Persistence Characteristics of Latin American Financial Markets

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Abstract

Static time series models usually assume stationarity, normality, and independence for the increments of financial rates of return. This paper investigates the empirical characteristics of financial rates of return from Latin American stock and currency markets and documents that their empirical rates of return are non-normal, non-stationary and non-ergodic, and that they exhibit long-term dependence. This paper measures the degree of long-term dependence of these financial time series by calculating their global, or homogeneous, Hurst exponents from their wavelet multiresolution analyses (MRA), i.e. from the wavelet resonance coefficients. Visualizations of these resonance coefficients and their power spectra are provided by scalograms and scalegrams, respectively. These visualizations help to identify the long-term dependence characteristics, which cannot be identified by the classical time series analysis, which is based on the stationarity and independence assumptions. Our findings are consistent with some empirical findings from financial market data in the USA, in Europe and in Asia, but extend their domain of empirical investigation.

1. INTRODUCTION

Financial researchers are continuously trying to improve the mathematical models that reliably identify the stochastic pricing processes of the financial markets. Currently, the most popular dynamic time series models are ARMA models and GARCH models. These models are based on the assumption of stationarity, where risk is only measured by second-order moments, This assumption is often combined with the assumption of normality (Gaussian distribution) of the "innovations" in the time series. The critique of these stationarity models is twofold. First, empirical financial time series are demonstrably not Gaussian and the parameters of the proposed distributions vary over time (Loretan and Phillips, 1994). Second, and more importantly, the conventional stationarity models are not able to properly model long-term dependence, i.e., long-term memory processes. Cochrane (1988) has already shown that ARIMA models concentrate on the first few autocorrelations to capture the short-run features of the time series, and that they, when used to estimate long-run properties of time series, produce misleading results.

We observe that empirical financial time series exhibit long-term memory behavior, unpredictability, singularities, and discontinuities, which might indicate that the occurrence of financial catastrophes in persistent markets and of turbulence in anti-persistent markets is more prevalent,than predicted by analysis based on the Gaussian stationarity assumption. In addition, the higher order moments such as skewness and kurtosis prove to matter when measuring financial risk. Finally, the complete distributions of empirical asset returns can be shown not to remain invariant, but to change over time.

Such behavior of empirical financial time series challenges the Efficient Market Hypothesis (EMH) of Fama (1970) based on martingale theory, which assumes stationarity and independence of price innovations. An increasing number of studies have documented that empirical financial time series are not Gaussian, but there has not been enough empirical studies focusing on the long-term dependence of financial time series. Mandelbrot (1969, 1972) already introduced the concept of the long-term persistence in economic series. Recently Peters (1994) proposed the Fractional Market Hypothesis that models such long-term dependence features of financial time series. Because of the renewed interest in Mandelbrot's fractional Brownian motion, fractionally integrated processes and long-memory processes, there is now emerging substantial evidence that theoretical long-memory processes do a better job in describing empirical financial data, such as forward premiums, interest rate differentials, and inflation rates.

This paper investigates the empirical characteristics of financial time series of six Latin American stock markets and five currency markets, with an emphasis on measuring the degree of persistence of each market. It is one of the first papers that identify empirical financial time series simultaneously in the frequency and time domains. Our results show that Latin American financial markets are not stationary, and exhibit long-term dependence, and, thus, are not ergodic. Which means that the use of statistical limit arguments to determine "significance" statistics of these market time series are erroneous.

The degrees of the markets' persistence are measured by global, or homeogeneous, Hurst exponents identified from the Wavelet Multiresolution Analysis (MRA) of Mallat (1989). It enables a simultaneous time-frequency description of time series data in localized details. With the help of scalograms, which are visualization of the wavelet resonance coefficients,[1] shocks to the financial markets and the strength of these shocks can be clearly identified. Scalograms also illustrate how market prices adjust to the price shocks and innovations in different ways. While scalograms provide the detailed analysis of the time series, scalegrams – which is the average of many scalegrams and equals the logarithm of the power spectrum of the time series – represents the classical autocorrelation function (ACF) of the time series in the frequency domain. It shows, especially, the periodicities, or, more precisely, "cyclicities" of markets which cannot be easily identified by the static methodologies.

The paper is organized as follows: section (1) provides a brief literature review of long-term dependence or memory; section (2) describes data and methodology; section (3) discusses the empirical results. Finally section (4) summarizes our conclusions.

2. LONG TERM DEPENDENCE

Mandelbrot (1969, 1972) discusses the non-Gaussian distributions of financial prices and introduces the concept of the long-term persistence in economic series. Since his commentary, financial researchers have been searching for models that could approximate such typical behavior of financial time series. Empirical studies on long-term dependence often rely on the study of Geweke and Porter-Hudak (1983), who propose a method for the calculation of the fractional differencing parameter d. Hosking (1981), and Granger and Joyeux (1980) take advantage of the well-known ARIMA models and proposed fractionally integrated ARMA models to measure long-term dependence. These models are extensively discussed in Beran (1992), Baillie (1996) and Robinson (1994). Baillie (1996) surveys the statistical and econometric work concerning long-memory and fractionally integrated processes that are associated with hyperbolically decaying autocorelations and impulse response weights.

The topic of long-term memory and persistence has recently attracted considerable attention in terms of a discussion of the behavior of second moment of a log-normal pricing

[1] Wavelet resonance coefficients are coefficients of correlation between the empirical time series and stylized

process. Baillie, Bollerslev, and Mikkelsen (1996) apply the FIGARCH (Fractionally-Integrated-GARCH) process to exchange rates, Bollerslev and Mikkelsen (1996) apply the FIGARCH process to stock prices, and Breidt, Crato, and de Lima (1993), Crato and de Lima (1994), and Harvey (1993) find similar evidence of long memory stochastic volatility in stock returns and exchange rates respectively.

The R/S (Range-Scale) analysis of Hurst (1951) is the most widely used methodology to test for long-term memory in time series. Greene and Fielitz (1977) and Aydogan and Booth (1988) used the original R/S analysis in common stock returns; while Lo (1991) uses the modified R/S statistic on returns from value and equal weighted CRSP indices from July 1962 to December 1987. Lo (1991) finds significant results from using the original R/S statistic but ,insignificant results from the application of his modified R/S statistic. Lo also reports that finding of a lack of long-range persistence on annual returns from 1872 to 1986. Booth, Kaen, and Koveos (1982) apply the basic rescaled range statistic to exchange rates. Cheung (1993a), taking monthly data from January 1974 through December 1989, finds some evidence of long memory in the French franc/US dollar rate, but no apparent departure from martingale behavior by the German mark, Swiss franc, or Japanese yen.

Regarding the efficiency of emerging financial markets, Los (2000) uses nonparametric efficiency tests to test for the efficiency of Asian Stock markets (Hong Kong, Indonesia, Malaysia, Singapore, Taiwan, and Thailand) and finds that none of the markets is stationary or shows independent innovations. Nonparametric tests for the efficiency of Asian currency markets are also presented in Los (1999), where he finds that no Asian currency market exhibited complete efficiency in 1997. Gençay, Selçuk and Whicher (2002) and Los (2003) have collected

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wavelets at various scales. These scales are proportional to the inverses of the frequencies.

the latest signal processing methodologies and technologies with some empirical results. Los (2003) collected them specifically to more carefully identify and measure the degree of long-term dependence, *i.e.*, the persistence and anti-persistence of financial time series. Several of these recently advanced signal processing approaches emerging in finance and economics have been implemented in this paper on the pricing series of the Latin American financial markets.

Recently, Sadique and Silvapulle (2001) examine the presence of long-term memory in weekly stock returns of seven countries by using R/S analysis, GPH procedures, and frequency and time domain versions of the score tests. They find that Korea, Malaysia, Singapore and New Zealand stock returns possess long-term memory, which, again, contradicts the classical Efficient Market Hypothesis (EMH). Tthe results of Sadique and Silvapulle (2001) contradict those of Cheung (1995), who uses Lo's modified R/S and fractional differencing to test for long-term memory of stock returns in eighteen countries in Asia, Europe and North America and finds little support for long-term memory in international stock returns. Such contradictions and inconsistencies in the empirical finance literature regarding dependence in financial market pricing need to be resolved in an accurate fashion, because these results affect the correct measurement of financial risk, and therefore the correct pricing of derivatives, the proper selection and management of investment portfolios, and, ultimately, the proper allocation of scarce international capital.

Less research has been done on the long-term memory processes of the stock prices and exchange rates of Latin American countries. In the early 1990s, the vast majority of the Latin American countries launched market–oriented reforms and these initiatives attracted a large amount of foreign capital flowing into Latin American financial markets. In addition, as the US interest rates declines since 1990, US investors were induced to look for higher returns abroad, especially in the emerging markets (Edwards, 1998). Investors seemed to believe that emerging markets always show higher rates of return on investments. However, *The Economist* reported in 1997 that since 1994, the stock markets return in the developed countries has been on average 40% as measured by MSCI World Index, while the emerging stock market return lost about 10% measured by the IFC investable Index during the same period (*Cf*. Los, 2000). Especially after the 1997 Asian Crisis and 1999 Brazil currency crisis, investors realize that emerging markets are highly volatile, with extremely high levels of profit but also of loss. Latin American markets, as one important segment of emerging markets, are small, speculative and exhibit high volatility in returns, and are vulnerable to crisis. The well-known 1994 Mexico crisis and 1999 Brazil crisis urge us to investigate the Latin American financial markets more carefully, and focus on the areas that have been ignored, while expanding the empirical domain of the investigation of dependence in financial market pricing.

3. DATA AND METHODOLOGY

3.1 Data

Our dataset covers six daily stock market data series and five daily foreign exchange rate series. The six stock markets include Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela. As Argentina dollarized its currency since the early 1980s, we do not include Argentina in our foreign exchange series. Since this paper focuses on measuring and identifying the persistence characteristics of the markets, and how market prices adjust to shocks over a long time periods, daily data maybe more preferable than higher frequency data. In any cae, they are more manageable, computation-wise. The data for daily stock indices are from the web site, “Yahoo, Finance!” and the data for foreign exchange rate series are from the site, "OANDA.com." Due to very restricted data availability, the number of observations for each country is different. Data description, period covered and each number of are presented in Exhibit 1. Note that Argentina has the same stock index as Uruguay, and Colombia shares the same stock index as Eucador and Peru.

3.2 Methodology

The first part of our analysis tests for the general characteristics of our financial time series such as the stationarity – both strict and wide sense - ergodicity, and the (in)dependence. The second part of our empirical analysis identifies the nature of the long-term dependence by measuring the Hurst exponent from the wavelet multi-resolution analysis (MRA). The wavelet MRA analysis is visualized in the form of graphical scalograms and scalegrams.

3.2.1 Measuring Stationarity, Ergodicity, and Independence

A stochastic process is said to be *stationary in the strict sense,* if the whole joint probability distribution remains in variant over time, *i.e.*, the joint distribution of any set of *n* observations $Xt_1, Xt_2, \ldots, Xt_n$ is the same as the joint distribution of $Xt_{1+k}, Xt_{2+k}, \ldots, Xt_{n+k}$ for all *n* and *k*. The process is said to be stationary in the *wide sense* if the first two moments of the distribution remain invariant over time and the autocovariance function has only the lag k as argument, *i.e.*, $E(X_t) = \mu$ and $Cov(X_t, X_{t+k}) = \gamma(k)$. In order to test for wide and strict sense stationarity, we calculate moving first, second, third, and fourth order moments with the *fixed* window size of 50 days to see if the series is stationary overtime.

Ergodicity is defined by Terence C. Mills (1999, p. 9) as follows: "… the process is ergodic, which roughly means that the sample moments for finite stretches of the realization approach their population counterparts as the length of the realization becomes infinite." In other words, if a process or time series is ergodic, its expected value, which is also called its ensemble average; can be replaced by a time average. If a time series is non-ergodic this replacement is logically invalid. To check for the ergodicity of the empirical series, we calculate the moving moments of increasing size windows for all series. If a series is ergodic, the plotted moments of increasing windows should be constant value straight lines parallel to the abscissa of time, indicating that the values of moments do not change as the number of observations increase.

Independent random variables have no history. They are immeasurable using the past historical information, only measurable with respect to current information. To see if a data series exhibits independence, we compare the ACF of pure Geometric Brownian Motion (GBM) and the ACF of our empirical data series. As the GBM assumes independence, and thus also no serial correlation, its ACF decays very fast after the first lag. A time series is long-term dependent, if its ACF decays at a hyperbolic rate, which is much slower than the fast decay of the GBM.

3.2.2 Measuring the Degree of Long-Term Dependence

If the innovations of the time series of the rates of return are independent, the series can be represented by the GBM, whereas, if is long-term dependent, it may be better described by a Fractal Brownian Motion (FBM). In the FBM, the rate of return is the first difference of the natural log of the price series:

$$x(t) = \ln[X(t)/X(t-1)] \qquad (1)$$

This rate of return is then fractionally differenced with white noise innovations

$$(1-L)^d x(t) = e(t), \text{ with } -0.5 < d < 0.5, \text{ and} \tag{2}$$

$$e(t) \sim \text{i.i.d.}(0, \sigma^2)$$

Here d is the *differencing exponent*

The ACF of a FBM can then be shown to be proportional to:

$$\gamma(\tau) = E\{x(t)x(t-\tau)\} \sim \sigma^2\tau^{2d-1} = \sigma^2\tau^{2H-2} \tag{3}$$

and its Power Spectrum to

$$P(\omega) = \sigma^2\omega^{-(2H+1)} \tag{4}$$

.where H = d + 0.5 is the *Hurst exponent* (Hurst, 1951).

The ACF and power spectrum of the FBM clearly have scaling properties, with the ACF scaling according to time t and the power spectrum scaling according to frequency ?. It is this frequency scaling property of the FBM, which allows us to compute the power spectral density to identify the Hurst exponent as a measure of the degree of long-term dependence. The global Hurst exponent can be identified from the (log) plot of the power spectrum P(ω) of the FBM against the logarithm of frequency ω. The slope coefficient of the resulting negative line is b = *(2H+1)*, so that $H = \frac{b-1}{2}$. This Hurst exponent must lie between 0 and 1. If it approaches zero ($H \downarrow 0$), the time series is said to be *blue noise*. If 0 < H < 0.5, the series is said to be anti-persistent, if H = 0.5, the series constitutes *white noise*[2], if 0.5 < H <1, the series' increments are said to be persistent, or *pink noise*, and if H approaches 1 ($H \uparrow 1$), the series is said to be *red noise*.

3.2.3 The Hurst Exponent and Wavelet MRA Plots

Unlike any other statistical, “global,” or average risk measurement, the wavelet MRA enables one to measure “local,” or instantaneous, risk and thus provides extremely accurate risk information about any time series. By risk we mean the second moment of measuring the variability or volatility of the series. The wavelet MRA analysis is presented using scalograms and scalegrams. A scalogram measures the power spectrum localized in time and frequency (~1/scale). In this paper, the wavelet resonance coefficients are computed by Mallat’s (1989) wavelet MRA with the use of the Morlet-6 wavelet, using Kodak’s online ION Script Research Systems Interactive Wavelet Program[3]. A scalogram, which is a visualization of the colorized wavelet resonance coefficients, identifies clearly the timing and power of price innovations to the financial markets. Scalegrams, or averaged scalograms,are used to compute the Hurst exponents from. The scalegrams show, especially, the cyclicties of the market pricing processes.

4. EMPIRICAL ANALYSIS

Table 2 reports the descriptive statistics of the six stock indices and five exchange rates studied in this paper. For each series, we have both the daily price and return series. It is clear in the table that none of the series are Gaussian, since all data series have non-zero excess skewness and non-normal kurtosis. Tthe series exhibit consistent features across countries in terms of kurtosis, since all return series are leptokurtic, and all price series are platykurtic. Table 3 has the distribution plots of some stock index price series and exchange rate series.

Table 4 reports the results of the test on ergodicity. The first four moments are computed with increasing window sizes of the data sets, and the results are plotted. If the series are ergodic, the plotted moments should converge and then stay constant as we increase the window

[2] Integrated white noise results in brown noise, *i.e.*, described by the Brownian motion.

size. However, these plots clearly show that none of the series are ergodic. There are sharp discontinuities and often divergences. Table 4 reports the plotted moments of stock indices (price and return series) and exchange rate (price and return series) of Mexico. The series of the other countries behave very similarly[4].

In addition to these increasing-window moments, the moving moments of the first four orders, $E\{X(t)^q\}$ and $E\{x(t)^q\}$ for q = 1, 2, 3 and 4, are computed with a constant window size of 50 days for each series. The plotted moments fluctuate in value and do not converge indicating that none of the series is stationary in either strict or wide sense, since all four moving moments are time-varying. These results are independent of the window size, since windows of different sizes show similar results. Table 5 reports the stationarity tests. Again, we use Mexico as our example. The first two moments of the exchange rate price and return series show some signs of convergence, but the last two moments do not appear to converge. The conclusion from the ergodicity and stationarity tests is that none of the financial series in this study meet the assumptions of the conventional lognormal price diffusion models.

Usually, the stationarity models would assume the empirical time series exhibit short-term dependence, which would be identified easily by their ACF. In Table 6, we compare the ACF of Chilean and Venezuelan stock indices and exchange rates (both price and return) with the ACF of simulated Geometric Brownian Motion[5]. It seems that the ACFs of stock price series die down faster than those of exchange rate series. However, they still exhibit long-term dependence, since their ACFs converge to zero at much slower rate than those of the GBM. The ACFs of the

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[3] Accessible via http://ion.researchsystems.com/IONScript/wavelet
[4] The plots of the other countries are available upon request.

[5] ACFs of stock indices and exchange rates for other countries behave similarly.

stock return series fluctuate around zero, but they do not die off. The ACFs of the exchange rates decline very slowly, and the ACFs of the exchange rate returns fluctuate.

Having shown that the empirical time series are long-term dependent, we next investigate whether these series are persistent or anti-persistent, by calculating their homogenous Hurst exponents. The identified Hurst exponents are reported in Table 7. The results show that the stock markets of Argentina, Chile and Venezuela are persistent, as their Hurst exponents are greater than 0.50. The Columbian stock market is surprisingly anti-persistent with H = 0.42. Only the Brazilian and Mexican stock indices confirm to the independence of the innovations of the GBM with Hurst exponents of 0.50. The exchange rates of all countries are persistent except for Mexico. The Hurst exponent of the Mexican exchange rate is 0.41, showing Mexican foreign exchange market to be ultra efficient compared to those of other countries in our data set.

Figure 1 (Panel A through D) reports the results of the wavelet Multiresolution Analysis (MRA) for selected markets[6]. There are three parts in each plot. Part a in each Panel is the plot of the original time series and the type of wavelet used to analyze the time series (Morlet-6 wavelet). Part b is the localizing wavelet scalogram, MRA, or local power spectrum. Finally, part c shows the global wavelet scalegram, equivalent to the conventional average power spectrum. Panel A of Figure 1 shows the regime changes for Mexican peso. The Mexican peso experienced a change from pegged to float regime on December 20, 1994, from float to fixed on May 4, 1995, and from fixed to float again on October 16, 1995. The timing and power (= magnitude of local risk or volatility) of these drastic currency regime changes are detected very sharply by the scalogram, where both floats are represented by substantial power at many frequencies, while there is considerablyless power during the pegged and fixed regimes. Starting

[6] The MRA plots for the other countries are available from the authors upon request.

from late 1998, a lot of noise trading is identified by the scalogram and occasional energy bursts where they coincide the Brazilian stock market crisis (September 10, 1998) and Brazilian currency float (January 15, 1999). The identified Hurst exponents for sub-periods show that the Mexican peso market has become more efficient over time. Before the first float, the identified Hurst exponent is 0.57, while it finally declined to 0.29 after the Brazilian stock market crisis. This trend is consistent with the global Hurst exponent for Mexican currency market reported in Table 7.

Panel B of Figure 1 shows the MRA of the Mexican peso return series. The Mexican peso crisis in December 1994 is represented by a striking vortex (= rapid frequency change from low to high frequency with almost immediate reversal of that change), which cuts through most of the frequencies with considerable power. The second float is represented by a smaller vortex with much less power. The figure shows the powerful shock the currency crisis brought to the FX market trading, and how the market was trying to adjust to this shock with increased. The scalegram also illustrates that Mexican peso innovations do not consist of white noise and shows clear cyclicities at weekly, quarterly and yearly frequencies.

Panel C of Figure 1 presents Brazilian currency (real) regime change from fixed to float. During the fixed exchange rate period, the scalogram shows almost no power. By contrast, starting from the Brazilian real float in January 1999, the scalogram detects a lot of noise trading in Brazilian currency markets. These energy bursts happens at high frequencies over a lengthy time period, indicating how the market was trying to adjust itself to the new regime. The global Hurst exponent for the overall period is 0.66 apparently indicating an overall persistent Brazilian currency market. However, the high persistence of the overall period is due mainly to the pegged regime whose Hurst exponent is 0.67. The Hurst exponent after the float is only 0.46

showing the market becomes anti-persistent and more efficient after the float, as clearly visualized by the scalogram. This contrast indicates that a global Hurst exponent of the complete time series does not describe the market innovations precisely and should be computed for each sub-period or a series of subperiods.

Panel D of Figure 1 presents Chilean stock index return plots. The scalogram shows that the shocks from Brazilian stock market crisis and Brazilian float affected the Chilean stock market. Another striking vortex in this scalogram is corresponding to the widespread selling event of Chilean shares in January 2002 caused by the tender of Enerquinta shares. This singular event manifested itself as a large drawdown of around 30% percent of returns in the return plot, and in the scalogram the corresponding vortex cuts through most of the frequencies with large power. The scalogram thus identifies the contagion from other markets and the shocks of single events in domestic markets. Again, the scalegram of Chilean stock index return indicates that this market is not truly identified by a GBM, since cyclicities can be identified at weekly, biweekly, quarterly, and two-year frequencies.

5. CONCLUSIONS

Though the popular Geometric Browian Motion price diffusion models claim to provide a good fit to financial time series data, their assumptions of independence, stationarity and normality are not be satisfied by the empirical data. In this study, we use some recent signal processing methods to check such fundamental characteristics that are of importance for (1) risk measurements, (2) asset and options valuations, for (3) portfolio selection and management, and for (4) international capital allocation. The series included in this paper are the financial data from Latin American stock markets and currency markets. The stationarity, ergodicity and independence of the available financial time series of each Latin American country is testedThe series ar also examined for long-term time dependence. The global degree of long-term dependence is identified by the homogenous Hurst exponents from wavelet multiresolution analysis.

The empirical evidence shows that the empirical financial data of Latin American financial markets possess characteristics that are different from what the conventional theoretic financial models assume. The first four moments of our empirical data series are non-stationary, non-ergodic and exhibit long-term dependence, and not independence of the innovations. When we compare the ACFs of the empirical data with those of simulated geometric Brownian motions, we can easily detect the difference between the two, especially for Mexico[7]. Identified by their Hurst exponents, most Latin American financial markets are persistent, with Columbian stock market and Mexican exchange market are anti-persistent. Only the Brazilian and Mexican stock markets are, perhaps overall, identified by Geometric Brownian Motions. The global Hurst Exponent only measures the general degree of dependence of the markets, but still fails to reflect how the market prices actually adjust to the shocks. Thus one needs to be very careful interpreting the values of reported global Hurst Exponents.

The MRA time-frequency analysis reveals financial time series are highly non-stationary, and show cyclicities and singularities. Scalograms facilitate detailed inspection of how the financial markets adjust to major interventions. Sstock and foreign exchange market adjustment phenomena are observable after major interventions. Vortices can be found, in the scalograms,

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[7] We also compare the ACFs of our empirical data with those of the simulated Fractional Brownian Motion. However, it appears that the global Fractional Brownian Motion characterization by the Hurst exponent cannot completely identify the empirical data either. Even more complex identifying models, perhaps Multifractal models, will soon be tested.

corresponding to the major interventions such as the Mexican currency crisis, Brazilian stock market and currency crises, and a single sharp selling event in Chilean stock market. These findings are consistent with current studies of the contagion effects among Latin American countries.

The implication of this paper is that extremely caution needs to be exercised when applying conventional stationary price diffusion models to empirical financial series. Especially for the speculative and highly volatile emerging markets, one needs to remember that the highly localized risks cannot be simply explained within the Markowitz mean-variance framework. The distributions of rates of returns change over time and sometimes even violently. It is impossible to predict returns in those Latin American financial markets which are persistent, because they show sharp and unpredictable discontinuities, although there are long periods of sheer price inertia that may give the impression of predictability. However, being theoretically predictable does not mean one can easily establish a valuation model and earn abnormal returns from it. Persistent series often show rare unexpected, but sharp discontinuities, as clearly shown by the singular drawdown in the Chilean stock market. In contrast, anti-peristent markets show ultra-fast mean price reversions. They give the impression to be unpredictable, but are actually much more predictable than the persistent markets. In both cases, though, the current theoretical diffucion models are far from sufficient to completely identify or realize the empirical financial markets.

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Table 1: Data description

Panel A: Stock Market Indices

Country	Index name	Period Covered	No. of Obs.
Argentina	BUSE Merval Indx (MERV)	10/08/96 – 10/26/01	1253
Brazil	BRSP BOVESPA IND(BVSP)	04/27/93 – 10/26/01	2104
Chile	SASE Select Inx (IPSA)	06/07/97 – 10/26/01	1089
Colombia	Peru: Lima General Inx (IGRA)	04/28/98 – 10/26/01	871
Mexico	MXSE IPC GRAL IN (MXX)	11/08/91 – 10/26/01	2480
Venezuela	IBC INDEX (IBC)	04/28/98 – 10/26/01	852

Panel B: Foreign Exchange Rates

Country	Index name	Period Covered	No. of Obs.
Brazil	Brazilian Real (BRL)	10/22/95 – 12/18/01	2250
Chile	Chile	06/01/97 – 10/31/01	1614
Colombia	Colombia	04/01/98 – 10/31/01	1310
Mexico	Mexican Peso (MXP)	01/04/93 – 11/30/01	3253
Venezuela	Venezuelan Bolivar (VEB)	05/01/96 – 12/01/01	2041

Table 2: Descriptive Statistics

This table reports the descriptive statistics of the price series, X(t), and the return series, x(t) = ln[X(t)/X(t-1), of stock indices and foreign exchange rates of Argentina (not included in the foreign exchange rate dataset), Brazil, Chile, Colombia, Mexico, and Venezuela.

	Stock Indices		Foreign Exchange Rates	
Argentina	X(t)	x(t)	X(t)	x(t)
Mean	546.92666	-0.0717289		
Variance	19665.256	5.309872		
Skewness	0.2846037	-0.5175271		
Kurtosis*	-0.3714249	5.1442814		
Brazil				
Mean	8441.0358	0.2936553	1.521298356	0.0419508
Variance	26180521	9.1399316	0.267834563	0.6143049
Skewness	0.098859	0.5147128	0.658967203	3.2949488
Kurtosis	-1.0184553	7.9328273	-0.663923268	72.755232
Chile				
Mean	113.63387	-0.03273	516.135	0.035
Variance	314.29688	2.8530028	5332.400	0.175
Skewness	0.5355462	-7.7918004	0.855	3.777
Kurtosis	-0.4322389	164.71036	0.523	68.627
Colombia				
Mean	1488.8049	-0.0545283	1917.441	0.043
Variance	47782.299	1.3545021	109411.123	0.228
Skewness	0.2620203	-0.0235501	-0.273	2.403
Kurtosis	-1.3365513	4.64514	-1.320	24.313
Mexico				
Mean	3748.3433	0.0560487	7.300334829	0.0336163
Variance	3172037.5	3.3820698	5.920033696	0.8722933
Skewness	0.4422013	-0.032757	-0.746398505	7.0552532
Kurtosis	-1.0336986	4.8992809	-0.938361995	242.41246
Venezuela				
Mean	5810.7764	0.0062416	591.0932425	0.0233582
Variance	1759102.5	5.4498896	8466.752941	0.0177385
Skewness	-0.2816602	1.2282356	0.128048915	-2.5937952
Kurtosis	-0.8718848	13.333014	-1.432647717	56.709366

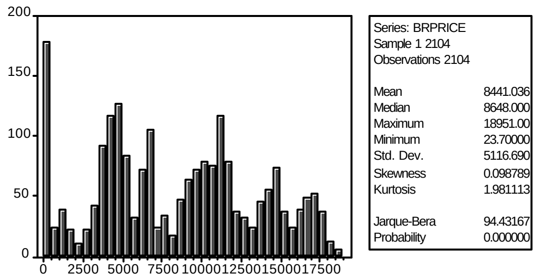
*: The coefficient of kurtosis is given as deviation from the normal kurtosis = 3, or nonnormal or excess kurtosis. For example excess kurtosis = -0.362 means actually kurtosis = 3 - 0.362 = 2.638

Table 3: Probability Distribution of Latin American Financial Time Series

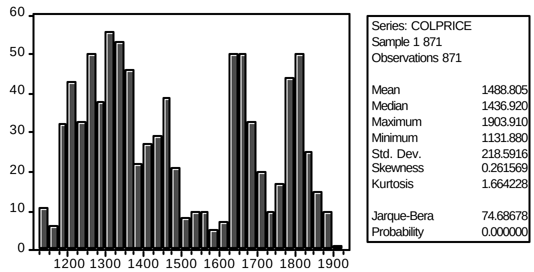
This table reports the histograms or frequency distribution plots of some selected stock indices (Panel A) and foreign exchange rates (Panel B)*.

Panel A: Stock Market Indices

Brazil: Price Series

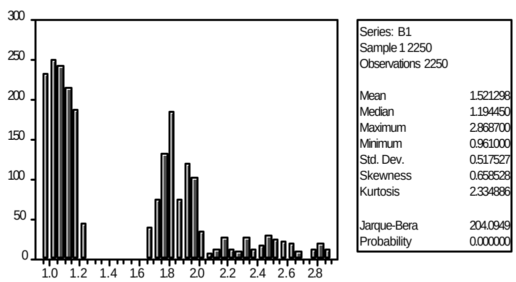


Colombia: Price Series

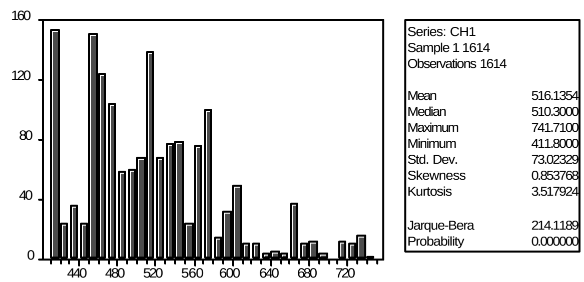


Panel B: Foreign Exchange Rates

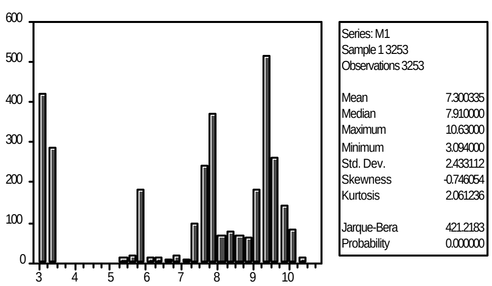
Brazil: Original Exchange Rate



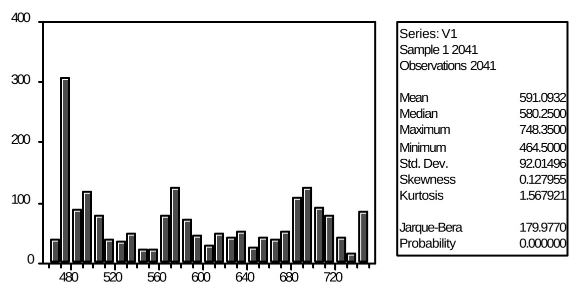
Chile: Original Exchange Rate



Mexico: Original Exchange Rate



Venezuela: Original Exchange Rate

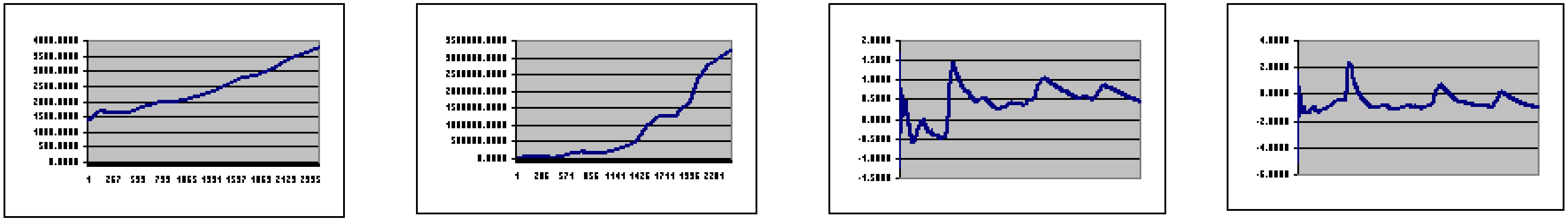


* Frequency distribution plots of other series are available from the authors upon request.

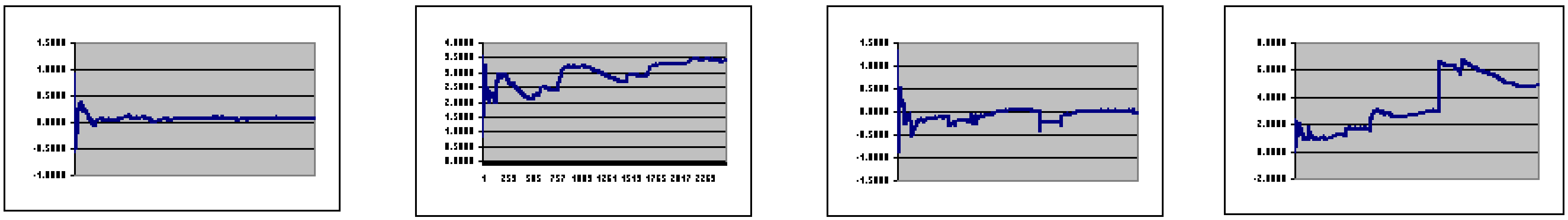
Table 4: Four Moments of Stock Indices and Exchange Rate of Mexico with Increasing Windows

Mean	Variance	Skewness	Kurtosis

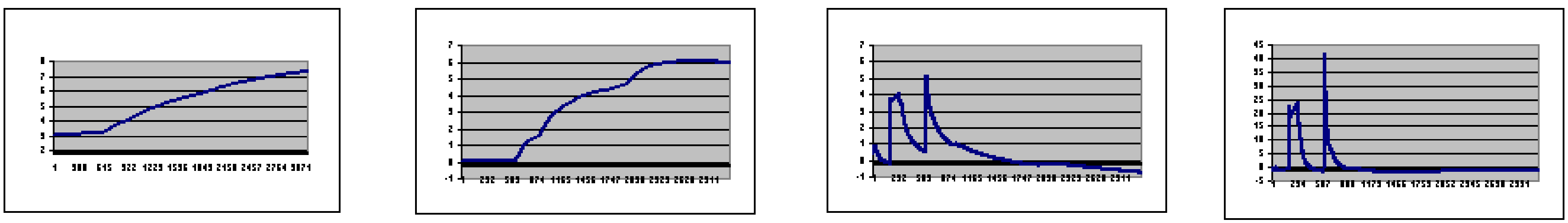
Stock Index Price



Stock Index return



Exchange Rate Price



Exchange Return

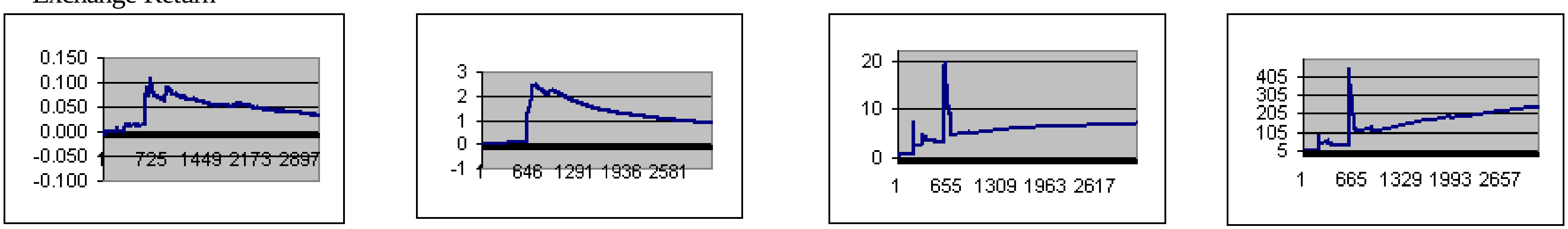
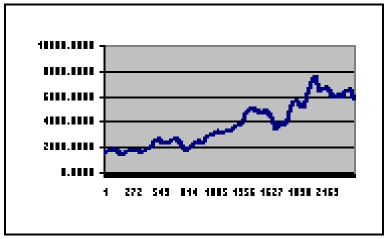
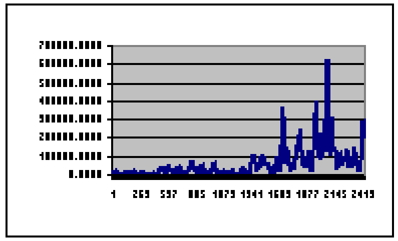
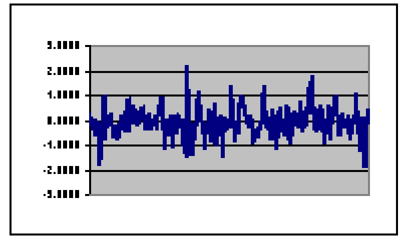
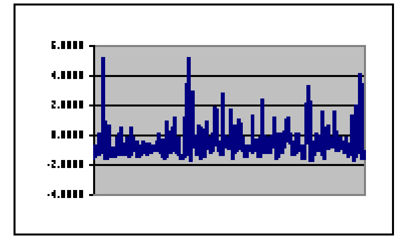


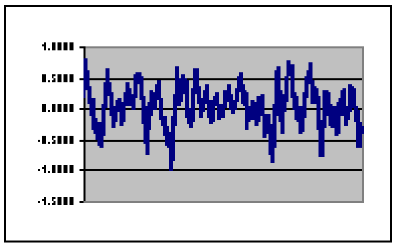
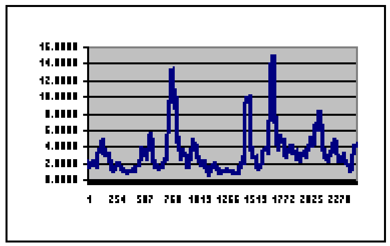
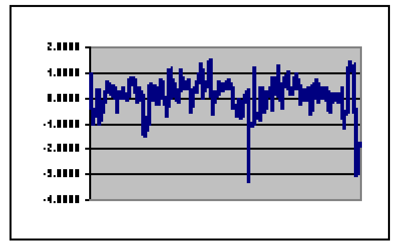
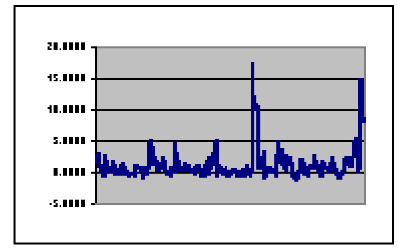
Table 5: Four Moving Moments of Stock Indices and Exchange Rate of Mexico with Fixed Window Size

Mean Variance Skewness Kurtosis

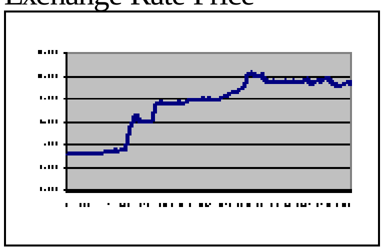
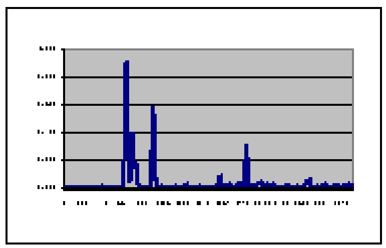
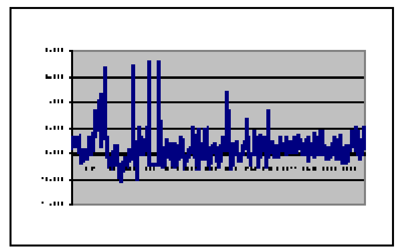
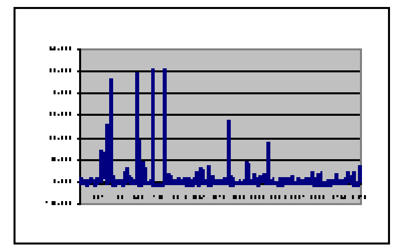
Stock Index Price

Stock Index Return

Exchange Rate Price

Exchange Return

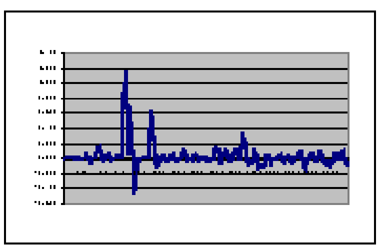
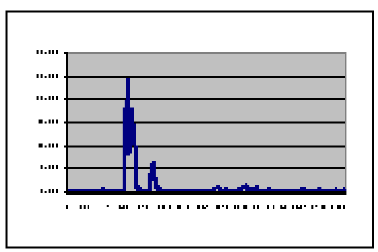
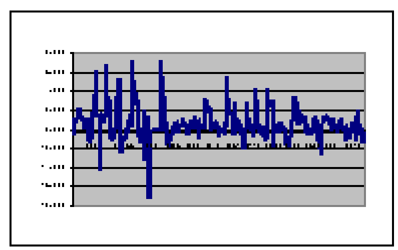
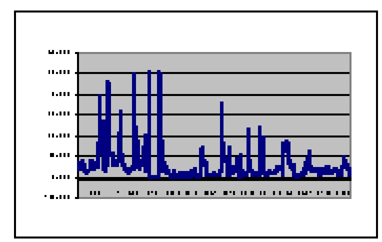
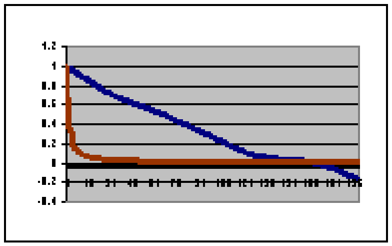





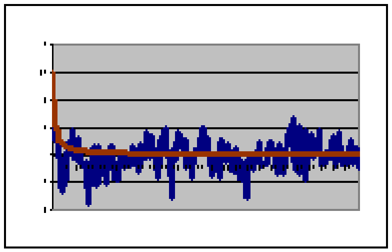
Table 6: Comparison of Empirical ACFs and Geometric Brownian Motion ACF

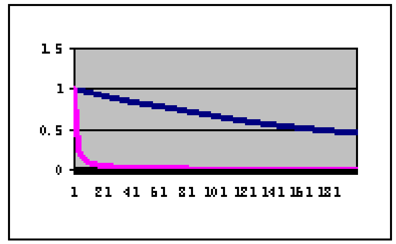
This table compares the ACF of Geometric Brownian Motion with the ACF of the empirical stock series and exchange rates of selected Latin American countries. *

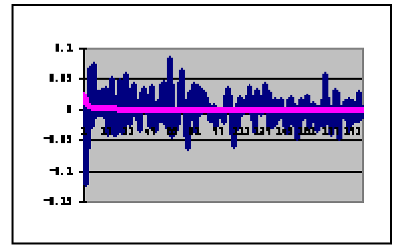
Stock Price	Stock Return	Exchange Rate	Exchange Return

Chile

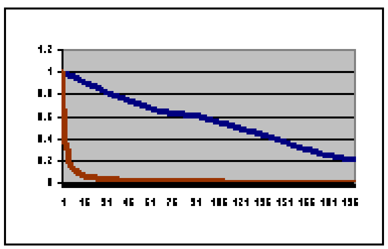


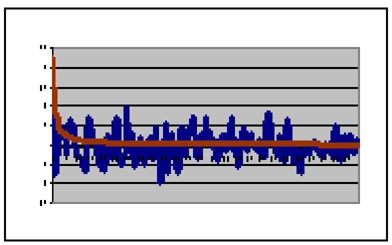


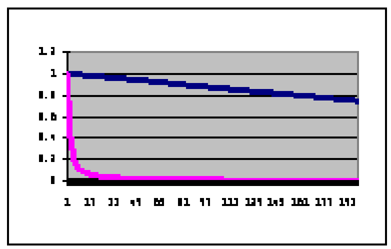


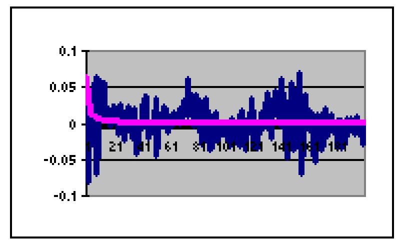


Venezuela









* The plots for the other Latin American countries are available from the authors upon request.

Table 7: Identified Hurst Exponents

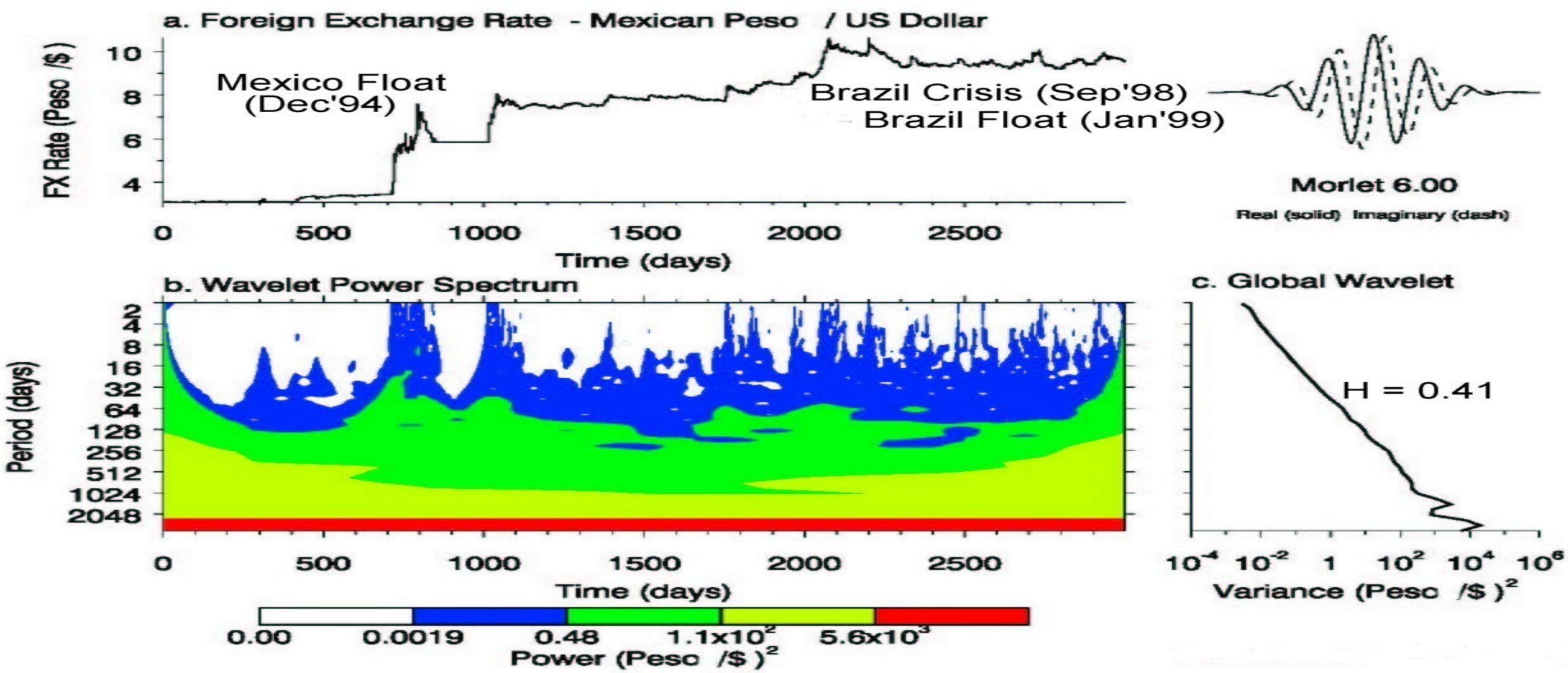
This table reports the identified global or homogeneous Hurst exponents of the stock indices and the foreign exchange rates. The homogeneous Hurst exponents are identified from the plot of (log) power spectrum P(ω) of the Fractal Brownian Motion against the logarithm of the frequency ω. The slope coefficient of the resulting negative line is $b = (2H+1)$, so that $H = \frac{b-1}{2}$. A Hurst exponent of 0.50 indicates that the market follows a Geometric Brownian Motion, while a Hurst exponent between 1 and 0.50 means the market is persistent, and a Hurst exponent between 0 and 0.50 means the market is anti-persistent.

	Stock Indices	**FX Rates**
Argentina	0.79	N/A
Brazil	0.50	0.66
Chile	0.79	0.66
Colombia	0.42	0.61
Mexico	0.50	0.41
Venezuela	0.79	0.66

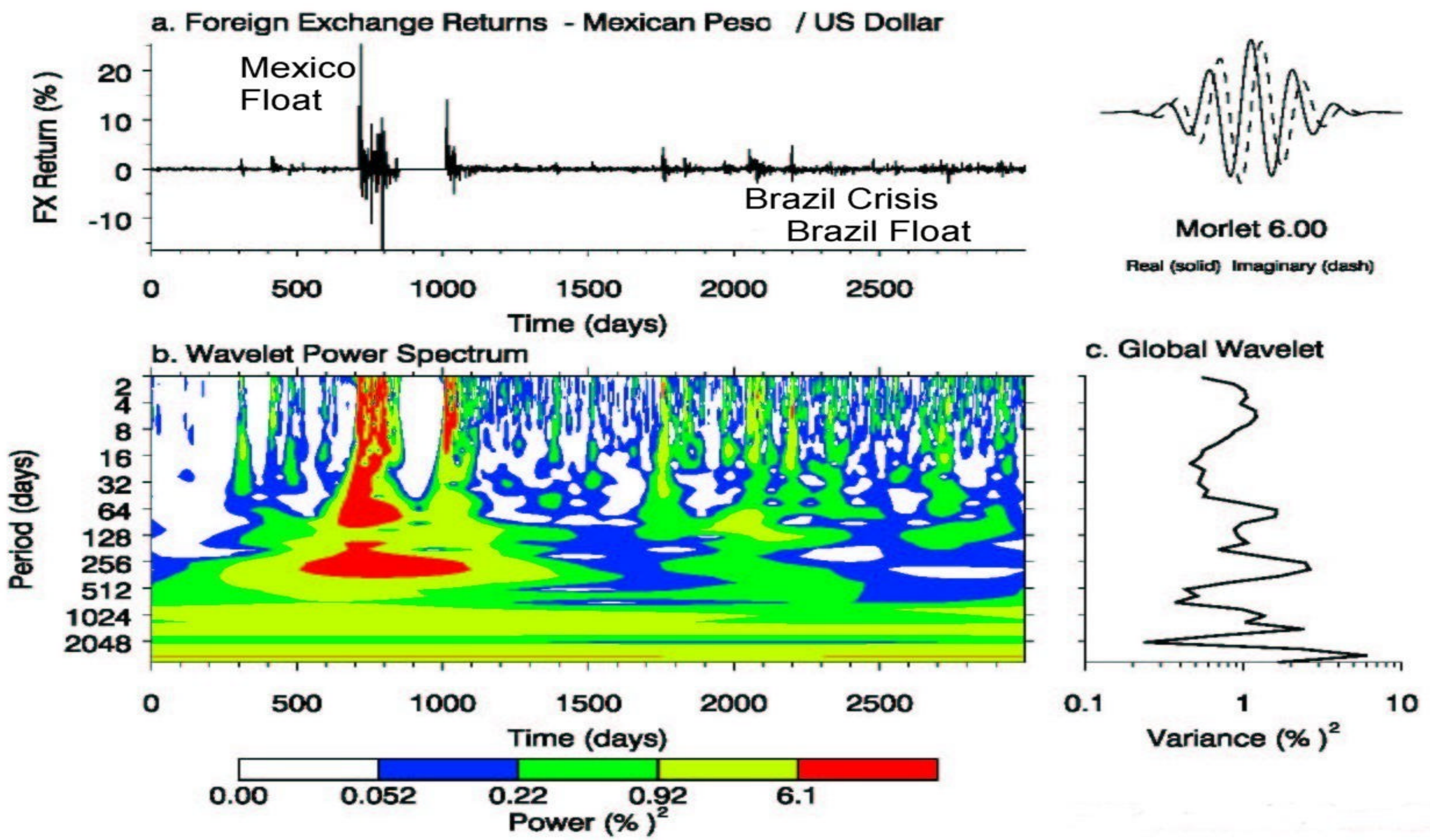
Table 1: Scalogram and Scalegram from Wavelet Analysis

This table with figures contains four sets of scalograms and scalegrams from wavelet analysis. Panel A is the exchange rate series of Mexican peso, Panel B is the exchange return series of Mexican peso, Panel C is the exchange rate series of Brazilian real, and Panel D is the Chilean stock indices returns*. There are three parts in each plot. Part a is the plot of original time series and the type of wavelet used to analyze the time series (*i.e.*, the Morlet 6.0 wavelet). Part b is the scalogram, which is a colorized plot of the magnitude of the wavelet resonance coefficients. Part c is the scalegram, which is the equivalent of the logarithm of the power spectrum, *i.e.*, the Fourier transform of the series' autocorrelation function (ACF). It can also be viewed as the statistical time average of the scalogram.

Panel A:

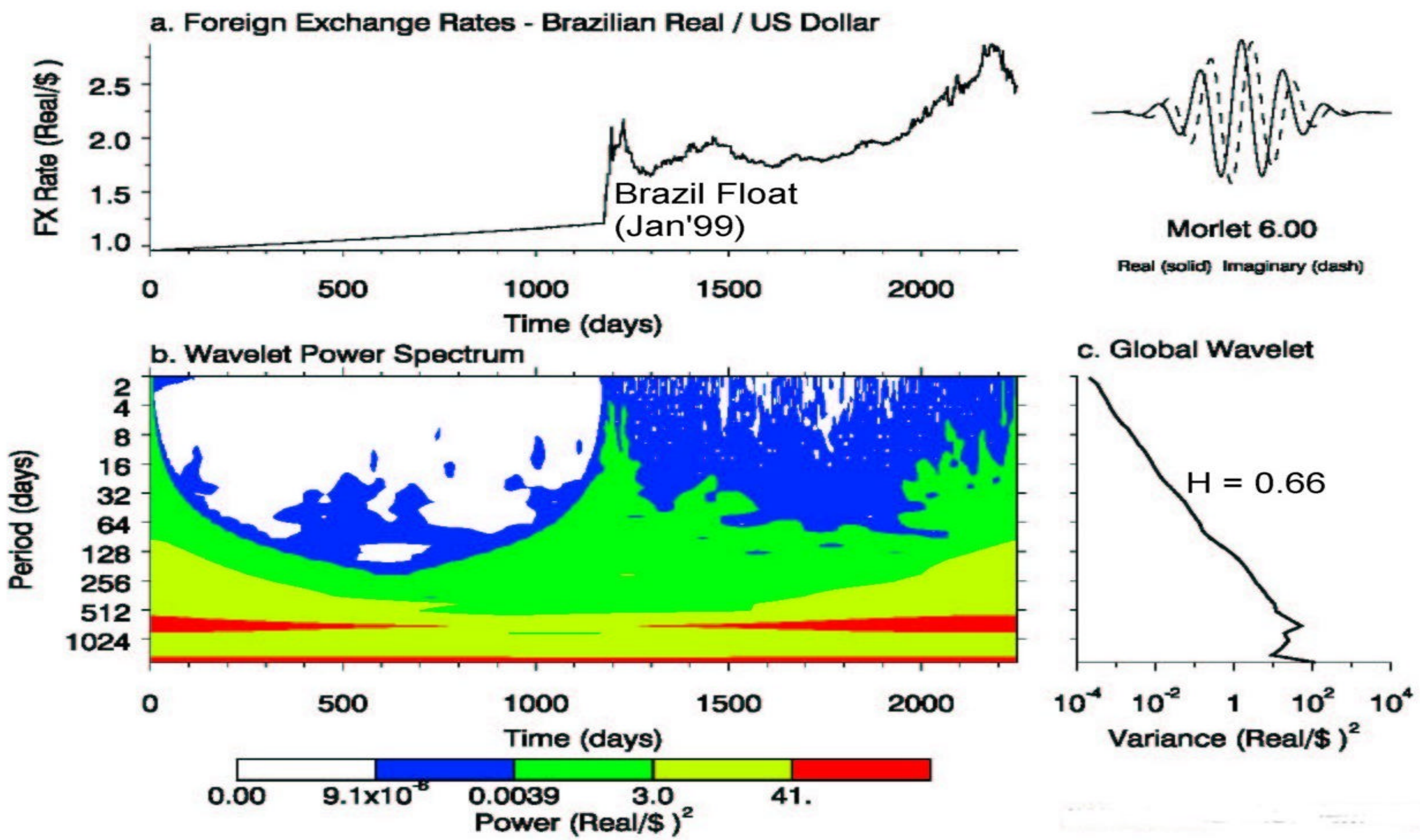


Panel B:



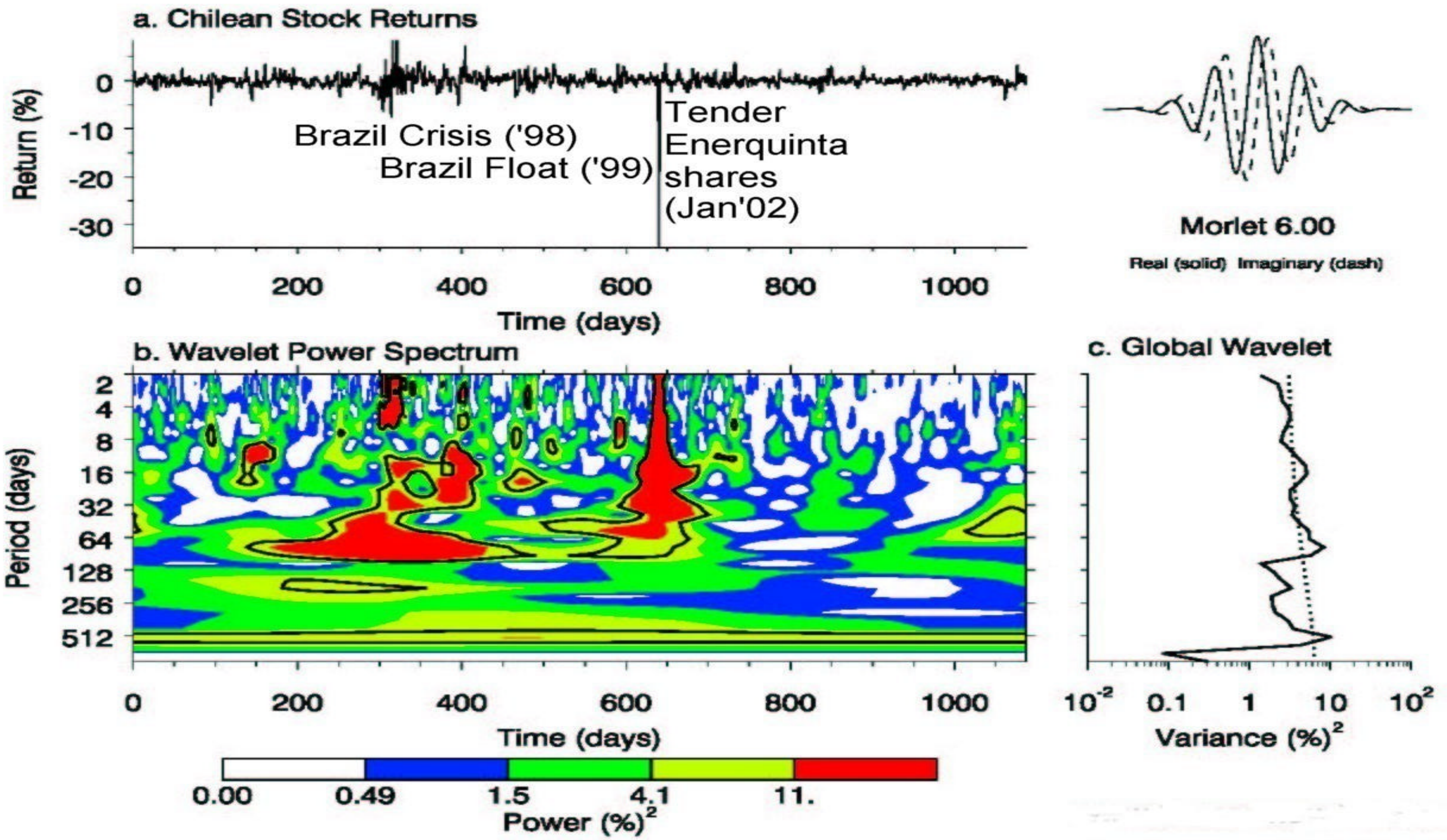
a. Foreign Exchange Returns - Mexican Peso / US Dollar
FX Return (%)
Mexico
Float
Brazil Crisis
Brazil Float
Time (days)
Morlet 6.00
Real (solid) Imaginary (dash)
b. Wavelet Power Spectrum
Period (days)
Time (days)
c. Global Wavelet
Variance (%)²
0.00
0.052
0.22
0.92
6.1
Power (%)²

Panel C:



a. Foreign Exchange Rates - Brazilian Real / US Dollar
FX Rate (Real/$)
2.5
2.0
1.5
1.0
Brazil Float
(Jan'99)
0
500
1000
1500
2000
Time (days)
Morlet 6.00
Real (solid) Imaginary (dash)
b. Wavelet Power Spectrum
Period (days)
2
4
8
16
32
64
128
256
512
1024
0
500
1000
1500
2000
Time (days)
0.00
9.1x10^-8
0.0039
3.0
41.
Power (Real/$)^2
c. Global Wavelet
H = 0.66
10^-4
10^-2
1
10^2
10^4
Variance (Real/$)^2

Panel D:


a. Chilean Stock Returns
Return (%)
0
-10
-20
-30
Brazil Crisis ('98)
Brazil Float ('99)
Tender
Enerquinta
shares
(Jan'02)
0
200
400
600
800
1000
Time (days)
Morlet 6.00
Real (solid) Imaginary (dash)
b. Wavelet Power Spectrum
Period (days)
2
4
8
16
32
64
128
256
512
Time (days)
c. Global Wavelet
10^{-2}
0.1
1
10
10^{2}
Variance $(\%)^2$
0.00
0.49
1.5
4.1
11.
Power $(\%)^2$

* The scalogram and scalegram plots for other series are available from the authors upon request.