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The EMBI in Latin America: Fractional integration, non-linearities and breaks

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ABSTRACT

This paper analyses the main statistical properties of the Emerging Market Bond Index (EMBI), namely long-range dependence or persistence, non-linearities, and structural breaks, in four Latin American countries (Argentina, Brazil, Mexico, Venezuela). For this purpose it uses a fractional integration framework and both parametric and semi-parametric methods. The evidence based on the former is sensitive to the specification for the error terms, whilst the results from the latter are more conclusive in ruling out mean reversion. Further, non-linearities do not appear to be present. Both recursive and rolling window methods identify a number of breaks. Overall, the evidence of long-range dependence as well as breaks suggests that active policies might be necessary for achieving financial and economic stability in these countries.

1. Introduction

The EMBI (Emerging Market Bond Index) is an index constructed by JP Morgan for dollar-denominated sovereign bonds issued by a selection of emerging countries. It is the most widely used and comprehensive benchmark for emerging sovereign debt markets; it is based on the interest differential between dollar-denominated bonds issued by developing countries and US Treasury bonds respectively, the latter traditionally being considered to be risk-free. This differential, also known as spread or swap, is expressed in basis points (bp). An increase in sovereign bond yields tends to drive up long-term interest rates in the rest of the economy, one of the reasons being the fact that sovereign credit risk is an important determinant of private credit risk as shown in various empirical studies such as Borensztein et al. (2013) and Cavallo and Valenzuela (2010); this increase then affects both investment and consumption decisions, and therefore the economy as a whole. On the fiscal side, higher government bond yields imply higher debt-servicing costs and can significantly raise funding costs. This could also lead to an increase in rollover risk, as debt might have to be refinanced at unusually high cost or, in extreme cases, it might not be possible any longer to roll it over (Gómez-Puig and Mari del Cristo, 2014). Large increases in government funding costs can therefore have real effects in addition to the purely financial effects of higher interest rates (see Caceres et al., 2010).

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This paper analyses the statistical properties of the EMBI in four Latin American countries, namely Argentina, Brazil, Mexico and Venezuela. Specifically, we examine long-range dependence or persistence, non-linearities and structural breaks. Although EMBI series are also available for countries in other emerging regions, in order to be able to make comparisons between more homogeneous economies we have decided to focus on Latin America only, and have chosen four of its most important economies as representative of the region as a whole; more specifically, we have included in the analysis Argentina, Brazil and Mexico as the three main members of Mercosur (the sub-regional bloc created to promote free trade and the fluid movement of goods, people, and currency), and Mexico as the main country in Central America. There are in fact very few existing studies on the behaviour of the EMBI in Latin America. Nogués and Grandes (2001) argue that in Argentina country risk is mainly determined by macroeconomic variables such as the external debt-to-exports ratio and growth expectations rather than the devaluation risk. An example of the very few time series studies is that by Flores-Ortega and Villalba (2013), who applied GARCH models to forecast the variance and return of several variables, including the Mexican EMBI, over the period from 2005 to 2011.

The existing literature mainly estimates structural models to shed light on the determinants of emerging markets sovereign spreads. By contrast, the present paper focuses on the individual EMBI series with the specific aim of obtaining evidence on their dynamic behaviour in response to shocks—whether the latter have permanent or transitory effects, and the speed of reversion to the mean when there is a long-run equilibrium level, are two crucial pieces of information for both market participants to be able to design their investment strategies and policy makers to be able to adopt appropriate policy measures to achieve economic and financial stability.

The rest of the paper is structured as follows. Section 2 outlines the empirical methodology used for the analysis. Section 3 describes the data and the main empirical results, while Section 4 offers some concluding remarks.

2. Methodology

The methods used here are based on the concept of fractional integration, which is more general than the standard approaches based on integer degrees of differentiation that simply consider the cases of stationarity $I(0)$ and non-stationarity $I(1)$. For the present purposes, we define an $I(0)$ process as a covariance-stationary one for which the infinite sum of the autocovariances is finite. This includes the white noise case, but also weakly dependent (stationary) ARMA-type processes. Instead a process is said to be fractionally integrated of order d (and denoted by $I(d)$) if it requires d-differences to make it stationary $I(0)$. In other words, a process $\{x_t,\ t = 0, \pm 1, \ldots\}$ is said to be $I(d)$ if it can be represented as:

$$(1-L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \le 0$, and $d > 0$, where L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$. Note, however that x_t can be the errors in a regression model such as

$$y_t = f(z_t; \theta) + x_t, \quad t = 0, \pm 1, \ldots, \tag{2}$$

where z_t is a set of deterministic terms that might include an intercept and/or a time trend, and f can also be of a non-linear form.

First we consider a linear model, where z_t contains an intercept and linear time trend, such that (2) and (1) become

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{3}$$

under the assumptions of white noise and autocorrelated errors in turn. We estimate the differencing parameter d using a Whittle parametric function in the frequency domain (Dahlhaus, 1989); other maximum likelihood methods (Sowell, 1992; Beran, 1995) produced essentially the same results (not reported). We also apply semi-parametric methods; in particular, we use a "local" Whittle approach introduced by Robinson (1995) and later developed by Abadir et al. (2007) and others. Further, the possibility of non-linear structures in the presence of fractional integration is examined taking the approach of Cuestas and Gil-Alana (2015), who use Chebyshev's polynomials in time as an alternative to linear trends. Such polynomials, defined as

$$\begin{aligned} &P_{0,T}(t) = 1, \\ &P_{i,T}(t) = \sqrt{2}\cos\left(i\pi(t-0.5)/T\right), \qquad t = 1, 2, \ldots, T; \quad i = 1, 2, \ldots \end{aligned} \tag{4}$$

offer various advantages. First, the fact that they are orthogonal means that one avoids the problem of near collinearity in the regressors matrix that typically occurs in the case of standard time polynomials; second, this specification makes it possible to approximate highly non-linear trends with rather low-degree polynomials (Bierens, 1997); third, their shape is ideally suited for modelling cyclical behaviour. We also investigate stability using recursive and rolling-window methods for the estimation of the fractional differencing parameter. Finally, a model combining fractional integration and structural breaks at unknown points in time (Gil-Alana, 2008) is estimated.

3. Data and empirical results

The EMBI series analysed are monthly and cover the period from January 1997 to June 2015. The data source is JP Morgan.

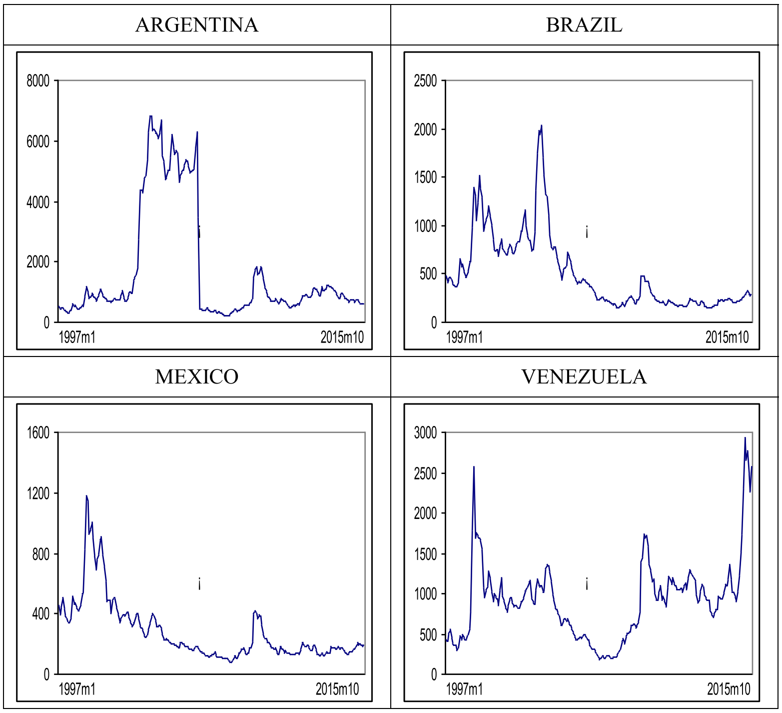

Fig. 1. EMBI.

Table 1
Estimates of d based on a parametric method.

Country	No regressors	An intercept	A linear time trend
(i) White noise errors			
Argentina	1.24 (1.11, 1.42)	1.24 (1.11, 1.43)	1.24 (1.11, 1.43)
Brazil	1.24 (1.11, 1.41)	1.30 (1.15, 1.48)	1.30 (1.15, 1.48)
Mexico	1.10 (0.98, 1.25)	1.19 (1.04, 1.39)	1.19 (1.04, 1.39)
Venezuela	1.11 (1.00, 1.26)	1.10 (0.98, 1.25)	1.10 (0.98, 1.25)
(ii) Autocorrelated errors			
Argentina	0.82* (0.71, 0.95)	0.80* (0.69, 0.95)	0.80* (0.69, 0.95)
Brazil	0.87 (0.73, 1.08)	0.80 (0.65, 1.04)	0.80 (0.63, 1.04)
Mexico	0.83* (0.70, 0.98)	0.63* (0.52, 0.79)	0.61* (0.47, 0.77)
Venezuela	0.84 (0.68, 1.01)	0.80 (0.64, 1.01)	0.81 (0.66, 1.01)

* Evidence of mean reversion at the 5% level. The values in parentheses refer to the 95% confidence intervals of the values of d.

Fig. 1 displays the plots of the four series. It can be seen that in the case of Argentina there is an upward shift around 2002 and a downward one after three and a half years, in July 2005. The Brazilian series exhibits two peaks, in January 1999 and August 2002 respectively, before a sharp decline. In the case of Mexico there is a peak in September 1998, followed by a downward trend. Finally, the Venezuelan series peaks in September 1998 (the same date as in Mexico), December 2008 and June 2015.

As a first step we consider the linear model given by Eq. (3) and estimate the fractional differencing parameter for the three standard cases found in the literature, i.e., those of no deterministic terms, ($\beta_0 = \beta_1 = 0$ in (3)), an intercept (β_0 unknown and $\beta_1 = 0$) and an intercept with a linear time trend (β_0 and β_1 unknown). The results are displayed in Table 1 for uncorrelated (white noise) and autocorrelated errors (as in Bloomfield, 1973) respectively, the latter being a non-parametric approach that produces errors decaying exponentially as in the ARMA case. In addition to the estimates we report the 95% confidence bands of the non-rejection values of d using Robinson's (1994) parametric approach, which is also based on the Whittle function in the frequency domain.

It can be seen that under the white noise specification the unit root null hypothesis is rejected in favour of orders of integration higher than 1 in the case of Argentina, Brazil and Mexico. For Venezuela the estimated value of d is also above 1 but the unit root null (i.e. $d = 1$) cannot be rejected. When using the exponential model of Bloomfield (1973), all the estimated parameters are below 1, and the unit root cannot be rejected for Brazil and Venezuela, but it is rejected in favour of mean reversion (i.e., $d < 1$) in the case of Argentina and Mexico.

Table 2
Estimates of d based on a semiparametric method.

	Argentina	Brazil	Mexico	Venezuela	Conf. intv.
10	1.038	0.688*	0.687*	0.936	(0.739, 1.260)
11	1.127	0.711*	0.736*	0.864	(0.752, 1.247)
12	1.201	0.728*	0.801	0.835	(0.762, 1.237)
13	1.143	0.755*	0.862	0.872	(0.771, 1.228)
14	1.071	0.724*	0.875	0.920	(0.780, 1.219)
15	1.071	0.701*	0.917	0.908	(0.787, 1.212)
16	1.089	0.739*	0.935	0.848	(0.794, 1.205)
17	1.091	0.773*	0.991	0.834	(0.800, 1.199)
18	1.079	0.749*	0.887	0.825	(0.806, 1.193)
19	1.102	0.717*	0.890	0.852	(0.811, 1.188)
20	1.120	0.688*	0.819	0.861	(0.816, 1.183)

* Evidence of mean reversion at the 5% level.

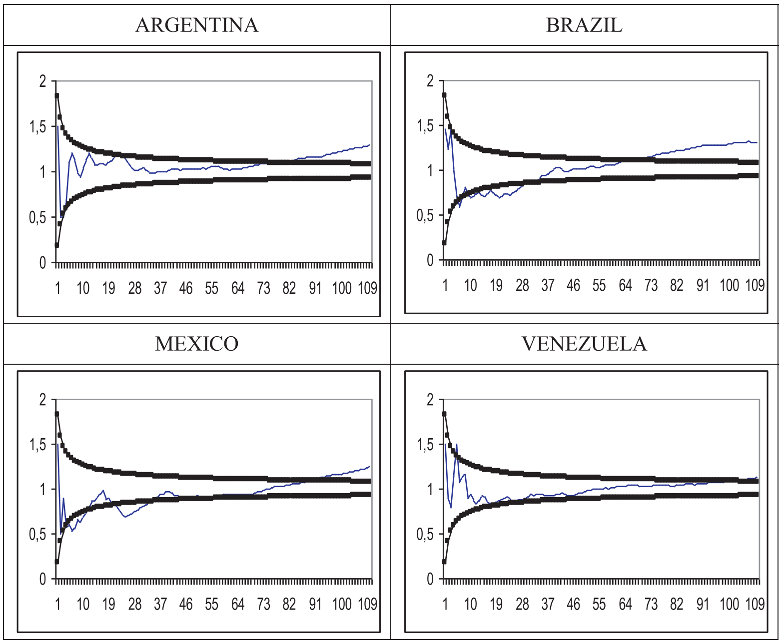

Fig. 2. Estimates of d based on the semiparametric method. The thick lines refer to the 95% confidence intervals in the $I(1)$ case.

Because of the differences in the findings depending on the specification of the error term, we also apply a semi-parametric method that does not require modelling assumptions about the error term. The results reported in Table 2 are for selected bandwidth parameters, while Fig. 2 displays the estimated values of d for the whole range of values ($m = 1, \ldots .T/2$); only for Brazil, and in some cases Mexico, is there any evidence of mean reversion.

The possibility of non-linear behaviour is then examined using the approach developed by Cuestas and Gil-Alana (2015). The model specification is the following:

$$y_t = \sum_{i=0}^{m} \theta_i P_{iT}(t) + x_t, \qquad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{5}$$

where $m = 2$ to allow for a certain degree of non-linearity. Table 3 displays the results for white noise u_t; similar values were obtained with autocorrelated errors.

Consistently with Table 1, the estimated values of d are above 1 and the unit root null is rejected in favour of $d > 1$ for Argentina, Brazil and Mexico, while it cannot be rejected in the case of Venezuela. However, the coefficients of the Chebyshev's polynomials are all statistically insignificant, which means that there is no evidence of non-linear trends.

Next we investigate if the fractional differencing parameter changes over time. The stability analysis is based on the results displayed in the lower panel of Table 1, i.e. those for the Bloomfield specification with an intercept, which is chosen using a battery of diagnostics tests on the residuals. Two different approaches are taken: a recursive one, starting with a sample of 60 observations corresponding to the first five years (1997–2001), and then adding six more observations at a time, and a rolling one with a window of 60 observations.

Table 3
Estimated coefficients in a model with non-linear deterministic trends.

	d	θ_1	θ_2	θ_3	θ_4
Argentina	1.22 (1.08, 1.35)	3399.78 (0.41)	88.39 (0.01)	−769.29 (0.38)	−1337.32 (−1.08)
Brazil	1.29 (1.14, 1.37)	212.60 (0.09)	273.69 (0.18)	2.701 (0.005)	−74.542 (−0.23)
Mexico	1.17 (1.02, 1.35)	34.89 (0.04)	170.54 (0.32)	87.33 (0.40)	45.82 (0.34)
Venezuela	1.10 (0.98, 1.25)	162.89 (0.08)	37.00 (0.03)	200.60 (0.36)	−58.35 (−0.16)

The values in parentheses in the first column are the 95% confidence intervals for d, whilst in the other columns they are t-values.

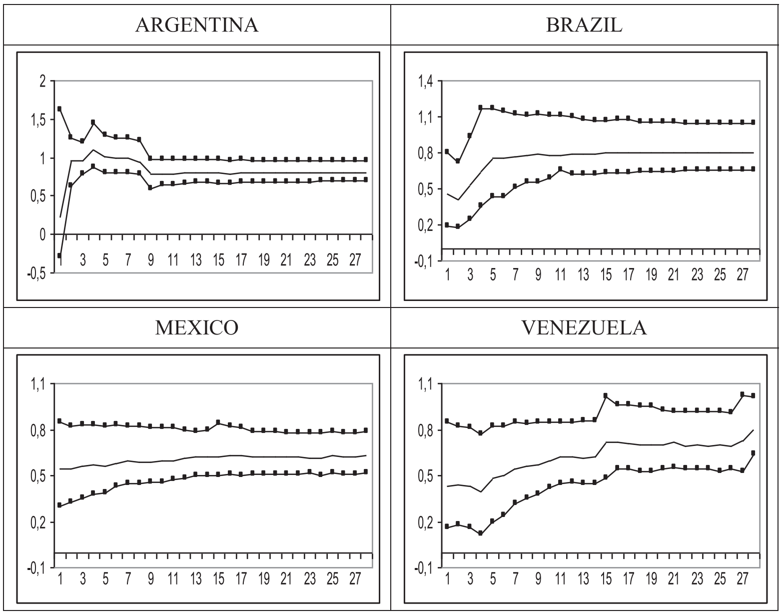

Fig. 3. Recursive estimates of d adding six observations at a time. The dotted lines refer to the 95% confidence bands for the values of d.

Table 4
Estimated break dates using Bai and Perron's (2003) method.

Series	Number of breaks	Break dates
Argentina	2	2001M12, 2005M7
Brazil	1	2004M8
Mexico	2	1999M12, 2003M4
Venezuela	3	2003M12, 2008M9, 2012M10

Fig. 3 displays the estimates of d using the recursive method. In the case of Argentina, the estimate of d is initially very low but increases when adding the observations for the following year, and then remains relatively stable. The results for Brazil are rather similar, with an increase in the estimated value of d around 2002. For Mexico and Venezuela the values are relatively stable, though in the latter case there is a slight increase over time.

The rolling window estimates are reported in Fig. 4. They suggest a higher degree of instability and the possible presence of structural breaks. For this reason we employ the Bai and Perron's (2003) tests for multiple breaks (see also Table 4). Two breaks are detected for Argentina, one in 2001M12, which coincides with the Corralito measures taken by the Argentine government in response to a massive bank run, and the other one in 2005M7, when, buoyed by a strong recovery in the Argentine economy, former president Kirchner obtained an overwhelming triumph in the legislative elections. Only one break is found in Brazil, specifically in 2004M8, i.e. in the early part of the presidency of Lula da Silva, a period that would be characterized by relatively high GDP growth. Two breaks are identified in Mexico, namely in 1999M12, when low GDP growth was a key issue during the presidential campaign, and 2003M4, during a year when inflation and interest rates reached record low levels. Three breaks are found in Venezuela (2003M12, 2008M9 and 2012M10), more than in any other case, which possibly reflects the higher degree of political instability in this country (see also Fig. 5, and 6).

Finally, we test for breaks in the context of an $I(d)$ model as in Gil-Alana (2008). The detected breaks coincide with those identified with the Bai and Perron (2003) method in the case of Argentina (2001M12 and 2005M7). For Brazil the break

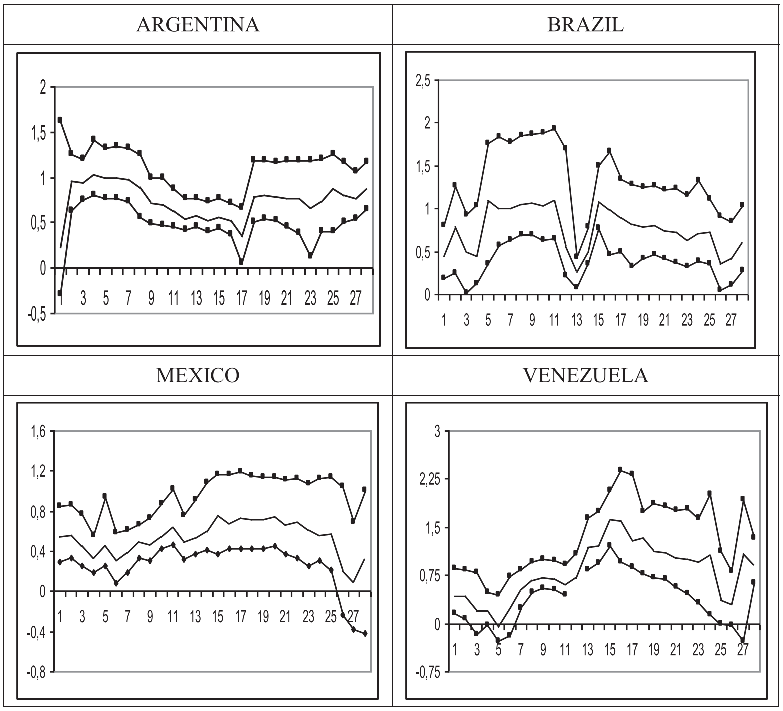

Fig. 4. Recursive estimates of *d* with rolling-windows of 60 observations. The dotted lines refer to the 95% confidence bands for the values of *d*.

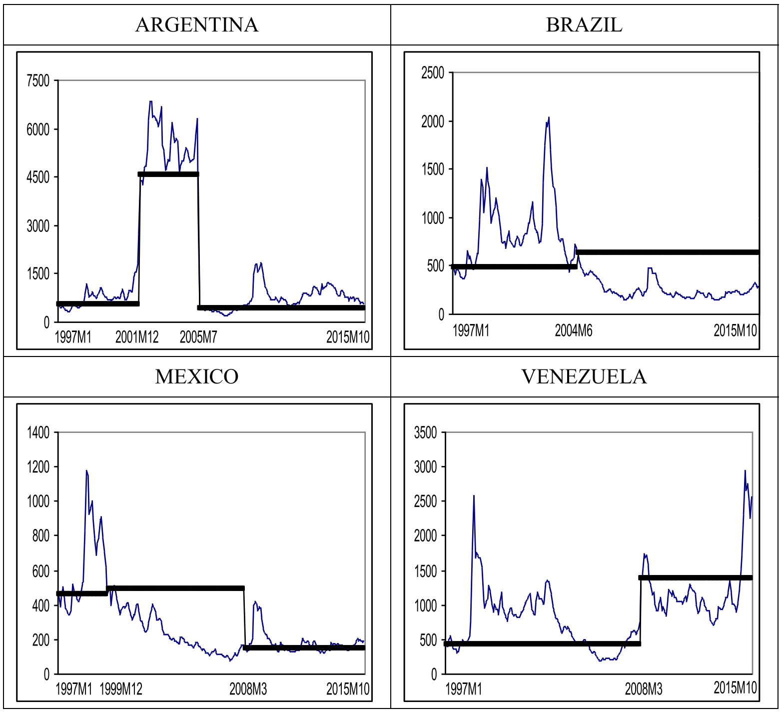

Fig. 5. Estimated trends in the model based on white noise errors.

date is found to be two months before (2004M6); for Mexico, the dates coincide for the first break (1999M12) but not for the second one, now estimated to occur in 2008M3; finally for Venezuela a single break is now found in 2008M9.

Tables 5 and 6 display the estimated coefficients for each country and each subsample under the assumption of white noise and autocorrelated (Bloomfield) disturbances respectively. For Argentina the unit root null cannot be rejected in the first two subsamples, but is rejected in favour of $d > 1$ after 2005M7. For Brazil, the two orders of integration are significantly

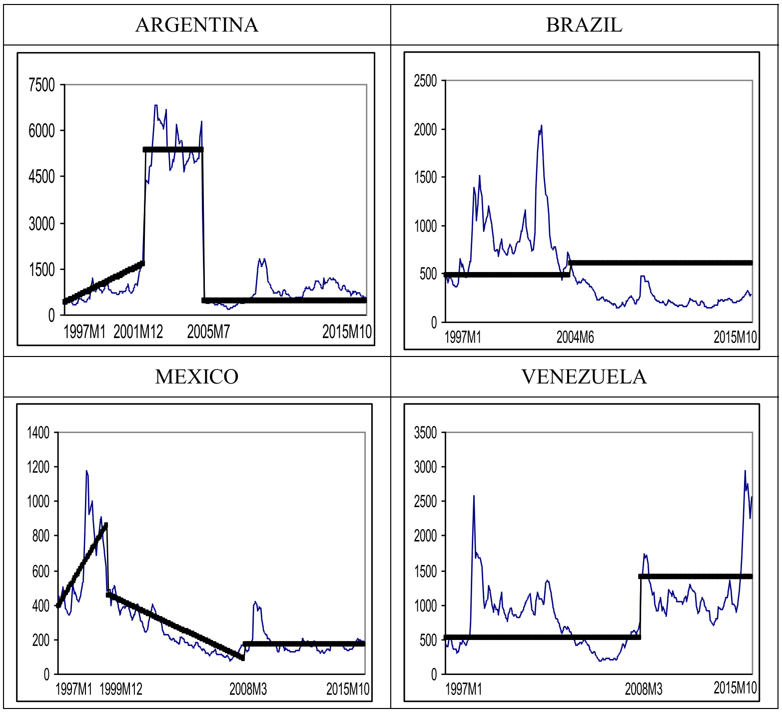

Fig. 6. Estimated trends in the model based on autocorrelated errors.

Table 5
Estimated coefficients with breaks and $I(d)$ behaviour and uncorrelated errors.

Series	Breaks	Date breaks	1st subsample	2nd subsample	3rd subsample
Argentina	2	2001M12 2005M7	1.16 (0.81, 1.69)	0.75 (0.49, 1.50)	1.24 (1.08, 1.46)
Brazil	1	2004M8	1.30 (1.09, 1.60)	1.21 (1.07, 1.41)	–
Mexico	2	1999M12 2003M4	1.24 (0.90, 1.82)	1.03 (0.81, 1.34)	1.17 (0.99, 1.43)
Venezuela	1	2008M9	1.01 (0.86, 1.22)	1.19 (1.02, 1.44)	–

Table 6
Estimated coefficients with breaks and $I(d)$ behaviour and autocorrelated errors.

Series	Breaks	Date breaks	1st subsample	2nd subsample	3rd subsample
Argentina	2	2001M12 2005M7	0.53(−0.02, 1.14)	0.23* (−0.12, 0.86)	0.82 (0.62, 1.13)
Brazil	1	2004M8	0.75 (0.43, 1.14)	0.89 (0.59, 1.20)	–
Mexico	2	1999M12 2003M4	0.15* (−0.43, 0.84)	0.49* (0.28, 0.85)	0.66 (0.33, 1.12)
Venezuela	1	2008M9	0.63* (0.46, 0.86)	0.96 (0.71, 1.31)	–

* Evidence of mean reversion at the 5% level.

higher than 1. For Mexico, the unit root null cannot be rejected in any of the three subsamples, while for Venezuela a unit root is found in the first subsample, and an order of integration significantly higher than 1 after the break in 2008M9.

When allowing for autocorrelated errors, the break dates coincide with those identified with white noise disturbances, but the estimates of d are much lower and the confident bands wider. For Argentina, the estimated values of d are 0.53, 0.23 and 0.82 respectively for the first, second and third subsample, although the confidence bands imply that mean reversion only takes place in the second subsample. For Brazil, the two estimates of d are smaller than 1 but the unit root null hypothesis cannot be rejected in either of the two subsamples. For Mexico the estimated value of d increases from 0.15 in the first subsample to 0.49 in the second one and to 0.66 in the third one, and mean reversion occurs in the first two cases. For Venezuela, the estimated value of d also increases from 0.63 to 0.96 and mean reversion is found only in the first subsample.

4. Conclusions

The EMBI is a key benchmark for emerging sovereign debt markets. However, very limited empirical evidence is available concerning its behaviour in Latin America. The present study fills this gap by examining it in four countries belonging to this region (Argentina, Brazil, Chile and Mexico), and investigating in particular long-range dependence or persistence, as well as possible non-linearities and structural breaks. Moreover, it uses a fractional integration framework which is more general than the standard approach based on the $I(0)/I(1)$ dichotomy.

Both parametric and semi-parametric methods are applied. The evidence based on the former is sensitive to the specification for the error terms, whilst the results from the latter are more conclusive in ruling out mean reversion. Further, non-linearities do not appear to be present. Both recursive and rolling window methods identify a number of breaks, which can be plausibly be interpreted in terms of some well-known political and economic developments in the countries of interest. Overall, the evidence of long-range dependence as well as breaks suggests that active policies might be necessary for achieving financial and economic stability in these countries.

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