Forecasting Exchange Rates: An Empirical Investigation of Advanced, Emerging and Frontier Market Economies

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Abstract

The purpose of this research is to investigate the application of different forecasting methods to predict the exchange rates of advanced, emerging and frontier market economies. To date, research on forecasting exchange rates has tended to focus mostly on advanced economies. Little attention has been paid on emerging and frontier market currencies and this research fills a major gap in the literature. Data are drawn from International Financial Statistics, monthly publications by the International Monetary Fund. Monthly data pertaining to 49 countries from 1972 M1 up to and including 2007 M12 are used for model derivation. The remaining observations i.e. 2008 M1 to 2010 M4 are held back for the purpose of out-of-sample forecast evaluation. The Lee and Strazicich (2003) unit root test was applied to examine the presence or otherwise of endogenous structural breaks. Three times series models, namely volatility, exponential smoothing, Naïve 1 plus a causal cointegration via ARDL (autoregressive distributive lags) model are used. Two- three- and four-way combinations of these four models are generated in an attempt to increase forecasting performance. The forecasting accuracy of all models is assessed via MAPE (mean absolute percentage error). Studies of forecasting exchange rates have used a variety of measures to assess forecasting accuracy. However, the MAPE is one of the most commonly used measures of error magnitude. This accuracy criterion has the advantage of being measured in unit-free terms. Granger Causality analyses are carried out to shed some light on the causal relationships between macroeconomic variables and exchange rate dynamics. The results show that single volatility models outperform other time series and a causal model in many of the emerging and frontier markets. These findings also provide additional evidence on leverage effects of advanced, emerging and frontier currencies exchange rates. Although statistically based forecast combination methods have not had much application in the field of exchange rate modelling, the results of this study show that such combinations often perform better than a single model for exchange rate prediction.

Key words: Exchange rates, volatility, time series models, ARDL-cointegration model, combination models, advanced, emerging and frontier economies.

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Chapter 1

Introduction

This thesis offers a thorough investigation of the exchange rate behaviour of countries classified as advanced, emerging and frontier market economies. As such, a unique feature of this research is that 80% of the data sets used (new geographical areas grouped as emerging and frontier markets currency exchange rates against the U.S. dollar), have never been subjected to statistical analysis before (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). It is shown that volatility models have wide application for advanced markets. Empirical research on exchange rates and its associate volatility in respect of emerging and frontier markets is almost non-existent. This study examines whether the traditional univariate volatility models that are used widely and successfully in the literature in relation to advanced countries, could perform equally well in the cases of emerging and frontier countries. This research also focuses on the rarely applied autoregressive distributive lag (ARDL)-cointegration method in order to investigate the long-and short-run relationships between exchange rates and macroeconomic fundamentals. This study also compares the forecasting performance of this causal econometric approach with time series approaches. Last but not least, combinations of forecasts methods derived from individual models are used to predict exchange rates. Several models are widely applied by academics and practitioners to forecast exchange rate volatility. Nowadays there is no consensus about which method is superior in terms of forecasting accuracy. Poon and Granger (2003) suggested that combination forecasting is a research priority in this field. Therefore, this study fills a major gap in the literature by considering combinations of forecasting methods for predicting exchange rates of advanced, emerging and frontier market economies.

The motivating factors for the examination of foreign exchange volatility are twofold. Firstly, like all other financial markets the market for foreign exchange has large temporal variations in volatility. Secondly, recent years have seen the development of models of conditional heteroscedasticity, which have been proven to be highly satisfactory tools to describe the phenomenon of heteroscedasticity in residuals over time. These two factors have led to a plethora of work on foreign exchange rate and associated volatility. The prime reason for focusing on advanced, emerging and frontier markets exchange rates derives from the fact that the financial linkages between these markets with global economy have risen significantly in recent decades. It is believed that advanced economies are the main participants in the financial globalisation process, but emerging and frontier markets have also started to participate. Emerging and frontier markets often receive foreign direct investment (FDI) and other financial flows from advanced economies. Mauro *et al.* (2006) stated that capital flows from advanced to emerging and frontier countries have significantly increased since the mid-1990s. This dramatic increase in capital flows to emerging and frontier countries has created new challenges for policy makers, academics, investors, individual firms and various agents for these countries. Exchange rate volatility plays a significant role in this financial globalisation process. So as to manage this process effectively, it is very important for the policy makers and various agents to be able to generate accurate forecasts of exchange rates and their anticipated volatilities. Thus, it would be of great importance to investigate whether established time series models, econometric models or a combination of both models perform equally well for emerging and frontier countries.

The reminder of the chapter is structured as follows. Section 1.1 introduces an overview of foreign exchange markets. The role of exchange rates in economic growth is discussed in Section 1.2. Section 1.3 explained the importance of forecasting exchange rates. Methodological approaches are reported in Section 1.4. Section 1.5 provides the research objectives and structure of the thesis is presented in Section 1.6.

1.1 Overview of the Foreign Exchange Market

On December 27, 1945, the Bretton Woods conference of representatives from the major economic industrialised countries agreed to begin a period of pegged but adjustable exchange rate. Prior to World War II, the 1930's had been a period of flexible exchange rates, characterised by extreme volatility and competitive exchange rate policies adopted by many countries. The Bretton Woods delegates believed that a more stable system of foreign exchange rates would promote the growth and international trade (Baillie and McManon, 1989). The prime feature of the Bretton Woods system was an obligation for each country to adopt a monetary policy that maintained the exchange rate. In 1971, the United States unilaterally terminated convertibility of the U.S. dollar to gold. This ended the Bretton Woods system and US dollar became a reserve currency for many countries. Moreover, many fixed currencies also started to be free floating. Exchange rate behaviour can influence the choice of exchange rate regime. An exchange rate can be totally flexible or completely free to float on foreign exchange (FOREX) market; on the other hand it could be fixed or pegged to one of the major currencies or a basket of currencies. Between these two extremes, there can be a few types of exchange rate arrangements and combinations. The IMF (International Monetary Fund) classified exchange rate regimes into eight categories- exchange rate arrangements with no separate legal tender, currency board arrangements, conventional fixed peg arrangements, pegged exchange rates with horizontal boards, crawling pegs, exchange rates within crawling bands, managed floating with no predetermined path for the exchange rate and independent floating.

The FOREX market was created in the 1970s, when international trade transitioned from fixed to floating exchange rates. In the transaction or execution of conversion, one currency is considered domestic or home currency and the other is regarded as foreign from a certain geographical or sovereign point of view, so is the term foreign exchange derived (Wang, 2009). An exchange rate is the price at which one national currency can be exchanged for another. The most common currency value notion is the bilateral exchange rate quoted by foreign exchange trader or reporter in a newspaper. This is also referred to as “nominal” exchange rate because it is the number of units of one currency offered in exchange for a unit of another. The FOREX market involves the purchase and sale of national currencies against foreign currencies. According to Wang (2009, 1) “a foreign exchange market is a market where a convertible currency is exchanged for another convertible currency or other convertible currencies”. There is no central marketplace for the exchange of currency. However, trading is conducted over-the-counter (OTC). This decentralised market allows traders to select form a number of different dealers to operate trade at agreed upon rates. The FOREX market is a network of commercial banks, central banks, brokers and customers who communicate with each other by telex and telephone throughout the world's major financial centres. The FOREX market is extremely active; for example, the spot currency market operates twenty-four hours a day and seven days in a week with currencies being traded in all of the major financial centres around the world. In FOREX market, the values are established for goods and services imported or exported between countries. International trade participants settle the resulting trade obligations by exchanging different currencies at agreed upon rates via bills of exchange, bankers' acceptances, bank drafts and letter of credit.

The FOREX market is now considered to be the largest financial market in the world because of its huge turnover. Global FOREX turnover was 20% higher in April 2010 than in April 2007, with average daily turnover of $4.0 trillion compared with $3.3 trillion[1]. The increase was driven by the 48% growth in turnover of spot transactions, which represent 37% of foreign exchange market turnover. Spot turnover rose to $1.5 trillion in April 2010 from $1.0 trillion in April 2007. FOREX market activity became more global, with cross-border transactions representing 65% of trading activity in April 2010, while local transactions accounted for 35%, the lowest share ever (Bank for International Settlement (BIS), 2010). The relative ranking of foreign exchange trading centres has changed slightly from the previous triennial survey of BIS. Banks located in the United Kingdom accounted for 37% of all foreign exchange market turnovers, against 35% in 2007, followed by the United States (18%), Japan (6%), Singapore (5%), Switzerland (5%), Hong Kong (5%) and Australia (4%).

The FOREX market is the most liquid financial market in the world. Liquidity in the FOREX market is secured from the vast number of participants located around the world and the availability of a wide range of electronic communication networks that provide the fastest brokerage services and direct-dealing capabilities. Moreover, the wide variety of trading venues, which range from telephone contact with dealer trading desks to single-dealer electronic portals or multi-bank portals, captures and reflects the total liquidity of the market and allows institutions, investment managers and corporation's direct access to the market and significant price transparency. These however, results the deeper and more consistent liquidity virtually twenty-four hours a day during the business week. It is worthwhile to mentioning here that this continuous liquidity act as a critical component of the efficient functioning of the other capital markets located around the world. These features significantly reduce the risk that a reduction in trading activity could leave an investor unable to liquidate or offset a position at or near the market value of the asset (Federal Reserve Bank of New York, 2009).

[1] Triennial Central Bank Survey, Report on global foreign exchange market activity in 2010, Monetary and Economic Department, Bank for International Settlements, December, 2010.

The growth of international capital flows, expansion in international securities markets, internationally diversified corporations and information technology have contributed to a significant expansion of the FOREX market in recent years. Every hour, FOREX market participants enter into millions of transactions across the globe. Dealers, non-financial customers and other financial institutions (e.g. non-reporting banks, hedge funds, pension funds, mutual funds, insurance companies and central banks) are the trading parties in the global FOREX market. Turnover by the other category (e.g. non-reporting banks, hedge funds, pension funds, mutual funds, insurance companies and central banks) grew by 42% to $1.9 trillion in April 2010 from $1.3 trillion in April 2007[2].

FOREX market is not reserved for traders or finance professionals only but for almost everyone, from multinational corporations operating in several countries to tourist travelling across two currency zones (Wang, 2009). This market serves business, non-business, governments, individuals, international organisations and institutions. The Foreign Exchange Committee of the Federal Reserve Bank of New York identified that corporations and investors are the main participants of the FOREX market, who require access the market place for a variety of reasons. Corporations enter into the FOREX market to export or import goods and services, repatriate earnings from abroad, make payment to foreign suppliers and service providers, invest in plant, equipment and businesses abroad, fund cross-currency balance-sheet needs and hedging purposes. On the other hand, global investors participate in the FOREX market to repatriate earnings from abroad, ensure adequate liquidity to meet obligations to related parties, settle the purchase or sale of foreign assets, manage portfolio risks and returns, offset sovereign risk and hedge the currency risk associated with holding foreign assets. These factors clearly show that how diverse are the needs of the participants of FOREX markets. It is difficult for the participants to use the wide variety of products and to tailor the settlement dates of such products to their needs. However, flexibility of the FOREX markets and its products allows participants to manage their risk and their day-to-day business operations more effectively and efficiently.

The vast majority of transactions in the FOREX market involve measurement against the U.S. dollar, which plays such an important role in facilitating international trade and

[2] Triennial Central Bank Survey, Bank for International Settlements, December, 2010.

investment because international contracts are denominated in U.S. dollars than in any other currency. Furthermore, globally traded goods and services are typically priced in U.S. dollar. The U.S. dollar's central role in currency markets makes it easier for business organisations and global investors to hold dollar-based assets and results in lower borrowing costs for dollar-based debtors. Therefore, it is not surprising that the U.S. dollar is dominant the FOREX market. Table 1.1 presents the currency distribution of global FOREX market turnover. It is clear that U.S. dollar represents the 85% of the global turnover. The second most active currency is the Euro (39.1%) followed by the Japanese yen (19%). The market share of the top three currencies increased by 3% and the biggest decline (14%) is evidenced in the case of British pound. The BIS's Triennial Central Bank Survey (2010) also highlighted the fact that the market share of emerging currencies increased with the biggest gains of the Turkish lira, Chinese renminbi and Korean won, followed by the Brazilian real and Singapore dollar. The renminbi now accounts for almost 1% of global turnover by currency, on a par with the Indian rupee and the Russian ruble. This explains the increasing participation of emerging currencies in the FOREX market. Research on exchange rates is mainly focused on advanced currencies. Very little attention has been paid to investigating the exchange rate behaviour of the emerging and frontier currencies. It is important both from academic and policy point of view to investigate the exchange rate behaviour of these economies. This study investigates the nominal exchange rates of advanced, emerging and frontier currencies against the U.S. dollar to fill the gap in the literature.

Exchange rates are important for countries macroeconomic purposes as well as for businesses and for individuals. Getting the exchange rate right is a critical objective of all international investors and policy makers (Rosenberg, 2003). One major research goal in the study of exchange rates is to find an acceptable forecasting model that predict and explain the movement of the nominal exchange rates in terms of other macroeconomic fundamentals. Several theoretical models[3] that have been popularised to explain the determination of exchange rates since the float began in 1973. In respect of quantitative forecasting techniques, several models (time series or causal econometric) are widely

[3] purchasing power parity (PPP), the monetary model, Dornbusch's sticky price monetary model, the flexible price monetary model, the portfolio balance model, other variants of the monetary model, the equilibrium and liquidity models, currency substitution models (for details of these models see Baillie and McManon (1989, 62-86) and Sarno and Taylor (2002, 99-123).

Table1.1: Currency distribution of global foreign exchange market turnover* (percentage shares of average daily turnover)

Currency	**1998**	**2001**	**2004**	**2007**	**2010**
U.S. dollar	86.8	89.9	88.0	85.6	84.9
Euro	------	37.9	37.4	37.1	39.1
Japanese Yen	21.7	23.5	20.8	17.2	19.0
British Pound	11.0	13.0	16.5	14.9	12.9
Other	80.5	35.7	37.3	45.2	44.2

Source: Triennial Central Bank Survey 2010, Bank for International Settlements. * Because two currencies are involved in each transaction, the sum of the percentage shares of individual currencies totals 200% instead of 100%.

applied by academics and practitioners to forecast exchange rates. The question may arises as to the choice of the most appropriate forecasting methods. An important consideration is that forecasts should be accurate, which can act as a basis for better decision-making (Moosa, 2000). Nowadays, there is no consensus about which method is superior in terms of forecasting accuracy. However, composite forecasts have received much attention in recent years in many different fields including Finance. Composite forecasting involves the combination of two or more forecasts derived from different models to produce the final forecast. A prime reason for doing this is to reduce the forecast error and to combine sometimes conflicting views to obtain collective knowledge. Therefore, this study fills a major gap in the literature by considering the combination of forecasts methods for predicting exchange rates over the economies studied.

1.2 The Role of Exchange Rates in Economic Growth: Evidence from Advanced, Emerging and Frontier Markets

Growth is the steady increase in aggregate output over time (Blanchard *et al.* 2010). Long-term sustainable economic growth depends on an ability to raise physical and human capital, efficient use of the productive assets and to ensure that the whole population of the country has access to these assets. This investment process operates by the financial intermediaries. The key factor behind this operation is household and foreign savings. These funds should be allocated for the productive use of an economy. Financial intermediaries spread risks and ensure the liquidity so that business organisation can operate the new capacity efficiently. Therefore, it is necessary to establish and expand existing financial institutions, instruments and markets to maintaining sustainable long-term economic growth for any economies. The role of banks and non-bank financial intermediaries are range from pension funds to financial markets (e.g. FOREX, stock), shifted household savings into enterprise investment, allocate funds and monitor investments and to price and spread risks. Like other macroeconomic variables (e.g. interest rates, inflation rates, money supply and GDP) exchange rates play major role in country's economic development.

The relationship between exchange rates and economic growth is an important phenomenon both from academic and policy point of view. Since the collapse of the Bretton Woods system, a majority of the world's economies transitioned to floating exchange rates systems. One key feature of flexible exchange rate systems is that they are highly volatile and such volatility may affect country's economic growth through the channels of international trade and investment (MacDonald, 2000). A high economic growth rate for any economy is most likely accompanied by a high investment rate and high export growth as well. Successful exports produce current account surpluses, resulting in nominal appreciation pressure on the currency unless the central bank intervenes in the foreign exchange market and accumulates foreign reserves (Ito *et al.*, 1999). Fast economic growth often encourages inflows of foreign capital in domestic economy. These capital flows put pressure on the nominal exchange rate to appreciate. For example, demand for the currency of an economy will rise when foreign investors plan to invest in that economy. Successful economic development for any economy results in currency appreciation with an improvement in the standard of living, while failure in economic development often results in a sharp currency depreciation. With the increasing global integration of world economies into the global trading system and participation in international production networks, exchange rates and their associated volatilities have taken on an added importance. Therefore, it is important for any country to maintain a stable and competitive exchange rate for sustained economic growth. The next section describes the characteristics of advanced, emerging and frontier markets.

1.2.1 Advanced Markets

"Advanced markets" are often referred as "developed or industrial" countries by different organisations (e.g. IMF, World Bank, United Nations and S&P). High levels of economic growth, security, high level of industrialisation, high standard of living, widespread infrastructure, a stable political environment and high human development index (HDI) are the main characteristics of this economy. These countries[4] that fall into these categories are regarded as powerful nations in terms of world leadership and economic development. However, developed countries' economic situation and prospects have evidenced slowdown in recent years. The global financial crisis, high oil prices and recent crisis in the Europe have tended to affect more in advanced economies. The unemployment level in the Euro areas are raising rapidly and obviously the Euro are debt crisis would likely to be associated with severe turmoil on financial markets and sharp rise in global risk aversion, leading to a contraction of economic activity in advanced economies. Rising unemployment, fiscal austerity and sovereign debt risk, deleveraging by firms and households and instable financial markets are the key reasons of the slowdown of the recent economic growth of these markets (United Nations, 2012a). In order to mobilise the economy, more demand in every aspect needs to be created. It is necessary for the decision makers to develop policies which will support the growth prospects of these economies. These policies need to be better coordinated across the major economies and concerned with continued expansionary monetary policies in developed countries and accompanied by accelerated financial sector reforms and enhanced development assistance for low-income countries (United Nations, 2012b).

The foreign direct investment (FDI) in respect of developed countries rose sharply in 2011 by 25% (to reach $1.24 trillion). While all three major developed economy investor blocs – the European Union (EU), North America and Japan – contributed to this increase, the driving factors differed for each. The FDI from the United States was driven by a record level of reinvested earnings (82 % of total FDI outflows), in part driven by transnational corporations (TNCs) building on their foreign cash holdings. The rise of FDI outflows from the EU was driven by cross-border merger and acquisitions (M&As). An appreciating

[4] Morgan Stanley Capital International(MSCI) Developed country group: Americas (Canada and United States), Europe and Middle East (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdome) and Pacific (Australia, Hong Kong, Japan, New Zealand and Singapore).

yen improved the purchasing power of Japanese TNCs, resulting in a doubling of their FDI outflows, with net M&A purchases in North America and Europe rising 132% (World Investment Report, 2012).

Financial globalisation has proceeded at more rapid pace over the past few decades. While the advanced economies continue to be the most financially integrated, more and more developing countries have meanwhile liberalised and at least partially opened up their financial systems. Global FDI inflows rose 16 per cent in 2011 (to $1,524 billion, up from $1,309 billion in 2010) surpassing the 2005–2007 pre-crisis level for the first time, despite the continuing effects of the global financial and economic crisis of 2008–2009 and the on-going sovereign debt crises. This increase occurred against a background of higher profits of TNCs and relatively high economic growth in developing countries during the year. Developing countries continued to account for nearly half of global FDI in 2011 as their inflows reached a new record high of $684 billion (World Investment Report, 2012). The increase in developing and transition economies was driven mainly by robust greenfield investments, while the growth in advanced countries was due largely to cross-border merger and acquisitions (M&As). Developing countries are divided into “emerging” and “frontier” markets by several organisations (such as MSCI, FTSE and S&P). Higher growth, greater financial integration of world’s capital markets and the increased freedom of capital to flow across national borders have increased the importance of these markets in the global economies. The next section describes the characteristics of the emerging markets.

1.2.2 Emerging Markets

Emerging markets generally exhibit strong economic growth and inflation is typically higher than average. According to Mody (2004), the common features of emerging economies are good growth prospects, high rates of return, high level of risk (e.g. political risk), extremely volatile and the absence of foreign investment and their transition to market economies. Volatility in this market arises from many sources, including natural disasters, domestic policy instability and external price shocks. Emerging markets are in transition in several senses, namely demographic characteristics (e.g. fertility rates, younger workforce, life expectancy and literacy rates), nature and depth of their economic and political institutions and greater interaction with international capital markets. The combination of high volatility and the transitional features of emerging markets generate a challenge in policymaking. Emerging markets now contain 86% of the world's population, 75% of the world's land mass and resources and account for 50% of world GDP at purchasing power parity (PPP)[5]. For more than two decades, emerging markets in Asia, Latin America and Eastern Europe have generated some of the most exciting global investment opportunities. High growth rate, new economic reforms and trade liberalisation are the main reasons behind this positive response from the western world.

The MSCI launched the first comprehensive emerging markets index in 1988. Since then the MSCI emerging markets indices have evolved considerably over time, moving from about 1% of the global equity opportunity set in 1988 to 14% in 2010. As of December 2012, the MSCI emerging markets index consists of the 21 countries[6]. International investors are much more excited to invest their fund in emerging markets because of their strong economic growth and the development of financial markets. The single major reason for investing in emerging markets is of course high returns. Over the last twenty years, emerging economies produced huge gains although those gains have also been accompanied by huge volatility[7]. In the 1980's, GDP growth in advanced and emerging countries was essentially the same. However, between 2000 and 2010, average growth in the emerging economies rose to point where it was three times higher, driven largely the Asian economies[8]. According to MSCI's report on "Emerging Markets: A 20-year Perspective"[9], emerging markets have on an average witnessed a 6% growth in GDP per capita over the last 20 years, while advanced markets have been growing at a slower rate of 5% in the same period. The MSCI report also highlighted the fact that China, Russia, Brazil, Chile, South Korea and Poland have witnessed the fastest growth in GDP per capita. However, China and India continue to have low GDP per capita given their large populations.

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[5] Source: Merrill Lynch, BP, CIA World Factbook, IMF World Economic Outlook, MSCI.

[6] Americas (Brazil, Chile, Colombia, Mexico and Peru), Europe, Middle East and Africa (Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa and Turkey) and Asia (China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand).

[7] For example, emerging market volatility in U.S. dollar terms at the peak of the credit crisis spiked to 0.69, compared to MSCI World volatility of 0.43.

[8] IMF, World Economic Outlook Database, April 2011.

[9] Available at: www.mscibarra.com

Emerging market currencies exhibit different characteristics as opposed to their advanced counterparts. For example, the former can be much more volatile and be subject to sharp devaluations. However, such currencies have appreciated against the dollar over the last decades. Griebeler (2010) argued that the vulnerability of emerging economies is clearly evidenced by the behaviour of their exchange rates which are highly volatile compared to advanced economies. The exchange rates of emerging markets fluctuate more in the short-run than do those of the industrial countries (Hall *et al.*, 2010). Hausmann *et al.* (2000) and Calvo and Reinhart (2001) argued that exchange rate volatilities have larger adverse impacts on foreign trade in developing countries than may do in advanced countries. Emerging economies tend to be more open with respect to trade than their advanced counterparts, so a given level of exchange rate volatility has a greater impact on international trade than on that of the latter countries. Moreover, substantial aspects of exports and imports of emerging countries are priced in U.S. dollar. Therefore, short-run fluctuations of exchange rates can significantly affect the international trade of these countries.

It is now well-established fact that Brazil, Russia, India, China and South Africa (BRICS) act as a powerful economic bloc in the world economy. Global economic leadership is progressively shifting from G7 to the BRICS (Maradiaga *et al*., 2012). The faster growth rates of China and India imply that their combined GDP will exceed that of the G7 OECD (Organisation for Economic Co-operation and Development) economies by around 2025 and by 2060 it will be more than 1.5 times larger, whereas in 2010 China and India accounted for less than one half of G7 GDP. The combined GDP of these two countries is forecasted to be larger than that of the entire OECD area (based on today's membership) in 2060, while it currently amounts to only one-third (OECD, 2012). Wilson and Purushothaman (2003) suggested that BRICS will overtake the G6 by 2040. China passed Japan in 2010 (The Guardian, 2012), whereas Brazil over took the UK in 2011 (The Wall Street Journal, 2011). An analysis from Price Waterhouse Coopers (PwC) suggested that China will overtake the U.S.A as the world's largest economy at some point around 2025 (BlackRock, 2011). BRICS represents 30% of the global economic growth (combined GDP of U.S. dollar 8.7 trillion in 2010), 25% of the global land mass and 40% of the world's population and these countries hold 40% of the world's currency reserve (Sule, 2011). BRICS are also playing major roles in international trade, although many emerging markets are expected to become less dependent on exports as local demands becomes an increasingly significant growth engine. A major portion of the international trade is priced in U.S. dollar. The U.S. dollar has lost some of its leadership as a stable and strong currency and that emerged the issue of using an alternative currency for international trade. China and Russia already started to use their local currency for international trade purposes (Maradiaga *et al*., 2012).

Even before the global financial crisis of 2008-2009, investment in the developing world was higher than in developed economies. Since the third quarter of 2009, more than half of the world's economic growth comes from transitional and emerging economies (United Nations, 2011). However, global economic growth started to decelerate on a broad front in mid-2011 and is estimated to have averaged 2.8 per cent over the last year. This economic slowdown is expected to continue into 2012 and 2013 (United Nations, 2012b). Emerging market capital flows were seriously affected during the emerging market crises of the late 1990s and the global financial crisis in 2008-2009. The recent Euro area crisis has damaged the willingness and ability of investors and lenders in the region to supply financing to business and borrowers in emerging markets. This reduction in supply will hold back growth in some of the emerging European countries (Suttle *et al.*, 2012). It is worthwhile mentioning here that Euro crisis is not the only factor damaging capital flows to emerging Asia. In China, prospects for slower growth and lower interest rates seem to have negative impacts on short-run capital flows. High oil price, ongoing political uncertainties and the crisis in Europe have tended to affect more emerging economies. Perhaps the rule of finance over trade in the modern age of accelerated globalisation is best illustrated by trading in FOREX markets (United Nations Conference on Trade and Development (UNCTAD), 2012).

The influence of advanced countries on the economies of emerging markets has increased in recent years. Emerging markets are now well established in the global economic context. Advanced economies are the main participants in the financial globalisation process. However, emerging markets have also started to participate in this process. Mauro *et al.* (2006) noted that capital flows from advanced to emerging countries have significantly increased since the mid-1990s. This dramatic increase in capital flows to emerging countries has created new challenges for policy makers, academics, investors, individual firms and various agents for these countries. Exchange rate volatility plays a significant role in this financial globalisation process. So as to manage this process effectively, it is very important for the policy makers and various agents to be able to generate accurate forecasts of exchange rates and their volatilities. Thus, this research would be of great importance to investigate whether the established time series, econometric or a combination of both models, accurately tested for advanced countries, perform equally well for emerging countries.

1.2.3 Frontier Markets

The term “frontier” was first invented in 1992 by the IFC (International Finance Corporation), the private sector arm of the World Bank, as a subset of very small emerging markets, with lower market capitalisation, less liquidity and where average per capita income is below $1,025 pa. Frontier markets also defined as ‘Pre-Emerging markets’. Many emerging markets are fast moving into advanced league-leaving behind dozens of newer economies. This ‘second division’ of smaller, faster growing and more risky countries collectively form a new group called ‘Frontier Markets’ in a global economy (The Royal Bank of Scotland (RBS), 2010). It was not long before China and India were fall into this category. The World Bank defined frontier market as high-risk and low-income countries. They are typically difficult to access for outside investors, fairly risky on the political and economic fronts but they have potential for huge returns and even bigger declines. These markets also characterised as being heavily protected, over regulated and subject to massive volatility. Frontier market GDP growth has been higher than that of advanced and emerging economies for every year since 2001. This huge growth rate is primarily because they have started from a much lower base - the GDP per capita of much of the advanced economies is $37,500 compared to just $1,845 for frontier markets and $2,390 for emerging markets (RBS, 2010). In the 1990s, an average annual GDP a typical growth of frontier market was 6.3% and almost 8% in 2000s (Hansakul and Wollensak, 2012). Generally speaking, emerging and frontier markets are gaining a higher share of global GDP while advanced countries contributions are decreasing over time. According to World Bank, in 2011 an average GDP growth rate was observed 4.9% in the case of frontier markets, while the 10 largest advanced economies experienced only 1.6%.

Even in this triple dip recession time, when advanced economies and even large emerging markets such as China and India’s economic growth are slowing down, continued strong economic growth rate is observed in frontier markets. Political unrest, corruption, natural disasters, lack of transparency, illiquidity, underdeveloped infrastructure, weak financial markets and institutions are the key barriers for economic success. State ownership limits competition in the banking sector also count as a shortcomings of these economies. Despite having these problems, energy wealth, low labour costs and trade concessions are the main competitive advantages of frontier markets. A larger, younger and cheap labour force (compared with advanced and emerging economies) is considered as one of the driving factors of these markets. The average age of the 2 billion people living in frontier market economies is 30.2 compared to 40.5 for the 1 billion living in advanced countries[10]. These markets are still in their early stages of economic development. However, some investors consider these economies to be an attractive investment opportunity for long-term economic growth, with strong return potential but with greater risk. Frontier markets are often characterised as being risky, highly volatile and inefficient. Recent policy developments have made it easier to invest in these previously overlooked economies. However, many investors argue that the risks and illiquidity of these markets may outweigh any potential benefits.

The MSCI developed frontier market indices by consists of 31 countries[11] across the world. MSCI uses economic development, size and liquidity and market accessibility criteria to determine the market classification. An investment in the frontier markets generates exposure to these countries, which has the potential to be the central drivers of global growth in the future. Investing in frontier markets provides an opportunity to gain exposure to markets that have recently been opened up to foreign investment. Foreign investors prefer to invest in the frontier markets because of the low correlation with advanced and emerging world stock markets, which ultimately help the investors to improve the diversification in their portfolios. However, high rates of inflation may present additional risk for the investors. The average inflation rate of MSCI frontier countries is 6% compared with 3.8% in MSCI emerging markets and 2.9% in MSCI advanced markets (except USA). For example, in Bangladesh, the inflation in 2012 is 9.15%. The existence of potential hyper-inflation could be a threat in terms of encouraging the foreign investment in these countries.

[10] IMF, World Economic Outlook Database.
[11] Americas (Argentina, Jamaica and Trinidad & Tobago), Europe and CIS (Bosnia Herzegovina, Bulgaria, Croatia, Estonia, Lithuania, Kazakhstan, Romania, Serbia, Slovenia and Ukraine), Africa (Botswana, Ghana, Kenya, Mauritius, Nigeria, Tunisia and Zimbabwe), Middle East (Bahrain, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia and United Arab Emirates), Asia (Bangladesh, Pakistan, Sri Lanka and Vietnam).

Although many researchers observe that exchange rates are an important indicator of the economic welfare of any country, most of the studies involving forecasting exchange rates tended to be focused on advanced and to some extent BRICS emerging markets (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). However, studies with frontier markets are almost non-existent. Therefore, a prime focus of this study is to investigate the frontier market exchange rates to fill a major gap of the literature.

1.3 The Importance of Forecasting Exchange Rates

Forecasting exchange rates has been of long interest to economists and policy makers. Forecasting is useful because it can reduce uncertainty and leads to better decision. Exchange rates are one of the key variables for the forecasting growth in many economies. It is therefore important to forecast exchange rates and associated volatility, since high volatility create major obstacles to economic growth of any country. Exchange rates and their associated volatility play significant roles in risk management, portfolio management, foreign investments, academic literature and any fields related to FOREX markets. Forecasting accurate exchange rate volatility is essential for derivatives pricing, asset allocation and dynamic hedging policies. Accurate forecasts can also act as an input for Value-at-Risk models. Forecasting is a critical element of financial and managerial decision processes (Majhi and Sahoo, 2009). Moosa (2000) identified following problems requiring exchange rate forecasting- spot speculation, uncovered interest arbitrage, long-term portfolio investment, hedging transaction exposure, measuring and hedging of economic exposure, hedging translation exposure, short- and long-term financing and investment decision, pricing and strategic planning and foreign direct investment.

Exchange rates are determined by the market forces. Market supply and demand drives exchange rates up and down every day, imposing risks on participants in the foreign exchange markets. Therefore, accurate exchange rate forecasts would allow businesses, investors and policy makers to make effective decisions when conducting international business and economic policies. Exchange rates are considered as the single most important economic variable for many economies, since they determine the international balance of payments (Levich, 2001). Exchange rates represent a key financial variable that affects decisions made by foreign exchange investors, exporters, importers, bankers, businesses, financial institutions, policymakers and tourists in the developed as well as developing world. Exchange rate fluctuations affect the value of international investment portfolios, competitiveness of exports and imports, value of international reserves, currency value of debt payments and the cost to tourists in terms of the value of their local currency. Movements in exchange rates thus have important implications for the economy's business cycle, trade and capital flows and are therefore crucial for understanding financial developments and changes in economic policy.

Accurate forecasts of exchange rates play an important role in many aspects of International Finance. For example, the evaluation of foreign borrowing or investment opportunities, forecasts of future spot exchange rates, short-term hedging, operating and strategic decisions and completive analysis (Levich, 2001). The business environment is constantly changing and it has become increasingly complex in recent decades. International firms need to forecast exchange rates in order to minimise uncertainty and identify and evaluate risk causing by exchange rates. It is important for international traders to forecast exchange rates in order to minimise risks caused by fluctuation of exchange rates. Due to globalisation, multinational (MNC) and transnational (TNC) corporations extend their business operations in the fastest growing emerging and frontier countries in order to gain competitive advantages over their rivals. Although MNC and TNC enjoyed many benefits from economic growth of these economies, recent financial crises highlight the instability of these growing economies. Therefore, many industrial leaders have called for greater transparency of the foreign exchange markets and an enhancement the predictability of currency exchange movements (Chen and Leung, 2003). It is, therefore, important for the MNC and TNC to understand exchange rate behaviour of these developing nations.

A useful measure of uncertainty concerning a country's economic environment is its exchange rate volatility. Forecasts of exchange rate volatility are important for the policy makers so that they can make effective decisions. Accurate forecasts of volatility might provide an early signal of future crises. Forecasts would help the policy makers in the design and implementation of more suitable exchange rate policies to tackle the upcoming economic crisis. Kaminsky and Reinhart (1998) and Perry and Lederman (1998) argued that large deviations of a nominal exchange rate from its purchasing power parity (PPP) level have proved to be one of the good indicators of a forthcoming crisis. In such cases, decision makers might review the existing exchange rate policy and implement the new policy such as the consideration of joining in a common exchange rate regime to maintain the macroeconomic stability (Ogawa, 2002a). Wypolz (2002) also argued that collective exchange rate targeting would help to promote macroeconomic stability and further economic integration in Asian economies. Forecasting exchange rate volatility can also be used as an important factor to determine the best exchange rate regime for a country (Hernandez and Montiel, 2001) and to evaluate whether monetary union is optimal for that country (Wyplosz, 2002).

It is important for policy makers to understand movements of exchange rates in order to keep inflation stable and maintain higher economic growth (Pandaa and Narasimhanb, 2007). It is necessary to understand which macroeconomic forces influence currency exchange rates, because variations in exchange rates have different implications for a country's economy and may require different policy responses (Dodge, 2005). For instance, a home currency may be responding to an increase in the foreign demand for goods and services which would lead to an increase in home country's aggregate demand. In such a case, the monetary policy response would be muted unless it facilitated the reallocation of resources between traded and non-traded sectors. Alternatively, an appreciation of the home currency may simply reflect a general weakening of the U.S. dollar. Therefore, easing monetary policy in order to offset the reduction in the foreign demand for home country's goods and services might be an issue for consideration (Bailliu and King, 2005).

Forecasting of exchange rates and their volatility are also important for central banks to intervene in the market. Accurate forecasts permit the central bank to understand movement of exchange rates and their consequences (Pandaa and Narasimhanb, 2007). It is important for the central bank to obtain internal forecasts to evaluate the fluctuation of exchange rates. It could reduce the risks of fluctuations if forecasts are generated via appropriate techniques. Policy makers are interested in the efficiency of foreign exchange markets. The efficient foreign exchange markets indicate that the level of exchange rates and associated volatility reflect underlying economic fundamentals. According to Pierdzioch *et al.* (2012, 974) "historical experience suggests that exchange rates are subject to recurrent large swings that do not necessarily reflect changes in fundamental macroeconomic conditions". Speculation, insider trading, corruptions, central bank's intervention and government policies may be the reasons to create the market inefficient.

1.4 Methodological Approaches

In this present study, three time series models, namely univariate volatility models, exponential smoothing models and Naïve 1 (or the no change model) are used for forecasting. The prime reason for considering volatility models is that they have been applied to a wide range of time series analyses, but applications in Finance have been particularly successful (Engle, 2001). However, the application of volatility models in emerging and frontier currencies has received far less attention in the literature. An objective of applying volatility models is to provide a volatility measure (called the *conditional variance*) that can be used in financial decision-making scenarios such as risk analysis, portfolio selection and derivative pricing (Engle, 2001). Exponential smoothing models are widely used to produce forecasts for the level of a time series (Gardner, 1985). Although these models have potential to forecast the exchange rates, there are few applications to be found in the field of foreign exchange. Finally, the Naïve 1 model is included in forecasting studies since it acts as yardstick with which other time series models may be compared (McKenzie and Mitchell, 2002).

This research also applies the autoregressive distributive lag (ARDL) approach to cointegration (Pesaran and Shin, 1995; 1999; Pesaran *et al.*, 1996 and Pesaran, 1997) to investigate the long-and short-run relationships of exchange rates with macroeconomic fundamentals. Cointegration relationships can be determined with relatively small samples using ARDL approach (Ghatak and Siddiki, 2001; Narayan, 2005). Therefore, countries involving small samples, especially emerging and frontier countries can be included for the first time in such analyses (Hammoudeh *et al.*, 2012). The ARDL model is rarely applied to the analysis of exchange rate series. Hence, this study permits an extensive assessment of the utility of the ARDL approach.

Last but not the least, combination models are applied to forecast the exchange rates. The prime reason behind combining time series and causal forecasting techniques in this study is straightforward: no single forecasting method is appropriate for all situations. Single model may be optimal conditional upon a particular sample realisation, information set, model specification or time period. It is possible to overcome the weakness of a forecasting model under particular conditions by implementing a combination of methods. Although the theoretical literature (Bates and Granger, 1969; Granger and Ramanathan, 1984 and Clemen, 1989) suggests that appropriate combinations of individual forecasts often have superior performance, such methods have not been widely exploited in the empirical exchange rate literature (Sarno and Valente, 2005; Altavilla and Grauwe, 2010).

1.5 Research Objectives

The subject matter of this research is to investigate the exchange rates of advanced, emerging and frontier markets against the U.S. dollar. In order to investigate this phenomenon the following research objectives have been identified:

- To check whether the volatility is present in advanced, emerging and frontier countries exchange rate series.
- To examine whether the traditional univariate volatility models, used widely and successfully in the literature in relation to advanced countries, could perform equally well in emerging and frontier countries.
- To investigate the impacts of good and bad news shocks upon advanced, emerging and frontier markets currencies exchange rates.
- To compare the performance of individual time series models for predicting exchange rates.
- To investigate the long- and short-run relationships of exchange rates with macroeconomic fundamentals and subsequently to examine exchange rates' speed of return to equilibrium.
- To compare the forecasting performance of a causal econometric approach with time series approaches in the context of advanced, emerging and frontier markets exchange rates.
- To investigate which models (time series, econometric or a combination of these methods) is superior in terms of predictive power of exchange rates.

1.6 Structure of the Thesis

The reminder of the thesis is structured as follows. Chapter 2 provides a comprehensive review of the relevant and significant literature on forecasting in the field of foreign exchange markets. The literature on application of time series models and ARDL-cointegration techniques for forecasting exchange rates is examined. A review of factors affecting exchange rates is presented. Literature on combination of forecasts methods for predicting exchange rate is also reviewed. Finally, the data sources used in the present study are described.

Chapter 3 applies time series models to forecasting exchange rates. In the first section, the theoretical background and results of the unit root test (with and without structure breaks) are discussed. In the second section, the theory and application of volatility models in advanced, emerging and frontier markets are presented. The theory and results of the rarely applied exponential smoothing models to the forecasting of exchange rates are reported. This is followed by the results of applying the Naïve 1 model. This chapter ends with summary and policy implications of time series models in the context of advanced, emerging and frontier market economies.

Chapter 4 presents the ARDL-cointegration analyses. This chapter starts with the explanation of independent macroeconomic variables that are used in the cointegration analyses applied to countries at varying stages of economic developments. Long-run results from cointegration of forecasting exchange rates in advanced, emerging and frontier markets are reported. Short-run results of these three markets are presented. The Granger Causality test results are reported followed by a comparison of forecast performance between time series and ARDL-cointegration models. Finally, a summary and policy implications are presented.

Chapter 5 analyses application of combinations of time series models and the causal ARDL-cointegration model for forecasting exchange rates. Results from combination methods of forecasting exchange rates for the three markets are discussed followed by a summary and policy implications.

Chapter 6 provides an overall summary, conclusions and policy implications of the empirical research presented in this thesis.

Chapter 2

Forecasting in the Field of Foreign Exchange Markets

The purpose of this chapter is to review the literature on forecasting exchange rates. This will involve the major contributions both academic and from a policy viewpoint. This chapter also identifies gaps in the exchange rate literature and describes the contributions of this study. FOREX market has become one of the most heavily researched areas in the Economies and Finance disciplines over the last three decades. The behaviour of exchange rates has received much attention among academics and practitioners. It is universally believed that forecasting exchange rates is one of the most difficult and challenging, yet most important tasks for business, government and other related parties such as arbitragers, speculators and hedgers. These parties often use different financial instruments (e.g. derivatives contracts) to minimise exchange rate risk. This requires forecasting exchange rates of not only the trading partner countries but also of other global currencies. Moreover, the recent international economic crisis has highlighted the need for banks to implement effective systems for estimating market risks (Pacelli, 2012). The international activity of the largest banks and the increasing exchange rate volatility emphasises the importance of exchange rate risk. Therefore, the effective use of forecasting models is required banks to manage this risk.

The determination of exchange rates is an important issue in International Finance. Due to the competitive and dynamic nature of the currency markets, it is difficult for the academics and practitioners to choose appropriate methods for forecasting exchange rates. Two different approaches called technical and fundamental analyses are used to forecast exchange rates. Technical analysis is based not on economic theory, but on chart analysis, which generates results by evaluating the recurring patterns in graphs of exchange rate movements. The success of this approach depends on the forecaster’s ability to discover patterns that repeat themselves. Fundamental analysis describes the fact that there are some economic variables (or fundamental) that influence the exchange rate determination. The variables used typically include money supply, income, interest rates, price level changes and current account. Its success depends on the correct specification of underlying economic relationships among macroeconomic variables that influence exchange rates. To forecast exchange rates in the short-run using fundamentals should be more difficult than to forecast in the medium and long-run. Due to incomplete information in the short-run, the market participants is to large extent based on technical analysis of short term trends or other patterns in the observed behaviour of the exchange rate (Taylor and Allen, 1992). On the other hand, the long-run behaviour of exchange rates is governed much more by fundamentals. Many successful traders combine a mixture of both approaches to generate results.

There is an ongoing debate about exchange rate predictability. A large number of methods (e.g. time series, econometrics or combination of both) are suggested in the literature for forecasting exchange rates. Meese (1990) and Frankel and Rose (1995) reviewed the empirical literature by focusing on whether theoretical and econometric models of exchange rate determination produce superior descriptions of the exchange rate series. The pioneering study of Meese and Rogoff (1983) showed the superiority of the random-walk model in out-of-sample exchange-rate forecasts. Applying fundamental as well as technical approaches, there is some evidence that exchange rate movements may be predictable for a longer time horizons using advanced econometric techniques for time series (Osinska, 2010). Assessing future changes in exchange rates with current macroeconomic data has been of long interest to international economists as well as policy makers worldwide since the seminal work of Meese and Rogoff (Groen, 2005). An interesting review on the forecasting performance of monetary approach has been produced by Neely and Sarno (2002).

Canales-Kriljenk and Habermeier (2004) summarised the earlier works on determination of exchange rates and its volatility by focusing on three principal views. First, at least over short time horizons and for countries with low inflation, exchange rate models that include macroeconomic fundamentals do not perform better than a random-walk in out-of-sample forecasting (Meese and Rogoff, 1983; Rogoff, 1999). Secondly, macroeconomic fundamentals play an important role in explaining the behaviour of exchange rates. Some authors hold that these fundamentals are important only in the long-run but have little to offer in explaining short-run movements, while others believe that macroeconomic fundamentals have explanatory power both in the long-and the short-run. Thirdly, neither the macroeconomic fundamentals nor the random-walk model have the power to explain the exchange rate behaviour in the short run. Lyons (2001) described that in the short-run, the exchange rate movements are explained by the market's microstructure factors, including inventory management and information aggregation by foreign exchange dealers. The microstructure approach suggests that non-dealers learn about fundamentals affecting the exchange rates. Their knowledge is reflected when they place the orders with dealers. Dealers then learn about fundamentals from the order flow. The outcome of this two-stage learning process results in the formation of a price. However, very limited research has been conducted using the microstructure theory because of the lack of data on customer order flow. These data are nearly non-existent in the cases of emerging and frontier markets economies.

In the last three decades or so, exchange rate economics has seen a number of important developments, with substantial contributions to both the theory and the empirical understanding of exchange rate determination. Important developments in econometrics and the increasing availability of high-quality data have also stimulated a large amount of empirical work on exchange rates (Neely and Sarno, 2002). The majority of the research on exchange rates has been conducted so far for the advanced or developed currencies. Very little attention has been given on emerging and frontier market currencies (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). Therefore, a prime focus of this study is on exchange rate forecasts of advanced, emerging and frontier markets currencies against the U.S. dollar in order to fill a gap of the literature. Furthermore, a majority of studies has concentrated on bilateral exchange rates between advanced countries rather than exchange rates of emerging versus advanced countries and frontier versus advanced countries. This study contributes to the existing literature by assessing the utility of forecasting techniques in these different contexts. The next section provides a review of application of time series models for forecasting exchange rates.

The reminder of the chapter is structured as follows. Section 2.1 provides a comprehensive review of the relevant and significant literature on application of time series models in the field of foreign exchange markets. The literature on econometric models for forecasting exchange rates is presented in Section 2.2. Literature on combination of forecasts methods for predicting exchange rate is also reviewed in Section 2.3. Finally, the data sources used in the present study are described in Section 2.4.

2.1 Forecasting of Exchange Rates via Time Series Models

The Bretton Woods fixed exchange rate system collapsed in 1971. By 1973, major world economies had been allowed to float freely against the dollar. Since then, both nominal and real exchange rates have experienced periods of substantial volatility. Volatility modeling and forecasting have attracted much attention in recent years, largely motivated by its importance in financial markets (Xiao and Aydemir, 2007). Volatility models have been very popular in empirical research in Finance since the early 1990s. The ARCH (autoregressive conditional heteroscedasticity) literature has developed rapidly since the release of Engle's seminal paper (1982) and that of Bollerslev (1986). A considerable amount of literature has been published on modelling volatility. Many studies attempt to compare the accuracy of various models in terms of producing out-of-sample forecasts. An excellent review of volatility forecasting can be found in Poon and Granger (2003). They examined 93 research papers and concluded that volatility models are very useful in measuring and forecasting volatility. ARCH-type models have also been reviewed by, Bollerslev *et al.* (1992), Bollerslev *et al.* (1994), Bera and Higgins (1993) and Diebold and Lopez (1995). Each of these contributions to the ARCH family has concentrated on refining both the mean and variance equations to better capture the stylised characteristics of the time series. The standard class of ARCH family models has certainly been extensively applied to exchange rate data, see, for example Bollerslev (1987), Hsieh (1988), Hsieh (1989), Engle *et al.*, (1990), Baillie and Bollerslev (1989, 1990), Diebold and Nerlove (1989), Bollerslev (1990), Engle and Gonzalez-Rivera (1991), Mundaca (1991), Higgins and Bera (1992), Drost and Nijman (1993), Bollerslev and Engle (1993), Neely (1993), West and Cho (1995), Byers and Peel (1995), Hu and Tsoukalas (1999), Johnston and Scott (2000), Kazantzis (2001), Chong *et al.* (2002), Mapa (2004), Alberg *et al.* (2006), Hussein and Jalil (2007), Umar (2010), Chortareas *et al.* (2011), Vee *et al.* (2011) and Pacelli (2012).

All financial markets react strongly to unexpected news or developments and the foreign exchange markets are no exception. The FOREX market appears to respond to the arrival of new unanticipated information in a rather chaotic manner. The history of floating exchange rates in the 1970's had been characterised by periods of extreme turbulence and volatility. This empirical evidence led Frenkel (1981) among others to note that exchange rates affected by news. News in this context is taken to mean any new information, which is of relevance to exchange rate. For example, news on key economic variables such as money supply, interest rates, real outputs, inflation rates etc. play an important role in exchange rate determination. News on oil prices can also be important for currencies because oil contributes a significant proportion of exports (Baillie and McManon, 1989). Generally speaking, news can be economic (e.g. announcements of economic data such as trade figures), internal to the market (e.g. deals and quotes reported over electronic screens), political news or any other private or public information (e.g. the customers' orders arriving at a given FOREX dealer). It is common in the literature for variations in the arrival of news in the FOREX market to be measured directly from the date on the volatility of prices/returns (see, for example, Engle and Ng, 1991). In one sense, this approach assumes that news drives volatility in the FOREX market. According to Moosa (2000, 30) "changes in exchange rates are thought to be unpredictable because they are determined by news that is unanticipated changes in the fundamental factors determines the exchange rate. Exchange rates are supposed to be as volatile or as stable as macroeconomic fundamental".

Volatility models can also accommodate bad or good news effects, which is known as *leverage effects* (Black 1976). Symmetric volatility models hypothesise that the impacts of good and bad news are of the same magnitudes whereas, the asymmetric models examine if bad news has greater impacts than good news. Longmore and Robinson (2004) applied volatility models on Jamaican dollar for the period 1998-2003 and diagnosed asymmetric effects on exchange rate. Balaban (2004) investigated the out-of-sample forecasting accuracy of the symmetric and asymmetric conditional variance models for the Deutsche mark/US dollar exchange rate volatility. In that study, daily exchange rate returns between 2 January 1974 and 30 December 1997 period were used for a 72-month rolling estimation procedure and the forecasts' performances were evaluated with respect to mean error (ME), mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE) measures. The results of Balaban (2004) suggested that although all the models are systematically over-predict volatility, the standard symmetric volatility model appeared as relatively good forecasts of monthly exchange rate volatility.

Edrington and Guan (2005) showed marginally smaller forecasting errors for Japanese yen/U.S. dollar using asymmetric volatility model relative to symmetric model. Sandoval (2006) studied seven Asian and emerging Latin American countries and reported the asymmetric effects on emerging exchange rates. Laakkonen and Lanne (2008) investigated the impact of positive and negative macroeconomic US and European news announcements in different phases of the business cycle on the high-frequency volatility of Euro/U.S. dollar exchange rate. They concluded that bad news increases volatility more than does good news. Kim (2008) found asymmetry in the Korean won/U.S. dollar, Korean won/Japanese yen, Korean won/Chinese yuan and Japanese yen/U.S. dollar. Olowe (2009) investigated the Nigeria-USA exchange rate by applying asymmetric volatility models and reported the existence of statistically significant asymmetric effect. Abdalla (2012) applied both symmetric and asymmetric volatility models to capture volatility clustering and leverage effects of daily observation of 19 Arab currencies. The author concluded that asymmetric volatility models provide evidence of leverage effect for all currencies except the Jordanian dinar.

A prime reason for applying time series models to foreign exchange markets is to predict the movement of exchange rates so as to provide valuable information for investors. Thus, many researchers and business practitioners have developed a variety of forecasting methods. The exponential smoothing model has been found to be an effective forecasting method (Gardner, 1985). This model has less technical modelling complexity than other time series models and thus makes it more popular in practice. Since Brown (1959) began to use simple exponential smoothing to forecast demand for inventories, exponential smoothing models have been widely used in business, Economics and Finance (e.g. Winters, 1960; Lilien and Kotler, 1983; Gardner, 1985; Sharda and Musser, 1986; Alon, 1997, Mahmoud *et al*., 1990; Foster *et al.*, 1992; Leung *et al.,* 2000; Taylor, 2004a; Balaban and Bayar, 2004; Taylor, 2004b and Padhan, 2012). Gardner (2006) presented the empirical results of 66 papers involving exponential smoothing models published between 1985 and 2006. According to Lai *et al.* (2006, 494) “the exponential smoothing model is regarded as an inexpensive technique that gives forecasts that is ‘good enough’ in a wide variety of applications”.

There is not much literature dedicated to the application of exponential smoothing model to exchange rate series. An application by Borhan and Hussain (2011) investigated the forecasting performance of different models including an exponential smoothing model in relation to monthly Bangladeshi taka/U.S. dollar rate. They concluded that Holt’s linear exponential smoothing model outperformed other models. Maria and Eva (2011) examined the forecasting performance of exponential smoothing models in the context of Romanian leu versus the Euro, United States dollar, British pound, Japanese yen, Chinese renminbi and the Russian ruble. These authors concluded that exponential smoothing models outperform the ARIMA models in some cases. Li (2010) used linear exponential smoothing model to create a new kind of nonlinear combination method to forecast exchange rate. Yu *et al.* (2007) reported that the exponential smoothing model was second best model in comparison with their hybrid models for forecasting exchange rates of Euro/U.S. dollar and Japanese yen/U.S. dollar. Dheeriyaa and Raj (2000) applied different exponential smoothing models to forecast the exchange rates of emerging countries. This study fills the gap of the literature by applying the exponential smoothing models in exchange rates series.

The Naïve 1 (no change model) time series model is often used as a benchmark model to compare the forecasting performance of different models in the Finance literature (e.g. Berga *et al.*, 2000; Thomakos and Guerard Jr., 2004 and Trück and Liang, 2012). This model is also used as a yardstick model to compare the forecasting performance of different models in exchange rate literature. For example, Dunis *et al.* (2008) used the Naïve model as one of the benchmark models for modelling the Euro/U.S. exchange rate. Newaz (2008) applied Naïve models along with other time series models to forecast the Indian rupee/SDR (special drawing rights) and noted that the Naïve models ranked third in this forecasting exercise. Khalid (2008) compared the forecasting performance of exchange rate models against the Naïve random walk model for the three developing countries- China, Pakistan and India. The author reported that model based on macroeconomic fundamentals worked best for the developing countries than the Naïve random walk model. Meade (2002) investigated the short-term foreign exchange forecasting accuracy of different methods including a Naïve model. The author concluded that, the accuracy of two to ten periods' ahead forecasts derived from linear and nonlinear models were similar to a no-change forecast. The next section provides a review of application of econometric models for forecasting exchange rates.

2.2 Forecasting of Exchange Rates via Econometric Models

It is important that non-stationary variables are treated in a different way than stationary variables when looking at financial data over time. Critically, if non-stationary variables are entered into regression-based analyses, the researcher may well face "the spurious regression problem". This problem occurs when two or more variables are following similar trends over time. In this instance, standard regression methods will produce results that superficially look good (e.g. high coefficient of determination, significant coefficients etc.) but are actually valueless. This problem gave rise to the concept of cointegration which has been one of the most important areas of research in time series econometrics since the seminal papers of and Granger (1983) and Engle and Granger (1987). Cointegration has had wide application in the analyses of general Economic data and the text by Engle and Granger (1991) contains a collection of papers that have been influential in the development of the topic. The essence of cointegration is that most time series in Economics and Finance are non-stationary, but sometimes, series are observed to move together over time. This implies that the series are bound by some relationship in the long-run. A cointegrating relationship may be considered as a long-run or equilibrium situation. If such an equilibrium relationship exists, cointegrated variables may deviate from equilibrium in the short term, but they will return to the equilibrium position in the long-run. If a cointegrating relationship does not exist, then the variables at hand are at liberty to wander without bound.

Generally speaking, there are three cointegration methods that have been historically employed in the Finance literature. These methods are the Engle-Granger 2-step (1987), method, the Engle-Yoo 3-step (1987) method and Johansen (1988) method. The Engle-Granger 2-step method requires all of the study variables to be stationary after first differencing. The cointegrating regression is then estimated via ordinary least squares. The method has the drawback that although the parameter values can be estimated in value, no inferences can be made from these estimates. The Engle-Yoo 3-step (1987) method starts as per the aforementioned Engle-Granger approach, but then introduces a third step whereby updated estimates of what is called the cointegrating vector and its standard errors are obtained. Due to its relative complexity and the fact that it suffers from the same deficiency as the Engle-Granger approach, the Engle-Yoo is the least used method of cointegration in the literature. A procedure that is superior to both methods is the Johansen (1988) method. The Johansen approach to cointegration is the most widely applied method of the three. Its distinct advantage is that it permits the testing of hypotheses concerning the cointegrating relationship. However, it should be noted that all three methods require pre-testing of the study variables in order to assess the level of integration. Such pre-testing is usually via the Augmented Dickey-Fuller (ADF) test or the Phillips-Perron (PP) test.

It is well-known that both the ADF and PP tests are not particularly robust (DeJong, *et al.*, 1992 and Schwert, 1989). These approaches suffer from serious flaws as discussed by Pesaran *et al.* (2001). Therefore, this research applies a fourth method - the *autoregressive distributive lag (ARDL)* approach to cointegration, which requires no such pre-testing (Johnston and DiNardo, 1997). This model was popularised by Pesaran and Shin (1995; 1999), Pesaran *et al.* (1996) and Pesaran (1997). As was mentioned earlier, this approach does not involve pretesting variables, which means that the test for the existence of relationships between variables is applicable irrespective of whether the underlying regressors are purely I(0), purely I(1) or a mixture of both. Moreover, more efficient cointegration relationships can be determined with small samples using ARDL approach (Ghatak and Siddiki, 2001; Narayan, 2005). Therefore, countries involving small samples, especially emerging and frontier countries' can be included in analysis (Hammoudeh, *et al.*, 2012). This model is rarely applied to the analysis of exchange rate series. Hence, this study permits an extensive assessment of the utility of the ARDL approach.

2.2.1 ARDL Cointegration

The application of ARDL model is well researched in several disciplines[12]. In the Finance literature, the ARDL model has been applied in several areas such as stock markets (Hammoudeh *et al.*, 2012; Fernández-Serrano and Sosvilla-Rivero, 2003; Hazem, 2005; Belke and Polleit, 2005; Satya and Girijasankar, 2003; Samitas and Kenourgios, 2007; Ma and Tian, 2009), equity markets (Tze-Haw and Chee Wooi, 2003; Kanas and Kouretas, 2005, James and Agus Eko, 2003) and international trade (Alam, 2003; Salvatore and Musella, 2004; Emran and Shilpi, 2001; Katsimi and Moutos, 2006; Hoque and Yusop, 2010). Well-known Financial cointegration studies include the study of bubbles in asset prices (Campbell and Shiller, 1987), the predictability of stock prices (Lettau and

[12] Defence (Lee & Chang, 2006; Kollias & Paleologou, 2003, Sezgin & Yildirim, 2002); real estate (Rapach & Strauss 2009); sports (Narayan & Smyth, 2003); food and beverage (Blake & Nied, 1997); tourism (Bankole, *et al.* 2010; Chaitip & Chaiboonsri, 2009) and economics. More specifically on inflation (Chaudhury *et al.*, 2011; Christev, 2005); money demand (Baharumshah *et. al*, 2009), unemployment (Alberto & James, 2008; Karanassou & Snower, 2007), Fisher effect (Ekaterini, 2005), interest rate (Garcia, 2004; Weth, 2002); wealth consumption (Blake, 2004); fiscal policy (Fernando & Santiago, 2006); growth (Mah, 2005; Davis & Hu, 2004); house market (Katrakilidis and Trachanas, 2012).

Ludvigson, 2001), the consumption-income relationship (Campbell, 1987), the role of productivity shocks in the post-war U.S. economy (King *et al.*, 1991), the demand for money (Johansen and Juselius, 1990) and the term structure of interest rates (Hall *et al.*, 1992).

One of the earliest applications of cointegration to exchange rate data was by Baillie and Bollerslev (1989). They applied the method to the seven major spot foreign exchange rates. This aroused interest in the statistical advantages of using cointegration-based error-correction (ECM) models over Box-Jenkins methods. They found that ECM containing more information dominated univariate models. Fiess and MacDonald (1999) studied the structural relationships between daily high, low and closing prices of German marks and Japanese yen against the U.S. dollar. Their results suggested that cointegration models outperform the random walk model at one-day-ahead forecast based on root mean square error (RMSE) and were demonstrated to have good prediction ability. Connolly and Limratanamongkol (2000) reported strong evidence of cointegration between the exchange rate series and the expected rates series. They suggested that at the shortest forecast horizon, the error-correction term dominates all other determinants of changes in expected exchange rates and indicates a sensible response by market participants to past mistakes in forecasting future rates. At longer forecast horizons, error-correction remains very important, but lagged changes in actual and expected rates also play a role. Trapletti *et al.* (2002) applied cointegration analysis on the U.S. dollar/German mark, U.S. dollar/Japanese yen and German mark/Japanese yen. They concluded that cointegration models generate additional information that allows for improving short-term forecasts.

A major application of cointegration has been in the context of the theory of Purchasing Power Parity (PPP) (Froot and Rogoff, 1995; Sarno and Taylor, 2002; Brooks, 2004). The basic proposition of PPP is that exchange rates adjust in order to preserve purchasing power parity; the price of a bundle of goods, expressed in common currency, should be the same across countries. PPP implies that the ratio of relative prices in two countries and the exchange rate between them should be cointegrated, assuming no arbitrage. An interesting study was conducted by Frankel *et al.*, (2002) on the choice of exchange rate regime and global transmission of interest rates. They used a large sample of developing and industrialised economies during 1970-1999. In most cases, they could not reject full transmission of international interest rates in the long run, even for countries with floating regimes. Barlow and Radulescu (2002) also used cointegration analysis to test PPP for the Romanian leu against the U.S. dollar. Zubaidi *et al.* (2004) investigated the behaviour of real exchange rates of six East-Asia countries in relation to their two major trading partners - the U.S. and Japan. They used monthly frequency data from 1976 to 2002 and the ARDL-cointegration procedure to test for the long-run PPP hypothesis. Their findings revealed that the East Asian countries are returning to some form of PPP-oriented rule as a basis for their exchange rate policies.

Khan and Zabir (2005) investigated both the long- and short-run relationships between real money balances, real income, inflation rate, foreign interest rate and real effective exchange rate with reference to Pakistan over the period 1982Q2-2002Q4 using ARDL approach. Their results indicated that in the long-run, real income, inflation rate, foreign interest rates and real effective exchange rate have significant impacts on real money balances in Pakistan. Nieh and Wang (2005) re-examined the Dornbusch's (1976) sticky-price monetary model to exchange rate determination by employing both conventional Johansen's (1988, 1990, 1994) maximum likelihood cointegration test and the ARDL bound test by Pesaran, Shin and Smith (2001) for the monthly data of Taiwan over the period 1986:01 to 2003:04. They concluded that there is no long-run equilibrium relationship between exchange rates and macro fundamentals. Dunaway *et al.* (2006) assessed the robustness of alternative approaches and models commonly used to derive equilibrium real exchange rate estimates. They used the China's currency to illustrate their analysis. Another study was conducted by Karfakis and Phipps (2000) on Australian's net export and the Australian dollar effective exchange rate.

Verheyen (2012) examined the effect of U.S. dollar/Euro exchange rate volatility on exports from 7 Euro zone countries to the U.S. and concluded that exchange rate volatility has a negative impact on exports. Walter *et al.* (2012) investigated the short- and long-run effects of exchange rates, income, interest rates and government spending on bilateral trade of four commodity groups between the U.S. and each of the other 6 members of the G-7. Applying the ARDL model, they concluded that U.S. imports and exports are relatively insensitive to changes in bilateral exchange rate in both the short- and long-run. Alam and Ahmed (2010) examined the import demand function for Pakistan covering from 1982:Q1 to 2008:Q2 by employing an ARDL approach. Their results supported the hypothesis that in Pakistan, there exists a long-run relationship between import demand, real economic growth, relative price of imports, real effective exchange rate and volatility of real effective exchange rate. Sabuhi-Sabouni and Piri (2008) studied the effects of short and long-run fluctuations of exchange rate on saffron export price. The fluctuations of exchange rate affected the saffron export prices more than other variables under study.

Aguirre *et al.* (2003) examined the relation between exchange rate volatility and the volume of exports, using Brazilian data. They concluded that exchange rate volatility had a significantly negative effect on Brazilian manufactured exports in the period 1986-2002. Using the ARDL bounds testing method to cointegration, De Vita and Abbott (2004) observed that short term volatility in exchange rate does not affect UK exports to the EU both at the aggregate and sectoral levels. However, their study revealed that there are significant negative effects of long term volatility on UK exports to EU. Ibarra (2011) studied the effect of the different types of capital flows on the real exchange rate in Mexico. The author concluded that not only portfolio investment but also FDI can strongly appreciate the recipient country's currency. Sari *et al.* (2010) examined the co-movements and information transmission among the spot prices of four precious metals, oil price and the U.S. dollar/Euro exchange rate. They reported that precious metal markets respond significantly to a shock in any of the prices of the other metal prices and the exchange rates.

This section illustrates that the ARDL model has become very popular in Economics and Finance literature. However, very few applications have been conducted in the field of nominal exchange rate modelling and their speed to return to equilibrium. Moreover, the majority of the cointegration research has been conducted so far for advanced or developed currencies. Very little attention has been given on emerging and frontier markets' currencies and their long- and short-term relationship with other macroeconomic variables (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al*., 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). A major focus of this study is to investigate the long- and short-run relationship of exchange rates with its main determinants for advanced, emerging and frontier markets' currencies against the U.S. dollar, which will help to fill the gap of the existing literature. Relative to other areas of financial research (e.g. stock markets, equity markets, international trade, etc.), the ARDL-cointegration model has received less attention as a forecasting model. This gives an opportunity of assessing the utility of this model in the context of exchange rates. Therefore, this study investigates whether ARDL-cointegration model is better than other time-series models (discussed in Chapter 3) in order to capture the exchange rates movements especially in the cases of advanced, emerging and frontier markets' currencies against the U.S. dollar to fills a gap of the existing literature. The next section reviews the factors affecting exchange rates. This will act as a basis for cointegration results presented latter.

2.2.2 A Review of Factors Affecting Exchange Rates

There is no consensus in the literature concerning the factors affecting exchange rates and their volatility (Tsen, 2010; Canales-Kriljenko and Habermeier, 2004). It is long believed that exchange rate behaviour is well described by the Naïve random walk model. Meese and Rogoff (1983) show that none of the structural models (Frankel-Bilson's flexible-price monetary model, Dornbusch-Frankel's sticky-price monetary model, Hooper-Morton's (1982) sticky-price asset model) outperform a simple random walk model. However, many empirical studies show that the monetary model generates better out-of-sample prediction than the random walk model (Zhang, 2003). Since the seminal contribution of Frenkel and Johnson (1976) the 'Monetary Approach of Exchange Rates' has remained an important research context in the area of International Finance and monetary management. The monetary approach to exchange rates hypothesises that solely contemporaneous excess supplies of money in the two trading countries determine the nominal exchange rate. Countries that follow relatively expansionary monetary policies experience a depreciation of their currencies, while countries that follow relatively restrictive monetary policies observe an appreciation. This has implications at the theoretical, empirical and policy level. It is not surprising that the monetary model of exchange rates is one of the most widely tested propositions in Economics (Islam and Hasan, 2006).

A large body of literature has been produced over the past thirty years concerning the empirical validity of the monetary model. Woo (1985) found that a reformulated monetary approach can outperform the random walk model in an out-of-sample forecast exercise. Somanath (1986) also found that a monetary model with a lagged endogenous variable forecasts better than the Naïve random walk model. McDonald and Taylor (1993, 1994) also claimed some predictive power for the monetary model. McDonald and Taylor (1993) studied the monetary model of the bilateral exchange rate of German mark and the U.S. dollar over a period of January 1976 to December 1990. Their findings supported the notion that a dynamic error correction model produces better predictive results at every forecast horizon. McDonald and Taylor (1994) used multivariate cointegration analyses and reported that an unrestricted monetary model outperforms the random walk and other models in an out-of-sample forecasting experiment for the sterling-dollar exchange rate. Baharumshah *et al.* (2009) examined the predictive power of the monetary model for the Malaysian ringgit against the U.S. dollar. Their results suggested that the monetary model outperforms the random walk model at four to eight quarter horizon.

Exchange rates are clearly influenced by a wide variety of macroeconomic fundamentals most notably, such as real GDP growth, government consumption (in percent of GDP), domestic investment, trade openness (measured by sum of export and import relative to GDP) and money supply (Amor *et al.* 2008). Carrera and Vuletin (2003) found that greater trade openness, increases per capital GDP and in terms of trade, reduce exchange rate volatility; conversely, positive monetary shocks and increase in capital inflows and in public expenditure increases this real volatility. The Foreign Exchange Consensus Forecasts (2011) revealed that relative growth, inflation differentials, trade and current account balance, interest rate differentials, equity flows and number of other factors significantly affect the exchange rates of 18 currencies against the U.S. dollar. Hvding *et al.* (2004) and Glăvan (2006) showed that level of foreign currency reserve helps to reduce exchange rate volatility. Faia *et al.* (2008) reported that political pressures affect exchange rate policies in emerging markets. Karim *et al*. (2007) and Ramus and Barry (2008) concluded that the currency exchange rate responds quickly to any surprise changes in the monetary policy. Moreover, Uddin (2006) noted that interest rates, inflation rates and balances of payment are the most important economic variables in determining exchange rate between Bangladeshi taka and U.S. dollar.

Yuan (2011) studied quarterly observations for four bilateral nominal exchange rates- the Australian dollar, the Canadian dollar, the British pound and the Japanese yen against the U.S. dollar with five sets of macroeconomic measurements- money supply, real gross domestic product, consumer price index, short-term and long-term interest rates and current account balance. The author concluded that from the modelling standpoint, no specification based on four prevailing macroeconomic models (the purchasing power parity, Mark's (1995) specification, the real interest differential (RID) model and the portfolio balance model (Hooper-Morton model) is superior to one another. Kim and Mo

(1995) used money supply, short and long-run interest rates, real wealth, cumulated trade balance and real income to generate the long-run forecast of the dollar/DM exchange rate. They reported that the random walk model outperformed the monetary structure models in the short run. However, using an error correction model, the monetary model generated better results in the long-run. Islam and Hasan (2006) used money supply, real income and interest rate to evaluate the monetary model of dollar-yen exchange rates by using the Gregory and Hansen (1996) cointegration test. Their results showed that the forecasting performance of the Monetary model outperforms random walk models. Verwij (2008) evaluated the classical monetary model, Uncovered Interest Rate Parity (UIRP) and 'Target' UIRP (TUIRP) models by using inflation rates, short term interest rates, industrial production and money supply. Montiel (1999) established that factors such as productivity growth, government spending, changes in the international environment and changes in commercial policies are important determinants of real exchange rates.

AbuDalu and Ahmed (2012) produced an empirical analysis of long- and short-run forcing variables of purchasing-power parity (PPP) for ASEAN-5 currencies- the Malaysian ringgit, Indonesian rupiah, the Philippines peso, Thailand bath and Singapore dollar against the Japanese yen. Their empirical results revealed that the domestic money supply was the significant long run forcing variable of PPP for real exchange rates. However, in the short-run, the domestic money supply for Malaysia, Indonesia, Philippines and Singapore was a significant forcing variable of PPP for countries real exchange rates. Moreover, their study reported that foreign interest rates and domestic money supply are short-run forcing variables for Thailand's real exchange rate. Apergis *et al.* (2012) explored causal links between the U.S. dollar/Euro exchange rate and three macroeconomic variables (the overall U.S. trade balance with the rest of the world, the interest rate differential between U.S. and the Euro area and the price of a barrel of oil expressed in U.S. dollars). Their results provided evidence in favour of the presence of a long-run relationship between the exchange rate and the spread between U.S. and Eurozone interest rates. Bergvall (2004) showed that amongst other factors, demand accounts for most of the long run variance in real effective exchange rate movements for Finland and Sweden, while for countries like Norway and Denmark, terms of trade and real oil price are found to be the most important determinants of long-run movement in real effective exchange rates.

Uz and Ketenci (2008) presented empirical evidence which links exchange rates to monetary variables in the newly entered ten EU members and Turkey. Using a panel version of various cointegration tests, they found a long-run relationship between nominal exchange rates and monetary variables such as monetary differentials, output differentials, interest rate differentials and price differentials. In addition, their empirical evidence showed that an error-correction framework of the out-of-sample predictability outperforms random walk after two years. Hwang (2001) used money supply, real income, short term interest rate and inflation rate to evaluate the forecast performance of the flxible-price (Frenkel-Bilson) model and the sticky-price (Dornbusch-Frankel) monetary model. Groen (2000) applied money supply, real income, price level and interest rates to verify the monetary exchange rate model as a long-run phenomenon. According to Styrin (2008, 1) " the cointegration implies that, over time, the exchange rate converges to the value determined by fundamentals such as relative money supplies, interest rate differentials etc.".

Chowdhury (2012) examined the dynamics, structural breaks and determinants of the real exchange rate (RER) of Australia. The Autoregressive Distributed Lag (ARDL) modelling results showed that a one per cent increase in terms of trade appreciates the RER between 0.96% and 1.05% in the long-run; government expenditure appreciates the RER by 0.46% to 0.53% in the long-run; net foreign liabilities appreciates the RER by 0.18% to 0.22% in the long-run; interest rate differential depreciates the RER by 0.007% to 0.01% in the long-run; trade openness depreciates the RER by 1.15% to 1.31% in the long-run and per-worker labour productivity depreciates the RER by 0.38% to 0.55% in the long-run. The author also concluded that the speed of adjustment towards equilibrium is high with short-run disequilibrium correcting by nearly 39% to 47% per quarter. Kumar (2010) identified productivity differentials, external openness, terms of trade and net foreign assets as main determinants of real exchange rate in India.

The theoretical literature suggests that real exchange rates are consistent with both external and internal balances and changes in response to permanent real shocks such as trade openness. Edwards (1989) showed that when a small closed country liberalises its trade, demand for tradables increases and demand for non-tradables decreases in response to the relative price changes (assuming that Mashall-Lerner condition holds) and that a real depreciation is necessary to maintain internal and external balances. Openness in the trade regime tends to depreciate the real exchange rate by reducing the price of non-tradables to tradables. Edwards (1989) also argued that the effects of tariffs on exchange rates are ambiguous. If tariffs improve the current account balance and increase the price of non-tradables, real exchange rate appreciates. On the other hand, real exchange rates depreciate if tariffs lead to a worsening of the current account deficit and reduce the demand for and the price of non-tradables. Therefore, the overall effect of openness is vague. Calvo and Drazen (1998), however, showed that the trade liberalisation of an uncertain duration could lead to an upward jump in consumption; hence a real appreciation will occur in the short-run. They argued that real exchange rate will depreciate only if trade liberalisation is of permanent nature, while a transitory reform could lead a real appreciation in the short run. In general, successful trade liberalisation has been associated with depreciation of real exchange rate either at the same time or beforehand (Krueger, 1978). Generally, the effect of trade openness on exchange rates is mixed. Some studies found positive influences on real exchange rate and that it depreciates after trade liberalisation (Chowdhury, 2012; Hau, 2002; Connolly and Devereux, 1995; Elbadawi, 1994; and Edwards, 1993). However, Li (2004) showed that credible trade liberalisation lead to real exchange rate depreciation but non-credible trade ones could lead to short-run real exchange rate appreciation. Nevertheless, insignificant effects of trade openness on real exchange rate also noted by Edwards (1987).

Oil prices are often considered as important determinants of exchange rates for both oil exporting and importing countries. Thus, changes in the oil price in the world market could have a significant impact on exchange rates. Askari and Krichene (2008) illustrated that oil prices are characterised by highly volatile, high intensity jumps and strong upward drift, thereby generating more volatile exchange rates. Seetanah *et al.* (2012) examined the sensitiveness of exchange rate is with respect to changes in the world oil price. They showed that exchange rate appears to be cointegrated with oil prices. Tsen (2010) examined the Malaysia ringgit/U.S. dollar exchange rate using the Monetary model. Using ARDL approach, a major finding of this study was that there is a long-run relationship between exchange rate and determinants such as money supply, relative demand, interest rate differentials and oil price. Chen and Chen (2007) showed that there is a relationship between real oil prices and real exchange rates in the G7 countries. Their results revealed that real interest rate differentials and productivity differentials have significant impacts on real exchange rates. Huang and Guo (2007) also reported that an increase in real oil price will lead to a minor appreciation of real effective exchange rate in long-run.

Some authors empirically proved that these fundamentals are important only in the long-run and not in short-run. Using both parametric and nonparametric estimation techniques, Chinn and Meese (1995) examined the forecasting performance of three structural exchange rate models for bilateral exchange rates (Canada, Germany, Japan and the United Kingdom), relative to U.S. dollar, over march 1973 to December 1990. They showed that three structural models cannot predict more accurately than a random walk model for short term horizons. However, for long run horizons (36 months), these structural models generated better result than the random walk model. MacDonald (1999) believed that macroeconomic fundamentals have explanatory power both in the long and short run. Loria *et al.* (2009) examined the Mexican peso against the U.S. dollar using the monetary model. The results of the cointegrated structural vector autoregressive (SVAR) model showed that there are robust short and long-run relationships between exchange rates and its determinants. Exchange rate behaviour is also influenced by fundamental shocks. Husted and MacDonald (1999) concluded that fundamentals instigate changes in many Asian countries' exchange rates. Baharumshah and Masih (2005) explained that monetary model produces good in-sample and out-of-sample forecasts for the Singaporean dollar and Malaysian ringgit against the Japanese yen. Moreover, Lim (1992) supported the role of fundamental factors (such as productivity, real domestic and foreign interest rates and the terms of trade) in the behaviour of the real exchange rates between the US and other G-10 countries. Nevertheless, Khalid (2008) analysed the capacity of existing exchange rate models by using the monthly data of China, Indian and Pakistan and concluded that for the developing economies, a model based on macroeconomic fundamentals performed better than the random walk model in both in and out sample.

Khalid (2008) reported that for the developing economies, a model based on macroeconomic fundamentals performs better than the random walk model both in and out sample. However, Bailliu and King (2005) stated that models of exchange rate determination based macroeconomic fundamentals have not had much success in forecasting exchange rates. Obstfeld and Rogoff (2000) noted that there is generally a very weak relationship between exchange rates and virtually any macroeconomic variable - a situation that they term the "exchange rate disconnect puzzle". Several explanations for exchange rate disconnection from macroeconomic fundamentals are to be found in the literature. Bailliu and King (2005) reported four major reasons for this weak relationship. First, the poor forecasting performance of structural exchange rate models may be because the parameters in the estimated equations are unstable over time (Canova, 1993; Rossi, 2005). Sarno and Taylor (2002) discussed this issue as the result of policy-regime shifting, implicit instability in key equations that underlie the economic specification or agent heterogeneity that would lead to different responses to macroeconomic developments over time. Secondly, forecasting performance based on macroeconomic fundamentals could be improved if the relationship between the exchange rates and its fundamentals is modeled as non-linear. Thirdly, it is possible that key assumptions underlying standard exchange rate models are invalid. For example, the hypothesis of purchasing power parity (PPP) does not hold in the short- and medium-term, although Taylor and Taylor (2004) reported some evidence that it may hold in the very long-term (i.e. using over 100 years of data). Moreover, in the case of short-run uncovered interest rate parity (UIP), the hypothesis that the interest rate differentials are unbiased predictors of future exchange rate movements is clearly rejected in the empirical literature; however, the results for long-run are much more positive (Chinn and Meredith, 2005). Finally, Flood and Rose (1995) noted that nominal exchange rates are much more volatile than the macroeconomic fundamentals to which they are linked in theoretical models. This excess volatility suggests that exchange rate models based on macroeconomic variables are unlikely to be very successful either at explaining or forecasting nominal exchange rates and that there are important variables that may be omitted from standard exchange rate models.

Several potential explanations on this argument have been observe, including important variables such as the presence of unobservable macroeconomic shocks that affect exchange rates, irrationality of market participants, speculative bubbles and herding behaviour (Bailliu and King, 2005). Evans and Lyons (2005) suggested microstructure theory as an alternative exchange rate model, which is primarily based on order flow. However, very limited research has been conducted using the microstructure theory because of the lack of data on customer order flow. These data are nearly non-exists in the cases of emerging and frontier market economies.

Different authors examined the behaviour of exchange rates in terms of different macroeconomic variables. The importance of each variable varies both from country to country and for any given currency, over time. Financial researchers are often interested in measuring the effect of an explanatory variable or variables on an exchange rate. The employment of appropriate econometric models for factors affecting on exchange rates is crucial not only for academic researchers but also for practitioners. The majority of the research has been conducted for advanced or developed countries’ currencies. Very little attention has been paid to emerging and frontier market currencies and their short- and long-run relationship with other macroeconomic variables (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). This study fills a gap in the literature by considering the short- and long-run relationships of exchange rates in terms of their main determinants for advanced, emerging and frontier markets’ currencies.

2.3 Forecasting of Exchange Rates via Combination Techniques

Combination models have been rarely applied to foreign exchange (FOREX) studies and so will form a major part of results presented here. Forecast combination is often used to improve forecast accuracy (Costantini and Pappalardo, 2011). Combining has a long history that predates its use in financial discipline. De Gooijer and Hyndman (2006, 459) stated that “combining forecasts, mixing, or pooling quantitative forecasts obtained from very different time series methods and different sources of information has been studied for the past three decades”. The early contributions of combination methods were made by Bates and Granger (1969), Newbold and Granger (1974) and Winkler and Makridakis (1983). Combining is expected to be useful when the researcher is uncertain as to which forecasting method is best. This may be because the researcher encounters a new situation, has a heterogeneous set of time series or expects the future to be especially turbulent. Clemen (1989) summarised the compelling evidence for the relative efficiency of combined forecasts, in a comprehensive bibliographic review. Combining is most useful when there is uncertainty as to the selection of the most accurate forecasting methods, uncertainty associated with the forecasting situation and a high cost for large forecast errors. Clemen (1989, 559) also reported that “forecast accuracy can be substantially improved through the combination of multiple individual forecasts”. Since then, this same conclusion has been drawn in many academic papers (e.g. Timmermann, 2006; Marcellion, 2004 and Zou and Yang, 2004).

The application of combining forecasts is well researched in the field of geography (Krishnamurti, 1999), media (Langlois and Roggman 1990; Galton, 1878), science (Levins, 1966; Winkler and Pesos, 1993; Weiberg, 1986), engineering (Armstrong *et al.*, 2000), management (Huffcutt and Woehr, 1999), industrial economics (National Industrial Conference Board, 1963; Wolfe, 1966; PoKempner and Bailey, 1970) and tourism (Shen *et al.*, 2011; Coshall and Charlesworth, 2010; Coshall 2009; Song and Li, 2008). Jore *et al.* (2009) examined the effectiveness of recursive-weight forecast combinations for a forecasting output growth, inflation and interest rates. Bjørnland *et al.* (2010) applied combination models to forecast inflation. Kapetanios *et al.* (2007) used combination techniques to forecast inflation and output growth. Hibon and Evgeniou (2005) proposed that the accuracy of the selected combinations is significantly better and less variable than that of the selected individual forecasts. Other studies including, Zou and Yang (2004), Terui and Dijk (2002), Goodwin (2000) and Fong-Lin (1998) also confirmed that combination model generates better results than the forecast made by single model.

In Finance, the combination concept also plays an important role. Andrawis *et al.* (2011) applied combination techniques to forecast NN5 Competition series - a set of 111 time series representing daily cash withdrawal amounts at ATM machines. They combined neural network, Gaussian process regression and linear models via simple average and concluded that combination models improved forecasting performance. Applying the combination approach to data from the NN3 and M1 Competition series, Theodosiou (2011) suggested that a simple combination of four statistical methods produced consistently better results in one-step ahead of monthly and quarterly data. Becker and Clements (2008) examined combination methods to forecasts the volatility of the S&P 500. They found that forecasts based on combination models were the dominant approach. Leung *et al.* (2001) used investment portfolio returns to combine forecasts. Batchelor and Dua (1995) examined forecasts of real GNP, inflation, corporate profits and unemployment for forecast horizons of 6, 12, and 18 months ahead. Using combination forecasts, they concluded that the mean square error (MSE) of the residuals was reduced by 16.4%. Lobo and Nair (1990) studied quarterly earnings forecasts for 96 firms from 1976 to 1983. Their results showed that combining methods reduced the mean absolute percentage error (MAPE) of the residuals by 5.2%.

Over the past half century, practicing forecasters have advised firms to use combination methods. Fang and Xu (2003) investigated the predictability of assets returns by developing an approach that combines technical analysis and conventional time series forecasts. They concluded that the combined strategies outperform both technical trading rules and time series forecasts on daily the Dow Jones average over the first 100 years. Terregrossa (1999) found that combining financial analysts' consensus forecasts with a capital assets pricing model (CAPM) stimulates *ex-ante* forecast leads to superior forecasts of 5 years earning per share (EPS) growth relatively to either component.

There have been very few applications of combining forecasts models in the foreign exchange field. MacDoland and Marsh (1994) applied combination methods in analyses of dollar/sterling, deutschemark/dollar and yen/dollar exchange rate series. They have demonstrated that forecasts made by individual models are not very accurate, are biased and do not take full account of available information. The combining forecasts, however, increased the accuracy of the predictions, but the gains mainly reflect the removal of systematic and unstable bias. Hu and Tsoukalas (1999) examined the out-of-sample forecasting performances of a number of conditional volatility models for a set of 11 European currencies against the German mark. They combined four individual volatility models and concluded that a volatility model outperformed the combination models. Zhang (2003) concluded that for short term (1 month) forecasting of British pound/U.S. dollar, both a neural network model and hybrid (ARIMA and ANN - artificial neural network) models possessed higher forecasting accuracy than the random walk model. For a longer time horizon (12 months), ANN models gave a comparable performance to the ARIMA model. However, the hybrid or combined model outperforms both the ARIMA and ANN models consistently over 1 month, 6 months and 12 months.

Dunis and Chen (2005) investigated the predictive powers of 16 alternative models applied to Euro/U.S. dollar and U.S. dollar/Japanese yen. No single model emerged as an overall optimum of their study. However, 'mixed' models incorporating market data of currency volatility, NNR (neural network regression) models and combinations of models performed best in most of the cases. Ince and Trafalis (2006) studied daily values of exchange rates for Euro/U.S. dollar, British pound/U.S. dollar, Japanese yen/U.S. dollar and Australian dollar/U.S. dollar. Using both parametric and nonparametric techniques, they concluded that most of their single or combined models were at least as good as a random walk forecasting models. Corte *et al.* (2007) provided a comprehensive evaluation of the short-horizon predictive ability of economic fundamentals and forward premia on monthly exchange rate returns in a framework that allows for volatility timing. They implemented Bayesian methods for estimation and ranking of a set of empirical exchange rate models and construct combined forecasts based on model averaging.

Lam *et al.* (2008) studied the Euro, British pound and Japanese yen against U.S. dollar. Their empirical results suggested that combined forecasts outperformed the benchmarks and generally yielded better results than simply relying on a single model. Anastasakis and Mort (2009) studied exchange rate forecasting using combination techniques. They applied parametric and nonparametric modeling methods for the daily prediction of the exchange rate market. They concluded that the combined method produces promising results and outperforms individual methods in the case of tested with two exchange rates- the U.S. dollar and the Deutche mark against the British pound. Altavilla and Grauwe (2010) used combination techniques in respect of quarterly exchange rates of the Euro, British pound and Japanese yen against the U.S dollar. They concluded that combining different forecasting procedures generally produced more accurate forecasts than can be attained from a single model. Maté (2011) applied multivariate analyses (especially principal components and factor analysis) to combining forecasts by using daily Euro/dollar exchange rates. Shahriari (2011) and Nouri *et al.* (2011) conducted a similar study on monthly Iranian rial/British pound exchange rate. Their findings suggest that combination of simple Naïve and cubic regression models fits the data better than individual models.

Combining forecasts is an appealing approach. Instead of choosing the single best model, it is sensible to ask whether a combination of models would help to improve forecast accuracy, assuming that each model has something to contribute. Combining forecasts improves accuracy and there are several ways of combining forecasts. One is to use different data sets and the other is to use different forecasting methods. According to Armstrong (2001, 2), “the more the data and methods differ, the greater is the expected improvement in forecast accuracy over the average of the individual forecasts”. It has been observed in the Finance literature that no single model performs consistently well across all time series and forecasting horizons. Thus, by combining forecasts, the researcher can reduce misspecification bias in the models and increase the prediction accuracy (Theodosiou, 2011). By combining, practitioners can avoid the possibility of choosing the worst forecasting methods for that particular point in time and hence, robustness the estimations across all forecasting horizons (Armstrong *et al.* 1983; De Gooijer and Hyndman, 2006). In this present study, the different methods are used to improve forecast accuracy by using combining forecasts. Although statistically based forecast combination methods have had minimal application in the field of exchange rate modelling, the evidence that exists suggests that combination models perform better than the worst single model predictions and sometimes out-perform the best single model (Anastasakis and Mort, 2009).

There have been very few applications of combination models in the foreign exchange field, yet these models have the potential to assist policy makers in making more effective decisions. The use of appropriate combination techniques in exchange rate forecasting is crucial not only for academic researchers but also for practitioners such as governments, banks, insurance companies, businessman, investors, international organisations (IMF, World Bank etc.), tourism authorities, individuals and other related parties such as speculators, hedgers and arbitrageurs. This present study addresses two outstanding issues raised by Poon and Granger (2003). Poon and Granger (2003) highlighted the fact that little attention has been paid to the performance of combination forecasts, since different forecasting approaches capture different volatility dynamics. They also point out that little has been done to consider whether forecasting approaches are significantly different in terms of performance. This study applies the combination forecasting techniques to exchange rate data to fill this major gap of the literature. Although many researchers observe that exchange rates are an important indicator of the economic welfare of any country, most of the studies on forecasting exchange rates are mainly focused on developed and to some extent secondary emerging markets (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). However, studies involving emerging and frontier markets are almost non-existent. Therefore, a prime focus of this study is on combination forecasts of each of advanced, emerging and frontier markets' currencies against U.S. dollar to fill this gap of the existing literature. Furthermore, the majority of studies have concentrated on bilateral exchange rates between advanced countries rather than exchange rates of emerging versus advanced countries and frontier versus advanced countries. This study contributes to the existing literature by assessing the utility of combination techniques in these different contexts.

2.4 Data Sources

Data were extracted from International Financial Statistics (IFS), which is published monthly by the International Monetary Fund (IMF). In this study, a total of 49 countries are examined. Of these 49 countries, 10 are defined as "advanced", 19 are "emerging" and 20 are "frontier" countries. Table 2.1 presents a list of these countries. The MSCI (Morgan Stanley Capital International) Barra's country classification[13] has been followed in this study. However, FTSE, S&P, IFC (International Finance Corporation), IMF (International Monetary Fund), World Bank, UN (United Nations), BNY (Bank of New York) Mellon New Frontier DR Index, investment banks Merrill Lynch and Deutsche Bank market indices are also considered to resolving any possible contradictions as to country classification. Their country selection is mainly based on the trading activity and volumes of their equity markets and their openness and accessibility to foreign investors. Although some countries (e.g. Bosnia Herzegovina, Bulgaria, Lithuania, Serbia, Slovakia, Ukraine and Ghana) defined as frontier markets by the MSCI, they are excluded from this study due to data unavailability. The Arab countries of Bahrain, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia and United Arab Emirates classified as frontier markets by the MSCI are also removed from the sample because of their fixed exchange rate policy. Five countries namely Bhutan, Brunei, Lao PDR, Nepal and Myanmar are included in this study, although they are not listed in any of the groups of the MSCI country classification. Nevertheless, these countries are considered as new Asian frontier markets (Gomez and Rauch, 2008; Hansakul and Wollensak, 2012).

[13] MSCI developed country group: Americas (Canada, United States), Europe and Middle East (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdome) and Pacific (Australia, Hong Kong, Japan, New Zealand and Singapore) as per December 2012.

MSCI emerging country group: Americas (Brazil, Chile, Colombia, Mexico, Peru), Europe, Middle East and Africa (Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa, Turkey) and Asia (China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand) as per December 2012.

MSCI frontier market group: Americas (Argentina, Jamaica and Trinidad & Tobago), Europe and CIS (Bosnia Herzegovina, Bulgaria, Croatia, Estonia, Lithuania, Kazakhstan, Romania, Serbia, Slovenia and Ukraine), Africa (Botswana, Ghana, Kenya, Mauritius, Nigeria, Tunisia and Zimbabwe), Middle East (Bahrain, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia and United Arab Emirates), Asia (Bangladesh, Pakistan, Sri Lanka and Vietnam) as per December 2012.

Table 2.1: Country classifications

Advanced Countries	**Emerging Countries**	**Frontier Countries**
Australia	Brazil	Bangladesh
Canada	Chile	Bhutan*
Denmark	China	Botswana
Euro area	Colombia	Brunei*
Japan	Czech Republic	Croatia
Norway	Hungary	Estonia
Singapore	India	Jamaica
Sweden	Indonesia	Kazakhstan
Switzerland	Malaysia	Kenya
UK	Mexico	Lao PDR*
	Peru	Mauritius
	Philippines	Myanmar*
	Poland	Nepal*
	Russia	Nigeria
	South Africa	Pakistan
	South Korea	Romania
	Taiwan	Sri Lanka
	Thailand	Trinidad & Tobago
	Turkey	Tunisia
		Vietnam

*Not listed as a frontier market according to MSCI.

Monthly data pertaining to these 49 countries from 1972 M1 up to and including 2007 M12 are used for model derivation. The remaining observations i.e. 2008 M1 to 2010 M4 inclusive are held back for the purpose of out-of-sample forecasts evaluation. Out-of-sample forecasting consequently involves a two years hold back period. All exchange rates are recorded in their respective local currency units respective to one U.S. dollar. Appendix 1 presents the list of currencies and sample period. The majority of these exchange rate series involves more than 400 observations. Due to different recording periods, some exchange rate series' starting periods differ. For cointegration analyses (Chapter 4), monthly macroeconomic variable data are also collected from the IMF's IFS publications. Those macroeconomic variables employed in this study include money supply, interest rates, real income (GDP), trade balance, inflation rate, current account balance, reserve assets, government expenditure, trade openness, oil prices, gold prices and country specific commodity prices. For example, these include iron and coffee prices for Brazil, jute prices for Bangladesh, coal prices for South Africa and copper prices for UK. The exchange rate and macroeconomic data for Taiwan are drawn from the Federal Reserve Bank of St. Louis[14].

The reminder of the thesis is structured as follows. Chapter 3 presents the application of time series models for forecasting exchange rates. The rarely applied ARDL cointegration analyses in exchange rate series are presented in Chapter 4. Chapter 5 reports the application of combination models for forecasting exchange rates and Chapter 6 provides a summary, conclusions and policy implications.

[14] http://research.stlouisfed.org/fred2/categories/32438.

Chapter 3

Time Series Models for Forecasting Exchange Rates

The previous chapter reviewed the literature on forecasting exchange rates. The aim of this chapter is to compare the performance of individual time series models for predicting exchange rates. This study also investigates whether the traditional univariate volatility models, used widely and successfully in the literature in relation to advanced countries, could perform equally well in emerging and frontier countries. Although exchange rate volatility is seen by many researchers as an important indicator of the economic welfare for any country, most of the studies on exchange rates modelling and volatility are focused on advanced markets. Little attention has been paid to emerging and frontier markets (Abdalla, 2012; Kamal *et al.*, 2012; Molana and Osei-Assibey, 2010 and Osinska, 2010). Empirical research on exchange rates and volatility in respect of frontier markets is almost non-existent (discussed in Chapter 2), although it is observed in the literature that exchange rate volatility in developing countries is approximately three times greater than that in industrial countries (Hausmann *et al.,* 2006). This study fills a gap in the literature by considering the countries that fall in the category of emerging and frontier market economies. Moreover, the majority of the studies have concentrated on nominal exchange rates between advanced countries and have not considered exchange rates of emerging versus advanced and frontier versus advanced countries. The current study therefore aims to contribute to the existing literature by forecasting exchange rates and volatility in relation to advanced, emerging and frontier countries. Additionally, the exponential smoothing model has received relatively less attention as a forecasting model in Finance. This permits an opportunity for assessing the utility of this model in a financial context.

The context of this investigation is time series forecasts of exchange rates. Time series models relate a variable to its past values and random errors. Time series analysis is particularly useful for identifying trends, seasonal and cyclical variations of exchange rate series. The rationale for using this approach is based on the idea that the past behaviour of exchange rates can be used to predict future behaviour. The method is purely statistical in nature and is not based on economic theory. Taylor and Allen (1992) stated that due to incomplete information in the short-run, the behaviour of foreign exchange participants is to a large extent based on more technical analysis. In the Finance literature, several types of time series models have been used for forecast exchange rates. Univariate time series forecasting techniques are used in this study. These techniques are based on the history of the variable to forecast (which in this case is the exchange rate). The underlying rationale for this methodology is that the effect of other variables is embodied in and reflected by the actual behaviour of the exchange rate (Moosa, 2000). In this present study, three time series models, namely univariate volatility models, exponential smoothing models and Naïve 1 or no change model are used for forecasting. The prime reason for considering volatility models is that they have been applied to a wide range of time series analyses, but applications in Finance have been particularly successful (Engle, 2001). A goal of volatility models is to provide a volatility measure (called the *conditional variance*) that can be used in financial decision-making scenarios such as risk analysis, portfolio selection and derivative pricing (Engle, 2001). Exponential smoothing models are also widely used to produce forecasts for the level of a time series (Gardner, 1985). Although these models have potential to forecast the exchange rates, there are few applications to be found in the field of foreign exchange. Finally, the Naïve 1 model is included in forecasting studies since it acts as yardstick with which other time series models may be compared (McKenzie and Mitchell, 2002).

The reminder of the chapter is structured as follows. Section 3.1 discusses the unit root tests with results. Section 3.2 presents the application of volatility models for forecasting exchange rates. Exponential smoothing models are presented in Section 3.3. Section 3.4 reports the application of Naïve 1 model for forecasting exchange rates and Section 3.5 provides a summary and policy implications.

3.1 Unit Root Test

This section introduces the unit root tests. The theoretical background of the unit root test with and without structure break(s) is discussed. The empirical results and discussion are also presented.

3.1.1 Unit Root Test without Structural Break

Many economic and financial time series such as exchange rates, assets prices and real GDP exhibit trending behaviour and are thus non-*stationarity* in the mean. A time series is said to be *stationary* if there is no systematic change in mean (no trend) over time, no systematic change in variance (constant spread) and no periodic variation (seasonality). Formal tests, such as Augmented Dickey-Fuller (ADF) test or the Phillips-Perron (PP) test are available for checking whether or not the series are trend stationarity. It is well-known that both the ADF and PP tests are not particularly robust because both suffer from relatively low power (DeJong, *et al.*, 1992). Ng and Perron (2001) developed a test to deal with this problem. This test modifies the Phillips (1987) and Phillips and Perron (1988) tests in a number of ways in order to increase the test's power. The null is that a particular series possess a unit root(s) i.e. the series is not trend stationary. Natural logarithms can be taken in order to reduce the temporal variation to make the series stationarity. The presence of seasonality in a series can readily be assessed graphically despite there being a formal test available. Seasonal differences of the data can be taken to satisfy this aspect of stationarity.

Before investigating the time series analyses, it is necessary that the data are stationary. More than sixty seven percent of exchange rate series examined here required natural logarithms to be taken in order to reduce the temporal variation. It is clear from the plots of exchange rate series (Appendix 2) that a trend is present to the greater or lesser extent to almost all the series. Ng-Perron tests were applied for trend stationarity purposes. Results for the Ng-Perron unit root test (MZa value) are presented in Table 3.1. The significance 5% MZa value is - 8.1000. Test statistic values less than -8.100 indicate a unit root(s) and that first order differencing is required. The EViews software package permits testing for unit roots in levels, first differences and second differences. The Ng-Perron unit root test suggests that the first order differencing (d=1) is required for all series except the Croatian kuna and Kazakhstani tenge. The later series required second order differencing (d=2). In these cases, a quadratic trend is therefore present. In the exchange rate literature, seasonality has been observed in intra-daily and intra-weekly returns in foreign exchange markets. A typically U-shaped pattern is often observed in intra-day volatility (Andersen and Bollerslev, 1998), even a doubly U-shaped pattern is found in exchanges where the daily trading schemes are interrupted by a lunch break (Gua, 2005). Each series was assessed graphically in order to detect the seasonality. No

Table 3.1: Ng-Perron's unit root test results

Country	Ng Perron MZa* Test Statistics	
	Level	First Order Difference
Advanced Countries:		
Australia	-1.452	-201.283
Canada	-1.183	-56.674
Denmark	-6.763	-192.036
Euro area	-1.637	-31.908
Japan	0.347	-23.061
Norway	-7.504	-185.729
Singapore	0.703	-172.702
Sweden	-1.647	-187.617
Switzerland	0.483	-184.837
UK	-2.129	-83.329
Emerging Countries:		
Brazil	-1.131	-64.023
Chile	0.423	-198.002
China	0.479	-215.00
Colombia	0.922	-180.172
Czech Republic	-1.508	-81.339
Hungary	-0.109	-52.833
India	0.842	-198.508
Indonesia	0.171	-134.727
Malaysia	-2.991	-209.876
Mexico	0.858	-120.832
Peru	0.237	-19.609
Philippines	0.630	-187.859
Poland	0.049	-109.059
Russia	-0.616	-19.502
South Africa	0.137	-215.000
South Korea	-0.934	-284.628
Taiwan	-0.435	-214.996
Thailand	-1.419	-214.793
Turkey	0.023	-70.093
Frontier Countries:		
Bangladesh	1.830	-202.187
Bhutan	0.842	-198.511
Botswana	1.523	-200.074
Brunei	0.703	-172.832
Croatia	-0.256	-7.310 (-159.28) **
Estonia	-2.443	-124.293
Jamaica	2.479	-87.951
Kazakhstan	0.082	-7.300 (-73.420) **
Kenya	0.286	-214.804
Lao PDR	0.656	-217.897
Mauritius	1.181	-168.529
Myanmar	-1.251	-215.000
Nepal	0.614	-214.997
Nigeria	1.226	-214.934
Pakistan	1.265	-215.000
Romania	0.332	-71.612
Sri Lanka	2.101	-204.058
Trinidad & Tobago	0.856	-209.739
Tunisia	0.441	-197.245
Vietnam	0.723	-125.512

* Asymptotic critical values at 5% (- 8.1000). ** Second order differencing required for Croatia and Kazakhstan. Test statistics shown in parentheses.

seasonal patterns were found in any series. Therefore, no seasonal differencing is required for any series.

3.1.2 Unit Root Test with Structural Break

A problem common with the conventional unit root tests-such as the ADF, PP and Ng and Perron tests is that they do not allow for the possibility of a structural break. Zivot and Andrews (1992) (hereafter, ZA) proposed a testing procedure where the time of the break is estimated rather than assumed as an exogenous phenomenon. By endogenously determining the time of structural breaks they argue that the results of unit root hypotheses previously suggested by earlier conventional tests, such as the widely-employed ADF and PP methodology, may be reversed. A problem with a stationary time series that is subject to a structural break(s) (such as a change in intercept and/or trend) is that if the break(s) is not catered for during model formulation, then application of a unit root test can lead to incorrect non-rejection of the null hypothesis of non-stationarity. It has become well recognised that unit root tests are biased in the face of structural breaks or unexpected shifts in time series data in general (Banerjee and Urga, 2005; Boero *et al*., 2010; Perron, 1989; Vogelsang and Perron, 1998) and for exchange rate series in particular (Barkoulas *et al*., 1999; Chowdhury, 2007, 2012; Sabaté *et al*., 2003). In such circumstances, unit root tests tend to have very low power.

An early approach to the structural break problem was that of Perron (1989), in which a single breakpoint was assumed and known to have occurred at time T_b. Three models were developed to cater for (A) a change in the level (or intercept) of the series effective at time $T_b + 1$, (B) a change in the growth rate (or slope) effective at time $T_b + 1$ and (C) a change in level and growth rate effective at time $T_b + 1$. The fact that the specification and choice of the breakpoint in these tests is dependent upon prior examination of the data has been criticised. It has been noted that exogenous predetermination of the breakpoint invalidates the distribution theory that underpins classical unit root testing (Christiano, 1992).

Permitting the date of a break to be regarded as unknown and endogenously determined leads to statistics discussed by Banerjee *et al*. (1992) and ZA (1992). The latter is well known and involves computation of t-statistics (critical values computed by ZA) with the potential break date, T_b, allowed to vary across the length of the sample. The test is sequential in nature and uses a different dummy variable for each possible break date. The selection of the time of a break is the result of an estimation process rather than of predetermination. The breakpoint is chosen where the t statistic from the ADF test for a unit root is at a minimum or most negative i.e. least favourable for the null of a unit root. Asymptotic critical 1%, 5% and 10% points for the t statistics are presented in ZA (1992). Three versions of the ZA test are available, corresponding to models A (intercept), B (trend) and C (both intercept and trend) of Perron mentioned above. Perron (1989) suggested that most economic time series can be adequately modelled using either model A or C (Waheed *et al.,* 2006).

The results for ZA tests for advanced markets are presented in Table 3.2. Similar test results for emerging and frontier markets are presented in Appendix 3A and 3B respectively. These results are generated by using syntax of Eviews 7. The null hypothesis for model A is that exchange rate series has a unit root with a structural break in the intercept. This model also tests whether a dummy variable is required addressing this break point. Results show that in the case of Australia, the null hypothesis is rejected at the 5% level ($-14.25 < -4.80$) and one concludes that allowing for a change in intercept, the data are stationary. Hence, no differencing is needed. The dummy is not statistically ($p > 0.05$) significant either and one concludes that no dummy is required for the case of Australia.

The null hypothesis for model C is that exchange rate series has a unit root with a structural break in the intercept and trend. This model also tests whether a dummy variable is required addressing this break point. The results suggest that the null hypothesis is rejected at the 5% level ($-7.45 < -5.08$) and one concludes that allowing for a change in trend, the data are stationary. Hence, no differencing is needed. The dummy is not statistically significant at the 5% level and one concludes that no dummy is required for the case of Australia. The similar results both for model A and C also found in the cases of Indonesia, Malaysia, Mexico, Russia, Thailand, Croatia, Kazakhstan, Lao PDR, Myanmar, Nigeria and Vietnam.

Table 3.2: Zivot-Andrews test results: Advanced countries

	Model A	**Model B**	**Model C**
Australia			
t-statistics	-14.248	-7.465	-7.449
Lag	2	2	2
Break	1984M07	2004M05	2004M05
DU (dummy) p-value	0.839	0.951	0.986
Canada			
t- statistics	-2.863	-2.785	-2.855
Lag	2	2	2
Break	2003M01	2001M1	2000M03
DU (dummy) p-value	2.25x10E-6	0.000	0.119
Denmark			
t- statistics	-3.180	-2.663	-3.717
Lag	3	3	3
Break	1980M08	1982M10	1985M10
DU (dummy) p-value	0.004	0.027	0.000
Euro area			
t- statistics	-3.582	-3.058	-3.954
Lag	1	1	1
Break	2002M11	2000M04	2002M05
DU (dummy) p-value	0.022	0.123	0.000
Japan			
t- statistics	-4.563	-3.405	-4.944
Lag	3	3	3
Break	1985M10	1993M05	1985M10
DU (dummy) p-value	1.71x10E-5	0.007	2.31x10E-5
Norway			
t- statistics	-2.997	-2.917	-3.159
Lag	2	2	2
Break	2002M03	2000M11	1999M02
DU (dummy) p-value	0.001	0.005	0.081
Singapore			
t- statistics	-4.504	-3.047	-3.873
Lag	2	2	2
Break	1997M07	1993M11	1989M12
DU (dummy) p-value	0.000	0.104	0.007
Sweden			
t- statistics	-3.458	-3.526	-3.850
Lag	10	10	10
Break	1981M02	2001M07	1999M11
DU (dummy) p-value	0.018	0.014	0.053
Switzerland			
t- statistics	-3.956	-3.326	-3.585
Lag	1	1	1
Break	1985M04	1977M11	1996M09
DU (dummy) p-value	0.000	0.137	0.066
UK			
t- statistics	-3.825	-3.162	-3.684
Lag	3	3	3
Break	1981M02	1984M05	1981M02
DU (dummy) p-value	0.001	0.034	0.004

Asymptotic Critical Values for the Zivot and Andrews Unit Root Tests:

Test	10%	5%	1%
A	-4.58	-4.80	-5.34 (intercept)
B	-4.11	-4.42	-4.93 (trend)
C	-4.82	-5.08	-5.57 (both)

However, the opposite results (i.e. fail to reject the null hypothesis for both model A and B) are found in rest of the 38 exchange rate series. These results suggest that data are not stationary. Hence, differencing is required to make the data stationary and dummy variables are also needed to address the break points. These results clearly contradict the findings obtained from the unit root test without structural breaks (discussed in section 3.1.1) for these above mentioned ten series. The break date for each series identified via ZA unit root test is reported in Table 3.2, Appendix 3A and 3B for advanced, emerging and frontier markets respectively.

The ZA test identified endogenously the point of the single most significant break in every time series examined in this study. Lumsdaine and Papell (1997) (hereafter, LP) extend the work of ZA (1992) to allow for two endogenous breaks under the alternative hypothesis and additionally allow for breaks in the level and the trend. Series are generally interpreted as broken trend stationary if the null hypothesis of unit root is rejected in favour of the alternative of two breaks. Lee and Strazicich (2003) (hereafter, LS) suggest that spurious regression problems may arise akin to that with ZA with a break under the null hypothesis (Byrne and Perman, 2006). Therefore, LS (2003) consider the case of whether there are two breaks, potentially under the null hypothesis and report evidence of improved power properties against ZA (1992) and LP (1997). They provide a minimum Lagrange Multiplier test with breaks in the level and trend which is not subject to spurious rejection in the presence of a break under the null and they also suggest that the size properties remain accurate for this test. Given the graphical evidence in Appendix 2 about multiple cycles and changing slope exchange rate series it is essential to take into account the possibility of multiple structural breaks when testing for a unit root. Therefore, this study uses the endogenous two-break unit root test of LS (2003). The next section describes the LS (2003) unit root test.

3.1.3 Unit Root Test with Two Structural Breaks

The LS (2003) test includes breaks under both the null and the alternative hypothesis, with rejections of the null unambiguously implying trend stationary. Consider the following data generating process:

$$y_t = \delta' Z_t + e_t \,, \qquad e_t = \beta e_{t-1} + \epsilon_t \tag{1}$$

where Z_t is a vector of exogenous variables and $\epsilon_t \sim$ iid $N(0, \sigma^2)$. As it was mention earlier in section 3.1.2 that Perron (1989) considered three structural break models – the "crash" model A allows for a one-time change in level; the "changing growth" model B allows for a change in trend slope and model C allows for a change in both the level and trend. LS (2003) analyse two alternative models[15]. Model A allows for two shifts in the level of exchange rates: $Z_t = [1, t, D_{1t}, D_{2t}]'$, where $D_{jt} = 1$ for $t \geq T_{Bj} + 1 (j = 1, 2)$ and 0 otherwise. T_{Bj} indicates the time period when a break occurs. Model C includes two changes in level and trend: $Z_t = [1, t, D_{1t}, D_{2t}\, DT_{1t}, DT_{2t}]'$, where $DT_{jt} = 1 - T_{Bj}$ for $t \geq T_{Bj} + 1 (j = 1, 2)$ and 0 otherwise.

In model A, the null and alternative hypotheses are given by equations (2) and (3) respectively:

$$y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + y_{t-1} + \vartheta_{1t} \tag{2}$$

$$y_t = \mu_1 + \gamma t + d_1 D_{1t} + d_2 D_{2t} + \vartheta_{2t} \tag{3}$$

where the error terms $(\vartheta_{1t}, \vartheta_{2t})$ are stationary processes; $B_{jt} = 1$ for $t = T_{Bj} + 1$

$(j = 1, 2)$ and 0 otherwise and $d = (d_1, d_2)'$.

In model C, the null and alternative hypotheses are given by equations (4) and (5) respectively:

[15] They omit an explicit discussion on model B arguing that it is commonly held that most economic time series can adequately described by model A or C (LS 2003, 1083).

$$y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + \theta_1 D_{1t} + \theta_2 D_{2t} + y_{t-1} + \vartheta_{1t} \quad (4)$$

$$y_t = \mu_1 + \gamma t + d_1 D_{1t} + d_2 D_{2t} + \varphi_1 DT_{1t} + \varphi_2 DT_{2t} + \vartheta_{2t} \quad (5)$$

where the error terms $(\vartheta_{1t}, \vartheta_{2t})$ are stationary processes; $B_{jt} = 1$ for $t = T_{Bj} + 1$ $(j = 1, 2)$ and 0 otherwise and $d = (d_1 d_2)'$. An Lagrange Multiplier score principle is used to estimate the LS (2003) unit root test statistic based on the following regression model:

$$\Delta y_t = \delta' \Delta Z_t + \emptyset \tilde{S}_{t-1} + u_t \quad (6)$$

where $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t \tilde{\delta}$, $t = 2, \ldots\ldots, T$; $\tilde{\delta}$ are coefficients in the regression of Δy_t on ΔZ_t ; $\tilde{\psi}_x$ is given by $y_t - Z_t \tilde{\delta}$, where y_1 and Z_1 denote the first observations of y_t and Z_t respectively. The unit root null hypothesis can be test by examining the t-statistics $(\tilde{\tau})$ associated with $\emptyset = 0$.

The LS (2003) unit root test results[16] of Model A and C for advanced countries are reported in Table 3.3A. According to the LM_T stats of Model A, the null hypothesis cannot be rejected at 5% level of significance in all cases. These indicate that neither of the data series is stationary. Therefore first order differencing is required to make the data stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1). Results also show that all the series have significant breaks at the level except Canada, Sweden and UK. Two significant breaks have indentified in seven series, namely Australia, Denmark, Japan, Norway and Singapore. Conversely, only one structural break has found statistically significant in the cases of the Euro area and

[16] The LS (2003) unit root test results are generated by using GAUSS programming language.

Table 3.3A: Lee and Strazicich (2003) unit root test results – Advanced countries

Country	**Model A**			**Model C**			
	LM_T stats*	**Break Dates**	**t stats Levels**	**LM_T stats***	**Break Dates**	**t stats Levels**	**t stats Trends**
Australia	-2.429 [11]	1986M6	3.901*	-4.685 [11]	1986M5	3.050*	0.632
		2001M4	-2.469*		1996M7	0.999	2.639*
Canada	-1.769 [11]	2001M4	-0.726	-3.665 [11]	1976M7	0.986	2.459*
		2003M5	-0.980		2004M5	-1.662	-5.320*
Denmark	-2.753 [10]	1984M11	2.527*	-3.770 [10]	1981M12	0.088	2.430*
		1985M8	2.137*		1988M2	-0.751	-1.222
Euro area	-2.074 [11]	2001M10	1.830	-4.715 [1]	2001M11	-0.531	-5.589*
		2006M4	-2.293*		2004M1	-0.429	3.767*
Japan	-3.195 [12]	1980M4	-5.466*	-5.181 [12]	1981M1	-0.596	3.544*
		1985M9	-4.622*		1987M3	-1.241	-3.454*
Norway	-2.070 [10]	1984M11	2.471*	-3.451 [10]	1983M7	0.962	1.936
		1986M4	2.087*		1996M1	2.087*	1.516
Singapore	-1.709 [5]	1997M12	3.426*	-4.166 [1]	1985M2	-0.320	2.123*
		1998M5	2.102*		1997M8	-0.315	4.182*
Sweden	-2.704 [10]	200M12	-0.282	-3.961 [10]	1982M8	0.222	2.028*
		2003M9	-1.343		1992M9	0.679	2.324*
Switzerland	-1.776 [7]	1978M11	-0.970	-4.450 [12]	1981M11	0.057	4.636*
		1981M8	-3.366*		1987M10	-2.476*	-1.732
UK	-2.732 [8]	1985M4	1.198	-4.072 [12]	1986M9	1.812	-3.395*
		2002M6	-1.665		2001M5	1.292	0.374

The lag length of the LM_T test is determined by a general to specific procedure choosing maximum lag on which the t-statistics are significant at the asymptotic 10% level, lag length chosen is in square bracket. Critical values are available from Lee and Strazicich (2003, Table 2).
*Indicate 5% significance level

Switzerland. None of the break date is found statistically significant in the cases of Canada, Sweden and UK.

According to the LM_T stats of Model C, the null hypothesis cannot be rejected at 5% level of significance in all cases. These indicate that neither of the data series is stationary. Therefore first order differencing is required to make the data stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1). Results also show that all the series have significant breaks. Two significant breaks have identified in seven series, namely Australia, Canada, the Euro area, Japan, Singapore, Sweden and Switzerland. Conversely, only one structural break has found statistically significant in the cases of Denmark, Norway and UK.

The LS (2003) unit root test results of Model A and C for emerging countries are reported in Table 3.3B. According to the LM_T stats of Model A, the null hypothesis cannot be rejected at 5% level of significance in all cases except Indonesia. These indicate that neither of the data series is stationary. Therefore first order differencing is required to make the data stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1). The null hypothesis is rejected at 5% level of significance for the series of Indonesia. This indicates that data are stationary; hence no differencing is required. This contradicts the finding of Ng Perron unit root test result. Results also show that all the series have significant breaks at level except Chile, Czech Republic, Peru and Poland. Two significant breaks have identified in nine series, namely Brazil, China, Hungary, India, Indonesia, Mexico, Russia, South Africa and Thailand. Conversely, only one structural break at the level has found statistically significant in the cases of Colombia, Malaysia, Philippines, South Korea, Taiwan and Turkey. None of the break date is found statistically significant in the cases of Chile, Czech Republic, Peru and Poland.

According to the LM_T stats of Model C, the null hypothesis cannot be rejected in all cases except Brazil, Indonesia and Russia and one concludes that data are not stationary. Therefore first order differencing is required to make the data stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1). Results also show that the null is rejected in the cases of Brazil, Indonesia and Russia. These indicate that data are stationary. Therefore no differencing is required to make these series stationary. This contradicts the finding of Ng Perron unit root test result where first differencing is suggested for stationary purpose. The findings also show that structural breaks are statistically significant in all cases except China. Two significant breaks are indentified in fifteen out of nineteen cases (Brazil, Chile, Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Poland, Russia, South Africa, South Korea, Taiwan, Thailand and Turkey). Only one break is found statistically significant in the cases of Colombia, Peru and Philippines. However, no break is found statistically significant in the case of China as per Model C.

Table 3.3B: Lee and Strazicich (2003) unit root test results - Emerging countries

Country	**Model A**			**Model C**			
	LM_T stats	**Break Dates**	**t stats Levels**	**LM_T Stats**	**Break Dates**	**t stats Levels**	**t stats Trends**
Brazil	-1.966* [6]	2002M11	2.575*	-5.945 [5]	1999M1	5.121*	-2.993*
		2003M1	2.831*		2002M8	1.499	2.977*
Chile	-2.122*[12]	2001M11	-0.818	-4.200* [12]	1984M7	-0.589	4.117*
		2002M11	0.961		2004M4	4.941*	-5.657*
China	-1.305* [11]	1986M6	9.873*	-3.687* [0]	1983M1	0.247	1.114
		1993M12	69.050*		1995M6	-0.113	0.535
Colombia	-1.722* [10]	2002M11	4.368*	-3.912* [10]	1990M4	0.057	2.559*
		2004M1	0.161		2001M10	-0.288	0.495
Czech Republic	-1.582*[1]	2000M6	1.076	-4.108* [1]	1997M1	-0.170	3.657*
		2002M6	-1.545		2002M5	-1.461	-4.600*
Hungary	-2.100* [11]	2000M6	2.420*	-4.984* [11]	1990M12	2.176*	4.008*
		2003M5	6.140*		1999M1	1.996*	0.916
India	-1.259* [8]	1991M6	13.354*	-4.647* [3]	1998M3	-0.169	5.682*
		1993M2	15.729*		2001M4	0.158	-2.973*
Indonesia	-5.837 [7]	1997M11	3.651*	-9.607 [8]	1997M10	-3.937*	9.117*
		1998M5	10.165*		1999M4	0.313	-8.066*
Malaysia	-2.113* [8]	1998M5	4.381*	-5.422 **[8]	1976M12	0.368	-0.452
		1998M12	1.750		1997M9	3.040*	4.923*
Mexico	-2.724* [9]	1994M12	8.803*	-5.046* [10]	1994M10	-1.831	5.117*
		1995M10	4.239*		1997M5	0.101	-4.922*
Peru	-0.573* [8]	1991M10	0.518	-5.012* [9]	1992M7	1.350	1.540
		1992M5	-0.194		2001M9	-1.164	-7.269*
Philippines	-1.920* [12]	1997M12	7.380*	-4.208* [11]	1977M2	0.037	-0.249
		2002M1	0.825		1999M5	-0.457	3.212*
Poland	-1.467* [11]	1990M1	-1.809	-5.678** [11]	1999M11	-2.019*	2.520*
		2003M4	-1.830		2003M4	-2.512*	0.918
Russia	-2.088* [9]	1998M8	20.421*	-6.608 [12]	1998M7	-3.219*	7.736*
		1999M1	-4.884*		2000M9	1.186	-8.810*
South Africa	-3.382* [8]	1998M6	4.050*	-5.376** [8]	1997M6	-0.431	4.238*
		2002M12	2.371*		2002M12	2.823*	-5.350*
South Korea	-2.825* [8]	1998M10	0.733	-4.331* [8]	1987M11	0.357	-3.571*
		1999M2	2.476*		1997M10	2.630*	3.456*
Taiwan	-1.521* [8]	1997M10	4.516*	-4.795 *[8]	1988M8	0.906	-1.870
		2005M6	1.791		1997M10	4.297*	3.842*
Thailand	-2.639* [10]	1997M11	6.188*	-5.776 **[8]	1997M5	-1.651	5.654*
		1998M5	5.255*		2002M7	1.619	-5.734*
Turkey	-1.665* [6]	2001M5	3.914*	-5.276* [6]	1999M4	0.028	2.328*
		2003M2	1.855		2002M1	-0.090	2.138*

The lag length of the LM_T test is determined by a general to specific procedure choosing maximum lag on which the t-statistics are significant at the asymptotic 10% level, lag length chosen is in square bracket. Critical values are available from Lee and Strazicich (2003, Table 2).
*Indicate 5% significance level
**Indicate 1% significance level

The LS (2003) unit root test results for frontier countries are reported in Table 3.3C. According to the LM_T stats of Model A, the null hypothesis cannot be rejected at 5% level of significance in all cases. These indicate that neither of the data series is stationary.

Table 3.3C: Lee and Strazicich (2003) unit root test results - Frontier countries

Country	Model A			Model C			
	LM_T stats*	Break Dates	t stats Levels	LM_T Stats	Break Dates	t stats Levels	t stats Trends
Bangladesh	-3.582 [10]	2000M7	3.201*	-4.912* [10]	1982M2	-2.057*	3.292*
		2001M5	4.839*		1996M12	-0.758	1.036
Bhutan	-1.259 [8]	1991M6	13.353*	-4.647* [3]	1988M3	-0.169	5.683*
		1993M2	15.728*		2001M4	0.158	-2.973*
Botswana	-2.879 [11]	1998M6	6.040*	-4.770* [11]	1995M12	-0.887	4.812*
		2001M11	6.753*		2003M2	0.330	-3.567*
Brunei	-1.707 [5]	1997M12	3.429*	-4.163* [1]	1985M2	-0.317	2.120*
		1998M5	2.101*		1997M8	-0.313	4.179*
Croatia	-2.014 [3]	2000M12	-1.283	-5.130* [10]	1995M8	1.331	-5.083*
		2003M4	-1.901		2000M12	-1.401	-0.869
Estonia	-1.976 [10]	2000M12	-1.964*	-4.538* [11]	1999M1	0.855	3.436*
		2002M3	0.345		2003M10	1.374	-3.651*
Jamaica	-1.347 [8]	1991M10	-0.909	-5.565** [8]	1991M7	-0.553	7.285*
		1992M4	-7.925*		1996M12	-0.467	-5.700*
Kazakhstan	-1.368 [2]	1999M12	0.702	-3.764* [9]	1997M1	0.246	-2.600*
		2003M12	-1.239		2000M3	0.298	0.232
Kenya	-2.074 [6]	1994M6	0.574	-6.470 [9]	1993M1	-1.285	6.362*
		1995M4	6.217*		2003M6	0.503	-5.029*
Lao PDR	-1.604 [12]	1997M12	1.397	-4.094*[3]	1997M8	-0.841	6.599*
		2001M7	3.412*		2000M11	-4.023*	-2.990*
Mauritius	-3.129 [10]	1992M10	2.561*	-5.082* [11]	1997M10	-1.057	4.151*
		1996M12	6.153*		2003M6	3.766*	-3.077*
Myanmar	-1.747 [1]	1985M9	-2.234*	-3.826* [11]	1986M1	0.019	-3.988*
		1986M12	-2.019*		1998M10	0.712	2.793*
Nepal	-1.247 [6]	1985M12	-1.872	-6.007 [9]	1991M3	-1.019	6.064*
		1995M8	1.323		2003M7	-0.382	-7.534*
Nigeria	-1.636 [11]	1990 M10	67.007*	-6.270 [10]	1998M11	-2.577*	7.871*
		2003M9	4.393*		2001M6	-0.227	-7.238*
Pakistan	-1.963 [11]	2000M11	3.289*	-4.957* [11]	1994M8	-0.007	1.427
		2001M10	-0.834		2000M10	-2.674*	-0.385
Romania	-1.918 [11]	2003M5	2.052*	-3.972* [7]	1998M11	-0.814	5.503*
		2004M2	2.050*		2002M11	0.931	-8.293*
Sri Lanka	-1.423 [11]	1998M5	5.350*	-4.469* [11]	1993M9	0.559	2.078*
		2004M5	2.342*		2000M12	1.107	3.243*
Trinidad &	-2.314 [2]	1985M12	5.656*	-4.886* [1]	1981M12	0.258	-2.437*
Tobago		1993M3	36.638*		1993M8	0.567	2.699*
Tunisia	-2.035 [1]	2001M1	1.477	-4.276* [10]	1982M5	1.541	3.706*
		2001M8	0.425		1999M11	1.515	1.439
Vietnam	-2.848 [12]	1989M2	15.124*	-4.610* [8]	1989M1	-1.730	5.455*
		2001M8	-4.601*		1990M9	-1.547	-4.086*

The lag length of the LM_T test is determined by a general to specific procedure choosing maximum lag on which the t-statistics are significant at the asymptotic 10% level, lag length chosen is in square bracket. Critical values are available from Lee and Strazicich (2003, Table 2).
*Indicate 5% significance level
**Indicate 1% significance level

Therefore first order differencing is required to make these series stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1) except for the series of Croatia and Kazakhstan, where second order differencing was suggested for stationary purpose. Results also show that all the series have significant breaks at level except Croatia, Kazakhstan, Nepal and Tunisia. Two significant breaks have indentified in eleven series, namely Bangladesh, Bhutan, Botswana, Brunei, Mauritius, Myanmar, Nigeria, Romania, Sri Lanka, Trinidad & Tobago and Vietnam. Conversely, only one structural break has found statistically significant in the cases of Estonia, Jamaica, Kenya, Lao PDR and Pakistan. None of the break date is found statistically significant in the cases of Croatia, Kazakhstan, Nepal and Tunisia. According to the LM_T stats of Model C, the null hypothesis cannot be rejected in all cases except Kenya, Nepal and Nigeria and one concludes that data are not stationary. Therefore first order differencing is required to make the data stationary. This supports the findings of Ng - Perron unit root test results (reported at Table 3.1 in section 3.1.1) except for the series of Croatia and Kazakhstan, where second order differencing was suggested for stationary purpose. Results also show that the null is rejected for the series of Kenya, Nepal and Nigeria. These indicate that data are stationary. Therefore no differencing is required. This contradicts the finding of Ng Perron unit root test results where first order differencing is suggested for stationary purpose. The findings also show that structural breaks are statistically significant in all cases. Two significant breaks are identified in sixteen out of twenty cases (Bangladesh, Bhutan, Botswana, Brunei, Estonia, Jamaica, Kenya, Lao PDR, Mauritius, Myanmar, Nepal, Nigeria, Romania, Sri Lanka, Trinidad & Tobago and Vietnam). Only one break is found statistically significant in the cases of Croatia, Kazakhstan, Pakistan and Tunisia.

Break points have important implications in the empirical analysis. As mentioned by Piehl *et al.,* (2003), knowledge of break point is central for accurate evaluation of any programme intended to bring about structural changes; such as the tax reforms, banking sector reforms, crisis and regime shifts etc. Based on the results of LS's Model A and C, it has been observed that almost all the series have breaks which are also clearly evidenced in the graphical presentation of exchange rate series presented at Appendix 2. Consequently LS (2003) unit root test is appropriate to address the structural break(s) for all series. Therefore the Ng-Perron and ZA unit root test results' are discounted and the LS (2003) unit root test results are considered in this study.

3.2 Volatility Models Applied to Forecasting Exchange Rates

This section introduces the application of volatility models for forecasting exchange rates. The theoretical background of the volatility models is discussed. The empirical results and discussion are also presented.

3.2.1 Theory

The volatility modelling process generates mean and conditional variance equations for the series being investigated. Generally, a standard ARIMA (Auto-Regressive Integrated Moving Average) model or a regression model is used to generate the mean equation for volatility analysis. Whichever is used, it contains error or residual term over time, ε_t. ARIMA models are very popular in the literature for their robustness in modelling misspecification (Chen, 1997). Lags of the differenced series appearing in the forecasting equation are called auto-regressive (AR) terms, lags of the forecast errors are called moving average (MA) terms and a time series which needs to be differenced to be made stationary is said to be an integrated (I) version of a stationary series. By combining the AR(p) and MA(q), an ARMA (p,q) model is obtained. Such a model states that the current value of some series Y_t depends linearly on its own previous values plus a combination of current and previous values of a *white noise* (random) error term. Box and Jenkins (1976) ARIMA models are, in theory, the most general class of models for forecasting a time series, which can be made stationary by transformations such as differencing and logarithmic transfers. The objective to form a parsimonious model, which describes all of the significant features of data of interest and which has significant parameters.

The ARIMA procedure is carried out on stationary data. The notation Z_t is used for the stationary data at time t, whereas Y_t is the non-stationary data at that time. The ARIMA(p,q) process considers linear models of the form:

$$Z_t = \mu + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \ldots\ldots + \theta_p Z_{t-p} - \varphi_1 \varepsilon_{t-1} - \varphi_2 \varepsilon_{t-2} - \ldots\ldots - \varphi_q \varepsilon_{t-q} + \varepsilon_t \quad (7)$$

where, ε_t , ε_{t-1} ,........ are present and past forecast errors and μ , θ_1 , θ_2, ….. , φ_1, φ_2 … … …are parameters to be estimated. When differencing has been used to generate stationarity, the model is said to be *integrated* and is written as ARIMA (p, d, q) in which p and q represent the order of the autoregressive terms and moving average respectively. The middle parameter d is simply the number of times that the series had to be differenced before trend stationarity was achieved. The seasonal part of an ARIMA model has the same structure as the non-seasonal part; it may have an AR factor, an MA factor and/or an order of differencing. In the seasonal part of the model, all of these factors operate across multiples of lags (the number of periods in a season). The conventional notation for ARIMA model is written as $(p, d, q)(P, D, Q)^s$, where P is the number of seasonal autoregressive (SAR) terms, D is the number of seasonal differences and Q is the number of seasonal moving average (SMA) terms. The first part of the parenthesis contains the orders of non-seasonal, whereas second part represents the seasonal parameters. In this study, the order of seasonality (S) equals to 12 (monthly). A useful device for initially assessing the values for p and q are the autocorrelation function (ACF) and partial autocorrelation function (PACF). The PACF and ACF determine the initial p and q terms respectively. By using the patterns of spikes in the actual ACF and PACF plots, researchers may identify the specific type of Box-Jenkins model that will adequately represent the data. Software uses iterative methods to find the optimal ARIMA model. The best model is selected based on following criteria; smallest AIC (Akaike's information criteria) or SBC (Schwarz's information criteria), a minimum value of the standard error of the residuals and *white noise* (random) residuals of the model (which shows that there is no significant pattern left in the ACFs of the residuals). The method of applying ARIMA models to exchange rate data is well-described in the Finance literature (Ince and Trafalis, 2006).

Engle (1982) presented a basis for formal theory of volatility modelling. At the root of volatility modelling is the distinction between conditional (stochastic) and unconditional (constant) errors. The *conditional variance* of the error terms is denoted by σ_t^2 and is time varying. Volatility modelling involves adding a variance equation to the original mean equation and which in turn models the conditional variance. Engle (1982) introduced the ARCH (autoregressive conditional heteroscedasticity) model. The ARCH(p) modelled conditional variance as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{8}$$

where, $\omega > 0$ and $\alpha_i > 0$.

ARCH methods have had wide application particularly in the field of financial volatility. However, ARCH models are now used with decreasing frequency, due to a number of difficulties:

- No clear best approach is known to determine the value of p i.e. the number of lags.
- The value of p required to capture all of the impact on the conditional variance might be very large. This would result in a complex ARCH model that is not parsimonious.
- The larger is the value of p, the greater is the possibility that a negative conditional variance could be the result.

To overcome these difficulties, many modifications of the basic ARCH(p) model have developed. One of the widely used volatility models goes under the name of a GARCH (generalised autoregressive conditional heteroscedasticity) scheme and was developed by Bollerslev (1986). The conditional variance is modelled as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{9}$$

where, $\omega > 0$ and $\alpha_i \geq 0$ and $\beta_j \geq 0$ to eliminate the possibility of a negative variance. However, it has been argued that in practice, this constraint may over-restrictive (Nelson and Cao, 1992; Tsai and Chan, 2008). The specification in equation (9) allows for the conditional variance to be dependent on past information. It is explained by past short-run (α_i) shocks represented by the lag of the squared residuals (ε_i^2) obtained from mean equation and by past longer-run (β_j) conditional variances (σ_j^2). Equation (9) is referred to as GARCH (p,q) process. In GARCH models, $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$ should be less than unity to satisfy stationarity conditions. If the β_j are all zero, equation (9) reduces to what is called an ARCH(p) process, which is the earliest form of the volatility model developed by Engle (1982). It is rare for the order (p,q) of a GARCH model to be high; indeed the literature suggests that the parsimonious GARCH(1,1) is often adequate for capturing volatility in financial data (see, for example, Chen and Lian, 2005).

Equation (9) may be extended to allow for the inclusion of exogenous or predetermined regressors, z in the variance equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + Z_t' \pi \tag{9.1}$$

It is worthwhile to mentioning here that the forecasted variances from this model are not guaranteed to be positive. Researcher may wish to introduce regressors in a form where they are always positive to minimise the possibility that a single, large negative value generates a negative forecasted value (Quantitative Micro Software, 2010).

This simple GARCH model has a shortcoming. This model also restricts the impact of shock to be independent of its sign, whereas there is evidence of an asymmetric response for financial markets. In the basic ARCH model only squared residuals enter the conditional variance equation. Therefore, the signs of the residual or shocks have no influence on conditional volatility. In macroeconomic analysis, financial markets and corporate finance, a negative shock usually implies bad news, leading to a more uncertain future (Wang, 2003). A stylised fact of financial volatility is that negative shocks (bad news) tend to have a larger impact on volatility than positive shocks (good news). For example, in the financial markets, volatility tends to be higher in a falling markets than in a rising markets. In the literature, the asymmetric news impact on volatility is commonly referred to as the *leverage effect* (Zivot, 2009).

The extensive literature on the impact of news on exchange rate volatility (Dominquez and Panthaki, 2006; Bauwens *et al.*, 2005; Andersen *et al.*, 2003; DeGennaro and Schrieves, 1997 among others) has shown that news regarding macroeconomic fundamentals increases volatility just after the announcement. A potential problem with applying the model of equation (8) to exchange rate data is that it presumes that the impact of positive and negative shocks are the same or symmetric. This is because the conditional variance in these equations depends on the magnitudes of the lagged residuals, not their sign. The possibility that a negative shock to exchange rate movements causes volatility to rise by more than positive shocks of the same magnitude in the financial markets remains worthy of analysis. Such a consideration led to the development of asymmetric volatility models, specially the threshold GARCH (TGARCH) by Glosten *et al*. (1993); Zakoïan (1994) and the exponential GARCH (EGARCH) by Nelson (1991).

The threshold model is a simple extension of the GARCH scheme with extra term(s) to add to account for possible asymmetries. TGARCH extends the GARCH (p,q) model of equation (9) via :

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 \xi_{t-i}) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (10)$$

where ξ_{t-i} are dummy variables equal to unity if $\varepsilon_{t-i} < 0$ i.e. a negative shock or bad news and equal to zero if $\varepsilon_{t-i} > 0$ i.e. a positive shock or good news. If $\gamma_i > 0$ in equation (10), then a negative shock increases the volatility. Again, the values of p and q tend to be low in empirical applications.

The EGARCH (p,q) model of Nelson (1991) can also accommodate asymmetric effects and therefore solves related to the important shortcomings of the symmetric models. This model specifies the conditional variance in a following way:

$$\log_e(\sigma_t^2) = \omega + \sum_{i=1}^{p}(\alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma\frac{\varepsilon_{t-i}}{\sigma_{t-i}}) + \sum_{j=1}^{q}\beta_j \log_e(\sigma_{t-j}^2) \quad (11)$$

Note that the left-hand side of equation (11) is the logarithm of the conditional variance. This indicates that the leverage effect is exponential. Therefore, the forecasts of the conditional variance are guaranteed to be nonnegative. One reason that EGARCH has been popular in financial applications is that the conditional variance, σ_t^2, is a exponential function, thereby removing the need for a constraint in the parameters to ensure a positive conditional variance (Longmore and Robinson, 2004). The model also permits asymmetries via the γ term in equation (4). The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. If $\gamma < 0$, negative shocks lead an increase in volatility and if $\gamma = 0$, the model is symmetric. The values of p and q are very rarely high and EGARCH models tends to be parsimonious. The EGARCH model has been commonly used to examine interest rates, futures markets to model foreign exchange rates and to analyse stock returns (see, for example, Hu *et al.*, 1997; Brunner and Simon, 1996; Tse and Booth, 1996 and Koutmos and Booth, 1995).

Ding *et al.* (1993) introduced a new class of ARCH model called Power ARCH (PARCH). This is another type of asymmetric model that examines powers of the conditional standard deviation i.e variance but rather than forcing that power to have a value of two as per the GARCH model. Rather than imposing a structure on the data, the PGARCH class of models estimates the optimal power term. The power of one is equivalent standard deviation, that of two is equivalent to the variance. In financial applications, the PGARCH model has particular application to time series that exhibit marked skewness and kurtosis (Longmore and Robinson 2004) which explains its regular application in that field. The asymmetric PGARCH (p,δ,q) scheme is defined as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}\right)^\delta + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^\delta \quad (12)$$

where δ is a positive coefficient and $\gamma_i$represents leverage effects and $\delta > 0$ and $\lceil \gamma_i \rceil \leq 1$. If $\delta = 2$ and $\gamma_1 = 0$, the PGARCH model of equation (12) reduces to a symmetric GARCH(1,1). Again, if $\gamma_1 = 0$, the model is symmetric.

Ding *et al.* (1993) and Hentschel (1995) have documented the applicability of the PARCH class of model to stock market data. Other studies such as Brooks *et al.* (2000), McKenzie and Mitchell (2002), Tooma and Sourial (2004) and Giot and Laurent (2004) also applied the PARCH model to investigate the stock market data. Tully and Lucey (2007) applied the asymmetric PGARCH model to investigate the macroeconomic influences on gold price. Their results suggested that the asymmetric PGARCH model provides the most adequate description for the data. However, little is known about the applicability of this type of model in exchange rates series. One such application by Tse and Tsui (1997) who applied APGARCH (Generalized Asymmetric Power ARCH) model to daily Malaysian/U.S and Singapore/U.S exchange rate data and their results indicated that the model fits the data well and optimal power term was found to be some value other than unity or two. They found asymmetry in the Malaysian currency whereas no such asymmetry was found for the Singapore dollar against U.S. Dollar. McKenzie and Mitchell (2002) applied the APGARCH volatility models in 17 high volume of trading currencies in the foreign exchange market. They found significant asymmetry terms for 5 out of 17 currencies. Their results confirmed the fact that unequal responses are also present in the exchange rate data series. Therefore, it will be an interesting investigation to apply the different volatility models in exchange rates series to add some value to a growing body of the exchange rate literature.

Before generating an optimal model for any given series, it is important to test for misspecification. The Ljung-Box Q-statistic is often used to test the serial correlation of the residuals. Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. There remains the practical problem of choosing the order of lag to use for the test. If you choose too small a lag, the test may not detect serial correlation at high-order lags. However, if you choose too large a lag, the test may have low power since the significant correlation at one lag may be diluted by insignificant correlations at other lags (Ljung and Box, 1979; Harvey, 1990, 1993). The Q squared

(Q_{SQ})-statistic is generally used to check the ARCH in the residuals. The Q-statistic is required to verify whether or not the mean equations are correctly specified whereas, the Q_{SQ} statistic is required to test the variance equation in order to avoid the model misspecification. If more than one volatility model with significant parameters is found, the model with maximum *Log Likelihood* criterion (LL) is taken to select the optimal one.

In the Finance literature, a variety measures have been used to assess and compare forecast performance. These include the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the Theil-U statistic. Studies of exchange rate volatility have also used a variety of measures to assess forecasting accuracy (Dunis and Williams, 2002). However, the MAPE is amongst the most commonly used measures of error magnitude. Makridakis (1993, 528) argued that the MAPE is “a relative measure that incorporates the best characteristics among the various accuracy criteria”. This accuracy criterion has the advantage of being measured in unit-free terms (Witt and Witt, 1991). In this study, MAPE is used to compare the accuracy of the forecasts obtained from the volatility models. MAPE measure below 5% is “excellent” forecasting, whereas 10% represents “highly accurate” forecasting (Lewis, 1982).

3.2.2 Results from Volatility Models of Forecasting Exchange Rates

The Model A of LS (2003) unit root test results are used to address the structure breaks in volatility analysis as Perron (1989) suggested that most macroeconomic time series can be adequately modelled using either model A or model C (Chatterji and Choudhury, 2011, 20; Waheed *et al.*, 2006; Lee and Strazicich, 2003, 1083). The volatility analysis conducted after incorporating the level and trend breaks suggested by the Model C of LS (2003) unit root test. The mean and variance equations for three sample countries (after incorporate the level and trend breaks suggested by Model C of LS (2003) unit root test) are presented in Appendix 3C. Results showed that the dummy variable(s) which addresses the “trend break(s)” came insignificant in all the cases. Moreover it has been observed in the literature that the model A of LS (2003) unit root test is applied in their respective studies by Tiwari *et al.*, 2013; Kumar and Webber, 2013; Hassan, 2013; Dua and Tuteja, 2013; Kum, 2012; Canarella *et al.*, 2012, 23; You and Sarantis, 2012; Adigüzel *et al.*, 2012; Vats and Kamaiah 2011; Acaravci and Ozturk, 2010; Gregoiou *et al.*, 2007; Waheed *et al.*, 2006;

Hooi and Smyth, 2005; Altinay, 2005. Therefore, this study considers the structural break(s) suggested by the Model A of LS (2003) for further analysis. To account for the structural break(s) suggested by Model A (mentioned is Section 3.1.3) for the appropriate series, dummy variables are introduced into the variance equation as "regressors" for the historical period (Quantitative Micro Software, 2010). The dummy is set equal to 0 for the period before the structural break and 1 during the time of structural break.

The mean equation advanced, emerging and frontier countries are presented in Appendix 4. The choice of ARIMA for the data is based on its being parsimonious, having significant parameters, errors that are white noise and minimum Schwarz Bayesian criterion (SBC) (Schwarz, 1978). The parameters included in an ARIMA model along with their significance levels ($p < 0.05$) are also presented in Appendix 4. The estimated mean equations are grouped according to advanced, emerging and frontier counties. As was mentioned earlier, the optimal model must possess white noise (or random) residuals. No significant spikes were observed in the residual ACF plot of each series. This indicates that all associated errors are white noise.

The mean equations in Appendix 4 act as a basis for generating the conditional variance equations for each exchange rate series. To obtain the optimal GARCH(p,q) model, all combinations of (p) = (0,1,2) and (q) = (0,1,2) were considered (except for p=q=0), as suggested by Angelidis *et al.* (2004). The threshold order determines the impact or otherwise of news shocks. The threshold order of zero means that the volatility model is symmetric i.e. the impact of good news equals the impact of bad news in terms of volatility effect. A threshold order one means the model is asymmetric, i.e. the impact of good news not equals the impact of bad news. All combinations of symmetric and asymmetric volatility models were run. In most instances more than one of the ARCH, GARCH, EGARCH and/or PGARCH models with significant parameters were found. The model with maximum Log Likelihood criterion (LL) was selected as optimal model for each series. It should be noted that EViews software package includes a constant in the variance equation by default. The parameter estimates are obtained in the EViews 7 software package via the Berndt, Hall, Hall and Hausman (1974) algorithm if the widely used Marquardt algorithm failed to converge.

The conditional variance equations associated with the mean equations for all series are present in Appendix 5, 6 and 7 along with the estimated values of parameters, LL, Q(12) and $Q_{SQ}(12)$. Significant volatility models are obtained for forty-nine countries' exchange rates series against the U.S. dollar. The coefficients of the mean equation are all significant ($p < 0.05$). It does not matter whether the constant term (ω) is not significantly different from zero. Ljung-Box Q(12) statistics tests for remaining serial autocorrelation in the residuals for up to 12 monthly lags. All are non-significant ($P > 0.05$) indicating that the mean equations are not incorrectly specified. The $Q_{SQ}(12)$ statistics tests for remaining ARCH in the variance equation up to a lag of 12 months and are all non-significant ($P > 0.05$), as is required in order to avoid model misspecification (Quantitative Micro Software, 2010). In Appendix 5, 6 and 7, D1 and D2 are representing the dummy one (for level break one) and dummy two (for level break two) respectively as suggested by Model A of LS (2003) unit root test. A major aim of this study is to check whether the volatility phenomenon is present in the sample countries. The analyses reveal that volatility is present in all series and thus a relevant aspect of research. The empirical results are sectionalised into forecasts involving advanced, emerging and frontier markets.

3.2.3 Results from Volatility Models of Forecasting Exchange Rates: Advanced Markets

The conditional variance equations for 10 advanced currencies against the U.S. dollar are reported in Appendix 5. The empirical results suggest that EGARCH volatility models are optimal for the exchange rate series in all cases except Canada, Denmark, Japan, Singapore and UK. This supports the findings of Hu and Tsoukalas (1999), who examined the out-of-sample forecasting performances of a number of conditional volatility models for a set of 11 European currencies against the German mark. They combined four individual volatility models and concluded that superior out-of-sample forecasting performance of the EGARCH model. The analyses show that in the EGARCH volatility models, ARCH parameters (α_i) range from 0.226 for Norway to 0.460 for Australia; while the coefficients on the lagged conditional variance GARCH (β_i) are ranges in value from -0.760 for the Euro area to 0.919 for Sweden. It is evident from Appendix 5 that $\beta_i > \alpha_i$ for all cases. This implies that there is a long-term impact of shocks on exchange rates of Australia, the Euro area, Norway, Sweden and Switzerland.

The findings also show that the GARCH (symmetric) volatility model fits the data well in the cases of Canada, Denmark, Singapore and UK. This supports the findings of Chong *et al.* (2002) who applied the GARCH model to the Malaysian ringgit/British pound in order to capture volatility and concluded that volatility models outperform the Naïve random walk model in forecasting the volatility of RM/Sterling exchange rates. For the GARCH (1,1) specification, the estimated parameters of α_1 and β_1 are significant at 5%. The positivity $(\alpha_1 + \beta_1 > 0)$ and stationarity $(\alpha_1 + \beta_1 < 1)$ constraints are met. The coefficients on both the lagged squared residual and lagged conditional variance terms in the conditional variance equation are highly statistically significant. Moreover, the sum of the coefficients on the lagged squared error and lagged conditional variance is very close to unity. This implies that the shocks to the conditional variance will be highly persistent in the cases of Canadian dollar/U.S. dollar, Danish krone/U.S. dollar, Singapore dollar/U.S. dollar and British pound/U.S. dollar. The large sums of the variance equation coefficients also indicate that a large positive or a large negative will lead future forecasts of the variance to be high for a protracted period. The results also indicate that the ARCH parameter (α_i) is less than GARCH parameter (β_i) in the cases of Canada, Demark, Singapore and UK. This implies that there is a relatively long-term impact of shocks on Canada-USA, Denmark-USA, Singapore-USA and UK-USA exchange rates. This indicates that the government's news releases, such as proposed changes in tax policy or spending or central bank's decisions to change or maintain the interest rates have long-term impacts on these exchange rates. These releases may cause large price swings as investors or traders buy and sell currencies in response to the information.

The asymmetric EGARCH (1,1) and GARCH (1,1) volatility models are statistically superior to other types of volatility models only in the cases of Australia and Japan. The asymmetry term (γ_1) which allows positive and negative shocks of equal magnitude to elicit an unequal response from the market. The results reveal that the estimated coefficients for the asymmetry term are negative (-0.137, -0.261) and are statistically significant. One of the aims of this study is to investigate the impacts of news shocks among advanced markets' currencies exchange rates against the U.S. dollar. The findings in Appendix 5 show that symmetric volatility models are statistically significant in the all cases except the Australia and Japan. This indicates that the impacts of positive and negative news or shocks are of the same magnitudes. However, asymmetric volatility models fit the data series in the cases of the Australia and Japan. The presence of significant γ_1 coefficients in Appendix 5 indicates that asymmetric responses to news shocks toAustralian dollar/ US dollar and Japanese yen/US dollar exchange rate. Results also showed that the $\gamma_1 < 0$ for these cases. This means the bad news or negative shocks lead to increase the volatility in exchange rates. Negative shocks such as bad news in the financial market or advertisement of economic policies by governments seem to increase volatility in the exchange rates more so than good news, such as disclosure of some good results of large local companies. Bollerslev *et al.* (1992), Kisinbay (2003) and Balaban (2004) empirically supported the phenomenon of no asymmetric effects in exchange return series. Moreover, Kisinbay (2003) reported that asymmetry responses are generally observed in stock market data, not in exchange rate series. The results of this study contradict the findings of these studies and conclude that asymmetry responses are equally present in Euro/dollar exchange rate series. This finding supports the analyses of Laakkonen and Lanne (2008), who studied the impact of positive and negative macroeconomic U.S. and European news announcements in different phases of the business cycle on the high-frequency volatility of Euro/U.S. dollar exchange rate. They concluded that bad news increases volatility more than good news.

This result also supports the theory. As exchange rates are bilateral, it is expected that they should be symmetric. However, currencies themselves are not symmetric. Some currencies have greater economic importance and some are not. For example, many multinational companies and financial institutions use the U.S. dollar as the base currency for profit and loss calculation. For these types of organisations, higher expected U.S. dollar/local currency volatility indicates higher risk in local currency denominated assets, not in U.S. dollar dominated assets. This may lead to the sale of the local currency denominated assets, which lowers the U.S. dollar/local currency exchange rate in near future and leads to asymmetric effect on exchange rates. Another possible explanation of an asymmetric effect in exchange rates is central bank intervention. It is documented in the literature that the central bank’s intervention creates higher volatility in the financial markets, which may eventually lead to an asymmetric impact on exchange rates. The next section presents the results of volatility models for emerging markets.

3.2.4 Results from Volatility Models of Forecasting Exchange Rates: Emerging Markets

The conditional variance equations for 19 emerging currencies against the U.S. dollar are reported in Appendix 6. The empirical results indicate that EGARCH volatility models fit the exchange rate series in all cases except Czech Republic, South Africa, Taiwan and Thailand. This supports the findings of Hsieh (1989), who concluded that standard GARCH (1,1) and EGARCH (1,1) models are more efficient for removing conditional heteroscedasticity from daily exchange rate movements. The author also reported that an EGARCH model fits the data better than does GARCH model. The results also show that in the EGARCH volatility models, ARCH parameters (α_i) are ranges from -0.048 for Turkey to 1.428 for Russia; while the coefficients on the lagged conditional variance GARCH (β_i) are ranges in value from 0.521 for China to 1.017 for Turkey. It is also evident from Appendix 5 that $\beta_i > \alpha_i$ for the cases of Chile, Colombia, India, Mexico, Philippines, Poland and Turkey. This implies that there is a long-term impact of shocks on exchange rates. In these cases possibly these country's local macroeconomic news, macroeconomic news of U.S. and global news such as financial crisis create the longer-term impacts on their corresponding exchange rates with U.S. dollar. Conversely, a short-term impact of shocks ($\alpha_i > \beta_i$) is evident in the cases of Brazil, China, Hungary, Indonesia, Malaysia, Peru, Russia and South Korea.

The GARCH (1,1) symmetric volatility model fits the Czech Republic-USA, South Africa-USA, Taiwan-USA and Thailand-USA exchange rate series respectively. The value of ARCH parameters (α_i) and GARCH parameters (β_i) are statistically significant. The results also show that in the GARCH volatility models, the ARCH parameters (α_i) are ranges in value from 0.109 for Thailand to 0.226 for South Africa; while the coefficients on the lagged conditional variance GARCH (β_i) are ranges in value from 0.308 for Thailand to 0.861 for Czech Republic. In all cases $\beta_i > \alpha_i$ indicates that the news announcements such as government policies, central bank's decisions regarding interest rate have a long-term impact on these exchange rates. As was mentioned earlier in Section 3.2.1, the PGARCH model has been infrequently applied in the exchange rate literature. In this study, the PGARCH volatility models are statistically inferior to other types of volatility models in all the cases.

Symmetric volatility models are statistically significant in all cases except Hungary, Indonesia, Malaysia, Philippines and Turkey. This means that the impacts of positive and negative news or shocks are of same magnitude. This supports the findings of Kisinbay (2003), who reported that asymmetric effects are not present in the exchange rate series that were examined. In a similar context, Jithitikulchai (2005) studied weekly Thai baht/U.S. dollar exchange rate and reported insignificant asymmetric coefficients of EGARCH and TGARCH volatility model. However, the presence of significant γ_1 coefficients in Appendix 6 indicates asymmetric responses to news (shocks) to exchange rates for Brazil Mexico and Turkey. Negative shocks increase the volatility in the exchange rates with U.S. dollar more so than good news. Although the phenomenon of no asymmetric effects in exchange return series is supported by Bollerslev *et al.* (1992) and Balaban (2004), the results of this study show that asymmetry responses are present in some of the emerging countries' exchange rate series. These results also support the findings of Kim (2008), who report the evidence of asymmetry in Korean won/U.S. dollar, Korean won/Japanese yen, Korean won/Chinese yuan and Japanese yen/U.S. dollar exchange rates. The findings also support the argument of Sandoval (2006), who suggested that an analyst has to be aware of the possible effect of asymmetry of Asian and emerging Latin American countries. The next section presents the results of volatility models for frontier markets.

3.2.5 Results from Volatility Models of Forecasting Exchange Rates: Frontier Markets

The conditional variance equations for 20 frontier currencies against the U.S. dollar are reported in Appendix 7. The empirical results also reveal that EGARCH volatility models are optimal for the exchange rate series in all cases except Brunei, Croatia, Kenya and Tunisia. This supports the findings of Alberg *et al.* (2006), who investigated the forecasting performance of various volatility models and concluded that EGARCH volatility model generates better result. This result also supports the findings of Balaban (2004), who reported that the EGARCH model outperforms the GARCH model in forecasting exchange rate volatility. The analyses also show that in the EGARCH volatility models, ARCH parameters (α_i) range from -0.341 for Trinidad & Tobago to 2.478 for Kazakhstan; while the coefficients on the lagged conditional variance GARCH (β_i) are ranges in value from -0.884 for Myanmar to 1.008 for Estonia. It is also evident from

Appendix 7 that $\beta_i > \alpha_i$ in the cases of Bangladesh, Bhutan, Botswana, Estonia, Jamaica, Lao PDR, Mauritius, Nigeria. This indicates that there is a relatively long-term impact of shocks on exchange rates. Natural disasters, political unrest, unstable economic situations and decision concerning macroeconomic fundamentals create these longer effects on these exchange rates. However, the short-term impact of shocks ($\alpha_i > \beta_i$) is found in the cases of Kazakhstan, Nepal, Pakistan, Romania, Sri Lanka, Trinidad & Tobago and Vietnam.

The GARCH symmetric volatility model fits the Brunei-USA, Croatia-USA, Kenya-USA and Tunisia-USA exchange rate series. The value of ARCH parameters (α_i) and GARCH parameters (β_i) are statistically significant. The results also show that in the GARCH volatility models, ARCH parameters (α_i) are ranges from 0.109 for Brunei to 0.656 for Kenya; while the coefficients on the lagged conditional variance GARCH (β_i) are ranges in value from 0.316 for Kenya to 0.897 for Tunisia. The $\beta_i > \alpha_i$ in all cases except Kenya, indicates that the news announcements such as government policies, central bank's decisions regarding interest rate have a long-term impact on these exchange rates. As was mentioned earlier in Section 3.2.1, the PGARCH model has been infrequently applied in the exchange rate literature. The results of this study suggest that the PGARCH volatility models are statistically inferior to other types of volatility models in all frontier market cases.

Symmetric volatility models are statistically significant in all cases except Estonia and Jamaica implying that the impacts of positive and negative news or shocks are the same in magnitude. However, asymmetric volatility models are optimal for Estonia and Jamaica. The presence of significant γ_1 coefficients in Appendix 7 indicates asymmetric responses to news shocks to exchange rates for these countries. This indicates that the bad news have significant greater impacts on their corresponding exchange rates with U.S. dollar. For example, Estonia and Jamaica are an export-oriented economy and the U.S. is one of its major targeted markets. Therefore, any news related to the U.S. economy, even the political news, has a significant influence on Estonia-USA and Jamaica-USA exchange rate. Moreover, local government's new releases, such as proposed changes in spending or tax policy or central bank's decisions regarding interest rates have greater impacts on these exchange rates. The current findings show that asymmetry responses are present in some of the frontier countries' exchange rate series. This result confirms the findings of Longmore and Robinson (2004), Olowe (2009) and Abdalla (2012), who reported the asymmetric effects in Jamaican dollar, Nigerian naira and 18 Arab currencies respectively. The next section evaluates the forecast generated by the optimal volatility model for each series.

3.2.6 Forecast Evaluation

Having estimated an optimal volatility model for each exchange rate series, this study now proceeds to forecast the values of exchange rates. There are two types of forecast available - static (for the historical period) and dynamic (for the hold back period). A static forecast method calculates a sequence of one-step ahead forecasts by using the actual values of exchange rates. In dynamic forecasting, previously forecasted values of the variable are used in forming forecasts of the current value (Quantitative Micro Software, 2010).

Forecast evaluation also a major aim of this study. All volatility models are assessed in terms of forecasting accuracy. In this study, MAPE is used to compare the accuracy of the forecasts obtained from the volatility models. The MAPE values for static forecasts for all series are presented in the second column of Appendix 8. It has been observed the minimum and maximum values of MAPE are 0.508% for Trinidad & Tobago to 8.413% for Peru respectively. The results also indicate that the MAPE value is less than or equal to 5% for all countries except the Euro area (5.591%) and Peru (8.413%). Volatility models have captured the structural breaks by treating them volatile episode and result in MAPE values are very low indicative a model adequacy. The best volatility model for each series is then used to produce monthly *ex post* forecast for 2008M1 to 2010M4 inclusive for each series by using dynamic forecasts method.

Conditional variance graphs for static forecasts for all exchange rates are presented at Appendix 9. Static forecasts are generated using the historical values of the exchange rate series. It is worthwhile visualising how the optimal EGARCH/GARCH/TGARCH volatility models depict and communicate historical patterns of volatility in the exchange rates series. Although within sample forecasting is not a prime consideration in this research, it may be opportune to look at a small subset of conditional variance plots to see the historic volatility of the exchange rate series. An instructive example is India (Appendix 9-17), which shows high conditional variance (high volatility) in exchange rate during the period of 1991 and 1993. The reasons for these high volatile periods are devaluation (July 1991) and bombing (March 1993). The government of India faced economic crisis at the end of 1990. The government was close to default and its foreign exchange reserves had dried up to the point that India could barely finance three weeks' worth of imports. The Indian government devalued the rupee by between 18 and 19 per cent in July of 1991. Another intervention period was March 1993. On March 12, 1993, there were a series bombing took place in Mumbai (Bombay). The attacks were the most destructive and coordinated bomb explosions in the country's history. The explosives went off within 75 minutes of each other across several districts of India's financial capital.

Dynamic forecasts use the previously forecasted values of exchange rates in order to generate further forecasts. This form of forecasting is applied to the holdback period, since in reality future values of exchange rates are unobserved. The plots of dynamic forecasts of the conditional variances are presented in Appendix 10. Examination of Figure 1 in Appendix 10 shows that the conditional variance decreases in the short-run and then remains stable up to a certain point for Australia. Similar results also observed in the cases of the Euro area, Sweden and Switzerland, Brazil, Hungary, South Korea, Turkey, Bhutan, Botswana, Jamaica, Romania. The opposite results have been observed for Canada, Japan, Norway, Singapore, UK, Colombia, India, Indonesia, Malaysia, Mexico, Peru, Poland, South Korea, Taiwan, Thailand, Bangladesh, Brunei, Croatia, Kazakhstan, Mauritius, Myanmar, Nepal, Nigeria, Pakistan, Sri Lanka, Trinidad & Tobago, Tunisia and Vietnam. Sharp increases in the forecasted conditional variances are evident in the case of Czech Republic. Conversely, sharp decrease of conditional variances is noticed in the case of Estonia.

3.3 Exponential Smoothing Models Applied to Forecasting Exchange Rates

This section introduces the exponential smoothing models for forecasting exchange rates. Relative to other disciplines, the exponential smoothing model has received relatively less attention as a forecasting model. This gives an opportunity of assessing the utility of this model in a financial context e.g. exchange rates. The theoretical background of the exponential smoothing models is discussed. The empirical results and discussion are also presented.

3.3.1 Theory

Exponential smoothing models (Gardner, 1985) are amongst the most widely used time series models in the fields of Economics and business analysis. According to Brooks, (2008, 241-242) “exponential smoothing is a time series modelling techniques (not based on the ARIMA approach) that uses only a linear combination of the previous values of a series for modelling it and for generating forecasts of its future values. Recent observations would be expected to have the most power in helping to forecast future values of an exchange rate series. If this is accepted, a model that places more weight on recent observations that those further in the past would be desirable. On the other hand, observations a long way in the past may still contain some information useful for forecasting future values of a series”.

The simplest one parameter model uses a linear function of the previous values of a series for generating forecasts of its future values. Distant observations may still contain a little information useful for forecasting future values of a series. An exponential smoothing model achieves this by imposing geometrically declining weights on the lagged values of a series. Moreover, the essence of these models is that new forecasts are derived by adjusting the previous forecasts to reflect forecast errors. In this way, the forecaster can continually revise forecasts based on previous experience data. The simplest model is the single parameter exponential smoothing model which is, Next forecast = Last forecast + a proportion of the last error. The simple, one parameter exponential smoothing model is applicable to series with no trend and seasonality and is defined as:

$$\widehat{Y}_t\,(k) = L(t) \qquad (13)$$

where $L(t) = \alpha\, Y(t) + (1 - \alpha)L(t - 1)$

$\widehat{Y}_t$ (k) is the forecasted value of the series at time k, Y(t) is the observed value of that series at time t and α is the smoothing (or 'weighting') parameter to be estimated with $0 \leq \alpha \leq 1$. The optimal value of α is defined as that which minimises the sum of the squares of the errors (SSE) and is found by means of a *grid search* of the form $\alpha = 0(0.1)1$ or $\alpha = 0(0.01)1$. High values of α in equation (13) imply that the impact of historical observations dies out quickly and vice versa.

Potentially more relevant to exchange rate forecasting are exponentially smoothing models that extend the simple model by incorporating a parameter (γ) reflecting any trend present, a parameter (φ) for any damped trend and/or a parameter (δ) for any seasonality. Both of these latter parameters lie between 0 and 1 inclusive and their optimal values are again found by minimising the SSE. Large values for γ, φ and δ give more weight to recent estimates of the trend, damped trend and seasonality components, with smaller values giving more weight to historical estimates of these components respectively. Table 3.3 presents the equations of each of the various exponential smoothing models. The simple exponential smoothing has a single level (α) parameter, Holt's exponential smoothing has level (α) and trend (γ) parameters, the damped-trend exponential smoothing has level (α) and damped trend (φ) parameters and the simple seasonal exponential smoothing has level (α) and seasonal (δ) parameters.

Winters' additive and multiplicative exponential smoothing models incorporate α, γ and δ parameters. The difference between the additive and multiplicative methods is that the amplitudes of the seasonal patterns remain constant in the former, even as the underlying level increases in the case of additive model, whereas, the amplitudes increases as the level increases in the latter. Winters' additive model is appropriate for a series with linear trend and a seasonal effect that does not depend on the level of the series. Winters' multiplicative model is appropriate for the same type of trend, but the seasonal effect that does depend on the level of the series. Figure 3.1 depicts the graphical presentation of the theoretical form of these exponential smoothing models. As was mentioned earlier that the exponential smoothing model has received relatively less attention as a forecasting model, this study fills a gap of the literature by applying the exponential smoothing model for predicting

Table 3.3: Exponential smoothing models

Exponential Smoothing Models	**Equations***
Simple	$\hat{Y}_t\,(k) = L(t)$ where $L(t) = \alpha\, Y(t) + (1-\alpha)L(t-1)$
Holt	$\hat{Y}_t\,(k) = L(t) + kT(t)$ where $L(t) = \alpha\{Y(t) + (1-\alpha)\{L(t-1) + T(t-1)\}$ and $T(t) = \gamma\{L(t) - L(t-1)\} + (1-\gamma)\, T(t-1)$
Damped-Trend	$\hat{Y}_t\,(k) = L(t) + \sum_{i=1}^{k} \varphi^i\, T(t)$ where $L(t) = \alpha\, Y(t) + (1-\alpha)\{L(t-1) + \varphi T(t-1)\}$ and $T(t) = \gamma\{L(t) - L(t-1)\} + (1-\gamma)\, \varphi T(t-1)$
Simple Seasonal	$\hat{Y}_t\,(k) = L(t) + S(t+k-s)$ where $L(t) = \alpha\{Y(t) - S(t-s)\} + (1-\alpha)\, L(t-1)$ and $S(t) = \delta\{Y(t) - L(t)\} + (1-\delta)\, S(t-s)$
Winters' Additive	$\hat{Y}_t\,(k) = L(t) + kT(t) + S(t+k-s)$ where $L(t) = \alpha\{Y(t) - S(t-s)\} + (1-\alpha)\{L(t-1) + T(t-1)\}$ $T(t) = \gamma\{L(t) - L(t-1)\} + (1-\gamma)T(t-1)$ and $S(t) = \delta\{Y(t) - L(t)\} + (1-\delta)\, S(t-s)$
Winters' Multiplicative	$\hat{Y}_t\,(k) = \{L(t) + kT(t)\}\, S(t+k-s)$ where $L(t) = \alpha\left\{\frac{Y(t)}{S(t-s)}\right\} + (1-\alpha)\{L(t-1) + T(t-1)\}$ $T(t) = \gamma\{L(t) - L(t-1)\} + (1-\gamma)T(t-1)$ and $S(t) = \delta\left\{\frac{Y(t)}{L(t)}\right\} + (1-\delta)\, S(t-s)$

α: level smoothing weight, γ: trend smoothing weight, φ: damped trend smoothing weight and δ: season smoothing weight. *Adapted from SPSS Inc. (2010).

Figure 3.1: Family of exponential smoothing models adapted from Gardner (1985)

Exponential Smoothing Models

Simple

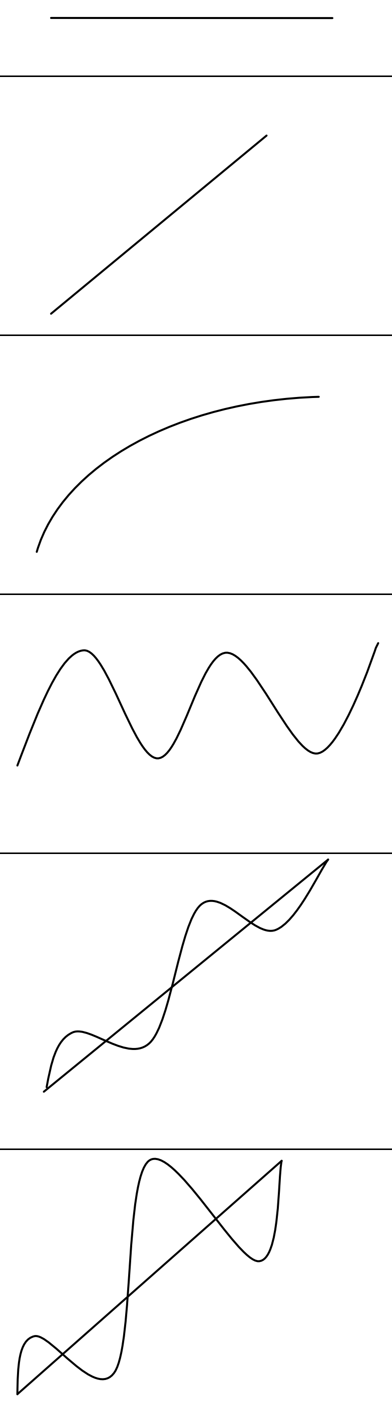
Holt

Damped-Trend

Simple Seasonal

Winters' Additive

Winters' Multiplicative



exchange rates of advanced, emerging and frontier markets. The next section discusses the results of applying the exponential smoothing models in exchange rates series.

3.3.2 Results and Discussion

The exponential smoothing models obtained for each country are reported in Table 3.4. Using SPSS version 19, the Expert Modeller procedure generates optimal (minimum SSE) exponential smoothing models for each exchange rate series. This process compares all previously mentioned (Table 3.3) exponential smoothing models in response of SSE. The Normalised Bayesian Information Criteria (NBIC) are also reported in Table 3.4. NBIC is a general measure of the overall fit of a model that attempts to account for model complexity. It is a score based on the mean squared error. It includes a penalty for the number of parameters in the model and the length of the series. The penalty removes the advantage of models with more parameters, making the statistic easy to compare across different models for the same series (SPSS Inc., 2010).

The estimated values of the parameters α, γ, φ and δ for all exchange rates are presented in Table 3.4. The Winters' additive model is optimal for Bangladesh, Mexico and Peru. The α value for Bangladesh, Mexico and Peru are 1.000, 0.999 and 1.000 respectively. These high values of α imply that the impact of historical observations dies out quickly. The parameter γ has a very low value for these countries. This indicates to give more weight to historical estimates of this component. Moreover, the estimated value for δ is very high for Mexico (0.999) when compared with Bangladesh (0.001) and Peru (0.001). This implies that the most recent observations have more significant impacts on Mexico-USA exchange rate. Conversely, smaller values of δ give more weight to historical estimates of this component for the country like Bangladesh and Peru.

The simple one parameter model is optimal for China and Trinidad & Tobago. High values of α (1.000) suggests that only the most recent observations significantly affect the Chinese yuan/U.S. dollar and Trinidad & Tobago dollar/U.S. dollar exchange rates. For the Euro area, the simple seasonal model is found to be superior to other models. The estimated parameters i.e. level (α) and seasonality (δ) are 0.999 and 1.000 respectively. These

Table 3.4: Results from exponential smoothing models

Country	Model	α	γ	φ	δ	NBIC
Advanced Countries						
Australia	Damped Trend	1.000	1.000	0.255	-------	-6.892
Canada	Damped Trend	1.000	1.000	0.201	-------	-8.268
Denmark	Damped Trend	1.000	1.000	0.300	-------	-3.427
Euro area	Simple Seasonal	0.999	-------	-------	1.000	-7.559
Japan	Damped Trend	1.000	1.000	0.300	-------	3.143
Norway	Damped Trend	1.000	1.000	0.300	-------	-3.726
Singapore	Damped Trend	1.000	1.000	0.299	-------	-7.204
Sweden	Damped Trend	1.000	1.000	0.300	-------	-3.608
Switzerland	Damped Trend	1.000	1.000	0.300	-------	-5.764
UK	Damped Trend	1.000	1.000	0.269	-------	-8.428
Emerging Countries						
Brazil	Damped Trend	1.000	0.999	0.299	-------	-4.577
Chile	Damped Trend	1.000	1.000	0.398	-------	4.382
China	Simple	1.000	-------	-------	-------	-3.771
Colombia	Damped Trend	1.000	1.000	0.400	-------	6.759
Czech Republic	Damped Trend	1.000	1.000	0.298	-------	-0.477
Hungary	Holt linear	1.000	0.100	--------	-------	2.400
India	Damped Trend	1.000	0.294	0.627	-------	-1.503
Indonesia	Damped Trend	1.000	1.000	0.200	-------	12.274
Malaysia	Simple Seasonal	0.999		-------	0.001	-5.516
Mexico	Winters' Additive	0.999	3.23×10^{-7}	-------	0.999	-3.204
Peru	Winters' Additive	1.000	0.100	-------	0.001	-6.444
Philippines	Damped Trend	1.000	1.000	0.341	-------	-0.908
Poland	Damped Trend	1.000	1.000	0.300	-------	-4.950
Russia	Damped Trend	0.999	0.273	0.860	-------	-0.512
South Africa	Damped Trend	1.000	1.000	0.301	-------	-3.285
South Korea	Damped Trend	1.000	1.000	0.500	-------	6.864
Taiwan	Damped Trend	1.000	0.711	0.496	-------	-1.894
Thailand	Damped Trend	1.000	1.000	0.299	-------	0.122
Turkey	Damped Trend	1.000	1.000	0.400	-------	-6.221
Frontier Countries						
Bangladesh	Winters' Additive	1.000	0.001	-------	0.001	-1.499
Bhutan	Damped Trend	1.000	0.294	0.627	-------	-1.503
Botswana	Damped Trend	1.000	1.000	0.242	-------	-4.615
Brunei	Damped Trend	1.000	1.000	0.299	-------	-7.203
Croatia	Damped Trend	1.000	0.421	0.738	-------	-3.007
Estonia	Damped Trend	1.000	1.000	0.300	-------	-2.226
Jamaica	Damped Trend	0.986	0.374	0.810	-------	-1.214
Kazakhstan	Damped Trend	0.874	0.999	0.641	-------	1.912
Kenya	Damped Trend	0.999	0.989	0.396	-------	0.591
Lao PDR	Damped Trend	0.900	1.000	0.513	-------	10.737
Mauritius	Damped Trend	1.000	0.960	0.422	-------	-2.377
Myanmar	Damped Trend	0.999	0.069	0.924	-------	-4.226
Nepal	Damped Trend	0.999	0.901	0.400	-------	-0.634
Nigeria	Damped Trend	0.887	0.250	0.563	-------	2.378
Pakistan	Damped Trend	1.000	1.000	0.401	-------	-1.434
Romania	Holt linear	1.000	0.100	-------	-------	-5.892
Sri Lanka	Holt linear	1.000	0.001	-------	-------	-0.603
Trinidad & Tobago	Simple	1.000	-------	-------	-------	-4.798
Tunisia	Damped Trend	1.000	1.000	0.296	-------	-7.954
Vietnam	Damped Trend	1.000	1.000	0.200	-------	11.501

α: level smoothing weight, γ: trend smoothing weight, φ: damped trend smoothing weight and δ: season smoothing weight. NBIC: Normalised Bayesian Information Criteria.

indicate that a constant seasonal effect is present in Euro/dollar series. A similar result is observed in the case of Malaysian ringgit/dollar. Holt's linear model is found to be optimal in the cases of Hungary, Romania and Sri Lanka. The estimated values of α for these countries is 1.000, but the values for estimated trend smoothing parameter (γ) are 0.100 for Hungary and Romania and 0.001 for Sri Lanka. According to this model, the exchange rates of these countries follow a linear trend with no seasonal effect.

Surprisingly enough, the damped trend model is found to be superior for 39 countries cases out of 49. This result supports the findings of McKenzie and Gardner (2010), who argued that over the past twenty years, damped trend exponential smoothing models have performed well in numerous empirical studies and it is now well established as highly accurate forecasting method. Fildes *et al.* (2008) reported that the damped trend can reasonably claim to be a benchmark forecasting method for all others to beat. Armstrong (2006) also recommended that the damped trend as a well-established forecasting method that should improve accuracy in practical applications. Theoretically, the damped trend model is appropriate for series with a linear trend that is dying out and which possess no seasonality. The results show that the α values are very high (equal to 1) in majority of the cases. This indicates that the most recent observation has significant impacts on future exchange rates of these countries. The values of estimated damped trend (φ) parameter is less than 0.4 in all cases except India (0.627), Russia (0.860), South Korea (0.500), Bhutan (0.627), Croatia (0.738), Jamaica (0.810), Kazakhstan (0.641), Lao PDR (0.513), Myanmar (0.924) and Nigeria (0.563). Large values for φ give more weight to recent estimates of the damped trend components, with smaller values giving more weight to historical estimates of this component for determining the future exchange rates of these countries.

The MAPE values (static) for all series are presented in the fourth column of Appendix 8. The results show that the MAPE values are less than 5% in all cases except Peru (6.96%). The optimal model for each series is then used to produce monthly *ex post* forecast for 2008M1 to 2010M4 inclusive (hold back period) for each series. Dynamic MAPE values are presented in the fifth column of Appendix 8. The dynamic MAPE values are less than 10% in all cases except Australia, Japan, Sweden and UK in the advanced markets group. By contrast, MAPE values are less than 10% for all emerging markets except Hungary, India, Philippines, Poland, Russia, South Africa, South Korea and Turkey. In the frontier markets group, MAPE values are higher than 10% is the cases of Bhutan, Botswana, Kenya, Nepal, Nigeria, Pakistan and Romania. Overall, the analyses show that the exponential smoothing models generate highly accurate forecasts (MAPE < 10%; Lewis, 1992) for 32 countries out of 49. These indicate that the exponential smoothing model is equally as good as other time series models as far as exchange rate forecasting is concerned. The results are in line with some recent studies, e.g. Borhan and Hussain (2011), Li (2010), Yu *et al.* (2007) and Dheeriyaa and Raj (2000), who noted that the exponential smoothing models generate better forecasts of exchange rates. Therefore, the current findings add to a growing body of literature on the application of exponential smoothing models to forecast exchange rate series. The next section discusses the application of Naïve models for forecasting exchange rates.

3.4 Naïve Models Applied to Forecasting Exchange Rates

This section introduces the Naïve models for forecasting exchange rates. Naïve models often act as a benchmark model for low frequency data e.g. quarterly data. For high frequency data this has an inherent logic. The theoretical background of the Naïve models is discussed. The results and discussion are also presented.

3.4.1 Theory

The Naïve 1 model assumes that a forecast of a series at a particular period equals the actual value at the last period available i.e. $\widehat{Y}_{t+1} = Y_t$ which is the simple exponential smoothing model with $\alpha = 1$. For exchange rate series, this says that the forecast for one time period should be equal to that of the previous. The Naïve 1 model is often included in forecasting studies since it acts as yardstick with which other models, like ARIMA and exponential smoothing class of models may be compared (McKenzie and Mitchell, 2002). The Naïve 2 model referred to as the constant growth model. This model assumes that the growth rate in the previous period applies to the generation of forecasts for the current period. For monthly data, the model is:

$$\hat{Y}_{t+12} = Y_t \left[1 + \frac{Y_t - Y_{t-12}}{Y_{t-12}}\right] \tag{14}$$

In this study, the Naïve 1 model is used as one of the time series models to forecast exchange rates. However, the Naïve 2 model is discounted because of its constant growth feature, which is not applicable in exchange rate behaviour.

3.4.2 Results and Discussion

The MAPE values associated with Naïve 1 model (static) for all series are presented in the sixth column of Appendix 8. The results show that the MAPE values are less than 5% for all 49 countries. In the instance of dynamic forecasting, the MAPE values (last column of Appendix 8) are less than 10 % in 28 out of 49 cases. The MAPE values are greater than 10% for the remaining sample countries. It is evident from the Appendix 8 that volatility models (dynamic) are overall optimal for 4 of 10 advanced market cases. Volatility models generate better forecasts for 9 and 14 cases out of 19 emerging and 20 frontier markets cases respectively. This is expected, as foreign exchange markets of emerging and frontier economies are more volatile than advanced markets. Exponential smoothing models are found to be superior in 4 cases for advanced and 3 cases for frontier exchange rate series, while this model generates better forecasts for 5 of 19 emerging market cases. The Naïve 1 model parallels the exponential smoothing model in terms of the overall forecast performance across countries. This model is found to be superior in 12 out of 49 cases only. It may be concluded that the application of volatility models has distinct relevance in the context of currency exchange rates.

3.5 Summary and Policy Implications

The main purpose of this chapter is to examine the forecasting performance of exchange rates and associated volatilities in advanced, emerging and frontier markets by using three time series methods. Ten advanced, nineteen emerging and twenty frontier markets' national currencies against the U.S. dollar are investigated. MAPE values are used to compare the accuracy of the forecasts obtained from the time series models. An extensive examination of the ARCH, GARCH, TGARCH, EGARCH and PGARCH models was performed. A variety of exponential smoothing models and the Naïve 1 model were applied to generate the optimal models for each series. Volatility models typically generate better forecasts. A basic yet major aim of this study is to check whether volatility is present in the sample countries of this study. The results reveal that all sample exchange rate series are volatile. One concludes that volatility concept has distinct relevance in the context of currency exchange rates. Moreover, volatility models perform extremely well in emerging and frontier markets exchange rate series. These results are as expected, since emerging and frontier markets are more volatile in respect of output, consumptions, interest rates or exchange rates than advanced markets (Hausmann *et al.*, 2006; Errunza, 1997 and Wilcox, 1992).

Another aim of this study was to investigate whether the traditional univariate volatility models that are widely and successfully used in the literature of advanced countries could perform equally well in emerging and frontier countries. The widely applied GARCH (1,1) volatility model is superior in only five advanced market cases – Canada, Denmark, Japan, Singapore and UK, four emerging market- Czech Republic, South Africa, Taiwan and Thailand and four Frontier markets cases –Brunei, Croatia, Kenya and Tunisia. This classical volatility model is also found to be inferior when compared with other volatility models in majority of the cases of emerging and frontier market exchange rate series. It is interesting to note that the EGARCH model is superior in 50% of the advanced market cases both for in-sample estimation and out-of-sample forecast evaluation. This finding parallels result found for the emerging and frontier market exchange rate series where EGARCH models are optimal and generate superior forecasts in 79% and 80% respectively. These results support the findings of Hsieh (1989), Hu and Tsoukalas (1999), Balaban (2004), Edrington and Guan (2005), Alberg *et al.*, (2006) and Abadalla (2012), who report that the EGARCH volatility models generate better forecasts than other volatility models in the context of exchange rate modelling. Hence, this study supports the existing literature concerning the superiority of the EGARCH model for modelling advanced, emerging and frontier market exchange rate series.

As was mentioned earlier that PARCH models are rarely applied in exchange rate literature. The results of this study show that the PGARCH volatility models are statistically inferior to other types of volatility models in all the exchange rate series. Although this result contradicts the findings of Tse and Tsui (1997), who reported the asymmetric PGARCH model is found to be superior to alternative models for daily Malaysian/U.S exchange rates series. However, the findings of this present study supports the results of McKenzie and Mitchell (2002), who reported that PARCH models are better applied to stock market data better than to exchange rate data. Therefore, the current findings add to a growing body of literature on the application of PARCH volatility models in exchange rate series.

The present study also investigates the leverage effects in advanced, emerging and frontier markets exchange rate series. The phenomenon of no asymmetric effects in exchange rates series is empirically supported by Bollerslev *et al.* (1992), Kisinbay (2003) and Balaban (2004). However, the current study found asymmetry effects in 8 out of 49 country cases. These countries are Japan, Hungary, Indonesia, Malaysia, Philippines, Turkey, Estonia and Jamaica. This indicates that the negative macroeconomic news of USA and local news announcements or the central bank's intervention in these countries have significantly greater impacts on their corresponding exchange rates with U.S. dollar. This finding supports those of Longmore and Robinson (2004), Edrington and Guan (2005), Sandoval (2006), Kim (2008), Laakkonen and Lanne (2008), Olowe (2009) and Abdalla (2012). The present study provides additional evidence on leverage effects of advanced currencies exchange rates. This study also reports the new evidence of leverage effects in some of the emerging and frontier markets exchange rate against the U.S. dollar.

As was mentioned earlier (in Section 3.3.1), application of exponential smoothing model is very limited in the exchange rate literature, yet this model has the potential to generate superior forecasts. Exponential smoothing models are optimal for 25% of the exchange rates. This model is ranked as the second best time series model in terms of forecasting. A variety of exponential smoothing models was applied to generate the optimal model for each series. Surprisingly enough, the damped trend model is found to be superior in 80% of exchange rate series. This result supports the argument of McKenzie and Gardner (2010), who noted that the damped trend exponential smoothing has performed well in numerous empirical studies and it is now well established as an accurate forecasting method. The findings are also in line with some recent studies, e.g. Borhan and Hussain (2011), Li (2010), Yu *et al.*, (2007) and Dheeriyaa and Raj (2000), who reported that the exponential smoothing model generally good forecasts of exchange rates. Therefore, the current findings add to a growing body of literature on the application of exponential smoothing models to forecast exchange rate series.

Summing up, the results presented in this chapter confirm the previous findings in the exchange rate literature that volatility models generate superior forecasts in advanced, emerging and frontier markets' exchange rate series. Additionally, asymmetric effects in some exchange rate series are reported. The application of PARCH volatility model is found to be insignificant when capturing the volatility effects inherent in several exchange rate series. The exponential smoothing model outperforms to other time series models in several cases. Overall, the exponential smoothing and Naïve 1 models are found to be second and third best forecasting model respectively when compared with volatility models. To conclude, all the results related to emerging and frontier markets are considered as new findings, which are never reported in the literature. Therefore, these findings will add value to a growing body of exchange rate literature.

The findings of this study are important for the policy makers. Due to globalisation, policy makers of multinational or transnational companies face new challenges in the management of their global financial recourses so that countries can take full advantage of the opportunities, while reducing the potential risk. Exchange rate volatility plays a vital role in this regard. Thus, volatility forecasts can help policy makers to manage their global financial resources more effectively. Moreover, the results of this study have importance to exporters and importers since exchange rate volatility has different impacts on their decisions regarding international transactions. For example, if exchange rate volatility is higher in a particular country, risk-averse traders might prefer to lower their transactions with that country because of the high unpredictability of their profits. On the other hand, risk-seeking traders might benefit from seeking out hedging opportunities. Furthermore, international investors and risk managers can reduce their risk level by assessing the volatility level of the currencies with which they interact. The findings of this study could also be used as an input in their portfolio diversification and risk management processes.

Overall, the current findings have substantial benefits for the various individual agents such as investment banks, foreign exchange brokers, stock market brokers, financing and investment societies, international investors, risk managers and portfolio managers. The results of this study could also be used as an input of pricing derivative securities. Volatility is one of the important variables in pricing derivative securities. It is important to know and measure the volatility of the underlying assets from now until the expiry date of derivative contract. Prospective investors who wish to hedge the volatility risk and the agent who wants to price the derivative contracts may found these results useful for measuring their dynamic hedge ratios.

The findings could also facilitate central banks' decisions in respect of intervention policy. The central bank of each country often generates internal forecasts of their local currency-US dollar exchange rate to measure and evaluate the exchange rate fluctuation. Therefore, the results of this study help the central bank to forecast excess volatility, which clearly suggests that there is a risk that exchange rates will move from its target zone. Thus, central bank can intervene to tackle this situation by forecasting the rate via the optimal models suggested in this study. The current findings could assist decision makers to choose more appropriate exchange rate policies for those countries, which have high degree of volatility. Moreover, policy makers can obtain an early signal of future crises by accurate forecasting of exchange rate volatility. In this regard, Kaminsky and Reinhart (1998) and Perry and Lederman (1998) reported that large deviations of nominal exchange rates from their PPP level have proved to be one of the important indicators of upcoming currency crisis. In such case, policy-makers might consider to join common exchange rate regimes to maintain the economic stability of their country. However, forecasting high exchange rate volatility in countries with flexible exchange rate regimes is likely to increase the desirability of entering into common exchange regime systems in order to promote economic stability (Ogawa, 2002a). Forecasted exchange rate volatility can also be used as an important factor to determine the best exchange rate regime for a country (Hernandez and Montiel, 2001) and to evaluate whether monetary union is optimal for that country (Wyplosz, 2002).

The presented findings have important implications for emerging and frontier countries. Exchange rate volatility is a key issue for these economies because these countries wish to encourage foreign direct investment from developed nations. Due to fast and intensive money flows from developed countries into emerging and frontier countries, it is important for policy makers to forecast the excess volatility to take the necessary measures to overcome the negative impacts of the volatility on the economy. A majority of emerging and frontier market economies are maintaining their reserves in an international currency such as the U.S. dollar. Therefore, the foreign reserve department can also use optimal volatility models, which are suggested in this study in order to maintain their reserve effectively and efficiently.

Chapter 4

Cointegration of Exchange Rate Series via the ARDL Model

The previous chapter discussed the time series approaches to forecasting exchange rates. This section introduces a causal econometric approach. The aim of this chapter is to investigate the long-and short-run relationships of exchange rates with macroeconomic fundamentals. This study also compare the forecasting performance of a causal econometric approach with time series approaches in the context of advanced, emerging and frontier markets exchange rates. The major advantage of econometric approaches over the time series models lies in their ability to analyse the explanatory relationships between the exchange rate (dependent variable) and its influencing factors (explanatory variables). Moreover, econometric analyses have its empirical utility in interpreting the change of exchange rates from an economist's perspective, proving policy recommendations as well as evaluating the effectiveness of the existing exchange rate policies. Conversely, time series models cannot help under circumstances in which interdependent relationships among exchange rate and other influential factors.

Exchange rates are clearly influenced by a wide variety of macroeconomic fundamentals. The importance of each variable varies both from country to country and, for any given currency, over time. Financial researchers often interested in measuring the effect of an explanatory variable or variables on a dependent variable. Therefore, the employment of appropriate econometric models for factors affecting on exchange rate is crucial not only for academic researchers but also for practitioners. An econometric approach called Autoregressive Distributive Lag (ARDL) cointegration model is used in this study. Relative to other Finance areas (e.g. stock markets, equity markets and international trade), the ARDL-cointegration model has received less attention in exchange rate determination. This gives an opportunity of assessing the utility of this model in the context of exchange rates. The ARDL model has become very popular in Economics and Finance literature (discussed in Section 2.2.1). However, very few applications have been conducted in the field of nominal exchange rate modelling and their speed to return to equilibrium. The majority of the cointegration research has been conducted so far for advanced or developed currencies. Very little attention has been given on emerging and frontier markets' currencies and their long- and short-term relationship with other macroeconomic variables (Abdalla, 2012; Kamal *et al.*, 2012; Molana and Osei-Assibey, 2010 and Osinska, 2010). A major focus of this study is to investigate the long- and short-run relationship of exchange rates with its main determinants for advanced, emerging and frontier markets' currencies against the U.S. dollar, which will help to fill the gap of the existing literature. This study also investigates whether ARDL-cointegration model is better than other time-series models (discussed in Chapter 3) in order to capture the exchange rates movements especially in the cases of advanced, emerging and frontier markets' currencies against the U.S. dollar to fills a gap of the existing literature.

The reminder of the chapter is as follows. Section 4.1 presents the independent variables to be used in the cointegration analyses. The ARDL approach to cointegration is described in Section 4.2. Section 4.3 reports the long-run results of cointegration modelling plus a discussion. The short-run results of cointegration modelling and discussions are provided in Section 4.4. The Granger Causality test results are presented in Section 4.5. Section 4.6 reports a comparison of forecast performance between time series and ARDL-cointegration models. Summary results and policy implications are presented in Section 4.7.

4.1 The Independent Variables to be used in the Cointegration Analyses

Exchange rates are clearly influenced by a wide variety of macroeconomic fundamentals. The importance of each variables varies both from country to country and, for any given currency, over time. As was mentioned earlier (Section 2.2.2 in Chapter 2), the macroeconomic fundamentals frequently observed in the exchange rate literature are interest rates, inflation rates, money supply, real income, trade balance and current account balance used to evaluate the relationship with exchange rates. Therefore, macroeconomic variables such as money supply (MS), interest rates (both short-and long-run, INRS, INRL), real income (GDP), trade balance (TB), inflation rates (INFR), current account balance (CA), reserve assets (RES) and government expenditure (GE) are used in the present study. It has also been observed in the literature that trade openness has rarely been considered as an important determinant of exchange rates modelling, yet this factor has been shown to play significant role in the exchange rates determination (e.g. Chowdhury, 2012; Li, 2004; Hau, 2002; Connolly and Devereux, 1995; Calvo and Drazen, 1998; Elbadawi, 1994; Edwards, 1993 and Edwards, 1987). Therefore, this study also used trade openness (TO) - measured by sum of exports and imports relative to GDP – as a potential determinant of exchange rate behaviour. Moreover, oil prices (OP), gold prices (GP) and country specific commodity prices such as iron and coffee prices for Brazil, jute prices for Bangladesh, coal prices for South Africa and copper prices for UK are also considered to analyse the short and long-run relationship between exchange rate and macroeconomic variables.

Data pertaining to these variables are taken from IMF's IFS data base. The data are monthly and span the time period from 1972M1 to 2010M4 inclusive. It is worthwhile mentioning here that the quarterly GDP, exports, imports, current account balance, reserve assets and government expenditures data are available in the IFS database. There are many different methods available to estimate high frequency data from lower frequency values. The spline method is a general technique for fitting and smoothing the twists and turns of a time line (for details see Marsh and Cormier, 2001). This study used the *quadratic match average* method to generate estimates of monthly figures from observed quarterly data. Quadratic match average method fits a local quadratic polynomial for each observation of the low frequency series, then use this polynomial to fill in all observations of the high frequency series associated with the period. The quadratic polynomial is formed by taking sets of adjacent points from the source data and fitting a quadratic so that the average of the high frequency points matches the low frequency data actually observed (Quantitative Micro Software, 2010).

4.2 The ARDL Approach to Cointegration

Economic theory often suggests that a certain subset of variables could be linked by a long-run equilibrium relationship. When a long-run relationship between Y_t and X_t exists, those variables are said to be cointegrated. The explanatory variables may influence the dependent variable with a time lag in a time series analysis. This often required to the inclusion of lags of the explanatory variable in the regression. Furthermore, the dependent variable may be correlated with lags of itself. Therefore, the lags of the dependent variable should be included in the regression as well. The Autoregressive Distributive Lag (ARDL) model plays a significant role to overcome this problem. Moreover, this model helps the researcher to evaluate the short-run and long-run relationship among variables.

The ARDL model refers to a model involving lags of both the dependent and explanatory variables. Pesaran and Shin (1995, 1999) pioneered this technique. The ARDL has numerous advantages: (a) by an appropriate augmentation, the approach avoids problems of serial correlation and of endogeneity that may be experienced by other cointegration techniques; (b) it avoids pre-testing of the variables for the presence of unit roots, an essential requirement with other cointegration techniques. In essence, the main advantage of the ARDL method lies in the fact that it can be applied irrespective of whether the variables are I(0) or I(1) and can avoid the pre-testing problems associated with the standard cointegration analysis which requires the classification of the variables into I(1) and I(0). The regressors may include lagged values of the dependent variable and current and lagged values of one or more explanatory variables. This model allows us to determine what the effects are of a change in a policy variable. Moreover, this model helps to describe the existence of an equilibrium/relationship in terms of long-run and short-run dynamics without losing long-run information. A simple ARDL(1,1) model is defined as:

$$Y_t = \mu + \varphi Y_{t-1} + \omega_0 X_t + \omega_1 X_{t-1} + e_t \qquad (15)$$

where Y_t and X_t are stationary variables and e_t is a white noise error process. A white-noise error process requires a mean of zero, a constant variance and absence of autocorrelation. The general notation for an ARDL model involving Y_t and k explanatory variables $X_{1t}, X_{2t}, \ldots, X_{kt}$ is ARDL($p, q_1, q_2, \ldots, q_k$) where p is the number of lags applied to Y_t, q_1 is the number of lags applied to X_{1t}, q_2 is the number of lags of X_{2t} ....., q_k is the number of lags associated with the kth explanatory variable, X_{kt}. Therefore:

$$Y_t = \mu + \varphi_1 Y_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + \varphi_p Y_{t-p}$$

$$+\omega_{1,1} X_{1,t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + \omega_{q\,1} X_{1,t-q1}$$

$$+\omega_{2,1} X_{2,t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + \omega_{q,2} X_{2,t-q2}$$

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$$+\omega_{k,1}X_{k,t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . +\omega_{qk,2}X_{k,t-qk} + e_t \quad (16)$$

is an ARDL(p,q) model. Dummy variables (e.g. Gulf crisis, 1991; Asian Crisis 1997; September 11, 2001 etc.) can be added to such a specification as the above. The latter are called deterministic variables and other deterministic variables which may or may not be included according to the researcher's choice include the intercept term and seasonal dummies.

If $\varphi = \omega_1 = 0$ in equation (15), we have the static, bivariate regression model. In static models, only the subscript t needs to be employed i.e. effects are regarded as being contemporaneous. This means that a change in one or more of the explanatory variables at time t causes an instant change in the dependent variable at time t in the static model. If $\omega_0 = \omega_1 = 0$ in equation (15), we have a dynamic AR(1) process. If $\omega_1 = 0$ in equation (15), we have called partial adjustment model. If $\varphi = 1$ and $\omega_1 = -\omega_0$ in equation (15), we have a model in first differences, namely $\Delta Y_t = \mu + \omega_0 \Delta X_t$.

Subtract Y_{t-1} from both sides of equation (15) and use the notation $\Delta Y_t = Y_t - Y_{t-1}$:

$$\Delta Y_t = \mu + (\varphi - 1)Y_{t-1} + \omega_0 X_t + \omega_1 X_{t-1} + e_t$$

$$\Delta Y_t = \mu + (\varphi - 1)Y_{t-1} + \omega_0 X_t - \omega_0 X_{t-1} + \omega_0 X_{t-1} + \omega_1 X_{t-1} + e_t$$

$$\Delta Y_t = \mu - (1 - \varphi)Y_{t-1} + \omega_0 \Delta X_t + (\omega_0 + \omega_1)X_{t-1} + e_t$$

$$\Delta Y_t = \omega_0 \Delta X_t - (1 - \varphi)\left[Y_{t-1} - \frac{\mu}{1-\varphi} - \frac{\omega_0 + \omega_1}{1-\varphi} X_{t-1}\right] + e_t$$

$$\Delta Y_t = \omega_0 \Delta X_t - (1 - \varphi)[Y_{t-1} - \alpha - \beta X_{t-1}] + e_t \quad (17)$$

where $\alpha = \frac{\mu}{1-\varphi}$ and $\beta = \frac{\omega_0+\omega_1}{1-\varphi}$

Equation (17) is a *reparameterisation* of equation (15). Equation (17) also called the *error correction form or error correction model (ECM)* of Equation (15). The value $(1 - \varphi)$ is called the adjustment parameter of the ARDL model and the speed at which the Y-variable returns to equilibrium is determined by it. The larger is the adjustment parameter, the faster is the return to equilibrium.

Suppose a particular ARDL model in which the Y_t variable is lagged by p time periods and there are k X_t variables which for simplicity are all lagged by q time periods. The particular error correction form for this ARDL model is:

$$\Delta Y_t = \pi + \sum_{i=1}^{q-1} \beta_i \Delta Y_{t-1} + \sum_{i=1}^{q-1} \gamma_i \, \Delta X_{1,t-i} + \sum_{i=1}^{q-1} \delta_i \Delta X_{2,t-1} + \ \dots\dots\dots + \sum_{i=1}^{q-1} \varepsilon_i \, \Delta X_{k,t-1}$$

$$+\left[\theta_1 Y_{t-1} + \theta_2 X_{1,t-1} + \ \theta_3 \, X_{2,t-1} + \ \dots\dots\dots + \ \theta_k \, X_{k,t-1}\right] + \ e_t \qquad (18)$$

where the term in square brackets is the error correction term and π is an intercept. The first part of the equation (18) with β_i, γ_i , δ_i and ε_i represents the short-run dynamics of the model, whereas the parameters θ_1, θ_2, θ_3 and θ_k represents the long-run relationship. An appropriate null is:

$H_0: \theta_1 = \theta_2 = \theta_3 = \cdots = \theta_k = 0$ (there is no long – run relationship)
$H_0: \theta_1 \neq \theta_2 \neq \theta_3 \neq \cdots \neq \theta_k \neq 0.$

The ARDL approach is a multi-stage procedure (Pesaran and Pesaran, 2009). First, it tests (H_0: all $\theta_i = 0$) the presence of cointegration among variables to identify the long-run relationship(s) between the dependent variable and its forcing or independent variables. Secondly, the ARDL models are constructed based on the results obtained in the first stage. More specifically, the long-run coefficients are estimated for the relations that yielded significant F-statistic in the first stage. The ARDL procedure estimates $(L+1)^k$ number of regressions to obtain lags for each variable, where L represents the maximum number of lags used and k is the number of variables in the model. Based on the model selection criterion such as Schwarz Bayesian (SBC) or Akaika Information Criterion (AIC), the ARDL procedure determines the optimal model by identifying the optimal lag for each variable in the system. Finally, short-run dynamic and the *speed of return to equilibrium* by estimating the error-correction model (ECM (-1)) are obtained. The next section describes the diagnostic tests, which are required to justify the optimal ARDL-cointegration model.

4.2.1 Diagnostic Tests

The ARDL technique requires a series of diagnostic tests- a Lagrange multiplier test of residual serial correlation, Ramsey’s Regression Specification Errors Test (RESET) for correct functional or mathematical form and a heteroscedasticity test in respect of residuals are used to assess the model assumptions. An F statistic test is used to verify whether the short run regression coefficients and the error correction coefficient (ECM (-1)) are all zero or not. All these tests are one-tailed.

The Lagrange multiplier test of residual serial correlation assesses the null hypothesis that there is no serial correlation in the residuals up to the specified order. Gujarati (2003) stated that the regression model is correctly specified. This refers to use the correct functional form in the model, which can be analysed using a test known as Ramsey’s RESET, which assess the null that the functional form of the model is correctly specified. The heteroscedasticity test examine whether the residuals are homoscedastic, namely that the error variances are constant. This is calculated from the regression of the squared residuals on squared fitted values and tests whether the squared fitted values in this regression are statistically significant. The null hypothesis for this test is that residuals are homoscedastic. Finally, a global F-statistic is used to assess the null hypothesis that the short run regression coefficients and the error correction coefficient (ECM-1) are all zero.

4.2.2 Granger Causality Test

Although regression analyses in general and cointegration techniques in particular deal with the dependence of one variable upon other variables, such techniques do not necessarily imply the notion of “causation”. In essence, the existence of a relationship between variables does not prove causality or the direction of influence (Gujarati and Porter, 2009). Nevertheless, there is a relatively simple test of causality due to Granger (1969). Note that some authors refer to this latter test as the Wiener-Granger causality test after its original instigator (Wiener, 1956).

Causality, as defined by Granger, is implied when past values of a particular series recorded over time, say $Y_{2,t}$, have explanatory power in a regression of another variable $Y_{1,t}$ upon its own lagged values and those of $Y_{2,t}$. Causality is said to exist if $Y_{1,t}$ can be predicted with greater accuracy by using past values of $Y_{2,t}$ than by not using such past values, all other factors being equal. When this is the case, then $Y_{2,t}$ is said to *Granger cause* $Y_{1,t}$. In the two variable case, application of the GC test involves the following pair of regressions:

$$Y_{1,t} = \sum_{i=1}^{k} \alpha_i Y_{2,t-i} + \sum_{j=1}^{k} \beta_j Y_{1,t-j} + e_{1,t} \quad \text{......(19)}$$

$$Y_{2,t} = \sum_{i=1}^{k} \lambda_i Y_{2,t-i} + \sum_{j=1}^{k} \delta_j Y_{1,t-j} + e_{2,t} \quad \text{......(20)}$$

in which it is assumed that the two error terms $e_{1,t}$ and $e_{2,t}$ are uncorrelated. k is the number of lags employed. Both of the variables $Y_{1,t}$ and $Y_{2,t}$ are assumed to be stationary. Deterministic terms reflecting such as an intercept, dummies and/or trend may be included in equations (19) and (20). The first of the above equations postulates that $Y_{1,t}$ depends on previous values of itself as well as those of $Y_{2,t}$ and the second equation requires a similar behaviour for $Y_{2,t}$.

There are four possible outcomes in respect of the above equations:

1. **Unidirectional causality from $\mathbf{Y_{2,t}}$ to $\mathbf{Y_{1,t}}$** is suggested when the estimated coefficients of the lagged $Y_{2,t-i}$ in (19) are significantly different from zero as a group and the estimated coefficients of the lagged $Y_{1,t-j}$ in (20) are not significantly different from zero. Testing the restrictions H_0: $\alpha_1 = \alpha_2 = ... \alpha_k = 0$ in (19) may be performed via an F, likelihood ratio (LR) or Wald test. If just one $Y_{2,t-i}$ coefficient is non-zero, this suggests that a past value of that variable appears to contain information that is useful for forecasting $Y_{1,t-j}$.
2. **Unidirectional causality from $\mathbf{Y_{1,t}}$ to $\mathbf{Y_{2,t}}$** is suggested when the estimated coefficients of the lagged $Y_{2,t-i}$ in (19) are not significantly different from zero and the estimated coefficients of the lagged $Y_{1,t-j}$ in (20) is significantly different from zero.

3. **Bilateral causality** is implied when the sets of $Y_{2,t-j}$ and $Y_{1,t-i}$ coefficients are significantly different from zero in respectively the regressions (19) and (20). This situation is also referred to as **feedback** (Gujarati, 2011).
4. **Independence** is indicated the respective sets of $Y_{2,t-j}$ and $Y_{1,t-i}$ coefficients are not significant in either of the regressions.

The critical assumption underlying application of the Granger Causality (GC) method is that the variables at hand are stationary. Of course, while individually non-stationary, the variables in question may be stationary upon differencing and could possibly then form a cointegrating relationship as evidenced by the ARDL method and its associated error correction mechanism. Once two variables are cointegrated, then following Granger's Representation Theorem, either $Y_{1,t-j}$ must cause $Y_{2,t-i}$ or vice versa or there is bilateral causation (Koop, 2006). Conversely, if two variables are not-cointegrated, then there is no point in testing for GC.

The Wald test is applicable when testing whether or not the lagged variables as a group in equations (19) and (20) have useful predictive content above and beyond the other regressors in the model (Greene, 2003). If that statistic exceeds its critical value, the user rejects the null hypothesis of a set of zero coefficients. A major practical problem in the implementation of GC tests lies in establishing an appropriate lag length, k, for the regressions of equations (19) and (20), in that different results can be obtained with different lengths of lag (Cameron, 2005). The direction of causality too may depend critically on the number of lagged terms included in the model. Often, researchers use one of the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SBC) to determine an appropriate value for k. However, the choice of AIC or SBC can result in different values for k and it might further be noted that AIC tends to overparameterise in the sense of overestimating the true lag order (Patterson, 2000) and that the SBC offers a more parsimonious model. Neither the use of the AIC nor the SBC guarantees other desirable features of an empirical model, such as white noise residuals and often an element of trial and error enters the process of selecting a value for k.

Equations (19) and (20) constitute what is called a two-variable or bivariate vector autoregressive (VAR) system. The pairwise Granger Causality tests have to be carried out twice, with the dependent variable changed. If there are more than two variables, the

block Granger Causality test should be used. It tests if a lagged variable would Granger cause the remaining variables in the system. If the researcher has three variables, $Y_{1,t}$, $Y_{2,t}$ and $Y_{3,t}$, and the objective is to determine if $Y_{3,t}$ Granger causes $Y_{2,t}$ and/or $Y_{1,t}$, restrictions are placed such that all of the coefficients of the lagged $Y_{3,t}$ variables in the system are zero. This block Granger Causality test first estimates the $Y_{1,t}$ and $Y_{2,t}$ equations with k lagged values of $Y_{1,t}$, $Y_{2,t}$ and $Y_{3,t}$ as regressors. Then the two equations are re-estimated with lagged $Y_{3,t}$ values omitted. Then such as the LR statistic (distributed as χ^2 variable) is derived and if its value is greater than the critical value, the zero restrictions imposed should be rejected which implies that $Y_{3,t}$ does Granger cause $Y_{1,t}$ and $Y_{2,t}$. As before, each variable can take its turn acting as the dependent variable to see if bilateral causality exists.

4.3 Results from Cointegration of Forecasting Exchange Rates: Long-run

The ARDL approach involves multiple-step procedure (discussed in Section 4.2). Four lags were selected as the maximum lag following Pesaran and Pesaran's (2009) recommendation for quarterly data. The SBC is chosen to determine the optimal model for each series because it balances the goodness of fit of the model against the number of unknown parameters that have to be estimated. As a rule, the SBC leans towards parsimony (the least number of estimated parameters). The diagnostic tests mentioned in Section 4.2.1 are used and in all cases the F statistic is reported along with its significance. The generated results are obtained by the Microfit 4.1 software package. Equation (18) was transformed where necessary to a logarithmic (semi-log or log-log) functional form if the diagnostic tests indicated violation of the model assumptions. The analyses show that semi-log models are statistically significant for all countries except Canada, Mexico and Vietnam, where the log-log model is found to be statistically significant. In semi-log model only the exchange rate (ER) appears in logarithmic form. However, all the variables are transformed into logarithmic form to generate the models for Canada, Mexico and Vietnam. The results are sectionalised into advanced, emerging and frontier markets.

4.3.1 Advanced Markets

The estimated long-run coefficients and error correction model denoted by ECM (-1) for all advanced countries are presented at Table 4.1. The results suggest that in the long-run, a one percent increase in Australian long-run interest rate (IRLAUS) is an associated with 3.3% increase (appreciation) in exchange rates of an Australian dollar/U.S. dollar, all other factors being equal. Similar results also found in the cases of Japan, Norway and Sweden, where a one percent increase in long-run interest rate leads to 4.60%, 8.7% and 1.3% increase (appreciation) in exchange rates against the U.S. dollar respectively, *ceteris paribus*. This supports the theoretical assumption of higher interest rate will lead to an appreciation in the currency. The fundamental assumption driving this is that if interest rate increases that will attract more foreign capital, increasing the demand for the local currency, hence, driving up its value. Moreover, if the interest rate is high domestic consumption falls, reducing the demand for imports at a given exchange rate, which eventually reduces the supply of currency, increasing its value. In the case of Sweden, the long-run interest rate of U.S. (IRLUS) has a significant negative impact on Swedish krona/U.S. dollar, *ceteris paribus*. An explanation for this is that if the foreign (in this case U.S.) interest rate increases, it will increase the domestic demand (in this case Sweden) for foreign bank deposits, hence demand increases. On the other hand, it will decrease a desire for domestic bank deposits, hence supply decreases. These will eventually lead to the deprecation effect of exchange rates.

The short-run interest rate is found to be statistically significant in the cases of Canada, the Euro area (IRSEA) and Switzerland (IRSSWI). These findings show that in the face of a one percent increase in domestic short-run interest rate, the exchange rates of Euro/U.S. dollar and Swiss franc/U.S. dollar increase by 5.9% and 7.3% respectively, *ceteris paribus*. The estimated coefficients are positive, as expected and highly significant. These results confirm the findings of MacDonald (1998), who reported that an increase in interest rate differentials in the home country appreciates the real exchange rates of Germany, Japan and the U.S. However, these results contradict the findings of Chowdhury (2012), who reported that interest rate differential depreciates the Australian real exchange rates. However, in the case of Canada, this analysis shows that a one percent increase in Canadian short-run interest rate (lnIRSC) is an associated with 0.17% decrease

Table 4.1: Estimated long-run coefficients and error correction model for advanced countries

Country	Long-run Coefficients and Error Correction Model	Diagnostic Tests
Australia	$\ln ER = 0.033 * IRLAUS - 0.054 * INFRAUS + 0.327x10^{-3} * TBAUS - 0.851x10^{-3} * TOAUS$ (4.705) (-5.216) (6.089) (-4.373) [0.000] [0.000] [0.000] [0.000] **ECM(-1) = -0.370 (-4.012) [0.000]**	SC:F = 1.350 [0.188] FF:F = 2.149 [0.143] HM:F = 1.0137 [0.315] F = 15.773 [0.000] **SBC = 973.557**
Canada	$\ln ER = -3.989 - 0.173 * \ln IRSC + 1.061 * \ln TBC - 0.008 * T$ (-4.825) (-2.701) (4.911) (-4.387) [0.000] [0.003] [0.000] [0.000] **ECM(-1) = -0.300 (-2.397) [0.008]**	SC:F = 1.691 [0.066] FF:F = 1.512 [0.220] HM:F = 0.167 [0.683] F = 9.856 [0.000] **SBC = 1259.6**
Denmark	$\ln ER = -0.002 * MSDM - 0.154 * TODM + 0.023 * D1$ (-2.426) (-5.395) (3.134) [0.008] [0.000] [0.001] **ECM(-1) = -0.008 (-2.114) [0.017]**	SC:F = 1.043 [0.408] FF:F = 0.009 [0.924] HM:F = 6.749 [0.100] F = 17.554 [0.000] **SBC = 723.586**
Euro area	$\ln ER = 0.468 - 0.125x10^{-3} * MSEA + 0.059 * IRSEA$ (3.340) (-6.744) (2.801) [0.001] [0.000] [0.002] **ECM(-1) = -0.111 (-3.330) [0.001]**	SC:F = 0.636 [0.806] FF:F = 0.257 [0.614] HM:F = 0.957 [0.330] F = 4.288 [0.001] **SBC =239.531**
Japan	$\ln ER = 0.046 * IRLJ + 0.045 * TBJ - 0.017 * OP - 2.145 * D1$ (4.952) (5.830) (-7.834) (-16.045) [0.000] [0.000] [0.001] [0.000] **ECM(-1) = -0.001 (-9.426) [0.000]**	SC:F = 2.207[0.110] FF:F = 8.570[0.400] HM:F = 0.189 [0.664] F = 19.991 [0.000] **SBC =930.478**
Norway	$\ln ER = 0.087 * IRLN - 0.057 * TON - 1.614 * D1$ (3.272) (-5.246) (-7.147) [0.000] [0.000] [0.000] **ECM(-1) = -0.011 (-2.534) [0.006]**	SC:F = 0.895 [0.552] FF:F = 0.152 [0.697] HM:F = 0.457 [0.499] F = 13.980 [0.000] **SBC =1010.2**
Singapore	$\ln ER = 0.924 - 0.406x10^{-3} * MSS + 0.016 * D1$ (14.369) (-5.900) (6.801) [0.000] [0.000] [0.000] **ECM(-1) = -0.024 (-2.996) [0.001]**	SC:F = 0.675[0.776] FF:F = 2.326 [0.128] HM:F = 1.970 [0.161] F = 9.797 [0.000] **SBC =1234.7**
Sweden	$\ln ER = 0.013 * IRLSWE - 0.001 * MSSWE - 0.029 * IRLUS - 0.015 * OP$ (2.257) (-8.209) (-4.098) (-2.420) [0.012] [0.000] [0.000] [0.008] **ECM(-1) = -0.107 (-3.528) [0.000]**	SC:F = 1.279 [0.228] FF:F = 0.515 [0.473] HM:F = 0.191 [0.662] F = 16.478 [0.000] **SBC =998.717**
Switzerland	$\ln ER = 0.073 * IRSSWI - 4.143 * D1$ (5.894) (-2.434) [0.000] [0.008] **ECM(-1) = -0.016 (-3.716) [0.000]**	SC:F = 0.902 [0.545] FF:F = 1.619 [0.204] HM:F = 1.153 [0.284] F = 25.037 [0.000] **SBC = 928.738**
UK	$\ln ER = -0.031 * TOUK + 0.012 * D1$ (-7.312) (3.054) [0.000] [0.000] **ECM(-1) = -0.015 (-2.405) [0.007]**	SC:F = 0.944 [0.503] FF:F = 0.171 [0.679] HM:F = 0.246 [0.620] F = 20.491 [0.000] **SBC = 990.670**

t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. SC is the test for serial correlation, FF is the test of functional form, HM is the test of homoscedasticity. F test is used to evaluate whether the coefficient of ECM (-1) significantly different from zero or not. T:Time trend. Dummy variables (D1 and D2) are used for the structural breaks in levels reported in Chapter 3.

(depreciation) in exchange rates of Canadian dollar/U.S. dollar, *ceteris paribus*. This result conforms to the flexible-price monetary model of exchange rate determination, where a rise in a domestic interest rate relative to foreign interest rate causes a depreciation of the domestic currency, because the interest rate differential can be interpreted as the expected rate of depreciation (Frankel, 1979).

Inflation rate has a depreciating effect on the Australian dollar/U.S. dollar exchange rate. The estimated long-run coefficient of domestic inflation rate (INFAUS) is 5.4% and it is statistically significant. The finding is consistent with traditional theory- an increase in the domestic (Australia) inflation rate will increase (Australia's) demand for foreign (U.S.) goods and decrease foreign (U.S.) desires for Australian goods. Hence, supply of the U.S. dollar in Australian economy will be reduced. This leads to depreciate effect on Australia-USA exchange rate. It has been observed that inflation has a significant impact on exchange rates (Verweij, 2008; Uddin, 2006). The results of this study show that effect of inflation on exchange rates is insignificant in all the sampled advanced countries, except Australia.

The literature suggests that trade balance impacts the demand and supply of a currency. A country's trade balance is the total value of its exports minus the total value of its imports. If this difference is positive, the country is said to have trade surplus and vice versa. The study findings show that trade balance has a positive impact on Australian dollar/U.S. dollar and Japanese yen/U.S. dollar rates. It is evident from Table 4.1 that in the long-run, in the face of a one percent increase in trade balance of Australia (TBAUS), Canada (lnTBC) and Japan (TBJ), the exchange rates of Australian dollar/U.S. dollar and Japanese yen/U.S. dollar increase by 0.32%, 1.06% and 4.5% respectively, *ceteris paribus.* The estimated coefficients are positive and highly significant. It has been observed that the historical trade balance data of these countries were positive as export revenue exceeds import payments during the study period. Thus a tendency of lower demand for U.S. dollar may drive the exchange rate to appreciate the value of Australian dollar and Japanese yen. This also indicates that when a country has a surplus trade balance, demand for its currency increases because foreign buyers exchange more of their home currency in order to buy its goods. This result confirms the findings of Uddin (2006), who reported that the trade balance has a positive impact on exchange rate of Bangladesh-USA.

The analyses show that money supply has a depreciating effect on Danish krone/U.S. dollar, Euro/U.S. dollar, Singapore dollar/U.S. dollar and Swedish krona/U.S. dollar. In the long-run, a one percent increase in domestic money supply of Denmark (MSDM), the Euro area (MSEA), Singapore (MSS) and Sweden (MSSWE) depreciate exchange rates by 0.2%, 0.13%, 0.4% and 0.1% respectively. The estimated coefficients are negative, as expected and highly significant. This finding supports the theory that when money supply increase, the value of the money would decrease. Therefore, when domestic money (in this case Danish krone, Euro, Singapore dollar and Swedish krona) exchange with other money (in this case U.S. dollar) the exchange rate would decrease simultaneously. Maitra and Mukhopadhyay (2012) reported strong evidence of cointegration between money supply and Indian rupee/U.S. dollar exchange rate. Siddiki (2002) also suggested that the depreciation impact of money supply on the unofficial market for exchange rates of Bangladeshi taka/U.S. dollar. This result also supports the findings of AbuDalu and Ahmed (2012), who noted that the money supply has a negative impact on exchange rates.

Trade openness has a depreciative effect in the cases of Australia, Denmark, Norway and UK. In the long-run, a one percent increase in trade openness depreciate the Australian dollar/U.S. dollar, Danish krone/U.S. dollar, Norwegian krone/U.S. dollar and British pound/U.S. dollar by 0.85%, 15.4%, 5.7% and 3.1% respectively, *ceteris paribus.* This finding indicates that after adopting the floating exchange rate system, a relaxation of the extent of impediments to the international trade resulted in exchange rate depreciation. Edwards (1989) provided an excellent theoretical justification for this finding (discussed in Chapter 2). Moreover, this analysis is consistent with theoretical argument as well as the results of numerous studies undertaken in the past with reference to different countries (Edwards, 1993; Elbadawi, 1994; Connolly and Devereux, 1995; Hau, 2002). However, the result contradicts the findings of Li (2004), who showed that credible trade liberalisation lead to real exchange rate depreciation but non-credible ones could lead short-run appreciation of exchange rates.

Oil prices are accepted to be volatile and to have significant impacts on exchange rates. For example, an increase in oil-price could appreciate the exchange rate of the net-oil exporting country whilst it could depreciate exchange rate of the net-oil importing country (Bergvall, 2004). It is evident from Table 4.1 that the oil price (OP) has significant impacts in the cases of Japan and Sweden. In the long-run, a one percent increase in oil price leads to

1.7% and 1.5% decrease (depreciation) of in Japanese yen/U.S. dollar and Swedish krona/U.S. dollar respectively. The coefficients are negative and highly significant as expected, because both Japan and Sweden are net-oil importing countries. These findings support the earlier studies such as Tsen (2010) and Huang and Guo (2007), who noted that the oil prices have a significant impact on exchange rates. The coefficient of the dummy variable (D1) for structural break is found statistically significant in the cases of Denmark, Japan, Norway, Singapore, Switzerland and UK.

The analyses show that interest rates, inflation rate, trade balance, money supply, trade openness and oil price are found to have significant long-run relationships with exchange rates of advanced countries. These results are in line with the exchange rate literature (e.g. Apergis *et al.* 2012; AbuDalu and Ahmed, 2012; Uddin, 2006; Kim and Mo, 1995; and Tsen, 2010). However, other variables such as GDP, current account balance, reserve assets, government expenditures and gold price are found to be statistically insignificant. These indicate that these variables do not influence the exchange rates (in the long-run) of advanced currencies against the U.S. dollar during the sample frame of this study. These contradict the findings of Chowdhury (2012), who noted that government expenditure is one of the important variables for the real exchange rate determination of Australia. Moreover, Yuan (2011) reported that current account balance is important macroeconomic variable for exchange rate modelling. Nevertheless, Glăvan (2006) found foreign exchange reserve as one of the significant variables that impact on exchange rate. The diagnostic tests for serial autocorrelation (SC), functional form (FF), the test of heteroscedasticity (HM) and in all cases the F statistic are reported for significance (in third column of Table 4.1). The diagnostics tests reveal no important evidence of model misspecification and autocorrelation.

Exchange rates vary according to the speed of adjustment given by the coefficient of the error correction term (ECM(-1)). The long-run parameters, shown in Table 4.1, capture the effects after all adjustments have been realised. The results of the error correction models for all advanced countries are also reported in Table 4.1. The analyses show that all coefficients of error correction model are negative, as expected. The F test concluded that the (ECM (-1)) are statistically different from zero ($p < 0.05$) in all cases. Thus the condition for a long-run stable equilibrium is satisfied. Kremers *et al.* (1992) asserted that the significance of the error correction term is an efficient and useful alternative of establishing cointegration. Form the Table 4.1 that the coefficient of ECM (-1), that is, the speed of the adjustment of Australia and Canada are -0.370 and -0.300 respectively indicating that the deviation from long-run equilibrium path is corrected by nearly 37% and 30% over each subsequent month. By contrast, Chowdhury (2012) reported the speed of adjustment to at 47%, while Traditi (1996) found even higher at 51% per quarter in the post-float sample and the 25% per quarter during the full sample period in the case of Australia.

The ECM (-1) for the Euro area and Sweden are -0.111 and -0.107 respectively. These indicate that the deviation from long-run equilibrium path is corrected by nearly 11.1%, and 10.7%, respectively. These, show the moderate speed of convergence to equilibrium, once shocked. The ECM (-1) for Denmark, Japan, Norway, Singapore, Switzerland and UK are -0.008, -0.001, -0.011, -0.024, -0.016 and -0.015 respectively. These indicate very slow return to equilibrium as the derivation from the long-term equilibrium is corrected only by 0.8%, 0.1%, 1.1%, 2.4%, 1.6% and 1.5% respectively over each subsequent month.

4.3.2 Emerging Markets

The estimated long-run coefficients for emerging countries are presented at Appendix 11. The results indicate that in the long-run, a one percent increase in short-run interest rate of Brazil (IRSBZ) leads to 5.5% decrease (depreciation) in exchange rate of Brazilian real/U.S. dollar, *ceteris paribus.* Similar results are also found in the cases of Chile, Russia and Thailand where exchange rates of Chilean peso/U.S. dollar, Russian ruble/U.S. dollar and Thai baht/U.S. dollar are depreciated by 9.4%, 11.1% and 4.1%, respectively. These results confirm to the flexible-price monetary model of exchange rate determination where a rise in domestic interest rate relative to foreign interest rate causes a depreciation of the domestic currency, because the interest the interest rate differential can be interpreted as the expected rate of depreciation (Frankel, 1979). However, the opposite effect has been observed in the cases of Indonesia, Mexico and South Korea. In those cases, exchange rates increase (appreciation) by 0.74%, 1.12% and 8.4% in terms of a one percent increase in short-run interest rate of Indonesia (IRSINDO), Mexico (lnIRSME) and South Korea (IRSSK), respectively. In the case of South Africa, the analysis shows that in the long-run, a one percent increase in long-run interest rate of South Africa (IRLSA) leads to 15.5%

increase in exchange rate of South African rand/U.S. dollar. These results support the theoretical assumption that higher domestic interest rates will lead to an appreciation in the currency. If interest rates increase that will attract more foreign capital, increasing the demand for the local currency, hence, driving up its value. Moreover, if interest rates are high then domestic consumption falls, thereby reducing the demand for imports at a given exchange rate, which eventually reduces the supply of currency, increasing its value. Similar findings were noted by MacDonald (1998). However, this result contradicts the findings of Chowdhury (2012), who reported that the interest rate differential depreciates the Australian real exchange rates.

It is evident from Appendix 11 that a country's inflation rates have a significant role in emerging markets exchange rates against the U.S. dollar. Inflation has a depreciating effect on the Colombian peso/U.S. dollar, Czech koruna/U.S. dollar, Indonesian rupiah/U.S. dollar and Philippines peso/U.S. dollar. The estimated coefficients for Colombo (INFRCO), Czech Republic (INFRCR), Indonesia (INFRINDO) and Philippines (INFRP) are 7.8%, 3.8%, 5.2% and 0.6% respectively and they are statistically significant. Such results, however, contradict the findings of Rehman (2010), who reported that there is a significant but positive relation between inflation and Pakistan-UK exchange rate. However, the findings of the present study conform to the traditional theory that an increase in home country's (Pakistan) inflation rate will increase the demand for foreign (U.S.) goods and decrease in foreign (U.S.) desires for home (Pakistan) country's goods and services, *ceteris paribus*. Therefore, the supply of the U.S. dollar in home economy will be reduced, hence depreciate of exchange rates of the home country's currency against the U.S. dollar. Theoretical literature suggests that inflation is one of the primary factors that affect the exchange rate of an ideal economy. However, the impact of inflation on exchange rates is noted an insignificant in all emerging markets except Colombo, Czech Republic, Indonesia and Philippines.

The derived results suggest that trade balance is an important determinant of exchange rate of emerging currencies against the U.S. dollar. In the long-run, a one percent increase in trade balance of Brazil (TBBZ), Chile (TBC), China (THCHI) and Taiwan (TBT), the exchange rate is increased by 0.16%, 0.02%, 0.03% and 0.21% respectively, *ceteris paribus.* The estimated coefficients are positive and statistically significant. These results are expected, as a country with a surplus trade balance appreciates the value of local currency. The historical trade balance data of Brazil, Chile, China and Taiwan are positive as export revenue exceeds the import payments during the study period. These results contradict the findings of Nieh and Wang (2005), who reported no long-run relationship between Taiwan-USA exchange rate and macro fundamentals. An opposing effect of trade balance on exchange rate is observed in the cases of India, Peru and Poland. The findings show that, in the long-run, a one percent increase in trade balance of these countries; exchange rates are dropped by 0.78%, 0.28% and 0.98% respectively, *ceteris paribus*. This is however, expected. The historical trade balance data of these countries is negative as export revenue never exceeds the import payments during the study period. Hence, a tendency of higher demands for U.S. dollar may drive the exchange rate to depreciate the value of local currency.

In the long-run, a one percent increase in money supply of Chile (MSC), Colombia (MSCO), Czech Republic (MSCR) and India (MSIN) leads to 0.3%, 0.2%, 0.2% and 0.5% decrease in exchange rate with U.S. dollar respectively, *ceteris paribus*. The estimated coefficients are negative, as expected and highly significant. This result supports the theory that when money supply increases, the value of the money would decrease. Therefore, the exchange rate would decrease simultaneously when domestic money (in this case Chilean peso, Colombian peso, Czech koruna and Indian rupee) exchange with the U.S. dollar. Siddiki (2002) also reported the depreciate impact of money supply on unofficial market for exchange rates of Bangladeshi taka/U.S. dollar. However, an appreciating effect of money supply on exchange rates has been observed in the cases of Malaysia and South Africa, where a percent increase in money supply of Malaysia (MSM) and South Africa (MSSA), exchange rates of Malaysian ringgit/U.S. dollar and South African rand/U.S. dollar appreciate by 0.09% and 0.31% respectively. This result is logical if money is considered as a capital. The increase of money supply represents the higher average rate of return per capital, which means more return. From this point of view, an increase money supply leads to increasing return on money. Therefore, people want to have this type of money in order to get more return. As a result, the exchange rate climbs up too. Maitra and Mukhopadhyay (2012) also reported strong evidence of cointegration between money supply and Indian rupee/U.S. dollar exchange rate.

Trade openness has an appreciation effect on the exchange rate of Brazil (TOBZ), Hungary (TOH), Peru (TOP) and Turkey (TOTU) against the U.S dollar. In the long-run, a one percent increase in trade openness appreciate Brazilian real/U.S. dollar, Hungarian forint/U.S. dollar, Peruvian nuevo sol/U.S. dollar and Turkish lira/U.S. dollar by 1.6%, 19.0%, 6.7% and 14.2% respectively, *ceteris paribus*. The coefficients are positive and statistically significant. Similar findings were noted by Li (2004), who showed that no-credible trade liberalisation could appreciate the exchange rate. Calvo and Drazen (1998) also found that the trade liberalisation of uncertain duration could lead to an upward jump in consumption. Therefore, a real appreciation will occur in the short-run. They argued that real exchange rate will depreciate only if trade liberalisation is of permanent nature, while a transitory reform could lead a real appreciation in the short run. However, a big depreciation effect has been observed in the case of South Africa (TOSA) where South African rand/U.S. dollar is depreciated by 15.8%. This finding is consistent with the finding of Chowdhury (2012), who noted a relaxation of the extent of impediments to the international trade resulted in exchange rate depreciation. This result also supports the findings of earlier studies e.g. Krueger, (1978), Edwards (1993), Elbadawi (1994), Connolly and Devereux, (1995) and Hau (2002). It is worthwhile mentioning here that the effect of trade openness has been observed to be insignificant in all emerging countries except for the Brazilian real/U.S. dollar, Hungarian forint/U.S. dollar, Peruvian nuevo sol/U.S. dollar, South African rand/U.S. dollar and Turkish lira/U.S. dollar. This result, however, is consistent with the findings of Edwards (1987), who noted that effect of trade openness on exchange rate can be insignificant.

The gold price was found to have significant long-run relationship in respect of the South African rand/U.S. dollar. A one percent increase in gold price leads to 1.1% increase of South African rand/U.S. dollar, *ceteris paribus*. The coefficient is negative and statistically significant. South Africa is one of the largest producers of gold in the world. Therefore, it is perhaps unsurprising to find a significant long-term relationship between gold price and rand/dollar exchange rate. The economic impact of an increase in gold price would increase in South Africa’s net export earnings. This will eventually improve the balance of payments, hence appreciation of the rand. However, Verma (2011) stated the high gold price would not create a positive shock to the South African economy. A plausible explanation for this is that South Africa's share of world gold output has declined from 66 per cent in 1970 to 10 per cent today and net gold exports represent just 2 per cent of the country's GDP. The coefficient of the dummy variable (D) for structural break is found statistically significant in the cases of Brazil, Chile, China, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Korea, Thailand and Turkey. The coefficient of the dummy variable for structural break (i.e Asian crisis (D1)) is found to be negative, as expected and statistically significant in the cases of Indonesia, Malaysia, Philippines, South Korea and Thailand.

These analyses show that interest rates, inflation rate, trade balance, money supply, trade openness and gold price are found to possess significant long-run relationships with exchange rates of emerging markets. These results are in line with advanced markets and existing exchange rate literature (e.g. Apergis *et al.* 2012; AbuDalu and Ahmed, 2012; Uddin, 2006 and Kim and Mo, 1995). However, other variables such as GDP, current account balance, reserve assets, government expenditures and oil prices are found to be statistically insignificant. These indicate that these variables do not influence the exchange rates of emerging currencies against the U.S. dollar during the sample period of this study. These contradict the findings of Chowdhury (2012), who noted that government expenditure is one of the important variables for the real exchange rate determination of Australia. In addition, Yuan (2011) and Glăvan (2006) reported that current account balance and foreign exchange reserve are important macroeconomic variables for exchange rate modelling respectively. Nevertheless, Tsen (2010) showed the long-run relationship of oil price with Malaysia-USA exchange rate. The diagnostic tests such as serial autocorrelation (SC), functional form (FF), the test of heteroscedasticity (HM) were conducted and in all cases F statistic are reported for significance. The tests results are presented in the third column of Appendix 11. The diagnostics tests reveal no important evidence of misspecification and autocorrelation.

The coefficients of error correction model (ECM (-1)) for all emerging countries are reported in Appendix 11. The long-run parameters, shown in Appendix 11, capture the effects after all adjustments have been realised. The speed of adjustment process is measured by the magnitude of the error correction term. The coefficient of error correction term, that is, the speed of the adjustment is found negative in all cases. The F test shows that the error correction coefficients are statistically different from zero ($p < 0.05$) in all cases. Thus the condition for a long-run stable equilibrium is satisfied. The coefficient of error correction term for India and South Africa is -0.200 and -0.106 respectively. The coefficients are correctly signed (negative for stability) and highly significant, indicating that the derivation from long-run equilibrium path is corrected nearly 20% and 10.6%

respectively over each subsequent month. In contrast, the coefficients of error correction for Brazil, Chile, Colombia, Czech Republic, Malaysia, Peru, Russia, Taiwan, Thailand and Turkey are -0.020, -0.062, -0.045, -0.063, -0.016, -0.034, -0.016, -0.013, -0.012 and -0.013 indicates slow speed of convergence to equilibrium. Nevertheless, the coefficient of error correction term that is, the speed of the adjustment for the rest of the countries are ranges from -0.003 to -0.006 indicates very slow speed of convergence to equilibrium, once shocked.

4.3.3 Frontier Markets

The estimated long-run coefficients for all frontier countries are presented at Appendix 12. In the long-run, a one percent increase in short-run interest rate of Bangladesh (IRSBD) leads to 3.5% increase in exchange rate of Bangladeshi taka/U.S. dollar, *ceteris paribus.* Similar results also observed in the cases of Croatia, Kazakhstan, Lao PDR and Nepal, where the exchange rate is appreciated by 3.4%, 10.2%, 17.5% and 29.8% respectively. Moreover, it is evident from findings that the long-run interest rate of the U.S. has a significant impact on the determination of exchange rate against the U.S. dollar. For example, every 1% increase in long-run interest rate of the U.S. (IRLUS) leads to 3.9% increase in Brunei dollar/U.S. dollar. The similar result has been observed in the cases of Mauritius (29.6%) and Myanmar (4.7%). These findings support the theoretical assumption that a higher domestic interest rate will lead to an appreciation in the currency. If interest rates increase, more foreign capital will be attracted, thereby increasing the demand for the local currency and driving up its value. Moreover, if interest rates are high, domestic consumption falls reducing the demand for imports at a given exchange rate, which eventually reduces the supply of currency and increases its value. Similar findings were noted by MacDonald (1998).

However, an opposite impact of interest rates on exchange rates is observed in Pakistan. The results show that in the long-run, a one percent increase in short-run interest rate of Pakistan (IRSP) is an associated with 4% decrease in exchange rate of Pakistan rupee/U.S. dollar, *ceteris paribus*. This supports the findings of Rehman *et al.* (2010), who reported that there is significant but negative relationship between interest rates and Pakistan/UK exchange rate. A similar result has been observed in the case of Romania where it is 3.7% decrease in the case of Romanian leu/U.S. dollar. These results confirm to the flexible-price monetary model of exchange rate determination where a rise in domestic interest rate relative to foreign interest rate causes a depreciation of the domestic currency, because the interest rate differential can be interpreted as the expected rate of depreciation (Frankel, 1979). The results also show that, the short-run interest rate of U.S. has a significant negative impact on exchange rate. For example, every one percent increases in short-run interest rate of U.S. (IRSUS) leads to 1.7% decrease in Brunei dollar/U.S. dollar.

The depreciating effect of inflation on exchange rates has been observed in the cases of Croatia, Kazakhstan, Nigeria and Tunisia. The estimated coefficients for Croatia (INFRC), Kazakhstan (INFRK), Nigeria (INFRN) and Tunisia (INFRTUI) are 0.9%, 23.4%, 29.3% and 0.9% respectively, *ceteris paribus.* All the coefficients are negative and statistically significant. This finding conforms to the traditional theory, namely that an increase in home country's inflation rate will increase the demand for foreign (U.S.) goods and decrease U.S. desires for home country's goods; hence supply of the U.S. dollar in home economy will be reduced. This results in depreciation of exchange rates of the home country's currency against the U.S. dollar. The literature suggests that inflation is one of the important factors that affect the exchange rate of an ideal economy. However, the effects of inflation on exchange rates are noted an insignificant in all cases except Croatia, Kazakhstan, Nigeria and Tunisia.

Generally, trade balance is an important determinant of exchange rate of frontier currencies against the U.S. dollar. In the long-run, a one percent increase in trade balance of Bangladesh (TBBD), Croatia (TBC), Kenya (TBKE), Mauritius (TBM), Romania (TBUS), Sri Lanka (TBS) and Tunisia (TBTUI), the exchange rate dropped by 0.2%, 4.5%, 0.60%, 0.77%, 0.2%, 0.12% and 0.93% respectively. Moreover, every one unit increase in trade balance of Bhutan (TBB), the exchange rate of Bhutan-USA is decrease by 0.6%. The estimated coefficients are negative and statistically significant. This is, however, expected as a country with deficit trade balance depreciates the value of local currency. Trade balance of these countries is negative as export revenue never exceeds the import payments during the study period. Hence, the tendency of higher demands for U.S. dollar may drive the exchange rate to depreciate the value of local currency. An opposite effect of trade balance on exchange rate is observed in the case of Botswana. The analyses show that trade balance has an appreciating effect on exchange rate of Botswana-USA. The coefficient is positive and statistically significant. This is expected, as a country with a surplus trade balance appreciates the value of local currency against the U.S. dollar. This result is logical as the historical trade balance data of Botswana showed positive as export revenues exceeds the import payments over the sample period.

In the long-run, a one percent increase in the GDP (real income) of Bangladesh (GDPBD), Brunei (GDPB), Nigeria (GDPN) and Sri Lanka (GDPS) leads to 0.1%, 0.12%, 2.3% and 0.71% increase in exchange rate of these national currencies against the U.S. dollar, *ceteris paribus*. The coefficients are positive and statistically significant. The positive GDP may signal an increased demand in the local currency and a prompt to increase interest rates to curb inflation. This would eventually strengthen the local currency (i.e. Bangladeshi taka, Brunei dollar, Nigerian naira and Sri Lankan rupee) against the foreign currency i.e. U.S. dollar. This result supports the findings of Groen (2000), who used real income as one of the variables to explain the monetary exchange rate model as a long-run phenomenon. It is worthwhile mentioning here that the effect of GDP on exchange rates has been observed in above mentioned frontier countries only. However, GDP is found to be insignificant in the rest of the frontier countries and all advanced and emerging countries.

The current account balance is a summary report of the flow of goods, services, transfer payments and income to and from the country, showing how the country is performing amongst other countries of the world. A positive value represent current account surplus and vice versa. The analyses show that the current account balance of Estonia (CAE) and Pakistan (CAP) has an important role to play in the exchange rate determination of these countries against the U.S. dollar. In the long-run, every one percent increase in current account balance of Estonia and Pakistan leads to 1.6% and 0.1% depreciation of exchange rate respectively. The coefficients are negative, as expected and statistically significant. It has been observe that Estonia and Pakistan had a persistent deficit current account balance during the study period. This may lead to a weakening of the Estonian kroon and Pakistan rupee as trade, income and transfer payments lead more kroon and rupee payments being made abroad. This result supports the findings of Obstfeld and Rogoff (2005) and Kandil (2004), who also reported the relationship between exchange rate fluctuations and current account balance.

It is evident in the Appendix 12 that in the long-run, the money supply of U.S. has a significant role to play in exchange rate determination of frontier countries. For example, a one percent increase in money supply of U.S. (MSUS) leads to 0.4% increase in Jamaican dollar/U.S. dollar. Similar results are also observed in the cases of Trinidad & Tobago, Tunisia and Vietnam, where the estimated coefficients of MSUS are 0.9%, 0.58% and 1.35% respectively. All the coefficients are positive and statistically significant. A plausible explanation is that when money supply of the U.S. increases, the value of the dollar falls and eventually leads to an appreciation of local currency (in this cases of Jamaican dollar, Trinidad & Tobago dollar, Tunisian dinar and Vietnamese dong) against the U.S. dollar. However, opposite impacts of the U.S. money supply have been observed in the case of Brunei, Nepal and Romania.

There is a long-run relationship between oil prices and exchange rates in the cases of Brunei and Trinidad & Tobago. An increase in oil-price (OP) could appreciate the exchange rate of the net-oil exporting country whilst it could depreciate exchange rate of the net-oil importing country (Bergvall, 2004). Results show that, in the long-run, every one percent increase in oil price leads to 0.7% increase in Brunei dollar/U.S. dollar, while the negative (0.9%) effect has been observed in the case of Trinidad & Tobago dollar/U.S. dollar, *ceteris paribus*. This is, however, expected as Brunei is the oil-exporting country and Trinidad & Tobago is the oil importer. This finding supports other studies such as Tsen (2010) and Huang and Guo (2007), which showed that the oil price has a significant impact on exchange rates. Moreover, dummy variables for structural breaks (D1) found statistically insignificant for all frontier markets except Bangladesh, Bhutan and Trinidad & Tobago.

Overall, the analyses indicate that interest rates, inflation rates, trade balance, real income (GDP), current account balance, money supply and oil prices have significant long-term impacts on exchange rates of frontier currencies against the U.S. dollar. Interestingly enough, using the GDP as a proxy of real income is found to have a significant impact on the exchange rates of some frontier currencies. This was, however reported as an insignificant variable in all the cases of advance and emerging markets. Moreover, trade openness (TO) found to be insignificant factor in exchange rates determination of frontier markets, which was noted as one of the important variables in the cases of advanced and emerging markets. Other variables such as reserve assets and government expenditures are also found to be insignificant variables. These findings are parallel with the advanced and emerging market groups. The diagnostic tests such as serial autocorrelation (SC), functional form (FF), the test of heteroscedasticity (HM) are conducted and in all cases F statistic for significance are reported in the third column of Appendix 12. The diagnostic tests reveal no important evidence of misspecification and autocorrelation.

The results of error correction model (ECM (-1)) for frontier countries are reported at Appendix 12. The coefficient of error correction term found negative, as expected. The F test shows that the error correction coefficients are statistically different from zero ($p < 0.05$) in all cases. Thus the condition for a long-run stable equilibrium is satisfied. The coefficients of error correction term for Botswana, Nigeria, Sri Lanka and Vietnam are -0.126, -0.118, -0.128, and -0.157 respectively, indicating moderate speed of convergence to equilibrium. This implies that derivation from the long-term equilibrium is corrected by 12.6%, 11.8%, 12.8% and 15.7% respectively over each subsequent month. In contrast, the coefficients of the error correction for Brunei, Jamaica, Myanmar, Pakistan, Romania, Trinidad & Tobago and Tunisia are -0.047, -0.018, -0.018, -0.012, -0.017 -0.039 and -0.027 respectively, indicating slow speed of convergence to equilibrium. Moreover, the coefficients of error correction term (ECM (-1)) for the rest of the countries range from -0.008 to -0.001, indicating a very slow speed of convergence to equilibrium, once shocked. The next section discusses the short-run results of ARDL-cointegration model.

4.4 Results from Cointegration of Forecasting Exchange Rates: Short-run

Having estimated a stable long-run exchange rate equation, this study now proceeds to estimate the dynamic (short-run) model. Practitioners such as speculators, hedgers and arbitrageurs are most interested knowing which macroeconomic variables impact on exchange rate determination in short-term. Therefore, the findings of this study will not only enrich the exchange rate literature but also offer information to practitioners to assist in making their decisions. Again an F-statistic is used to verify that the short run regression coefficients are significantly different from zero. The results are sectionalised into advanced, emerging and frontier markets.

4.4.1 Advanced Markets

The short-run coefficients obtained by applying the ARDL approach to advanced countries are reported in Table 4.2. The short-run dynamics in the model are captured by the lagged differences of the variables. The findings indicate that the recent past of exchange rate and the other macroeconomic variables play significant roles in exchange rate determination. For example, the short-run coefficient of exchange rate is statistically significant for the one month lag ($\Delta \mathrm{lnER}_{t-1}$) in all series. The sign of the coefficient of this lag ($\Delta \mathrm{lnER}_{t-1}$) is positive in all cases. However, in the cases of Sweden and UK, two months lagged difference ($\Delta \mathrm{lnER}_{t-2}$) are observed. The sign of this coefficient is negative and statistically significant in all cases. The positive (negative) sign of lagged difference coefficient indicates the appreciation (depreciation) of today's exchange rate (ER_t).

The short-run coefficient of the interest rate of Australia is statistically significant for the first month lag ($\Delta \mathrm{IRLAUS}_{t-1}$). The sign is positive, which indicates that if long-run interest of Australia improves then exchange rate appreciates. The similar result has been observed in the cases of Japan ($\Delta \mathrm{IRLJ}_{t-1}$) and Norway ($\Delta \mathrm{IRLN}_{t-1}$). However, the negative effect is observed in the case of Sweden ($\Delta \mathrm{IRLSWE}_{t-1}$). In contrast, the short-run interest rate is found important determinant of exchange rate in the cases of Canada, the Euro area and Switzerland. The analyses show that the lagged difference of short-run interest rate of Canada ($\Delta \mathrm{lnIRSC}_{t-1}$) has a negative effect on today's rate, while it is positive in the case of the Euro area ($\Delta \mathrm{IRSEA}_{t-1}$). Nevertheless, the short-run coefficient of interest rate of Switzerland is statistically significant for the consecutive two lags. The sign of the coefficient on the first month lag ($\Delta \mathrm{IRSSWI}_{t-1}$) is positive while it is negative for second month lag ($\Delta \mathrm{IRSSWI}_{t-2}$). The positive (negative) sign indicates that if short-run interest rate improves then exchange rate appreciates (depreciates) in that period (short-run).

Money supply has a negative and statistically significant short-term impact on exchange rates. This result is observed in the cases of Denmark ($\Delta \mathrm{MSDM}_{t-1}$), the Euro area ($\Delta \mathrm{MSEA}_{t-1}$), Singapore ($\Delta \mathrm{MSS}_{t-1}$) and Sweden ($\Delta \mathrm{MSSWE}_{t-1}$). It is evident form the Table 4.2 that money supply has a depreciating effect on Danish krone/U.S. dollar, Euro/U.S. dollar, Singapore dollar/U.S. dollar and Swedish krona/U.S. dollar in the short-run. This finding supports the theory that when money supply increases, *ceteris paribus*, the value of the money would decrease. Therefore, when domestic money (in this case

Table 4.2: Estimated short- run coefficients using ARDL approach for advanced countries

Country	Short-run Coefficients and Error Correction Model
Australia	$\Delta \mathrm{lnER}_t = 0.229\,\Delta \mathrm{lnER}_{t-1} + 0.001\Delta \mathrm{IRLAUS}_{t-1} - 0.002\Delta \mathrm{INFAUS}_{t-1} + 0.121\mathrm{x}10^{-4}\Delta \mathrm{TBAUS}_{t-1} + 0.315\mathrm{x}10^{-5}\Delta \mathrm{CAAUS}_{t-1}$ (4.882) (3.755) (-3.340) (3.721) (3.730) [0.000] [0.000] [0.001] [0.000] [0.000] **F = 15.773 [0.000]**
Canada	$\Delta \mathrm{lnER}_t = -0.120 + 0.187\,\Delta \mathrm{lnER}_{t-1} - 0.121\Delta \mathrm{lnER}_{t-2} - 0.005\Delta \mathrm{lnIRSC}_{t-1} + 0.198\Delta \mathrm{lnTBC}_{t-1} - 0.229\mathrm{x}10^{-3}\Delta \mathrm{T}_{t-1}$ (-3.174) (3.785) (-2.470) (-2.031) (3.765) (-3.194) [0.002] [0.000] [0.007] [0.021] [0.000] [0.002] **F = 9.856 [0.000]**
Denmark	$\Delta \mathrm{lnER}_t = 0.307\Delta \mathrm{lnER}_{t-1} - 0.129\mathrm{x}10^{-4}\Delta \mathrm{MSDM}_{t-1} + 0.117\Delta \mathrm{TODM}_{t-1} + 0.123\Delta \mathrm{D1}_{t-1}$ (6.656) (-2.188) (2.326) (3.456) [0.000] [0.015] [0.010] [0.000] **F = 17.554 [0.000]**
Euro area	$\Delta \mathrm{lnER}_t = 0.052 + 0.249\Delta \mathrm{lnER}_{t-1} - 0.139\mathrm{x}10^{-4}\Delta \mathrm{MSEA}_{t-1} + 0.007\Delta \mathrm{IRSEA}_{t-1}$ (2.679) (2.661) (-3.514) (2.191) [0.004] [0.003] [0.001] [0.014] **F = 4.288 [0.001]**
Japan	$\Delta \mathrm{lnER}_t = 0.237\Delta \mathrm{lnER}_{t-1} + 0.224\Delta \mathrm{IRLJ}_{t-1} - 0.003\Delta \mathrm{TBJ}_{t-1} - 0.002\Delta \mathrm{OP}_{t-1} - 0.119\Delta \mathrm{D1}_{t-1}$ (5.056) (6.440) (-2.830) (-3.015) (-4.658) [0.000] [0.000] [0.002] [0.001] [0.000] **F = 19.991 [0.000]**
Norway	$\Delta \mathrm{lnER}_t = 0.277\Delta \mathrm{lnER}_{t-1} + 0.011\Delta \mathrm{IRLN}_{t-1} + 0.348\Delta \mathrm{TON}_{t-1} - 0.359\Delta \mathrm{TON}_{t-2} - 0.014\Delta \mathrm{D1}_{t-1}$ (6.047) (3.154) (2.443) (-3.766) (-3.503) [0.000] [0.001] [0.007] [0.000] [0.000] **F = 13.980 [0.000]**
Singapore	$\Delta \mathrm{lnER}_t = 0.022 + 0.281\Delta \mathrm{lnER}_{t-1} - 0.984\mathrm{x}10^{-5}\Delta \mathrm{MSS}_{t-1} + 0.024\Delta \mathrm{D1}_{t-1}$ (2.767) (6.090) (-2.614) (2.767) [0.003] [0.000] [0.005] [0.003] **F = 9.797 [0.000]**
Sweden	$\Delta \mathrm{lnER}_t = 0.380\Delta \mathrm{lnER}_{t-1} - 0.135\,\Delta \mathrm{lnER}_{t-2} - 0.002\Delta \mathrm{IRLSWE}_{t-1} - 0.252\mathrm{x}10^{-3}\Delta \mathrm{OP}_{t-1} - 0.236\mathrm{x}10^{-4}\Delta \mathrm{MSSWE}_{t-1} + 0.005\Delta \mathrm{IRLUS}_{t-1}$ (7.950) (-2.832) (-2.764) (-2.377) (-3.260) (4.361) [0.000] [0.002] [0.003] [0.009] [0.001] [0.000] **F = 16.478 [0.000]**
Switzerland	$\Delta \mathrm{lnER}_t = 0.306\Delta \mathrm{lnER}_{t-1} + 0.015\Delta \mathrm{IRSSWI}_{t-1} - 0.007\Delta \mathrm{IRSSWI}_{t-2} - 0.065\Delta \mathrm{D1}_{t-1}$ (6.761) (5.891) (-2.800) (-2.434) [0.000] [0.000] [0.003] [0.008] **F = 25.037 [0.000]**
UK	$\Delta \mathrm{lnER}_t = 0.242\Delta \mathrm{lnER}_{t-1} - 0.127\,\Delta \mathrm{lnER}_{t-2} + 0.796\,\Delta \mathrm{TOUK}_{t-1} + 0.050\,\Delta \mathrm{D1}_{t-1}$ (5.094) (-2.688) (5.322) (2.149) [0.000] [0.004] [0.000] [0.016] **F = 20.491 [0.000]**

t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. The null for F test is that the short run regression coefficients are all zero. Dummy variables (D1 and D2) are used for the structural breaks in levls reported in Chapter 3.

Danish krone, Euro, Singapore dollar and Swedish krona) exchange with other money (in this case U.S. dollar) the exchange rate would decrease simultaneously. The short-run coefficient for trade openness in respect of Denmark and UK are statistically significant for the first month lag ($\Delta \mathrm{TON}_{t-1}$). The sign is positive, which indicates that if trade openness of these countries improves then exchange rate appreciates. Nevertheless, the short-run coefficient of trade openness of Norway is statistically significant for the consecutive two lags. The sign of the coefficient on the first month lag ($\Delta \mathrm{TON}_{t-1}$) is positive while it is negative for second month lag ($\Delta \mathrm{TON}_{t-2}$). The positive (negative) sign indicates that if trade openness improves then exchange rate appreciates (depreciates) in that period (short-run), *ceteris paribus.* Given the importance of the interest rates, money supply and trade openness, other variables such as trade balance, inflation, current account balance and oil price have a significant shot-run impact on exchange rates of advanced countries. The short-run effects of these variables in the model can be explained in an analogous way. The F test result shows that the short-run coefficients are significantly different from zero ($p < 0.05$) in all cases.

4.4.2 Emerging Markets

The results of the short-run coefficients for all emerging countries are presented in Appendix 13. All the coefficients in the short-run are statistically significant. It is evident from the results that recent past behaviour of exchange rates and of the macroeconomic variables have important roles to play in the determination of exchange rates of emerging countries against the U.S. dollar. The short-run coefficient of the exchange rate is statistically significant for the one month lag ($\Delta \mathrm{lnER}_{t-1}$) in all cases except China, Malaysia, Poland and Turkey. The sign of the coefficient of this lag ($\Delta \mathrm{lnER}_{t-1}$) is positive in all cases indicating that the today's rate ($\Delta \mathrm{lnER}_{t}$) is positively affected by the last month's rate. However, in the cases of Brazil, Peru, Poland, South Korea and Thailand, two months lagged difference ($\Delta \mathrm{lnER}_{t-2}$) have been observed. The signs of these coefficients are negative and statistically significant in all cases. In the case of Indonesia, the short-run coefficient of exchange rate is statistically significant for the second, third and fourth lags. The sign of the coefficient on the second, third and fourth month lags ($\Delta \mathrm{lnER}_{t-2}$, $\Delta \mathrm{lnER}_{t-3}$ and $\Delta \mathrm{lnER}_{t-4}$) are all negative. The negative sign is indicative of a deprecation of today's exchange rate($\Delta \mathrm{lnER}_{t}$).

A short-run impact of interest rates on exchange rates has been observed for some countries. For example, in the case of Brazil, the coefficient of the first month lag of interest rate ($\Delta \mathrm{IRSBZ}_{t-1}$) is found statistically significant. The sign of this coefficient is negative, indicating that if short-run interest rate of Brazil rises then the exchange rate of Brazilian real/U.S. dollar depreciates in the that period (short-run). A similar result is found in the case of Chile ($\Delta \ln \mathrm{IRSC}_{t-1}$). These results confirm to the flexible-price monetary model of exchange rate determination whereby a rise in domestic interest rate relative to foreign interest rate causes a depreciation of the domestic currency, because the interest rate differential can be interpreted as the expected rate of depreciation. However, the positive effect of interest rate on exchange rate has been observed in the cases of Mexico ($\Delta \ln \mathrm{IRSME}_{t-1}$), South Korea ($\Delta \mathrm{IRSSK}_{t-1}$), and Thailand ($\Delta \mathrm{IRST}_{t-1}$). These findings support the theoretical assumption that higher domestic interest rate will lead to an appreciation in the currency. If the interest rate increases, it will attract more foreign capital, increasing the demand for the local currency, hence, driving up its value. Moreover, if the interest rate is high, domestic consumption falls, reducing the demand for imports at a given exchange rate, which eventually reduces the supply of currency, increasing its value. Furthermore, in the cases of Russia and South Africa, the short-run coefficient of interest rate is statistically significant for the subsequent two lags. The sign of the coefficients on the first month lag ($\Delta \mathrm{IRSR}_{t-1}$ and $\Delta \mathrm{IRSSA}_{t-1}$) are positive, while its second month lag ($\Delta \mathrm{IRSR}_{t-2}$ and $\Delta \mathrm{IRSSA}_{t-2}$) change to negative. These results support the findings of AbuDalu and Ahmed (2012), who reported the short-run relationship between exchange rate and interest rate.

The analyses also show that trade balance has a mixed effects on exchange rates. A positive sign of the coefficients of trade balance is observed in the cases of Brazil ($\Delta \ln \mathrm{TBBZ}_{t-1}$), Chile ($\Delta \ln \mathrm{TBC}_{t-1}$), China ($\Delta \ln \mathrm{TBCHI}_{t-1}$) and Poland ($\Delta \ln \mathrm{TBPO}_{t-1}$). This indicates that if trade balance improves then exchange rate appreciates in that period (short-run). However, in the case of Taiwan, the short-run coefficient of trade balance is statistically significant for the subsequent two lags. The sign of the coefficient on the first month ($\Delta \ln \mathrm{TBT}_{t-1}$) is positive while the sign of its second lag ($\Delta \ln \mathrm{TBT}_{t-2}$) is negative. The positive (negative) sign indicates that if the trade balance improves then exchange rate of New Taiwan dollar/U.S. dollar appreciate (depreciate) in that period (short-run). These results are expected, as a country with surplus trade balance appreciates the value of local currency. The trade balances of Brazil, Chile, China, Poland and Taiwan are positive as export revenue exceeds the import payments during the study period. The positive impacts of trade balance on exchange rate of those countries against U.S. dollar have been observed in the long-run situation as well. Conversely, the opposite effect of trade balance on exchange rate in short-run is observed in the cases of India ($\Delta \mathrm{lnTBIN}_{t-1}$) and Peru ($\Delta \mathrm{lnTBP}_{t-1}$). This is however, expected. The trade balances of these countries are negative, as export revenue never exceeds the import payments during the study period. Hence, the tendency of higher demands for U.S. dollar may drive the exchange rates to depreciate the value of local currency in short-run. The result is in line with long-run situation as well. However, in the case of Indonesia, the trade balance of first month lag ($\Delta \mathrm{lnTBINDO}_{t-1}$) is found to play an important role in the determination of exchange rate of Indonesian rupiah/U.S. dollar. The sign of the coefficient is positive, indicating that the impact of change in trade balance appreciate the Indonesian rupiah/U.S. dollar in the short-run. Interestingly enough, this impact is observed in the short-run situation only. In the long-run, the effect of trade balance on exchange rate is found statistically insignificant in the case of Indonesia.

The short-run coefficient of trade openness of Brazil is statistically significant for the first month lag ($\Delta \mathrm{TOBZ}_{t-1}$). The sign is positive, which indicates that if trade openness of Denmark improves then exchange rate appreciates. The similar results have been observed in the cases of Peru, South Africa and Turkey. These support the findings of Li (2004), who reported that trade openness could lead to short-run real exchange rate appreciation. However, the negative short-run impact on exchange rates has been observed in the case of Hungary. There is a negative short-run impact of inflation on exchange rates has been observed in the cases of Colombia ($\Delta \mathrm{INFRCO}_{t-1}$), Czech Republic ($\Delta \mathrm{INFRCR}_{t-1}$), Indonesia($\Delta \mathrm{INFRINDO}_{t-1}$) and Philippines($\Delta \mathrm{INFRP}_{t-1}$). The coefficients are negative and statistically significant for the first month lag. These findings are consistent with theory to the effect that an increase in domestic inflation rate will increase demand for foreign goods and decrease foreign desires for domestic goods and services. Thereby supply of the U.S. dollar in domestic economy becomes reduced. This leads to the depreciation of exchange rates against the U.S. dollar. The analyses also show that money supply has a mixed short-run impact on some of the exchange rate series. For example, the negative impact has been observed in the cases of Chile ($\Delta \mathrm{MSC}_{t-1}$), Colombia ($\Delta \mathrm{MSCO}_{t-1}$), Czech Republic ($\Delta \mathrm{MSCR}_{t-1}$) and India (($\Delta \mathrm{MSIN}_{t-1}$). However, the effect of money supply is found to be positive in the cases of Malaysia ($\Delta \ln MSM_{t-1}$) and South Africa ($\Delta MSSA_{t-1}$). The short-run impacts of money supply on exchange rates can be explained in an analogous way.

The current findings also show that the short-run coefficient of gold price (ΔGP_{t-1}) is statistically significant in the case of South Africa. The sign of this coefficient is negative indicating that if gold price improves then exchange rate of South African rand/U.S. dollar depreciates in the shot-run. The opposite effect has been observed in the long-run situation. This short-run result, however, supports the findings of Verma (2011), who reported that an increase of gold price does not create a positive shock to the South African economy. Last but not least, the dummy variable for structural breaks is found negative and statistically significant in the cases of Indonesia, Malaysia, Philippines, Russia, South Korea, Thailand and Turkey which clearly show that the short term impact of Asian Crisis on these exchange rate series. The F test result shows that the short-run coefficients are significantly different from zero ($p < 0.05$) in all cases.

4.4.3 Frontier Markets

The estimated short-run coefficients using ARDL approach for all frontier countries are presented in Appendix 14. All the coefficients in the short-run are statistically significant. Like the advanced and emerging country groups, recent past (short memory) of exchange rate and the macroeconomic variables have an important role to play in the determination of exchange rates in the frontier markets. For example, the short-run coefficient of the exchange rate is statistically significant for the one month lag ($\Delta \ln ER_{t-1}$) in all cases except Bangladesh, Brunei and Nigeria. The sign of the coefficient of this lag ($\Delta \ln ER_{t-1}$) is positive in all cases indicating that the current month's rate is positively affected by the last month's rate. However, in the cases of Estonia, Lao PDR and Romania, the subsequent two lags found statistically significant. The sign of the coefficient of first month lag is positive ($\Delta \ln ER_{t-1}$), while the sign of its second month lag ($\Delta \ln ER_{t-2}$) changes to negative in the cases of Estonia and Romania. However, both sign is positive in the case of Lao PDR. The negative (positive) sign indicates the deprecation (appreciation) effects on exchange rate at time t ($\Delta \ln ER_t$).

The short-run coefficient of short-run interest rates is statistically significant in the case of Bangladesh. The sign of the coefficient on the first month lag ($\Delta lRSBD_{t-1}$) is positive. The positive sign indicates that if interest rate improves then exchange rate of Bangladeshi taka/U.S. dollar appreciates. Similar results are also observed in the cases of Kazakhstan, Nepal and Nigeria. The same impact is observed in the long-run situation of these countries. However, the first month lag ($\Delta \mathrm{lRSC}_{t-1}$) and second month lag ($\Delta \mathrm{lRSC}_{t-2}$) are statistically significant in the case of Croatia. Both lags positively affect the exchange rate of Croatian kuna/U.S. dollar at time t ($\Delta \mathrm{lnER}_t$). These findings support the theoretical assumption of a higher domestic interest rate leading to an appreciation in the currency. If interest rates are to increase, they will attract more foreign capital increasing the demand for the local currency thereby driving up its value. Moreover, if interest rates are high domestic consumption falls, reducing the demand for imports at a given exchange rate, which eventually reduces the supply of currency and increasing its value. However, the negative impact of interest rate on exchange rate been observed in the cases of Pakistan and Romania. This result confirms the flexible-price monetary model of exchange rate determination where a rise in domestic interest rate relative to foreign interest rate causes a depreciation of the domestic currency, because the interest rate differential can be interpreted as the expected rate of depreciation. The results also show that the lagged difference of short-run interest rate of the U.S. ($\Delta \mathrm{lRSUS}_{t-1}$) has a significant negative impact on exchange rate in the cases of Brunei.

The lagged difference of long-run interest rate of the U.S. ($\Delta \mathrm{lRLUS}_{t-1}$) plays an important role in the determination of short run exchange rate of Brunei, Mauritius and Myanmar against the U.S. dollar. In Appendix 14, the sign of the coefficient on first month lag ($\Delta \mathrm{lRLUS}_{t-1}$) is positive and statistically significant in all cases. The positive sign indicates that if the interest rate (long-run) of U.S. rises then exchange rate of these countries against the U.S. dollar appreciates. It is worthwhile mentioning here that the interest rate is found to be statistically significant in the long-run situation in the case of Lao PDR. However, results show that interest rates have an insignificant impact on exchange rate in those countries against the U.S. dollar. Moreover, short-run interest plays positive role in the determination of exchange rate of Nigeria. Nevertheless, no significant impact of short-run interest rate of Nigeria on Nigerian naira/U.S. dollar has been observed in the long-run situation.

The results also show that the money supply of U.S. has a short-run impact on exchange rates. For example, the positive short-run coefficient of U.S. money supply is statistically significant in the case of Jamaica, the sign indicating that if money supply of U.S. rises then exchange rate of the Jamaican dollar/U.S. dollar appreciates. Similar results also observed in the cases of Trinidad & Tobago, Tunisia and Vietnam. A plausible explanation of this result is that when the money supply of U.S. increases, the value of the dollar falls and that eventually leads to an appreciation of local currency (e.g. Jamaican dollar, Trinidad and Tobago dollar, Tunisian dinar and Vietnamese dong) against the U.S. dollar. However, opposite short-run impacts of the U.S. money supply on exchange rate are observed in the case of Brunei, Nepal and Romania. Trade balance has a negative short-run impact in the cases of Bangladesh ($\Delta \mathrm{TBBD}_{t-1}$), Kenya ($\Delta \mathrm{TBKE}_{t-1}$) and Tunisia ($\Delta \mathrm{TBTUI}_{t-1}$). The short-run coefficients of trade balance are negative for first month lag and statistically significant. Nevertheless, the positive influence has been observed in the cases of Bhutan, Botswana, Mauritius, Romania and Sri Lanka. The positive (negative) sign indicates that if trade balance improves then exchange rate appreciates (depreciates) in that period (short-run).

There is a mixed set of findings concerning the impacts of GDP on exchange rates for the frontier markets. Analyses show that the short-run coefficient of GDP of Bangladesh is statistically significant on its first month lag ($\Delta \mathrm{GDPBD}_{t-1}$). The sign of this coefficient is negative, indicating that if GDP improves, the exchange rate of Bangladeshi taka/U.S. dollar depreciates. A similar result has also been observed in the cases of Nigeria ($\Delta \mathrm{GDPN}_{t-1}$) and Sri Lanka ($\Delta \mathrm{GDPS}_{t-1}$). The positive GDP may signal an increased demand in the local currency and to increase interest rates to curb inflation. This would eventually strengthen the local currency. This finding, however, contradicts the relationship between positive GDP and exchange rates. Nevertheless, the short-run impact of GDP on exchange rate is found to be positive in the case of Brunei ($\Delta \mathrm{GDPB}_{t-1}$). It is worthwhile mentioning here that in the long-run situation, the relationship of GPD and exchange rate found positive in the cases of Bangladesh, Brunei, Nigeria and Sri Lanka. Given the importance of the interest rates, money supply, trade balance and GDP, other variables such as inflation, current account balance and oil prices have a significant shot-run impact on exchange rates of frontier countries against the U.S. dollar. The short-run effects of these variables in the model can be explained in a similar way. The F test shows that the short-run coefficients are significantly different from zero ($p < 0.05$) in all cases.

4.5 Results from Granger Causality Test

Since there is cointegration between exchange rates and macroeconomic variable, this study moves on to test the direction of causalities. As was mentioned earlier in Section 4.2.2, the variables $Y_{1,t}$, $Y_{2,t}$, $Y_{3,t} \ldots Y_{k,t}$ are assumed to be stationary for the Granger Causality test. Both the Ng-Perron and Phillips-Perron unit root tests are applied for all cointegrated variables. The unit root tests results for advanced, emerging and frontier markets are shown in Appendix 15, 16 and 17 respectively. The unit root tests show that all of the cointegrated variables are non-stationary in levels. Only when the variables are differentiated once do, they became stationary. Therefore, all of the cointegrated variables are integrated of order one i.e I(1). In order to examine the Granger Causality, four lags were selected as the maximum lag following Pesaran and Pesaran's (2009) recommendation[17]. The block Ganger Causality test between the exchange rates and macroeconomic variables (and vice versa) was performed where there were more than one independent variable. In this case, the result of the LR (χ^2) test was obtained via the Microfit 4.1 software package. Conversely, when there was only one independent variable, the pairwise Granger Causality test was performed. In this case, an F statistic was generated by the EViews 7 software package. The test results are sectionalised into advanced, emerging and frontier markets.

4.5.1 Advanced Markets

The Granger Causality tests for all advanced countries are presented at Appendix 18. The result of the LR (χ^2) test is reported in Appendix 18A. The results suggest that in the long-run, macroeconomic variables do Granger cause exchange rate in all the cases. The null of block Granger Causality is rejected since the LR (χ^2) is statistically significant ($p < 0.05$). This means that the country specific macroeconomic variables do jointly Granger cause exchange rates. The results of Granger Causality test can be explained as follows. For example, in the case of Australia, the null of block Granger Causality is rejected when the exchange rate (LNER) acts as a dependent variable. This indicates that long run interest rate (IRLAUS), inflation rates (INFRAUS), trade balances (TBAUS) and trade openness (TOAUS) do jointly Granger cause the exchange rate of Australian dollar/ USA dollar. By

[17] Lee (2012) also applied 4 lags in daily exchange rate series for causality analysis.

interchanging the dependent variable, the block Granger Causality test was used to examine the direction of causality among other variables. The results suggest that exchange rates (LNER), long run interest rates (IRLAUS), trade balances (TBAUS) and trade openness (TOAUS) do jointly Granger cause of inflation rate of Australia (INFRAUS). Moreover, exchange rate (LNER), long run interest rate (IRLAUS), inflation rate (INFRAUS) and trade balance (TBAUS) do jointly Granger causes the trade openness of Australia (TOAUS). However, we failed to reject the null of block Granger Causality ($p > 0.05$) when long run interest rate of Australia (IRLAUS) is used as a dependent variable. This indicates that the exchange rate (LNER), inflation rate (INFRAUS), trade balance (TBAUS) and trade openness (TOAUS) do not jointly Ganger cause the long run interest rate of Australia (IRLAUS). Similar results also found in the case of trade balance of Australia (TBAUS). The unidirectional causality i.e from macroeconomic variables to exchange rate is found in all cases. Moreover, unidirectional causality i.e from exchange rate to macroeconomic variables is found in the majority cases. The results of the block Ganger Causality for rest of the advanced countries can be explained in an analogous way

As was mentioned earlier in Section 4.5, when there was only one independent variable, the pairwise Granger Causality test was performed. The F statistics for the pairwise Granger Causality test for Singapore, Switzerland and UK are reported in Appendix 18B. The null hypothesis is rejected in every cases ($p < 0.05$) indicating that country specific macroeconomic variables do Granger cause exchange rates. The unidirectional causality from macroeconomic variables to exchange rate is found in the case of Singapore and Switzerland. The bilateral causality i.e macroeconomic variable to exchange rate and vice versa is evident in the case of UK. The null of pairwise Granger Causality is rejected in the case of UK since the F is statistically significant ($p < 0.05$) when the exchange rate (LNER) and trade openness (TOUK) act as dependent variable. This indicates that the bilateral causality from exchange rate (LNER) to trade openness (TOUK) of UK and vice versa. The results of pairwise Ganger Causality for rest of the Singapore and Switzerland can be explained in an analogous way.

4.5.2 Emerging Markets

The results of Granger Causality tests for all emerging countries are reported at Appendix 19. The result of the LR (χ^2) test is reported in Appendix 19A. The results suggest that in the long-run, macroeconomic variables do Granger cause exchange rate in all the cases. The null of block Granger Causality is rejected since the LR (χ^2) is statistically significant ($p < 0.05$). This means that the country specific macroeconomic variables do jointly Granger cause exchange rates. The null of Granger block Causality for Brazil, for example, is rejected since the LR (χ^2) is statistically significant ($p < 0.05$) when the dependent variables are exchange rates (LNER) and interest rates (IRSBZ). This indicates that the macroeconomic variables i.e. interest rates (IRSBZ), trade balances (TBBZ) and trade openness (TOBZ) do Granger cause exchange rate of Brazil and USA. Result also showed that exchange rate (LNER) along with two other macroeconomic variables i.e. TBBZ and TOBZ jointly Granger cause the interest rate of Brazil. In contrast, the null of Granger block causality cannot be rejected ($p > 0.05$) when the dependent variables are trade balance (TBBZ) and trade openness (TOBZ) of Brazil.

The null of block Granger Causality is rejected in the cases of Chile, Colombia and India since the LR (χ^2) is statistically significant ($p < 0.05$) in all dependent variables cases. For example, in the case of Chile, the macroeconomic variables such as trade balance (TBC), interest rate (IRSC), money supply (MSC) and current account (CAC) jointly Granger causes the exchange rates (LNER) of Chile and USA. The null also rejected when dependent variable is changed to TBC, IRSC, MSC and CAC. This indicates the bidirectional causality from exchange rate to macroeconomic variables and vice versa. Overall, the results suggested that the unidirectional causality i.e from macroeconomic variables to exchange rates is found in the cases of Brazil, Czech Republic, Indonesia, Peru and South Africa. Moreover, the unidirectional causality i.e exchange rate to from macroeconomic variables in all the cases except Czech Republic. Nevertheless, bidirectional causality is observed in the cases of Chile, Colombia and India.

The F statistic for the pairwise Granger Causality test for China, Hungary, Malaysia, Mexico, Philippines, Poland, Russia, South Korea, Taiwan, Thailand, Turkey are reported in Appendix 19B. The null hypothesis i.e 'macroeconomic variable does not Granger cause exchange rate' is rejected ($p < 0.05$) in the cases of Hungary, Malaysia, Russia and Taiwan. This indicates that country specific macroeconomic variable do Granger cause exchange rates of these countries against the U.S. dollar. The unidirectional causality i.e from exchange rate to macroeconomic variables is found in the case of Mexico, Philippines, Poland and South Korea. Bidirectional causality i.e macroeconomic variable to exchange rate and vice versa is observed in Russia. In contrast, no causality is showed in the cases of China and Turkey. The null of pairwise Granger Causality cannot reject since the F is statistically insignificant ($p > 0.05$). Therefore, one concludes that there is no causal impact from exchange rate (LNER) to trade balance (TBCHI) and vice versa in the case of China. Similar results also found in the case of Turkey. The results of Ganger Causality for rest of the emerging countries can be explained in a similar way.

4.5.3 Frontier Markets

The Granger Causality tests for all frontier countries are presented at Appendix 20. The result of the LR (χ^2) test is reported in Appendix 20A. These results are generally consistent with the results of advanced and emerging countries. For example, there is a one-way effect running from country specific macroeconomic variables to exchange rate in all cases except Pakistan and Sri Lanka. For instance, the null of block Granger Causality is rejected for Craotia since the LR (χ^2) is statistically significant ($p < 0.05$). This indicates that the macroeconomic variables such as interest rates (IRSC), inflation rates (INFRC), and trade balance (TBC) jointly Granger cause the exchange rate (LNER). The null is also rejected when the dependent variable is changed to IRSC and INFRC. However, we failed to reject the null of bloack Granger Causality ($p > 0.05$) when trade balance of Croatia (TBC) is used as dependent variable. Similar results are also found for all the countries except Bangladesh and Kazakhstan.

The Causality test also shows a bilateral effect running from macroeconomic variables to exchange rates and vice versa in the cases of Bangladesh and Kazakhstan. The null of block Granger Causality is rejected in those two countries since the LR (χ^2) is statistically significant ($p < 0.05$) for all dependent variables. For example, in the case of Bangladesh, the macroeconomic variables such as GDP (GDPBD), interest rate (IRSBD) and trade balance (TBBD) do jointly Granger cause the exchange rate (LNER) of Bangladeshi taka and USA dollar. The null was also rejected when the dependent variable is changed to GDPBD, IRSBD and TBBD. This indicates bidirectional causality from exchange rate to macroeconomic variables and vice versa. Similar results also found in the case of Kazakhstan.

The F statistic for the pairwise Granger Causality test for Bhutan, Botswana, Estonia, Jamaica, Kenya, Lao PDR, Myanmar and Vietnam are reported in Appendix 20B. The null hypothesis i.e 'macroeconomic variable does not Granger cause exchange rate' is rejected ($p < 0.05$) in all cases except Jamaica and Kenya. This indicates that country specific macroeconomic variable does Granger cause exchange rates of these countries against the U.S. dollar. The unidirectional causality i.e from macroeconomic variables to exchange rate is found in all cases except Jamaica and Kenya. The unidirectional causality i.e from exchange rate to macroeconomic variables is found in the case of Jamaica and Kenya. No bidirectional causality is observed in any of the frontier market cases. The results of Ganger Causality for remainder of the frontier countries can be explained in a similar way. The next Section compares the forecast performance of ARDL-cointegration model with time series models (discussed in Chapter 3).

4.6 A Comparison of Forecast Performance between Time Series and ARDL-cointegration Models

The individual forecasts obtained from the four forecasting models (volatility, exponential smoothing, Naïve 1 and ARDL-cointegration) are generated over the holdback period. To ensure consistency with previous exchange rates forecasting studies, the MAPE measure is used for accuracy comparison. The performance rankings of the alternative models based on the MAPE for advanced, emerging and frontier markets are presented in Appendix 21. Both the static (for the historic period) and dynamic (for the hold back period) MAPE values for all 49 countries are reported. The analyses show that the MAPE (static) is less than 5% for all cases except the Euro area (volatility model – 5.591%) and Peru (volatility model – 8.413%; Exponential smoothing model – 6.955%). The best models are then used to produce monthly *ex post* forecast and for 2008M1 to 2010M4 inclusive for each series. The four forecasting models are ranked against each other on the basis of minimum MAPE (dynamic).

Overall, a volatility model (24 cases) is found to be superior to all of the other models in forecasting exchange rates in 49 national currencies against the U.S. dollar. An important observation is that single volatility model outperforms the other models in 8 and 13 cases of emerging and frontier markets respectively, whereas it is outperforms in only 3 of 10 in the cases of the advanced markets. This is expected, as emerging and frontier markets are more vulnerable than advanced markets (Errunza, 1997). The exponential smoothing model was superior for the markets, like Canada, Czech Republic, Indonesia, Mexico, Poland, South Korea, Brunei, Jamaica and Romania. This model also outperforms the volatility and Naïve 1 models in these cases. Naïve 1 is found to be superior to other forecasting models in the cases of Japan, Brazil, Malaysia, Peru, Philippines, Taiwan, Bangladesh, Sri Lanka and Trinidad & Tobago. However, a cointegration model performs best for five advanced markets: Denmark, Norway, Singapore, Switzerland and UK, one emerging market-Turkey and one frontier market – Bhutan. Largely, this model is ranked fourth in the cases of emerging and frontier markets. This is because of the lack of power of the macroeconomic variables in forecasting the exchange rates of these countries. It has been difficult to find significant macroeconomic variables for the cointegration analyses for emerging and frontier markets. This might be why cointegration analysis of exchange rate series of emerging (save for the BRICS countries) and frontier markets does not exist in the empirical literature.

An important observation is that the level of performance achieved by the individual forecasting models varies across the 49 countries. Figure 4.1, 4.2 and 4.3 present the MAPE values of four individual models for advanced, emerging and frontier markets respectively. It is evident from Figure 4.1 that the MAPE values of the time-series models are more or less similar in all cases, whereas considerable variations are observed in the cointegration model. Moreover, the MAPE values generated from cointegration models are comparatively very high in the cases of Australia, Japan and Sweden. However, the results are different in emerging markets. Figure 4.2 shows that the MAPE values amongst the four individual models are more or less similar in the case of Malaysia only, whereas significant differences are observed in the remaining countries. Moreover, the MAPE values generated from cointegration model are comparatively high in the cases of Chile, China, Colombia, Czech Republic, India, Indonesia, Mexico, Peru, Poland, South Africa, South Korea, Taiwan and Thailand.

Figure 4.1: Forecast MAPEs (dynamic) of individual models: Advanced countries

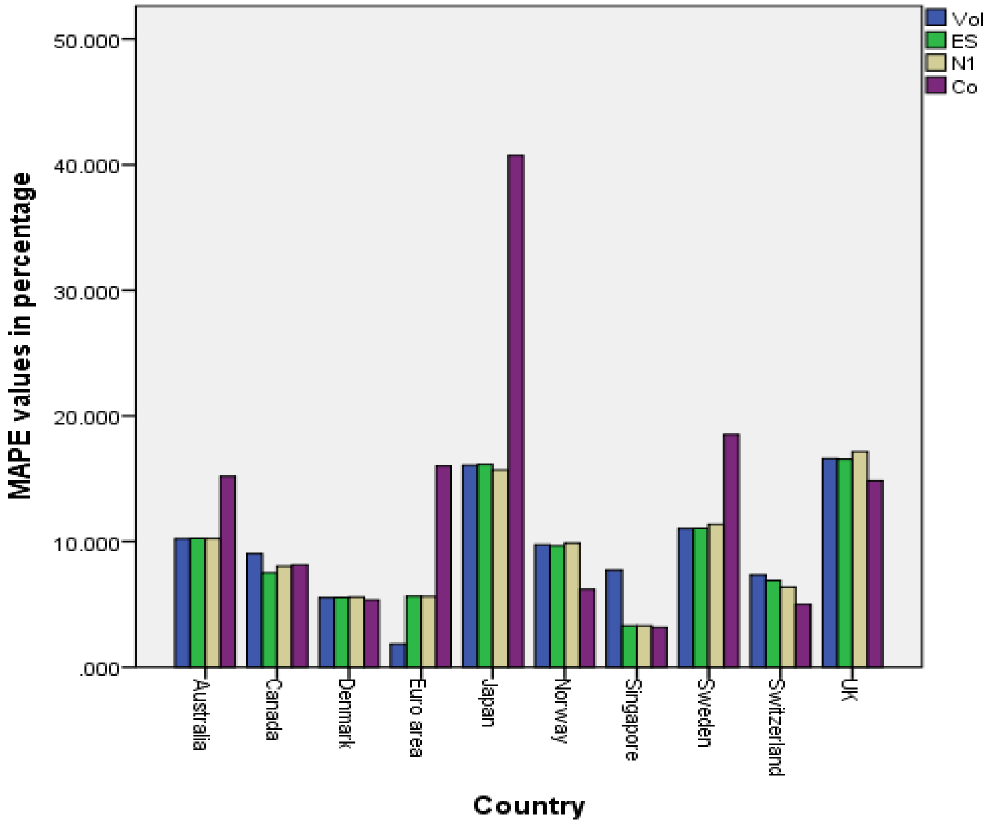


Figure 4.2: Forecast MAPEs (dynamic) of individual models: Emerging countries

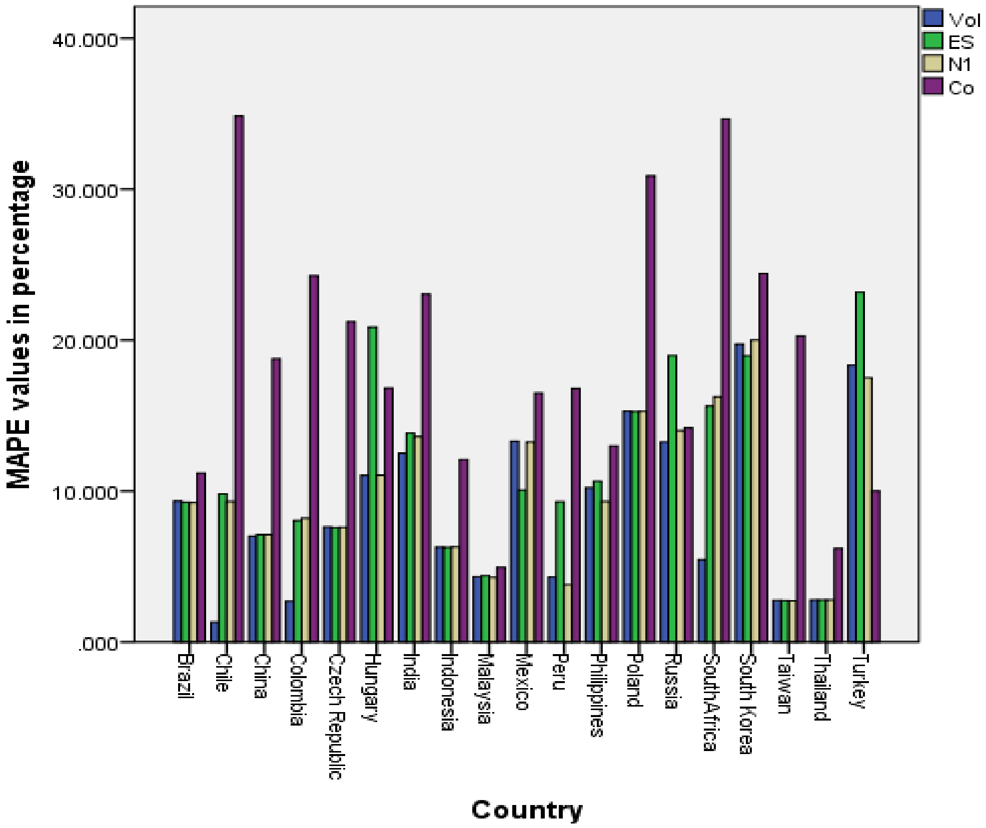


Figure 4.3: Forecast MAPEs (dynamic) of individual models: Frontier countries

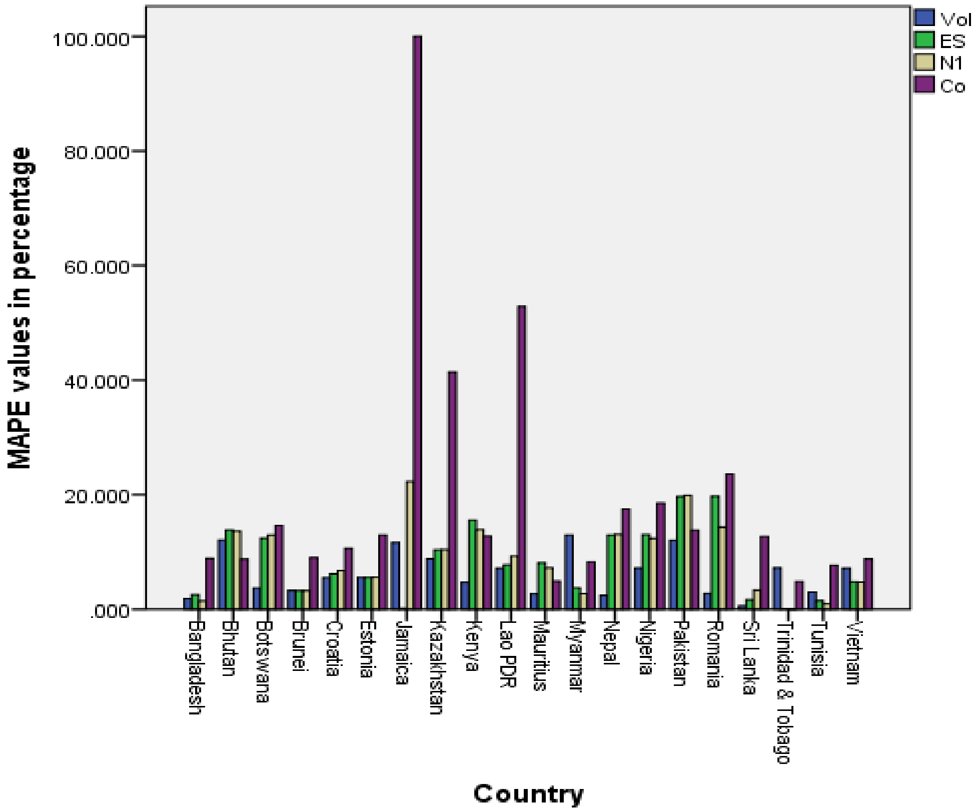


Figure 4.3 presents the MAPE values obtained from four individual models for frontier markets. This Figure shows that the MAPE values amongst the three individual time series models are more or less similar in the cases of Brunei and Estonia, whereas considerable variations of the MAPE values amongst the four models are observed in remaining cases. In the cases of Jamaica, Kazakhstan and Lao PDR, for example, the MAPE of the least accurate model (the cointegration model) is very high when compared to that of the most accurate (the volatility model). It is also evident form Figure 4.3 that the MAPE values generated from time-series models are comparatively very less for the cointegration model. It can be concluded from this analysis that time-series models, especially volatility models in this case, generate better forecasts for the frontier markets exchange rate series against the U.S. dollar. These findings are parallel with the emerging country group, however contrary to the findings for the advanced country group. These results are expected, as emerging and frontier markets are more volatile than advanced markets (Hausmann *et al.*, 2006; Wilcox, 1992).

Figure 4.4, 4.5 and 4.6 present graphical depictions of the performance of each forecasting method on the advanced, emerging and frontier countries exchange rate series respectively.

Figure 4.4: Boxplots of the MAPE (dynamic) values obtained from the individual forecasting models: Advanced countries

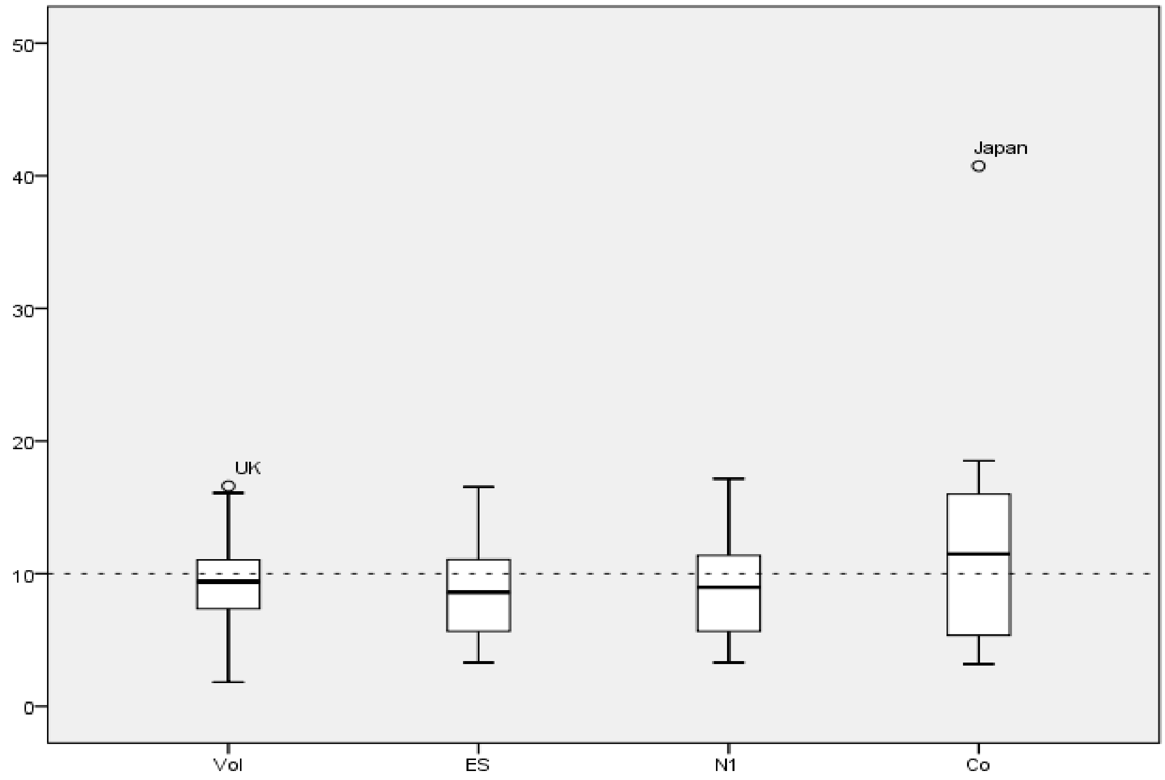


Figure 4.5: Boxplots of the MAPE (dynamic) values obtained from the individual forecasting models: Emerging countries

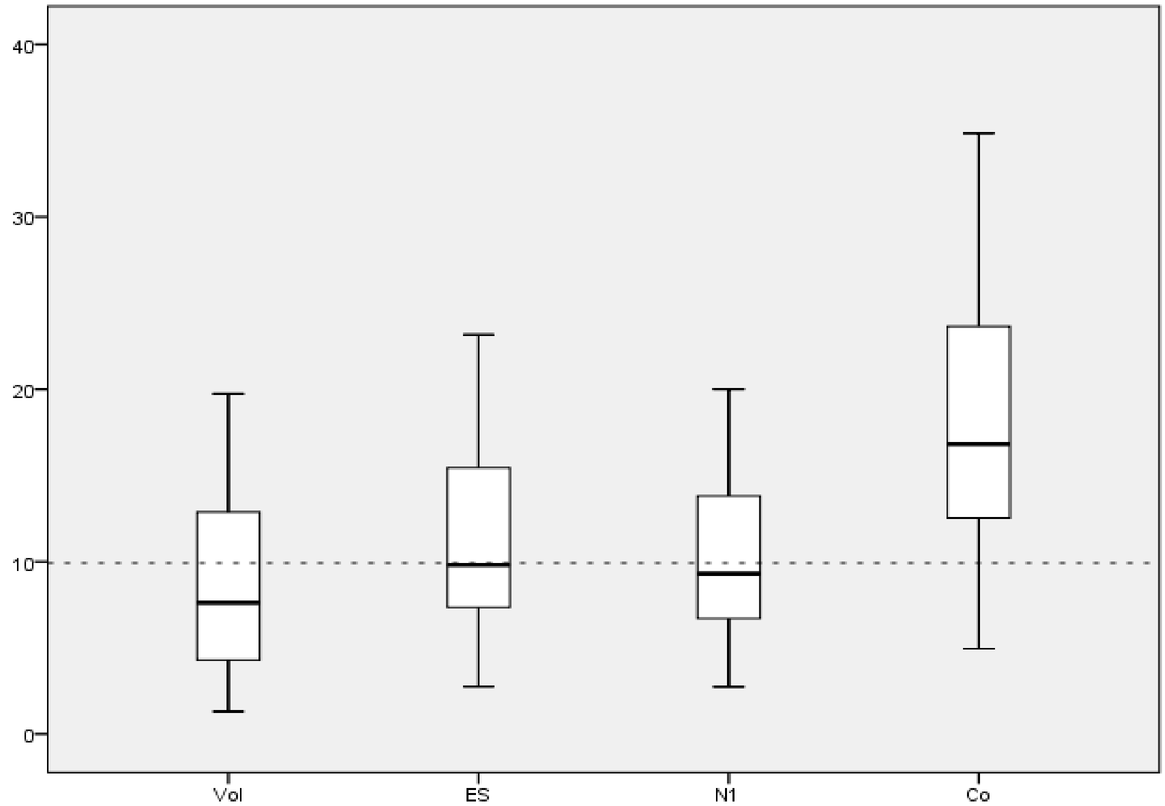
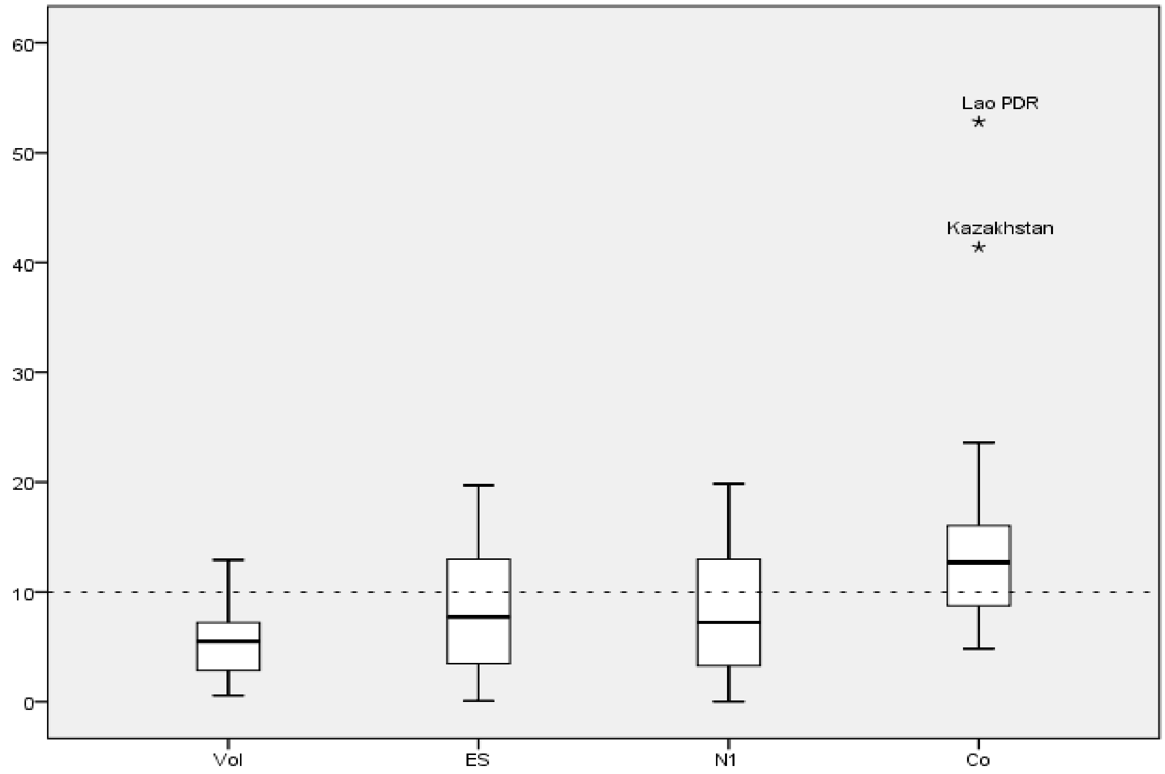


Figure 4.6: Boxplots of the MAPE (dynamic) values obtained from the individual forecasting models: Frontier countries



These figures show the distribution of the MAPE measures, summarised by four boxplots representing each of the forecasting methods included in the analysis. The dotted horizontal line in Figure 4.4, 4.5 and 4.6 represents the 10% limit "highly accurate forecasting" suggested by Lewis (1982). Figure 4.4 shows that time series models are the most accurate methods in terms of the MAPE generated over the holdback period, resulting in the lowest median, upper and lower quartile percentage points for the distribution of errors amongst the methods investigated. However, Figure 4.5 and 4.6 show that volatility model is the most accurate methods for the emerging and frontier markets, resulting in the lowest median, upper and lower quartile percentage points for the distribution of errors amongst the four methods investigated. Conversely, the single cointegration model is the least accurate method with highest median, upper and lower quartiles percentage points for the distribution of errors amongst the four methods investigated for all exchange rate series.

Four countries namely Japan, Jamaica, Kazakhstan and Lao PDR show very high MAPE values for cointegration model. Jamaica was omitted from the graphs, to better facilitate the graphical comparison between the various forecasting methods. The empirical results suggest that no single forecasting method is able to outperform all others in all situations. For example, the volatility model outperforms its competitors in terms of overall performance, but is outperformed by the exponential smoothing, Naïve 1 and cointegration model in 24 of the 49 country cases. It is thus believed that combining the forecasts generate by these individual methods may be a favourable option and this is the subject of Chapter 5 of this theses.

4.7 Summary and Policy Implications

This chapter has analysed the long-run determinants and short-run dynamics of the exchange rate of advanced, emerging and frontier currencies against the U.S. dollar. The results are vary for the various market economies studied even though some are at same level of development and have similar structural features, for example, BRICS, ASEAN, SAARC etc. The major findings of this chapter suggest that macroeconomic variables such as interest rates, inflation rates, money supply, trade balance, trade openness, GDP, oil prices and gold price have important long- and short-run role in the determination of exchange rates of advanced, emerging and frontier markets against the U.S. dollar. This work parallels the findings of the major papers concerning developed countries in terms of variables were used. However, this study has emphasised the role of trade openness in exchange rate determination and that is rarely considered in the literature (Edwards, 1993; Elbadawi, 1994; Connolly and Devereux, 1995; Hau, 2002; Li, 2004), despite its being a highly significant factor in exchange rate modelling.

Trade openness has a depreciative effect in the cases of Australia, Denmark, Norway, UK and South Africa. This finding indicates that after adopting the floating exchange rate system, a relaxation of the extent of impediments to the international trade resulted in exchange rate depreciation. Edwards (1989) provided an excellent theoretical justification for this finding (discussed in Chapter 2). This analysis is consistent with the theoretical argument as well as with the results of numerous studies undertaken in the past in respect of different countries (Edwards, 1993; Elbadawi, 1994; Connolly and Devereux, 1995; Hau, 2002). On the other hand, an appreciation effect of trade openness on the exchange rate has noted in the cases of Brazil, Hungary, Peru and Turkey. Similar findings were noted by Li (2004), who showed that no-credible trade liberalisation could appreciate the exchange rate. Calvo and Drazen (1998) also found that the trade liberalisation of uncertain duration could lead to an upward jump in consumption. Therefore, a real appreciation will occur in the short-run. They argued that real exchange rates will depreciate only if trade liberalisation is of permanent nature, while a transitory reform could lead a real appreciation in the short run. It is worthwhile mentioning here that the effect of trade openness has been observed to be insignificant in all emerging and frontier countries except for the Brazilian real/U.S. dollar, Hungarian forint/U.S. dollar, Peruvian nuevo sol/U.S. dollar, South African rand/U.S. dollar and Turkish lira/U.S. dollar. This result, however, is consistent with the findings of Edwards (1987), who noted that effect of trade openness on exchange rate can be insignificant.

Oil prices and gold prices have significant impacts on the exchange rate determination. Long-run relationships between oil prices and exchange rates were observed in the cases of Japan, Sweden, Brunei and Trinidad & Tobago. This finding supports earlier studies such as Tsen (2010) and Huang and Guo (2007), who noted that oil prices have significant impacts on exchange rates. The gold price was found to have significant positive long-run relationship with the South African rand/U.S. dollar exchange rate. South Africa is one of the largest producers of gold in the world. Therefore, it is perhaps unsurprising to find the relationship between gold price and rand/dollar exchange rate. The economic impact of increases in gold price would augment South Africa’s net export earnings. This will eventually improve the balance of payments; hence result in appreciation of the rand. The dummy variables for structural breaks are found statistically insignificant for all other markets except Switzerland, Indonesia, Malaysia, Mexico, Philippines, Russia, Thailand, Turkey, Bangladesh, Trinidad and Tobago. A dummy variable for the structural breaks (e.g. Asian crisis) had a negative coefficient as expected and was statistically significant in the cases of Indonesia, Malaysia, Philippines, South Korea and Thailand.

Although research has not been conducted for many of the emerging and frontier markets before, it is possible to generalise the macroeconomic variables that impact on exchange rates. These variables are interest rates, inflation rates, trade balances, money supply, GDP, trade openness, current account balance, oil prices and gold prices. These are in line with the existing exchange rate literature (e.g. Apergis *et al*. 2012; AbuDalu and Ahmed, 2012; Maitra and Mukhopadhyay, 2012; Verma, 2011; Abbas *et al.* 2011; Tsen, 2010; Verweij, 2008; Uddin, 2006; Obstfeld and Rogoff, 2005; Groen, 2000 and Kim and Mo, 1995). Note that other variables such as reserve assets and government expenditures are found to be insignificant in terms of long-run equilibrium. These variables do not impact upon the exchange rates in the long-run for any of 49 currencies against the U.S. dollar during the sample period employed. This result contradicts the findings of Chowdhury (2012), who noted that government expenditure is an important variable for the real exchange rate determination of Australia. Moreover, Glăvan (2006) reported that foreign exchange reserve is a significant variable for exchange rate determination. In addition, country specific commodity prices e.g. iron and coffee prices for Brazil, jute prices for Bangladesh, coal prices for South Africa and copper prices for UK are also found to be insignificant in the exchange rate determination. A plausible reason for these variables being insignificant is that commodity prices reflect a country's export figures. Since this study considered trade balance as an explanatory variable, individual commodity prices becomes less powerful variables in the exchange rate determination of these countries. However, further study on the relationship between exchange rates and country specific commodity prices should be conducted to investigate this further.

Exchange rates vary according to the speed of adjustment parameter as exemplified by the coefficient of the error correction term (ECM (-1)). These analyses show that very slow return to equilibrium for all advanced countries except Australia, Canada, the Euro area and Sweden. A fast return to equilibrium is observed in the case of Australia and Canada whereas it is moderate in the cases of the Euro area and Sweden. In the emerging country group, the speed of convergence is moderate in the cases of India and South Africa and it is slow in the cases of Brazil, Chile, Colombia, Czech Republic, Malaysia, Peru, Russia, Taiwan, Thailand and Turkey. However, very slow return to equilibrium is observed in the rest of the emerging countries. A moderate speed of convergence to equilibrium was noted in some of the frontier markets namely, Botswana, Nigeria, Sri Lanka and Vietnam Botswana, Nigeria, Sri Lanka and Vietnam. The slow speed of adjustment process is observed in the cases of Bangladesh, Brunei, Jamaica, Myanmar, Pakistan, Romania, Trinidad & Tobago and Tunisia. A very slow speed of convergence to equilibrium is observed for rest of the frontier countries. The findings of each group of countries are mixed, which is however expected, as each country within the same group has different economic policies. All of the results related to emerging and frontier markets may be regarded as innovative findings that add to a growing body of literature on exchange rate modelling via cointegration analysis.

This study attempts to investigate the relationship between exchange rate and macroeconomic variables by using ARDL-cointegration technique. After observing the cointegration among variables, this study also examines the direction of causality among variables via using Granger Causality tests. The findings of the Granger Causality test indicate that in the long-run, the unidirectional causality from country specific macroeconomic variables to exchange rates is found in all the cases except China, Poland, South Korea, Thailand, Turkey, Jamaica, Kenya, Pakistan and Sri Lanka. The bidirectional causality i.e macroeconomic variable to exchange rate and vice versa is found in the cases of UK, Chile, Colombia, India, Russia, Kazakhstan and Bangladesh. On the contrary, no causality is showed in the cases of China and Turkey. In general, these findings imply that macroeconomic variables are significant in predicting changes in exchange rates. Thus, it can be claimed that exchange rate variability is fundamentally linked to economic variables.

Relative to other Finance areas, the ARDL-cointegration model has received less attention in exchange rate determination. This gives an opportunity of assessing the utility of this model in the context of exchange rates. Therefore, this study also examined whether the ARDL-cointegration approach performs better than the time series models (discussed in Chapter 3) in an out-of-sample forecasting exercise. The findings show that the cointegration model generated less accurate forecasts when compared to the volatility, exponential smoothing and Naïve 1 model in all cases. It is therefore, concluded that this model plays considerably less significant role in the exchange rate determination possibly because of lack of power of the macroeconomic variables to forecast the exchange rates of these countries. This results support the argument of Flood and Rose (1995), who noted that the nominal exchange rates are much more volatile than the macroeconomic fundamentals to which they are linked in theoretical models. Excess volatility suggests that exchange rate models based on macroeconomic variables are unlikely to be very successful either at explaining or forecasting nominal exchange rates and that there are important variables that may be omitted from standard exchange rate models.

It has been difficult to find significant macroeconomic variables for the cointegration analysis for emerging and frontier markets in this study. Nevertheless, this was an investigative exercise. This might be why cointegration analysis of exchange rate series of emerging (save for the BRICS countries) and frontier markets does not exist in the empirical literature. Information asymmetry, heterogeneous investors, government policies regarding the macroeconomic variables and different market trading mechanisms might be the reasons for these poor forecasts. The results contradict the findings of Khalid (2008), who reported that for the developing economies a model based on macroeconomic fundamentals performs better than the random walk model both in- and out-sample. However, the results of this study support the arguments of Bailliu and King (2005), who reported that models of exchange rate determination based on macroeconomic fundamentals have not had much success in forecasting exchange rates. Obstfeld and Rogoff (2000) also noted that there is generally a very weak relationship between the exchange rate and virtually any macroeconomic variable- a situation they term the “exchange rate disconnect puzzle”.

Several explanations of exchange rate disconnection from macroeconomic fundamentals have been observed in the literature. Bailliu and King (2005) reported four major reasons for this weak relationship (discussed in Section 2.2.2 in Chapter 2). Several potential explanations are presented in the literature, including important variables such as presence of unobservable macroeconomic shocks that affect exchange rates, the irrationality of market participants, speculative bubbles and herding behaviour (Bailliu and King, 2005). Evans and Lyons (2005) suggested “microstructure theory” as an alternative exchange rate model. However, very limited research has been conducted by using the microstructure theory because of the lack of data on customer order flow. These data are nearly non-existent in the cases of emerging and frontier markets economies. In this study, although the ARDL-cointegration model generate less superior forecasts compared with other time series models, this model helps to understand the causal relationship of exchange rates with other macroeconomic variables. This is, however, never possible to explain by the time series analysis.

The findings of this study have important policy implications. The analyses facilitate the policy makers in making effective foreign exchange policies both at the micro and macroeconomic levels. On the macro level, the results will help a country’s government to undertake necessary measures related to the variables that affect exchange rates in order to maintain a stable position for their national currencies against the U.S. dollar. On a micro level, the results of this study are important for those companies who conduct cross-border business and finance their overseas operations or plan for the payment of costs and expenses overseas or hedge against these costs or against the potential losses associated with these costs. Therefore, the presented results are significant input for the policy makers to ensure financial stability, while protecting the home country's or home company's fiscal interests. Moreover, banks and even individuals would find these results are useful as they are assisted by the network of financial institutions and brokers. Since these people are buying and selling currencies in order to invest or to engage in international trade with their speculative motive.

Exchange rates are found to be affected by macroeconomic variables is the same direction as suggested by theory. Thus these variables can be considered as important tools for the policy makers who seek to minimise the exchange rate variability especially the under and/or overvaluation. A desirable level of an exchange rate can be achieved through influencing the exchange rate determinants that reduce exchange rate risks and maintain the international competiveness of exports and imports of the economy. The exchange rate of an economy affects aggregate demand through its impact on export and import prices and policy makers may exploit this connection. The results of this study suggest the key drivers of exchange rates determination. Therefore, the policy makers should focus on the effective macroeconomic management (i.e. monetary, fiscal, trade, investment, foreign debt policies etc.) by taking into consideration of such economic variables for maintaining stable exchange rate environment.

From a monetary policy perspective, it is important to understand which forces are actually driving a currency, because variations in exchange rates have different implications for a country's economy and may require different policy responses (Dodge, 2005). For instance, a home currency may be responding to an increase in the foreign demand for goods and services which would lead to an increase in home country's aggregate demand. In such a case, the monetary policy response would be muted unless it facilitated the reallocation of resources between traded and non-traded sectors. Alternatively, an appreciation of the home currency may simply reflect a general weakening of the U.S. dollar. Therefore, easing the monetary policy in order to offset the reduction in the foreign demand for home country's goods and services might be an issue for consideration (Bailliu and King, 2005).

The findings of this present study could also facilitate the central bank of the study countries to formulate the exchange rate policy. The central bank monitors the foreign exchange market to facilitate exchange rate adjustment towards a rate consistent with its fundamental. Therefore, the results of this study are useful for the central bank to maintain the stability in the foreign exchange markets. The long-run success of exchange rate determination is dependent on a commitment to sound economic fundamentals and this is not a case of advanced countries only but for emerging and frontier countries. However, there are some external variables which are beyond the control of the policy makers such as the capital flows and terms of trade. Excessive variability of these variables, especially in the emerging and frontier markets could fuel variability in the exchange rates.

Chapter 5

Combining Forecasts of Exchange Rates

The previous chapter discussed the causal ARDL-cointegration approach to forecasting exchange rates. The aim of this chapter is to combine the previously discussed time series and causal models for predicting exchange rates. The prime reason behind combining time series and causal forecasting techniques in this study is straightforward: no single forecasting method is appropriate for all situations. Single models may be optimal conditional upon a particular sample realisation, information set, model specification or time period. It is possible to overcome the weakness of a forecasting model under particular conditions by implementing a combination of methods. Although the theoretical literature (Bates and Granger, 1969; Granger and Ramanathan, 1984 and Clemen, 1989) suggests that appropriate combinations of individual forecasts often have superior performance, such methods have not been widely exploited in the empirical exchange rate literature (Sarno and Valente, 2005).

The context of this investigation is combination forecasts of advanced, emerging and frontier market exchange rates against the U.S. dollar. Four single models have been used to forecast the exchange rates- univariate volatility models, exponential smoothing models, Naïve 1 model and cointegration via ARDL (autoregressive distributive lags) models. Combination forecasting, therefore, permits the researcher to unite the advantages of the econometric models with those of the time series class of models mentioned earlier. Two combination approaches called the *equal weights* and *variance-covariance methods* are applied in this study. The statistically based forecast combination methods have had minimal application in the field of exchange rate modelling. The results of this study show that combination models perform better than the single model prediction.

There have been very few applications of combination models in the foreign exchange field (discussed in Section 2.3 in Chapter 2), yet these models have the potential to assist policy makers in making more effective decisions. Moreover, the use of appropriate combination techniques in exchange rate forecasting is crucial not only for academic researchers but also for practitioners such as governments, banks, insurance companies, businessman, investors, international organisations (IMF, World Bank etc.), tourism authorities, individuals and other related parties such as speculators, hedgers and arbitrageurs. This present study addresses two outstanding issues raised by Poon and Granger (2003). Poon and Granger (2003) highlighted the fact that little attention has been paid to the performance of combination forecasts, since different forecasting approaches capture different volatility dynamics. They also point out that little has been done to consider whether forecasting approaches are significantly different in terms of performance. This study applies the combination forecasting techniques in the exchange rate data to fill a major gap of the literature. Although many researchers observe that exchange rates are an important indicator of the economic welfare of any country, most of the studies on forecasting exchange rates are mainly focused on developed and to some extent secondary emerging markets (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). However, studies with emerging and frontier markets are almost non-existent. Therefore, a prime focus of this study is on combination forecasts of each of advanced, emerging and frontier markets currencies against the U.S. dollar to fills a gap of the literature. Furthermore, the majority of studies have concentrated on bilateral exchange rates between advanced countries rather than exchange rates of emerging versus advanced countries and frontier versus advanced countries. This study contributes to the existing literature by assessing the utility of combination techniques in these different contexts.

The reminder of the chapter is structured as follows. The explanation of combination methods is presented in Section 5.1. Section 5.2 reports the results plus a discussion and Section 5.3 provides the summary and policy implications.

5.1 Methods of Combining Forecasts

Bates and Granger (1969) first studied the idea of combination forecasting. In this seminal work, the authors proposed a linear combination of two forecasts with weights selected to minimize the predicted forecast error variance. There are different methods suggested in the literature on how to combine models. According to Menezes *et al.* (2000, 3) “the methods now available to the forecaster range from the robust simple average to the far more theoretically complex such as state-space methods and attempt to model non-stationarity in the combining weights”. Equal weighting is appealing because of its simplicity and easy to describe. Armstrong (2001, 4) concluded from his review of combining forecasts is that “when you are uncertain about which method is best, you should weight forecasts equally”. Another simple method proposed by Granger and Ramanathan (1984) is a linear mixture of the individual forecasts with combining weights determined by OLS (ordinary least square - assuming unbiasedness) from the matrix of past forecasts and the vector of past observations. However, the OLS estimates of the weights are criticised due to the likely presence of serial correlation in the combined forecast errors (see Aksu and Gunter, 1992 for details). They recommended the use of OLS combination forecasts with the weights restricted to sum to unity. Moreover, Granger (1989) provided several extensions of the original idea of Bates and Granger (1969), including combining forecasts with horizons longer than one period. Clements and Hendry (1998) derived combination weights by utilizing the regression models.

Some researchers prefer to use unequal weights instead of fixed equal weights for the combination purpose. Deutsch *et al.*, (1994) changed the fixed weights by using regime-switching models and smooth transition autoregressive (STAR) models. Fiordaliso (1998) proposed a time-dependent weighting scheme in a nonlinear way. Diebold and Pauly (1990) used Bayesian shrinkage techniques to allow the incorporation of prior information into the estimation of combining weights. Zou and Yang (2004) considered combining forecasts from similar models, with weights sequentially updated. Combination of forecasts from linear and nonlinear time series models, with OLS weights as well as weights determined by a time-varying method was examined by Terui and Van Dijk (2002). The superior performance of combining forecasts over individual approaches was illustrated in the extensive empirical evaluation conducted by Winkler and Markridakis (1983) and Russel and Adam (1987).

Bunn (1985) addressed the relative performance of combining methods as a function of the individual forecast errors- variance ratios, correlation coefficient and sample size by applying six combination methods, namely equal weights, optimal, optimal with independent assumption, outperformance, Bayesian probabilities and quasi-Bayes probabilities. Menezes *et al.* (2000) applied seven combination methods to evaluate the performance of different combining methods with the aim of providing practical guidelines based on three properties of the forecast errors; variance, asymmetry and serial correlation. According to Shen *et al.* (2011, 3) “some studies suggest that methods that weight better-performing forecasts more heavily are likely to perform better than the simple average combination technique, although there is a significant amount of empirical evidence to show that simple combination forecasts with equal weights outperform more sophisticated combination forecasts (e.g. Markidakis and Winkler, 1983; Stock and Watson, 2004)". Although the literature contains a great diversity of methods to combine forecasts, in this present study, two combination approaches known as equal-weights and variance-covariance (hereafter refer to as var-cov) methods are applied. The equal weights methods is simple and easy to understand and the var-cov has the inherent logic of minimising the variance of the errors. The next section briefly describes the equal weights and var-cov methods of combination.

Consider the case of two individual forecasts of Y, denoted by $\widehat{Y}_1$ and $\widehat{Y}_2$. The latter are to be combined to estimate Y, via:

$$\widehat{Y}_{COMBINED\,(t)} = a\widehat{Y}_{MODEL\,1(t)} + (1-a)\widehat{Y}_{MODEL\,2(t)} \tag{21}$$

where, t represents time, a and $(1-a)$ are weight attached to $\widehat{Y}_{1,t}$ and $\widehat{Y}_{2,t}$ respectively and $0 < a < 1$. A simple method of combining two forecasts is to take their arithmetic mean i.e. set $a = \frac{1}{2}$ in equation (21). This simple but often effective method of forecast combination is one of the two such methods applied in this study, since there is evidence that equal weights can be accurate for many types of forecasting (Armstrong, 2001).

Let $e_{COMBINED(t)}$ be the error attached to this combined forecast and let Y_t be the true value of the variable Y. Therefore, the forecast errors from equation (21) are:

$$e_{COMBINED(t)} = Y_{(t)} - \widehat{Y}_{COMBINED\,(t)} \text{ or}$$

$$e_{COMBINED(t)} = Y_{(t)} - a\,\widehat{Y}_{MODEL1(t)} - (1-a)\,\widehat{Y}_{MODEL2(t)} \tag{22}$$

Let $e_{COMBINED1,t}$ be the error attached to the single forecast $\widehat{Y}_{MODEL1(t)}$ and similarly for $e_{COMBINED2,t}$ thus:

$e_{MODEL1,t} = Y_{(t)} - \widehat{Y}_{MODEL\ 1\ (t)}$ and $e_{MODEL2,t} = Y_{(t)} - \widehat{Y}_{MODEL\ 2(t)}$

or, $\widehat{Y}_{MODEL\ 1\ (t)} = Y_{(t)} - e_{MODEL1,t}$ and $\widehat{Y}_{MODEL\ 2\ (t)} = Y_{(t)} - e_{MODEL2,t}$ (23)

Put equation (22) into (23)

$e_{COMBINED(t)} = Y_t - aY_t + ae_{MODEL1,t} - (1-a)(Y_t - e_{MODEL2,t})$

$e_{COMBINED(t)} = Y_t - aY_t + ae_{MODEL1,t} - Y_t + e_{MODEL2,t} + aY_t - ae_{MODEL2,t}$

$e_{COMBINED(t)} = ae_{MODEL1,t} + e_{MODEL2,t} - ae_{MODEL2,t}$

$e_{COMBINED(t)} = ae_{MODEL1,t} + (1-a)e_{MODEL2,t}$ (24)

Using Theorem[18] 2 in equation (24) and equation (A) the variance of the errors of the combined forecasts is, therefore:

$$\text{var } e_{COMBINED(t)} = a^2 \text{ var } e_{MODEL\ 1\ (t)} + (1-a)^2 \text{ var } e_{MODEL\ 2\ (t)} + 2\,a(1-a)\text{cov}\,(e_{MODEL\ 1\ (t)}, e_{MODEL\ 2(t)}) \quad (25)$$

---

[18] Equation (A) $var\ (ax) = a^2\ var\ x$ if a is constant

Theorem 1: Consider $E(x+y)$ where x and y are two variables.

$E\ (x+y) = \frac{\sum(x+y)}{n} = \frac{\sum x}{n} + \frac{\sum y}{n} = E(x) + E(y)$

Hence, $E(x+y) = E(x) + E(y)$ ………… Equation (C)

Theorem 2: Recall that $\text{var x} = \text{E}\ (\text{x}^2) - [\text{E(x)}]^2$ so by analogy

$\text{var}(x+y) = E(x+y)^2 - [E(x+y)^2]$

$= E(x+y)^2 - [E(x) + E(y)]^2$ by Equation(C)

$= E(x^2 + y^2 + 2xy) - \{[E(x)]^2 + [E(y)]^2 + 2E(x)E(y)\}$

$= E(x)^2 + E(y)^2 + 2E(xy) - [E(x)]^2 - [E(y)]^2 - 2E(x)E(y)$

So $\text{var}(x+y) = \text{var x} + \text{var y} + 2\ \text{cov}\ (xy)$

where, $\text{cov}\ (xy) = E(xy) - E(x)E(y)$; [Cov(xy)is the covariance between x and y] in which 'cov' represents the covariance of the errors obtained from the two models. From equation (25)

$$\text{var } e_{\text{COMBINED(t)}} = a^2 \text{var } e_{\text{MODEL1,t}} + \text{var } e_{\text{MODEL2,t}} + a^2 \text{var} e_{\text{MODEL 2,t}} - 2a \text{ var } e_{\text{MODEL2,t}} + 2a \text{ cov}\left(e_{\text{MODEL1,t}} e_{\text{MODEL2,t}}\right) - 2a^2 \text{cov}\left(e_{\text{MODEL1,t}} e_{\text{MODEL2,t}}\right)$$

Differentiating with respect to a,

$$\frac{\text{dvar}}{\text{da}} = 2a \text{ var} e_{\text{MODEL1,t}} + 2a \text{ var} e_{\text{MODEL2,t}} - 2 \text{ var} e_{\text{MODEL2,t}}$$

$+2 \text{ cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right) - 4a \text{ cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right) = 0$ at minimum variance of $e_{\text{COMBINED,t}}$.

Hence,

$$a\left\{\text{var} e_{\text{MODEL1,t}} + \text{var} e_{\text{MODEL 2,t}} - 2 \text{ cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right)\right\} - \text{var} e_{\text{MODEL 2,t}} + \text{cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right) = 0$$

and

$$a_1^* = \frac{\text{var } e_{\text{MODEL 2,t}} - \text{cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right)}{\text{var } e_{\text{MODEL 1,t}} + \text{var } e_{\text{MODEL 2,t}} - 2 \text{ cov}\left(e_{\text{MODEL1,t}}, e_{\text{MODEL2,t}}\right)} \quad (26)$$

where a_1^* is the weight of $\hat{Y}_{1,t}$ in equation (26) that minimises the variance of the errors of the combined forecasts. By definition $a_2^* = (1 - a_1^*)$. This is called the var-cov method of forecast combination.

There are suggestions that the weighting procedure of equation (26) is over-complicated. Following the proposal of Bates and Granger (1969), Li (2007) ignored the covariance terms in equation (26) in a study of quarterly UK outbound tourism to the United States and further suggested that since $\text{var} e_{\text{MODEL 1(t)}}$ and $\text{var} e_{\text{MODEL 2(t)}}$ are unknown, they could be replaced with $\sum_{t=1}^{t} e_{\text{MODEL 1(t)}}^2$ and $\sum_{t=1}^{t} e_{\text{MODEL 2(t)}}^2$ respectively, to derive the weight:

$$a_1^* = \frac{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}}}{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}}} \tag{27}$$

This assumes that $E(e_{\mathrm{MODEL}}) = 0$, whereby,

$\mathrm{Var}(e_{\mathrm{MODEL}}) = E(e^2_{\mathrm{MODEL}}) - [E\,(e_{\mathrm{MODEL}})]^2 = \sum_{t=1}^{t} \frac{e^2_{\mathrm{MODEL}}}{n}$; then n's in equation (27) cancel out.

This var-cov approach in equation (27) can be extended to combining more than two forecasts model. For example, when combining three forecasting models, it may be established that:

$$a_1^* = \frac{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}}}{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}}}$$

$$a_2^* = \frac{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}}}{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}}}$$

and $a_3^* = 1 - a_1^* - a_2^*$.

Four-way model combinations involve three-way products of the sum of squared error terms. For example,

$$a_1^* = \frac{\sum_{t=1}^{t} e^2_{\mathrm{M\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 3(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 4(t)}}}{\sum_{t=1}^{t} e^2_{\mathrm{M\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 3(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{M\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 4(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{M\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 3(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 4(t)}} + \sum_{t=1}^{t} e^2_{\mathrm{M\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 3(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 4(t)}}}$$

where $\sum_{t=1}^{t} e^2_{\mathrm{M\ 2(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 3(t)}} \sum_{t=1}^{t} e^2_{\mathrm{M\ 4(t)}}$ are the sum of the squared errors associated with models 2, 3 and 4 respectively.

$$a_2^* = \frac{\sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 1(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 3(t)}} \sum_{t=1}^{t} e^2_{\mathrm{MODEL\ 4(t)}}}{\text{Same denominator as above}}$$

$$a_3^* = \frac{\sum_{t=1}^{t} e_{MODEL\ 1(t)}^2 \sum_{t=1}^{t} e_{MODEL\ 2(t)}^2 \sum_{t=1}^{t} e_{MODEL\ 4(t)}^2}{\text{Same denominator as above}} \text{ and}$$

$$a_4^* = 1 - a_1^* - a_2^* - a_3^*$$

The above var-cov approach to obtaining weights is the second method of combination applied in this study.

5.1.1 Test of Forecast Unbiasedness

In this present study, MAPE (mean absolute percentage error) is used to measure forecasting accuracy. According to Lewis (1982), a MAPE values below 10% are consider as highly accurate forecasting. However, the test of forecast unbiasedness is just as important as the low MAPE for any optimal model. Therefore, the Wald test is performed to check the forecasts' unbiasedness for all competing models derived from the individual models and/or the combined models (average method and var-cov method). "The Wald test computes a test statistic based on the unrestricted regression. The Wald statistic measures how close the unrestricted estimates come to satisfying the restrictions under the null hypothesis. If the restrictions are in fact true, then the unrestricted estimates should come close to satisfying the restrictions" (Quantitative Micro Software 2010, 146).

Assume, $\widehat{Y}_t$ is the forecasted values of Y_t over the time. Suppose we regress Y_t against $\widehat{Y}_t$:

$$Y_t = \alpha + \beta\widehat{Y}t \tag{28}$$

The composite hypothesis H_0: $\alpha = 0$ and $\beta = 1$ is a sufficient condition for $\widehat{Y}_t$ to be an unbiased estimator of Y_t. We reject H_0 if the significance is less than 0.05 since this is a one-tailed test. Acceptance of the null indicates that the forecasts in question are unbiased estimators of Y_t.

The nonparametric Wald-Wolfowitz's runs test is carried out when all the combination models are indicative of biased forecasts. This test is essentially a test of randomness of error and is based on the order or sequence in which observations were originally obtained. Consider the forecasts $\hat{Y}$ and the observation Y. The new variable defining the direction of the errors has the value of 1 if $Y - \hat{Y} > 0$ and equals 0 if $Y - \hat{Y} < 0$. The Wald-Wolfowitz test is based on runs which are defined as a succession of identical symbols which are followed and preceded by different symbols or no symbols at all (Siegel and Castellan, 1988). For example, suppose that a series of model residuals had the following values for the variable direction of the errors:

x x y y y x y y y y x x y x x

This starts with a run of two x's, then a run of three y's. Then there is a run of one x followed by a run of four y's, two x's, one y and lastly two x's. There is a total of r = 7 runs here. The total number of runs in a sample provides an indication of whether or not the sample is random. For example, if very few runs occur (e.g. ten x's followed by ten y's or vice versa, hence r = 2) then a time trend or some bunching due to a lack of independence in the residuals is suggested. Conversely, if a great many runs occur (e.g. the sequence x y x y x y x y x y x y x y x, hence r = 15) then systematic short-term cyclical fluctuations would seem to be influencing the residuals. In passing, note that this analysis is based on the order of events and provides information that is not indicated by the frequency of the events. For example, reconsider the example above where the no. of runs r = 15. If we had examined just the frequency, we would find that we have eight x's and seven y's and based on that information alone, we would have little reason to doubt the randomness of the residuals' signs. It is only the runs test, focusing on the order of events, which reveals the striking lack of randomness in the signs attached to these fifteen residuals. For the runs test, the appropriate hypotheses are:

H_0: the x's and y's appear in random order and
H_1: the order of x's and y's deviates from randomness.

We reject the H_0 if significance is less than 0.05, since this is a one-tailed test. Acceptance of the null indicates that the forecasts are biased. The applications of Wald and runs tests are almost non-existence in the field of forecasting exchange rates. Applying the Wald and runs tests, this present study fills a gap of the existing literature.

5.2 Results from Combination Methods of Forecasting Exchange Rates

Forecasts obtained from the volatility, exponential smoothing, Naïve 1 and cointegration models were combined via the equal weights and var-cov methods. The estimation period is from 1972 M1 to 2007 M12 while the forecast (holdback period) runs from 2008 M1 to 2010 M4. In total, 4 individual forecasts, 6 two-way combination forecasts, 4 three-way combination forecasts and one four-way combination forecasts by equal and var-cov methods are generated for each currency pair. The MAPE's were computed for forecasts generated by the single models, models combined in pairs, in threes and all four together. The Wald test was used to check for unbiasedness in the forecasts of all competing models. The runs test (Wald-Wolfowitz) was carried out when all competing models indicative of biased forecasts. Finally, the optimal model was select based on the lowest MAPE with an unbiased feature. The results are sectionalised into forecasts involving advanced, emerging and frontier markets.

5.2.1 Advanced Markets

MAPE values for all 26 models for 10 advanced currencies against the U.S. dollar are reported in Appendix 22. The empirical results suggest that no single forecasting method is able to outperform all others in all situations. For example, as noted (Appendix 22.1), the single cointegration model outperforms its competitors in the cases of Denmark, Norway, Singapore, Switzerland and UK. The single volatility model outperforms in the cases of Australia, the Euro area and Sweden, but it outperformed by Naïve 1 and exponential smoothing models in 2 of the 10 country cases. It is thus possible that combining the forecasts generated by these individual methods may be a favourable option. An important observation is that the level of performance achieved by the individual forecasting models varies across the 10 advanced markets.

The results also show that the MAPE values for all single time series models are less than 10% except in the cases like Australia, Japan, Sweden and UK. The MAPE obtained from a cointegration model exceed 10% in the cases of Australia, the Euro area, Japan, Sweden and UK. By contrast, the MAPE values obtained from combination models via equal weights produce better results (less than 10%) than the single models for Canada, Denmark, the Euro area, Norway, Singapore and Switzerland. Moreover, the var-cov approach of combination models improved the MAPE values in many cases such as the Euro area, Norway and Singapore when compared with the equal weights approach of combination. Figure 5.1 shows the MAPE values amongst the 26 individual forecasting models. It is evident from Figure 5.1 that the MAPE values are more or less similar in the cases of Canada, Denmark, Switzerland and UK, whereas considerable variations are observed in the cases of Australia, the Euro area, Japan, Norway, Singapore and Sweden. In the cases of Australia, the Euro area, Japan and Sweden, the MAPE of the cointegration model is considerably higher than other forecasting models.

Figure 5.2 presents a graphical depiction of the performance of each forecasting method on the advanced countries' exchange rate series. The dotted horizontal line in Figure 5.2 represents the 10% limit "highly accurate forecasting" suggested by Lewis (1982). This figure shows the distribution of the MAPE measures is summarised in 26 boxplots, each of the 26 forecasting methods included in the analysis. A high MAPE value is observed for the various models in the cases of Japan and UK. Japan was omitted from the graphs, to better facilitate the graphical comparison between the various forecasting models. It is evident from Figure 5.2 that the combination forecasting method (ES-N1-Co via var-cov) is the most accurate method in terms of the MAPE measures for forecasting horizon, resulting in the lowest median, upper and lower quartiles for distribution of errors amongst the 26 methods investigated. Combination models via var-cov method are found to have consistently lower medians in the sample. Moreover, it is evident from Figure 5.2 that the four combination models via var-cov: ES-Co, Vol-ES-Co, ES-N1-Co and N1-Co-Vol generates the lowest median amongst the 26 forecasting methods investigated. Furthermore, the single cointegration model is the least accurate method in terms of the MAPE measure for forecasting horizon, resulting in the highest median, upper and lower quartiles for the distribution of errors amongst the methods investigated. An important observation is that high median and quartiles of the cointegration method are reduced by significant level when this model is combined with other forecasting models.

Figure 5.1: Bar charts of the MAPE values obtained across the advanced countries' exchange rate series for the 26 forecasting models

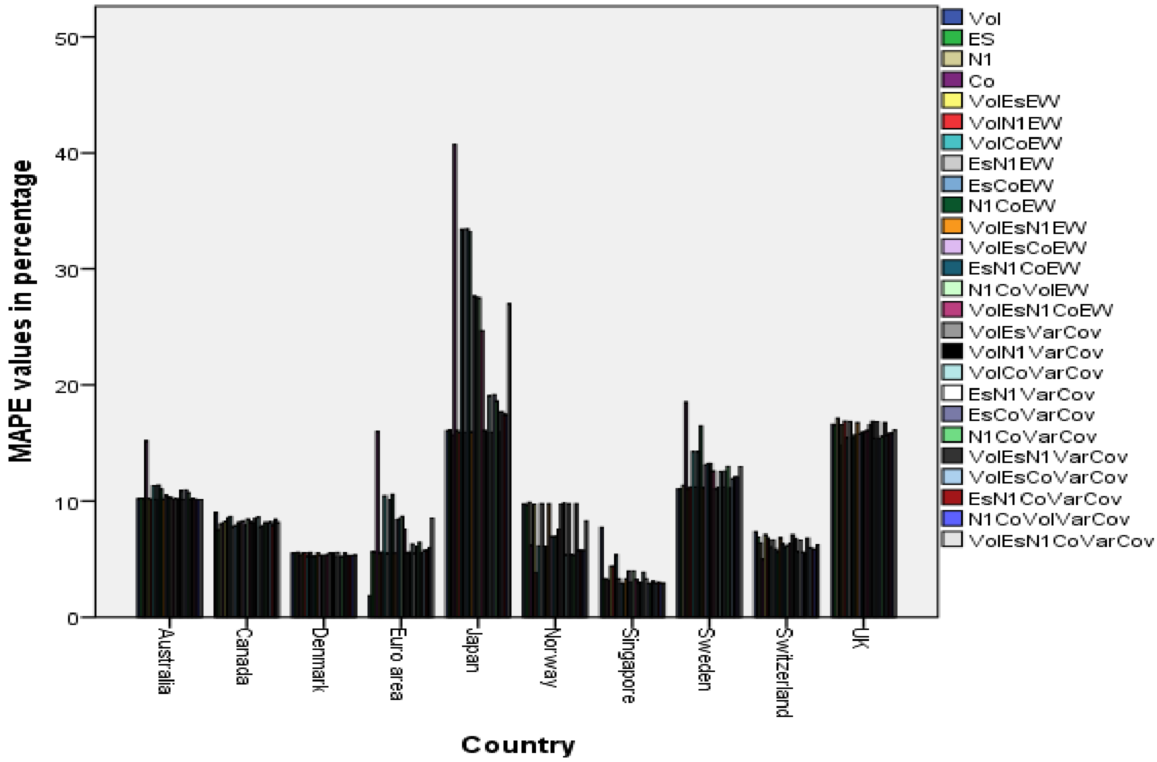


Figure 5.2: Boxplots of the MAPE values obtained from the 26 forecasting models: Advanced countries

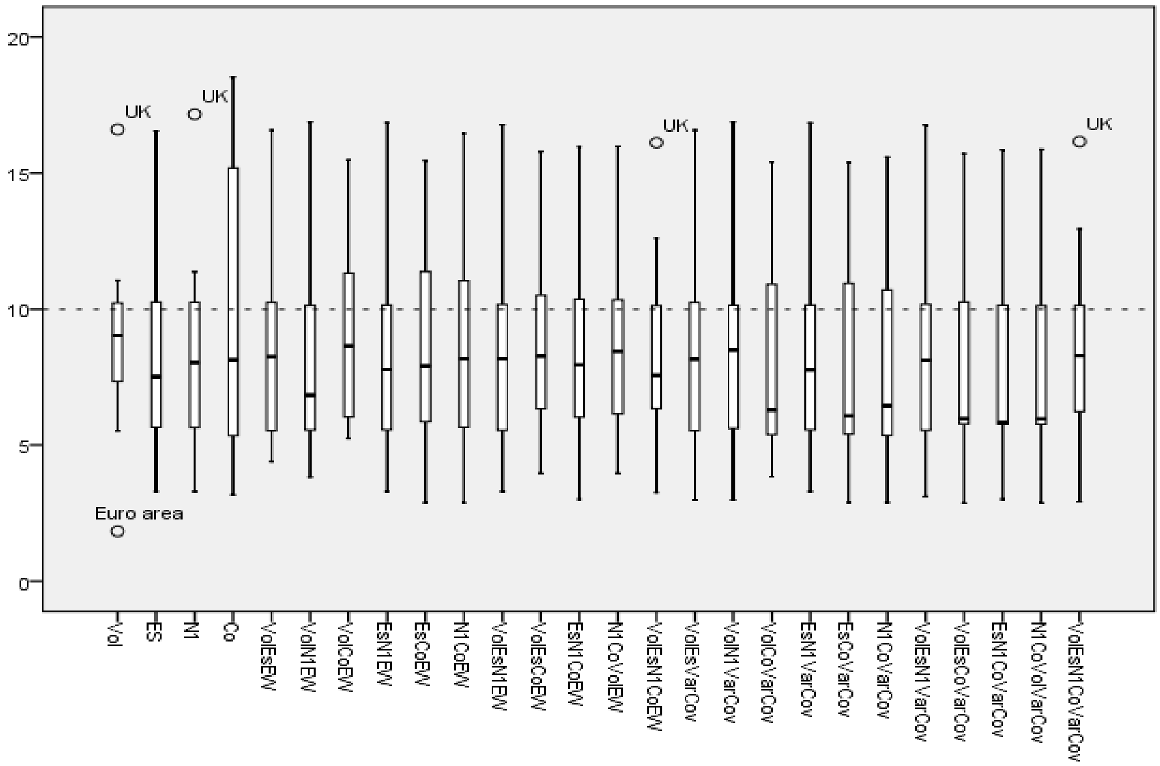


Table 5.1 reports the optimal forecasting models for the advanced countries. The results show that the two-way var-cov and equal weights combination approach has lower error rates than the other models in the case of Denmark and Norway respectively. The three-way var-cov model is more accurate than the other models in the case of Australia and Singapore. The single model outperforms other models in the cases of Canada, the Euro area, Japan, Sweden, Switzerland and UK. Initially the model was selected based on lowest MAPE. However, the results changed dramatically after conducting the Wald test. As was mentioned in Section 5.1.1 the test of forecast unbiasedness is just as important as a low MAPE value. Therefore, the models with the lowest MAPE are eliminated if they fail the Wald test because they are biased. The fourth column of the Table 5.1 reports the Wald test results for all advanced countries. The results show that none of the single models satisfies the test of unbiasedness. A combination model via the var-cov approach is superior to the other models in all cases. It is worthwhile mentioning here that the optimal model for Australia, Denmark and Singapore remain unchanged after Wald test of unbiasedness. However, the optimal model and corresponding MAPE values change in the cases of the Euro area, Norway, Sweden and Switzerland. All the competing models evidenced bias in the cases of Canada, Japan and UK.

The runs test was conducted to check the randomness of the errors. The test results show that three-way var-cov methods: Vol-ES-Co and Vol-ES-N1 were optimal in the cases of Canada and Japan respectively, whereas the two-way var-cov (ES-Co) combination method with comparatively higher MAPE value (15.379%) were optimal in the case of UK. It is worthwhile mentioning that the MAPE values evidenced highly accurate forecasts (less than 10%) for all countries except Australia, Japan, Sweden and UK. The optimal model results for all 10 advanced countries are reported in Table 5.2. It is clear that the var-cov approach is superior to other models in all cases. No four-way combination model claimed the overall minimum MAPE value for any exchange rate series. It is evident that the combination of forecasts delivers a statistically significant advantage for forecasting exchange rates of advanced currencies. This supports the argument of Altavilla and Grauwe (2010) concerning the likely utility of combination methods over single time series and econometric model when forecasting exchange rates. In terms of the 10 countries for which the combination model is the optimal, the var-cov method generates the minimum MAPE model in all cases. The findings of this study suggest that the cointegration model plays a big role in exchange rate determination of advanced currencies.

Table 5.1: The derivation of an optimal model for advanced countries

Country	**Optimal Model (according to MAPE)**	**MAPE**	**Optimal Model (after Wald test)**	**MAPE**	**Optimal Model (after Runs test)**	**MAPE**
Australia	N1-Co-Vol (var-cov)	10.116	N1-Co-Vol (var-cov)	10.116		
Canada	ES	7.515			Vol-ES-Co (var-cov)	8.210
Denmark	ES-Co (var-cov)	5.220	ES-Co (var-cov)	5.220		
Euro area	Vol	1.837	ES-N1 (var-cov)	5.521		
Japan	N1	15.700			Vol-ES-N1 (var-cov)	15.975
Norway	Vol-N1 (equal weights)	3.820	N1-Co (var-cov)	5.360		
Singapore	Vol-ES-Co (var-cov)	2.882	Vol-ES-Co (var-cov)	2.882		
Sweden	Vol	11.046	Vol-ES-Co (var-cov)	11.923		
Switzerland	Co	5.005	Vol-ES-Co (var-cov)	5.980		
UK	Co	14.832			ES-Co (var-cov)	15.379

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model

Table 5.2: Optimal model for advanced countries

Country	**Optimal Model***	**MAPE**	**Wald Test F statistics****	**Runs Test (Significance)*****
Australia	N1-Co-Vol (var-cov)	10.116	1.893 (0.171)	
Canada	Vol-ES-Co (var-cov)	8.210		0.357
Denmark	ES-Co (var-cov)	5.220	0.879 (0.427)	
Euro area	ES-N1 (var-cov)	5.521	0.350 (0.708)	
Japan	Vol-ES-N1(var-cov)	15.975		0.598
Norway	N1-Co (var-cov)	5.360	0.427 (0.657)	
Singapore	Vol-ES-Co (var-cov)	2.882	1.085 (0.353)	
Sweden	Vol-ES-Co (var-cov)	11.923	2.310 (0.510)	
Switzerland	Vol-ES-Co (var-cov)	5.980	1.527 (0.175)	
UK	ES-Co (var-cov)	15.379		1.000

*Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
**F statistics significance levels are reported in the round brackets.
***Significance at the 0.05 level

The cointegration model contributes to 8 of these 10 cases, volatility models are involved in 6 of these 10 minimum error combination models and exponential smoothing models are involved 8 of these 10 cases. This supports the fact that these time series and econometric models possess utility in the context of exchange rates determination, but their main utility is when combined with other modelling techniques. The Naïve 1 or "no change" model has been proven to be reliable in many forecasting contexts. Moreover, this model is often regarded as benchmark model for exchange rate determination. In this study, the Naïve 1 model appears in only 4 of these 10 minimum error combination models. However, the findings reinforce that this model has very little role to play in forecasting exchange rates of advanced currencies against the U.S. dollar. This supports the findings of the Thomakos and Guerard (2004), who studied the U.S model yielded the largest RMSE (root mean square error) compare with other individual and combined model. However, like other models, the Naïve 1 model only has merit when combined with other forecasting techniques.

Figure 5.3 shows that the MAPE values obtained from the optimal model are less than 10% in all cases except Australia (10.109%), Japan (15.975%), Sweden (11.923%) and UK (15.379%). This shows that highly accurate forecasts are generated in all countries except Australia, Japan, Sweden and UK. The Wald test result confirms (sig > 0.05) that the forecasts made by the optimal model is unbiased for all countries except Canada, Japan and UK. The runs test verifies the randomness of the errors associated with the optimal model for the cases of Canada, Japan and UK. In all of these cases, the hypothesis of random residuals is not rejected (sig > 0.05) and one concludes that the errors are random. Plots of the direction of errors over time for Canada, Japan and UK are presented in Figures 5.4, 5.5 and 5.6 respectively. These plots reveal error overestimation the exchange rates from June 2008 and July 2008 in the cases of Canada and UK respectively. However, the underestimations started from October 2008 for Japan.

There is an immediate response of global financial crisis which is detected in the cases of Canadian dollar/U.S. dollar (Figure 5.4) and British pound/U.S. dollar rates (Figure 5.6). However, the lagged effects are evident in Japanese yen/U.S. dollar rate. These plots clearly show that the recent global financial crisis still has consistent effects in the exchange rate determination for those countries. Conversely, no systematic or consistent patterns of the effects of financial crisis have been found for the countries like Australia, Denmark, the Euro area, Norway, Singapore, Sweden and Switzerland. From a practical viewpoint, it is clear that combination forecasts have the potential to produce forecasts of superior accuracy relative to the individual forecasts. This is not surprising, as different models capture different features in exchange rate series. The results of this study show that if the top performing individual forecasts (time series and econometric) are combined, this may lead to a dominant combination forecast, superior to both its individual constituents and other competing models. In this present context, combination models are the best model in every case.

Figure 5.3: Bar charts of the MAPE values obtained for the optimal forecasting model: Advanced countries

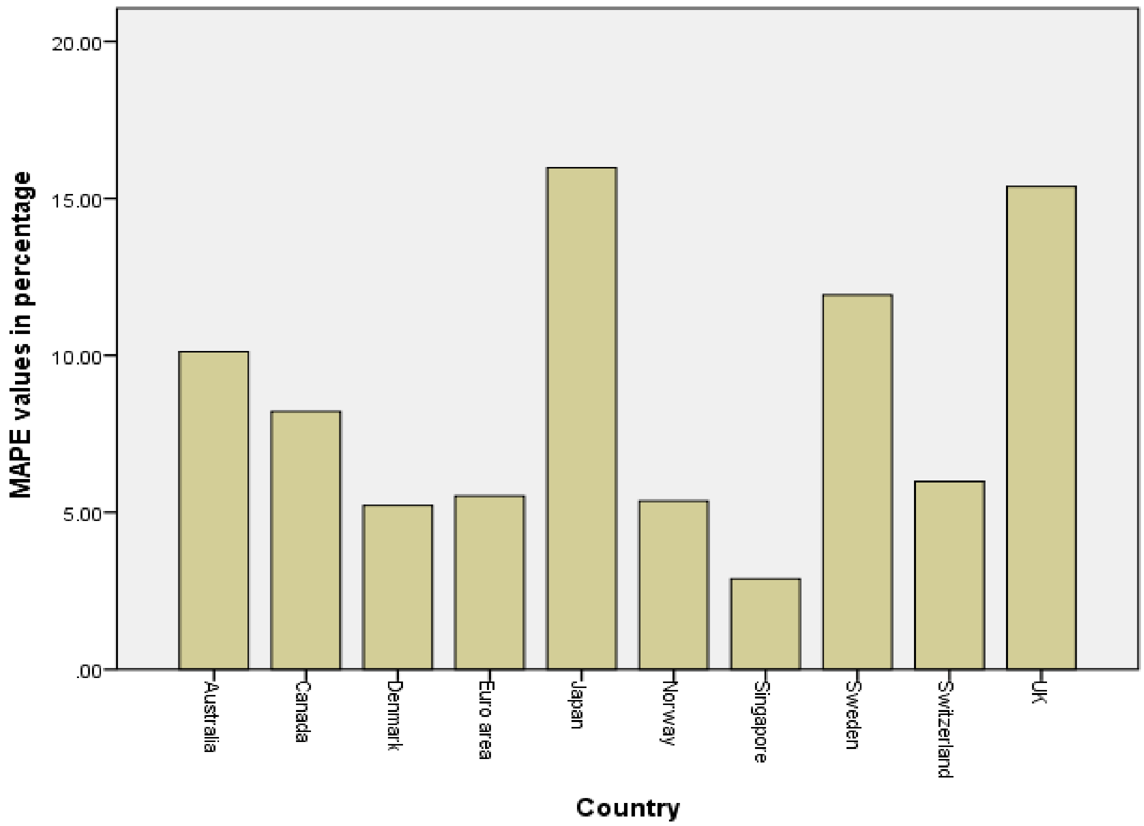


Figure 5.4: Plot of the direction of errors against the date: Canada

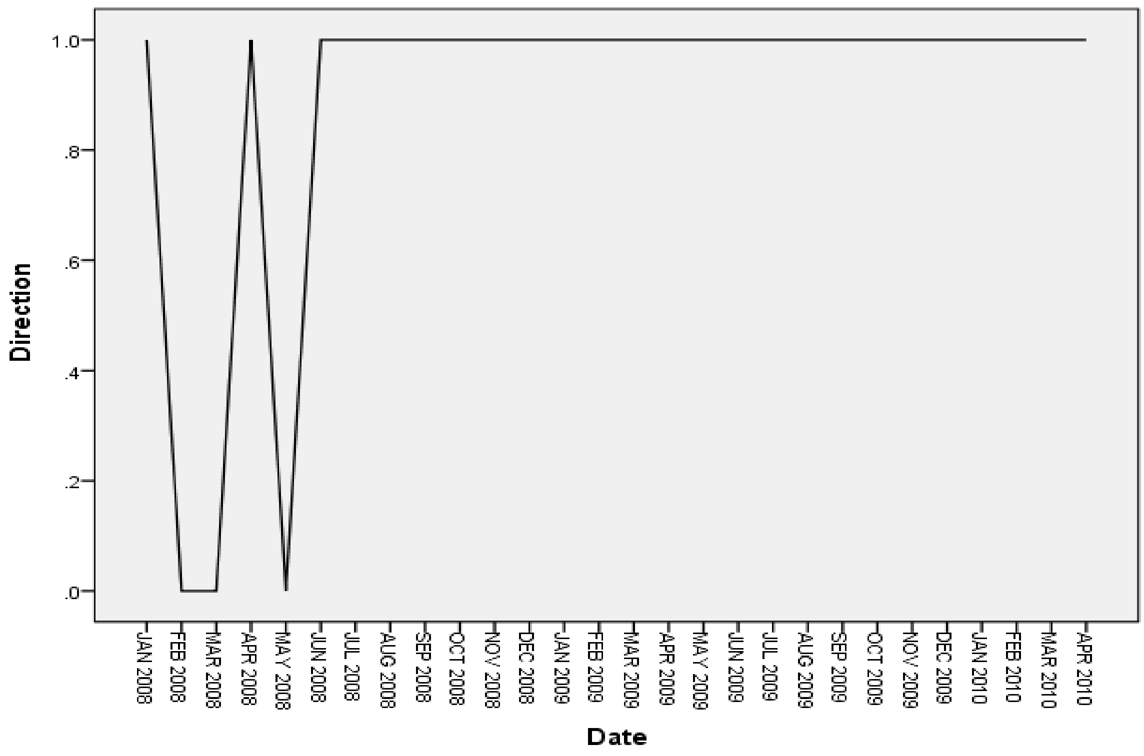


Figure 5.5: Plot of the direction of errors against the date: Japan

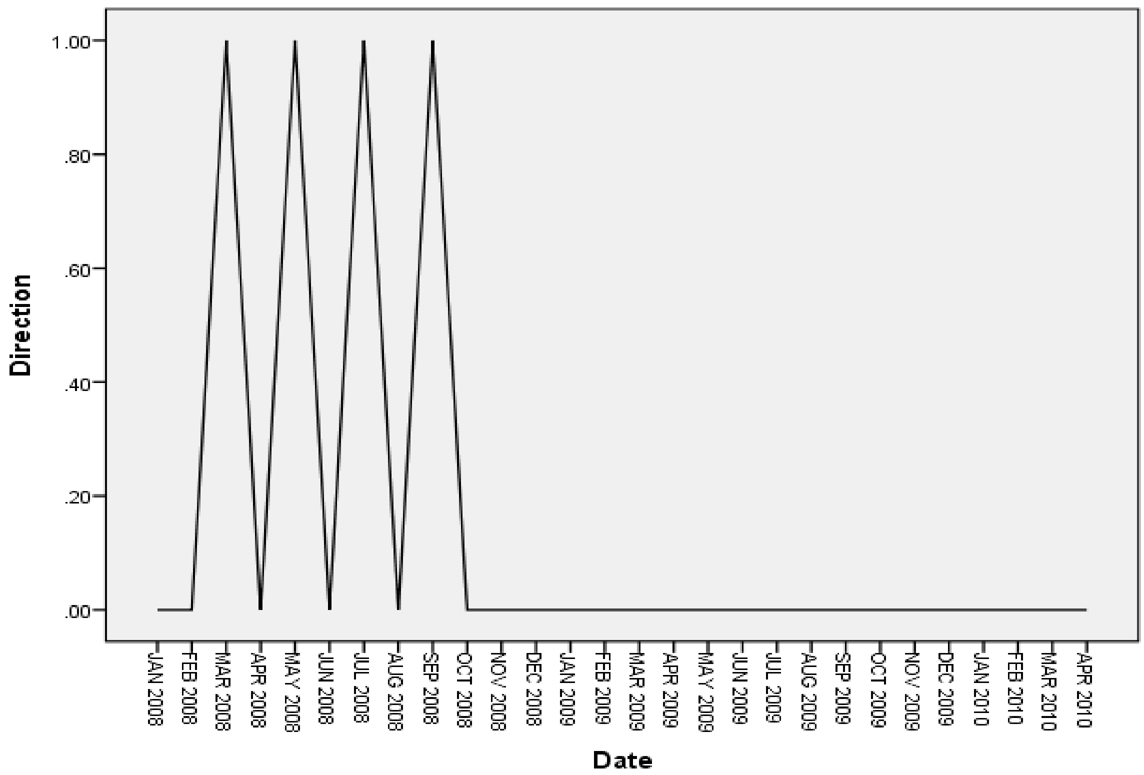
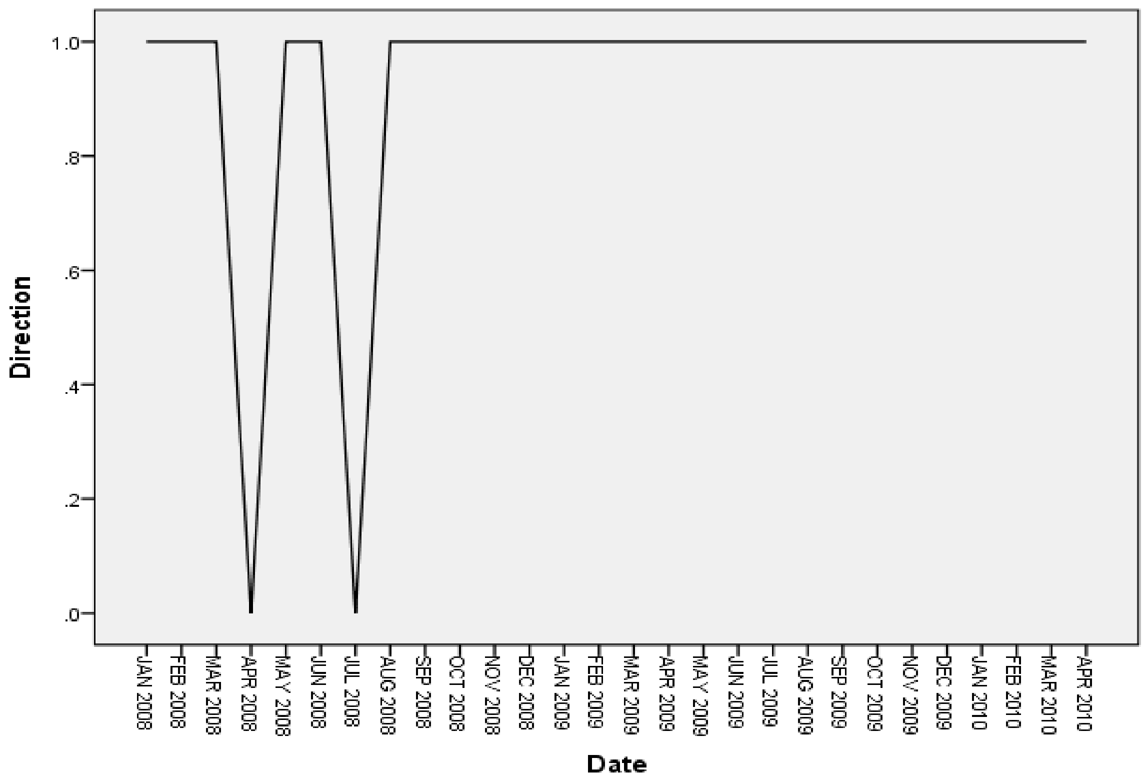


Figure 5.6: Plot of the direction of errors against the date: UK



5.2.2 Emerging Markets

The optimal models for 19 emerging national currencies against the U.S. dollar are reported in Appendix 23. The empirical results suggest that no single forecasting method is able to outperform all others in all situations. For example, as noted in Appendix 23.1, the single volatility model outperforms in 8 of 19 cases. This confirms that single volatility model has an important role in forecasting exchange rates of emerging countries' against the U.S. dollar, which is, however, the opposite of the result when compared with advanced countries, where the cointegration model generates minimum MAPE. This is expected, as emerging markets are more volatile than advanced markets (Wilcox, 1992). Volatility models, therefore, fit the emerging markets exchange rates series well. Results also show that the Naïve 1 model outperforms in the cases of Brazil, Malaysia, Peru, Philippines and Taiwan. Exponential smoothing model fits the data set of Czech Republic, Indonesia, Mexico, Poland and South Korea, whereas cointegration model generate better forecast in Turkey. An important observation is that the level of performance achieved by the individual forecasting models varies across the 19 emerging markets. As it was noted earlier that Naïve 1, cointegration and exponential smoothing model outperform in many cases of the sample countries. It is thus believed that combining the forecasts generated by these individual methods may be a favourable option.

The MAPE values for all single time series models are less than 10% except for the series involving Hungary, India, Mexico, Philippines, Polan, Russia, South Africa, South Korea and Turkey. The MAPE values obtained from the single cointegration model exceed 10% in all cases except Malaysia and Thailand. However, the MAPE values generated from the combination models via equal weights produce better MAPE values (less than 10%) in 13 of these 19 cases. Moreover, the var-cov approach of combination models improved the MAPE values in 14 of these 19 cases. Figure 5.7 shows that the MAPE values amongst the 26 individual forecasting models. It is evident from Figure 5.7 that the MAPE values are more or less similar in the cases of Brazil, Malaysia, Philippines and South Korea whereas, considerable variations are observed in the cases of Brazil, Chile, China, Colombia, Czech Republic, Hungary, India, Indonesia, Mexico, Peru, Russia, South Africa, Taiwan, Thailand and Turkey. It is also observed that the MAPE of the single cointegration model is considerably higher than other forecasting models in the cases of Chile, China, Colombia, Czech Republic, Peru, Poland, Russia, South Korea, Taiwan, Thailand and Turkey.

Figure 5.7: Bar charts of the MAPE values obtained across the emerging countries' exchange rate series for the 26 forecasting models

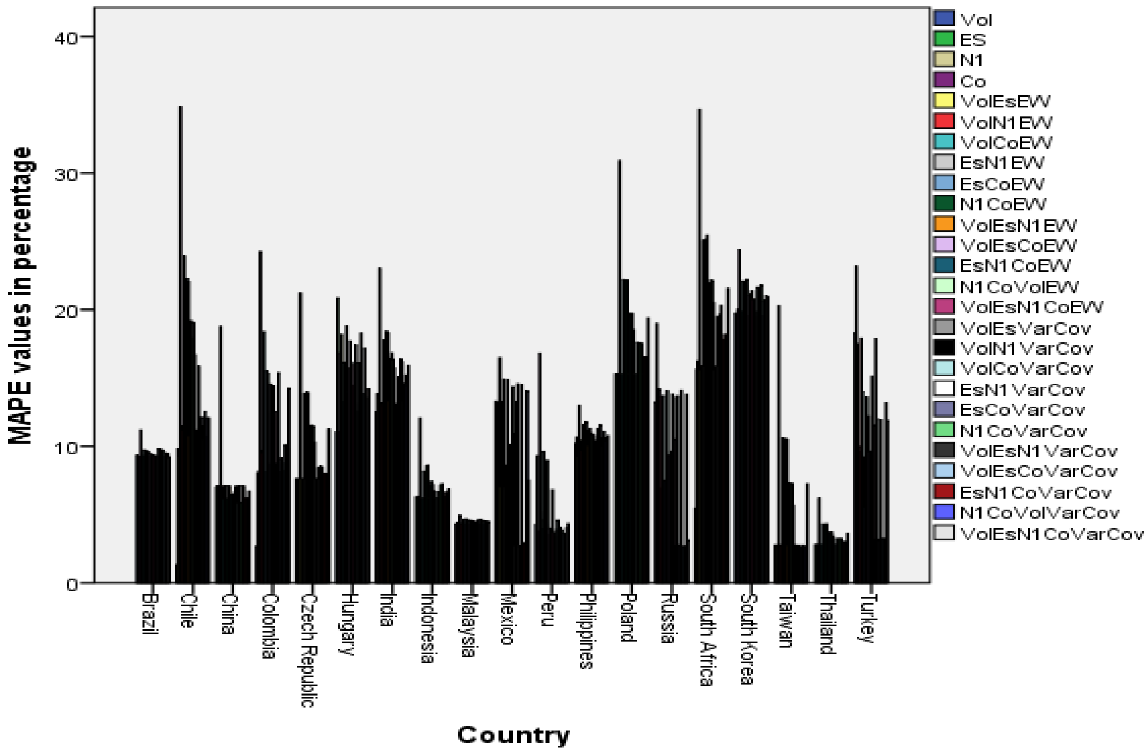


Figure 5.8 presents a graphical depiction of the performance of each forecasting method on the emerging countries' exchange rate series. This figure shows the distribution of the MAPE measures is summarised in boxplots for each of the 26 forecasting methods included in the analysis. The dotted horizontal line in Figure 5.8 represents the 10% limit "highly accurate forecasting" suggested by Lewis (1982). It is evident from Figure 5.8 that the single volatility forecasting method is the most accurate method in terms of the MAPE measures for forecasting horizon, resulting in the lowest median, upper and lower quartiles for distribution of errors amongst the 26 methods investigated. Combination models via var-cov method are found to have consistently lower medians when compare with equal weight method in the sample. Furthermore, the single cointegration model is the least accurate method in terms of the MAPE measure for forecasting horizon, resulting in the highest median, upper and lower quartiles for the distribution of errors amongst the methods investigated. An important observation is that high median and quartiles of the cointegration method are reduced by significant level when it is combined with other time series forecasting models.

Figure 5.8: Boxplots of the MAPE values obtained from the 26 forecasting models: Emerging countries

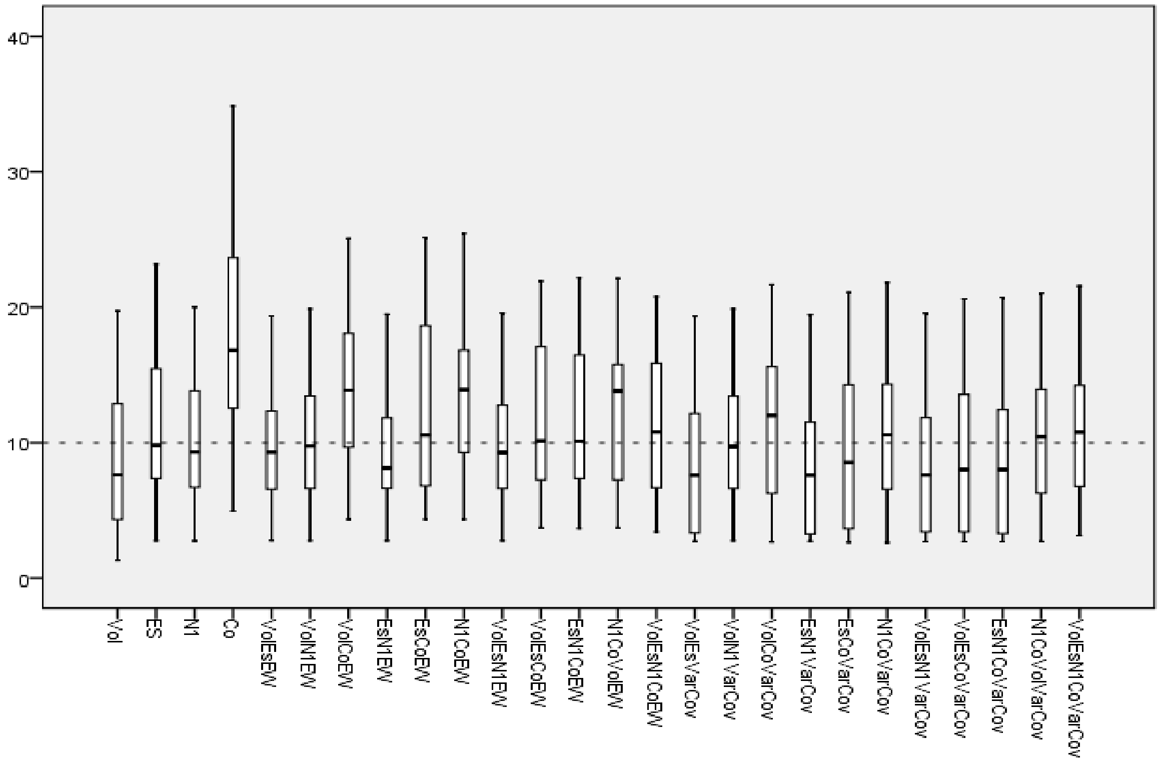


Table 5.3 reports the optimal models for all emerging countries. Initially the optimal model was selected based on the lowest MAPE. The single volatility model has lowest MAPE for 9 of these 19 cases, while a combination model has lowest error in 10 of these 19 cases. The exponential smoothing model produce better forecasts in the cases of Czech Republic, South Korea and Malaysia and Philippines, whereas Naïve 1 fits the series of Malaysia and Philippines. However, these results changes dramatically after conducting the Wald test as presented in the fourth column of the Table 5.3. As was mentioned in Section 5.1.1 the test of forecast unbiasedness is just as important as a low MAPE value. Therefore, the models with the lowest MAPE are eliminated if they fail the Wald test because they are biased. This shows that single volatility models satisfy the test of unbiasedness in 1 of these 19 cases. A combination model via var-cov approach satisfies the unbiasedness test in all cases except Chile, Hungary and Thailand. It is worthwhile mentioning that the optimal models for Brazil, Hungary, Mexico, Peru, Poland, Russia, Thailand and Turkey remained unchanged after the unbiasedness test. However, the optimal model and corresponding MAPE values changed in the cases of Chile (10.742%), Colombia (8.213%), Czech Republic (7.594%), Indonesia (6.193%), Malaysia (4.328%), South Africa (15.540%) and South Korea (19.342%).

Table 5.3: The derivation of an optimal model for emerging countries

Country	**Optimal Model (according to MAPE)**	**MAPE**	**Optimal Model (after Wald test)**	**MAPE**	**Optimal Model (after Runs test)**	**MAPE**
Brazil	Vol-ES-N1-Co (var-cov)	9.196	Vol-ES-N1-Co (var-cov)	9.196		
Chile	Vol	1.310	Vol-ES-N1 (equal weights)	10.742		
China	Vol-Co (var-cov)	5.844	All competing models are biased		All competing models are biased	
Colombia	Vol	2.708	Vol-ES-N1 (var-cov)	8.213		
Czech Republic	ES	7.577	Vol-ES (var-cov)	7.594		
Hungary	Vol	11.034	Vol	11.034		
India	Vol	12.513			Vol	12.513
Indonesia	Vol-ES-N1 (var-cov)	6.159	Vol-ES (var-cov)	6.193		
Malaysia	N1	4.273	Vol-ES-N1 (var-cov)	4.328		
Mexico	ES-Co (var-cov)	2.653	ES-Co (var-cov)	2.653		
Peru	ES-N1-Co (var-cov)	3.357	ES-N1-Co (var-cov)	3.357		
Philippines	N1	9.312			Vol	10.218
Poland	ES-N1 (var-cov)	15.255	ES-N1 (var-cov)	15.255		
Russia	Vol-ES-N1 (var-cov)	2.674	Vol-ES-N1 (var-cov)	2.674		
South Africa	Vol	5.463	Vol-ES (var-cov)	15.540		
South Korea	ES	18.964	Vol-ES (var-cov)	19.342		
Taiwan	N1-Co (var-cov)	2.626	Vol-ES (var-cov)	2.759		
Thailand	Vol-ES (equal weights)	2.779	Vol-ES (equal weights)	2.779		
Turkey	ES-Co (var-cov)	3.123	ES-Co (var-cov)	3.123		

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.

There is dramatic increase in MAPE values in the cases of Chile, Colombia, Czech Republic, Indonesia, Malaysia, South Africa, South Korea and Taiwan after conducting the unbiasedness test. All of the competing models were biased in the cases of China, India and Philippines after Wald test. The single volatility model was found to be optimal in the cases of India and Philippines after checking the randomness of the error via runs test. However, the hypothesis of randomness of error is rejected for all competing models for China, so they are biased in the case of Chinese yuan/U.S. dollar. The reason might be that Chinese yuan was stable against the U.S. dollar for over 10 years on the level around 8.30. Since 2007, an appreciation of the yuan against the U.S. dollar has been evidenced. The rate was equal to 6.80 at the end of 2010. The huge reserve of the U.S. dollar in China makes it possible to peg Chinese yuan against the U.S. dollar at almost an unchanged level (Osinska, 2010).

The optimal models for all 19 emerging countries are reported in the Table 5.4. In contrast with the findings of advanced countries, the volatility model has much more significant role usually in combination with other models such as exponential smoothing. Conversely, the cointegration model has less significant role to play in the determination of exchange rates of emerging countries against the U.S. dollar. These results demonstrate that the volatility and exponential smoothing models are significant contributors (both single and combined) in 15 and 15 of these 19 cases respectively. Moreover, the single volatility generated better forecasts in 3 of total 19 cases. This confirms that time series models have a significant role in forecasting exchange rates of emerging countries against the U.S. dollar, which is, however, just the opposite result when compared with advanced countries.

It is also clear that the var-cov approach of combination methods is superior in 14 of these 19 cases; an equal weights combination model is optimal only in the cases of Chile and Thailand. However, the single volatility model generates the minimum MAPE in the cases of Hungary, India and Philippines, while the single exponential model and Naïve 1 model generated better forecasts in none of the cases. It is worthwhile mentioning here that none of the single models generated better forecasts in the advanced countries. These results differ from the findings of Hu and Tsoukalas (1999), who reported that single EGARCH volatility model is the superior for out-of-sample forecasting of 11 European currencies against German Mark. However, the findings of this present study are consistent with those of Lam *et al.* (2008), Altavilla and Gruwe (2010) and Anastasakis and Mort (2009), who

Table 5.4: Optimal model for emerging countries

Country	**Optimal Model***	**MAPE**	**Wald Test F statistics****	**Runs Test (Significance)*****
Brazil	Vol-ES-N1-Co (var-cov)	9.196	1.629 (0.127)	
Chile	Vol-ES-N1 (equal weights)	10.742	2.278 (0.128)	
China	Vol- Co (var-cov)	5.844	All competing models are biased	All competing models are biased
Colombia	Vol-ES-N1(var-cov)	8.213	0.820 (0.452)	
Czech Republic	Vol-ES (var-cov)	7.594	0.242 (0.787)	
Hungary	Vol	11.034	1.086 (0.354)	
India	Vol	12.513		0.096
Indonesia	Vol-ES (var-cov)	6.193	1.666 (0.396)	
Malaysia	Vol-ES-N1 (var-cov)	4.328	2.014 (0.318)	
Mexico	ES-Co (var-cov)	2.653	2.434 (0.107)	
Peru	ES-N1-Co (var-cov)	3.357	1.229 (0.309)	
Philippines	Vol	10.218		0.096
Poland	ES-N1 (var-cov)	15.255	2.265 (0.124)	
Russia	Vol-ES-N1 (var-cov)	2.674	2.714 (0.085)	
South Africa	Vol-ES (var-cov)	15.540	2.274 (0.123)	
South Korea	Vol-ES(var-cov)	19.342	2.752 (0.131)	
Taiwan	Vol-ES (var-cov)	2.759	0.824 (0.450)	
Thailand	Vol-ES (equal weights)	2.779	0.452 (0.641)	
Turkey	ES-Co (var-cov)	3.123	2.434 (0.107)	

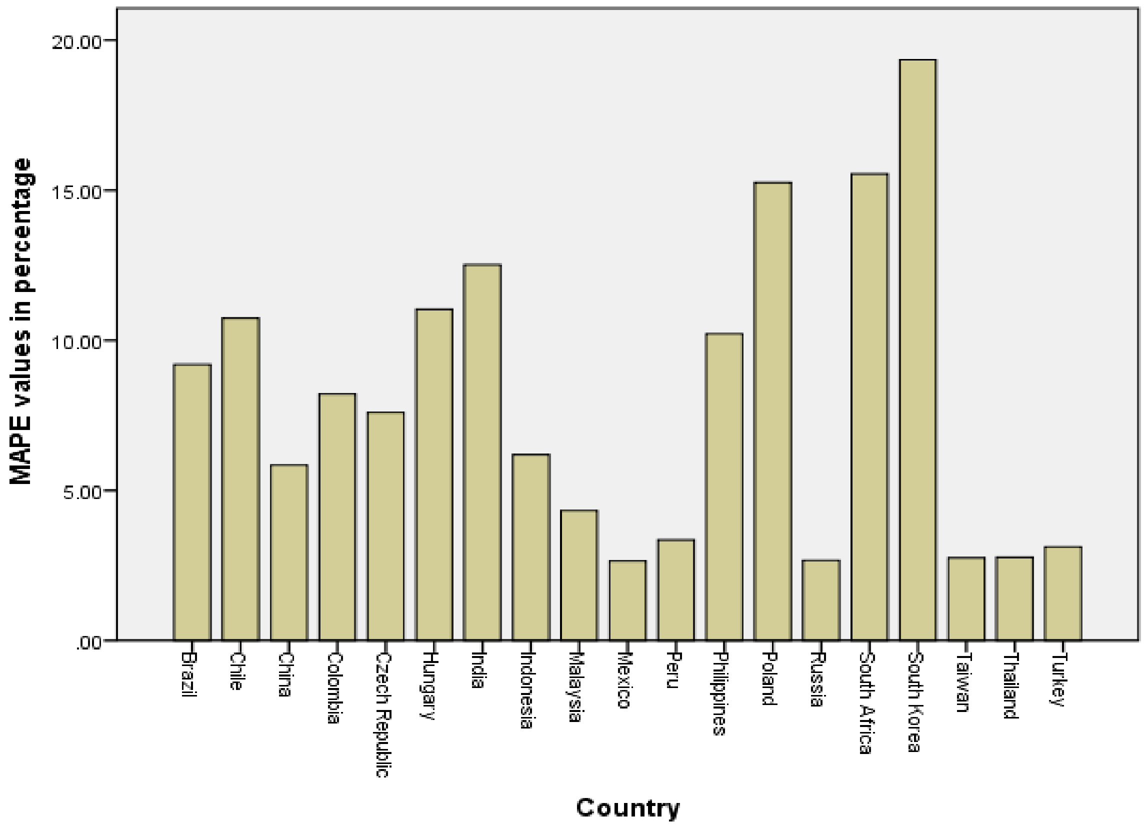
*Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
** F statistics's significance levels are reported in the round brackets.
*** Significance at the 0.05 level

found that the combined method produces promising results and outperforms individual methods in the case of advanced countries.

Nevertheless, in the emerging countries group, the results show that the single volatility model produces unbiased forecasts in 3 of these 19 cases. As in the case of emerging countries, only one four-way combination model claimed the overall minimum MAPE value for Brazil-USA exchange rate series. Volatility models are involved in 15 of these 19 minimum error combination models, exponential smoothing models are involved 15 of these 19 cases and cointegration via ARDL model contributes only in 5 of these 19 cases. This supports the fact that this class of models possesses utility in the context of exchange rate determination, but their main utility is when combined with other modelling techniques. The Naïve 1 model is often regarded as benchmark model for exchange rate determination. The results suggest that Naïve 1 model appears in only 7 of these 19 minimum error combination models. However, these findings reinforce that the Naïve 1 model has little role to play in forecasting exchange rates of emerging market currencies against the U.S. dollar, but like other models, it only has merit when combined with other forecasting techniques. The findings of this study show that the time series models (both single and combined) produce better forecast results in 14 of these 19 cases. The cointegration model with time series contributes for 5 of these 19 cases. The result of the emerging market is mixed as compare with advanced countries, where combination models generates better forecast for almost all the countries. The time series models (either single or combined) generate better forecasts for almost all the emerging countries except Brazil, Mexico and Turkey.

Figure 5.9 shows that the MAPE values obtained from the optimal model are less than 10% is all cases except Chile, Hungary, India, Poland, South Africa and South Korea. The results also show that excellent forecasts (MAPE < 5%) are generated for Malaysia, Mexico, Peru, Russia, Taiwan, Thailand and Turkey. Moreover, highly accurate forecasts (MAPE < 10%) are made for Brazil, Colombia, the Czech Republic, Indonesia, Malaysia, Mexico, Peru, Russia, Taiwan and South Turkey. The Wald test results confirm that the forecasts made by optimal models are unbiased for all countries except China, India and Philippines. The runs test verifies the randomness of the error associated with the optimal model for the cases of India and Philippines. In all cases, the hypothesis of random

Figure 5.9: Bar charts of the MAPE values obtained for the optimal forecasting model: Emerging countries



residuals is not rejected i.e. that the forecasts are unbiased. However, the result is the reverse in the case of China. All competing models are found to be biased.

A plot of the direction of error over time for India and Philippines is presented in Figures 5.10 and 5.11 respectively. These plots reveal error overestimates in the exchange rates for both countries from February 2008. An immediate response towards global financial crisis is evident in the cases of Indian rupee/U.S. dollar and Philippines peso/U.S. dollar rates. A similar response is apparent in Canada and UK’s exchange rates against U.S. dollar. However, the changes are much quicker for Indian and Philippines in comparison with Canada, UK and Japan. This suggests that the recent global financial crisis still has consistently strong effects in the exchange rate determination for Indian rupee/U.S. dollar and Philippines peso/U.S. dollar. However, no systematic or consistent patterns of the effects of recent financial crisis have been found for rest of the emerging countries.

Figure 5.10: Plot of the direction of errors against the date: India

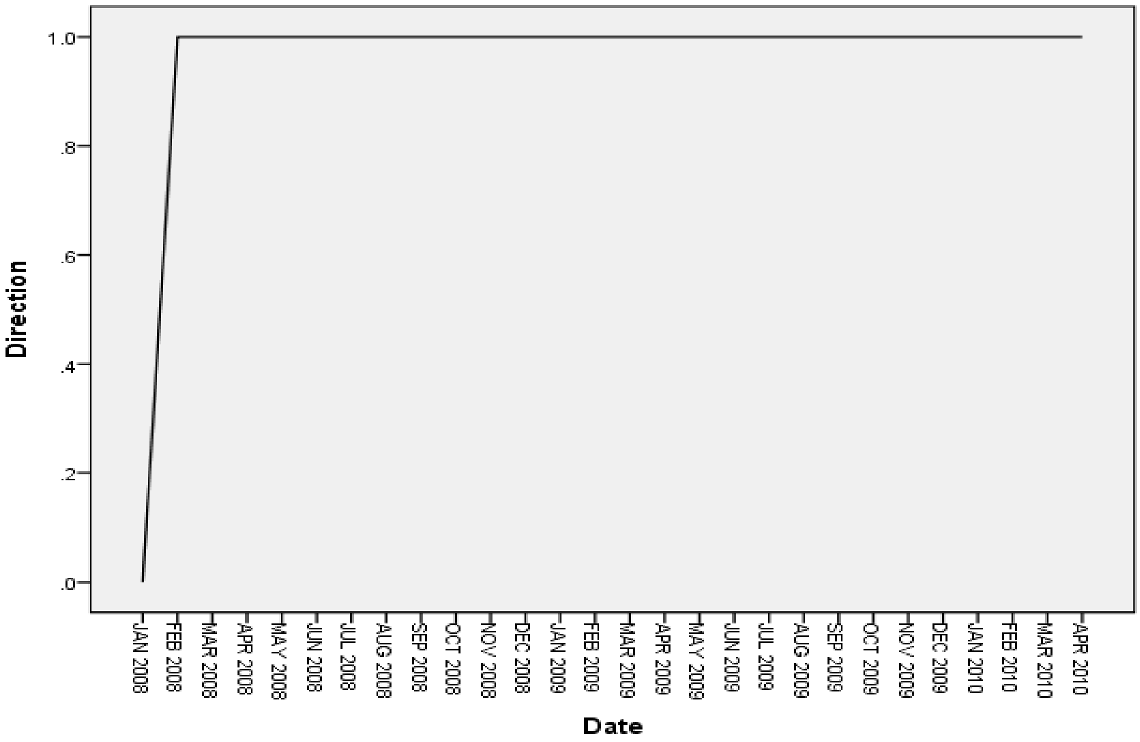
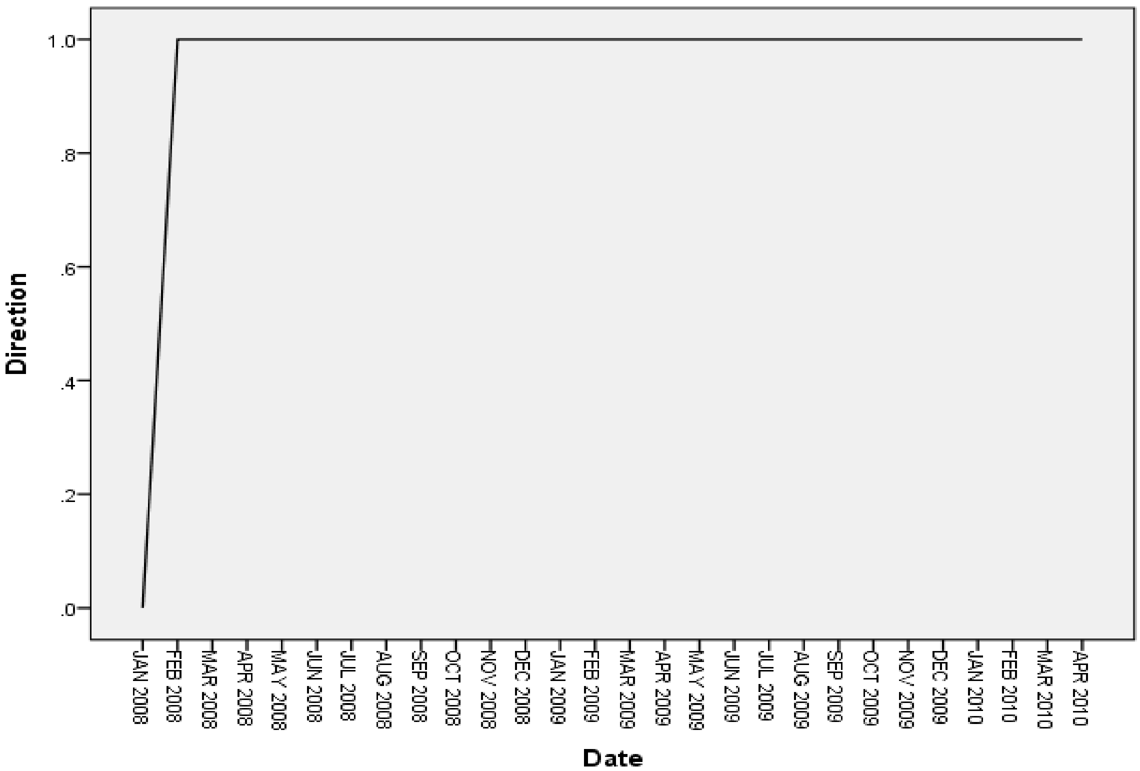


Figure 5.11: Plot of the direction of errors against the date: Philippines

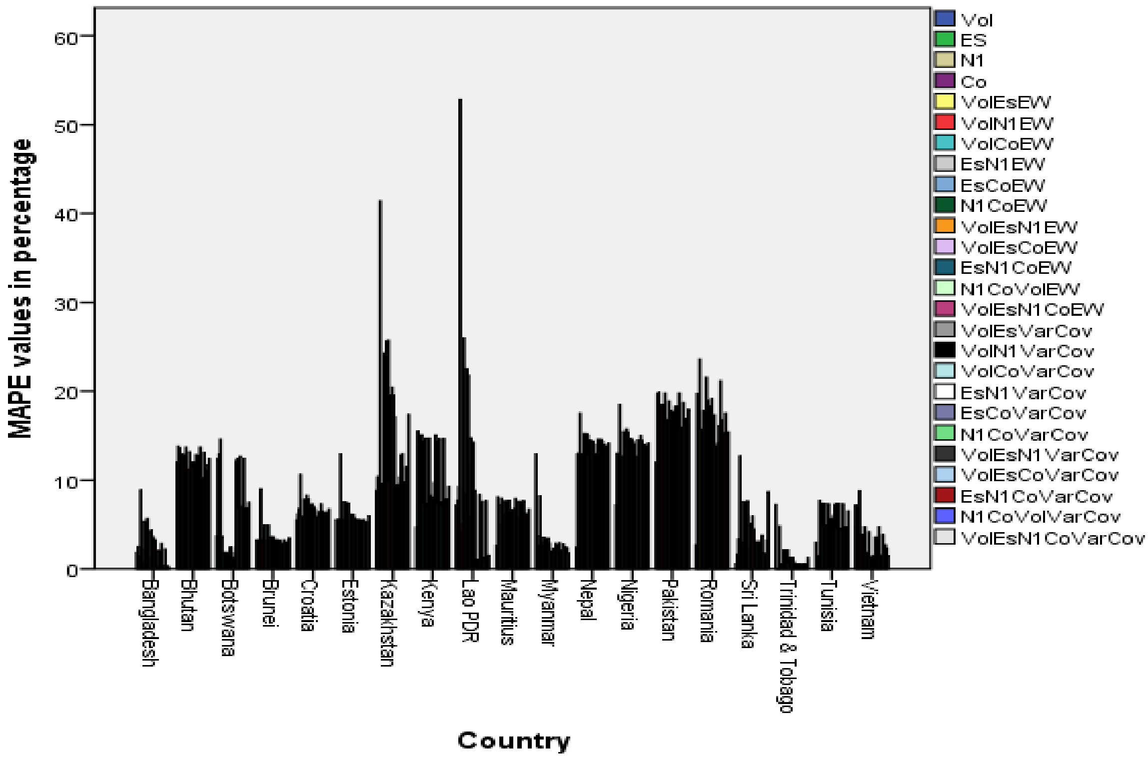


5.2.3 Frontier Markets

MAPE values of single and combination models for 20 Frontier markets currencies against the U.S. dollar are reported in Appendix 24. The empirical results suggest that no single forecasting method is able to outperform all others in all situations. For example, as noted in Appendix 24.1, the single volatility model outperforms in 13 of 20 cases. The single exponential smoothing model outperforms in 4 cases, whereas Naïve 1 model generate better forecast according to MAPE in 3 cases. The single cointegration model outperforms other model in Bhutan. This confirms that single volatility model has an important role in forecasting exchange rates of frontier countries' against the U.S. dollar, which is, however, just the opposite result when compared with advanced countries. Conversely, the results are parallel when compared with emerging countries. This is expected, like emerging markets, frontier markets are volatile than advanced markets. Volatility model, therefore, fits the frontier markets exchange rate series well. Furthermore, the findings show that the cointegration model plays considerably less significant role in the exchange rate determination of emerging and frontier countries possibly because of lack of power of the macroeconomic variables to forecast the exchange rates of these countries. An important observation is that the level of performance achieved by the individual forecasting models varies across the 20 frontier markets. As it was noted earlier that exponential smoothing, Naïve 1 and cointegration model outperform in many cases of the sample frontier countries. Combining the forecasts generated by these individual methods is thus a favourable option.

The MAPE values for all single time series models are less than 10% in all cases Bhutan, Botswana, Jamaica, Kazakhstan, Myanmar, Nepal, Pakistan and Romania. Nonetheless, the MAPE values obtained from cointegration models exceed the 10% limits in 12 of these 20 cases. On the other hand, the overall minimum MAPE values generated from the combination models via equal weights produced better MAPE (less than 10%) in 15 of these 20 cases. Likewise, var-cov approach of combination models generates better forecasts with low MAPE (less than 10%) in 16 of these 20 cases. Figure 5.12 presents the bar charts of the MAPE values amongst the 26 individual forecasting models. It is evident from Figure 5.12 that the MAPE values are more or less similar in the case of Bhutan whereas, considerable variations are observed in the cases of Bangladesh, Botswana, Brunei, Croatia, Estonia, Jamaica, Kazakhstan, Lao PDR, Mauritius, Myanmar, Nepal, Nigeria, Pakistan, Romania, Sri Lanka, Trinidad & Tobago, Tunisia and Vietnam. In the cases of Botswana, Estonia, Jamaica, Kazakhstan, Kenya, Lao PDR, Myanmar, Trinidad

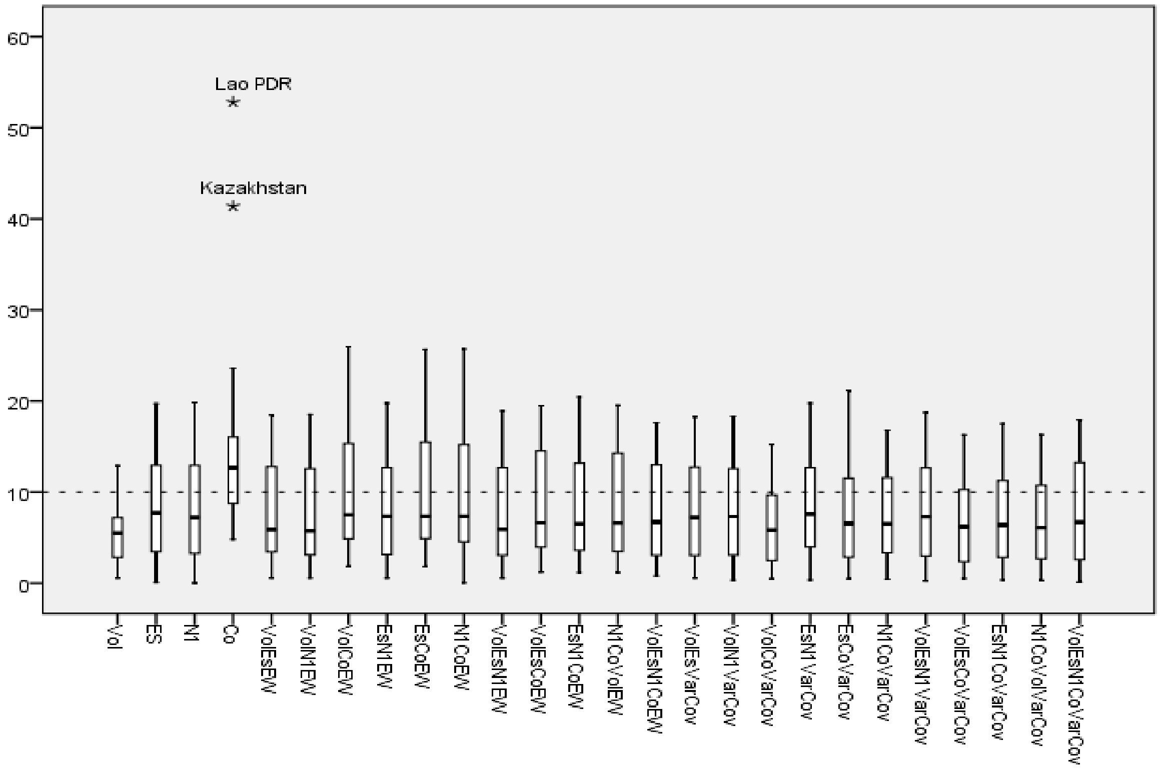
Figure 5.12: Bar charts of the MAPE values obtained across the frontier countries' exchange rate series for the 26 forecasting models



& Tobago for example, the MAPE of the cointegration model is considerably higher than other forecasting models. Jamaica was omitted from the graphs, to better facilitate the graphical comparison between the various forecasting models.

Figure 5.13 presents a graphical depiction of the performance of each forecasting method on the frontier countries' exchange rate series. This figure shows the distribution of the MAPE measures is summarised in boxplots for each of the 26 methods included in the analysis. Three frontier countries namely, Jamaica, Kazakhstan and Lao PDR show high MAPE values. Jamaica was omitted from the graphs, to better facilitate the graphical comparison between the various forecasting models. The dotted horizontal line in Figure 5.8 represents the 10% limit "highly accurate forecasting" suggested by Lewis (1982). It is evident from Figure 5.13 that the single volatility forecasting method is the most accurate method in terms of the MAPE measures for forecasting horizon, resulting in the lowest median, upper and lower quartiles for distribution of errors amongst the 26 methods investigated. Combination models are found to have consistently lower medians in the sample when compared with

Figure 5.13: Boxplots of the MAPE values obtained from the 26 forecasting models: Frontier countries



single exponential smoothing, Naïve 1 and cointegration model. Furthermore, the single cointegration model is the least accurate method in terms of the MAPE measure for forecasting horizon, resulting in the highest median, upper and lower quartiles for the distribution of errors amongst the methods investigated. An important observation is that high median and quartiles of the MAPE values of the cointegration method are reduced significantly when combined with other forecasting models.

Table 5.5 reports the optimal models for frontier countries. The results show that the single volatility model generates better forecasts than the other models in 9 of these 20 cases, while the exponential smoothing model produces better forecasts in the case of Jamaica. The Naïve 1 model produces the minimum error result in the cases of Trinidad and Tobago and Tunisia. Conversely, combination models generate minimum error in 7 of these 20 cases in respect of MAPE. However, the current findings are interpreted in a different way after conducting the Wald test. As was mentioned in Section 5.1.1 the test of forecast unbiasedness is just as important as a low MAPE value. Therefore, the models with the lowest MAPE are eliminated if they fail the Wald test because they are biased. The fourth

Table 5.5: The derivation of an optimal model for frontier countries

Country	**Optimal Model (according to MAPE)**	**MAPE**	**Optimal Model (after Wald test)**	**MAPE**	**Optimal Model (after Runs test)**	**MAPE**
Bangladesh	Vol-ES-N1-Co (var-cov)	0.117			Vol-ES-N1-Co (var-cov)	0.117
Bhutan*	Co	8.738			Vol-Co (var-cov)	9.921
Botswana	N1-Co (equal weights)	0.049	N1-Co (equal weights)	0.049		
Brunei*	ES-Co (var-cov)	2.898	ES-Co (var-cov)	2.898		
Croatia	Vol	5.507	Vol	5.507		
Estonia	ES-N1-Co (var-cov)	5.230	ES-N1-Co (var-cov)	5.230		
Jamaica	ES	0.177	Vol-Co (var-cov)	4.019		
Kazakhstan	Vol	8.799			Vol	8.799
Kenya	Vol	4.706	N1-Co-Vol (equal weights)	7.795		
Lao PDR*	Vol-Co (var-cov)	1.059	Vol-Co (var-cov)	1.059		
Mauritius	Vol	2.677	Vol-Co (var-cov)	5.847		
Myanmar*	Vol-ES-N1-Co (equal weights)	1.690	Vol-ES-N1-Co (equal weights)	1.690		
Nepal*	Vol	2.424	Vol	2.424		
Nigeria	Vol	7.193	Vol	7.193		
Pakistan	Vol	12.038			Vol	12.038
Romania	Vol	2.739	Vol	2.739		
Sri Lanka	Vol	0.575	Vol-ES (var-cov)	1.610		
Trinidad & Tobago	N1	0.011			Vol-ES-N1-Co (var-cov)	1.254
Tunisia	N1	0.921	N1-Co-Vol (var-cov)	4.738		
Vietnam	Vol-ES-Co (equal weights)	1.320	Vol-ES-Co (equal weights)	1.320		

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model. *Not listed as a frontier markets according to MSCI.

column of the Table 5.5 presents the results of Wald test. The results show that single time series models satisfied the test of unbiasedness in only 4 of these 20 cases.

A combination model via var-cov approach generates bias-free models in 7 of these 20 cases, while the combination model via equal weights produce better results in comparison with other models for the series of Botswana, Kenya, Myanmar and Vietnam. The results show that the optimal model for Botswana, Brunei, Croatia, Estonia, Lao PDR, Myanmar, Nepal, Nigeria, Romania and Vietnam remains unchanged after the unbiasedness test. However, the optimal model and corresponding MAPE values changed in the cases of Jamaica (4.019%), Kenya (7.795%), Mauritius (5.847%), Sri Lanka (1.610%) and Tunisia (4.738%). Dramatic increases of MAPE values are observed for Jamaica, Kenya, Mauritius, Sri Lanka and Tunisia after conducting the unbiasedness test. All the competing models exhibited bias in the forecasted exchange rate series of Bangladesh, Bhutan, Kazakhstan, Pakistan and Trinidad & Tobago. The four-way var-cov (Vol-ES-N1-Co) model is found optimal in the cases of Bangladesh, Myanmar and Trinidad & Tobago after checking the randomness of the error via runs test. The single volatility model was optimal for Croatia, Kazakhstan, Nepal, Nigeria, Pakistan and Romania.

The optimal models for all 20 frontier countries are reported in Table 5.6. As opposed to the findings of advanced and emerging countries, the single volatility model has a significant role to play in the exchange rate determination of frontier markets against the U.S. dollar. The single volatility model generates better forecasts in 30% of the cases. Moreover, combinations of volatility with other models generate better forecasts in 60% of cases. Additionally, volatility models (both single and combined) generate better forecasts in 17 out of 20 cases. The exponential smoothing model is the second best contributing model in this category. This model (both single and combined) contributes in 7 out of 20 cases. Conversely, the cointegration model generates an overall minimum MAPE values in 65% cases. This demonstrates that both time series and cointegration models have are adequate descriptors of exchange rate determination of frontier countries against the U.S. dollar.

It is also clear from the findings that the var-cov approach for combining methods generates minimum error in 10 of these 20 cases; an equal weights combination model produce minimum error for Botswana, Kenya, Myanmar and Vietnam. However, the single

Table 5.6: Optimal model for frontier countries

Country	**Optimal Model***	**MAPE**	**Wald Test F statistics****	**Runs Test (Significance)*****
Bangladesh	Vol-ES-N1-Co (var-cov)	0.117		0.379
Bhutan●	Vol-Co (var-cov)	9.921		0.096
Botswana	N1-Co (equal weights)	0.049	4.765 (0.173)	
Brunei●	ES-Co (var-cov)	2.898	0.451(0.640)	
Croatia	Vol	5.507	2.274(0.123)	
Estonia	ES-N1-Co (var-cov)	5.230	0.531 (0.594)	
Jamaica	Vol-Co(var-cov)	4.019	2.815 (0.078)	
Kazakhstan	Vol	8.799		0.096
Kenya	N1-Co-Vol (equal weights)	7.795	1.889(0.647)	
Lao PDR●	Vol-Co (var-cov)	1.059	1.160(0.796)	
Mauritius	Vol-Co (var-cov)	5.847	1.259(0.301)	
Myanmar●	Vol-ES-N1-Co (equal weights)	1.690	2.154 (0.136)	
Nepal●	Vol	2.424	1.527(0.175)	
Nigeria	Vol	7.193	1.664(0.328)	
Pakistan	Vol	12.038		1.000
Romania	Vol	2.739	2.180 (0.133)	
Sri Lanka	Vol- ES (var-cov)	1.610	0.146 (0.274)	
Trinidad & Tobago	Vol-ES-N1-Co (var-cov)	1.254		0.065
Tunisia	N1-Co-Vol (var-cov)	4.738	3.119 (0.061)	
Vietnam	Vol-ES-Co (equal weights)	1.320	1.129 (0.339)	

*Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
**F statistics's significance levels are reported in the round brackets.
*** Significance at the 0.05 level.
● Not listed as a frontier markets according to MSCI.

volatility model generates the minimum error in the cases of Croatia, Kazakhstan, Nepal, Nigeria, Pakistan and Romania. The single exponential smoothing and Naïve 1 model generate better forecast in none of the cases. The results also show that the volatility models are involved in 11 of these 20 minimum error combination models, exponential smoothing models are involved in 7 of these 20 cases and cointegration via ARDL model contributes only in 13 of these 20 cases. This supports the fact that this class of models possesses utility in the context of exchange rates determination in frontier market economies, but their main advantage is when combined with other modelling techniques. As it was mentioned earlier that the Naïve 1 model is often regarded as benchmark model for exchange rate determination. This model appears in 6 of these 20 minimum error combination models. However, the findings here reinforce that the "no change" model has little role to play in forecasting exchange rates of frontier markets currencies against the U.S. dollar, but like other models only, when combined with other forecasting techniques. The results also show that the time series models (both single and combined) produce better forecasts in 7 of these 20 cases. On the other hand, in 13 of these 20 cases, the combination made by times series with econometric models generates better results in forecasting exchange rates against the U.S. dollar. The results are similar like emerging countries.

Figure 5.14 shows that the MAPE values obtained from the optimal model is less than 10% in all cases except Pakistan. The results also show that the excellent forecasts (MAPE < 5%) are generated for Bangladesh, Botswana, Brunei, Jamaica, Lao PDR, Myanmar, Nepal, Romania, Sri Lanka, Trinidad & Tobago, Tunisia and Vietnam. Moreover, highly accurate forecasts (MAPE < 10%) are made for Croatia, Estonia, Kazakhstan, Kenya and Mauritius. The Wald test results confirm that the forecasts made by optimal model are unbiased (sig > 0.05) for all countries except Bangladesh, Bhutan, Kazakhstan, Pakistan and Trinidad & Tobago. The runs test verifies the randomness of the residuals associated with the optimal model for those countries. In all these cases, the hypothesis of random residuals is not rejected. This supports the findings of the Wald test that the forecasts are unbiased.

A plot of the direction of errors over time for Bangladesh, Bhutan, Kazakhstan, Pakistan and Trinidad & Tobago are presented in the Figures 5.15, 5.16, 5.17, 5.18 and 5.19 respectively. These plots reveal the error overestimates of the exchange rates for all these countries from the first quarter of 2008. An immediate response to the global financial crisis is noticed in all cases. Similar responses were found in Canada, UK, India and Philippines exchange rates against the U.S. dollar. However, the responses are much quicker for Bangladesh, Bhutan, Kazakhstan and Pakistan as compared with Trinidad &

Figure 5.14: Bar charts of the MAPE values obtained for the optimal forecasting model: Frontier countries

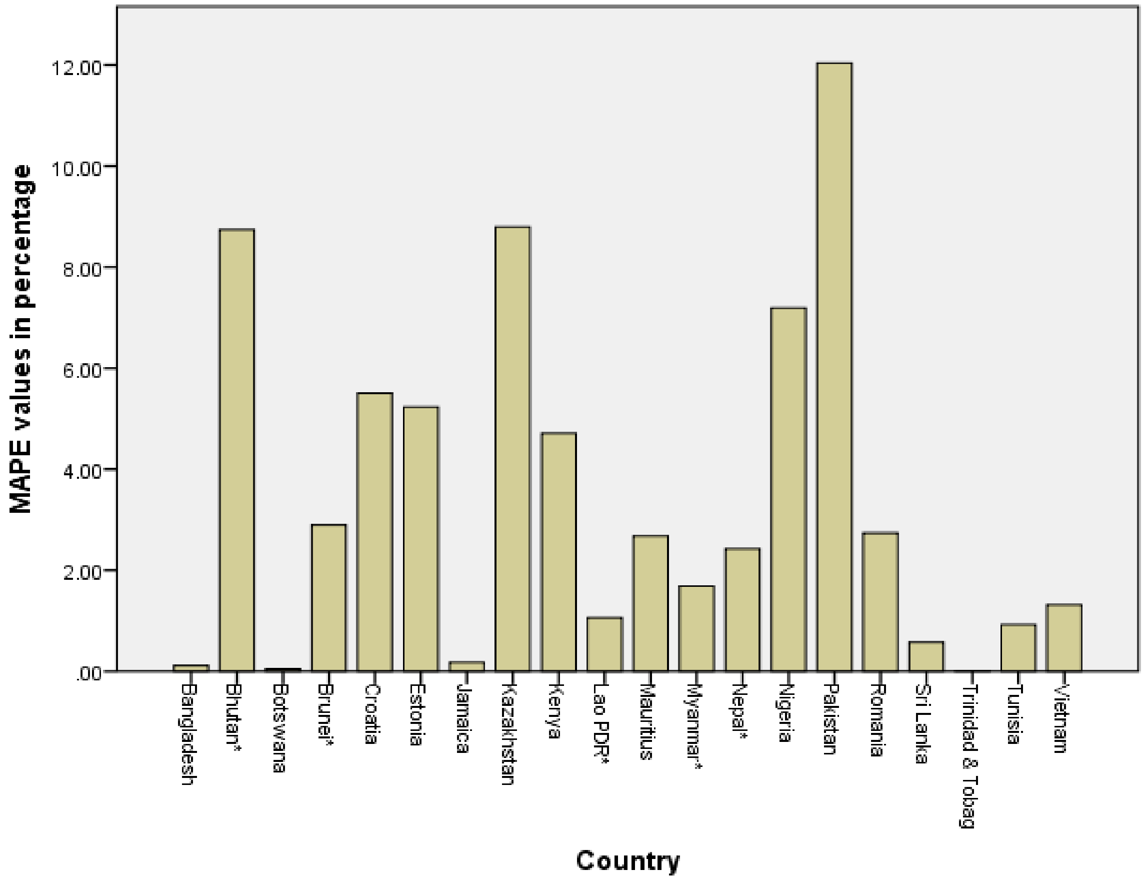


Figure 5.15: Plot of the direction of errors against the date: Bangladesh

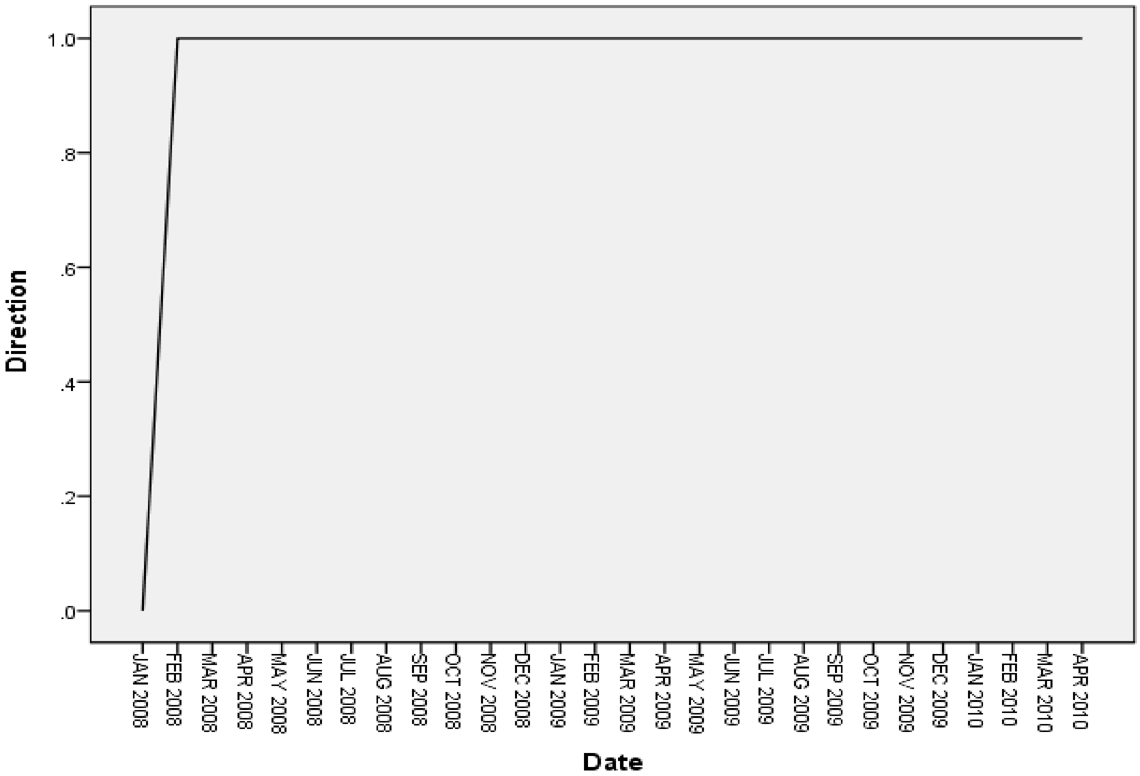


Figure 5.16: Plot of the direction of errors against the date: Bhutan

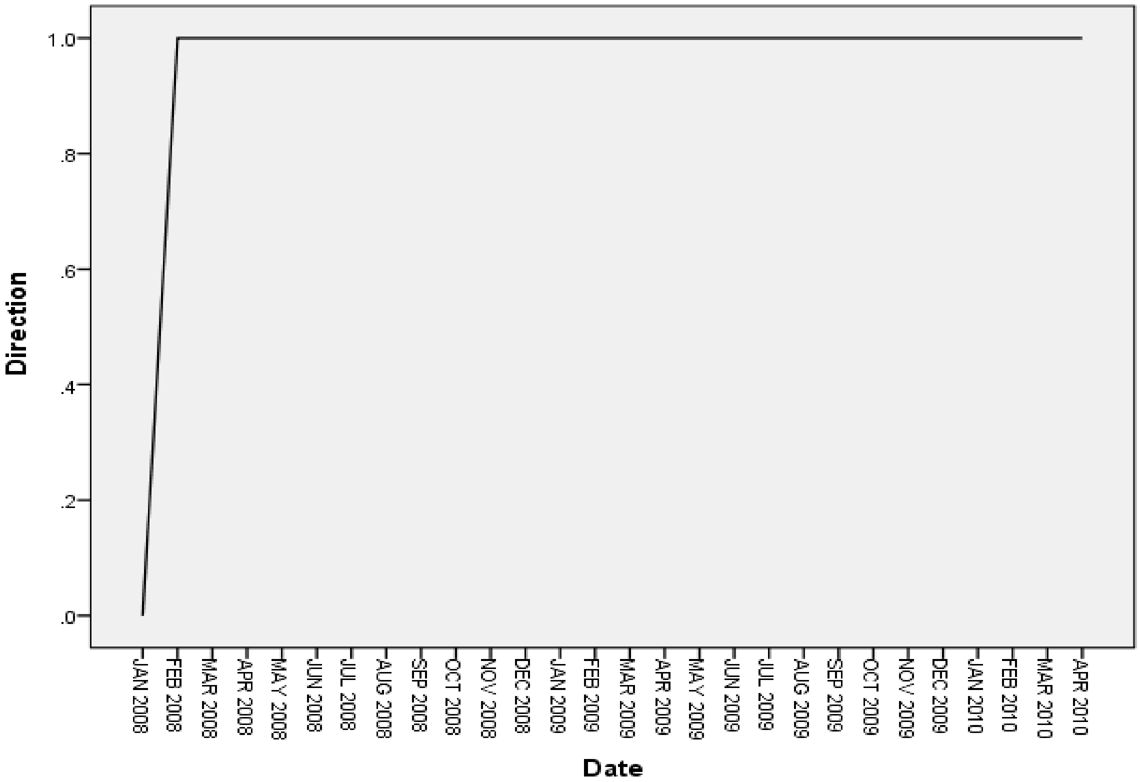


Figure 5.17: Plot of the direction of errors against the date: Kazakhstan

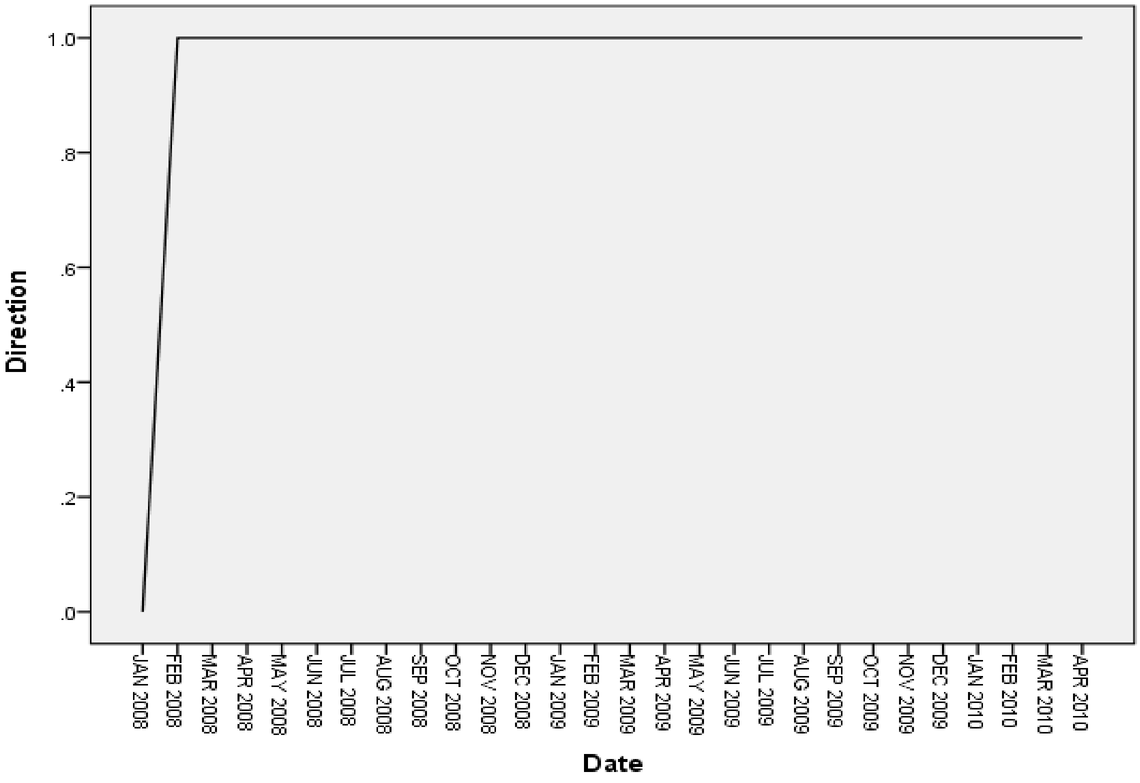


Figure 5.18: Plot of the direction of errors against the date: Pakistan

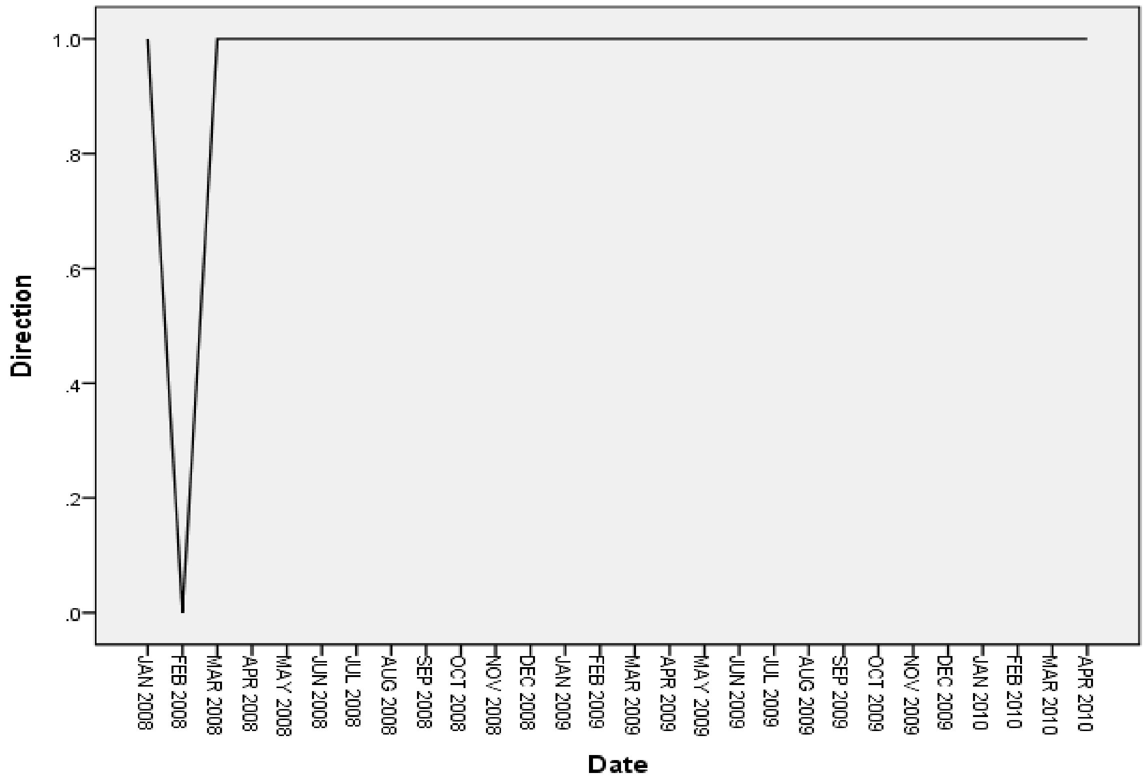
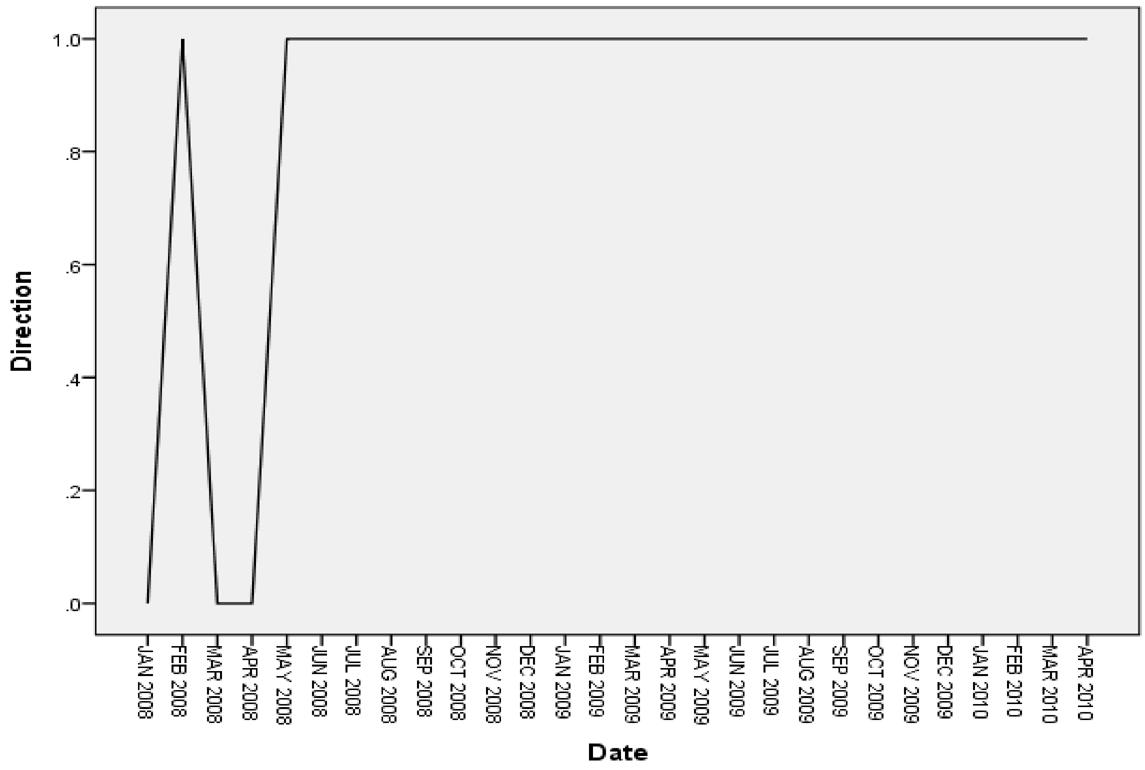


Figure 5.19: Plot of the direction of errors against the date: Trinidad & Tobago



Tobago. The plots also show that the consistently strong effects of recent global financial crisis still exists in the exchange rates determination for Bangladesh, Bhutan, Kazakhstan, Pakistan and Trinidad & Tobago. Nevertheless, no systematic or consistent pattern of the effects of recent financial crisis has been found for rest of the other frontier countries.

5.3 Summary and Policy Implications

Summary results for all advanced, emerging and frontier countries are presented in Table 5.7. The results are different for the various market economies studied. The major findings of this chapter suggest that the volatility model has a much more significant predictive role usually when combined with another model such as exponential smoothing in the exchange rate determination of emerging and frontier markets. This result is expected as individual emerging markets are relatively highly volatile when compared with the advanced markets (Harvey, 1995 and Errunza, 1997). It is also evident that the exponential smoothing model plays significant role in the determination of exchange rates of emerging and frontier markets. Furthermore, the findings show that the cointegration model plays a major role in the exchange rate determination of advanced currencies. However, this model plays considerably less significant role in the exchange rate determination of emerging and frontier countries against the U.S. dollar possibly because of the lack of power of the macroeconomic variables to forecast the exchange rates of these countries.

Both time series and cointegration models play important roles in the exchange rate determination of advanced countries. This may be expected because advanced countries are less economically vulnerable when compared to emerging and frontier countries. Moreover, they are the key controllers of the exchange markets. However, time series models (both single and combined) play important roles in forecasting exchange rates of emerging and frontier markets. These findings have not been appeared in the literature before as the focus tends to be on advanced markets. The empirical results suggest that no single forecasting method is able to outperform all others in all situations. For example, as noted in Table 5.7, no single time series or cointegration model claims the overall minimum optimal MAPE model in advanced countries' exchange rates series. In contrast, the single time series generates minimum error in 9 emerging and frontier markets exchange rate series against the U.S. dollar. The single cointegration model produces better

Table 5.7: Summary results

Models	**Advanced Countries**	**Emerging Countries**	**Frontier Countries**
Single models			
Vol		Hungary India Philippines	Croatia Kazakhstan Nepal Nigeria Pakistan Romania
ES			
N1			
Co			
Combination models-Equal weights			
Vol-ES			
Vol-N1			
Vol-Co			
ES-N1			
ES-Co			
N1-Co			Botswana
Vol-ES-N1		Chile	
Vol-ES-Co			Vietnam
ES-N1-Co			
N1-Co-Vol			Kenya
Vol-ES-N1-Co			Myanmar
Combination models-Var-cov			
Vol-ES		Czech Republic Indonesia South Africa South Korea Taiwan Thailand	Sri Lanka
Vol-N1			
Vol-Co		China	Bhutan Jamaica Lao PDR Mauritius
ES-N1	Euro area	Poland	
ES-Co	Denmark UK	Mexico Turkey	Brunei
N1-Co	Norway		
Vol-ES-N1	Japan	Colombia Malaysia Russia	
Vol-ES-Co	Canada Singapore Sweden Switzerland		
ES-N1-Co		Peru	Estonia
N1-Co-Vol	Australia		Tunisia
Vol-ES-N1-Co		Brazil	Bangladesh Trinidad &Tobago

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co -cointegration via ARDL model forecasts for none of the cases. It is thus believed that combining the forecasts generated by these individual methods is a favourable option.

The results also show the dominance of the combination methods especially the var-cov approach over the single forecasting models for most of the countries studies. In terms of the 49 exchange rates series, the var-cov method generates the minimum MAPE model in 34 cases while the equal weights combination model is optimal only in 5 cases: Chile, Botswana, Vietnam, Kenya and Myanmar. Thus this class of models possesses utility in the context of forecasting exchange rates, but its main advantage is when forecasts are combined. The findings of this study suggest the likely utility of combination methods over single time series and the econometric model when forecasting exchange rates. In the small amount of Finance literature on combination method, different combination techniques are used, but the findings of this study offer some support for the fact that combination models generate better results. This is consistent with the studies conducted by Altavilla and Grauwe (2010), Anastasakis and Mort (2009) and Lam *et al*. (2008).

Figure 5.20 presents a graphical depiction of the performance of each forecasting method on the advanced, emerging and frontier countries’ exchange rate series. This figure shows the distribution of the MAPE measures is summarised in 26 boxplots. Four countries namely: Lao PDR, Kazakhstan, Chile and South Africa show high MAPE for single cointegration model. Japan and Jamaica are omitted from the graphs, to better facilitate the graphical comparison between the various forecasting methods. It can be concluded that the single cointegration model is the less accurate forecasting model when compared with other time series models for frontier markets exchange rates against the U.S. dollar. This is because of the lack of power of the macroeconomic variables of these countries to forecast the exchange rates against the U.S. dollar. It is evident from Figure 5.20 that the volatility forecasting method is the most accurate method in terms of the MAPE measures for forecasting horizon, resulting in the lowest median, upper and lower quartiles for distribution of errors amongst the 26 methods investigated, while Vol-ES-Co (var-cov) forecasting method is the second best method in the sample. Furthermore, the cointegration with the highest MAPE values is found the least accurate forecasting method for these exchange rate series. However, cointegration model generates better forecasts when it is combined with other forecasting models.

Figure 5.20: Boxplots of the MAPE measures obtained across the 49 exchange rate series for the 26 forecasting models

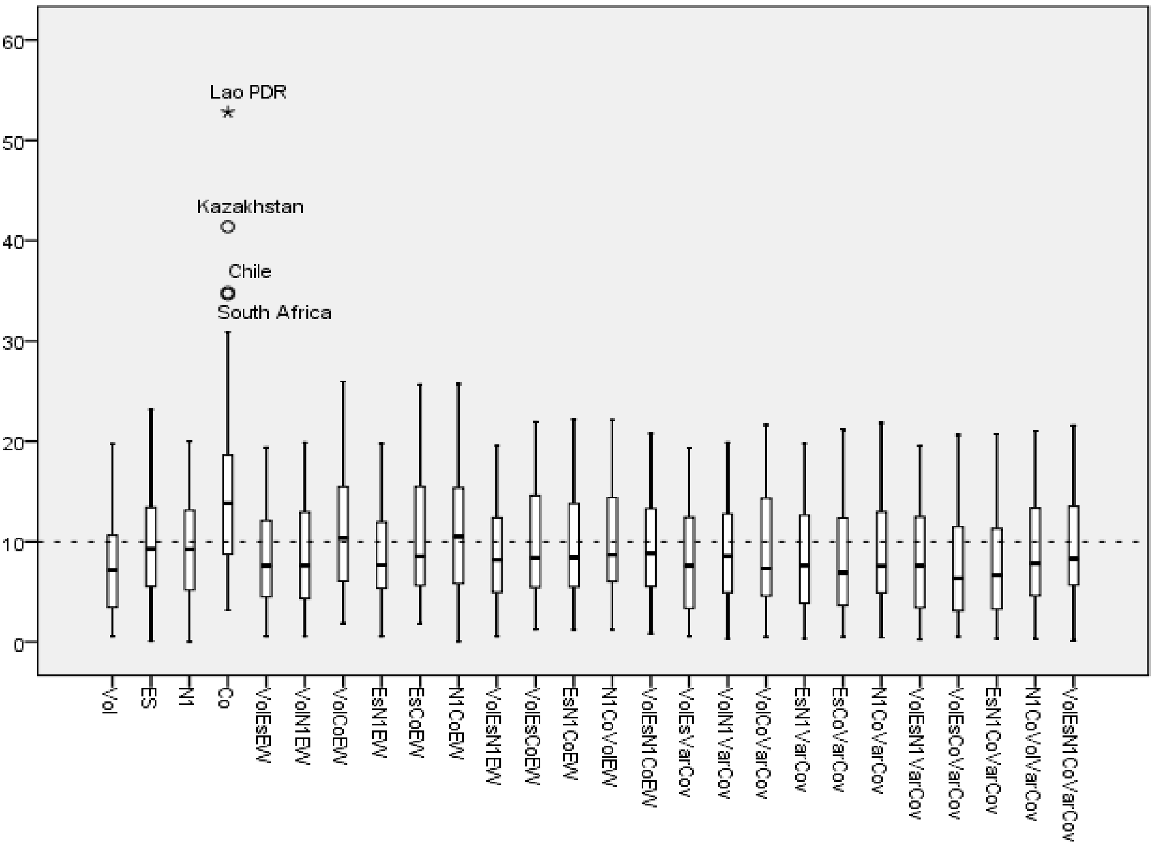
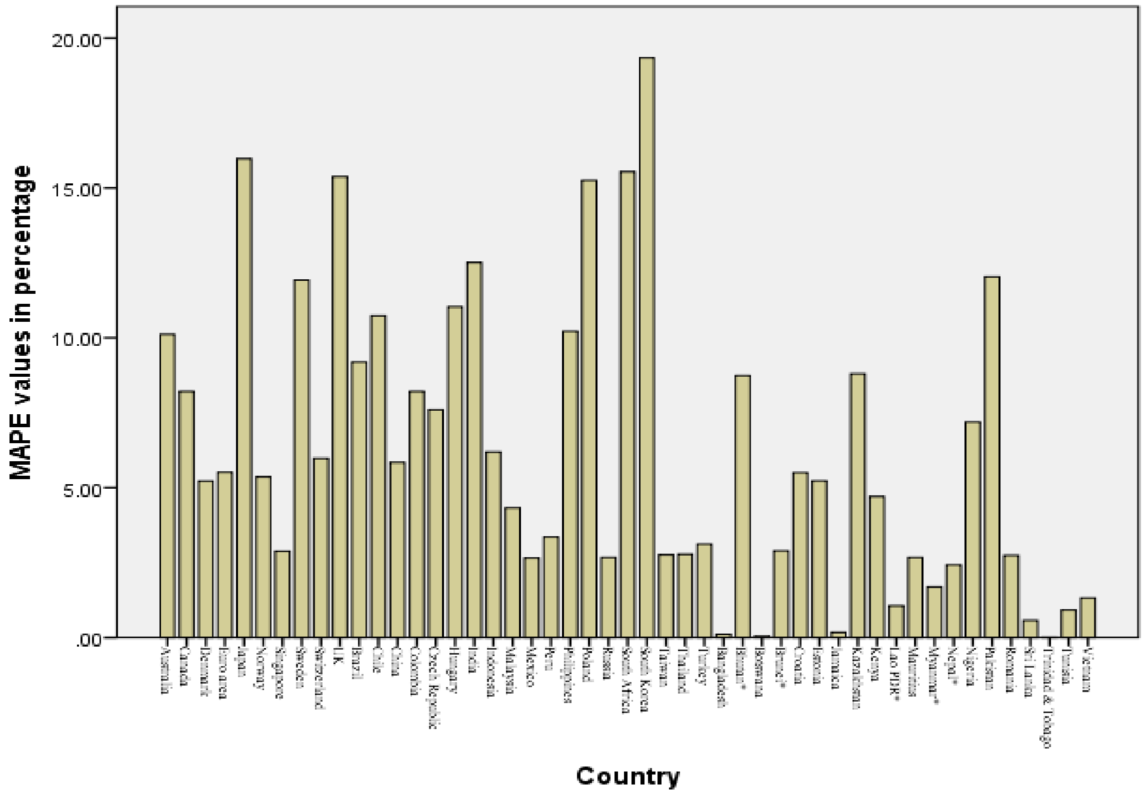


Figure 5.21 presents a graphical depiction of the MAPE values obtained from the optimal model for all sample exchange rate series. It is evident from Figure 5.21 that the MAPE values are found to be less than 10% in 37 of these 49 cases and it is higher than 10% in remainder. The empirical results show that the volatility models contribute to the model involving minimum MAPE on 38 occasions. The exponential smoothing, Naïve 1 and cointegration models appear respectively in 30, 18 and 26 times. An unbiased optimal model is found in 39 of these 49 cases. However, the optimal models are biased in 10 cases: Canada, Japan, UK, India, Philippines, Bangladesh, Bhutan, Kazkhstan, Pakistan and Trinidad & Tobago. It might be arguable that this percentage reduction in MAPE is not worth the effort. It is particularly important for the foreign exchange markets because even reduction in MAPE by relatively small to select the optimal model make huge difference when dealers are using millions or billions of money for their transactions.

Figure 5.21: Bar charts of the MAPE values obtained for the optimal forecasting model for all countries



To summarise, the single time series models generate better forecasts in 9 cases (18.35%), the combination between time series models yield better results in 14 cases (28.58%) and the combination of time series and econometric models takes the lead in 26 (53.07%) of these 49 cases. The findings of this study reinforce that volatility, exponential smoothing, Naïve 1 and cointegration models have a significant role to play in forecasting exchange rates when combined with other predictive techniques. It is worthwhile mentioning here that the frequency with which cointegration models appeared in optimal combination forecast in frontier markets (e.g. Bangladesh, Bhutan, Botswana, Brunei, Estonia, Jamaica, Kenya, Lao PDR, Mauritius, Myanmar, Trinidad & Tobago, Tunisia and Vietnam) is surprisingly unrelated to this relatively low level of economic development. The reason might be the lack of power of the macroeconomic variables to forecast the exchange rates of these countries against the U.S. dollar. It has been difficult to find significant macroeconomic variables for the cointegration analysis for emerging and frontier markets. This might be why cointegration analysis of exchange rates series of emerging (save for the BRICS countries) and frontier markets does not exist in the empirical literature.

The present study expands on the few studies that used combination models by applying an assessment of unbiasedness (Wald test), in conjunction with runs test in the context of exchange rate determination. The runs test results show that there is an immediate reaction to the global financial crisis in the cases of Canada, UK, India, Philippines, Bangladesh, Bhutan, Kazakhstan, Pakistan and Trinidad & Tobago. However, lagged effects are shown in Japanese yen/U.S. dollar rate. During the crisis, Asian currencies have been depreciating sharply against the U.S. dollar as a result of the sell-off of local currencies accompanying the capital outflows. The only exception is the Japanese yen, which has appreciated substantially against the U.S. dollar as investors both in Japan and abroad unwind their yen-carry trades and repay their yen loans. The findings of this study show that global financial crisis still has consistent effects in the exchange rate determination for those countries. Conversely, no systematic or consistent patterns of the effects of financial crisis have been found for the rest of sample countries. This is a new finding and never been reported in the literature before.

Focusing on the forecasting accuracy among various forecasting models applied in advanced, emerging and frontier countries is one contribution of this study. The dynamics of exchange rate movements appear in different forms when considering group of advanced countries, emerging and frontier countries and they have different implications for policy makers and foreign exchange markets and individual agents in each of these groups. The key question of this study was whether the best possible combination models have better predictive performance than the best possible individual forecasts. Moreover, the models that are used successfully for forecasting exchange rates for advanced countries do not perform particularly well in emerging and frontier countries. Nevertheless, focusing on the predictive accuracy among various exchange rate models applied to advanced, emerging and frontier countries is considered to be one of the major contributions of this study. An extensive examination of the combination approach was performed and it was revealed that, the var-cov method of combination models performs extremely well in all advanced countries' exchange rate against U.S. dollar.

Mixed results are found in the cases of emerging and frontier countries. The combination model fits the data well in two-thirds of the sample emerging and frontier countries. However, single time series model perform extremely well for the rest of the emerging and frontier countries (see table 5.7). The results of this study provide a strong claim for using forecast combination techniques as an alternative to applying a single model. The findings also lead us to think that combination-based approach has a bright future in applications to the more unstable advanced currencies and fast expanding emerging markets and frontier countries. This perspective is particularly revealing, if we keep in mind that it is in those emerging and frontier markets that will generate most of the growth opportunities of the coming decades. It is obvious that the process of combination, which is applied in this study, is tedious. However, this process can be automated via the design of macros in Excel if the number of models becomes large.

These results are important for the policy makers. Without a subjective opinion about the best models to apply forecasting problems, it may be useful to rely on combined forecasts which have a higher probability of being best model in advanced and some emerging and frontier countries. These results can also be used as inputs into business planning models - such as Capital assets pricing model (CAPM), Arbitrage pricing theory (APT), portfolio optimisation and risk management. The CAPM only requires one variable additional to stock return; namely market return, defined as the principal index in the country over the most traded stocks. The findings of the previous studies (Korsgaard, 2009; Hartmann and Pierdzioch, 2006) suggested that stock returns are to a certain degree sensitive to exchange rate fluctuations. The APT's beta coefficient reflects the sensitivity of the underlying assets to various economic factors such as currency exchange rates, interest rates, oil prices, etc. Therefore, the forecasting models suggested in this chapter can help the companies to price their individual or portfolio returns reasonably accurate way. It is widely believed that exchange rate fluctuations have significant implications for financial decision-making and for firm profitability. Firms that export to foreign markets may be benefited from a depreciation of the local currency because its products become more affordable to the foreign consumers. Conversely, firms that rely on import may face their profit shrink as a consequence of increasing cost of production. Moreover, the returns of the firm are also affected by changes in the exchange rate. Therefore, forecasts made by the optimal model-proposed in this study, will help the management of the company and the investors to take some preventive actions to minimise their risk of competitiveness, which occurs due to the fluctuations in exchange rates.

On the evidence of the data examined in this study, combination methods generate considerably better forecasts of exchange rates and can serve as a judgment-free benchmark forecast to compare with the policymaker's projections. Due to fast and intensive money flow from advanced countries into emerging and frontier countries, it is a new challenge for policy makers and various other agents to forecast exchange rates for those countries. Moreover, to minimise risk, multinational organisations are obliged to hedge their assets by future contracts and many other financial instruments. This requires forecasting currencies exchange rates of not only the trading partner countries but also of the other global currencies. Therefore, forecasts made by the combination methods will not only help policy makers to face the new challenges in an effective way, but also it will assist the multinational companies to mitigate their international transaction's risk.

The findings of this present study could also facilitate the central bank to formulate the policy. It is important for the central bank to obtain internal forecasts to evaluate whether an exchange rate will fluctuate within a target zone. It could reduce the risks of fluctuations if forecasts are made via combination techniques. Moreover, more accurate forecasts made by combination techniques can also be used as a part of the decision as to which exchange rate regime would be best for a country in question (Hernandez and Montiel, 2001) and also monetary union is optimal for that country (Wyplosz, 2002). These findings also generate some useful information for the individual agents, including foreign exchange and stock brokerage societies, investment banks, financing and investment societies, stock brokers, international investors and portfolio managers. Additionally, the accurate forecasts of exchange rate will guide the business planning models such as capital budgeting, resource allocation and policy monitoring. Therefore, the results of this study will not only enrich the exchange rate literature on combination forecasting but they also offer material information to the practitioners for making decisions. As a result, combination forecasting is recommended to be used more frequently in practice.

Chapter 6

Summary, Conclusions and Policy Implications

The purpose of this research was to investigate the application of different forecasting methods to the prediction of the exchange rates of advanced, emerging and frontier market economies. Research on forecasting exchange rates to date has tended to focus mostly on advanced economies. Very little attention has been given on emerging and frontier market currencies (Abdalla, 2012; Kamal *et al.*, 2012; Hall *et al.*, 2010; Molana and Osei-Assibey, 2010 and Osinska, 2010). Therefore, a prime focus of this study was on exchange rate forecasts of advanced, emerging and frontier markets currencies against the U.S. dollar in order to answer a major research need. Furthermore, a majority of studies has concentrated on bilateral exchange rates between advanced countries rather than exchange rates of emerging versus advanced countries and frontier versus advanced countries. This study contributes to the existing literature by assessing the utility of forecasting techniques in these different contexts.

Chapter 3 demonstrated the application of time series models in forecasting exchange rates. The purpose of that chapter was to compare the performance of individual time series models (volatility, exponential smoothing and Naïve 1) in the prediction of exchange rates. The results presented in this chapter confirmed previous findings to the effect that volatility models generate superior forecasts in advanced, emerging and frontier markets exchange rate series. A basic yet major aim of this study was to check whether volatility is present in the sampled countries of this study. The results reveal that all sample exchange rate series are volatile. One concludes that the volatility concept has distinct relevance in the context of currency exchange rates. This chapter also investigated whether the traditional univariate volatility models, used widely and successfully in the literature in relation to advanced countries, could perform equally well in emerging and frontier countries.

The widely applied GARCH (1,1) volatility model is superior in only five advanced market cases – Canada, Denmark, Japan, Singapore and UK, four emerging market- Czech Republic, South Africa, Taiwan and Thailand and four Frontier markets cases –Brunei, Croatia, Kenya and Tunisia. This classical volatility model is also found to be inferior when compared with other volatility models in majority of the cases of emerging and frontier market exchange rate series. It is interesting to note that the EGARCH model is superior in 50% of the advanced market cases both for in-sample estimation and out-of-sample forecast evaluation. This finding parallels result found for the emerging and frontier market exchange rate series where EGARCH models are optimal and generate superior forecasts in 79% and 80% respectively. These results support the findings of Hsieh (1989), Hu and Tsoukalas (1999), Balaban (2004), Edrington and Guan (2005), Alberg *et al.*, (2006) and Abadalla (2012), who report that the EGARCH volatility models generate better forecasts than other volatility models in the context of exchange rate modelling. Hence, this study supports the existing literature concerning the superiority of the EGARCH model for modelling advanced, emerging and frontier market exchange rate series.

Another interesting aspect of the results of this chapter was the application of PARCH model in exchange rate series. As was mentioned earlier, PARCH models are rarely applied in exchange rate literature. The results of this study show that the PGARCH volatility models are statistically inferior to other types of volatility models in all the exchange rate series. Although this result contradicts the findings of Tse and Tsui (1997), who reported the asymmetric PGARCH model is found to be superior to alternative models for daily Malaysian/U.S exchange rates series. However, the findings of this present study supports the results of McKenzie and Mitchell (2002), who reported that PARCH models are better applied to stock market data better than to exchange rate data. Therefore, the current findings add to a growing body of literature on the application of PARCH volatility models in exchange rate series.

Asymmetric (leverage) effects in some exchange rate series are found. The phenomenon of no asymmetric effects in exchange rates series is empirically supported by Bollerslev *et al.* (1992), Kisinbay (2003) and Balaban (2004). However, the current study found asymmetry effects in 8 out of 49 country cases. These countries are Australia, Japan, Hungary, Indonesia, Malaysia, Philippines, Turkey, Estonia and Jamaica. This indicates that the negative macroeconomic news pertaining to the USA and local announcements or the central bank's intervention in these countries have significantly greater impacts on their corresponding exchange rates with U.S. dollar. This finding supports those of Longmore and Robinson (2004), Edrington and Guan (2005), Sandoval (2006), Kim (2008), Laakkonen and Lanne (2008), Olowe (2009) and Abdalla (2012), who noted the leverage effects in exchange rate series. The present study provides additional evidence on leverage effects of advanced currencies exchange rates. This study also reports the new evidence of leverage effects in some of the emerging and frontier markets exchange rate against the U.S. dollar.

Relative to applications in other disciplines, the exponential smoothing model has received less attention as a forecasting model. This presented an opportunity for assessing the utility of this model in a financial context of exchange rates. The analyses showed that this model has the potential to generate superior forecasts in some instances. Exponential smoothing models are optimal for 25% of the exchange rates. A variety of exponential smoothing models was applied to generate the optimal model for each series. Surprisingly enough, the damped trend exponential smoothing model is found to be superior in 80% of exchange rate series. This result supports the argument of McKenzie and Gardner (2010), who noted that the damped trend exponential smoothing has performed well in numerous empirical studies and is now well established as an accurate forecasting method. These findings are also in line with some recent studies, e.g. Borhan and Hussain (2011), Li (2010), Yu *et al.* (2007) and Dheeriyaa and Raj (2000), who reported that the exponential smoothing model generate good forecasts of exchange rates. Overall, the exponential smoothing and Naïve 1 models are found to be the second and third best forecasting models respectively when compared with volatility models. All of the results related to emerging and frontier markets are considered as new findings, which contribute significantly to the literature on exchange rate behaviour.

Chapter 4 compared the forecasting performance of time series and an econometric ARDL model. A major objective of this chapter was to investigate the long-and short-run relationships of exchange rates in respect of macroeconomic fundamentals. The ARDL model has become very popular in the Economics and Finance disciplines. However, very few applications have been conducted in the field of nominal exchange rate modelling and their speed to return to equilibrium. By applying the ARDL-cointegration model, this study fills the major gap of exchange rate literature. The results of the associated cointegration analyses vary accordingly the various market economies studied, even though some are at same level of development and have similar structural features, for example, BRICS, ASEAN, SAARC, N-11 (Next-11) etc. The major findings of this chapter suggested that macroeconomic variables such as interest rates, inflation rates, money supply, trade balance, trade openness, GDP, oil prices and gold prices have important long- and short-run role in the determination of exchange rates of advanced, emerging and frontier markets against the U.S. dollar. This work parallels the findings of the major papers concerning developed countries in terms of variables were used. However, this study has emphasised the role of trade openness in exchange rate determination despite its being a highly significant factor in exchange rate modelling.

Trade openness has a depreciative effect in the cases of Australia, Denmark, Norway, UK and South Africa. This finding indicates that after adopting the floating exchange rate system, a relaxation of the extent of impediments to the international trade resulted in exchange rate depreciation. Edwards (1989) provided an excellent theoretical justification for this finding (discussed in Chapter 2). This analysis is consistent with the theoretical argument as well as with the results of numerous studies undertaken in the past in respect of different countries (Edwards, 1993; Elbadawi, 1994; Connolly and Devereux, 1995; Hau, 2002). On the other hand, an appreciation effect of trade openness on the exchange rate has noted in the cases of Brazil, Hungary, Peru and Turkey. Similar findings were noted by Li (2004), who showed that no-credible trade liberalisation could appreciate the exchange rate. Calvo and Drazen (1998) also found that the trade liberalisation of uncertain duration could lead to an upward jump in consumption. Therefore, a real appreciation will occur in the short-run. They argued that real exchange rates will depreciate only if trade liberalisation is of permanent nature, while a transitory reform could lead a real appreciation in the short run. It is worthwhile mentioning here that the effect of trade openness has been observed to be insignificant in all emerging and frontier countries except for the Brazilian real/U.S. dollar, Hungarian forint/U.S. dollar, Peruvian nuevo sol/U.S. dollar, South African rand/U.S. dollar and Turkish lira/U.S. dollar. This result, however, is consistent with the findings of Edwards (1987), who noted that effect of trade openness on exchange rate can be insignificant.

Oil prices and gold prices have significant impacts on the exchange rate determination. Long-run relationships between oil prices and exchange rates were observed in the cases of Japan, Sweden, Brunei and Trinidad & Tobago. This finding supports earlier studies such as Tsen (2010) and Huang and Guo (2007), who noted that oil prices have significant impacts on exchange rates. The gold price was found to have significant positive long-run relationship with the South African rand/U.S. dollar exchange rate. South Africa is one of the largest producers of gold in the world. Therefore, it is perhaps unsurprising to find the relationship between gold price and rand/dollar exchange rate.

Although research has not been conducted for many of the emerging and frontier markets examined here, it is possible to generalise the macroeconomic variables that impact on exchange rates in this context. These variables are interest rates, inflation rates, trade balances, money supply, GDP, trade openness, current account balance, oil prices and gold prices. These are in line with the existing exchange rate literature (e.g. Apergis *et al*. 2012; AbuDalu and Ahmed, 2012; Maitra and Mukhopadhyay, 2012; Verma, 2011; Abbas *et al*. 2011; Tsen, 2010; Verweij, 2008; Uddin, 2006; Obstfeld and Rogoff, 2005; Groen, 2000 and Kim and Mo, 1995). Note that other variables such as reserve assets and government expenditures are found to be insignificant in terms of long-run equilibrium. These variables do not impact upon the exchange rates in the long- and short-run for any of 49 currencies against the U.S. dollar during the sample period employed. This result contradicts the findings of Chowdhury (2012), who noted that government expenditure is an important variable for the real exchange rate determination of Australia. Moreover, Glăvan (2006) reported that foreign exchange reserve is a significant variable for exchange rate determination. In addition, country specific commodity prices e.g. iron and coffee prices for Brazil, jute prices for Bangladesh, coal prices for South Africa and copper prices for UK are also found to be insignificant in the exchange rate determination. A plausible reason for these variables being insignificant is that commodity prices reflect a country's export figures. Since this study considered trade balance as an explanatory variable, individual commodity prices becomes less powerful variables in the exchange rate determination of these countries. However, further study on the relationship between exchange rates and country specific commodity prices should be conducted to investigate this further.

Exchange rates vary according to the speed of adjustment parameter as exemplified by the coefficient of the error correction term (ECM (-1)). These analyses show that very slow return to equilibrium for all advanced countries except Australia, Canada, the Euro area and Sweden. A fast return to equilibrium is observed in the case of Australia and Canada whereas it is moderate in the cases of the Euro area and Sweden. In the emerging country group, the speed of convergence is moderate in the cases of India and South Africa and it is slow in the cases of Brazil, Chile, Colombia, Czech Republic, Malaysia, Peru, Russia, Taiwan, Thailand and Turkey. However, very slow return to equilibrium is observed in the rest of the emerging countries. A moderate speed of convergence to equilibrium was noted in some of the frontier markets namely, Botswana, Nigeria, Sri Lanka and Vietnam Botswana, Nigeria, Sri Lanka and Vietnam. The slow speed of adjustment process is observed in the cases of Bangladesh, Brunei, Jamaica, Myanmar, Pakistan, Romania, Trinidad & Tobago and Tunisia. A very slow speed of convergence to equilibrium is observed for rest of the frontier countries. The findings of each group of countries are mixed, which is however expected, as each country within the same group has different economic policies. All of the results related to emerging and frontier markets may be regarded as innovative findings that add to a growing body of literature on exchange rate modelling via cointegration analysis.

Chapter 4 attempts to investigate the relationship between exchange rate and macroeconomic variables by using ARDL-cointegration technique. After observing the cointegration among variables, this study also examined the direction of causality among variables via Granger Causality tests. The findings of the Granger Causality test indicate that in the long-run, the unidirectional causality from country specific macroeconomic variables to exchange rates is found in all the cases except China, Poland, South Korea, Thailand, Turkey, Jamaica, Kenya, Pakistan and Sri Lanka. The bidirectional causality i.e macroeconomic variable to exchange rate and vice versa is found in the cases of UK, Chile, Colombia, India, Russia, Kazakhstan and Bangladesh. On the contrary, no causality is showed in the cases of China and Turkey. In general, these findings imply that macroeconomic variables are significant in predicting changes in exchange rates. Thus, it can be claimed that exchange rate variability is fundamentally linked to economic variables.

Relative to applications of cointegration models in other Finance areas, the ARDL-cointegration model has received less attention in respect of exchange rate determination. This presented an opportunity of assessing the utility of this model in the context of exchange rates. This study examined whether the ARDL-cointegration approach performs better than the time series models in an out-of-sample forecasting exercise. The findings showed that the cointegration model generated less accurate forecasts when compared to the volatility, exponential smoothing and Naïve 1 model in all cases. Overall, it was concluded that the macroeconomic variables used by the ARDL scheme play considerably less significant role in the exchange rate determination possibly because of lack of power of these variables to forecast the exchange rates of these countries. The prime reason behind these results is that the nominal exchange rates are much more volatile than the macroeconomic fundamentals to which they are linked in theoretical models. Excess volatility suggests that exchange rate models based on macroeconomic variables are unlikely to be very successful at either explaining or forecasting nominal exchange rates and that there may be important variables (e.g. terms of trade and capital flows) that may be omitted from standard exchange rate models.

Finally, Chapter 5 combined the time series and econometric models for forecasting the exchange rates. There have been very few applications of combination models in the foreign exchange field, yet these models have the potential to assist policy makers in making more effective decisions. Moreover, the use of appropriate combination techniques in exchange rate forecasting is crucial for both academic researchers and policy makers. This present study addressed two outstanding issues raised by Poon and Granger (2003). Poon and Granger (2003) highlighted the fact that little attention has been paid to the performance of combination forecasts, since different forecasting approaches capture different volatility dynamics. They also pointed out that little has been done to consider whether forecasting approaches are significantly different in terms of performance. This study applied combination forecasting techniques in the exchange rate data in order to fill a major gap in the literature. The results vary according to various market economies studied.

The major findings of that chapter suggested that the volatility model has a much more significant predictive role, usually when combined with another model such as exponential smoothing, Naïve 1 and cointegration models in the exchange rate determination of emerging and frontier markets. This result was expected as individual emerging markets are relatively highly volatile when compared with the advanced markets (Harvey, 1995 and Errunza, 1997). It is also evident that the exponential smoothing model plays significant role in the determination of exchange rates of emerging and frontier markets. Furthermore, the findings showed that the cointegration model plays a major role in the exchange rate determination of advanced currencies. However, this model plays a considerably less significant role in the exchange rate determination of emerging and frontier countries against the U.S. dollar. Thus, this class of models possesses utility in the context of forecasting exchange rates, but its main advantage is when forecasts are combined. To summarise, the single time series models generate better forecasts in 9 cases (18.35%), the combination between time series models yield better results in 14 cases (28.58%) and the combination of time series and econometric models takes the lead in 26 (53.07%) of these 49 cases. The findings of this study reinforce the fact that volatility, exponential smoothing, Naïve 1 and cointegration models have a significant role to play in forecasting exchange rates when combined with other predictive techniques.

Focusing on the forecasting accuracy of the various forecasting models is another contribution of this study. The present study expands on the very few studies that have used combination models, by here applying an assessment of unbiasedness (the Wald test), in conjunction with the runs test in the context of exchange rate determination. The runs test's results showed that there is an immediate reaction to the global financial crisis in some of the exchange rate series. The key question of this study was whether the best possible combination models have better predictive ability than the best possible individual forecasts. An extensive examination of the combination approach was performed and it was revealed that, the variance-covariance method of combination models performs extremely well for all advanced countries' exchange rates against U.S. dollar. Mixed results were found in the cases of emerging and frontier countries. Combination models fit the data well in two-thirds of the sample emerging and frontier countries. However, single volatility model perform extremely well for the rest of the emerging and frontier countries. The results of this study provide a strong claim for using forecast combination techniques as an alternative to applying a single model. The findings also lead us to think that combination-based approach has a bright future in applications to the more unstable advanced currencies and fast expanding emerging markets and frontier countries. This perspective is particularly revealing, if we keep in mind that it is in those emerging and frontier markets that will generate most of the growth opportunities of the coming decades.

The findings of this research are important for the policy makers. The analyses have the potential to assist policy makers in their determination of effective foreign exchange policies both at the macro- and microeconomic-levels. At the macro-level, the results of Chapter 3 could facilitate central banks' decisions in respect of intervention policies. The central bank of each country often generates internal forecasts of their local currency-U.S. dollar exchange rate to measure and evaluate exchange rate fluctuations. Therefore, the findings of this research could help the central bank to forecast excess volatility, which clearly suggests that there is a risk that exchange rates will move from its target zone. Thus, the central bank can intervene to tackle this situation by forecasting the exchange rate via the optimal models suggested in this study. The analyses could assist decision makers to choose more appropriate exchange rate policies for those countries that have high degree of volatility. Policy makers might obtain an early signal of future crises by accurate forecasting of exchange rate volatility. Forecasted exchange rate volatility can also be used as an important factor to determine the best exchange rate regime for a country (Hernandez and Montiel, 2001) and to evaluate whether monetary union is optimal for that country (Wyplosz, 2002).

The presented findings in Chapter 3 have important implications for emerging and frontier countries. Exchange rate volatility is a key issue for these economies because these countries wish to encourage foreign direct investment from developed nations. Due to fast and intensive money flows from developed countries into emerging and frontier countries, it is important for policy makers to forecast excess volatility in order to take necessary measures to overcome the negative impacts of the volatility on the economy. A majority of emerging and frontier market economies are maintaining their foreign exchange reserves in an international currency such as the U.S. dollar. Therefore, the foreign reserve department can also use optimal volatility models, which are suggested in this study in order to maintain their reserve effectively and efficiently.

The results of the ARDL-cointegration analyses also have important policy implications at the macro-level. The presented methodologies of Chapter 4 might help a country's government to undertake necessary measures related to the variables that affect exchange rates in order to maintain a stable position for their national currencies against the U.S. dollar. The macroeconomic variables suggested in Chapter 4 could be considered as important tools for the policy makers who seek to minimise the exchange rate variability especially in terms of the under and/or overvaluation. A desirable level of an exchange rate can be achieved through influencing the exchange rate determinants that reduce exchange rate risks and maintain the international competiveness of exports and imports of the economy. The exchange rate of an economy affects aggregate demand through its impact on export and import prices and policy makers may exploit this connection. Policy makers should focus on effective macroeconomic management (i.e. monetary, fiscal, trade, investment, foreign debt policies etc.) by taking into consideration of such economic variables for maintaining stable exchange rate environment.

From a monetary policy perspective, it is important to understand which forces actually drive a currency, because variations in exchange rates have different implications for a country's economy and may require different policy responses. For instance, a home currency may be responding to an increase in the foreign demand for goods and services that would lead to an increase in home country's aggregate demand. In such a case, the monetary policy response would be muted unless it facilitated the reallocation of resources between traded and non-traded sectors. Alternatively, an appreciation of the home currency may simply reflect a general weakening of the U.S. dollar. Therefore, easing the monetary policy in order to offset the reduction in the foreign demand for home country's goods and services might be an issue for consideration.

The findings of Chapter 4 could also facilitate the central bank such as those studied countries to formulate exchange rate policies. The central bank monitors the foreign exchange market to facilitate exchange rate adjustment towards a rate consistent with its fundamental. Therefore, the results of this study are useful for the central bank in order to maintain the stability in the foreign exchange markets. The long-run success of exchange rate determination is dependent on a commitment to sound economic fundamentals for advanced, emerging and frontier countries. However, there are some external variables (e.g. terms of trade and capital flows) which are beyond the control of the policy makers. Excessive variability of these macroeconomic variables, especially in the emerging and frontier markets could fuel variability in the exchange rates. The results of the combination of forecasting models presented in Chapter 5 could also facilitate the central bank to formulate the policy. Without a subjective opinion concerning the best models to apply to forecasting problems, it may be useful to focus on combined forecasts which have a higher likelihood of being best models in advanced and some emerging and frontier countries. It is important for the central bank to obtain internal forecasts to evaluate the present and upcoming situation causes by exchange rates. It could reduce the risks of fluctuations if forecasts are made via combination techniques.

The findings of this research are important for policy makers at the micro-level. Due to globalisation, policy makers of multinational or transnational companies face new challenges in the management of their global financial recourses so that countries can take full advantage of the opportunities, while reducing potential risks. Exchange rate volatility plays a vital role in this regard. Volatility forecasts can help policy makers to manage their global financial resources more effectively. The presented results in Chapter 3 have importance for exporters and importers since exchange rate volatility has different impacts on their decisions regarding their competitiveness and international transactions. Furthermore, international investors and risk managers can reduce their risk levels by assessing the volatility level of the currencies with which they interact. The analyses of this study could also be used as an input in their portfolio diversification and risk management processes.

Overall, the current findings have substantial potential benefits for making effective decisions by various individual agents such as investment banks, foreign exchange brokers, stock market brokers, financing and investment societies, international investors, risk managers and portfolio managers. Such results as presented here could also be used as an input of pricing derivative securities. Volatility is one of the important variables in pricing derivative securities. It is important to measure the volatility of the underlying assets from now until the expiry date of the derivative contract. Prospective investors who wish to hedge the volatility risk and the agent who wants to price the derivative contracts may found these results useful for measuring their dynamic hedge ratios.

At a micro-level, the results of Chapter 4 are important for those companies who conduct cross-border business and finance their overseas operations or plan for the payment of costs and expenses overseas or hedge against these costs or against the potential losses associated with these costs. Therefore, the presented findings could act as significant inputs for the policy makers in an attempt to ensure financial stability, while at the same time protecting the home country's or home company's fiscal interests. Banks and even individuals would find these results are useful as they are assisted by the network of financial institutions and brokers, since these people are buying and selling currencies in order to invest or to engage in international trade with their speculative motive.

Finally, the analyses of Chapter 5 are important for policy makers in several aspects. Without a subjective opinion concerning the best models to apply forecasting problems, it may be useful to focus on combined forecasts which have a higher probability of being best model in advanced and some emerging and frontier countries. These results can also be used as inputs into business planning models - such as Capital assets pricing model (CAPM), Arbitrage pricing theory (APT), portfolio optimisation and risk management. The CAPM only requires one variable additional to stock returns; namely market returns, defined as the principal index in the country over the most traded stocks. The findings of previous studies (Korsgaard, 2009; Hartmann and Pierdzioch, 2006) suggested that stock returns are to a certain degree sensitive to exchange rate fluctuations. The APT's beta coefficient reflects the sensitivity of the underlying assets to various economic factors such as currency exchange rates, interest rates, oil prices, etc. Therefore, the forecasting models suggested in this chapter could help the companies to price their individual or portfolio returns reasonably accurate way.

It is widely believed that exchange rate fluctuations have significant implications for financial decision-making and for firm profitability. Firms that export to foreign markets may benefit from a depreciation of the local currency because its products become more affordable to the foreign consumers. Conversely, firms that rely on imports may face their profit shrink as a consequence of increasing cost of production. The returns of the firm are also affected by changes in the exchange rates. Therefore, forecasts made by the optimal model- proposed in this study, could help the management of the company and investors to take preventive actions to minimise their risk of competitiveness, which occurs due to the fluctuations in exchange rates.

On the basis of the models used in this study, combination methods generate considerably better forecasts of exchange rates and can serve as a judgment-free benchmark forecast to compare with the policymaker's projections. Due to fast and intensive money flow from advanced countries into emerging and frontier countries, it is a new challenge for policy makers and various other agents to forecast exchange rates for those countries. To minimise risk, multinational organisations are obliged to hedge their assets by future contracts and many other financial instruments. This requires forecasting currency exchange rates of not only the trading partner countries but also of the other global currencies. Therefore, forecasts made by the combination methods will not only help policy makers to face the new challenges in an effective way, but also it will assist the multinational companies to mitigate their risks in respect of their international transactions.

These findings also generate some useful information for the individual agents, including foreign exchange and stock brokerage societies, investment banks, financing and investment societies, stock brokers, international investors and portfolio managers. Additionally, accurate forecasts of exchange rates could guide business planning models such as those related to capital budgeting, resource allocation and policy monitoring. Therefore, the results of this study not only enrich the exchange rate literature on combination forecasting but they also offer pertinent information to practitioners in respect of modelling. Consequently, combination forecasting is recommended to be used more frequently in practice.

Overall, the findings of this research suggest that the macroeconomic variables used by the ARDL-cointegration model play considerably less significant roles in exchange rate determination for the three market economies. Further research should be conducted by considering other variables, for example, terms of trade (measured by price of exportable goods/price of importable goods), capital flows, commodity prices and recent redefinitions of the trade openness variable. Terms of trade is considered as a determinant of real exchange rates, since foreign price shocks account for large fluctuations in real exchange rates in both advanced, emerging and frontier markets (Neary, 1988; Chowdhury, 2012). Edwards (1989) stated that changes in terms of trade generate substitution and income effects. This author also explained that the income effect results from a decrease in import prices or an increase in export prices, which tend to increase the relative prices of nontradables to tradables and appreciates the real exchange rates. It might be interesting to investigate the effect of terms of trade on nominal exchange rates of these three economies.

Greater financial integrations of world capital markets and increased freedom of capital to flow across national borders have increased the importance of financial flows in the determination of exchange rates. Despite all of the attention the capital flows (e.g. net bond flows, net equity flows and foreign direct investments) receive in the FOREX market, there has not been much rigorous empirical testing to determine whether these flows have statistically significant and quantitatively important impact on nominal exchange rates for these three economies.

In this study country specific commodity prices such as iron and coffee prices for Brazil, jute prices for Bangladesh, gold and coal prices for South Africa and copper prices for UK were considered. No relationship was found between these commodity prices and exchange rates except gold prices in the case of South Africa. Further research on relationship between commodity prices and exchange rate can be conducted by considering natural gas and timber prices for Canada, soybean prices for Brazil, cocoa prices for Indonesia, coffee prices for Colombia, India and Mexico and rice prices for China, Vietnam and Thailand. Moreover, tourism revenues might be a significant variable for this investigation for countries like UK, India, Peru, Mauritius, Nepal etc.

In the present study, trade openness was defined as the sum of exports and imports divided by country's GDP, which is the most popular and traditional measure. However, Squalli and Wilson (2006) noted that the world's biggest trading countries namely the USA, Germany, Japan and China are consistently determined to be closed economies by using this traditional measure. These authors advocated a more pragmatic approach to measuring trade openness. They combined both the trade intensity (measured by exports + imports/GDP) of a given country together with its relative share of world trade to create a composite trade intensity (CTI) measure that is better able to classify the degree of trade openness enjoyed by countries. Using CTI, their results suggested that large trading countries namely USA and Germany are classified as open economies, alongside Singapore and Hong Kong which have traditionally been described as open. Therefore, it would be of interest for future research to see whether the cointegration results change to any great extent when considering terms of trade, capital flows, commodity prices and CTI as a measure of "trade openness" in the estimation process.

Another interesting future avenue for development could be comparing the forecasting performance of both the ARDL-cointegration and more conventionally applied Johansen-cointegration techniques in FOREX studies. The Johansen approach to cointegration is the most widely applied cointegration method (Setia and Sharma, 2012; Ibarra, 2011; Abbas *et al*., 2011; McMillan, 2005; Gokcan and Ozmen, 2002; Hwang, 2001; Mark and Sul, 2001; Kouretas and Georgoutsos, 2000; Karfakis and Phipps, 1999; Feyzioglu, 1997). Its distinct advantage is that it permits the testing of hypotheses concerning the cointegrating relationship. No comparative studies have been conducted comparing this conventional approach with the simpler, less rigid ARDL-cointegration technique. Moreover, studies on an application of Johansen-cointregration approach to exchange rate behaviour of emerging and frontier economies are almost non-existent. Therefore, it would be an idea to apply the Johansen-cointegration technique in exchange rate series of these markets to fill a major gap in the literature.

Overall, three major contributions of this study are reported in the field of Finance. Firstly, a unique feature of this research is that 80% of the data sets used (new geographical areas grouped as emerging and frontier markets currency exchange rates against the U.S. dollar), have never been subjected to statistical analysis before. Secondly, the application of the ARDL-cointegration method used to investigate the long-and short-run relationships of exchange rates with macroeconomic fundamentals. Thirdly, this study also compared the forecasting performance of this causal econometric approach with time series approaches to fills a major gap of the literature. This led to consideration of combination methods for forecasting exchange rates for the three market economies.

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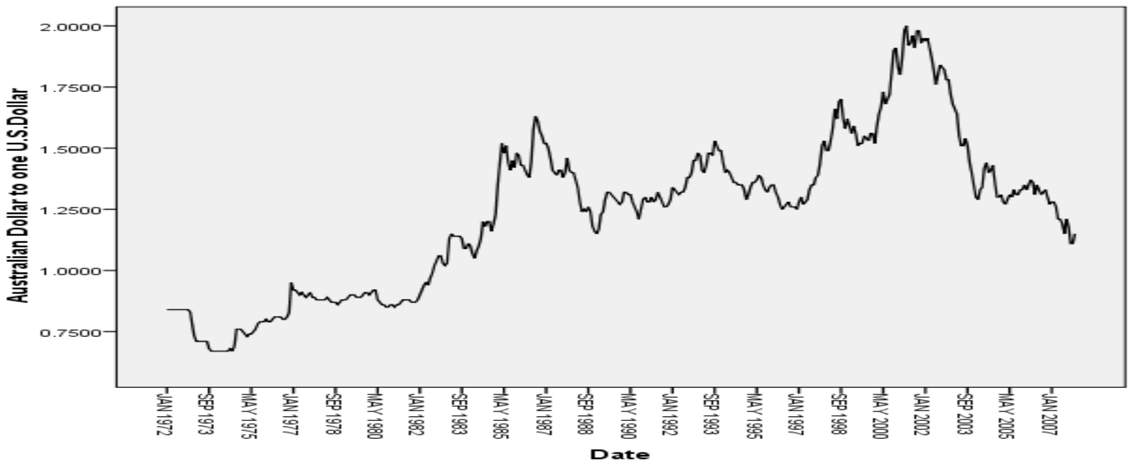
Appendices

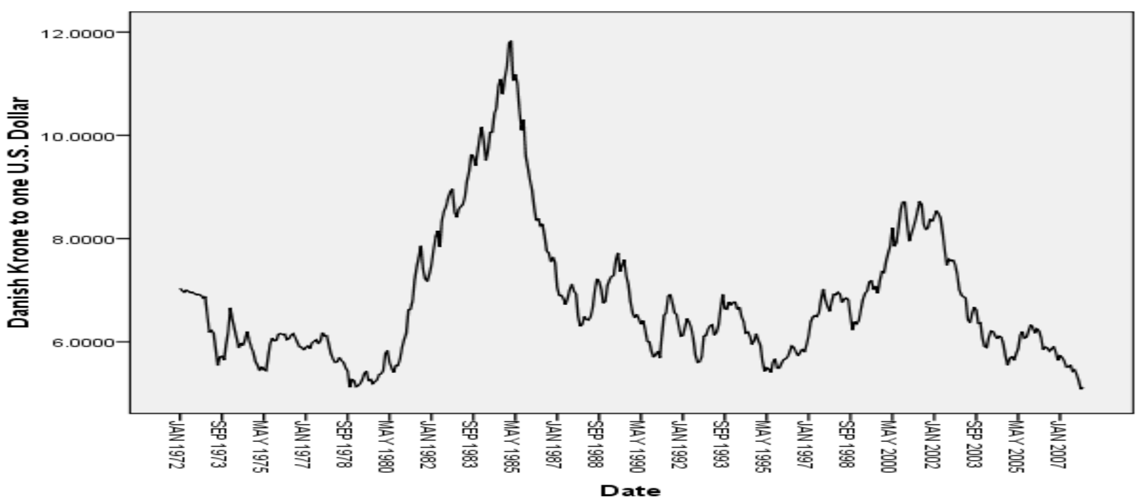
Appendix 1: List of currencies and sample period

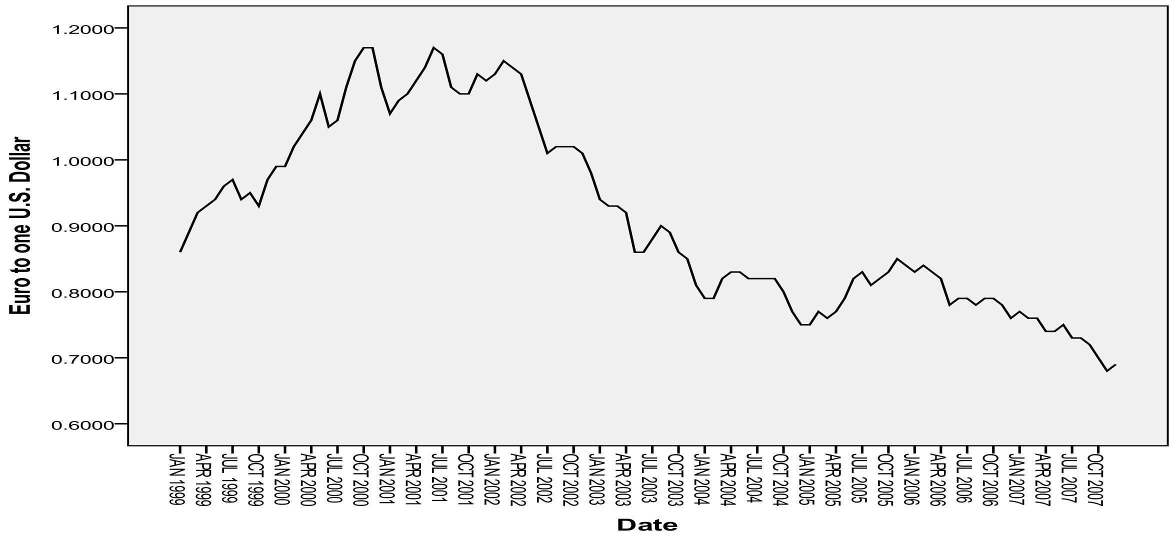
Country	Currency	Data Period	No. of Observations
Advanced Countries:			
Australia	Australian dollar	1972M1 - 2010 M4	422
Canada	Canadian dollar	1972M1 - 2010 M4	432
Denmark	Danish krone	1972M1 - 2010 M4	432
Euro area	European euro	1999M1 - 2010 M4	108
Japan	Japanese yen	1972M1 - 2010 M4	432
Norway	Norwegian krone	1972M1 - 2010 M4	432
Singapore	Singapore dollar	1972M1 - 2010 M4	432
Sweden	Swedish krona	1972M1 - 2010 M4	432
Switzerland	Swiss franc	1972M1 - 2010 M4	432
UK	British pound	1972M1 - 2010 M4	432
Emerging Countries:			
Brazil	Brazilian real	1996M1 - 2010 M4	144
Chile	Chilean peso	1973M10 - 2010 M4	411
China	Chinese renminbi	1972M10 - 2010 M4	423
Colombia	Colombian peso	1972M1 - 2010 M4	432
Czech Republic	Czech koruna	1993M1 - 2010 M4	180
Hungary	Hungarian forint	1972M1 - 2010 M4	432
India	Indian rupee	1972M1 - 2010 M4	432
Indonesia	Indonesian rupiah	1978M11 - 2010 M4	350
Malaysia	Malaysian ringgit	1972M1 - 2010 M4	432
Mexico	Mexican peso	1987M1 - 2010 M4	252
Peru	Peruvian nuevo sol	1990M1 - 2010 M4	216
Philippines	Philippine peso	1972M1 - 2010 M4	432
Poland	Polish zloty	1988M1 - 2010 M4	240
Russia	Russian ruble	1996 M1- 2010 M4	144
South Africa	South African rand	1979M1 - 2010 M4	348
South Korea	South Korean won	1979M12 - 2010 M4	337
Taiwan	New Taiwan dollar	1984M1 - 2010 M4	288
Thailand	Thai baht	1984M1 - 2010 M4	279
Turkey	Turkish new lira	1994M1 - 2010 M4	168
Frontier Countries:			
Bangladesh	Bangladeshi taka	1972M1 - 2010 M4	432
Bhutan	Bhutanese ngultrum	1972M1 - 2010 M4	432
Botswana	Botswana pula	1972M1 - 2010 M4	432
Brunei	Brunei dollar	1972M1 - 2010 M4	432
Croatia	Croatian kuna	1992M1 - 2010 M4	192
Estonia	Estonian kroon	1992M6 - 2010 M4	187
Jamaica	Jamaican dollar	1972M1- 2010 M4	432
Kazakhstan	Kazakhstani tenge	1994M1 - 2010 M4	168
Kenya	Kenyan shilling	1975M9 - 2010 M4	388
Lao PDR	Lao kip	1987M9 - 2010 M4	244
Mauritius	Mauritian rupee	1972M1 - 2010 M4	432
Myanmar	Myanmar kyat	1974M11 - 2010 M4	398
Nepal	Nepalese rupee	1981M8 - 2010 M4	317
Nigeria	Nigerian naira	1972M1 - 2010 M4	432
Pakistan	Pakistani rupee	1981M1 - 2010 M4	313
Romania	Romanian leu	1993M1 - 2010 M4	180
Sri Lanka	Sri Lankan rupee	1972M1 - 2010 M4	432
Trinidad & Tobago	Trinidad & Tobago dollar	1972M1 - 2010 M4	432
Tunisia	Tunisian dinar	1972M1 - 2010 M4	432
Vietnam	Vietnamese dong	1986M1 - 2010 M4	264

Appendix 2: Plots of exchange rates over time (national currency per U.S. dollar)

Advanced Countries:



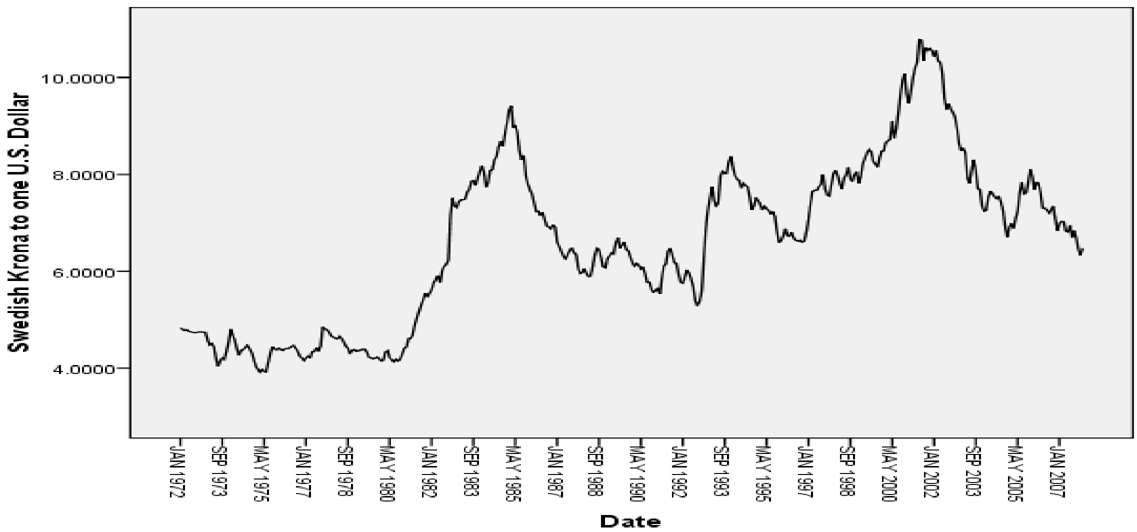



Euro to one U.S. Dollar
Date


Japanese Yen to one U.S. Dollar
Date


Norwegian Krone to one U.S. Dollar
Date

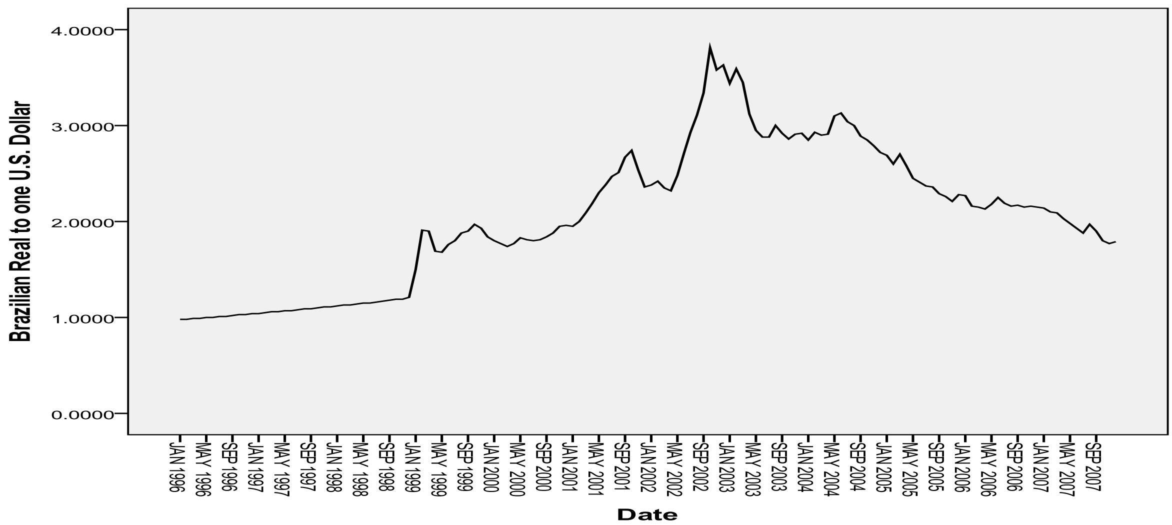
Singapore Dollar to one U.S. Dollar
3.0000
2.5000
2.0000
1.5000
1.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

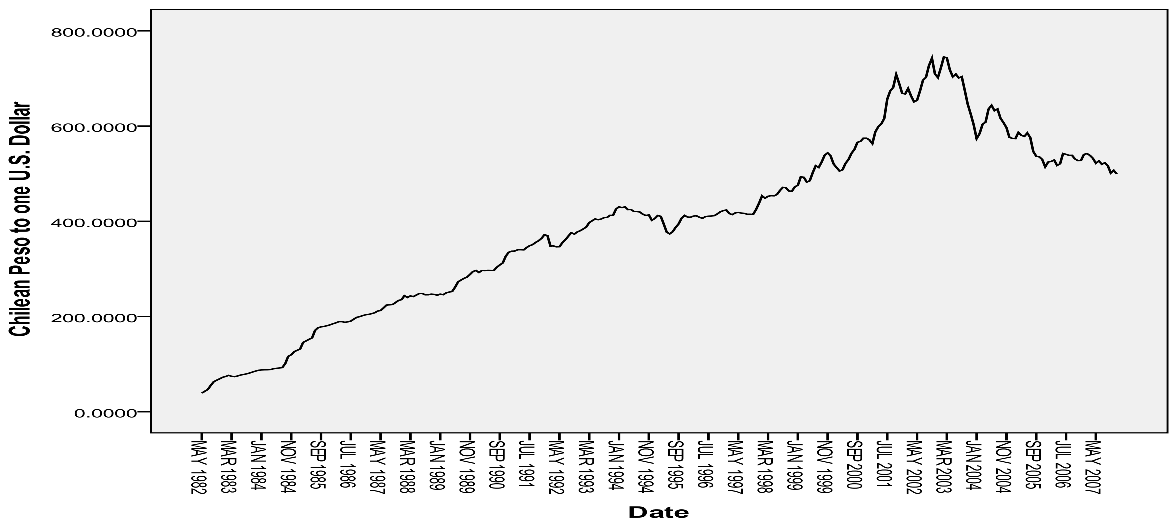


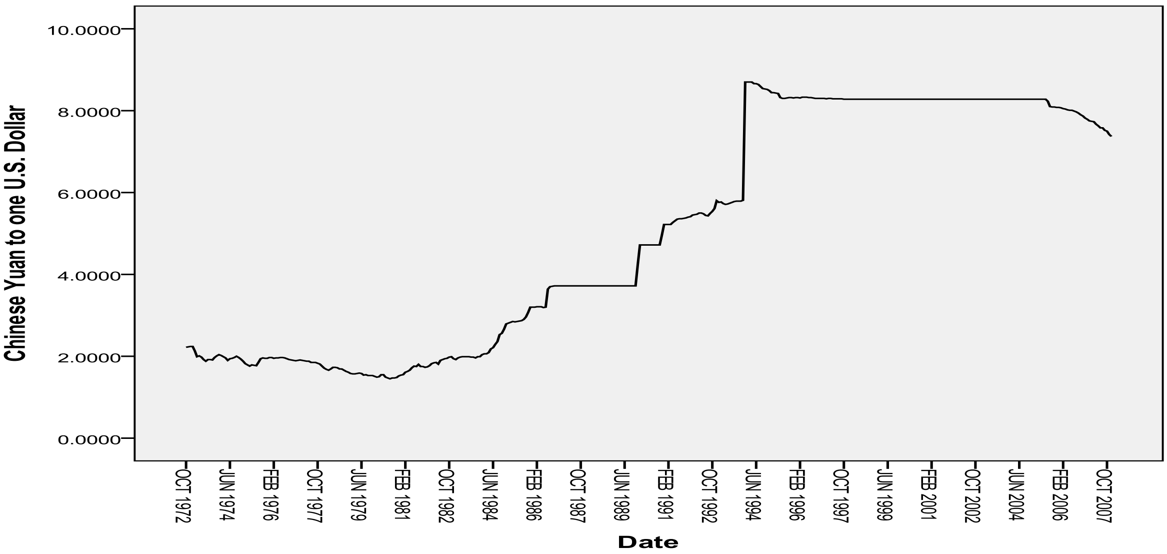
Swedish Krona to one U.S. Dollar
10.0000
8.0000
6.0000
4.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

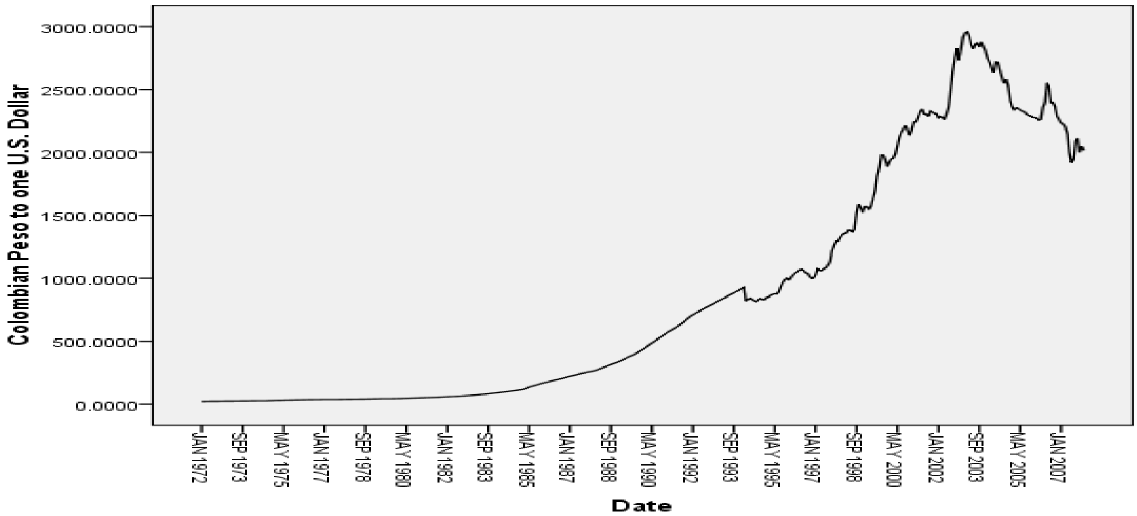
Swiss Franc to one U.S. Dollar
4.0000
3.5000
3.0000
2.5000
2.0000
1.5000
1.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

Emerging Countries:

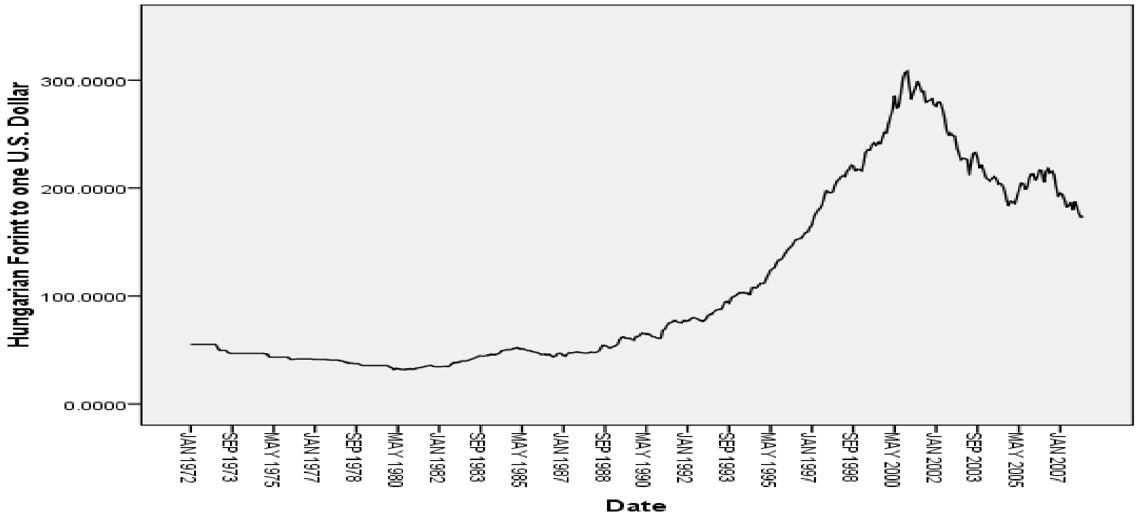


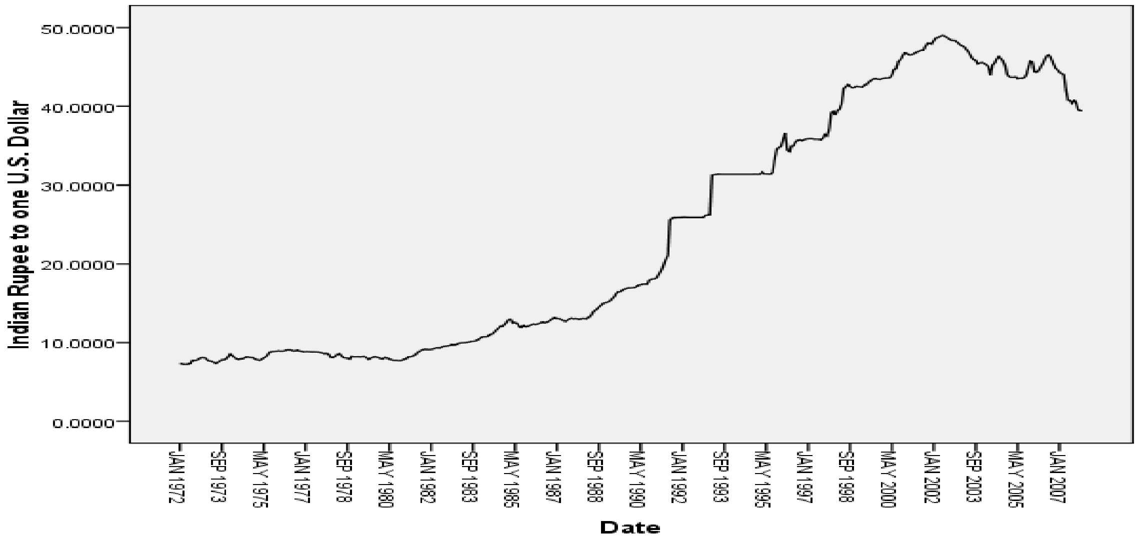


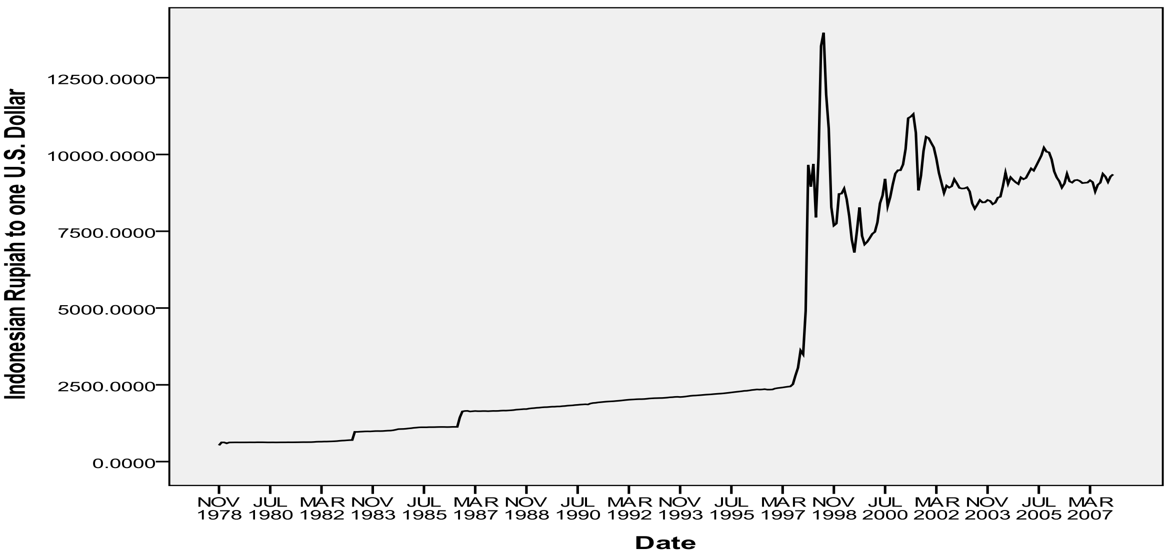

Chinese Yuan to one U.S. Dollar
10.0000
8.0000
6.0000
4.0000
2.0000
0.0000
OCT 1972
JUN 1974
FEB 1976
OCT 1977
JUN 1979
FEB 1981
OCT 1982
JUN 1984
FEB 1986
OCT 1987
JUN 1989
FEB 1991
OCT 1992
JUN 1994
FEB 1996
OCT 1997
JUN 1999
FEB 2001
OCT 2002
JUN 2004
FEB 2006
OCT 2007
Date

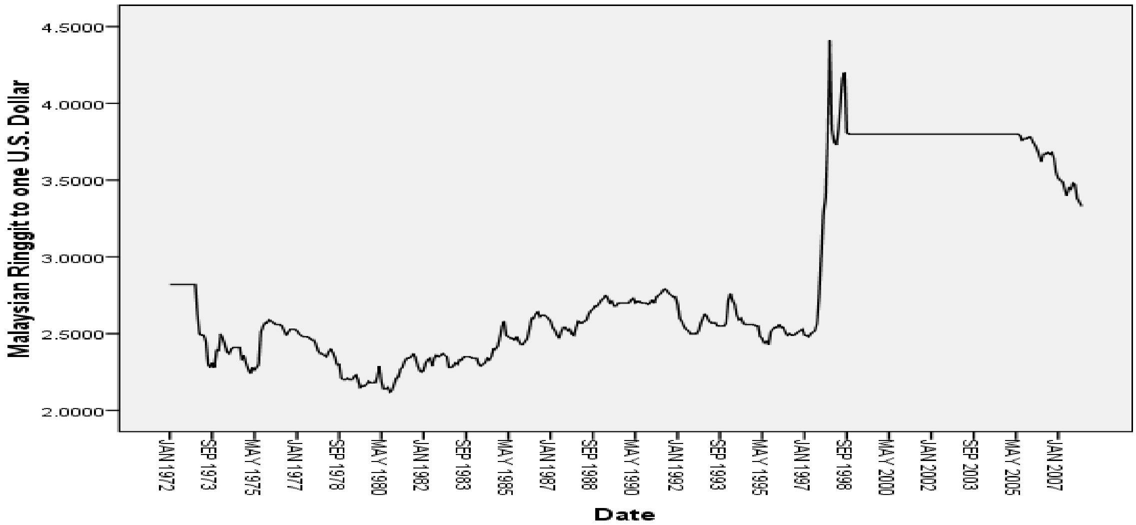

Colombian Peso to one U.S. Dollar
3000.0000
2500.0000
2000.0000
1500.0000
1000.0000
500.0000
0.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

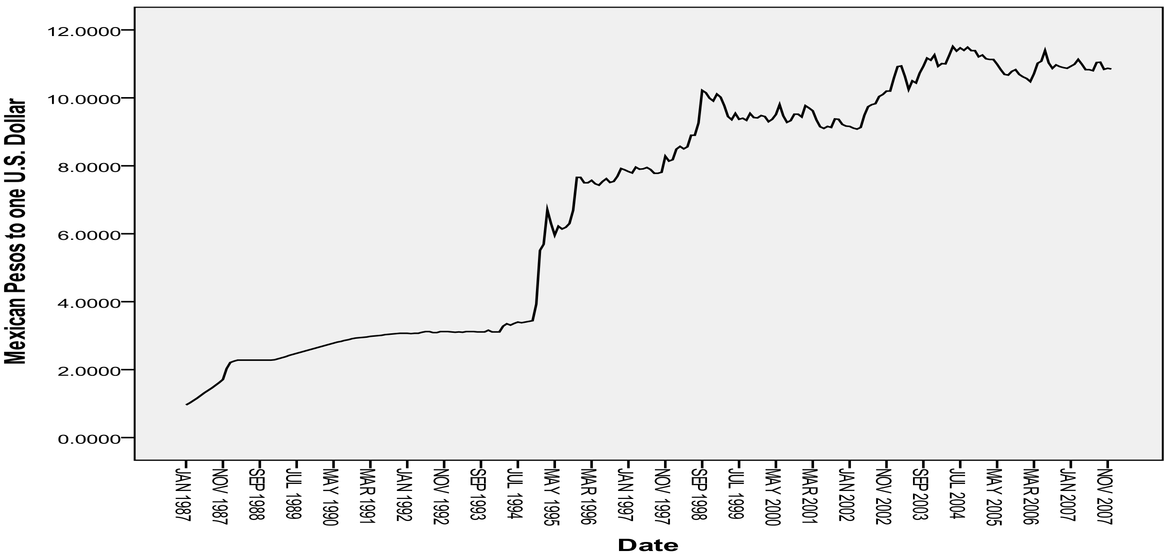

Czech Koruna to one U.S. Dollar
45.0000
40.0000
35.0000
30.0000
25.0000
20.0000
15.0000
JAN 1993
JUN 1993
NOV 1993
APR 1994
SEP 1994
FEB 1995
JUL 1995
DEC 1995
MAY 1996
OCT 1996
MAR 1997
AUG 1997
JAN 1998
JUN 1998
NOV 1998
APR 1999
SEP 1999
FEB 2000
JUL 2000
DEC 2000
MAY 2001
OCT 2001
MAR 2002
AUG 2002
JAN 2003
JUN 2003
NOV 2003
APR 2004
SEP 2004
FEB 2005
JUL 2005
DEC 2005
MAY 2006
OCT 2006
MAR 2007
AUG 2007
Date

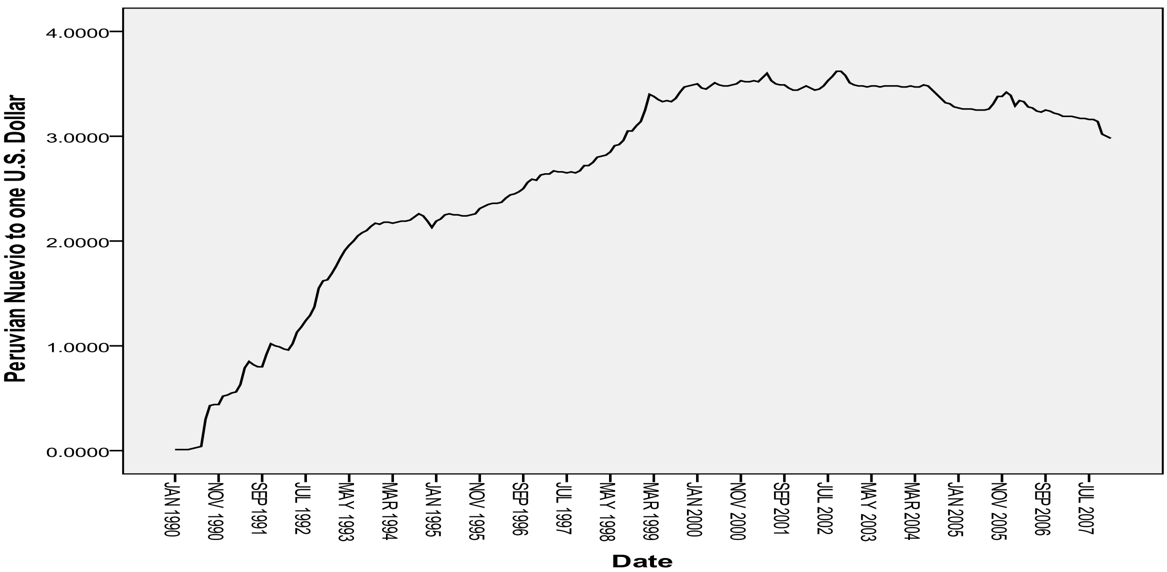

Hungarian Forint to one U.S. Dollar
300.0000
200.0000
100.0000
0.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

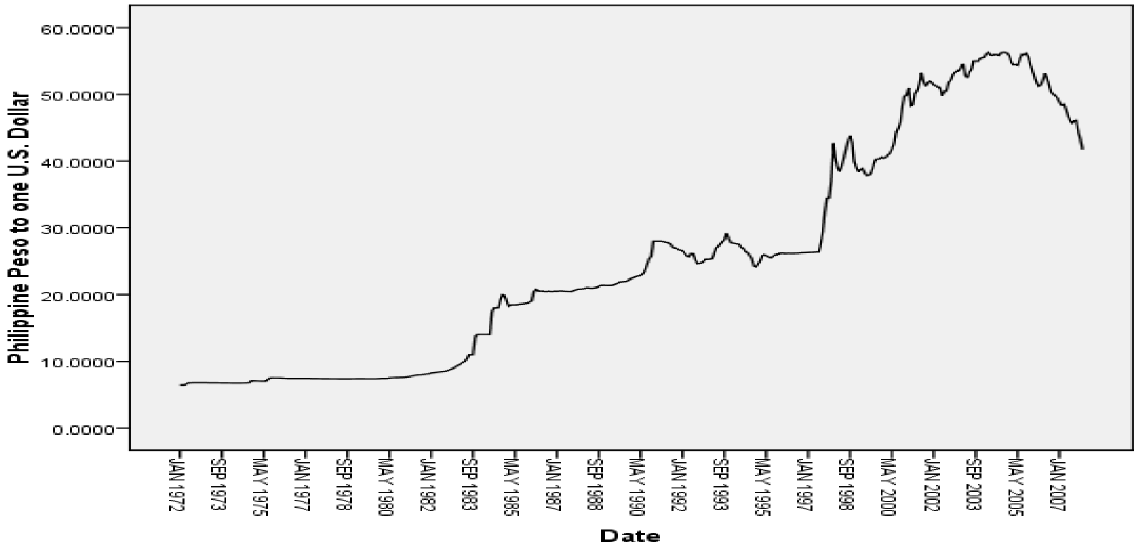

Indian Rupee to one U.S. Dollar
50.0000
40.0000
30.0000
20.0000
10.0000
0.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

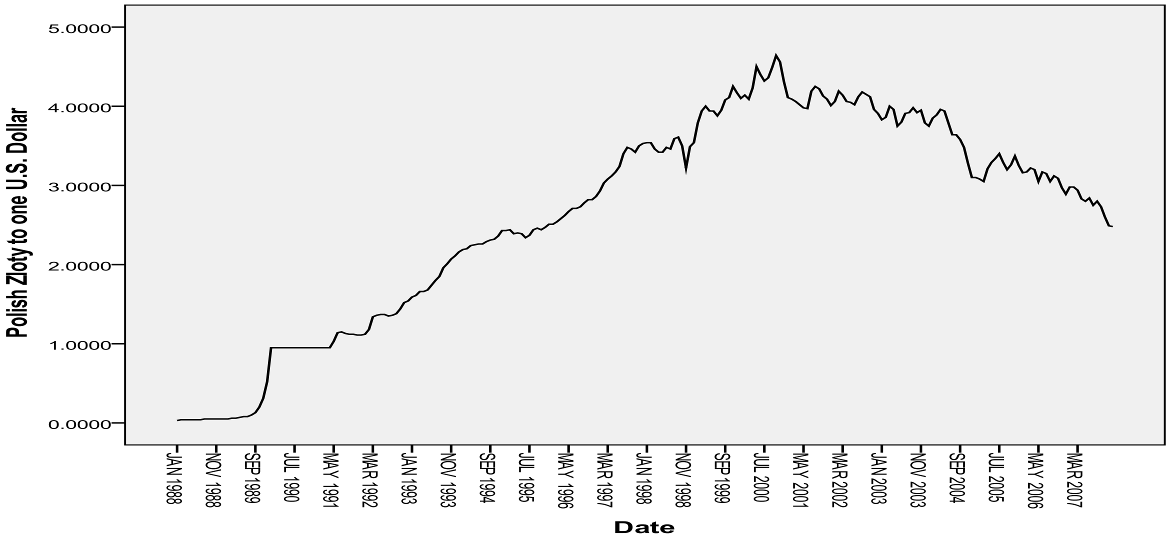

Indonesian Rupiah to one U.S. Dollar
12500.0000
10000.0000
7500.0000
5000.0000
2500.0000
0.0000
NOV 1978
JUL 1980
MAR 1982
NOV 1983
JUL 1985
MAR 1987
NOV 1988
JUL 1990
MAR 1992
NOV 1993
JUL 1995
MAR 1997
NOV 1998
JUL 2000
MAR 2002
NOV 2003
JUL 2005
MAR 2007
Date

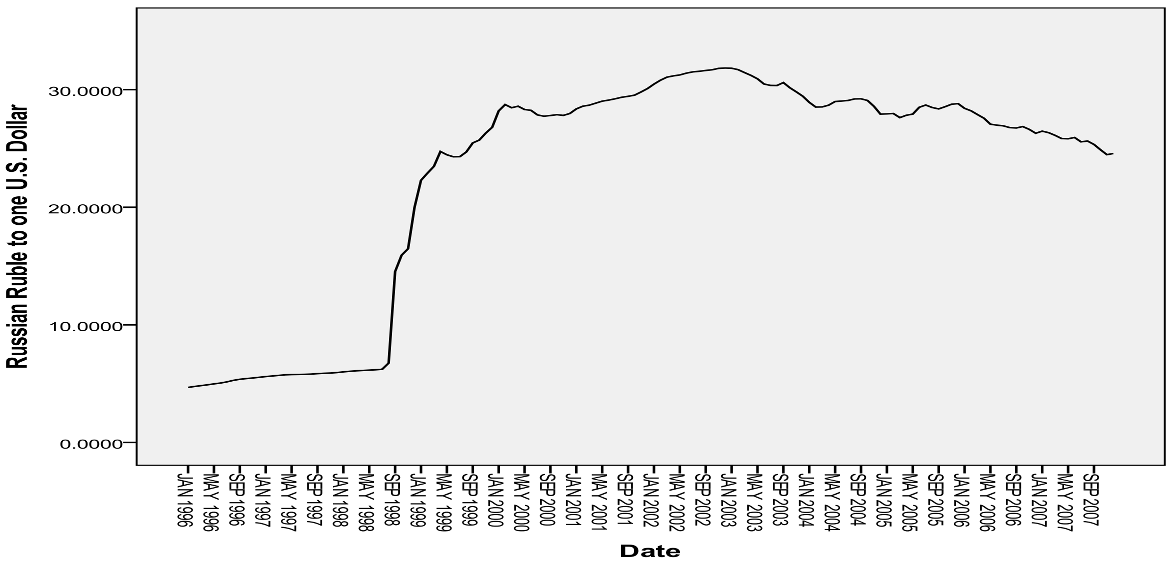

Malaysian Ringgit to one U.S. Dollar
Date

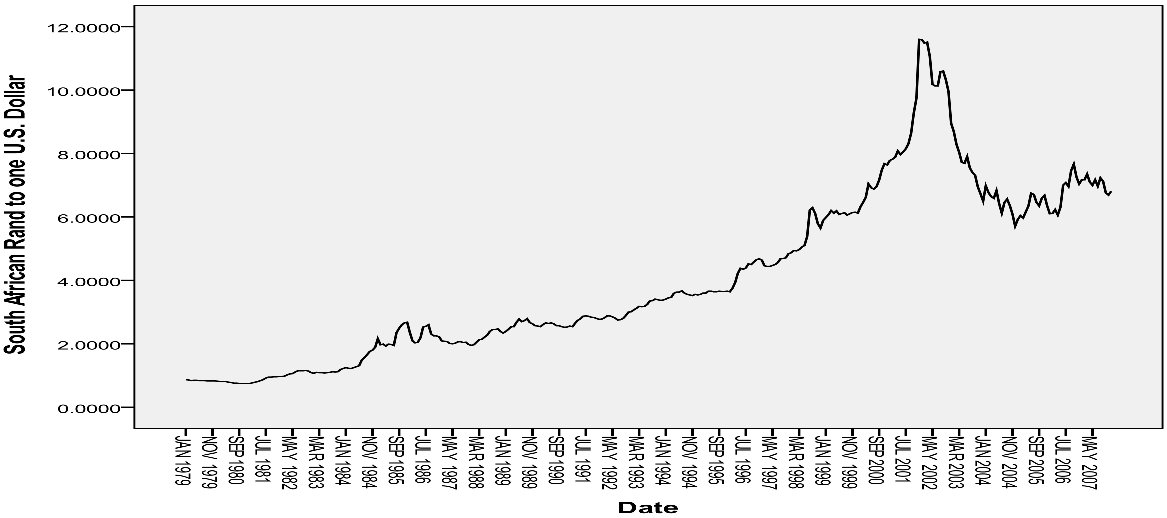

Mexican Pesos to one U.S. Dollar
Date

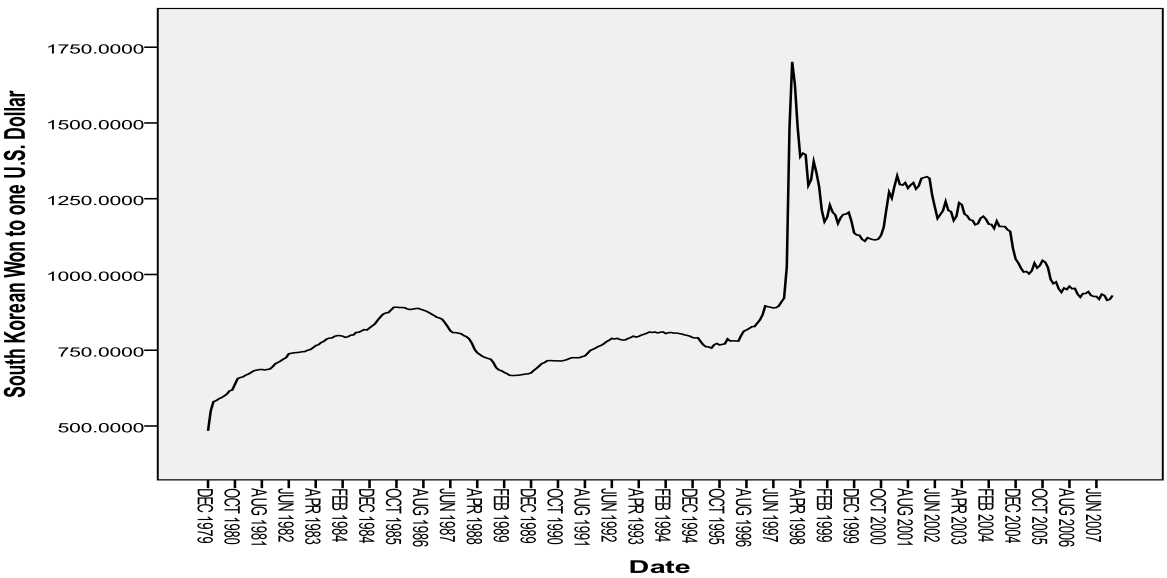

Peruvian Nuevio to one U.S. Dollar
Date

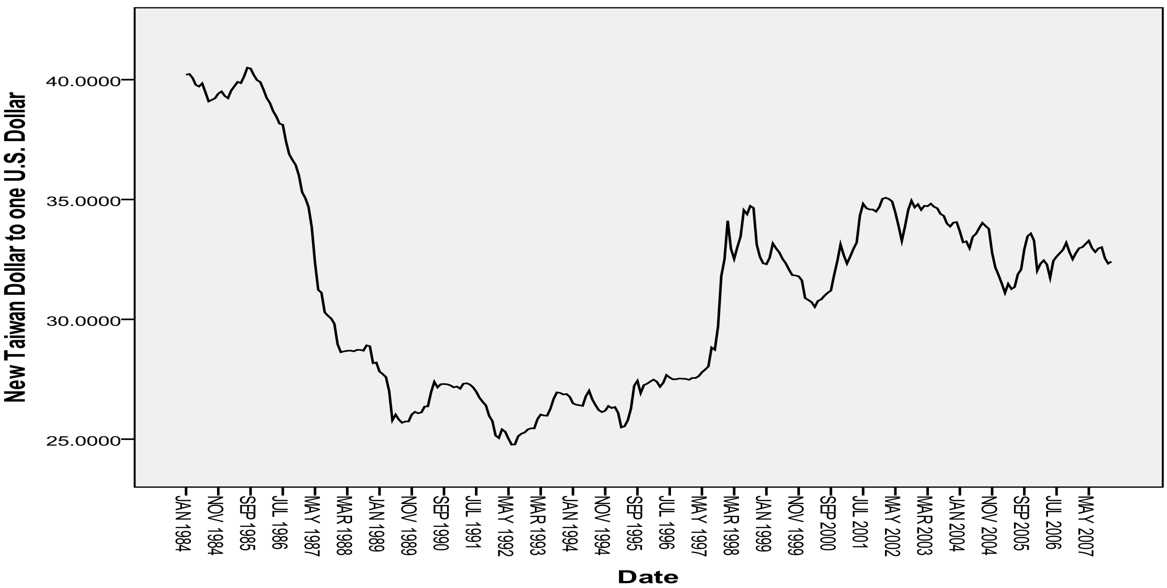

60.0000
50.0000
40.0000
30.0000
20.0000
10.0000
0.0000
Philippine Peso to one U.S. Dollar
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

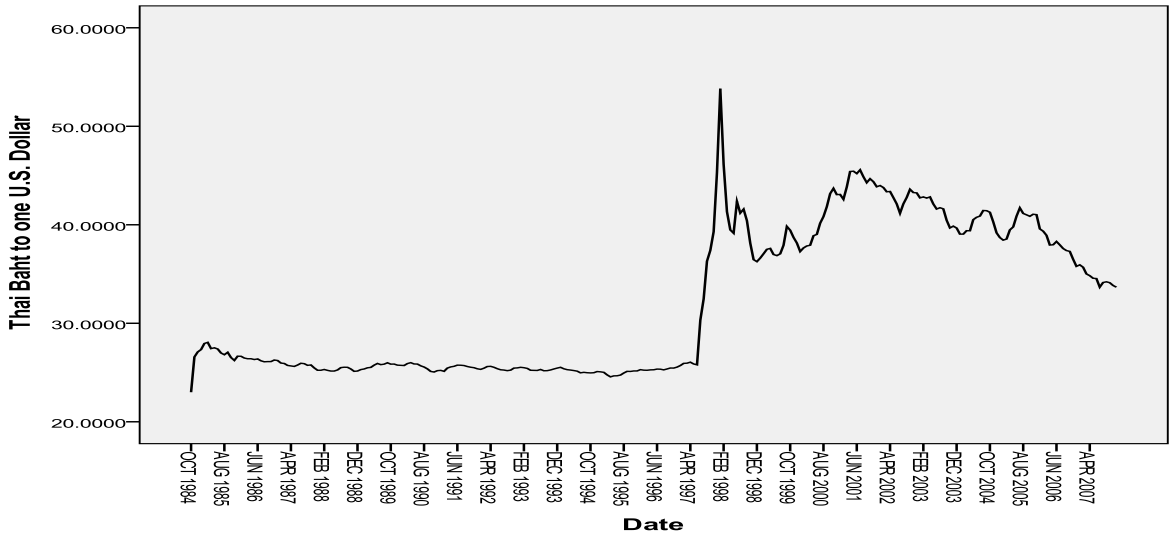

5.0000
4.0000
3.0000
2.0000
1.0000
0.0000
Polish Zloty to one U.S. Dollar
JAN 1988
NOV 1988
SEP 1989
JUL 1990
MAY 1991
MAR 1992
JAN 1993
NOV 1993
SEP 1994
JUL 1995
MAY 1996
MAR 1997
JAN 1998
NOV 1998
SEP 1999
JUL 2000
MAY 2001
MAR 2002
JAN 2003
NOV 2003
SEP 2004
JUL 2005
MAY 2006
MAR 2007
Date

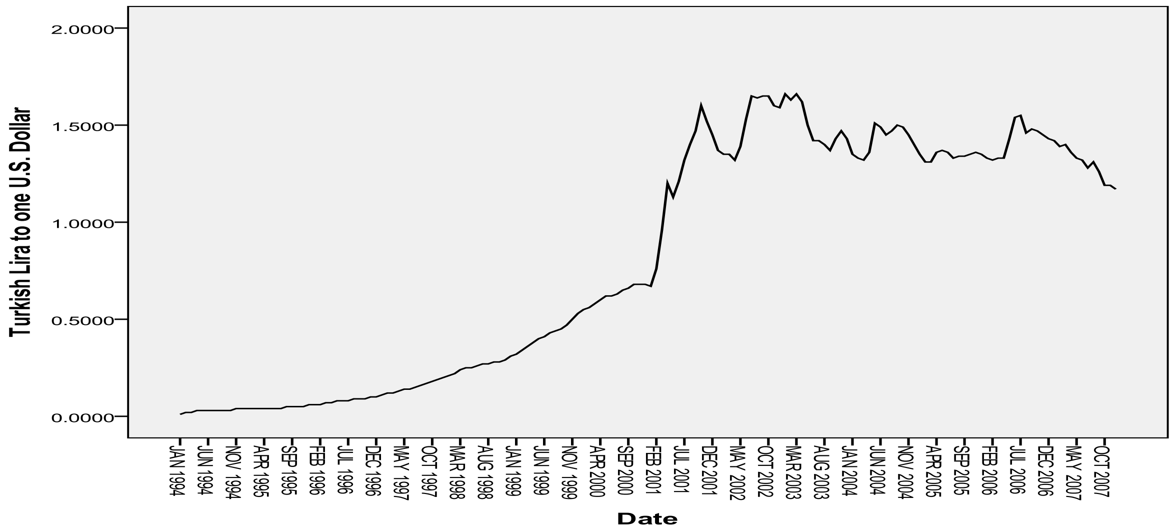

30.0000
20.0000
10.0000
0.0000
Russian Ruble to one U.S. Dollar
JAN 1996
MAY 1996
SEP 1996
JAN 1997
MAY 1997
SEP 1997
JAN 1998
MAY 1998
SEP 1998
JAN 1999
MAY 1999
SEP 1999
JAN 2000
MAY 2000
SEP 2000
JAN 2001
MAY 2001
SEP 2001
JAN 2002
MAY 2002
SEP 2002
JAN 2003
MAY 2003
SEP 2003
JAN 2004
MAY 2004
SEP 2004
JAN 2005
MAY 2005
SEP 2005
JAN 2006
MAY 2006
SEP 2006
JAN 2007
MAY 2007
SEP 2007
Date


South African Rand to one U.S. Dollar
12.0000
10.0000
8.0000
6.0000
4.0000
2.0000
0.0000
Date

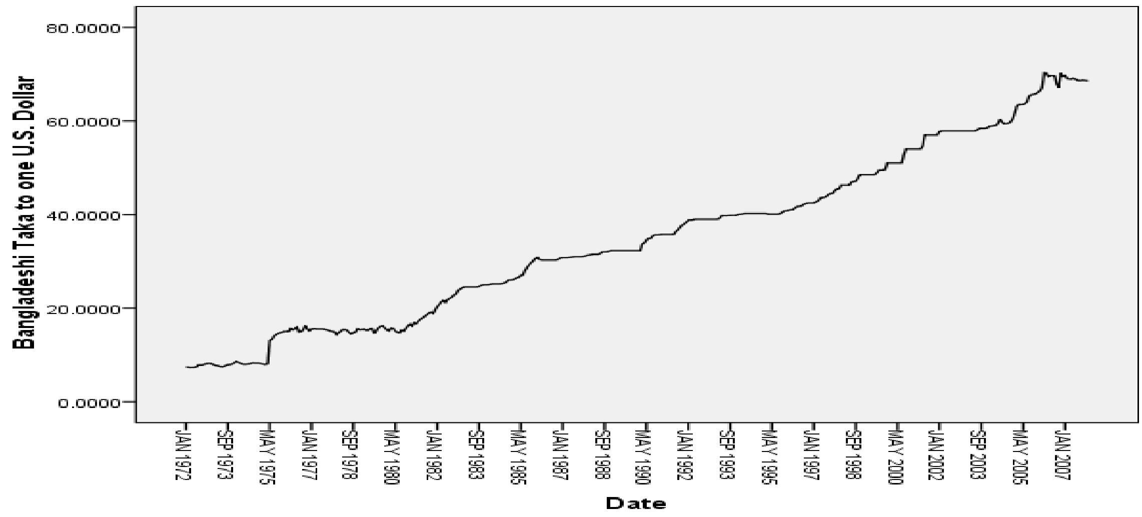

South Korean Won to one U.S. Dollar
1750.0000
1500.0000
1250.0000
1000.0000
750.0000
500.0000
Date

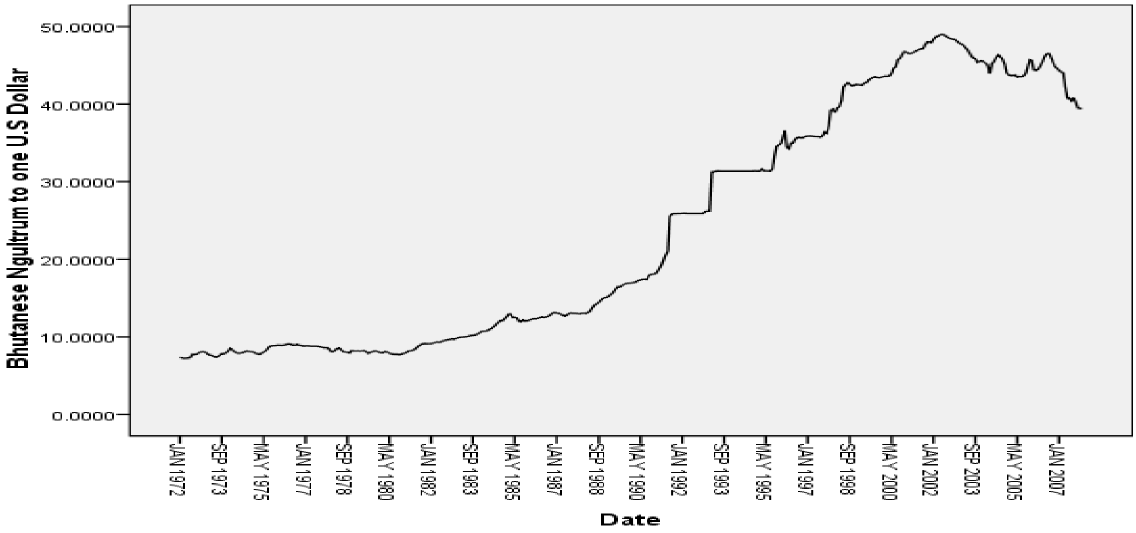

New Taiwan Dollar to one U.S. Dollar
40.0000
35.0000
30.0000
25.0000
Date

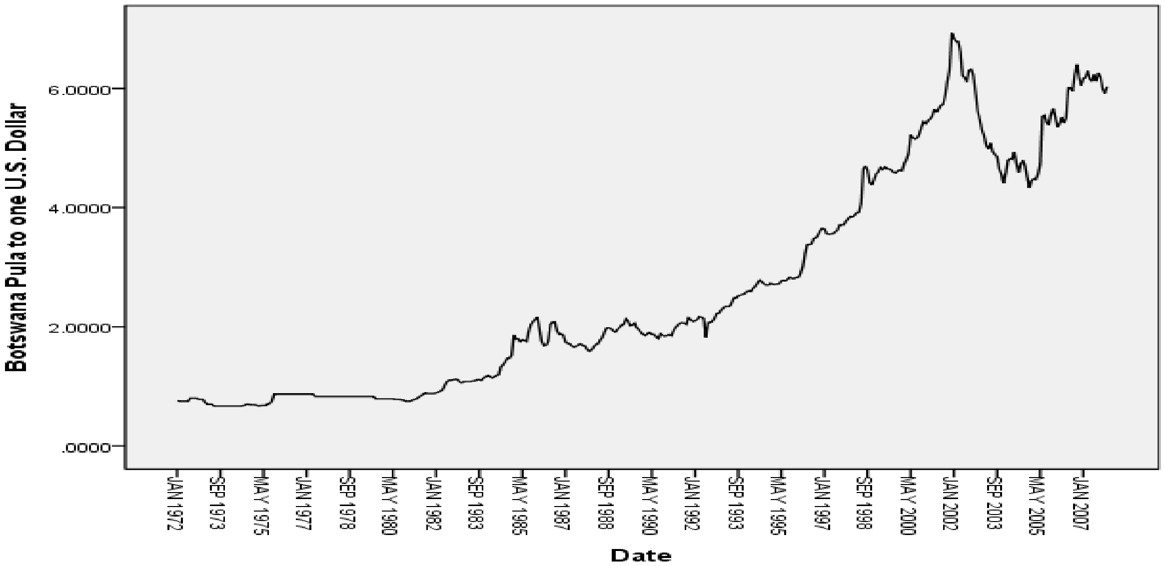




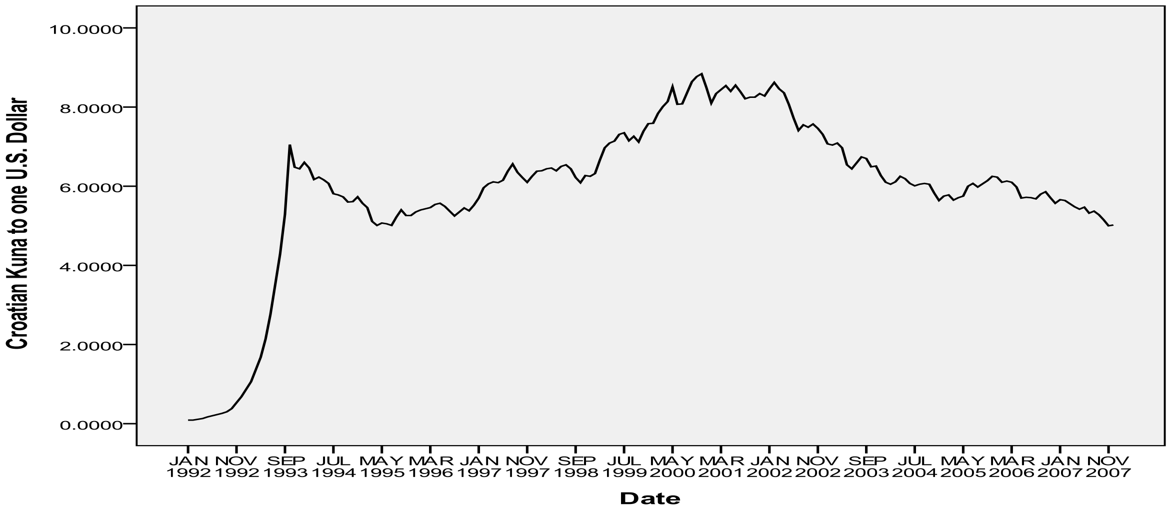
Frontier Countries:

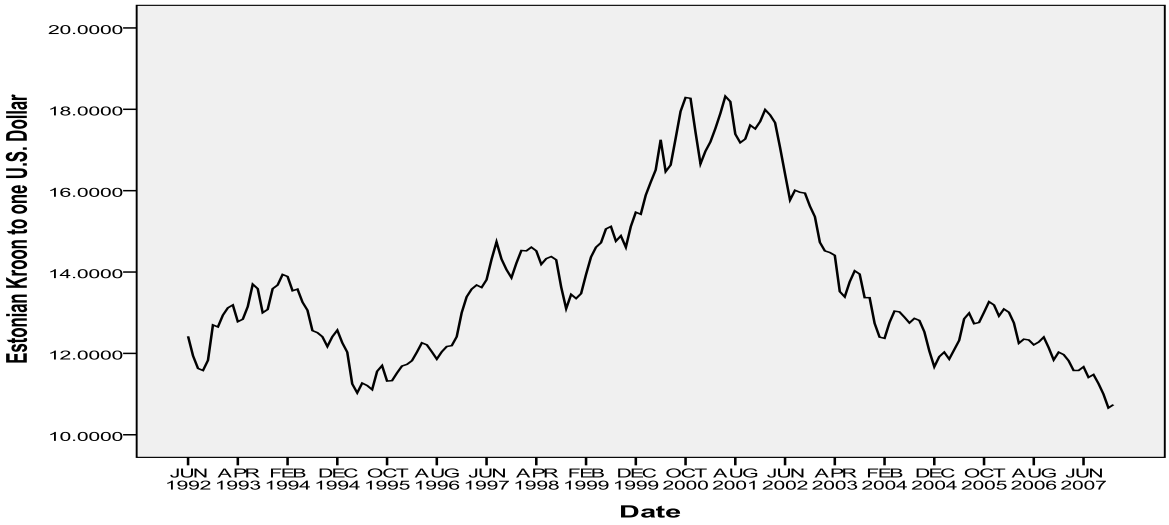


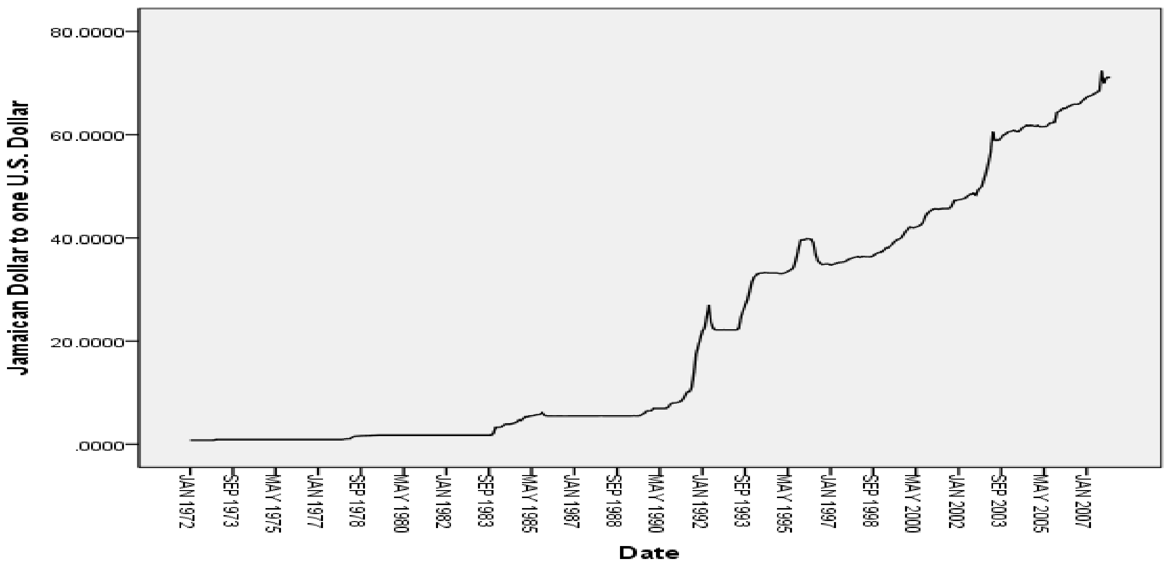

Bhutanese Ngultrum to one U.S Dollar
50.0000
40.0000
30.0000
20.0000
10.0000
0.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

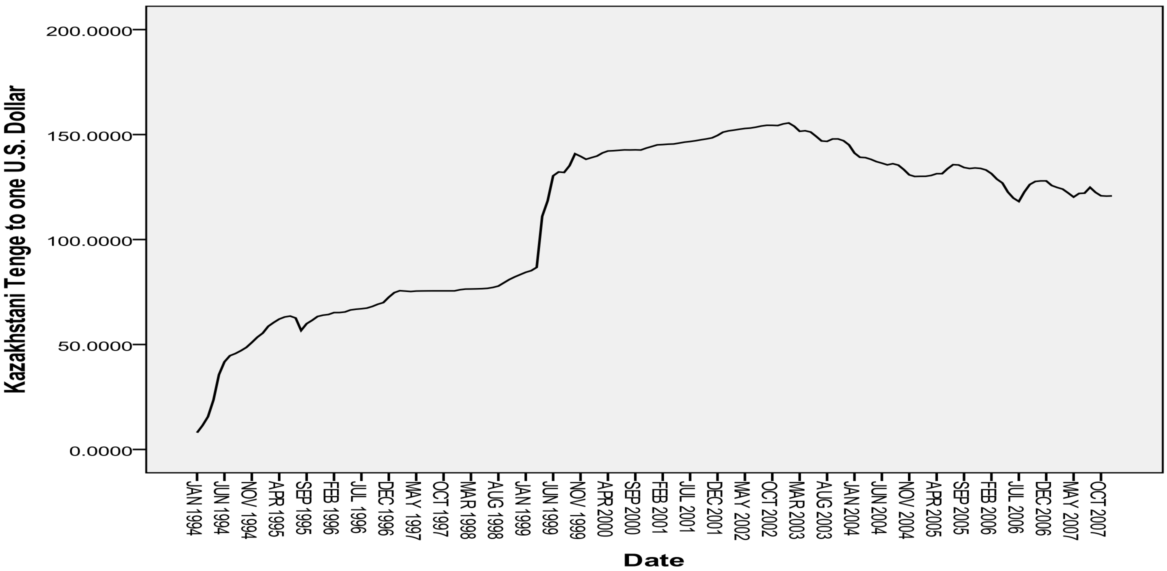

Botswana Pula to one U.S. Dollar
6.0000
4.0000
2.0000
.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

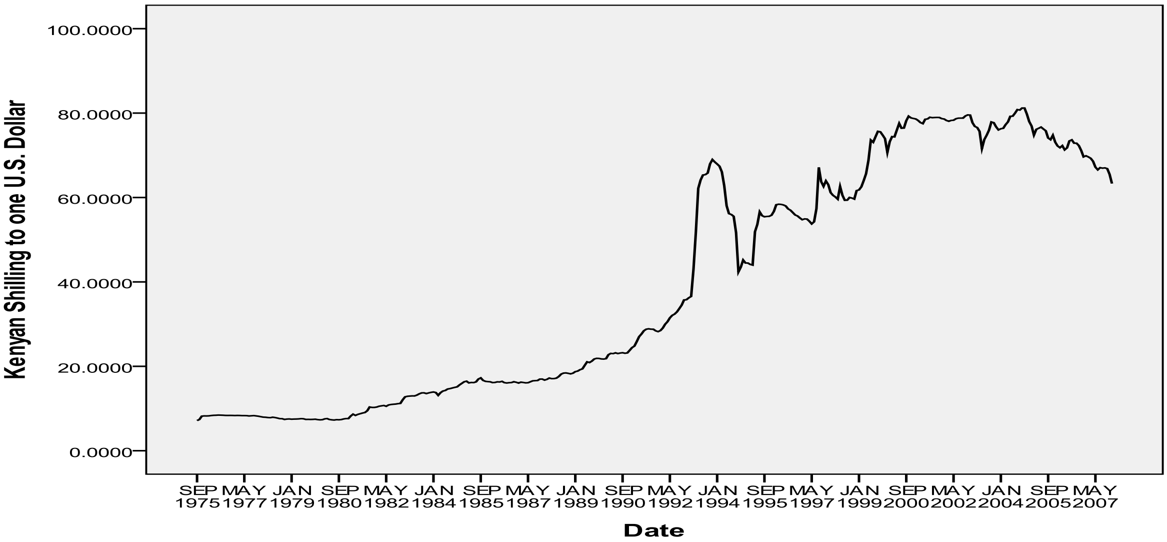

Brunei Dollar to one U.S. Dollar
3.0000
2.5000
2.0000
1.5000
1.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

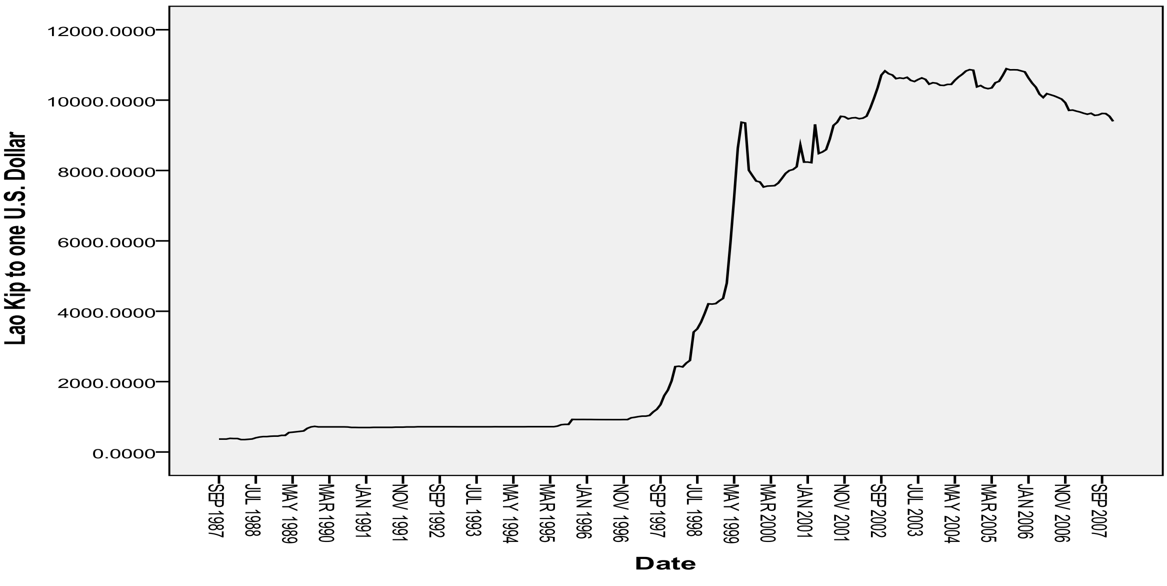

Croatian Kuna to one U.S. Dollar
10.0000
8.0000
6.0000
4.0000
2.0000
0.0000
JAN 1992
NOV 1992
SEP 1993
JUL 1994
MAY 1995
MAR 1996
JAN 1997
NOV 1997
SEP 1998
JUL 1999
MAY 2000
MAR 2001
JAN 2002
NOV 2002
SEP 2003
JUL 2004
MAY 2005
MAR 2006
JAN 2007
NOV 2007
Date

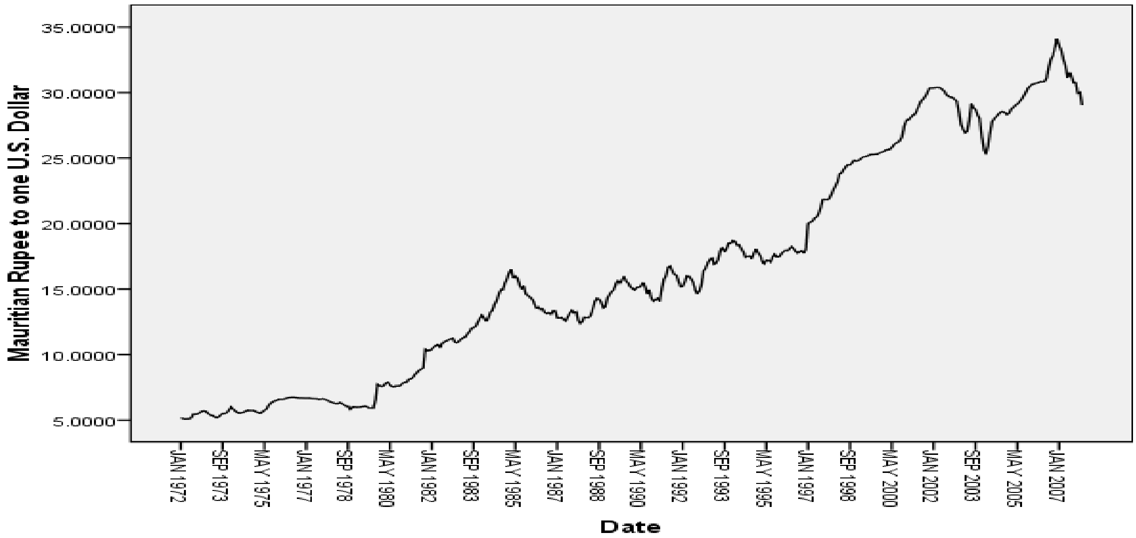

Estonian Kroon to one U.S. Dollar
20.0000
18.0000
16.0000
14.0000
12.0000
10.0000
JUN 1992
APR 1993
FEB 1994
DEC 1994
OCT 1995
AUG 1996
JUN 1997
APR 1998
FEB 1999
DEC 1999
OCT 2000
AUG 2001
JUN 2002
APR 2003
FEB 2004
DEC 2004
OCT 2005
AUG 2006
JUN 2007
Date


Jamaican Dollar to one U.S. Dollar
80.0000
60.0000
40.0000
20.0000
.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

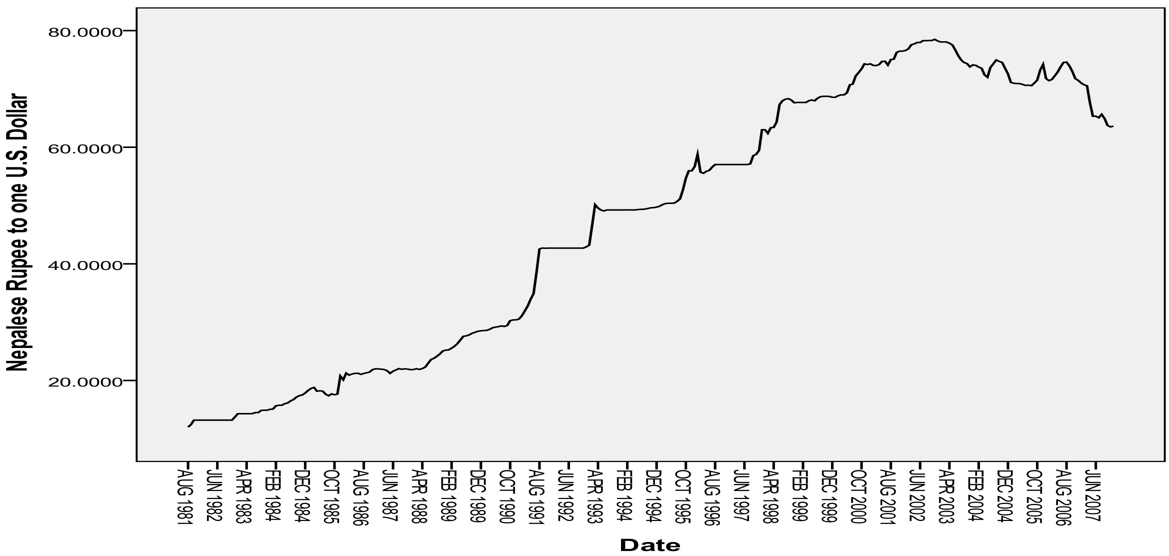

Kazakhstani Tenge to one U.S. Dollar
200.0000
150.0000
100.0000
50.0000
0.0000
JAN 1994
JUN 1994
NOV 1994
APR 1995
SEP 1995
FEB 1996
JUL 1996
DEC 1996
MAY 1997
OCT 1997
MAR 1998
AUG 1998
JAN 1999
JUN 1999
NOV 1999
APR 2000
SEP 2000
FEB 2001
JUL 2001
DEC 2001
MAY 2002
OCT 2002
MAR 2003
AUG 2003
JAN 2004
JUN 2004
NOV 2004
APR 2005
SEP 2005
FEB 2006
JUL 2006
DEC 2006
MAY 2007
OCT 2007
Date

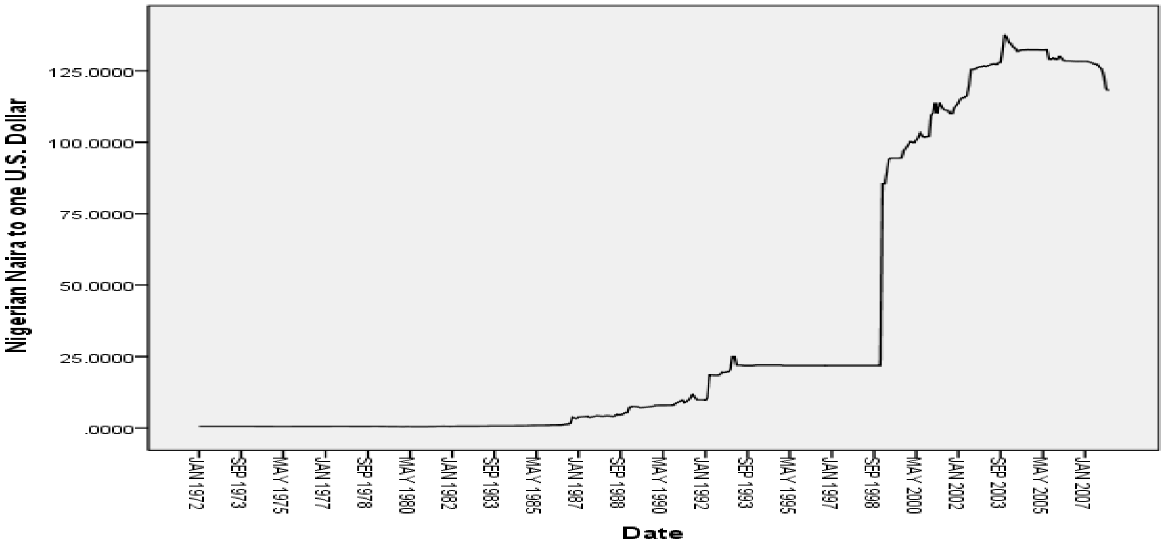

Kenyan Shilling to one U.S. Dollar
100.0000
80.0000
60.0000
40.0000
20.0000
0.0000
SEP 1975
MAY 1977
JAN 1979
SEP 1980
MAY 1982
JAN 1984
SEP 1985
MAY 1987
JAN 1989
SEP 1990
MAY 1992
JAN 1994
SEP 1995
MAY 1997
JAN 1999
SEP 2000
MAY 2002
JAN 2004
SEP 2005
MAY 2007
Date

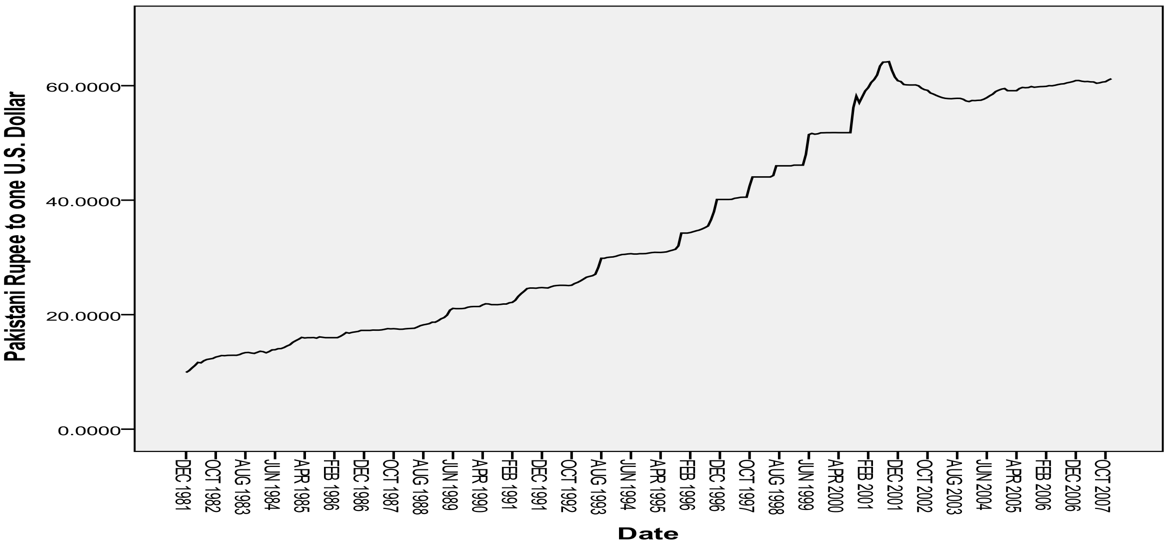

Lao Kip to one U.S. Dollar
12000.0000
10000.0000
8000.0000
6000.0000
4000.0000
2000.0000
0.0000
SEP 1987
JUL 1988
MAY 1989
MAR 1990
JAN 1991
NOV 1991
SEP 1992
JUL 1993
MAY 1994
MAR 1995
JAN 1996
NOV 1996
SEP 1997
JUL 1998
MAY 1999
MAR 2000
JAN 2001
NOV 2001
SEP 2002
JUL 2003
MAY 2004
MAR 2005
JAN 2006
NOV 2006
SEP 2007
Date

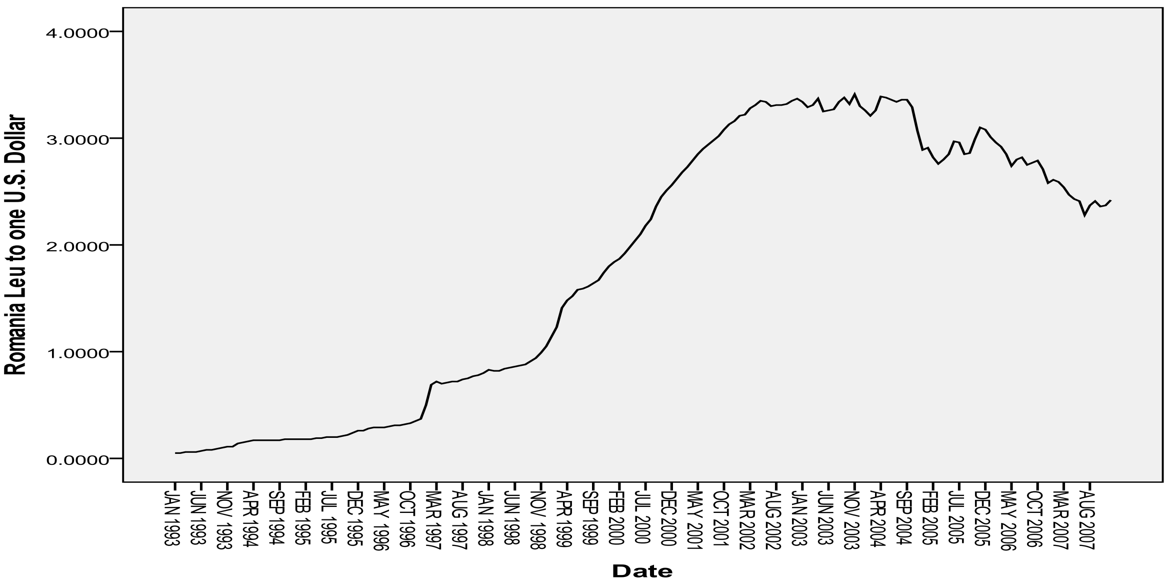

Mauritian Rupee to one U.S. Dollar
35.0000
30.0000
25.0000
20.0000
15.0000
10.0000
5.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

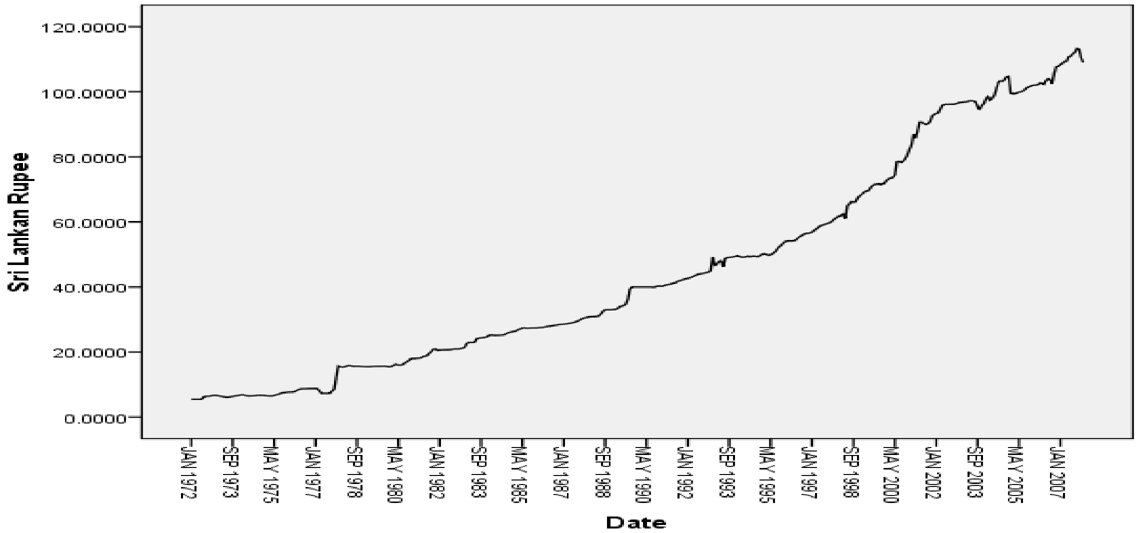

Myanmar Kyat to one U.S. Dollar
9.0000
8.0000
7.0000
6.0000
5.0000
4.0000
NOV 1974
JUL 1976
MAR 1978
NOV 1979
JUL 1981
MAR 1983
NOV 1984
JUL 1986
MAR 1988
NOV 1989
JUL 1991
MAR 1993
NOV 1994
JUL 1996
MAR 1998
NOV 1999
JUL 2001
MAR 2003
NOV 2004
JUL 2006
Date

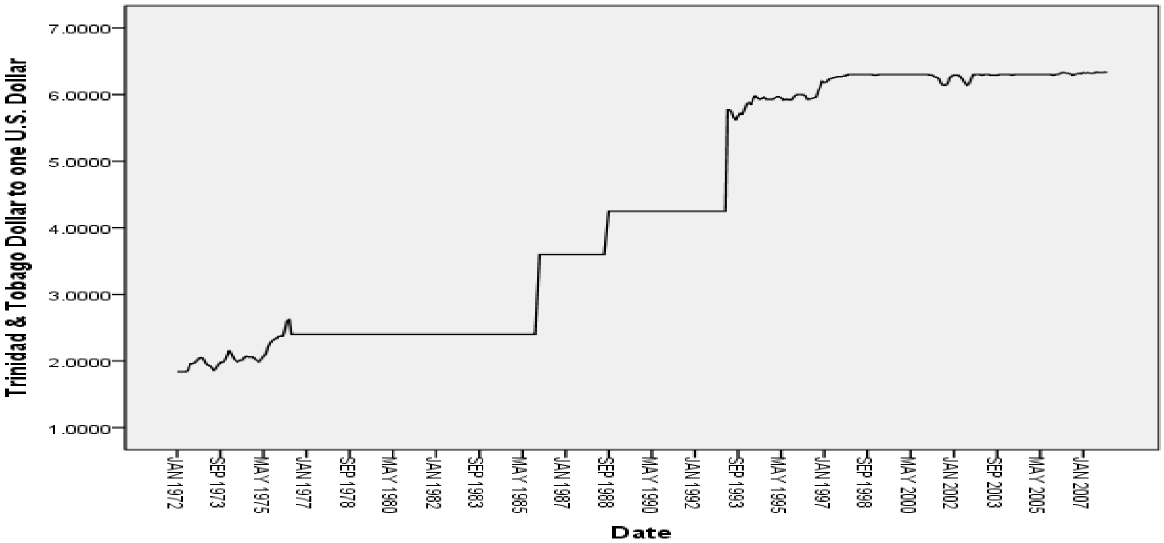

Nepalese Rupee to one U.S. Dollar
80.0000
60.0000
40.0000
20.0000
AUG 1981
JUN 1982
APR 1983
FEB 1984
DEC 1984
OCT 1985
AUG 1986
JUN 1987
APR 1988
FEB 1989
DEC 1989
OCT 1990
AUG 1991
JUN 1992
APR 1993
FEB 1994
DEC 1994
OCT 1995
AUG 1996
JUN 1997
APR 1998
FEB 1999
DEC 1999
OCT 2000
AUG 2001
JUN 2002
APR 2003
FEB 2004
DEC 2004
OCT 2005
AUG 2006
JUN 2007
Date


Nigerian Naira to one U.S. Dollar
125.0000
100.0000
75.0000
50.0000
25.0000
.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date

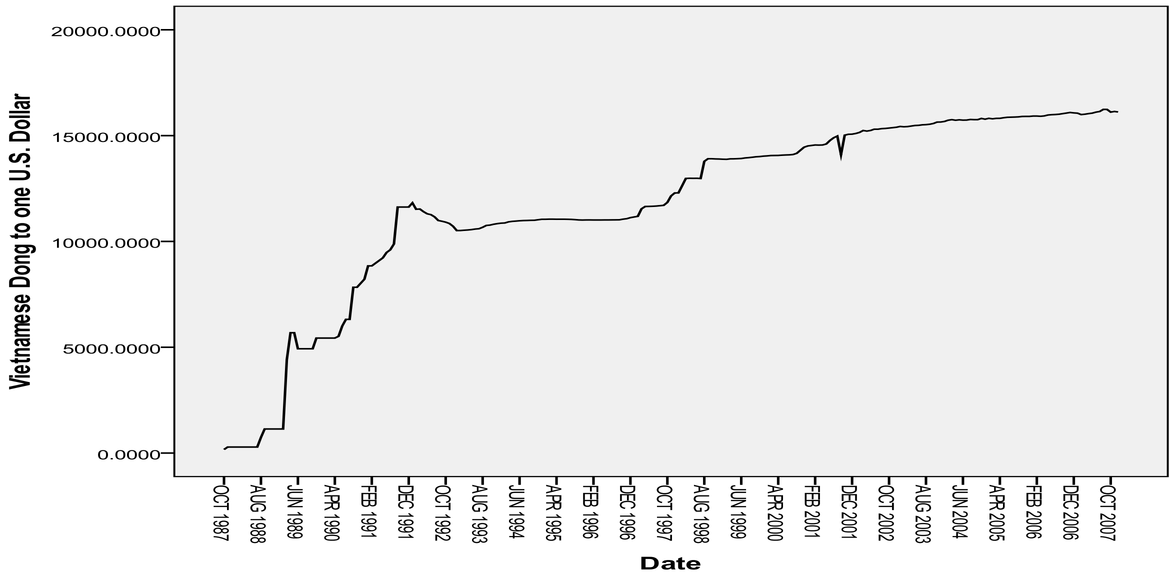

Pakistani Rupee to one U.S. Dollar
60.0000
40.0000
20.0000
0.0000
DEC 1981
OCT 1982
AUG 1983
JUN 1984
APR 1985
FEB 1986
DEC 1986
OCT 1987
AUG 1988
JUN 1989
APR 1990
FEB 1991
DEC 1991
OCT 1992
AUG 1993
JUN 1994
APR 1995
FEB 1996
DEC 1996
OCT 1997
AUG 1998
JUN 1999
APR 2000
FEB 2001
DEC 2001
OCT 2002
AUG 2003
JUN 2004
APR 2005
FEB 2006
DEC 2006
OCT 2007
Date


Romania Leu to one U.S. Dollar
4.0000
3.0000
2.0000
1.0000
0.0000
JAN 1993
JUN 1993
NOV 1993
APR 1994
SEP 1994
FEB 1995
JUL 1995
DEC 1995
MAY 1996
OCT 1996
MAR 1997
AUG 1997
JAN 1998
JUN 1998
NOV 1998
APR 1999
SEP 1999
FEB 2000
JUL 2000
DEC 2000
MAY 2001
OCT 2001
MAR 2002
AUG 2002
JAN 2003
JUN 2003
NOV 2003
APR 2004
SEP 2004
FEB 2005
JUL 2005
DEC 2005
MAY 2006
OCT 2006
MAR 2007
AUG 2007
Date


Sri Lankan Rupee
120.0000
100.0000
80.0000
60.0000
40.0000
20.0000
0.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date


Trinidad & Tobago Dollar to one U.S. Dollar
7.0000
6.0000
5.0000
4.0000
3.0000
2.0000
1.0000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date


Tunisian Dinar to one U.S. Dollar
1.4000
1.2000
1.0000
.8000
.6000
.4000
.2000
JAN 1972
SEP 1973
MAY 1975
JAN 1977
SEP 1978
MAY 1980
JAN 1982
SEP 1983
MAY 1985
JAN 1987
SEP 1988
MAY 1990
JAN 1992
SEP 1993
MAY 1995
JAN 1997
SEP 1998
MAY 2000
JAN 2002
SEP 2003
MAY 2005
JAN 2007
Date



Vietnamese Dong to one U.S. Dollar
20000.0000
15000.0000
10000.0000
5000.0000
0.0000
OCT 1987
AUG 1988
JUN 1989
APR 1990
FEB 1991
DEC 1991
OCT 1992
AUG 1993
JUN 1994
APR 1995
FEB 1996
DEC 1996
OCT 1997
AUG 1998
JUN 1999
APR 2000
FEB 2001
DEC 2001
OCT 2002
AUG 2003
JUN 2004
APR 2005
FEB 2006
DEC 2006
OCT 2007
Date

Appendix 3A: Zivot-Andrews test results: Emerging countries

	Model A	Model B	Model C
Brazil			
t- statistics	-2.598	-4.099	-5.991
Lag	1	1	1
Break	2005M04	2003M01	2002M05
DU (dummy) p-value	0.011	5.98 x10E-5	5.17 x10E-6
Chile			
t- statistics	-3.317	-3.486	-4.730
Lag	12	12	12
Break	2003M09	2003M01	2001M03
DU (dummy) p-value	5.14 x10E-7	0.000	0.000
China			
t- statistics	-3.208	-3.337	-3.782
Lag	1	1	1
Break	1984M05	1995M12	1994M01
DU (dummy) p-value	3.70 x10E-5	3.87 x10E-5	0.045104
Colombia			
t- statistics	-1.960	-2.261	-2.318
Lag	8	8	8
Break	2003M02	1999M08	1999M04
DU (dummy) p-value	3.68 x10E-5	0.000	0.383
Czech Republic			
t- statistics	-3.001	-3.665	-4.180
Lag	1	1	1
Break	1997M02	2000M09	1999M02
DU (dummy) p-value	0.002	0.000	0.004
Hungary			
t- statistics	-3.464	-3.016	-2.889
Lag	11	11	11
Break	1991M01	2000M11	2002M11
DU (dummy) p-value	0.002	0.000	0.142
India			
t- statistics	-3.434	-1.932	-1.942
Lag	1	1	1
Break	1991M02	2004M01	2004M05
DU (dummy) p-value	7.05 x10E-5	0.000	0.602
Indonesia			
t- statistics	-4.920	-2.879	-7.396
Lag	10	10	10
Break	1997M08	2002M02	1997M12
DU (dummy) p-value	1.27 x10E-5	0.108	7.59 x10E-12
Malaysia			
t- statistics	-6.241	-2.759	-6.888
Lag	1	1	1
Break	1997M07	2004M05	1997M08
DU (dummy) p-value	3.57 x10E-8	0.094	7.10 x10E-12
Mexico			
t- statistics	-9.404	-3.165	-9.849
Lag	4	4	4
Break	1994M12	1998M07	1994M12
DU (dummy) p-value	1.40 x10E-18	0.013	1.10 x10E-19

Appendix 3A (Cont.)

	Model A	Model B	Model C
Peru			
t- statistics	-2.714	-3.528	-3.846
Lag	5	5	5
Break	1997M10	1999M11	1998M11
DU (dummy) p-value	0.004	0.002	0.015
Philippines			
t- statistics	-3.786	-2.825	-3.552
Lag	8	8	8
Break	1983M10	2004M02	1982M12
DU (dummy) p-value	0.000	0.002	0.001
Poland			
t- statistics	-1.338	-5.229	-5.304
Lag	2	2	2
Break	2004M05	2000M09	2000M04
DU (dummy) p-value	0.042	1.15 x10E-7	0.022
Russia			
t- statistics	-11.451	-3.857	-11.597
Lag	3	3	3
Break	1998M09	2000M02	1998M09
DU (dummy) p-value	2.85 x10E-22	0.000	3.12 x10E-20
South Africa			
t- statistics	-3.524	-3.299	-4.789
Lag	8	8	8
Break	1997M08	2002M01	2000M02
DU (dummy) p-value	0.035	0.051	0.000
South Korea			
t- statistics	-3.623	-2.549	-5.450
Lag	8	8	8
Break	1996M12	2002M11	1997M11
DU (dummy) p-value	0.002	0.101	5.33 x10E-7
Taiwan			
t- statistics	-4.320	-4.038	-4.344
Lag	1	1	1
Break	1986M08	1987M06	1986M08
DU (dummy) p-value	0.000	0.000	0.011
Thailand			
t- statistics	-8.087	-2.657	-7.93
Lag	8	8	8
Break	1997M07	2004M06	1997M07
DU (dummy) p-value	5.11 x10E-14	0.054	1.85 x10E-14
Turkey			
t- statistics	-3.289	-2.708	-6.177
Lag	6	6	6
Break	2001M02	2002M11	2001M02
DU (dummy) p-value	0.001	0.003	9.36 x10E-9

Asymptotic Critical Values for the Zivot and Andrews Unit Root Tests:

Test	10%	5%	1%
A	-4.58	-4.80	-5.34 (intercept)
B	-4.11	-4.42	-4.93 (trend)
C	-4.82	-5.08	-5.57 (both)

Appendix 3B: Zivot-Andrews test results: Frontier countries

	Model A	Model B	Model C
Bangladesh			
t- statistics	-3.542	-3.800	-3.800
Lag	1	1	1
Break	2000M08	1996M07	1994M02
DU (dummy) p-value	0.005	0.051	0.051
Bhutan			
t- statistics	-3.434	-1.932	-1.941874
Lag	1	1	1
Break	1991M02	2004M01	2004M05
DU (dummy) p-value	7.05 x10E-5	0.000	0.601
Botswana			
t- statistics	-3.625	-3.234	-3.489
Lag	1	1	1
Break	2002M11	2001M05	1996M02
DU (dummy) p-value	0.004	0.059	0.034
Brunei			
t- statistics	-4.505	-3.051	-3.877
Lag	2	2	2
Break	1997M07	1993M11	1989M12
DU (dummy) p-value	0.000	0.104	0.007
Croatia			
t- statistics	-5.800	-5.645	-5.721
Lag	3	3	3
Break	1998M11	2001M04	2002M03
DU (dummy) p-value	0.040	0.134	0.299
Estonia			
t- statistics	-2.714	-2.724	-3.574
Lag	2	2	2
Break	2002M05	2000M10	1999M11
DU (dummy) p-value	0.001	0.008	0.009
Jamaica			
t- statistics	-3.446	-3.280	-5.390
Lag	4	4	4
Break	1990M09	1995M09	1991M08
DU (dummy) p-value	0.003	0.006	6.57x10E-6
Kazakhstan			
t- statistics	-6.702	-3.630	-10.357
Lag	2	2	2
Break	1999M04	2001M11	1999M04
DU (dummy) p-value	2.72 x10E-10	0.001	1.21 x10E-18
Kenya			
t- statistics	-2.581	-3.521	-4.626
Lag	7	7	7
Break	2002M12	1999M07	1993M03
DU (dummy) p-value	0.006	0.000	0.000
Lao PDR			
t- statistics	-5.545	-1.758	-5.149
Lag	2	2	2
Break	1997M07	2002M08	1997M07
DU (dummy) p-value	9.73 x10E-10	0.040	3.12 x10E-09

Appendix 3B (Cont.)

	Model A	Model B	Model C
Mauritius			
t- statistics	-3.177	-2.731	-3.233
Lag	1	1	1
Break	1996M12	2002M08	1979M10
DU (dummy) p-value	0.038	0.115	0.009
Myanmar			
t- statistics	-5.142	-4.154	-5.533
Lag	1	1	1
Break	1985M10	1995M04	1985M10
DU (dummy) p-value	0.000	0.237	1.23x10E-05
Nepal			
t- statistics	-1.519	-3.337	-3.345
Lag	1	1	1
Break	2003M04	2000M12	2000M06
DU (dummy) p-value	0.008	5.60x10E-05	0.3757
Nigeria			
t- statistics	-14.398	-2.251	-13.625
Lag	1	1	1
Break	1999M01	1988M02	1999M01
DU (dummy) p-value	5.25x10E-39	0.099	1.13x10E-40
Pakistan			
t- statistics	-3.413	-2.166	-3.420
Lag	3	3	3
Break	1995M10	2001M05	1998M06
DU (dummy) p-value	0.002	0.044	0.002
Romania			
t- statistics	-3.009	-3.757	-3.628
Lag	2	2	2
Break	1996M11	2001M02	2000M09
DU (dummy) p-value	0.000	0.000	0.339
Sri Lanka			
t- statistics	-4.525	-2.909	-3.325
Lag	1	1	1
Break	1998M06	1991M10	1998M06
DU (dummy) p-value	1.09x10E-5	0.013	9.81x10E-6
Trinidad & Tobago			
t- statistics	-3.549	-2.608	-5.864
Lag	1	1	1
Break	1993M04	1998M05	1993M04
DU (dummy) p-value	0.002	0.032	3.37x10E-8
Tunisia			
t- statistics	-3.275	-3.282	-4.136
Lag	2	2	2
Break	2002M11	2001M11	1999M11
DU (dummy) p-value	0.005	0.008	0.003
Vietnam			
t- statistics	-6.413	-1.919	-7.843
Lag	1	1	1
Break	1989M03	2003M10	1989M03
DU (dummy) p-value	1.35 x10E-11	0.151	4.22 x10E-16

Asymptotic Critical Values for the Zivot and Andrews Unit Root Tests:

Test	10%	5%	1%
A	-4.58	-4.80	-5.34 (intercept)
B	-4.11	-4.42	-4.93 (trend)
C	-4.82	-5.08	-5.57 (both)

Appendix 3C: Mean and variance equations for sample countries after incorporate the level and trend breaks suggested by Model C of LS (2003) unit root test.

Appendix 3C1: Mean equations (ARIMA)

Australia – Advanced market	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.333
z statistic	6.212
Significance	0.000
Brazil – Emerging market	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.441
z statistics	5.249
Significance	0.000
Myanmar –Fontier market	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.263
z statistics	4.211
Significance	0.000

Appendix 3C2: Conditional variance equations – Sample countries

	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$	$\boldsymbol{D1}$	$\boldsymbol{D2}*$	$\boldsymbol{D3}*$	$\boldsymbol{D4}*$
Australia							
EGARCH(1,1)	-2.213	0.500	0.763	0.979	0.001		0.001
z statistics	-2.989	2.989	7.415	2.746	0.409		1.225
Significance	0.008	0.003	0.000	0.000	0.683		0.221
	LL =951.023	**SBC= -4.315**					
Brazil							
EGARCH(1,0)	-9.746	0.638		3.767	0.038		-0.017
z statistics	-26.218	2.909		4.737	1.680		-1.590
Significance	0.000	0.004		0.000	0.093		0.112
	LL= 225.948	**SBC= -2.952**					
Myanmar							
EGARCH(1,1)	0.006	0.038	0.556		9.41×10^{-08}	-2.81×10^{-07}	$\cdot 1.12 \times 10^{-05}$
z statistics	6.286	2.240	10.409		0.009	-0.024	-1.670
Significance	0.000	0.025	0.000		0.993	0.981	0.095
	LL= 382.513	**SBC= -1.822**					

D1- level break, D2- trend break 1, D3- trend break 2 and D4 - time trend.
*Insignificant at 5% level

Appendix 4: Mean equation (ARIMA)

Advanced Countries:

Australia (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.331
z statistic	6.212
Significance	0.000

Canada	**MA(1)**	**MA(11)**
ARIMA(0,1,11)(0,0,0)^{12}	0.170	0.113
z statistics	3.345	2.459
Significance	0.001	0.014

Denmark	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.345
z statistics	7.239
Significance	0.000

Euro area	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.279
z statistics	2.888
Significance	0.004

Japan	**AR(12)**	**MA(1)**	**MA(12)**
ARIMA(12,1,12)(0,0,0)^{12}	-0.366	0.289	0.444
z statistics	-3.849	6.011	5.395
Significance	0.000	0.000	0.000

Norway	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.345
z statistics	6.608
Significance	0.000

Singapore	**Constant**	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	-0.008	0.268
z statistics	-7.612	5.501
Significance	0.000	0.000

Sweden	**AR(1)**	**AR(2)**
ARIMA(2,1,0)(0,0,0)^{12}	0.394	-0.160
z statistics	7.372	-3.683
Significance	0.000	0.000

Switzerland	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.379
z statistics	6.728
Significance	0.000

UK	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.273
z statistics	4.908
Significance	0.000

Appendix 4 (Cont.)

Emerging Countries:

Brazil (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.551
z statistics	7.075
Significance	0.000

Chile (log)	**AR(1)**	**AR(2)**	**MA(1)**	**MA(12)**
ARIMA(2,1,12)(0,0,0)^{12}	1.444	-0.447	-0.965	0.080
z statistics	19.942	-6.426	-36.922	3.778
Significance	0.000	0.000	0.000	0.000

China (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.485
z statistics	7.263
Significance	0.000

Colombia (log)	**AR(1)**	**MA(1)**	**MA(2)**
ARIMA(1,1,2) (0,0,0)^{12}	1.004	0.307	-0.310
z statistics	125.02	2.640	-5.328
Significance	0.000	0.008	0.000

Czech Republic (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.350
z statistics	4.582
Significance	0.000

Hungary (log)	**AR(1)**	**MA(1)**	**MA(2)**
ARIMA(1,1,2)(0,0,0)^{12}	0.988	-0.508	-0.348
z statistics	115.769	-22.910	-15.089
Significance	0.000	0.000	0.000

India (log)	**Constant**	**AR(1)**
ARIMA(1,1,0) (0,0,0)^{12}	0.044	0.335
z statistics	3.161	2.263
Significance	0.002	0.024

Indonesia (log)	**Constant**	**MA(1)**
ARIMA(0,0,1)(0,0,0)^{12}	10.978	0.227
z statistics	8.764	4.082
Significance	0.000	0.000

Malaysia (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.148
z statistics	2.653
Significance	0.001

Mexico (log)	**AR(1)**
ARIMA(1,1,0)(0,0,0)^{12}	0.523
z statistics	11.444
Significance	0.000

Peru (log)	**AR(1)**	**MA(1)**	**MA(2)**
ARIMA(1,1,2)(0,0,0)^{12}	0.975	-0.607	-0.378
z statistics	285.964	-8.240	-5.281
Significance	0.000	0.000	0.000

Appendix 4 (Cont.)

Philippines (log)	**MA(1)**	
ARIMA(0,1,1)(0,0,0) 12	0.420	
z statistics	7.410	
Significance	0.000	
Poland (log)	**AR(1)**	
ARIMA(1,1,0)(0,0,0) 12	0.407	
z statistics	5.360	
Significance	0.000	
Russia	**AR(1)**	
ARIMA(1,1,0)(0,0,0) 12	0.735	
z statistics	16.979	
Significance	0.000	
South Africa (log)	**MA(1)**	**MA(8)**
ARIMA(0,1,8)(0,0,0) 12	0.365	0.206
z statistics	6.336	4.194
Significance	0.000	0.000
South Korea (Log)	**MA(1)**	**MA(9)**
ARIMA(0,1,9)(0,0,0) 12	0.584	0.115
z statistics	233.638	13.824
Significance	0.000	0.000
Taiwan (log)	**AR(1)**	
ARIMA(1,1,0)(0,0,0) 12	0.402	
z statistics	6.767	
Significance	0.000	
Thailand (log)	**MA(1)**	
ARIMA(0,1,1)(0,0,0) 12	0.367	
z statistics	4.101	
Significance	0.000	
Turkey (log)	**MA(1)**	
ARIMA(0,1,1)(0,0,0) 12	0.429	
z statistics	9.896	
Significance	0.000	
Frontier Countries:		
Bangladesh	**Constant**	**MA(1)**
ARIMA(0,1,1)(0,0,0) 12	0.109	0.164
z statistics	3.576	2.610
Significance	0.000	0.000
Bhutan (log)	**Constant**	**AR(1)**
ARIMA(1,1,0) (0,0,0) 12	0.033	0.318
z statistics	3.015	1.967
Significance	0.002	0.042
Botswana (log)	**AR(1)**	
ARIMA(1,1,0) (0,0,0) 12	0.373	
z statistics	6.236	
Significance	0.000	

Appendix 4 (Cont.)

Brunei	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.287
z statistics	6.157
Significance	0.000

Croatia (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.336
z statistics	3.622
Significance	0.000

Estonia	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.380
z statistics	4.627
Significance	0.000

Jamaica (log)	**Constant**	**AR(1)**
ARIMA(1,1,0)(0,0,0)^{12}	0.042	0.465
z statistics	21.927	21.583
Significance	0.000	0.000

Kazakhstan (log)	**Constant**	**MA(1)**	**MA(2)**
ARIMA(0,1,2)(0,0,0)^{12}	0.321	0.792	0.284
z statistics	6.463	24.112	13.175
Significance	0.000	0.000	0.000

Kenya (log)	**MA(1)**
ARIMA(0,1,1) (0,0,0)^{12}	0.410
z statistics	6.398
Significance	0.000

Lao PDR (log)	**AR(1)**	**AR(2)**
ARIMA(2,1,0)(0,0,0)^{12}	0.546	0.308
z statistics	4.620	3.128
Significance	0.000	0.001

Mauritius (Square root)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.402
z statistics	6.084
Significance	0.000

Myanmar (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.188
z statistics	4.549
Significance	0.000

Nepal (log)	**AR(1)**
ARIMA(1,1,0)(0,0,0)^{12}	0.257
z statistics	6.341
Significance	0.000

Nigeria (log)	**AR(1)**	**MA(1)**
ARIMA(1,1,1)(0,0,0)^{12}	0.974	-0.971
z statistics	81.274	-1422.715
Significance	0.000	0.000

Appendix 4 (Cont.)

Pakistan (log)	**Constant**	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.153	0.276
z statistics	3.808	2.465
Significance	0.000	0.014

Romania (log)	**AR(1)**	**AR(2)**
ARIMA(2,1,0)(0,0,0)^{12}	0.455	0.259
z statistics	4.034	2.433
Significance	0.000	0.015

Sri Lanka (log)	**Constant**	**AR(1)**
ARIMA(1,1,0)(0,0,0)^{12}	0.120	0.500
z statistics	11.826	12.232
Significance	0.000	0.000

Trinidad & Tobago	**AR(1)**	**MA(1)**
ARIMA(1,1,1)(0,0,0)^{12}	-0.974	0.951
z statistics	-255.717	118.250
Significance	0.000	0.000

Tunisia (log)	**MA(1)**
ARIMA(0,1,1)(0,0,0)^{12}	0.302
z statistics	6.021
Significance	0.000

Vietnam	**Constant**	**AR(1)**
ARIMA(1,1,0)(0,0,0)^{12}	22.822	0.109
z statistics	8.346	2.579
Significance	0.000	0.010

Appendix 5: Conditional variance equations - Advanced countries

	ω	α_1	α_2	β_1	γ_1	$D1$	$D2$
Australia							
EGARCH(1,1)	-1.824	0.460		0.798	-0.137	1.398	0.240
z statistics	-2.931	4.699		10.062	-1.726	2.397	1.962
Significance	0.003	0.000		0.000	0.044	0.016	0.048
	LL = 952.703	**SBC= -4.322**	**Q(12)=14.035 (0.231)**	**Q_{SQ}(12)=2.888 (0.992)**			
Canada							
GARCH(1,1)	1.50 x10^{-06}	0.022		0.976			
z statistics	1.484	1.979		78.091			
Significance	0.137	0.048		0.000			
	LL= 1211.138	**SBC= -5.549**	**Q(12)=12.304 (0.265)**	**Q_{SQ}(12)=6.708 (0.753)**			
Denmark							
GARCH (1,1)	0.001	0.075		0.883		0.039	-0.019
z statistics	0.953	2.408		13.317		1.980	-2.161
Significance	0.341	0.016		0.000		0.048	0.031
	LL= 173.206	**SBC= -0.719**	**Q(12)=9.516 (0.574)**	**Q_{SQ}(12)=2.795 (0.993)**			
Euro area							
EGARCH(0,1)	-13.323			-0.760		-1.591	
z statistics	-4.940			-2.155		-3.416	
Significance	0000			0.031		0.001	
	LL= 262.949	**SBC= -4.740**	**Q(12)=10.417 (0.493)**	**Q_{SQ}(12)=11.258 (0.422)**			
Japan							
GARCH(1,1)	6.043	0.351		0.361	-0.261	3.304	8.274
z statistics	3.383	2.809		2.476	-2.035	3.235	3.449
Significance	0.001	0.005		0.013	0.013	0.001	0.001
	LL= -1186.68	**SBC= 5.794**	**Q(12)=12.409 (0.191)**	**Q_{SQ}(12)=15.488 (0.078)**			
Norway							
EGARCH(1,1)	-0.936	0.226		0.804		0.257	-0.310
z statistics	-2.847	2.524		11.773		1.980	-2.023
Significance	0.004	0.011		0.000		0.046	0.044
	LL= 221.065	**SBC= -0.941**	**Q(12)=4.327 (0.959)**	**Q_{SQ}(12)=2.983 (0.991)**			
Singapore							
GARCH (1,1)	5.91x10^{-05}	0.369		0.611		0.328	-0.381
z statistics	4.371	5.754		13.128		17.285	-19.364
Significance	0.000	0.000		0.000		0.000	0.000
	LL= 1005.46	**SBC= -4.567**	**Q(12)=6.928 (0.805)**	**Q_{SQ}(12)=9.342 (0.590)**			
Sweden							
EGARCH(1,1)	-0.469	0.228		0.919			
z statistics	-4.167	3.236		50.564			
Significance	0.000	0.001		0.000			
	LL= 206.338	**SBC= -0.891**	**Q(12)=14.268 (0.161)**	**Q_{SQ}(12)=3.780 (0.957)**			

Appendix 5 (Cont.)

	ω	α_1	α_2	β_1	γ_1	$D1$	$D2$
Switzerland							
EGARCH (1,1)	-0.916	0.326		0.891		0.118	
z statistics	-5.213	4.988		36.769		2.009	
Significance	0.000	0.000		0.000		0.044	
	LL=685.544	**SBC= -3.111**	**Q(12)=12.050 (0.360)**	**Q_{SQ}(12)=12.804 (0.306)**			
UK							
GARCH(1,1)	$1.55x10^{-05}$	0.121		0.805			
z statistics	2.054	3.792		14.904			
Significance	0.040	0.000		0.000			
	LL= 1240.410	**SBC= -5.699**	**Q(12)=7.823 (0.729)**	**Q $_{SQ}$(12)=4.749 (0.943)**			

The significance levels associated with Q(12) and QSQ(12) are shown in brackets. D1 and D2 are dummy one and two respectively.

Appendix 6: Conditional variance equations - Emerging countries

	ω	α_1	α_2	β_1	β_2	γ_1	$D1$	$D2$
Brazil								
EGARCH (1,1)	-2.903	0.992		0.588			0.847	0.936
z statistics	-2.886	4.239		3.161			2.340	2.410
Significance	0.004	0.000		0.002			0.019	0.014
	LL= 180.304	**SBC= -2.313**	**Q(12)=7.616**	**Q_{SQ}(12)=0.403**				
			(0.747)	**(1.000)**				
Chile								
EGARCH (1,1)	-0.019	0.127		0.984				
z statistics	-0.582	2.478		266.98				
Significance	-0.560	0.013		0.000				
	LL=-1108.895	**SBC= 5.538**	**Q(12)=7.352**	**Q_{SQ}(12)=7.582**				
			(0.499)	**(0.542)**				
China								
EGARCH (1,1)	-4.393	1.190		0.521			2.092	5.299
z statistics	-4.757	7.589		4.906			3.562	3.528
Significance	0.000	0.000		0.000			0.000	0.000
	LL= 817.337	**SBC= -3.787**	**Q(12)=3.335**	**Q $_{SQ}$(12)=5.912**				
			(0.986)	**(0.879)**				
Colombia								
EGARCH (1,1)	-0.523	0.877		1.000			-0.301	
z statistics	-6.273	4.808		228.187			-1.979	
Significance	0.000	0.000		0.000			0.047	
	LL= -1012.16	**SBC= 4.806**	**Q(12)=19.877**	**Q $_{SQ}$(12)=10.158**				
			(0.091)	**(0.338)**				
Czech Republic								
GARCH(1,1)	0.012	0.124		0.861				
z statistics	1.374	2.251		18.894				
Significance	0.169	0.024		0.000				
	LL=-186.393	**SBC= 2.199**	**Q(12)=3.278**	**Q $_{SQ}$(12)=15.733**				
			(0.986)	**(0.151)**				
Hungary								
EGARCH (1,0)	0.802	0.860				-0.169	2.502	2.005
z statistics	14.848	9.401				-4.378	6.826	4.316
Significance	0.000	0.000				0.000	0.000	0.000
	LL= -953.624	**SBC= 4.316**	**Q(12)=9.178**	**Q_{SQ}(12)=5.667**				
			(0.450)	**(0.782)**				
India								
EGARCH (1,1)	-0.511	0.608		0.954			0.970	-0.721
z statistics	-3.542	4.752		27.844			3.377	-5.702
Significance	0.000	0.000		0.000			0.000	0.000
	LL= -53.905	**SBC= 0.349**	**Q(12)=4.125**	**Q $_{SQ}$(12)=1.752**				
			(0.260)	**(0.781)**				
Indonesia								
EGARCH (1,1)	1.125	1.401		0.777		-0.361	2.094	0.837
z statistics	5.423	12.554		33.646		-3.615	3.803	2.965
Significance	0.000	0.000		0.0000		0.000	0.000	0.003
	LL= -1993.64	**SBC= 11.559**	**Q(12)=8.312**	**Q $_{SQ}$(12)=0.398**				
			(0.685)	**(1.000)**				

Appendix 6 (Cont.)

	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{D1}$	$\boldsymbol{D2}$
Malaysia								
EGARCH (1,1)	-1.316	1.038		0.900		-0.365	-0.379	
z statistics	-27.869	21.133		248.82		-8.948	-3.959	
Significance	0.000	0.000		0.000		0.000	0.000	
	LL= 887.796	**SBC= -4.973**	**Q(12)=15.227**	**Q_{SQ}(12)=1.379**				
			(0.173)	**(1.000)**				
Mexico								
EGARCH (1,1)	-0.756	0.650		0.931			0.747	0.083
z statistics	-8.159	9.103		6.821			6.821	2.106
Significance	0.000	0.000		0.000			0.000	0.035
	LL= 178.522	**SBC= -1.296**	**Q(12)=16.060**	**Q_{SQ}(12)=8.132**				
			(0.139)	**(0.701)**				
Peru								
EGARCH (1,1)	-2.954	1.046		0.684				
z statistics	-5.234	7.311		8.851				
Significance	0.000	0.000		0.000				
	LL= 432.015	**SBC= -3.887**	**Q(12)=12.750**	**Q_{SQ}(12)=6.027**				
			(0.174)	**(0.737)**				
Philippines								
EGARCH(1,1)	-0.190	0.254		0.983		-0.160	-0.177	
z statistics	-35.441	17.518		965.83		-10.79	-3.656	
Significance	0.000	0.000		0.000		0.000	0.000	
	LL= -86.511	**SBC= 0.486**	**Q(12)=2.342**	**Q_{SQ}(12)=3.094**				
			(0.126)	**(0.989)**				
Poland								
EGARCH (1,2)	-0.932	0.638		0.522	0.387			
z statistics	-6.917	11.288		4.535	3.693			
Significance	0.000	0.000		0.000	0.000			
	LL= 322.958	**SBC=-2.599**	**Q(12)=7.716**	**Q_{SQ}(12)=19.747**				
			(0.739)	**(0.050)**				
Russia								
EGARCH (1,1)	-1.836	1.428		0.803			2.878	0.710
z statistics	-9.565	7.402		26.939			11.127	3.098
Significance	0.000	0.000		0.000			0.000	0.002
	LL= 34.794	**SBC= -0.281**	**Q(12)=14.720**	**Q_{SQ}(12)=5.174**				
			(0.196)	**(0.922)**				
South Africa								
GARCH (1,1)	1.64×10^{-5}	0.226		0.731			0.010	-0.067
z statistics	1.346	5.494		34.814			4.693	-2.089
Significance	0.178	0.000		0.000			0.000	0.037
	LL= 324.079	**SBC= -1.749**	**Q(12)=12.403**	**Q_{SQ}(12)=5.936**				
			(0.259)	**(0.821)**				
South Korea								
EGARCH(1,0)	4.488	1.138					0.843	
z statistics	149.943	15.261					3.551	
Significance	0.000	0.000					0.000	
	LL=-1360.73	**SBC= 8.186**	**Q(12)=17.359**	**Q_{SQ}(12)=17.992**				
			(0.067)	**(0.055)**				

Appendix 6 (Cont.)

	ω	α_1	α_2	β_1	β_2	γ_1	$D1$	$D2$
Taiwan								
GARCH(1,1)	0.031	0.204		0.506			0.187	
z statistics	2.936	2.964		3.970			1.655	
Significance	0.003	0.003		0.000			0.008	
	LL= -88.879	**SBC= 0.720**	**Q(12)=10.037 (0.527)**	**Q_{SQ}(12)=5.810 (0.886)**				
Thailand								
GARCH (1,1)	0.221	0.109		0.308			6.002	-0.250
z statistics	4.880	1.970		2.203			2.343	-28.305
Significance	0.000	0.048		0.027			0.019	0.000
	LL= -236.470	**SBC=1.822**	**Q(12)=6.339 (0.175)**	**Q_{SQ}(12)=12.113 (0.355)**				
Turkey								
EGARCH (1,1)	0.134	-0.048		1.017		-0.216	-0.083	
z statistics	822.709	-368.92		1105.34		-12.69	-9.341	
Significance	0.000	0.000		0.000		0.000	0.000	
	LL=395.944	**SBC= -4.557**	**Q(12)=9.502 (0.576)**	**Q_{SQ}(12)=9.904 (0.470)**				

The significance levels associated with Q(12) and QSQ(12) are shown in brackets. D1 and D2 are dummy one and two respectively.

Appendix 7: Conditional variance equations – Frontier countries

	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{D1}$	$\boldsymbol{D2}$
Bangladesh								
EGARCH (1,1)	-0.181	0.111		0.921			0.354	-0.429
z statistics	-3.389	4.261		37.843			4.061	-9.605
Significance	0.000	0.000		0.000			0.000	0.000
	LL= -246.919	**SBC= 1.244**	**Q(12)=8.765**	**Q_{SQ}(12)=0.516**				
			(0.646)	**(1.000)**				
Bhutan								
EGARCH (1,1)	-0.656	0.667		0.916			1.046	-0.866
z statistics	-3.032	5.066		16.957			2.592	-4.823
Significance	0.002	0.000		0.000			0.009	0.000
	LL=-40.931	**SBC= -0.289**	**Q(12)= 3.669**	**Q_{SQ}(12)= 4.616**				
			(0.979)	**(0.948)**				
Botswana								
EGARCH (1,1)	-0.764	0.532		0.922			0.086	0.452
z statistics	-16.086	17.237		166.601			1.990	2.178
Significance	0.000	0.000		0.000			0.046	0.029
	LL=614.923	**SBC= -2.775**	**Q(12)=5.391**	**Q_{SQ}(12)=9.108**				
			(0.911)	**(0.612)**				
Brunei								
GARCH (1,1)	0.001	0.109		0.705			0.001	-0.001
z statistics	5.109	3.189		11.743			16.681	-19.302
Significance	0.000	0.001		0.000			0.000	0.000
	LL= 994.008	**SBC= -4.548**	**Q(12)=6.898**	**Q_{SQ}(12)=11.422**				
			(0.807)	**(0.409)**				
Croatia								
GARCH (1,1)	0.004	0.387		0.531				
z statistics	2.176	3.423		5.353				
Significance	0.000	0.000		0.000				
	LL= 83.251	**SBC= -0.762**	**Q(12)=19.684**	**Q_{SQ}(12)=12.944**				
			(0.051)	**(0.297)**				
Estonia								
EGARCH (1,1)	0.031	-0.026		1.008		-0.065	0.113	
z statistics	68.734	-23.932		36.371		-4.737	3.719	
Significance	0.000	0.000		0.000		0.000	0.000	
	LL= -39.091	**SBC= 0.561**	**Q(12)=6.958**	**Q_{SQ}(12)=8.944**				
			(0.802)	**(0.627)**				
Jamaica								
EGARCH (0,1)	-0.183			0.946		-0.305	0.095	
z statistics	-21.679			375.718		-24.46	4.266	
Significance	0.000			0.000		0.000	0.000	
	LL= 128.471	**SBC= -0.060**	**Q(12)=3.682**	**Q_{SQ}(12)= 6.120**				
			(0.055)	**(0.865)**				
Kazakhstan								
EGARCH (1,1)	-1.454	2.478		0.719				
z statistics	-28.783	28.671		17.563				
Significance	0.000	0.000		0.000				
	LL= -288.420	**SBC= 3.638**	**Q(12)=13.275**	**Q_{SQ}(12)=6.169**				
			(0.209)	**(0.801)**				

Appendix 7 (Cont.)

	ω	α_1	α_2	β_1	β_2	γ_1	$D1$	$D2$
Kenya								
GARCH (1,1)	0.004	0.656		0.316			-1.071	
z statistics	1.124	12.289		9.540			-14.186	
Significance	0.261	0.000		0.000			0.000	
	LL=-385.583	**SBC= 2.069**	**Q(12)=17.322 (0.099)**	**Q_{SQ}(12)=1.431 (1.000)**				
Lao PDR								
EGARCH (1,1)	0.005	0.798		0.952			-0.459	
z statistics	0.677	15.599		422.714			-3.402	
Significance	0.499	0.000		0.000			0.000	
	LL= -1321.90	**SBC= 11.107**	**Q(12)=8.854 (0.546)**	**Q_{SQ}(12)= 6.849 (0.740)**				
Mauritius								
EGARCH (1,1)	-0.783	0.593		0.861			0.185	0.305
z statistics	-8.801	8.757		40.493			2.020	3.452
Significance	0.000	0.000		0.000			0.044	0.000
	LL= -24.992	**SBC= 0.200**	**Q(12)= 16.551 (0.056)**	**Q_{SQ}(12)=1.838 (0.999)**				
Myanmar(Burma)								
EGARCH (1,1)	-0.640	-0.084		0.855			0.569	0.053
z statistics	-6.704	-4.112		38.451			2.428	1.997
Significance	0.000	0.000		0.000			0.015	0.046
	LL=372.872	**SBC= -1.788**	**Q(12)=12.110 (0.182)**	**Q_{SQ}(12)=7.820 (0.715)**				
Nepal								
EGARCH (1,1)	-1.019	1.086		0.114			0.614	
z statistics	-14.444	8.914		1.807			21.765	
Significance	0.000	0.000		0.007			0.000	
	LL= -272.771	**SBC= 1.823**	**Q(12)=13.527 (0.260)**	**Q_{SQ}(12)=1.566 (1.000)**				
Nigeria								
EGARCH (0,1)	0.039			0.998			0.063	-0.324
z statistics	61.126			98.090			9.315	-41.89
Significance	0.000			0.000			0.000	0.000
	LL=-144.933	**SBC=0.758**	**Q(12)=4.948 (0.895)**	**Q_{SQ}(12)=0.679 (1.000)**				
Pakistan								
EGARCH (1,0)	-2.234	0.689					1.576	
z statistics	-27.268	6.992					4.323	
Significance	0.000	0.000					0.000	
	LL= -159.975	**SBC= 1.118**	**Q(12)=14.749 (0.194)**	**Q_{SQ}(12)=0.505 (1.000)**				
Romania								
EGARCH (1,1)	-3.056	0.775		0.658			0.765	-0.030
z statistics	-3.594	3.419		6.633			1.881	-1.991
Significance	0.000	0.000		0.000			0.006	0.046
	LL= 382.991	**SBC =-4.117**	**Q(12)=11.868 (0.294)**	**Q_{SQ}(12)=7.356 (0.691)**				

Appendix 7 (Cont.)

	ω	α_1	α_2	β_1	β_2	γ_1	$D1$	$D2$
Sri Lanka								
EGARCH (1,1)	-1.536	1.562		0.739			0.427	1.678
z statistics	-33.575	36.573		55.589			3.439	8.830
Significance	0.002	0.000		0.000			0.000	0.000
	LL=-197.835	**SBC=1.019**	**Q(12)=4.988 (0.932)**	**Q_{SQ}(12)=14.855 (0.189)**				
Trinidad & Tobago								
EGARCH (1,1)	-10.229	1.111		-0.341			3.987	8.950
z statistics	-41.102	15.745		-10.430			26.263	18.768
Significance	0.000	0.000		0.000			0.000	0.000
	LL= 900.273	**SBC = -4.088**	**Q(12)=12.119 (0.277)**	**Q_{SQ}(12)=0.886 (1.000)**				
Tunisia								
GARCH (1,1)	6.55×10^{-6}	0.089		0.897				
z statistics	5.176	3.096		32.147				
Significance	0.000	0.002		0.000				
	LL=1150.44	**SBC = -5.282**	**Q(12)=3.676 (0.978)**	**Q_{SQ}(12)=2.853 (0.993)**				
Vietnam								
EGARCH (1,0)	8.327	1.442					5.174	2.576
z statistics	154.256	20.659					33.578	12.903
Significance	0.000	0.000					0.000	0.000
	LL=-1628.89	**SBC= 12.562**	**Q(12)=10.094 (0.522)**	**Q_{SQ}(12)=4.353 (0.958)**				

The significance levels associated with Q(12) and QSQ(12) are shown in brackets. D1 and D2 are dummy one and two respectively.

Appendix 8: Forecast accuracy of individual time series models: Advanced, emerging and frontier countries

Country	**Volatility Model**		**Exponential Smoothing Model**		**Naïve 1 Model**	
	Static	**Dynamic**	**Static**	**Dynamic**	**Static**	**Dynamic**
Advanced:						
Australia	1.654	10.222(1)	1.702	10.257(3)	1.720	10.244(2)
Canada	0.949	9.027(3)	0.945	7.515(1)	0.930	8.040(2)
Denmark	1.913	5.531(1)	1.926	5.548(2)	2.040	5.582(3)
Euro area	5.591	1.837(1)	1.870	5.655(3)	1.890	5.642(2)
Japan	2.027	16.086(2)	1.999	16.153(3)	2.050	15.700 (1)
Norway	1.730	9.757(2)	1.745	9.666(1)	1.860	9.881(3)
Singapore	0.936	7.743(2)	0.911	3.297(1)	0.940	3.297(1)
Sweden	1.718	11.046(1)	1.725	11.057(2)	1.870	11.364 (3)
Switzerland	2.178	7.347(3)	2.184	6.903(2)	2.300	6.383(1)
UK	1.854	16.602(2)	1.859	16.543(1)	1.852	17.159(3)
Emerging:						
Brazil	2.525	9.327(3)	2.506	9.265(2)	2.670	9.229(1)
Chile	1.906	1.310(1)	1.486	9.815(3)	1.740	9.304 (2)
China	0.868	7.018 (1)	0.810	7.120(2)	0.810	7.120 (2)
Colombia	1.145	2.708 (1)	1.201	8.058(2)	1.610	8.190(3)
Czech Republic	1.939	7.616(3)	1.935	7.577 (1)	2.020	7.597(2)
Hungary	1.458	11.034(1)	1.470	20.855 (3)	1.490	11.051(2)
India	0.964	12.513(1)	0.944	13.836(3)	1.000	13.609(2)
Indonesia	2.220	6.293(2)	2.095	6.275(1)	2.130	6.302 (3)
Malaysia	0.817	4.322(2)	0.956	4.393(3)	0.900	4.273(1)
Mexico	1.664	13.313(3)	2.006	10.059(1)	1.710	13.252(2)
Peru	8.413	4.292(2)	6.955	9.287(3)	2.470	3.799 (1)
Philippines	0.989	10.218 (2)	0.958	10.654(3)	1.050	9.312(1)
Poland	2.804	15.299(3)	2.891	15.274 (1)	2.970	15.286(2)
Russia	1.395	13.247(1)	1.274	18.985(3)	1.570	14.005 (2)
South Africa	2.222	5.463(1)	2.222	15.617(2)	2.370	16.242 (3)
South Korea	1.032	19.742(2)	1.056	18.964(1)	1.190	20.002 (3)
Taiwan	0.809	2.765(3)	0.803	2.753(2)	0.880	2.740 (1)
Thailand	1.126	2.790(1)	1.129	2.791(2)	1.210	2.793(3)
Turkey	4.333	18.335(1)	4.196	23.168(3)	3.980	17.499 (2)
Frontier:						
Bangladesh	0.992	1.851(2)	1.054	2.521(3)	0.957	1.458 (1)
Bhutan*	0.937	12.080(1)	0.945	13.836 (3)	1.000	13.609(2)
Botswana	1.745	3.696(1)	1.718	12.390 (2)	1.799	12.925(3)
Brunei*	0.911	3.244(2)	3.100	3.220(1)	0.945	3.220(1)
Croatia	1.794	5.507(1)	3.110	6.195(2)	3.760	6.775 (3)
Estonia	1.769	5.530(1)	1.827	5.533(2)	1.900	5.572(3)
Jamaica	1.719	11.627(2)	1.165	0.177(1)	1.275	22.293(3)
Kazakhstan	1.533	8.799(1)	1.557	10.373(3)	2.130	10.394(2)
Kenya	1.497	4.706 (1)	1.480	15.538 (3)	1.610	13.925(2)
Lao PDR*	1.055	1.942(1)	1.783	7.741(2)	1.930	9.265(3)

Appendix 8 (Cont.)

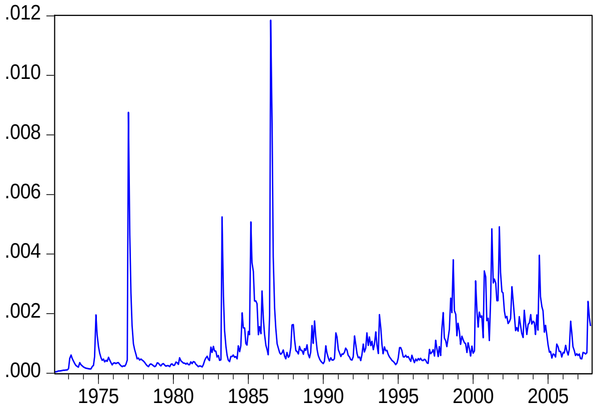
Country	Volatility Model		Exponential Smoothing Model		Naïve 1 Model	
	Static	**Dynamic**	**Static**	**Dynamic**	**Static**	**Dynamic**
Mauritius	1.320	7.177 (1)	1.295	8.125(3)	1.410	7.229(2)
Myanmar*	1.082	2.677(1)	1.114	3.710(3)	1.110	2.701(2)
Nepal*	0.893	12.930 (1)	0.900	12.940 (2)	0.950	13.037(3)
Nigeria	1.728	2.424(1)	1.741	13.015(3)	1.704	12.374(2)
Pakistan	0.679	7.193 (1)	0.642	19.686(2)	0.740	19.859(3)
Romania	2.573	12.038 (1)	2.598	19.723(3)	2.980	14.354(2)
Sri Lanka	0.948	2.739 (2)	1.332	1.642 (1)	1.060	3.337(3)
Trinidad &Tobago	0.508	0.575 (3)	0.475	0.085 (2)	0.461	0.011(1)
Tunisia	1.568	7.229 (3)	1.563	1.467 (2)	1.636	0.921 (1)
Vietnam	0.519	3.009 (1)	1.740	4.776(3)	1.901	4.753(2)

Figures in brackets indicate the rank of the forecasting methods. Accuracy evaluation is based on the MAPE (dynamic) forecast error measure. * Not listed as a frontier markets according to MSCI.

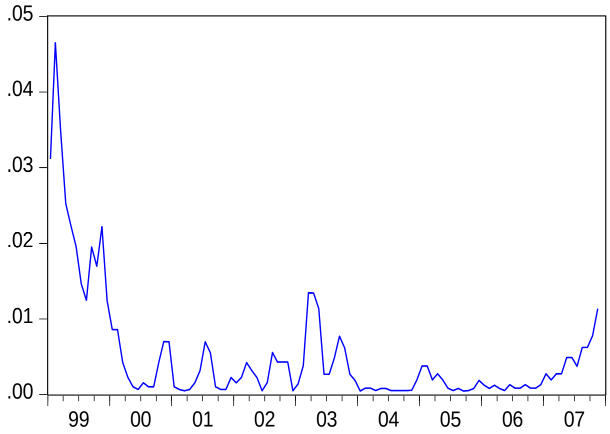
Appendix 9: Plots of static forecasts of the conditional variance against date

Advanced Countries

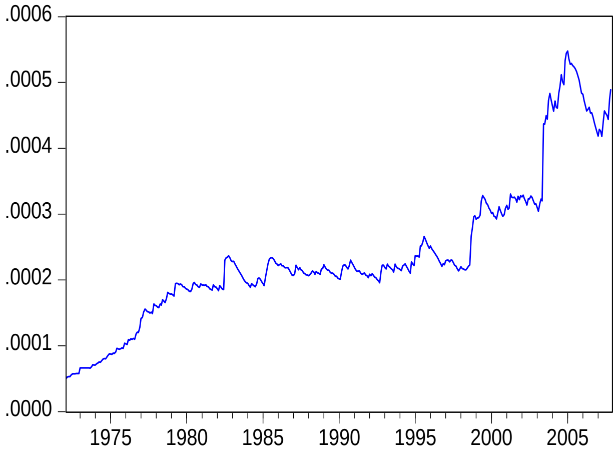
1. Australia



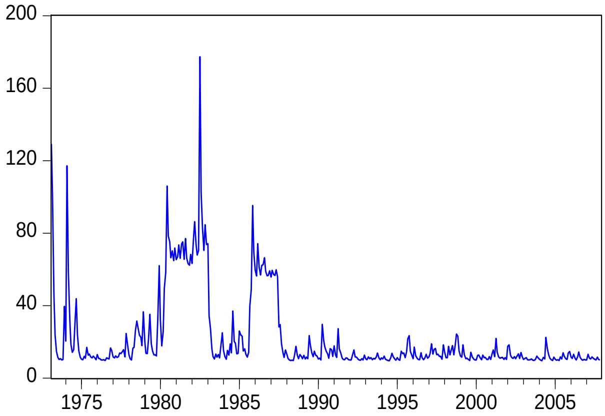
4. Euro area



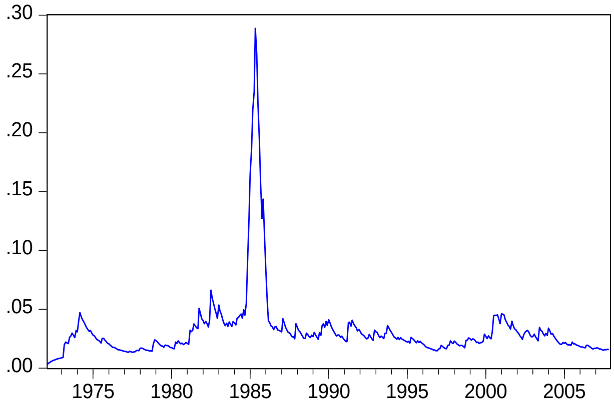
2. Canada



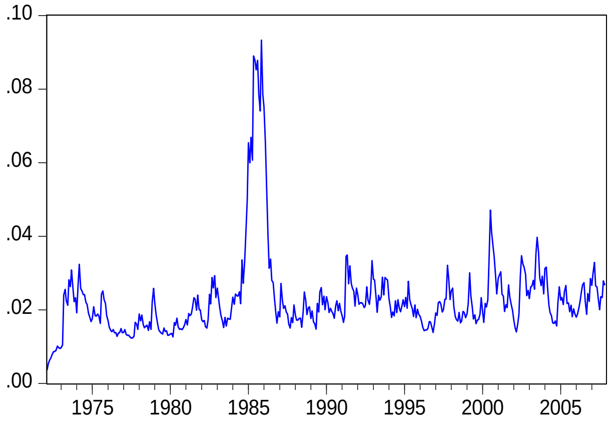
5. Japan



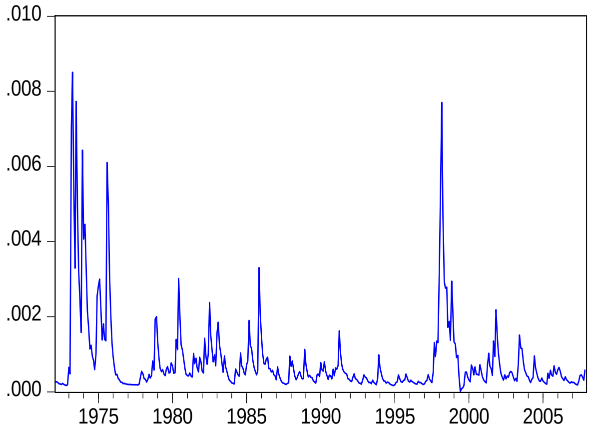
3. Denmark



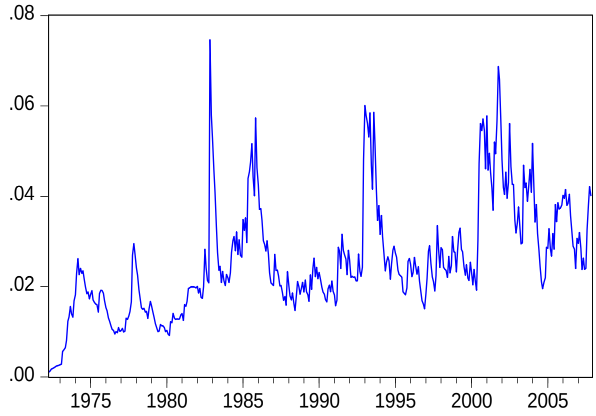
6. Norway



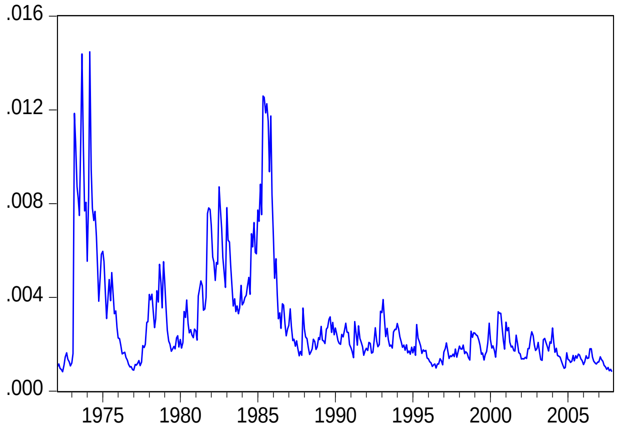
7. Singapore



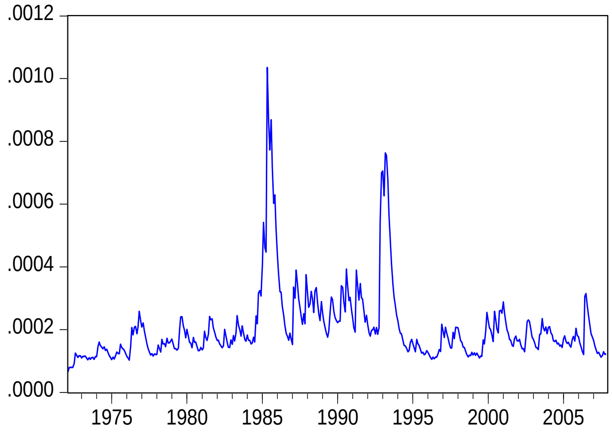
8. Sweden



9. Switzerland

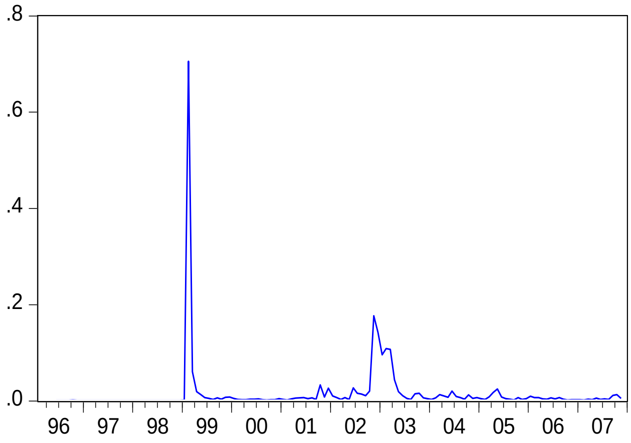


10. UK

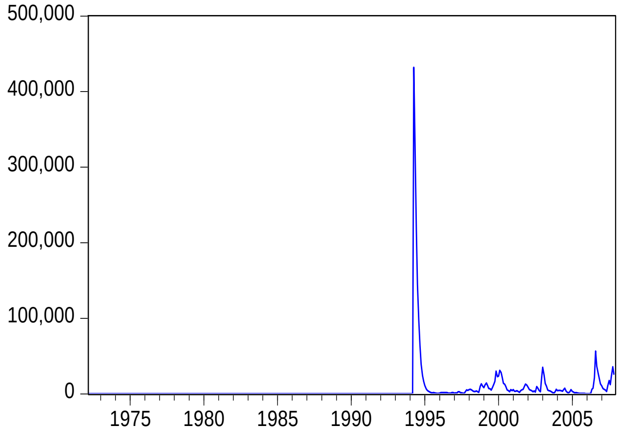


Emerging Countries:

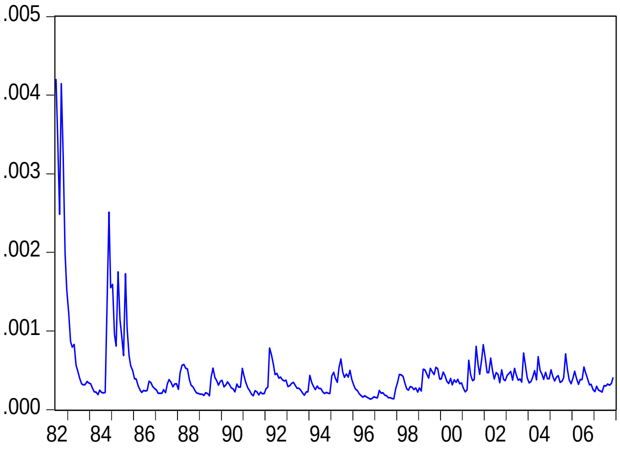
11. Brazil



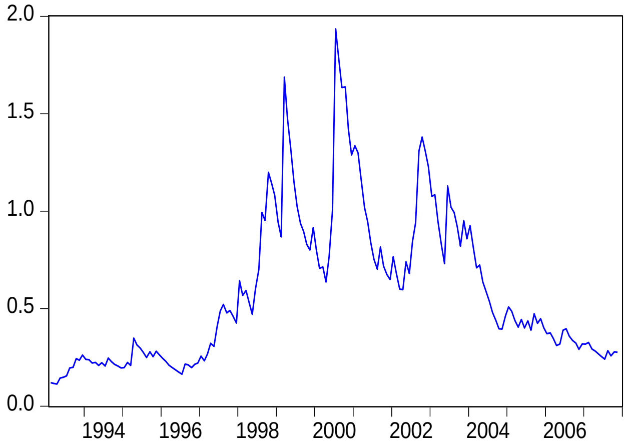
14. Colombia



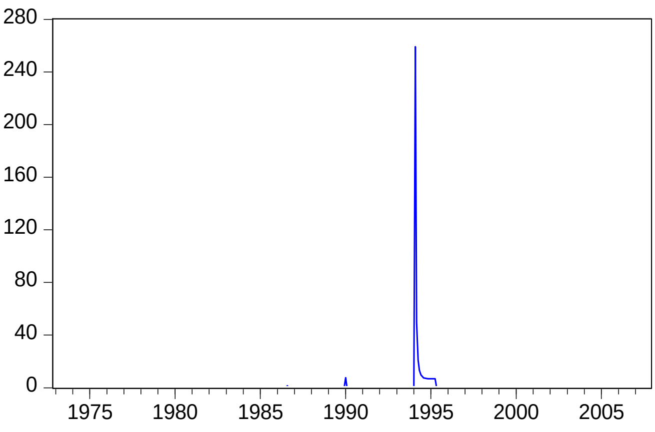
12. Chile



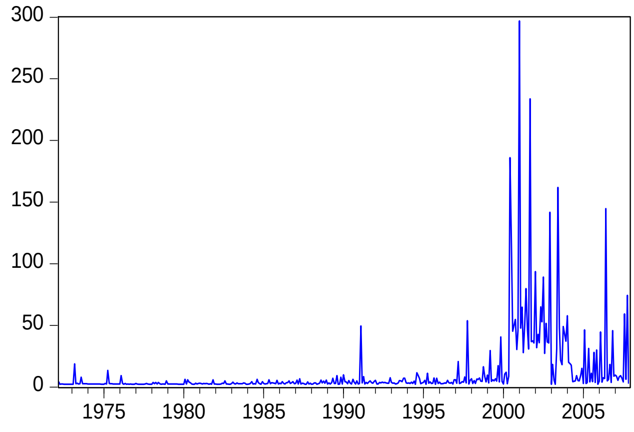
15. Czech Republic



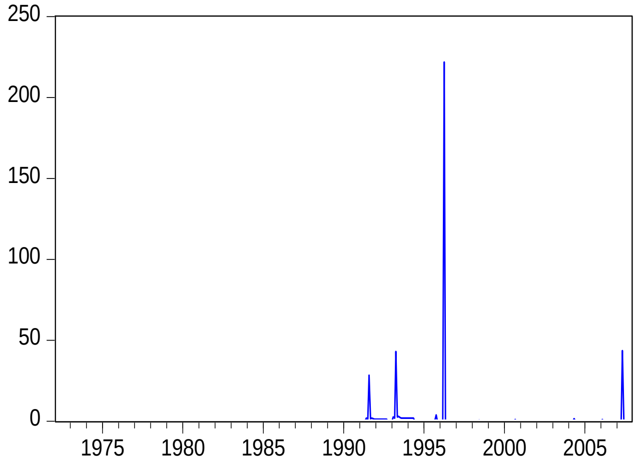
13. China



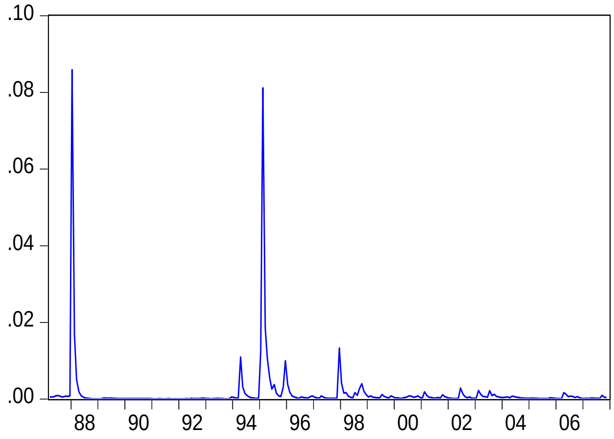
16.Hungary



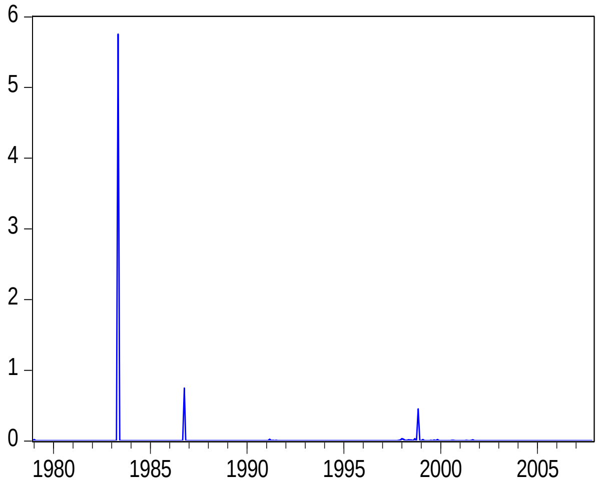
17. India



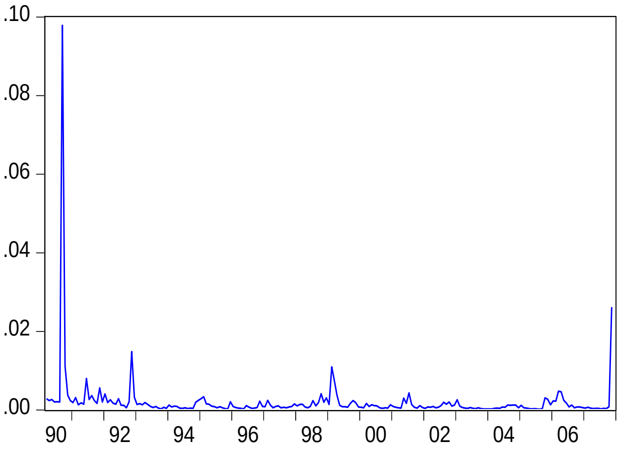
20.Mexico



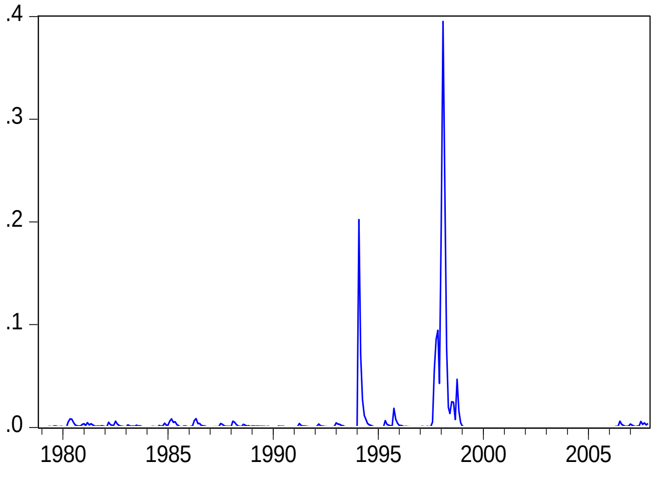
18.Indonesia



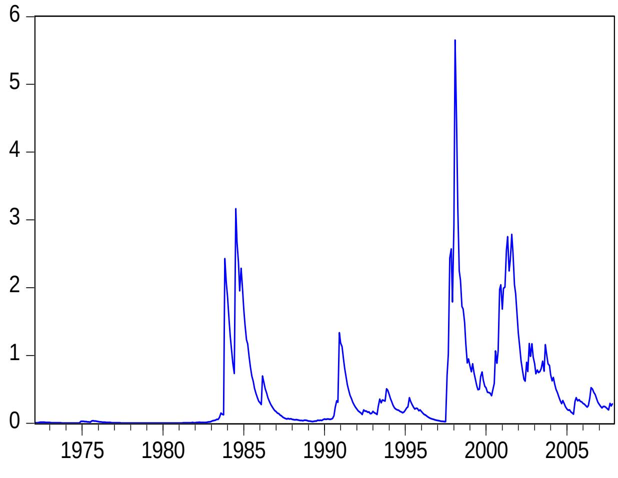
21.Peru



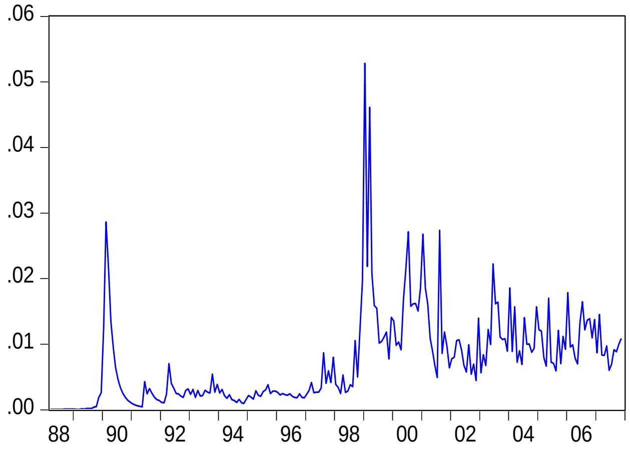
19.Malaysia



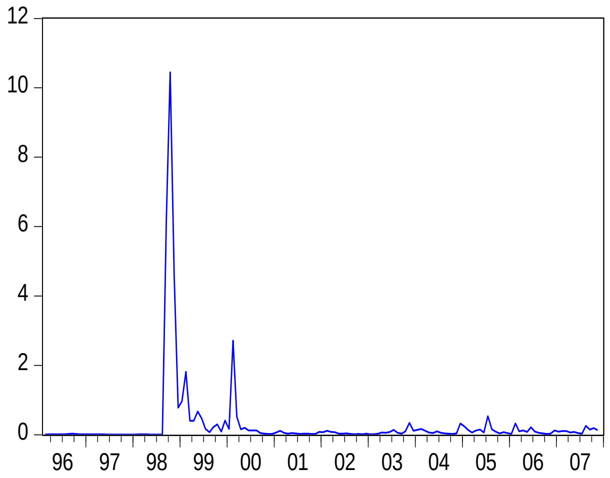
22.Philippines



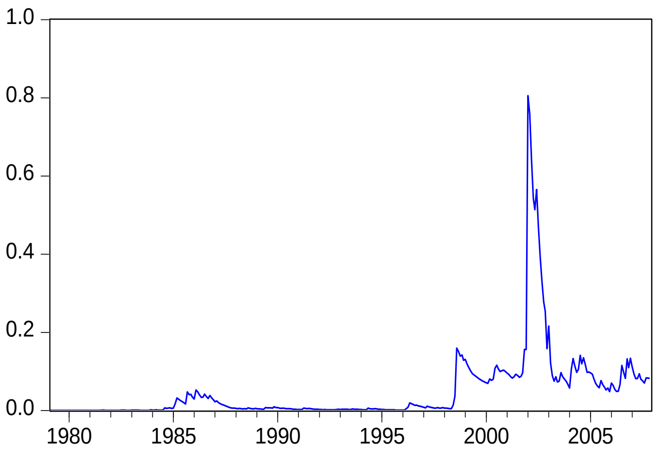
23.Poland



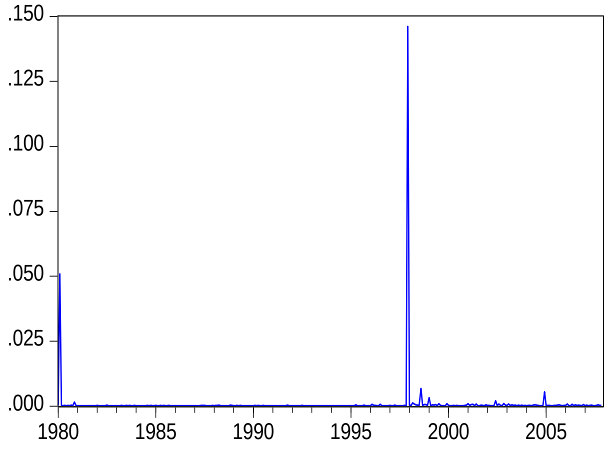
24. Russia



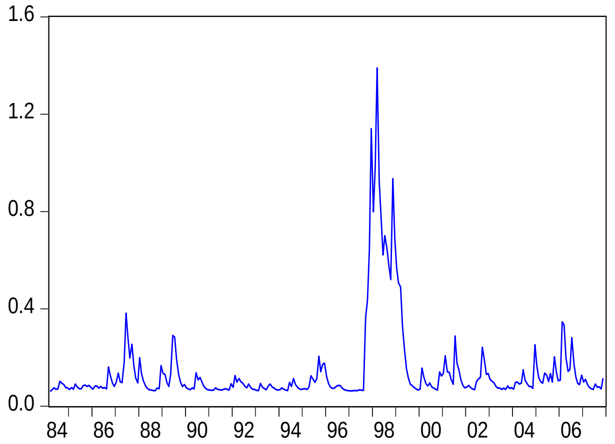
25.South Africa



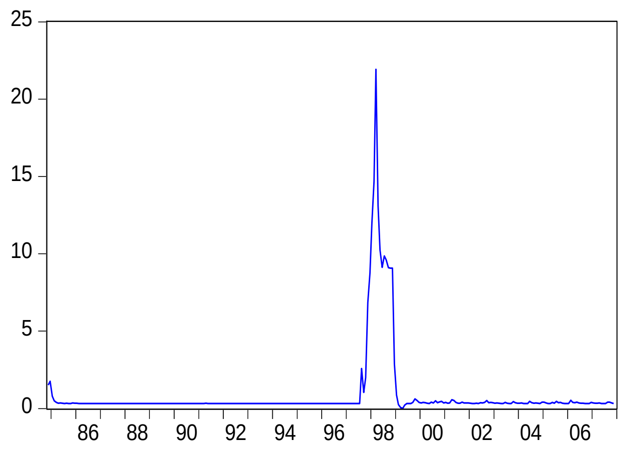
26. South Korea



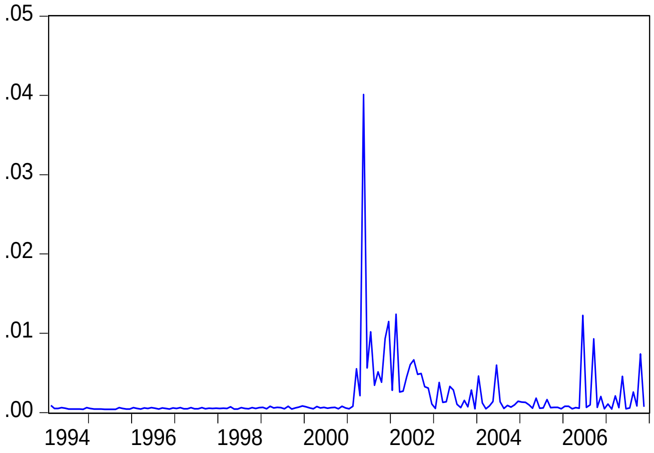
27.Taiwan



28. Thailand

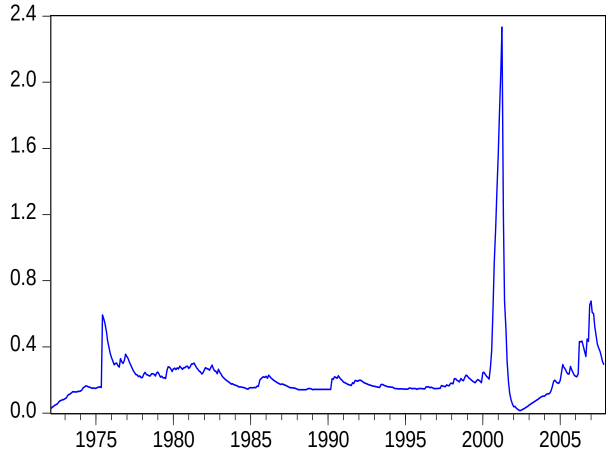


29.Turkey

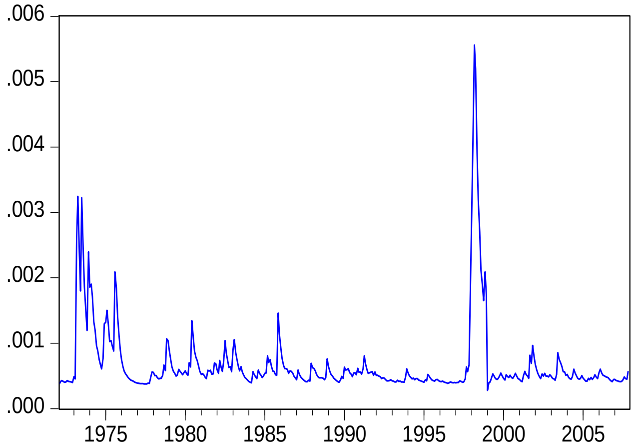


Frontier Countries

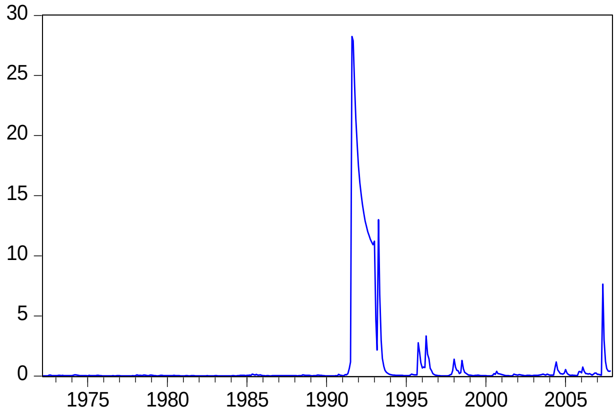
30.Bangladesh



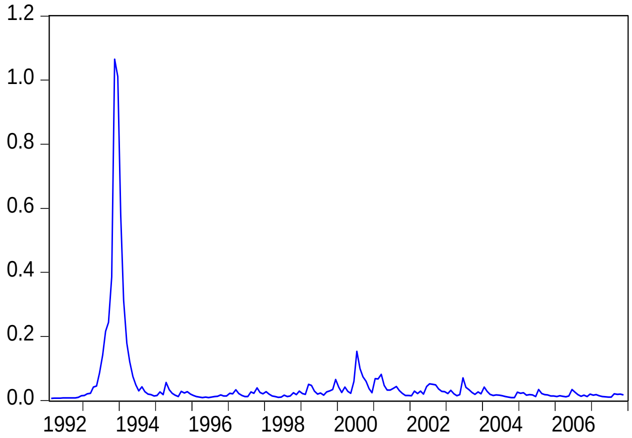
33.Brunei*



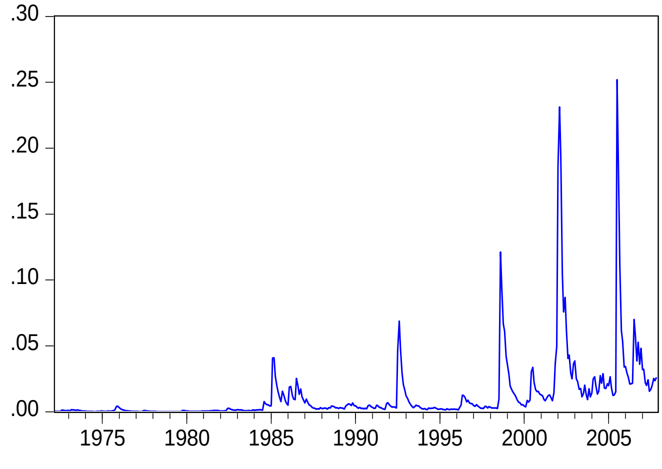
31.Bhutan*



34.Croatia



32.Botswana



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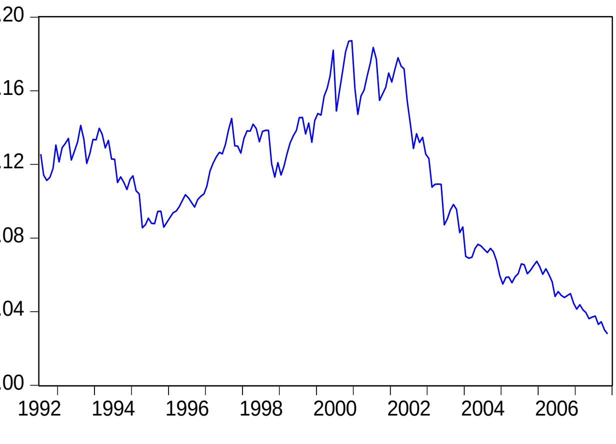

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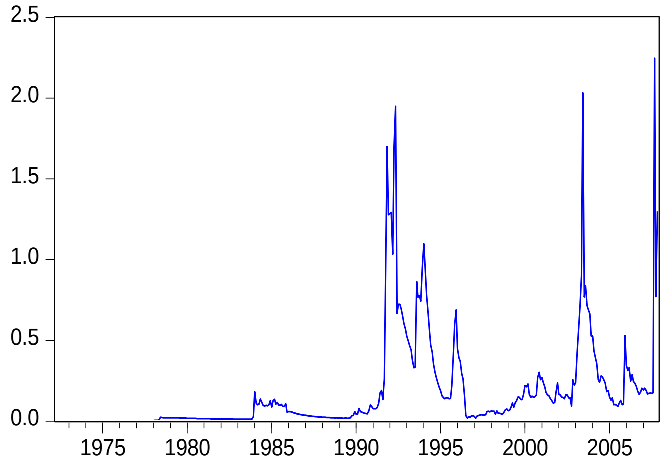

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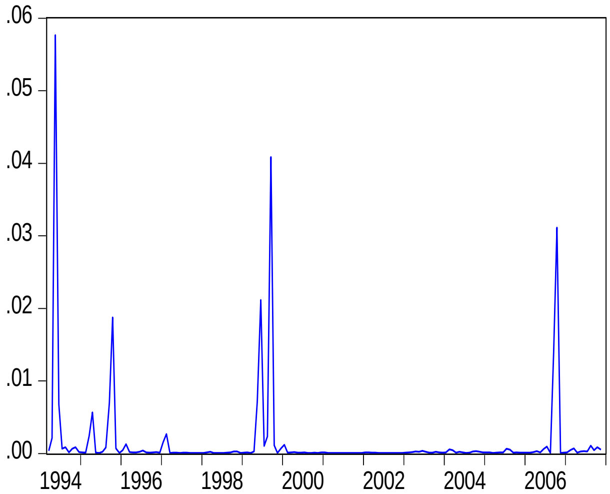

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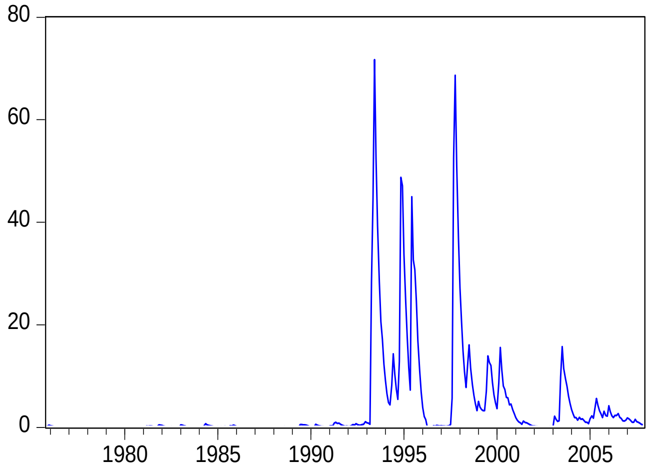

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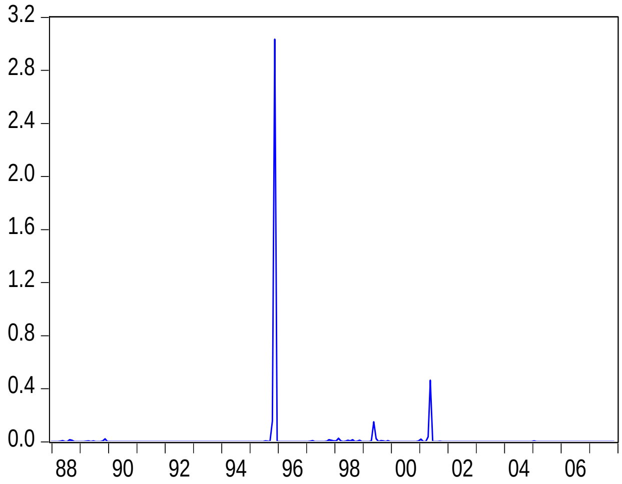

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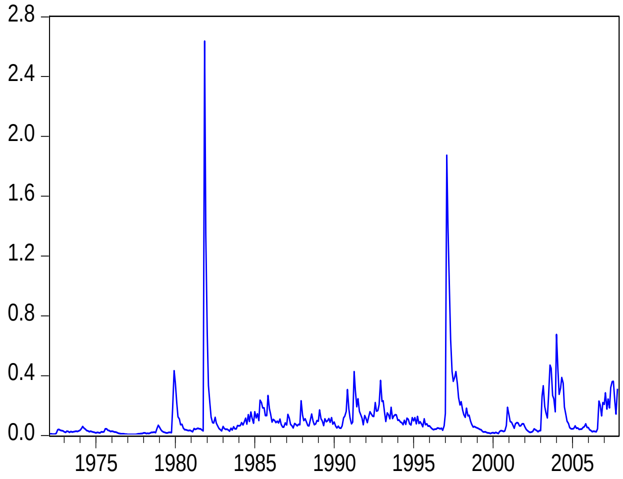

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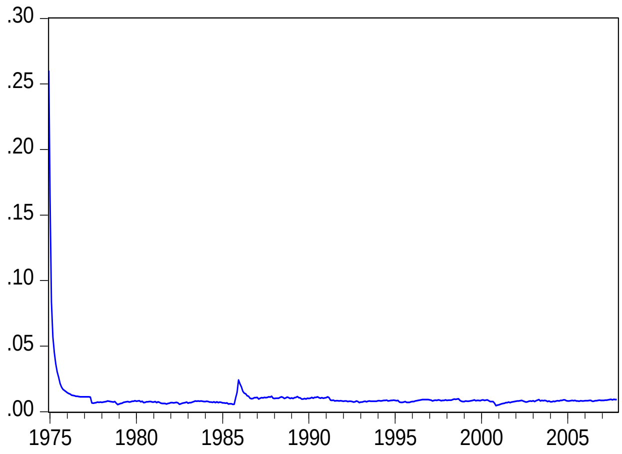

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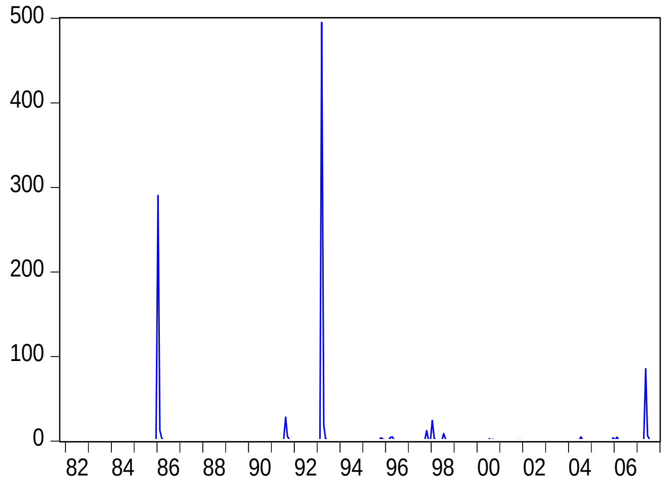

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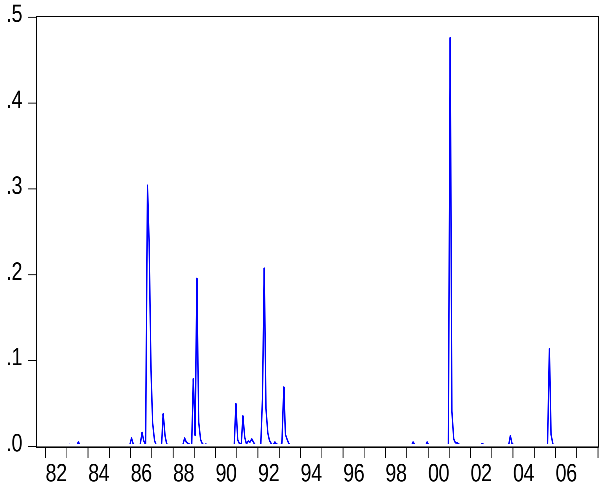

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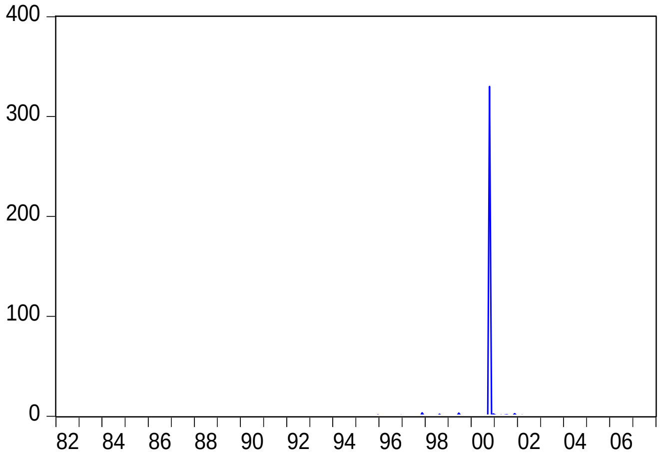

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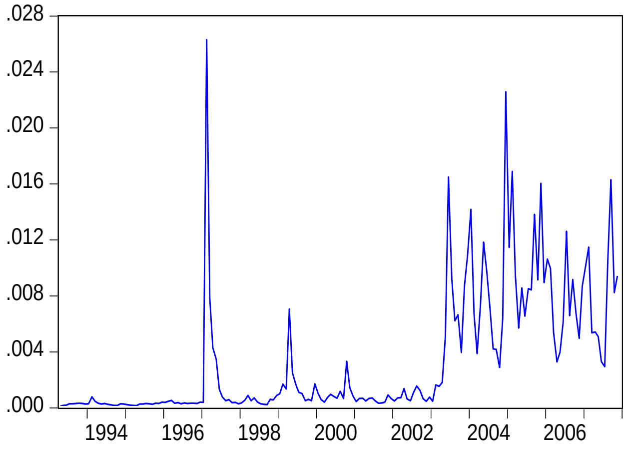
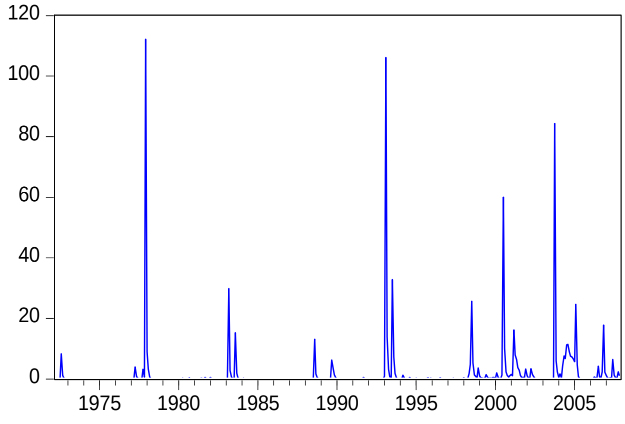
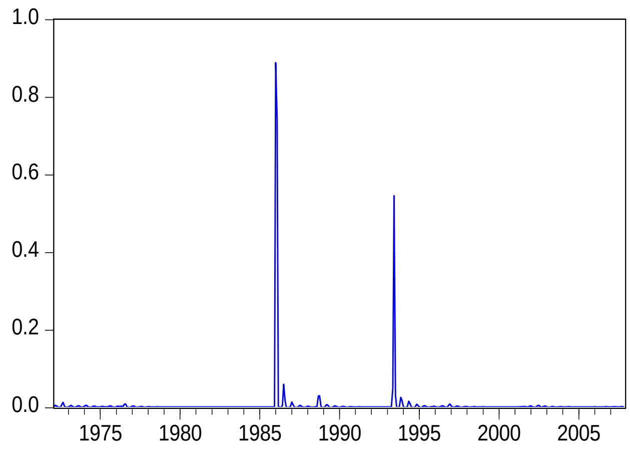


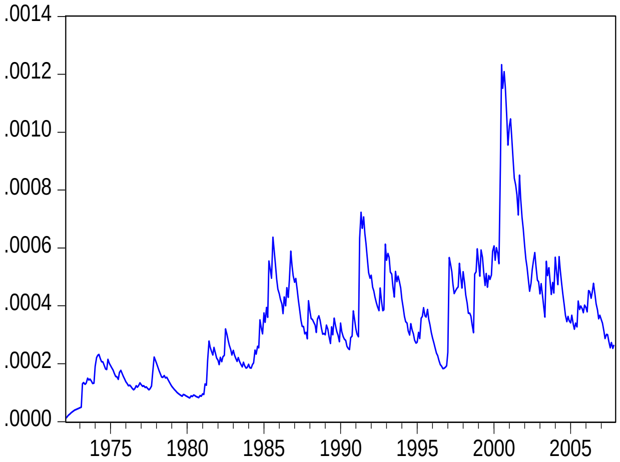
46. Sri Lanka



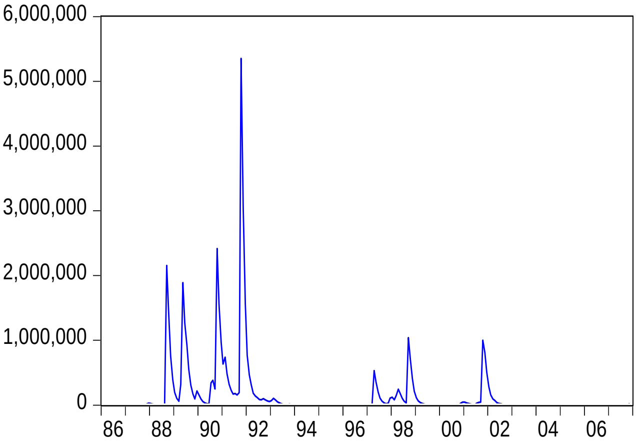
47. Trinidad & Tobago



48. Tunisia



49. Vietnam



Appendix 10: Plots of dynamic forecasts of the conditional variance against date

Advanced Countries

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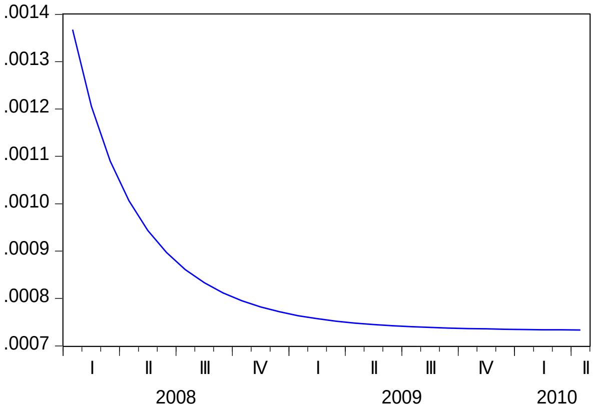
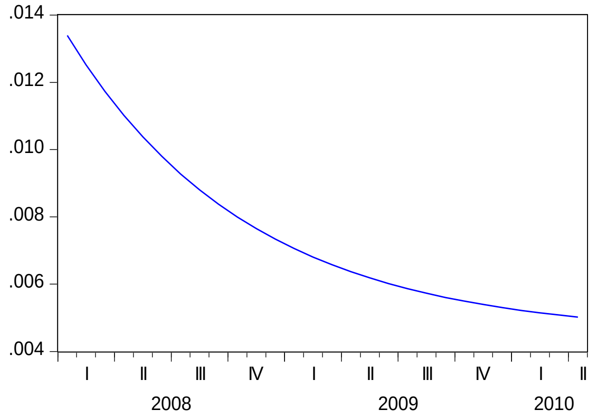
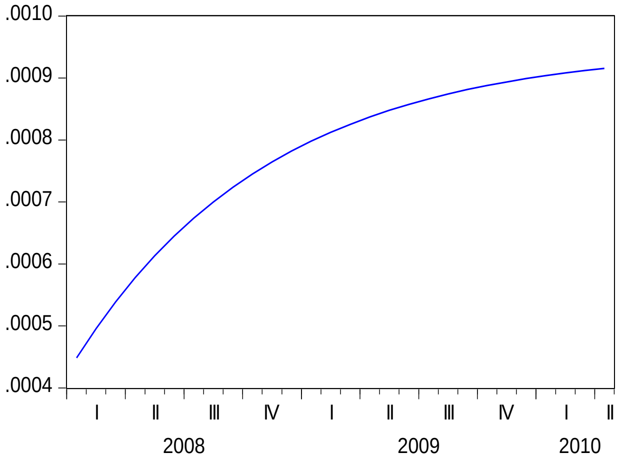


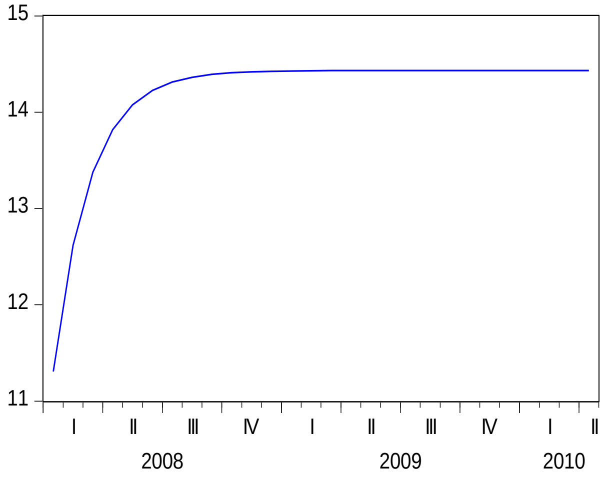
4. Euro area



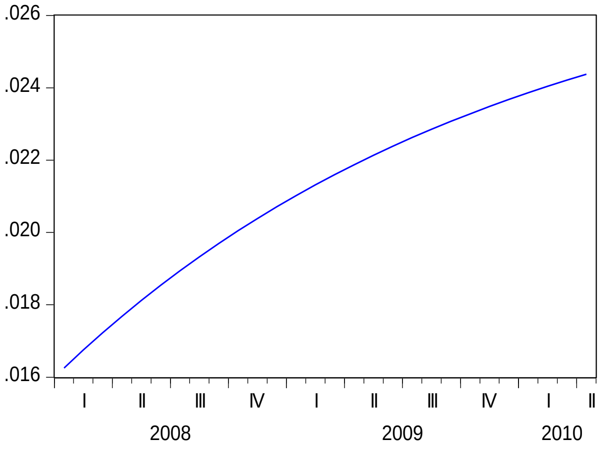
2.Canada



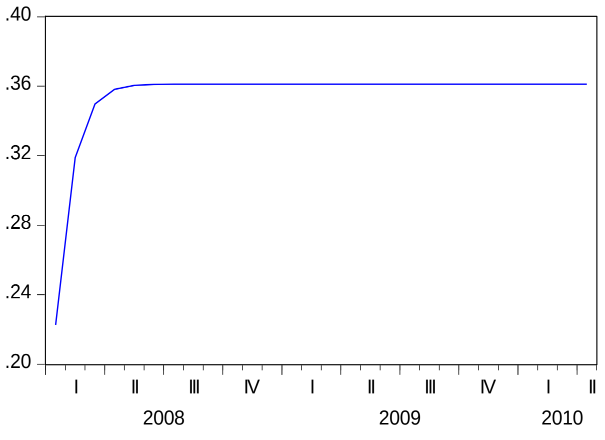
5.Japan



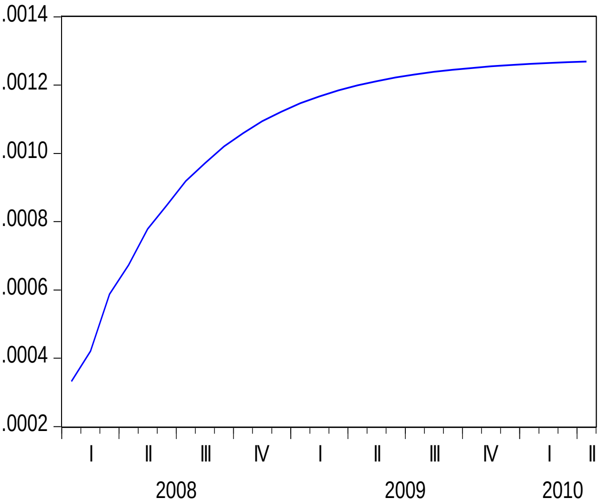
3.Denmark



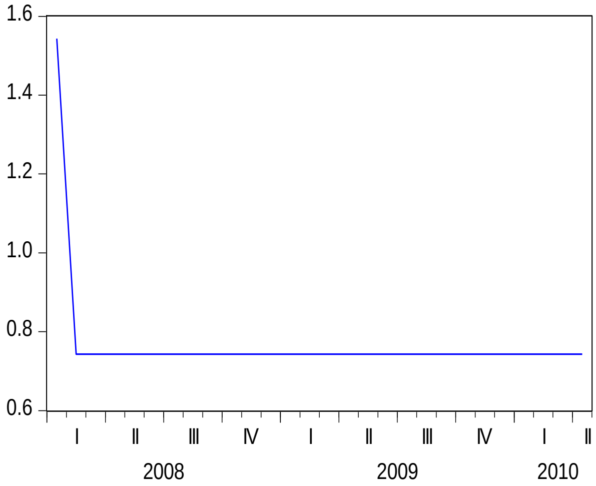
6. Norway



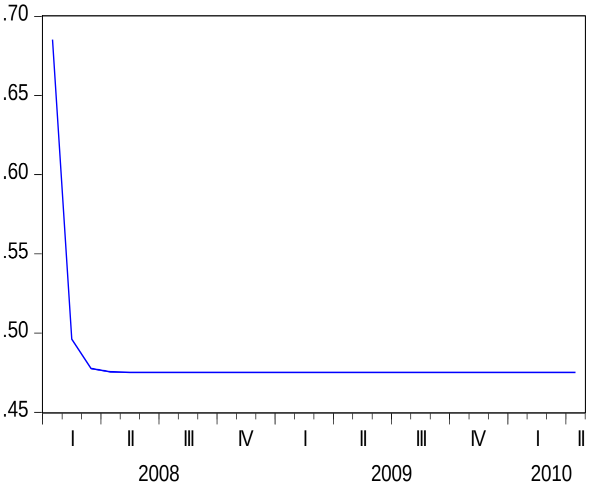
7. Singapore



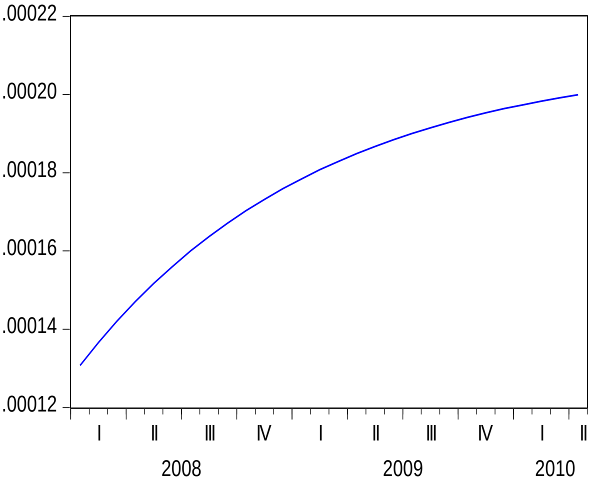
9. Sweden



8. Switzerland



10. UK



Emerging Countries:

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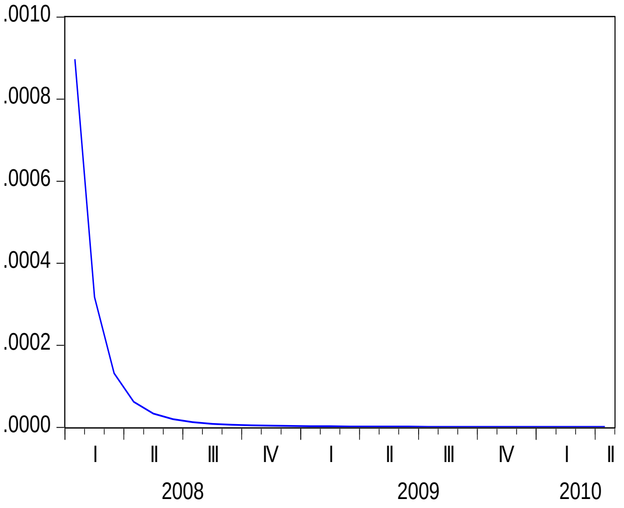
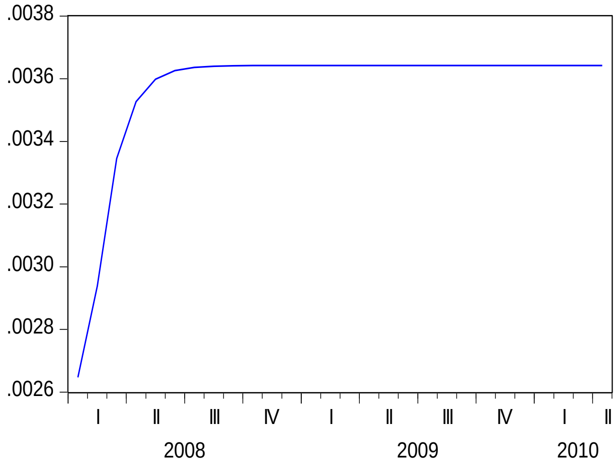
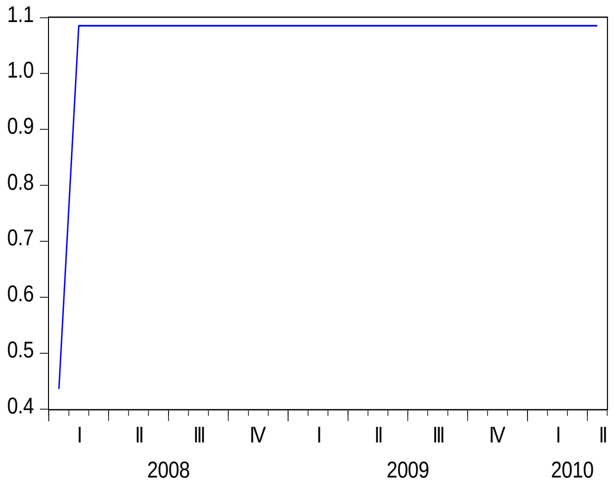


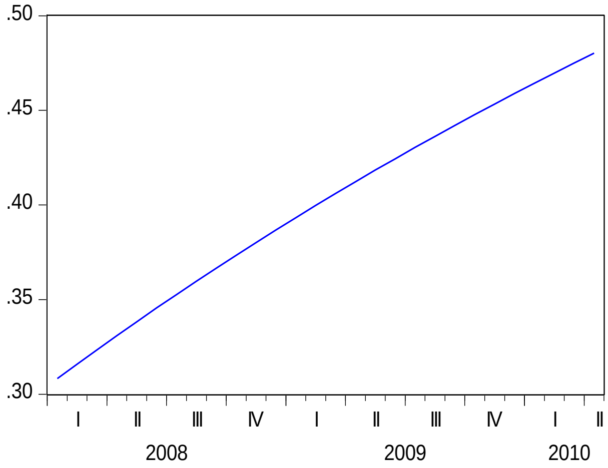
14. Colombia



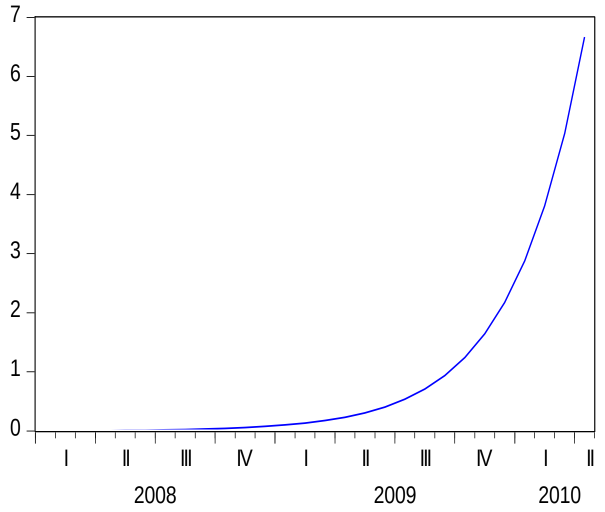
12. Chile



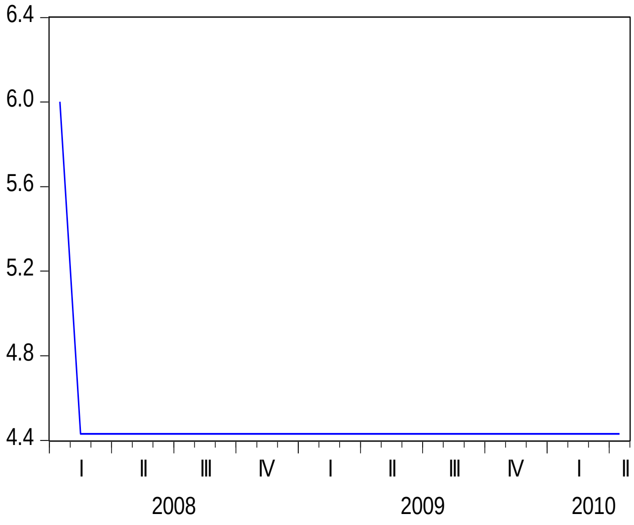
15. Czech Republic



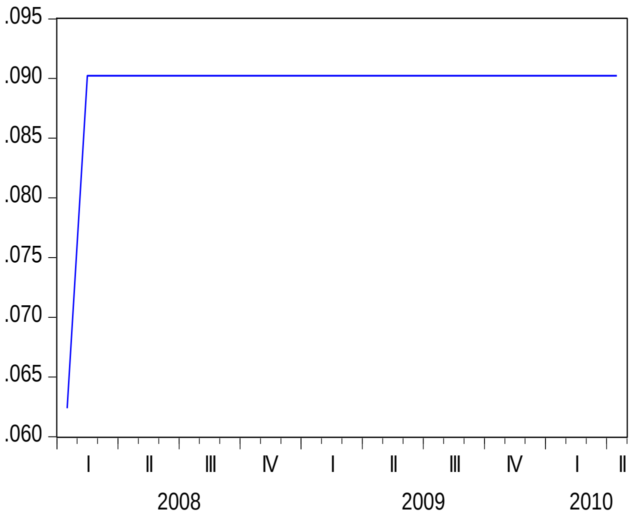
13. China



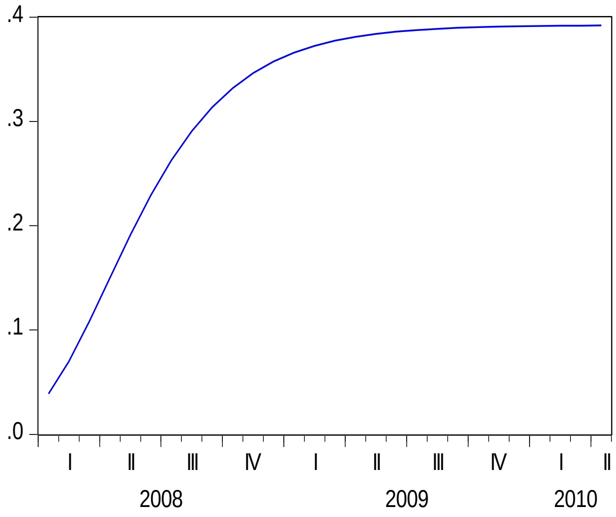
16. Hungary



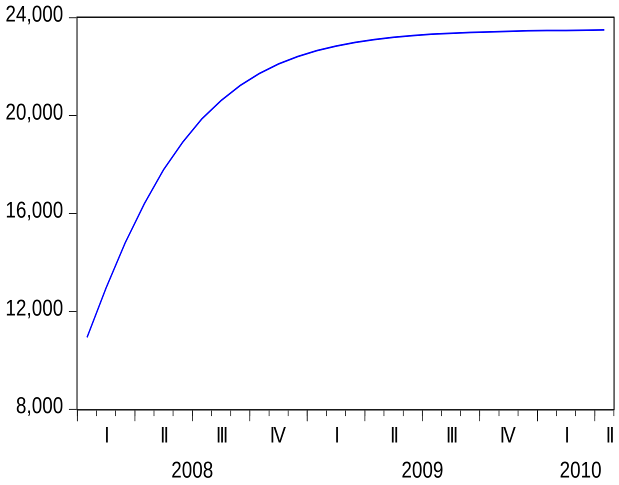
17. India



20.Mexico



18. Indonesia



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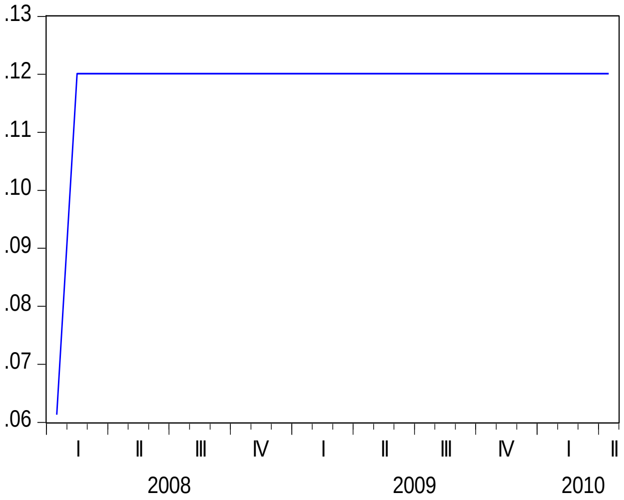

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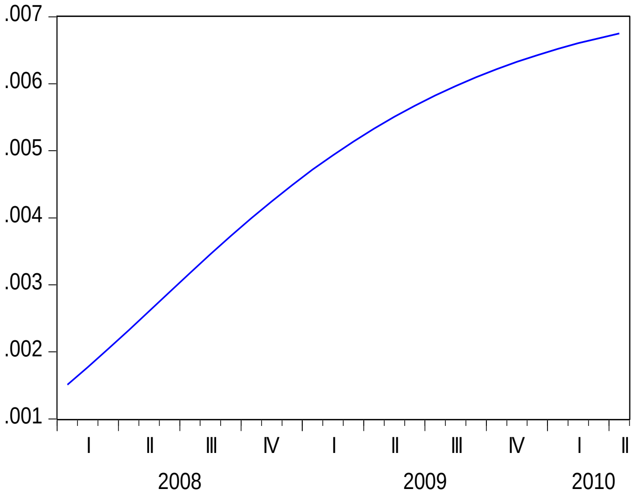
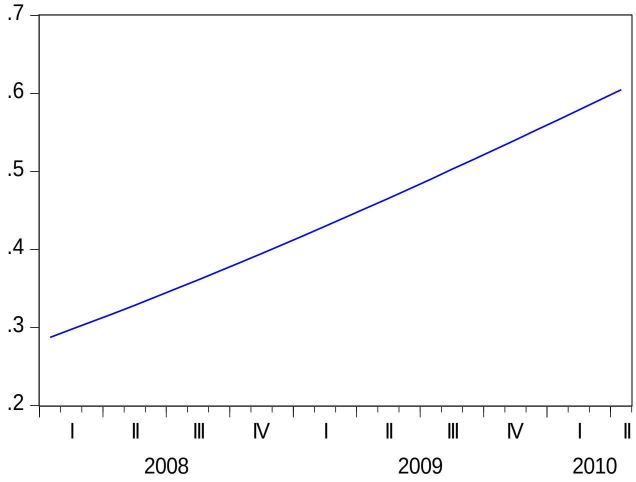
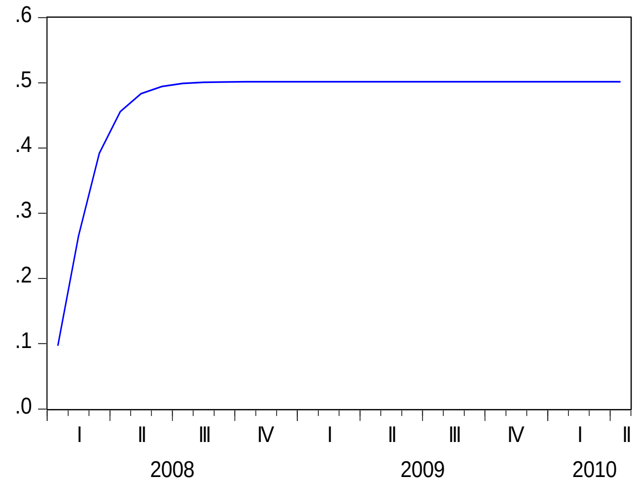


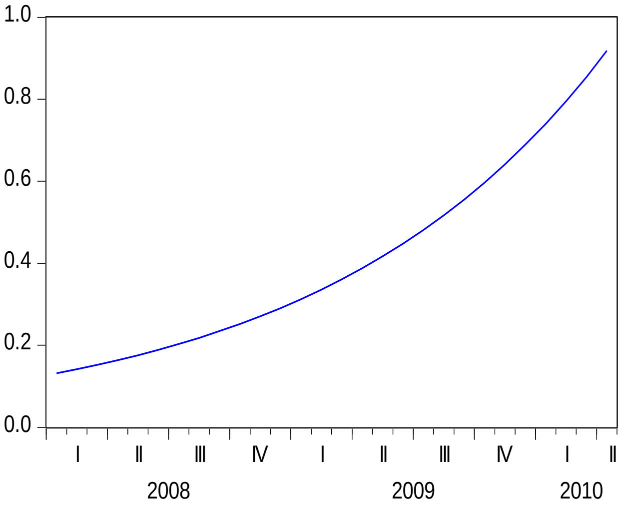
22. Philippines



23.Poland



24.Russia



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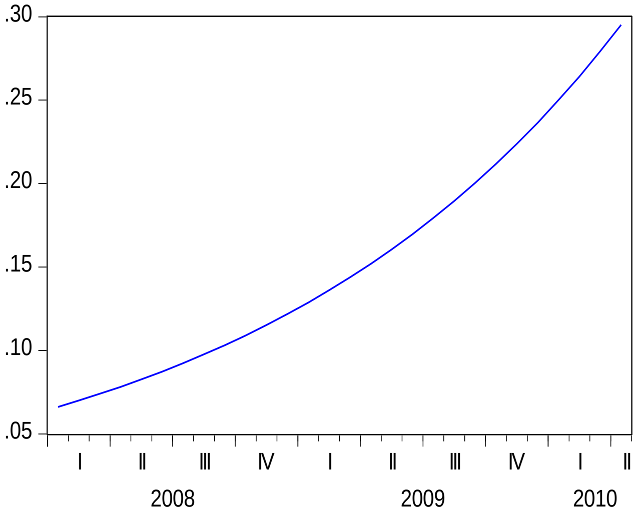

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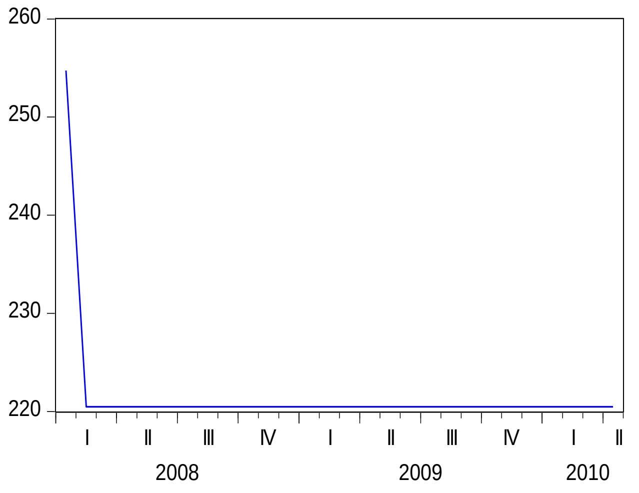
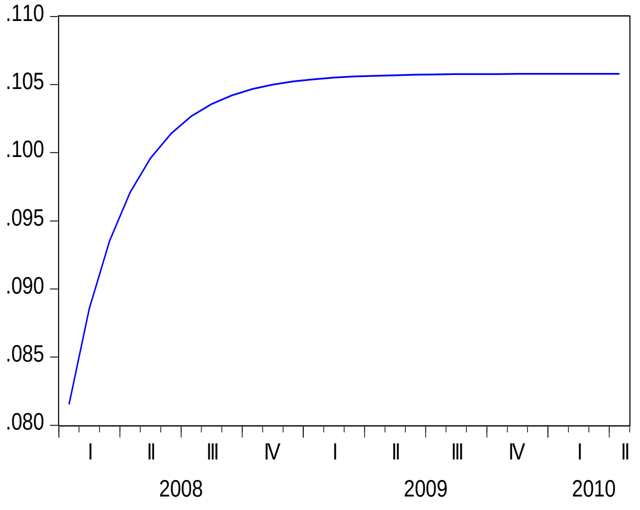


27.Taiwan



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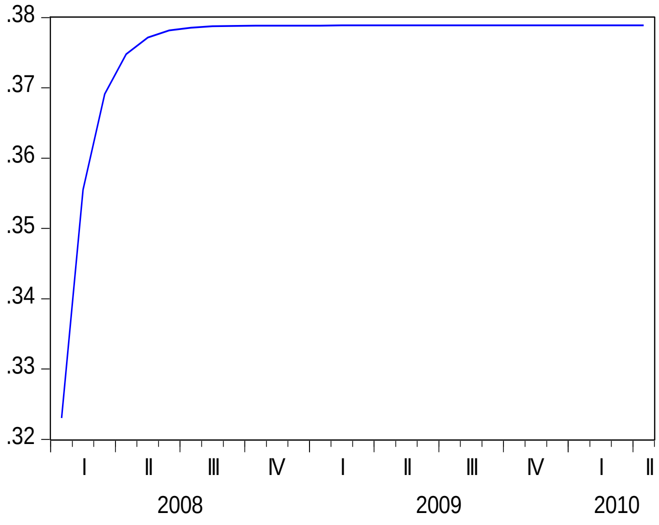

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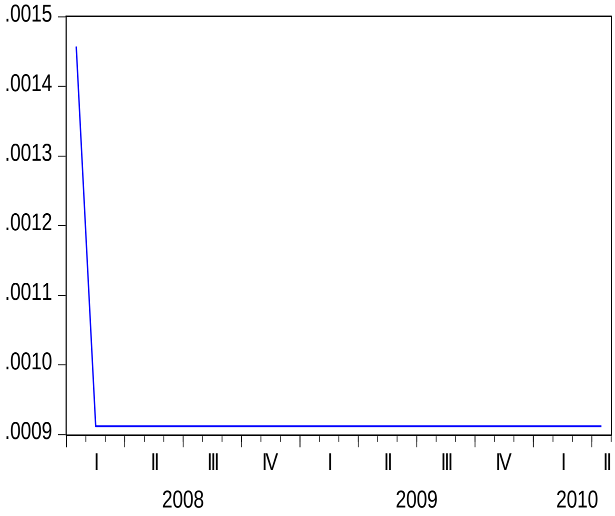
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2009
2010

Frontier Countries:

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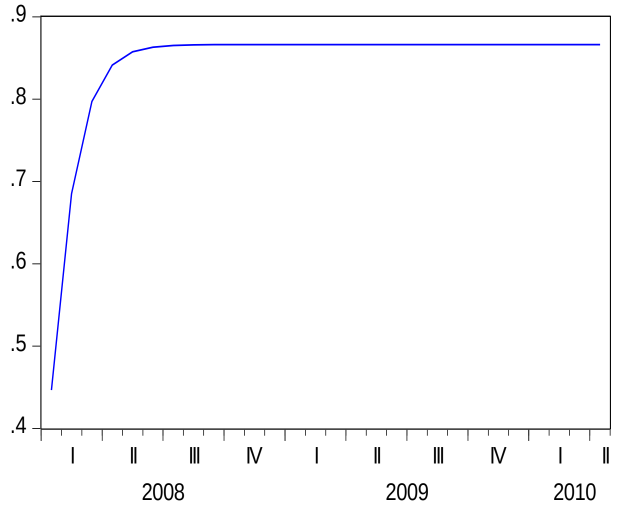

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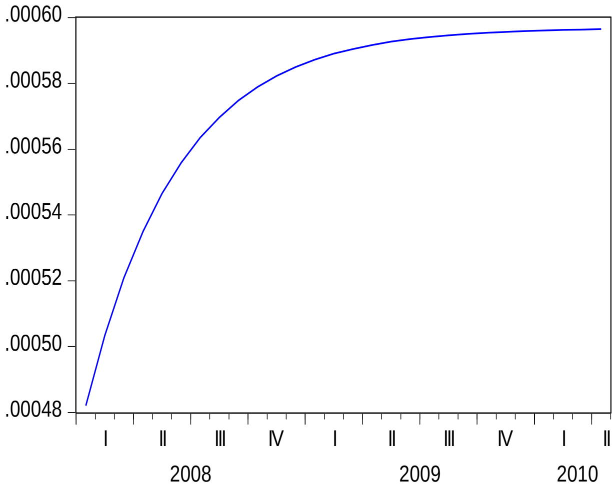
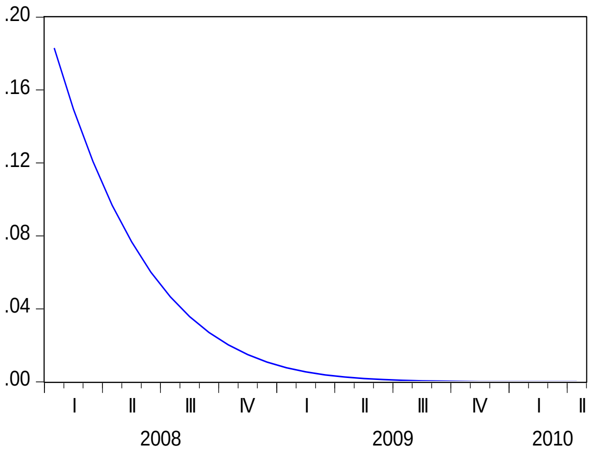
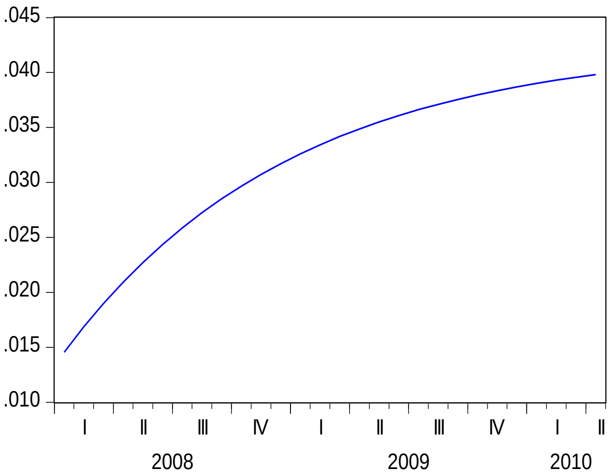


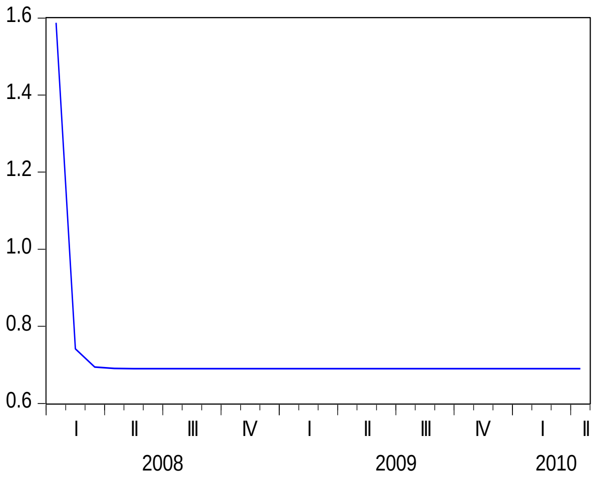
31.Bhutan



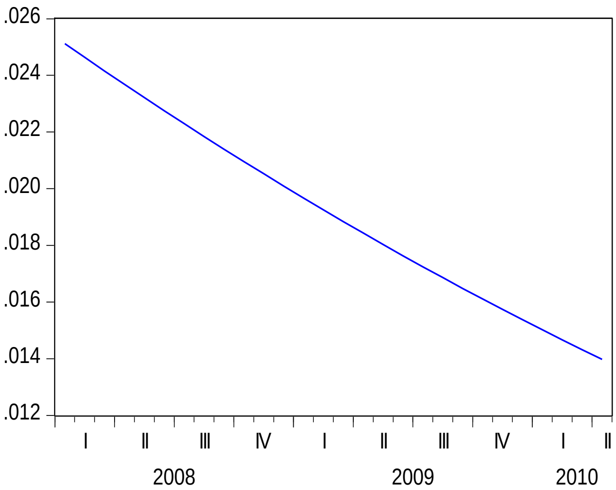
34.Croatia



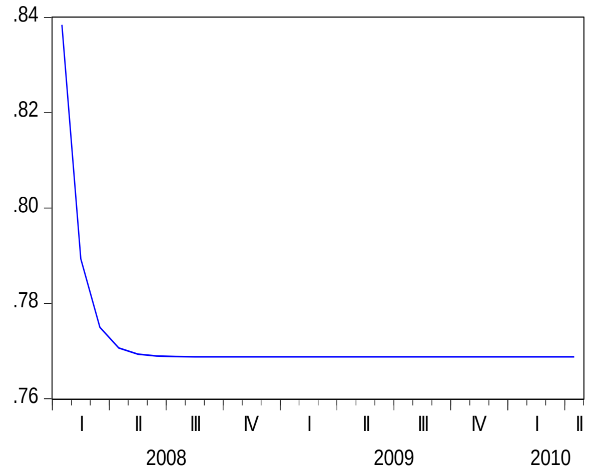
32.Botswana



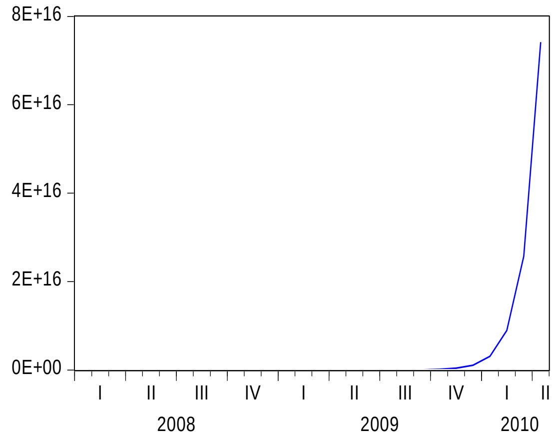
35.Estonia



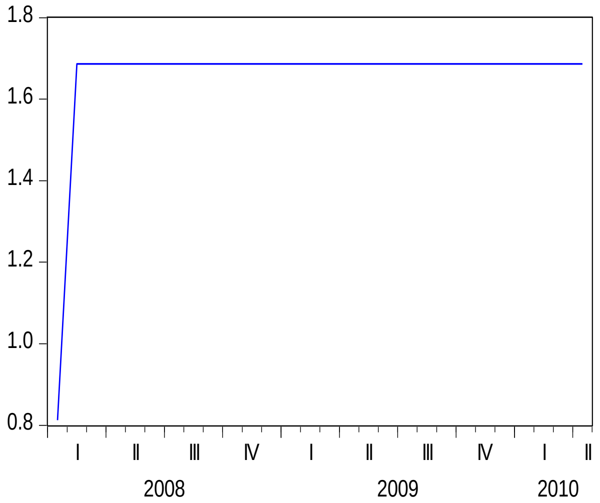
36.Jamaica



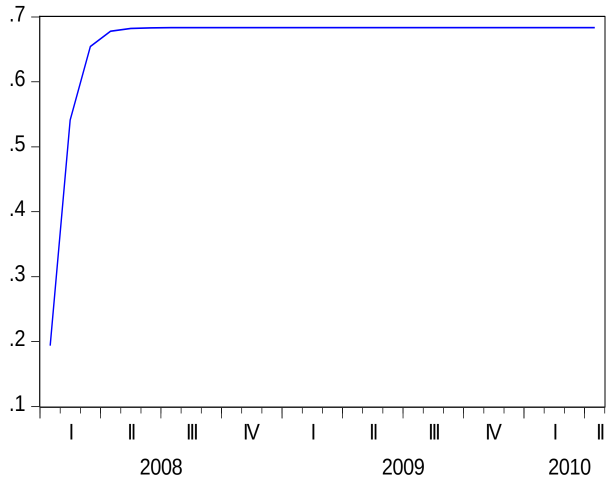
39.Lao PDR



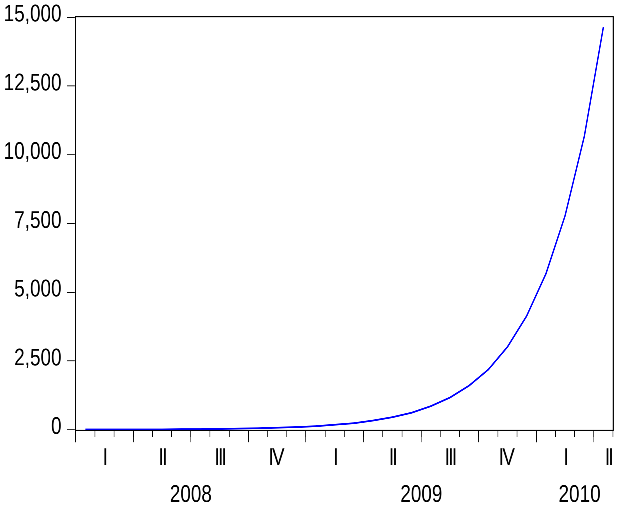
37.Kazakhstan



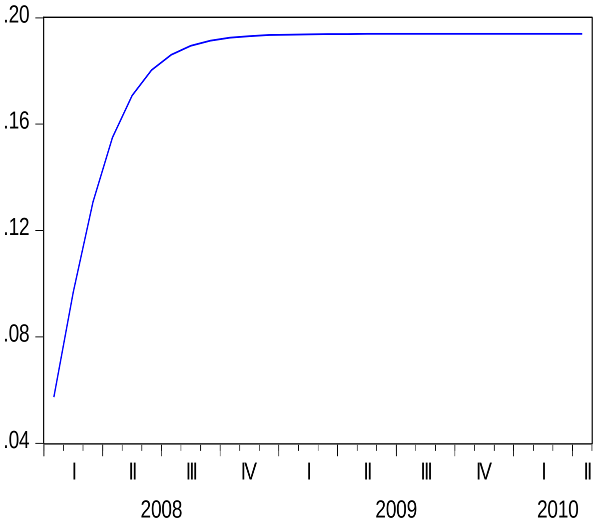
40.Mauritius



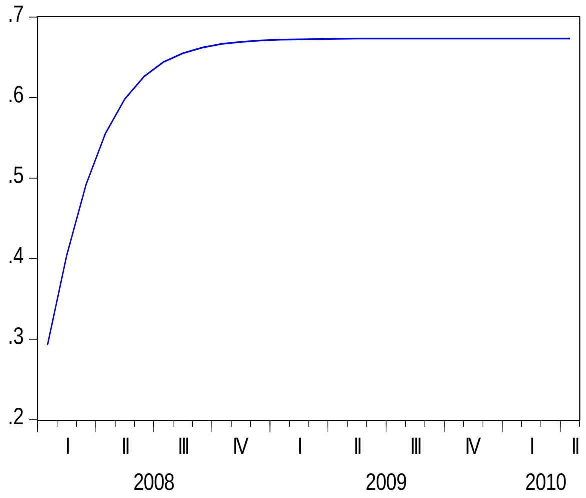
38.Kenya



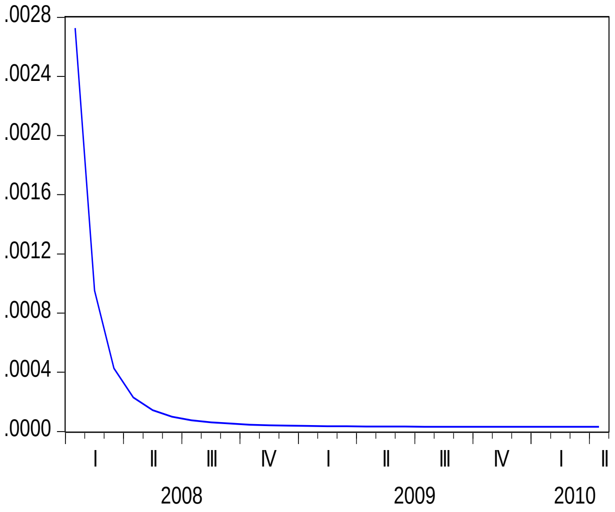
41.Myanmar



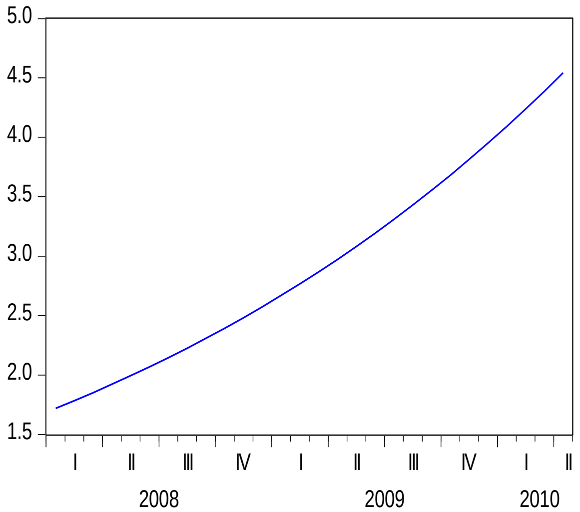
42.Nepal



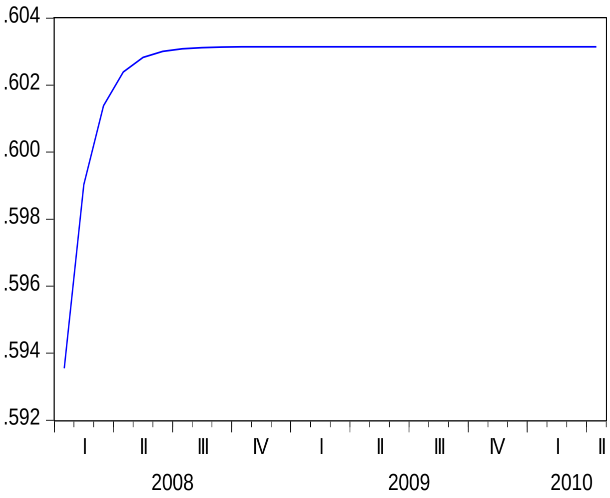
45.Romania



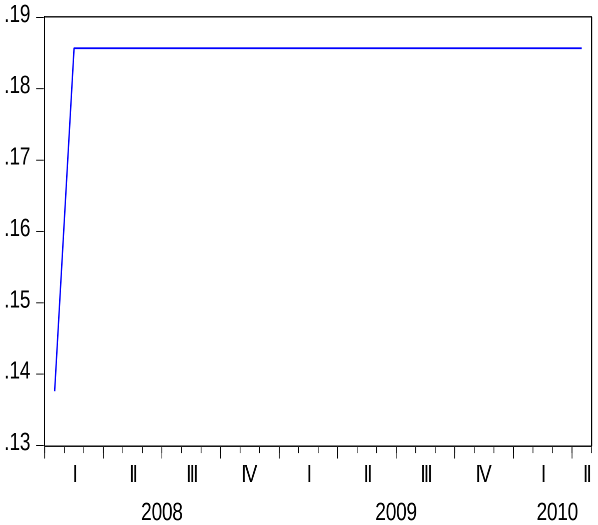
43.Nigeria



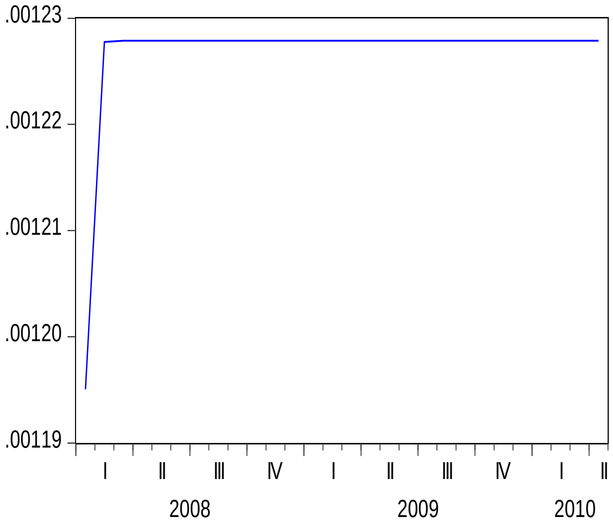
46.Sri Lanka



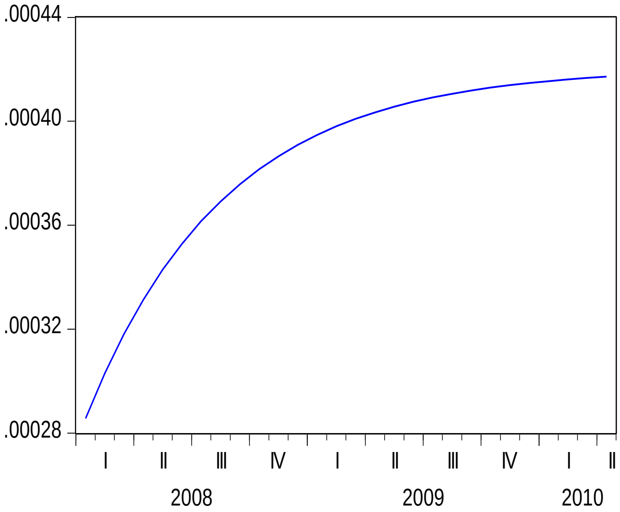
44.Pakistan



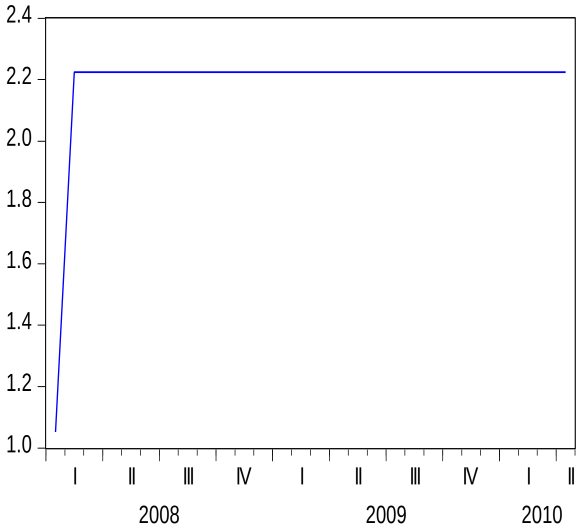
47.Trinidad & Tobago



48.Tunisia



49.Vietnam



Appendix 11: Estimated long-run coefficients and error correction model for emerging countries

Country	**Long-run Coefficients and Error Correction Model**	**Diagnostic Tests**
Brazil	$\ln ER = -0.055 \ast IRSBZ + 0.161x10^{-3} \ast TBBZ + 0.016 \ast TOBZ + 0.001 \ast D1$ (-2.412) (2.155) (2.846) (2.186) [0.007] [0.015] [0.002] [0.014] **ECM(-1) = -0.020 (-2.231) [0.010]**	SC:F = 0.505 [0.908] FF:F = 0.772 [0.318] HM:F = 0.634 [0.427] F = 14.876 [0.000] **SBC = 256.641**
Chile	$\ln ER = 0.018 + 0.244x10^{-4} \ast TBC - 0.094 \ast IRSC - 0.003 \ast MSC - 0.006\, CAC - 0.012 \ast D1$ (1.658) (2.864) (-3.875) (-3.309) (-3.785) (-3.190) [0.048] [0.002] [0.000] [0.000] [0.000] [0.000] **ECM(-1) = -0.062 (-2.741) [0.003]**	SC:F = 1.953 [0.055] FF:F = 0.289 [0.593] HM:F = 11.149 [0.100] F = 6.543 [0.000] **SBC =343.457**
China	$\ln ER = 0.030 \ast TBCHI + 0.125 \ast D2$ (2.158) (3.156) [0.016] [0.000] **ECM(-1) = -0.003 (-1.943) [0.026]**	SC:F = 0.147 [1.000] FF:F = 8.562 [0.082] HM:F = 0.020 [0.888] F = 21.289 [0.000] **SBC = 141.685**
Colombia	$\ln ER = 11.194 - 0.078 \ast INFRCO - 0.002 \ast MSCO$ (10.589) (-7.919) (-2.905) [0.000] [0.000] [0.002] **ECM(-1) = -0.045 (-3.085) [0.002]**	SC:F = 0.643[0.803] FF:F = 0.255 [0.615] HM:F = 0.748[0.388] F = 11.331 [0.000] **SBC = 381.494**
Czech Republic	$\ln ER = 6.504 - 0.002 \ast MSCR - 0.038 \ast INFRCR$ (12.402) (-6.076) (-3.378) [0.000] [0.000] [0.001] **ECM(-1) = - 0.063 (-3.450) [0.001]**	SC:F = 0.338[0.981] FF:F = 0.031 [0.860] HM:F =1.636 [0.203] F = 8.349 [0.000] **SBC = 367.348**
Hungary	$\ln ER = 0.190 \ast TOH$ (15.097) [0.000] **ECM(-1) = -0.006 (-2.070) [0.019]**	SC:F = 1.462 [0.146] FF:F = 3.437 [0.066] HM:F = 3.666 [0.057] F = 7.339 [0.001] **SBC = 345.195**
India	$\ln ER = -0.005 \ast MSIN - 0.778x10^{-3} \ast TBIN$ (-2.666) (-4.159) [0.004] [0.000] **ECM(-1) = -0.200 (-4.069) [0.000]**	SC = 0.292 [0.990] FF:F = 0.701 [0.403] HM:F = 0.002 [0.996] F = 10.043 [0.000] **SBC = 1009.7**
Indonesia	$\ln ER = 0.744x10^{-3} \ast IRSINDO - 0.052 \ast INFRINDO - 46.578 \ast D1$ (3.913) (-7.026) (-7.021) [0.000] [0.000] [0.000] **ECM(-1) = -0.005 (-5.126) [0.000]**	SC:F = 1.078 [0.378] FF:F = 0.994 [0.320] HM:F = 3.744 [0.054] F = 20.970 [0.000] **SBC = 481.312**
Malaysia	$\ln ER = 0.091 \ast \ln MSM - 3.499 \ast D1$ (11.656) (-3.323) [0.000] [0.001] **ECM(-1) = -0.016 (-2.400) [0.008]**	SC:F = 2.399 [0.060] FF:F = 1.102 [0.294] HM:F = 9.352 [0.200] F = 30.466 [0.000] **SBC = 1105.5**
Mexico	$\ln ER = 1.117 \ast \ln IRSME + 1.663 \ast D1$ (5.422) (3.483) [0.000] [0.014] **ECM(-1) = -0.004 (-2.955) [0.002]**	SC:F = 0.624 [0.824] FF:F = 4.540 [0.340] HM:F = 0.533 [0.466] F= 79.135 [0.000] **SBC = 556.190**

Appendix 11 (Cont.)

Country	**Long-run Coefficients and Error Correction Model**	**Diagnostic Tests**
Peru	$\ln ER = -0.284\text{x}10^{-3} * TBP + 0.067 * TOP + 0.022 * D1$ (-4.908) (2.474) (4.515) [0.000] [0.007] [0.000] **ECM(-1) = -0.034 (-6.823) [0.000]**	SC:F = 7.863[0.060] FF:F = 0.798 [0.373] HM:F = 29.533 [0.070] F = 41.517 [0.000] **SBC = 485.635**
Philippines	$\ln ER = -0.006 * INFRP - 16.425 * D1$ (-6.335) (-2.170) [0.000] [0.015] **ECM(-1) = - 0.003 (-2.312) [0.010]**	SC:F = 3.749 [0.100] FF:F = 4.220 [0.401] HM:F = 0.131 [0.717] F = 32.009 [0.000] **SBC = 1028.3**
Poland	$\ln ER = -0.980\text{x}10^{-3} * TBPO - 0.001 * D1$ (-3.235) (-5.456) [0.001] [0.000] **ECM(-1) = -0.005 (-2.288) [0.011]**	SC:F = 1.516 [0.125] FF:F = 0.724 [0.396] HM:F = 1.975 [0.162] F = 11.062 [0.001] **SBC = 346.952**
Russia	$\ln ER = 3.981 - 0.111 * IRSR - 6.881 * D1$ (18.885) (-4.747) (-2.871) [0.000] [0.000] [0.002] **ECM(-1) = -0.016 (-3.143) [0.002]**	SC:F = 15.070 [0.065] FF:F = 5.784 [0.180] HM:F = 6.795 [0.075] F = 131.894 [0.000] **SBC = 322.912**
South Africa	$\ln ER = 0.307\text{x}10^{-3} * MSSA + 0.155 * IRLSA - 0.158 * TOSA + 0.011 * GP$ (3.096) (4.515) (-4.465) (2.607) [0.002] [0.000] [0.000] [0.004] **ECM(-1) = -0.106 (-2.776) [0.003]**	SC:F = 1.784 [0.055] FF:F = $0.796\text{x}10^{-5}$ [0.998] HM:F = 1.039 [0.309] F = 20.282 [0.000] **SBC = 686.113**
South Korea	$InER = 0.084 * IRSSK - 0.678 * D1$ (4.718) (-3.312) [0.000] [0.000] **ECM(-1) = -0.009 (-2.294) [0.011]**	SC:F = 2.826[0.051] FF:F = 0.249 [0.618] HM:F = 4.624 [0.052] F = 68.915 [0.000] **SBC = 798.554**
Taiwan	$\ln ER = 3.138 + 0.209\text{x}10^{-3} * TBT$ (19.413) (2.060) [0.000] [0.020] **ECM(-1) = -0.013 (-2.427) [0.008]**	SC:F = 1.278 [0.231] FF:F = 2.852 [0.092] HM:F = 0.047 [0.828] F = 16.756 [0.000] **SBC = 844.777**
Thailand	$\ln ER = 3.683 - 0.041 * IRST - 1.751 * D1$ (29.315) (-2.563) (-2.812) [0.000] [0.005] [0.002] **ECM(-1) = -0.012 (-2.063) [0.020]**	SC:F = 1.487[0.129] FF:F = 3.944 [0.080] HM:F = 7.869[0.070] F = 25.093 [0.000] **SBC = 620.559**
Turkey	$\ln ER = 0.142 * TOTU + 4.935 * D1$ (1.687) (4.021) [0.045] [0.000] **ECM(-1) = -0.013 (-4.915) [0.000]**	SC:F = 1.502 [0.129] FF:F = 9.486[0.200] HM:F = 29.940 [0.000] F = 22.964 [0.000] **SBC = 259.352**

All Exchange rates (ER) are log transformed. t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. SC is the test for serial correlation, FF is the test of functional form, HM is the test of homoscedasticity and in all cases F statistics are reported. F test is used to evaluate whether the coefficient of ECM (-1) significantly different from zero or not. Dummy variables (D1 and D2) are used for the structural breaks in levels reported in Chapter 3.

Appendix 12: Estimated long-run coefficients and error correction model for frontier countries

Country	**Long-run Coefficients and Error Correction Model**	**Diagnostic Tests**
Bangladesh	$\ln ER = 0.001 * GDPBD + 0.035 * IRSBD - 0.002 * TBBD + 0.843 * D1$ (2.917) (7.117) (-1.757) (1.761) [0.002] [0.000] [0.039] [0.039] **ECM(-1) = -0.004 (-2.919) [0.002]**	SC:F = 1.334[0.196] FF:F = 4.844 [0.280] HM:F = 6.850[0.080] F = 6.622 [0.000] **SBC = 1087.6**
Bhutan*	$\ln ER = -0.006 * TBB + 0.002 * D1$ (-2.831) (1.971) [0.002] [0.024] **ECM(-1) = -0.002 (-3.630) [0.000]**	SC:F = 0.756[0.696] FF:F = 7.196 [0.080] HM:F = 0.022[0.882] F = 6.617 [0.002] **SBC = 848.984**
Botswana	$\ln ER = 0.008 * TBUS$ (3.971) [0.000] **ECM(-1) = -0.126 (-3.291) [0.001]**	SC:F = 1.103[0.356] FF:F = 1.690 [0.180] HM:F = 0.027[0.869] F = 19.358[0.000] **SBC = 387.308**
Brunei*	$\ln ER = 0.896 - 0.001 * MSUS - 0.017 * IRSUS + 0.039 * IRLUS + 0.1210x10^{-3} * GDPB + 0.007 * OP$ (8.396) (-6.978) (-2.558) (2.539) (4.482) (3.066) [0.000] [0.000] [0.005] [0.005] [0.000] [0.002] **ECM(-1) = -0.047 (-4.226) [0.000]**	SC:F = 3.692 [0.800] FF:F = 1.082 [0.299] HM:F = 2.627 [0.106] F = 7.347 [0.000] **SBC = 1236.3**
Croatia	$\ln ER = 0.034 * IRSC - 0.895x10^{-3} * INFRC - 0.045 * TBC$ (1.802) (-1.713) (-2.255) [0.036] [0.044] [0.011] **ECM(-1) = -0.003 (-1.812) [0.035]**	SC:F = 0.907[0.541] FF:F = 0.185 [0.667] HM:F = 4.429[0.307] F = 1.447 [0.000] **SBC = 403.989**
Estonia	$\ln ER = -0.016 * CAE$ (-2.230) [0.012] **ECM(-1) = -0.775x10^{-3} (-1.957) [0.025]**	SC:F = 0.659[0.789] FF:F = 2.977 [0.086] HM:F = 2.123[0.147] F = 9.451 [0.000] **SBC = 426.639**
Jamaica	$\ln ER = 0.004 * MSUS$ (10.554) [0.000] **ECM(-1) = -0.018 (-2.626) [0.004]**	SC:F = 3.681[0.075] FF:F = 1.174 [0.279] HM:F = 3.516[0.061] F = 21.941[0.000] **SBC = 800.530**
Kazakhstan	$\ln ER = 0.102 * IRSK - 0.234 * INFRK$ (1.703) (-2.320) [0.044] [0.010] **ECM(-1) = -0.762x10^{-3} (-1.395) [0.016]**	SC:F = 0.425[0.951] FF:F = 0.683 [0.410] HM:F = 1.586[0.210] F = 12.953 [0.000] **SBC = 351.853**
Kenya	$\ln ER = -0.597x10^{-3} * TBKE$ (-3.959) [0.000] **ECM(-1) = - 0.002 (-2.976) [0.001]**	SC:F = 1.610[0.086] FF:F = 0.508 [0.477] HM:F = 1.851[0.174] F = 37.389 [0.000] **SBC = 841.242**
Lao PDR*	$\ln ER = 0.175 * IRSL$ (4.301) [0.000] **ECM(-1) = -0.002 (-2.657) [0.004]**	SC:F = 1.007 [0.444] FF:F = 0.848 [0.358] HM:F = 0.019 [0.888] F = 23.521 [0.000] **SBC = 425.204**

Appendix 12 (Cont.)

Mauritius	$\text{lnER} = 0.296 * \text{IRLUS} - 0.767\text{x}10^{-3} * \text{TBM}$ (3.947) (-4.507) [0.000] [0.000] **ECM(-1) = -0.004 (-1.726) [0.045]**	SC:F = 0.713[0.739] FF:F = 0.064 [0.800] HM:F = 4.268[0.059] F = 25.608 [0.000] **SBC = 1060.7**
Myanmar*	$\text{lnER} = 1.580 + 0.047 * \text{IRLUS}$ (13.792) (2.682) [0.000] [0.008] **ECM(-1) = -0.018 (-2.324) [0.021]**	SC:F = 1.704[0.064] FF:F = 0.916 [0.339] HM:F = 0.026[0.873] F = 17.904 [0.000] **SBC = 1129.2**
Nepal*	$\text{InER} = 0.298 * \text{IRSN} - 0.003 * \text{MSUS}$ (0.284) (-0.012) [0.007] [0.009] **ECM(-1) = -0.001 (-0.304) [0.007]**	SC:F = 0.914[0.533] FF:F = 0.214 [0.800] HM:F = 0.729[0.394] F = 18.249 [0.000] **SBC = -340.834**
Nigeria	$\text{InER} = -0.293 * \text{INFRN} + 0.023 * \text{GDPN}$ (-2.660) (1.917) [0.008] [0.005] **ECM(-1) = -0.118 (-1.848) [0.005]**	SC:F = 0.215 [0.998] FF:F = 0.023 [0.879] HM:F = 0.174 [0.677] F = 7.772 [0.000] **SBC = -1109.1**
Pakistan	$\text{lnER} = 5.010 - 0.040 * \text{IRSP} - 0.001 * \text{CAP}$ (3.809) (-0.327) (-1.387) [0.000] [0.004] [0.010] **ECM(-1) = -0.012 (-1.641) [0.010]**	SC:F = 1.792[0.049] FF:F = 0.342 [0.559] HM:F = 0.316 [0.575] F = 20.091[0.000] **SBC = 899.876**
Romania	$\text{lnER} = 13.585 - 0.013 * \text{MSUS} - 0.037 * \text{IRSR} - 0.002 * \text{TBUS}$ (2.998) (-3.085) (-2.771) (-3.196) [0.003] [0.002] [0.006] [0.002] **ECM(-1) = -0.017 (-2.332) [0.021]**	SC:F = 1.145[0.329] FF:F = 0.226 [0.635] HM:F = 0.306[0.581] F = 17.827 [0.000] **SBC = 289.866**
Sri Lanka	$\text{InER} = 0.711\text{x}10^{-3} * \text{GDPS} - 0.116\text{x}10^{-3} * \text{TBS} + 0.184 * \text{T}$ (2.976) (-3.644) (11.329) [0.003] [0.000] [0.000] **ECM(-1) = -0.128 (-2.873) [0.004]**	SC:F = 1.399[0.163] FF:F = 0.228 [0.633] HM:F = 12.087[0.100] F = 10.198 [0.000] **SBC = -469.604**
Trinidad & Tobago	$\text{InER} = 0.009 * \text{MSUS} + 4.173 * \text{TOTT} - 0.009 * \text{OP} + 4.029 * \text{D1}$ (12.042) (11.395) (-5.598) (2.582) [0.000] [0.000] [0.000] [0.010] **ECM(-1) = -0.039 (-3.336) [0.001]**	SC:F = 0.444[0.945] FF:F = 1.672 [0.197] HM:F = 2.940[0.087] F = 67.265[0.000] **SBC = 1171.9**
Tunisia	$\text{InER} = -0.009 * \text{INFRTUI} - 0.930\text{x}10^{-3} * \text{TBTUI} + 0.584\text{x}10^{-3} * \text{MSUS}$ (-3.767) (-2.324) (2.968) [0.000] [0.021] [0.004] **ECM(-1) = -0.027 (-3.021) [0.001]**	SC:F = 1.492[0.124] FF:F = 0.405 [0.525] HM:F = 32.362[0.051] F = 15.774 [0.000] **SBC = 1111.9**
Vietnam	$\text{lnER} = 1.354 * \text{lnMSUS}$ (75.207) [0.000] **ECM(-1) = -0.157 (-5.416) [0.000]**	SC:F = 5.842[0.790] FF:F = 0.938 [0.334] HM:F = 27.545[0.630] F = 21.799 [0.000] **SBC = 194.427**

All Exchange rates (ER) are log transformed. t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. SC is the test for serial correlation, FF is the test of functional form, HM is the test of homoscedasticity and in all cases F statistics are reported. F test is used to evaluate whether the coefficient of ECM (-1) significantly different from zero or not. T: Time trend. Dummy variables (D1 and D2) are used for the structural breaks in levels reported in Chapter 3. *Not listed as a frontier markets according to MSCI.

Appendix 13: Estimated short-run coefficients using ARDL approach for emerging countries

Country	**Short-run Coefficients**
Brazil	$\Delta \mathrm{lnER}_t = 0.330\Delta \mathrm{lnER}_{t-1} - 0.344\Delta \mathrm{lnER}_{t-2} - 0.001\Delta \mathrm{IRSBZ}_{t-1} + 0.948\Delta \mathrm{TBBZ}_{t-1} + 1.088\Delta \mathrm{TOBZ}_{t-1} + 0.021\Delta \mathrm{D1}_{t-1}$ (4.166) (-4.465) (-2.796) (2.638) (2.772) (3.146) [0.000] [0.000] [0.002] [0.004] [0.003] [0.000] **F = 14.876 [0.000]**
Chile	$\Delta \mathrm{lnER}_t = 0.624 + 0.293\ \Delta \mathrm{lnER}_{t-1} + 0.152\mathrm{x}10^{-5}\Delta \mathrm{TBC}_{t-1} - 0.211\mathrm{x}10^{-3}\Delta \mathrm{MSC}_{t-1} - 0.005\ \Delta \mathrm{IRSC}_{t-1} - 0.374\mathrm{x}10^{-3}\Delta \mathrm{CAC}_{t-1} - 0.012\Delta \mathrm{D1}_{t-1}$ (3.296) (3.605) (3.878) (-3.693) (-2.260) (-3.382) (-3.160) [0.001] [0.000] [0.003] [0.000] [0.012] [0.001] [0.000] **F = 6.543 [0.000]**
China	$\Delta \mathrm{lnER}_t = 0.002\ \Delta \mathrm{TBCHI}_{t-1} + 0.005\Delta \mathrm{D2}_{t-1}$ (4.371) (4.452) [0.000] [0.000] **F= 21.289 [0.000]**
Colombia	$\Delta \mathrm{lnER}_t = 0.502 + 0.239\ \Delta \mathrm{lnER}_{t-1} - 0.004\Delta \mathrm{INFRCO}_{t-1} - 0.102\mathrm{x}10^{-3}\Delta \mathrm{MSCO}_{t-1}$ (3.806) (3.232) (-3.500) (-4.113) [0.000] [0.001] [0.001] [0.000] **F = 11.331 [0.000]**
Czech Republic	$\Delta \mathrm{lnER}_t = 0.410 + 0.241\ \Delta \mathrm{lnER}_{t-1} - 0.157\mathrm{x}10^{-3}\Delta \mathrm{MSCR}_{t-1} - 0.002\mathrm{x}10^{-3}\Delta \mathrm{INFRCR}_{t-1}$ (3.951) (3.253) (-4.256) (-2.991) [0.000] [0.001] [0.000] [0.001] **F = 8.349 [0.000]**
Hungary	$\Delta \mathrm{lnER}_t = 0.222\Delta \mathrm{lnER}_{t-1} - 0.022\Delta \mathrm{TOH}_{t-1}$ (2.741) (-1.992) [0.007] [0.023] **F = 7.339 [0.001]**
India	$\Delta \mathrm{lnER}_t = 0.165\Delta \mathrm{lnER}_{t-1} - 0.125\mathrm{x}10^{-5}\Delta \mathrm{TBIN}_{t-1} - 0.173\mathrm{x}10^{-5}\Delta \mathrm{MSIN}_{t-1}$ (3.270) (-3.401) (-3.157) [0.001] [0.001] [0.002] **F = 10.043 [0.000]**
Indonesia	$\Delta \mathrm{lnER}_t = -0.129\Delta \mathrm{lnER}_{t-2} - 0.270\Delta \mathrm{lnER}_{t-3} - 0.113\Delta \mathrm{lnER}_{t-4} - 0.003\Delta \mathrm{INFINDO}_{t-1} + 0.188\mathrm{x}10^{-4}\Delta \mathrm{TBINDO}_{t-1} - 0.185\Delta \mathrm{D1}_{t-1} - 0.190\Delta \mathrm{D1}_{t-2}$ (-2.604) (-5.497) (-2.246) (-4.511) (2.880) (5.105) (-3.809) [0.005] [0.000] [0.012] [0.000] [0.002] [0.000] [0.000] **F = 20.970 [0.000]**
Malaysia	$\Delta \mathrm{lnER}_t = 0.066\ \Delta \mathrm{lnMSM}_{t-1} + 0.062\Delta \mathrm{lnMSM}_{t-2} - 0.055\Delta \mathrm{D1}_{t-1}$ (2.899) (2.703) (8.670) [0.004] [0.007] [0.000] **F = 30.466 [0.000]**
Mexico	$\Delta \mathrm{lnER}_t = 0.295\Delta \mathrm{lnER}_{t-1} + 0.164\Delta \mathrm{lnER}_{t-2} + 0.102\ \Delta \mathrm{lnIRSME}_{t-1} + 0.094\Delta \mathrm{D1}_{t-1}$ (5.006) (3.468) (9.956) (5.311) [0.000] [0.000] [0.000] [0.000] **F= 79.135 [0.000]**
Peru	$\Delta \mathrm{lnER}_t = 0.396\Delta \mathrm{lnER}_{t-1} - 0.273\Delta \mathrm{lnER}_{t-2} - 0.974\mathrm{x}10^{-5}\Delta \mathrm{TBP}_{t-1} + 0.375\Delta \mathrm{TOP}_{t-1} + 0.102\Delta \mathrm{D1}_{t-1}$ (6.570) (-4.668) (-4.921) (3.449) (3.263) [0.000] [0.000] [0.000] [0.001] [0.000] **F = 41.517 [0.000]**

Appendix 13 (Cont.)

Country	Short-run Coefficients
Philippines	$\Delta \mathrm{lnER}_t = 0.236\,\Delta \mathrm{lnER}_{t-1} - 0.195\mathrm{x}10^{-4}\Delta \mathrm{INFRP}_{t-1} - 0.094\Delta \mathrm{D1}_{t-1}$ (4.936) (-1.892) (-6.010) [0.004] [0.029] [0.000] **F = 32.009 [0.000]**
Poland	$\Delta \mathrm{lnER}_t = 0.522\mathrm{x}10^{-5}\Delta \mathrm{TBPO}_{t-1} - 0.121\mathrm{x}10^{-4}\Delta \mathrm{D1}_{t-1}$ (3.325) (-2.459) [0.001] [0.007] **F = 11.062 [0.001]**
Russia	$\Delta \mathrm{lnER}_t = -0.061 - 0.345\Delta \mathrm{lnER}_{t-1} - 0.577\Delta \mathrm{lnER}_{t-2} + 0.002\Delta \mathrm{IRSR}_{t-1} - 0.662\mathrm{x}10^{-3}\Delta \mathrm{IRSR}_{t-2} + 0.537\Delta \mathrm{D1}_{t-1}$ (-3.535) (-4.637) (-10.142) (5.909) (-4.872) (16.168) [0.000] [0.000] [0.000] [0.000] [0.000] [0.000] **F = 131.894 [0.000]**
South Africa	$\Delta \mathrm{lnER}_t = 0.210\,\Delta \mathrm{lnER}_{t-1} + 0.450\mathrm{x}10^{-7}\Delta \mathrm{MSSA}_{t-1} + 0.031\Delta \mathrm{IRSSA}_{t-1} - 0.011\,\Delta \mathrm{IRSSA}_{t-2} + 0.514\Delta \mathrm{TOSA}_{t-1} - 0.163\mathrm{x}10^{-3}\Delta \mathrm{GP}_{t-1}$ (3.887) (1.803) (7.356) (-2.537) (4.066) (-2.605) [0.000] [0.036] [0.000] [0.006] [0.000] [0.005] **F = 20.282 [0.000]**
South Korea	$\Delta \mathrm{lnER}_t = 0.501\,\Delta \mathrm{lnER}_{t-1} - 0.283\Delta \mathrm{lnER}_{t-2} + 0.008\,\Delta \mathrm{IRSSK}_{t-1} - 0.165\Delta \mathrm{D1}_{t-1}$ (9.674) (-5.659) (6.688) (-7.145) [0.000] [0.000] [0.000] [0.000] **F = 68.915 [0.000]**
Taiwan	$\Delta \mathrm{lnER}_t = 0.040 + 0.320\,\Delta \mathrm{lnER}_{t-1} + 0.212\mathrm{x}10^{-3}\Delta \mathrm{TBT}_{t-1} - 0.367\mathrm{x}10^{-3}\Delta \mathrm{TBT}_{t-2}$ (2.242) (5.802) (2.561) (-2.661) [0.013] [0.000] [0.005] [0.004] **F = 16.756 [0.000]**
Thailand	$\Delta \mathrm{lnER}_t = 0.072 + 0.351\,\Delta \mathrm{lnER}_{t-1} - 0.164\Delta \mathrm{lnER}_{t-2} + 0.003\Delta \mathrm{IRST}_{t-1} - 0.112\Delta \mathrm{D1}_{t-1}$ (2.052) (6.249) (-2.844) (3.489) (-6.844) [0.020] [0.000] [0.002] [0.000] [0.000] **F = 25.093 [0.000]**
Turkey	$\Delta \mathrm{lnER}_t = 0.019\Delta \mathrm{TOTU}_{t-1} + 0.113\Delta \mathrm{D1}_{t-1} - 0.212\Delta \mathrm{D1}_{t-2}$ (2.146) (2.405) (-4.530) [0.016] [0.007] [0.000] **F = 22.964 [0.000]**

t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. The null for F test is the short run regression coefficients are all zero. Dummy variables (D1 and D2) are used for the structural breaks in levels reported in Chapter 3.

Appendix 14: Estimated short-run coefficients using ARDL approach for frontier countries

Country	Short-run Coefficients
Bangladesh	$\Delta \mathrm{lnER}_t = -0.004\,\Delta \mathrm{GDPBD}_{t-1} + 0.001\Delta \mathrm{IRSBD}_{t-1} - 0.895\mathrm{x}10^{-5}\Delta \mathrm{TBBD}_{t-1} + 0.029\Delta \mathrm{D}_{t-1}$ (-2.846) (3.662) (-3.957) (2.200) [0.002] [0.000] [0.000] [0.014] **F = 6.622 [0.000]**
Bhutan*	$\Delta \mathrm{lnER}_t = 0.190\Delta \mathrm{lnER}_{t-1} + 0.944\mathrm{x}10^{-6}\Delta \mathrm{TBB}_{t-1} + 0.014\Delta \mathrm{D1}_{t-1}$ (3.498) (1.986) (3.106) [0.001] [0.023] [0.000] **F = 6.617 [0.002]**
Botswana	$\Delta \mathrm{lnER}_t = 0.216\Delta \mathrm{lnER}_{t-1} + 0.004\Delta \mathrm{TBUS}_{t-1} - 0.005\Delta \mathrm{TBUS}_{t-2}$ (4.656) (3.604) (-4.635) [0.000] [0.000] [0.000] **F = 19.358[0.000]**
Brunei*	$\Delta \mathrm{lnER}_t = -0.619\mathrm{x}10^{-4}\Delta \mathrm{MSUS}_{t-1} - 0.017\Delta \mathrm{IRSUS}_{t-1} + 0.039\Delta \mathrm{IRLUS}_{t-1} + 0.121\mathrm{x}10^{-3}\,\Delta \mathrm{GDPB}_{t-1} + 0.007\Delta \mathrm{OP}_{t-1}$ (-6.978) (-2.558) (2.539) (4.482) (3.066) [0.005] [0.005] [0.005] [0.000] [0.002] **F = 7.347 [0.000]**
Croatia	$\Delta \mathrm{lnER}_t = 0.210\,\Delta \mathrm{lnER}_{t-1} + 0.195\mathrm{x}10^{-4}\Delta \mathrm{IRSC}_{t-1} + 0.852\mathrm{x}10^{-4}\Delta \mathrm{IRSC}_{t-2} + 0.229\mathrm{x}10^{-5}\,\Delta \mathrm{INFRC}_{t-1} - 0.012\Delta \mathrm{INFRUS}_{t-1}$ (3.167) (1.690) (6.947) (1.971) (-2.434) [0.002] [0.046] [0.000] [0.024] [0.008] **F = 1.447 [0.000]**
Estonia	$\Delta \mathrm{lnER}_t = 0.336\Delta \mathrm{lnER}_{t-1} - 0.185\Delta \mathrm{lnER}_{t-2} - 0.124\mathrm{x}10^{-4}\Delta \mathrm{CAE}_{t-1}$ (4.544) (-2.566) (-1.983) [0.000] [0.005] [0.024] **F = 9.451 [0.000]**
Jamaica	$\Delta \mathrm{lnER}_t = 0.3400\Delta \mathrm{lnER}_{t-1} - 0.106\Delta \mathrm{lnER}_{t-2} + 0.172\Delta \mathrm{lnER}_{t-3} + 0.297\mathrm{x}10^{-4}\Delta \mathrm{MSUS}_{t-1}$ (8.336) (-2.067) (3.602) (3.110) [0.000] [0.019] [0.000] [0.002] **F = 21.941[0.000]**
Kazakhstan	$\Delta \mathrm{lnER}_t = 0.246\Delta \mathrm{lnER}_{t-1} + 0.778\mathrm{x}10^{-3}\Delta \mathrm{IRSK}_{t-1} - 0.0.178\mathrm{x}10^{-3}\Delta \mathrm{INFRK}_{t-1}$ (3.196) (3.629) (-3.004) [0.002] [0.000] [0.003] **F = 12.953 [0.000]**
Kenya	$\Delta \mathrm{lnER}_t = 0.381\Delta \mathrm{lnER}_{t-1} - 0.123\mathrm{x}10^{-8}\Delta \mathrm{TBKE}_{t-1}$ (8.010) (-2.281) [0.000] [0.011] **F = 37.389 [0.000]**
Lao PDR*	$\Delta \mathrm{lnER}_t = 0.341\Delta \mathrm{lnER}_{t-1} + 0.167\Delta \mathrm{lnER}_{t-2}$ (5.273) (2.574) [0.000] [0.005] **F = 23.521 [0.000]**
Mauritius	$\Delta \mathrm{lnER}_t = 0.311\Delta \mathrm{lnER}_{t-1} + 0.014\Delta \mathrm{IRSLUS}_{t-1} + 0.323\mathrm{x}10^{-5}\Delta \mathrm{TBUS}_{t-1}$ (6.788) (4.745) (2.479) [0.000] [0.000] [0.007] **F = 25.608 [0.000]**

Appendix 14 (Cont.)

Country	**Short-run Coefficients**
Myanmar*	$\Delta \ln ER_t = 0.028 + 0.201\Delta \ln ER_{t-1} + 0.006\ \Delta IRLUS_{t-1}$ (2.078) (4.176) (4.833) [0.019] [0.000] [0.000] **F=17.904 [0.000]**
Nepal*	$\Delta \ln ER_t = 0.315\Delta \ln ER_{t-1} + 0.040\ \Delta IRSN_{t-1} - 0.014\Delta MSUS_{t-1}$ (5.844) (2.569) (-2.497) [0.000] [0.005] [0.006] **F = 18.249 [0.000]**
Nigeria	$\Delta \ln ER_t = 0.086\Delta IRSN_{t-1} - 0.407x10^{-3}\Delta GDPN_{t-1}$ (3.874) (-4.040) [0.000] [0.000] **F = 7.772 [0.000]**
Pakistan	$\Delta \ln ER_t = 0.010 + 0.384\Delta \ln ER_{t-1} - 0.001\ \Delta IRSP_{t-1} - 0.287x10^{-5}\Delta CAP_{t-1}$ (2.115) (7.233) (-3.651) (-2.589) [0.017] [0.000] [0.001] [0.005] **F = 20.091[0.000]**
Romania	$\Delta \ln ER_t = 0.552\ \Delta \ln ER_{t-1} - 0.223\Delta \ln ER_{t-2} - 0.222x10^{-3}\Delta MSUS_{t-1} - 0.006\Delta IRSR_{t-1} + 0.292x10^{-4}\ \Delta TBUS_{t-1}$ (7.019) (-2.834) (-2.625) (-2.584) (1.805) [0.000] [0.002] [0.004] [0.005] [0.032] **F = 17.827 [0.000]**
Sri Lanka	$\Delta \ln ER_t = 0.144\ \Delta \ln ER_{t-1} - 0.196x10^{-5}\Delta GDPS_{t-1} + 0.206x10^{-4}\Delta TBS_{t-1} - 0.155x10^{-4}\Delta TBS_{t-2} + 0.005\ \Delta T_{t-1}$ (2.992) (-4.026) (4.070) (-3.003) (3.445) [0.001] [0.000] [0.000] [0.003] [0.001] **F = 10.198 [0.000]**
Trinidad & Tobago	$\Delta \ln ER_t = 0.624\ \Delta \ln ER_{t-1} - 0.351\Delta \ln ER_{t-2} + 0.349x10^{-4}\Delta MSUS_{t-1} + 0.161\Delta TOTT_{t-1} - 0.003\Delta OP_{t-1} + 0.298\Delta D1_{t-1}$ (13.041) (-6.561) (3.069) (3.532) (-3.028) (20.079) [0.000] [0.000] [0.002] [0.000] [0.003] [0.000] **F = 67.265 [0.000]**
Tunisia	$\Delta \ln ER_t = 0.336\ \Delta \ln ER_{t-1} - 0.254x10^{-3}\Delta INFRTUI - 0.256x10^{-6}\Delta TBTUI + 0.161x10^{-4}\Delta MSUS_{t-1}$ (7.345) (-2.665) (-2.381) (2.160) [0.000] [0.004] [0.009] [0.015] **F = 15.774 [0.000]**
Vietnam	$\Delta \ln ER_t = 0.170\Delta \ln ER_{t-1} + 0.077\Delta \ln MSUS_{t-1}$ (2.796) (5.530) [0.003] [0.000] **F = 21.799 [0.000]**

t statistics are reported in the round brackets and corresponding significance levels are reported in the square brackets. The null for F test is the short run regression coefficients are all zero. Dummy variables (D1 and D2) are used for the structural breaks in levels reported in Chapter 3. *Not listed as a frontier markets according to MSCI.

Appendix 15: Unit root test results: Advanced Countries

Country	Ng Perron MZa* Test Statistics		Phillips – Perron Test Statistics**	
	Level	**First Order Difference**	**Level**	**First Order Difference**
Australia				
LNER	-1.452	-201.283	-1.461 (0.553)	-15.484 (0.000)
IRLAUS	-1.620	-205.530	-1.295 (0.633)	-17.656 (0.000)
INFRAUS	-7.307	-36.934	-1.781 (0.390)	-10.159 (0.000)
TBAUS	-4.326	-24.901	-0.961 (0.768)	-12.392 (0.000)
TOAUS	0.068	-74.295	-1.404 (0.581)	-3.589 (0.006)
Canada				
InER	-1.183	-56.674	-1.172 (0.688)	-16.369 (0.000)
InIRSC	-4.413	-155.343	-1.703 (0.429)	-17.257 (0.000)
InTBC	-1.566	-8.290	-3.618 (0.006)	-11.783 (0.000)
Denmark				
LNER	-6.763	-192.036	-1.654 (0.454)	-14.906 (0.000)
MSDM	3.066	-8.851	2.840 (1.000)	-26.391 (0.000)
TODM	-0.321	-8.848	0.061 (0.962)	-9.882 (0.000)
Euro area				
LNER	-1.637	-31.908	-0.122 (0.943)	-7.490 (0.000)
MSEA	2.832	-11.476	5.999 (1.000)	-8.465 (0.000)
IRSEA	-5.819	-34.755	-1.213 (0.667)	-5.620 (0.000)
Japan				
LNER	0.347	-23.061	-1.484 (0.541)	-15.141 (0.000)
IRLJ	-0.214	-208.324	-0.737 (0.835)	-17.619 (0.000)
TBJ	-0.967	-64.757	-2.013 (0.281)	-9.486 (0.000)
OP	-3.700	-195.809	-2.819 (0.056)	-15.582 (0.000)
Norway				
LNER	-7.504	-185.729	-1.684 (0.439)	-14.685 (0.000)
IRLN	-1.446	-214.784	-0.924 (0.780)	-20.154 (0.000)
TON	1.599	-71.085	-0.876 (0.796)	-3.289 (0.016)
Singapore				
LNER	0.703	-172.702	-1.681 (0.441)	-15.251 (0.000)
MSS	1.237	-18.437	-0.266 (0.927)	-21.759 (0.000)
Sweden				
LNER	-1.647	-187.617	-1.534 (0.516)	-13.951 (0.000)
IRLSWE	-2.297)	-196.335	-1.003 (0.753)	-15.890 (0.000)
MSSWE	4.023	-12.247	5.439 (1.000)	-22.666 (0.000)
IRLUS	-2.951	-98.599	-1.264 (0.647)	-14.802 (0.000)
OP	-3.700	-195.809	-2.819 (0.056)	-15.582 (0.000)
Switzerland				
LNER	0.483	-184.837	-2.434 (0.133)	-15.021 (0.000)
IRSSWI	-2.951	-98.599	-2.127 (0.234)	-15.522 (0.000)
UK				
LNER	-2.129	-83.329	-2.463 (0.125)	-15.626 (0.000)
TOUK	-1.991	-27.774	-3.463 (0.051)	-9.478 (0.000)

***** Asymptotic critical values at 5% (- 8.1000).
**Significance level shown in parentheses

Appendix 16: Unit root test results: Emerging Countries

Country	Ng Perron MZa* Test Statistics		Phillips – Perron Test Statistics**	
	Level	**First Order Difference**	**Level**	**First Order Difference**
Brazil				
LNER	-1.131	-64.023	-1.763 (0.397)	-7.714 (0.000)
IRSBZ	-4.714	-12.029	-3.536 (0.008)	-15.591 (0.000)
TBBZ	-7.879	-41.307	-1.171 (0.656)	-4.971 (0.000)
TOBZ	-0.490	-16.218	-2.065 (0.259)	-5.550 (0.000)
Chile				
LNER	0.423	-198.002	-6.688 (0.060)	-14.065 (0.000)
TBC	-4.144	-44.446	-0.694 (0.845)	-6.045 (0.000)
IRSC	0.011	-126.257	-2.928 (0.063)	-11.280 (0.000)
MSC	0.908	-10.780	-1.705 (0.428)	-18.346 (0.000)
CAC	-1.228	-393.596	-2.173 (0.217)	-22.054 (0.000)
China				
LNER	0.479	-215.000	-0.696 (0.845)	-19.374 (0.000)
TBCHI	2.547	-13.306	5.957 (1.000)	-8.407 (0.000)
Colombia				
LNER	0.922	-180.172	-1.767 (0.397)	-13.867 (0.000)
INFRCO	-2.752	-37706.4	-1.862 (0.350)	-13.021 (0.000)
MSCO	1.237	-18.437	-0.266 (0.927)	-21.759 (0.000)
Czech Republic				
LNER	-1.508	-81.339	0.453 (0.985)	-9.873 (0.000)
MSCR	1.416	-31.137	-0.469 (0.893)	-14.238 (0.000)
INFRCR	-1.615	-10.229	-1.992 (0.290)	-9.958 (0.000)
Hungary				
LNER	-0.109	-52.833	-0.107 (0.947)	-16.586 (0.000)
TOH	-0.576	-20.365	-1.599 (0.481)	-6.630 (0.000)
India				
LNER	0.842	-198.508	-0.846 (0.805)	-16.617 (0.000)
MSIN	-4.840	-19.626	-5.097 (0.000)	-17.430 (0.000)
TBIN	10.938	-15.572	2.027 (0.999)	-11.745 (0.000)
Indonesia				
LNER	0.171	-134.727	-1.071 (0.728)	-14.941 (0.000)
IRSINDO	-4.404	-136.983	-3.005 (0.036)	-20.332 (0.000)
INFRINDO	-6.892	-1146.18	-3.779 (0.063)	-8.806 (0.000)
Malaysia				
LNER	-2.991	-209.876	-1.147 (0.698)	-16.166 (0.000)
INMSM	1.379	-8.325	-1.318 (0.622)	-24.793 (0.000)
Mexico				
LNER	0.858	-120.832	-3.562 (0.007)	-10.932 (0.000)
InIRSME	-0.432	-115.249	-2.151 (0.225)	-11.473 (0.000)
Peru				
LNER	0.237	-19.609	-8.182 (0.000)	-10.833 (0.000)
TBP	-0.613	-11.079	0.226 (0.974)	-7.056 (0.000)
TOP	0.292	-5.910	-1.081 (0.723)	-6.632 (0.000)
Philippines				
LNER	0.630	-187.859	-1.116 (0.711)	-15.870 (0.000)
INFRP	-4.082	-15.210	-3.834 (0.073)	-9.932 (0.000)
Poland				
LNER	0.049	-109.059	-4.501 (0.000)	-7.787 (0.000)
TBPO	3.385	-296.951	-0.064 (0.951)	-10.515 (0.000)
Russia				
LNER	-0.616	-19.502	-2.151 (0.225)	-9.653 (0.000)
IRSR	-4.256	-113.279	-4.452 (0.054)	-16.153 (0.000)

Appendix 16 (Cont.)

Country	Ng Perron MZa* Test Statistics		Phillips – Perron Test Statistics**	
	Level	**First Order Difference**	**Level**	**First Order Difference**
South Africa				
LNER	0.137	-215.000	-1.437 (0.564)	-13.283 (0.000)
MSSA	5.082	-9.545	10.459 (1.000)	-21.329 (0.000)
IRLSA	-2.895	-132.514	-1.363 (0.601)	-12.560 (0.000)
TOSA	-7.914	-17.470	-1.449 (0.558)	-10.123 (0.000)
GP	3.159	-13.264	3.863 (1.000)	-17.404 (0.000)
South Korea				
LNER	-0.934	-284.628	-2.727 (0.070)	-10.863 (0.000)
IRSSK	-2.055	-8.586	-2.232 (0.196)	-16.094 (0.000)
Taiwan				
LNER	-0.435	-214.996	-1.958 (0.306)	-11.454 (0.000)
TBT	2.238	-8.167	0.941 (0.996)	-6.429 (0.000)
Thailand				
LNER	-1.419	-214.793	-1.613 (0.475)	-12.592 (0.000)
IRST	-4.809	-13.087	-2.713 (0.073)	-18.777 (0.000)
Turkey				
LNER	0.023	-70.093	-4.957 (0.700)	-14.946 (0.000)
TOTU	-2.887	-11.060	-3.369 (0.414)	-11.609 (0.000)

***** Asymptotic critical values at 5% (- 8.1000).
**Significance level shown in parentheses

Appendix 17: Unit root test results: Frontier Countries

Country	Ng Perron MZa* Test Statistics		Phillips – Perron Test Statistics***	
	Level	**First Order Difference**	**Level**	**First Order Difference**
Bangladesh				
LNER	1.830	-202.187	-2.069 (0.257)	-19.220 (0.000)
GDPBD	3.836	-16.289	16.147 (1.000)	-45.203 (0.000)
IRSBD	-0.653	-214.556	-1.825(0.368)	-19.817 (0.000)
TBBD	-0.012	-13.907	-3.781 (0.003)	-16.112(0.000)
Bhutan				
LNER	0.842	-198.511	-1.282 (0.639)	-14.985 (0.000)
TBB	-4.570	-1854.76	-1.866 (0.348)	-13.197 (0.000)
Botswana				
LNER	1.523	-200.074	-0.249 (0.929)	-16.654 (0.000)
TBUS	3.500	-22.398	4.976 (1.000)	-6.268 (0.000)
Brunei				
LNER	0.703	-172.832	-1.680 (0.440)	-15.274 (0.000)
MSUS	1.237	-18.437	-0.266(0.927)	-21.759 (0.000)
IRSUS	-3.530	-13.033	-2.151 (0.225)	-15.594 (0.000)
IRLUS	-2.865	-61.128	-1.287 (0.637)	-14.839 (0.000)
GDPB	2.236	-12.645	9.191 (1.000)	-5.442 (0.000)
OP	3.931	-207.510	1.078 (0.997)	-17.091 (0.000)
Croatia				
LNER	-0.256	-7.310 (-159.28)**	-7.001 (0.000)	-4.114 (0.001)
IRSC	-5.625	-727.75	-2.760 (0.066)	-16.033 (0.000)
INFRC	0.516	-9.131	-5.293 (0.700)	-15.206 (0.000)
TBC	2.456	-11.397	0.555 (0.988)	-9.443 (0.000)
Estonia				
LNER	-2.443	-124.293	-0.885 (0.791)	-9.732 (0.000)
CAE	3.018	-10.406	1.500 (0.999)	-8.611 (0.000)
Jamaica				
LNER	2.479	-87.951	-0.708 (0.842)	-14.685 (0.000)
MSUS	1.237	-18.437	-0.266 (0.927)	-21.759 (0.000)
Kazakhstan				
LNER	0.082	-7.300 (-73.420)**	-6.968 (0.200)	-12.852 (0.000)
IRSK	0.136	-9.470	-1.931 (0.317)	-10.527 (0.000)
INFRK	0.540	-8.314	-3.742 (0.064)	-5.040 (0.000)
Kenya				
LNER	0.286	-214.804	-1.305 (0.628)	-13.152 (0.000)
TBKE	-1.661	-68.593	-0.931 (0.778)	-14.773 (0.000)
Lao PDR				
LNER	0.656	-217.897	-1.001 (0.753)	-9.897 (0.000)
IRSL	5.499	-117.930	1.903 (0.999)	-13.095 (0.000)
Mauritius				
LNER	1.181	-168.529	-1.253 (0.653)	-14.951 (0.000)
IRLUS	-2.865	-61.128	-1.287 (0.637)	-14.839 (0.000)
TBM	3.199	-8.433	1.817 (0.999)	-8.335 (0.000)
Myanmar				
LNER	-1.251	-215.000	-2.525 (0.108)	-18.182 (0.000)
IRLUS	-1.918	-11.712	-1.965 (0.302)	-14.678 (0.000)
Nepal				
LNER	0.614	-214.997	-3.093 (0.028)	-14.190 (0.000)
IRSN	-7.707	-117.798	-2.356 (0.155)	-18.360 (0.000)
MSUS	0.923	-10.223	-1.564 (0.499)	-18.587 (0.000)
Nigeria				
LNER	1.226	-214.934	-0.102 (0.947)	-19.894 (0.000)
INFRN	3.801	-14.366	5.364 (1.000)	-14.323 (0.000)
GDPN	6.407	-11.388	9.780 (1.000)	-11.606 (0.000)

Appendix 17 (Cont.)

Country	Ng Perron MZa* Test Statistics		Phillips – Perron Test Statistics***	
	Level	First Order Difference	Level	First Order Difference
Pakistan				
LNER	1.265	-215.000	-2.711 (0.073)	-11.400 (0.000)
IRSP	-7.117	-124.453	-7.595 (0.800)	-12.057 (0.000)
CAP	-7.228	-104.407	-0.758 (0.829)	-10.121 (0.000)
Romania				
LNER	0.332	-71.612	-4.536 (0.900)	-16.024 (0.000)
MSUS	1.416	-31.137	-0.469 (0.893)	-14.238 (0.000)
IRSR	-0.604	-15.605	-1.623 (0.469)	-8.810 (0.000)
TBUS	0.805	-21.513	-0.060 (0.951)	-6.164 (0.000)
Sri Lanka				
LNER	2.101	-204.058	-1.719 (0.421)	-12.395 (0.000)
GDPS	6.192	-9.538	22.653 (1.000)	2.599 (0.000)
TBS	5.628	-15.071	-4.487 (0.900)	-14.809 (0.000)
Trinidad & Tobago				
LNER	0.856	-209.739	-1.213(0.670)	-15.729 (0.000)
MSUS	1.237	-18.437	-0.266 (0.927)	-21.759 (0.000)
TOTT	-4.393	-174.691	-1.509 (0.529)	-14.516 (0.000)
OP	3.931	-207.510	1.077 (0.997)	-17.092 (0.000)
Tunisia				
LNER	0.441	-197.245	-0.792 (0.820)	-14.350 (0.000)
INFRTUI	1.846	-7.490	-1.018 (0.7482)	-63.932 (0.000)
TBTUI	4.729	-8.466	9.214 (1.000)	-11.486 (0.000)
MSUS	1.237	-18.437	-0.266 (0.927)	-21.759 (0.000)
Vietnam				
LNER	0.723	-125.512	-10.224 (0.800)	-13.036 (0.000)
LNMSUS	0.561	-14.700	-1.620 (0.471)	-15.104 (0.000)

***** Asymptotic critical values at 5% (- 8.1000).
**Second order differencing required for Croatia and Kazakhstan. Test statistics shown in parentheses.
***Significance level shown in parentheses.

Appendix 18A: Block Granger Causality test results: Advanced Countries

Country	Variables		LR χ^2	Probability	Decision
	Dependent	Independent			
Australia	LNER	IRLAUS INFRAUS TBAUS TOAUS	60.505	0.000	Reject H_0
	IRLAUS	LNER INFRAUS TBAUS TOAUS	18.860	0.276	Cannot Reject H_0
	INFRAUS	LNER IRLAUS TBAUS TOAUS	27.326	0.038	Reject H_0
	TBAUS	LNER IRLAUS INFRAUS TOAUS	23.116	0.111	Cannot Reject H_0
	TOAUS	LNER IRLAUS INFRAUS TBAUS	37.571	0.002	Reject H_0
Canada	LNER	LNIRSC LNTBC	1.493	0.038	Reject H_0
	LNIRSC	LNER LNTBC	8.015	0.432	Cannot Reject H_0
	LNTBC	LNER LNIRSC	8.206	0.414	Cannot Reject H_0
Denmark	LNER	MSDM TODM	18.752	0.016	Reject H_0
	MSDM	LNER TODM	14.161	0.078	Cannot Reject H_0
	TODM	LNER MSDM	33.418	0.000	Reject H_0
Euro area	LNER	MSEA IRSEA	16.628	0.034	Reject H_0
	MSEA	LNER IRSEA	8.533	0.383	Cannot Reject H_0
	IRSEA	LNER LNER	15.815	0.045	Reject H_0

Appendix 18A (Cont.)

Country	**Variables**		**LR χ^2**	**Probability**	**Decision**
	Dependent	**Independent**			
Japan	LNER	IRLJ TBJ OP	23.843	0.021	Reject H_0
	IRLJ	LNER TBJ OP	16.973	0.151	Cannot Reject H_0
	TBJ	LNER IRLJ OP	14.069	0.296	Cannot Reject H_0
	OP	LNER IRLJ TBJ	17.602	0.128	Cannot Reject H_0
Norway	LNER	IRLN TON	24.366	0.002	Reject H_0
	IRLN	LNER TON	22.757	0.004	Reject H_0
	TON	LNER IRLN	10.833	0.211	Cannot reject H_0
Sweden	LNER	IRLSWE MSSWE IRLUS OP	31.776	0.011	Reject H_0
	IRLSWE	LNER MSSWE IRLUS OP	29.184	0.023	Reject H_0
	MSSWE	LNER IRLSWE IRLUS OP	39.358	0.001	Reject H_0
	IRLUS	LNER IRLSWE MSSWE OP	11.734	0.762	Cannot reject H_0
	OP	LNER IRLSWE MSSWE IRLUS	25.120	0.068	Cannot reject H_0

Appendix 18B: Pairwise Granger Causality test results: Advanced Countries

Country	**Null Hypothesis**	**F-Statistic**	**Probability**	**Decision**
Singapore	MSS does not Granger Cause LNER	2.741	0.028	Reject H_0
	LNER does not Granger Cause MSS	1.729	0.143	Cannot reject H_0
Switzerland	IRSSWI does not Granger Cause LNER	3.865	0.004	Reject H_0
	LNER does not Granger Cause IRSSWI	2.390	0.051	Cannot reject H_0
UK	TOUK does not Granger Cause LNER	3.974	0.004	Reject H_0
	LNER does not Granger Cause TOUK	2.993	0.019	Reject H_0

Appendix 19A: Block Granger Causality test results: Emerging Countries

Country	Variables		LR χ^2	Probability	Decision
	Dependent	Independent			
Brazil	LNER	IRSBZ TBBZ TOBZ	38.254	0.000	Reject H_0
	IRSBZ	LNER TBBZ TOBZ	51.698	0.000	Reject H_0
	TBBZ	LNER IRSBZ TOBZ	20.777	0.054	Cannot reject H_0
	TOBZ	LNER IRSBZ TBBZ	13.680	0.322	Cannot reject H_0
Chile	LNER	TBC IRSC MSC CAC	31.827	0.011	Reject H_0
	TBC	LNER IRSC MSC CAC	45.485	0.000	Reject H_0
	IRSC	LNER TBC MSC CAC	36.778	0.002	Reject H_0
	MSC	LNER TBC IRSC CAC	32.534	0.009	Reject H_0
	CAC	LNER TBC IRSC MSC	28.034	0.031	Reject H_0
Colombia	LNER	INFRCO MSCO	22.165	0.005	Reject H_0
	INFRCO	LNER MSCO	16.051	0.042	Reject H_0
	MSCO	LNER INFRCO	17.629	0.024	Reject H_0
Czech Republic	LNER	MSCR INFRCR	27.429	0.001	Reject H_0
	MSCR	LNER INFRCR	4.945	0.763	Cannot reject H_0
	INFRCR	LNER MSCR	10.695	0.220	Cannot reject H_0

Appendix 19A (Cont.)

Country	**Variables**		**LR** χ^2	**Probability**	**Decision**
	Dependent	**Independent**			
India	LNER	MSIN TBIN	11.187	0.041	Reject H_0
	MSIN	LNER TBIN	48.115	0.000	Reject H_0
	TBIN	LNER MSIN	18.094	0.021	Reject H_0
Indonesia	LNER	IRSINDO INFRINDO	56.633	0.000	Reject H_0
	IRSINDO	LNER INFRINDO	42.098	0.000	Reject H_0
	INFRINDO	LNER IRSINDO	8.407	0.395	Cannot reject H_0
Peru	LNER	TBP TOP	56.833	0.001	Reject H_0
	TBP	LNER TOP	5.881	0.661	Cannot reject H_0
	TOP	LNER TBP	26.201	0.001	Reject H_0
South Africa	LNER	MSSA IRLSA TOSA GP	30.888	0.014	Reject H_0
	MSSA	LNER IRLSA TOSA GP	16.249	0.436	Cannot reject H_0
	IRLSA	LNER MSSA TOSA GP	21.270	0.168	Cannot reject H_0
	TOSA	LNER MSSA IRLSA GP	63..223	0.000	Reject H_0
	GP	LNER MSSA IRLSA TOSA	22.730	0.121	Cannot reject H_0

Appendix 19B: Pairwise Granger Causality test results: Emerging Countries

Country	Null Hypothesis	F statistics	Probability	Decision
China	TBCHI does not Granger Cause LNER	0.881	0.476	Cannot reject H_0
	LNER does not Granger Cause TBCHI	1.568	0.182	Cannot reject H_0
Hungary	TOH does not Granger Cause LNER	2.938	0.023	Reject H_0
	LNER does not Granger Cause TOH	1.682	0.158	Cannot reject H_0
Malaysia	LNMSM does not Granger Cause LNER	4.718	0.001	Reject H_0
	LNER does not Granger Cause LNMSM	1.158	0.329	Cannot reject H_0
Mexico	LNIRSME does not Granger Cause LNER	0.686	0.603	Cannot reject H_0
	LNER does not Granger Cause LNIRSME	3.975	0.004	Reject H_0
Philippines	INFRPH does not Granger Cause LNER	0.116	0.977	Cannot reject H_0
	LNER does not Granger Cause INFRPH	6.648	0.000	Reject H_0
Poland	TBPO does not Granger Cause LNER	0.784	0.537	Cannot reject H_0
	LNER does not Granger Cause TBPO	2.486	0.044	Reject H_0
Russia	IRSR does not Granger Cause LNER	3.703	0.007	Reject H_0
	LNER does not Granger Cause IRSR	11.660	0.000	Reject H_0
South Korea	IRSSK does not Granger Cause LNER	0.357	0.839	Cannot reject H_0
	LNER does not Granger Cause IRSSK	16.696	0.000	Reject H_0
Taiwan	TBT does not Granger Cause LNER	6.018	0.000	Reject H_0
	LNER does not Granger Cause TBT	0.460	0.765	Cannot reject H_0
Thailand	IRST does not Granger Cause LNER	0.850	0.495	Cannot reject H_0
	LNER does not Granger Cause IRST	5.806	0.000	Reject H_0
Turkey	TOTU does not Granger Cause LNER	0.710	0.587	Cannot reject H_0
	LNER does not Granger Cause TOTU	2.005	0.097	Cannot reject H_0

Appendix 20A: Block Granger Causality test results: Frontier Countries

Country	Variables		LR χ^2	Probability	Decision
	Dependent	**Independent**			
Bangladesh	LNER	GDPBD IRSBD TBBD	38.574	0.000	Reject H_0
	GDPBD	LNER IRSBD TBBD	26.172	0.010	Reject H_0
	IRSBD	LNER GDPBD TBBD	25.030	0.015	Reject H_0
	TBBD	LNER GDPBD IRSBD	30.135	0.003	Reject H_0
Brunei	LNER	MSUS IRSUS IRLUS GDPB OP	33.265	0.032	Reject H_0
	MSUS	LNER IRSUS IRLUS GDPB OP	43.468	0.002	Reject H_0
	IRSUS	LNER MSUS IRLUS GDPB OP	87.986	0.000	Reject H_0
	IRLUS	LNER MSUS IRLUS GDPB OP	88.955	0.000	Reject H_0
	GDPB	LNER MSUS IRSUS IRLUS OP	26.580	0.148	Cannot reject H_0
	OP	LNER MSUS IRSUS IRLUS GDPB	37.179	0.011	Reject H_0

Appendix 20A (Cont.)

Country	Variables		LR χ^2	Probability	Decision
	Dependent	Independent			
Croatia	LNER	IRSC INFRC TBC	173.194	0.000	Reject H_0
	IRSC	LNER INFRC TBC	855.321	0.000	Reject H_0
	INFRC	LNER IRSC TBC	47.390	0.000	Reject H_0
	TBC	LNER IRSC INFRC	10.383	0.582	Cannot reject H_0
Kazakhstan	LNER	IRSK INFRK	31.248	0.000	Reject H_0
	IRSK	LNER INFRK	187.147	0.000	Reject H_0
	INFRK	LNER IRSK	99.282	0.000	Reject H_0
Mauritius	LNER	IRLUS TBM	13.324	0.010	Reject H_0
	IRLUS	LNER TBM	23.313	0.003	Reject H_0
	TBM	LNER IRLUS	7.564	0.477	Cannot reject H_0
Nepal	LNER	IRSN MSUS	7.918	0.044	Reject H_0
	IRSN	LNER MSUS	7.1845	0.517	Cannot reject H_0
	MSUS	LNER IRSN	14.830	0.063	Cannot reject H_0
Nigeria	LNER	INFRN GDPN	14.002	0.041	Reject H_0
	INFRN	LNER GDPN	13.084	0.109	Cannot reject H_0
	GDPN	LNER INFRN	14.572	0.038	Reject H_0
Pakistan	LNER	IRSP CAP	9.400	0.310	Cannot reject H_0
	IRSP	LNER CAP	36.822	0.000	Reject H_0
	CAP	LNER IRSP	12.534	0.129	Cannot reject H_0

Appendix 20A (Cont.)

Country	**Variables**		**LR χ^2**	**Probability**	**Decision**
	Dependent	**Independent**			
Romania	LNER	MSUS IRSR TBUS	22.705	0.030	Reject H_0
	MSUS	LNER IRSR TBUS	31.679	0.002	Reject H_0
	IRSR	LNER MSUS TBUS	15.860	0.198	Cannot reject H_0
	TBUS	LNER MSUS IRSR	47.504	0.000	Reject H_0
Sri Lanka	LNER	GDPS TBS	2.002	0.981	Cannot reject H_0
	GDPS	LNER TBS	15.886	0.044	Reject H_0
	TBS	LNER GDPS	19.753	0.011	Reject H_0
Trinidad & Tobago	LNER	MSUS IRSTT OP	19.332	0.041	Reject H_0
	MSUS	LNER IRSTT OP	16.807	0.157	Cannot reject H_0
	IRSTT	LNER MSUS OP	9.941	0.621	Cannot reject H_0
	OP	LNER MSUS IRSTT	48.018	0.000	Reject H_0
Tunisia	LNER	INFRTUI TBTUI MSUS	10.774	0.048	Reject H_0
	INFRTUI	LNER TBTUI MSUS	20.061	0.066	Cannot reject H_0
	TBTUI	LNER INFRTUI MSUS	6.928	0.862	Cannot reject H_0
	MSUS	LNER INFRTUI TBTUI	30.292	0.003	Reject H_0

Appendix 20B: Pairwise Granger Causality test results: Frontier Countries

Country	Null Hypothesis	F statistics	Probability	Decision
Bhutan	TBB does not Granger Cause LNER	0.662	0.019	Reject H_0
	LNER does not Granger Cause TBB	1.604	0.173	Cannot reject H_0
Botswana	TBUS does not Granger Cause LNER	2.818	0.025	Reject H_0
	LNER does not Granger Cause TBUS	0.694	0.597	Cannot reject H_0
Estonia	CAE does not Granger Cause LNER	2.000	0.047	Reject H_0
	LNER does not Granger Cause CAE	0.194	0.941	Cannot reject H_0
Jamaica	MSUS does not Granger Cause LNER	1.765	0.172	Cannot reject H_0
	LNER does not Granger Cause MSUS	3.424	0.034	Reject H_0
Kenya	TBKE does not Granger Cause LNER	1.364	0.211	Cannot reject H_0
	LNER does not Granger Cause TBKE	2.411	0.015	Reject H_0
Lao PDR	IRSL does not Granger Cause LNER	2.879	0.025	Reject H_0
	LNER does not Granger Cause IRSL	0.755	0.557	Cannot reject H_0
Myanmar	IRLUS does not Granger Cause LNER	3.962	0.004	Reject H_0
	LNER does not Granger Cause IRLUS	1.119	0.347	Cannot reject H_0
Vietnam	LNMSUS does not Granger Cause LNER	0.195	0.041	Reject H_0
	LNER does not Granger Cause LNMSUS	1.274	0.281	Cannot reject H_0

Appendix 21: Forecast accuracy of individual models: Advanced, emerging and frontier countries

Country	Volatility Model		Exponential Smoothing Model		Naïve 1 Model		Cointegration Model	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
Advanced:								
Australia	1.654	10.222(1)	1.702	10.257(3)	1.720	10.244(2)	1.748	15.187(4)
Canada	0.949	9.027(4)	0.945	7.515(1)	0.930	8.040(2)	0.926	8.131 (3)
Denmark	1.913	5.531(2)	1.926	5.548(3)	2.040	5.582(4)	1.937	5.351(1)
Euro area	5.591	1.837(1)	1.870	5.655(3)	1.890	5.642(2)	1.677	16.009(4)
Japan	2.027	16.086(2)	1.999	16.153(3)	2.050	15.700 (1)	1.968	40.736(4)
Norway	1.730	9.757(3)	1.745	9.666(2)	1.860	9.881(4)	1.695	6.197(1)
Singapore	0.936	7.743(3)	0.911	3.297(2)	0.940	3.297(2)	0.917	3.172(1)
Sweden	1.718	11.046(1)	1.725	11.057(2)	1.870	11.364 (3)	1.659	18.526(4)
Switzerland	2.178	7.347(4)	2.184	6.903(3)	2.300	6.383(2)	2.089	5.005(1)
UK	1.854	16.602(3)	1.859	16.543(2)	1.852	17.159(4)	1.789	14.832(1)
Emerging:								
Brazil	2.525	9.327(3)	2.506	9.265(2)	2.670	9.229(1)	2.191	11.188(4)
Chile	1.906	1.310(1)	1.486	9.815(3)	1.740	9.304 (2)	1.404	34.849(4)
China	0.868	7.018 (1)	0.810	7.120(2)	0.810	7.120 (2)	0.907	18.757(4)
Colombia	1.145	2.708 (1)	1.201	8.058(2)	1.610	8.190(3)	2.155	24.254 (4)
Czech Republic	1.939	7.616(3)	1.935	7.577 (1)	2.020	7.597(2)	1.868	21.222(4)
Hungary	1.458	11.034(1)	1.470	20.855 (3)	1.490	11.051(2)	1.959	16.816(3)
India	0.964	12.513(1)	0.944	13.836(3)	1.000	13.609(2)	1.954	23.040 (4)
Indonesia	2.220	6.293(2)	2.095	6.275(1)	2.130	6.302 (3)	2.246	12.087(4)
Malaysia	0.817	4.322(2)	0.956	4.393(3)	0.900	4.273(1)	0.996	4.952(4)
Mexico	1.664	13.313(3)	2.006	10.059(1)	1.710	13.252(2)	1.151	16.501(4)
Peru	8.413	4.292(2)	6.955	9.287(3)	2.470	3.799 (1)	1.272	16.792(4)
Philippines	0.989	10.218 (2)	0.958	10.654(3)	1.050	9.312(1)	1.018	12.989(4)
Poland	2.804	15.299(3)	2.891	15.274 (1)	2.970	15.286(2)	1.932	30.892(4)
Russia	1.395	13.247(1)	1.274	18.985(3)	1.570	14.005 (2)	1.379	14.180(3)
South Africa	2.222	5.463(1)	2.222	15.617(2)	2.370	16.242 (3)	2.182	34.650(4)
South Korea	1.032	19.742(2)	1.056	18.964(1)	1.190	20.002 (3)	1.195	24.413(4)
Taiwan	0.809	2.765(3)	0.803	2.753(2)	0.880	2.740 (1)	0.799	20.274(4)
Thailand	1.126	2.790(1)	1.129	2.791(2)	1.210	2.793(3)	1.436	6.185(4)
Turkey	4.333	18.335(3)	4.196	23.168(4)	3.980	17.499 (2)	3.433	10.008(1)
Frontier:								
Bangladesh	0.992	1.851(2)	1.054	2.521(3)	0.957	1.458 (1)	0.831	8.863(4)
Bhutan*	0.937	12.080(2)	0.945	13.836 (4)	1.000	13.609(3)	0.906	8.738 (1)
Botswana	1.745	3.696(1)	1.718	12.390 (2)	1.799	12.925(3)	1.980	14.589(4)
Brunei*	0.911	3.244(2)	3.100	3.220(1)	0.945	3.220(1)	0.926	9.003(3)
Croatia	1.794	5.507(1)	3.110	6.195(2)	3.760	6.775 (3)	1.742	10.617(4)
Estonia	1.769	5.530(1)	1.827	5.533(2)	1.900	5.572(3)	1.720	12.939(4)
Jamaica	1.719	11.627(2)	1.165	0.177(1)	1.275	22.293(3)	1.475	99.992(4)
Kazakhstan	1.533	8.799(1)	1.557	10.373(3)	2.130	10.394(2)	1.033	41.396(4)
Kenya	1.497	4.706 (1)	1.480	15.538 (4)	1.610	13.925(3)	1.461	12.772(2)

Appendix 21 (Cont.)

Country	**Volatility Model**		**Exponential Smoothing Model**		**Naïve 1 Model**		**Cointegration Model**	
	Static	**Dynamic**	**Static**	**Dynamic**	**Static**	**Dynamic**	**Static**	**Dynamic**
Lao PDR*	1.320	7.177 (1)	1.295	8.125(3)	1.410	7.229(2)	0.330	52.821(4)
Mauritius	1.082	2.677(1)	1.114	3.710(3)	1.110	2.701(2)	1.309	4.889(2)
Myanmar*	0.893	12.930 (1)	0.900	12.940 (2)	0.950	13.037(3)	0.979	8.246(4)
Nepal*	1.728	2.424(1)	1.741	13.015(3)	1.704	12.374(2)	0.912	17.522(4)
Nigeria	0.679	7.193 (1)	0.642	19.686(2)	0.740	19.859(3)	3.876	18.513(4)
Pakistan	2.573	12.038 (1)	2.598	19.723(4)	2.980	14.354(3)	0.852	13.821 (2)
Romania	0.948	2.739 (2)	1.332	1.642 (1)	1.060	3.337(3)	2.035	23.597(4)
Sri Lanka	0.508	0.575 (3)	0.475	0.085 (2)	0.461	0.011(1)	0.999	12.698(4)
Trinidad & Tobago	1.568	7.229 (4)	1.563	1.467 (2)	1.636	0.921 (1)	0.518	4.822(3)
Tunisia	0.519	3.009 (1)	1.740	4.776(3)	1.901	4.753(2)	1.553	7.687(4)
Vietnam	1.320	7.177 (1)	1.295	8.125(3)	1.410	7.229(2)	2.554	8.776(4)

Figures in brackets indicate the rank of the forecasting methods. Accuracy evaluation is based on the MAPE (dynamic) forecast error measure. * Not listed as a frontier markets according to MSCI.

Appendix 22: MAPE - Advanced Countries

Appendix 22.1: MAPE - Advanced Countries (Individual models)

Country	**Individual models**			
	VOL	**ES**	**N1**	**CO**
Australia	10.222	10.257	10.244	15.187
Canada	9.027	**7.515**	8.040	8.131
Denmark	5.531	5.548	5.582	5.351
Euro area	**1.837**	5.655	5.642	16.009
Japan	16.086	16.153	**15.700**	40.736
Norway	9.757	9.666	9.881	6.197
Singapore	7.743	3.297	3.297	3.172
Sweden	**11.046**	11.057	11.364	18.526
Switzerland	7.347	6.903	6.383	**5.005**
UK	16.602	16.543	17.159	**14.832**

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 22.2
MAPE - Advanced Countries (Equal weights)

Country	**Equal weights**										
	2-way combination						**3-way combination**				**4-way combination**
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL-ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Australia	10.240	10.129	11.326	10.139	11.377	11.043	10.164	10.509	10.363	10.338	10.122
Canada	8.245	8.534	8.652	7.778	7.912	8.174	8.178	8.267	7.955	8.449	8.210
Denmark	5.540	5.557	5.246	5.565	5.246	5.251	5.554	5.322	5.326	5.326	5.363
Euro area	5.530	5.617	10.451	**5.521**	10.122	10.560	5.534	8.379	8.452	8.671	7.561
Japan	16.120	15.893	33.412	15.926	33.445	33.218	15.979	27.657	27.528	27.506	24.669
Norway	9.712	**3.820**	6.099	9.774	6.096	6.097	9.768	6.965	6.971	6.979	7.566
Singapore	4.393	4.393	5.390	3.297	2.896	2.896	3.297	3.961	3.013	3.961	3.252
Sweden	11.050	11.204	14.261	11.210	14.273	16.460	11.155	13.098	13.231	13.223	12.610
Switzerland	7.117	6.836	6.044	6.643	5.867	5.651	6.858	6.330	6.038	6.156	6.343
UK	16.572	16.880	15.478	16.851	15.454	15.714	16.769	15.791	15.961	15.979	16.115

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 22.3
MAPE - Advanced Countries (var-cov)

Country	Var-cov										
	2-way combination						3-way combination				4-way combination
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL- ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Australia	10.240	10.131	10.905	10.142	10.943	10.708	10.166	10.257	10.137	**10.116**	10.126
Canada	8.162	8.499	8.633	7.767	7.887	8.171	8.121	8.210	7.937	8.423	8.176
Denmark	5.540	5.556	5.223	5.565	**5.220**	5.221	5.554	5.300	5.300	5.301	5.374
Euro area	5.530	5.616	6.290	**5.521**	6.081	6.443	5.533	5.779	5.791	5.969	8.507
Japan	16.120	15.889	19.089	15.921	19.162	18.613	15.975	17.691	17.467	17.433	27.008
Norway	9.711	9.819	5.391	9.771	5.409	**5.360**	9.767	5.794	5.775	5.764	8.281
Singapore	2.986	2.986	3.835	3.297	2.900	2.900	3.106	**2.882**	3.017	2.883	2.927
Sweden	11.050	11.197	12.557	11.205	12.588	12.962	11.149	11.921	12.083	12.073	12.942
Switzerland	7.104	6.775	5.669	6.622	5.610	5.512	6.817	5.980	5.825	5.877	6.2301
UK	16.572	16.874	15.398	16.843	15.379	15.585	16.762	15.712	15.856	15.871	16.155

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 23: MAPE - Emerging Countries
Appendix 23.1: MAPE - Emerging Countries (Individual models)

Country	**Individual models**			
	VOL	**ES**	**N1**	**CO**
Brazil	9.327	9.265	9.229	11.188
Chile	**1.310**	9.815	9.304	34.849
China	7.018	7.120	7.120	18.757
Colombia	**2.708**	8.058	8.190	24.254
Czech Republic	7.616	**7.577**	7.597	21.222
Hungary	**11.034**	20.855	11.051	16.816
India	**12.513**	13.836	13.609	23.040
Indonesia	6.293	6.275	6.302	12.087
Malaysia	4.322	4.393	**4.273**	4.952
Mexico	13.313	10.059	13.252	16.501
Peru	4.292	9.287	3.799	16.792
Philippines	10.218	10.654	**9.312**	12.989
Poland	15.299	15.274	15.286	30.892
Russia	13.247	18.985	14.005	14.180
South Africa	**5.463**	15.617	16.242	34.650
South Korea	19.742	**18.964**	20.002	24.413
Taiwan	2.765	2.753	2.740	20.274
Thailand	2.790	2.791	2.793	6.185
Turkey	18.335	23.168	17.499	10.008

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 23.2: MAPE - Emerging Countries (Equal weights)

Country	Equal weights										
	2-way combination						3-way combination				4-way combination
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL- ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Brazil	9.293	9.268	9.733	9.247	9.661	9.576	9.267	9.427	9.322	9.370	9.232
Chile	11.461	11.205	23.938	9.560	22.275	22.055	10.742	19.193	17.938	19.046	16.710
China	7.070	7.070	6.102	7.120	6.153	6.153	7.085	6.440	6.474	6.440	6.611
Colombia	9.676	9.477	18.406	8.124	15.525	15.325	8.717	14.536	12.482	14.403	12.501
Czech Republic	7.594	7.606	13.857	7.584	13.955	13.893	7.595	11.511	11.535	11.470	10.307
Hungary	18.192	13.261	16.144	15.816	18.798	13.933	15.721	17.708	16.124	14.446	15.975
India	13.175	13.061	17.770	13.723	18.436	18.318	13.320	16.458	16.823	16.380	15.742
Indonesia	6.186	6.173	8.148	6.289	8.559	8.626	6.168	7.154	7.428	7.194	6.742
Malaysia	4.358	4.298	4.638	4.333	4.673	4.613	4.330	4.556	4.540	4.516	4.485
Mexico	7.026	13.283	14.907	6.988	8.621	14.876	9.052	10.135	10.114	14.354	10.914
Peru	4.611	3.950	9.607	5.182	4.359	8.978	3.530	3.992	3.678	6.825	3.691
Philippines	10.436	9.761	11.604	9.962	11.822	11.140	10.045	11.288	10.965	10.831	10.776
Poland	15.287	15.268	22.187	**15.255**	22.168	22.136	15.270	19.742	19.714	19.725	18.517
Russia	6.960	13.627	13.692	7.389	7.489	14.071	9.309	9.352	9.618	13.797	10.515
SouthAfrica	15.540	15.853	25.057	15.930	25.134	25.446	15.775	21.911	22.171	22.119	20.493
SouthKorea	19.353	19.873	22.078	19.483	21.688	22.207	19.571	21.041	21.127	21.387	20.780
Taiwan	2.759	2.753	10.589	2.746	10.548	10.503	2.752	7.332	7.275	7.302	5.683
Thailand	**2.779**	2.792	4.327	2.792	4.322	4.331	2.792	3.710	3.710	3.711	3.424
Turkey	9.569	17.913	13.968	9.190	5.591	13.616	12.196	9.627	9.401	15.126	11.579

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 23.3**:** MAPE - Emerging Countries (var-cov)

Country	**Variance- covariance**										
	2-way combination						**3-way combination**				**4-way combination**
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL- ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Brazil	9.294	9.268	9.814	9.247	9.756	9.693	9.267	9.509	9.421	9.463	**9.196**
Chile	11.179	10.801	15.844	9.549	12.136	11.494	10.449	12.515	10.729	12.095	12.089
China	7.069	7.069	**5.844**	7.120	5.869	5.869	7.086	6.175	6.195	6.175	6.701
Colombia	8.763	8.566	15.366	8.125	9.126	8.785	8.213	10.114	8.180	9.794	14.254
Czech Republic	7.594	7.606	8.433	7.585	8.558	8.466	7.595	8.011	8.020	7.994	11.240
Hungary	17.416	12.569	16.104	13.156	18.310	12.881	13.825	17.170	14.127	13.563	14.189
India	13.116	13.020	15.081	13.721	16.405	16.183	13.273	14.598	15.210	14.499	15.900
Indonesia	6.193	6.182	6.662	6.288	7.146	7.264	**6.159**	6.344	6.633	6.354	6.857
Malaysia	4.357	4.298	4.599	4.331	4.647	4.567	4.328	4.528	4.508	4.480	4.492
Mexico	2.712	13.282	14.573	2.715	**2.653**	14.523	2.928	2.857	2.860	14.070	7.490
Peru	3.499	3.919	4.587	3.380	4.075	3.872	3.606	3.604	**3.357**	4.053	4.352
Philippines	10.429	9.719	11.286	9.878	11.594	10.564	9.984	11.056	10.580	10.439	10.761
Poland	15.287	15.268	17.607	**15.255**	17.575	17.525	15.270	16.553	16.516	16.530	19.399
Russia	2.733	13.602	13.679	2.752	2.761	14.092	**2.674**	2.683	2.690	13.784	3.140
South Africa	15.540	15.841	19.499	15.922	19.654	20.298	15.766	17.796	18.191	18.109	21.562
South Korea	19.342	19.871	21.640	19.464	21.104	21.814	19.555	20.607	20.707	21.037	20.917
Taiwan	2.759	2.753	2.662	2.746	2.645	**2.626**	2.753	2.697	2.680	2.688	7.265
Thailand	2.791	2.792	3.235	2.792	3.236	3.237	2.792	3.004	3.005	3.005	3.627
Turkey	3.153	17.900	12.009	3.149	**3.123**	11.939	3.238	3.227	3.230	13.176	11.907

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.

Appendix 24: MAPE - Frontier Countries
Appendix 24.1: MAPE - Frontier Countries (Individual models)

Country	**Individual models**			
	VOL	**ES**	**N1**	**CO**
Bangladesh	1.851	2.521	1.458	8.863
Bhutan*	12.080	13.836	13.609	**8.738**
Botswana	3.696	12.390	12.925	14.589
Brunei*	3.244	3.220	3.220	9.003
Croatia	**5.507**	6.195	6.775	10.617
Estonia	5.530	5.533	5.572	12.939
Jamaica	11.627	**0.177**	22.293	99.992
Kazakhstan	**8.799**	10.373	10.394	41.396
Kenya	**4.706**	15.538	13.925	12.772
Lao PDR*	7.177	7.741	9.265	52.821
Mauritius	**2.677**	8.125	7.229	4.889
Myanmar*	12.930	3.710	2.701	8.246
Nepal*	**2.424**	12.940	13.037	17.522
Nigeria	**7.193**	13.015	12.374	18.513
Pakistan	**12.038**	19.686	19.859	13.821
Romania	**2.739**	19.723	14.354	23.597
Sri Lanka	**0.575**	1.642	3.337	12.698
Trinidad & Tobago	7.229	0.085	**0.011**	4.822
Tunisia	3.009	1.467	**0.921**	7.687
Vietnam	7.177	4.776	4.753	8.776

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.*Not listed as a frontier markets according to MSCI

Appendix 24.2
MAPE - Frontier Countries (Equal weights)

Country	**Equal weights**										
	2-way combination						**3-way combination**				**4-way combination**
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL- ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Bangladesh	2.186	0.715	5.341	1.050	5.672	4.220	1.316	4.388	3.640	3.419	3.186
Bhutan*	12.958	12.845	10.361	13.723	11.239	11.125	13.176	11.520	12.030	11.444	12.042
Botswana	3.680	1.820	1.852	1.810	1.841	**0.049**	2.439	2.459	1.209	1.217	1.831
Brunei*	3.232	3.232	4.906	3.220	4.919	4.919	3.227	3.579	3.588	3.579	2.987
Croatia	5.915	5.758	7.826	5.939	8.314	7.902	5.869	7.243	7.293	6.968	6.745
Estonia	5.520	5.537	7.541	5.549	7.447	7.365	5.535	6.178	6.091	6.138	5.723
Jamaica	11.743	11.886	3.985	12.001	4.078	4.120	11.878	6.254	6.407	6.307	7.631
Kazakhstan	9.578	9.582	24.308	10.383	25.651	25.724	9.840	19.508	20.452	19.556	17.143
Kenya	15.102	14.316	7.273	14.711	7.359	7.180	14.710	8.314	8.054	7.795	9.716
Lao PDR*	4.288	5.050	25.985	8.503	22.532	21.770	5.946	14.744	11.972	14.236	8.832
Mauritius	7.952	7.499	6.111	7.672	6.228	6.002	7.708	6.654	6.541	6.646	6.790
Myanmar*	3.065	2.689	3.538	3.104	2.850	3.453	2.927	1.980	1.945	2.280	**1.690**
Nepal*	12.958	12.774	15.249	12.756	15.231	15.047	12.830	14.480	14.345	14.357	14.002
Nigeria	12.691	12.399	15.440	12.646	15.764	15.395	12.554	14.632	14.603	14.386	14.043
Pakistan	18.439	18.519	15.489	19.771	16.735	16.815	18.908	16.889	17.773	16.942	17.627
Romania	15.747	13.170	17.792	16.931	21.553	18.976	15.283	18.365	19.154	16.646	17.361
Sri Lanka	1.928	3.038	7.573	2.237	6.147	7.661	2.386	4.955	5.118	5.942	4.505
Trinidad & Tobago	0.576	0.577	2.149	0.580	2.145	2.139	0.577	1.259	1.251	1.254	0.830
Tunisia	7.242	7.341	4.896	7.353	4.897	4.944	7.313	5.580	5.654	5.646	6.048
Vietnam	3.892	3.881	2.733	4.764	1.827	1.841	4.180	**1.320**	1.342	1.322	1.475

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model. Optimal model (showed in bold) before the test of unbiasedness. *Not listed as a frontier markets according to MSCI.

Appendix 24.3
MAPE - Frontier Countries (Var-cov)

Country	**Var-cov**										
	2-way Combination						**3-way combination**				**4-way combination**
	VOL-ES	**VOL-N1**	**VOL-CO**	**ES-N1**	**ES-CO**	**N1-CO**	**VOL- ES-N1**	**VOL-ES-CO**	**ES-N1-CO**	**N1-CO-VOL**	**VOL-ES-N1-CO**
Bangladesh	2.083	0.337	2.080	0.371	2.899	0.437	0.262	2.229	0.352	0.318	**0.117**
Bhutan*	12.853	12.763	9.921	13.721	10.269	10.236	13.088	10.778	11.073	11.745	12.388
Botswana	12.173	12.419	6.788	12.649	6.915	7.077	12.409	6.747	6.864	6.808	7.483
Brunei*	3.232	3.232	2.907	3.220	**2.898**	**2.898**	3.228	3.031	3.026	3.031	3.480
Croatia	5.895	5.758	6.441	5.916	7.311	6.526	5.852	6.343	6.400	6.132	6.730
Estonia	5.520	5.536	5.477	5.549	5.416	5.370	5.535	5.266	**5.230**	5.252	5.983
Jamaica	11.740	11.875	4.019	11.999	4.058	4.082	11.870	3.902	3.889	3.890	8.829
Kazakhstan	9.405	9.403	9.494	10.383	12.803	12.972	9.671	9.783	11.515	9.804	17.394
Kenya	15.082	14.296	7.332	14.631	7.542	7.098	14.657	7.877	7.831	7.820	9.266
Lao PDR*	1.093	1.082	**1.059**	8.371	6.571	7.579	1.242	1.076	7.673	1.070	1.497
Mauritius	7.944	7.475	5.847	7.610	5.854	5.874	7.665	6.236	6.195	6.172	6.722
Myanmar*	2.915	2.689	2.107	2.958	2.086	2.086	2.817	2.437	2.445	2.362	1.767
Nepal*	12.958	12.773	14.597	12.755	14.569	14.328	12.829	13.946	13.785	13.800	14.139
Nigeria	12.681	12.399	14.517	12.634	15.010	14.443	12.543	13.945	13.902	13.629	14.158
Pakistan	18.263	18.321	15.231	19.770	15.890	15.924	18.733	16.309	16.917	16.334	17.950
Romania	13.875	12.920	14.179	16.106	21.182	16.785	14.032	15.316	17.534	14.237	15.431
Sri Lanka	1.610	3.000	3.108	1.664	1.626	3.772	1.796	1.668	1.720	3.205	8.676
Trinidad & Tobago	0.576	0.577	0.507	0.580	0.505	0.503	0.577	0.541	0.541	0.540	1.254
Tunisia	7.242	7.336	4.544	7.350	4.539	4.516	7.308	4.751	4.735	4.738	6.552
Vietnam	3.563	3.559	1.503	4.764	1.501	1.502	3.848	2.338	2.739	2.338	1.458

Vol- volatility model; ES - exponential smoothing model; N1- Naïve 1 or no change model; Co - cointegration via ARDL model.
Optimal model (showed in bold) before the test of unbiasedness.
*Not listed as a frontier markets according to MSCI.