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Building Confidence Intervals with Block Bootstraps for the Variance Ratio Test of Predictability

Eduardo José Araújo Lima[*]
Benjamin Miranda Tabak[**]

Abstract

This paper compares different versions of the multiple variance ratio test based on bootstrap techniques for the construction of empirical distributions. It also analyzes the crucial issue of selecting optimal block sizes when block bootstrap procedures are used, by applying the methods developed by Hall *et al.* (1995) and by Politis and White (2004). By comparing the results of the different methods using Monte Carlo simulations, we conclude that methodologies using block bootstrap methods present better performance for the construction of empirical distributions of the variance ratio test. Moreover, the results are highly sensitive to methods employed to test the null hypothesis of random walk.
Keywords: resample, bootstrap, variance ratio, random walk
JEL Classification: C00, C15, C16

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1. Introduction

Among the different methods developed to test the presence of serial correlations in time series, the variance ratio test (*VR*) became quite popular after the studies of Lo and MacKinlay[1] (1988, 1989), Poterba and Summers (1988) and Cochrane (1988). It has been highly utilized to test the random walk hypothesis (RWH) not only in financial time series, but also in macroeconomic data.

The Lo and MacKinlay (1988) VR methodology, for testing the RWH against stationary alternatives exploits the fact that the variance of random walk increments is linear in any and all sampling intervals. If stock prices are generated by a random walk, then the variance ratio, VR(q), which is (1/q) times the ratio of the variance of q-holding-period returns to that of one-period-holding returns, should be unity for all q, where q is any integer greater than one[2]. The VR test exploits an important property of the RWH – that variance of the increments in a random walk is linear in any and all sampling intervals (q). Empirical applications naturally employ different values for the aggregation parameter, q, and estimate multiple variance ratios. Examining multiple VR estimates requires a multiple comparison statistical approach.

VR tests that base multiple comparisons in extreme statistics may lead to wrong inferences[3]. One of the solutions can be to combine several VR statistics of different horizons in one scalar measure, such as the Wald statistics suggested by Cecchetti and Lam (1994), or the z-statistic of Chow and Denning (1993).

Lo and MacKinlay (1989) found that the two-sided test has good finite-sample power against several relevant alternative hypotheses and sizes generally close to the nominal level, and that the test is robust against any heteroscedasticity. Furthermore, the finite-sample null distribution of the test statistic is quite asymmetric and non-normal. However, as Richardson and Stock (1990) indicate, Lo and MacKinlay's asymptotic

[1] It is worth mentioning that several studies, using variance ratios in different contexts, preceded the research of Lo and MacKinlay (1988). However, none of these previous studies formalized the sample theory for the test statistics. For this reason, most researchers attribute the variance ratio test to Lo and MacKinlay (1988).

2 Lo and MacKinlay demonstrate that this property holds asymptotically even when the disturbances of a random walk stochastic process are subject to some types of heteroscedasticity. Under the random walk hypothesis, the unity of *VR(q)* holds for each *q*.

3 Chow and Denning (1993) showed that failing to control test size for multiple comparisons causes an inappropriately large probability of Type I error.

distribution might not be an accurate approximation when q is large and the sample size is small. Additionally, the asymptotical approximations, which are used in the construction of a majority of test statistics, have low accuracy when applied to small samples, which may also lead to errors in the test's interpretation. One of the solutions to try to minimize this kind of problem is to use resample methods to derive the empirical distribution of these statistics[4].

Many researchers have employed different versions of bootstrap schemes to derive finite sample VR statistics[5]. However, very little is known about the power and size of these different bootstrap methodologies and which ones perform better. This paper seeks to contribute to the literature by comparing several of these bootstrap methods for the construction of empirical distributions. For this purpose, the results of different bootstrap methods applied to the VR test will be compared, such as standard, weighted and block bootstrap. In addition, in the case of the block bootstrap, we will treat the crucial issue of selecting the optimal size of the blocks, using the methods of Hall et al. (1995) and Politis and White (2004). The effects over the results of the VR test caused by the selection of the block size will also be shown empirically. A Monte Carlo simulation will be employed to analyze the performance of these tests in finite samples (size and power). A comparison of bootstrap techniques with the multiple VR according to Chow and Denning (1993) is made and the results suggests that the latter has very low power for near unit root processes, and has poor performance vis-a-vis bootstrap techniques.

The remainder of this paper is organized as follows. In section 2, we present a brief literature review about resampling procedures and its application to the VR test. In section 3 the methodology used in this paper is discussed. The performance of different

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[4] The use of resampling methods applied to the *VR* test cannot be considered as innovative, but it is, however, recent. Literature reviews related to the use of resampling techniques in time series can be found in Li and Maddala (1996), Berkowitz and Kilian (2000), Ruiz and Pascual (2002) and Alonso *et al.* (2002).

[5] In particular, to illustrate the application of different resampling techniques to the *VR* test, we can mention Kim *et al.* (1991), who used randomization in order to calculate the empirical distribution of the individual *VR* test. Pan *et al.* (1997), used standard bootstrap to test the martingale hypothesis in daily data of future currency prices, Malliaropulos and Priestley (1999) considered a version of the weighted bootstrap to the application of the tests of Lo and MacKinlay (1988). Chang *et al.* (2004) and Lima and Tabak (2004) applied the multiple *VR* test using the procedures of Cecchetti and Lam (1994). Malliaropulos and Priestley (1999), and Patro e Wu (2004), used randomization and the bootstrap.

methodologies, using a Monte Carlo study, is presented in section 4. Section 5 concludes the paper.

2. Resampling in time series

Besides randomization, the most popular resampling methods in the literature are the jackknife, the subsampling and the bootstrap.

Randomization or shuffling, introduced by Fisher (1935) in the context of significance tests, in a general way, is well and robustly applied to problems that seek to obtain the probability of occurrence of, for example, a given series data or sequence of observed data, under the null hypothesis of randomness. In this kind of procedure, the order or associations among the data series is important. However, Kim et al. (1998) mention that, in the presence of persistent heteroscedasticity, the usual method of randomization is not appropriate because it destroys the time dependence in the variance when treating the errors as interchangeable (see Patro and Wu (2004)).

The jackknife[6] technique, assigned to Quenouille (1949) and Tukey (1958), was originally introduced to reduce estimator biases in serial data that are independent and identically distributed (iid). Later, Shao and Wu (1989) proposed a variant of the method, in which the jackknife replies are obtained excluding d observations of the original series where d, is an integer smaller than the size of the original series. However, Miller (1974) mentions that an area where the jackknife technique is not successful is in time series analysis. In fact, the jackknife technique, just as originally proposed, is applied only to iid data, and it is inconsistent, for example, as a variance estimator, (see Liu and Singh (1992)). This deficiency in the procedure was, in a certain way, surpassed by the studies of Künsch (1989) and Liu and Singh (1992) who, in an independent way, created the Moving Blocks Jackknife method – MBJ.

The MBJ of Künsch (1989) was defined for stationary processes with a dependence on short duration, while Liu and Singh (1992) defined a jackknife method

[6] According to Miller (1974), Tukey created the name *jackknife estimator* in an unpublished work, aiming to propose a tool of simple utilization and that would solve several statistical problems (a rough-and-ready statistical tool). Jackknife would be, in this way, some sort of Swiss jackknife.

in restricted blocks for a sequence of random variable m-dependents[7]. It is important to mention that the method must be consistent when applied to more general methods of dependence[8]. However, we should note that when blocks are involved, the method obliges us to choose the size of these blocks that will be removed from the original series for the construction of the resampled series, and, according to our evaluation, the literature does not present, for MBJ methods, any rule explicitly defined for selecting the size of the block.

As an alternative to other resampling methods, Politis and Romano (1994a) developed a subsampling method for stationary observations. This procedure works with subsets of the original series, where each subset of observations is treated as a time subset. The main motivation of the method is that because the subsets elapse from the original series maintaining the same time sequence, the probability distribution of the original series is automatically held in the subsets. This is more advantageous, according to Politis et al. (1997), than block bootstrap methods. This is especially true in terms of informational gain regarding the data generator process, because the union of random and independent blocks used in the block bootstraps methods, theoretically leads to the construction of a pseudo-series of distributions different from the original series. However, just like in the jackknife method, the main question is the selection of subset size, because the definition of this size directly affects the performance of finite samples. Politis et al. (1997) propose a calibration method, arguing that this procedure generates good properties for finite samples. The authors base their conclusions on the results that, in the context of iid observations, the calibration procedure enhances the asymptotical correction. However, it is broadly agreed that the method cannot be applied to independent observations, where additional research is necessary to explore the theoretical and practical properties of the method[9].

The fourth type of resampling, the bootstrap, was introduced by Efron (1979), as a procedure used to measure the accuracy of estimators, and it is based in the idea that

[7] According to Liu and Singh (1992), the notion of an m-dependence is probably the most basic model of time dependence. Be $\{X_1, X_2,...\}$ a sequence of random variables, A and B two events such that A depends on $\{X_1,...,X_k\}$ and B depends on $\{X_{k+m+1}, X_{k+m+2},...\}$. The sequence $\{X_i\}$ is said to be *m*-dependent if any pair of A and B events are independent.

[8] Despite believing in their results, Liu and Singh (1992) mention the need for additional studies.

[9] VR test applications, with the use of subsampling procedures, can be analyzed in the works of Politis *et al.* (1997), Whang and Kim (2003) and Hoque *et al.* (2007).

the sample is the main, and better, source of information about the data generator process. Classically, the method was developed for the application of iid data samples. Under this premise, the technique produces an adaptive model to the marginal sample distribution.

This simpler model has been highly criticized. Intuitively, the standard bootstrap fails when it tries to reproduce possible serial dependence among the observations of the original series, because it changes the pattern of the series when it assumes that the position of the observations in the series can be changed without the adoption of any based criteria. In this way, it is expected that the statistics calculated from the resampled series are not consistent.

In the context of the VR test, Malliaropulos (1996) used the standard bootstrap in the construction of the value of acceptability of the test. Politis et al. (1997) criticized the results obtained by Malliaropulos (1996), affirming that the methodology used is only employed to the random walk hypothesis test with iid increments. However, Liu and Singh (1992) noted that Efron's (1979) bootstrap would work very well with independent and not identically distributed data, where we can expect some robustness in the presence of heteroscedasticity.

During the 80's, after the work of Singh (1981), which showed that the scheme suggested by Efron (1979) did not work for dependent data, the original method was modified and adapted to different situations. Consequently, and according to Ruiz and Pascual (2002), many different methods of the bootstrap model were developed for applications in time series data.

Wu (1986) proposed a weighted bootstrap method, also known in the literature as the wild bootstrap, which results in consistent variance of test statistics, even in the presence of heteroscedasticity. In this procedure, each observation of the original series is weighted, resampled with reposition from a standard normal distribution. Neumann and Kreiss (1998) tested the validity of this method, in the context of time series. Examples of its use, in the non-parametric implementation of the random walk test, can be found in Malliaropulos and Priestley (1999) and Chang et al. (2004).

According to Malliaropulos and Priestley (1999), since the weighted bootstrap resamples from normalized returns instead of working with the original series of returns, it takes into consideration the non-constancy of the variance of the returns, since the information in each sample is preserved. To corroborate this affirmative, we can cite the work of Cribari-Neto and Zarkos (1999), who compared weighted bootstrap methods with estimators consistent to heteroscedasticity. They concluded that the performance of the weighted bootstrap overcame other estimators in both conditions of homo and heteroscedasticity, in the context of estimation of the estimators' variance, and from heteroscedasticity tests in linear regressions, under the hypothesis of normality and non-normality.

The idea of developing a block bootstrap instead of resampling based on individual observations was originally presented by Hall (1985). Even so, Carlstein (1986) proposed the Nonoverlapping Block Bootstrap (NBB) methodology to univariate time series, while Künsch (1989) and Liu and Singh (1992) proposed an overlapped block bootstrap known as Moving Blocks Bootstrap (MBB), which was applied to stationary time series. According to Lahiri (1999), the methods that use overlapped blocks are preferable to those that use non-overlapping blocks.

Despite the fact that Li and Maddala (1996) suggested that the literature for block bootstrap methods are concentrated in the estimation of sample parameters, such as the average and the variance, Liu and Singh (1992) mentioned that the results can be applied to more general statistics.

Berkowitz and Kilian (2000) suggested that the MBB method can be highly sensitive to the selection of the size of the block, while Liu and Singh (1992) indicated the stationarity problem of the resampled series by the MBB methodology.

Trying to solve this issue, Politis and Romano (1994b) developed the Stationary Bootstrap (SB). Before the SB, however, Politis and Romano (1992) proposed the Circular Block Bootstrap (CBB).

The basic steps of these two types of bootstrap are similar to the MBB, in which existing differences in data form are concatenated. In the CBB and the SB, the data are concentrated in a circular manner, in such a way that the last observation of the original series will always be guided from the first observation. The SB method still differs in another point, since it resamples data in blocks of different sizes. In other words, while the samples generated by the MBB and CBB are constructed in blocks of the same size, the SB uses blocks of random sizes, following a geometric distribution.

Politis and Romano (1994b) verified that the SB process is less sensitive to a bad specification of block size, when compared to MBB and CBB methods. However, following Lahiri (1999), the use of blocks of random size leads to bigger mean squared errors than the ones obtained when blocks with non-random sizes are used. The main results of this article indicate that, for a given block size, the methods of NBB, MBB, CBB and SB presented, asymptotically, the same size of bias. Even so, the variance of the estimators in SB are always, at least, twice the variance of the estimators for NBB and CBB. According to Politis and White (2004), it occurs because of the additional randomization generated by blocks of random size.

Furthermore, despite the fact that Lahiri (1999) concludes, by theoretical demonstration, that the NBB, MBB, CBB and SB methods have the same amount of asymptotic bias, it does not occur with the variance. After comparing the asymptotic minimal values of the mean squared error of each of these four methods, Lahiri (1999) concludes that the MBB and CBB methods are asymptotic equivalents, in the sense of mean square error (MSE). This theoretical discovery was corroborated by simulation results[10], for which Lahiri (1999) affirms that there are advantages in the use of the MBB and CBB methods in relation to SB and NBB methods, even in samples of moderate size.

Before we go to the next session, there are two important issues related to block bootstrap procedures that need to be mentioned. The first is the challenge of the technique of resampling the data in order to assure that the structure of dependence of the original series is preserved. In the block bootstrap methods, this dependence is assured in each block. Nevertheless, it is known that these methods treat each block as independents when in fact, they are dependent on the original time series. This can generate some form of bias in the estimates, depending on the dependence level of the data in the sample studied.

[10] In these simulations, Lahiri (1999) estimates the variance of the mean of the sample and calculates the MSE of the estimators for the four block bootstrap methods (NBB, MBB, CBB e SB), for three different types of models that generate observations (ARMA(1,1), AR(1) e MA(1)) with independent innovations.

Liu and Singh (1992), just like Davison and Hall (1993) and Li and Madala (1996), warn about the bias of the variance estimators obtained trough the block bootstrap technique, as a consequence of non-reproduction, or effective modification of the dependence structure of the time series. As the block bootstrap is used in the construction of the empirical distribution of VR tests, it is important to mention the interpretation given by Levich and Thomas (1993) for resampled series. These authors note that since it operates with the sequence of price changes, the initial and final price levels of the resampled series would be restricted to be exactly the same as in the original data series, and the resampled series would have distributions with identical properties of the original series. However, the properties of the resampled time series would be modified randomly. In this way, the simulations of the series using bootstrap generate one of many possible trajectories that an asset price or an exchange, for example, could have followed in the levels of the initial and final dates of the series, with the original distribution of the return remaining constant.

Another extremely important question for block algorithms, as well as for the jackknife and subsampling methods, is the selection of the optimal block size that will be used, since the definition of this size has a direct effect over the performance in finite samples. However, in contrast to what occurs with the jackknife and subsampling methods, the literature presents well-defined rules for the selection of optimal block size in the bootstrap method.

Li and Maddala (1996) mention, without great details, some rules for the selection of the size of the block, based on specific models or with consideration about the MSE. The selection of block size was also approached in the works of Hall et al. (1995), Berkowitz and Kilian (2000) and Politis and White (2004), among others.

Hall et al. (1995) showed that the optimal size of the block depends on the statistics to be estimated. In this way, they conclude that the ideal size of the block for problems of estimation of bias or variance, estimation of functions of one-sided distribution and two-sided distribution function would be equal to $n^{1/3}$, $n^{1/4}$ and $n^{1/5}$, respectively, with n equal to the sample size of the time series.

Critics to this rule and alternate proposals can be found in Berkowitz and Kilian (2000) and Politis and White (2004). In the first case, Berkowitz and Kilian (2000) propose a procedure of automatic selection for finite samples, based on the data and independent of the sample size and of the persistence or time structure of the associated process. Politis and White (2004) propose estimators of the optimal size of the block based on the notion of spectral estimation with the use of the flat-top lag-windows methodology, developed by Politis and Romano (1995).

Since the bootstrap provides good estimates for critical points, it can be argued that selection of the test used is an empirical matter to be addressed by the relative performance of the tests in size and power comparisons.

3. Methodology and simulation design

Extensive Monte Carlo simulations were conducted to compare empirical size and power of alternatives joint VR tests presented in the previous section. The experimental design is similar to those of Lo and MacKinlay (1989) and Whang and Kim (2003). The sample sizes considered were 64, 256, e 1024. For the bootstrap tests, the number of bootstrap replications was set to 1000.

The bootstrap method is conducted by first shuffling, with replacement the observations, then computing VR(q) for a replication of 1000 times. The p-value for the sample VR(q) is determined from the frequency table of the bootstrap distribution.

Furthermore, in past work, the random walk hypothesis was considered rejected when at least some of the VR statistics provided evidence against it. Richardson (1993) notes that failure to include a joint test that combines all of the information from several VR statistics would tend to yield stronger results. To provide a joint test that takes into account the correlations between VR statistics at various horizons, we consider the Wald test in a similar manner to that of Goetzmann (1993) and Cecchetti and Lam (1994) as follows:

$$W(q) = \{VR(q) - E[VR(q)]\}' \Sigma^{-1} \{VR(q) - E[VR(q)]\} \sim \chi_q^2 \qquad (1)$$

This joint variance-ratio $W(q)$ statistic follows a χ^2 distribution with q degrees of freedom. However, the simulation results presented in Cecchetti and Lam (1994) indicate that the empirical distributions of VR statistics have a large degree of positive skewness, suggesting that inference based on the χ^2 distribution will be misleading. Accordingly, we calculated the Wald statistic for each bootstrapped VR estimator vector and also used the bootstrapped distribution of Wald statistics for hypothesis testing, as in Lee et al. (2001).

To compare the results, we considered five different types of bootstraps to derive the sampling distribution of the variance-ratio statistics: the standard bootstrap, the wild bootstrap, as in Malliaropulos and Priestley (1999), and three versions of block bootstraps (MBB, CBB and SB).

The size of the test was estimated under both the Gaussian iid null and the heteroscedastic null hypotheses. We compared the power of the test against two alternatives of empirical interest: AR(1), ARIMA(1,1,1). For comparison, we also report the empirical size and power of the MCT (Multiple Comparisons Test proposed by Chow e Denning (1993)).

Additionally, when block bootstrap methods were used, the selection of the optimal size of the block was treated using the rules of Hall et al. (1995) and Politis and White (2004)[11], as we also demonstrate, empirically, the effect of this selection over the VR test results.

The empirical distribution of the VR test was derived based on 1,000 bootstrap samples, following the suggestions of Efron and Tibshirani (1986). All of the resampled series had the same size[12].

For the realization of the joint test for VR, and aiming to avoid problems of inferences in finite samples, we calculated Wald statistics, following Cecchetti and Lam (1994), for each VR vector of the bootstrap samples, building the empirical distribution of the Wald statistics.

To analyze the performance of the tests in finite samples (size and power), we performed Monte Carlo simulations. The picture of these simulations was similar to the ones adopted by Lo and MacKinlay (1989) and Whang and Kim (2003).

[11] It is worth mentioning that the rule of selection of the optimal block size of Politis and White (2004) is automatized.

[12] To keep the ideal identity $n = bl$, we can use b blocks of size l and one block of size $n - n'$ to complete the resampled series.

The size of the test was estimated under the random walk, $p_t = p_{t-1} + \varepsilon_t$ [13], with homoscedastic increments, where $\varepsilon_t \sim iid(0,1)$, and with heteroscedastic increments, with $\varepsilon_t = \sqrt{h_t}\eta_t$, where $h_t = 0.01 + \gamma_1 h_{t-1} + 0.2\varepsilon_{t-1}^2$, and $\gamma_1 = 0.75$, that is, following a GARCH process.

The power of the test was estimated using as alternatives the models AR(1), represented by $p_t = \phi \ p_{t-1} + \varepsilon_t$, with $\phi = 0.85$ and 0.96 and ε_t following a GARCH (1,1) process, in the same form that was specified in the case of the size of the test, and with the ARIMA (1,1,1) model , given by $p_t = y_t + z_t$, where $y_t = 0.85 y_{t-1} + \varepsilon_t$, with $\varepsilon_t \sim iid(0,1)$, and $z_t = z_{t-1} + \tau_t$, with $\tau_t \sim iid(0,1/2)$, that is, the variance of the random walk innovation is equal to two times the innovation variance of the stationary process AR(1).

The simulations were estimated for three different sizes of the sample, with 64, 256, and 1024 observations. Since in the construction of the simulated series there was the problem of non-immediate convergence to the specified model, the first 500 observations of the simulated series were discarded[14].

In relation to the selection of the aggregation value q, we followed the suggestion of Lo and MacKinlay (1989), maintaining the maximum value of the parameter q equal to half of the sample size to avoid reducing the test power.

As well as in the bootstrap methods, in the Monte Carlo procedure, we also defined the number of simulations that needed to be made. In the present case, since the empirical distributions of the VR test was constructed using bootstrap, we simulated the power and the size of the test with 2.000 Monte Carlo repeats.

With respect to the estimation of the p-value for the statistics of VR, two-sided p-values were used, for a 5% significance level. That is, if the original VR statistic was inside the 2.5% and 97.5% percentiles of the bootstrap samples, the random walk hypothesis was accepted with 5% significance.

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[13] $p_t = \ln(P_t)$.

[14] For example, see Lundbergh and Teräsvirta (2002) and Brooks (2002).

4. Monte Carlo Evidence

Several Monte Carlo experiments were made to verify the quality of the asymptotical approximation of the statistics of VR tests. Different methods were used in the construction of empirical distribution: CBBH (Circular Block Bootstrap with the optimal block rule of Hall et al (1995)), CBBP (Circular Block Bootstrap with the optimal block rule of Politis and White (2004)), MBBH (Moving Block Bootstrap with the rule of Hall et al.), MBBP (Moving Block Bootstrap with the rule of Politis and White), MCT, SBH (Stationary Bootstrap with the rule of Hall et al.), SBP (Stationary Bootstrap with the rule of Politis and White), STD (Standard Bootstrap following Efron (1979)) and WU (Weighted Bootstrap, following Malliaropulos and Priestley (1999)).

With respect to the size of the test under the null hypothesis of random walk iid, we can observe in the data in Table 01 that the empirical sizes in the two-sided test of VR, with 5% significance, suffer modifications, depending on the method used in the VR test. In a general way, it is observed that the empirical size of the SBP, CBBH, MBBH and MBBP methods gets closer to the nominal value than the others, and the best performances to different sizes of the sample are found using the CBBH and MBBH methods. The MCT method is the one that is more apart from the nominal value of 5%, with an average difference that is always positive in the different sizes of the analyzed samples.

By analyzing the results of the size of the test under the null hypothesis of a heteroscedastic random walk, presented in Table 02, we can verify that, in a general way, empirical sizes further deviate from their nominal values and the tests become less conservative if compared to the previous results of the homoscedastic version.

It can be noted that the block methods that use the Politis and White (2004) rule, CBBP and MBBP, have an empirical size closer to the nominal size than ones that use the Hall et al. (1995) rule, which is exactly the opposite of what occurs in the homoscedastic version. It can be said that that the SBH, MCT, SBP and WU methods present the best performance in relation to the size of the test, with the exception that the SBH method is very conservative. However, it does not indicate that other methods perform poorly in relation to the size of the test. We can also observe that for small samples (64 observations), the CBB and MBB methods with the optimal block rule of Politis and White (2004) result in an empirical size very close to 5%.

Table 01 – Empirical size of the two-sided variance ratio test in the homoscedastic multiple version, with nominal size of 5% – Comparison between methods and rules of optimal block size (Politis and White (2004) and Hall *et al.* (1995))

		Methods								
		Politis and White			Hall *et al.*					
N	q máx.	MBBP	CBBP	SBP	MBBH	CBBH	SBH	WU	STD	MCT
64	4	0.024	0.026	0.017	0.045	0.044	0.004	0.055	0.053	0.033
	8	0.025	0.026	0.018	0.042	0.041	0.003	0.061	0.046	0.058
	16	0.035	0.035	0.028	0.049	0.050	0.012	0.066	0.055	0.093
	32	0.038	0.039	0.032	0.052	0.051	0.020	0.069	0.053	0.128
256	4	0.038	0.040	0.025	0.013	0.013	0.000	0.059	0.059	0.018
	8	0.045	0.044	0.027	0.024	0.025	0.001	0.065	0.064	0.028
	16	0.043	0.045	0.033	0.031	0.030	0.006	0.062	0.058	0.044
	32	0.047	0.046	0.042	0.042	0.042	0.016	0.060	0.055	0.063
	64	0.057	0.057	0.053	0.047	0.048	0.027	0.060	0.058	0.098
	128	0.075	0.078	0.070	0.061	0.058	0.046	0.086	0.082	0.144
1024	4	0.038	0.038	0.026	0.002	0.002	0.000	0.053	0.051	0.022
	8	0.038	0.038	0.029	0.008	0.008	0.000	0.049	0.050	0.031
	16	0.037	0.037	0.032	0.020	0.021	0.001	0.044	0.047	0.042
	32	0.046	0.046	0.046	0.030	0.030	0.009	0.051	0.049	0.058
	64	0.051	0.051	0.049	0.041	0.041	0.021	0.056	0.055	0.073
	128	0.061	0.062	0.061	0.055	0.057	0.040	0.063	0.061	0.092
	256	0.079	0.079	0.079	0.076	0.075	0.072	0.077	0.080	0.134
	512	0.239	0.238	0.233	0.237	0.244	0.212	0.231	0.232	0.187

The empirical size of the test, for a nominal value of 5%, was estimated under the model of random walk, $p_t = p_{t-1} + \varepsilon_t$, with homoscedastic increments, with $\varepsilon_t \sim iid(0,1)$, where $p_t = \ln(P_t)$. The empirical sizes of the Chow and Denning test (MCT) were estimated for comparison ends. Each set of lines for a given sample size was constructed by an independent simulation experiment and separated from the others, based on 2.000 replications. The results from the block bootstrap methods with the application of the Politis and White (2004) rule are presented in the columns 3 to 5, while the results from the block bootstrap methods using the Hall *et al.* (1995) rule are available in the columns 6 to 8. In the last three columns, are presented the results from the weighted and standard bootstrap methods, and the results obtained by the Chow and Denning statistics. The q maximum of 64, for example, means that the multiple test was done to horizons from q = 2 to 64.

It is worth noting that when a maximum q value equals half the size of the sample, it is used in the ascertainment of the size of the test. The procedure for the construction of Wald statistics reveals a weakness in relation to the covariance matrix, which starts to present problems of singularity. It gets more evident, in Tables 01 and 02, to samples of 1024 observations and a maximum q of 512 when the empirical size of the test becomes greater than the nominal size. This fact can also be attributed to the lack of precision with which autocorrelations of greater orders are estimated for a given fixed size of the sample, since the ratio between the variances with values of aggregation q is a proxy of the linear combination of the q-1 autocorrelations (Lo and MacKinlay (1989)).

In relation to the values here presented for the MCT test, it should be remembered that they are different from its correspondents presented by Chow and Denning (1993) because of the differences in the pictures of the test.

Table 02 – Empirical size of the two-sided variance ratio test in the heteroscedastic multiple version, with nominal size of 5% – Comparison between the methods and rules of optimal blocks (Politis and White (2004) and Hall *et al.* (1995))

		Methods								
		Politis and White			Hall *et al.*					
N	q máx.	MBB	CBB	SB	MBB	CBB	SB	WU	STD	MCT
64	4	0.041	0.042	0.022	0.081	0.081	0.008	0.074	0.095	0.041
	8	0.048	0.048	0.030	0.087	0.087	0.009	0.071	0.099	0.062
	16	0.048	0.049	0.037	0.080	0.081	0.017	0.075	0.091	0.092
	32	0.045	0.046	0.034	0.067	0.072	0.021	0.078	0.072	0.126
256	4	0.073	0.073	0.048	0.046	0.047	0.001	0.068	0.164	0.024
	8	0.106	0.105	0.070	0.082	0.082	0.005	0.074	0.198	0.035
	16	0.107	0.106	0.084	0.110	0.111	0.015	0.071	0.178	0.049
	32	0.097	0.096	0.086	0.112	0.112	0.040	0.068	0.148	0.072
	64	0.084	0.085	0.077	0.101	0.103	0.058	0.071	0.119	0.102
	128	0.096	0.099	0.088	0.109	0.108	0.070	0.105	0.121	0.149
1024	4	0.099	0.099	0.046	0.023	0.023	0.001	0.055	0.229	0.015
	8	0.141	0.142	0.096	0.098	0.099	0.005	0.054	0.270	0.024
	16	0.171	0.170	0.120	0.148	0.146	0.017	0.062	0.261	0.038
	32	0.156	0.159	0.137	0.173	0.171	0.050	0.059	0.215	0.045
	64	0.138	0.138	0.131	0.166	0.165	0.072	0.060	0.175	0.061
	128	0.123	0.124	0.120	0.154	0.150	0.093	0.068	0.143	0.082
	256	0.147	0.147	0.149	0.174	0.175	0.130	0.123	0.144	0.119
	512	0.385	0.375	0.401	0.492	0.490	0.416	0.588	0.291	0.164

The empirical size of the test, for a nominal value of 5%, was estimated under the model of random walk, $p_t = p_{t-1} + \varepsilon_t$ ($p_t = \ln(P_t)$), with heteroscedastic increments, with $\varepsilon_t = \sqrt{h_t}\eta_t$, where $h_t = 0.01 + \gamma_1 h_{t-1} + 0.2\varepsilon_{t-1}^2$, and $\gamma_1 = 0.75$. The empirical sizes of the Chow and Denning (MCT) test were estimated for ends of comparison. Each set of lines for a given sample size was built by an independent simulation experiment and separated from the others, based in 2.000 replications. The results of the block bootstrap methods with the application of the Politis and White (2004) rule are presented in columns 3 to 5, while the results of the block bootstrap method using the Hall *et al.* (1995) rule are reported in columns 6 to 8. In the last three columns, are presented the results from the weighted and standard bootstrap methods, and the results obtained by the Chow and Denning statistics. The q maximum of 64, for example, means that the joint test was done to horizons from q = 2 to 64.

The power of the test in comparison to the alternatives AR(1), given by $p_t = \phi \quad p_{t-1} + \varepsilon_t$, with $\phi = 0.85$ and 0.96 and ε_t following a GARCH (1,1) process, for a fixed size of the sample, was not possible to verify. Like in Lo and MacKinlay (1989), the power of the test initially increases and later decreases with the value of aggregation q, given the behavior of the AR(1)[15] model. In this case, the power of the test enhances with the value of aggregation q, for a given size of the sample.

Based on the data available in Tables 03 and 04 we can verify that when the coefficient of the AR(1) model moves from 0.85 to 0.96, the power of all analyzed tests decreases, with no exception. However, the variation of the average of the power test when $\phi = 0.85$ and becomes 0.96 it is much higher in the MCT test. This suggests that while a variation on the methods that use bootstrap is 64.83% on average, in the MCT method the average power of the test falls from 42.7% ($\phi = 0.85$) to 6.12% ($\phi = 0.96$) and represents a variation of 194.22%.

For these two alternatives, the tests that possess the greatest power are the STD, MBBH and CBBH, respectively, with certain equivalence among them.

With respect to the power of the test, Chow and Denning (1993) relate that in a general way, the proposed test (MCT) has low power in small samples in comparison to the alternatives AR(1) but improves as the size of the sample increases, and the AR coefficient decreases (from $\phi = 0.96$ to $\phi = 0.85$). Our results indicate that, comparatively, the MCT method has the lowest power among the methods studied. This weak performance for the MCT was also reported by Fong et al. (1997), who examined the performance of two multiple tests, the MCT and the RS Wald (Richardson and Smith (1991)), with simulations based on 2500 replications and samples with 250, 500 and 750 observations.

Under the alternative ARIMA (1,1,1), Table 05 reports that in general, the power of the test is higher in the WU, STD, CBBH and MBBH procedures. Again, the MCT, relatively to the other tests, shows a low average power for the researched samples.

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[15] According to Lo and MacKinlay (1989), the coefficients of the first order autocorrelation of AR(1) increments an increase in absolute value (become more negative) as the interval of the increments increase. It implies that, despite the fact that p_t possess a root next to one, the behavior of its first

Table 03 – Power of the variance ratio test in the multiple version, in relation to the AR heteroscedastic alternative $(\phi = 0.85)$ – Comparison between methods and rules of optimal block (Politis and White (2004) and Hall *et al.* (1995))

		Methods								
		Politis and White			Hall *et al.*					
N	q máx.	MBB	CBB	SB	MBB	CBB	SB	WU	STD	MCT
64	4	0.055	0.054	0.041	0.123	0.120	0.013	0.094	0.122	0.024
	8	0.067	0.069	0.052	0.150	0.148	0.017	0.106	0.146	0.026
	16	0.081	0.081	0.066	0.146	0.144	0.022	0.116	0.146	0.028
	32	0.073	0.073	0.052	0.117	0.113	0.019	0.123	0.129	0.030
256	4	0.170	0.171	0.123	0.200	0.202	0.029	0.231	0.424	0.098
	8	0.309	0.310	0.276	0.438	0.439	0.139	0.335	0.581	0.138
	16	0.511	0.516	0.496	0.668	0.670	0.383	0.472	0.734	0.154
	32	0.656	0.655	0.655	0.805	0.809	0.634	0.597	0.825	0.155
	64	0.738	0.738	0.726	0.840	0.841	0.719	0.690	0.862	0.155
	128	0.737	0.746	0.725	0.822	0.825	0.691	0.765	0.847	0.155
1024	4	0.207	0.204	0.203	0.365	0.364	0.082	0.651	0.881	0.486
	8	0.425	0.424	0.448	0.919	0.921	0.599	0.865	0.985	0.755
	16	0.580	0.582	0.719	0.995	0.995	0.966	0.955	0.999	0.896
	32	0.771	0.777	0.923	1.000	1.000	0.999	0.982	1.000	0.914
	64	0.943	0.950	0.978	1.000	1.000	1.000	0.989	1.000	0.918
	128	0.983	0.985	0.985	1.000	1.000	1.000	0.990	1.000	0.918
	256	0.990	0.992	0.989	1.000	1.000	1.000	0.996	1.000	0.918
	512	0.997	0.998	0.998	1.000	1.000	1.000	1.000	1.000	0.918

The power of the test was estimated with an AR(1) model, given by $p_t = 0.85 p_{t-1} + \varepsilon_t$, with ε_t following a GARCH (1,1), with $\varepsilon_t = \sqrt{h_t}\,\eta_t$, where $h_t = 0.01 + \gamma_1 h_{t-1} + 0.2\varepsilon_{t-1}^2$, with $\gamma_1 = 0.75$. The power of the Chow and Denning test (MCT) was estimated for ends of comparison. Each set of lines for a determined sample size was built by an independent and separated experiment, based on 2.000 replications. The results of the block bootstrap methods with application of the Politis and White (2004) rule are presented in the columns 3 to 5, while the results of the block bootstrap methods with the use of the Hall *et al.* (1995) rule are available in the columns 6 to 8. In the last three columns, the results of the weighted and standard bootstrap are presented, and also the results provided by the Chow and Denning statistics. The maximum q of 64, for example, means that the multiple test was made for the horizons of q = 2 to 64.

It is worth mentioning that the SB method should have, theoretically, better performance if we talk about more elaborate methods with blocks of random size. However, in the realized simulations, this method had one of the poorest relative performances in terms of power of the test. It gets more evident under the alternative ARIMA (1,1,1).

differences gets farther from a random walk as the time interval of the increments increase. However, if q increases too much, the power of the test decreases.

Table 04 – Power of the variance ratio test in the multiple version, in relation to the heteroscedastic AR alternative $(\phi = 0.96)$ – Comparison between methods and rules of optimal block (Politis and White (2004) and Hall *et al.* (1995))

		Method								
		Politis and White			Hall *et al.*					
N	q máx.	MBB	CBB	SB	MBB	CBB	SB	WU	STD	MCT
64	4	0.042	0.042	0.028	0.080	0.081	0.008	0.073	0.099	0.026
	8	0.040	0.041	0.024	0.080	0.080	0.012	0.065	0.097	0.041
	16	0.045	0.046	0.031	0.074	0.071	0.016	0.074	0.088	0.067
	32	0.038	0.038	0.031	0.060	0.058	0.012	0.075	0.078	0.092
256	4	0.081	0.082	0.047	0.061	0.062	0.005	0.065	0.171	0.024
	8	0.101	0.102	0.068	0.118	0.115	0.012	0.062	0.193	0.031
	16	0.127	0.129	0.100	0.157	0.153	0.040	0.069	0.204	0.032
	32	0.140	0.139	0.124	0.171	0.167	0.073	0.073	0.195	0.032
	64	0.160	0.164	0.146	0.174	0.175	0.095	0.103	0.199	0.033
	128	0.209	0.206	0.190	0.225	0.224	0.138	0.199	0.241	0.038
1024	4	0.142	0.143	0.087	0.037	0.035	0.001	0.093	0.315	0.034
	8	0.231	0.231	0.174	0.179	0.179	0.017	0.128	0.417	0.045
	16	0.360	0.361	0.329	0.365	0.366	0.110	0.193	0.518	0.065
	32	0.534	0.536	0.520	0.564	0.564	0.379	0.303	0.641	0.094
	64	0.706	0.705	0.702	0.754	0.752	0.675	0.487	0.786	0.112
	128	0.867	0.870	0.870	0.887	0.888	0.863	0.718	0.897	0.112
	256	0.962	0.964	0.960	0.968	0.965	0.950	0.937	0.968	0.112
	512	0.994	0.995	0.995	0.998	0.999	0.995	1.000	0.998	0.112

The power of the test was estimated with an AR(1) model, given by $p_t = 0.96 p_{t-1} + \varepsilon_t$, with ε_t following a GARCH (1,1), with $\varepsilon_t = \sqrt{h_t}\,\eta_t$, where $h_t = 0.01 + \gamma_1 h_{t-1} + 0.2\varepsilon_{t-1}^2$, with $\gamma_1 = 0.75$. The power of the Chow and Denning test (MCT) was estimated for ends of comparison. Each set of lines for a determined sample size was built by an independent and separated experiment, based on 2.000 replications. The results of the block bootstrap methods with application of the Politis and White (2004) rule are presented in the columns 3 to 5, while the results of the block bootstrap methods with the use of the Hall *et al.* (1995) rule are available in the columns 6 to 8. In the last three columns, the results of the weighted and standard bootstrap are presented, and also the results provided by the Chow and Denning statistics. The maximum q of 64, for example, means that the multiple test was made for the horizons of q = 2 to 64.

Another result that must be mentioned is related to the power of the VR test with the use of the standard bootstrap, considering that it was, in its classic form, built for application for iid data samples. As Singh (1981) point out, if the original data present some type of heteroscedasticity or serial correlation, the standard bootstrap does not preserve its properties. Hence, the calculated statistics from the resampled data by this method will not be persistent. Politis and Romano (1997) affirm that the mentioned methodology can be applied only to the random walk test with iid increments. However, we were surprised that despite much criticism, the power of the standard bootstrap was very high relatively to the alternative research methods. This probable contradiction would already have been, in a certain way, solved in the work of Liu and Singh (1992) and Politis et al. (1997), which affirm that Efron's bootstrap would reasonably work well with independent and non-identically distributed data, where some robustness can be expected in the presence of heteroscedasticity.

Table 05 – Power of the variance ratio test in the multiple version, in relation to the ARIMA(1,1,1) alternative – Comparison between methods and rules of optimal block (Politis and White (2004) and Hall *et al.* (1995))

		Method								
		Politis and White			Hall *et al.*					
N	Q máx.	MBB	CBB	SB	MBB	CBB	SB	WU	STD	MCT
64	4	0.039	0.039	0.028	0.067	0.066	0.004	0.080	0.071	0.030
	8	0.043	0.044	0.028	0.074	0.073	0.010	0.084	0.072	0.035
	16	0.045	0.044	0.028	0.073	0.072	0.017	0.086	0.069	0.038
	32	0.051	0.051	0.037	0.077	0.074	0.020	0.097	0.075	0.045
256	4	0.119	0.119	0.083	0.085	0.086	0.005	0.218	0.216	0.100
	8	0.216	0.217	0.184	0.199	0.198	0.036	0.327	0.315	0.157
	16	0.365	0.366	0.345	0.350	0.349	0.139	0.453	0.435	0.183
	32	0.466	0.467	0.436	0.470	0.475	0.288	0.528	0.504	0.183
	64	0.498	0.493	0.469	0.509	0.510	0.365	0.530	0.509	0.183
	128	0.535	0.535	0.503	0.547	0.547	0.400	0.564	0.540	0.184
1024	4	0.385	0.386	0.351	0.238	0.241	0.036	0.784	0.788	0.649
	8	0.723	0.723	0.720	0.782	0.787	0.386	0.949	0.952	0.913
	16	0.874	0.873	0.923	0.985	0.987	0.901	0.996	0.996	0.989
	32	0.930	0.929	0.979	1.000	1.000	0.996	1.000	1.000	0.997
	64	0.951	0.953	0.993	1.000	1.000	0.998	1.000	1.000	0.999
	128	0.952	0.953	0.986	0.999	0.999	0.988	0.997	0.999	0.999
	256	0.945	0.949	0.967	0.988	0.987	0.966	0.985	0.986	0.999
	512	0.972	0.971	0.975	0.991	0.989	0.979	0.989	0.985	0.999

The power of the test was estimated with an ARIMA (1,1,1) model, given by $p_t = y_t + z_t$, where $y_t = 0.85 y_{t-1} + \varepsilon_t$ with $\varepsilon_t \sim iid(0,1)$ and $z_t = z_{t-1} + \tau_t$, and $\tau_t \sim iid(0,1/2)$. The power of the Chow and Denning test (MCT) was estimated for ends of comparison. Each set of lines for a determined sample size was built by an independent and separated experiment, based on 2.000 replications. The results of the block bootstrap methods with application of the Politis and White (2004) rule are presented in the columns 3 to 5, while the results of the block bootstrap methods with the use of the Hall *et al.* (1995) rule are available in the columns 6 to 8. In the last three columns, the results of the weighted and standard bootstrap are presented, and also the results provided by the Chow and Denning statistics. The maximum q of 64, for example, means that the multiple test was made for the horizons of q = 2 to 64.

5. Concluding Remarks

Based on the simulation results it can be concluded that among the analyzed methodologies, the ones that use block bootstrap methods (MBB and CBB), with the application of the optimal size rule as elaborated by Hall et al. (1995), can be considered trustworthy for the construction of the empirical distribution of the VR test. A comparison of bootstrap techniques with multiple VR due to Chow and Denning (1993) was made and our results suggests that the latter has very low power for near unit root processes, and has poor performance vis-a-vis bootstrap techniques.

It is worth reminding that, when a maximum q equal to half the size of the sample is used in the investigation of the size of the test, the construction of Wald statistics revealed some fragility with respect to the covariance matrix which leads to present singularity problems. This fact can also be attributed to the lack of precision of autocorrelations of higher orders for a given fixed size of the sample, since the VR with aggregation value q is a proxy of a linear combination of the $q-1$ autocorrelations (Lo and MacKinlay (1989)). In this way, the maximum value of the parameter q should be equal to 1/4 of the size of the sample, when the multiple VR test with the Wald statistics is used.

This study allows researchers to assess the performance of each variant of the VR test through the use of resampling techniques. It must be noted that the contribution of the article to the literature is important, since it verifies the random walk hypothesis with the use of different types of bootstrap procedures applied to the VR test. Moreover, it verifies if there are qualitative differences between the used methodologies for analyzing the performance of these tests in finite samples using Monte Carlo simulations.

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