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Av. Universitaria 1801, Lima 32 – Perú.
Teléfono: (51-1) 626-2000 anexos 4950 - 4951
Fax: (51-1) 626-2874
econo@pucp.edu.pe
www.pucp.edu.pe/departamento/economia/

Encargado de la Serie: Jorge Rojas Rojas
Departamento de Economía – Pontificia Universidad Católica del Perú,
jorge.rojas@pucp.edu.pe

Ricardo Quineche y Gabriel Rodríguez

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PALABRAS CLAVE: Estadísticos de Raíz Unitaria, Rezago, Detrending por GLS, Criterios de Información, Método secuencial de lo general a lo especifico t-sig.

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Data-Dependent Methods for the Lag Length Selection in Unit Root Tests with Structural Change

Ricardo Quineche Uribe
Central Bank of Peru, PUCP

Gabriel Rodríguez
Pontificia Universidad Católica del Perú

Abstract

We analyze the choice of the truncation lag for unit root tests as the ADF^{GLS} and the M^{GLS} tests proposed by Elliott et al. (1996) and Ng and Perron (2001) and extended to the context of structural change by Perron and Rodríguez (2003). We consider the models that allows for a change in slope and a change in the intercept and slope at unknown break date, respectively. Using Monte-Carlo experiments, the truncation lag selected according to several methods as the AIC, BIC, $MAIC$, $MBIC$ is analyzed. We also include and analyze the performance of the hybrid version suggested by Perron and Qu (2007) which uses OLS instead of GLS detrended data when constructing the information criteria. All these methods are compared to the sequential t-sig method based on testing for the significance of coefficients on additional lags in the ADF autoregression. Results show that the M^{GLS} tests present explosive values associated with large values of the lag selected which happens more often when AIC, AIC^{OLS} and t-sig are used to select the lag length. The values are so negative that imply an over rejection of the null hypothesis of a unit root. On the opposite side, lag length selected using $MAIC$, $MAIC^{OLS}$, $MBIC$, $MBIC^{OLS}$ methods lead to very small values of the M-tests implying very conservative results, that is, no rejection of the null hypothesis. These opposite power problems are not observed in the case of the ADF^{GLS} test for which it is highly recommended. **Keywords:** Unit Root Tests, Structural Change, Truncation Lag, GLS Detrending, Information Criteria, Sequential General to Specific t-sig Method. **JEL Classification:** C22, C52.

Resumen

En este documento se analiza la elección del rezago (truncación) que se utiliza en la aplicación de estadísticos de raíz unitaria tales como el ADF^{GLS} y los tests M^{GLS} propuestos por Elliott et al. (1996) y Ng y Perron (2001) y extendidos al contexto de cambio estructural por Perron y Rodríguez (2003). Dos modelos son considerados: uno que admite un cambio estructural en la pendiente y el otro que admite un cambio estructural en pendiente e intercepto. Se usan simulaciones de Monte Carlo usando varios métodos para seleccionar el largo del rezago: AIC, BIC, $MAIC$, $MBIC$. También se incluye y analiza la performance de la propuesta híbrida sugerida por Perron y Qu (2007) la cual usa MCO en lugar de MCG para eliminar los componentes determinísitcos cuando se construyen los criterios de información. Todos estos métodos se comparan con el método secuencial t-sig que está basado en la significancia de los rezagos adicionales que se incluyen en la regresión ADF. Los resultados muestran que los estadísticos M^{GLS} presentan valores (negativos) explosivos asociados con elevados valores del rezago seleccionado cuando AIC, AIC^{OLS} y t-sig son utilizados. Los valores son tan negativos que implican un sobre rechazo de la hipótesis nula de una raíz unitaria. En el lado opuesto, seleccionar la longitud del rezago usando $MAIC$, $MAIC^{OLS}$, $MBIC$, $MBIC^{OLS}$ conduce a valores muy pequeños de los estadísticos M lo que implica resultados muy conservadores, es decir, no rechazo de la hipótesis nula. Estos problemas de potencia no son observados en el caso del estadístico ADF^{GLS} por lo cual es muy recomendable. **Palabras Claves:** Estadísticos de Raíz Unitaria, Rezago, Detrending por GLS, Criterios de Información, Método Secuencial de lo General a lo Específico t-sig. **Classificación JEL:** C22, C52.

Data-Dependent Methods for the Lag Length Selection in Unit Root Tests with Structural Change[1]

Ricardo Quineche Uribe
Central Bank of Peru, PUCP

Gabriel Rodríguez[2]
Pontificia Universidad Católica del Perú

1 Introduction

Testing for the presence of a unit root in a time series is now a common starting point that is available as an option in several popular statistical packages. For some surveys, see Stock (1994) and Haldrup and Jansson (2006). Among the most used statistical tests is the Augmented Dickey-Fuller (ADF) proposed by Said and Dickey (1984) based on Dickey and Fuller (1979). Another set of statistics is the family of M tests that was originally proposed by Stock (1999) and further analyzed by Perron and Ng (1996). The M tests are composed of three statistics: $MZ_{\widehat{\alpha}}$, MSB, $MZ_{t_{\widehat{\alpha}}}$. In an important paper, Elliott, Rothenberg and Stock (1996) -hereinafter ERS(1996)- proposed a feasible point optimal test (P_T^{GLS}) and an ADF^{GLS} test, both of which are constructed using GLS detrended data in order to increase the power performance of the tests. Ng and Perron (2001) used the same strategy applied to the family of M tests, as well to a feasible optimal point test denominated MP_T^{GLS}. The tests proposed and analyzed in ERS (1996) and Ng and Perron (2001) are efficient in the sense that they have local asymptotic power functions close to the Gaussian local power envelope.

Perron and Rodríguez (2003) extended the class of M^{GLS}, P_T^{GLS} and ADF^{GLS} tests to two cases in the context of structural change: (i) a first model (Model I) where a change in the slope of trend function is allowed to occur at an unknown time; (ii) a second model (Model II) where a change in the intercept and slope occurs at an unknown date. Perron and Rodríguez (2003) also show that the asymptotic power functions of these unit root tests are close to the Gaussian power envelope, and consequently that they are efficient[3].

An issue that arises in the implementation of all the above-mentioned unit root tests is the choice of the truncation lag, k. The choice of this parameter is crucial as it can determine whether we are faced with a stationary or non-stationary series. When a very low k is chosen, the size of the tests may be in danger. In the opposite case, when k is very high, it implies a loss of power of the tests. In some of the literature related to the selection of the lag length in unit root tests, there is no structural change. For instance, Schwert (1989), Ng and Perron (1995), Agiakloglou and Newbold (1992, 1996), ERS (1996), and Ng and Perron (2001) showed that the value of k has important implications for the size and power of the tests.

Said and Dickey (1984), in their empirical application, chose the value of k based on testing of whether additional lags are jointly significant by using a F-test on the estimated coefficients (F-sig method). They included the possible values of $k = 6, 7, 8, 9, 10$. The value of k selected with this

[1] This paper is drawn from the Thesis of Ricardo Quineche at the Department of Economics, Pontificia Universidad Católica del Perú. We thank useful comments of Luis García, José Tavera (PUCP) and Jorge Rojas (PUCP). Any remaining errors are our responsibility.

[2] Address for Correspondence: Gabriel Rodríguez, Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, Telephone: +511-626-2000 (4998), Fax: +511-626-2874. E-Mail Address: gabriel.rodriguez@pucp.edu.pe.

[3] In the case of both methods, the break date is selected using the so named infimum and supremum methods; see below.

method was $k = 6$, but the authors also concluded that for the model used, the unit root test was not affected over the selected range of k.

Using Monte Carlo experiments, Schwert (1989) also showed that the value of k has important implications for the size and power of the ADF test, in particular when there is strong negative moving average correlation in the residuals. Indeed, Ng and Perron (1995) constitutes the first study dealing with the analysis of lag-length selection using different criteria. They prove that the choice of the data-dependent rule has a bearing on the size and power of the test. Moreover, they show that information-based rules such as the Akaike information criteria (AIC) and Bayesian information criteria (BIC) tend to select values of k that are consistently smaller than those chosen through sequential testing for the significance of coefficients on additional lags (t-sig method), and the size distortions associated with the former methods are correspondingly larger[4]. Agiakloglou and Newbold (1992, 1996) demonstrate for typical sample sizes that though the spurious rejection problem is somewhat alleviated by a particular criteria or by selecting k, as argued by Ng and Perron (1995), it may be far from being resolved. ERS (1996) show that the choice of k has a considerable effect on the size of P_T^{GLS} and ADF^{GLS}. In order to select k, they try AIC, BIC and sequential likelihood ratio statistics. Finally, they use the BIC to select k by setting the lower bound at 3, because with zero as the lower bound larger size distortions result.

Ng and Perron (2001) consider a class of Modified Information Criteria (MIC) with a penalty factor that is sample dependent. The distinction between the MIC and standard information criteria is that the former takes account of the fact that the bias in the estimate of the sum of the autoregressive coefficients is highly dependent on k. In the Monte-Carlo experiments, they find that the MIC yields huge size improvements on the ADF^{GLS} and the P_T^{GLS}. They also show that both the use of the MIC and allowing for GLS data detrending in the M test results in a class of M^{GLS} tests that have desirable size and power properties. In conclusion, the MIC (in particular the $MAIC$ version) is a superior rule for selecting lag length.

However, Seo (2005) expresses concern regarding the power of the tests proposed by Ng and Perron (2001). Moreover, Ng and Perron (2001) show that all tests constructed using MIC have exact sizes close to nominal size even in the presence of large negative moving average components, though these can be conservative in certain cases. For local alternatives, the power of the tests is close to the Gaussian local asymptotic power envelope. The drawback mentioned by Seo (2005) is that for non-local alternatives the power can be very small. In fact, for a given sample size T, the power can decrease as the autoregressive parameter moves further away from 1. This issue is known as the power reversal problem.

Ng and Perron (2001) appear to recognize this issue. It is the reason why they propose as an alternative the use of OLS detrended data instead of GLS detrended data in the estimation of the autoregression ADF to construct the spectral density at the frequency zero. This procedure is not affected by the power reversal issue, but it leads to tests that are too conservative in common sample sizes and hence it is not recommended. Perron and Qu (2007) propose a hybrid solution to the power reversal problem that is constructed in two steps. In the first step, they use the autoregression ADF with OLS detrended data in order to construct the MIC[5]. Once the order is selected, the second step consists in estimating the autoregression ADF (also to construct the spectral density at the frequency zero) by using GLS detrended data. This hybrid procedure appears to improve

[4] The sequential t-sig method was initially proposed by Campbell and Perron (1991).

[5] Other criteria (for example, AIC, BIC) may also be used. This is the approach taken in the rest of this paper.

the size and power of the tests in finite samples[6].

Even though in the context of structural change the selection of k is still crucial, there is no further literature about the criteria that ought to be used for choosing k. Perron (1997) uses the t-sig and F-sig procedures to select k; see Campbell and Perron (1991). His results indicate that tests based on the t-sig procedure are slightly more powerful than those based on F-sig. In their simulations, Perron and Rodríguez (2003) consider three data-dependent methods to select k: BIC, t-sig and $MAIC$. The results show substantial differences: the use of t-sig yields finite sample critical values that are much smaller than the asymptotic ones; with the $MAIC$, the result is the reverse; finally, with the BIC, the differences are not so large but still important. For these reasons, they recommend the use of those finite sample critical values *"adjusted for the effect of using a data-dependent method to select k"*.

Using Monte-Carlo experiments, the truncation lag selected in line with a class of information criteria (AIC, BIC, $MAIC$, $MBIC$ and their versions, employing OLS instead of GLS detrended data when constructing the modified information criteria, as proposed by Perron and Qu (2007)) are compared to those based on sequential testing for the significance of coefficients on additional lags (t-sig) for the $MZ_{\widehat{\alpha}}^{GLS}$ tests and ADF^{GLS} test proposed by Perron and Rodríguez (2003)[7].

This paper -at least to our knowledge- represents the first attempt to study the behavior of different methods of selecting lag length in unit root tests in the context of structural change. Actually, the development of this paper started when doing empirical applications, we applied the M^{GLS} tests to some time series (see Section 5 of Empirical Applications) and the explosive results caught our attention[8]. We follow Ng and Perron (1995) who study certain lag length selection criteria, but there is no structural change. The results may be summarized as follows: (i) there is a tendency to select a larger k for several of the methods used; (ii) higher values of k are closely related to the presence of explosive values in the family of M-tests; and (iii) the source of this explosiveness is linked with the construction of spectral density at the frequency zero. The simulations suggest that the sum of the parameters in the autoregression ADF are close to unity. In this way, the value of the spectral density at the frequency zero is high in many cases. Because the estimator of the spectral density at the frequency zero enters the family of M-tests either in the denominator or preceded by the minus sign in the numerator, explosion occurs; (iv) the other criteria for selecting small values of k are related with very small values of the M-tests, producing very conservative tests with serious power problems. This creates a problematic scenario because on the one hand we have tests over-rejecting, and on the other we have tests under-rejecting; (v) empirical applications to four series confirms the findings in the simulations; and (vi) the issues raised above are also present when the hybrid case proposed by Perron and Qu (2007) is used.

The paper proceeds as follows. In Section 2, the GLS approach with structural break and the test statistics are reviewed. In Section 3, the selection rules are presented. In Section 4, the finite sample properties of the tests for different selection rules are analyzed using the Monte Carlo

[6] Seo (2005) argues that the source of the problem is the construction of spectral density at the frequency zero. More specifically, he argues that the autoregressive construction of this estimator is inadequate when the process is moving average and consequently an infinite number of lags is needed to approximate the autoregression. Seo (2005) proposes the construction of spectral density (based on a moving average) at the frequency zero in two steps. Seo (2005) also shows that this procedure has considerable advantages compared to Perron and Qu (2007).

[7] We use the MZ_{α}^{GLS} test as the representative of the others M^{GLS} tests. The same analysis that we present in this paper was done for the other tests and the results were similar. These Tables are available on request. In order not to overburden practitioners with endless tables, we opt for the MZ_{α}^{GLS} test.

[8] In order to complete the information, some previous related findings were drawn from Rodríguez (1999).

simulation. In Section 5, an empirical application shows the relevance of these results. Finally, Section 6 concludes.

2 GLS Detrending with Structural Break and the Statistics

In this Section, we describe the DGP, the models and the GLS detrending approach in the context of structural change. Further, we present the statistical tests that will be used in the coming Sections.

2.1 GLS Detrending with Structural Break

Following Perron and Rodríguez (2003), the data generating process (DGP) is:

$$\begin{aligned} y_t &= d_t + u_t, \\ u_t &= \alpha u_{t-1} + v_t, \end{aligned}$$

for $t = 0, 1, 2, ..., T$, where $v_t = \sum_j^{\infty} \gamma_j e_{t-j}$, e_t is a martingale difference sequence, and v_t is an unobserved stationary mean-zero process where the condition $\sum_j^{\infty} j|\gamma_j| < \infty$ is satisfied. We assume that $u_0 = 0$ throughout, though the results generally hold for the weaker requirement that $E(u_0^2) < \infty$ (even as $T \to \infty$). The process e_t has a non-normalized spectral density at frequency zero given by $\sigma^2 = \sigma_\epsilon^2 \gamma(1)^2$, where $\sigma^2 = \lim_{T\to\infty} T^{-1} \sum_{i=0}^{\infty} E(e_t^2)$. Given the above conditions, it is possible to apply a functional central limit theorem to say that $T^{-1/2} \sum_{t=1}^{[rT]} v_t \Rightarrow \sigma W(r)$, where $\Rightarrow$ denotes weak convergence in distribution and $W(r)$ is a Wiener process defined on $C[0, 1]$. In the first equation, $d_t = \psi' z_t$, where z_t is a set of deterministic components that will be specified bellow.

In an important paper, ERS (1996) improved the power of unit root tests using GLS detrended data. The same strategy was followed by Ng and Perron (2001) where, additionally, they propose a modified information criteria to select the lag length. For any series y_t, $y_t^{\overline{\alpha}} \equiv [y_1, (1 - \overline{\alpha} L) y_t]$, $t = 2, 3, 4....., T$ is defined for a chosen $\overline{\alpha}+ = 1 + \overline{c}/T$. The GLS detrended series is defined as $\widetilde{y}_t \equiv y_t - \widehat{\psi}' z_t$, where $\widehat{\psi}$ is the estimate that minimizes $S(\overline{\alpha}, \psi) = \sum_{t=0}^{T} (y_t^{\overline{\alpha}} - \psi' z_t^{\overline{\alpha}})^2$.

Perron and Rodriguez (2003) extend the GLS approach to the unit root tests in the context of an unknown structural break. The first model (Model I) considers a single structural change in the slope, that is, $y_t = \mu_1 + \beta_1 t + \beta_2 t \mathbf{1}(t > T_B)(t - T_B) + u_t$, where $\mathbf{1}(.)$ is the indicator function and T_B is the time of change and can be expressed as a fraction of the whole sample as $T_B = \delta T$ for some $\delta \in (0, 1)$. In this case, the vector of estimates that minimizes $S(\overline{\alpha}, \psi, \delta)$ is $\widehat{\psi}(\delta) = (\hat{\mu_1}, \hat{\beta}_1, \hat{\beta}_2)$. The second model (Model II) includes a single structural change in intercept and slope, that is $y_t = \mu_1 + \mu_2 \mathbf{1}(t > T_B) + \beta_1 t + \beta_2 t \mathbf{1}(t > T_B)(t - T_B) + u_t$, where T_B is the time of change. In this case, the vector of estimates that minimizes $S(\overline{\alpha}, \psi, \delta)$ is $\widehat{\psi}(\delta) = (\hat{\mu_1}, \hat{\mu_2}, \hat{\beta}_1, \hat{\beta}_2)$[9].

[9] The model known as the *crash model* (break only in intercept) has an asymptotic distribution equivalent to the model where $d_t = \mu + \beta t$ by ERS (1996). However, see Rodríguez (2007) for more details and considerations about differences in critical values and adequacy of the distributions.

2.2 The Statistics

The class of M-tests, originally proposed by Stock (1999) and further analyzed by Perron and Ng (1996, 2001), exploit the features of series converging with different rates of normalization under the null and the alternative hypotheses. These are shown to have far less size distortions than the tests of Phillips and Perron (1988) in the presence of important negative serial correlation in the first-differences of the data. They are defined by:

$$MZ_{\widehat{\alpha}}^{GLS} = \frac{T^{-1}\widetilde{y}_T^2 - s^2}{2T^{-2}\sum_{t=1}^{T}\widetilde{y}_{t-1}^2},\ MSB^{GLS} = [\frac{T^{-2}\sum_{t=1}^{T}\widetilde{y}_t^2}{s^2}]^{1/2},\ MZ_{t_{\widehat{\alpha}}}^{GLS} = \frac{T^{-1}\widetilde{y}_T^2 - s^2}{[4s^2T^{-2}\sum_{t=1}^{T}\widetilde{y}_{t-1}^2]^{1/2}}.$$

The statistics are modified versions of the $Z_{\widehat{\alpha}}$ test of Phillips and Perron (1988), Bhargava's (1986) R_1 statistic, and the $Z_{t_{\widehat{\alpha}}}$ test of Phillips and Perron (1988), respectively. Further, the MP_T^{GLS} is a modified version of the feasible optimal point test P_T^{GLS} proposed by ERS (1996). In the case of the feasible optimal point test, Perron and Rodríguez (2003) defines it by:

$$P_T^{GLS}(c,\bar{c}) = \frac{\inf_{\delta\in[\varepsilon,1-\varepsilon]} S(\bar{\alpha},\delta) - \inf_{\delta\in[\varepsilon,1-\varepsilon]} \bar{\alpha}S(1,\delta)}{s^2},$$

where $S(\bar{\alpha},\delta)$ and $S(1,\delta)$ are the sums of squared errors from a GLS regression with $\alpha = \bar{\alpha}$ and $\alpha = 1$, respectively. The term s^2 is an autoregressive estimate of (2π times) the spectral density at frequency zero of u_t, defined by $s^2 = s_{\eta k}^2/[1-\hat{b}(1)]^2$, where $s_{\eta k}^2 = (T-k_{\max})^{-1}\sum_{t=k+1}^{T}\hat{\eta}_{tk}^2$, $\hat{b}(1) = \sum_{j=1}^{k}\hat{b}_j$, with $\hat{b}_j$ and $\{\hat{\eta}_{tk}\}$ obtained from the autoregression:

$$\Delta\hat{u}_t = \alpha_0\widetilde{y}_{t-1} + \textstyle\sum_{j=1}^{k} b_j\Delta\widetilde{y}_{t-j} + \eta_{tk}.$$

Therefore, another test of interest is the so-called ADF test (see Dickey and Fuller (1979) and Said and Dickey (1984)) which is the t-statistic for testing $\alpha_0 = 0$ in above autoregression, denoted by ADF^{GLS}. The advantages of using this autoregressive-based spectral density estimator over the more traditional kernel-based methods are discussed in Perron and Ng (1998). As we mentioned before, Seo (2005) proposes a moving average estimator of the spectral density at the frequency zero. According to his results, the procedure can indeed improve size and power in finite samples. In fact, the M and the MP_T tests are associated with more reliable size properties when the sample is moderate[10].

Perron and Rodríguez (2003) show that the asymptotic distributions of the different statistics are the same for both models. Following ERS (1996) and Ng and Perron (2001), the parameter $\bar{c}$ is selected in such a way that 50% of the Gaussian power envelope is attained. Using the test $P_T^{GLS}(c,c)$, in both cases, $\bar{c} = -22.5$.

Given that the break date is considered to be unknown, Perron and Rodríguez (2003) use two methods to select it. The first method is to select the break date as the point that minimizes the statistical tests. This method is known as the infimum method; see Zivot and Andrews (1992) for further details. The second method is based on the maximum absolute value of the t-statistic associated with the dummy variable of the break in the slope; see Perron (1997) for further details.

[10] We do not follow this moving average two-step procedure in this paper. However, it is to be included in future research.

3 Selection of the Truncation Lag (k)

According to Said and Dickey (1984), the order of truncation, k, is assumed to satisfy some conditions to ensure consistency of the least squares estimates from the autoregression ADF: $\Delta\widetilde{y}_t = \alpha_0\widetilde{y}_{t-1} + \sum_{j=1}^{k} b_j\Delta\widetilde{y}_{t-j} + e_{tk}$: (i) the lag length k must be chosen as a function of T such that: $\frac{k^3}{T} \to 0$ and $k \to 0$ as $T \to \infty$. This assumption is imposed to ensure that the number of regressors does not increase so fast as to induce excess variability in the estimators; (ii) there is $c_1 > 0$ and $c_2 > 0$ such that: $c_1c_2 > T^{1/c_2}$. This is a lower bound condition that restricts k to at least a polynomial rate in T. Intuitively it means that k is forbidden from being so small as to provide an inadequate approximation to the true model. Said and Dickey (1984) show that when k satisfies both conditions, the least squares estimates $\widehat{b}(k) = (\hat{b}_1, \hat{b}_2, \hat{b}_3, ..., \hat{b}_k)$ are $\sqrt{T}$-consistent, and $\hat{\alpha_0}$ provides a basis for testing the unit root hypothesis.

However, the theoretical conditions (i) and (ii) provide little practical guidance for choosing k. There are two methods for selecting k: rules of thumb[11] and data-dependent rules. As Ng and Perron (1995) show, rules of thumb ignore that the value of k that both ensures an exact size close to the nominal size and produces high power is highly dependent on the actual DGP. Hence, we focus on this type of rule.

The AIC and the BIC belong to the class of information-based rules where the value of k is chosen by minimizing an objective function that trades off parsimony against reductions in the sum of squared residuals. Following Hannan and Deistler (1988) and Ng and Perron (2001), the objective function is: $IC_k = \ln\hat{\sigma}_k^2 + \frac{kC_T}{T-k_{\max}}$, with $C_T > 0$ and $C_T/T \to 0$ as $T \to \infty$, where $\hat{\sigma}_k^2 = s_{\eta k}^2 = (T - k_{\max})^{-1}\sum_{t=k+1}^{T}\hat{\eta}_{tk}^2$ is an estimate of the regression error variance, $\frac{C_T}{T-k_{\max}}$ is the penalty attached to an additional regressor, and T is the number of observations available[12]. The various criteria differ in C_T, the weight applied to overfitting, but all use k as the penalty for overfitting. The AIC obtains when $C_T = 2$, and the BIC obtains when $C_T = \ln(T - k_{\max})$. Notice that for any $T > \exp(2)$, the penalty imposed by the AIC is smaller than for the BIC. Definitions are: $AIC_k = \ln\hat{\sigma}_k^2 + \frac{2k}{T-k_{\max}}$ and $BIC_k = \ln\hat{\sigma}_k^2 + \frac{k\ln(T-k_{\max})}{T-k_{\max}}$.

More recently, Ng and Perron (2001) proposed a class of Modified Information Criteria (MIC) that selects k as $k_{mic} = argmin_k\ MIC_k$, where: $MIC_k = \ln\hat{\sigma}_k^2 + \frac{C_T[\widehat{\tau}_T(k)+k]}{T-k_{\max}}$, with $\widehat{\tau}_T(k) = (\hat{\sigma}_k^2)^{-1}\widehat{\alpha}_0^2\sum_{t=k_{max+1}}^{T}\widetilde{y}_{t-1}^2$. It captures the relevant cost of selecting different orders in finite samples since it depends not only on k, but also on the nature of the deterministic components and the detrending procedure. It also captures information from the estimator $\widehat{\alpha}_0$, the parameter of interest. Hence, the penalty term also depends on these factors. The modified Akaike ($MAIC$) is obtained when $C_T = 2$, and the modified BIC is obtained when $C_T = \ln(T - k_{\max})$: $MAIC_k = \ln\hat{\sigma}_k^2 + \frac{2(\tau_T(k)+k)}{T-k_{\max}}$ and $MBIC_k = \ln\hat{\sigma}_k^2 + \frac{\ln(T-k_{\max})[\widehat{\tau}_T(k)+k]}{T-k_{\max}}$.

Ng and Perron (2001) and Seo (2005) argue that the M-tests have a power reversal problem for non local alternatives. The use of OLS detrended data instead of GLS detrended data is not recommended by Ng and Perron (2001) because this approach leads to very conservative tests. Perron and Qu (2007) propose a hybrid solution that consists of two steps. In the first step, OLS detrended data is used to select the lag length using AIC, BIC, $MAIC$ or $MBIC$. The second

[11] Any rule that fixes k as a deterministic function of T fits into this category. Fixing k at a value totally independent of T and the DGP also fits in this category.

[12] Note that in all experiments we use $T - k_{\max}$ as the available number of observations, which is fixed. Following Ng and Perron (2005), this is the best way to proceed.

step consists in estimating the autoregression ADF using GLS detrended data to construct the spectral density estimator. In the simulations, we consider this hybrid approach and the methods will be denoted by AIC^{OLS}, BIC^{OLS}, $MAIC^{OLS}$ and $MBIC^{OLS}$. As Perron and Qu (2007) argue, using OLS detrended data is preferable to using GLS detrended data not only when using the $MAIC$ or $MBIC$, but also when using any information criteria such as the AIC or BIC. The reason is that when α is not local to one, the estimates of the coefficients of the trend function are biased when using GLS detrended data. It implies that the series $\widetilde{y}_t$ does not have mean zero or may be trending. In this sense, the autoregression ADF estimated in this way is mis-specified and the estimate of $\widehat{\alpha}_0$ is biased and the bias varies with the lag order. The bias induces serial correlation in the errors and therefore additional lags are needed to compensate for that. With the $MAIC$ and $MBIC$, the effect is more pronounced because they involve $\widehat{\alpha}_0$ which is sensitive to the lag order regardless of the underlying process. However, with OLS detrended data, the series $\widetilde{y}_t$ has basically mean zero and hence this problem does not occur.

The t-sig procedure was proposed by Campbell and Perron (1991). It was used by Perron (1989) and Perron (1997) to select k and is a general to specific recursive procedure based on the t-statistic on the coefficient associated with the last lag in the estimated autoregressive regression ADF[13]. More specifically, the procedure selects the value of k such that the coefficient on the last lag in the autoregression ADF of order k is significant and that the last coefficient in a regression of order greater than k is insignificant, up to a maximum order $k_{\max}$. First we must select a priori a value for $k_{\max}$. Then, the autoregression ADF with $k_{\max}$ lags is estimated. A two-tailed t-test is used to assess whether the coefficient on the $k_{\max}$-th lag is significant and if so, the value of k chosen is this maximum value. Otherwise, the next step is to estimate a regression with $k_{\max}$-1 lags and perform the t-test again. This procedure is repeated until a rejection occurs or the sequential testing leads to the boundary of zero lags. The t-sig is given by: $t_{\hat{b}_k} = T^{1/2}\widehat{b}_k(\hat{\sigma}_k^2 T M_k^{-1}(1))^{-1/2}$, with $M_k = \sum_{t=k+1}^{T}(y_{t-1}, \Delta y_{t-1}, \Delta y_{t-2}, ..., \Delta y_{t-k})' \times (y_{t-1}, \Delta y_{t-1}, \Delta y_{t-2}, ..., \Delta y_{t-k})$ where $M_k^{-1}(1)$ is the lower-right (1×1) scalar of M_k^{-1} and $\widehat{b}_k$ is the coefficient obtained by estimating the autoregression ADF.

4 Finite Sample Simulations

For the finite sample simulations, we use two DGPs: one for a moving average (MA) case and the other for the autoregressive (AR) case. In the MA case we have: $y_t = y_{t-1} + u_t$, $u_t = v_t$, with $v_t = \theta e_{t-1} + e_t$. In the autoregressive case we have: $y_t = y_{t-1} + u_t$, $u_t = \phi u_{t-1} + v_t$, $v_t = e_t$. For both cases $e_t \sim i.i.d.\ N(0, 1)$ with bounded fourth moment. The results obtained are based on 1000 simulations for a sample size $T = 100$ and for different values of $\theta = -0.8, -0.4, 0.0, 0.4, 0.8$ and $\phi = -0.8, -0.4, 0.4, 0.8$. The simulations were performed in the Gauss Program and random numbers were generated for e_t with time as seed.

We follow the recommendation of Perron and Rodríguez (2003) by using GLS detrended data with the same non-centrality parameter $\bar{c}$ for constructing s^2 and the tests, which is $\bar{c} = -22.5$. This parameter was selected as the point that allows us to attain 50% of the power of the Gaussian

[13] It is possible to use a double-side t-test on the last lag at 5.0% level of significance. However, Ng and Perron (1995), Perron (1997) and other empirical applications using this method have used 10.0% level of significance in order to select a higher lag length k to preserve the size well. This approach is then denoted by t-sig (10%). As we will see in the simulations, this approach has severe consequences on the M-tests precisely because the method selects higher values of k with high probabilities.

power envelope. For the comparison between the M^{GLS} tests and the ADF^{GLS} test, we use the $MZ_{\widehat{\alpha}}^{GLS}$ test as the representative of the other M^{GLS} tests. The break date was selected using the infimum method. The methods using these issues are denoted by AIC, BIC, $MAIC$, $MBIC$ and t-sig (10). Furthermore we include in the simulations the hybrid approach suggested by Perron and Qu (2007). In this case, the methods are denoted by AIC^{OLS}, BIC^{OLS}, $MAIC^{OLS}$ and $MBIC^{OLS}$. In fact we performed extensive additional simulations. For example, we included all other tests from the family of M-tests. We also used the supremum method to select the break date. Further, we used $\bar{c} = 0$ as another option to construct the spectral density at the frequency zero (keeping $\bar{c} = -22.5$ to detrend the data). In order not to overburden practitioners with endless tables, we only include a selected set of results. Other results or Tables are available upon request.

4.1 Frequency Distribution of k

Following Ng and Perron (1995), we first examine the number of times that $k = i$ $(i = 0, 1, 2, ..., 10)$ is being selected by each procedure during 1000 simulations for a sample size $T = 100$. All tests require the estimation of the augmented autoregression ADF.

Tables 1 and 2 show the results of the frequency count of selected lag lengths k for the MA(1) and AR(1) cases, respectively. For the *i.i.d.* case, the AIC, BIC, $MAIC$ and $MBIC$ have probabilities to select $k = 1$ of 56.2%, 93.2%, 74.4% and 81.6%, respectively. The t-sig criterion selects $k = 0$ with 14.2% of probability but the choice of other lag lengths is distributed relatively equally along all values of k. There is a non-zero probability of selecting any k. In particular, t-sig has a probability of around 53% of selecting $k \geq 7$. Further, the selection of $k = 5$ or $k = 6$ has non-trivial probabilities: 9.9% and 7.9%, respectively. The OLS versions appear to select $k = 0$ in the correct way: 50.2%, 89.3%, 80.2% and 87.1%, respectively. The AIC^{OLS} is the only criterion with small probabilities of selecting high values of k (between 2.2% and 12.6%). A value of $k = 2$ is mostly selected for the MIC versions (around 14%).

When $\theta = -0.8$, the t-sig criterion selects k with equally probabilities in the range of the simulations. The value of $k = 0$ is selected for AIC^{OLS}, BIC^{OLS}. $MAIC^{OLS}$ and $MBIC^{OLS}$ appears to be distributed along all values of k. The probabilities are higher for the t-sig criterion. The AIC selects $k = 1$ with 64% of probability and other k with probabilities around 2%, although 25% is distributed between $k = 2, 3, 4$. The BIC selects $k = 1$ with 94.2% and almost no other lag. As in the *i.i.d.* case, the $MAIC$ criterion shows 45% of probability of selecting k between 1 and 4. Probabilities of selecting a higher k are around 10.8%. The results for the BIC and $MBIC$ are very similar to those of the $MAIC$.

When $\theta = 0.8$, no method selects $k = 0$ and almost no methods select $k = 1$, except for BIC (12.3%) and BIC^{OLS} (12.5%). The $MBIC$ and $MBIC^{OLS}$ are concentrated around k=2 (78% and 76.4%, respectively). The t-sig criterion presents high probabilities of selecting high values of k. For instance, for $k = 3, 5, 7$ and 9, the percentages are 8.2%, 18.3%, 23.3% and 26.2%, respectively. It is worth noting that the evolution of the probabilities are not monotonically increasing in the value of k. For odd values of k, probabilities are high. Similar results are observed for the BIC^{OLS} but there is no probability of selecting $k \geq 6$. For the $MAIC^{OLS}$ the probability of selecting higher k and even values of k is greater. This kind of non-monotonicity in the values of k is also observed for the $MAIC$ but in favor of the even values.

The summary of the Table 1 suggests that selection of high values of k has high probabilities with all methods. Strong results are found in the cases of the AIC and the t-sig.

Table 2 shows the results for the case of AR(1). When $\phi = -0.8$, the AIC selects values of k concentrated in $k = 1, 2$ (68%). Thereafter, probabilities of selecting higher values of k are around 2%. The BIC is concentrated around $k = 1$ (92.7%). In the case of the $MAIC$, it is concentrated in selecting $k = 1, 2$ (70.3% and 14.7%, respectively). There are no significant probabilities of selecting $k \geq 6$ (less than 1%). The $MBIC$ presents similar characteristics to those observed for the $MAIC$ but there is no significant probabilities of selecting $k \geq 5$. The t-sig criterion presents probabilities distributed along all values of k. Selection of $k \geq 6$ has probabilities between 10.4% and 17%. The OLS versions describe probabilities concentrated around $k = 1$: 53.6%, 91%, 73.3% and 77.8%, respectively. The AIC^{OLS} shows probabilities around 2%-3% of selecting higher values of k. All other criteria do not have probability of selecting $k \geq 5$.

When $\phi = 0.8$, all methods have high probabilities of selecting $k = 1$. For instance, we have 10.2% for the t-sig up to 88.6% for the BIC. The t-sig criterion shows 64% of probability of selecting $k \geq 7$. Similar results are observed for the AIC and AIC^{OLS}. All other methods have probabilities below 1% of selecting $k \geq 5$.

The conclusion from Table 2 is that the AIC, AIC^{OLS} and t-sig methods are not recommended.

4.2 Mean Values of the $MZ_{\widehat{\alpha}}^{GLS}$

Now, we examine the values of the $MZ_{\widehat{\alpha}}^{GLS}$ test in order to determine whether the rejection of the null hypothesis is linked to the k selected. Results show that for several cases, explosive values of MZ_{α}^{GLS} are found. In order to analyze these results we calculate the mean value of the MZ_{α}^{GLS} for each case. Tables 3 and 4 present the results for the moving average and autoregressive cases, respectively.

In the *i.i.d.* case, the explosive values are observed for $k \geq 5$ for AIC, AIC^{OLS}, BIC^{OLS} and t-sig. However, BIC^{OLS} does not select a $k \geq 6$. Other methods give reduced values of the tests: $MAIC$, $MBIC$, $MAIC^{OLS}$ and $MBIC^{OLS}$. When $\theta = -0.8$, the results are similar to the above mentioned. We observe good values (non-explosive) when $MAIC$, $MBIC$, $MAIC^{OLS}$ and $MBIC^{OLS}$ methods are used. However, these values are very small, indicating that the test will not have power. When $\theta = 0.8$, normal values are observed for BIC, $MAIC$, BIC^{OLS}, $MAIC^{OLS}$, $MBIC^{OLS}$. Nevertheless, the values are smaller, suggesting a rejection of the null hypothesis. Note that even for a high value of k ($k = 9$ or 10) when the method used is the $MAIC$ the values of the statistic are very small, indicating conservative results.

Table 4 shows the results for the AR(1) case. When $\phi = -0.8$ we observe a similar pattern: explosive values of the test for $k \geq 4$ for the AIC, AIC^{OLS} and t-sig. For $k \leq 3$ the values obtained for the tests are very small. When $\phi = 0.8$, very similar results are obtained. Apparently, normal results could be found when $k = 2, 3$.

The summary suggests that small values of k may appear with relatively good test values. However, there are too many explosive values and the probabilities of selecting a high value of k is not zero. Otherwise, when $MAIC$ is used and a low or high value of k is selected, we always have small test values, implying conservative results (no power).

The above results leads us to a trade-off with respect to the selection of k, the method used and the test values. In fact, using AIC, AIC^{OLS} and t-sig gives high probabilities of selecting high values of k, which induces explosive test values. Thus, the test is too liberal (too much rejection of the null hypothesis). On the other hand, using $MAIC$, $MAIC^{OLS}$ gives test values at the other extreme: they are too small and consequently the test is very conservative (no power).

4.3 Frequency Distribution of the $MZ_{\widehat{\alpha}}^{GLS}$ Values

In this section we analyze the idea that explosive values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are associated with the value of k. We examine the number of times that the $MZ_{\widehat{\alpha}}^{GLS}$ is smaller than a threshold (say κ). Bearing in mind that an explosive value can be somewhat subjective, we consider six possible thresholds: $\kappa = -500, -1000, -5000, -10000, -50000$, and -100000. We analyze the case of *i.i.d.* and the results are presented in Table 5.

First of all, we find that if the value of $k < 3$, no explosive value is found. It means that no matter what criteria we use, if the criteria selects a value of $k < 3$ then we will not get an explosive value for the $MZ_{\widehat{\alpha}}^{GLS}$. Even for $k \leq 5$ this is the case, though the probabilities of finding test values of less than k=-500 is 2.6% and less than $\kappa = -1000$ is 1.6%. Secondly, for all thresholds analyzed we find that the frequency count of explosive values of $MZ_{\widehat{\alpha}}^{GLS}$ increases as the value of k is larger. For example, for a lag $k = 7$, the probability of getting a value of $MZ_{\widehat{\alpha}}^{GLS}$ smaller than $\kappa = -1000$ is 13.4%; for a $k = 9$ it is 31%, and for $k = 10$, 40.2%. The probabilities of finding values of the $MZ_{\widehat{\alpha}}^{GLS}$ smaller than $\kappa = -100000$ are 18% and 22.7% if $k = 9$ or $k = 10$ are selected.

In general, the results show that there is a strong relationship between the explosive values of the $MZ_{\widehat{\alpha}}^{GLS}$ and the values of the lag length. So, if the criteria used for selecting k results in a high value of k, the probability of obtaining an explosive value of $MZ_{\widehat{\alpha}}^{GLS}$ is greater. Furthermore, the fact that we find explosive values for greater values of k, no matter the criteria used for selecting it, serves to alert us to the statistic $MZ_{\widehat{\alpha}}^{GLS}$.

It is indeed the case that the explosive performance of the M-tests is related to the construction of s^2 and consequently the number of lags used in the autoregression ADF. A higher value of s^2 determines, via the formula of the $MZ_{\widehat{\alpha}}^{GLS}$, a very negative value for this test[14]. Because $s^2 = s_{\eta k}^2/[1 - \hat{b}(1)]^2$, the potential reasons for having an extremely high value of s^2 are: (i) a high (or huge) value of $s_{\eta k}^2$; (ii) the estimates of $\hat{b}(1)$ should be very close to one. In this sense, the denominator of s^2 goes to zero and then $s^2 \to \infty$. In the formula of the $MZ_{\widehat{\alpha}}^{GLS}$, s^2 enters preceded by the minus sign, so explosive values are generated[15]. In previous Tables we found that some criteria have high probability of selecting a high value of k. Hence, $\hat{b}(1) = \sum_{j=1}^{k} \hat{b}_j \to 1$ when k is increasing and explosion occurs. On the other hand, the other criteria select small values of k and we have small value of $\hat{b}(1)$. It implies a small value of the test and consequently no rejection or under-rejection.

4.4 Frequency Distribution of $\widehat{b}(1)$ in Explosive $MZ_{\widehat{\alpha}}^{GLS}$ Values

Now we analyze the idea that explosive values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are associated with the value of $\widehat{b}(1)$, that is, the conjecture (ii) enunciated above. According to the formula for $MZ_{\widehat{\alpha}}^{GLS}$, a cause of explosion could also be the value of $\widehat{b}(1)$. To do so, we examine the number of times that $\widehat{b}(1)$ is between certain values for explosive $MZ_{\widehat{\alpha}}^{GLS}$ values. Table 6 presents the results for the case of *i.i.d.* disturbances.

For all thresholds, we can see that the number of times that $\widehat{b}(1)$ is between 0.9 and 1.1 increases as k gets larger. For example, using $\kappa = -5000$ as a threshold, the probability of getting a value of $\widehat{b}(1)$ between 0.9 and 1.1 with a lag length $k = 7$ is 10.8%, while with a lag length $k = 9$ it is

[14] Using the different formulas of the M-tests, a similar argument is possible.

[15] In the cases of the MSB^{GLS} and MP_T^{GLS}, the s^2 appears in the denominator. Based on the argument set out above, higher values of s^2 imply very small values of these statistics. Therefore, an over-rejection is found.

24.7%, and for a $k = 10$ we have 33.7%. For threshold $\kappa = -10000$ (which is high) the probabilities for $k = 7$ and $k = 8$ are 9.8% and 14.1%, respectively. Also for a huge threshold $\kappa = -100000$, the corresponding probabilities for $k = 7, 9$ and 9 are 7.3%, 11.5% and 18%, respectively. The conclusion is that they are significant probabilities. Therefore, it seems that the fact that $\widehat{b}(1)$ is close to 1 is related to a larger k, which is also related to the explosive values of $MZ_{\widehat{\alpha}}^{GLS}$.

4.5 The Behavior of the Estimated Variance of the ADF Regression

In this section we analyze the idea that explosive values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are associated with the estimated variance of the residuals in the autoregression ADF, that is $\hat{\sigma}_k^2 = s_{\eta k}^2$. According to the formula for $MZ_{\widehat{\alpha}}^{GLS}$, a cause of explosion could also be the value of $\hat{\sigma}_k^2$, which means that the true cause of the explosive values is the DGP itself. To this end, we examine the behavior of $\hat{\sigma}_k^2$ in normal and explosive $MZ_{\widehat{\alpha}}^{GLS}$ values. Tables 7 and 8 show the results for the case of *i.i.d.* disturbances.

Tables 7 and 8 suggest that, for all the thresholds used, we find no difference in the behavior of the estimated variance of the ADF regression between the normal $MZ_{\widehat{\alpha}}^{GLS}$ values and the explosives ones. For example, using $\kappa = -10000$ as a threshold, the mean, maximum, and minimum values for the estimated variance are almost the same for all values of k. This means that the cause of the explosive MZ_{α}^{GLS} values is not the DGP itself but the $\widehat{b}(1)$ estimation that implies the value of the k selected.

4.6 The Statistic ADF^{GLS}

While the MZ_{α}^{GLS} test (and the entire family of M-tests) exhibits a problem that seems to be caused by the value of k and which is also caused by the value of $\widehat{b}(1)$, the statistic ADF^{GLS} is shown to work well. Even though the statistic ADF^{GLS} also requires the estimation of $\widehat{b}(1)$, it does not show any explosive values at all. This appears to confirm that there is a problem in the calculation of the MZ_{α}^{GLS} in the construction of the s^2. Tables 9 and 10 show the mean value of the statistic ADF^{GLS} for each selection criteria. As we can see, the mean value of the ADF^{GLS} is not explosive no matter which selection criteria we use. There are some large negative values when $\theta = -0.8$ (Table 9), but it is standard in the sense that in this case we have strong negative moving average type correlation and the tests are oversized.

5 Empirical Applications

The development of this paper started when doing empirical applications, we applied the M^{GLS} tests to some time series and the explosive results caught our attention. We use four time series in order to illustrate the issues discussed in previous sections. Three of the time series are the unemployment rates of the Spanish communities of Cantabria, Galicia and Murcia covering the (quarterly) period 1976:3-2012:2 (144 observations). The fourth variable is the monetary policy rate of Peru for the (monthly) period 2003:1-2010:8 (92 observations)[16]. The series are presented in Figures 1 to 4. We present only results for the infimum method to select the break date. Models I and II are estimated and the two values of $\bar{c} = -22.5$ and $\bar{c} = 0$ are used in order to construct s^2.

[16] The source for the unemployment rates in the three Spanish communities is the Instituto Nacional de Estadística de España. In the case of the monetary policy rate of Peru, the source is the Central Reserve Bank of Peru.

Table 11 shows the lag length selected by the different methods. There are no big differences between the selected lags in either Model I or II. Further, there is not much difference in the results from constructing s^2 with both values of $\bar{c}$, except for the cases of the unemployment rate in Murcia and the Peruvian monetary policy rate. For the four series, AIC, $MAIC$ and t-sig select high values of k (around 8 and 10) when using $\bar{c} = -22.5$. The exceptions are the unemployment rate of Murcia and the Peruvian monetary policy rate where $MAIC$ selects 4 and 1, respectively. When $\bar{c} = 0$, similar conclusions are reached. Similar evidence transpires when the AIC^{OLS} and $MAIC^{OLS}$ methods are used. In the cases of the methods BIC^{OLS} and $MBIC^{OLS}$, they select the smallest lags of all methods, including $k = 0$ for the unemployment rates of Cantabria and Murcia.

Table 12 shows the results of the $MZ_{\widehat{\alpha}}^{GLS}$ test using the lags selected in the previous Table. Let us consider the series of the unemployment rate of Cantabria. Using $\bar{c} = -22.5$, irrespective of the model, AIC, AIC^{OLS} and t-sig show explosive values. All other methods select a small value of the $MZ_{\widehat{\alpha}}^{GLS}$ test, which are not sufficient to reject the null hypothesis. Using $\bar{c} = 0$, all methods find small values of the $MZ_{\widehat{\alpha}}^{GLS}$ test, indicating non-rejection of the null hypothesis in none of the cases.

For the unemployment rate of Galicia we have similar results. The explosive values are observed using the AIC^{OLS} method. The AIC and t-sig methods show values of around -220 which represent unusual values. In all other cases, the values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are very conservative. In the case of the series of the unemployment rate of Murcia, results are similar using $\bar{c} = -22.5$. Using the value $\bar{c} = 0$ we find no explosive values for the $MZ_{\widehat{\alpha}}^{GLS}$ test. However, using this value, all values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are very small (in absolute value), implying non-rejection of the null hypothesis in all cases.

In the case of the Peruvian rate, the values are very negative for the t-sig criteria. We also find unusual negative values when AIC and AIC^{OLS} are used. When we use $\bar{c} = 0$, all methods (except the t-sig) give plausible values. When the Model II is used things are relatively worse, even for the BIC method. Only $MAIC$ and $MBIC$ appear to give plausible values. There is nothing strange about this, as in Table 11 these methods selected $k = 1$ or $k = 2$, that is, a low value of k.

The empirical results confirm the evidence we found in the simulations, that is, that very negative or explosive values of the $MZ_{\widehat{\alpha}}^{GLS}$ test are linked to the larger values of k.

6 Conclusions

Testing for the presence of a unit root in a time series data is now a common starting point that has become available as an option in several popular statistical packages. Using GLS detrended data, Perron and Rodríguez (2003) extended the class of M^{GLS}, P_T^{GLS} and ADF^{GLS} tests to two cases in the context of structural change: (i) a first model (Model I) where a change in the slope of trend function is allowed to occur at an unknown time; (ii) a second model (Model II) where a change in the intercept and slope occurs at an unknown date. Perron and Rodríguez (2003) also show that the asymptotic power functions of these unit root tests are close to the Gaussian power envelope, and consequently that they are efficient.

An issue that arises in the implementation of all the above-mentioned unit root tests is the choice of the truncation lag, k. There is some literature related to the selection of the lag length in unit root tests where there is no structural change. For instance, Schwert (1989), Ng and Perron (1995), Agiakloglou and Newbold (1992, 1996), ERS (1996), and Ng and Perron (2001) showed that the value of k has an important implication on the size and power of the tests. This paper -at least to our knowledge- represents a first attempt to study the behavior of different methods of selecting the lag length in unit root tests in the context of structural change. We follow Ng and Perron (1995), who study some criteria for selecting lag length but without structural change. The results may be summarized as follows: (i) there is a tendency to select a larger k for several of the methods used; (ii) higher values of k are closely related to the presence of explosive values in the family of M-tests; (iii) the source of this explosiveness is linked with the construction of the spectral density at the frequency zero. The simulations suggest that the sum of the parameters in the autoregression ADF is close to unity. In this way, the value of the spectral density at the frequency zero is high and huge in many cases. Because the estimator of the spectral density at the frequency zero enters the family of the M-tests, either in the denominator or preceded by the minus sign in the numerator, explosion occurs; (iv) the other criteria that select small values of k are related with very small values of the M-tests, producing very conservative tests with serious power problems. This situation results in a complicated scenario because on the one hand we have tests over-rejecting, and on the other we have tests under-rejecting; (v) empirical applications to four series confirm the findings in the simulations; (vi) the issues raised above are also present when the hybrid case proposed by Perron and Qu (2007) is used.

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Table 1. Frequency count of selected lag lengths k for the MZ_{α}^{GLS}; Moving Average case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
						θ= 0.8					
AIC	0,000	0,001	0,024	0,196	0,068	0,279	0,043	0,198	0,042	0,108	0,041
BIC	0,000	0,123	0,148	0,500	0,053	0,158	0,002	0,016	0,000	0,000	0,000
MAIC	0,000	0,005	0,262	0,089	0,362	0,041	0,151	0,019	0,047	0,007	0,017
MBIC	0,000	0,021	0,780	0,021	0,164	0,001	0,013	0,000	0,000	0,000	0,000
T-sig (10)	0,000	0,000	0,002	0,082	0,025	0,183	0,038	0,233	0,062	0,262	0,113
AIC_OLS	0,000	0,002	0,014	0,199	0,042	0,282	0,032	0,214	0,047	0,122	0,046
BIC_OLS	0,000	0,125	0,118	0,519	0,038	0,173	0,003	0,022	0,000	0,002	0,000
MAIC_OLS	0,000	0,010	0,317	0,099	0,354	0,035	0,126	0,013	0,029	0,006	0,011
MBIC_OLS	0,051	0,017	0,764	0,018	0,140	0,001	0,009	0,000	0,000	0,000	0,000
						θ= 0.3					
AIC	0,000	0,578	0,075	0,094	0,053	0,066	0,037	0,035	0,020	0,018	0,024
BIC	0,000	0,947	0,023	0,025	0,003	0,002	0,000	0,000	0,000	0,000	0,000
MAIC	0,000	0,555	0,341	0,050	0,033	0,009	0,003	0,003	0,003	0,001	0,002
MBIC	0,000	0,601	0,342	0,035	0,018	0,003	0,001	0,000	0,000	0,000	0,000
T-sig (10)	0,006	0,170	0,010	0,057	0,050	0,084	0,077	0,107	0,111	0,161	0,167
AIC_OLS	0,018	0,545	0,060	0,095	0,056	0,064	0,042	0,040	0,023	0,029	0,028
BIC_OLS	0,113	0,830	0,018	0,030	0,008	0,001	0,000	0,000	0,000	0,000	0,000
MAIC_OLS	0,307	0,352	0,268	0,037	0,027	0,004	0,002	0,001	0,001	0,000	0,001
MBIC_OLS	0,844	0,083	0,068	0,004	0,001	0,000	0,000	0,000	0,000	0,000	0,000
						θ= 0					
AIC	0,000	0,562	0,131	0,073	0,047	0,059	0,038	0,032	0,022	0,017	0,019
BIC	0,000	0,932	0,049	0,015	0,003	0,001	0,000	0,000	0,000	0,000	0,000
MAIC	0,000	0,744	0,144	0,051	0,033	0,013	0,006	0,002	0,003	0,002	0,002
MBIC	0,000	0,816	0,135	0,031	0,012	0,005	0,001	0,000	0,000	0,000	0,000
T-sig (10)	0,142	0,031	0,028	0,038	0,049	0,099	0,079	0,113	0,116	0,152	0,153
AIC_OLS	0,502	0,126	0,086	0,050	0,040	0,055	0,039	0,033	0,022	0,027	0,020
BIC_OLS	0,893	0,084	0,010	0,010	0,002	0,001	0,000	0,000	0,000	0,000	0,000
MAIC_OLS	0,802	0,101	0,053	0,025	0,009	0,003	0,003	0,000	0,002	0,000	0,002
MBIC_OLS	0,871	0,090	0,031	0,008	0,000	0,000	0,000	0,000	0,000	0,000	0,000
						θ= -0.5					
AIC	0,000	0,583	0,175	0,067	0,040	0,030	0,027	0,026	0,018	0,015	0,019
BIC	0,000	0,904	0,086	0,009	0,000	0,001	0,000	0,000	0,000	0,000	0,000
MAIC	0,000	0,201	0,350	0,196	0,127	0,066	0,029	0,016	0,010	0,004	0,001
MBIC	0,000	0,225	0,381	0,208	0,109	0,044	0,017	0,012	0,003	0,001	0,000
T-sig (10)	0,099	0,142	0,060	0,037	0,045	0,063	0,070	0,094	0,101	0,140	0,149
AIC_OLS	0,261	0,377	0,131	0,047	0,034	0,028	0,031	0,027	0,018	0,023	0,023
BIC_OLS	0,626	0,336	0,031	0,005	0,000	0,002	0,000	0,000	0,000	0,000	0,000
MAIC_OLS	0,022	0,226	0,357	0,189	0,117	0,052	0,019	0,012	0,003	0,003	0,000
MBIC_OLS	0,022	0,242	0,376	0,195	0,107	0,034	0,013	0,009	0,001	0,001	0,000
						θ= -0.8					
AIC	0,000	0,640	0,137	0,078	0,056	0,025	0,018	0,017	0,010	0,009	0,010
BIC	0,000	0,942	0,050	0,008	0,000	0,000	0,000	0,000	0,000	0,000	0,000
MAIC	0,000	0,148	0,116	0,121	0,156	0,108	0,128	0,085	0,053	0,040	0,045
MBIC	0,006	0,150	0,127	0,123	0,164	0,111	0,127	0,080	0,048	0,035	0,029
T-sig (10)	0,230	0,061	0,051	0,056	0,053	0,065	0,075	0,078	0,091	0,109	0,131
AIC_OLS	0,640	0,140	0,067	0,051	0,031	0,015	0,011	0,021	0,008	0,009	0,007
BIC_OLS	0,914	0,074	0,011	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000
MAIC_OLS	0,181	0,121	0,140	0,112	0,137	0,092	0,093	0,062	0,026	0,020	0,016
MBIC_OLS	0,183	0,127	0,145	0,111	0,139	0,096	0,090	0,058	0,024	0,017	0,010

Table 2. Frequency count of selected lag lengths k for the MZ_{α}^{GLS}; Autoregressive case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
						ϕ= 0.8					
AIC	0,000	0,451	0,130	0,092	0,060	0,077	0,052	0,046	0,035	0,028	0,029
BIC	0,000	0,886	0,071	0,026	0,008	0,007	0,002	0,000	0,000	0,000	0,000
MAIC	0,000	0,799	0,115	0,041	0,021	0,009	0,006	0,004	0,001	0,002	0,002
MBIC	0,000	0,860	0,110	0,024	0,004	0,001	0,000	0,001	0,000	0,000	0,000
T-sig (10)	0,000	0,102	0,025	0,042	0,037	0,078	0,081	0,134	0,140	0,171	0,190
AIC_OLS	0,000	0,397	0,124	0,094	0,054	0,088	0,060	0,060	0,043	0,039	0,041
BIC_OLS	0,000	0,856	0,088	0,036	0,010	0,008	0,002	0,000	0,000	0,000	0,000
MAIC_OLS	0,000	0,824	0,106	0,034	0,016	0,007	0,004	0,003	0,002	0,002	0,002
MBIC_OLS	0,002	0,879	0,099	0,016	0,002	0,001	0,000	0,001	0,000	0,000	0,000
						ϕ= 0.4					
AIC	0,000	0,567	0,119	0,072	0,049	0,057	0,033	0,037	0,022	0,023	0,021
BIC	0,000	0,924	0,056	0,015	0,003	0,002	0,000	0,000	0,000	0,000	0,000
MAIC	0,000	0,767	0,143	0,039	0,033	0,009	0,002	0,003	0,002	0,000	0,002
MBIC	0,000	0,822	0,134	0,026	0,016	0,001	0,001	0,000	0,000	0,000	0,000
T-sig (10)	0,000	0,167	0,034	0,043	0,049	0,083	0,082	0,106	0,115	0,156	0,165
AIC_OLS	0,001	0,519	0,115	0,075	0,052	0,069	0,040	0,044	0,026	0,031	0,028
BIC_OLS	0,022	0,883	0,068	0,019	0,006	0,002	0,000	0,000	0,000	0,000	0,000
MAIC_OLS	0,088	0,700	0,135	0,035	0,028	0,009	0,001	0,002	0,001	0,000	0,001
MBIC_OLS	0,537	0,388	0,057	0,015	0,003	0,000	0,000	0,000	0,000	0,000	0,000
						ϕ= -0.4					
AIC	0,000	0,579	0,115	0,075	0,051	0,044	0,040	0,036	0,024	0,017	0,019
BIC	0,000	0,923	0,051	0,020	0,004	0,001	0,001	0,000	0,000	0,000	0,000
MAIC	0,000	0,740	0,136	0,065	0,033	0,015	0,005	0,002	0,003	0,000	0,001
MBIC	0,000	0,809	0,125	0,046	0,015	0,003	0,001	0,001	0,000	0,000	0,000
T-sig (10)	0,031	0,156	0,040	0,047	0,056	0,084	0,074	0,094	0,116	0,141	0,161
AIC_OLS	0,091	0,454	0,110	0,075	0,059	0,048	0,046	0,042	0,031	0,022	0,022
BIC_OLS	0,288	0,631	0,052	0,021	0,004	0,003	0,001	0,000	0,000	0,000	0,000
MAIC_OLS	0,015	0,750	0,130	0,060	0,027	0,012	0,003	0,002	0,001	0,000	0,000
MBIC_OLS	0,021	0,801	0,122	0,041	0,012	0,003	0,000	0,000	0,000	0,000	0,000
						ϕ= -0.8					
AIC	0,000	0,577	0,106	0,076	0,050	0,048	0,035	0,041	0,028	0,013	0,026
BIC	0,000	0,927	0,050	0,012	0,008	0,001	0,000	0,002	0,000	0,000	0,000
MAIC	0,000	0,703	0,147	0,073	0,045	0,017	0,006	0,006	0,001	0,001	0,001
MBIC	0,001	0,763	0,142	0,059	0,021	0,008	0,004	0,002	0,000	0,000	0,000
T-sig (10)	0,000	0,167	0,039	0,048	0,056	0,078	0,083	0,104	0,117	0,138	0,170
AIC_OLS	0,000	0,536	0,101	0,079	0,059	0,054	0,038	0,051	0,035	0,018	0,029
BIC_OLS	0,000	0,910	0,059	0,017	0,009	0,003	0,000	0,002	0,000	0,000	0,000
MAIC_OLS	0,000	0,733	0,147	0,064	0,039	0,012	0,001	0,002	0,002	0,000	0,000
MBIC_OLS	0,000	0,778	0,136	0,055	0,023	0,006	0,001	0,000	0,001	0,000	0,000

Table 3. MZ_{α}^{GLS} mean value; Moving Average case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
						θ= 0.8					
AIC	n.a.	-18	-15	-53	-16	-681522	-35115773	-124772903	-617854	-35932244	-1309910
BIC	n.a.	-28	-14	-43	-13	-1008261	-23	-431128	n.a.	n.a.	n.a.
MAIC	n.a.	-24	-17	-18	-18	-23	-18	-20	-19	-51	-21
MBIC	n.a.	-22	-14	-10	-13	-10	-12	n.a.	n.a.	n.a.	n.a.
T-sig (10)	n.a.	n.a.	-11	-53	-14	-1028308	-39736223	-109045838	-6270722	-24167202	-169313935
AIC_OLS	n.a.	-18	-16	-52	-47	-673694	-47186810	-115549746	-440911	-31816439	-1334339
BIC_OLS	n.a.	-28	-13	-43	-13	-921590	-28	-317108	n.a.	-2275	n.a.
MAIC_OLS	n.a.	-27	-16	-17	-17	-20	-17	-21	-20	-53	-26
MBIC_OLS	-13	-15	-13	-10	-12	-10	-10	n.a.	n.a.	n.a.	n.a.
						θ= 0.3					
AIC	n.a.	-21	-17	-49	-176	-6929	-10839091	-1016201	-1134840	-71283	-2383741
BIC	n.a.	-20	-16	-50	-1535	-70	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-18	-16	-15	-15	-14	-16	-20	-27	-9	-14
MBIC	n.a.	-18	-16	-15	-14	-16	-30	n.a.	n.a.	n.a.	n.a.
T-sig (10)	-15	-21	-15	-41	-105	-5721	-5205789	-440361	-6292169	-36653575506	-38863782057
AIC_OLS	-13	-21	-19	-49	-172	-7155	-15130986	-860051	-317121	-83787	-1253560
BIC_OLS	-12	-21	-18	-49	-600	-53	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-13	-14	-15	-14	-14	-15	-9	-12	-22	n.a.	-15
MBIC_OLS	-11	-9	-10	-8	-10	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
						θ= 0					
AIC	n.a.	-18	-26	-44	-78	-22307	-9394498503	-74883457	-41999	-573270	-1475539
BIC	n.a.	-17	-29	-46	-298	-57	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-16	-15	-13	-14	-13	-12	-16	-21	-12	-16
MBIC	n.a.	-16	-15	-13	-15	-16	-15	n.a.	n.a.	n.a.	n.a.
T-sig (10)	-16	-21	-30	-55	-69	-8220	-6922447	-22980156	-39940372	-28964609	-8801191
AIC_OLS	-15	-21	-29	-50	-86	-14490	-9153699344	-72566112	-442893079	-467927	-1412500
BIC_OLS	-15	-22	-35	-95	-145	-2139	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-14	-14	-14	-12	-12	-7	-10	n.a.	-17	n.a.	-16
MBIC_OLS	-14	-15	-14	-10	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
						θ= -0.5					
AIC	n.a.	-25	-15	-22	-139	-9099	-16227	-278324	-11548994	-8109894	-7630175
BIC	n.a.	-24	-14	-10	n.a.	-122	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-22	-16	-14	-12	-11	-11	-9	-7	-9	-6
MBIC	n.a.	-21	-16	-14	-12	-12	-12	-9	-6	-8	n.a.
T-sig (10)	-38	-21	-15	-21	-111	-228421	-289016	-661438	-22372036	-1015716736	-6673271
AIC_OLS	-38	-20	-15	-20	-133	-9916	-14157	-269866	-19330939	-5292065	-6305034
BIC_OLS	-37	-18	-11	-11	n.a.	-135563	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-40	-21	-16	-13	-12	-10	-9	-9	-7	-7	n.a.
MBIC_OLS	-40	-21	-16	-13	-12	-10	-9	-9	-5	-8	n.a.
						θ= -0.8					
AIC	n.a.	-43	-30	-128	-66394	-359113	-1188	-13971	-141772	-4224730	-13646386
BIC	n.a.	-43	-32	-9	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-45	-30	-22	-16	-11	-11	-9	-7	-5	-5
MBIC	-48	-45	-29	-22	-16	-11	-11	-9	-6	-5	-4
T-sig (10)	-48	-37	-28	-119	-65682	-1362898	-269125	-879363	-213226	-2016594	-4731701
AIC_OLS	-48	-39	-29	-176	-359447	-598654	-1980	-7737188	-186635	-4224821	-19494206
BIC_OLS	-48	-33	-22	-11	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-48	-37	-27	-20	-14	-10	-11	-8	-6	-6	-5
MBIC_OLS	-49	-37	-27	-20	-14	-10	-11	-8	-6	-5	-4

Table 4. MZ_{α}^{GLS} mean value; Autoregressive case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
$\phi = 0.8$											
AIC	n.a.	-23	-41	-3252	-3138	-758506	-1638575	-28393908	-474780	-5368640	-307106478
BIC	n.a.	-23	-47	-67	-19940	-2154	-1932	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-22	-21	-21	-18	-20	-27	-14	-9	-175	-96
MBIC	n.a.	-22	-21	-16	-20	-23	n.a.	-14	n.a.	n.a.	n.a.
T-sig (10)	n.a.	-26	-38	-12029	-179	-764507	-32918997	-20060731	-20124981	-402207066	-14736378
AIC_OLS	n.a.	-24	-42	-3184	-3454	-665275	-1506621	-35211358	-174947	-4151032	-220740481
BIC_OLS	n.a.	-23	-43	-64	-15967	-18672	-4076	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	n.a.	-22	-21	-19	-18	-46	-32	-11	-9	-64	-95
MBIC_OLS	-7	-21	-22	-15	-20	-22	n.a.	-10	n.a.	n.a.	n.a.
$\phi = 0.4$											
AIC	n.a.	-19	-28	-48	-2286016	-795704	-2447773	-73861829	-162828	-30779079	-329983
BIC	n.a.	-18	-29	-72	-26821	-325	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-17	-18	-15	-14	-15	-12	-14	-63	n.a.	-10
MBIC	n.a.	-17	-18	-16	-14	-11	-14	n.a.	n.a.	n.a.	n.a.
T-sig (10)	n.a.	-19	-26	-55	-74	-535870	-19476261	-6997689	-63620394	-4219504	-79589080
AIC_OLS	-19	-19	-28	-47	-2154135	-657359	-2023233	-48955422	-257800298	-22913324	-268955
BIC_OLS	-10	-18	-28	-64	-18668770	-325	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-13	-16	-17	-14	-13	-17	-10	-13	-7	n.a.	-14
MBIC_OLS	-9	-11	-12	-10	-10	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
$\phi = -0.4$											
AIC	n.a.	-15	-22	-31	-64	-30381879	-1018545	-811472	-397872475	-63676	-659133
BIC	n.a.	-15	-23	-41	-90	-206	-41	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-14	-13	-12	-12	-10	-12	-12	-12	n.a.	-5
MBIC	n.a.	-14	-13	-13	-13	-12	-13	-8	n.a.	n.a.	n.a.
T-sig (10)	-28	-15	-24	-31	-53	-69006533	-186664	-275519	-102775596	-6137296121	-176577170
AIC_OLS	-27	-15	-21	-31	-70	-27850087	-885727	-570325	-312874164	-1263701	-570832
BIC_OLS	-26	-13	-23	-30	-90	-2138	-41	n.a.	n.a.	n.a.	n.a.
MAIC_OLS	-25	-14	-13	-12	-12	-9	-12	-13	-18	n.a.	n.a.
MBIC_OLS	-21	-14	-13	-12	-13	-12	n.a.	n.a.	n.a.	n.a.	n.a.
$\phi = -0.8$											
AIC	n.a.	-10	-15	-22	-302611	-21142	-2107494	-956405	-2240903	-3568629	-1692928
BIC	n.a.	-10	-17	-24	-40	-276	n.a.	-51	n.a.	n.a.	n.a.
MAIC	n.a.	-9	-9	-8	-8	-7	-7	-7	-6	-9	-3
MBIC	-31	-9	-9	-8	-8	-7	-7	-4	n.a.	n.a.	n.a.
T-sig (10)	n.a.	-11	-15	-21	-133	-37987	-295877	-50797050	-2865827	-130078692	-25710577
AIC_OLS	n.a.	-10	-15	-22	-256453	-55104	-1603435	-11314140	-2835398	-2623931	-1588005
BIC_OLS	n.a.	-10	-16	-24	-40	-4697	n.a.	-51	n.a.	n.a.	n.a.
MAIC_OLS	n.a.	-9	-9	-8	-8	-7	-6	-9	-5	n.a.	n.a.
MBIC_OLS	n.a.	-9	-9	-8	-8	-7	-6	n.a.	-6	n.a.	n.a.

Table 5. Frequency count of MZ_{α}^{GLS} values

	MZ_{α}^{GLS}					
k	< -500	< -1 000	< -5 000	< -10 000	< -50 000	< -100 000
0	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000
3	0.001	0.000	0.000	0.000	0.000	0.000
4	0.006	0.002	0.000	0.000	0.000	0.000
5	0.026	0.016	0.009	0.006	0.005	0.005
6	0.075	0.056	0.037	0.032	0.029	0.027
7	0.165	0.134	0.108	0.098	0.077	0.073
8	0.249	0.211	0.152	0.141	0.119	0.115
9	0.351	0.310	0.247	0.235	0.205	0.180
10	0.441	0.402	0.337	0.318	0.264	0.227

Table 6. Frequency count of b(1) values in explosives MZ_{α}^{GLS}

	b(1)								
	MZ_{α}^{GLS} < -500			MZ_{α}^{GLS} < -1 000			MZ_{α}^{GLS} < -5 000		
k	[0,9 1[	1	]1, 1,1]	[0,9 1[	1	]1, 1,1]	[0,9 1[	1	]1, 1,1]
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	0.007	0.000	0.003	0.007	0.000	0.003	0.006	0.000	0.003
6	0.035	0.001	0.014	0.035	0.001	0.014	0.022	0.001	0.014
7	0.082	0.000	0.044	0.081	0.000	0.044	0.064	0.000	0.044
8	0.128	0.002	0.066	0.126	0.002	0.066	0.084	0.002	0.066
9	0.203	0.003	0.101	0.198	0.003	0.100	0.146	0.003	0.098
10	0.230	0.002	0.166	0.225	0.002	0.164	0.182	0.002	0.153

	b(1)								
	MZ_{α}^{GLS} < -10 000			MZ_{α}^{GLS} < -50 000			MZ_{α}^{GLS} < -100 000		
k	[0,9 1[	1	]1, 1,1]	[0,9 1[	1	]1, 1,1]	[0,9 1[	1	]1, 1,1]
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	0.003	0.000	0.003	0.003	0.000	0.002	0.003	0.000	0.002
6	0.018	0.001	0.013	0.016	0.001	0.012	0.015	0.001	0.011
7	0.055	0.000	0.043	0.040	0.000	0.037	0.037	0.000	0.036
8	0.074	0.002	0.065	0.056	0.002	0.061	0.054	0.002	0.059
9	0.137	0.003	0.095	0.116	0.003	0.086	0.105	0.003	0.072
10	0.169	0.002	0.147	0.138	0.002	0.124	0.117	0.002	0.108

Table 7. Descriptive statistics of S_k^2 in normal MZ_α^{GLS}

	S_k^2								
	MZ_α^{GLS} < -500			MZ_α^{GLS} < -1 000			MZ_α^{GLS} < -5 000		
k	Min	Max	Variance	Min	Max	Variance	Min	Max	Variance
0	0.485	1.360	0.019	0.485	1.360	0.019	0.485	1.360	0.019
1	0.482	1.327	0.019	0.482	1.327	0.019	0.482	1.327	0.019
2	0.445	1.293	0.018	0.445	1.293	0.018	0.445	1.293	0.018
3	0.445	1.271	0.018	0.445	1.271	0.018	0.445	1.271	0.018
4	0.490	1.324	0.018	0.442	1.324	0.018	0.442	1.324	0.018
5	0.430	1.258	0.018	0.430	1.258	0.018	0.430	1.258	0.018
6	0.500	1.244	0.018	0.500	1.244	0.017	0.422	1.244	0.018
7	0.481	1.235	0.017	0.481	1.235	0.018	0.481	1.235	0.017
8	0.477	1.238	0.017	0.477	1.238	0.017	0.477	1.238	0.017
9	0.480	1.221	0.017	0.480	1.221	0.017	0.470	1.221	0.017
10	0.471	1.221	0.017	0.471	1.221	0.017	0.471	1.221	0.017

	S_k^2								
	MZ_α^{GLS} < -10 000			MZ_α^{GLS} < -50 000			MZ_α^{GLS} < -100 000		
k	Min	Max	Variance	Min	Max	Variance	Min	Max	Variance
0	0.485	1.360	0.019	0.485	1.360	0.019	0.485	1.360	0.019
1	0.482	1.327	0.019	0.482	1.327	0.019	0.482	1.327	0.019
2	0.445	1.293	0.018	0.445	1.293	0.018	0.445	1.293	0.018
3	0.445	1.271	0.018	0.445	1.271	0.018	0.445	1.271	0.018
4	0.442	1.324	0.018	0.442	1.324	0.018	0.442	1.324	0.018
5	0.430	1.258	0.018	0.430	1.258	0.018	0.430	1.258	0.018
6	0.422	1.244	0.018	0.422	1.244	0.018	0.422	1.244	0.018
7	0.481	1.235	0.017	0.481	1.235	0.018	0.408	1.235	0.018
8	0.477	1.238	0.017	0.477	1.238	0.017	0.443	1.238	0.018
9	0.470	1.221	0.017	0.470	1.221	0.017	0.470	1.221	0.017
10	0.471	1.221	0.017	0.471	1.221	0.017	0.430	1.221	0.017

Table 8. Descriptive statistics of S_k^2 in explosives MZ_α^{GLS}

	S_k^2								
	MZ_α^{GLS} < -500			MZ_α^{GLS} < -1 000			MZ_α^{GLS} < -5 000		
k	Min	Max	Variance	Min	Max	Variance	Min	Max	Variance
0	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
1	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
3	0.694	0.694	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
4	0.442	0.805	0.017	0.522	0.697	0.015	n.a.	n.a.	n.a.
5	0.536	1.084	0.018	0.536	1.084	0.020	0.536	1.084	0.028
6	0.422	1.115	0.016	0.422	1.115	0.019	0.524	1.115	0.017
7	0.408	1.116	0.017	0.408	1.098	0.017	0.408	1.098	0.017
8	0.443	1.119	0.017	0.443	1.119	0.018	0.443	1.119	0.018
9	0.449	1.145	0.017	0.449	1.145	0.017	0.449	1.145	0.018
10	0.430	1.145	0.017	0.430	1.145	0.018	0.430	1.145	0.018

	S_k^2								
	MZ_α^{GLS} < -10 000			MZ_α^{GLS} < -50 000			MZ_α^{GLS} < -100 000		
k	Min	Max	Variance	Min	Max	Variance	Min	Max	Variance
0	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
1	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
3	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
4	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
5	0.536	0.821	0.012	0.536	0.821	0.014	0.536	0.821	0.014
6	0.524	1.115	0.014	0.524	1.115	0.016	0.524	1.115	0.015
7	0.408	1.098	0.017	0.408	1.090	0.017	0.478	1.090	0.015
8	0.443	1.119	0.018	0.443	1.119	0.018	0.502	1.119	0.017
9	0.449	1.145	0.018	0.449	1.145	0.019	0.449	1.145	0.019
10	0.430	1.145	0.018	0.430	1.145	0.019	0.473	1.145	0.019

Table 9. ADF^{GLS} mean value; Moving Average case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
						θ= 0,8					
AIC	n.a.	-3,318	-2,720	-3,418	-2,497	-3,324	-2,843	-3,393	-3,024	-3,576	-3,455
BIC	n.a.	-3,770	-2,571	-3,306	-2,396	-3,419	-2,696	-3,577	n.a.	n.a.	n.a.
MAIC	-3,348	-3,469	-2,808	-2,535	-2,532	-2,441	-2,321	-2,293	-2,197	-2,186	-1,868
MBIC	-2,805	-2,762	-2,496	-2,050	-2,279	-1,960	-1,999	n.a.	n.a.	n.a.	n.a.
T-sig (10)	n.a.	n.a.	-2,848	-3,477	-2,491	-3,399	-2,713	-3,350	-2,843	-3,377	-3,158
						θ= 0,3					
AIC	-2,600	-3,202	-2,696	-3,418	-3,427	-3,465	-3,922	-3,450	-3,608	-4,138	-3,813
BIC	-2,558	-3,186	-2,530	-3,436	-4,148	-3,156	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	-2,763	-2,653	-2,628	-2,389	-2,423	-2,527	-2,504	-2,281	-2,396	-1,988	n.a.
MBIC	-2,441	-2,206	-2,299	-2,316	-2,187	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
T-sig (10)	-2,950	-3,302	-2,618	-3,421	-3,150	-3,454	-3,428	-3,291	-3,213	-3,324	-3,287
						θ= 0					
AIC	-3,018	-3,248	-3,410	-3,386	-3,317	-3,489	-3,825	-3,726	-3,721	-3,933	-3,935
BIC	-2,953	-3,329	-3,345	-3,185	-3,857	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	-2,868	-2,687	-2,566	-2,348	-2,329	-2,314	-2,422	-2,104	n.a.	-2,030	-2,575
MBIC	-2,846	-2,811	-2,687	-2,467	-2,756	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
T-sig (10)	-3,124	-3,431	-3,345	-3,585	-3,273	-3,350	-3,407	-3,273	-3,166	-3,296	-3,285
						θ= -0,5					
AIC	-6,252	-3,690	-2,909	-2,747	-3,177	-3,163	-3,392	-3,576	-3,689	-3,611	-3,664
BIC	-5,951	-3,424	-2,683	-2,485	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	-6,303	-3,681	-3,073	-2,778	-2,564	-2,447	-2,330	-2,267	-2,025	-2,200	-1,941
MBIC	-6,357	-3,610	-3,048	-2,785	-2,621	-2,504	-2,338	-2,395	-2,025	-2,163	n.a.
T-sig (10)	-6,142	-3,663	-3,045	-2,921	-3,151	-3,180	-3,315	-3,360	-3,223	-3,263	-3,239
						θ= -0,8					
AIC	-9,049	-5,339	-4,062	-3,562	-3,221	-3,211	-3,196	-3,480	-3,812	-3,996	-3,420
BIC	-8,963	-4,906	-3,461	-2,574	-2,794	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	-9,458	-5,907	-4,531	-3,751	-3,223	-2,842	-2,731	-2,522	-2,415	-2,287	-2,210
MBIC	-9,417	-5,909	-4,497	-3,749	-3,198	-2,823	-2,715	-2,549	-2,398	-2,282	-2,263
T-sig (10)	-9,042	-5,275	-4,155	-3,933	-3,464	-3,471	-3,369	-3,540	-3,278	-3,207	-3,170

Table 10. ADF^{GLS} mean value; Autoregressive case

	k=0	k=1	K=2	K=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
						ϕ= 0,8					
AIC	n.a.	-3,121	-3,496	-3,566	-3,537	-3,735	-4,106	-3,768	-3,939	-4,011	-3,987
BIC	n.a.	-3,070	-3,659	-3,554	-3,846	-4,072	-4,929	n.a.	n.a.	n.a.	n.a.
MAIC	n.a.	-2,998	-2,819	-2,519	-2,410	-2,463	-2,722	-1,933	-2,278	n.a.	-2,026
MBIC	-2,007	-2,972	-2,877	-2,518	-2,553	-2,886	n.a.	-2,454	n.a.	n.a.	n.a.
T-sig (10)	n.a.	-3,319	-3,586	-3,601	-3,435	-3,621	-3,703	-3,463	-3,486	-3,577	-3,474
						ϕ= 0,4					
AIC	-2,529	-3,036	-3,253	-3,461	-3,423	-3,476	-3,946	-3,550	-3,543	-3,811	-3,861
BIC	-2,264	-2,984	-3,308	-3,884	-5,114	-3,733	n.a.	n.a.	n.a.	n.a.	n.a.
MAIC	-2,666	-2,773	-2,760	-2,466	-2,439	-2,454	-2,320	-2,103	-2,333	-1,397	n.a.
MBIC	-2,251	-2,382	-2,407	-2,314	-2,135	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
T-sig (10)	n.a.	-3,134	-3,233	-3,575	-3,162	-3,414	-3,417	-3,368	-3,253	-3,387	-3,302
						ϕ= -0,4					
AIC	-4,426	-2,942	-3,134	-3,227	-3,425	-3,465	-3,602	-3,645	-3,713	-3,745	-4,062
BIC	-4,349	-2,829	-3,197	-3,275	-3,448	-5,556	-6,124	n.a.	n.a.	n.a.	n.a.
MAIC	-4,050	-2,851	-2,677	-2,489	-2,487	-2,278	-2,561	-2,290	-2,230	n.a.	-1,619
MBIC	-3,893	-2,828	-2,733	-2,585	-2,690	-2,541	-3,006	-2,208	n.a.	n.a.	n.a.
T-sig (10)	-4,566	-3,025	-3,291	-3,221	-3,243	-3,383	-3,402	-3,371	-3,260	-3,256	-3,304
						ϕ= -0,8					
AIC	n.a.	-3,003	-3,225	-3,270	-3,325	-3,392	-3,660	-3,696	-3,425	-3,669	-3,633
BIC	n.a.	-2,944	-3,234	-3,155	-3,260	-5,352	n.a.	-3,636	n.a.	n.a.	n.a.
MAIC	n.a.	-2,804	-2,703	-2,518	-2,514	-2,290	-2,384	-2,546	-2,409	-2,073	-1,555
MBIC	n.a.	-2,791	-2,733	-2,575	-2,666	-2,421	-2,642	-2,986	n.a.	-2,073	n.a.
T-sig (10)	n.a.	-3,149	-3,214	-3,363	-3,204	-3,290	-3,411	-3,453	-3,192	-3,122	-3,297

Table 11. Lag length selection for the unemployment rate of Cantabria, Galicia, Murcia and for the Peruvian monetary policy rate

	AIC	BIC	MAIC	MBIC	t-sig	AIC_OLS	BIC_OLS	MAIC_OLS	MBIC_OLS
Cantabria									
Model I									
cbar1=-22.5	9	0	10	0	9	9	0	10	0
cbar1=0	9	0	6	0	10	9	0	6	0
Model II									
cbar1=-22.5	9	0	10	0	9	9	4	6	0
cbar1=0	9	0	6	0	10	9	0	4	0
Galicia									
Model I									
cbar1=-22.5	10	4	10	4	10	9	4	6	4
cbar1=0	10	4	6	2	10	9	4	4	4
Model II									
cbar1=-22.5	8	8	10	4	8	9	8	4	0
cbar1=0	8	4	6	2	10	9	8	4	0
Murcia									
Model I									
cbar1=-22.5	9	0	4	0	8	9	0	4	0
cbar1=0	4	0	4	0	8	9	0	4	0
Model II									
cbar1=-22.5	9	4	4	0	9	10	4	4	0
cbar1=0	4	0	4	0	8	10	4	4	0
Peruvian monetary policy rate									
Model I									
cbar1=-22.5	2	1	1	1	9	9	2	1	1
cbar1=0	9	1	1	1	9	8	1	1	1
Model II									
cbar1=-22.5	5	3	3	1	6	3	2	1	1
cbar1=0	4	3	1	0	4	8	2	2	2

Table 12. MZ_{α}^{GLS} values for the unemployment rate of Cantabria, Galicia, Murcia and for the Peruvian monetary policy rate

	AIC	BIC	MAIC	MBIC	t-sig	AIC_OLS	BIC_OLS	MAIC_OLS	MBIC_OLS
Cantabria									
					Model I				
cbar1=-22.5	-3140463	-9	-35	-9	-50078041	-50078041	-9	-20	-9
cbar1=0	-24	-9	-24	-9	-24	-48	-9	-11	-9
					Model II				
cbar1=-22.5	-118561417	-9	-57	-9	-171933035	-171933035	-12	-20	-9
cbar1=0	-24	-9	-24	-9	-25	-48	-9	-12	-9
Galicia									
					Model I				
cbar1=-22.5	-223	-25	-42	-21	-223	-411796057	-25	-26	-11
cbar1=0	-23	-17	-22	-17	-23	-51	-17	-16	-8
					Model II				
cbar1=-22.5	-542	-36	-45	-23	-408	-157656	-409	-26	-5
cbar1=0	-24	-18	-24	-18	-25	-54	-36	-18	-5
Murcia									
					Model I				
cbar1=-22.5	-965	-5	-14	-5	-101	-965	-5	-14	-5
cbar1=0	-10	-5	-10	-5	-23	-31	-5	-10	-5
					Model II				
cbar1=-22.5	-1273	-15	-15	-5	-997	-790155	-15	-15	-5
cbar1=0	-11	-5	-11	-5	-24	-36	-11	-11	-5
Peruvian monetary policy rate									
					Model I				
cbar1=-22.5	-93	-48	-48	-48	-31806	-196	-92	-48	-48
cbar1=0	-42	-40	-40	-40	-8353	-20876	-40	-40	-40
					Model II				
cbar1=-22.5	-5746	-140	-119	-48	-55916673	-238	-92	-48	-48
cbar1=0	-432	-256	-40	-44	-432	-9693	-57	-45	-45

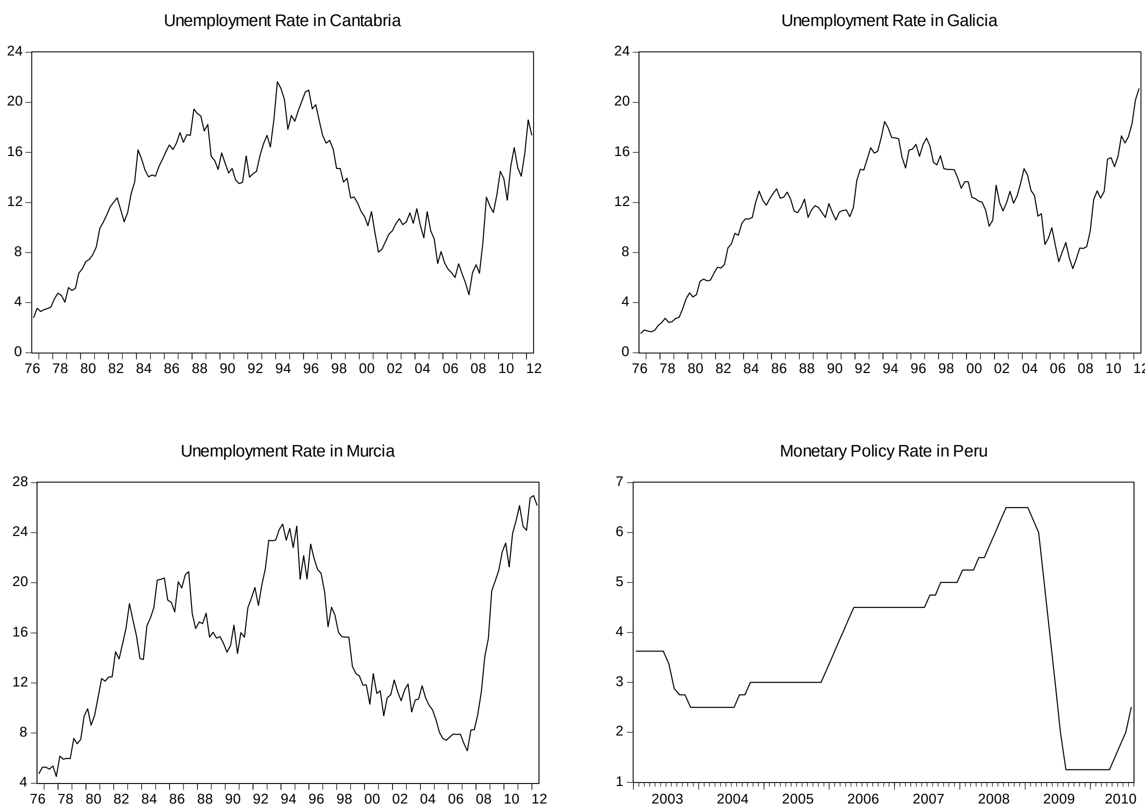

Figure 1. Time Series used in Empirical Análisis

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Departamento de Economía - Pontificia Universidad Católica del Perú
Av. Universitaria 1801, Lima 32 – Perú.
Telf. 626-2000 anexos 4950 - 4951
http://www.pucp.edu.pe/economia