilde{a}_T := \inf_{x\in\mathbb{R}^+}\left(P(|\varepsilon_t\varepsilon_{t+1}| > x) \leq T^{-1}\right) \qquad \text{(A.2)}$$

where it also holds that $TP(|\varepsilon_t| > a_T x) \leq x^{-\alpha}$ for all $x > 0$. The relation between the order of magnitudes of a_T and $\tilde{a}_T$ are given next.

Lemma A.2 (Davis and Resnik, 1986) *It holds that*

$$a_T, \tilde{a}_T \to \infty$$

and, in particular, that the sequences $a_T, \tilde{a}_T$ *are regularly varying with index* α^{-1}. *Moreover, as* $T \to \infty$,

$$\begin{aligned} a_T &= T^{\alpha} L(T) = o(\tilde{a}_T) \\ \tilde{a}_T &= o(a_T^{1+\epsilon}) \text{ for any } \epsilon > 0 \\ \tilde{a}_T^{-1} a_T^2 &= T^{1/\alpha} L(T) \end{aligned}$$

for L *a slowly varying function at infinity.*

Let us turn to the properties of sample second order moments and cross product moments of an heavy tailed sequence. The next theorem holds under the assumptions made in Section 3.2 for the analysis of the asymptotic properties of the bootstrap.

Theorem A.1 (Davis and Resnick, 1986, Theorem 3.3) *Let* $\{\varepsilon_t\}$ *satisfy Assumptions 1(ii),(iii) of Section 3.2. Then, with* $\mu_T := E\left(\varepsilon_t \varepsilon_{t+1} \mathbb{I}(|\varepsilon_t \varepsilon_{t+1}| \leq \tilde{a}_T\right)$,

$$\left(\frac{1}{a_T^2} \sum_{t=1}^{T} \varepsilon_t^2, \frac{1}{\tilde{a}_T} \sum_{t=1}^{T-h} (\varepsilon_t \varepsilon_{t+1} - \mu_T), \ldots\ldots, \frac{1}{\tilde{a}_T} \sum_{t=1}^{T-h} (\varepsilon_t \varepsilon_{t+h} - \mu_T) \right) \xrightarrow{w} (\mathcal{S}_0, \mathcal{S}_1, \ldots, \mathcal{S}_h) \quad \text{(A.3)}$$

where $\mathcal{S}_0$ *is stable with index* $\alpha/2$, $\mathcal{S}_i$ *are stable with index* α *for* $i = 1, .., h$ *and* $\mathcal{S}_j$ *are mutually independent for* $j = 0, 1, ..., h$. *The term* μ_T *can be omitted if Assumption 1(iv) also holds.*

The proof of this theorem exploits properties of regular variation and Karamata's theorem (see Feller, 1971, p.283) as detailed in Davis and Resnick (1985*a*,*b*, 1986). In particular, we have

$$T\tilde{a}_T^{-1} E|\varepsilon_t \varepsilon_{t+1}| \mathbb{I}\left(|\varepsilon_t \varepsilon_{t+1}| < \tilde{a}_T\right) \to \alpha/(1-\alpha) \quad \text{(A.4)}$$

$$T\tilde{a}_T^{-2} E\left(\varepsilon_t^2 \varepsilon_{t+1}^2 \mathbb{I}\left(|\varepsilon_t^2 \varepsilon_{t+1}^2| < \tilde{a}_T\right)\right) = O(1) \quad \text{(A.5)}$$

and, for $\eta < \alpha$,

$$\limsup_{T \to \infty} T\tilde{a}_T^{-\eta} E|\varepsilon_t \varepsilon_{t+1}|^{\eta} \mathbb{I}\left(|\varepsilon_t \varepsilon_{t+1}| \leq \tilde{a}_T\right) < \infty \quad \text{(A.6)}$$

and

$$TE\left(|\varepsilon_{t+i}\varepsilon_{t-1}|^{\eta}\,\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|>\tilde{a}_T\right)\right)=O\left(\tilde{a}_T^{\eta}\right). \tag{A.7}$$

A.2 On the empirical autocorrelation coefficients

With $\hat{\rho}_T$ denoting the empirical autocorrelation coefficient of order one, or equivalently the OLS estimator of ρ in the $\mathrm{AR}^+(1)$ model, properties of $\hat{\rho}_T$ have been investigated in Davis and Resnick (1986). In particular, consistency and asymptotic distributional behaviour require assumptions 1(ii) and (iii), i.e. that the innovations ε_t's are in the domain of attraction of an α-stable distribution. We collect the consistency property in the following lemma, where $\hat{\rho}_T=\sum_{t=1}^{T-1}x_tx_{t+1}/\sum_{t=2}^{T}x_t^2$.

Lemma A.3 (Davis and Resnick, 1986) *Under Assumption 1(i)–(iii), then $\hat{\rho}_T\to_p\rho_0$.*

To state the asymptotic distribution of $\hat{\rho}_T$, we let $n_T:=\tilde{a}_T^{-1}a_T^2$, with $\tilde{a}_T$ and a_T as given in the previous section. The following lemma holds.

Lemma A.4 (Davis and Resnick, 1986) *Under the assumption of Lemma A.3,*

$$n_T\left(\hat{\rho}_T-\rho_0-d_T\right)\to_w Z:=\frac{1-\rho_0^2}{\left(1-\rho_0^{\alpha}\right)^{1/\alpha}}\frac{\mathcal{S}_1}{\mathcal{S}_0} \tag{A.8}$$

where $\mathcal{S}_0$ and $\mathcal{S}_1$ are independent stable random variables with index $\alpha/2$ and α, respectively and $a_T,\tilde{a}_T$ are defined in (A.2). The centering factor d_T satisfies

$$d_T:=\frac{T}{1-\rho}E\left(\varepsilon_1\varepsilon_2\mathbb{I}(|\varepsilon_1\varepsilon_2|\leq\tilde{a}_T)\right)\left(\sum_{t=1}^{T-1}x_{t+1}^2\right)^{-1} \tag{A.9}$$

and can be omitted if Assumption 1(iv) also holds.

We end this section by presenting the following lemma, which provides the order of magnitude of the studentized sample autocorrelation.

Lemma A.5 *Under Assumption 1,*

$$t_T:=\frac{\hat{\rho}_T-\rho_0}{\hat{\sigma}_T S_{xx}^{-1/2}}=O_p(T^{1/2}n_T^{-1}).$$

B Proofs

In this appendix, we use the following notation. For a given sequence X_T^* computed on the bootstrap data, $X_T^* = o_p^*(1)$ means that for any $\epsilon > 0$, $P^*(||X_T^*|| > \epsilon) \xrightarrow{p} 0$, as $T \to \infty$. Similarly, $X_T^* = O_p^*(1)$ means that, for every $\epsilon > 0$, there exists a constant $M > 0$ such that, for all large T, $P(P^*(||X_T^*|| > M) < \epsilon)$ is arbitrarily close to one. Also, $\mathbb{I}(\cdot)$ denotes the indicator function; $\lfloor \cdot \rfloor$ denotes the integer part of its argument.

B.1 Proof of Lemma 1

Consider first the wild bootstrap (ii):, and note that under symmetry $\varepsilon_t = |\varepsilon_t| w_t$ with w_t an i.i.d. sequence, $P(w_t^* = \pm 1) = \frac{1}{2}$, and recall that $\varepsilon_t^* = |\varepsilon_t| w_t^*$. Then as,

$$\begin{aligned}
\mathcal{D}\left(\varepsilon_1^*, ..., \varepsilon_{T-1}^* | \{x_t\}_{t=1}^T\right) &= \mathcal{D}(\varepsilon_1^*, ..., \varepsilon_{T-1}^* | \{\varepsilon_t\}_{t=1}^{T-1}, x_T) = \mathcal{D}(\varepsilon_1^*, ..., \varepsilon_{T-1}^* | \{|\varepsilon_t|\}_{t=1}^{T-1}, x_T) \\
&= \mathcal{D}(\varepsilon_1, ..., \varepsilon_{T-1} | \{|\varepsilon_t|\}_{t=1}^{T-1}, x_T)
\end{aligned}$$

it follows that,

$$\mathcal{D}\left(r_T^* | \{x_t\}_1^T\right) = \mathcal{D}(r_T^* | \{|\varepsilon_t|\}_1^{T-1}, x_T) = \mathcal{D}(r_T | \{|\varepsilon_t|\}_1^{T-1}, x_T).$$

Consider next the permutation bootstrap (i) and observe that

$$\begin{aligned}
\mathcal{D}\left(\varepsilon_1^*, ..., \varepsilon_{T-1}^* | \{x_t\}_{t=1}^T\right) &= \mathcal{D}(\varepsilon_1^*, ..., \varepsilon_{T-1}^* | \{\varepsilon_t\}_{t=1}^{T-1}, x_T) \\
&= \mathcal{D}(\varepsilon_{\pi(1)}, ..., \varepsilon_{\pi(T-1)} | \{\varepsilon_t\}_{t=1}^{T-1}, x_T) \\
&= \mathcal{D}(\varepsilon_{\pi(1)}, ..., \varepsilon_{\pi(T-1)} | \left\{\varepsilon_{(t)}\right\}_{t=1}^{T-1}, x_T) \\
&= \mathcal{D}(\varepsilon_{\pi\circ(1)}, ..., \varepsilon_{\pi\circ(T-1)} | \left\{\varepsilon_{(t)}\right\}_{t=1}^{T-1}, x_T) \\
&= \mathcal{D}(\varepsilon_1, ..., \varepsilon_{T-1} | \left\{\varepsilon_{(t)}\right\}_{t=1}^{T-1}, x_T).
\end{aligned}$$

where $\pi \circ (t)$ denotes a permutation of the order statistic (t). Next, as for the wild bootstrap,

$$\mathcal{D}\left(r_T^*|\left\{x_t\right\}_1^T\right)=\mathcal{D}(r_T^*|\left\{\varepsilon_{(t)}\right\}_1^{T-1},x_T)=\mathcal{D}(r_T|\left\{\varepsilon_{(t)}\right\}_1^{T-1},x_T).$$

The results for the permutation-wild bootstrap and for the t_T^* statistics follow similarly.
□

B.2 Proof of Lemma 2

Consider the difference between $r_T^\dagger$ (based on estimated ρ and unrestricted residuals) and r_T^* (based on true ρ and true errors), where

$$r_T^\dagger=\hat{\rho}_T^\dagger-\hat{\rho}_T=S_{1\varepsilon}^\dagger S_{11}^{\dagger-1},$$

such that by Berk (1974, eq. (2.15))

$$\begin{aligned}|r_T^\dagger-r_T^*| &\leq \frac{|S_{11}^{*-1}|^2|S_{11}^\dagger-S_{11}^*|}{1-|S_{11}^{\dagger-1}||S_{11}^\dagger-S_{11}^*|}\left(|S_{1\varepsilon}^*|+|S_{1\varepsilon}^\dagger-S_{1\varepsilon}^*|\right)\\ &\quad+|S_{11}^{*-1}||S_{1\varepsilon}^\dagger-S_{1\varepsilon}^*|\end{aligned}$$

With $a_T,\tilde{a}_T$ as defined in Section A, the result follows by establishing: *(i)* $|S_{11}^\dagger-S_{11}^*|=o_{p^*}\left(a_T^{1+\varepsilon}\right)$, $a_T^2S_{11}^{*-1}=O_{p^*}\left(1\right)$, *(ii)* $|S_{1\varepsilon}^\dagger-S_{1\varepsilon}^*|=o_{p^*}\left(\tilde{a}_T\right)$ and finally *(iii)* $|S_{1\varepsilon}^*|=O_{p^*}\left(\tilde{a}_T\right)$. In this case, we find using also that $\tilde{a}_T=o\left(a_T^{1+\varepsilon}\right)$ for all $\varepsilon>0$,

$$\begin{aligned}|r_T^\dagger-r_T^*| &= \frac{O_{p^*}\left(a_T^{-3+\varepsilon}\right)}{1+o_{p^*}\left(1\right)}\left[O_{p^*}\left(\tilde{a}_T\right)+o_{p^*}\left(\tilde{a}_T\right)\right]+o_{p^*}\left(\tilde{a}_Ta_T^{-2}\right)\\ &= O_{p^*}\left(a_T^{-3+\varepsilon}\right)O_{p^*}\left(\tilde{a}_T\right)+o_{p^*}\left(\tilde{a}_Ta_T^{-2}\right)=o_{p^*}\left(\tilde{a}_Ta_T^{-2}\right)\end{aligned}$$

for $0<\varepsilon<1$. Hence, as claimed, $n_T(r_T^\dagger-r_T^*)=o_{p^*}(1)$ for $n_T:=a_T^2\tilde{a}_T^{-1}$. We proceed by establishing *(i)-(iii)*.

Establishing *(i)* $|S_{11}^\dagger-S_{11}^*|=O_{p^*}\left(a_T^{1+\varepsilon}\right)$, $a_T^2S_{11}^{*-1}=O_{p^*}\left(1\right)$:

We present here the result for the case of the wild bootstrap as this is the most involved case. By definition, $x_t^\dagger=\hat{\rho}_T^{T-t}x_T^\dagger+\sum_{i=0}^{T-t-1}\hat{\rho}_T^i\varepsilon_{t+i}^\dagger$, and hence with $x_T^\dagger=0$

without loss of generality we find

$$\begin{aligned} S_{11}^{\dagger} &= \sum_{t=2}^{T-1} x_t^{\dagger 2} = \sum_{t=2}^{T-1} \left(\sum_{i=0}^{T-t-1} \hat{\rho}_T^i \varepsilon_{t+i}^{\dagger} \right)^2 = \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \hat{\rho}_T^{2i} \varepsilon_{t+i}^{\dagger 2} + \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \sum_{j \neq i, j=0}^{T-t-1} \hat{\rho}_T^{i+j} \varepsilon_{t+i}^{\dagger} \varepsilon_{t+j}^{\dagger} \\ &= \underbrace{\sum_{m=1}^{T-1} \hat{\varepsilon}_m^2 \left(\sum_{i=0}^{m-1} \hat{\rho}_T^{2i} \right)}_{(\mathrm{sq}^{\dagger})} + \underbrace{2 \sum_{m=1}^{T-1} \sum_{k=1}^{T-1-m} \varepsilon_m^{\dagger} \varepsilon_{m+k}^{\dagger} \left(\sum_{i=0}^{m-1} \hat{\rho}_T^{2i+k} \right)}_{(\mathrm{cp}^{\dagger})} \end{aligned}$$

Similarly, $x_t^* = \rho^{T-t} x_T^* + \sum_{i=0}^{T-t-1} \rho^i \varepsilon_{t+i}^*$, and hence with $x_T^* = 0$ without loss of generality we find

$$\begin{aligned} S_{11}^{*} &= \sum_{t=2}^{T-1} x_t^{*2} = \sum_{t=2}^{T-1} \left(\sum_{i=0}^{T-t-1} \rho_0^i \varepsilon_{t+i}^{*} \right)^2 = \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \rho_0^{2i} \varepsilon_{t+i}^{*2} + \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \sum_{j \neq i, j=0}^{T-t-1} \rho_0^{i+j} \varepsilon_{t+i}^{*} \varepsilon_{t+j}^{*} \\ &= \underbrace{\sum_{m=1}^{T-1} \varepsilon_m^2 \left(\sum_{i=0}^{m-1} \rho_0^{2i} \right)}_{(\mathrm{sq}^{*})} + \underbrace{2 \sum_{m=1}^{T-1} \sum_{k=1}^{T-1-m} \varepsilon_m^{*} \varepsilon_{m+k}^{*} \left(\sum_{i=0}^{m-1} \rho_0^{2i+k} \right)}_{(\mathrm{cp}^{*})}. \end{aligned}$$

Here we have used the fact that $\varepsilon_t^{\dagger 2} = \hat{\varepsilon}_t^2 w_t^{*2} = \hat{\varepsilon}_t^2$ and similarly $\varepsilon_t^{*2} = \varepsilon_t^2$. Consider first the difference $\mathrm{sq}^{\dagger} - \mathrm{sq}^{*}$, which equals

$$\sum_{m=1}^{T-1} \varepsilon_m^2 \left(\sum_{i=0}^{m-1} (\hat{\rho}_T^{2i} - \rho_0^{2i}) \right) + \sum_{m=1}^{T-1} (\hat{\varepsilon}_m^2 - \varepsilon_m^2) \left(\sum_{i=0}^{m-1} \hat{\rho}_T^{2i} \right)$$

where

$$\left| \sum_{m=1}^{T-1} \varepsilon_m^2 \left(\sum_{i=0}^{m-1} (\hat{\rho}_T^{2i} - \rho_0^{2i}) \right) \right| \leq c_T \left(\sum_{m=1}^{T-1} \varepsilon_m^2 \right) |\hat{\rho}_T - \rho_0| = O_p(\tilde{a}_T) = o_p\left(a_T^{1+\varepsilon}\right),$$

with $c_T = O_p(1)$ by the mean-value theorem and the fact that $|\hat{\rho}_T| < 1$ for T large enough. Similarly,

$$\left| \sum_{m=1}^{T-1} (\hat{\varepsilon}_m^2 - \varepsilon_m^2) \left(\sum_{i=0}^{m-1} \hat{\rho}_T^{2i} \right) \right| \leq c (\hat{\rho}_T - \rho_0)^2 \sum_{t=1}^{T-1} x_{t+1}^2 = O_p\left(\tilde{a}_T^2 a_T^{-2}\right) = o_p\left(a_T^{1+\varepsilon}\right)$$

using the fact that $\hat{\varepsilon}_t - \varepsilon_t = -(\hat{\rho}_T - \rho_0) x_{t+1}$.

Now we consider the difference of the cross-product terms, $\mathrm{cp}^{\dagger}-\mathrm{cp}^{*}$:

$$\sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}\varepsilon^*_m\varepsilon^*_{m+k}\left(\sum_{i=0}^{m-1}\hat{\rho}_T^{2i+k}-\rho_0^{2i+k}\right)+\sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}\left(\varepsilon^{\dagger}_m\varepsilon^{\dagger}_{m+k}-\varepsilon^*_m\varepsilon^*_{m+k}\right)\left(\sum_{i=0}^{m-1}\hat{\rho}_T^{2i+k}\right)$$
$$=:\xi_{1T}+\xi_{2T}.$$

First, rewrite ξ_{1T} as,

$$\begin{aligned}\xi_{1T} &= \sum_{m=1}^{T-1}\sum_{n=m+1}^{T-1}\varepsilon_m\varepsilon_n w^*_m w^*_n\sum_{i=0}^{m-1}\left(\hat{\rho}_T^{2i+n-m}-\rho_0^{2i+n-m}\right)\\ &= \sum_{m=1}^{T-1}\sum_{n=m+1}^{T-1}\varepsilon_m\varepsilon_n w^*_n w^*_m R_{T,m,n}\end{aligned}$$

such that consequently,

$$\begin{aligned}E^*\left(\xi_{1T}^2\right) &= E^*\Big(\sum_{m=1}^{T-1}\sum_{n=m+1}^{T-1}\varepsilon_m\varepsilon_n w^*_n w^*_m R_{T,m,n}\Big)^2\\ &= \sum_{m=1}^{T-1}\sum_{n=m+1}^{T-1}\sum_{p=1}^{T-1}\sum_{q=p+1}^{T-1}\varepsilon_m\varepsilon_n\varepsilon_p\varepsilon_q E^*\left(w^*_m w^*_n w^*_p w^*_q\right)R_{T,m,n}R_{T,p,q}\\ &= c\sum_{m=1}^{T-1}\sum_{n=m+1}^{T-1}\varepsilon_m^2\varepsilon_n^2 R^2_{T,m,n}\le c_T\left(\hat{\rho}_T-\rho_0\right)^2\Big(\sum_{m=2}^{T-1}\varepsilon_m^2\Big)^2=O_p\left(\tilde{a}_T^2\right)=o_p(a_T^{2(1+\varepsilon))})\end{aligned}$$

where, $c_T=O_p(1)$ and, for T large enough, $R^2_{T,m}=O_p((\hat{\rho}_T-\rho_0)^2)$. Regarding ξ_{2T}, we have

$$\xi_{2T}=\sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}\left(\hat{\varepsilon}_m\hat{\varepsilon}_{m+k}-\varepsilon_m\varepsilon_{m+k}\right)w^*_m w^*_{m+k}\underbrace{\Big(\sum_{i=0}^{m-1}\hat{\rho}_T^{2i+k}\Big)}_{\gamma_{T,m}}$$

and hence

$$\begin{aligned}E^*(\xi_{2T}^2) &= \sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}\left((\hat{\varepsilon}_m-\varepsilon_m)\hat{\varepsilon}_{m+k}+\varepsilon_m(\hat{\varepsilon}_{m+k}-\varepsilon_{m+k})\right)^2\gamma^2_{T,m}\\ &\le c(\hat{\rho}_T-\rho_0)^2\Big(\sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}x^2_{m+1}\hat{\varepsilon}^2_{m+k}+\sum_{m=1}^{T-1}\sum_{k=1}^{T-1-m}x^2_{m+k+1}\varepsilon^2_m\Big)\\ &\le c(\hat{\rho}_T-\rho_0)^2\Big(\sum_{m=1}^{T-1}x^2_{m+1}\Big)\Big(\sum_{m=1}^{T-1}\hat{\varepsilon}^2_m+\sum_{m=1}^{T-1}\varepsilon^2_m\Big)\end{aligned}$$

$$= \quad O_p(\tilde{a}_T^2 a_T^{-4}) O_p(a_T^4) = O_p(\tilde{a}_T^2) = o_p(a_T^{2(1+\varepsilon)}).$$

Collecting terms, we find $S_{11}^{\dagger} - S_{11}^{*} = o_{p^*}\left(a_T^{1+\varepsilon}\right)$, as desired.

Establishing *(ii)* $|S_{1\varepsilon}^{\dagger} - S_{1\varepsilon}^{*}| = o_{p^*}(\tilde{a}_T)$:

By definition, using $x_T^{\dagger} = x_T^{*} = 0$,

$$\begin{aligned} S_{1\varepsilon}^{*} &= \sum_{t=1}^{T-1} x_{t+1}^{*}\varepsilon_t^{*} = \sum_{t=2}^{T-1} x_t^{*}\varepsilon_{t-1}^{*} = \sum_{t=2}^{T-1}\left(\sum_{i=0}^{T-t-1} \rho_0^i \varepsilon_{t+i}^{*}\right)\varepsilon_{t-1}^{*} \\ &= \sum_{t=2}^{T-1} \varepsilon_{t-1} w_{t-1}^{*}\left(\sum_{i=0}^{T-t-1} \rho_0^i \varepsilon_{t+i} w_{t+i}^{*}\right) \end{aligned}$$

and

$$\begin{aligned} S_{1\varepsilon}^{\dagger} &= \sum_{t=1}^{T-1} x_{t+1}^{\dagger}\varepsilon_t^{\dagger} = \sum_{t=2}^{T-1} x_t^{\dagger}\varepsilon_{t-1}^{\dagger} = \sum_{t=2}^{T-1}\left(\sum_{i=0}^{T-t-1} \hat{\rho}_T^i \varepsilon_{t+i}^{\dagger}\right)\varepsilon_{t-1}^{\dagger} \\ &= \sum_{t=2}^{T-1} \hat{\varepsilon}_{t-1} w_{t-1}^{*}\left(\sum_{i=0}^{T-t-1} \hat{\rho}_T^i \hat{\varepsilon}_{t+i} w_{t+i}^{*}\right) \end{aligned}$$

Hence,

$$S_{1\varepsilon}^{\dagger} - S_{1\varepsilon}^{*} = \sum_{t=1}^{T-1} x_{t+1}^{\dagger}\varepsilon_t^{\dagger} - \sum_{t=1}^{T-1} x_{t+1}^{*}\varepsilon_t^{*} = \underbrace{\sum_{t=1}^{T-1}\left(x_{t+1}^{\dagger} - x_{t+1}^{*}\right)\varepsilon_t^{*}}_{A_T} + \underbrace{\sum_{t=1}^{T-1} x_{t+1}^{\dagger}\left(\varepsilon_t^{\dagger} - \varepsilon_t^{*}\right)}_{B_T}.$$

Regarding A_T, notice that

$$A_T = \sum_{t=1}^{T-1}\left(x_{t+1}^{\dagger} - x_{t+1}^{\#}\right)\varepsilon_t^{*} + \sum_{t=1}^{T-1}\left(x_{t+1}^{\#} - x_{t+1}^{*}\right)\varepsilon_t^{*} =: A_{1T} + A_{2T}$$

with $\{x_t^{\#}\}$ being a bootstrap sample based on ρ_0 and resampling $\hat{\varepsilon}_t$. First,

$$\begin{aligned} E^{*}\left(A_{1T}\right)^2 &= E^{*}\left(\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}\left(\hat{\rho}_T^i - \rho_0^i\right)\hat{\varepsilon}_{t+i} w_{t+i}^{*}\varepsilon_{t-1} w_{t-1}^{*}\right)^2 \\ &= \sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}\sum_{m=2}^{T-1}\sum_{j=0}^{T-t-1}(\hat{\rho}_T^i - \rho_0^i)(\hat{\rho}_T^j - \rho_0^j)\hat{\varepsilon}_{t+i}\varepsilon_{t-1}\hat{\varepsilon}_{m+j}\varepsilon_{m-1} E^{*}\left(w_{m+j}^{*} w_{t+i}^{*} w_{m-1}^{*} w_{t-1}^{*}\right) \end{aligned}$$

$$
\begin{aligned}
&= \sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}\left(\hat{\rho}_T^i-\rho_0^i\right)^2\hat{\varepsilon}_{t+i}^2\varepsilon_{t-1}^2 \le c_T\left(\hat{\rho}_T-\rho_0\right)^2\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}\gamma^{2i}\hat{\varepsilon}_{t+i}^2\varepsilon_{t-1}^2 \\
&= c_T\left(\hat{\rho}_T-\rho_0\right)^2 Q_T = o_p\left(\tilde{a}_T^2\right)
\end{aligned}
$$

where for the last inequality we have used that, for T large enough and for some positive constants $\gamma < 1$ and $c_T \in O_p(1)$,

$$
|\hat{\rho}_T^i-\rho_0^i| = |\hat{\rho}_T-\rho_0|\left|\sum_{k=1}^{i}\hat{\rho}_T^{i-k}\rho_0^{k-1}\right| \le c_T|\hat{\rho}_T-\rho_0|i\gamma^i\ . \tag{B.10}
$$

The order of magnitude $o_p\left(\tilde{a}_T^2\right)$ follows by considering the following inequalities,

$$
\begin{aligned}
Q_T &\le c\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}\varepsilon_{t+i}^2\varepsilon_{t-1}^2 + c\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}(\hat{\varepsilon}_{t+i}-\varepsilon_{t+i})^2\varepsilon_{t-1}^2 \\
&\le c\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}\varepsilon_{t+i}^2\varepsilon_{t-1}^2 + c\left(\hat{\rho}_T-\rho_0\right)^2\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}x_{t+1+i}^2\varepsilon_{t-1}^2 \\
&= Q_{1T} + c\left(\hat{\rho}_T-\rho_0\right)^2 Q_{2T},
\end{aligned}
$$

with Q_{1T} and Q_{2T} implicitly defined. Decompose Q_{1T} as,

$$
Q_{1T} = \sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}\varepsilon_{t+i}^2\varepsilon_{t-1}^2\left(\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|\le\tilde{a}_T\right)+\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|>\tilde{a}_T\right)\right),
$$

and note that

$$
\begin{aligned}
E\left(\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}\varepsilon_{t+i}^2\varepsilon_{t-1}^2\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|\le\tilde{a}_T\right)\right) &= \sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}E\left(\varepsilon_{t+i}^2\varepsilon_{t-1}^2\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|\le\tilde{a}_T\right)\right) \\
&\le cTE\left(\varepsilon_t^2\varepsilon_{t-1}^2\mathbb{I}\left(|\varepsilon_t\varepsilon_{t-1}|\le\tilde{a}_T\right)\right) = O\left(\tilde{a}_T^2\right)
\end{aligned}
$$

by Karamata's Theorem, see (A.5). Likewise, for some $\eta \in (0,\alpha)$ such that $\eta/2 < 1$, and using again Karamata's Theorem, see (A.7),

$$
E(\sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}\varepsilon_{t+i}^2\varepsilon_{t-1}^2\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|>\tilde{a}_T\right))^{\frac{\eta}{2}} \le cTE\left(|\varepsilon_{t+i}\varepsilon_{t-1}|^{\eta}\,\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}|>\tilde{a}_T\right)\right) = O\left(\tilde{a}_T^{\eta}\right).
$$

Collecting terms, $Q_{1T} = O_p\left(\tilde{a}_T^2\right)$. Likewise, $Q_{2T} = \sum_{t=2}^{T-1}\sum_{i=0}^{T-t-1}i^2\gamma^{2i}x_{t+1+i}^2\varepsilon_{t-1}^2 =$

$O_p\left(\tilde{a}_T^2\right)$, and hence

$$\left(\hat{\rho}_T-\rho\right)^2 Q_T = o_p\left(1\right)\left(O_p\left(\tilde{a}_T^2\right)+o_p\left(1\right)O_p\left(\tilde{a}_T^2\right)\right) = o_p\left(\tilde{a}_T^2\right).$$

Next, consider $B_T = \sum_{t=1}^{T-1} x_{t+1}^{\dagger}(\varepsilon_t^{\dagger}-\varepsilon_t^*)$:

We prove that the required rate is obtained for the permutation-wild bootstrap[1]. In this case, $x_t^{\dagger}$ and x_t^* are generated with bootstrap shocks defined as $\varepsilon_t^{\dagger} = \hat{\varepsilon}_{\pi(t)}w_t^*$ and $\varepsilon_t^* = \tilde{\varepsilon}_{\pi(t)}w_t^* = \varepsilon_{\pi(t)}w_t^*$, respectively. For this choice we find

$$B_T = \sum_{t=1}^{T-1}\left(\sum_{i=0}^{T-t-1}\hat{\rho}_T^i\hat{\varepsilon}_{\pi(t+1+i)}w_{t+1+i}^*\right)\left(\hat{\varepsilon}_{\pi(t)}-\varepsilon_{\pi(t)}\right)w_t^*$$

and

$$E^*\left(B_T^2\right) = E^*(\hat{\varepsilon}_{\pi(t+1+i)}^2\left(\hat{\varepsilon}_{\pi(t)}-\varepsilon_{\pi(t)}\right)^2)\sum_{t=1}^{T-1}\sum_{i=0}^{T-t-1}\hat{\rho}_T^{2i}$$

where the double summation term is of order T. Next, using standard properties of expectations under random permutations,

$$\begin{aligned}
E^*(\hat{\varepsilon}_{\pi(t+1+i)}^2\left(\hat{\varepsilon}_{\pi(t)}-\varepsilon_{\pi(t)}\right)^2) &\leq \frac{1}{T^2}\sum_{t=1}^{T-1}\hat{\varepsilon}_t^2\sum_{t=1}^{T}\left(\hat{\varepsilon}_t-\varepsilon_t\right)^2 \\
&= O_p\left(\frac{a_T^2}{T^2}\right)\left(\hat{\rho}-\rho_0\right)^2\sum_{t=1}^{T}x_{t+1}^2 = O_p\left(\frac{a_T^2}{T^2}\right)O_p\left(\frac{\tilde{a}_T^2}{a_T^4}\right)O_p\left(a_T^2\right) \\
&= O_p\left(T^{-2}\tilde{a}_T^2\right)
\end{aligned}$$

Hence, in P-probability, $B_T = O_p^*\left(T^{-1/2}\tilde{a}_T\right) = o_p^*\left(\tilde{a}_T\right)$.

[1] For our main result to hold we require B_T to be of order $o_P^*\left(\tilde{a}_T\right)$ in P-probability. However, unless the bootstrap shocks involve the permutation (i.e. $\{\pi\left(t\right)\}_1^{T-1}$ is a uniformly distributed random permutation of $\{1,...T-1\}$), such rate cannot be achieved. To see this, notice that without permutation

$$\varepsilon_t^{\dagger}-\varepsilon_t^* = -\left(\hat{\rho}_T-\rho_0\right)x_{t+1}w_t^*$$

such that $B_T = -\left(\hat{\rho}_T-\rho_0\right)\sum_{t=1}^{T-1}\left(\sum_{i=0}^{T-t-1}\hat{\rho}_T^i\hat{\varepsilon}_{t+1+i}w_{t+1+i}^*\right)x_{t+1}w_t^*$. Hence,

$$E^*\left(B_T^2\right) = \left(\hat{\rho}_T-\rho_0\right)^2\sum_{t=1}^{T-1}\sum_{i=0}^{T-t-1}\hat{\rho}_T^{2i}\hat{\varepsilon}_{t+1+i}^2x_{t+1}^2 = O_p\left(\frac{\tilde{a}_T^2}{a_T^4}\right)O\left(a_T^4\right) = O_p\left(\tilde{a}_T^2\right)$$

and B_T is of order $O_p^*\left(\tilde{a}_T\right)$ rather than $o_p^*\left(\tilde{a}_T\right)$.

Establishing *(iii)* $|S^*_{1\varepsilon}| = O_{p^*}(\tilde{a}_T)$:

We omit without loss of generality the permutation and consider instead the wild bootstrap which is the most involved case. By definition,

$$S^*_{1\varepsilon} = \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \rho_0^i \varepsilon_{t+i}\varepsilon_{t-1} w^*_{t-1} w^*_{t+i}$$

such that

$$E^*\left(S^{*2}_{1\varepsilon}\right) = \sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \rho_0^{2i} \varepsilon^2_{t+i}\varepsilon^2_{t-1} \left(\mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}| \leq \tilde{a}_T\right) + \mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}| > \tilde{a}_T\right)\right)$$

Next, as for *(ii)* using Karamata's Theorem (A.5),

$$E(\sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \rho_0^{2i} \varepsilon^2_{t+i}\varepsilon^2_{t-1} \mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}| \leq \tilde{a}_T\right)) \leq cTE\left(\varepsilon^2_t \varepsilon^2_{t-1} \mathbb{I}\left(|\varepsilon_t\varepsilon_{t-1}| \leq \tilde{a}_T\right)\right) = O\left(\tilde{a}^2_T\right).$$

Likewise, for some $\eta \in (0, \alpha)$ such that $\eta/2 < 1$, and using Karamata's Theorem (A.7) again,

$$E(\sum_{t=2}^{T-1} \sum_{i=0}^{T-t-1} \rho_0^{2i} \varepsilon^2_{t+i}\varepsilon^2_{t-1} \mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}| > \tilde{a}_T\right))^{\frac{\eta}{2}} \leq$$

$$cTE\left(|\varepsilon_{t+i}\varepsilon_{t-1}|^\eta \mathbb{I}\left(|\varepsilon_{t+i}\varepsilon_{t-1}| > \tilde{a}_T\right)\right) \sum_{i=0}^{\infty} \left|\rho^i\right|^\eta = O\left(\tilde{a}^\eta_T\right)$$

Collecting terms, $E^*\left(S^{*2}_{1\varepsilon}\right) = O_p\left(\tilde{a}^2_T\right)$ as desired. $\square$

B.3 Proof of Theorem 1

In order to prove the theorem, we need to introduce an *infeasible restricted* bootstrap, based on the true parameters. For this bootstrap, the bootstrap sample is generated recursively as

$$x^\star_t = \beta'_0 z^\star_{t+1} + \varepsilon^\star_t, \; t = 1, ..., T-k,$$

again initialized at $x^\star_t = x_t$, $t = T-k+1, ..., T$. The bootstrap shocks are generated as $\varepsilon^\star_t := \varepsilon_{\pi^*(t)} w^*_t$, where as before $\pi^*(t)$, $t = 1, ..., T-k$ is a uniformly distributed random permutation of $\{1, ..., T-k\}$, while w^*_t is either equal to 1 (wild bootstrap) or i.i.d. Rademacher (permutation wild bootstrap). The bootstrap statistic (based on unrestricted parameter estimation) is then given by

$$r_T^\star = R'\hat{\beta}_T^\star - r$$

where $\hat{\beta}_T^\star$ is the OLS estimator of β computed on $\{x_t^\star\}$. This bootstrap satisfies the following lemma (its proof mimics the one given for Lemma 1 and is therefore omitted).

LEMMA B.6 *With $r_T^\star$ the infeasible restricted bootstrap, and r_T the original statistic, it follows that for the permutation, permutation-wild and wild bootstrap schemes the following holds:*

(i) For the permutation bootstrap,

$$\mathcal{D}(r_T^\star|\{x_t\}_1^T) = \mathcal{D}(r_T|\{\varepsilon_{(t)}\}_1^{T-1}, x_T)$$

where $\{\varepsilon_{(t)}\}_1^{T-1}$ denotes the order statistics of $\{\varepsilon_t\}_1^{T-1}$;

(ii) For the wild bootstrap, if the distribution of ε_t is symmetric,

$$\mathcal{D}(r_T^\star|\{x_t\}_1^T) = \mathcal{D}(r_T|\{|\varepsilon_t|\}_1^{T-1}, x_T)\ ;$$

(iii) For the combined permutation-wild bootstrap, if the distribution of ε_t is symmetric,

$$\mathcal{D}(r_T^\star|\{x_t\}_1^T) = \mathcal{D}(r_T|\left\{\varepsilon_{|t|}\right\}_1^{T-1}, x_T)\ .$$

The same results hold with $r_T, r_T^\star$ replaced by $t_T, t_T^\star$, respectively.

Given the results in Lemma B.6, we now proceed by showing that in P-probability

$$n_T(r_T^* - r_T^\star) = o_p^*(1) \tag{B.12}$$

where $n_T := \tilde{a}_T^{-1}a_T^2$. This implies the desired result that the (normalized) bootstrap statistics, conditionally on the data, mimic the distribution of the (normalized) original statistic, conditional on suitable statistics.

Without loss of generality, we set $z_t = 0$ for $t = T-k+1, ..., T$. As in the proof of Lemma 2 it suffices to establish that: *(i)* $||S_{11}^\star - S_{11}^*|| = o_{p^*}\left(a_T^{1+\varepsilon}\right)$, $a_T^2||S_{11}^{*-1}|| = O_{p^*}(1)$, *(ii)* $||S_{1\varepsilon}^\star - S_{1\varepsilon}^*|| = o_{p^*}(\tilde{a}_T)$ and finally *(iii)* $||S_{1\varepsilon}^\star|| = O_{p^*}(\tilde{a}_T)$. In order to do so, one can follow exactly the same steps as done there, where the results in the following lemmas are now required (their proof is omitted for the sake of brevity).

Lemma B.7 *Under the assumptions of Theorem 1, the restricted and unrestricted OLS estimators $\tilde{\beta}_T$ and $\hat{\beta}_T$ satisfy, under the null hypothesis,*

$$||\tilde{\beta}_T - \beta_0|| = O_p(||\hat{\beta}_T - \beta_0||) = O_p\left(\tilde{a}_T a_T^{-2}\right) = o_p(1)$$

Moreover, with $\tilde{\varepsilon}_t - \varepsilon_t = -(\tilde{\beta}_T - \beta_0) z_{t+1}$,

$$\sum_{t=1}^{T-k} |\tilde{\varepsilon}_t^2 - \varepsilon_t^2| = o_p\left(\tilde{a}_T^2\right)$$

Lemma B.8 *The bootstrap process x_t^* satisfies*

$$x_t^* = \sum_{i=0}^{t-k-1} \tilde{\theta}_{T,i} \varepsilon_{t+i}^* \tag{B.13}$$

where, for T large enough, $|\tilde{\theta}_{T,i}| \leq c_T \rho^i$ for some $\rho \in [0,1)$ and $c_T = O_p(1)$. The unfeasible bootstrap process $x_t^\star$ satisfies (B.13) with ε_{t+i}^* replaced by $\varepsilon_{t+i}^\star$ and $\tilde{\theta}_{T,i}$ replaced by θ_i, with $|\theta_i| \leq c\rho^i$.

B.4 Proof of Lemma A.5

Proof of Lemma A.5. Recall that $\hat{\rho}_T - \rho_0 = O_p(\tilde{a}_T a_T^{-2})$, and that $S_{xx}^{-1/2} = O_p(a_T^{-1})$. Next,

$$\hat{\sigma}_T^2 = T^{-1}\left(S_{\varepsilon\varepsilon} - S_{\varepsilon x}^2 S_{xx}^{-1}\right),$$

where $S_{\varepsilon\varepsilon} = O_p\left(a_T^2\right)$ and $S_{\varepsilon x} = O_p\left(\tilde{a}_T\right)$, and consequently $\hat{\sigma}_T^2 = O_p\left(T^{-1}\left(a_T^2 + \tilde{a}_T^2 a_T^{-2}\right)\right) = O_p\left(T^{-1} a_T^2\right)$. Collecting terms the result holds. $\square$