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A Note on the Size of the ADF Test with Additive Outliers and Fractional Errors. A Reappraisal about the (Non)Stationarity of the Latin-American Inflation Series*

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ABSTRACT

This note analyzes the empirical size of the augmented Dickey and Fuller (ADF) statistic proposed by Perron and Rodríguez (2003) when the errors are fractional. This ADF is based on a searching procedure for additive outliers based on first-differences of the data named τ_d. Simulations show that empirical size of the ADF is not affected by fractional errors confirming the claim of Perron and Rodríguez (2003) that the procedure τ_d is robust to departures of the unit root framework. In particular the results show low sensitivity of the size of the ADF statistic respect to the fractional parameter (d). However, as expected, when there is strong negative moving average autocorrelation or negative autoregressive autocorrelation, the ADF statistic is oversized. These difficulties are fixed when sample increases (from T = 100 to T = 200). Empirical application to eight quarterly Latin- American inflation series is also provided showing the importance of taking into account dummy variables for the detected additive outliers.

Keywords: additive outliers, ARFIMA erros, ADF Test

JEL: C2, C3, C5

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Una nota sobre el tamaño del Test ADF con outliers aditivos y errores fraccionales. Una re-evaluación de la (no) estacionariedad de las series de inflación latinoamericanas

RESUMEN

En esta nota se analiza el tamaño empírico del estadístico Dickey y Fuller aumentado (ADF), propuesto por Perron y Rodríguez (2003), cuando los errores son fraccionales. Este estadístico se basa en un procedimiento de búsqueda de valores atípicos aditivos basado en las primeras diferencias de los datos denominado τ_d. Las simulaciones muestran que el tamaño empírico del estadístico ADF no es afectado por los errores fraccionales confirmando el argumento de Perron y Rodríguez (2003) que el procedimiento τ_d es robusto a las desviaciones del marco de raíz unitaria. En particular, los resultados muestran una baja sensibilidad del tamaño del estadístico ADF respecto al parámetro fraccional (d). Sin embargo, como es de esperar, cuando hay una fuerte autocorrelación negativa de tipo promedio móvil o autocorrelación autorregresiva negativa, el estadístico ADF tiene un tamaño exacto mayor que el nominal. Estas dificultades desaparecen cuando aumenta la muestra (a partir de T = 100 a T = 200). La aplicación empírica a ocho series de inflación latinoamericana trimestral proporciona evidencia de la importancia de tener en cuenta las variables ficticias para controlar por los *outliers* aditivos detectados.

Palabras clave: Outliers aditivos, errores ARFIMA, Test ADF.

Clasificación JEL: C2, C3, C5

INTRODUCTION

Additive outliers affect inference of parameters in different circunstances. For example they affect inference of the autoregressive and moving average estimates of *ARM A(p, q)* models; see Cheng and Liu (1993), Chan (1992, 1995). They also affect other topics like causality tests (see Baldé and Rodríguez, 2005), fractional estimates (see Fajardo *et al.*, 2009; Chareka *et al.*, 2006). In the context of a unit root, additive outliers have been also analyzed since the contribution of Franses and Haldrup (1994). These authors show that additive outliers contaminate the limiting distribution of the unit root statistics; see also Vogelsang (1999) and Perron and Rodríguez (2003). Vogelsang (1999) suggests to use M-tests based on GLS detrended data because they are robust to the presence of negative moving average au- tocorrelation which is induced by the presence of additive outliers. Another alternative procedure is to estimate an ADF statistic corrected for dummy variables related to the identified additive outliers in a preliminary step. Rodríguez (2004) used four Latin-American inflation series and show that even the M-tests indicate a rejection of the null hypothesis of a unit root. When applying an ADF corrected for dummy variables, some countries show a non-rejection of the null hypothesis of a unit root indicating nonstationarity of the inflation series which is an opposite results obtained from the standard unit root tests.

The procedure mentioned above needs the location of the additive outliers. Perron and Rodríguez (2003) have suggested a powerful test, denoted by τ_d, which works with first-differenced data[1]. This procedure is more powerful than other based on levels of the data, for example; see Perron and Rodríguez (2003) for a detailed discussion. These authors claim that τ_d is powerful even for departures from the unit root case[2]. The purpose of this note is to show that this claim is correct. We do it analyzing the empirical size of the ADF statistic (using τ_d to locate additive outliers) when the DGP contains *ARFIMA*(p, d, q) errors. The experiment deals with different values of the fractional parameter (d) to observe different departures from the unit root hypothesis. Also different structure of autocorrelation is analyzed (moving average and autoregressive).

The Monte-Carlo simulations show that the ADF statistic corrected for dummy variables associated to the additive outliers suffers of size distortions in only few cases. For example, when the moving average parameter is close to −1 empirical size is greater than nominal size. Negative autoregressive autocorrelation has impact on the size of the ADF statistic too. However, most of these issues are fixed when sample size increases from $T = 100$ to $T = 200$ in simulations. In general, the ADF test appears to be slightly undersized. When fractional parameter is higher, distortions appear but at the same time when correlation is higher. Therefore, fractional parameter itself does not cause problems or distortions on the size of the ADF test.

After simulations, we present an empirical application using quarterly inflation series ranging from 1970:1 until 2010:4 of 8 countries. We use a sample of eight countries and the spirit of this exercise is very similar to Rodríguez (2004) where four countries were only used. In this note, we add more countries and more observations. In particular, the Phillips and Perron (1988) statistic shows a strong rejection of the null hypothesis of a unit root which is not rare given the sensitivity of this statistic to the presence of strong negative moving average correlation which is the case here because additive outliers are clearly present and literature has shown that they are related to this type of correlation. Similar results are obtained with the ADF statistic and even with the M-tests and MP_T tests using GLS detrended data as suggested by Elliott, Rothenberg and Stock (1996) and Ng and Perron (2001), respectively. Only Uruguay and Venezuela show non rejection of the null. However, when applying the ADF test augmented by dummy variables related to the location of the additive outliers identified by the procedure τ_d, none of the countries reject the null hypothesis of a unit root.

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1 Of course, there are many other procedures to identify outliers, for example, those proposed in Tsay (1986), Chang, Tiao and Chen (1988), Shin, Sharkar and Lee (1996), Chen and Liu (1993) and Gómez and Maravall (1992a, 1992b). Another interesting approach is proposed by Lucas (1995a, 1995b), and Hoek, Lucas and van Dijk (1995). See Rodríguez (2004) for a comparison with other approaches.

2 However, this procedure is not robust to departures from the assumption of normality in the errors. It is mentioned and discussed by Perron and Rodríguez (2003). See also Burridge and Taylor (2006) for more evidence about this drawback and the correction they propose based on the extreme value theory.

This note is organized as follows. Section 1 presents the model, discusses the issue of outlier detection and briefly revises the method proposed by Perron and Rodríguez (2003). In section 2, I present the results from the simulations. Section 3 shows the empirical application and Section 4 concludes.

1. THE ISSUE OF OUTLIER DETECTION AND TESTING FOR UNIT ROOTS WITH ADDITIVE OUTLIERS

The issue of outlier detection in the unit root framework is the approach taken by Perron and Rodríguez (2003) which is based on Vogelsang (1999)[3]. The data-generating process entertained is of the following general form:

$$y_t = d_t + \sum_{j=1}^{m} \delta_j D(T_{ao,j})_t + u_t \tag{1}$$

where $D(T_{ao,j})_t = 1$ if $t = T_{ao,j}$ and 0 otherwise. This permits the presence of m additive outliers occurring at dates $T_{ao,j}$ (j = 1,...,m). The term d_t specifies the deterministic components. In most cases, $d_t = \mu$ if the series is non-trending or $d_t = \mu + \beta t$ if the series is trending. The noise function is integrated of order one, i.e, $u_t = u_{t-i} + v_t$; where v_t is a stationary process. While Perron and Rodríguez (2003), use an *ARMA(p, q)* for the process v_t, in this paper, we assume that v_t is an *ARFIMA(p, d, q)* process.

As shown in Perron and Rodríguez (2003), the original procedure of Vogelsang (1999) has severe size distortions when applied in an iterative fashion to search for additive outliers. The reason for this is that the limiting distribution of the statistic is only valid in the first step of the iterations as specified in Theorem 1 of Perron and Rodríguez (2003). In subsequent steps, the asymptotic critical values used need to be modified.

Perron and Rodríguez (2003) have proposed a more powerful iterative strategy using a test based on first-differences of the data. Consider data generated by (1) with $d_t = \mu$ and a single outlier occurring at date T_{ao} with magnitude δ. Then,

$$\Delta y_t = \delta[D(T_{ao})_t - D(T_{ao})_{t-1}] + v_t, \tag{2}$$

where $D(T_{ao})_t = 1$, if $t = T_{ao}$ (0, otherwise) and $D(T_{ao})_{t-1} = 1$, if $t = T_{ao} + 1$ (0, otherwise). If the data are trending, a constant should be included. In this case, we are interested

[3] Let $|t_{\hat{\delta}}(T_a$ denote the t-statistic for testing $\delta = 0$ in (1). Following Chen and Liu (1993), the presence of an additive outlier can be tested using $\tau = \sup_{T_{ao}} |t_{\hat{\delta}}(T_{ao})|$. Assuming that $\lambda = T_{ao}/T$ remains fixed as T grows, Vogelsang (1999) showed that as $T \to \infty$, the limiting distribution of $|t_{\hat{\delta}}(T_a$ is non-standard. More precisely, $|t_{\hat{\delta}}(T_a \Rightarrow H(\lambda) = W^*(\lambda)/(\int_0^1 W^*(r)^2 dr)^{1/2}$, where $W^*(\lambda)$ denotes a demeaned standard Wiener process. If (1) also includes a time trend, $W^*(\lambda)$ will denote a detrended Wiener process. Furthermore, from the continuous mapping theorem it follows that, $\tau \Rightarrow \sup_{\lambda \in (0,1)} |H(\lambda)| \equiv H^*$. This distribution is invariant with respect to any nuisance parameters, including the correlation structure of the noise function.

in $\tau_d = \sup_{T_{ao}} |t_{\hat{\delta}}(T_{ao})|$, where $t_{\hat{\delta}}(T_{ao}) = \frac{\hat{\delta}}{\left[(\hat{R}_v(0) - \hat{R}_v(1))/2\right]^{1/2}}$. and $R_u(j)$ is the autocovariance function of v_t at delay j.[4]

To detect for multiple outliers, we can follow a strategy similar to that suggested by Vogelsang (1999), by dropping the observation labelled as an outlier before proceeding to the next step. The important feature is that, unlike for the case of the test based on levels, the limit distribution of the test τ_d is the same as each step of the iterations when dealing with multiple outliers. The disadvantage of this procedure, compared to that based on the level of the data, is that the limiting distribution depends on the specific distribution of the errors v_t, though not on the presence of serial correlation and heteroskedasticity[5]. This problem is exactly the same as that for finding outliers in stationary time series.

In this note, we analyze the empirical size of the *ADF* test corrected for detected additive outliers when errors v_t are *ARFIMA*(p, d, q) process. It is equivalent to using the t-statistic for testing that $\alpha = 1$ in the following regression:

$$y_t = \mu + \alpha y_{t-1} + \sum_{j=0}^{k+1} \delta_j D(T_{ao,j})_{t-j} + \sum_{i=0}^{k} d_i \Delta y_{t-i} + v_t, \tag{3}$$

where $D(T_{ao,j})_t = 1$ if $t = T_{ao,j}$ and 0 otherwise, with $T_{ao,j}$ ($j = 1, 2,..., m$) being the dates of the outliers identified using the statistic τ_d. Notice that $k + 2$ one-time dummy variables have to be included in (3) to remove all possible influences of the additive outliers.

2. MONTE CARLO RESULTS

In order to analyze the empirical size of the ADF statistic, we consider the following experiment. Let y_t follow (1) where $u_t = u_{t-1} + v_t$ (a unit root process) and v_t is an *ARFIMA*(p, d, q) process, that is $\rho(L)(1 - L)^d v_t = \theta(L)\epsilon_t$, where ϵ_t is an *i.i.d.* $N(0; 1)$. More exactly, in one case we consider $p = 1$ ($\rho(L) = 1 - \rho L$) and $q = 0$, that is $p(L)(1 - L)^d v_t = \epsilon_t$, while in the other $p = 0$ case and $q = 1$ ($\theta(L) = 1 + \theta L$), that is $(1 - L)^d v_t = 0(L)\epsilon_t$. The fractional parameter $d \in [-0.48$ to $0.48]$ with a step of 0.12.

Each Table and each value of θ or ρ present three rows named *"without", "with*", and *"total"*. The row named "*without"* indicates the size of the ADF statistic when no additive outliers has been found. The word *"with"* indicates the size of the ADF statistic when additive outliers have been identified. Therefore, the row entitle *"total"* means simply the sum of the two previous rows. If size is correct we expect that this row should be close to the nominal size of 5.0%.

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4 $\hat{R}_u(j) = T^{-1}\sum_{t=1}^{T-j} \hat{v}_t \hat{v}_{t-j}$ with $\hat{v}_t$ the least-squares residuals obtained from regression (2). Then, $\hat{R}_u(j)$ is a consistent estimate of $R_u(j)$.

5 The dependence of the distribution or departures of the normality of v_t has been mentioned by Perron and Rodríguez (2003). However, Burridge and Taylor (2006) deals with this issue using extreme value theory.

In order to save space we present only selected Tables. Each experiment is performed using 10,000 replications, nominal size at 5.0% and we use tabulated critical values (Table 1 of Perron and Rodríguez (2003)) for $T = 100$ and $T = 200$. Other extensive Tables are available upon request. In all Tables, the total iterative procedure is applied, that is, we search for all outliers and procedure finish when no outliers are found. Two sets of Tables are presented. In one case, the lag lenght of (3) is fixed to be $k = 1$ while in the other case, we use the procedure t-sig proposed by Campbell and Perron (1991) for $k \in [0, 5]$. In each Table, three cases are presented. In the first case, no outliers are in the process, that is, $\delta_i = 0$ for $i = 1, 2, 3, 4$. In the second case, we consider medium sized additive outliers: $\delta_i = 5, 3, 2, 2$. The final case is for high sized addtive outliers, that is, $\delta_i = 10, 5, 5, 5$. In summary, the design of the experiment follow closely Perron and Rodríguez (2003). When there are outliers a maximum of four additive outliers is considered and they are located at positions $0.20T$, $0.40T$, $0.60T$ and $0.80T$, respectively.

Table 1 shows the results for the case where errors are ARFIMA(0, *d,* 0). The first set of columns are the case where no outliers are present in the data. The other columns shows medium and high sized additive outliers, respectively. The results show that the size of the ADF is oversized for every $d < 0$. More negative values of d imply more oversized ADF tests. This is true for the case where no outliers are found and when they are present in the data. For other values of d, the ADF is slighthly undersized but close to the nominal size of 5%. Given these results, in what follows, we do not consider cases where $d < 0$.

Tables 2a-2c show size of the ADF test for *ARFIMA*(0, *d*, 1) errors, that is when there exists moving average correlation. In order to save space, we only show results for $d = 0.00$, 0.24, and 0.48. Table 2a indicates that ADF test is oversized for $\theta = -0.8$ and for $\theta = -0.4$. Small distortion is also found for $\theta = 0.8$. In all other cases of 6 and for cases where there are or not additive outliers, exact size is close to 5%. Table 2b shows the case for $d = 0.24$. Again, ADF test is oversized for $\theta = -0.8$ but distortions are smaller than before. In all other cases, size is better although slightly undersized. When $d = 0.48$ (Table 2c), that is, when memory of the errors is large the size of the ADF test is very close to the nominal size of 5%. It is true when there are or not additive outliers and for both sample sizes. In summary, there is some difficulties when θ goes to -1 but the performance is better when d goes to 0.5.

Tables 3a-3c show size of the ADF test for *ARFIMA*(1, *d*, 0) errors, that is, when there exists autoregressive autocorrelation. Again, in order to save space, we only show results for $d = 0.00$, 0.24, and 0.48. Table 3a indicates that ADF test has good exact size except for the case where $\rho = -0.8$ and when the process is contaminated for medium and high sized additive outliers. It is worth to mention that the distortions are smaller compared to the previous Tables and we observe that size is better when sample size is higher. Table 3b shows the case for $d = 0.24$. In this case, the ADF test has exact size close to the 5% although we observe small oversized results when $\rho = 0.8$. This results is more evident when $d = 0.48$ (Table 3c) even when there is no outliers in the process. This problem is not fixed when sample size is higher. It is more evident for extreme values of ρ (–0.8 and 0.8).

Table 1. Size of the ADF Test; ARFIMA(0, *d*, 0) Errors*

		$\delta_1 = 0, \delta_2 = 0, \delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3, \delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5, \delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$d = -0.48$	Without	0.792	0.940	0.075	0.051	0.000	0.000
	With	0.038	0.048	0.779	0.938	0.737	0.979
	Total	0.830	0.988	0.854	0.989	0.737	0.979
$d = -0.36$	Without	0.487	0.767	0.032	0.021	0.000	0.000
	With	0.023	0.037	0.514	0.792	0.428	0.761
	Total	0.510	0.805	0.546	0.813	0.428	0.761
$d = -0.24$	Without	0.229	0.385	0.009	0.005	0.000	0.000
	With	0.011	0.018	0.242	0.403	0.188	0.361
	Total	0.240	0.403	0.251	0.408	0.188	0.361
$d = -0.12$	Without	0.088	0.122	0.002	0.001	0.000	0.000
	With	0.004	0.007	0.092	0.129	0.076	0.116
	Total	0.092	0.129	0.094	0.130	0.076	0.116
$d = 0.00$	Without	0.037	0.036	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.038	0.038	0.037	0.038
	Total	0.038	0.038	0.038	0.038	0.037	0.038
$d = 0.12$	Without	0.022	0.022	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.023	0.023	0.023	0.022
	Total	0.023	0.023	0.023	0.023	0.023	0.022
$d = 0.24$	Without	0.021	0.026	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.022	0.028	0.022	0.026
	Total	0.022	0.028	0.022	0.028	0.022	0.026
$d = 0.36$	Without	0.023	0.032	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.024	0.033	0.022	0.030
	Total	0.024	0.034	0.024	0.033	0.022	0.030
$d = 0.48$	Without	0.022	0.030	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.026	0.033	0.025	0.035
	Total	0.023	0.031	0.026	0.033	0.025	0.035

*Lag lenght fixed at one

Table 2a. Size of the ADF Test; ARFIMA(0, *d*, 1) Errors with *d* = 0.00*

		$\delta_1 = 0, \delta_2 = 0, \delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3, \delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5, \delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.819	0.846	0.250	0.221	0.000	0.000
	With	0.043	0.045	0.651	0.692	0.845	0.891
	Total	0.862	0.891	0.901	0.913	0.845	0.891
$\theta = -0.40$	Without	0.094	0.103	0.012	0.006	0.000	0.000
	With	0.005	0.005	0.110	0.114	0.086	0.101
	Total	0.099	0.108	0.122	0.120	0.086	0.101
$\theta = 0.00$	Without	0.037	0.036	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.038	0.038	0.037	0.038
	Total	0.038	0.038	0.038	0.038	0.037	0.038
$\theta = 0.40$	Without	0.059	0.060	0.000	0.000	0.000	0.000
	With	0.002	0.002	0.045	0.053	0.054	0.056
	Total	0.061	0.062	0.045	0.053	0.054	0.056
$\theta = 0.80$	Without	0.094	0.098	0.000	0.000	0.000	0.000
	With	0.002	0.003	0.064	0.079	0.082	0.090
	Total	0.096	0.101	0.064	0.079	0.082	0.090

*Lag lenght fixed at one

Table 2b. Size of the ADF Test; ARFIMA(0, *d*, 1) Errors with *d* = 0.24*

		$\delta_1 = 0, \delta_2 = 0, \delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3, \delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5, \delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.264	0.223	0.048	0.027	0.000	0.000
	With	0.013	0.001	0.266	0.223	0.246	0.220
	Total	0.277	0.234	0.314	0.250	0.246	0.220
$\theta = -0.40$	Without	0.023	0.025	0.001	0.000	0.000	0.000
	With	0.001	0.002	0.023	0.025	0.021	0.024
	Total	0.024	0.027	0.024	0.025	0.021	0.024
$\theta = 0.00$	Without	0.021	0.026	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.022	0.028	0.022	0.026
	Total	0.022	0.028	0.022	0.028	0.022	0.026
$\theta = 0.40$	Without	0.023	0.024	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.024	0.024	0.025	0.026
	Total	0.024	0.025	0.024	0.024	0.025	0.026
$\theta = 0.80$	Without	0.033	0.028	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.029	0.029	0.042	0.035
	Total	0.034	0.029	0.029	0.029	0.042	0.035

*Lag lenght fixed at one

Table 2c. Size of the ADF Test; ARFIMA(0, *d*, 1) Errors with $d = 0.48$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.059	0.041	0.004	0.001	0.000	0.000
	With	0.003	0.002	0.058	0.040	0.053	0.040
	Total	0.062	0.043	0.062	0.041	0.053	0.040
$\theta = -0.40$	Without	0.033	0.052	0.000	0.000	0.000	0.000
	With	0.002	0.003	0.030	0.053	0.030	0.049
	Total	0.035	0.055	0.030	0.053	0.030	0.049
$\theta = 0.00$	Without	0.022	0.030	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.026	0.033	0.025	0.035
	Total	0.023	0.031	0.026	0.033	0.025	0.035
$\theta = 0.40$	Without	0.018	0.020	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.032	0.041	0.048	0.055
	Total	0.019	0.021	0.032	0.041	0.048	0.055
$\theta = 0.80$	Without	0.024	0.019	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.044	0.048	0.078	0.079
	Total	0.025	0.020	0.044	0.048	0.078	0.079

*Lag lenght fixed at one

Table 3a. Size of the ADF Test; ARFIMA(1, *d*, 0) Errors with $d = 0.00$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.037	0.037	0.080	0.053	0.018	0.004
	With	0.001	0.001	0.026	0.018	0.139	0.095
	Total	0.038	0.038	0.106	0.071	0.157	0.099
$\rho = -0.40$	Without	0.035	0.037	0.009	0.004	0.000	0.000
	With	0.002	0.002	0.046	0.044	0.041	0.039
	Total	0.037	0.039	0.055	0.048	0.041	0.039
$\rho = 0.00$	Without	0.037	0.036	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.038	0.038	0.037	0.038
	Total	0.038	0.038	0.038	0.038	0.037	0.038
$\rho = 0.40$	Without	0.035	0.036	0.000	0.000	0.000	0.000
	With	0.002	0.002	0.033	0.035	0.037	0.038
	Total	0.037	0.038	0.033	0.035	0.037	0.038
$\rho = 0.80$	Without	0.040	0.040	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.035	0.040	0.049	0.046
	Total	0.041	0.041	0.035	0.040	0.049	0.046

*Lag lenght fixed at one

Table 3b. Size of the ADF Test; ARFIMA (1, *d*, 0) Errors with *d* = 0.24*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.031	0.044	0.010	0.016	0.001	0.000
	With	0.001	0.001	0.012	0.019	0.022	0.031
	Total	0.032	0.045	0.022	0.035	0.023	0.031
$\rho = -0.40$	Without	0.025	0.034	0.001	0.000	0.000	0.000
	With	0.001	0.002	0.022	0.033	0.025	0.033
	Total	0.026	0.036	0.023	0.033	0.025	0.033
$\rho = 0.00$	Without	0.021	0.026	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.022	0.028	0.022	0.026
	Total	0.022	0.028	0.022	0.028	0.022	0.026
$\rho = 0.40$	Without	0.022	0.024	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.025	0.025	0.027	0.026
	Total	0.023	0.026	0.025	0.025	0.027	0.026
$\rho = 0.80$	Without	0.072	0.056	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.064	0.073	0.096	0.092
	Total	0.073	0.058	0.064	0.073	0.096	0.092

*Lag lenght fixed at one

Table 3c. Size of the ADF Test; ARFIMA (1, *d*, 0) Errors with *d* = 0.48*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.062	0.096	0.013	0.025	0.000	0.000
	With	0.001	0.002	0.031	0.063	0.045	0.085
	Total	0.063	0.098	0.044	0.088	0.045	0.085
$\rho = -0.40$	Without	0.038	0.058	0.000	0.000	0.000	0.000
	With	0.002	0.004	0.034	0.059	0.033	0.057
	Total	0.040	0.062	0.034	0.059	0.033	0.057
$\rho = 0.00$	Without	0.022	0.030	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.026	0.033	0.025	0.035
	Total	0.023	0.031	0.026	0.033	0.025	0.035
$\rho = 0.40$	Without	0.020	0.020	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.041	0.047	0.057	0.064
	Total	0.021	0.022	0.041	0.047	0.057	0.064
$\rho = 0.80$	Without	0.177	0.124	0.000	0.000	0.000	0.000
	With	0.001	0.002	0.095	0.116	0.146	0.141
	Total	0.178	0.126	0.095	0.116	0.146	0.141

*Lag lenght fixed at one

Previous results (undersized or oversized results) may be due to the selection of the lag length which has been fixed to unity. In order to observe if this issue is important, we present similar simulations as in the previous Tables but now the lag length is selected using the procedure t-sig as suggested by Campbell and Perron (1991) considering a $k \in [0, 5]$. Table 4 presents results for *ARFIMA*(*0, d,* 0) errors and for $d \geq 0$. The message is that ADF test has exact size close to the 5%. In some cases, it presents slight smaller exact size.

Table 5a-5c are similar to Tables 2a-2c but selecting lag length with the procedure t-sig. In all Tables, the ADF test is oversized but clearly different or smaller compared to the case where $k = 1$. We found oversized ADF test only when $d = 0.0$. In other cases, when memory is larger, results are better in particular for $T = 200$.

Finally, Tables 6a-6c are similar to Tables 3a-3c but using the procedure t-sig. The results indicate that ADF test has good size for almost every case. More clearly, the exact size is under nominal size for $\rho < 0$ but is closer to 5% when $\rho \geq 0$. The conclusion suggests that using a data dependent rule to select the lag length fixes the problems detected before[6].

3. EMPIRICAL APPLICATION

The Latin-American inflation series offer a good example of the strong presence of big sized additive outliers in a possible nonstationary time series. Figure 1 shows quarterly inflation series for eight Latin-American countries: Argentina, Bolivia, Chile, Colombia, Ecuador, Peru, Uruguay and Venezuela. The frequency is quarterly and the sample spans 1970:1 until 2010:4. Many or all these countries have experimented with different stabilization programs to stop high inflation episodes. Intervention of this kind, in most of these cases, has introduced additive outliers in the evolution of their inflation series. For example, the periods of high inflation in Argentina and Peru were located between 1985 and 1990, where the most important stabilization programs were applied. For example, in the case of Argentina, the most known governmental plans were the *Austral*

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[6] It is worth to mention that we simulated data using another DGP. Let $\{y_t\}$, $t \in \mathbb{Z}$ be a weakly stationary process. Let $\{z_t\}$, $t \in \mathbb{Z}$ be a process contaminated by additive outliers, which is described by

$$z_t = y_t + \sum_{j=1}^{m} w_j X_{j,t},$$

where m is the maximum number of outliers and the unknown parameter ω_j indicates the magnitude of the j_{th} outlier. The $X_{j;t}$ is a random variable with probability distribution $\Pr(X_j = -1) = \Pr(X_j = 1) = p_j/2$ and $\Pr(X_j = 0) = 1 - p_j$. Therefore, X_j is the product of a Bernouilli (p_j) and a Rademacher random variables; the latter equals 1 or –1, both with probability 1/2. Furthermore, y_t and X_j are independent random variables. The model (4) is based on the parametric models proposed by Fox (1972). This DGP is also used by Franses and Haldrup (1994), Fajardo *et al.* (2009), among others. In order to save space, results from this model are not included but they indicate very similar conclusions as in the previous DGP. Such Tables are available upon request.

Program (June 1985), the program of February of 1987, the *Austral II Program* (October 1987), The *Spring Program* (August 1988), the *BB Program* (1989), The *Bonex Program* (January 1990) and the *Cavallo's Program* (March 1991) where the dates in parenthesis correspond to the start date of the programs. In the Peruvian case, we can mention two principal stabilization programs. These are the *Salinas' Program* (September 1988) and the *Fujimori's Program* (July-August 1990). In the Bolivian case, the episode of high inflation was in the middle of 1980's. Many small stabilization programs were applied during the period between 1982 and 1984 but it was the program applied in August 1985 which stopped the high inflation. High inflation in Chile was located around 1975. Diverse programs were applied between 1975 and 1977 until the shock plan applied at the end of 1977 until 1979. A related research to this note is Rodríguez (2004) where four Latin-American countries were analyzed. In this note, we add more countries and more observations. For more details related to the inflationary process in some of these countries, see Rodríguez (2004).

One important issue from Figure 1 is the following. Observing the vertical axis, four countries (Argentina, Bolivia, Chile and Peru) show huge additive outliers. The other countries show also presence of additive outliers but their magnitudes are very different (smaller) in comparison with the above mentioned four countries. It implies that the procedure τ_d will identify more additive outliers in the former countries and less additive outliers in all other countries.

Table 7 shows results from the application of standard and new unit root tests. We apply two standard unit root statistics: the Phillips and Perron and the Augmented Dickey and Fuller statistics; see Phillips and Perron (1988) and Said and Dickey (1984), respectively. Other tests are the M-tests based on GLS detrending data as suggested by Ng and Perron (2001). In all cases, lag length has been selected using the dependent recursive rule named t-sig as proposed by Campbell and Perron (1991)[7]. Almost in all cases, all statistics suggest a rejection of the null hypothesis of a unit root. This result is particularly clear for the Phillips and Perron (1988) test where the rejection is strong. It is not surprising if we remember that this statistic is very oversized when there are strong negative moving average correlation. Given the evidence that this type of correlation implies the presence of additive outliers (see Franses and Haldrup, 1994; Vogelsang, 1999), the results of the PP test is not rare. The results are clearer in countries like Peru where the size of the additive outliers is huge. Even the robust M-tests proposed by Stock (1999) indicate a rejection of the null hypothesis of a unit root except for the cases of Uruguay and Venezuela.

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7 I also use the MAIC approach as suggested by Ng and Perron (2001). Results are very similar and conclusions are not modified. I present the results using the t-sig method to be coherent (in terms of comparison) with the method used in simulations.

Table 4. Size of the ADF Test; ARFIMA (0, *d*, 0) Errors*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$d = 0.00$	Without	0.043	0.037	0.000	0.000	0.000	0.000
	With	0.003	0.002	0.047	0.040	0.040	0.036
	Total	0.046	0.039	0.047	0.040	0.040	0.036
$d = 0.12$	Without	0.029	0.024	0.000	0.000	0.000	0.000
	With	0.002	0.001	0.028	0.021	0.028	0.023
	Total	0.031	0.025	0.028	0.021	0.028	0.023
$d = 0.24$	Without	0.028	0.023	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.026	0.022	0.024	0.021
	Total	0.029	0.024	0.026	0.022	0.024	0.021
$d = 0.36$	Without	0.027	0.023	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.025	0.022	0.022	0.020
	Total	0.028	0.024	0.025	0.022	0.022	0.020
$d = 0.48$	Without	0.023	0.021	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.021	0.021	0.019	0.021
	Total	0.024	0.022	0.021	0.021	0.019	0.021

Lag length selected using the sequential $t - sig$ method

Table 5a. Size of the ADF Test; ARFIMA (0, *d*, 1) Errors with $d = 0.00$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.356	0.282	0.130	0.087	0.000	0.000
	With	0.018	0.012	0.302	0.233	0.396	0.285
	Total	0.374	0.294	0.432	0.320	0.396	0.285
$\theta = -0.40$	Without	0.072	0.057	0.005	0.003	0.000	0.000
	With	0.005	0.003	0.078	0.056	0.072	0.053
	Total	0.077	0.060	0.083	0.059	0.072	0.053
$\theta = 0.00$	Without	0.043	0.037	0.000	0.000	0.000	0.000
	With	0.003	0.002	0.047	0.040	0.040	0.036
	Total	0.046	0.039	0.047	0.040	0.040	0.036
$\theta = 0.40$	Without	0.051	0.039	0.000	0.000	0.000	0.000
	With	0.002	0.001	0.044	0.039	0.045	0.039
	Total	0.053	0.040	0.044	0.039	0.045	0.039
$\theta = 0.80$	Without	0.048	0.041	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.050	0.040	0.038	0.039
	Total	0.049	0.042	0.050	0.040	0.038	0.039

Lag length selected using the sequential $t - sig$ method

Table 5b. Size of the ADF Test; ARFIMA (0, *d*, 1) Errors with $d = 0.24$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.115	0.057	0.019	0.008	0.000	0.000
	With	0.007	0.003	0.112	0.054	0.114	0.054
	Total	0.122	0.060	0.131	0.062	0.114	0.054
$\theta = -0.40$	Without	0.029	0.023	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.029	0.022	0.026	0.022
	Total	0.030	0.024	0.029	0.022	0.026	0.022
$\theta = 0.00$	Without	0.028	0.023	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.026	0.022	0.024	0.021
	Total	0.029	0.024	0.026	0.022	0.024	0.021
$\theta = 0.40$	Without	0.030	0.023	0.000	0.000	0.000	0.000
	With	0.001	0.000	0.028	0.020	0.026	0.018
	Total	0.031	0.023	0.028	0.020	0.026	0.018
$\theta = 0.80$	Without	0.033	0.024	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.027	0.022	0.029	0.021
	Total	0.034	0.025	0.027	0.022	0.029	0.021

Lag length selected using the sequential $t - sig$ method

Table 5c. Size of the ADF Test; ARFIMA (0, *d*, 1) Errors with $d = 0.48$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\theta = -0.80$	Without	0.059	0.045	0.002	0.001	0.000	0.000
	With	0.004	0.002	0.055	0.044	0.054	0.043
	Total	0.063	0.047	0.057	0.045	0.054	0.043
$\theta = -0.40$	Without	0.027	0.024	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.024	0.022	0.024	0.022
	Total	0.028	0.025	0.024	0.022	0.024	0.022
$\theta = 0.00$	Without	0.023	0.021	0.000	0.000	0.000	0.000
	With	0.001	0.001	0.021	0.021	0.019	0.021
	Total	0.024	0.022	0.021	0.021	0.019	0.021
$\theta = 0.40$	Without	0.023	0.021	0.000	0.000	0.000	0.000
	With	0.000	0.001	0.020	0.021	0.022	0.019
	Total	0.023	0.022	0.020	0.021	0.022	0.019
$\theta = 0.80$	Without	0.029	0.021	0.000	0.000	0.000	0.000
	With	0.000	0.000	0.021	0.020	0.029	0.022
	Total	0.029	0.021	0.021	0.020	0.029	0.022

Lag length selected using the sequential $t - sig$ method

Table 6a. Size of the ADF Test; ARFIMA (1, d, 0) Error seith $d = 0.00$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.045	0.040	0.061	0.043	0.008	0.002
	Whit	0.001	0.001	0.021	0.011	0.089	0.055
	Total	0.045	0.041	0.082	0.054	0.087	0.057
$\rho = -0.40$	Without	0.044	0.037	0.006	0.005	0.000	0.000
	Whit	0.002	0.002	0.045	0.037	0.045	0.040
	Total	0.047	0.039	0.051	0.042	0.045	0.040
$\rho = 0.00$	Without	0.043	0.037	0.000	0.000	0.000	0.000
	Whit	0.003	0.002	0.047	0.040	0.040	0.040
	Total	0.046	0.039	0.047	0.040	0.040	0.040
$\rho = 0.40$	Without	0.046	0.037	0.000	0.000	0.000	0.000
	Whit	0.002	0.001	0.039	0.034	0.040	0.041
	Total	0.048	0.038	0.039	0.034	0.040	0.041
$\rho = 0.80$	Without	0.053	0.040	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.048	0.036	0.045	0.044
	Total	0.054	0.041	0.048	0.036	0.045	0.044

*Lag length selected using the sequential $t - sig$ method

Table 6b. Size of the ADF Test; ARFIMA (1, d, 0) Error seith $d = 0.24$*

		$\delta_1 = 0, \delta_2 = 0,$ $\delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3,$ $\delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5,$ $\delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.026	0.023	0.011	0.013	0.000	0.000
	Whit	0.001	0.000	0.012	0.010	0.021	0.024
	Total	0.027	0.023	0.022	0.022	0.021	0.024
$\rho = -0.40$	Without	0.026	0.022	0.000	0.000	0.000	0.000
	Whit	0.001	0.002	0.026	0.022	0.025	0.024
	Total	0.027	0.023	0.026	0.022	0.025	0.024
$\rho = 0.00$	Without	0.028	0.023	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.026	0.022	0.024	0.022
	Total	0.029	0.024	0.026	0.022	0.024	0.022
$\rho = 0.40$	Without	0.030	0.022	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.029	0.020	0.028	0.024
	Total	0.031	0.023	0.029	0.020	0.028	0.024
$\rho = 0.80$	Without	0.057	0.037	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.048	0.040	0.054	0.044
	Total	0.058	0.038	0.048	0.040	0.054	0.044

*Lag length selected using the sequential $t - sig$ method

Table 6c. Size of the ADF Test; ARFIMA (1, *d*, 0) Error seith $d = 0.48$*

		$\delta_1 = 0, \delta_2 = 0, \delta_3 = 0, \delta_4 = 0$		$\delta_1 = 5, \delta_2 = 3, \delta_3 = 2, \delta_4 = 2$		$\delta_1 = 10, \delta_2 = 5, \delta_3 = 5, \delta_4 = 5$	
		T = 100	T = 200	T = 100	T = 200	T = 100	T = 200
$\rho = -0.80$	Without	0.024	0.022	0.006	0.007	0.000	0.000
	Whit	0.001	0.000	0.015	0.014	0.021	0.021
	Total	0.025	0.022	0.021	0.021	0.021	0.021
$\rho = -0.40$	Without	0.023	0.021	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.023	0.020	0.020	0.019
	Total	0.024	0.022	0.023	0.020	0.020	0.019
$\rho = 0.00$	Without	0.023	0.021	0.000	0.000	0.000	0.000
	Whit	0.001	0.001	0.021	0.021	0.022	0.020
	Total	0.024	0.022	0.021	0.021	0.022	0.020
$\rho = 0.40$	Without	0.025	0.021	0.000	0.000	0.000	0.000
	Whit	0.000	0.001	0.023	0.021	0.026	0.021
	Total	0.026	0.022	0.023	0.021	0.026	0.021
$\rho = 0.80$	Without	0.061	0.032	0.000	0.000	0.000	0.000
	Whit	0.001	0.000	0.055	0.041	0.065	0.055
	Total	0.062	0.032	0.055	0.041	0.065	0.055

*Lag length selected using the sequential $t - sig$ method

Table 7. Standard and New Unit root Tests

	Phillips-Perron			ADF			MZ_α^{GLS}	MZ_t^{GLS}	MSB^{GLS}	P_T^{GLS}	k
	Value	$\hat{\alpha}$	k	Value	$\hat{\alpha}$	k	Value	Value	Value	value	
Argentina	−9.475[a]		1	−4.976[a]		1	−29.142[a]	−3.817[a]	0.131[a]	0.841[a]	1
Bolivia	−6.594[a]		3	−4.615[a]		3	−54.306[a]	−5.211[a]	0.096[a]	0.451[a]	3
Chile	−2.812[b]		12	−2.641[c]		12	−11.509[b]	−2.378[b]	0.206[a]	2.211[b]	12
Colombia	−3.125[b]		8	−0.683		8	−1.720	−0.822	0.477	12.672	8
Ecuador	−2.702[c]		8	−2.243		8	−7.339[c]	−1.911[b]	0.260[c]	3.354[c]	8
Peru	−9.380[a]		5	−2.769[c]		5	−10.101[b]	−2.247[b]	0.222[b]	2.426[b]	5
Uruguay	−2.404		8	−1.450		8	−3.452	−1.292	0.374	7.092	8
Venezuela	−3.186[b]		5	−2.199		5	−4.089	−1.414	0.345	6.011	5

Lag length selected using the recursive method $t - sig$; [a,b,c] indícate statistically significancy at 1.0%, 5.0%, and 10.0%, respectively

Figure 1. Quarterly Latin-American Inflation Series

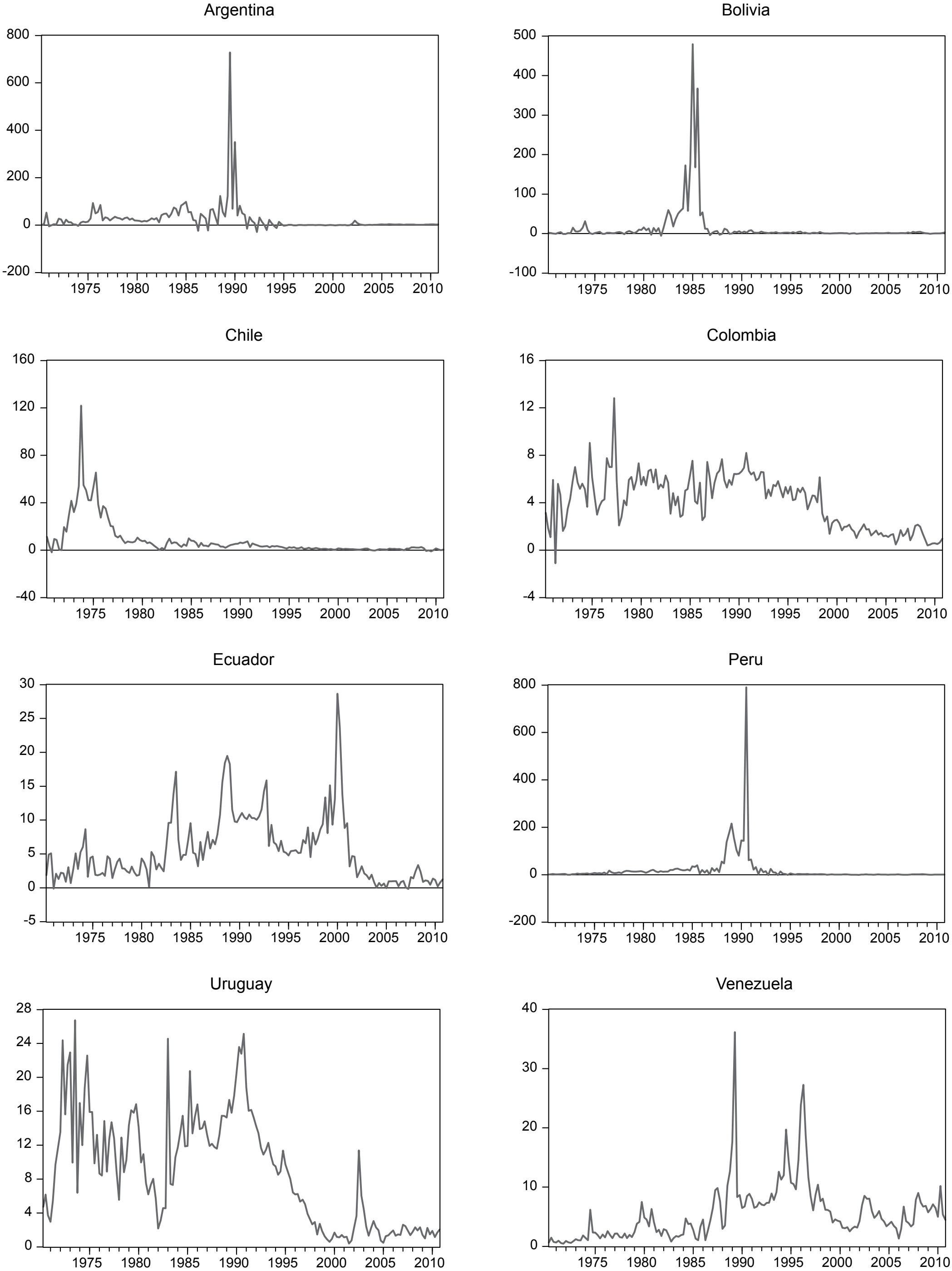

Table 8 shows the results of the ADF statistic corrected for the presence of the additive outliers. The results indicate a non-rejection of the null hypothesis of a unit root for all countries implying that Latin-American inflation series are nonstationary. Rodríguez (2004) found a similar result but only for Argentina and Peru using a shorter sample size. Charemza *et al.* (2005) also find results in favour of nonstationarity of a big set of inflation series when the innovations are treated as draws from a symmetric stable Paretian distribution with infinite variance. This suggest that an appropriate treatment of extreme values is important in this context.

Table 8. ADF Test corrected for Additive Outliers usinf τ_d

Country	Value	Coefficient	k	Outliers
Argentina	−1.723	0.880	7	3
Bolivia	−0.131	0.977	13	16
Chile	−2.353	0.865	12	14
Colombia	−0.329	0.986	8	3
Ecuador	−0.899	0.949	12	2
Peru	1.423	1.098	19	19
Uruguay	−1.378	0.958	10	3
Venezuela	−1.469	0.904	7	5

Lag length selected using the recursive method $t - sig$; [a,b,c] indicate statistically significancy at 1.0%, 5.0%, and 10.0%, respectively

4. CONCLUSIONS

This note analyzes the empirical size of the ADF statistic when there are additive outliers and $ARFIMA(p, d, q)$ errors. Results indicate that a few cases implies oversized ADF tests. In most cases, the statistic is slightly undersized or very close to the nominal size of 5%. There are some difficulties when θ goes to -1 or when ρ goes to $|1|$.

An empirical application for eight Latin-American countries indicates the difficulties that standard and new unit root tests have to verify if there is or no a unit root in the inflation time series. An application of an ADF test with dummies associated to the location of the identified additive outliers confirms that all inflation time series are nonstationary. It is a similar result as obtained by Rodríguez (2004) but using larger sample size and more countries. Results also are consistent with those found by Charemza *et al.* (2005) where results are in favour of nonstationarity of a big set of inflation series when the innovations are treated as draws from a symmetric stable Paretian distribution with infinite variance. It is equivalent to say that an appropiate treatment of extreme values is important.

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