



# Nonlinearities and financial contagion in Latin American stock markets<sup>☆</sup>



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## ABSTRACT

We use the Hinich (1996) portmanteau bicorrelation test to graphically represent nonlinear events detected in Latin American stock markets. We identify the starting, the ending, the intensity, and the persistence of nonlinear episodes. The six episodes identified in the period studied were found to be contemporaneous with international financial crises, which allows us to speculate that the contagion caused by financial crises induces nonlinear dependencies. We advocate that this test could be complementary to traditional tests employed in the study of financial contagion. We observe systematic nonlinear structure in the stock index return series that have been associated with temporary lack of market efficiency. This new approach can help financial analysts and regulators to assess graphically the state of dependence measured by the bicorrelation test as frequently as new information arrives.

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## 1. Introduction

A key lesson from finance theory is the importance of diversification when forming portfolios, especially in an international context. However, in times of financial crises, diversification may not prove to be effective if there is financial contagion across markets. This is important in order to keep the financial stability of markets, and there is a growing body of literature about the integration of financial markets and the way they behave. See, for example, [Sharma and Seth \(2012\)](#) for a review of papers on stock market integration.

The present paper gives us a better understanding of the functioning of emerging financial markets and the connections among them. The way financial markets interact is important because of the spillover effects they have with each other. When an international event occurs, it impacts directly on the emerging markets but also hits indirectly through the financial contagion, which is triggered by the event. Hence, financial analysts must be aware of international co-movements and make decisions to safeguard (or even take advantage) of this connection.

Recently, [Gilmore et al. \(2008\)](#), in studying market integration in Central European equity markets, criticized previous empirical studies that used static cointegration techniques yielding differing findings

that may, in part, be sample dependent. They argue that previous studies assume stability in long-run relationships and that assumption may not be warranted. Instead, they argue that linkages between equity markets may be time-varying and episodic. A similar result, namely, time-varying and episodic nonlinearity for univariate time series, has been reported by an increasing number of articles in the literature. This line of research started with the seminal contribution of [Hinich and Patterson \(1985\)](#) and it has been an active line of research in recent years. See, for example, [Lim and Hinich \(2005\)](#), [Panagiotidis \(2005\)](#), and [Bonilla et al. \(2006\)](#).

We know that during financial crises, emerging financial markets are more vulnerable, and it is expected that they would present certain co-movements as the literature describes. Nonetheless, questions arise: Is the possible dependence introduced by financial crises linear or nonlinear? How long would it be? When is it going to end? How intense would it be?

Motivated by this concern, this paper attempts to answer these questions, and in order to do so, we introduce a new graphical representation of the statistics generated by the [Hinich \(1996\)](#) test. With this simple graphical representation, we are able to identify the starting, the ending, the intensity, and persistence of nonlinear episodes.

We use daily data for six Latin American stock market indexes – Brazil, Venezuela, Peru, Chile, Argentina, and Mexico – together with the [Hinich \(1996\)](#) portmanteau bicorrelation test to detect the persistence and contagion of the nonlinear events.

This study is within the recent literature focused on emerging markets in general and in Latin American countries in particular. Latin American financial markets are an interesting case study, namely,

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because these countries are considered to have volatile capital markets that have also shown to have episodic events of nonlinear behavior. There are many papers that document the special characteristics of these markets, and the impact that international financial crises have on them. See, for example, Calvo and Reinhart (1996), Chen et al. (2002), Coronado et al. (2015), and Loaiza-Maya et al. (2015).

Our study follows Lim (2007) in the application of the Hinich (1996) portmanteau biconrelation test in a rolling window framework, but we complement it with a new graphical representation. This allows us to explore research questions dealing with the intensity of nonlinear behavior measured by the number of windows that contain a particular day exhibiting nonlinear dependence. In addition, we can investigate the persistence of nonlinear behavior, measured by the length of time with consecutive presence of nonlinear dependence, and the contagion across indexes, that is evidenced by the simultaneous nonlinear dependence in more than one index.

The graphical approach enables us to determine for each day the number of times that the day is present in windows with significant nonlinearity. Afterwards, we compare for each day and for all six Latin American stock markets the nonlinear episodes. Using this new tool, we are able to depict the initial and the final day of episodes of nonlinear dependence and compare each episode across the sample for the stock markets studied.

It is important to emphasize that the statistical method is the primary tool for the analysis, but the graphical representation, which is based on the aforementioned technique, provides a new perspective on the tests.

We also identify six episodes that show simultaneous presence of nonlinear dependence in five of the six emerging markets considered within our study. Furthermore, we investigated whether those episodes could be related to political or economic events in the region and found that all of them are contemporary to major international crises.

We consider the new tool – the graphical study of the higher order moment of the distribution of returns – as complementary to the standard methods used in the financial contagion literature. In a similar way, Fry et al. (2010) proposed the use of coskewness to define a new class of contagion tests.

## 2. The data

We use daily data from Bloomberg for six Latin American stock market indexes. In particular, we use IBOV (Brazil), IBVC (Venezuela), IGBVL (Peru), IGPA (Chile), Merval (Argentina), and MEXBOL (Mexico). The sample period for the indexes is from January 1, 1994, to November 20, 2012. We calculate the rate of return as  $R_t = \ln(P_t/P_{t-1})$  where  $P_t$  is the closing value of the index on day  $t$ . This can be interpreted as a continuously compounded daily return—see, for example, Brock et al. (1991).

We choose to work with daily data because it contains more information than longer period data. We do not have available intraday data for all markets, which is another type of data commonly used in the study of nonlinearities (Romero-Meza et al. (2010), Brooks and Hinich (2006)).

Because of the length of the time series (from 1994 to 2012), there could be concerns about the possibility of structural breaks. However, one important property of the Hinich (1996) portmanteau test is the possibility to apply it in small size windows. In our case, each window has 50 observations, thus the stationarity assumption is not stringent. Given our sample period, we select more than 90 windows. Therefore, the possibility of structural break would not affect most of the windows, and consequentially our results would be well-founded. It is important to mention that the data sample cover the period in which the recent most significant global financial crisis occurred, and therefore, we capture the financial turmoil together with periods of low volatility.

## 3. Empirical evidence

Before checking for potential nonlinear behavior, we remove any linear dependence in the data by fitting an AR( $p$ ) model to the logarithmic first difference (continuously compounded rate of return) of each index. Thus, we make sure that the rejection of the null hypothesis of pure noise at the specified threshold level is due only to significant nonlinearity. We then divide the data into a set of overlapping rolling windows of 50 observations in length and apply the Hinich (1996) portmanteau biconrelation test, which we briefly discuss in what follows.

Let the sequence  $\{z(t)\}$  denote the standardized sampled data process, where the time unit  $t$  is an integer. The standardization is

$$z(t_k) = \frac{y(t_k) - \mu_y}{\sigma_y}$$

which is done “frame-by-frame,” where  $\mu_y$  is the sample mean and  $\sigma_y^2$  is the sample variance within each frame. In the rolling sample approach, the  $H$  statistic is computed for the first window of a specified length, and then the sample is rolled one point forward eliminating the first observation and including the next one for re-estimation of the  $H$  statistic. This process continues until the last observation is used. In other words, the start date and end date successively increase by one observation. For instance, in a fixed-length rolling window of 50 observations, the first window starts from day 1 and ends on day 50, the second window comprises observations running from day 2 through day 51, and so on. The last window is built with the last 50 observations. Therefore, if  $n$  is the window length, then the  $k$ th window is  $\{z(t_k), z(t_k + 1), \dots, z(t_k + n - 1)\}$ . The next window is  $\{z(t_k + 1), z(t_k + 1 + 1), \dots, z(t_k + 1 + n - 1)\}$ .

The null hypothesis for each window is that  $z(t)$  is the realization of a stationary pure white noise process that has zero biconrelation. The alternative hypothesis is that the process generated within the window is random with some non-zero biconrelations  $C_{zzz}(r, s) = E[z(t)z(t+r)z(t+s)]$ .

The Hinich (1996) portmanteau  $H$  statistics and its corresponding distribution is

$$H = \sum_{s=2}^L \sum_{r=1}^{s-1} G^2(r, s) \sim \chi^2_{(L-1)(L/2)}$$

Where

$$G(r, s) = (n-s)^{1/2} C_{zzz}(r, s)$$

and

$$C_{zzz}(r, s) = (n-s)^{-1} \sum_{t=1}^{n-s} z(t)z(t+r)z(t+s)$$

for  $0 \leq r \leq s$ .

Once the  $C$  and  $H$  statistics are computed, we select the AR( $p$ ) fit that reduces the presence of linear correlation in each of the indexes to less than 0.05% (in this case we used an AR(3)). We then identify the start and end date of each significant  $H$  statistic window. Given the applied rolling procedure, it is possible for a specific day to be present in several windows.

Fig. 1(a) shows a sub-sample for IBOV (Brazil), ranging from 01-01-1996 to 03-31-1999. Analyzing area A, we can observe that a nonlinear event took place in the time window from 07-26-1996 to 10-04-1996, although the effect is only significant within that specific window. The adjacent windows do not provide evidence of nonlinear dependence. Therefore, we infer that the nonlinear event that took place within those days is significant at a 95% confidence level, but not relevant enough to generate an  $H$  significant effect in the immediately prior or following windows. In contrast, the days contained in the window

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