Testing for intensity, persistence and financial contagion in Latin America: A new use of the Hinich Bicorrelation test

Abstract

We use the Hinich bicorrelation test in a rolling window framework and combined it with a new method that graphically represents nonlinear events in stock indexes. The proposed approach was applied to detect nonlinear episodes in Latin American stocks markets, proving able to determine their start and end dates, intensity and persistence. The six episodes identified in the period studied were found to be contemporaneous with international financial crises, suggesting that the contagion caused by financial crises may induce nonlinear dependencies. The approach is complementary to traditional tests employed in the study of financial contagion. The adoption of the proposed approach would enable financial analysts and regulators to assess graphically the state of dependence measured by the bicorrelation test in real time.

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JEL Classification: F36 - Financial Aspects of Economic Integration, G14 - Information and Market Efficiency; Event Studies, G15 - International Financial Markets, C12 - Hypothesis Testing: General

Key words: Nonlinear behavior, Hinich portmanteau bicorrelation test, Latin American stock market, contagion, efficient market hypothesis.

1 Introduction

The efficient market hypothesis (EMH) has been an active topic of research for both practitioners and academics. The weak-form version of EMH has been studied empirically using statistical tools such as serial correlation, run tests, variance ratio tests, unit root tests and spectral analysis. The evidence, however, even from different studies of the same stock market, can be contradictory (see Lim (2007)). A major limitation of the standard tests is their focus on testing the all-or-nothing notion of absolute market efficiency. In recent years, however, studies have tended increasingly to use the rolling sample approach to market efficiency testing (see Cajueiro and Tabak (2004, 2005), Lim (2007), and Lim and Brooks (2009)). This dynamic approach has the added advantage of enabling researchers to compare the efficiency of different sub-periods in a particular stock market.

A key lesson from financial theory is the importance of diversification in portfolio selection, especially in an international context. In times of financial crises, however, diversification may not be effective if there is financial contagion across stock markets. Examples of the literature on cross-country stock market and bond market linkages are Forbes and Rigobon (2002) and Dungey et al. (2006), respectively. There is a growing body of knowledge on the integration of financial markets, see for example Sharma and Seth (2012) that studied a selection of 100 different research papers from among the thousands that have been published on stock market integration.

A relatively recent article on market integration in Central European equity markets by Gilmore et al. (2008) critiques previous empirical studies using static cointegration techniques that yielded differing results which may in part have been sample dependent. The authors contend that the assumption made in these earlier works of stability in the long-run relationship might not be warranted, suggesting instead that the linkages between equity markets may be time-varying and episodic.

A similar finding of time-varying and episodic nonlinearity for univariate financial series has in fact been reported in an increasing number of works. This line of research started with the seminal contribution of Hinich and Patterson (1985), which applied the bispectrum test to investigate nonlinearities on the New York Stock Exchange. Studies of nonlinearities in developed capital markets have been published by various authors, including Scheinkman and LeBaron (1989), and specifically for the U.S. by Hsieh (1991), for the UK by Abhyankar et al. (1995) and Opong et al. (1999), and for Germany by Kosfeld and Robé (2001). Nonlinearities in developing capital markets have been analyzed generally by Cajueiro and Tabak (2004) and Lim (2007), and more specifically by Ammerman and Patterson (2003) for Taiwan, Antoniou et al. (1997) for Turkey, Panagiotidis (2005) for Greece, Lim and Hinich (2005) for Asian markets, Bonilla et al. (2006) for several Latin American stock markets and Romero-Meza et al. (2007) for the Chilean stock market.

A recent survey paper by Lim and Brooks (2011) reviewed the weak-form market efficiency literature on the predictability of stock returns based on past price changes, and found more than 300 papers from the last five years applying a range of methods.

The study of nonlinearities is closely linked to the concept of market efficiency. If a financial (stock or currency) market satisfies the weak-form of the efficient market hypothesis (EMH), then future prices cannot be predicted from past prices and the rate of return must follow a random walk. As a consequence, we should not expect to find any kind of serial dependencies in the data because their presence would be an indicator of he possibility of return predictability.

Previous studies have found episodic nonlinear dependence in several financial markets and for several financial and economic time series; however the phenomenon has been relatively little studied for nonlinear events that share common periods of time and thus were caused by common external economic or political factors. Moreover, we conjecture that these cases of nonlinear dependence might be sensitive to the choice of starting day in the testing procedure.

In an effort to shed light on these common factors and the possible sensitivity to the starting day, the present study follows Lim (2007) in applying the Hinich bicorrelation test using a rolling window approach, but complements it with a new graphical representation. This added feature enables us to identify the number of times a given day is contained in a window presenting nonlinear behavior. This constitutes a new and important extension of the previous literature, allowing us to explore a number of interesting research questions regarding: i) the *intensity* of nonlinear behavior, measured by the number of windows that contain a particular day exhibiting nonlinear dependence; ii) the *persistence* of nonlinear behavior, measured by the length of time consecutive nonlinear dependence is present; and iii) the *contagion* across indexes, as evidenced by simultaneous nonlinear dependence in more than one index.

Our study contributes to the literature in several respects. First, we propose a new approach to the application of the Hinich portmanteau bicorrelation test (H) in a rolling sample methodology that detects periods of efficiency/inefficiency and measures their *intensity* and *persistence*. The relative efficiency of stock markets can then be assessed by comparing the total length of time these markets exhibit significant nonlinear serial dependence. In Lim (2007) a similar methodology is proposed to evaluate the relative efficiency of several stock markets, but we make new use of it in the context of financial integration and *contagion*. Thus, our second contribution is the use of a graphical approach to determine, for each day, the number of times it is present in windows with significant nonlinearity. Then, for each day, we compare all Latin American markets to establish whether it exhibits nonlinear dependence. This new application of the tool can depict the first and last days of nonlinear dependence episodes and compare each period for the emerging stock markets studied. We identify six episodes where there is simultaneous presence of nonlinear dependence in five of the six emerging markets considered in the study. Furthermore, we investigate whether these episodes could be related to political or economic events in the region and find that all of them do in fact coincide with major international crises.

We consider this tool to be complementary to the standard methods found in the literature on financial integration such as cointegration since, as will be seen below, we will apply higher-order moments of the distribution of returns. Similarly, Fry et al. (2010) propose the use of co-skewness to define a new class of test of contagion.

The structure of the remainder of this paper is as follows. Section 2 briefly describes the Hinich portmanteau bicorrelation test and the rolling window approach. Section 3 presents the data to be used in this study. Section 4 presents the empirical results obtained. Final conclusions are given in section 5.

2 The Hinich Portmanteau Bicorrelation Test

The Hinich test has been analyzed in detail in more previously published papers (Hinich, 1996, Bonilla et al., 2006, Lim, 2007); what follows is a brief review of its main features. The statistic used by the test is denoted the *H* statistic.

The test is applied via a rolling sample procedure in which the *H* statistic is calculated iteratively for successive windows, each one embracing the same fixed number of observations corresponding to a set number of days within the sample period. The sample is rolled forward one observation after each H-statistic calculation, thus dropping one observation and adding a new one with each forward roll until the last observation has been included. As an example, with a fixed window length of 50 observations, the first window spans the observations day 1 through day 50, the second window starts with day 2 and ends with day 51, and so on. In formal terms, if n is the window length, then the $k-th$ window is $\{z(t_k), z(t_k+1), \ldots, z(t_k+n-1)\}$ and the following window is $\{z(t_{k+1}), z(t_{k+1}+1), \ldots, z(t_{k+1}+n-1)\}$.

The observations sampled in each window are standardized using the formula $z(t_k) = \frac{y(t_k) - m_y}{s_y}$, where t is a time counter integer representing the day, m_y is the sample mean and s_y^2 is the sample variance. The sequence of standardized samples is denoted $\{z(t)\}$.

For each window, the null hypothesis is that $z(t)$ are realizations of a stationary pure white noise process that has zero bicorrelation. The alternative hypothesis is that the process generated within the window is random with some non-zero bicorrelations $C_{zzz}(r,s) = E\,[z(t)z(t+r)z(t+s)]$ in the set $0 < r < s < L$, where L is the number of lags that define the window. A more complete review of the rolling windows approach is found in Lim and Brooks (2009).

The Hinich portmanteau H statistic and its corresponding distribution are given by

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

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 $0 \le r \le s$

The number of lags L is specified as $L = n^b$ with $0 < b < 0.5$, where b is a parameter chosen by the analyst. Based on results from Monte Carlo simulations (see Hinich and Patterson, 2005), the recommended value for the parameter is $b = 0.4$, which maximizes the power of the test while ensuring a valid approximation to the asymptotic distribution.

A window is significant in this test procedure if the H statistic rejects the null of pure noise at the specified threshold level. In order to reduce detection of linear dependence caused by non-zero correlations, the data set is filtered by an autoregressive AR(p) model. This ensures that rejection of the null hypothesis of pure noise at the specified threshold level is due only to significant nonlinearity. As for the window length, it should be long enough to validly apply the test yet short enough to capture nonlinear episodes within a window, considerations which have led to the recommendation that the number of observations per window be set at 50 (Brooks and Hinich, 1998).

3 The Data

Our analysis is based on daily data for six Latin American stock market indexes: IBOV (Brazil), IBVC (Venezuela), IGBVL (Peru), IGPA (Chile), MERVAL (Argentina) and MEXBOL (Mexico). The data themselves were obtained from Bloomberg. The sample period in every case was January 1st, 1994 to November 20th, 2012. The data were transformed using the formula $Rt = Ln\left(\frac{Pt}{Pt-1}\right)$, where *Pt* is the closing value of the stock market index on day *t*. The result can be interpreted as a continuously compounded daily return (see Brock et al., 1991).

4 Empirical Results

Before checking the index series for potentially nonlinear behavior, any linear dependencies between them were removed by fitting an AR(p) to the log differences. This ensured that the null hypothesis of pure noise at the specified threshold level would be rejected only if there were significant nonlinearity.

The data were then divided into a set of overlapped rolling windows, each one 50 observations long, and the Hinich portmanteau bicorrelation test was applied to the residuals of the fitted AR(p) model.

<Insert table 1 around here>

The number and percentage of windows found to have significant *C* and *H* statistics are given in Table 1. The results are consistent with earlier findings reported in Bonilla et al. (2006) and Romero-Meza et al. (2007) in terms of the episodic nature of both linear and nonlinear dependence; here, however, we have extended the analysis using our new methodology to identify the intensity and persistence of the nonlinear dependence.

Once the C and H statistics were computed, we selected the AR(p) fit that reduced the presence of linear correlations in all indexes to less than 0.05%. In the present case, we chose to use an AR(3). We then identified the start and end dates of each significant H statistic window. Because a rolling procedure was used, a specific day could be present in more than one window. For each index we graphed the number of times each day was contained in a significant H statistic window. Graph 1 shows the results for IBOV (Brazil); graphs for the other five indexes are given in the appendix.

<Insert graph 1 around here>

Two main inferences can be extracted from Graph 1. The first relates to the intensity of certain nonlinear events and the second to the persistence of the nonlinear behavior.

In terms of overall intensity, some of the windows that generated a significant H statistic might not, in our view, be relevant in the context of the whole period under analysis. Lim (2007) uses the percentage of H-significant windows to measure the relative efficiency of a market.

According to his methodology, the least efficient would be Venezuela and the most efficient would be Chile. We propose an alternative analysis focused on not only the percentage of H-significant windows but also its distribution and clustering across time.

For example, in Graph 2, which displays a subsample of Graph 1 for the period January 1st, 1996 to March 31st, 1999, we observe that a nonlinear event occurred in the time window covering July 26th, 1996 to October 4th, 1996 (Area A in the graph). However, the effect is only significant within that specific window; the immediately adjacent windows show no evidence of nonlinear dependence. We therefore infer that the nonlinear event that took place between the indicated dates, though significant at a 95% confidence level, was not strong enough to generate an H-significant effect in the window immediately preceding or following. In contrast, the 3 days contained in the window shown as Area B (07-15-1997 to 07-17-1997) are contained in 48 H-significant windows, meaning that the nonlinear event which occurred over those days is significant in 48 different windows at a 95% confidence level. We can therefore infer that the relative intensity of the nonlinear event detected in Area A is lower that of the event detected in Area B.

<Insert graph 2 around here>

As regards the persistence of nonlinearity, we would argue that an event that generates nonlinear dependence is not only intense enough to be detected in more than 1 window, but may also outlast the duration of the windows that originally contained it (in this case, more than 50 trading days, the fixed window length). For example, there is evidence of permanent nonlinear dependence in area C of Graph 2. Between 05-07-97 to 03-30-98, all 327 days show significant H statistics. In this case, we can infer that the event which originated the nonlinear dependence is persistent enough to be reflected throughout a period much longer than the length of a single set of windows.

The results of the procedure for the other five indexes were similar (see graphs 5 through 9 in appendix). There is evidence of varying levels of both nonlinear intensity and persistence, with peaks of up to 48 windows with significant H statistics for a single day and strong clustering around certain events.

To determine whether any nonlinear events occurred across markets, we graphed the number of indexes that showed evidence of nonlinear dependence for each day in the period under analysis. As can be seen in Graph 3, there were six periods during which five of the six analyzed indexes showed significant H statistics simultaneously. This observation does not, of course, take account of either the intensity or the persistence of each period, but it does reveal the cross-temporal synchronicity between indexes.

<Insert graph 3 around here>

For each of the six events registered across five indexes we then graphed the period stretching from 5 days before the start of the event to 5 days after its end. For purposes of plotting the graphs, we defined a nonlinear dependence event as a period of consecutive days during which there were no days on which less than 2 indexes showed a significant H statistic and at least one day on which 5 indexes did.

<Insert table 2 around here>

Our findings for each event are summarized in Table 2, which shows the event start and end dates (the event date range), the start and end dates of the days on which 5 indexes displayed simultaneous nonlinear behavior (the peak date range), and the order in which each event was detected across the indexes.

<Insert graph 4 around here>

To exemplify our results, Event 1 is plotted in Graph 4 (the graphs for events 2 through 6 are available from the authors on request). The event starts on Nov 24th, 1994 with the detection of nonlinear dependence in MERVAL (Argentina), then appears in IBVC (Venezuela) followed by MEXBOL (Mexico) and IGBVL (Peru), and peaks between February 17th, 1995 and March 20th, 1995 in IBOV (Brazil). The event declines as nonlinearity decreases in each index until May 19th, 1995, when only IGBVL (Peru) still evidences significant H statistics.

To determine what might explain these nonlinearity events, we identified the key international economic events that occurred within the time frame of each one.

> **Event 1 and 2: the Tequila Crisis** or "*the December mistake*." This was triggered by the macroeconomic decision to devalue the Mexican peso on December 19th, 1994. The result was one of the worst financial crises in Mexico's history, causing a massive spillover of financial turmoil into other Latin American countries, especially Argentina, Brazil, Peru and Venezuela.
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> **Event 3: the Asian crisis.** In July 1997, the government of Thailand was forced to unpeg the baht from the US dollar and allow it to float freely. The massive currency devaluation spread to neighboring countries, leading to huge capital outflows from most countries of the developing world.
>
> **Event 4: the Ruble crisis.** On August 17th, 1998, the Russian government devaluated its currency, defaulted on its domestic debt and

ceased payments on foreign debt, provoking a financial crisis that also came to be known as the Russian flu.

Event 5: the subprime crisis. Although the origins of this crisis can be traced back to August 2007, the peak dates of nonlinear behavior coincide with the financial panic that occurred in July 2008 after the rescue of Fannie Mae, Freddie Mac and Bear Stearns in the United States, followed by the bankruptcy of Lehman Brothers and the multimillion rescue plan announced by the US government.

Event 6: The first peak of nonlinear behavior (05-31-2011 to 07-14-2011) can be related to Moody's downgrade of Irish bank bonds to junk status in April 2011 and **the rescue of Portugal** the following month. The second peak (08-03-2011 to 08-10-2011) coincides with the sharp increase in **Greek CDS** after the rejection of the European bailout plan by former Greek Prime Minister Georgios Papandreou.

As can be seen, all of the nonlinear event peaks coincide with major international financial crises. The opposite, however, is not the case given that our threshold for qualifying a nonlinear *contagion* event as major requires the presence of nonlinear dependence in 5 indexes simultaneously. For instance, the European crisis started in early August of 2007 but over the entire year the "highest" peak we found was 4 indexes with synchronized nonlinear dependence.

Our findings are consistent with previous analyses of the systematic but episodic nature of nonlinear dependence in LATAM stock index returns, but to our knowledge, this is the first study to identify the sequence and synchronicity of index nonlinearity.

5 Conclusions

The Hinich bicorrelation test in a rolling window framework was combined with a new graphical representation of the nonlinear events detected in the index stock returns of six Latin American stock markets. The data considered ranged from January of 1994 to November of 2012. The number of times that a given day on each market is present in the nonlinear events is established and compared to the other markets. The starting and ending periods of the nonlinear events are also determined, as well as the intensity and persistence of the nonlinear dependence.

Six episodes in which at least five of the six markets display simultaneous nonlinear dependence are identified for further study. These episodes are found to be contemporaneous with international financial crises, leading to the conjecture that the contagion provoked by these crises induced the nonlinear dependence.

Our results are consistent with findings in the financial econometrics literature that reject the random walk hypothesis for financial markets. They confirm the universally accepted phenomenon of nonlinear behavior in financial data for the case of the Latin American stock market indexes. We also found that there are common external factors that may trigger nonlinear dependence across financial markets.

The approach developed here is complementary to the tests traditionally employed to study contagion given that the bicorrelation test measures nonlinearity in the mean, a dimension less explored in the financial integration literature. We observed systematic nonlinear structures in the stock index return series that were associated with the lack of market efficiency. This new methodology could help financial analysts and regulators to assess graphically the state of dependence measured by the bicorrelation test as new information arrives, that is, in real time. In particular, we found that the financial markets of Mexico, Brazil and Argentina tend to present high nonlinear dependence in very similar time frames. By identifying the first and last days of each episode of nonlinear dependence, it is possible to identify which market the external shock first impacted and which markets are impacted in turn.

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Appendix

Tables and Graphs to be inserted in main text according to editor

Table 1: Rolling window results for Latin American Stock Indexes.

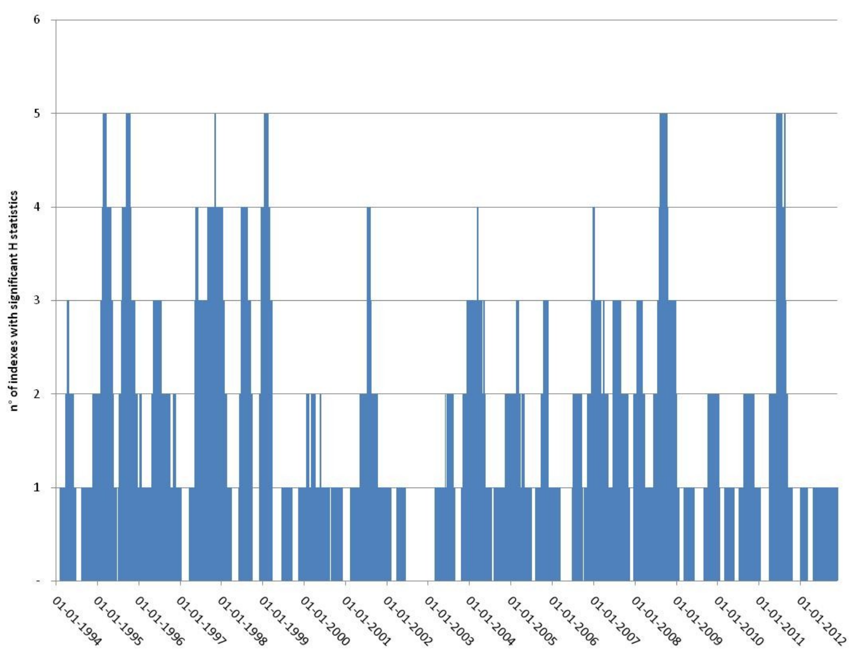
Table 2: Summary of results for simultaneous nonlinear events

Graph 1: Frequency of significant H-statistic windows for each calendar day.

IBOV (Brazil), 01-01-1994 to 11-20-2012

Graph 2: Frequency of significant H-statistic windows for each calendar day.
IBOV (Brazil), 01-01-1996 to 01-01-1999

Graph 3: Frequency of significant H-statistic index for each calendar day.
All indexes, 01-01-1994 to 11-20-2012



Graph 4: Frequency of significant H-statistic windows for each calendar day. All indexes, 12-01-1994 to 07-01-1995

Graph 5: Frequency of significant H-statistic windows for each calendar day. Mexbol (Mexico), 01-01-1994 to 11-20-2012

Graph 6: Frequency of significant H-statistic windows for each calendar day.

Merval (Argentina), 01-01-1994 to 11-20-2012

Graph 7: Frequency of significant H-statistic windows for each calendar day.
IGVC(Venezuela), 01-01-1994 to 11-20-2012

Graph 8: Frequency of significant H-statistic windows for each calendar day. IGBVL(Peru), 01-01-1994 to 11-20-2012

Graph 9: Frequency of significant H-statistic windows for each calendar day.
IGPA(Chile), 01-01-1994 to 11-20-2012