Department of
Economics and Finance

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. In addition to being useful for measuring the performance of this asset class, it is the most widely used and comprehensive benchmark for emerging sovereign debt markets, and it also helps increase their visibility.

The EMBI 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). A spread of 100 bp means that the yield on bonds issued by the government in question is one percent (1%) higher than that on the risk-free US Treasury Bills: riskier bonds (with a higher default probability) pay higher interest. An increase in sovereign bond yields tends to drive up long-term interest rates in the rest of an economy, affecting both investment and consumption decisions. 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).

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.

The rest of the paper is structured as follows. Section 2 briefly reviews the existing literature on the EMBI in Latin America. Section 3 outlines the empirical

3. 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 nonstationarity 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 $\{x_t$

said to be I(d) if it can be represented as:

$$(1 \quad L) \; x_t \quad u \; , \quad t \quad 0, \; 1, \ldots, \qquad (1)$$

with x_t L is the lag-operator ($Lx_t \quad x_{t \; 1}$) and u_t is I 0 .

Note, however that x_t can be the errors in a regression model such as

$$y_t \quad f(z_t; \quad) \quad x_t, \quad t \quad 0, \; 1, \ldots, \qquad (2)$$

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

$$y_t \quad {}_0 \quad {}_1 t \quad x_t, \qquad (1 \quad L)^d x_t \quad u_t, \; t \quad 1, 2, \ldots, \qquad (3)$$

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 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 ials in time as an alternative to linear trends. Such polynomials, defined as

As a first step we consider the linear model given by equation (3) and estimate the fractional differencing parameter for the three standard cases found in the literature, i.e., those $_0$ $_1$

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

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.

[Insert Table 3 about here]

Consistently with Table 1, the estimated values of d are above 1 and the unit root null hypothesis 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 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

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Nogués, J. and M. Grandes (2001) Country risk: Economic policy, contagions effect or political noise?, *Journal of Applied Economics* 1, 4, 125-162.

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Sowell, F. (1992) Maximum likelihood estimation of stationary univariate fractionally integrated time series models, *Journal of Econometrics* 53, 165.188.

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Figure 1: EMBI

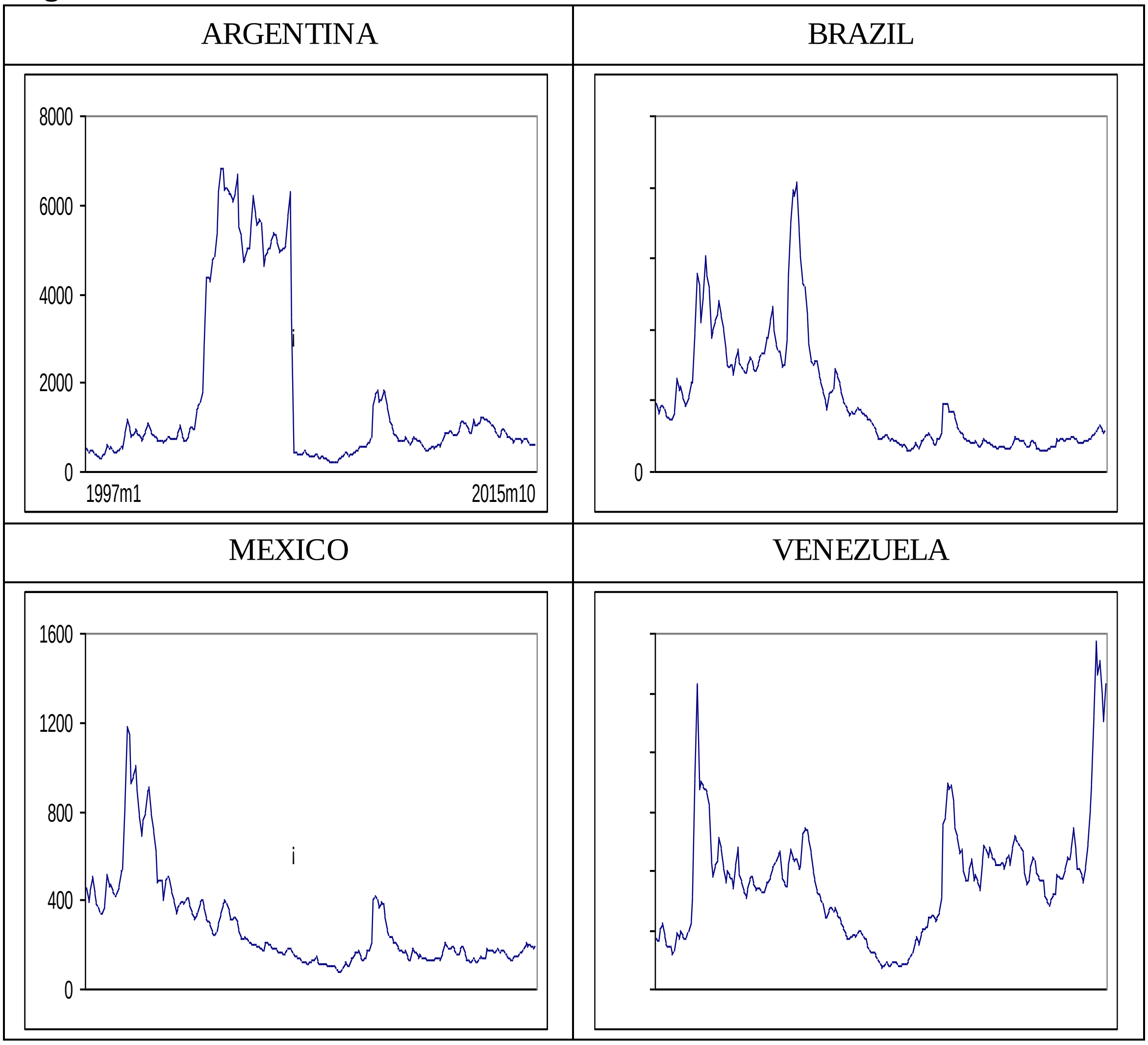


Figure 2: Estimates of d based on the semiparametric method

ARGENTINA	BRAZIL
MEXICO	VENEZUELA

FigurMCID 1>BDC BT/F3 12 Tf1 0 0 1 2t0(e)-55 BT-124(3:)21 BT-62(R)-27(e)-55 c0 0 1 2t0(s)-48Tf1vee

Figure 4: Recursive estimates of d with rolling-windows of 60 observations

Figure 3: Estimated trends in the model based on white noise errors

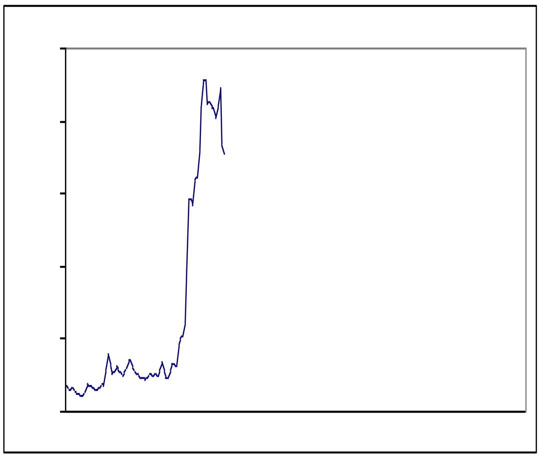
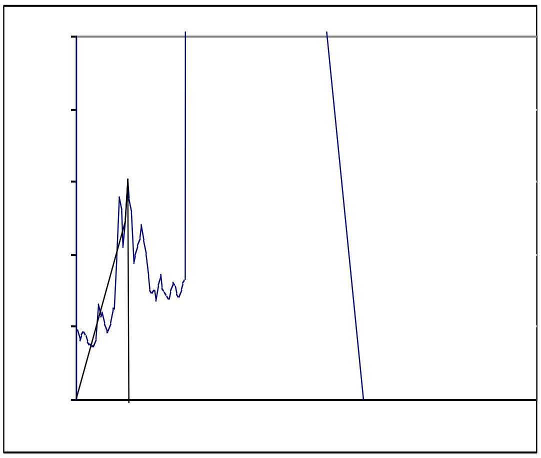
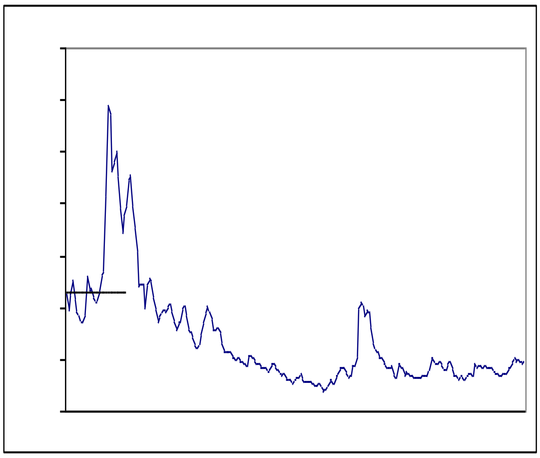
ARGENTINA	BRAZIL
	
MEXICO	VENEZUELA
	

Figure 4: