Some Aspects of Exchange Rate Behavior in Emerging Market Economies

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I hereby declare that the work presented in the thesis entitled "Some Aspects of Exchange Rate Behavior in Emerging Economies" has been carried out by me under the supervision of Professor Bandi Kamaiah, Department of Economics, University of Hyderabad, and to best of my knowledge no part of this thesis was earlier submitted for the award of any research degree or diploma of any University or Institution.

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This is to certify that the research embodied in the present thesis entitled “Some Aspects of Exchange Rate Behavior in Emerging Economies” has been carried out by Alpana Vats under my supervision for the full period prescribed under PhD ordinances of the University and no part of this thesis was earlier submitted for the award of any research degree of any University.

Professor Bandi Kamaiah
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Abbreviations

ACF	Autocorrelation Function
ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARS	Argentine Peso
BDS	Broack, Dechert, Sheinkman, LeBaron
BRL	Brazilian Real
CEE	Central and Easter Europe
CIS	Commonwealth of Independent States
CLP	Chilean Peso
CNY	Chinese Yuan
COP	Colombian Peso
CZK	Czech Koruna
DF-GLS	Dicky Fuller Generalized Least Square
EGP	Egyptian Peso
EMH	Efficient Market Hypothesis
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedastic
GARCH	Generalized Autoregressive Conditional Heteroskedastic
GPH	Geweke-Porter-Hudak
HUF	Hungarian Forint
IDR	Indonesian Rupiah
IDEU	European Union
IGARCH	Integrated Generalized Autoregressive Conditional Heteroskedastic
IID	Independent and Identically Distributed

INR	Indian Rupee
KRW	Korean Won
LKR	Lankan Rupee
MAD	Moroccan Dirham
MENA	Middle East and North Africa
MYR	Malaysian Ringgit
MXN	Mexican Peso
PACF	Partial Autocorrelation Function
PEN	Peruvian Nuevo
PHP	Philippine Peso
PKR	Pakistan Rupee
PLN	Polish Zloty
PPP	Purchasing Power Parity
QMLE	Quasi Maximum Likelihood Estimator
RUB	Russian Rubble
RWH	Random Walk Hypothesis
THB	Thailand Baht
TRY	Turkish Lira
TWD	Taiwanese Dollar
VND	Vietnamese Dong
ZAR	South African Rand

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CHAPTER 1

BACKGROUND, ISSUES AND OBJECTIVES

1.1 Introduction

Foreign exchange market efficiency, which is the answer to the question if prices ‘fully reflect’ the available information, has been the concern of some many distinguished researchers over time and results have been somewhat in favor of efficiency. Although of late there have been some challenging results against the Efficient Market Hypothesis (EMH), overall, for most developed countries foreign exchange market efficiency has been upheld, whilst the developing countries have shown mixed and inconclusive results.

Earlier studies on price independence had taken, until recently, more or less for granted that movements in financial market prices are stochastic in nature, if not actually a random walk, and it seems unlikely that a pattern in financial market returns could be explained by a deterministic process, given the assumption that price movement in financial market is due to the flow of news. However, nowadays, there is a broad agreement that future financial prices are predictable.

The predictable behavior of financial time series was uncovered by the efforts on the part of researchers, Fama (1991), Lo and Mackinlay (1989) and others, who upon observing some departure from efficiency tried to find plausible explanations for the phenomenon and these actions led to the creation of a set of tests capable of detecting linear as well as nonlinear patterns in time series data. Some financial series depart from Random Walk Hypothesis (RWH) and show long range dependence in returns and volatility which is ignored by other models as suggested by Mandelbrot (1971). There is growing evidence of informational efficiency in developed economies due to its matured market, well developed infrastructure for trading, quick information dissemination, and active and informed traders. However, emerging markets are characterized as restricted, illiquid and highly regulated with frequent intervention in exchange market leading to inefficiency.

This thesis aims at investigating the behavior of foreign exchange rates of 25 emerging market economies with special reference of market efficiency using linear, nonlinear and long-memory models.

1.2 Efficient Market Hypothesis

In finance, EMH asserts that financial markets are 'informationally efficient', or that prices of traded assets, e.g., stocks, bonds, or property, reflect all available information. The EMH states that it is impossible to consistently outperform the market by using any information that the market already knows, except through luck. Information or news in the EMH is defined as anything that may affect prices, which is not known in the present and thus appears randomly in the future.

The EMH was first modeled by Louis Bachelior, a French mathematician, in his dissertation titled, "The Theory of Speculation", in 1900. His work was largely ignored until 1950s. Few studies indicated that the US stock prices and related financial series followed a random walk model. Alfred Cowels in the 1930s and 1940s suggested that professional investors were in general unable to outperform the market. The EMH emerged as a prominent theory in the mid-1960s. Paul Samuelson circulated Bachelier's work among economists. In 1964, Bachelier's dissertation along with few other empirical studies was published in an anthology edited by Paul Coonter. In 1965, Eugene Fama published his dissertation arguing in favor of the RWH, and Samuelson published a proof for a version of the EMH. In 1970, Fama published a review of both the theory and the evidence for the hypothesis. The paper extended and refined the theory, included definitions for three forms of market efficiency: weak, semi-strong and strong, each of which have different implications for how the markets work.

1.2.1. Weak-Form Efficiency

- Future prices cannot be predicted by analyzing past prices.
- Excess returns cannot be earned in the long run by using investment strategies based on historical prices or other historical data.
- Technical analysis techniques will not be able to consistently produce excess returns, though some forms of Fundamental Analysis may still provide excess returns.
- Prices exhibit no serial dependencies, i.e., there are no ‘patterns’ to asset prices. This implies that future price movements are determined entirely by information not contained in the price series. Hence, prices must follow a random walk.

1.2.2 Semi-Strong-Form Efficiency

- Semi-strong-form efficiency implies that asset prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information.
- Semi-strong-form efficiency implies that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns.
- To test for semi-strong-form efficiency, the adjustments to previously unknown news must be of a reasonable size and must be instantaneous. To test for this, consistent upward or downward adjustments after the initial change must be looked for. If there are

any such adjustments it would suggest that investors had interpreted the information in a biased fashion and hence in an inefficient manner.

1.2.3 Strong-form efficiency

- Prices reflect all information, public and private, and no one can earn excess returns.
- If there are legal barriers to private information becoming public, as with insider trading laws, strong-form efficiency is impossible, except in the case where the laws are universally ignored.
- To test for strong-form efficiency, a market needs to exist where investors cannot consistently earn excess returns over a long period of time. Even if some money managers are consistently observed to beat the market, no refutation even of strong-form efficiency follows: with hundreds of thousands of fund managers worldwide, even a normal distribution of returns (as efficiency predicts) should be expected to produce a few dozen ‘star’ performers.

1.3 Random Walk Model

In an efficient market the future price is not related to its past price, viz., it shows a random walk. Given a time series (X_t), RWH corresponds to Φ = 1 in the first-order regressive model:

$$X_t = \mu + \Phi X_{t-1} + \varepsilon_t$$

$$\varepsilon \sim N(0,\sigma^2)$$

where μ is an unknown drift parameter.

Following Campbell, Lo and MacKinlay (1997), there are three different versions of the random walk model: Random Walk 1, Random Walk 2, and Random Walk 3. The Random Walk 1

(RW1) or strict white noise process requires sequences of price changes to be independent and identically distributed. If we assume sequences of price changes to be independent and drop the identically distributed assumption, we get the Random Walk 2 (RW2) version. Finally, the Random Walk 3 (RW3) or white noise process is obtained by relaxing the independent and the identically distributed assumption.

The least restrictive of these categories is RW3. In a market that complies with RW3 it is not possible to use information on past prices to predict future prices, i.e., price movements in a market conforming to RW3 have uncorrelated increments.

A market conforming to RW3 is characterized by a random walk and is therefore weak form efficient. In such a market the absence of serial correlation in returns implies that prices are not being driven by insider manipulation or lack of investor liquidity over long periods.

1.3.1 Testing Random Walk Hypothesis

The test for RW3 implies studying the Partial Auto-Correlation Function (PACF) of random increments of past price information of each market up to *k* lagged values, and examining if they are statistically different from zero. Weak-form efficiency implies that the expected increases in the price of an asset should not exceed the normal return μ over the specified interval, i.e.,

$$E[\Delta p_t | I_{t-1}] = \mu$$

where Δp_t are incremental changes in log prices at time *t*, and I_{t-1} represents the information set available to market participants at time $t-1$. To satisfy weak-form efficiency in conforming to RW3, future changes in asset price must be uncorrelated with past changes in prices. This yields a simple test of the null hypothesis that all $\gamma_t = 0$ with an alternative hypothesis of $\gamma_t \neq 0$ in an estimation with *k* lags on the dependent variable given by:

$$\Delta p_t = \mu + \sum_{n=1}^{k} \gamma_{t-n}\, \Delta p_{t-n} + \varepsilon_t$$

where ε_t is the random price innovation with mean equal to zero. The Box-Pierce *Q*-statistic yields a joint test of the PACF coefficients for the existence of autocorrelation. However, the test of a market conforming to RW3 imposes no further restrictions on the price increments at time *t*.

In the case of RW3, however, it may be possible to use information on the variance of past prices to predict future volatility of the market. Conforming to RW2 imposes an additional condition, i.e., the increments are Independent and Non-Identically Distributed (INID). Thus, a test for conforming to RW2 implies a test for RW3 plus a test to ascertain the correlation of squared incremental price changes. This means that the variance of future innovation cannot be forecasted from past variances in the time series. If squared random increments of past price information in the market are not significantly different from zero, the market conforms to RW2 and it is not possible to predict future volatility by looking at past volatility. In the case of RW2, variance can change over time (may be heteroskedastic), but it must change over time in an unpredictable manner.

If a market conforms to the random walk characteristic of RW1, it is neither possible to predict future price movements nor future volatility by examining information on past prices. In the case of RW1, the random price increments can also be described as white noise, and Independent and Identically Distributed (IID). A test for RW1 implies a test for heteroskedasticity in the historical time series of price innovations. RW1 process imposes a much heavier restriction on innovations in asset prices; it is generally thought to characterize only the most mature and efficient financial markets. To test whether individual markets conform to RW1, White test for heteroskedasticity is used.

1.5 Foreign Exchange Market of Emerging Economies

Globally, operations in the foreign exchange market started in a major way after the breakdown of the Bretton Woods system in 1971, which also marked the beginning of the floating exchange rate regime in several countries. Over the years, the foreign exchange market has emerged as the largest market in the world. According to Bank of International Settlement, the average daily turnover of foreign exchange market has increased from US$1.5 trillion in 2001 to US$3.98 trillion in 2010. By geographical location, almost 36.7% of trading is conducted in the UK, 17.9% in the US, and 6.2% in Japan. The four next largest trading centers are Singapore, Switzerland, Hong Kong and Australia, which account for nearly 19% of the total trading. Share of foreign exchange trading in emerging market economies has increased from US$14.1 billion (0.9%) in 1995 to US$302.1 billion (6%) in 2010.

The 1990s witnessed a perceptible policy shift in many emerging markets toward reorientation of their financial markets in terms of new products and instruments, development of institutional and market infrastructure and realignment of regulatory structure consistent with the liberalized operational framework. The changing contours were mirrored in the rapid expansion of foreign exchange market in terms of participants, transaction volumes, decline in transaction costs, and more efficient mechanisms of risk transfer. The exchange rate policy is guided by the need to reduce speculative activities, help maintain an adequate level of reserves, and develop an orderly foreign exchange market. At the same time, the regulatory framework governing the foreign exchange market and the operational freedom available to market participants are, to a large extent, influenced by the exchange rate regime followed by an economy.

The experience with capital flows in the 1990s has had an important bearing on the choice of the exchange rate regime by the emerging market economies in recent years. The emphasis on corner solutions--a fixed peg a la the currency board without monetary policy independence or a freely floating exchange rate retaining discretionary conduct of monetary policy--is distinctly on the decline. The trend seems to be clearly in favor of intermediate regimes with country-specific features and no fixed targets for the level of the exchange rate. This flexibility in the movement of foreign exchange rate has opened up a new area of research of exchange rate behavior in deregulated environment.

The debate on appropriate policies relating to foreign exchange markets has now converged around a generally accepted view that exchange rates should be flexible and not fixed or pegged.

Broadly, the overall distribution of exchange rate regimes across the globe among main categories remained more or less stable during the last decade, though some countries exhibited a tendency to shift across and within exchange regimes. Presently, there are more floating regimes (79 countries including 53 managed floats and 26 independent floats) than soft pegs (60 countries) or hard pegs (48 countries). Managed floats are found in all parts of the globe, while conventional fixed pegs are mostly observed in the Middle East, North Africa and parts of Asia. On the other hand, hard pegs are found primarily in Europe, Sub-Saharan Africa (the CFA zones) and small island economies (e.g., Eastern Caribbean).

During the last two decades, there was a general tendency among the emerging market economies to adopt a more flexible exchange rate regime. In emerging Asia, there is a broad consensus that the soft US dollar peg followed by a number of Asian countries contributed to the regional financial crisis in 1997-98. Since the Asian Financial Crisis, several Asian economies have adopted more flexible exchange rate regimes, except for Hong Kong, which continued with its currency board arrangement and China, which despite some adjustments, virtually maintained its exchange rate peg to the US dollar. After experiencing a transitional regime, Malaysia pegged its currency to the US dollar on September 1, 1998, but recently (July 2005) shifted over to the managed float regime. In contrast, Thailand, Indonesia, Korea, the Philippines and Taiwan have floated their currencies since the crisis, while adopting a monetary policy strategy based on inflation targeting. The Taiwanese government replaced its earlier managed foreign exchange rate by a floating rate in 1989, consequent to an increase in its trade surplus and the resulting rise in the foreign exchange reserves. After experiencing hyperinflation in 1980s, Vietnam pegged its currency to that of a low inflation country, the US. Pakistan had opted for managed float rate system in 1982, but later shifted to free flexible exchange rate policy and the Pak-rupee depreciated since the adoption of flexible exchange rate system. The neighboring country India, shifted to market determined exchange rate in 1993, but the central bank continues to trade extensively in the market.

Most of the Latin American economies have a history of very high inflation rates. As such, inflation control has been the major objective of exchange rate policies of these countries in recent years. Starting from the end of 1994, a floating rate policy was maintained in Mexico, with the Bank of Mexico intervening in the foreign exchange market under exceptional circumstances to minimize volatility and ensure an orderly market. Chile adopted exchange rate flexibility in 1999, after experiencing an exchange rate band for the preceding 17 years starting from 1982. After pursuing various forms of exchange rate pegs for more than four decades, which included occasional devaluation and also a change of the currency, Argentina finally moved away from its currency board linked to the US dollar in January 2002. Brazil, after having a floating exchange rate regime with minor interventions in 1990s, adopted an independently floating exchange rate regime in the aftermath of its currency crisis in 1992.

Before introducing the euro in 1999, most CEE's currencies were pegged to highly stable currencies, such as the Deutsche Mark, the US dollar or SDR. However, their exchange rate regimes drastically changed prior to joining EU in 2004. Czech Republic, Hungary, Poland, and Romania adopted soft-peg regimes (managed floating or free floating) with inflation targeting. After the adoption of soft peg, Czech koruna appreciated continuously. In mid-2008 it was 40 % higher than the January 1999 level, but has been declining since then. The Polish zloty also showed uptrend after 2004, but has been sharply depreciating since mid-2008. The Hungarian forint showed slight depreciation until inflation targeting was adopted in May 2001, fluctuating in the range of ±10%. However, it has declined since mid-2008.

MENA countries opted for a fixed adjustable exchange rate regime in the early 1970s. The adoption of fixed rates was originally justified by the desire to dampen inflationary pressures and achieve macroeconomic stability. However, once the immediate threats of high inflation had been avoided, most MENA countries moved to intermediate regimes. Only a few countries actually turned to fully flexible exchange rate regime. The 1990s was the decade of economic reforms in MENA countries and certain countries achieved considerable progress toward market economy and financial integration during the period. Prices and trade regimes were liberalized and foreign direct investment was encouraged while exchange rates became more flexible. However, although some countries moved to more flexible regimes, they continued to manage heavily their currencies, though sometimes they officially declared themselves to be floaters.

South Africa also witnessed transition from direct monetary control in 1970s to informal inflation targeting and managed floating regime in 1990s, and further, to adoption of a formal inflation targeting monetary policy framework and floating exchange rate regime from the year 2000.

1.6 Motivation

The developed markets, characterized by high level of liquidity, sophisticated investors with access to high quality and reliable information and few institutional impediments, support informational efficiency in the foreign exchange market. However, in the emerging markets, unlike the matured ones, market structures, market participants and the availability of information as well as its quality change rapidly through time. Furthermore, emerging markets are typically characterized by low liquidity, thin trading, possibly less well-informed investors with access to unreliable information and considerable volatility. After the end of Bretton Woods system, countries had the flexibility to choose from free float, managed float, adjustable pegs, crawling pegs, basket pegs, target zones or bands, fixed exchange rates, currency unions, and currency boards. Managing exchange rate became a daunting exercise for central banks. A number of emerging market economies have faced currency crises during the last one-and-a-half decades. The currency crises depleted the economic wealth of these countries. Post crisis, the financial system of emerging economies has been subjected to substantial reforms with far reaching consequences. The reforms mainly focused on exchange rate deregulations. The reforms process led to dramatic improvements in transparency level of the foreign exchange markets. Today the exchange rate is determined by the market forces of demand and supply and market participants play a dominant role in the determination of exchange rate. In most of the countries dirty float has been replaced by free float so far the market is concerned, though at times the central banks intervene to control the excess volatility in the market through indirect interventions like issuing policy statements. Over the years more flexibility has been provided by the central banks to market participants including banks and institutions to operate in the foreign exchange market. Liberalization resulted in institutional and regulatory framework which, in turn, affected the informational efficiency of the market.

The behavior of foreign exchange (forex) returns has been extensively debated over the years. Researchers have examined the efficient market and random walk characterization of returns and alternatives to random walk. Linear and nonlinear dependence in forex returns ensures potential excess profit opportunities in the market. Mean-reversion is one of the competing alternatives to random walk. If the returns exhibit a tendency to return to trend path, such tendency is termed as mean-reversion (Fama and French, 1988; and Porterba and Summers, 1988). The mean-reversion view is in contrast to RWH, and thus, market efficiency.

Another aspect of forex returns which departs from RWH is long memory or long-range dependence. Long memory or long-range dependence is a process in which the autocovariances are not absolutely summable. Long memory implies that the underlying time series realizations are temporally dependent at distant lags. The autocorrelation functions of such stationary series decay hyperbolically. This was originally proposed by Hurst (1951). Later, Granger and Joyeux (1980) and Hosking (1981) proposed the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to examine the issue of long memory. The persistent temporal dependence between distant observations indicates possibilities of predictability and hence provides opportunity to speculators to forecast future returns based on past information and make abnormal profits. Presence of long memory has important theoretical and practical implications.

It violates the EMH. The asset pricing model would also be invalid in the presence of long memory.

Furthermore, persistence in volatility invalidates market efficiency. The long memory in volatility indicates presence of predictable components and thus provides scope of excess returns based on past history of volatility. The conventional models of volatility fail to capture such persistence of long memory in volatility. The models which use short memory such as derivative pricing, value at risk would not be reliable.

Against this backdrop and in context of changes in forex arrangements in emerging economies, the present study attempts to examine weak-form market efficiency, long memory, volatility, and structural breaks in 25 emerging market economies.

1.7 Objectives and Outline

The following are the main objectives of the study:

- To investigate unit root in the exchange rates of emerging markets and address the issues accounting for structural breaks;
- To empirically examine exchange rate return behavior by testing validity of RWH;
- To examine nonlinear dependence in forex returns and test for random walk in the presence of nonlinear trend;
- To examine long-run memory in forex; and
- To detect long run in volatility in exchange rate returns following Baillie *et al*. (1996).

With the above objectives, the thesis has been organized in seven chapters. The first chapter discusses about different forms of market efficiency, different versions of RWH with their definitions. It also gives a brief overview of foreign exchange market in emerging market economies, followed by a discussion on various objectives, research methodology and data used in the study.

The second chapter investigates the presence of unit root in exchange rate series using the conventional unit root tests. The results corresponding to structural breaks in the series may be spurious. Hence unit root tests with exogenously determined one and two structural breaks are also carried on the exchange rate series. The chapter discusses the reasons for significant breaks in the exchange rate series.

The third chapter examines random walk in exchange rate markets of selected 25 emerging markets using both parametric and nonparametric tests. Portmantaeu autocorrelation test suggested by Ljung Box, variance ratio test (Lo and Mackinlay,1989), Chow-Denning test, rank and sign test (Wright, 2000), and runs test are used to examine the mean reversion in forex rates.

Linear models fail to capture nonlinear dependence in forex returns. The presence of nonlinear dependence in forex returns indicates possibility of predictability, and thus, violates the notion of market efficiency. In this context, a set of nonlinearity tests is applied to uncover nonlinear dependence in the underlying stock returns. The tests employed in the study have different power against different forms of nonlinear processes. The tests are implemented on residuals extracted after removing linear dependence in weekly returns by fitting an AR(p) model. The fourth chapter discusses the nonlinear models used in the study.

The fifth chapter investigates long-range dependence in forex return series. ARFIMA model of Granger and Joyeux (1980) and Hosking (1981) is used to analyze long-memory pattern in return series. Modified rescaled range test (Lo, 1991), Geweke and Porter-Hudak’s (1983) semi-parametric approach, and Gaussian semi-parametric test proposed by Robinson (1995) have been used to detect the presence of long memory in forex returns.

Recent international studies have provided evidence of long memory in returns volatility. The conventional ARCH model cannot capture the slow decay of autocorrelation function in conditional variance. Keeping this in mind, the study uses Baillie *et al*.'s (1996) model to capture the very slow hyperbolic decay in the autocorrelation of the volatility process. For comparison purposes, GARCH and IGARCH models are also estimated.

The issue of long-range dependence in volatility is discussed in the sixth chapter. Long memory in both conditional mean and conditional variance is investigated by combining a fractionally integrated regression function and a fractionally integrated heteroskedastic function, i.e., by estimating ARFIMA-FIGARCH models using both normal and t-distribution. The results are further assessed using the Pearson goodness-of-fit test. Finally, the conclusion is offered in the seventh chapter.

1.8 Data

The study covers forex market of 25 emerging economies of which eleven are Asian, five are South American, one is North American, four are European, two are African countries and two are Middle East countries. The forex of these countries have gained importance in international trade in the last decade. Percentage share of daily average turnover in these currencies increased from over 1.2% in 1998 to more than 5% in 2010. Table 1.1 gives the average daily turnover in nominal and percentage terms for the select currencies considered in this study.

- Asian Countries: Chinese Yuan (CNY), Indonesian Rupiah (IDR), Malaysian Ringgit (MYR), Taiwanese Dollar (TWD), Pakistan Rupee (PKR), Philippine Peso (PHP), Korean Won (KRW), Thailand Baht (THB), Lankan Rupee (LKR), Indian Rupee (INR), and Vietnamese Dong (VND).

- Middle East and North Africa (MENA): Egyptian Peso (EGP), Turkish Lira (TRY), and Moroccan Dirham (MAD)
- Latin America: Chilean Peso (CLP), Colombian Peso (COP), Brazilian Real (BRL), Peruvian Nuevo (PEN), Argentine Peso (ARS), and Mexican Peso (MXN)
- Central and Eastern Europe (CEE) : Czech Koruna (CZK), Hungarian Forint (HUF), and Polish Zloty (PLN),
- Commonwealth of Independent States (CIS): Russian Rubble (RUB)
- Africa: South African Rand (ZAR)

These countries have adopted different exchange arrangements during post-deregulation period. (see Table 1.2).The study has used different data range for different currencies as shown in Table 1.3. The study has used weekly return (every Wednesday) for bilateral nominal exchange rates of these currencies against the US dollar.

Table 1.1: Foreign Exchange Market Turnover of Emerging Economies

(in billions of US dollars and percentage)

Countries	**1998**		**2001**		**2004**		**2007**		**2010**	
	Amt	**%**	**Amt**	**%**	**Amt**	**%**	**Amt**	**%**	**Amt**	**%**
Korea	3.6	0.2	9.8	0.6	20.5	0.8	35.2	0.8	43.8	0.9
Russia	6.9	0.3	9.6	0.6	29.8	1.1	50.2	1.2	41.7	0.8
India	2.4	0.1	3.4	0.2	6.9	0.3	38.4	0.9	27.4	0.5
China	0.2	0.0	…	…	0.6	0.0	9.3	0.2	19.8	0.4
Mexico	8.7	0.4	8.6	0.5	15.3	0.6	15.3	0.4	17.0	0.3
Turkey	…	…	1.0	0.1	3.5	0.1	4.1	0.1	16.8	0.3
South Africa	8.9	0.4	9.9	0.6	9.8	0.4	14.0	0.3	14.4	0.3
Brazil	5.1	0.2	5.5	0.3	3.8	0.1	5.8	0.1	14.1	0.3
Poland	2.7	0.1	5.1	0.3	6.5	0.3	9.2	0.2	7.8	0.2
Thailand	3.1	0.1	1.9	0.1	3.1	0.1	6.3	0.1	7.4	0.1
Malaysia	1.1	0.1	1.4	0.1	1.7	0.1	3.5	0.1	7.3	0.1
Czech Republic	5.1	0.2	2.1	0.1	2.4	0.1	5.0	0.1	5.1	0.1
Philippines	0.8	0.0	1.1	0.1	0.7	0.0	2.3	0.1	5.0	0.1
Hungary	1.4	0.1	0.6	0.0	2.8	0.1	6.9	0.2	4.2	0.1
Indonesia	1.8	0.1	3.9	0.2	2.3	0.1	3.0	0.1	3.4	0.1
Colombia	…	…	0.4	0.0	0.8	0.0	1.9	0.0	2.8	0.1
Argentina	2.2	0.1	…	…	0.7	0.0	1.1	0.0	1.6	0.0
Peru	…	…	0.2	0.0	0.3	0.0	0.8	0.0	1.4	0.0

Note: Data has been taken from Triennial Survey conducted by BIS, Published in April 2011. Other countries which are not included in the table above have thinly traded exchange rate market with low turnover.

Table 1.2: De Facto Foreign Exchange Arrangements in Emerging Economies

Conventional Fixed Peg	Crawling Peg	Managed Floating	Independently Floating
MAD (Composite)	CNY (USD)	MYR*	BRL (Inflation Targeting)
RUB (Composite)		COP (Inflation Targeting)	CLP (Inflation Targeting)
LKR (USD)		EGP*	CZK (Inflation Targeting)
VND (USD)		PEN (Inflation Targeting)	HUF (Inflation Targeting)
ARS (USD)		PKR*	MXN (Inflation Targeting)
		IDR (Inflation Targeting)	PLN (Inflation Targeting)
		THB (Inflation Targeting)	TWD
		INR*	TRY (Inflation Targeting)
			PHP (Inflation Targeting)
			KRW (Inflation Targeting)
			ZAR (Inflation Targeting)

Note: * No explicitly stated nominal anchor but monitor various indicators.

Table 1.3: Data Sample

Currency	Data Period
Asia	
CNY	06/01/1994-17/11/2010
IDR	11/05/1991-17/11/2010
MYR	31/03/1989-17/11/2010
TWD	03/04/1989-17/11/2010

PKR	29/12/1988-17/11/2010
PHP	13/01/1992-17/11/2010
KRW	01/11/1988-17/11/2010
THB	01/02/1985-17/11/2010
LKR	09/02/1986-17/11/2010
INR	01/01/1991-17/11/2010
VND	18/06/1993-17/11/2010
MENA	
EGP	06/09/1993-17/11/2010
TRY	22/02/1994-17/11/2010
MAD	31/01/1989-17/11/2010
Latin America	
BRL	01/07/1994-17/11/2010
CLP	03/09/1989-17/11/2010
COP	08/09/1992-17/11/2010
PEN	12/08/1992-17/11/2010
ARS	03/01/1992-17/11/2010
MXN	14/01/1992-17/11/2010
CEE/CIS	
CZK	02/08/1993-17/11/2010
HUF	06/08/1993-17/11/2010
PLN	18/06/1993-17/11/2010
RUB	09/07/1993-17/11/2010
Africa	
ZAR	03/01/1983-17/11/2010

CHAPTER 2

UNIT ROOT IN FOREIGN EXCHANGE RATE IN THE PRESENCE OF STRUCUTURAL BREAK

2.1 Introduction

The issue of presence of a unit root in exchange rate is important both from theoretical and practical point of view. A random walk process shows 'unit root' and 'uncorrelated increments'. In general, random walk in exchange rate series is supported either because a unit root component is detected in the exchange rate series or because the increment in exchange rate is found to be serially uncorrelated. If exchange rate does not contain a unit root it implies that it would return to its mean over time. On the contrary, if exchange rate contains a unit root, it implies that it would follow a random walk and exchange rate movement would be unpredictable.

While the recent empirical studies tend to be more supportive of the absence of unit root, i.e., mean reversion, the earlier studies supported unit root in exchange rate, i.e., random walk. A number of empirical studies using a variety of techniques to test unit root in exchange rate for diverse time periods are available in the literature for developed as well as developing countries. The voluminous evidences, however, are mixed and remain inconclusive.

Most of the earlier studies that examined the presence of a unit root in exchange rate have used traditional unit root tests, such as the Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests. However, these tests are known to be less powerful and biased toward non-rejection of null of unit root for short span data. In other words, the traditional unit root tests may incorrectly conclude that there is a unit root in the exchange rate. Frankel (1986 and 1990) pointed out that the tests typically employed to examine the long-run stability of the exchange rate—if based on data covering 15 years or so—may have very limited power to reject the null hypothesis.

Perron and Phillips (1987) and West (1988), among others, also suggested that traditional unit root tests may suffer from lack of power when the deterministic time trend is misspecified. Further, if the variables present structural changes, these tests may conclude that the analyzed series are I(1), when in fact they are stationary around a deterministic time trend or even a broken time trend (Perron, 1989 and 1990; and Rappoport and Reichlin, 1989).

Perron (1989) argues that in presence of a structural break, the conventional unit root tests, such as ADF (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) are biased toward non-rejection of the null hypothesis of unit root. Subsequently, Perron and Vogelsgang (1992), Zivot and Andrews (1992), Perron (1997), and Lee and Strazicich (2004) suggested test statistics that allow endogenous single structural break in the series while testing for unit roots. It has been further argued that a single endogenous break in a series is insufficient and leads to loss of information when actually more than one break exists. Motivated by this, Lumsdaine and Papell (1997), Clemente *et al*. (1998), and Lee and Strazicich (2003) proposed unit root tests based on multiple structural breaks. This chapter focuses on the presence of unit root in exchange rates of 25 emerging markets in presence of one and two breaks. The chapter is organized as follows: Introduction is followed by a brief review of literature, and a discussion on the methodology used in the study. Subsequently, the results of the empirical tests employed in the study are presented, and finally, the findings are summarized in the conclusion.

2.2 A Brief Review of Literature

In the 1980s, empirical studies commonly failed to support mean reversion, as the hypothesis of mean reversion for the real exchange rate was outperformed by the random walk hypothesis. Adler and Lehmann (1983), Edison (1987), Huizinga (1987), and Corbae and Ouliaris (1988) show that the real exchange rate follows a random walk and fails to support Purchasing Power Parity (mean reversion). This inability to detect mean reversion has often been interpreted as indicating that real exchange rates are governed by permanent shocks.

As the test using short span data have little power to reject unit root in a series, many authors have used longer period to test unit root in exchange rate series. Using longer time periods, Abauf and Jorian (1990), Johnson (1990), Kim (1990), Grili and Kaminsky (1991), Glen (1992), Breuer (1994), MacDonald (1995), Lothian and Taylor (1996), Lothian (1997), Olekalns and Wilkins (1998), Kuo and Mikkola (1999), and Chen and Wu (2000) find that shocks to real exchange rates have finite life. The use of long time series has however been criticized, as it combines regimes of fixed and floating rates, and can be subject to large sample biases (Engel, 2000) and may spuriously reject unit root in presence of breaks. Other tests with improved power and advanced time series techniques have shown mixed results. Abuaf and Jorion (1990), Sarno and Taylor (1998), and Kuo and Mikkola (1999) provide results that support long-run PPP. In the same line, Lothian and Taylor (1997) state that rejection of mean reversion, i.e., PPP reflects the low power of unit root tests. Cheung and Lai (1998) test for PPP by using sequential unit root tests which extend the ADF test to account for possible breaks in the real exchange rate series, and they argue that permanent shocks are not relevant in PPP analysis over the current float. Subsequently, pioneered by Perron (1989), unit root tests that allow for break in deterministic components came into existence. The majority of the previous research has found significant estimates of the break parameters. When the break points or margins of structural instability are taken into account, then most of the exchange rates could be modeled as stationary around a broken trend.

Stock and Watson (1996) provided ample evidence that a large set of macroeconomic variables is subject to structural instability. Exchange rates might be affected by one-time shocks generated by structural changes in the underlying economies and/or measures taken by policy-making authorities. During the transition process many crucial steps performed by authorities are likely to either cause or aid in bringing a kind of structural change. A change in an exchange rate regime and/or official modification of an exchange rate level might be mirrored by a structural break in the evolution of an exchange rate.

Recent innovations in time series econometrics provide appropriate devices for analyzing the subject of structural change. Perron (1989) accounted for structural change in a time series by adding a dummy variable corresponding to a predetermined break date to the augmented test of Dickey and Fuller (1979). Perron and Vogelsang (1992) endogenized the break date for non-trending data in a subsequent work. Later, Bai (1997) and Bai and Perron (1998) proposed a technique that enables one to estimate breaks either simultaneously or sequentially in the case of non-trending and regime-wise stationary data. Zivot and Andrews (1992) suggested a test for a unit root that allows for a one-time change in the constant and/or the slope of the trend function of the series.

2.3 Methodology

2.3.1 Unit Root Tests Without Structural Break

Two conventional unit root tests like ADF and PP tests are used to examine the linear stationarity in real exchange rate series. An important practical issue in the implementation of the ADF test is the specification of the lag length. If the lag length is too small then the serially correlated error terms will bias the result. If lag length is too large, then the power of the test is affected. Ng and Perron (1995) suggested the following data dependent lag length selection procedure that leads to stable size of the test and minimal power loss. First, an upper bound lag length is set. Next, the ADF test regression with maximum lag length is estimated. If the absolute value of the *t*-statistic testing the significance of the last lagged difference is greater than the critical value at 10% significance level, then the unit root test is performed with the maximum lag length. Otherwise, the lag length is reduced by one and the process is repeated. PP test uses the Newey-West bandwidth criteria. The null hypothesis of ADF and PP unit root tests is that a time series y_t is I(1). Stationarity tests, on the other hand, are for the null that y_t is I(0).

Next the DF-GLS^u test (Elliott, 1999), a test for autoregressive unit root is performed on the data. This test is similar to (augmented) Dickey-Fuller test, but shows better overall performance in terms of small sample size and power. The DF-GLS^u test has substantially improved power when an unknown mean or trend is present.

For $y^d_{t,}$ a locally detrended series of y_t, the DF-GLS tests the null $\rho_0 = 0$ against the alternative $\rho_1 < 1$ in the following:

$$\Delta y_t^d = \rho_0 y_{t-1}^d + \sum_{i=1}^{k} \rho_t \Delta y_{t-i}^d + \varepsilon_t^d \tag{1}$$

where $\varepsilon^d{}_t$ is a serially uncorrelated error process, $y^d{}_t$ is defined as $y_t^d = y_t - \gamma z_t$ and $z_t = (1, t)$, for the locally detrended series with a constant and a linear trend, and $z_t = 1$, for series without a linear trend. Finally, γ is the vector of least squares regression coefficients of:

$$\tilde{y}_t = \left[(1-\bar{\rho}^2)^{1/2} y_1, (1-\bar{\rho}L) y_2, ...(1-\bar{\rho}L) y_T\right]$$
$$\tilde{z}_t = [(1-\bar{\rho}^2)^{1/2} z_{1,} (1-\bar{\rho}L) z_2, ...(1-\bar{\rho}L) z_T]$$

where L is the lag operator, i.e., $Lz_t = z_{t-1}$ and $\bar{\rho} = 1 + \bar{c}/T$.

P_T is defined as $P_T = [S(\bar{\rho} - \bar{\rho}S(1)]/\hat{\omega}^2$, where S stands for the sum of the squared residual of a regression under the local alternative ($\bar{\rho}$) or under the null, and $\hat{\omega}^2$ is the spectral density obtained from Equation (1).

Elliott (1999) assumes that the data $\{y\}^T{}_{t=1}$ are generated according to:

$$y_t = d_t + u_t, \qquad \text{and}$$
$$u_t = \rho u_{t-1} + \upsilon_t$$

where d_t is a deterministic component which may or may not contain a deterministic linear trend, and υ_t is a stationary error process which may or may not be serially correlated. Elliott (1999) assumed that $u_0 = 0$ when $\rho = 1$, so that $u_1 = \upsilon_t$. But when $\rho < 1$, u_t has zero mean and variance $(\upsilon_t)/(1-\rho^2)$. Since the alternative assumption involves the unknown parameter ρ, that does not appear asymptotically, the likelihood test statistics and the power of the tests will differ from the optimal test of Elliott (1999). To implement the DF GLS^u test, Equation (1) is estimated by least squares method, with $y^d{}_t$, y_t, and γ as defined above. For DF GLS^u test, $\bar{c} = -10$ is used for both the test with a constant and the test with a constant and a linear trend.

2.3.2 Unit Root Tests in Presence of Structural Break

If there are structural breaks in the series, the above tests may conclude that the series analyzed are I(1) when in fact they are stationary around a deterministic time trend or even around a broken time trend. To overcome this, Perron (1989) proposed a model allowing for known or exogenous structural break in the ADF tests. The model imposes the null hypothesis that a given series has a unit root with drift and an exogenous structural break against the alternative of stationarity about a deterministic trend which has an exogenous structural break. However, the problem with imposing an exogenous structural break is that selecting the break point *a priori* based on an *ex post* examination or knowledge of the data could lead to over-rejection of the unit root hypothesis (Perron and Vogelsang, 1992). Perron's (1989) model was further extended by Zivot and Andrews (1992) by endogenizing break point determination.

Zivot and Andrews (1992) proposed three models for testing unit root, namely, (1) Crash Model: allows a break in the level (or intercept) of the series (Model A); (2) Changing Growth Model: allows for a break in the slope or the rate of growth (Model B); (3) Crash-Cum-Growth Model: allows both effects to occur simultaneously (Model C), i.e., one-time change in both the level and the slope of the series. The three models are specified as follows:

$$\Delta x_t = \alpha_0 + \alpha_1 DU_t + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta x_{t-1} + \varepsilon_t \quad \ldots \quad \text{(A)}$$

$$\Delta x_t = \alpha_0 + \gamma DT_t^* + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta x_{t-1} + \varepsilon_t \quad \ldots \quad \text{(B)}$$

$$\Delta x_t = \alpha_0 + \alpha_1 DU_t + \gamma DT_t^* + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta x_{t-1} + \varepsilon_t \ \ldots \quad \text{(C)}$$

where the dummy variables are defined as follows:

$$DU_t = \begin{cases} 1 \text{ if } t > TB, \\ 0 \text{ otherwise} \end{cases}$$

$$DT_t^* = \begin{cases} t - TB \text{ if } t > TB, \\ 0 \text{ otherwise} \end{cases}$$

The null hypothesis in the above equations is that $\rho = 0$, which implies that x_t has unit root. The alternative hypothesis is that $\rho < 0$, which implies that x_t is breakpoint stationary. This study uses Model A and Model C to determine stationarity of the data series. The break date is selected where the *t*-statistic of the ADF unit root test is at a minimum (most negative). Consequently, a break date is chosen where the evidence is least favorable for the null of unit root. To implement the sequential trend break model, some region must be chosen such that the end points of the sample are not included. The trimming region used in the study is (0.10*T* and 0.90*T*) where *T* is the sample size. Lag length (*k*) is selected based on general-to-specific approach, setting maximum number of lags equal to 12 and using the 10% critical value to determine the significance of the *t*-statistics on the last lag.

The other test proposed by Lumsdaine and Papell (1997) extends the Zivot and Andrews' model to allow for two structural breaks. The extended Model A (called Model AA) allows for two breaks in the intercept and the extended Model C (called Model CC) allows for two breaks in the intercept as well as slope of the trend.

Model AA is represented as:

$$\Delta x_t = \alpha_0 + \alpha_1 DU_{1t} + \alpha_2 DU_{2t} + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \emptyset_i \Delta x_{t-1} + \varepsilon_t$$

Model CC is represented as:

$$\Delta x_t = \alpha_0 + \alpha_1 DU_{1t} + \gamma_1 DT_{1t} + \alpha_2 DU_{2t} + \gamma_2 DT_{2t} + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \emptyset_i \, \Delta x_{t-1} + \varepsilon_t$$

The null and alternate hypotheses are the same as in the one-break case. DU_{1t} and DU_{2t} are indicator dummy variables for a mean shift occurring at TB_1 and TB_2, respectively, where $TB_2 > TB_1+2$, and DT_{1t} and DT_{2t} are the trend shift variables:

$$DU_{1t} = \begin{cases} 1 \text{ if } t > TB_1, \\ 0 \quad \text{otherwise} \end{cases}$$

$$DU_{2t} = \begin{cases} 1 \text{ if } t > TB_2, \\ 0 \quad \text{otherwise} \end{cases}$$

$$DT_{1t} = \begin{cases} t - TB_1 \text{ if } t > TB_1, \\ 0 \quad \text{otherwise} \end{cases}$$

$$DT_{2t} = \begin{cases} t - TB_2 \text{ if } t > TB_2, \\ 0 \quad \text{otherwise} \end{cases}$$

The lag length is selected using general-to-specific approach and the break points are chosen using the same approach as that of Zivot and Andrews' (1992) test.

As noted by Nunes *et al*. (1997) and Lee and Strazicich (2001), the weakness of the DF-type endogenous break unit root test is that it excludes the possibility of a unit root with break. If a break exists under the null of unit root, it will exhibit size distortions and result in spurious rejection of the null hypothesis of unit root too often. Moreover, it gives incorrect estimate of the break point. Lee and Strazicich (2003 and 2004) proposed the alternative endogenous break unit root tests that are unaffected by structural breaks, based on the Lagrange Multiplier (LM) principle. Lee and Strazicich by extending the LM unit root test of Schmidt and Phillips (1992), developed two models, namely, Model AA which allows for two shifts in intercept and Model CC that allows for two shifts each in intercept and trend.

Let the data generating process $\{y_t\}$ be given by:

$$\{y_t\} = \delta' Z_t + e, \quad e_t = \beta e_{t-1} + \varepsilon_t$$

where Z_t is a vector of exogenous variables, e_t is a vector of (first-order auto-correlated) errors, δ' is a vector of parameters, β is a constant, and ε_t is an error term with zero mean and constant variance. In the present study, Model CC is employed which is as follows: Let $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]$

where Z_t is a vector of variables, t is the time trend, D_{jt} and DT_{jt} (j=1, 2) are dummy variables defined as follows:

$$D_{jt} = \begin{cases} 1 \text{ for } t > TB_j + 1 \\ 0 \text{ otherwise} \end{cases}$$

$$DT_{jt} = \begin{cases} 1 \text{ for } t > TB_j + 1 \\ 0 \text{ otherwise} \end{cases}$$

In the above equation TB_j is the time period when a break occurs. For Model CC, in which the process y_t includes two trend breaks each in the intercept and slope, the null (β =1) and alternative (β < 1) hypotheses may be formulated as follows:

Null: $y_t = \mu^{(N)} + d_{11}^{(N)} B_{1t} + d_{12}^{(N)} B_{2t} + d_{21}^{(N)} BT_{1t} + d_{22}^{(N)} BT_{2t} + y_{t-1} + \nu_{1t}$

Alternative: $y_t = \mu^{(A)} + d_{11}^{(A)} D_{1t} + d_{12}^{(A)} D_{2t} + d_{21}^{(A)} DT_{1t} + d_{22}^{(A)} DT_{2t} + \nu_{2t}$

In the above equations, the superscripts N and A denote the null and alternative respectively, ν_{1t} and ν_{2t} are stationary error terms, and B_{jt} and BT_{jt} are defined as follows :

$$B_{jt} = \begin{cases} 1 \text{ for } t > TB_j + 1 \\ 0 \text{ otherwise} \end{cases}$$

$$BT_{jt} = \begin{cases} 1 \text{ for } t > TB_j + 1 \\ 0 \text{ otherwise} \end{cases}$$

Under the null hypothesis, it is assumed that:

$$d_{11}^{(N)} = d_{12}^{(N)} = 0$$

$$d_{21}^{(N)} = d_{22}^{(N)} = 0$$

The two break LM unit root test statistic is obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \bar{S}_{t-1} + \mu_t$$

where $\bar{S}_t = y_t - \hat{\psi}_x - Z_t \hat{\delta}_t$, $t = 2, \ldots, T$, $\hat{\delta}_t$ are coefficients in the regression of Δy_t on ΔZ_t, $\hat{\psi}_x$ is given by $y - Z\hat{\delta}_t$; and y and Z represent the first observations of y_t and Z_t, respectively.

The null of unit root is given by $\phi = 0$ and the LM test statistics are given by $\hat{\rho} = T\hat{\phi}$ and $\bar{\tau}$ is the *t*-statistic for testing the null of unit root. The location of structural break (*TB*) is determined by selecting all possible break points for the minimum *t*-statistics given by:

$$inf\ \hat{\rho}\ (\lambda) = inf\ \hat{\tau}(\lambda)$$

The search is carried out over the trimming region (0.10*T*, 0.90*T*), where *T* is the sample size. Similar to the Zivot-Andrews' test in which the number of lagged augmentation terms are determined by general-to-specific procedure as suggested by Ng and Perron (1995), starting from the maximum of $k = 12$ lagged terms. The procedure looks for significance of the last augmented term.

Enders (2004) argues that Perron and Vogelsang (1992) unit root test is more appropriate if the date of break is uncertain. Also, Srestha and Chowdhary (2005) argue that in case of structural breaks, the testing power of Perron-Vogelsang unit root test is superior to that of Zivot-Andrews' test. Perron and Vogelsang (1992) and Perron (1997) proposed a class of test statistics that allow for two different forms of structural break, i.e., Additive Outlier (AO) and Innovational Outlier (IO) models. The AO model allows for a sudden change in mean (crash model), while the IO models allow for more gradual change only in intercept (Model IO1) as well as a gradual change in slope with intercept (Model IO2). Perron and Vogelsang (1992) applied these two models for non-trending data, while Perron (1997) modified them for use with trending data.

Clemete *et al*. (1998) based their approach on Perron and Vogelsang's (1992) model, but allowed for possibilities of two structural breaks in the mean of the series.

2.4 Empirical Results

Table 2.1 presents the descriptive statistics of log of foreign exchange rates of the 25 emerging market economies. Log of all currencies except CLP, EGP, MAD, KRW, ARS and THB are negatively skewed. Most of the currencies under consideration are mesokurtic. However, CNY, HUF, MAD, PEN, RUB, INR and MXN are leptokurtic. Preliminary statistics suggest that the standard deviation is highest for TRY. Jarque-Bera statistic, which measures departure from normality, is high for all currencies and indicates non-normal distribution for all currencies.

Table 2.2 presents the results of ADF and PP unit root tests performed on the log of exchange rate series without breaks. The results of both the tests employed on the model without trend show rejection of unit root in the case of four currencies, i.e., PEN, RUB, TRY and INR at 1% or 5% significance level. With the inclusion of trend, ADF rejects the null of unit root only for

INR, and PP rejects the null of unit root in the case of two currencies, i.e., PEN and INR. Other currencies show the presence of unit root in their series at least at 5% significance level. KPSS test results also show stationarity of all currencies[1]. The new generation DF-GLS^{u} unit root test supports the results of ADF and PP tests. DF-GLS^{u} test results reject the null of unit root for PEN, RUB, TRY and INR in only for the model without trend at 1% or 5% significance level.

As the unit root in the series may be due to the misspecification of the possible structural breaks in the series, the study employs Zivot-Andrews unit root test, which allows for the possibility of one break in the series. The results of Zivot and Andrews (1992) test are presented in Table 2.3a. For the model without deterministic trend (Model A), Zivot-Andrews test results support mean reversion in seven currencies, namely, IDR, MYR, MXN, RUB, THB, INR and ARS, and for the model with a break in both intercept and trend (Model C), the results support mean reversion in nine currencies, i.e., IDR, MYR, MXN, PEN, TRY, RUB, THB, INR and ARS.

It may be pertinent to note that ignoring a structural break may lead to biases and weak power of unit root test. Similarly, ignoring more than one break also results in reduction in power of the test. Lumsdaine-Papell test, an extension of Zivot-Andrews test allows for two breaks in intercept or slope or both. The results of Lumsadiane and Papell (1997) test are presented in Table 2.3b. The results of Lumsdaine-Papell test, allowing for two breaks in intercept (Model AA), reject the null of unit root for five currencies, i.e., IDR, MYR, RUB, PHP, THB and ARS. When Lumsdaine-Papell unit root test is employed allowing for two breaks in both intercept and slope, the null of unit root is rejected in the case of eight currencies, i.e., CNY, IDR, MYR EGP, RUB, TRY, THB and ARS.

[1] Results of KPSS test is not reported here.

Next, Lee and Strazicich (2003) test is employed on the foreign exchange series as this test has an advantage over Zivot-Andrews and Lumsdaine-Papell multiple break tests. It includes breaks both under null and alternate hypothesis. It provides minimum LM test with breaks in intercept and slope, which is not subject to spurious rejection in the presence of a break under the null, and the authors suggest that the size properties remain accurate in this test. It is clearly evident from Table 2.3c that when two breaks are allowed in both intercept and slope, unit root is rejected in four currency series, i.e., IDR, MXN, THB and ARS.

The break dates identified by the Zivot-Andrews and Lumsdaine-Papell are identical for most of the series. However, the break points identified by Lee-Strazicich and Lumsdaine-Papell two-break tests are entirely different.

As argued by Anders (2004) and Srestha and Chowdhary (2005), Perron and Volsevegan (1992) and Clemente *et al*. (1998) tests are superior to that of Zivot and Andrews (1992) test in terms of power. This study employs Perron 97 (an extension of Perron and Volsvegan (1992) model) and Clemente *et al*. (1998) tests.The results of these two tests are given in Tables 2.4a, 2.4b and 2.4c.

When Perron 97 test is performed on the log series of exchange rates for Model AO, the unit root is rejected only for INR series at 1% significance level. In the case of Model IO1, similar to Zivot-Andrews' (Model A) test results, the unit root is rejected for seven currencies, i.e., IDR, MYR, MXN, RUB, THB, INR and ARS, while for Model IO2, the unit root is rejected for three additional currencies, i.e., PEN, TWD and TRY, similar to the results of Zivot-Andrews (Model C) (refer Table 2.4a).

Clemente *et al*. (1998) test, which allows for two breaks in the mean of the series, rejects the presence of unit root in the case of PEN for Model AO (refer Table 2.4b). For one-break IO model, the test rejects unit root for ten currencies, i.e., IDR, EGP, MXN, RUB, TWD, TRY, PHP, THB, INR and ARS. For two-break IO model, the unit root is rejected for CNY, IDR, MYR, EGP, MXN, RUB, THB, INR, VND and ARS. The break dates given by Perron 97 and Clemente *et al*. (1998) are more or less identical. The break dates for all the tests employed ranges from 1996-1998, 2001, 2005-2006, to 2008. The possible reasons for breaks in the currencies are discussed in the Appendix of this chapter.

2.5 Concluding Remarks

The chapter examined the unit root in log of exchange rate series of 25 emerging market economies during their post-liberalization period. To test unit root in exchange rates first conventional unit root tests like ADF and PP tests and new generation DF-GLS^{u} without breaks were employed. These tests consistently revealed stationarity, i.e., mean reversion in the case of PEN, INR, RUB and TRY. Since these tests ignore the possibility of breaks in the series, unit root tests which allow for possible breaks in the series were also performed. The various one and two endogenous break tests like Zivot-Andrews, Lumsdaine-Papell, and Lee-Strazicich were performed on the data series. Further, new models like Innovative and Additive Outlier models, suggested by Perron (1997) and Clemente *et al*. (1998) were used to test the presence of unit root in currencies of 25 emerging market economies. These all tests unanimously supported the presence of unit root in ten currencies, i.e., CLP, COP, CZK, HUF, MAD, PLN, PKR, KRW, ZAR and LKR. Also, there was strong evidence for stationarity in IDR, THB, ARS, INR, RUB, MYR and MXN. Other currencies have shown mixed result. Overall, the results indicate efficient exchange market in CEE countries and South Africa. However, there is evidence of informational inefficiency in Asian and Latin American countries.

Table 2.1: Descriptive Statistics of Foreign Exchange Rates of Emerging Economies

Currency	LNBRL	LNCNY	LNIDR	LNMYR	LNCLP	LNCOP	LNCZK	LNEGP	LNHUF
Min.	-0.1863	1.8922	7.5893	0.8906	5.8140	6.5361	2.6807	1.1909	4.5296
Mean	0.5788	2.0766	8.6739	1.1649	6.2152	7.4198	3.2866	1.4917	5.2645
Median	0.6239	2.1135	9.0873	1.2322	6.2431	7.5840	3.3064	1.5285	5.3171
Max.	1.3637	2.1658	9.7126	1.5206	6.6253	7.9943	3.7349	1.8336	5.7563
Range	1.5500	0.2737	2.1233	0.6300	0.8114	1.4582	1.0541	0.6427	1.2268
Std. Dev.	0.3968	0.0736	0.6712	0.1744	0.1986	0.4295	0.2441	0.2480	0.2791
Observations	856	880	994	1129	1003	951	903	900	902
Skewness	-0.3483	-1.4071	-0.7235	-0.2947	0.0271	-0.6320	-0.3059	0.0131	-0.8048
Kurtosis (Excess)	-0.9254	0.4166	-1.3455	-1.6342	-0.8423	-1.0390	-0.7295	-1.8174	0.2117
Jarque-Bera	47.8508	296.7357	161.6879	141.9798	29.7703	106.0784	34.1003	123.8898	99.0517

Table 2.1 (Cont.)

Currency	LNMAD	LNPEN	LNPLN	LNRUB	LNTWD	LNTRY	LNPKR	LNPHP	LNKRW
Min.	1.9756	0.2461	0.5639	-0.0156	3.1977	-4.0174	2.9280	3.1420	6.5031
Mean	2.2017	1.0650	1.1538	2.7424	3.4077	-0.5874	3.7912	3.6832	6.8826
Median	2.1801	1.1369	1.1696	3.2920	3.4566	0.2471	3.9484	3.7927	6.8781
Max.	2.4820	1.2924	1.5468	3.5954	3.5586	0.5548	4.4577	4.0334	7.5153
Range	0.5064	1.0463	0.9829	3.6110	0.3609	4.5722	1.5297	0.8914	1.0123
Std. Dev.	0.1031	0.2010	0.2196	0.9606	0.1092	1.2982	0.4296	0.2940	0.2266
Observations	1138	952	909	906	1129	874	1142	984	1151
Skewness	0.6294	-1.2547	-0.3883	-1.2395	-0.3263	-1.0435	-0.3973	-0.5318	0.0413
Kurtosis (Excess)	0.1013	1.3584	-0.7633	0.2252	-1.4839	-0.3655	-1.1126	-1.3256	-1.1694
Jarque-Bera	75.6277	322.9924	44.9023	233.9120	123.6251	163.4814	88.9533	118.4230	65.9152

Table 2.1 (Cont.)

Currency	LNZAR	LNLKR	LNINR	LNVND	LNARS	LNMXN	LNTHB
Min.	0.0598	3.3404	2.8962	-9.2581	0.0187	1.1186	3.1634
Mean	1.4304	4.1754	3.6712	9.5693	0.5418	2.1128	3.4517
Median	1.5013	4.1961	3.7685	9.6304	0.0005	2.2623	3.4527
Max.	2.5273	4.7880	3.9485	9.8781	1.3794	2.7281	3.9843
Range	2.4675	1.4476	1.0524	19.1361	1.3608	1.6095	0.8210
Std. Dev.	0.5936	0.4440	0.2116	0.1695	0.5852	0.4481	0.2161
Observations	1455	1262	1037	894	984	984	1346
Skewness	-0.3667	-0.2629	-1.2469	-0.4266	0.1917	-1.3354	0.2627
Kurtosis (Excess)	-0.8230	-1.2925	1.2208	-0.9145	-1.8905	0.4770	-1.5543
Jarque-Bera	73.6808	102.3758	333.1112	58.2707	152.5625	301.7910	150.9705

Table 2.2: Results of Conventional Unit Root Tests

		ADF		PP		DFGLS[u]	
	Currency	***t*-statistics (constant)**	***t*-statistics (trend)**	***t*-statistics (constant)**	***t*-statistics (trend)**	***t*-statistics (constant)**	***t*-statistics (trend)**
Asia	CNY	0.9486 (16)	-0.8005 (16)	3.22175	-0.9269	3.199	0.388
	IDR	-1.5265 (11)	-1.3556 (11)	-1.51030	-1.2998	-1.391	-1.369
	MYR	-1.5435 (14)	-1.1413 (14)	-1.12155	-0.2290	-1.130	-0.833
	TWD	-1.8319 (4)	-1.4188 (4)	-1.3357	-1.38752	-1.159	-1.249
	PKR	-1.3372 (7)	-1.6467 (7)	1.5455	-1.6216	-1.314	-1.511
	PHP	-1.7369 (11)	-0.8874 (11)	-1.3744	-0.5516	-1.266	-0.914
	KRW	-1.8229 (10)	-2.1273 (10)	-1.7490	-2.0438	-1.570	-1.830
	THB	-1.4480 (23)	-1.3575 (19)	-1.1905	-1.0474	-1.083	-1.087
	LKR	-2.2950 (4)	-0.3157 (4)	-2.4935	0.01888	-2.117	-0.593
	INR	-4.2639[a] (6)	-3.7154[b] (6)	-4.9255[a]	-3.8849[b]	-4.431[a]	-2.283
	VND	-0.4056 (11)	-1.5217 (11)	-0.3608	-1.31402	-0.405	-1.421
MENA	EGP	-0.6739 (1)	-0.7110 (1)	-0.59711	-0.90534	-0.551	-0.858
	TRY	-3.8619[a] (8)	-0.7236 (8)	-5.0841[a]	-1.77253	-4.009[a]	-1.164
	MAD	-2.0887(4)	-2.1570 (4)	-1.9632	-1.99805	-1.962	-1.995
Latin America	BRL	-1.6588 (3)	-0.9412 (3)	-1.69236	-0.84414	-1.532	-0.913
	CLP	-1.9343 (10)	-1.3632 (10)	-1.92508	-1.09968	-1.736	-1.144
	COP	-2.0055 (12)	-1.9064 (11)	-2.3968	-0.3535	-2.178	-0.518
	PEN	-3.6698[a] (9)	-2.2846 (11)	-7.16228[a]	-4.5381[a]	-6.024[a]	-2.354
	ARS	-1.1061 (11)	-2.9857 (11)	-0.0708	-1.5714	-0.092	-1.308
	MXN	-2.1442 (10)	-1.7751 (10)	-2.14814	-1.53328	-1.922	-1.365
CEE/CIS	CZK	-0.5565 (8)	-1.6179 (8)	-0.57621	-1.60466	-0.596	-1.474
	HUF	-2.5959 (8)	-1.9565 (10)	-2.57583	-1.90661	-2.268	-1.452
	PLN	-2.5892(8)	-2.3381 (8)	-2.6294	-2.31058	-2.331	-1.700
	RUB	-3.22793[b](11)	-2.1099 (11)	-3.95339[a]	-2.17797	-2.892[b]	-1.570
Africa	ZAR	-2.3507 (1)	-2.6384 (3)	-2.2892	-1.94545	-2.011	-1.880

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.3a: Results of Zivot-Andrews One-Break Unit Root Test

		Intercept (Model A)		(Intercept and Trend) (Model C)	
	Currency	***t*-statistics**	**Break Date**	***t*-statistics**	**Break Date**
Asia	CNY	-3.9581 (13)	29.08.2007	-3.9276 (13)	14.04.2004
	IDR	-8.1836[a] (11)	19.11.1997	-8.8367 [a](11)	26.11.1997
	MYR	-6.7846 [a](18)	08.01.1997	-6.7615[b] (18)	08.01.1997
	TWD	-4.4767(5)	22.10.1997	-5.0230 (5)	22.10.1997
	PKR	-3.3722 (7)	03.10.2001	-3.2177 (7)	03.10.2001
	PHP	-4.4103 (11)	16.07.1997	-4.4042 (11)	16.07.1997
	KRW	-3.7512 (11)	13.08.1997	-4.7078 (11)	29.10.1997
	THB	-8.2242 [a](24)	25.06.1997	-6.8254[a] (13)	12.02.1992
	LKR	-1.9308 (4)	22.12.2004	-4.4145 (4)	21.06.2000
	INR	-5.3064 [b](11)	29.10.1997	-5.3044 [b](11)	06.11.2002
	VND	-4.0278 (11)	23.10.1997	-3.9339 (11)	23.10.1997
MENA	EGP	-3.9314 (6)	04.07.2001	-4.6601 (6)	29.01.2003
	TRY	-2.1633 (10)	24.01.1996	-6.9064[a] (10)	28.02.2001
	MAD	-3.7984 (4)	10.09.2003	-4.3693 (4)	04.12.2002
Latin America	BRL	-3.4986 (9)	20.01.1999	-4.9874 (9)	17.04.2002
	CLP	-2.8308 (10)	04.08.2004	-4.1570 (10)	22.10.2004
	COP	-2.5904(4)	06.08.1997	-4.1282(4)	07.08.2002
	PEN	-4.2282 (14)	29.10.1997	-5.2334[b](14)	05.08.1998
	ARS	-15.5620[a] (11)	09.01.2002	-17.5336[a] (11)	09.01.2002
	MXN	-9.3923[a] (10)	14.12.1994	-9.3957[a](10)	14.12.1994
CEE/CIS	CZK	-3.4120 (9)	15.01.1997	-3.8633 (9)	13.01.1999
	HUF	-2.8776 (10)	22.05.2002	-3.1874 (10)	27.11.1996
	PLN	-3.4607 (8)	05.05.2004	-3.6602 (8)	13.01.1999
	RUB	-7.1022 [a](11)	19.08.1998	-9.4917[a](11)	26.08.1998
Africa	ZAR	-3.8907 (8)	23.10.2002	-4.0036 (8)	29.01.2003

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.3b: Results of Lumsdaine-Papell Unit Root Test with Two Breaks

		Break in Intercept (MODEL AA)			Break in Both Intercept and Trend (MODEL CC)		
	Currency	***t*-statistics**	**Break Date 1**	**Break Date 2**	***t*-statistics**	**Break Date 1**	**Break Date 2**
Asia	CNY	-5.2888(13)	27.04.2005	17.10.2007	-7.3321[b](13)	24.11.2004	17.10.2007
	IDR	-8.5426[a](11)	18.01.1995	12.11.1997	-9.1202[a](11)	19.11.1997	13.09.2000
	MYR	-7.2291[a](18)	01.01.1997	28.02.2007	-7.9390[a](18)	01.01.1997	12.09.2007
	TWD	-5.2225(5)	15.10.1997	29.09.2004	-6.3689(5)	15.01.1997	21.02.2001
	PKR	-4.2392(7)	04.09.1996	10.07.2002	-4.7443(13)	24.06.1998	20.09.2006
	PHP	-6.4363[b](11)	09.07.1997	10.05.2000	-6.0794(11)	09.07.1997	21.09.2005
	KRW	-4.9684(11)	22.10.1997	19.03.2003	-6.7133(11)	22.10.1997	07.12.2005
	THB	-11.0326[a](24)	18.06.1997	11.10.2006	-11.6863[a](24)	18.06.1997	11.04.2001
	LKR	-2.9524(4)	15.04.1998	15.12.2004	-5.3203(4)	05.01.1994	14.06.2000
	INR	-5.8250(11)	05.11.1997	19.03.2003	-6.0282(11)	05.06.2002	07.03.2007
	VND	-5.5808(11)	15.10.1997	07.05.2008	-6.7367(11)	15.10.1997	22.08.2007
MENA	EGP	-6.0659(6)	28.06.2000	22.01.2003	-11.3872[a](6)	08.09.1999	22.01.2003
	TRY	-2.6604(10)	20.11.2002	21.06.2006	-8.4928[a](10)	02.09.1998	21.02.2001
	MAD	-4.8457(4)	27.11.2002	18.10.2006	-5.3552(4)	08.06.1994	15.05.2002
Latin America	BRL	-4.4597(9)	13.01.1999	16.03.2005	-6.4325(9)	13.01.1999	10.04.2002
	CLP	-3.8404(10)	06.08.1997	28.06.2006	-5.1618(10)	22.02.1995	06.08.2003
	COP	-3.7096(4)	21.04.1999	28.07.2004	-5.0426(4)	07.04.1999	05.06.2002
	PEN	-5.3454(14)	20.09.1995	27.05.1998	-5.7778(14)	29.07.1998	11.01.2006
	ARS	-19.3361[a](11)	02.01.2002	06.02.2008	-23.6408[a](11)	02.01.2002	02.03.2005
	MXN	-4.0169(10)	11.01.1995	29.12.2004	-4.3816(10)	30.08.1995	16.03.2005
CEE/CIS	CZK	-3.9781(9)	08.01.1997	03.09.2003	-4.8949(9)	06.01.1999	08.008.2007
	HUF	-3.8637(10)	27.03.2002	28.06.2006	-4.3447(10)	12.01.2000	22.08.2007
	PLN	-4.3221(8)	13.11.1996	12.05.2004	-5.2044(8)	22.03.2000	22.08.2007
	RUB	-7.4454[a](11)	19.08.1998	05.02.2003	-9.8923[a](11)	19.08.1998	30.04.2008
Africa	ZAR	-4.6897(8)	03.06.1998	09.10.2002	-5.0338(8)	30.10.1996	25.09.2002

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.3c: Results of Lee-Starzichich Structural Break Unit Root Test with Two Breaks

	Currency	*t*-statistics	Break Date 1	Break Date 2
Asia	CNY	-3.9575 (13)	20.07.2005	15.08.2007
	IDR	-5.5098[b] (11)	13.03.1996	04.02.1998
	MYR	-4.8437 (14)	15.03.1995	30.04.1997
	TWD	-4.5346 (4)	08.10.1997	23.02.2005
	PKR	-4.5753 (10)	12.09.2001	16.07.2008
	PHP	-3.9533 (11)	06.08.1997	16.03.2005
	KRW	-4.5777 (11)	05.11.1997	03.05.2006
	THB	-5.6462[b] (19)	09.07.1997	24.07.2002
	LKR	-4.4505 (12)	12.01.1994	28.02.2001
	INR	-3.6615 (6)	11.08.1993	01.11.2000
	VND	-3.2995 (11)	20.05.1998	02.05.2007
MENA	EGP	-4.7402 (11)	13.09.2000	12.05.2004
	TRY	-4.3302 (8)	20.02.2002	24.09.2008
	MAD	-4.7308 (4)	05.01.2000	26.02.2003
Latin America	BRL	-5.0622 (9)	06.01.1999	30.07.2003
	CLP	-4.0450 (10)	15.02.1995	22.08.2001
	COP	-4.6857 (8)	23.12.1998	10.03.2004
	PEN	-2.5192 (9)	31.08.1994	29.12.1999
	ARS	-7.6976[a](12)	26.12.2001	03.02.2003
	MXN	-5.7464[b] (12)	30.11.1994	16.10.1996
CEE/CIS	CZK	-4.1623 (9)	10.05.2000	10.09.2008
	HUF	-4.6149 (4)	03.05.2000	17.09.2008
	PLN	-4.6671 (11)	11.10.2000	29.10.2008
	RUB	-4.2415 (15)	19.02.1999	31.03.1999
Africa	ZAR	-4.1574 (8)	11.06.1986	08.11.2000

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.4a: Results of Perron 97 Unit Root Test

		Perron 97 (IO1: Intercept)		Perron 97 (IO2: Intercept and Trend)		Perron97 (AO)	
	Currency	***t*-statistics**	**Break Date**	***t*-statistics**	**Break Date**	***t*-statistics**	**Break Date**
Asia	CNY	-3.8560 (13)	15.08.2007	-4.4307 (17)	20.07.2005	-3.7505	22.06.2005
	IDR	-8.2402[a] (11)	12.11.1997	-8.9083[a] (11)	12.11.1997	-2.7872	16.08.2000
	MYR	-6.7783[a] (18)	25.12.1996	-6.7539[a] (18)	25.12.1996	-2.5826	11.08.2010
	TWD	-4.6883 (4)	08.10.1997	-5.2061[b] (4)	08.10.1997	-2.9283	07.08.2002
	PKR	-3.3799 (7)	12.09.2001	-3.2180 (7)	12.09.2001	-2.2051	09.06.1999
	PHP	-4.4075 (11)	02.07.1997	-4.4020 (11)	02.07.1997	-2.7774	25.06.2003
	KRW	-3.7523 (11)	30.07.1997	-4.7065 (11)	15.10.1997	-3.0533	23.02.2000
	THB	-8.2187[a] (24)	11.06.1997	-9.2662[a] (24)	11.06.1997	-2.9856	04.02.2004
	LKR	-1.9293 (4)	08.12.2004	-4.3967 (4)	07.06.2000	-2.6360	13.10.2010
	INR	-5.2995[b] (11)	29.10.1997	-5.3074[b] (6)	23.10.2002	-5.0198[a]	11.04.2001
	VND	-4.0272 (11)	08.10.1997	-3.9345 (11)	08.10.1997	-1.9643	28.07.1999
MENA	EGP	-3.9332 (6)	20.06.2001	-4.6561 (6)	15.01.2003	-1.8285	23.02.2005
	TRY	-2.2166 (10)	08.11.1995	-6.8538[a] (8)	14.02.2001	-4.1899	19.12.2001
	MAD	-3.7749 (4)	27.08.2003	-4.3606 (4)	20.11.2002	-3.6182	29.08.2001
Latin America	BRL	-3.4428 (4)	06.01.1999	-4.9925 (9)	15.04.2002	-4.1759	12.03.2003
	CLP	-2.8225 (10)	28.07.2004	-4.1316 (10)	07.02.2001	-3.1524	30.10.2002
	COP	-2.5505 (3)	30.07.1997	-4.3539 (8)	22.05.2002	-3.8946	01.01.2003
	PEN	-4.2036 (14)	14.10.1997	-5.2273[b] (14)	22.07.1998	-4.0949	07.03.2001
	ARS	-16.2582[a] (29)	26.12.2001	-22.1594[a] (38)	26.12.2001	-3.2387	23.07.1997
	MXN	-9.3907[a] (10)	30.11.1994	-9.3927[a] (10)	30.11.1994	-4.2887	02.04.1997
CEE/CIS	CZK	-3.4054 (9)	01.01.1997	-3.8745 (9)	30.12.1998	-3.0694	26.07.2000
	HUF	-3.0195 (10)	01.03.1995	-3.1921 (10)	13.11.1996	-2.5049	22.09.1999
	PLN	-3.4601 (8)	21.04.2004	-3.6942 (8)	30.12.1998	-3.1565	01.03.2000
	RUB	-7.1245[a] (11)	12.08.1998	-9.4544[a] (11)	12.08.1998	-3.1293	04.10.2000
Africa	ZAR	-3.8922 (8)	18.09.2002	-4.0192 (8)	15.01.2003	-3.3133	29.05.2002

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.4b: Results of Clemente, Montanes and Reyes Structural Break Test: Additive Outlier Method

		One Break		Two Breaks		
	Currency	***t*-statistics**	**Break Date**	***t*-statistics**	**Break Date 1**	**Break Date 2**
Asia	CNY	-2.784 (7)	13.02.2008	-4.960 (4)	24.05.2006	23.01.2008
	IDR	-2.975 (24)	04.02.1998	-3.605 (10)	09.07.1997	28.10.1998
	MYR	-3.176 (14)	30.07.1997	-1.484 (14)	02.04.1997	07.06.2006
	TWD	-3.504 (12)	26.11.1997	-3.768 (9)	26.11.1997	02.04.2008
	PKR	-2.878 (10)	04.11.1998	-2.511 (10)	08.11.1995	04.11.1998
	PHP	-3.043 (11)	14.01.1998	-3.309 (11)	14.01.1998	24.01.2001
	KRW	-3.126 (17)	01.10.1997	-2.213 (11)	31.12.1997	18.02.1998
	THB	-2.004 (12)	04.02.1998	-5.004 (11)	30.07.1997	20.09.2006
	LKR	-2.549 (2)	22.04.1998	-3.290 (1)	05.07.1995	21.06.2000
	INR	-4.772 [b](7)	26.11.1997	-4.676 (1)	21.01.1998	29.10.2008
	VND	-1.985 (1)	11.06.2008	-1.177)7)	28.01.1998	12.12.2001
MENA	EGP	-3.157 (2)	02.01.2002	-3.215 (3)	10.01.2001	12.02.2003
	TRY	-3.061 (5)	22.10.2008	-1.846 (0)	25.10.1995	18.03.2009
	MAD	-2.398 (1)	01.02.2006	-4.276 (0)	22.12.1999	12.03.2003
Latin America	BRL	-1.896 (9)	10.03.1999	-2.723 (9)	10.03.1999	10.05.2006
	CLP	-2.607 (1)	10.03.1999	-3.421 (0)	09.08.2000	05.01.2005
	COP	-3.025 (0)	09.12.1998	-3.455 (1)	21.07.1999	27.06.2007
	PEN	-3.076 (14)	25.06.2008	-5.890[b] (0)	08.07.1998	08.11.2006
	ARS	-2.199 (17)	09.01.2002	-2.341 (17)	09.01.2002	19.03.2003
	MXN	-2.471 (15)	22.03.1995	-1.906 (10)	28.12.1994	01.07.1998
CEE/CIS	CZK	-2.389 (0)	05.01.2005	-3.078 (0)	04.06.1997	13.08.2003
	HUF	-2.711 (1)	07.05.2008	-3.073 (0)	21.04.1999	08.01.2003
	PLN	-2.883 (8)	26.10.2005	-4.164 (0)	07.05.1997	21.07.2004
	RUB	-3.129 (5)	05.08.1998	-2.722 (5)	05.06.1996	05.08.1998
Africa	ZAR	-3.300 (1)	21.02.1996	-3.403 (5)	19.08.1992	20.05.1998

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Table 2.4c: Results of Clemente, Montanes and Reyes Structural Break Test: Innovative Outlier Method

		One Break		Two Breaks		
	Currency	***t*-statistics**	**Break Date**	***t*-statistics**	**Break Date 1**	**Break Date 2**
Asia	CNY	-3.319 (12)	09.08.2006	-6.420[a] (12)	13.07.2005	15.08.2007
	IDR	-8.158[a] (11)	05.11.1997	-9.151[a] (11)	09.07.1997	12.11.1997
	MYR	-3.888 (11)	25.12.1996	-6.590[a] (11)	25.12.1996	29.03.2006
	TWD	-4.714[b] (4)	16.07.1997	-5.388 (4)	24.05.1995	08.10.1997
	PKR	-2.429 (7)	19.12.2007	-4.188 (7)	11.10.1995	02.04.2008
	PHP	-5.139[a] (11)	02.07.1997	-5.369 (11)	02.07.1997	03.05.2000
	KRW	-3.473 (10)	08.05.1996	-3.978 (10)	05.11.1997	11.02.1998
	THB	-6.069[a] (24)	11.06.1997	-10.454[a] (19)	11.06.1997	21.06.2006
	LKR	-3.24 (4)	08.04.1998	-4.221 (4)	03.05.1995	08.04.1998
	INR	-5.451[a] (6)	29.10.1997	-6.155[a] (6)	02.08.1995	29.10.1997
	VND	-2.335 (11)	05.03.1997	-5.740[a] (1)	08.10.1997	12.03.2008
MENA	EGP	-4.760[a] (0)	13.09.2000	-6.491[a] (0)	13.09.2000	15.01.2003
	TRY	-4.802[b] (8)	18.10.1995	-3.816 (8)	24.09.2008	29.10.2008
	MAD	-2.851 (4)	27.08.2003	-4.517 (4)	13.11.1996	20.11.2002
Latin America	BRL	-2.999 (3)	06.01.1999	-4.305 (3)	06.01.1999	09.03.2005
	CLP	-2.928 (10)	15.10.1997	-3.437 (10)	29.03.2000	30.07.2003
	COP	-3.493 (3)	04.06.1997	-3.736 (3)	21.06.1995	23.07.1997
	PEN	-3.661 (9)	07.12.1994	-5.008 (14)	14.10.1997	04.01.2006
	ARS	-14.816[a] (12)	26.12.2001	-14.708[a] (11)	26.12.2001	05.02.2003
	MXN	-6.097[a] (10)	30.11.1994	-8.140[a] (10)	30.11.1994	27.03.2002
CEE/CIS	CZK	-2.451 (8)	20.02.2002	-3.251 (8)	13.11.1996	20.02.2002
	HUF	-3.277 (1)	01.03.1995	-3.328 (8)	13.11.1996	08.05.2002
	PLN	-3.183 (8)	05.05.2004	-4.300(8)	13.11.1996	05.05.2004
	RUB	-7.480[a] (11)	12.08.1998	-8.041[a] (11)	17.07.1996	12.08.1998
Africa	ZAR	-3.365 (1)	07.02.1996	-3.810 (1)	23.12.1987	07.02.1996

Note: [a] and [b] indicate significance at 1% and 5% levels, respectively. Figures in parentheses are lag selected based on Ng and Perron (2001) criteria.

Appendix

Currencies	Break Dates	Possible Reasons
BRL	17.04.2002	General election in Brazil, real depreciated against dollar.
CNY	24.11.2004 13.07.2005 15.08.2007 17.10.2007	} China accepted the obligations of Article VIII, Sections 2, 3 and 4 of the Article of agreement. CNY which was pegged to USD was devalued and allowed to float in a narrow range around a fixed based rate. } China's inflation accelerated at the quickest pace and trade surplus swelled, adding pressure on central bank to raise interest rate and let currency appreciate faster to stabilize the economy.
IDR	18.01.1995 09.07.1997 05.11.1997 12.11.1997 19.11.1997 26.11.1997 13.09.2000	} East Asian Crisis There was huge capital outflow as IMF decided to withhold a loan of $400 mn. IDR spiraled to over 11,000 against USD. High inflation and interest rate. Major earthquake in May 2000 caused severe damage to many parts of the country.
MYR	25.12.1996 01.01.1997 08.01.1997 29.03.2006 12.09.2007	} East Asian Crisis Malaysia abandoned fixed peg against dollar in July 2005 resulting in appreciation in ringgit. In March 2006, short selling of currency was removed.
EGP	08.09.1999 13.09.2000 15.01.2003 22.01.2003	Recession in Gulf economy Liquidity squeeze in the economy forced government to draw on foreign currency reserves. There was depletion of foreign exchange reserves by 25%. } Egyptian pound was formally floated in January 2003, and shifted to unified exchange rate system
MXN	30.11.1994 14.12.1994 16.10.1996 27.03.2002	} Mexican Crisis Slowdown in the US impacted the growth of Mexico.
RUB	17.07.1996 12.08.1998 19.08.1998 26.08.1998 19.10.1998 30.04.2008	Russian presidential election } Russian Rubble crisis Russian presidential election
THB	12.02.1992	Social and political protest

	11.10.1996 11.06.1997 18.06.1997 25.06.1997 09.07.1997 11.04.2001 21.06.2006 11.10.2006	South East Asian Financial Crisis General elections Military rule in Thailand
INR	02.08.1995 29.10.1997 26.11.1997 11.04.2001 23.10.2002 06.11.2002	South East Asian Financial Crisis Communal violence at Godhara and other places
ARS	26.12.2001 02.01.2002 09.01.2002 03.02.2003 02.03.2005 06.02.2008	The fixed 1:1 peso-dollar parity was abandoned. The peso depreciated drastically in float regime. General election Debt restructuring by the government.
TRY	18.10.1995 02.09.1998 14.02.2001 21.02.2001	Affected by Russian financial crisis and domestic political turmoil, real GNP turned negative Economic and Political Crisis
TWD	16.07.1997 08.10.1997	South East Asian Financial Crisis
PEN	08.07.1998 08.11.2006	President Fujimori introduced many legal and economic reforms. Signed milestone peace accord with Ecuador. Peruvian general election
PHP	02.07.1997	South East Asian Financial Crisis

CHAPTER 3

VARIANCE RATIO TESTS OF RANDOM WALK IN FOREIGN EXCHANGE MARKET OF EMERGING ECONOMIES

3.1 Introduction

An efficient market is governed by the law of demand and supply with all the relevant information reflected in the exchange rate so that the rate is at fundamental equilibrium. Any shock to this equilibrium deviates the rate from this point permanently and it exhibits random walk. However in an informationally inefficient market, all the information is not reflected in the rate and there is departure from equilibrium point, which is short lived and the exchange rate shows reverting behavior and the possibility of predictability. Random walk process shows 'unit root' and 'uncorrelated increments'. In general, random walk in exchange rate series is supported either because a 'unit root' component is detected in the exchange rate series or because the increment in exchange rate is found to be serially uncorrelated. In Chapter II, we have already discussed about the presence of unit root in the exchange rate series. The present chapter re-examines the random walk in foreign exchange series using Ljung-Box test, the relatively new Variance Ratio (VR) test. While there are two implications of random walk (unit root and uncorrelated increments), the present chapter focuses on the aspect of uncorrelated increments. In addition to this, other nonparametric tests like 'runs' test is also used to investigate the efficiency of foreign exchange market of 25 emerging economies.

3.2 Review of Recent Literature

Many researchers (e.g., Ayadi and Pyun, 1994; Huang, 1995; Urrutia, 1995; Grieb and Reyes, 1999; Chang and Ting, 2000; Darrat and Zhong, 2000; and Lee *et al*., 2001;) have used Lo-MacKinlay VR tests to examine the Random Walk Hypothesis (RWH) mostly in emerging stock markets. Huang (1995) finds that stock markets in Korea, Malaysia, Hong Kong, Singapore, and Thailand are not efficient in its weak form. Darrat and Zhong (2000) find that two Chinese stock markets (Shanghai and Shenzhen) do not follow random walk process although they are more in favor of model comparison approach due to its more decisive result. Liu and He (1991) and Ajayi and Karemera (1996) used a VR test and rejected the RWH for major and Asian foreign exchange rates. Using VR test, Smoluk *et al.* (1998) find random walk behavior in UK pound/US dollar real exchange rate. Although the pound-dollar real exchange rate shows mean reverting tendencies due to the Purchasing Power Parity (PPP), frequent and strong shocks to the nominal exchange rate assume that the series follows a random walk since these shocks directly influence the real exchange rate. The RWH is also not rejected for the pound-dollar monthly nominal exchange rate and it suggests that a random walk in nominal exchange rates should lead to a random walk in real exchange rates. Lee *et al*. (2001) employed a joint VR test and technical trading rules to investigate the random walk behavior for nine Asian foreign exchange rates for the period 1988-1995. They first tested the serial correlation version of RWH by using the VR test of Lo and MacKinlay (1988). They performed a joint VR test to see if all variance ratios over a particular lag length simultaneously equal unity. The joint VR test results show little evidence of serial correlation for all the exchange rates, except the Korean Won (Hoque *et al*., 2007). Kawakatsu and Morey (1999), Abraham *et al*. (2002), Ryoo and Smith (2002), Smith *et al*. (2002), Smith and Ryoo (2003), Buguk and Brorsen (2003), and Lima and Tabak (2004) applied the Chow-Denning and multiple VR tests to examine the RWH. Kawakatsu and Morey (1999) study the effect of financial liberalization on the efficiency of emerging equity markets and find that markets have been already efficient prior to the actual liberalization. Ryoo and Smith (2002) find that price limit system prevents Korean stock market to follow random walk process since market approaches to a random walk when price limits are relaxed. Smith *et al.* (2002) reject RWH for seven medium and small size African stock markets due to the presence of serial correlation in return series. Smith and Ryoo (2003) find serial correlation of returns in four European emerging stock markets (Greece, Hungary, Poland and Portugal).

Lima and Tabak (2004) suggest that liquidity and market capitalization may affect the market efficiency based on their findings in different classes of shares in stock markets of China, Hong Kong and Singapore.

In addition to Lo-MacKinlay and Chow-Denning tests, Hoque *et al*. (2007) used two new VR tests (Wright's (2000) ranks and sign tests and Whang-Kim (2003) subsampling tests) to re-examine the RWH for eight emerging equity markets in Asia and found that stock markets in Indonesia, Malaysia, Philippines, Singapore, and Thailand show significant mean-reverting and predictable behavior in their weekly return series, while Taiwanese and Korean stock markets exhibit mean-reverting behavior to a certain extent, largely unpredictable patterns are observed in the same series.

Ahmed *et al.* (2005) report their findings that the return series of South Asian foreign exchange markets were stationary during the period 1999-2004. They reject RWH for those markets by using the runs test. Liu and He (1991) used Lo-MacKinlay VR technique and Box-Pierce *Q*-statistics on five currencies: Canadian dollar, Swiss franc, Deutche mark, Japanese yen and pound sterling, and rejected the RWH for the period August 1974-March 1989.

A similar study by Ajayi and Karemera (1996) on South Asian nations during the period 1986-1991 rejects the RWH for currencies of these countries and reports that rejection is not robust to heteroscedasticity in exchange series.

Wu and Chen (1998) used panel root test to examine the stationarity of forward premia and interest rate differentials for nine OECD countries and found it supporting the hypothesis of foreign exchange efficiency.

Lee *et al*. (2001) used joint VR test and technical trading rule to examine the price predictability of nine Asian currencies. The results of this study suggest that there is little evidence of correlation in exchange rate, except the Korean won. Also, technical analysis shows significant profit for Korean won, Singapore dollar and Taiwan dollar. Broadly, the nine currencies mostly follow a random walk process.

Chang (2004) used VR with bootstrapping resampling technique on Canadian dollar, Swiss franc, Deutche mark, Japanese yen, and pound sterling for the period 1974-1998 and rejected the RWH for Japanese yen. He also found that RWH could not be rejected for Canadian dollar, Swiss franc, Deutche mark and pound sterling for the subsample period from 1989 onwards.

Belaire-Franch and Opong (2005) used Lo-MacKinlay VR test and Wright's (2000) ranks and sign tests to examine the euro exchange rate against the Australian dollar, Canadian dollar, Japanese yen, pound sterling, US dollar, New Zealand dollar, Norway kroner, Singapore dollar, Sweden kroner, Swiss franc and rejected random walk for Canadian dollar, Singapore dollar, New Zealand dollar, Swiss franc, and Norway kroner.

In a similar study, Lima and Tabak (2007) found that the RWH cannot be rejected for emerging market currencies. Wickremsinghe (2008) tested weak and semi-strong efficiency using autocorrelation, Ljung-Box test, cross-correlation test and concluded that EMH does not apply for Sri Lankan foreign exchange market.

Kisaka *et al*. (2008) rejected RWH for Kenyan shilling using runs test, unit root test, and Ljung-Box *Q* test.

Chen (2009) employing Chow-Denning multiple VR test on 10 Pacific Basin economies, rejected the RWH for all currencies, except for Indian rupee, Malaysian ringgit, and Philippine peso.

Lima and Tabak (2009) using VR, multiple VR, and technical trading rule refuted RWH for Brazilian exchange rate for long-investment horizon, but found it consistent with RWH in the short run. Additionally, the study found that the prediction power of variable moving average and trading range breakeven technical rules is not economically significant.

3.3 Methodology

3.3.1Autocorrelation Tests

Ljung-Box *Q*-Test: Ljung and Box (LB) (1978) statistic is a variant of Box and Pierce (1970) *Q*-statistic, which is used to test the joint hypothesis that all the autocorrelation coefficients up to lag *m* are simultaneously equal to zero. LB *Q*-statistic is defined as:

$$Q = n(n+2)\sum_{k=1}^{m}\left(\frac{\rho_k^2}{n-k}\right)$$

where *n* is the number of observations, *m* is the number of lags, and ρ_k is the autocorrelation coefficient at lag *k*. *Q* follows a chi-square distribution with *m* degrees of freedom.

3.3.2 Individual Variance Ratio Tests

If the data generating process of time series is a random walk, the expected value of $VR(x;\ k)$:

$VR(k) = \frac{\hat{\sigma}^2(k)}{\hat{\sigma}^2(1)}$ should be equal to unity for all horizons k.

where,

$$\hat{\sigma}^2(k) = \frac{1}{m}\sum_{t=k}^{T}(X_t - X_{t-k} - k\hat{\mu})^2$$

$$m = k(T-k+1)(T-k)/T$$

$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T}(X_t - X_{t-1})$ and

$$\hat{\sigma}^2(1) = \frac{1}{T-1}\sum_{t=1}^{T}(X_t - X_{t-1} - \hat{\mu})^2$$

The test statistics $M_1(k)$ is given by:

$$M_1(k) = \frac{VR(k)-1}{\phi(k)^{\frac{1}{2}}}$$

which under the assumption of homoscedasticity, is asymptotically distributed as N (0, 1). The asymptotic variance, $\phi(k)$, is given by:

$$\phi(k) = \frac{2(2k-1)(k-1)}{3kT}$$

The test statistic $M_2(k)$, which is robust under heteroscedasticity assumption, is given by:

$$M_2(k) = \frac{VR(k)-1}{\phi^*(k)^{1/2}}$$

where,

$$\phi^*(k)=\sum_{j=1}^{k-1}\left[\frac{2(k-j)}{k}\right]^2\delta(j)$$

$$\delta(j)=\frac{\sum_{t=j+1}^{T}(X_t-X_{t-1}-\hat{\mu})^2\,(X_{t-j}-X_{t-j-1}-\hat{\mu})^2}{\left[\sum_{t=1}^{T}(X_t-X_{t-1}-\hat{\mu})^2\right]^2}$$

The statistics used to test the hypothesis have an asymptotically standard normal distribution. Nonetheless, statistical inference based on the asymptotic distribution could be misleading in finite samples. If returns are positively (negatively) autocorrelated, the VR should be higher (lower) than unity. A time series (in level) is said to be mean reverting, if *VR*(*x*; *k*) is significantly lower than unity at long horizons *k*. In contrast, a time series is mean averting, i.e., explosive, if *VR*(*x*; *k*) is significantly higher than unity at long horizons (Poterba and Summers, 1988). Some of the VR tests used in this study are discussed below.

Lo and MacKinlay (1988) Test: Since the pioneer work of Lo and MacKinlay (1988), it has been the most widely used econometric tool. If a time series of returns follows a random walk, then in a finite sample the increments in the variance are linear in the observation interval, i.e., the variance of returns should be proportional to the sample interval. Thus, the variance of monthly returns should be four times the variance of weekly returns.

Lo and MacKinlay (1988) proposed the asymptotic distribution of *VR*(*x*; *k*) by assuming that *k* is fixed when $T\rightarrow\infty$. They showed that if x_t is i.i.d., i.e., the assumption of homoscedasticity, then under null hypothesis is *V*(*k*) = 1, test statistics used to test the VR in a series has two variants. The first test statistic is $M_1(k)$, with the assumption of homoscedasticity and asymptotic distribution of N (0, 1), and the other $M_2(k)$, which is robust under heteroscedasticity with asymptotically standard normal distribution.

If the VR is less than unity, it indicates the presence of negative serial correlation which is consistent with mean-reverting behavior in the series. A VR greater than unity indicates the presence of positive serial correlation or an explosive function in the series. Thus, Lo-MacKinlay derived an asymptotic standard normal test statistic $M_1(k)$, that provides the statistical significance of variance ratios, as well as an alternative statistic, $M_2(k)$, which is robust to heteroscedasticity and non-normal disturbances. Lo and MacKinlay (1989) further showed that the VR test is more reliable than the Box-Pierce Q-test which is traditionally used for detecting serial correlation.

Chen and Deo (2006): The conventional VR tests, such as the Lo-MacKinlay test, are asymptotic tests in that their sampling distributions are approximated by their limiting distributions. Indeed, the practical use of the statistic has been impeded by the fact that the asymptotic theory provides a poor approximation to the small-sample distribution of the VR statistic. In general, the ability of the asymptotic distribution to approximate the finite-sample distribution depends crucially on the value of the horizon k. More specifically, rather than being normally distributed (when standardized by T) as the theory states, the statistic is severely biased and right skewed for large k (relative to T) (Lo and MacKinlay, 1989), which makes its application problematic. In other words, the finite-sample null distribution of the test statistic is quite asymmetric and non-normal.

A solution was provided by Chen and Deo (2006), who suggested a simple power transformation of the VR statistic, when k is not too large. It provides a better approximation to the normal distribution in finite samples and is able to solve the well-known right-skewness problem. Chen and Deo showed that the transformed VR statistic leads to significant gains in power against its mean-reverting alternatives. Furthermore, the distribution of the transformed VR statistic is shown, both theoretically and through simulations, to be robust to conditional heteroscedasticity.

Wright's (2000) Ranks and Sign VR Test: Lo-MacKinlay and Chow-Denning tests are asymptotic tests, whose sampling distributions are approximated based on their limiting distributions. Wright's (2000) ranks and sign tests are an improvement over these tests as they have two advantages over the Lo-MacKinlay test, when the sample size is relatively small: (1) As the ranks (R_1 and R_2) and sign (S_1 and S_2) tests have an exact sampling distribution, there is no need to resort to asymptotic distribution approximation; and (2) The tests may be more powerful than the conventional VR tests against a wide range of models displaying serial correlation, including fractionally integrated alternatives. The tests based on ranks are exact under the i.i.d. assumption, whereas the tests based on signs are exact even under conditional heteroscedasticity. Moreover, Wright (2000) showed that ranks-based tests display low-size distortions, under conditional heteroscedasticity. Wright's S_2 test is not considered in this paper as his Monte-Carlo simulation results clearly indicate that its size and power properties are quite inferior to those of S_1.

3.3.3 Multiple Variance Ratio Tests

The Lo-MacKinlay test is an individual test where the null hypothesis is tested for an individual value of *k*. The question whether or not a time series is mean reverting requires that the null hypothesis holds true for all values of *k*. In view of this, it is necessary to conduct a joint test where multiple comparisons of VRs over a set of different time horizons are made.

However, conducting individual tests for a number of *k* values may be misleading as it leads to over-rejection of the null hypothesis of a joint test, above the nominal size.

Chow and Denning (1993) Test: Chow and Denning (1993) stressed that the sequential procedure of Lo and MacKinlay (1988) leads to an oversized testing strategy. Thus, the limitation of Lo-MacKinlay's test is that it ignores the joint nature of testing for the RWH. Nonetheless, statistical inference based on the asymptotic distribution could be misleading in finite samples. Furthermore, Chow and Denning (1993) have shown that to test for multivariate VR it is important to control for the joint-size test statistic. They provide a procedure for the multiple comparisons of the set of variance estimates and unity. For the set of '*m*' test statistics, the RWH is rejected, if any one of the estimated variance ratios is significantly different from unity. Hence, only the maximum absolute value in the set of test statistics is considered. The authors show that the multivariate test statistic has a Studentized maximum modulus distribution with *m* parameters which is number of *k* values and *T* degrees of freedom, equal to the sample size. He also suggested heteroscedasticity robust version of the Multiple Variance test.

Whang and Kim (2003) Subsampling Test: Whang and Kim (2003) developed a multiple VR test that uses the subsampling technique of Politis *et al*. (1997), which is a data-intensive method of approximating the sampling distribution. It shows better properties than the conventional VR tests, when the sample size is relatively small. The Monte-Carlo experiment results reported by Whang and Kim (2003) confirmed that their new VR test has excellent power in small samples, coupled with little or no serious size distortions.

Belaire-Franch and Contreras (2004) Tests: Belaire-Franch and Contreras (2004) proposed to substitute the standard VR tests by Wright's ranks- and sign-based tests as per Chow and Denning's (1993) procedure to create multiple rank and sign VR tests. The ranks-based procedures are exact under the i.i.d. assumption, whereas the sign-based procedures are exact under both i.i.d. and martingale difference sequence assumption. Belaire-Franch and Contreras showed that the counterpart of R_1 and R_2 ranks-based tests CD(R_1) and CD(R_2), respectively are more powerful than their sign-based counterparts, CD(S_1) and CD(S_2).

3.3.4 Wald-Type Tests

Richardson and Smith (1991) Test: Richardson and Smith (1991) suggested a joint test based on the following Wald statistic:

$$RS(k) = T(VR - 1_k)'\emptyset^{-1}(VR - 1_k)$$

where *VR* is the ($k \times 1$) vector of sample *k* VRs, and 1_k is the ($k \times 1$) unit vector and is the covariance matrix of VR. The joint *RS*(*k*) statistic follows a χ^2 distribution with *k* degrees of freedom.

The usefulness of this test relies on the fact that, whenever VR tests are computed over long lags with overlapping observations, the distribution of the VR test is non-normal; then, neither the Lo-MacKinlay test nor the Chow-Denning procedure gives valid inferences.

Moreover, Fong *et al*. (1997) argued that Richardson and Smith's (1991) joint VR test is more powerful than the Chow-Denning multiple comparison test for empirically relevant alternatives, and it displays low-size distortion in the presence of heteroscedastic increments. However, their simulation results are based on an Autoregressive Conditional Heteroscedasticity (ARCH) process with slope coefficient 0.1, which is ‘practically’ an i.i.d. process. Therefore, the inference drawn by Fong *et al*. (1997) did not hold under heteroscedasticity.

3.3.5 Bootstrapping Variance Ratio Tests

As already noted, Wright (2000) (based on ranks and sign) and Whang and Kim (2003) (using the subsampling method) proposed VR tests that do not rely on asymptotic approximations in order to overcome the difficulties (severe bias and right skewness) associated with use of VR tests based on asymptotic approximations. As an alternative, some researchers proposed to employ the bootstrap method, which is a resampling method that approximates the sampling distribution of a test statistic (Efron, 1979) to the VR test statistic. The bootstrap is a distribution-free randomization technique, which can be used to estimate the sampling distribution of the VR statistic, when the distribution of the original population is unknown. We describe the two most used bootstrapping VR tests, i.e., the one suggested by Kim (2006) in a theoretical framework, and by Malliaropulos and Priestley (1999) in an empirical framework.

Kim (2006): Kim (2006) used the wild bootstrap that is a resampling method that approximates the sampling distribution of the VR statistic, and is applicable to data with unknown forms of conditional and unconditional heteroscedasticity. Kim applied wild bootstrap to Lo-MacKinlay and Chow-Denning’s heteroscedastic robust version. Kim showed that the subsampling test of Whang and Kim (2003) displays small-sample properties far inferior to that of the wild bootstrap test under a small sample size.

3.3.6 Runs Test

The study uses the Wald and Wolfowitz (1940) runs test to test for the randomness of the series. Runs test is a strong test for checking randomness in investigating serial dependence in foreign exchange (forex) rate movements and compares the expected number of runs from a random process with the observed number of runs. The test is nonparametric and is independent of the normality and constant variance of the data. A run is defined as a series of identical signs that are preceded or followed by a different sign or no sign at all, i.e., given a sequence of observations, the runs test examines whether the value of one observation influences the values taken by the later observations. If there is no influence (the observations are independent), the sequence is considered random. It is assumed that the sample proportion of positive, negative and zero price changes are good estimates of the population's proportions. Runs test shows the cutting point, the number of runs, the number of cases below the cutting point, the number of cases greater than or equal to the cutting point, and the test statistics Z with its observed significance level. The total number of runs is a measure of randomness, since too many or too few runs suggest dependence between observations.

To perform this test A is assigned to each return that equals or exceeds the mean value and B for the items that are below the mean. Let nA and nB be the sample sizes of items A and B respectively. The test statistic is U, the total number of runs. For samples of large size, that is when both nA and nB are greater than 20, the test statistic is approximately normally distributed:

$$Z = \frac{U - \mu_U}{\sigma_U}$$

where, $\mu_U = \frac{2n_A n_B}{n} + 1$

$$\sigma_U = \sqrt{\frac{2n_A n_B(2n_A n_B - n)}{n^2(n-1)}}$$

$n = n_A + n_B$

3.4 Empirical Results

Table 3.1 presents the basic statistics of the weekly log returns of 25 currencies considered in this study. The preliminary statistics suggest that the top three currencies showing highest return are TRY, RUB and IDR. The bottom three currencies showing the minimum mean returns are CNY, MYR and MAD. CNY shows negative mean return over the period. Also, CNY is the only currency which is negatively skewed showing a tendency of depreciation. All currencies have positive excess kurtosis (kurtosis > 3), which indicates leptokurtic distribution. Jarque-Bera statistic, a measure of deviation from normality is very high for all currencies suggesting non-normality in all currencies. Standard deviation is highest in the case of IDR. LB *Q*-statistic at lag 15, suggests autocorrelation in all currencies, except BRL at 5% significance level. The ARCH-LM test, testing the ARCH effect in series suggests ARCH in all series, except CNY, VND and EGP.

First, Lo-MacKinlay test is employed under the maintained hypothesis of homoscedasticity and then the possibility of heteroscedasticity is allowed for in the null hypothesis. By using one week as the base observation interval, the RWH is tested by calculating $VR(k)$ and $M_1(k)$ for k=2, 4, 8, 16. In addition, heteroscedasticity-consistent VR test is also performed by calculating the $VR(k)$ and $M_2(k)$ for each of the cases k=2, 4, 8, 16. The results are presented in Table 3.2.

As can be seen from Table 3.2, four currencies HUF, RUB, TRY and VND have VR less than 1 for all *k*, indicating negative correlation and mean reversion in these series, and seven currencies, CNY, CLP, COP, CZK, EGP, TWD and INR have VR greater than 1, indicating positive correlation or explosive function in these series. 20 currencies, except CZK, MXN, PKR, ZAR and LKR have rejected random walk at 5% significance level for at least one interval length under the maintained hypothesis of homoscedasticity. It is noteworthy that for countries that have fixed or pegged exchange agreement mean reversion is expected. In specific, given a pegged exchange rate agreement, large deviations from the fixed rates will likely induce central bank interventions to correct misalignments and hence mean reversion would follow.

Since the results obtained from $M_1(k)$ is under the maintained hypothesis of homoscedasticity, the rejections of the random walk may either be due to heteroscedasticity or serial correlation. To investigate this, heteroscedasticity-consistent VR test $M_2(k)$ is employed. The test results, presented in Table 3.2, indicate that six currencies, i.e., CNY, CLP, COP, EGP, PEN and TWD, that rejected RWH under homoscedasticity are robust to heteroscedasticity. This implies that the VR is different from 1 due to autocorrelation, rather than heteroscedasticity for these six currencies.

As Lo-MacKinlay test ignores the joint nature of testing for RWH, the study employed Wald test proposed by Richardson and Smith (1991) and multiple VR test proposed by Chow and Denning (1993). The results of Wald test are presented in Table 3.3. The test rejects RWH for all currencies, except CZK, HUF, PKR and ZAR at 5% significance level. However, Chow-Denning test results (see Table 3.2) suggest rejection of random walk for 18 currencies, i.e., BRL, CNY, MYR, CLP, COP, EGP, MAD, PEN, PLN, RUB,TWD, TRY, PHP, KRW, THB, INR, VND and ARS, under the maintained hypothesis of homoscedasticity and for four currencies, i.e., CNY, EGP, PEN and TWD under the hypothesis of heteroscedasticity.

However, the above tests were criticized for the assumption made under these tests. Richardson and Smith's (1991) Wald test was criticized for its assumptions that the underlying time series does not exhibit conditional heteroscedasticity, and Lo-MacKinlay and Chow-Denning tests were criticized for their assumption of asymptotic distribution, which leads to right-skewed distribution rather being normally distributed. In view of this, Chen and Deo (2006) VR test with a simple power transformation, when *k* is not too large, providing a better approximation to the normal distribution in finite samples and capable of solving the right-skewness problem is used. Also, the distribution of the transformed VR statistic, suggested by Chen and Deo (2006) is robust to conditional heteroscedasticity. The results of this test (see Table 3.3) suggest rejection of RWH for five currencies, i.e., CNY, EGP, PEN, RUB, and TWD.

Next, Whang and Kim (2003) subsampling test which shows better power in small samples coupled with little or no size distortions is also employed on the data. Table 3.4 presents the results of the subsampling test. The various columns indicate the *p*-values of the test statistics for various block lengths given in parentheses. The test rejects RWH for 12 currencies, i.e., BRL, CNY, CLP, COP, EGP, MXN, PEN, TWD, KRW, THB, INR and ARS.

To overcome the problem of asymptotic approximations and right skewness some researchers have proposed the bootstrap method, which is a resampling method that approximates the sampling distribution of a test statistic to the VR test statistic. The bootstrap is a distribution-free randomization technique, which can be used to estimate the sampling distribution of the VR statistic, when the distribution of the original population is unknown. In this study, we have employed Kim (2006) bootstrapping VR tests. The test results suggest that the eight currencies for which RWH was rejected by Lo-MacKinlay test, the Kim (2006) test also rejected RWH for those currencies (see Table 3.5). The bootstrapped Chow-Denning VR test has also rejected RWH for the same eight currencies, i.e., CNY, CLP, COP, EGP, PEN, TWD, INR and ARS at 5% significance level.

The above tests give diverse and conflicting results. Next, the nonparametric test proposed by Wright (2000) based on ranks and sign is also conducted on the data to examine the RWH in foreign exchange market of 25 countries considered in this study. The results are shown in Table 3.6. The table reports R_1, R_2 and S_1 at different k values, such as 2, 4, 8, and 16. The R_1 and R_2 tests are more powerful than the conventional $M_1(k)$ and $M_2(k)$ of Lo-MacKinlay VR test. The table reports only S_1, as it is shown by Wright (2000) through Monte-Carlo simulation that S_1 has better power properties than S_2. Following the rule of thumb: "reject null if there are more than two rejections at any level of significance", the RWH may be rejected for these currencies. Besides, Wright (2000) points out that, if S_1 rejects the null, then S_2 must also reject it. It is evident from the table that the tests support RWH in CZK, HUF, MAD and PLN. The joint Wright (2000) test gives by and large similar results with an additional currency, MXN, supporting the RWH at 5% significance level.

Runs, another nonparametric test is also employed to test the dependence in returns of exchange rate series (see Table 3.7). It is used to test the null that the data is generated through random process. Columns 4 and 5 of the table give the Z-statistic and p-values. The results of runs test suggest randomness in CLP, CZK, EGP, HUF, MAD, PLN, PHP, KRW, THB and ZAR.

3.5 Concluding Remarks

The present chapter investigated the behavior of weekly foreign exchange returns of 25 emerging economies by testing the RWH. The major objective of this chapter was to test the weak-form efficiency of forex market of these emerging market economies. Toward this end, both parametric and nonparametric tests were used to analyze the weekly return on 25 currencies. The results by and large suggest random walk in PHP and MAD in addition to CEE currencies and ZAR, and mean reversion, i.e., predictability in CNY, CLP, EGP, PEN, TWD, INR and ARS. Other currencies have shown mixed results and hence remain inconclusive.

Table 3.1: Summary Statistics of Forex Returns

	Asia								
Currency	**RCNY**	**RIDR**	**RMYR**	**RTWD**	**RPKR**	**RPHP**	**RKRW**	**RTHB**	**RLKR**
Min.	-0.0200	-0.2877	-0.1390	-0.0381	-0.0754	-0.1207	-0.1147	-0.1639	-0.0384
Mean	-0.0003	0.0015	0.0000	0.0001	0.0013	0.0005	0.0004	0.0001	0.0011
Median	-0.0200	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004
Max.	0.0068	0.4700	0.1661	0.0590	0.1357	0.1290	0.2686	0.1308	0.0590
Range	0.0268	0.7577	0.3050	0.0971	0.2111	0.2496	0.3833	0.2947	0.0974
Std. Dev.	0.0120	0.0368	0.0120	0.0064	0.0094	0.0139	0.0177	0.0121	0.0056
Observations	879	993	1128	1128	1141	983	1150	1345	1261
Skewness	-5.1124	3.4138	0.0235	1.3394	4.2438	1.0942	4.9815	0.7617	1.9250
Kurtosis (Excess)	55.8359	57.5392	72.9159	18.2641	61.6708	23.6775	74.4708	55.5945	25.9648
Jarque-Bera	118012.92	138911.4	249886.2	16015.34	184239.48	23158.32	270497.28	173340.58	36200.87
ARCH LM Test	8.3817 (0.9076)	115.6133 [a] (0.0000)	490.4775 [a] (0.0000)	224.8454 [a] (0.0000)	108.1585[a] (0.0000)	126.939 [a] (0.0000)	351.468 [a] (0.0000)	363.6008 [a] (0.0000)	72.4826 [a] (0.0000)
Ljung-Box Stat.(15)	205.8537 [a] (0.0000)	52.3452 [a] (0.0000)	136.545 [a] (0.0000)	59.9816 [a] (0.0000)	69.4625 [a] (0.0000)	43.9323 [a] (0.0001)	135.3288 [a] (0.0000)	160.1256 [a] (0.0000)	44.9880 [a] (0.0001)

Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

Table 3.1 (Cont.)

	Asia		Middle East			Latin America			
Currency	**RINR**	**RVND**	**REGP**	**RTRY**	**RMAD**	**RBRL**	**RCLP**	**RCOP**	**RPEN**
Min.	-0.0473	-0.0358	-0.0269	-0.2058	-0.0738	-0.1342	-0.0606	-0.0725	-0.0496
Mean	0.0009	0.0007	0.0006	0.0050	0.0000	0.0008	0.0003	0.0011	0.0008
Median	0.0000	0.0001	0.0000	0.0045	0.0000	0.0234	0.0004	0.0007	0.0000
Max.	0.1120	0.0675	0.1523	0.4614	0.0770	0.2596	0.0692	0.0732	0.0540
Range	0.1593	0.1034	0.1792	0.6672	0.1508	0.3938	0.1298	0.1457	0.1036
Std. Dev.	0.0093	0.0047	0.0073	0.0319	0.0123	0.0023	0.0127	0.0141	0.0078
Observations	1036	893	899	873	1137	855	1002	950	951
Skewness	3.1710	5.6496	11.8857	5.8017	0.2485	2.7524	0.0177	0.2154	0.9312
Kurtosis (Excess)	36.0473	70.9077	226.9695	78.3905	4.7553	29.1974	3.5405	5.7292	10.6074
Jarque-Bera	57827.41	191830.1 6	195083.6	228424.32	1083.005	31449.5	523.39	1306.61	4595.938
ARCH LM Test (15)	159.5674 [a] (0.0000)	16.8227 (0.3296)	0.5392 (1.0000)	121.211[a] (0.0000)	130.060 [a] (0.0000)	114.0308[a] (0.0000)	186.1348[a] (0.0000)	209.1404 [a] (0.0000)	182.8319 [a] (0.0000)
Ljung-Box Stat.(15)	55.8411 [a] (0.0000)	52.9119 [a] (0.0000)	25.3713[b] (0.0452)	52.3668 [a] (0.0000)	26.4152 [b] (0.0339)	24.8194 (0.0524)	41.7166 [a] (0.0002)	36.0080 [a] (0.0018)	158.1891 [a] (0.0000)

Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

Table 3.1 (Cont.)

	Latin America		CEE/CIS				Africa
Currency	**RARS**	**RMXN**	**RCZK**	**RHUF**	**RPLN**	**RRUB**	**RZAR**
Min.	-0.0642	-0.1082	-0.0688	-0.0750	-0.0644	-0.6003	-0.1585
Mean	0.0014	0.0014	-0.0006	0.0008	0.0006	0.0038	0.0013
Median	0.0000	-0.0002	-0.0012	0.0008	0.0000	0.0009	0.0006
Max.	0.3691	0.3247	0.0978	0.1109	0.1322	0.7253	0.1775
Range	0.4333	0.4329	0.1665	0.1859	0.1966	1.3256	0.3360
Std. Dev.	0.0202	0.0196	0.0170	0.0188	0.0186	0.0445	0.0226
Observations	983	983	902	901	908	905	1454
Skewness	12.1711	5.9799	0.3999	0.5719	1.1916	5.7671	0.5366
Kurtosis (Excess)	197.4951	86.4758	2.9443	3.9049	6.7029	159.3788	10.1888
Jarque-Bera	1621820.8	312147.49	349.84	621.58	1914.7023	962868.93	6359.0247
ARCH LM Test (15)	358.7266 [a] (0.0000)	77.8449 [a] (0.0000)	172.8272 [a] (0.0000)	223.9141[a] (0.0000)	209.2039 [a] (0.0000)	320.9051 [a] (0.0000)	172.2358 [a] (0.0000)
Ljung-Box Stat.(15)	309.1946 [a] (0.0000)	102.5118 [a] (0.0000)	29.3578 [b] (0.0145)	29.1469 [b] (0.0154)	40.8783 [a] (0.0003)	491.4915 [a] (0.0000)	25.2879 [b] (0.0462)

Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

Table 3.2: Lo-MacKinlay and Chow-Denning Variance Ratio Test Results

	Currency		k=2	k=4	k=8	k=16	Chow-Denning
Asia	CNY	*VR(k)*	1.1630	1.4259	1.8625	2.7578	
		$M_1(k)$	4.8332[a]	6.7495[a]	8.6452[a]	11.8398[a]	11.8398[a]
		$M_2(k)$	2.6280[a]	3.8606[a]	5.2524[a]	7.4355[a]	7.4355[a]
	IDR	*VR(k)*	0.9718	1.0187	1.1984	1.2291	
		$M_1(k)$	-0.8899	0.3150	2.1131[a]	1.6403	2.1131
		$M_2(k)$	-0.2387	0.0689	0.4561	0.3948	0.4561
	MYR	*VR(k)*	0.8875	0.9222	1.0355	1.1735	
		$M_1(k)$	-3.7797[a]	-1.3956	0.4032	1.3240	3.7797[a]
		$M_2(k)$	-1.0359	-0.4261	0.1223	0.4108	1.0359
	TWD	*VR(k)*	1.1274	1.2716	1.4463	1.5882	
		$M_1(k)$	4.2775 [a]	4.8754 [a]	5.0674 [a]	4.4878 [a]	5.0674 [a]
		$M_2(k)$	2.5825 [a]	3.0858 [a]	3.0111 [a]	2.6450 [a]	3.0858 [a]
	PKR	*VR(k)*	0.9571	0.9469	0.9770	1.1068	
		$M_1(k)$	-1.4495	-0.9592	-0.2622	0.8194	1.4495
		$M_2(k)$	-1.1534	-0.6221	-0.1342	0.3815	1.1534
	PHP	*VR(k)*	0.9003	0.9150	0.9984	1.0801	
		$M_1(k)$	-3.1263 [a]	-1.4240	-0.0172	0.5705	3.1263 [a]
		$M_2(k)$	-1.4429	-0.7024	-0.0084	0.2954	1.4429
	KRW	*VR(k)*	0.9217	1.1655	1.4078	1.4691	
		$M_1(k)$	-2.6563 [a]	2.9997 [a]	4.6752 [a]	3.6144 [a]	4.6752 [a]
		$M_2(k)$	-0.6729	0.6418	1.0757	0.9855	1.0757
	THB	*VR(k)*	0.9929	1.0798	1.3289	1.4811	
		$M_1(k)$	-0.2601	2.7543 [a]	4.7717 [a]	4.0084 [a]	4.0772 [a]
		$M_2(k)$	-0.0670	0.7388	1.0819	1.0758	1.0819
	LKR	*VR(k)*	0.9553	1.0216	1.1397	1.2329	
		$M_1(k)$	-1.5867	0.4091	1.6768	1.8786	1.8786
		$M_2(k)$	-0.5777	0.1699	0.8084	1.0760	1.0760
	INR	*VR(k)*	1.1496	1.3077	1.4797	1.6228	
		$M_1(k)$	4.8142 [a]	5.2939 [a]	5.2197 [a]	4.5544 [a]	5.2939 [a]
		$M_2(k)$	1.2518	1.6606	0.0608	2.2512	2.2512
	VND	*VR(k)*	0.8212	0.8265	0.8160	0.8934	
		$M_1(k)$	-5.3417 [a]	-2.7718 [a]	-1.8593	-0.7234	5.3417 [a]
		$M_2(k)$	-1.5915	-0.9365	-0.7867	-0.3910	1.5915
MENA	EGP	*VR(k)*	1.0460	1.1147	1.3211	1.6034	
		$M_1(k)$	0.3796	1.8386	3.2549 [a]	4.1100 [a]	4.1100 [a]
		$M_2(k)$	0.5946	0.9598	2.0895 [b]	3.0758 [a]	3.0758 [a]

	TRY	*VR(k)* $M_1(k)$ $M_2(k)$	0.8762 -3.6568 [a] -1.3120	0.9402 -0.9438 -0.2657	0.9649 -0.3508 -0.1030	0.9875 -0.0836 -0.0288	 3.6568 [a] 1.3120
	MAD	*VR(k)* $M_1(k)$ $M_2(k)$	0.9084 -3.0873 [a] -1.8841	0.9423 -1.0404 -0.6435	1.0015 0.0170 0.0111	0.9758 -0.1855 -0.1310	 -3.0873 [a] 1.8841
Latin America	BRL	*VR(k)* $M_1(k)$ $M_2(k)$	0.9980 -0.0574 -0.0181	1.0904 1.4127 0.5126	1.2557 2.5273[b] 1.0919	1.3429 2.2777[b] 1.1109	 2.5273[b] 1.1109
	CLP	*VR(k)* $M_1(k)$ $M_2(k)$	1.0636 2.0124 [b] 1.2614	1.1111 1.8799 1.2226	1.3199 3.4236[a] 2.2552[b]	1.4872 3.5038[a] 2.3940[a]	 3.5038[a] 2.3940
	COP	*VR(k)* $M_1(k)$ $M_2(k)$	1.0103 0.3190 1.6644	1.1737 2.8619[a] 1.5797	1.3966 4.1320[a] 2.4320[b]	1.5792 4.0555[a] 2.5126[b]	 4.1320[a] 2.5126[b]
	PEN	*VR(k)* $M_1(k)$ $M_2(k)$	1.1214 3.7440 [a] 1.5850	1.2188 3.6072 [a] 1.6323	1.5764 6.0095 [a] 2.9737 [a]	1.7657 5.3648 [a] 2.8896 [a]	 6.0095 [a] 2.9737 [b]
	ARS	*VR(k)* $M_1(k)$ $M_2(k)$	0.8833 -3.6562 [a] -1.6278	0.9802 -0.3325 -0.1327	1.5632 5.9695 [a] 1.3925	2.4249 10.1492 [a] 2.2020	 10.1492 [a] 2.2020
	MXN	*VR(k)* $M_1(k)$ $M_2(k)$	0.9614 -1.2101 -0.2799	1.1139 1.9086 0.4724	1.1393 1.4762 0.4014	1.2585 1.8412 0.5653	 1.9086 0.5653
CEE/CIS	CZK	*VR(k)* $M_1(k)$ $M_2(k)$	1.0082 0.2453 0.1846	1.0559 0.8972 0.6485	1.0930 0.9442 0.6667	1.1426 0.9729 0.6919	 0.9729 0.6919
	HUF	*VR(k)* $M_1(k)$ $M_2(k)$	0.9342 -1.9736 -1.2937	0.9540 -0.7385 -0.4623	0.9988 -0.0126 -0.0078	0.9730 -0.1841 -0.1176	 1.9736 1.2937
	PLN	*VR(k)* $M_1(k)$ $M_2(k)$	0.9050 -2.7725 [a] -1.6460	0.9658 -0.5506 -0.3129	1.0619 0.6302 0.3541	1.1250 -0.856 0.4994	 2.7725 [b] 1.6460
	RUB	*VR(k)* $M_1(k)$ $M_2(k)$	0.5376 -13.909 [a] -1.8118	0.6231 -6.0611 [a] -0.7709	0.7145 -2.9040 [a] -0.4077	0.8704 -0.8860 -0.1565	 13.909 [a] 1.8118
Africa	ZAR	*VR(k)* $M_1(k)$ $M_2(k)$	0.9476 -1.9984 [b] -1.0656	0.9795 -0.4172 -0.2174	1.0363 0.4677 0.2548	1.1026 0.8887 0.5325	 1.9984 1.0656

Note: [a,] and [b] indicate 1% and 5% significance levels, respectively.

Table 3.3: Results of Chen-Deo and Wald Tests

			Chen-Deo Test		Wald Test
	Currency	**No. of Obs.**	**VR Sum**	QP_n	
Asia	CNY	880	0.4406	26.2464[a]	157.7033[a]
	IDR	994	0.0712	1.0767	16.3621[a]
	MYR	1129	-0.0076	3.2804	26.0270[a]
	TWD	1129	0.2604	10.0311[b]	28.4544[a]
	PKR	1142	-0.0034	2.6465	6.0451
	PHP	984	0.0232	4.1363	15.0513[a]
	KRW	1151	0.1488	3.4455	84.8380[a]
	THB	1346	0.1540	2.4434	29.6269[a]
	LKR	1262	0.0590	4.9727	13.2466[a]
	INR	1037	0.2673	5.0937	32.1499[a]
	VND	894	-0.1359	6.9821	37.3369[a]
MENA	EGP	900	0.1790	10.9906[b]	18.8226[a]
	TRY	874	0.0238	4.5546	24.9771[a]
	MAD	1138	-0.0342	7.1692	16.8520[a]
Latin America	BRL	856	0.1187	3.6186	10.2641[b]
	CLP	1003	0.1675	7.5170	20.2440[a]
	COP	951	0.1881	8.3763	24.9691[a]
	PEN	952	0.3139	15.2665[a]	58.3022[a]
	ARS	984	0.2211	8.8209	196.8720[a]
	MXN	984	0.0823	3.2907	32.5440[a]
CEE/CIS	CZK	903	0.0604	1.1047	1.6480
	HUF	902	-0.0221	2.6859	6.8643
	PLN	909	0.0106	5.8449	16.4585[a]
	RUB	906	-0.3158	10.1783[b]	269.1932[a]
Africa	ZAR	1455	0.0095	2.8786	8.8400

Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

Table 3.4: Results of Whang and Kim Subsample Test (2003)

	Currency	*p*-value for Different Blocks					
Asia	CNY	0.0000 (47)	0.0000 (71)	0.0000 (97)	0.0000 (123)	0.0000 (149)	0.0000 (175)
	IDR	0.0000 (47)	0.0098 (75)	0.0774 (103)	0.1205 (131)	0.1389 (159)	0.1462 (187)
	MYR	N.A (51)	0.4413 (82)	0.4675 (113)	0.4640 (144)	0.4979 (175)	0.4886 (206)
	TWD	0.0000 (51)	0.0000 (82)	0.0000 (113)	0.0041 (144)	0.0000 (175)	0.0000 (175)
	PKR	0.5674 (51)	0.5849 (82)	0.6190 (113)	0.6623 (144)	0.6939 (175)	0.7618 (206)
	PHP	0.6884 (47)	0.6381 (75)	0.5914 (103)	0.5815 (131)	0.5794 (159)	0.5960 (187)
	KRW	0.0000 (55)	0.0253 (82)	0.0173 (113)	0.0040 (144)	0.0040 (175)	0.0000 (206)
	LKR	0.0786 (54)	0.1677 (87)	0.2574 (120)	0.2831 (153)	0.3178 (186)	0.0214 (194)
	INR	0.0000 (49)	0.0000 (78)	0.0000 (107)	0.0000 (136)	0.0000 (165)	0.0214 (194)
	VND	0.5206 (45)	0.5808 (71)	0.6010 (97)	05292 (123)	0.5101 (149)	0.4687 (175)
	THB	0.0000 (55)	0.0000 (89)	0.0000 (123)	0.0000 (157)	0.0000 (191)	0.0000 (225)
MENA	EGP	0.0000 (45)	0.0084 (71)	0.0000 (97)	0.0103 (123)	0.0106 (149)	0.0000 (175)
	TRY	0.6128 (45)	0.5716 (71)	0.5946 (97)	0.5459 (123)	0.5255 (149)	0.5222 (175)
	MAD	0.6440 (51)	0.4905 (82)	0.4878 (113)	0.4356 (144)	0.4393 (175)	0.4249 (206)
Latin America	BRL	0.0000 (44)	0.0000 (70)	0.0000 (96)	0.0177 (122)	0.0508 (148)	0.0176 (174)
	CLP	0.0000 (47)	0.0000 (75)	0.0000 (103)	0.0000 (131)	0.0000 (159)	0.0000 (187)
	COP	0.0000 (46)	0.0000 (73)	0.0000 (100)	0.0000 (127)	0.0000 (154)	0.0000 (181)
	PEN	0.0000 (46)	0.0000 (73)	0.0000 (100)	0.0000 (127)	0.0000 (154)	0.0000 (181)
	ARS	N.A. (47)	N.A. (75)	0.0000 (103)	0.0000 (131)	0.0000 (159)	0.0000 (187)
	MXN	0.0000 (47)	0.0165 (75)	0.0272 (103)	0.0035 (131)	0.0036 (159)	0.0113 (187)

CEE/CIS	CZK	0.4825 (45)	0.2897 (71)	0.2419 (97)	0.1500 (123)	0.1101 (149)	0.1099 (175)
	HUF	0.9393 (45)	0.8652 (71)	0.8832 (97)	0.8421 (123)	0.8353 (149)	0.8501 (175)
	PLN	0.7080 (46)	0.5849 (73)	0.5983 (100)	0.5742 (127)	0.5205 (154)	0.5137 (181)
	RUB	0.0209 (45)	0.0635 (71)	0.1619 (97)	0.2656 (123)	0.2787 (149)	0.3037 (175)
Africa	ZAR	0.4023 (58)	0.4240 (94)	0.3857 (130)	0.4492 (166)	0.4477 (202)	0.4380 (238)

Note: [a,] and [b] indicate 1% and 5% significance levels, respectively.

Table 3.5: *p*-value of Bootstrapped Lo-MacKinlay and Chow-Denning Test

	Currencies	**q=2**	**q=4**	**q=8**	**q=16**	**Chow-Denning**
Asia	CNY	0.001[a]	0.000[a]	0.0000[a]	0.000[a]	0.000[a]
	IDR	0.8360	0.9520	0.6785	0.7070	0.9445
	MYR	0.3635	0.7215	0.9005	0.7010	0.6075
	TWD	0.0015[a]	0.0015[a]	0.0005[a]	0.0055[a]	0.0035[a]
	PKR	0.2645	0.5790	0.9150	0.6940	0.5335
	PHP	0.1440	0.5165	0.9815	0.7345	0.3045
	KRW	0.5530	0.5545	0.2700	0.3015	0.5395
	THB	0.9500	0.4840	0.2805	0.2350	0.5335
	LKR	0.6320	0.8845	0.4455	0.2710	0.5155
	INR	0.1850	0.0515[b]	0.0215[b]	0.0090[a]	0.0235[b]
	VND	0.1030	0.4195	0.5145	0.7785	0.196
MENA	EGP	0.6785	0.3865	0.0155[b]	0.0005[a]	0.0015[a]
	TRY	0.1880	0.8475	0.7155	0.6075	0.387
	MAD	0.0405[b]	0.5520	0.9785	0.9205	0.1135
Latin America	BRL	0.9935	0.6705	0.2830	0.2315	0.4885
	CLP	0.2050	0.2255	0.0220[b]	0.0165[b]	0.037[b]
	COP	0.8535	0.1160	0.035[b]	0.0150 [b]	0.0275[b]
	PEN	0.1015	0.0965	0.0015[a]	0.0000[a]	0.000[a]
	ARS	0.0815[c]	0.9005	0.1215	0.0290	0.047[b]

	MXN	0.8430	0.6945	0.7250	0.5960	0.91
CEE/CIS	CZK	0.8475	0.5220	0.4870	0.4580	0.798
	HUF	0.2158	0.6902	0.9812	0.9521	0.4237
	PLN	0.1070	0.7860	0.7270	0.5745	0.224
	RUB	0.0235[b]	0.5240	0.7600	0.9025	0.0965
Africa	ZAR	0.3195	0.8375	0.8005	0.5960	0.572

Note: [a,] and [b] indicate 1% and 5% significance levels, respectively.

Table 3.6: Wright (2000) Ranks and Sign Test

	Currency		**q=2**	**q=4**	**q=8**	**q=16**	**Joint Wright**
Asia	CNY	R_1	3.2231[a]	6.2791[a]	8.8282[a]	12.4543[a]	12.4543[a]
		R_2	2.8581[a]	5.5992[a]	7.3553[a]	10.3700[a]	10.3700[a]
		S_1	2.6646[a]	5.5529[a]	8.9054[a]	13.2987[a]	13.2987[a]
	IDR	R_1	3.0676[a]	4.2824[a]	4.6956[a]	4.4184[a]	4.6956[a]
		R_2	2.8606[a]	4.1848[a]	4.8583[a]	4.4825[a]	4.8583[a]
		S_1	0.7299	1.9337	2.5479[a]	2.7180[a]	2.7180[b]
	MYR	R_1	-0.1999	0.4829	1.9417	3.1392[a]	3.1392[a]
		R_2	-0.1978	0.6498	2.3415[a]	3.4948[a]	3.4948[a]
		S_1	6.8482[a]	11.1565[a]	17.2877[a]	24.8741[a]	24.8741[a]
	TWD	R_1	5.1997[a]	6.8016[a]	6.5020[a]	5.6818[a]	6.8016[a]
		R_2	5.4361[a]	6.8204[a]	6.3615[a]	5.3199[a]	6.8204[a]
		S_1	3.9302[a]	4.8860[a]	4.3735[a]	3.5699[a]	4.8860[a]
	PKR	R_1	-2.7276[a]	-0.1063	3.0296[a]	4.9897[a]	4.9897[a]
		R_2	-3.0720[a]	-0.5783	2.2060[a]	4.0294[a]	4.0294[a]
		S_1	-1.0954	1.5191	4.6688[a]	6.9459[a]	6.9460[a]
	PHP	R_1	0.3513	2.4333[a]	4.6491[a]	5.810[a]	5.8101[a]
		R_2	-0.2021	1.6501	3.5256[a]	4.4082[a]	4.4082[a]
		S_1	-0.0319	2.0970[a]	4.1836[a]	5.1936[a]	5.1936[a]
	KRW	R_1	1.3088	2.0124[a]	2.6325[a]	2.7755[a]	2.7755[b]
		R_2	1.3984	2.2596[a]	2.9161[a]	2.6597[a]	2.9161[a]
		S_1	1.2385	1.5920	2.2380[a]	3.1688[a]	3.1688[a]
	THB	R_1	1.6141	3.2375[a]	4.2611[a]	4.3949[a]	4.3949[a]
		R_2	1.1809	3.0346[a]	4.2422[a]	4.4652[a]	4.4652[a]
		S_1	1.3906	2.9441[a]	4.4384[a]	4.6011[a]	4.6011[a]
	LKR	R_1	0.5114	3.5751[a]	5.7996[a]	6.7675[a]	6.7675[a]
		R_2	-0.6182	2.1495[a]	4.1191[a]	4.6301[a]	4.6300[a]
		S_1	2.3937[a]	5.6146[a]	8.1491[a]	10.9048[a]	10.9048[a]
	INR	R_1	0.7590	2.8267[a]	4.0405[a]	5.6345[a]	5.6345[a]
		R_2	1.3648	3.1928[a]	4.1707[a]	5.0719[a]	5.0719[a]
		S_1	-0.5592	1.2123	2.9776[a]	5.2320[a]	5.2320[a]
	VND	R_1	-1.2303	1.9446	4.5456[a]	6.5132[a]	6.5132[a]
		R_2	-3.2543[a]	0.0801	2.5258[a]	4.2110[a]	4.2110[a]

		S_1	3.2460[a]	6.5825[a]	9.8761[a]	14.0797[a]	14.0797[a]
MENA	EGP	R_1	-0.0431	-1.7264	0.8504	2.9780[a]	5.0431[a]
		R_2	-4.7336[a]	-1.4298	1.496	3.5618[a]	4.7336[a]
		S_1	-3.4352[a]	-0.9805	0.4905	1.9284	3.4352[a]
	TRY	R_1	5.8893[a]	8.8252[a]	11.6517[a]	14.9070[a]	14.9070[a]
		R_2	3.8522[a]	6.0947[a]	8.0554[a]	10.1067[a]	10.1067[a]
		S_1	7.9535[a]	12.2656[a]	17.2769[a]	23.1575[a]	23.1575[a]
	MAD	R_1	-0.4258	0.3811	1.2371	1.2113	1.2371
		R_2	-1.2905	-0.1474	0.7484	0.6624	1.2905
		S_1	0.6228	1.7596	3.1932[a]	4.4147[a]	4.4147[a]
Latin America	BRL	R_1	1.9796[a]	2.1489[a]	3.2222[a]	4.1078[a]	4.1078[a]
		R_2	0.9024	1.4627	2.5998[a]	3.2181[a]	3.3181[a]
		S_1	4.0013[a]	4.4238[a]	6.6594[a]	9.3273[a]	9.3274[a]
	CLP	R_1	2.3278[a]	3.0440[a]	4.8363[a]	4.7025[a]	4.8362[a]
		R_2	2.2438[a]	2.4128[a]	4.0958[a]	4.0972[a]	4.0972[a]
		S_1	2.4009[a]	3.4110[a]	5.1316[a]	4.9755[a]	5.1316[a]
	COP	R_1	2.636[a]	5.8857[a]	7.4730[a]	7.4779[a]	7.4779[a]
		R_2	1.9233[a]	5.1772[a]	6.6526[a]	6.5193[a]	6.6526[a]
		S_1	3.1795[a]	5.6362[a]	7.5680[a]	8.3512[a]	8.3512[a]
	PEN	R_1	1.3628	1.8124	4.5116[a]	5.4793[a]	5.4793[a]
		R_2	1.9927[a]	2.0910[a]	4.9044[a]	5.6233[a]	5.6233[a]
		S_1	-0.0324	1.0573	2.6200[a]	3.3722[a]	3.3722[a]
	ARS	R_1	-1.2958	0.0871	2.0675[a]	4.9479[a]	4.9479[a]
		R_2	-0.7587	0.4788	2.3075[a]	5.2652[a]	5.2652[a]
		S_1	4.8162[a]	9.7177[a]	16.2169[a]	24.1620[a]	24.1620[a]
	MXN	R_1	-2.1216[a]	-1.0435	-0.6640	-0.8855	2.1216
		R_2	-2.6136[a]	-0.9451	-0.6893	-1.0266	2.6136[b]
		S_1	-2.3283[a]	-1.5344	-0.8141	-0.3225	2.3283
CEE/CIS	CZK	R_1	1.2490	1.6113	1.3737	1.0585	1.6113
		R_2	0.8282	1.2156	1.544	0.8402	1.2156
		S_1	1.5316	1.6196	1.8010	1.7512	1.8010
	HUF	R_1	-0.5372	0.0640	0.9724	1.4705	1.4705
		R_2	-1.2928	-0.5351	0.3092	0.4966	1.2928
		S_1	-0.3665	0.5698	1.6049	2.5185	2.5185[b]
	PLN	R_1	-0.1009	1.1648	2.1966[a]	2.3263[a]	2.3263[b]
		R_2	-1.4216	0.0341	1.0172	1.1277	1.4212
		S_1	1.0620	2.2706[a]	3.0684[a]	3.6189[a]	3.6189[a]
	RUB	R_1	6.1265[a]	11.0324[a]	15.3004[a]	19.4277[a]	19.4277[a]
		R_2	4.5778[a]	9.3102[a]	13.3513[a]	16.8037[a]	16.8037[a]
		S_1	6.5485[a]	11.0695[a]	15.4516[a]	21.0225[a]	21.0225[a]
Africa	ZAR	R_1	1.2509	2.9849[a]	3.9625[a]	4.1566[a]	4.1566[a]
		R_2	0.3325	1.9471[a]	2.8921[a]	3.1818[a]	3.1818[a]
		S_1	0.4721	2.4531[a]	3.9497[a]	4.8706[a]	4.8706[a]

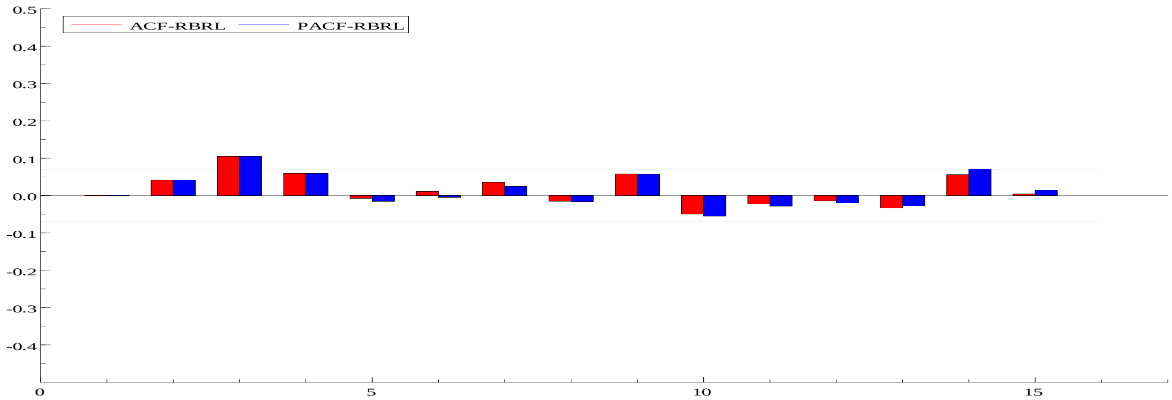
Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

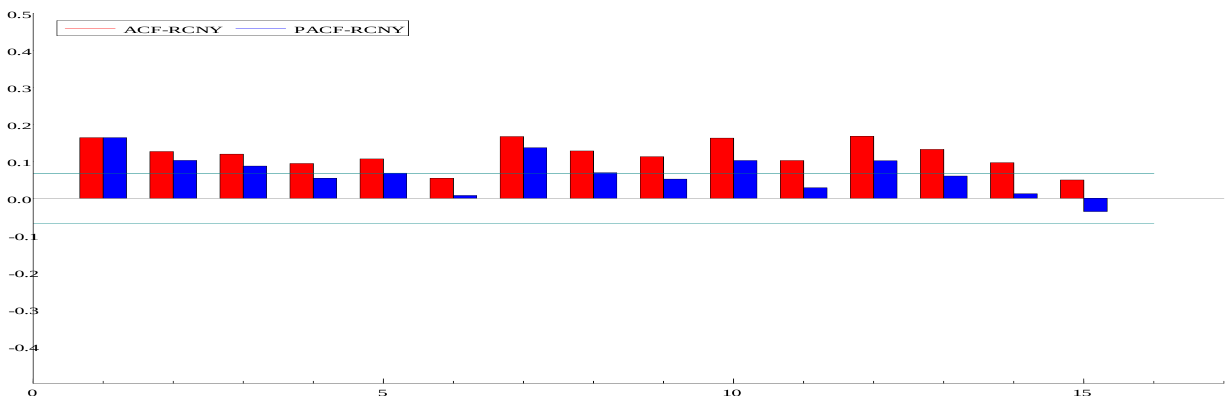
Table 3.7: Results of Runs Test

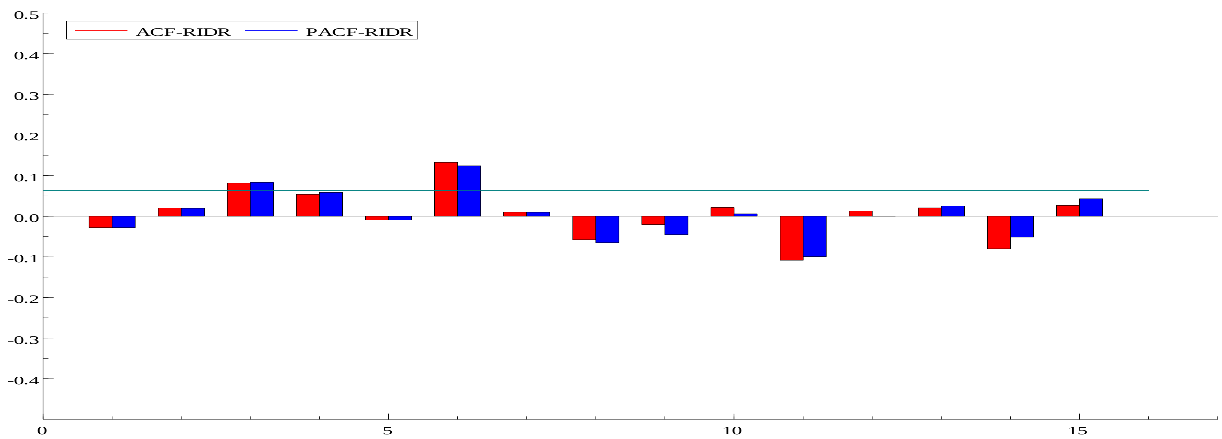
	Currency	*N*<=Mean	*N*>Mean	*N* (Runs)	*Z*-statistic	Prob. (*Z*)
Asia	CNY	180	699	161	-13.09	0.00[a]
	IDR	599	394	440	-2.41	0.02[b]
	MYR	413	715	457	-4.34	0.00[a]
	TWD	586	542	502	-3.71	0.00[a]
	PKR	763	378	477	-1.98	0.05[b]
	PHP	531	452	480	-0.60	0.55
	KRW	619	531	564	-0.51	0.61
	THB	748	597	647	-1.00	0.32
	LKR	787	474	506	-5.20	0.00[a]
	INR	664	372	413	-4.38	0.00[a]
	VND	685	208	286	-3.20	0.00[a]
MENA	EGP	590	309	429	1.66	0.10
	TRY	450	423	345	-6.24	0.00[a]
	MAD	539	598	558	-0.59	0.55
Latin America	BRL	415	440	389	-2.68	0.01[a]
	CLP	499	503	477	1.58	0.11
	COP	491	459	434	-2.69	0.01[a]
	PEN	558	393	424	-2.55	0.01[a]
	ARS	775	208	268	-5.83	0.00[a]
	MXN	491	492	526	2.14	0.03[b]
CEE/CIS	CZK	471	431	432	-1.28	0.20
	HUF	451	450	462	0.7	0.48
	PLN	476	432	436	-1.19	0.23
	RUB	654	251	248	-9.61	0.00[a]
Africa	ZAR	760	694	728	0.08	0.94

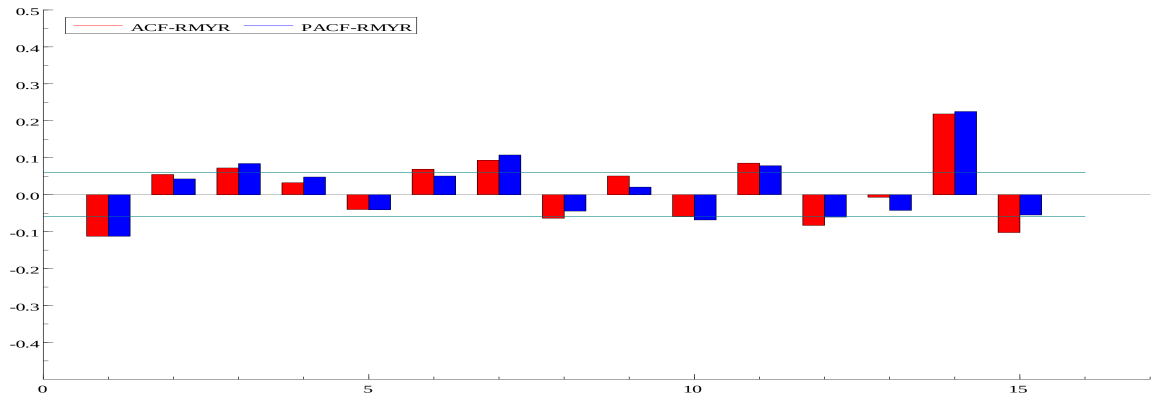
Note: [a], and [b] indicate 1% and 5% significance levels, respectively.

Figure 3.1: Correlogram of ACF and PACF on Exchange Returns





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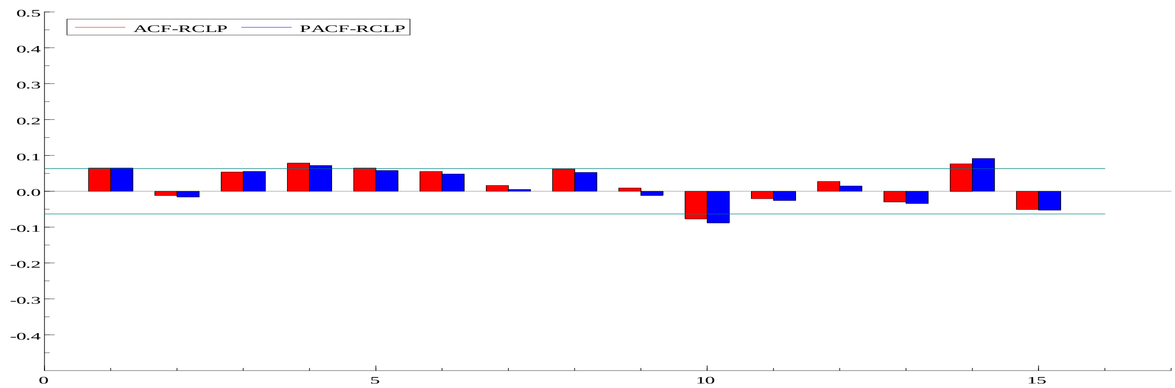
-0.2
-0.3
-0.4
0
5
10
15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-0.3
-0.4
0
5
10
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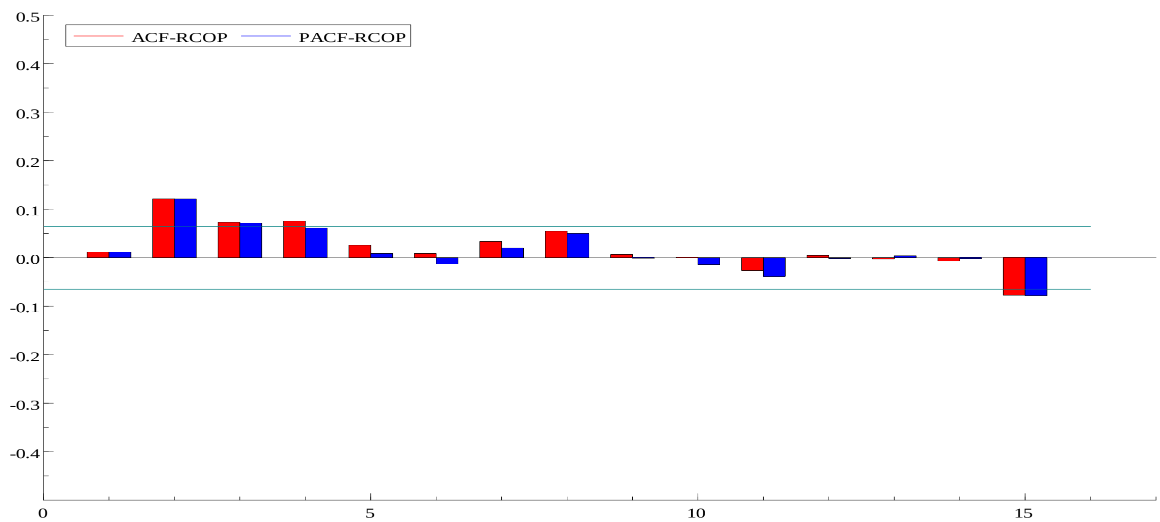
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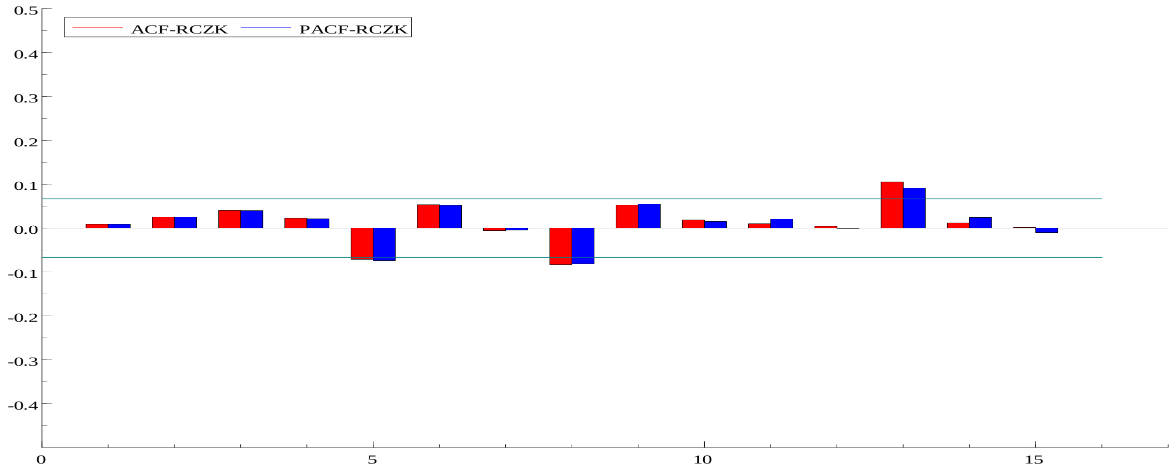
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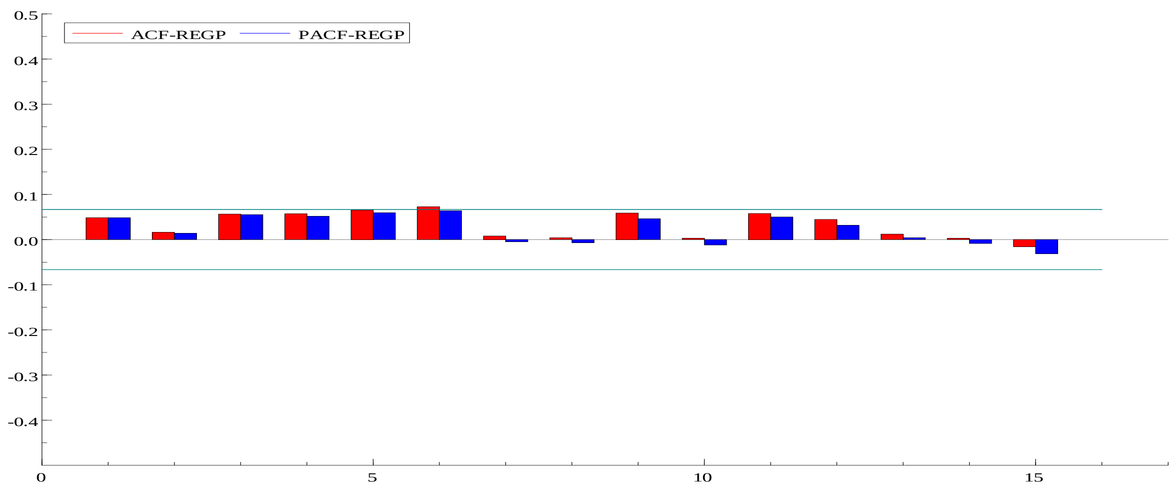
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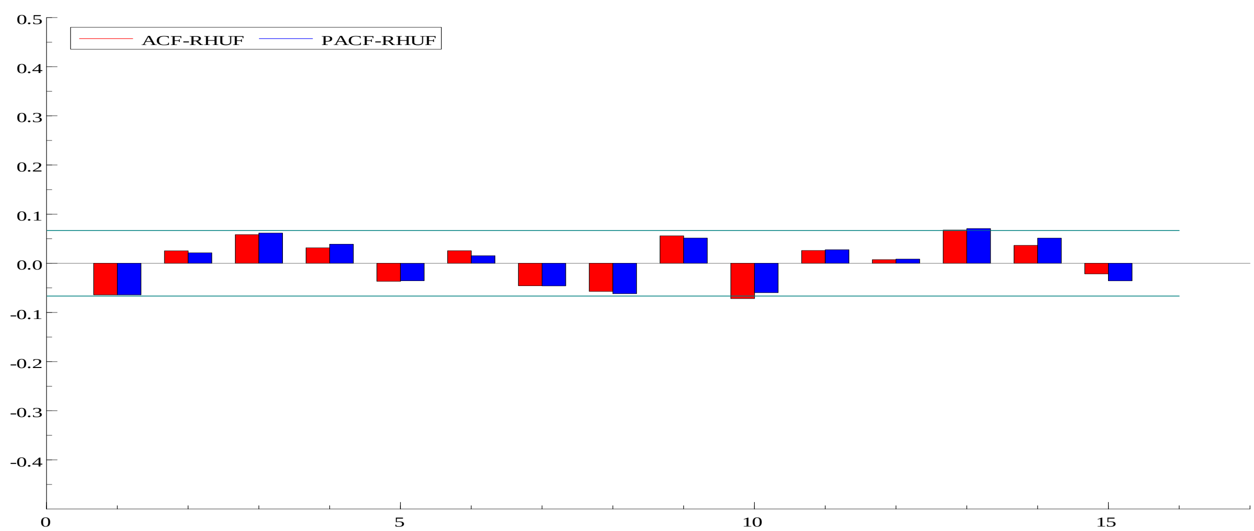
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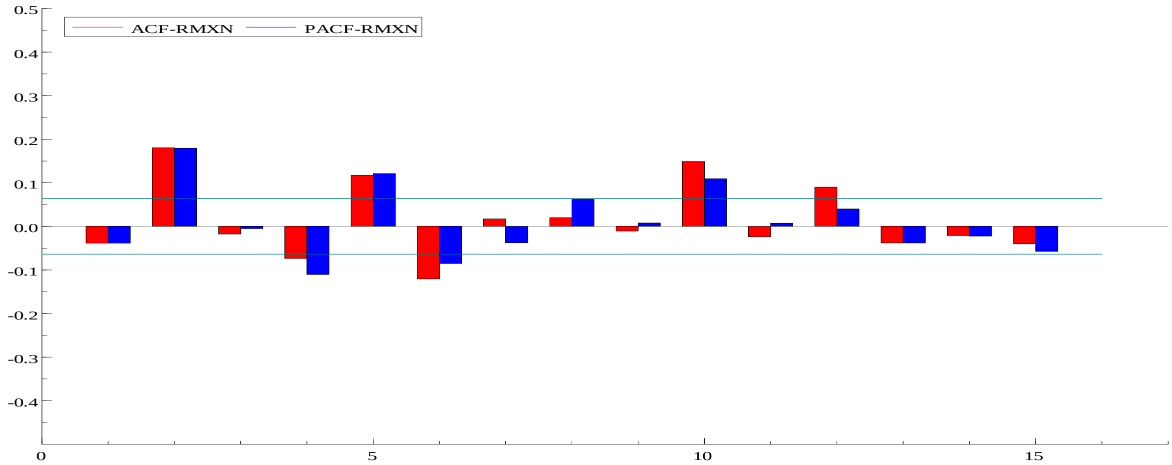
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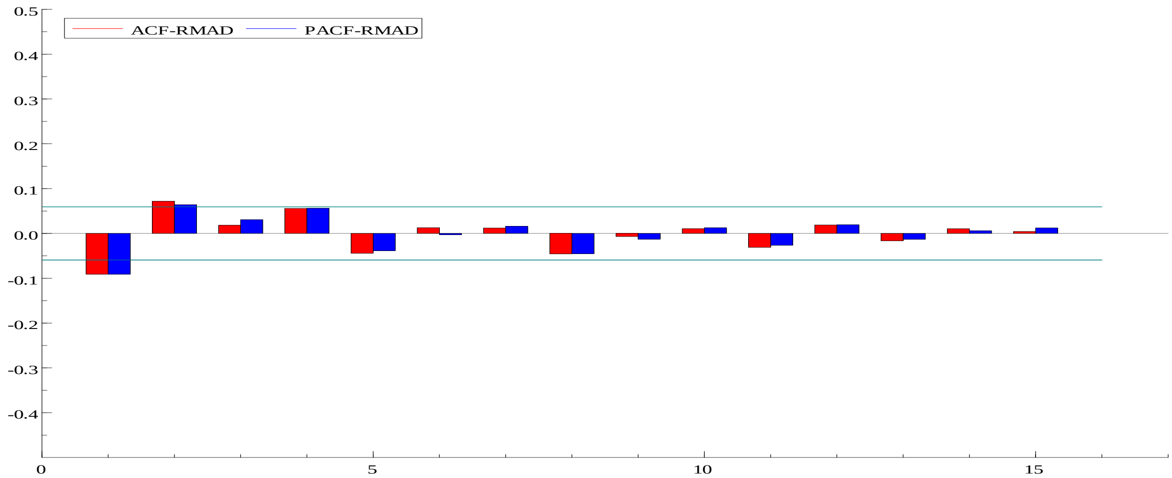
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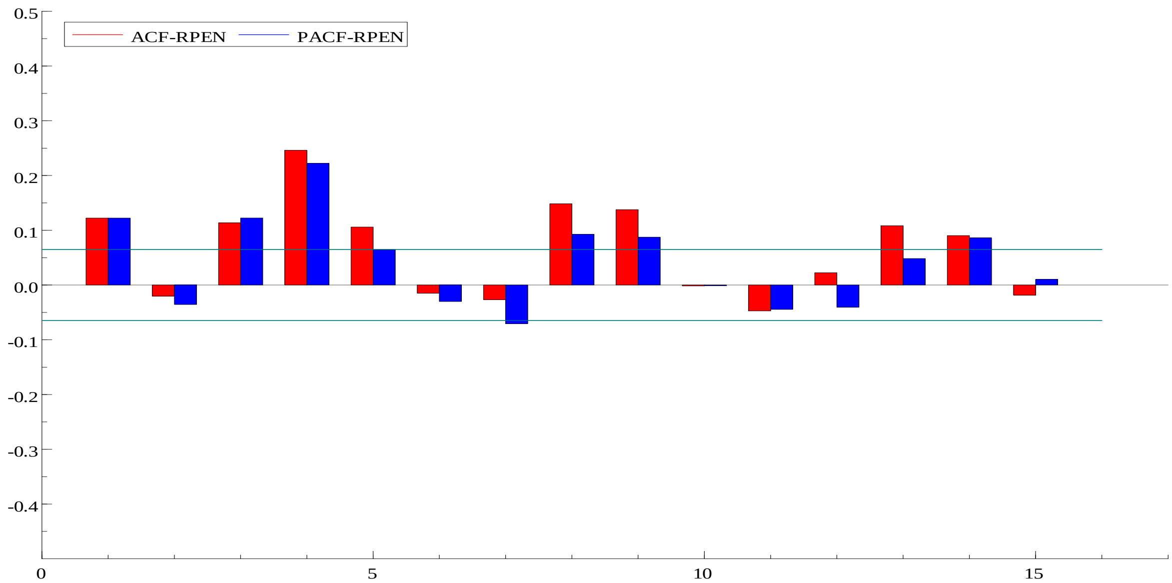
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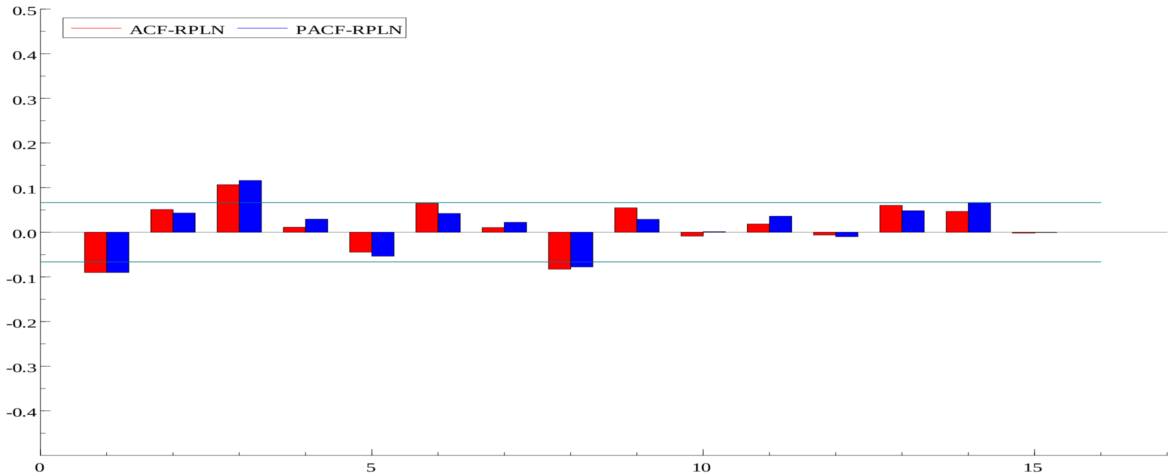
0
5
10
15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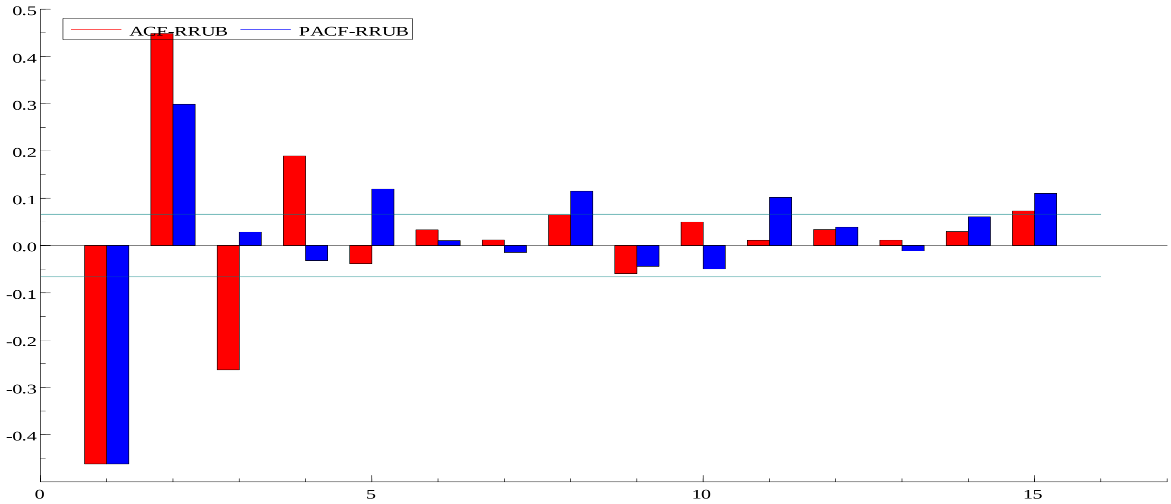
0
5
10
15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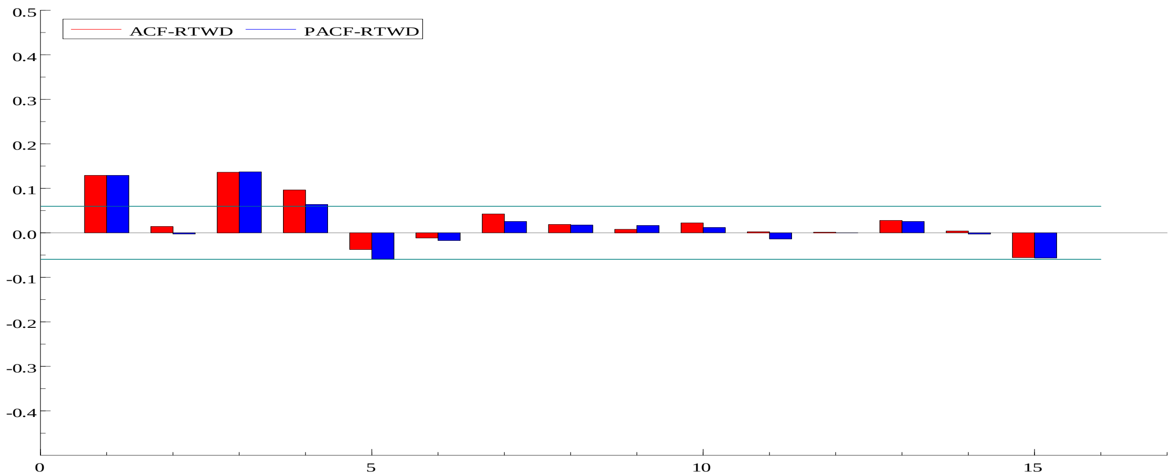
0
5
10
15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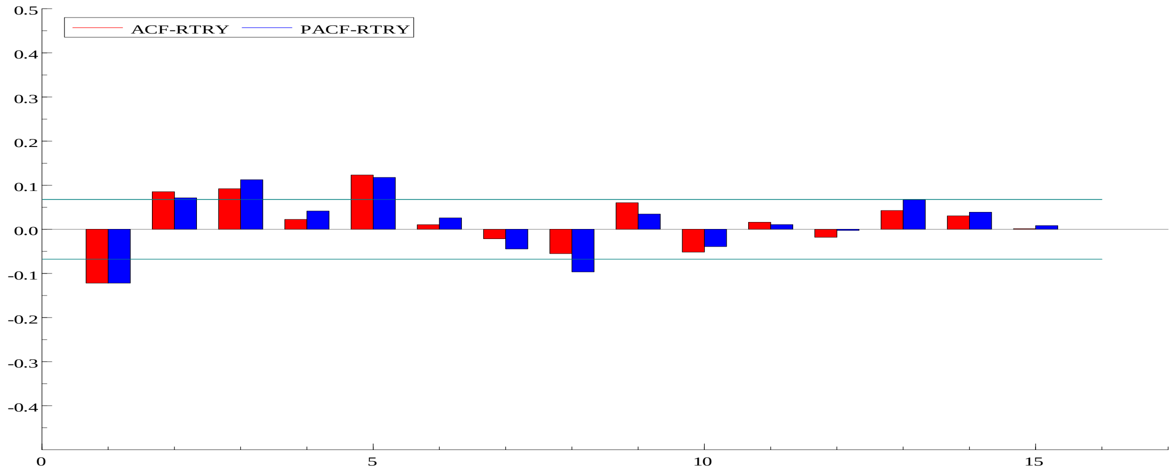
10
15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-0.4
0
5
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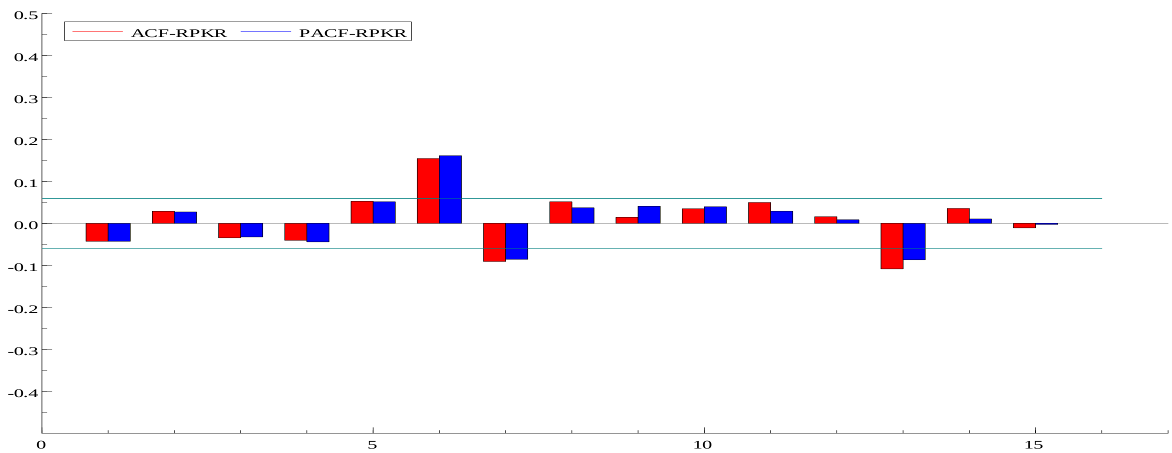
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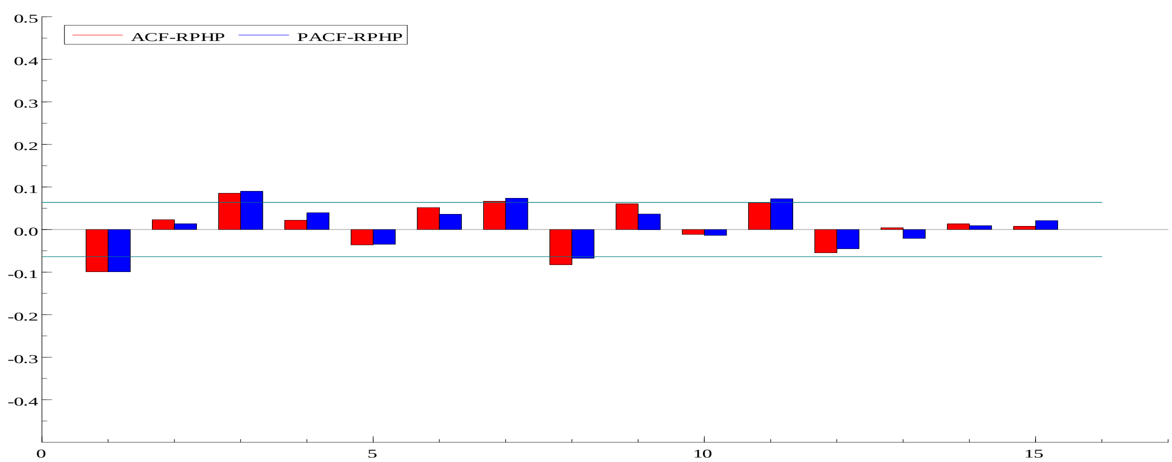
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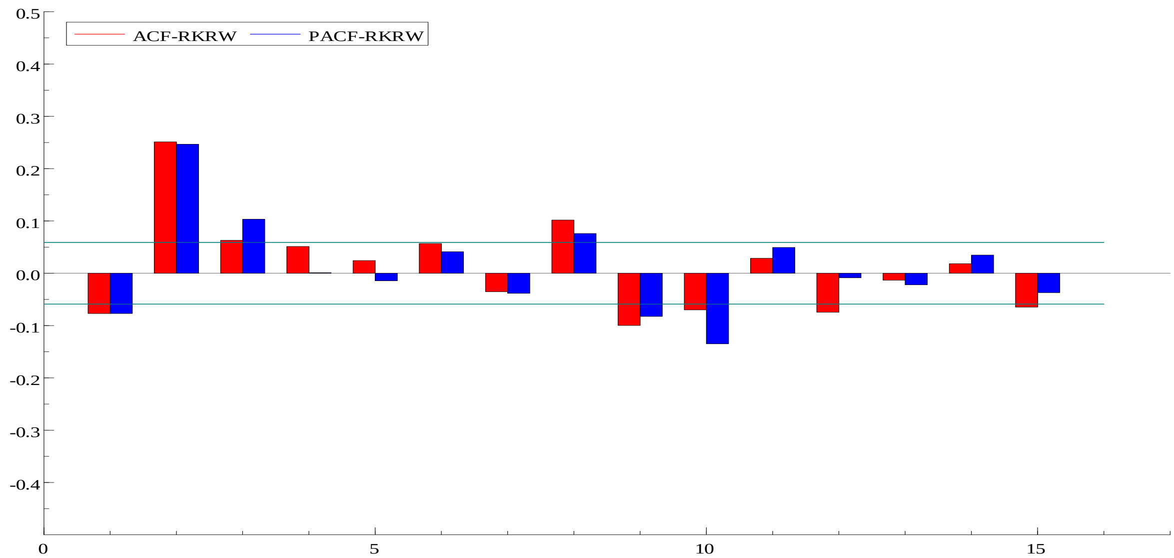
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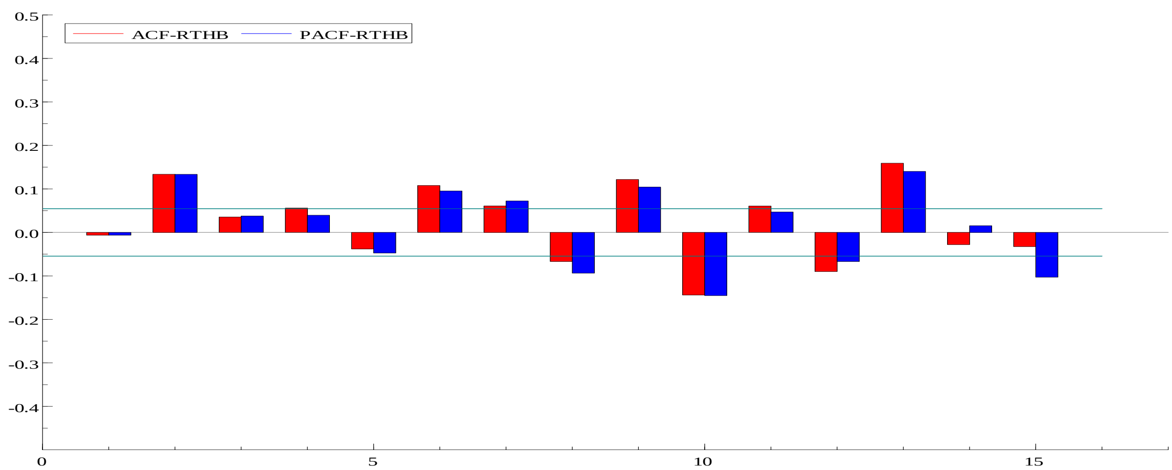
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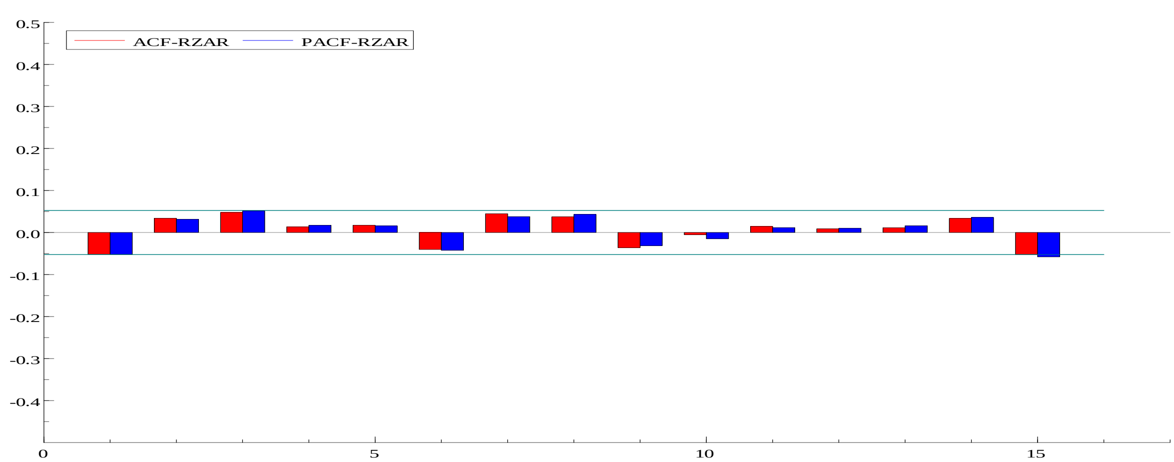
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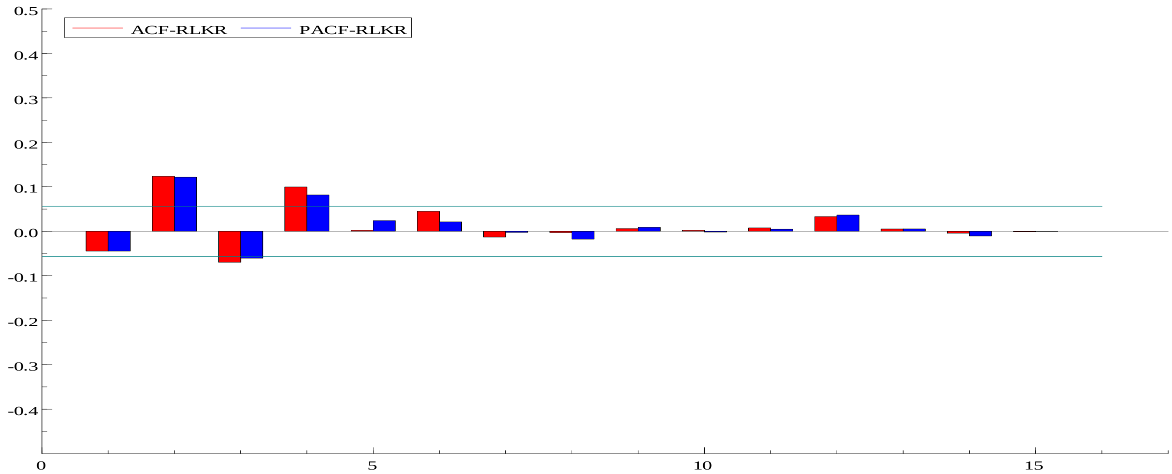
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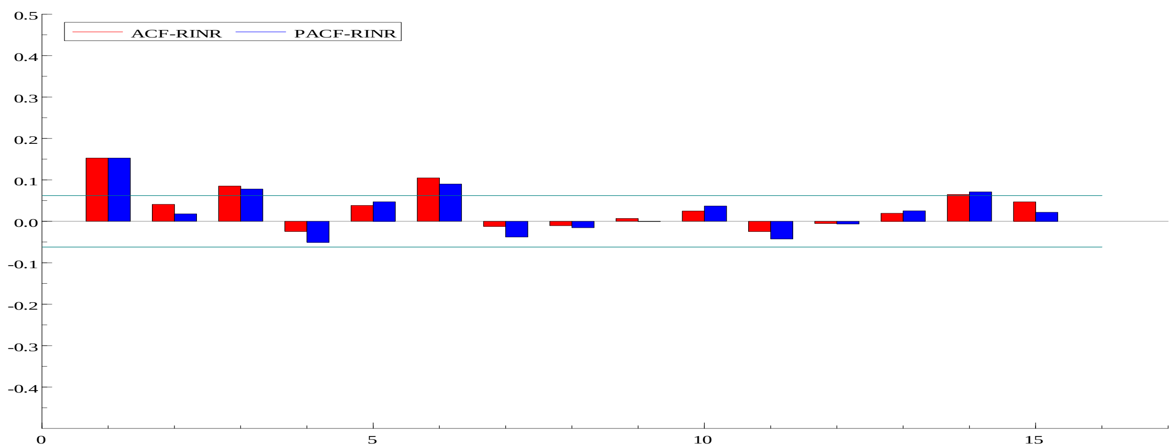
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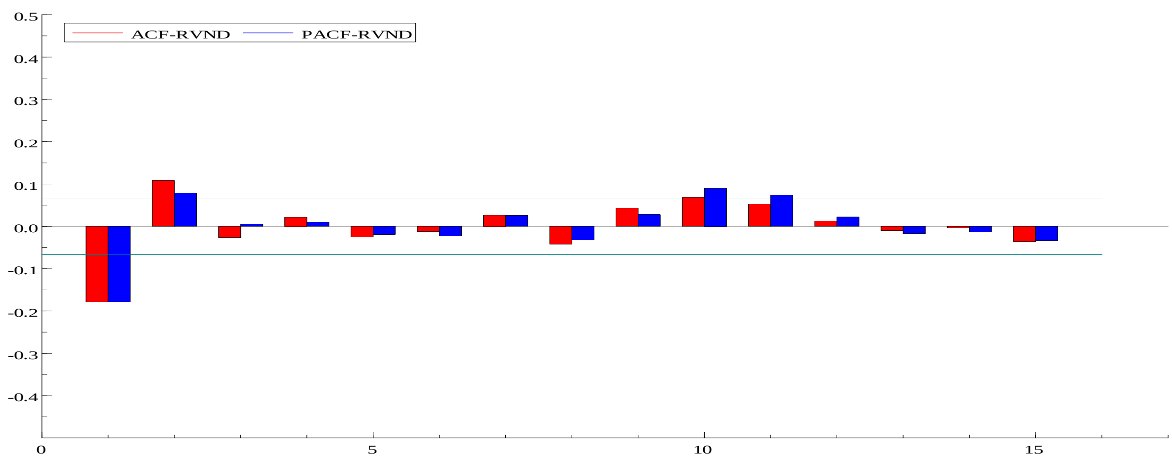
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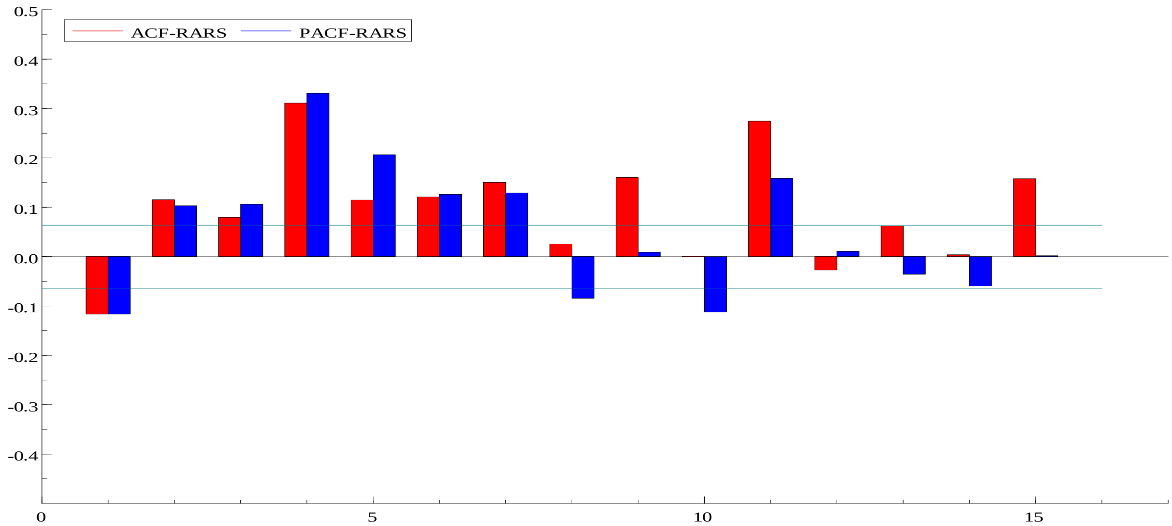
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CHAPTER 4

NONLINEARITY IN FOREIGN EXCHANGE RETURNS OF EMERGING ECONOMIES

4.1 Introduction

Most of the time series models discussed in the previous chapters are linear. Since absence of linear dependence does not necessarily mean independence, but merely a lack of linear autocorrelation (Granger and Anderson, 1978; and Sakai and Tokumaru, 1980), studies on the Random Walk Hypothesis (RWH) should use tests capable of detecting both linear and nonlinear dependencies. Although linear models remain at the forefront of academic and applied research, it has often been found that simple linear time series models usually leave certain aspects of economic and financial data unexplained. It is therefore absolutely important to test for nonlinear dependence in the series, to verify whether what is considered as random walk is actually not a nonlinear process which looks random.

The focus on nonlinearity has been increasing over the past years, because firstly, nonlinear models are used in an attempt to improve the forecasting accuracy of linear models, secondly to explain some aspects of the economic activity more than that permitted by linear models (e.g., to explain fluctuations in the economy and financial market that appear random), and finally because of the market efficiency implication of nonlinearity, which questions the assumptions of the underlying linear model. According to Abhyankar *et al*. (1995), “The presence of well behaved nonlinear structure would be inconsistent with market efficiency, if accompanied by risk-neutrality and negligible transaction costs.” Many studies have documented nonlinearity in economic activity, starting with the pioneer work of Hsieh (1989). There are increasing research evidences supporting nonlinearity in financial time series. This chapter tests nonlinear behavior of foreign exchange rate of emerging market economies.

4.2 Review of Literature

A number of empirical studies show that the behavior of the exchange rate is in fact nonlinear in nature (Lukkonen *et al*., 1988; Hseih, 1989, De Grauwe *et al*., 1993, Granger and Teräsvirta, 1993; Steurer, 1995, Brooks, 1996, Micheal *et al*., 1997; Taylor and Peel, 1997; Sarantis, 1999; Sarno, 2000a and 2000b; Taylor and Peel, 2000; and Baum *et al*., 2001). Nonlinearity can arise due to transaction costs (e.g., Dumas, 1992; Sercu *et al.*, 1995; and Goswami *et al.*, 2002), diversity in agents' beliefs (e.g., Brock and Hommes, 1998; and De Grauwe and Grimadi, 2004), or heterogeneity in investors' objectives and investment horizons (e.g., Guilaume *et al.*, 1995). A few papers have uncovered significant nonlinear real exchange rate behavior (e.g., Michael *et al.*, 1997; Sarantis, 1999; Baum *et al.*, 2001; Taylor *et al.*, 2001; and Liew *et al.*, 2003). However, these papers assume that the series (or their differences) are stationary when testing the linearity hypothesis, so they do not investigate formally the interaction between nonstationarity and nonlinearity. In two recent papers, Sollis *et al.* (2002) and Kapetanios *et al.* (2003), this issue was addressed by developing formal unit root tests against the alternative of nonlinear mean reversion. Sollis *et al.* (2002) applied their test to real exchange rates against the US dollar for 17 OECD countries and found nonlinear mean reversion in six countries. Kapetanios *et al.* (2003) applied their test to the real exchange rates of few industrial countries and Chortareas *et al*. (2004) and Liew *et al.* (2004) applied it to the Asian countries and gave supportive results.

Cushman (2008) applies the nonlinear trend idea to a number of individual OECD real exchange rates for the recent floating period, and in some cases it appears that the null of unit root can be rejected with nonlinear trend stationarity being the most likely alternative. The statistical significance, however, is not generally strong. The stock markets have also attracted the attention of researchers with substantial evidence supporting the presence of nonlinearity in stock returns series (Scheinkman and LeBaron, 1989; Hseih, 1991; Abhyankar *et al*., 1995 and 1997; Barkoulas and Travlos, 1998; and Opong *et al*., 1999). However, much of this evidence has been drawn from the widely traded financial markets of the well-developed countries. Though more efforts are now being directed toward the emerging market economies' exchange rate and stock markets in light of their increasing importance in the investment world and the world economy, most of the earlier empirical studies on emerging economies' foreign exchange markets have assumed linearity. This study employs statistical tests that are capable of detecting both linear and nonlinear structures in financial series. The present study utilizes the 'nonlinearity toolkit' of Patterson and Ashley (2000) consisting of the McLeod and Li (1983) test, Engle (1982) Lagrange Multiplier (LM) test, Brock-Dechert-Scheinkman (BDS) test (Brock *et al*., 1996), Tsay (1986) test, Hinich (1982) bispectrum test, and Hinich (1996) bi-correlation test. Except the bispectrum test, each of these statistical tests actually tests for serial dependence of any kind, whether linear or nonlinear. Hence, data pre-whitening is necessary prior to the application of these five tests in order to remove any linear structure from the data, so that any remaining serial dependence is due to the nonlinear data generating mechanism. The linear filtering procedure also serves to address the concern of spurious autocorrelation generated by thin trading. Specifically, Hong and Lee (2005) argued that since one can never be sure of the degree of significant autocorrelation that could be attributed to thin trading, an alternative approach would be to remove all linear serial correlations from the data and determine whether stock returns still contain predictable nonlinearities.

To test the presence of nonlinear serial dependence in the data generating process of foreign exchange return series, this study employs a battery of univariate nonlinearity tests, rather than drawing conclusion from the application of a single test such as the BDS test. The reason behind this can be attributed to the results of various Monte-Carlo simulations which reveal that most of the existing nonlinearity tests have varying power against different classes of nonlinear processes and none dominates the other (see e.g., Ashley *et al*., 1986; Ashley and Patterson, 1989; Hsieh, 1991; Brock *et al*., 1991 and 1996; Lee *et al*., 1993; Barnett *et al*., 1997; and Patterson and Ashley, 2000). As pointed out by Panagiotidis (2005), the application of a battery of nonlinear tests would provide a deeper insight into the properties of the series by generating useful information from the various tests, while minimizing the probability of missing something and thus, drawing a wrong conclusion. More importantly, Patterson and Ashley (2000) has made available a 'nonlinearity toolkit' that provides convenient and consistent access to a selection of the best tools available for statistically detecting nonlinearity in the generating mechanism of a given time series. This toolkit has been used in the literature by Panagiotidis (2002 and 2005), Panagiotidis and Pelloni (2003), Ashley and Patterson (2006), and Lim (2007). It is important to note that the main objective is not to determine the precise nature of the nonlinearity, but to determine whether or not nonlinearity exists in the full sample of the returns series under study.

As noted earlier, all the nonlinearity tests in the toolkit, except the bispectrum test, test the null hypothesis that the series under consideration is an independent and identically distributed (i.i.d.) process. Hence, data pre-whitening is necessary prior to the application of these five tests in order to remove linear serial dependence from the data, if any. The residuals of the fitted model, $\{e_t\}$, which are by construction serially uncorrelated, are then tested for nonlinear independence using each procedure. In contrast, the bispectrum test provides a direct test for nonlinearity, irrespective of any linear serial dependence that might exist. Ashley *et al*. (1986) presented an equivalence theorem to prove that the Hinich bispectrum test is invariant to linear filtering of the data, even if the filter is estimated. In this case, the test is robust even if linear pre-whitening model fails to remove all linear serial dependence in the data.

4.3 Methodology

4.3.1 McLeod-Li Test

The McLeod and Li (1983) test can be used as a portmanteau test of nonlinearity, focusing on the autocorrelation function of the square of the pre-whitened data, and tests whether corr(e_t^2, e_{t-k}^2) is nonzero for some *k*.

$$r_a^2(k) = \frac{\sum_{t=k+1}^{n} e_t^2 e_{t-k}^2}{\sum_{t=1}^{n} e_t^2} \quad \text{for } k=0, 1, \ldots\ldots, n\text{-}1$$

Under the null hypothesis that $\{e_t\}$ is an i.i.d. process, McLeod and Li showed that, for sufficiently large *m*,

$$Q(m) = \frac{n(n+2)}{n-k} \sum_{k=1}^{m} r_a^2\,(k)$$

is asymptotically distributed as chi-squared with *m* degrees of freedom under the null hypothesis of a linear generating mechanism for the data.

4.3.2 Engle LM Test

Engle (1982) proposed an LM test that explicitly examines nonlinearity in the second moments, in particular for ARCH disturbances. Since it is an LM test, the test statistic is based on the R^2 of an auxiliary regression as follows:

$$e_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, e_{t-1}^2 + v_t$$

If the sample size is *N*, under the null hypothesis of a linear generating mechanism for $\{e_t\}$, the test statistic NR^2 for this regression is asymptotically distributed as χ_p^2. Lee (1991) shows that the test has the same formulation against GARCH alternatives.

4.3.3 Brock-Dechert-Scheinkman Test

Brock *et al*. (1996) developed the BDS test based on the concept of correlation integral. The test statistic is asymptotically distributed as a normal variable under the null hypothesis of i.i.d. against an unspecified alternative using a nonparametric technique.

Given a sample of i.i.d. observations, $\{x_t : t = 1, 2, 3, \dots \dots, n\}$, Brock *et al.* showed that:

$$W_{m,n}(\varepsilon) = \sqrt{n}\frac{T_{m,n}(\varepsilon)}{V_{m,n}(\varepsilon)}$$

has a limiting standard normal distribution, where $W_{m,n}(\varepsilon)$ is the BDS statistic. Regarding other notations, *n* is the sample size, *m* is the embedding dimension, and the metric bound (ε) is the maximum difference between pairs of observations counted in computing the correlation integral. $T_{m,n}(\varepsilon)$, which has an asymptotic normal distribution with zero mean and variance $V_m^2(\varepsilon)$, measures the difference between the dispersion of the observed data series in a number of spaces with the dispersion that an i.i.d. process would generate in the same spaces, i.e., $C_{m,n}(\varepsilon) - C_{1,n}(\varepsilon)^n$.

4.3.4 Tsay Test

The Tsay (1986) test is used to detect quadratic serial dependence in the data, using quadratic terms lagged up to *k* periods. Suppose the *K* = *k*(*k*+1)/2 column vectors *V*1, . . . , *Vk* contain all the possible cross-products of the form $e_{t-i}e_{t-j}$, where $i \in [1, k]$ and $j \in [i, k]$.

Thus, $\nu_{t,1} = e_{t-1}^2$, $\nu_{t,2} = e_{t-1}e_{t-2}$, $\nu_{t,3} = e_{t-1}e_{t-3}$, … …, $\nu_{t,k} = e_{t-1}e_{t-k}$, $\nu_{t,k+1} = e_{t-2}^2$, $\nu_{t,k+2} = e_{t-2}e_{t-3,}$ $\nu_{t,k+3} = e_{t-2}e_{t-4}$, … … . , $\nu_{t,k} = e_{t-k}^2$

Let also $\widehat{v_{t,i}}$ denote the projection of $\nu_{t,i}$ on the sub-space orthogonal to $e_{t-1}, e_{t-2}, \dots \dots e_{t-k}$ (i.e., the residuals from a regression of $\nu_{t,i}$ on $e_{t-1} \dots \dots . . e_{t-k}$).

The parameters $\gamma_1, \gamma_2, \dots \dots . \gamma_k$ are then estimated by applying ordinary least squares to the following regression equation:

$$e_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i \, \widehat{v_{t,i}} + \eta_t$$

The Tsay test statistic is then just the usual *F*-statistic testing the null hypothesis that $\gamma_1, \gamma_2, \dots \dots . \gamma_k$ are all zero.

4.3.5 Hinich Bispectrum Test

The Hinich (1982) test involves estimating the bispectrum of the observed time series to test for the null hypotheses of Gaussianity and linearity. Let $\{y_t\}$ denote a third-order stationary time series, where the time unit *t* is an integer. The third-order cumulant function of $\{y_t\}$ in the time domain is defined as $C_{yyy}\,(r, s) = E(y_t y_{t+r} y_{t+s})$ for each (*r*, *s*) when E$\{y_t\}$=0, in which $S \ll r$ and $r = 0, 1, 2, 3, \dots.$

The bispectrum in the frequency domain is the double Fourier transform of the third-order cumulant function. More specifically, the bispectrum at frequency pair (f_1, f_2) denoted as

$B_{yyy}(f_1, f_2)$, is the double Fourier transform of $C_{yyy}(r, s)$ in the principal domain $\Omega = \{(f_1, f_2): 0 < f_1 < 0.5, f_2 < f_1, 2f_1 + f_2 < 1\}$ and can be expressed as follows:

$$B_{yyy}(f_1, f_2) = \sum_{r=-\infty}^{\infty} \sum_{s=-\infty}^{\infty} C_{yyy}(r, s)\exp[-i2\pi(f_1 r + f_2 s)]$$

Linearity and Gaussianity can be tested using a sample estimator of the skewness function $\psi(f_1, f_2)$ with $\psi^2(f_1, f_2) = \frac{|B_{yyy}(f_1, f_2)|^2}{S_{yy}(f_1)S_{yy}(f_2)S_{yy}(f_1+f_2)}$

where $S_{yy}(f)$ is the power spectrum, i.e., the Fourier transform of the second-order moment, at frequency f.

The skewness function is constant over all frequencies $(f_1, f_2) \in \Omega$ if $\{y_t\}$ is linear, while it is flat at zero if the data generating process is Gaussian. A nonlinear process is thus, implied if the skewness function in the frequency domain is not flat as a function of frequency pairs. It is worth noting that the flatness conditions are necessary, but not sufficient for general linearity and Gaussianity (Barnett *et al*., 1997). On the other hand, flatness of the skewness function is necessary and sufficient for third-order nonlinear dependence, and hence, the Hinich (1982) linearity test is in fact testing the null hypothesis on the lack of third-order nonlinear dependence.

4.3.6 Hinich Bi-Correlation Test in Moving Time Windows Framework

The research framework adopted in this study was first proposed by Hinich and Patterson (1995), published as Hinich and Patterson (2005), to detect the epochs of transient dependence in a discrete-time pure white noise process (i.i.d. random variates). The framework involves a procedure for dividing the full sample period into equal-length non-overlapping moving time windows, in which the window length is an arbitrary choice, and then the portmanteau correlation and bi-correlation test statistics (denoted by *C* and *H* respectively) are computed for each window to detect linear and nonlinear serial dependence, respectively. The test assumes that $\{e_t\}$ are realizations of a stationary i.i.d. process, and tests for serial independence using the bi-correlation of the data, which is effectively a correlation between the current return and previous autocorrelation coefficients.

Under the null hypothesis of i.i.d., the bi-correlations $C_3(r,s) = E[e_t e_{t+r} e_{t+s}]$ are all equal to 0 for all r, s except when *r*=*s*=0. The alternative hypothesis is that the process has some non-zero bi-correlations in the set $0 < r < s < L$, where L is the number of lags. In other words, if there exists third-order nonlinear dependence in the data generating process, then $C_3(r,s) \neq 0$ for at least one pair of *r* and *s* value.

The bi-correlation test statistic and its corresponding distribution are:

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

where $G(r,s) = (n-s)^{\frac{1}{2}} C_3(r,s)$ and the (*r*, *s*) sample bi-correlation coefficient is:

$$C_3(r,s) = (n-s)^{-1} \sum_{t=1}^{n-s} e_t\, e_{t+r} e_{t+s} \text{ for } 0 \ll r \ll s.$$

Since it is difficult to quantify how much significant autocorrelation could be attributed

to thin trading or price limits, this study instead focuses on whether returns still contain predictable nonlinearities after removing all linear dependence. The autocorrelation structure in each window is removed by an autoregressive AR(*p*) fit, in which the number of lags is selected such that there is no significant *C*- statistic at the specified threshold level[2]. It is worth highlighting that the AR fitting is employed purely as a pre-whitening operation, and not to obtain a model of best fit. The portmanteau bi-correlation test is then applied to the residuals of the fitted model of each window, so that any further rejection of the null hypothesis of pure white noise is only due to significant *H*-statistic.

The number of lags L is specified as $L = n^b$ with $0 < b < 0.5$, where b is a parameter under the choice of the user. Based on the results of Monte-Carlo simulations, Hinich and Patterson (1995 and 2005) recommended the use of $b = 0.4$ which is a good compromise between: (1) using the asymptotic result as a valid approximation for the sampling properties of *H*-statistic for moderate sample sizes, and (2) having enough sample bi-correlations in the statistic to have reasonable power against non-independent variates. Another element that must be decided upon is the choice of the window length. In fact, there is no unique value for the window length. The larger the window length, the larger the number of lags and hence the greater the power of the test, but it increases the uncertainty in the event time when the serial dependence occurs. In this study, the data are split into a set of equal-length non-overlapping moving time windows of 26 observations[3].

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[2] In the literature, in particular in those on long-term dependence, pre-filtering by means of an AR-GARCH procedure is commonly adopted to remove short-term autocorrelation and time-varying volatility. However, this procedure is unnecessary since the bi-correlation test relies on the property that the bi-correlation coefficient is equal to zero for a pure noise process, and the null hypothesis is rejected only when there exist some non-zero bi-correlations suggesting nonlinear dependence in the conditional mean (additive nonlinearity), but not the presence of conditional variance dependence (multiplicative nonlinearity).

[3] This window length is sufficiently long enough to validly apply the bi-correlation test and yet short enough for the data generating process to have remained roughly constant (see Monte-Carlo results in Hinich (1996) and Hinich and Patterson (1995 and 2005)).

4.4 Empirical Results

The present analysis utilizes the toolkit that consists of the McLeod-Li test, Engle LM test, BDS test, Tsay test, Hinich bi-correlation test and Hinich bispectrum test, to determine whether or not nonlinearity exists in the foreign exchange returns series of the emerging markets. With the exception of the bispectrum test, the other five test for serial dependence of any kind, whether linear or nonlinear. Hence, data pre-whitening is necessary prior to the application of these five tests in order to remove linear structure from the data, if any, so that any remaining serial dependence is due to a nonlinear data generating mechanism.

In the ‘nonlinearity toolkit’, the linear dependence is removed from the data by fitting an autoregressive model of order p, i.e., AR(p), for values from p = 0 to 10, and the optimal lag is chosen by minimizing the Schwarz’s Bayesian Information Criterion.

Given the varying power of these nonlinearity tests against the different classes of nonlinear processes, it is not surprising to observe from Table 4.1 that no ‘unanimous’ verdict on the existence of nonlinearity can be reached for all indices under study. In particular, the bispectrum test failed to reject the null of linearity in BRL, CLP, CZK, HUF and TRY at 5% significance level. McLeod-Li test is conducted on the series for lags 20 and 24. The test rejected the null of linear dependence for all the return series, except CNY, EGP, HUF, TRY and VND at 5% significance level. Engel LM test is conducted up to 5 lags. The results of Engel LM test also support nonlinearity in all forex returns, except CNY, EGP, HUF, PKR and VND at 5% significance level. BDS test supports nonlinearity in all currency returns. Other tests like bi-correlation and Tsay provide evidence of nonlinearity in all currencies, except CNY and EGP. The results in Table 1 on the whole provide strong evidence of nonlinearity in all the forex returns series, though ‘unanimous’ verdict from all the tests is obtained only for 16 returns series.

Though the results in the preceding paragraph reveal strong evidence of nonlinearity in returns series, it is possible that those significant results are actually driven by the activity within a small number of sub periods. To address this possibility, the Hinich window test is employed. The whole sample period is divided into equal-length non-overlapping moving time windows of 26 weekly observations, and then the *H*-statistic of Hinich (1996) is computed to detect nonlinear serial dependence in each time window. In the empirical analysis, a window is defined as significant if the *H*-statistic rejects the null hypothesis at the specified threshold level (or cut-off point) for the *p*-value set at 5%. To offer further improvement to the size of the test in small samples, bootstrapping with 10,000 replications that satisfy the null hypothesis is used to determine a threshold for the *H*-statistic that has a test size of 5%.

The first row of Table 4.2 provides the total number of non-overlapping windows. The second row shows the total number of significant *H* windows, indicating the presence of nonlinear serial dependence in the time periods identified in the final row of the same table. Given that the *H*-statistic is highly significant in the full sample analysis, one would expect these nonlinear features to be persistent throughout the data or at least many more of the time windows to exhibit significant *H*-statistic. Instead, the table shows that the significant test results in the whole series are actually triggered by activity within a few relatively short 'pockets' of highly nonlinear data. For instance, nonlinear predictable patterns are detected in 6 out of the total 33 windows (equivalent to 18.18%) for CNY. Even for the currency with the highest number of significant *H* windows, ARS, the percentage is only 37.84%. Table 2 also gives the dates when these episodic nonlinearities occurred, which is potentially useful for future investigation into the causes of these detected episodic behavior.

These currencies have been taken for further studies .The episodic behavior of the underlying nonlinearity can be observed graphically. The graphical representation of five currencies having more than 20% significant windows has been provided in Figures 4.1 to 4.5. These graphs show the persistence of nonlinearity in five series. The histograms in Figures 4.1 to 4.5 show the percentile (i.e., 1 – *p*-value) into which the *H*-statistic falls in each window for IDR, RUB, PKR, VND and ARS, respectively. Thus, a very significant window is plotted as a value near 1.0. It can be observed from these figures that the episodic occurrence of these nonlinear dependencies appears within the data only infrequently. Another salient feature is the transient nature of these nonlinearities, in which some windows appear highly significant, but then quickly disappear, or become too weak to be detected, in subsequent windows. Thus, it can be observed that the underlying nonlinear process for foreign exchange returns of emerging market economies is not stable over time; the significant windows tend to be sporadic and brief. A series of events of political and economic nature in these countries, like change in central banks' monetary policy, privatization process, change in export-import policy, policy changes on capital flow, etc., could have impacted the behavior of these currencies.

4.5 Concluding Remarks

Motivated by the possible existence of nonlinear dependence in exchange rate return series, this chapter investigates the weak-form efficiency of foreign exchange markets of 25 emerging economies. Using a battery of nonlinearity tests, the statistical results reveal that for the return series of eight currencies i.e. CNY, PKR, VND, EGP, BRL, CLP, CZK, HUF the null of linearity is rejected by atleast one of the six tests used in this study at atleast 5 percent significance. However, for the rest 17 currencies the tests unanimously suggest nonlinear dependence. The Hinich window test is used to further investigate the presence of nonlinearity in the return series. It is observed that only for five currencies i.e. IDR, PKR, VND, ARS and RUB the *H*-statistics is significant for at least 20% windows. The nonlinearity observed is episodic in nature, i.e., returns of these currencies are characterized by a few brief periods of highly significant nonlinearity, followed by long time periods in which the returns follow pure noise process. Thus, the underlying nonlinear process for foreign exchange returns of emerging market economies is not stable over time. The significant windows tend to be sporadic and brief, thus making the series unpredictable.

Table 4.1: *p*-values of Nonlinearity Tests

	Asia											Middle East		
Tests	**CNY AR(2)**	**IDR AR(0)**	**MYR AR(1)**	**TWD AR(3)**	**PKR AR(0)**	**PHP AR(1)**	**KRW AR(3)**	**THB AR(10)**	**LKR AR(2)**	**INR AR(1)**	**VND AR(1)**	**EGP AR(0)**	**TRY AR(5)**	**MAD AR(1)**
McLeod-Li														
Lag(20)	0.495	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.006	0.003	0.245	0.369	0.054	0.001
Lag(24)	0.458	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.007	0.003	0.064	0.323	0.065	0.001
Hinich Bispectral	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.627	0.000
Engel LM														
For lag=1	0.062	0.002	0.008	0.016	0.553	0.003	0.004	0.000	0.002	0.000	0.007	0.045	0.008	0.000
For lag=2	0.082	0.000	0.018	0.028	0.062	0.002	0.001	0.001	0.002	0.000	0.017	0.091	0.016	0.000
For lag=3	0.141	0.000	0.018	0.038	0.096	0.001	0.001	0.000	0.002	0.000	0.037	0.127	0.023	0.000
For lag=4	0.168	0.000	0.012	0.000	0.016	0.030	0.002	0.000	0.002	0.000	0.051	0.167	0.037	0.000
For lag=5	0.223	0.000	0.001	0.000	0.019	0.020	0.002	0.000	0.002	0.000	0.062	0.216	0.031	0.000
BDS														
$\varepsilon/\sigma=1, m=2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
$\varepsilon/\sigma=1, m=3$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
$\varepsilon/\sigma=1, m=4$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bi-Correlation	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.020	0.064	0.000	0.000
Tsay	0.080	0.000	0.000	0.001	0.012	0.000	0.000	0.000	0.017	0.002	0.026	0.137	0.001	0.000

Table 4.1 (Cont.)

	Latin America						CEE/CIS				Africa
Tests	**BRL AR(0)**	**CLP AR(0)**	**COP AR(2)**	**PEN AR(5)**	**ARS AR(8)**	**MXN AR(6)**	**CZK AR(0)**	**HUF AR(10)**	**PLN AR(3)**	**RUB AR(2)**	**ZAR AR(0)**
McLeod-Li											
Lag(20)	0.007	0.000	0.000	0.000	0.000	0.021	0.000	0.403	0.000	0.015	0.000
Lag(24)	0.008	0.000	0.000	0.000	0.000	0.025	0.000	0.346	0.000	0.019	0.000
Hinich Bispectral	0.607	0.346	0.000	0.000	0.000	0.000	0.280	0.546	0.000	0.000	0.049
Engel LM											
For lag=1	0.002	0.000	0.000	0.002	0.011	0.003	0.001	0.926	0.001	0.013	0.000
For lag=2	0.003	0.000	0.000	0.001	0.028	0.005	0.000	0.627	0.000	0.006	0.000
For lag=3	0.006	0.000	0.000	0.001	0.031	0.006	0.000	0.607	0.000	0.004	0.000
For lag=4	0.010	0.000	0.000	0.001	0.000	0.009	0.000	0.601	0.000	0.004	0.000
For lag=5	0.010	0.000	0.000	0.001	0.000	0.009	0.000	0.583	0.000	0.004	0.000
BDS											
$\varepsilon/\sigma=1, m=2$	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000
$\varepsilon/\sigma=1, m=3$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\varepsilon/\sigma=1, m=4$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bi-Correlation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.026	0.000	0.000	0.000
Tsay	0.000	0.000	0.000	0.001	0.000	0.002	0.000	0.049	0.000	0.000	0.001

Table 4.2: Results of Hinich Window Test

	Asia							
	CNY	**IDR**	**MYR**	**TWD**	**PKR**	**PHP**	**KRW**	**THB**
Total No. of Windows	33	38	43	43	43	37	44	51
Number of Significant *H* windows	6 (18.18%)	10 (26.32%)	7 (16.28%)	4 (9.30%)	9 (20.93%)	2 (5.41%)	8 (18.18%)	10 (19.61%)
Date of Significant H Windows	1) 19/01/94-13/07/94 2) 18/01/95-12/07/95 3) 17/01/96-10/07/96 4) 16/07/97-07/01/97 5) 07/07/04-29/12/04 6) 05/01/05-29/06/05	1) 13/11/91-06/05/92 2) 06/11/96-30/04/97 3) 07/05/97-29/10/97 4) 05/11/97-29/04/98 5) 04/11/98-28/04/99 6) 27/04/05-19/10/05 7) 26/04/06-18/10/06 8) 24/10/07-16/04/08 9) 23/04/08-15/10/08 10) 21/04/10-13/10/10	1) 11/04/90-03/10/90 2) 08/04/92-30/09/92 3) 27/03/02-18/09/02 4) 25/09/02-19/03/03 5) 26/03/03-17/09/03 6) 24/09/03-17/03/04 7) 24/03/03-15/09/04	1) 11/04/90-03/10/90 2) 26/09/01-20/03/02 3) 27/03/02-18/09/02 4) 22/03/06-13/09/06	1) 12/07/89-03/01/90 2) 01/01/97-25/06/97 3) 30/12/98-23/06/99 4) 27/06/01-19/12/01 5) 24/12/03-16/06/04 6) 22/06/05-14/12/05 7) 21/12/05-14/06/06 8) 20/12/06-13/06/07 9) 19/12/07-11/06/08	1) 19/07/95-10/01/96 2) 05/07/06-27/12/06	1) 08/11/89-02/05/90 2) 07/11/90-01/05/91 3) 06/11/91-29/04/92 4) 01/05/96-23/10/96 5) 30/04/97-22/1097 6) 21/04/04-13/10/04 7) 20/04/05-12/10/05 8) 15/10/08-08/04/09	1) 10/02/88-03/08/88 2) 29/01/97-23/07/97 3) 28/01/98-22/07/98 4) 10/08/98-01/02/89 5) 08/08/90-30/01/91 6) 04/01/01-18/07/01 7) 23/07/03-14/01/04 8) 19/07/06-10/01/07 9) 16/01/08-09/07/08 10) 14/01/09-08/07/09

Table 4.2 (Cont.)

	Asia			Middle East			Latin America	
	INR	**LKR**	**VND**	**EGP**	**TRY**	**MAD**	**BRL**	**CLP**
Total No. of Windows	39	48	34	34	33	43	35	38
Number of Significant *H* Windows	5 (12.82%)	8 (14.58%)	8 (23.53%)	2 (5.88%)	5 (15.15%)	1 (2.33%)	4 (11.43%)	4 (10.53%)
Date of Significant *H* Windows	1) 03/01/96-26/06/96 2) 03/07/96-25/12/96 3) 02/07/97-24/12/97 4) 29/12/99-21/06/00 5) 27/06/01-19/12/01	1) 10/09/86-04/03/87 2) 23/03/88-14/09/88 3) 21/09/88-15/03/89 4) 10/09/97-04/03/98 5) 09/09/98-03/03/99 6) 25/02/09-19/08/09 7) 26/08/09-17/02/10	1) 29/06/93-10/01/94 2) 17/01/94-11/07/94 3) 28/01/97-30/07/97 4) 06/10/99-29/03/00 5) 04/04/01-26/09/01 6) 03/10/01-27/03/02 7) 29/09/04-23/03/05 8) 27/09/06-21/03/07	1) 12/08/99-09/02/00 2) 11/02/09-05/08/09	1) 02/03/94-24/08/94 2) 01/03/95-23/08/95 3) 20/08/03-11/02/04 4) 16/02/05-10/08/05 5) 13/08/08-04/02/09	1) 03/02/93-28/07/93	1) 28/06/00-12/06/00 2) 13/12/00-23/05/01 3) 02/04/03-10/09/03 4) 02/02/05-06/07/05	1) 08/09/93-02/03/94 2) 03/09/97-25/02/98 3) 21/02/07-15/08/07 4) 22/08/07-13/02/08

	Latin America				CEE/CIS				Africa
	COP	**PEN**	**ARS**	**MXN**	**CZK**	**HUF**	**PLN**	**RUB**	**ZAR**
Total No. of Windows	36	36	37	37	34	34	34	34	55
Number of Significant *H* Windows	5 (13.89%)	4 (11.11%)	14 (37.84%)	5 (13.51%)	1 (2.94%)	5 (14.71%)	1 (2.94%)	8 (23.53%)	8 (14.55%)
Date of Significant *H* Windows	1) 15/08/01-06/02/02 2) 12/02/03-06/08/03 3) 11/08/04-02/02/05 4) 08/02/06-02/08/06 5) 20/02/08-13/08/08	1) 25/08/99-16/02/00 2) 23/02/00-16/08/00 3) 01/08/02-12/02/03 4) 18/02/04-11/08/04	1) 13/07/94-04/01/95 2) 10/01/96-03/07/96 3) 10/07/96-01/01/97 4) 08/01/97-02/07/97 5) 09/07/97-31/12/97 6) 07/01/98-01/07/98 7) 08/07/98-30/12/98 8) 07/07/99-29/12/99 9) 03/01/01-27/06/01 10) 01/01/03-25/06/03 11) 02/07/03-24/12/03 12) 28/06/06-20/12/06 13) 27/12/06-20/06/07 14) 02/07/08-24/12/08	1) 21/07/93-12/01/94 2) 20/07/94-11/01/95 3) 18/01/95-12/07/95 4) 19/07/95-10/01/96 5) 15/07/98-06/01/99	1) 26/01/05-20/07/05	1) 13/08/97-04/02/98 2) 06/02/02-31/07/02 3) 02/02/05-27/07/05 4) 30/01/08-23/07/08 5) 30/07/08-21/01/09	1) 11/06/08-03/12/08	1) 20/07/94-11/01/95 2) 17/07/96-08/01/97 3) 14/01/98-08/07/98 4) 10/07/02-01/01/03 5) 09/07/03-31/12/03 6) 04/01/06-28/06/06 7) 04/07/07-26/12/07 8) 31/12/08-24/06/09	1) 08/07/87-30/12/87 2) 06/07/88-28/12/88 3) 04/01/89-28/06/89 4) 28/12/94-21/06/95 5) 25/12/96-18/06/97 6) 14/12/05-07/06/06 7) 12/12/07-04/06/08 8) 11/06/08-03/12/08

Figure 4.1: *p*-value of *H*-statistics (IDR)

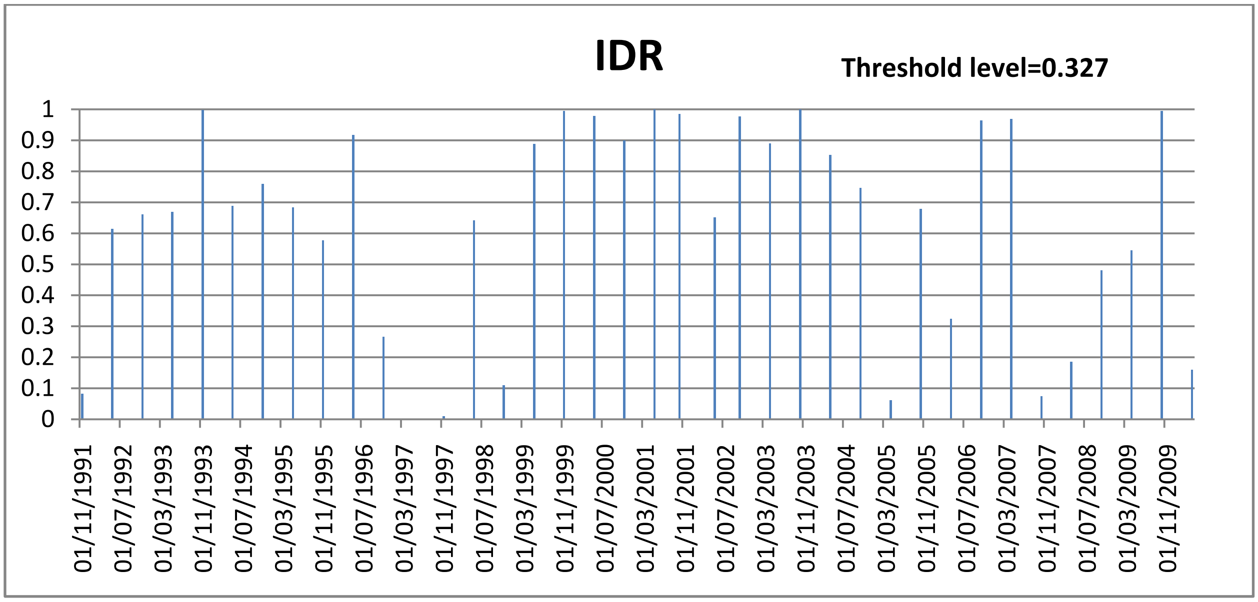


Figure 4.2: *p*-value of *H*-statistics (RUB)

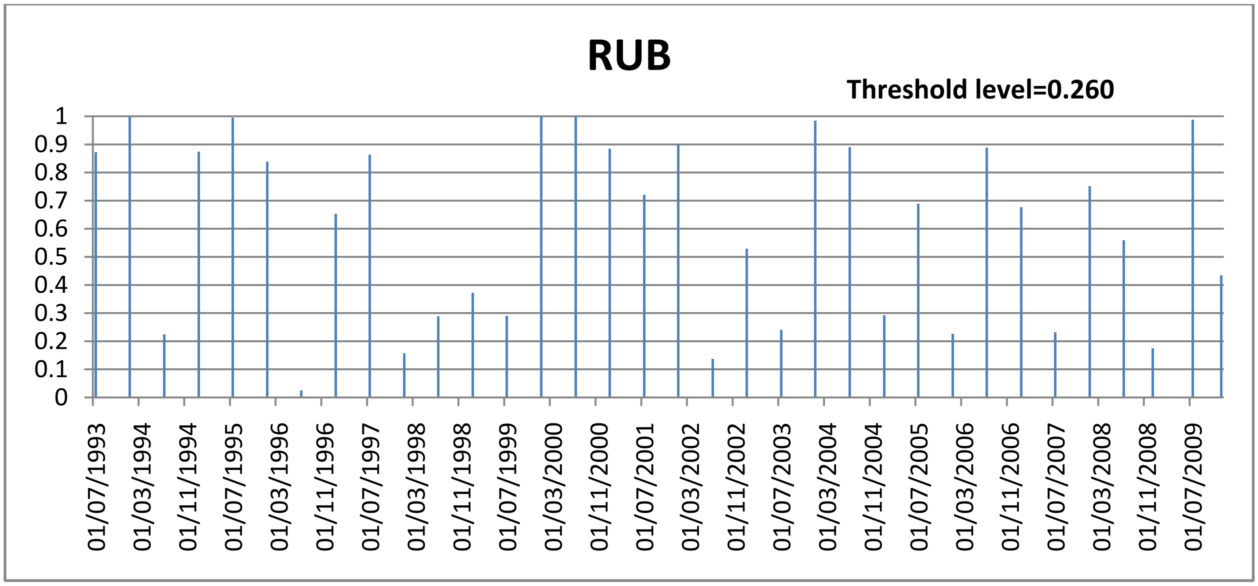


Figure 4.3: *p*-value of *H*-statistics (PKR)

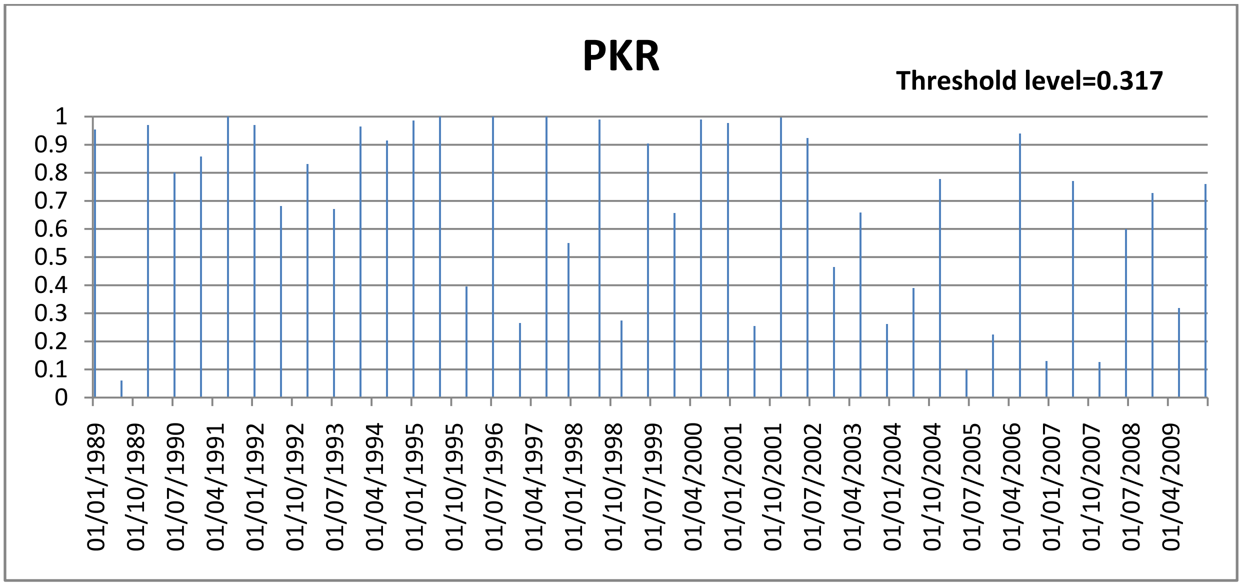


Figure 4.4: *p*-value of *H*-statistics (VND)

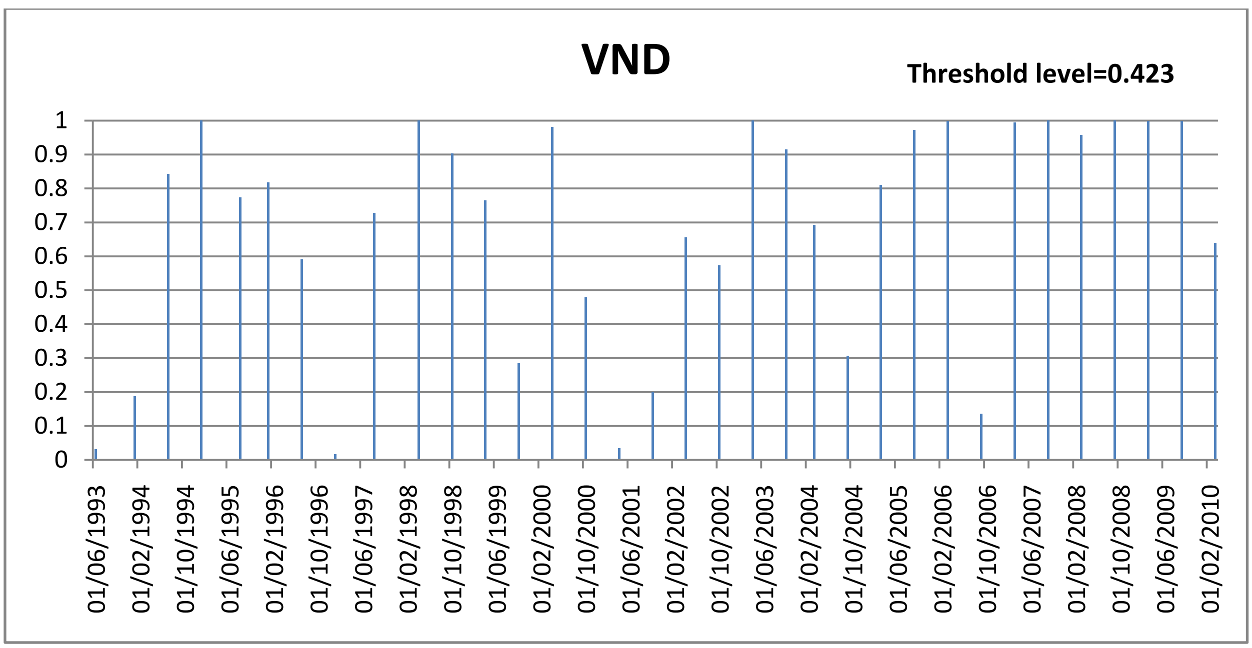
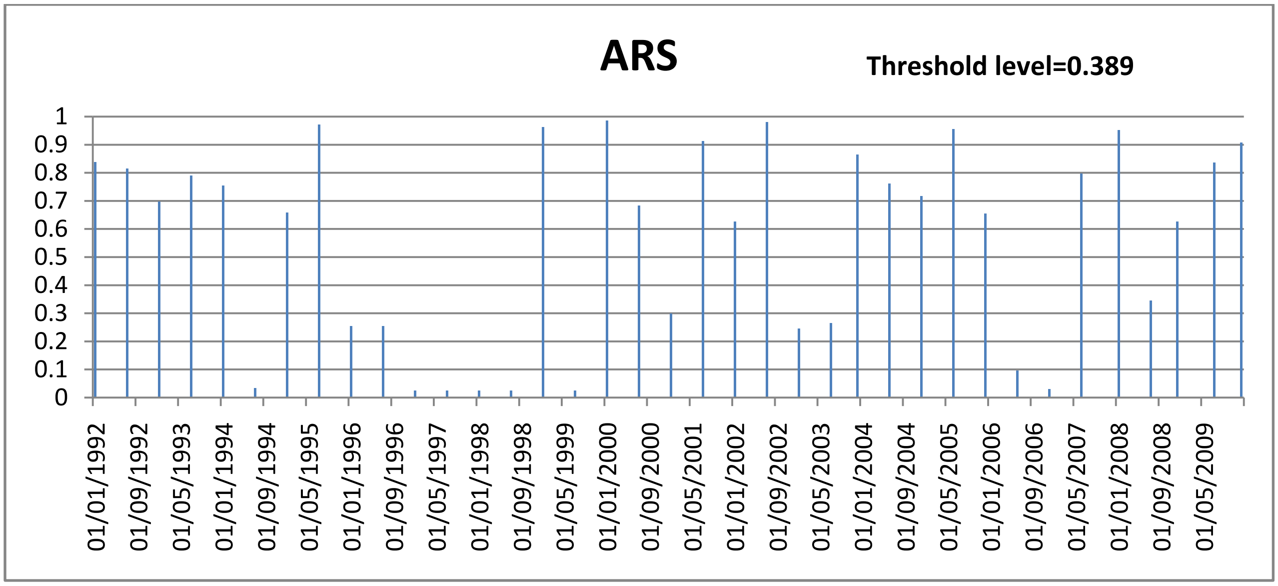


Figure 4.5: *p*-value of *H*-statistics (ARS)



CHAPTER 5

LONG MEMORY IN FOREIGN EXCHANGE RETURNS

5.1 Introduction

Long memory is an important dimension of exchange rate behavior. The long memory property has been widely studied in economic series and its implications for economic theory have been extensively discussed. The most considerable economic implication is the contradiction of the weak-form of market efficiency (Fama, 1970), allowing investors and portfolio managers to make predictions and construct speculative strategies. The price of an asset determined in an efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. Consequently, pricing derivative with martingale methods may not be appropriate if the underlying continuous stochastic processes exhibit long memory. Therefore, exploring long memory property is necessary for derivative market participants, risk managers and asset allocation decisions makers, whose intention is to reasonably forecast the exchange rate movements.

Considerable research has been performed concerning long memory property and its implications in various science fields from physics, climatology and hydrology to its applications in stock markets, exchange rates and macroeconomic indicators.

Long memory also known as the long-range dependence, describes the high-order correlation structure of a series. The presence of long-range dependence contradicts the weak form of market efficiency hypothesis. If a time series possesses long memory, there is persistent dependence between observations even considerably separated in time. In contrast, if correlation among observations is negligible at long lags, the series is said to exhibit short memory. A time series may have long memory, either in mean or in variance or in both. This means that the effect of shocks on financial time series takes a very long time to disappear. One way to model such behavior is through fractionally integrated time series processes that lie conceptually somewhere between I(0) and I(1) processes. Fractionally integrated models may be either stationary or non-stationary. Even if they are weakly stationary the autocorrelation function of I(0) process shows exponential decay and the series with long memory tails off hyperbolically and eventually dies out. Fractionally integrated processes have been applied both to ARMA models leading to ARFIMA models and to models of conditional volatility to lead to fractionally integrated GARCH and fractionally integrated stochastic volatility models.

This chapter examines long memory in mean which is modeled by ARFIMA model. Modeling of long memory in volatility using FIGARCH models and dual memory using ARFIMA-FIGARCH models have been discussed in the following chapter of the thesis.

There is strong evidence that the return R_t has little or no autocorrelation, but the squared return R_t^2 or absolute return $|R_t|$ exhibit noticeable autocorrelation. This implies there is no significant long memory in the return series, but appreciable long-range dependence exists in the volatility time series, as discussed by Campbell *et al.* (1996).

5.2 Review of Literature

Long memory modeling has been studied in econometrics and finance since Mandelbrot (1969) introduced the long memory specifications for price processes. Fractionally integrated models have been being widely used since 1980s when Geweke and Porter-Hudak (1983) developed the log periodogram regression estimator for the order of integration parameter d in the ARFIMA model of Granger and Joyeux (1980) and Hosking (1981).

Lo (1991) found little evidence of long-term memory in historical US stock market returns, while Cheung and Lai (1995) investigated the presence of long memory in stock returns for 18 indices using a modified *R*/*S* statistic and the Geweke-Porter-Hudak (GPH) test. While *R*/*S* statistic mostly showed negative results, GPH test confirmed long memory in stock returns for only five indices.

Ding *et al*. (1993) found that there is substantially more correlation between absolute returns than returns themselves and showed that ARCH-type models both based on squared returns and those based on absolute returns can produce the property of long memory in volatility. With regard to spurious long memory, Ding and Granger (1996) pointed out that many other data generating mechanisms can produce processes with features same as that of long memory, and show that at least time-varying parameter models could be considered in this class. Lobato and Savin (1998) found no evidence of long memory in daily stock returns, but strong evidence of long memory in squared returns. Though Willinger *et al*. (1999) found empirical evidence of long-range dependence in stock price returns, the evidence was not absolutely conclusive. Granger and Hyung (1999) showed for S&P 500 that absolute stock returns tend to show the long memory property due to the presence of structural breaks in the series rather than due to a true I(d) process, concluding that linear process with breaks can imitate autocorrelations as well as other properties of fractionally integrated processes. Using the spectral regression method, Barkoulas *et al*. (2000) found significant and robust evidence of positive long-term persistence in the Greek stock market. Henry (2002) investigated long-range dependence in nine international stock index returns and found evidence of long memory in four indices, i.e., the German, Japanese, South Korean and Taiwanese markets, but not for the markets of the UK, USA, Hong Kong, Singapore and Australia.

Chen (2000) calculated the classical rescaled range statistic of Hurst for stock indices of seven Asia-Pacific countries and concluded that all the index returns have long memory. Diebold and Inoue (2000), however, concluded upon the strong connection between long memory and regime switching, showing that stochastic regime switching can be easily confused with long memory.

Sadique and Silvapulle (2001) examined the presence of long memory in weekly stock returns of seven countries: Japan, Korea, New Zealand, Malaysia, Singapore, the USA and Australia. They found evidence of long-term dependence in four countries: Korea, Malaysia, Singapore and New Zealand.

Cajueiro and Tabak (2005) stated that the presence of long-range dependence in asset returns seems to be a stylized fact. They studied the individual stocks in the Brazilian stock market and found evidence that firm-specific variables can explain, at least partially, the long-range dependence phenomena. With the same point of view, Perron and Qu (2006) analytically showed how a stationary short-memory process with level shifts can generate spurious long memory.

Granger and Hyung (2004) research came to support the conclusions of Diebold and Inoue and showed that occasional breaks generate slowly decaying autocorrelations and other properties of I(d) processes, and thus, it is not easy to distinguish between the two types of processes. They demonstrated that at least a part of the long memory may be caused by the presence of neglected breaks in the series and suggested that their finding improves volatility prediction by combining I(d) model and occasional-break model.

Early research indicated considerable empirical evidence in support of long memory dynamics in exchange rates, while more recent research reveals that the empirical evidence is inconclusive, with results being sensitive to the particular sample examined. For example, Booth *et al*. (1982) applying classical rescaled-range (R/S) analysis to daily exchange rates, found evidence of negative long-term dependence during the fixed exchange rate period (1965-1971) and positive long-term dependence during the post-1974 flexible exchange rate period in three major exchange rates. Cheung (1993), employing the popular Geweke and Porter-Hudak (1983) estimator on five major exchange rates from 1974 to 1987, found evidence of long memory dynamics. Pan *et al*. (1996) provided additional evidence of long memory dynamics in the same sample, utilizing the modified *R*/*S* and variance-ratio tests. Baillie and Bollerslev (1989 and 1994) also found evidence of fractional integration in exchange rates. In contrast, Barkoulas *et al*. (2003) found little convincing evidence of long memory in 18 currency return series over the period 1974-1995. They concluded that exchanges rates are best represented as a martingale, rather than fractionally integrated. Some examples of recent studies analyzing nominal exchange rate dynamics using fractional integration (looking at futures, in particular) include Fang *et al*. (1994), Crato and Ray (2000), and Wang (2004). Volatility dynamics in foreign exchange rates (mainly the Deutsche mark vis-à-vis the US dollar rate) have also been examined with the FIGARCH-model, initially by Baillie *et al*. (1996), and subsequently the papers that have used this approach are Andersen and Bollerslev (1997 and 1998), Tse (1998 – examining the Japanese Yen-US dollar rate), Baillie *et al*. (2000), Kihc (2004), and Morana and Beltratti (2004 – analyzing volatility).

5.3 Detecting Long Memory in Time Series

There are various definitions of long memory process. Especially, long memory can be expressed either in the time domain or in the frequency domain. In the time domain, a stationary discrete time series is said to be long memory, if its autocorrelation function decays to zero like a power function. This implies that the dependence between the successive observations decays slowly as the number of lags tends to infinity. On the other hand, in the frequency domain, a stationary discrete time series is supposed to be long memory if the spectral density is unbounded at low frequencies.

ACF and Fractional Integration: A standard approach to examine long memory within time series is through the examination of the sample autocorrelation function. In particular, if the sample autocorrelations take a long time to decline to zero, then the process is said to exhibit long memory. That is, if the autocorrelations decay very slowly as the lag length increases, then current values of the series are related to their own distant values. Absolute returns and squared returns show this pattern.

There are currently a significant number of estimation methods for and tests of long memory models. Probably one of the reasons for this large collection of tools for estimation and testing is the fact that good estimation techniques remain elusive, and many of the tests used for long memory have been shown through finite sample experiments to perform quite poorly. Therefore, in our study we consider some of the most widely used estimators and tests: the *R*/*S* statistic, GPH and Robinson estimators – the nonparametric and semi-parametric approaches – and ARFIMA/FIGARCH model – the parametric approach.

5.3.1 The Nonparametric Approach: Rescaled Range Statistic

The original statistical measurement of long memory introduced by Hurst (1951), and subsequently used by Mandelbrot (1975) is the *R*/*S* statistic (rescaled range statistic). The classical rescaled range statistic is defined as:

$$R/S\,(n) = \frac{1}{S_n} * \left[Max \sum_{j=1}^{k} (X_j - \overline{X_n}) - Min \sum_{j=1}^{k} (X_j - \overline{X_n})\right], 1 \leq k \leq n \qquad (1)$$

where S_n is the sample standard deviation:

$S_n = \left[\frac{1}{n}\sum_j (X_j - \overline{X_n})^2\right]^{\frac{1}{2}}$

The first term of Equation (1) represents the maximum of the partial sums of the first *k* deviations of X_j from the sample mean. Given that the sum of all *n* deviations of the X_j's from their mean is zero, this term is always non-negative. In the same way, the second term is always non-positive, and hence, the difference between the two terms, known as the range, is always non-negative. Madelbrot and Wallis (1969) used the *R*/*S* statistic to detect long memory patterns using the following rationale: for a random process there is a scaling relationship between the rescaled range and the number of observations '*n*' of the form:

$$R/S(n) \sim nH \quad (2)$$

where *H* is the Hurst exponent. For a white noise process *H* = 0.5, while for a persistent, long memory process *H* > 0.5. The difference *d* = (*H* – 0.5) represents the degree of fractional integration in the process.

Mandelbrot and Wallis suggest estimating the Hurst coefficient by plotting the logarithm of *R*/*S*(*n*) against log(*n*). For large *n*, the slope of such a plot should provide an estimate of *H*. A major limitation of the rescaled range is its sensitivity to short-range dependence. Any departure from the predicted behavior of the *R*/*S* statistic under the null hypothesis need not be an indication of long-range dependence, but may simply be an indication of short-term memory. Lo (1991) shows the following result from the limiting distribution of the rescaled range:

$$\frac{1}{\sqrt{n}} R/S(n) \Rightarrow V \quad (3)$$

where *V* is the range of a Brownian bridge on the unit interval.

To differentiate between long-range and short-term dependence, Lo (1991) proposes a modification of the *R*/*S* statistic to ensure that its statistical behavior is invariant over a general class of short memory processes, but deviates for long memory processes. His version of the *R*/*S* test statistic differs only in the denominator. Rather than using the sample standard deviation, Lo's formula applies the standard deviation of the partial sum, which includes not only the sums of squares of deviations of X_j, but also the weighted autocovariances (up to lag q):

$$\widehat{\sigma^2}_n(q) = \frac{1}{n}\sum_{j=1}^{n}(X_j - \overline{X_n})^2 + 2\sum_{j=1}^{q}\omega_j(q)\hat{\gamma}_j \quad (4)$$

$$\omega_j(q) = 1 - \frac{j}{q+1} \qquad q < n \quad (5)$$

where γ_j are the usual autocovariance estimators.

If $q = 0$, Lo's statistic reduces to Hurst's *R*/*S* statistic. This statistic is highly sensitive to the order of truncation q, but there are no statistical criteria for choosing q in the framework of this statistic. If q is too small, the statistic does not account for the autocorrelation of the process, while if q is too large, it accounts for any form of autocorrelation and the power of this test tends to its size.

Therefore, while in principle this adjustment to the *R*/*S* statistic ensures its robustness in the presence of short-term dependency, selecting an appropriate lag order q still remains a problem. Moreover, Teverovsky *et al*. (1999) prove that Lo's modification of *R*/*S* statistic is too strict. They show that Lo's method has a strong preference for accepting the null hypothesis of no long-range dependence, irrespective of whether long-range dependence is present in the data or not. They also conclude that an acceptance of the null hypothesis of no long-range dependence based on the modified *R*/*S* statistic should never be viewed as conclusive, but should always be accompanied and supported by further analysis of the data.

5.3.2 Semi-Parametric Approach

a) Geweke-Porter-Hudak Estimator: Geweke and Porter-Hudak (1983) suggested a semi-parametric procedure to obtain an estimate of the fractional differencing parameter *d* based on the slope of the spectral density function around the angular frequency $x = 0$. More specifically, let $I(x)$ be the periodogram of *y* at frequency *x* defined by:

$$\mathrm{I}(I(\xi) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} e^{it\xi}\,(y - \overline{y})\right|^2 \quad (6)$$

Then the spectral regression is defined by:

$$\ln\{I(\xi_\lambda)\} = \beta_0 + \beta_1 \ln\left\{4\,sin^2\left(\frac{\xi_\lambda}{2}\right) + \eta_\lambda\right\} \quad (7)$$

where $\xi_\lambda = \frac{2\pi\lambda}{T}\,(\lambda = 0, \ldots., T-1)$ denotes the Fourier frequencies of the sample, T is the number of observations, and $n = g(T) << T$ is the number of Fourier frequencies included in the spectral regression.

Assuming that $\lim_{T\to\infty} g(T) = \infty, \lim\{g(T)/T\} = 0, \lim_{T\to\infty} \ln(T)^2 \big/ g(T) = 0$

the negative of the slope coefficient in the spectral regression provides an estimate of *d*. Geweke and Porter-Hudak (1983) prove consistency and asymptotic normality for $d < 0$, while Robinson (1990) proves consistency for $d \in (0, 0.5)$.

The spectral regression estimator is not $T^{1/2}$ consistent as it converges at a slower rate. The theoretical variance of the error term in the spectral regression is known to be $\pi^2/6$.

A choice must be made with respect to the number of low-frequency periodogram ordinates used in the spectral regression. Improper inclusion of medium or high-frequency periodogram ordinates will contaminate the estimate of *d*. At the same time, too small regression sample will lead to imprecise estimates.

We report fractional differencing parameter for $T^{0.5}$, $T^{0.55}$ and $T^{0.60}$ to investigate the sensitivity of our results to the choice of the sample size of the spectral regression.

b) Robinson Log Periodogram Estimator: Robinson (1995a) proposed a modified Log-Periodogram Regression Estimator (LPE) of the long memory parameter *d*. The asymptotic properties of *d*(0) is derived from -1/2 < *d* < 1/2 as opposed to the GPH method described above, which attempted a proof only in the case of -1/2 < *d* < 0.

Let $\bar{a}$ and S_t be defined as:

$$\bar{a} = (m - l)^{-1} \sum_{i=l+1}^{m} a_j \qquad (8)$$

$$S_t = \sum_{j=l+1}^{m} (a_j - \bar{a})^2 \qquad (9)$$

where a_j = -ln{4sin^2(ω_j/2)}. The long memory parameter estimate $\bar{d}$ can be expressed as:

$$\bar{d}(l) = \sum_{i=l+1}^{m} (a_j - \bar{a}) \ln \mathrm{I}(\omega_j) / S_t \qquad 0 \leq l < m < n \qquad (10)$$

where $I(\omega_j)$ is the usual periodogram as defined above.

Equation (10) denotes the long memory parameter $\bar{d}(l)$ as proposed by Robinson (1995a). l is chosen to trim out low frequencies. Consistency and asymptotic normality under Guassianity are developed in Robinson.

Robinson (1995b) proposed a Gaussian Semi-Parametric Estimator (GSE), which maximizes an approximates form of frequency domain Gaussian likelihood. Unlike the previously proposed estimation methods by Robinson, the GSE estimator does not assume Gaussianity in the asymptotic theory and is shown to be more efficient.

The fractional autoregressive moving average process as denoted by:

$$f(\omega) \sim C\omega^{-2d} \text{as } \omega \to 0^{+} \tag{11}$$

satisfies the time domain property,

$$\gamma_j \sim g j^{2d-1} \text{ as j} \to \infty \tag{12}$$

where $g < 0$ for $-0.5 < d < 0$ and $g > 0$ for $0 < d < 0.5$. Robinson (1995b) adopts the expression H, where H is the self-similarity parameter introduced by Kolmogorov (1940). The long memory parameter d is equivalent to H – 1/2. We replaced the self-similarity parameter H as represented in Robinson with the long memory parameter d.

Let G_0 and H_0 denote the true parameter values. Consider the objective function:

$$Q(G,d) = 1/m \sum_{j=1}^{m} \left\{ \log G\omega_j{}^{-2d} + \left(\frac{\omega_j^{2d}}{G}\right) I(\omega_j) \right\} \tag{13}$$

The estimate would therefore be:

$$(\widehat{G}, \widehat{d}) = \arg\min Q(G,d), \qquad 0 < G < \infty \qquad H \in \Theta$$

Alternatively, if we are only interested in estimating d, we can represent the above equation as:

$$\hat{d} = \arg\min [\log G(d) - 2d 1/m \sum_{j=1}^{m} \log\omega_j] \tag{14}$$

$H \in \Theta$

$$\text{where } G(d) = 1/m \sum_{j=1}^{m} \omega_j^{2d} I(\omega_j) \tag{15}$$

Equation (15) denotes the Gaussian likelihood estimate of the long memory parameter $\hat{d}$. The estimate is shown to be asymptotically normal with zero mean and variance $(2m^{1/2})^{-1}$.

5.3.3 Parametric Approach: ARFIMA Model

All the estimation techniques discussed above, are included in the two-step estimation procedure (This distinction was first made by Sowell, 1992). These procedures only estimate the differencing parameter, and in the second step, the estimated differencing parameter is used to transform the observed series into a series that presumably follows an ARMA(*p*, *q*) model. The limitation of these models is that they use information only at low frequencies and therefore they do not take account of the short-term properties of the series when estimating the fractional differencing parameter. This has important implications since the estimate of the long-term parameter could be contaminated by the presence of short-term components. Therefore, a more appropriate technique is the ARFIMA process introduced by Granger and Joyeux (1980) and Hosking (1981). This is a one-step estimation procedure: the process accounts for long-term dynamics through the fractional integration parameter *d*, while traditional AR and MA components capture only the short-term dynamics of the time series. The parameters are simultaneously estimated using maximum likelihood estimation.

The ARFIMA (*p*, *d*, *q*) model is represented by:

$$\Phi(L)(1-L)^d(y_t-\mu)=\Theta(\mathrm{L})\mathrm{u_t} \text{ where } \mathrm{u_t} \sim \text{i.i.d.}(0,\sigma_u^2) \qquad (16)$$

where L is the lag operator, d is the fractional differencing parameter, and u_t is the white noise. All the roots of $\Phi(L)$ and $\Theta(\mathrm{L})$ lie outside the unit circle.

Granger and Joyeux (1981) show that:

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-\mathrm{d})\Gamma(\mathrm{k}+1)} \qquad (17)$$

where $\Gamma(.)$ is the gamma function.

If -0.5 < d < 0.5 the process is invertible and for such processes, the effect of shocks to t on y_t decays at a slow rate to zero. If d=0, then the process is stationary, the so-called short memory, and the effect of shocks to t on y_t decays geometrically. For d=1 the process is a unit root process. For 0 < d < 0.5 the process exhibits positive dependence between distant observations implying long memory, and for -0.5 < d < 0 the process exhibits negative dependence between distant observations, the so-called anti-persistence.

The use of the fractional difference operator allows obtaining a continuum of possibilities between the polar cases of unit root processes and of integrated processes of order 0. It is well known that, for standard ARMA processes, the autocorrelation function decreases exponentially. Contrary to this process, Hosking (1981) shows that the autocorrelation function for fractionally integrated process decays 'slowly' at a hyperbolical rate:

$$\rho(\tau) \propto \tau^{2d-1} \text{as } \tau \to \infty \qquad (18)$$

The autocorrelation of such fractionally integrated processes remain significant at long lags.

5.4 Empirical Results

To test long memory, nonparametric and semi-parametric techniques were applied to return series, as well as to absolute and squared return series which are considered the most popular proxies for volatility in financial markets. The results of modified rescaled range test are reported in Table 5.1.

The return series show long memory in case of CNY, EGP, HUF, PEN, RUB, and TRY. The absolute return series is more persistent than the squared return series. In absolute return series 21 currencies, except MXN, RUB, TWD, and TRY, show long-range dependence. However, the squared returns of 10 currencies, i.e., CNY, CLP, COP, CZK, HUF, MAD, PEN, PLN, THB, and ZAR, show long-range dependence.

Table 5.2 presents the estimates of *d* proposed by Geweke and Porter-Hudak (1983) for $T^{0.5}$, $T^{0.55}$ and $T^{0.6}$. The GPH tests indicate long memory in weekly return series of CNY, IDR, EGP, HUF, RUB and ARS. The absolute return series of BRL, IDR, CLP, COP, MAD, CZK, EGP, MXN, PEN, TWD,KRW, TRY, PKR, PHP, ZAR, LKR, INR and ARS show long-range dependence. The squared returns of IDR, MYR, CLP, COP, PEN, MXN, CZK, PLN, PKR, TWD, PHP, THB, ZAR, INR and ARS show long-range dependence.

The estimates of *d* obtained by Robinson (1995) method for $T^{0.7}$, $T^{0.8}$ and $T^{0.9}$ are presented in Table 5.3. The results show that weekly returns on BRL, CNY, IDR, LKR, MYR, COP, EGP, MXN, PEN, KRW, THB, INR, VND, RUB and ARS show long-range dependence. However the absolute return series of all currencies show long-range dependence. Similarly, squared return series of all currencies, except CNY, EGP and VND, show long memory.

It can be seen that the absolute return series appear to be more persistent than the squared return series in all the tests conducted. This property is known as 'Taylor property' (Taylor, 1986), which implies that the time series dependencies on financial volatility as measured by the autocorrelation function of returns are stronger for absolute returns than for the squared returns.

Since there is no consistency in all the three tests conducted, *d* is estimated using ARFIMA(*p*, *d*, *q*). For choosing the right order of ARFIMA models, different specifications of the ARFIMA(*p*, *d*, *q*) with p, q = 0:2 were estimated for each return series. The Bayesian Information Criterion is used to choose the model that best describes the data. The selected orders and the estimation results are reported in Table 5.4. For CNY, IDR, PHP, THB, EGP, TRY, COP, CLP, PEN, MXN, RUB and INR, $0 < d < 0.5$, suggests long-range dependence in return of these currencies at 5% significance level. However, for PKR, VND, MAD, ARS, HUF and ZAR, $-0.5 < d < 0$, implies anti-persistence in these currencies, although the results are insignificant.

5.5 Concluding Remarks

The chapter examined long-range dependence in return, absolute return and squared return of foreign exchange rates of 25 emerging economies. The study employed three tests, namely, Lo's modified rescaled range test, Geweke and Porter-Hudak (1983) test, and Gaussian semi-parametric test of Robinson (1995) on weekly return, absolute return and squared return of foreign exchange rates of 25 emerging economies. The test also employed ARFIMA model to estimate the fractional difference parameter *d* of long memory. The results of the study support Taylor's property which implies that the time series dependencies on financial volatility as measured by the autocorrelation function of returns are stronger for absolute returns than for the squared returns. The results suggest by and large long memory in CNY, EGP, HUF, PEN, RUB, IDR, and MXN and hence are not characterized by random walk process. This implies that these currencies do not show weak form of efficiency. Results also show that return series of six currencies, viz., CZK, MAD, PLN, TWD, PKR and ZAR reject long memory. Returns of other currencies show mixed results.

Table 5.1: Rescale Range Test Statistics

		Return (R)	Absolute Return $\lvert R \rvert$	Squared Return (R^2)
Asia	CNY	3.0415[a]	3.793[a]	2.1483[a]
	IDR	1.4529	2.7263[a]	1.7194
	MYR	1.5388	2.3544[a]	1.8008
	TWD	1.2366	1.7961	1.5306
	PKR	1.7206	2.0946[b]	1.7887
	PHP	1.5334	1.9164[b]	1.7877
	KRW	1.3097	2.4058[a]	1.144
	THB	1.6054	2.7604[a]	2.1183[a]
	LKR	1.6802	2.0581[a]	1.3735
	INR	1.5026	2.7168[a]	1.7237
	VND	1.7072	2.134[a]	1.5908
MENA	EGP	1.9806[b]	2.1788[a]	1.2651
	TRY	2.5515[a]	1.3305	0.919
	MAD	1.2055	2.1233[a]	1.9671[b]
Latin America	BRL	1.6406	2.5648[a]	1.2388
	CLP	1.4121	3.2736[a]	2.6042[a]
	COP	1.8021	2.7083[a]	2.5628[a]
	PEN	2.3121[a]	2.5869[a]	2.2875[a]
	ARS	1.6588	2.362[a]	1.4772
	MXN	1.2985	1.5043	1.2856
CEE/CIS	CZK	1.557	2.2319[a]	2.0196[b]
	HUF	1.9615[b]	2.8347[a]	2.4983[a]
	PLN	1.8567	2.666[a]	2.1825[a]
	RUB	1.9342[b]	1.4684	1.1538
Africa	ZAR	1.3719	4.0364[a]	2.7661[a]

Note: [a] and [b] indicate 1% and 5% significance levels, respectively.

Table 5.2: Geweke and Porter-Hudak (1983) Test Estimator

	Currency	Return			Absolute Return			Squared Return		
		α=0.5	α=0.55	α=0.6	α=0.5	α=0.55	α=0.6	α=0.5	α=0.55	α=0.6
Asia	CNY	0.60023 (4.2145)	0.5854 (5.2431)	0.4491[a] (4.7217)	0.8275 (5.784)	0.6593 (5.6855)	0.6036 (6.3748)	0.1633 (1.1414)	0.1168 (1.0068)	0.0927 (0.9787)
	IDR	0.2463[a] (2.8983)	0.0904 (1.1946)	0.0199 (0.3352)	0.618 (4.5018)	0.5581 (5.0198)	0.4097[a] (4.4974)	0.2681 (1.9525)	0.2592[b] (2.331)	0.2212[b] (2.4276)
	MYR	0.1691 (1.2798)	0.1463 (1.3678)	0.1302 (1.4942)	0.7961 (6.1086)	0.7213 (6.746)	0.5218 (5.9887)	0.3999[a] (3.027)	0.3843[a] (3.5939)	0.3398[a] (3.8997)
	TWD	0.0400 (0.3026)	0.0679 (0.6354)	0.1359 (1.5599)	0.2066 (1.5641)	0.3281[a] (3.0684)	0.3376[a] (3.8744)	0.114 (0.8631)	0.3069[a] (2.8707)	0.4171[a] (4.7867)
	PKR	-0.0188 (-0.1420)	0.0695 (0.6584)	0.1126 (1.3034)	0.4274[a] (3.2353)	0.3885[a] (3.679)	0.4415[a] (5.1103)	0.2024 (1.5322)	0.2453[b] (2.3222)	0.303[a] (3.5072)
	PHP	0.2357 (1.7166)	0.185 (1.6635)	0.0992 (1.0883)	0.5754 (4.1908)	0.53[a] (5.0631)	0.519 (5.6964)	0.5071 (3.6933)	0.3654[a] (3.2863)	0.3481[a] (3.8203)
	KRW	-0.2750 (-2.0815)	-0.158 (-1.4962)	-0.1493 (-1.7277)	0.0873 (0.6606)	0.2582 (2.4452)	0.3558[a] (4.1185)	-0.0766 (-0.5797)	-0.0001 (-0.0006)	0.0737 (0.8527)
	THB	0.0671 (0.5352)	0.058 (0.5754)	0.0076 (0.0933)	0.7582 (6.011)	0.5672 (5.6288)	0.6352 (7.7747)	0.4872[a] (3.8882)	0.3467[a] (3.4406)	0.4961[a] (6.072)
	LKR	0.0621 (0.4873)	0.0242 (0.235)	0.0316 (0.3777)	0.2853[b] (2.2382)	0.2421[a] (2.3478)	0.2154[a] (2.5764)	0.0247 (0.1934)	0.0063 (0.0611)	0.0385 (0.46)
	INR	0.0907 (0.6736)	0.121 (1.1027)	-0.0049 (-0.055)	0.5592 (4.1531)	0.3825[a] (3.486)	0.4299[a] (4.8063)	0.2949[b] (2.1904)	0.1852 (1.6877)	0.2521[a] (2.8179)
	VND	0.2401 (1.6781)	0.1521 (1.3115)	0.1725 (1.8218)	0.2021 (1.4125)	0.1756 (1.5146)	0.1425 (1.505)	0.1999 (1.397)	0.1135 (0.9788)	0.0927 (0.9788)
MENA	EGP	0.4221[a] (2.9504)	0.2496[b] (2.1831)	0.3312[a] (3.5329)	0.4036[a] (2.8211)	0.4292[a] (3.7544)	0.2726[a] (2.9071)	0.0714 (0.4993)	0.066 (0.5772)	0.0362 (0.3859)
	TRY	0.0751 (0.5248)	0.0923 (0.7959)	0.0651 (0.6872)	0.1778 (1.2428)	0.1085 (0.9353)	0.1964[b] (2.0737)	0.0082 (0.0571)	0.0211 (0.1823)	0.0886 (0.9353)
	MAD	-0.1230 (-0.9306)	-0.0497 (-0.4645)	-0.0565 (-0.654)	0.219 (1.6574)	0.2736[b] (2.5586)	0.1984[b] (2.2959)	0.1043 (0.7892)	0.1495 (1.3984)	0.1294 (1.4977)

	Currency	Return			Absolute Return			Squared Return		
		α=0.5	α=0.55	α=0.6	α=0.5	α=0.55	α=0.6	α=0.5	α=0.55	α=0.6
Latin America	BRL	0.0204 (0.1425)	-0.0114 (-0.097)	-0.0204 (-0.2134)	0.4556 [a] (3.1845)	0.4426[a] (3.761)	0.4602[a] (4.8114)	0.0109 (0.0761)	0.0561 (0.4766)	0.1252 (1.3091)
	CLP	0.1364 (0.9934)	0.1132 (1.0182)	0.1287 (1.4252)	0.6403 (4.6642)	0.5135 (4.6186)	0.4736 [a] (5.246)	0.5445 (3.9663)	0.4175 [a] (3.7549)	0.3825[a] (4.2367)
	COP	0.1090 (0.7778)	0.0681 (0.6038)	0.0403 (0.4387)	0.4247 [a] (3.051)	0.4613[a] (4.0923)	0.4614 [a] (5.0172)	0.36 [b] (2.57)	0.4523 [a] (4.0123)	0.4391[a] (4.7739)
	PEN	0.1522 (1.0862)	0.111 (0.9848)	0.0711 (0.7731)	0.4879 [a] (3.4825)	0.4686 [a] (4.1574)	0.4626 [a] (5.03)	0.4279 [a] (3.0547)	0.494 [a] (4.3828)	0.4315[a] (4.6919)
	ARS	0.2022 (1.4732)	0.3845 [a] (3.4584)	0.4608 [a] (5.0575)	0.4662 [a] (3.3954)	0.5596 (5.0333)	0.5879 (6.4526)	0.1734 (1.2629)	0.2314 [a] (2.0813)	0.3089[a] (3.3846)
	MXN	0.0345 (0.2516)	0.1269 (1.1412)	0.1546 (1.6969)	0.0757 (0.5521)	0.251[b] (2.2575)	0.4145 [a] (4.5492)	0.0936 (0.6816)	0.155 (1.3936)	0.2139[b] (2.3473)
CEE/CIS	CZK	0.0719 (0.5131)	0.1182 (1.0341)	0.1472 (1.5695)	0.5327 (3.8021)	0.5383 (4.7093)	0.4984 [a] (5.3156)	0.5089 (3.6321)	0.615 (5.3797	0.5159[a] (5.5028)
	HUF	0.2967 [a] (2.1177)	0.1742 (1.5239)	0.1165 (1.2428)	0.6704 (6.4555)	0.6150 (6.1063)	0.5232 (5.5805)	0.6344 (4.528)	0.5762 (5.0407)	0.4613 (4.9199)
	PLN	0.2381 (1.6995)	0.1898 (1.6607)	0.092 (0.9817)	0.8351 (5.961)	0.5735 (5.0168)	0.5065 (5.4022)	0.6853 (4.8916)	0.5743 (5.0242)	0.4289[a] (4.5741)
	RUB	0.2415 (1.7234)	0.2607 [b] (2.281)	0.1657 (1.7676)	0.1929 (1.3771)	0.2071 (1.8117)	0.1755 (1.8723)	0.0349 (0.2489)	0.0485 (0.4242)	0.0621 (0.6626)
Africa	ZAR	-0.0017 (-0.0138)	-0.0315 (-0.3201)	0.0919 (1.15)	0.4961 [a] (4.0905)	0.4439 [a] (4.5035)	0.3212 [a] (4.0201)	0.451 [a] (3.7183)	0.367 [a] (3.7231)	0.2297[a] (2.8748)

Note: [a] and [b] indicate 1% and 5% significance levels, respectively. Figures in parentheses are *t*-statistics.

Table 5.3: Robinson (1995b) Estimator

	Currency	Return			Absolute Return			Squared Return		
		α=0.7	α=0.8	α=0.9	α=0.7	α=0.8	α=0.9	α=0.7	α=0.8	α=0.9
Asia	CNY	0.2033[a]	0.1306[a]	0.1190[a]	0.3233[a]	0.2542[a]	0.2184[a]	0.0647	0.3127	0.1419
		(0.0030)	(0.0030)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1900)	(0.2950)	(0.4180)
	IDR	0.2350[a]	0.1014[a]	0.0151	0.7064	0.5031	0.3235[a]	0.5199	0.5950	0.2587[a]
		(0.0000)	(0.0150)	(0.5800)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	MYR	0.2612[a]	0.1182[a]	0.0788[a]	0.5402	0.2687[a]	0.2143[a]	0.4681[a]	0.1468[a]	0.1654[a]
		(0.0000)	(0.0090)	(0.0070)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	TWD	0.0848	0.0987	0.0650	0.2729[a]	0.2212[a]	0.1955[a]	0.2940[a]	0.2064[a]	0.1145[a]
		(0.1840)	(0.0170)	(0.0140)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	PKR	0.0741	-0.0237	-0.0139	0.3773[a]	0.1776[a]	0.1275[a]	0.3982[a]	0.1038[a]	0.6580
		(0.1900)	(0.5210)	(0.5930)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0040)	(0.0100)
	PHP	0.1213	0.0769	-0.0473	0.3916[a]	0.2542[a]	0.1862[a]	0.2539[a]	0.1948[a]	0.1437[a]
		(0.0640)	(0.0840)	(0.1060)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	KRW	0.1136[b]	0.1847[a]	0.0160	0.4322[a]	0.4601[a]	0.3166[a]	0.1485[a]	0.4240[a]	0.1998[a]
		(0.0330)	(0.0000)	(0.5420)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	THB	0.1606[a]	0.1639[a]	0.0665[a]	0.6400	0.4307[a]	0.2789[a]	0.5916	0.2612[a]	0.2090[a]
		(0.0010)	(0.0000)	(0.0060)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	LKR	0.1276[a]	0.1036[a]	0.0401	0.2921[a]	0.2400[a]	0.2465[a]	0.1597[a]	0.1285[a]	0.1748[a]
		(0.0120)	(0.0060)	(0.1260)	(0.0000)	(0.0000)	(0.0000)	(0.0030)	(0.0000)	(0.0000)
	INR	0.1305[a]	0.1496[a]	0.1537[a]	0.2475[a]	0.2105[a]	0.2480[a]	0.0494	0.9744	0.2947[a]
		(0.0070)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1520)	(0.0000)	(0.0000)
	VND	-0.0022	0.0152	0.0913[a]	0.0896	0.1607[a]	0.2180[a]	-0.0184	0.2255	0.2913
		(0.9720)	(0.7240)	(0.0020)	(0.1150)	(0.0000)	(0.0000)	(0.7730)	(0.5780)	(0.2170)
MENA	EGP	0.1576[a]	0.0767	0.0644[b]	0.1944[a]	0.0882[a]	0.1139[a]	0.1885	0.1467	0.1759
		(0.0090)	(0.0540)	(0.0250)	(0.0040)	(0.0270)	(0.0000)	(0.3430)	(0.2810)	(0.0650)
	TRY	0.1152	0.0450	-0.0326	0.3544[a]	0.3536[a]	0.2094[a]	0.1610[a]	0.2243[a]	0.1007[a]
		(0.1020)	(0.3370)	(0.3280)	(0.0000)	(0.0000)	(0.0000)	(0.0050)	(0.0000)	(0.0010)
	MAD	0.0508	0.0789	-0.0205	0.2391[a]	0.2559[a]	0.1540[a]	0.2473[a]	0.3281[a]	0.2174[a]
		(0.3650)	(0.0610)	(0.4740)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

	Currency	Return			Absolute Return			Squared Return		
		α=0.7	α=0.8	α=0.9	α=0.7	α=0.8	α=0.9	α=0.7	α=0.8	α=0.9
Latin America	BRL	0.0991	0.1348[a]	0.0519	0.3930[a]	0.3099[a]	0.3019[a]	0.0900	0.1527[a]	0.2064[a]
		(0.0970)	(0.0030)	(0.1250)	(0.0000)	(0.0000)	(0.0000)	(0.1210)	(0.0010)	(0.0000)
	CLP	0.0801	0.0733	0.1442	0.3356[a]	0.2639[a]	0.1735[a]	0.4062[a]	0.3183[a]	0.2036[a]
		(0.418)	(0.344)	(0.080)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	COP	0.1210	0.1230[a]	0.0397	0.3825[a]	0.3119[a]	0.2601[a]	0.2845[a]	0.2717[a]	0.2537[a]
		(0.1100)	(0.0100)	(0.2240)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	PEN	0.2496[a]	0.1439[a]	0.1174[a]	0.4296[a]	0.3137[a]	0.2534[a]	0.2960[a]	0.2237[a]	0.2711[a]
		(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	ARS	0.5271	0.218[a]	0.0162	0.8837	0.2817[a]	0.1179[a]	0.6809	0.2006[a]	0.6971
		(0.0000)	(0.0000)	(0.5770)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0230)
	MXN	0.0353	0.1038[a]	0.0523[a]	0.3950[a]	0.3996[a]	0.2840[a]	0.1762[a]	0.1955[a]	0.1653[a]
		(0.4840)	(0.0050)	(0.0510)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CEE/CIS	CZK	0.0935	0.0733	0.0241	0.4023[a]	0.2977[a]	0.1192[a]	0.4429[a]	0.3418[a]	0.1553[a]
		(0.1590)	(0.1150)	(0.4690)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	HUF	0.0666	0.0526	-0.0055	0.3731[a]	0.2814[a]	0.1512[a]	0.4343[a]	0.3966[a]	0.1978[a]
		(0.2450)	(0.2020)	(0.8550)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	PLN	0.0967	0.0761	-0.0429	0.4249[a]	0.3184[a]	0.1867[a]	0.4102[a]	0.3641[a]	0.1844[a]
		(0.1600)	(0.0830)	(0.1540)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	RUB	0.1009	0.0815[b]	-0.1735	0.2548[a]	0.5580	0.3872[a]	0.1979[a]	0.6254	0.2528[a]
		(0.0720)	(0.0230)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Africa	ZAR	0.0012	0.0348	-0.0216	0.3159[a]	0.3087[a]	0.2080[a]	0.1932[a]	0.2621[a]	0.1619[a]
		(0.9820)	(0.3340)	(0.3940)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: [a] and [b] indicate 1% and 5% significance levels, respectively. Figures in parentheses are *p*-values of test statistics.

Table 5.4: Estimates of ARFIMA Model

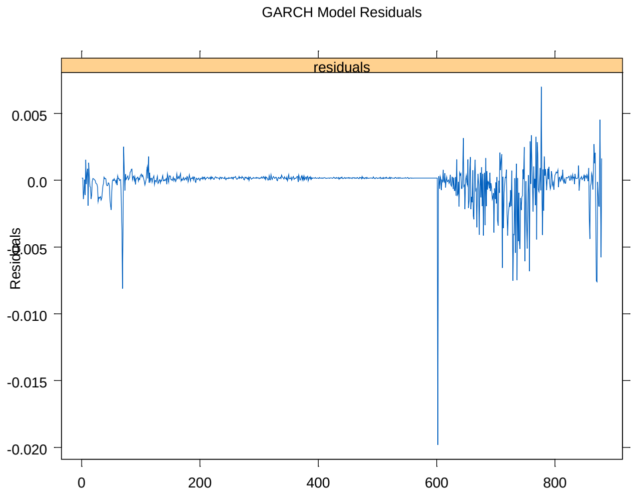
	Currency	*d*	AR(1)	AR(2)	MA(1)	MA(2)	Log Likelihood	BIC	LB(20)	$LB^2(20)$	ARCH(5)
Asia	CNY ARFIMA (0,*d*,0)	0.1546[a] (0.0000)					-526.6113	1046.447	31.0675 (0.0543)	6.1841 (0.9986)	2.2178 (0.8183)
	IDR ARFIMA (0, *d*,0)	0.0162[a] (0.0000)					-2694.214	5395.326	64.3737 (0.0000)	877.8979 (0.0000)	403.8025 (0.0000)
	MYR ARFIMA(2,*d*,2)	0.0173 (0.6317)	-0.2834 (0.0000)	-0.9381 (0.0000)	-0.2087 (0.0000)	-0.9757 (0.0000)	-1773.015	3581.158	86.6625 (0.0000)	348.1725 (0.00000	150.3462 (0.0000)
	TWD ARFIMA (0,*d*,1)	0.0702 (0.0726)			-0.0492 (0.3235)		-1067.069	2148.189	40.8150 (0.0039)	292.4264 (0.0000)	127.0485 (0.00000
	PKR ARFIMA (0,*d*,0)	-0.0114 (0.62)					-1546.178	3099.392	73.8495 (0.0000)	132.8113 (0.0000)	34.463 (0.0000)
	PHP ARFIAM (0,*d*,1)	0.1273[a] (0.0002)			0.2326 (0.0000)		-1708.393	3430.561	29.3506 (0.0811)	188.8627 (0.0000)	74.4651 (0.0000)
	KRW ARFIMA (0,*d*,2)	0.0805 (0.1717)			0.1679 (0.0134)	-0.2349 (0.0000)	-2237.347	4496.671	60.3669 (0.0000)	283.4893 (0.0000)	145.801 (0.0000)
	THB ARFIMA (1,d,0)	0.1603 [a] (0.0000)	-0.1782 (0.0000)				-2147.347	4309.099	133.5269 (0.0000)	836.4266 (0.0000)	295.9484 (0.0000)
	LKR ARFIMA (0,*d*,0)	0.0773 (0.3373)	-0.7657 (0.0000)		-0.6515 (0.0000)		-1044.174	2109.761	49.7099 (0.0002)	92.0091 (0.0000)	74.6192 (0.000)
	INR ARFIMA (0,*d*,0)	0.1214[a] (0.0000)					-1375.662	2758.264	37.5083 (0.01020	164.2391 (0.0000)	173.0438 (0.0000)
	VND ARFIMA (0,*d*,2)	-0.0177 (0.7605)			0.1177 (0.0857)	-0.1028 (0.0344)	-558.4698	1137.3132	30.2275 (0.0663)	18.6034 (0.0000)	13.3953 (0.0199)
MENA	EGP ARFIMA (0,*d*,0)	0.0689[a] (0.0086)					-978.2195	1963.237	24.6021 (0.2171)	1.4325 (0.0000)	0.0876 (0.9994)
	TRY ARFIMA (1,*d*,2)	0.2302 [a] (0.0000)	-0.697 (0.0000)		-0.3695 (0.0000)	0.3265 (0.0000)	-2179.798	4386.669	31.2231 (0.0523)	132.1013 (0.0000)	52.772 (0.0000)

	Currency	***d***	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**	**Log Likelihood**	**BIC**	**LB(20)**	**$LB^2(20)$**	**ARCH(5)**
	MAD ARFIMA (0,*d*,0)	-0.0341 (0.1435)					-1840.728	3688.489	15.6827 (0.7361)	162.6076 (0.0000)	75.0469 (0.0000)
Latin America	BRL ARFIMA(0,*d*,0)	0.0369 (0.1696)					-1932.283	3871.313	31.5257 (0.0486)	135.0842 (0.0000)	74.1115 (0.0000)
	CLP ARFIMA (0,*d*,0)	0.0618[b] (0.0129)					-1660.738	3335.182	35.8917 (0.0158)	625.4978 (0.00000	153.9580 (0.0000)
	COP ARFIMA(0,*d*,1)	0.1747[a] (0.0000)			0.1678 (0.003)		-1755.09	3516.981	28.5701 (0.0966)	539.9661 (0.0000)	152.000 (0.0000)
	PEN ARFIMA (2,*d*,2)	0.1934[b] (0.0432)	0.2761 (0.0000)	-0.8764 (0.0000)	0.3667 (0.0000)	-0.7935 (0.0000)	-1041.477	2117.225	86.3095 (0.0000)	479.5012 (0.0000)	103.9149 (0.0000)
	ARS ARFIMA (2,*d*,2)	-0.2155 (0.3694)	1.3228 (0.1101)	-0.3615 (0.6365)	1.3864 (0.0645)	-0.5926 (0.6422)	-1993.853	4022.144	117.7569 (0.0000)	334.5627 (0.0000)	282.2894 (0.0000)
	MXN ARFIMA (2,*d*,2)	0.094[a] (0.0098)	-1.164 (0.000)	-0.7114 (0.0000)	-1.0333 (0.000)	-0.7222 (0.0000)	-2025.165	4084.768	35.3362 (0.0184)	66.7086 (0.0000)	38.1864 (0.0000)
CEE/CIS	CZK ARFIMA (0,*d*,0)	0.0181 (0.4882)					-1755.09	3516.981	36.9154 (0.0120)	559.8836 (0.0000)	147.8137 (0.0000)
	HUF ARFIMA(0,*d*,0)	-0.0151 (0.56)					-1842.188	3691.176	39.8157 (0.0053)	846.0848 (0.0000)	181.0665 (0.0000)
	PLN ARFIMA (0,*d*,1)	0.1231 (0.70)		0.2080 (0.000)			-1840.049	3693.714	24.7802 (0.2100)	623.509 (00000)	151.2251 (0.0000)
	RUB ARFIMA (1,*d*,1)	0.1763[a] (0.0007)	-0.7329 (0.0000)		-0.2051 (0.0051)		-2476.304	4973.022	43.7640 (0.0016)	118.3903 (0.0000)	97.8061 (0.0000)
Africa	ZAR ARFIMA (0,*d*,0)	-0.0078 (0.7052)					-3239.0743	6486.765	28.0184 (0.1090)	365.8526 (0.0000)	152.026 (0.0000)

Note: [a] and [b] indicate 1% and 5% significance levels, respectively. Figures in parentheses are *p*-values of test statistics.

Figure 5.1: Plot of Volatility of Weekly Return Series

CNY



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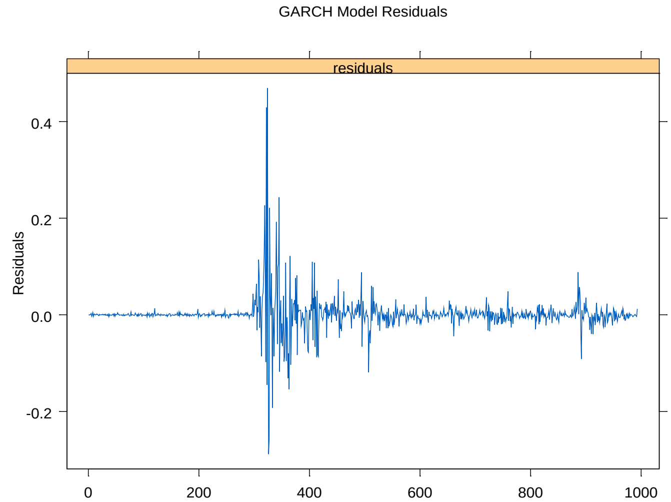

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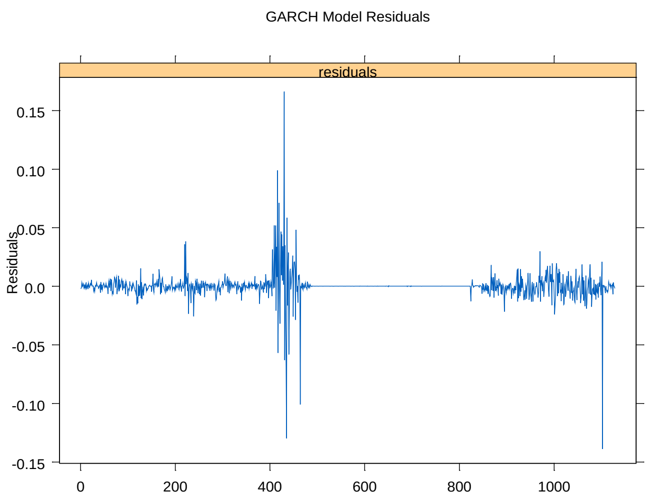

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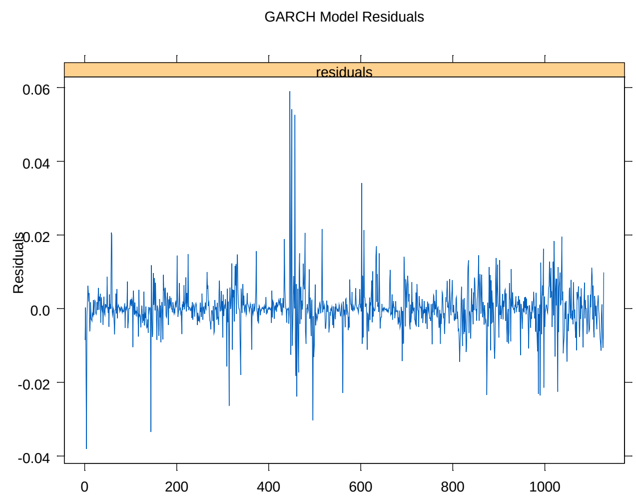

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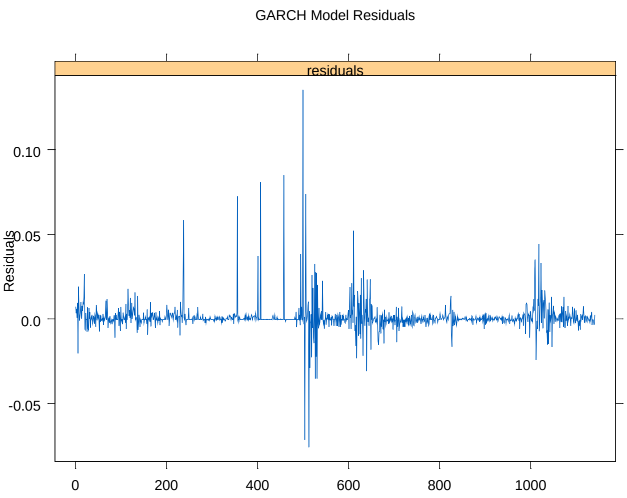

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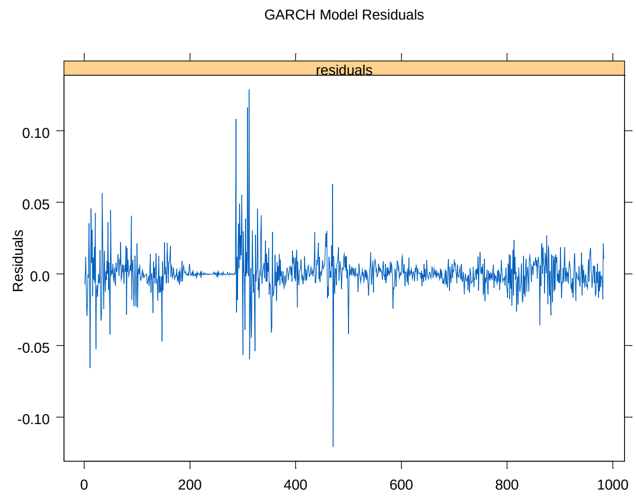

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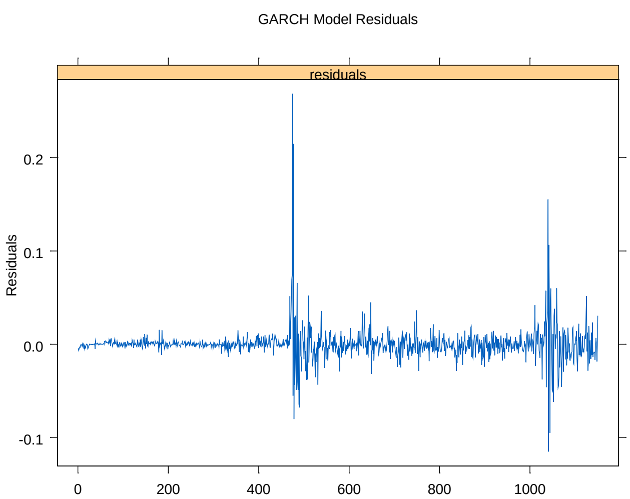

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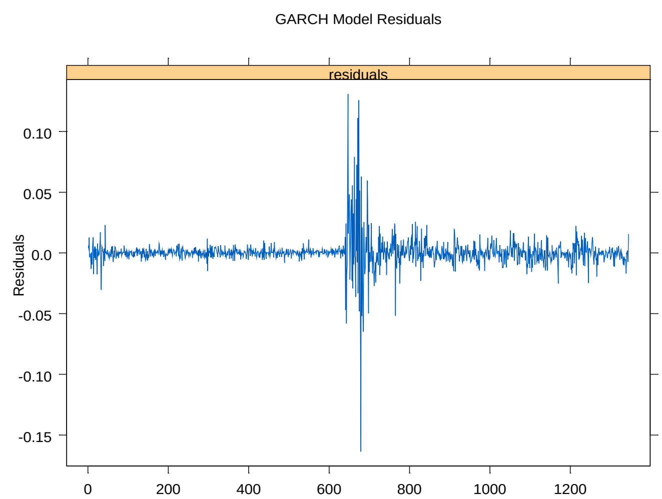

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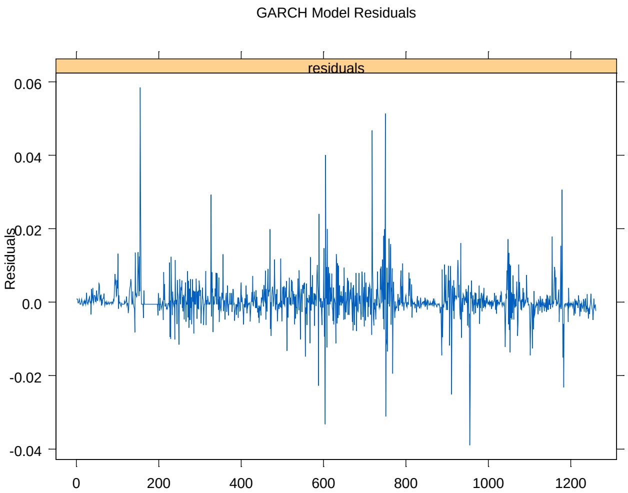
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1000
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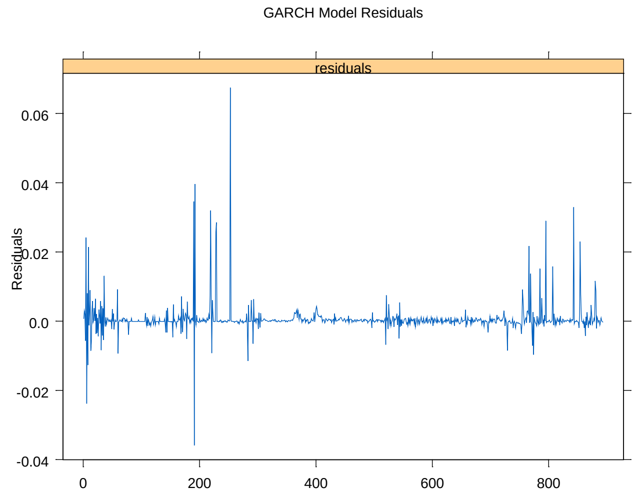
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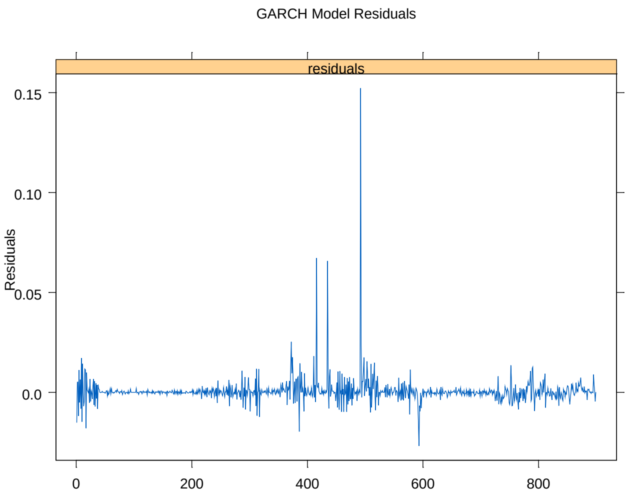
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Residuals
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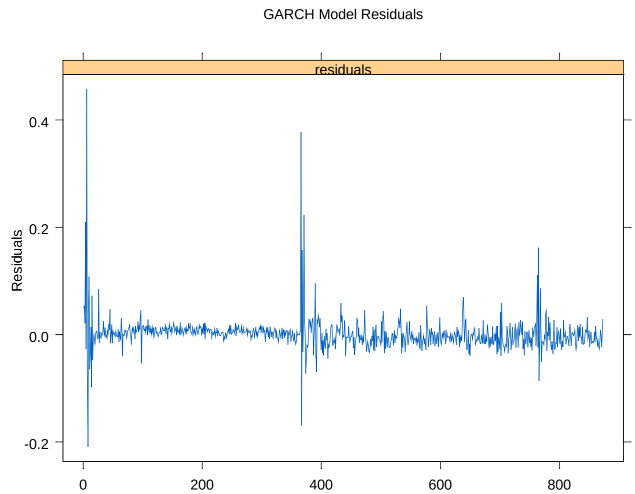
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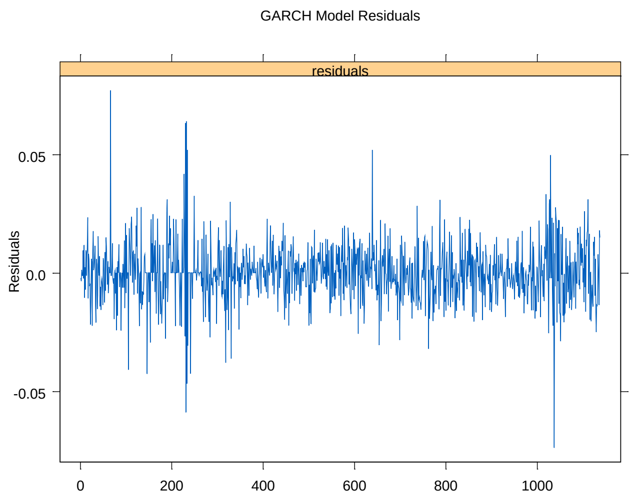

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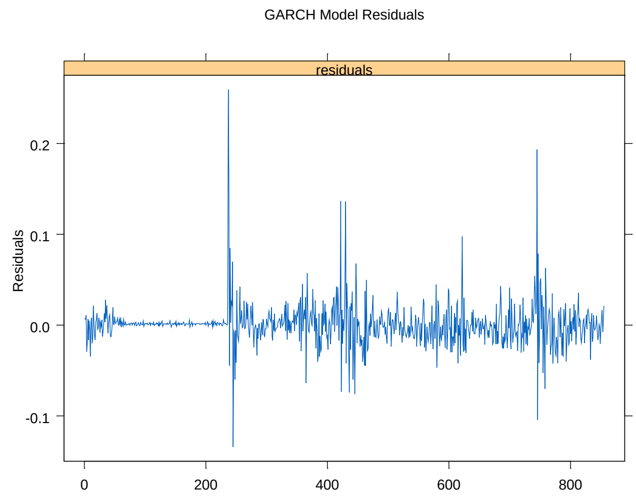

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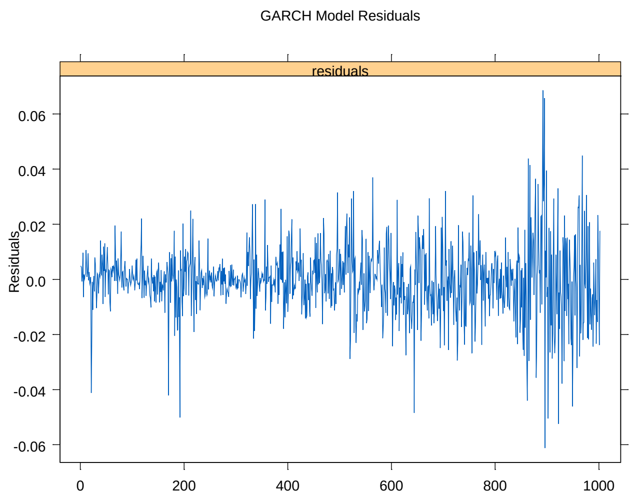

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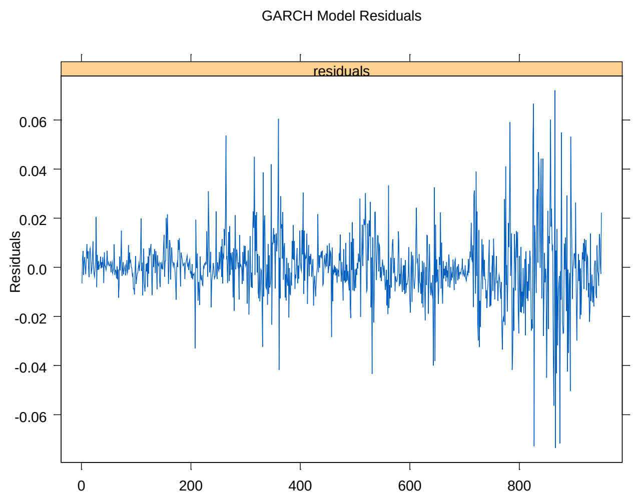

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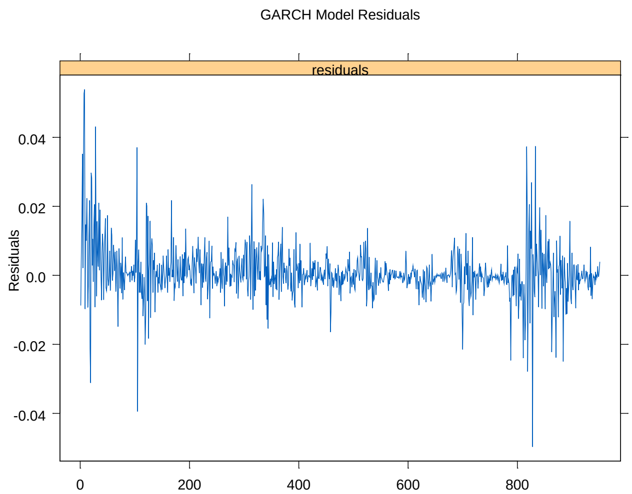

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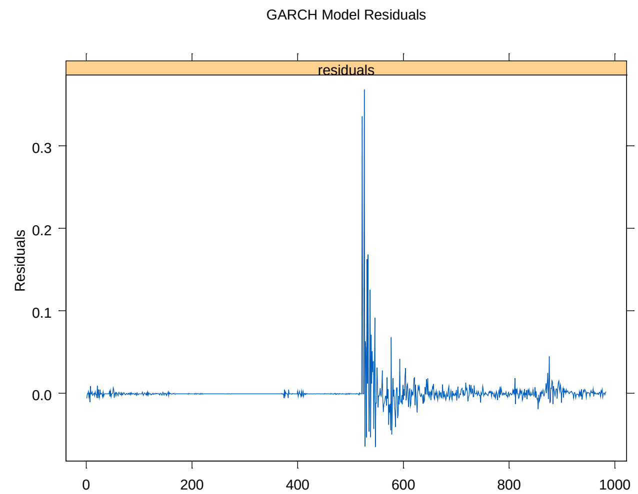

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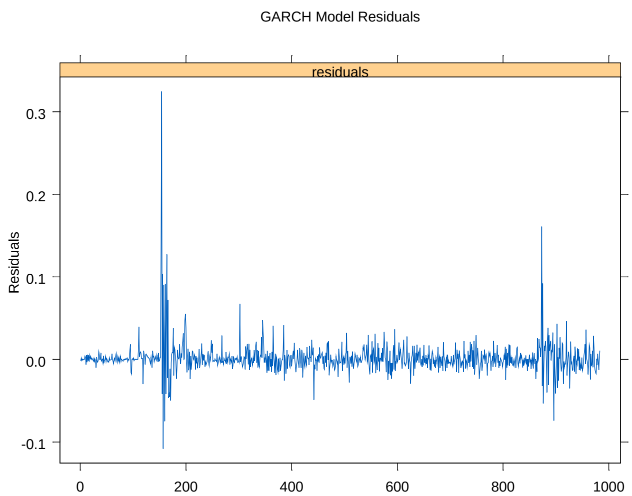

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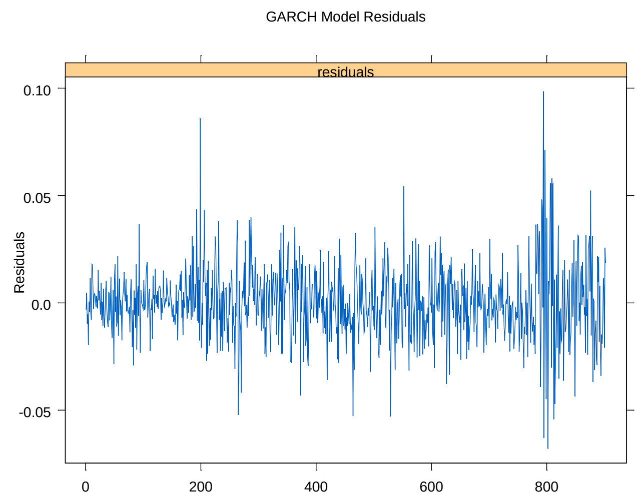

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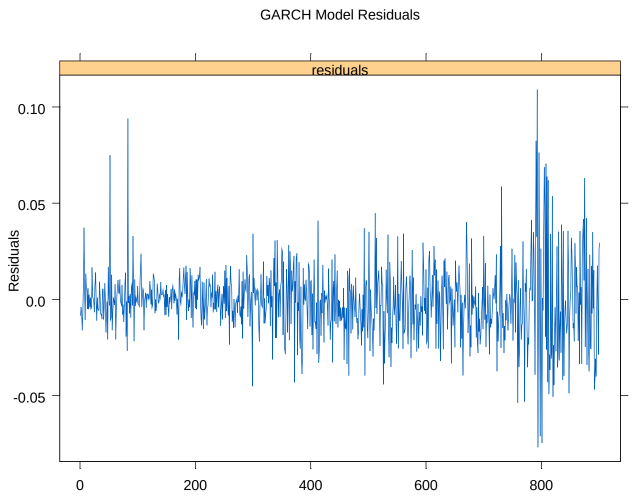

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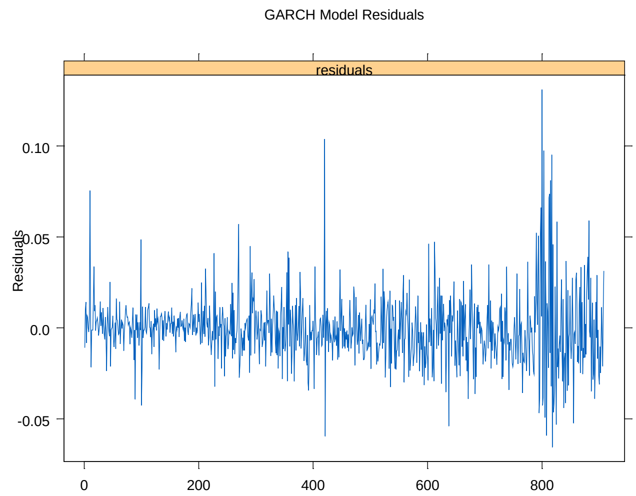

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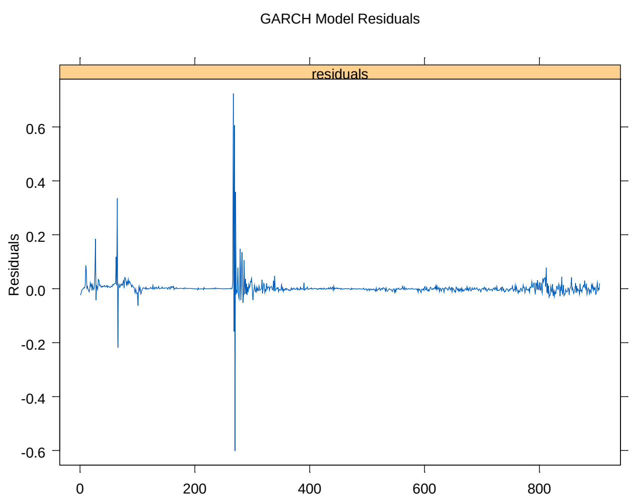

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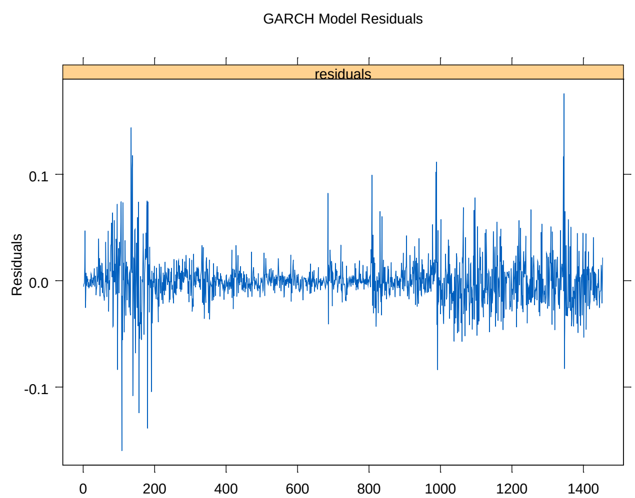

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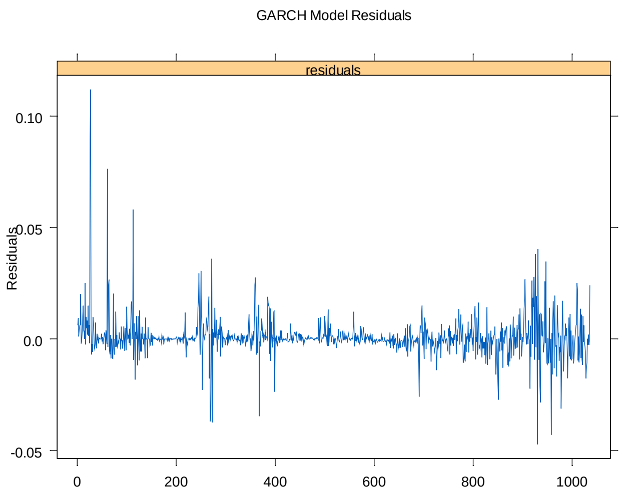
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-0.05
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400
600
800
1000

CHAPTER 6

SOME EVIDENCE OF LONG MEMORY IN VOLATILITY AND DUAL MEMORY

6.1 Introduction

The preceding chapter discussed long memory in returns of emerging market economies. It is well known that volatility of financial assets returns often exhibits long memory property when the autocorrelation in the series is characterized by very slow decay. Such a feature is crucial as its presence is connected to the predictability of volatility in foreign exchange market. Volatility is an indicator of vulnerability of financial markets and the economy. Modeling long memory in volatility has gained importance in recent years due to practical implications. Log squared, squared returns and absolute returns are used as proxies of returns volatility in empirical studies. The autocorrelation of these returns appears to decay at a slower rate. Standard generalized autoregressive conditional heteroscedastic models do not account for long memory in volatility. Therefore, using such models would give misleading inferences regarding the presence of long memory in variance. Volatility is an important input in derivative pricing portfolio risk management strategies and is also vital in business cycles.

The literature on long memory in returns and long memory in volatility evolved independently, as the phenomena seemed different and distinct. However, market shocks have a simultaneous impact on the conditional mean and conditional variance. Therefore, some recent empirical studies have focused on the relationship between conditional mean and conditional variance. Beine *et al*. (2002) suggested that a dual long memory feature represents the dynamics of foreign exchange rate returns. Nagayasu (2003) examined the efficiency of the Japanese equity market using the dual long memory model.

In light of the above, the present chapter aims to probe long memory in volatility and dual long memory, i.e., simultaneous effect of shock on conditional mean and conditional variance in foreign exchange markets of emerging economies.

6.2 Review of Literature

Most financial time series show long memory process in volatility. The fractionally integrated models are widely used and quite popular in financial time series analysis. Granger (1980) proved that in long memory process the autocorrelation of unknown shocks decays slowly contrary to the short memory in which memory decays exponentially faster. As the persistence of shocks depends on several sources, it reflects in volatility which indicates a long memory property. According to Ding *et al*. (1993), the volatility tends to change quite slowly at times, and the effects of unknown shocks can take a considerable time to decay. Consequently, it is necessary to have a model that allows for intermediate degrees of volatility persistence. As we saw in the last chapter, Granger and Joyeux (1980) and Hosking (1981) proposed the Autoregressive Fractionally Integrated Moving Average (ARFIMA) specification which accounts for long persistence in conditional mean of a series. This model captures the short-run behavior of the time series through the Autoregressive Moving Average (ARMA) parameters. Thus, the fractional differencing parameter $(1 - L)^d$ is added to model the long-run dependence in the ARFIMA model. A characteristic of this long memory process is that the autocorrelation function has a hyperbolically decaying shape. In other words, the autocorrelation of shocks decays slowly to zero. Baillie *et al*. (1996) introduced the Fractionally Integrated Autoregressive Conditional Heteroscedasticity (FIGARCH) model which relates to financial volatility dynamics and allows for long memory in conditional variance. Further, Ling and Li (1997a) extended the ARFIMA process to an autoregressive fractionally integrated moving average with GARCH model (ARFIMA-GARCH), which has a fractionally integrated conditional mean with the GARCH to describe time-dependent heteroscedasticity. An evidence of long-range dependence in financial asset volatility introduced by Robinson and Hidalgo (1997) can be modeled by long memory.

Bollerslev and Mikkelsen (1999) confirmed the assumption that long memory models yield the most accurate empirical out-of-sample volatility forecasts. In this regard, a number of studies have used long memory models for both daily returns of assets and the high-frequency ones. Some recent studies analyzing nominal exchange rate dynamics using fractional integration (looking at futures, in particular) include Fang *et al*. (1994), Crato and Ray (2000), and Wang (2004). Volatility dynamics in foreign exchange rates (mainly the Deutsche mark vis-à-vis the US dollar rate) have also been examined with the FIGARCH model, introduced by Baillie *et al*. (1996), and subsequent papers that have used this approach are Andersen and Bollerslev (1997 and 1998), Tse (1998 – examining the Japanese Yen-US dollar rate), Baillie *et al*. (2000), Kihc (2004), and Morana and Beltratti (2004 – analyzing volatility).

The idea of a dual long memory process was first introduced by Teyssiere (1997), who showed through Monte-Carlo simulations that ignoring long memory in the conditional mean of a dual long memory process leads to significant biases in the estimation of the conditional volatility process. Consequently, in order to asses the robustness of the FIGARCH model the possibility of a fractional root in the conditional mean is introduced. He concluded that the ARFIMA-FIGARCH model captures more or less the dynamics of daily exchange rates, due to the fact that the fractional parameter in the mean equation was found to be quite low, confirming the presence of long memory only in conditional volatility. Other authors who investigated long memory using the technique proposed by Teyssiere (1997) are Beine *et al*. (1999), who also estimated

FIGARCH model for modeling daily exchange rates and concluded that allowing for a fractional root in the conditional mean appears to be pertinent, but does not lead to other parameter estimates compared to the volatility sides. Kang and Yoon (2007) investigated dual long memory in the returns and volatility of Korean stock market with a slightly different approach than that proposed by Teyssiere (1997). They first estimated the ARFIMA model for conditional mean, and based on the results obtained they further analyzed dual long memory applying the joint ARFIMA-FIGARCH model. They found evidence of long memory in both moments and concluded that the dual long memory model provides a better explanation for long memory dynamics in both conditional mean and variance. Similar results were obtained by Kasman *et al*. (2008) who investigated the presence of dual long memory in eight CEE emerging stock markets and found strong evidence of long memory in both conditional mean and variance, and inferred that the ARFIMA-FIGARCH model outperforms ARFIMA-GARCH and ARFIMA-HYGARCH models in terms of out-of-sample forecast. Finally, more recent and interesting studies are those by Baillie and Morana (2007 and 2009). Baillie and Morana (2007) proposed a new model for long memory in volatility, designed to account for both long memory features and structural change in the conditional variance process, though these approaches are not followed in the present study.

6.3 Methodology

6.3.1. FIGARCH

GARCH-class models provide viable alternatives for volatility modeling. Two components of GARCH models, i.e., by allowing a highly persistent long-run component and a short-run transitory component in volatility, can be used to capture the high persistence in volatility. Since the initiation of the GARCH model (Engle, 1982; and Bollerslev, 1986), several researchers observed that the parameters of the GARCH model sum up to very close to 1, indicating a high degree of volatility persistence to a shock. Following this, the Integrated GARCH (IGARCH) model was developed (Engle and Bollerslev, 1986), in which the parameters of the model are constrained to be equal to 1, such that the shocks impact future volatility indefinitely.

The idea, that the volatility shocks are persistent but not infinite, led Baillie *et al*. (1996) to apply the idea of fractional integration introduced by Granger (1980) and Hosking (1981) for the mean, to a GARCH framework.

The FIGARCH(p, d, q) model is given by:

$$\phi(L) = (1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]\nu_t \quad (1)$$

where $\nu_t = \varepsilon_t^2 - \sigma_t^2$

It is assumed that all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle.

If d = 0, the FIGARCH(p, d, q) becomes a classical GARCH(p, q) process, and if d = 1, the process becomes an IGARCH process.

Equation (1) can be rearranged as follows:

$$[1-\beta(L)]\sigma_t^2 = \omega + [1-\beta(L)-\phi(L)(1-L)^2]\varepsilon_t^2 \quad (2)$$

and subsequently the conditional variance of ε_t^2 is given by:

$$\sigma_t^2 = \frac{\omega}{[1-\beta(L)]} + \left[1 - \frac{\phi(L)}{[1-\beta(L)]}(1-L)^2\right]\varepsilon_t^2 \quad (3)$$

Equation (3) can be written as:

$$\sigma_t^2 = \frac{\omega}{[1-\beta(L)]} + \lambda(L)\varepsilon_t^2 \quad (4)$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 + \cdots$. Since the impact of a shock on the conditional variance of FIGARCH(*p*, *d*, *q*) decreases at a hyperbolic rate when $0 \leq d < 1$, Baillie *et al*. (1996) states that the long-term dynamics of the volatility are taken into account by the fractional integration parameter *d*, while the short-term dynamics are modeled through the traditional GARCH parameters.

Skewness and kurtosis are expected to be important in a number of financial market applications, including the pricing of financial assets. Since the ARCH processes capture time-varying conditional variances, they also capture time-varying conditional kurtosis. However, the Gaussian density is unable to capture the fat tails present in the unconditional distributions of financial market returns. The GARCH class of processes has therefore been combined with a number of distributions with tails fatter than the normal, for example, the Student's *t*-distribution (Bollerslev, 1987).

The parameters of volatility models can be estimated by using nonlinear optimization procedures to maximize the logarithm of the Gaussian likelihood function. Under the assumption that the random variable z_t ~ N(0, 1), the log-likelihood of Gaussian or normal distribution (L_{Norm}) can be expressed as:

$$L_{Norm} = -\frac{1}{2}\sum_{t=1}^{T}[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2] \qquad (5)$$

where *T* is the number of observations. However, it is widely observed that the distribution of residuals tends to show asymmetry and leptokurtosis. To capture excess kurtosis and skewness, the skewed Student's *t*-distribution is considered. If z_t ~ SkST(0, 1, *k*, *v*) the log-likelihood of the skewed Student's *t*-distribution (L_{SkST}) is as follows:

$$L_{SkSt} = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)] + \ln\left(\frac{2}{k+{}^{1}/_{k}}\right) + \ln(s)\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma^2) + 1(1+\nu)ln\left[1 + \frac{(sz_t+m)^2}{\nu-2}k^{-2I_t}\right]\right] \quad (6)$$

where $I_t = 1$, if $z_t \geq -{}^{m}/_{s}$ or $I_t = -1$ if $z_t < -{}^{m}/_{s}$, and k is the asymmetry parameter. The constants, $m = m\ (k, \nu)$ and $s = \sqrt{s^2(k,\nu)}$, the mean and standard deviation of the skewed Student's *t*-distribution are given as follows:

$$m(k,\nu) = \frac{\Gamma\left({}^{(\nu-1)}/_{2}\right)\sqrt{(\nu-2)}}{\sqrt{\pi}\,\Gamma\left({}^{\nu}/_{2}\right)} \quad (7)$$

$$s^2(k,\nu) = \left(k^2 + \frac{1}{k^2} - 1\right) - m^2 \quad (8)$$

The value of ln(k) represents the degree of asymmetry of residual distribution. For example, if ln(k) > 0 (ln(k) < 0), the density is right (left) skewed. When k = 1, the skewed Student's *t*-distribution equals the general Student's *t*-distribution.

The parameter ν measures the degree of freedom. The lower the value of ν, the greater the number of extreme values (i.e., the fatter are the distribution tails than the normal distribution). When ν approaches infinity, excess kurtosis becomes zero and it results in normal distribution. If the standardized residuals are not normal, assuming that the conditional mean and variance are correctly specified, the GARCH estimates are consistent but asymptotically inefficient, with the degree of inefficiency increasing with the degree of departure from normality. The skewed Student's *t*-distribution should therefore reduce the excess kurtosis and skewness in the standardized residuals and provide efficiency gains. Moreover, if the distribution exhibits excess kurtosis, the Quasi Maximum Likelihood Estimates are consistent but may be biased in finite samples.

Therefore, in order to capture skewness and kurtosis, skewed Student's *t*-distribution should be considered. This distribution was proposed by Fernandez and Steel (1998), and subsequently, extended by Lambert and Laurent (2000).

6.4 Empirical Results

The previous chapter examined the existence of long memory using modified rescaled range test, Geweke-Porter-Hudak (GPH) test and Gaussian semi-parametric test of Robinson (1995) on absolute return $|R_t|$ and squared return R_t^2, as a proxy of volatility measure. The tests supported long memory in absolute return $|R_t|$ and squared return R_t^2 *of* (proxies of volatility) CLP, COP, PEN, PKR, CZK, THB, INR, MAD, ARS, PLN and ZAR. Other currencies showed mixed results. Against this background, this chapter examined the long memory in volatility using GARCH-class models. First, parametric GARCH model is estimated and then the performance of GARCH(1, 1), IGARCH(1, 1), FIGARCH(1, *d*, 1), and FIGARCH(1, *d*, 0) specifications in modeling the long memory property in the volatility of exchange rates are compared. The estimation results of GARCH(1, 1), IGARCH(1, 1),FIGARCH(1, *d*, 1), and FIGARCH(1, *d*, 0) are given in Tables 6.1 to 6.4, respectively. It can be seen from the tables that FIGARCH(1, *d*, 1) fits best for CNY, IDR, INR, BRL, PEN and MXN and FIGARCH(1, *d*, 0) fits best for PHP, THB, COP and CZK, based on Akaike Information Criterion (AIC). Hence, these 10 currencies show the possibility of long memory property in volatility. For other currencies, GARCH or IGARCH models perform better and hence long memory property in volatility of these currencies is rejected. Now, we consider only those 10 currencies for further analysis, for which FIGARCH(1, 0) or FIGARCH(1, 1) model shows better performance. Further, the FIGARCH models should also ensure positivity constraint [4]. The FIGARCH models ensure positivity constraint in conditional variance only for COP, IDR, INR, PEN, PHP and THB. Estimates of long memory parameter (*d*) are found to be significantly different from zero, indicating that the volatility of these currencies exhibits long memory process. Additionally, the degree of parameter (*d*) indicates that the long memory property of INR, PEN and PHP is very high. However, there are limitations in using FIGARCH model for these currencies. Examining the distributional property, it is observed that standardized residuals exhibit skewness and excess kurtosis, except for THB which has negligible skewness (see Table 6.3 and Table 6.4). We can see that Gaussian distribution is inappropriate for capturing dynamics of exchange rate returns in these currencies. Therefore, FIGARCH model is estimated under skewed Student's *t*-distribution for INR, IDR, COP and PEN and under Student's *t*-distribution for THB. FIGARCH(1, 1) could not be estimated under skewed Student's *t*-distribution for PHP, while FIGARCH(1, 1) is found to be the best fit for PHP under normal distribution. The Box-Pierce statistic of the standardized residuals indicates correlation up to 20 lags for the above-mentioned five currencies, except PHP, indicating that the mean equation is necessary for modeling the long memory property. Thus, it is advisable that the dual long memory test should be simultaneously performed in returns and volatility.

In Chapter 5 we considered the long memory property in conditional mean (ARFIMA), while in the present chapter we consider long memory in conditional variance, separately. However, long memory dynamics are commonly observed in both conditional mean and conditional variance. Therefore, it is worthwhile to analyze the dual long memory in both conditional mean and variance. In this regard, we have estimated the ARFIMA-FIGARCH

[4] Baillie (1986) *et al*. considered both $\omega > 0$ and $0 \leq \beta_1 < d \leq 1$ as the necessary and sufficient condition for conditional variance of the FIGARCH(1, *d*, 0) model to be positive, almost surely for all t.

model, which gives a relationship between conditional mean and conditional variance of a process that simultaneously exhibit long memory properties. First the ARFIMA(*n*, *d*, *s*)-FIGARCH(*p*, *d*, *q*) model are estimated for n,s,p,q = 0,1. The model has been selected on the basis of minimum AIC. Second, the Ljung-Box *Q*-statistic for serial correlation is calculated to determine whether the standardized residuals and squared standardized residuals of the estimated models are i.i.d. series. If the conditional mean and variance equations are correctly specified, then all Q-statistics should support the null hypothesis of i.i.d. series. The $Q(20)$ and $Q_s\left(20\right)$ statistics test the serial correlation of the standardized residuals and squared standardized residuals, up to 20th order lag. Also, LM ARCH statistic of Engle (1982) is used to test the presence of the remaining ARCH effects in the residuals. Table 6.5 compares the estimates of ARFIMA-FIGARCH model under Gaussian and skewed Student's *t*-distribution. The skewed Student's *t*-distribution is found to outperform the normal distribution for the above-mentioned four currencies, except PHP and THB. For IDR, INR, COP and PEN, the *t*-statistic of tail is highly significant. In addition, the asymmetric parameter is not equal to zero, indicating that the distribution of exchange rate returns is skewed. Lower value of $P(60)$ test statistics of skewed Student's *t*-distribution in comparison to Gaussian distribution reconfirms the relevance of skewed Student's *t*-distribution for returns on IDR, INR, COP and PEN. However, for THB and PHP, Student's *t*-distribution and normal distribution, respectively are the best performing ones. However, IDR returns indicate strong evidence of long memory in volatility, but in general do not support the presence of long memory in return.

6.5 Concluding Remarks

This chapter empirically investigated the presence of long memory in volatility of exchange returns of 25 emerging economies. For this, the GARCH class of models were estimated and their performances were compared. FIGARCH models perform better for six currencies, i.e., INR, IDR, PHP, THB, COP and PEN, indicating long memory in volatility of these currencies. Further, ARFIMA-FIGARCH model is estimated to capture the presence of long memory in conditional mean and conditional variance, simultaneously. The study suggests dual memory property in three Asian currencies, i.e., INR, THB and PHP, and two Latin American countries, i.e., COP and PEN, suggesting inefficient foreign exchange markets in these regions.

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CHAPTER 7

SUMMARY, FINDINGS AND IMPLICATIONS

The daily turnover of foreign exchange market of emerging economies has increased manifold in the last two decades with introduction of an array of new instruments and products, development of institutional and market infrastructure, and realignment of regulatory structure consistent with the liberalized operational framework. Motivated by the phenomenal development in foreign exchange market of emerging economies and its increasing integration with the world economy, this study was performed to examine the behavior of the exchange rate of emerging economies in the liberalized environment. Twenty five emerging economies which have gained importance in world trade and have significant share in foreign exchange market have been chosen for the study. These countries have graduated from conservative exchange rate regime to a more flexible market-oriented regime. The regulatory framework governing the foreign exchange market and the operational freedom available to market participants are, to a large extent, influenced by the exchange rate regime followed by the country. This study attempted to investigate the exchange rate behavior of 25 important emerging economies which are operating under different exchange rate regime in different parts of the world.

Most of the quantitative techniques used to study exchange rate behavior are borrowed from stock market. There are two schools of thoughts – technical and fundamental – which explain the behavior of exchange rates. The Efficient Market Hypothesis (EMH) is one of the important theories based on rational expectation and no-trade argument of neoclassical finance. The main architect of the theory is Eugene Fama, who provided strong theoretical foundations and also framework to test the market efficiency. In an efficient market, prices quickly absorb new information and reflect all the available information, and thus the price processing mechanism does not provide extra normal returns. Facilitation of conducive investment and optimal allocation of capital which are vital functions of a market would be affected adversely in an inefficient market. Testing of market efficiency, therefore, assumes importance because of theoretical and practical implications.

Most of the studies in context of foreign exchange market aim at testing the Purchasing Power Parity (PPP) theory. If PPP is valid, the market is considered to be mean reverting and predictable or otherwise unpredictable and efficient. A majority of the studies have used unit root, panel unit, variance ratio, cointegration techniques, etc., to examine the mean reversion in the real foreign exchange rate. However, these tests ignore important issues such as structural break, nonlinearity and long memory in the exchange rate series. There are very few studies which have examined unit root in the presence of structural break, nonlinearity and long memory behavior of foreign exchange rates of emerging economies. The predictability of exchange rate in presence of structural break, nonlinearity and long memory in series would invalidate the random walk hypothesis and hence the weak form of market efficiency.

Against this backdrop, the present study has addressed five issues related to the behavior of exchange rates in 25 emerging economies which follow different exchange rate regimes. The study has examined the presence of unit root in the exchange rate series without and with the possibility of one and two structural breaks. Also, the study has utilized both linear and nonlinear models to test the predictability of foreign exchange market. Different tests have been performed to examine the linear and nonlinear behavior of rates. Furthermore, the study has also attempted to detect long memory in foreign exchange returns and volatility.

The data used in the study have been taken at weekly frequency from Bloomberg database. The study has used weekly return on Wednesday, with a view that Wednesday data minimize the weekend effect on the results of the tests. The study differs from the previous studies in respect of employing sophisticated tests, checking for robustness of models, use of new and comprehensive data sets and addressing issues which are seldom discussed in the context of emerging economies exchange rate markets.

The first issue that has been taken up in this study is an empirical assessment of the mean reversion hypothesis. That is, the study attempts to ascertain the presence of unit root in the exchange rate series. This is examined using both conventional and new generation unit root tests. However, in view of the possibility that these tests might give spurious result in presence of possible structural break, unit root tests with one and two structural breaks are also conducted on the series. The conventional and new generation unit root tests unanimously supported mean reversion in four currencies, i.e., PEN (Peruvian Nuevo), INR (Indian Rupee), RUB (Russian Rubble) and TRY (New Turkish Lira). The unit root tests with one and two breaks supported unit root in 10 currencies i.e., CLP (Chilean Peso), COP (Colombian Peso), CZK (Czech Koruna), HUF (Hungarian Forint), MAD (Moroccan Dirham), PLN (Polish Zloty), PKR (Pakistani Rupee), KRW (Korean Won), ZAR (South African Rand) and LKR (Lankan Rupee). The study has also identified the events associated with the significant structural break dates as indicated by the tests. These events are political or economic crises, change in exchange rate regime, elections, political uncertainties, cross-border tensions, etc. It is interesting to note that the currencies which have shown unit root or non-stationarity follow managed or free float exchange rate arrangements (barring LKR and MAD).

The study empirically tested weak form of efficiency of foreign exchange market of emerging economies by testing the Random Walk Hypothesis (RWH). To examine this, data on foreign exchange returns of 25 emerging economies for different time period are analyzed using both parametric and nonparametric tests. The parametric tests used in the study are Lo-Mackinlay (1988), Chow-Denning (1993) , Chen and Deo (2006), Whang and Kim (2003) subsampling test, Kim (2006) bootstrap test and non parametric tests used are Wright (2000) ranks and signs test, Belaire-Franch and Contreras (2004) test and runs test.

The parametric tests supported random walk in CZK, HUF, MAD, PLN, PHP and ZAR. The nonparametric tests supported RWH for the same currencies. Here also it can be noted that all the currencies showing random walk are either managed float or free float, barring MAD, which is pegged to a composite basket of currencies. There is strong evidence of mean reversion in CNY (Chinese Yuan), CLP (Chilean Peso), EGP (Egyptian Pound), PEN (Peruvian Nuevo), TWD (Taiwan Dollar), INR (Indian Rupee) and ARS (Argentine Peso). Of these currencies, CNY and ARS are following pegged exchange rate agreement. It is noteworthy that for countries that have fixed or pegged exchange rate agreement, mean reversion is expected. In specific, given a pegged exchange rate agreement, large deviations from the fixed rates are likely to induce central bank interventions to correct the misalignments and hence the mean reversion would follow.

Nonlinear dependence in returns directly contrasts the Efficient Market Hypothesis (EMH). It is due to the fact that nonlinear dependence indicates potential for predictability. The conventional linear tests cannot capture such dependence. Given the fact that there has not been much empirical work in this context, the present study applied the nonlinearity tools containing various nonlinearity tests which have different powers against different classes of nonlinear process, to uncover the nonlinear dependence in foreign exchange returns of the selected 25 currencies. The test results show strong evidence of nonlinear dependence in the return series of 17 currencies. However, windowed test procedure applied in the study showed a nonlinear structure that is not consistent throughout the sample period and is confined to a few pockets, thus suggesting episodic nonlinear dependence surrounded by long periods of pure noise. This evidence indicates failure on the part of researchers to exploit the detected nonlinearity in making improved point forecasts. In particular, though the presence of nonlinearity implies the potential of returns predictability, the dependence structures do not seem to be persistent enough for investors to benefit from it. Following the interpretation of Ammermann and Patterson (2003), these dependencies show up at random intervals for a brief period of time, but then disappear again before they could be exploited.

The study further investigated the long memory property in the exchange rate series. If there is persistent dependence between observations that are considerably separated in time, the process is said to have long memory. A time series may have long memory either in returns or variance or both. To examine long memory property in returns series, fractionally integrated technique, i.e., ARFIMA model suggested by Granger and Joyeux (1980) and Hosking (1981), is employed. Additionally, modified rescaled range test, GPH and Robinson tests are also used to study the long memory behavior. The results suggest long memory in return series of CNY (Chinese Yuan), EGP (Egyptian Pound), HUF (Hungarian Forint), PEN (Peruvian Nuevo), RUB (Russian Rubble), IDR (Indonesian Rupiah) and MXN (Mexican Peso). However, long memory is rejected in return series of CZK, MAD, PLN, TWD, PKR and ZAR by all the tests.

Next long memory in volatility of exchange returns of 25 emerging economies is examined. For this, absolute returns and squared returns which are proxies of volatility are used by the study. The tests have suggested long memory in volatility of THB (Thai Baht), INR (Indian Rupee), MAD (Moroccan Dirham) , ARS (Argentine Peso) , PLN (Polish Zloty) , CLP (Chilean Peso) , COP (Colombian Peso), PEN (Peruvian Nuevo), CZK (Czech Koruna) and ZAR (South African

Rand). Another method suggested by Baillie *et al*. (1996), based on fractionally integrated GARCH model is also employed. The test confirmed long-range dependence in volatility of INR, THB, COP and PEN. Additionally, the test also suggests long memory in Philippine Peso (PHP) and IDR. Further, dual memory, i.e., long memory in mean and variance is tested simultaneously using ARFIMA-FIGARCH model. The dual memory model suggested duality in long memory in three Asian currencies, i.e., INR, THB and PHP and two Latin American currencies, i.e., COP and PEN.

To conclude, the time series econometric techniques applied in the study by and large suggest random walk behavior in Central and Eastern Europe (CEE) countries and Brazil. There is strong support of predictability in CNY, RUB, INR, PEN and EGP. Other currencies however have shown mixed results.

The three CEE emerging economies selected in our study joined European Union in 2004 and presently follow the free floating exchange rate system. High inflation in CEE countries in early 1990s exerted a strong pressure in favor of depreciation, which has been progressively alleviated through progresses made in the disinflation process. Nonetheless, the opening-up of the capital account allowed for considerable capital inflows putting pressure towards nominal appreciation. As a consequence, nominal exchange rates started exhibiting significant swings.

Similarly, the Brazilian foreign exchange has undergone tremendous change in the last few years. Until February 2005, exchange transfers abroad were limited to a set of transactions covered under specific Central Bank regulations. From March 2005, the regulatory burden was significantly reduced and now free negotiation between agents authorized to operate in the foreign exchange market and their clients is permitted. This applies to transactions of any nature, without set limits and without requiring Central Bank prior authorization. In other words, all foreign exchange transactions are permitted observing the legality purpose and the responsibilities defined in the appropriate documentation. There is no restriction on receiving or sending foreign exchange transfers. These transfers may be done directly through an authorized bank without prior approval of the Central Bank. This provision applies to all legal residents in Brazil and all legal transactions, including the accumulation of assets abroad. In the case of exports and imports, new law has been introduced which further simplified and deregulated procedures applicable to export receipts and import payments. These measures helped in making the foreign exchange market deep and liquid, leading to market efficiency.

Changes in nominal exchange rate patterns have shaped the exchange rate regimes. Initially, fixed exchange rate regimes were adopted to back disinflationary policies in the early 1990s. However, from the mid-1990s, progressive shift has been made towards more flexible exchange rate regimes. More exchange rate flexibility has become necessary as a result of increased capital inflows. On the one hand, a deep restructuring of the economy through privatization has attracted considerable amount of Foreign Direct Investment (FDI). On the other hand, the resulting brighter economic perspectives have made these countries more attractive to international investors. Moreover, the modernization of the financial markets going in tandem with the opening-up of the capital account has paved the way for short-term portfolio investment. Increased capital account liberalization coupled with eventual capital inflows made pegged exchange rate regimes very difficult and costly to maintain and thereby led to a progressive widening of the fluctuation bands and subsequently to free floating regime.

There is strong evidence of inefficiency in Asian markets irrespective of the exchange rate regimes followed by them. Currencies in Asia have increasingly reduced their variability, and appear more managed suggesting monetary authorities’ intervention in foreign exchange markets. However, the developments of exchange market suggest that the intervention led to inefficiency in foreign exchange market of several economies. Additionally, all the Asian currencies, barring PKR, CNY, LKR and VND (Viet Nam Dong), showed break in 1997-1998, i.e., during the period of East Asian Crisis. The possible reasons why PKR, LKR and VND have not shown break is very low turnover and thin trading in these markets. Various political events like general elections, social protests, etc., have caused break in trend behavior of currencies, e.g., BRL (Brazilian Real) (2002), THB (1992 and 2001), INR (2002), RUB (2003 and 2008), TRY (2001), MXN (1994), and PEN (2001).

The study indicates that though there is no clear evidence of relationship between floating market regime and efficiency, but there is clear evidence of relationship between the pegged system and inefficiency or price predictability of the market.

The limitations of the study indicate the scope for further research. The data used in the study is of weekly frequency. The study with daily frequency or tick-by-tick data may be used to examine the behavior of the currencies. This would help to understand the dynamics of the market further and would also throw light on episodic dependence and speed of price adjustment. Further, foreign exchange markets of some counties, like Sri Lanka, Morrocco and Pakistan, are illiquid and thinly traded and the various tests employed on LKR, MAD and PKR may not portray the true picture. Lastly, the sources of long memory and also volatility shifts in long memory should be further investigated and application of wavelet methods may give new insights into issues of long memory in foreign exchange returns.

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