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EMPIRICAL RISK MANAGEMENT IN EMERGING MARKETS

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ABSTRACT

This research considers different aspect of modelling risk in the emerging markets. It places particular emphasis on modelling default probability in emerging bond markets, modelling country risk in emerging stock markets, modelling market risk in emerging stock markets and examining the appropriate asymmetric volatility model in emerging stock market as well as examining whether the long term memory in volatility exists in emerging stock market.

More specifically, the aims of this study is to answer the following research questions: (1) what are the main factors determine and what is the best model to explain default probability in emerging bond market; (2) which model is the best to use to modelling country risk in emerging markets; (3) what is the best model to be used for explaining market risk in emerging stock markets; (4) what is the best asymmetric model to be used in emerging stock markets and is the SEMIFAR model successful at modelling long memory in the volatility of emerging stock markets.

The study shows that the fluctuation in default probability in emerging bond markets can be explained by macroeconomic variable and financial variable. With regard to the second research question, it was found that the Kalman Filter model (in particular the Random Walk technique) was the best model to predict country risk in emerging stock markets. The result of the study shows that the most successful model to capture market risk (or extreme risk) in emerging stock market is the conditional t. The study also shows

that emerging stock markets are more sensitive to bad news than to good news as indicated by their higher volatility during down-market as compared to up-market. It was found that the TGARCH model is the most appropriate model to be used for explaining asymmetry volatility in emerging stock markets. Finally, the result of this study reveals the existence of long term memory in emerging stock markets and the successfulness of SEMIFAR model to capture the phenomenon.

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CHAPTER 1. INTRODUCTION

This introductory chapter sets out the background and motivation of the thesis. It includes a discussion of emerging markets, a discussion of the main types of risks facing investors in these markets, and the main findings of all of the empirical studies carried out in the thesis. It highlights the research questions of the thesis and the overall contribution this thesis makes.

1.1. BACKGROUND AND MOTIVATION

Emerging markets are an important factor in the future economic growth of developed and developing economies. This is shown in the huge increase in volume of investment in these markets. Many investors are endeavouring to make the most of the opportunities these markets can offer. In 1982, based on a survey conducted by the International Finance Corporation (IFC), thirty two developing country stock markets had a market capitalisation of $67 billion representing about 2.5 percent of world market capitalization. By the end of 1999, total market capitalisation of emerging stock markets had exceeded $3,000 billion or equivalent to 8.5 percent of world equity market capitalization. In 2003, the market capitalization share was 11.1 percent of world equity market capitalization. Similar to developed countries, investing in emerging markets can take two forms: stock investment and bond investment. However due to different characteristics of developing and developed markets, investing in emerging markets is riskier (based on their volatility) than in established developed markets. For example, Harvey (1995) and Aggarwal et.al (1999) found that volatility in emerging markets is higher than that of developed markets. The very high volatility in emerging markets is observed in both the local and the dollar returns. The implication of a more volatile market is that expected returns in emerging markets can be high at times. Harvey (1995) shows that equities in emerging markets promise U.S. investors both higher expected returns and risk than in developed markets. Barry and Rodriguez (1997) find that the risk and return performance in Latin America's equity market has been among the most volatile in the world. In other words, a potential advantage that emerging market offers for investors is the higher potential returns than that of developed market but of course for the increased risk.

Emerging markets can also provide diversification benefits for a portfolio invested solely in developed markets. For instance, research by Divecha et.al (1992) and Errunza (1977) concluded that investment in emerging markets increases the opportunity set for investors allowing them to improve the risk-return trade-off in their portfolio. This is because there is low correlation between emerging markets and the world-developed index (Solnik, 2000). Furthermore as both the correlation and the covariance between stock and bond returns in emerging countries are higher than in developed countries, investing in emerging market debt and emerging market equity could enhance investor total returns (Kelly, et.al, 1998). However it should be noted that research findings with regard to the diversification benefits are mixed. Bekaret and Urias (1996, 1999) measure the diversification benefits from emerging equity markets using data on closed-end funds (country and regional funds) and American Depository Receipts (ADRs). They generally find that investors give up a substantial part of the diversification benefits of investing in foreign markets when they do so by holding closed-end funds. On the contrary, Errunza et.al (1999) show that most of diversification benefits can be obtained using domestically traded assets (ADRs and country funds). In recent study, Fletcher and Marshall (2005) examine the diversification benefits for a U.K. investor using three different sets of international assets including global industry portfolios, country equity portfolios, and investment sector portfolios of unit trusts. They found evidence of diversification benefits for a U.K. investor both in developed equity markets and using U.K. international unit trusts. Therefore the evidence indicates that the performance of the portfolio of UK investors would be improved if they broaden their asset allocations by including international asset class.

In the next sections, we provide a discussion of emerging markets, the types of risk examined in the thesis, the importance and overall contribution of the thesis, and a summary of the findings from each empirical study in the thesis.

1.2. EMERGING MARKETS

The major argument for investing in emerging market is their prospective for higher economic growth rates than for developed countries. To begin, it is important to define what we mean by an emerging market. Olsson (2002) describes emerging markets as simply "all those countries not considered developed", where developed countries refer to the major European countries plus the U.S., Canada, Japan, Australia and New Zealand.

Another definition of emerging market is proposed by the International Finance Corporation (IFC) which uses income per capita and market capitalization relative to GNP for classifying equity markets. According to the IFC, an equity market is classified as an emerging market if it meets either one of the two criteria as follows: (1) a market resides in a low or middle-income economy, or (2) the ratio of investable market capitalization to GNP is low. The IFC identified 81 such countries in their Emerging Stock Markets Factbook 2000. The IFC also developed the

Emerging Markets Data Base (EMDB) Index which constitutes countries that meet the income criteria and have an investable market capitalization to GNP ratio in the top of 25 percent of all emerging markets for three consecutive years[1].

As argued in the introduction, emerging markets are important because they offer high growth potential and returns. In addition to that emerging markets also offer diversification benefits due to low correlation with developed markets (Cadle, 2000). These two attractions are the two main reasons for investing in emerging markets. However higher potential returns of emerging markets are associated with higher risk. Goetzmann and Jorion (1999) compare the performance between emerging stock markets returns and developed stock markets returns. They find developed markets had an average dollar return of 6.9 percent, with a volatility of 19.8 percent whereas emerging markets had an average dollar return of 9.1 percent with a volatility of 34.8 percent. However it should be noted here that the performance of emerging markets depended greatly on the time period selected for analysis.

According to many researchers, the diversification potential of emerging markets is arguably the primary benefit of emerging market investments (Bekaert et.al, 1998). For example, the statistics reported by Errunza et.al (1999) show that the average correlation of the S&P 500 Index with the authors' sample of nine emerging markets is 0.09 whereas the comparable average correlation with their sample of seven developed markets is 0.40. Harvey (1995) reported the correlation between

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[1] Since 1999 the IFC no longer publishes the EMDB Index and it is produced by Standard and Poor's Index Services instead.

developed and emerging markets is less than 0.10. Nonetheless it should be emphasised here that the diversification benefits of emerging market shares are likely to diminish as developing countries become more closely integrated with the global economy and correlations between the equity returns of developing and developed countries increase (Mullin, 1993). This is particularly true when a crisis happens. For example, Bertero and Mayer (1990), King and Wadhwani (1990), and King et.al (1994) found greater integration of world stock markets in the period surrounding the crash of 1987. This finding suggests that international diversification is least effective during periods when it is most needed.

In this thesis we are going to consider twenty eight emerging market countries which consist of four groups as follows: Emerging Market Latin America, Emerging Market East Asia, Emerging Market Europe and Other Emerging Market. The number of countries and their classification according to regions is based on a paper by Froot et al (2001). Their paper examines the portfolio flows of international investors for both developed markets and emerging markets. One of the striking findings is that the inflows have positive forecasting power for future equity returns and this power is statistically significant in emerging markets. In addition to location, emerging markets can also be classified based on income levels, political status, economic performance, level of indebtedness and market potential (Olsson, 2002). These emerging market countries are all different with respect to physical attribute, social condition, economic performance, and political situation (Olsson, 2002).

Therefore the knowledge of type of risks and risk modelling in emerging markets is vital because emerging markets are becoming more significant, they offer potential diversification benefits and they have potential to increase return. Therefore this thesis is important as it provides discussion regarding types of main risks that should be considered by an investor before investing in emerging markets, measurements of risks in emerging markets and the recommendation of what is the best model used for a particular risk.

1.3. RISK

According to Webster dictionary, risk is defined as "a hazard; a peril; exposure to loss or injury." Thus, risk refers to the chance that some unfavourable event will occur (Brigham and Houston, 2004). In finance, risk is generally defined as the volatility or uncertainty of unexpected future outcomes, generally the value of assets or liabilities that are of interest (Jorion, 1997), (Olsson, 2002). Horcher (2005) differentiates between the terms risk and exposure. Risk refers to the probability of loss; while exposure is the possibility of loss, although they are often used interchangeably, risk arises as a result of exposure.

The most relevant risk for an investor or a company that invests in financial instruments is financial risk which is referred to as possible losses in financial markets. Having understood the existence of risk, it is important to establish financial risk management. Horcher (2005) defines financial risk management as a process to deal with the uncertainties resulting from financial markets. Specifically in relation to this study, Luis (2002) views that risk management is an essential ingredient in emerging markets fixed income. In emerging markets, limiting credit risk, sovereign and corporate, is a central aim of the investment process and of portfolio management. With regard to managing risk in emerging markets, Olsson (2002) proposed several steps that must be followed including identification of risk, measurement of risk (or modelling risk) and management of risk. Generally, financial risks are classified into the broad categories of credit risks, market risks, liquidity risks, operational risks, and legal risks (Jorion, 1997). In the next section the type of risks considered in this thesis will be explained in more detail. Specifically we examine credit risks, market risks, and country risk.

1.3.1. Credit Risk

There are many definitions of credit risk. Santomero and Babbel (1998) distinguish credit risk with respect to the instruments attached to it. For direct loan, credit risk represents the risk that the borrower will not repay, will repay late, or otherwise will not make payments in accord with terms set forth in a credit agreement, and that recoveries will be insufficient to compensate the institution for the resources invested. While for securities, credit risk is defined as the risk of formal default or bankruptcy and insufficient recovery to recoup the initial investment plus interest. Jorion (2001) defines credit risk as the risk of financial loss due to counter party failure to perform their obligation. Credit risk is defined as the risk that the counterparty may not pay amounts owed when they fall due (Olsson, 2002). Fabozi (2001) explained credit risk in greater detail. According to Fabozi, credit risk can be described as having three components as follows:

a. Default Risk

Default risk is defined as the possibility that the issuer will fail to meet its obligations as specified in the bond indenture. While the bond market views default as the lack of timely payment of interest and principal, technical default may occur due to the issuer's violation of other terms of the indenture, for example failure to maintain a certain financial ratio at a certain level. This is the type of credit risk analysed in the first empirical study. Estimating default risk or default probability of emerging market bonds has extremely important implication for an investor in emerging markets as it provides forward looking estimation of the likelihood of default of the bond and therefore the likelihood of repayment.

b. Credit Spread Risk

The yield on bonds is made up of two major components, being the yield on Treasury bonds of the same maturity plus a spread. Part of this spread reflects the risk of default and is referred to as the credit spread. If investors are concerned that the risk of default is increasing, the credit spread will increase to allow for this. The increase in the required yield will reduce the price of the bond.

c. Downgrade Risk

Downgrade risk is the risk that a bond might be reclassified as a riskier security by a credit rating agency, such as Moody's Investor Service and Standard & Poor's, in the process will be assigned a lower rating. Basically bond ratings group bonds into risk classes. When an issue is re-categorized, or its credit rating changed, the yield will be adjusted to reflect the new rating. As mentioned earlier, credit ratings should be used as indicators of probable default. Basically bond ratings group bonds into risk classes. Bonds in the top four categories, BBB and higher, represent investment grade securities. The highest among them, AAA, are known as prime grade. The remaining, below BBB, represents the non-investment grade securities, or what are more commonly referred to as junk bonds or, because of the associated higher required returns, are called high-yield bonds. The average rating for emerging markets that are included in the EMBI Global Index is BB.

There are several new approaches or models of credit risk including the term structure of credit risk approach, mortality rate approach, RAROC models, Option models, CreditMetrics and Credit Risk+ (Saunders and Cornett, 2003). Under the term structure of credit risk approach, one can derive the default probability of bond which is considered as an important element of credit risk. This is explained by Beloreshki (2002) who argues that the credit risk implicit in holding a bond depends on (1) the probability that the issuer may default, (2) the expected recovery contingent upon an event of default and (3) the term structure of default and recovery rates. The aim of the first empirical study in this thesis is to derive the probability of default which is vital for emerging market bonds as it reflects their credit quality. We focus on bonds because the default probability can be derived directly based on the inverse relation between the market price of the bond and the bond's yield.

1.3.2. Market Risk

Market risks arise from changes in the prices of financial assets and liabilities (or volatilities) and are measured by changes in the value of open positions or in earnings (Jorion, 1997). According to Ramos et.al (2000), market risk is defined as risk due to changes in the prices and/or rates prevailing in the financial markets. Furthermore, market risk can be divided into interest rate risk, equity risk, commodity price risk and exchange rate risk. Fisher and Jordan (1987) classify systematic risk for stocks as market risk. For the purposes of analyzing stocks, systematic risk is defined as the part of total variability that is correlated with the variability of the overall stock market. And this systematic risk is measured by the beta coefficient on the market model which is assumed to be constant.

In the next empirical studies in this thesis, we focus on one aspect of market risk namely, equity risk. Both the second and the third empirical studies will focus on equity risk in emerging markets. However since the research setting is focused on emerging markets, the equity risk that is the basis of the second empirical study has also a connection to country risk. This is because for investors who invest in international markets, they face another type of risk not only equity risk but also country risk. The definition proposed by Meldrum (2000) perfectly reflects this characteristic: "All business transactions involve some degree of risk. When business transactions occur across international borders, they carry additional risks not present in domestic transactions. These additional risks, called country risks, typically include risks arising from a variety of national differences in economic structures, policies, socio-political institutions, geography and currencies." Harvey (1991) and Harvey and Zhou (1993) all define beta risk relative to a global market proxy. This means that one alternative measure for country risk is country beta. And this country beta (or country risk) provides the basis for the second empirical study.

For investors, the important information with regard to market risk is how to quantify them. The risk of a stock can be measured by its price volatility, its beta and by the value at risk method (Madura, 2006). Since the introduction of modern portfolio theory by Markowitz (1952), standard deviation had become a common metric for measuring market risk. Standard deviation measures how far the possible outcomes spread out about the mean. Everything else equal, a stock or a portfolio with a high standard deviation has higher risk than a portfolio with a low standard deviation. In 1994, JP Morgan introduced a new metric for measuring market risk namely Value at Risk (or VAR) which consequently challenges the use of standard deviation. The usual method for measuring VAR relies on the assumption that asset returns follow normal distribution and as a consequence extreme risk is not captured successfully. While assessing the probability of rare and extreme events is an important issue in the risk management of financial portfolios. In this case extreme value theory provides the solid fundamentals needed for the statistical modelling of such events and the computation of extreme risk measures. The focus of the third empirical study in this thesis is on the use of extreme value theory to compute VAR. This is important for emerging markets as the historical evidence suggests that financial crisis is more likely to take place in emerging markets.

1.4. The Importance and Overall Contribution of the thesis

A number of recent papers have focused on emerging markets and risk which indicates the importance of the topic of emerging markets to finance research. This explosion of research has focused particular on two main topics of risk, country risk and the credit risk. In the following sections a number of important recent papers on risk and emerging markets are summarised to provide a basis of the empirical work in this thesis. One of the important issues of investing in developing markets is not just the volatility of returns but also default risk. For instance, Stein and Paladino (2001) examine country default risk using the stochastic optimal controls models of Fleming and Stein. In this research they argue that a factor which triggers a country into default is not solely the debt ratio but the difference between the actual ratio of debt to GDP and the maximum ratio between debt to GDP (which is denoted as DEF factor). They compare the results between default countries and no default countries (the control countries). It was found that the DEF was significantly positive among the default countries whereas for the control countries the DEF was not significant.

Furthermore, based on these findings they construct contingency analysis to develop early warning signals in order to detect the vulnerability of a particular economy to shocks that subsequently will lead to a default/rescheduling. The result shows that in eighty four percent of the periods of rescheduling the DEF variable has been positive. To sum up, countries that have large and positive DEF are expected to default.

Another important issue of investing in developing markets is country risk. For example, Hoti (2005) modelled country spillover effects by using information contained in the country risk rating provided by the International Country Risk Guide (ICRG). This paper concentrates on emerging market Europe, in particular countries in the Balkan Peninsula. In this paper, risk spillovers between country risk returns across countries were analysed by employing the symmetric vector autoregressive moving average-generalised autoregressive conditional heteroscedasticity (VARMA-GARCH) model. This model allows an analysis of risk spillovers between country risk returns across countries. It was found that the model is successful in describing the dynamics in the conditional variance and the country spillover effects in the country risk ratings.

A new approach to quantify the sovereign risk was proposed by Oshiro and Saruwatari (2005). In their model, which is basically the extended version of Black-Scholes-Merton (BSM) option pricing model, country risk is represented by the probability of default. The application of the BSM option pricing model to sovereign risk requires the information either the market value of the asset or the market value of equity in the country. However since both of these inputs are not readily available, in this research they use information from stock market indices as a proxy for the equity value of the country. The model was applied for two countries, Argentina and

Thailand in order to reflect the Argentina's debt crisis in November 2001 and Thailand's currency crisis in July 1997. The probability of default obtained from the model is then compared with S&P's sovereign ratings. It was found that the model performs better than S S&P's sovereign ratings in providing early warning indicator for both crises.

Apoteker and Barhelemy (2005) apply a newly developed non-parametric methodology for country risk signalling which is referred to as the RiskMonitor CDM-Model. This methodology was applied on fifty developing countries which cover eight different regions. The methodology is able to classify nine early warning signals which then transforms into three types of crises including cyclical crises, exchange rate crises and transfer crises. Furthermore, they also consider three different time horizons including less than one year, one to three years, and three to five years. The results show that the RiskMonitor CDM model successfully generates warning signals for crises in the countries sample over the 1980-2002 period.

Cruces (2006) use the information of the sovereign credit ratings published by Institutional Investor and models them in order to examine three main stylized facts: volatility clustering, asymmetric adjustments, and serial correlation in credit revisions. The results show that ratings could exhibit volatility clustering, asymmetric adjustments, and non-zero expected revisions that are serially correlated. The findings of this research have three important implications to investors and regulators alike. For portfolio investors, they can select from two securities that have the same rating the one that has more favourable revision as it carries a smaller default risk. For regulators, it is important to realise that ratings alone is not sufficient to measure default risk and as a consequence the capital adequacy ratio should be adjusted not only based on rating but also based on other factor.

Weigel and Gemmill (2006) study what variables that determine credit risk in emerging markets. In their study, credit risk is represented by distance-to-default. The variables are classified into three categories: global, regional and country-specific variable. The distance-to-default for each country was estimated by fitting the structural model of Cathcart and El-Jahel model. It was found that the variations in the distance-to-default are largely explained by non domestic factors. More specifically, the largest part of the variance (45%) is explained by regional factors, followed by global factor which explains twenty percent of the variance. The domestic factor on the other hand only can explain eight percent of the variance. The rest of the variance (20%) is remained unexplained. The finding of this research has an important implication for investors in emerging market suggesting that the credit risk of emerging markets is non-diversifiable.

The main findings of all of these research papers can be summarized as follows: (1) the variation in the conditional variance and country spillover effect can be modelled using a model of conditional volatility; (2) the extension version of the BSM option pricing model can be used as an early warning system for Argentina's debt crisis and Thailand's currency crisis; (3) the warning signals for crises in developing countries can be estimated using the RiskMonitor CDM model; and (4) the creditworthiness of Argentina, Brazil, Mexico and Venezuela can be measured by distance-to-default which extracted form the extension version of structural model and prices of Brady bonds. Distance-to-default is largely explained by regional and global factors. All in all, these research papers show that modelling risk becomes one of the significant issues in empirical research in emerging market and therefore this thesis has an important role in developing these arguments further.

1.4.1. RESEARCH QUESTIONS

Based on the above, it is clear that emerging markets are important not only for practitioners but also for researchers. By the same token, knowledge and understanding about the type of risks is important in order for an investor to gain the greatest benefits from these markets. Although there has been considerable literature on risk in emerging markets some areas require future research. More specifically, there is little prior literature examining what are the best models to capture risk in comprehensive sample of emerging market countries. For instance, the paper by Brooks et.al (2002) compare different models to estimate country risk only in developed markets. On the other hand, Fernandez (2003) applies the same methodology as McNeil and Frey (2000) only for one emerging country, the Chilean financial market. This provides the major motivation of this research. In this thesis, we propose to find the best model for risk management purposes in emerging markets. This is important because it offers a systematic study of risks in emerging markets. Modelling default probability and country risk provide important insights regarding the appropriate credit and country risk model and risk management in emerging markets. Equally important, the application of extreme value theory in emerging markets offers the solution to find the best model for market risk in emerging markets. Finally, the examination of asymmetric and long term memory in volatility provides understanding about the nature of volatility in emerging stock markets and what is the best model to capture it. Therefore the overall objective of the research is to examine the appropriate risk measurements in emerging markets. Specifically the research questions of this thesis are: (1) what are the main factors determine and what is the best model to explain default probability in emerging bond markets; (2) which model is the best to use to modelling country risk in emerging markets; (3) what is the best model to be used for explaining market risk in emerging stock markets; (4) what is the best asymmetric model to be used in emerging stock markets and is the SEMIFAR model successful at modelling long memory in the volatility of emerging stock markets. The nature of the research is empirical and it will comprise four studies as follows: (1) implied default probability in emerging market bonds; (2) time varying country risk in emerging markets; (3) extreme value theory in emerging markets; and (4) anatomy of volatility and long term memory in emerging markets.

1.4.2. CONTRIBUTION

The contribution of this thesis to the literature is as follows. In the first empirical study we extend the study conducted by Ciraolo et.al (2002) by including more recent data in order to examine the suitability of their original model and to capture South American Economic Crisis of 2002. In addition to the more recent data we also consider an alternative research method in that instead of using Kalman Filter, we use GMM method to estimate the term structure of interest rates. Finally we include more variables to explain the behaviour of default probability using the logit model and compare the performance between the original model used by Ciraolo et.al (2002) and the other seven models used in this thesis.

In the second empirical study, to the best of our knowledge this is the first research which tries to examine which is the best time varying country risk model in emerging markets. We follow the same approach as in Brooks et.al (2002) by including more models under the Kalman Filter class. More specifically, while in

Brooks et.al (2002) they only consider random walk model, we add two more models namely random coefficient and autoregressive. Furthermore, we compare the performance of GARCH (1,1) model with normal distribution with t-distribution and generalised error distribution (GED).

With regard to the contribution of the third empirical study, we believe that this is the first study which tries to implement the same methodology as outlined in Fernandez (2003) research paper for emerging stock markets. In this study we compare the performance of the unconditional EVT, the conditional EVT, the conditional t and the conditional normal in estimating VAR. Following Fernandez (2003) we also assess the suitability of the empirical quantile in estimating VAR.

The contribution of the fourth empirical study is that it searches for the most appropriate model for capturing the asymmetric feature in emerging markets. In particular, we compare the performance of the EGARCH model, the TGARCH model and the PGARCH model. In addition to that we believe that this is the first study which tries to implement the SEMIFAR model for comprehensive samples of emerging stock market.

Therefore in general this thesis contributes to prior empirical evidence by using more up to date comprehensive samples including more econometric models as by refining the econometric approach.

1.5. FIRST EMPIRICAL STUDY

The thesis considers different aspects of modelling risks in emerging markets. In the first empirical study we discuss default probability in emerging markets and examine the appropriateness of macroeconomics and financial variables to explain in sample forecasting results using the logit model. The valuation of risky bonds requires the other two main inputs namely default probability and recovery rate in addition to the information about the coupon rate, maturity date and the principal value of the bond. The pricing on risky bonds is an ongoing topic of interest to practitioners and researchers. For example, one of the pillars from The Basel II requires banks to carefully implement credit risk measurement which include the calculation of default probability, loss given default and exposure at default for their lending (BCBS, 2004). An early attempt at the pricing of defaultable securities was pioneered by Merton (1974) and is based on option pricing theory. The idea behind this model is very intuitive whereby a company is said to be default when the market value of its assets which can be used to repay debt, are less than the value of debts. In other words, if the market value of the firm's equity falls then this will give an indication that the firm is becoming riskier and the probability of default is expected to increase as well. Although Merton's model is appealing in terms of its relative simplicity it also has one main drawback which actually reflects on the assumption of the model. The assumption states that the default can take place only at the maturity date of the bond. This implies that if the firm's value falls down to minimal level before the maturity of the debt but the firm is able to recover and meet the debt's payment at maturity; the default would be avoided in Merton's approach.

To overcome the drawback of Merton's approach, the other model proposed in literature is referred to as the structural model. Basically this model can be regarded as an extension of Merton's model. Under this model the firm may default at any time and not necessarily at the maturity of the debt. The structural model was firstly introduced by Black and Cox (1976) and subsequently developed among others by Longstaff and Schwartz (1995). However, structural models, which directly capture the default incentives and solvency of the issuer, can be problematic when empirically modelling sovereign debt. For instance, Deutsche Bank Research (1998, p.3) states that "the Russian budget itself is of course largely fictitious in the sense that it can make the deficit pretty much what you want". Beyond this measurement issue, the incentives of a sovereign to default are complex (Duffie et.al (2003)).

The most relevant pricing model for risky bonds in emerging markets is the last building block of pricing defaultable bond which is referred to as reduced-form model. Unlike structural models, under reduced-form models default probability can be derived directly from the market value of the bond. This is based on the observation that a risky bond can be decomposed into risk free component and risky component. Since a risky bond's price will be lower than the price of an otherwise equivalent risk-free bond, a reduced form model derives an "implied" default probability from the price difference. Reduce-form models for pricing sovereign debt have recently been used by Merrick (2001) and Duffie et.al (2003).

Based on these arguments it is clear that default probability is an important empirical phenomenon. Yet few authors have tried to explain what sort of factors that might have influenced on default probability in emerging stock markets. An exception is Ciralo (2002) who examined factors which determine default probability in emerging stock markets. In this study we extend the work by Ciraolo et.al (2002) in three aspects. Firstly, in order to investigate the power of the model in explaining the default probability of emerging market bonds and particularly to capture South American Economic Crisis of 2002 more recent data are included. Secondly, Generalised Method of Moments (GMM) method is used to estimate the term structure of interest rate as opposed to Kalman Filter used Ciraolo et.al (2002). Finally the performance between the original model used by Ciraolo et.al (2002) and the other seven models are compared by incorporating other variables to explain the behaviour of default probability using the logit model. The pricing model used in this study can be viewed as an application of the discrete-time version of the Duffie and Singleton (1999) reduced-form model. It was found that using the algorithm process the model successfully generated the implied default probability for all countries samples. There are five candidate explanatory variables to be included into the original logit model of which due to the availability of the data reduces to three independent variables. As a result we have eight competing logit models (including the original model) to be selected as the best model. Based on the Akaike Information Criteria (AIC) it was found that the original model still outperforms the other models as it produces the lowest value of AIC. The results of this study have important implications for investors or regulator in implementing credit-risk modelling. Firstly, we show that the impact of economic and financial variables on default probability is not symmetrical. Secondly, by predicting default probability using estimated financial factors, fund manager can infer the likelihood of changing in bond prices which is very important input for trading strategy.

1.6. SECOND EMPIRICAL STUDY

Understanding risk measurement is central to investment and risk management. Information about conditions in other countries is of relevance for international investors. For instance, portfolio performances of institutional investors which follow passive investment strategy are mainly determined by performance of the indices. In this case, the knowledge about country risk in a particular country becomes necessary condition before the decision to invest is decided. Thus, in the second empirical study the issue of country risk in emerging markets is investigated. With regard to country risk in emerging markets we use time varying beta as a proxy of country risk. Hence the important research objectives are to answer the following two main questions: (1) which distribution of GARCH (1,1) model is the best for modelling time varying beta? and (2) which model is the best to use to modelling country risk in emerging markets?. Although there has been extensive research on time varying beta the only previous paper that tries to relate time varying beta with country risk is by Brooks et.al. (2002). This paper analyses time varying beta as a proxy of country risk in developed markets. Therefore contributions of this thesis to literature are to examine the time varying country risk in emerging markets and secondly by comparing the performance of GARCH (1,1) model with normal distribution with the other two distributions including t-distribution and generalised error distribution (GED).

The main reasons to include the other two distributions is that financial time series generally exhibit fat tails in comparison to the normal distribution. The departure of stock price changes from normality has been well documented since the seminal works of Mandelbrot (1963) and Fama (1965). Furthermore, according to

Kim and Kon (1994), security return distributions play a vital role in financial market theory and practice. In the second empirical study there are three different main models examined including GARCH (1,1), Schwert Seguin and Kalman Filter. For the later, following Brooks et.al (2002), we investigate three further different types of model including the Random Walk model, Autoregressive order one (AR(1)) and Random Coefficient model. Our sample is comprehensive is that it includes 28 countries which encompass four regions, i.e. Emerging Market Latin America, Emerging Market East Asia, Emerging Market Europe and Other Emerging Markets.

It was found that, based on in sample forecast, the GARCH (1,1) under t-distribution generate the lowest forecast errors as compared to GARCH (1,1) under a normal error distribution and generalized error distribution. These findings are in line with the theory underpinning the fat tails behaviour of asset returns which is usually indicated by kurtosis. Furthermore, the greatest amount of kurtosis that can be generated by the GED is six (the laplace distribution), which is twice the implied kurtosis of the normal distribution, and (two-thirds) less than can be captured by the student-t distribution (Verhoeven and McAleer, 2003). The results, in general, suggest that the Kalman Filter technique dominates the other two techniques. In particular, within the class of Kalman Filter model the Random Walk technique was found to be the best model. Our results are in line with the findings of other researchers for example Brooks et.al. (1998) and Faff et.al. (2000). The results of this study have practical implications for investors who especially focus on investing in foreign markets, more specifically for calculating the appropriate cost of capital. Another implication is that fund manager can use the information about low-high beta value to rank country risk in emerging markets.

1.7. THIRD EMPIRICAL STUDY

Another important risk facing by investors in emerging market is market risk. The usual method for estimating market risk is called value at risk (VAR) method. However traditional VAR approaches for estimating market risk typically do not provide accurate estimates of the likelihood or size of rare, catastrophic events that are of most interest to financial market regulators and risk managers. This is because under the traditional VAR asset returns is assumed to follow the normal distribution which consequently ignores the existence of fat tails characteristic. On the other hand, one of the goals of financial risk management is the accurate calculation of the magnitudes and probabilities of large potential losses due to extreme events such as stock market crashes, currency crises, trading scandals, or large bond defaults (Zivot and Wang, 2002). In this case, EVT offers a potential solution to the problem of estimating the tails. Therefore the third empirical study focuses on the application of advance technique to measure market risk namely Extreme Value Theory (EVT) in order to test its ability as risk measurement. In particular the focus is on the implementation of EVT to recent crisis in the South American. In this study we follow McNeil and Frey (2002) approach which is also adopted by Fernandez (2003). As a starting point of analysis we adopt the approach suggested by Engle (2001).

The third empirical study is important for finding the best model in calculating value at risk which can take into account extreme returns. In this case, the basic question regarding the third empirical study is what is the best model to be used for explaining market risk in emerging stock markets? There are four competing models including the conditional EVT, the conditional normal, the conditional t distribution and the unconditional EVT. The main difference between the conditional EVT and the unconditional EVT lies on the method of estimating the value at risk. The former model generated the VAR based on the VAR of residual while the later model directly obtained the VAR from the return distribution based on the Generalized Pareto Distribution (GPD). Applying the EVT approach to data for emerging equity markets, it was found that the conditional t is the most successful model to capture extreme risk. The second best model is the conditional EVT. These findings are in line with the conclusions of Fernandez (2003). The findings of this study have important implications for investor and regulators alike in terms of modeling market risk which can provide a more robust description of extreme returns. This implies that EVT is an important element for risk management process and for calculating VAR which takes into accounts tail or maximum loss. Portfolio managers and investors are interested to know not only extreme returns but also extreme risks. In this case, portfolio managers or investors who would like to invest in emerging stock markets will have information about the maximum possibility loss that might occur under extreme events such as financial crisis and large market fall. The results show that the use of conventional methodologies such as the normal distribution model to estimate market risk in emerging markets may lead to underestimation of risk.

1.8. FOURTH EMPIRICAL STUDY

In the final empirical study, this thesis examined the best asymmetric volatility model for emerging stock markets and examined whether the SEMIFAR model is successful at modelling the long term memory in the volatility of emerging stock markets. In the previous empirical studies volatilities of asset returns are estimated using the basic GARCH model. Although GARCH (1,1) provides a reasonably good model for analyzing financial time series however it should be used with caveat as it can not accurately capture one of important stylized facts of asset return namely asymmetric response of volatility. This is because under the basic GARCH model, only squared residuals enter equation and as a result the signs of the residuals or shocks have no effects on conditional volatility (Zivot and Wang, 2002, Brooks, C. 2002).

Since the seminal work of Black (1976) with regard to asymmetric news impact or leverage effect, there has been extensive research on the area of asymmetric volatility. However to the best of our knowledge none of these studies focuses on finding the most appropriate model for capturing the asymmetric feature in stock markets particularly in emerging markets. Therefore this can be regarded as the contribution of this research. In order to follow the methodologies of the three previous empirical studies, the aim of the research is to compare the performance of three asymmetric volatility models including EGARCH model (developed by Nelson in 1991), TGARCH model which is also referred to as GJR model (developed by Glosten, Jagannathan and Runkle in 1993) and PGARCH model (proposed by Ding, Granger and Engle in 1993). It was found that, based on the results of the AIC, Bayesian information criterion (BIC) and the likelihood test that the TGARCH model is the most appropriate model to be used for explaining asymmetry in volatility in emerging stock markets. Our results are in line with the finding of Panagiotidis (2005) who found that the TGARCH model is more successful than EGARCH model for capturing the asymmetric feature in the Athens Stock Exchange. The results of this research have several implications for portfolio managers on the knowledge that positive and negative news impact emerging market differently and the best asymmetric volatility model to capture it.

The standard GARCH model and the GJR model used in the previous empirical studies imply short memory. However it is argued that for emerging stock markets, shocks to volatility persist for a very long time affecting significantly stock price (Camargo and Martinez, 2003). Therefore it becomes important to assess the existence of long term memory in volatility in emerging stock markets. The only paper which studies long term memory in volatility on emerging markets was written by Beran and Ocker (2001) and it focuses only on nine emerging market countries. The SEMIFAR model is used in the fourth empirical study for modelling long term memory in volatility and the sample of emerging market data is extended into 28 countries as in the previous empirical studies and this can be regarded as the contribution of this research. Three tests are used to examine the presence of long term memory in volatility including the classical R/S statistic, the modified R/S statistic and Hurst coefficient. The results of these three statistics show that there is evidence of long term memory in volatility in emerging stock markets. Based on the autocorrelation function (or ACF) plot of residual and normal probability plots (or QQ plots) of residuals, it can be concluded that the SEMIFAR model seems to be very successful at modelling the long term memory in volatility. Thus the findings of the fourth empirical study are in lines with the findings of Beran and Ocker (2001). The results of this study help international investors and portfolio managers deepen their understanding of volatility characteristics in emerging stock markets. This suggests that it is important to incorporate the long memory feature in the modelling of volatility in order to produce good volatility forecasts. The presence of persistence in volatility implies the market is relatively inefficient and the volatility pattern is dependent on previous volatility. Therefore the findings will also be useful for investors and fund managers in implementing trading strategy based on volatility such as positive feedback and negative feedback trading.

Overall the main findings of this thesis are as follows. The first empirical study shows that default probabilities of emerging market bonds can be generated using the discrete time version of reduced form model. It was also shown that default probabilities are a function of several macro economic variables. Based on the model selection criteria, the original model as proposed by Ciraolo et.al (2002) is still the best model to use for predicting changes in default probabilities. Country risk assessment is central to the international investment. This issue is addressed in the second empirical study. Using the GARCH (1,1), Schwert Seguin and Kalman Filter, we find that the Kalman Filter technique outperforms the other two techniques. More specifically, within the class of Kalman Filter model the Random Walk technique was the best model. The empirical evidence of the third empirical study suggests that the conditional t model is the best model for capturing extreme risk in emerging markets. The most widely used volatility model is GARCH (1,1) which assumes symmetrical response in volatility. The result of fourth empirical study shows evidence of asymmetric volatility in emerging markets and the TGARCH models was found to be the most successful model to capture it. In addition to that, the GARCH (1,1) assumes short memory and it was found evidence of long memory in volatility in emerging stock markets. We find that the SEMIFAR model seems to be very successful at modelling the long term memory in volatility in emerging stock markets.

The remainder of the thesis proceeds as follows. Chapter 2 review the literature on the default probability and credit risk, the literature on time varying beta, the literature on the application of extreme value theory and the literature on asymmetric volatility and long term memory in asset return and volatility. Chapter 3 discusses all the methodologies used in each empirical study. Chapter 4 describes the sample data that is used in these analyses and provides a discussion of the variable analysed in future empirical chapters. Chapter 5 through 8 discuss each of the empirical issues discussed in this chapter in more detail. Chapter 9 presents some concluding comments and provides some suggestions for further research on the issues covered in the thesis.

CHAPTER 2. LITERATURE REVIEWS OF ALL EMPIRICAL STUDIES

2.1. FIRST EMPIRICAL STUDY: THE DETERMINANTS OF EMERGING MARKET BOND DEFAULT PROBABILITY

This chapter will be devoted to discuss factors which influence the default probability of emerging market bond in our sample. The aims are two folds. Firstly, we want to see how good the variables that should in theory determine the default probability. Secondly, by doing so we can predict what will happen to the default probability if there is a change in that particular economic variable.

Previous studies emphasise on credit spreads rather than on default probability and they focused mainly on corporate bonds. The analysis of default risk, however, has probably been the area of most concern and empirical measurement over the years since the initial pioneering work by Hickman (1958). Beaver (1968) studied the probability of default on corporate bond using univariate method. He found that the probability of default will be greater for the firm when (1) the existing cash balance is smaller; (2) the expected net cash flow (measured before payments to creditors and stockholders) is smaller; and (3) the net cash flow is more variable. In an examination of various measures used to assess these factors, it was found that the ratio of net cash flow (income before depreciation, depletion, and amortization charges) to total debt was particularly useful.

The most popular study of predictor of default is Altman Z-score model (1968), which is a classificatory model for corporate borrowers. Using a statistical technique known as multiple discriminant analysis, Altman developed a model using the combination of ratios, which gave the best prediction of bankruptcy. Altman calculated the Z-score as follows:

$$\boxed{Z = 1.2\,X_1 + 1.4\,X_2 + 3.3\,X_3 + 0.6\,X_4 + 1.0\,X_5}$$

where:

X_1 = (Current Asset-Current Liabilities)/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Profit Before Interest and Tax/Total Assets

X_4 = Market Value of Preferred and Ordinary Shares/Book Value of total Liabilities

X_5 = Sales/Total Assets

When using this model, Altman concluded that a company with Z-score less than 1.81 is classified as a company with high probability of bankruptcy, while a company that has Z-score higher than 3.0 is categorized as a firm with low probability of bankruptcy. The last category is for companies that have Z-score between 1.81 and 3.0 and classified as intermediate companies or companies in ignorance zone. It can be seen from the equation above that primarily is a linear analysis in that five measures are objectively weighted and summed up to arrive at an overall score that then becomes the basis for classification of firms into one of the a priori groupings, i.e. distressed and nondistressed (Altman, 2000). The Altman's model was able to predict with 95% accuracy one year prior to insolvency and with 72% accuracy two years prior to insolvency. The accuracy diminished substantially as the lead-time to insolvency extended beyond two years.

However little is known about the determinants that affect the default probability of emerging market bond issues. Standard & Poor's (1998) define default as the failure to meet a principal or interest payment on the due date (or within the specified grace period) contained in the original terms of the debt issue. Standard & Poor's considers each sovereign issuer's debt in default in any of the following circumstances: (1) For local and foreign currency bonds, notes, and bills, when either scheduled debt services was not paid on the due date, or an exchange offer of new debt contained terms less favourable than the original issue; (2) For central bank currency, when notes were converted into new currency of less than equivalent face value; (3) For bank loans, when either scheduled debt service was not paid on the due date, or a rescheduling of principal and/or interest was agreed to by creditors.

The important previous literature in the area of default probability of emerging markets are Sachs and Cohen (1982), Edwards (1984 and 1986), Haque et (1996) and Sachs (1985). Sachs and Cohen (1982) found that the probability of default is a decreasing function of the propensity to invest. This is because they assume that the cost of default is a function of future output, which will depend on the present propensity to invest. Edwards (1984) examined the determinants of the spread between the interest rate charged to a particularly country and the LIBOR. He proposed nine variables that might affect the level of the spread as follows: the debt-output ratio, the ratio of debt service to exports, ratio of international reserves to GNP, loan duration, loan volume, propensity to invest, ratio of the current account to GNP, average propensity to import and growth of per capita GDP. It was found that the level of the spread is positively related to the debt/GNP ratio and the debt service ratio. On the other hand, the spread is negatively related to the International reserves to GNP ratio and the propensity to invest.

Sachs (1985) investigated the role of various macroeconomic policies and fundamentals for the debt-crisis and provided the empirical rationale for using certain economic fundamentals in the determination of the risk-premium in international capital markets. In particular, he emphasized the importance of trade and exchange rate policy for a developing country's performance. Edwards (1986), in his study of bond pricing, compared the pricing of bonds and bank loans to test whether two markets are significantly different and found that the bond data confirm some of the most important implications of foreign borrowing models. Using data of yields on LDC bonds traded in the secondary market, he found a positive effect of higher debt ratios on the risk premium.

Cantor and Packer (1996) analysed the determinants of spreads on sovereign bonds for 49 countries in 1995, relating spreads to per capita income, GDP growth, inflation, the fiscal balance, the external balance, and external debt, to indicators of economic development and default history, and to the average of Moody's and Standard and Poor's country credit ratings. Haque et al (1996) investigated the economic determinants of developing country creditworthiness for some 60 developing countries and found that economic fundamentals-the ratio of non-gold foreign exchange reserves to imports, the ratio of the current account to GDP, growth, and inflation-explain a large amount of variation in credit ratings and all developing country ratings were adversely affected by increases in international interest rates, independent of domestic economic fundamentals. Min (1998) performs an empirical analysis of emerging market bond spread determination. He classified the explanatory variables into four groups of variables: Liquidity and solvency variables, macroeconomic fundamentals, external shocks and dummy variables. It was found that the first two groups of factors influence emerging market bond spreads. Liquidity and solvency variables such as debt-to-GDP ratio, debt-service ratio, net foreign assets and international-reserves-to-GDP ratio are found to be significant and of the expected sign. These variables capture the country's ability to repay the debt. Macroeconomic fundamentals such as the domestic inflation rate and terms of trade capture the quality of the country's economic policy, which determines its future ability to service its debt.

Westphalen (2001) studied the determinants of sovereign bond credit spreads changes. Based on the structural models he proposed several explanatory variables to be included in the model as follows: changes in the yield curve level (or spot interest rate), changes in the slope of the yield curve, changes in distance to default, the changes in the volatility of the local stock market, and changes in the world economy. It was found that credit spread changes exhibited negative relationship with changes in the yield level, changes in the slope of the yield curve and the returns of the MSCI world stock index. On the other hand, the spread is positively related to volatility of the local stock market. The last variable i.e. the changes in the distance to default showed mixed results.

Sy, Amadou N.R. (2001) analysed the emerging market sovereign bond spreads using regression analysis. He analyses two groups of variables: domestic variables and external variables. Within the group of domestic variables he include the following variables: ratings, ratings x investment grade dummy, duration (log) and log (rating) x log (duration) whereby within the group of external variables the following variables are included: EMBI+ spreads (log), USHY spreads (log), US 3-month yields (log), US 10-year yields (log), US yield curve slope (US10yr-US3m) (log), Oil price, Crisis dummy, Crisis dummy x log(duration), and fixed effects (in bp).

In the following, we will identify a set of variable in order to test their influence on the time series of default probability changes. Since the default probabilities we are using are based on government bond, we expect them to be affected mainly by financial and macroeconomic variables, rather than by firm-specific factors. The exact definitions of the variables we use are:

1. Ratio of total external debt to GDP

   The higher the ratio the greater the probability of a government to default on the bond issued. As pointed out by Hanson (1974), Harberger (1980), Sachs (1984) and Edwards (1984), the static effect of a higher ratio of total external debt to GDP is to increase default probability.

2. Ratio of international reserves to GDP

   This indicator measures the level of international liquidity held by a country. The lower the ratio of international reserves the greater the threat of sudden liquidity crisis and hence the greater the probability of default. Thus we expect that there is a negative relationship between the ratios of international reserves to GDP with the default probability.

3. Inflation Rate

   Inflation rate is measured by an increase in the consumer price index. This variable can be regarded as a proxy for the quality of economic management. Thus, the higher the inflation rate, the higher the default probability. In other words, the relationship between inflation rate and default probability is expected to be positive.

4. Changes in the spot interest rate

   Longstaff and Schwartz (1995) show that a higher spot rate increases the risk-neutral drift of the firm value process. Similarly, a higher spot rate also increases the risk-neutral growth rate of the country wealth as specified in Gibson and Sundaresan (1999) and Westphalen (2001), leading to a decrease in the default probability.

5. Real rate of annual GDP growth

   The economic growth is usually measured by an increase in GDP (or GDP growth) after taking into account the effect of inflation. As the economic growth can be interpreted as an increase in income of a particular country therefore we can expect that there is a negative relation between economic growth and default probability which means that it is unlikely a country that experiences a positive economic growth would default in its bond issues.

Most data on the financial and macro economic variables are available monthly. Hence to compare the estimated weekly default probabilities with monthly economic/financial variables, we divide the monthly economic/financial variable by 4. This is a crude measure of the financial/economic variables. We then estimate the relationship between default probability as dependent variables and the economic/financial variables and assess their significance using logit model. The dependent variable is assigned 1 if default occurs and 0 if otherwise.

2.2. SECOND EMPIRICAL STUDY

Measuring risk is one of the most important topics in finance. In the context of market risk, the usual measure of risk is the beta of a stock or a portfolio. The beta parameter is derived from the Capital Asset Pricing Model (the CAPM) which is considered as a breakthrough in finance theory developed by Sharpe. The usual method of obtaining betas relies on a regression analysis, which essentially averages the historical co-movements between the return on stock and the return on the market. As defined by Sharpe, beta coefficient is the slope term in the simple linear regression function where the rate of return on a market index is the independent variable and a security's rate of return is the dependent variable. This approach assumes that beta is a constant. Therefore, if the assumption is correct, analysts can use the CAPM to predict the asset return. However, it is well known that beta parameter is not constant overtime. There is an extensive literature on testing stability of beta in the market model. In what follows, we will provide a summary of the existing literature which examine the issue of time varying betas.

The issue of time-varying beta risk is one that has been gained much attention from researchers. There are numerous studies have examined the time-varying beta, most of them at corporate level. Blume (1971, 1975) provided the earliest evidence of time varying beta. He found the average correlation for individual securities is 0.61, whereas a portfolio consists of fifty securities has average correlation of 0.98. His results indicated that beta coefficients were highly stable for portfolios containing large numbers of securities but unstable for individual securities. Furthermore, he showed that portfolio betas tend to regress toward the mean of one with the tendency stronger for the lower risk portfolios than the higher risk portfolios. In order to provide more reliable estimation and to avoid bias, Blume (1971) proposed a new method to measure beta by assigning beta series from the second sub-period as dependent variable and beta series from the first sub-period as explanatory variable. Denoting β_{i1} as the beta of the i-th security in the first period and β_{i2} as the beta in the succeeding period, BLUME obtained the following result: β_2=0.343 + 0.677 β_1. The performance between the unadjusted beta and adjusted betas are then compared using mean square errors. He concluded that the adjusted betas provide more accurate measure of future risk estimation. Blume (1975) also showed that beta estimates exhibit mean reversion over time or in other words tend to regress toward the mean of one. He suggested that source of this mean reversion of beta can be explained by the fact that the risk of existing projects tend to decline and therefore leading to a fall in the company's equity beta.

Motivated by the work of Blume's (1971), Levy (1971) investigated the issue of stationarity of beta coefficients using 500 common stocks traded on the New York Stock Exchange over the period of 10 years. The portfolio was formed used exactly the same procedure as in Blume (1971). However, unlike Blume (1971), Levy used shorter time intervals: 13, 25 and 52 weeks. The main reason for using the shorter time periods is because Levy argued that portfolio managers usually have short time perspective. It was found that for individual securities the average correlation coefficient is 0.486 whereas for portfolio of fifty securities the correlations increase to 0.972. The main conclusions of his research are as follows. Firstly, by adding more securities into the portfolio, the beta coefficients become more stable (or stationary). Moreover, like Blume, it was found that for portfolios consist of 50 securities stability is almost ideal. In addition, for short interval over 26 week onwards, the forecast results did not deviate significantly with the ones obtained in Blume's using 7 years period. Secondly, beta for individual securities is unpredictable. Thirdly, similar findings of Blume's (1971) were also found in which beta coefficients tend to move toward means of unity. However unlike Blume, the tendency is stronger for the higher risk portfolios than for the lower risk portfolios. Levy also found that using prior betas as predictors of future betas resulted in overestimation for the high betas portfolios and underestimations for low betas portfolios.

Another foremost empirical study in the area of time varying beta was conducted by Levitz (1971). Using returns calculated every four weeks, Levitz studied the behaviour of beta of portfolios with 30 and 40 securities from the end of January 1963 through January 1972. The sample period was divided into a three-year period and a one-year period. Three partitioned sets were examined (2/63-1/66 vs 2/66-1/67, 2/66-1/69 vs 2/69-1/70, 2/68-1/71 vs 2/71-1/72). It was found that the average correlation coefficient was not less than 0.97 when there were at least 30 stocks in each portfolio, regardless the time frames. Levitz also accredited the adjument beta model proposed by Blume (1971). More specifically, Levitz modified the idea proposed by Blume to estimate the future market risk by directly specified the model. Levitz proposed the following model: Future market risk = 0.30 + 0.75 x historical market risk.

The notion of Blume (1975) that source of mean reversion of beta is due to the fact that the risk of existing projects tends to decline and therefore leading to a fall in the company's equity beta is theoretically supported by Brenner and Smidt (1977). They derived the simple equation (more detail is explained in Brenner and Smidt (1978)) to show the relationship between the beta of a stock, the risk of the real asset and the value of the underlying asset. In this article, Brenner and Smidt compared the results of non stationarity of beta coefficients based on two interrelated hypotheses. The first hypothesis is the usual one in which the beta coefficient generated from the market model is assumed to be constant while the second hypothesis is based on the constant absolute amount of risk (or the constant risk of the real asset). They tested the stationarity of the beta coefficient and the absolute amount of systematic risk using the chow test. The sample consists of 762 stocks traded in the New York Stock Exchange and the time period of analysis is from July 1957 to June 1968 (or 120 consecutive months). They used two types of risk free rate, yield on Treasury Bills and return on a zero-beta portfolio, resulting in total of four models would be compared. There are seven time intervals used in this study: 120 month; two successive 60 month periods; and four successive 30 month periods. Their research findings suggest that there is very little difference between the two hypotheses. According to Brenner and Smidt, the reasonable explanation of this finding is that both market models are incorrect specifications of the true data generating process.

Altman et.al (1974) provided evidence of beta stability of the French Stock market. Using weekly returns of 316 common stocks from the period January 1, 1964 to November 30, 1971, Altman et.al compared their research findings with the results from U.S stock market studies, in particular with Blume (1971) and Levy (1971). Altman et.al (1974) emphasized that it *"appeared that the single stock beta estimates for French securities were more "stationary" than for U.S securities in the 1960's.* For instance, the average annual correlation coefficient of betas is 0.587 for French stock while for U.S stock (based on Levy's study (1971)) is 0.486. Moreover, when the estimation period move up to 4 years the average correlation coefficient of betas increases quite substantially. Thus, they concluded that for single security, the longer the estimation period, the higher the correlation coefficient of betas. Altman et.al

(1974) also investigated the stationary of portfolio betas. The analysis were done for portfolios containing 1,2,3,4,5,10,20,31 and 50 securities. Based on the comparisons with Levy's findings, it was found that the correlation coefficients of betas for portfolios of French stocks dominated U.S. stocks except for the portfolios made of 50 stocks. They concluded that portfolio consists of 10 stocks or more (with the optimal 50 stocks) will provide extremely reliable measure of future risk. Thus their findings in this case are consistent with the results of Blume and Levy. Altman et al. who also observed a regression tendency for betas estimated in successive time periods. However, his result supported the finding of Levy's in which the tendency is stronger for the higher risk portfolios than for the lower risk portfolios.

Baesel (1974) also supported the findings of Blume (1971) who suggested that individual security betas are unstable. Using a transition matrix technique, Baesel (1974) analysed sample of 160 common stocks from the period of January 1950 to 1967. Baesel varied the estimation period from 12 to 108 months to determine the impact of the length of the estimation period on the stability of estimated betas. He found that the length of the estimation period has an influence to the stability of the beta. In particular it was proposed that the longer the estimation period the more stable the beta coefficients. More specifically, based on his research findings, the optimal period is 9 years. Furthermore, his finding also has a practical implication for forecasting beta in which the forecasting will be most useful only for very high or low beta securities (these are securities lie down on the highest or lowest extremes of the diagonal transition matrix). In contrast, if medium beta securities are chosen, the likelihood is that the results will differ substantially from the expectation. In summary, Baesel concluded that the stability of beta is dependent upon the estimation interval used and upon the extremity of the beta chosen.

Porter and Ezzell (1975) re-examined the Blume's study (1971) in order to determine whether the conclusion of Blume's (1971) is affected by different methodology. More specifically, while in Blume's the portfolios were formed based on ranking individual securities in ascending order of beta, Porter and Ezzell (1975) created a portfolio by randomly select individual securities. They used the set of data which they argued to be similar with Blume and used the same non-overlapping periods (seven years) of analysis. They concluded that beta coefficients are relatively not stable if the portfolios are randomly selected and are totally unrelated to the number of securities in the portfolio. Therefore their conclusions contradict with the findings of Blume's (1971).

All previous studies on beta stationary, such as Baesel and Altman et.al, use the same estimation period for both the first and second subperiods. Roenfeldt, Griepentrog and Pflaum (1978) assessed whether variation in the length of the second sub period will affect the stability of individual security betas. To address this research issue, Roenfeldt et.al use transition matrix with the four year period is assigned as the initial estimation period and the subsequent estimation period vary from one year, two years, three years and four years. They used monthly returns of 666 firms taken from Compustat for 1963-1974 and the Standard and Poor's 500 Index was used as the proxy of the return on the market portfolio. They concluded that forecasting betas based on a four-year previous period are more reliable for subsequent four, three and two year periods but not for one year period. Nonetheless, one year forecast will be better obtained using previous four-year estimation period rather than using one year preceding period.

Alexander and Chervany (1980) argued that Baesel's conclusions are flawed because they are not based on any statistical test but rely only on the transition matrices. Using formal measure of stability of beta namely the mean absolute deviation, Alexander and Chervany (1980) showed that betas in extreme positions of the diagonal transition matrix are less stable than those in interior pentiles and the optimal estimation internal was generally four-six years. In addition, Alexander and Chervany (1980) supported the finding of Blume who showed that the beta coefficients are more stable for portfolio containing large number of securites. They also noted that the results of Blume (1971) and Porter and Ezzell (1975) actually are parallel if the beta stability is measured by the mean absolute deviation. In other words, the beta is relatively more stable as the number of securities in the portfolio increases, regardless of how the portfolios are formed.

Bos and Newbold (1984) analysed ten years of monthly data from January 1970 to December 1979. They found that 58% of stocks had varying beta. In particular they investigated the relative superiority of an AR(1) beta process, a random coefficient model and a market model. However they could not find conclusive evidence to support what the best model to use to describe the stochastic behaviour of beta. This is because they find little evidence that beta is autocorrelated rather than purely random. The major contribution of Bos and Newbold in the area of time-varying beta risk is that they proposed the use of first order autoregressive process model. As with Fabozzi and Francis (1978), Bos and Newbold argued that there are two main factors that affect variation in beta coefficient. The first factor is microeconomic factor such as operational changes in the company or changes in the business environment in the company. The second factor is macroeconomic factor such as the rate of inflation and general business condition. It should be noted here that these two main factors were not empirically tested.

Ohlson and Rosenberg (1982) formulated a general specification for beta that allows for both autocorrelated (predictable) variation and random (unpredictable) variation within the same model. The model specifies the beta coefficient in the following way:

$$\beta t = \bar{\beta} + \varepsilon_t + \delta_t$$

where:

$$\delta_t = \Phi\delta_{t-1} + d_t$$

If we compare the Ohlson and Rosenberg model with the pure AR(1) specification used by Bos and Newbold, we can determine the first nested model as follows:

$$(\beta t - \bar{\beta}) = \Phi(\beta_{t-1} - \bar{\beta}) + n_t$$

where $n_t = \varepsilon_t - \Phi\varepsilon_{t-1} + d_t$ is a correlated error component with nonzero lag-one autocorrelation. Therefore the nested model implies an ARMA(1,1) process for the beta coefficient. Based on over a fifty-year period, Ohlson and Rosenberg (1982) found that the beta of an equally-weighted index demonstrated two types of highly significant stochastic variation: a stationary first-order autoregressive process and random behaviour.

Collins et.al (1987) conducted an extensive examination of the Ohlsen and Rosenberg model using weekly data. The model was tested based on a large sample of individual securities and random portfolios of various sizes. It was found that the beta instability increases as the number of securities in the portfolio increases. Thus this finding contradicts with the findings of Blume (1971) who concluded that the nonstationarity declines with the increase in portfolio size. Collins et.al explained this phenomenon by introducing the idea of background noise. They argued that this reflected a higher ratio of beta variance to background noise in larger portfolios. As the size of the portfolio increases, the background noise decreases at a faster rate than the variability in beta. They also examined the rejection frequencies of the null hypothesis of constant beta for different estimation periods. When they analysed five-year subperiods they found that 34% of stocks had varying betas. With ten-year sub-periods they found that 65% of stocks had varying betas. Therefore the results show a clear pattern of increasing the length of estimation period with increasing beta instability. In general, their results confirm the findings of Ohlsend and Rosenberg to support the proposition that beta coefficient exhibits random and autoregressive behaviour.

Another significant contribution in the area of time-varying beta is on the modelling "market model" regression with time-varying beta proposed by Schwert and Seguin (1990). The detail of the model is provided in section four of the methodology empirical II. Their main finding is that the systematic risks are related to firm size. In particular, they showed that the systematic risk of small (large) firms tends to increase (decrease) with an increase in aggregate stock market volatility. Furthermore, their finding implies that the spread between the systematic risk of small and large firms is larger during periods of high aggregate stock market volatility and is smaller when aggregate stock market volatility is lower.

There has been several studies applied Schwert and Seguin market model to examine time-varying behaviour of beta coefficient. Episcopos (1996) applied the SS market model to a sample of eleven industry stock indexes from the Toronto Stock Exchange. He used daily closing prices from 30 July 1990 to 30 June 1994. The variance of industry returns is modelled using the modified EGARCH model in which the effect of nontrading days is taken into account and the model uses a Generalised Error Distribution (GED). It was found a negative δ coefficient in 8 of 11 industries examined. However it should be noted that a significant positive relationship between the volatility of the TSE300 composite index and the systematic risk of industry only exist for the consumer products, communications and media and merchandising industry indexes. This result suggests that these three indexes tend to behave like small market capitalisation firms.

Koutmos, Lee, and Theodossiou (1994) extend the study of time-varying betas by applying the SS market model to the stock index returns of several international stock markets. This data included weekly aggregate stock market returns for Australia, Belgium, Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom and the United States. Koutmos et.al found a statistically significant negative relationship between world market volatility and the systematic risk of the large capitalization markets of Japan and the United States. They also report that the systematic risk of the smaller capitalization markets of Australia, Germany, and Switzerland tended to increase when world market volatility increased. Since Australia, Germany and Switzerland have higher volatility persistence than the other countries; his finding also implies that stock markets with high volatility persistence exhibit higher systematic risk during periods of high world market volatility.

Reyes (1999) examines the relationship between firm size and time-varying betas of U.K. stocks. The data include monthly returns on two stock indices: (1) Financial Times Actuaries- All Share Stock Index (FTA) representing large capitalisation stocks and (2) Smaller Companies Stock Index (UKSM). By restricting his analysis to one market, he was able to test directly the size effect on time-varying betas. He extends the SS market methodology by explicitly modelling conditional heteroscedasticity in the market model residual returns. In particular he used MA(1)-GARCH(1,1) as specification of the conditional volatility of the Europe, Australia, and Far East Stock Index (EAFE) which was used as a proxy for the market portfolio. He found that the estimated beta coefficient of UKSM is larger than that of the FTA, which is consistent with the finding of Schwert and Seguin. However the δ coefficients were found not to be statistically significant. He concluded failure to account for the conditional heteroscedasticity in the market model residuals could underestimate the systematic risk of small firms and overestimate large firm betas.

Evidence of beta instability has also been found in Finland. The study conducted by Bos et.al (1995) showed that there was significant time series betas instability in Finnish individual stocks. They used monthly returns from 1983 to 1989 and a sample of 37 stocks. In this study three stock market indices were used as a proxy for the market portfolio namely the Finish stock market index, the Swedish stock market index and the S&P 500 index. The market model which uses non Finnish market returns as the explanatory variable is referred to as international market model. They report that the systematic risks of international market model based on the Swedish stock market index are found to be statistically significant. In contrast international beta coefficients of Finnish stocks based on the S&P 500 index are not statistically significant. Using the CUSUM of squares, they found evidence of time varying beta for domestic and international beta coefficients. For domestic betas it was found 21 stocks had varying betas while for international betas the number of stocks that had varying betas are the same, i.e. 15 for both the Swedish and the S&P 500 index.

A number of studies on the Australian equity market have also found evidence of individual stock beta instability. Faff et.al (1992) analysed ten years of data from 1978 to 1987 which they split into two five-year sub periods, 1978 to 1982 and 1983 to 1987. They employed a locally best invariant test for the AR(1) coefficient model. They used two different market indices as a proxy of the return on the market portfolio. The first was an equally weighted index of all firms in the Price Relative File. The second was a value weighted index supplied by CRIF. In addition, the analysis was conducted using two types of return calculation: discrete and continuous. Based on equally weighted index and continuous return, it was found that 11% of stocks had varying betas in the first sub-period, while in the second sub-period it was found that 13% of stocks had varying betas; both at 5 percent significance level. While for discrete returns the number of stocks that had varying betas are 15% and 22.6% for the first and the second sub-period respectively. In general it was found that number of stocks that had varying betas is greater when returns calculated using discrete returns than continuous returns. Furthermore they examined whether there was any relation between the nonstationary behaviour with firm characteristics. In particular three factors are investigated namely: riskiness, size and industrial sector. They concluded that there is a clear pattern between nonstationarity and the degree of riskiness but not with the size of the firm and industrial sector. More specifically, it was shown that the level of nonstationarity is higher for riskier firms (higher beta) than that of low risk firms (lower beta). Faff et.al also examined the beta stationarity for portfolio. It was found that there is a positive relation between the size of portfolio and the number of cases of beta instability. Therefore these findings are consistent with the results of Collins et al. (1987).

Brooks et.al (1992) analysed the same data as Faff et.al (1992) but using an alternative econometric methodology. More specifically, in addition to employing a locally best invariant (LBI) test they also used the approximately point optimal invariant (APOI) test suggested by Brooks and King (1991). Brooks et.al also used the same sub period of analysis as in Faff et.al. In addition, they also compared the performance between the random coefficient model and the Autoregressive order one model (Rosenberg model). In both sub-periods, it was found that 14% of stocks had varying beta using 5% significance level. Another finding which exactly the same as the results of Faff et.al is that it was found that beta instability tends to rise as the size of the portfolio increases. Therefore, comparing these results with the results obtained by Faff et.al, it is clear that there are very similar. Finally, they proposed that the Hildreth-Houck random coefficient is the most appropriate model to describe time-varying behaviour of Australian equities market.

Brooks et.al (1994) investigated the effect of portfolio formation on beta stability. In this study, they used exactly the same set of data as in Faff et.al (1992) and Brooks et.al (1992). The purpose of Brooks' et.al research is to investigate the effect of portfolio formation on beta stability. The analyses were performed for portfolios containing 5, 10 and 20 securities and the performance of two models are examined namely the Hildreth-Houck random coefficient model and Rosenberg's AR(1) coefficient model. There are five types of portfolio examined in this study including: (1) portfolios formed from the complete sample of all stocks, (2) portfolios formed from the sub-sample of all stocks identified to have a constant beta, (3) portfolios formed from the sub-sample of all stocks identified to have a varying beta, (4) portfolios formed from the sub-sample of all stocks identified to have a Hildreth-Houck beta, and (5) portfolios formed from the sub-sample of all stocks identified to have a Rosenberg beta. The sample period was partitioned into two non-overlapping five-year periods. For the second sub period and based on the first type portfolios, it was found that as the size of the portfolio increases the beta instability tends to rise. Therefore these findings are consistent with the results of Collins et.al (1987), Faff et.al (1992) and Brooks et.al (1992). This evidence also presented for portfolios formed based on the second type but only for the first sub period. While for portfolios formed based on the third type the evidence existed for both periods. In general, the findings of the research give evidence to support that the Hildreth-Houck random coefficient is the most appropriate model to describe time-varying behaviour. Furthermore, it was found that forming stocks into portfolio cannot automatically diversify away beta instability. This phenomenon can be explained by the influence of background noise effect or macroeconomic factor.

Pope and Warrington (1996) also examined the issue of time varying beta in Australia by applying the Hildreth-Houck random coefficient model. They examine 191 companies using monthly returns data from January 1984 to December 1989. Using the Breusch-Pagan test, they found that of the 191 companies 23 percent had betas which were random coefficients at the 10 percent significance level. Therefore they argued that these findings are comparable to those of Faff et.al (1992) and Brooks et.al (1992). At 10 percent significance level, Faff et.al found 21.9% of their sample exhibited time varying betas whereas Brooks et.al found that 22.3% of their sample exhibited time varying betas. The findings of Pope and Warrington support the Hildreth-Houck specification model for time varying beta.

All the previous literature on time varying beta focused on the developed markets. However, research on time varying beta in emerging markets is rare. The first study with focused on the emerging markets was conducted by Bos and Fetherston (1992). They studied the Korean stock market using monthly data from 1980 to 1988. Three tests were used to identify nonstationarity behaviour of beta coefficients including CUSUM test, CUSUM squares test and Quandt's likelihood ratio (LR) test. Using these three tests, their findings of nonstationarity for stocks on the Korea stock exchange are as follows. The percentage of stocks outside the 5% limit under CUSUM test is 2.3% whereas under CUSUM squares test and LR test are 57% and 53.9% respectively. Thus, they concluded that the CUSUM test did not perform as well as the CUSUM squares test and LR test. In summary, Bos and Fetherston (1992) found that 61 percent of 128 Korean stocks had beta instability based on the three tests.

Kok (1994) examined the performance of three methods of predicting beta values of 75 component stocks of the Kuala Lumpur Stock Exchange (KLSE) Composite Index over the three periods, January 1983 to June 1986, July 1986 to December 1989 and January 1990 to December 1991 using weekly returns. In addition to the basic market model, they used the adjusted beta model of Blume and Vasicek's adjusted beta model. The relative performance of the three methods in predicting security betas are compared using the mean square error. It was found that Vasicek's estimated beta coefficients outperformed Blume's estimated beta coefficients.

In recent paper, Ibrahim (2004) also investigated time-varying beta in the Kuala Lumpur Stock Exchange. He used daily data from January 5, 1988 to December 26, 2000 and the sample consists of 60 individual shares. In this study the Kuala Lumpur Composite Index was used as a proxy for the market portfolio. The time varying beta behaviour was assessed using the modified Schwert and Seguin model in order to take into account the effect of the Asian financial crisis. The variance of stock returns is modelled using the GARCH(1,1)-in-Mean process. Using the entire simple period he found that there was a negative relation between beta and aggregate stock market volatility, regardless of the size. In other words, the systematic risk tended to decrease when the stock market volatility increase. This conclusion also holds when the analysis is done for the first sub period (1988 to 1992) and the third sub period (1997 to 2000). Interestingly, for the second sub period (1993 to 1997) the relation between aggregate stock market volatility and beta coefficients was positive.

Brooks et.al (1998) studied time varying beta in the Singapore stock market. The aims of their study were three folds. Firstly to investigate whether betas are adjusted for thin trading. Secondly to examine whether beta instability is affected by the choice of the market return as proxy by either the Straits Times Index or the Morgan Stanley Country Index for Singapore. Finally to examine whether survivorship bias affected the results of beta instability. The sample consists of 41 firms and the time period of analysis starts from 1986 to 1993. In order to examine the possibility of thin trading the Dimson (1979) model was employed. The results between betas generated by OLS and the Dimson (1979) model are compared using Wilcoxon signed rank test. In general it was found the evidence of beta instability over the period 1986 to 1993. On average basis, they found that about 40% of stocks had varying beta. The results also indicate that beta values are insensitive whether they were estimated by OLS or the Dimson (1979) technique. Furthermore, it was found that the choice of market return has no greater impact on the results of beta instability. Finally, the results of beta instability are insensitive to survivorship bias.

Brooks and Faff (1997) also examined the issue on how to forecast beta in Malaysia. In their study they used betas data from Kok (1994). They extended the study of Kok by investigating the performance of the other two models. In particular they added Brooks and Faff's (1996) weighting scheme models. The relative performance of the five methods in predicting security betas are compared using three statistic measures: the mean forecast error, the mean absolute forecast error and the mean squared forecast error. They concluded that in the first period, the Brooks and Faff (1996) technique performs best. In contrast, the Vasicek (1973) technique performs best in the second period. These findings also imply that the Brooks and Faff (1996) technique works best for moderate mean reversion whereas the Vasicek (1973) technique works best for slower mean reversion.

Grieb and Reyer (2001) examined the relation between market capitalization and time varying beta in Brazilian stock market. The samples consist of 19 large capitalization stocks and 19 small capitalization stocks, taken from IFC, which all are considered as investable stocks by foreign investors. They employed the original Schwert-Seguin market model and the modified Schwert-Seguin market model. The later was used to identify the impact of stock market liberalization on the returns of Brazilian investable stocks. They found that there was a positive relation between beta and aggregate stock market volatility, irrespective with the capitalization size of the stocks. In other words, they noted that the Brazilian stock market behaves like small capitalisation stocks of the US market. Furthermore they concluded that the liberalization of the Brazilian stock market had affected betas of Brazilian investable stock to have time varying characteristics.

Several studies have also been conducted to examine the issue of time varying beta for mutual funds. Francis and Fabozzi (1980) examined the stability of mutual fund systematic risk. However unlike Klemkosky and Maness (1978) and Kon and Jen (1978), Francis and Fabozzi used the random coefficient model in their study. This sample was 85 mutual funds from the period of February 1965 to November 1972. The Standard and Poor's 500 Composite Average was used as the market index. The null hypothesis of constant variance of beta coefficient is obtained using the estimation procedure provided by Theil and is generated by using a two-stage generalized least square estimation. In order to quantify the magnitude of the betas' randomness the coefficient of variation was employed. It was found that only 10 of 85 funds have beta coefficients whcih were a random coefficient at 10 percent significant level. Furthermore, only seven of the ten funds had a coefficient variation between 25% and 50%. Based on these findings, Francis and Fabozzi concluded that the most appropriate model to test for the stationarity of beta in the case of mutual funds are statistical models that allowed for only a small number of structural shifts.

Black, Fraser and Power (1992) found evidence of the beta instability in the UK unit Trust for the period 1980-1989. The sample consists of 30 authorised UK unit trusts. To examine the time varying behaviour of beta, Black et.al applied the random walk model and the monthly return was used. The stationary hypothesis was determined by using the adjusted Dickey Fuller statistic. In particular if the null hypothesis that the series is stationary level 1 (or I(1)) is rejected then we can infer that the series reveal non stationary behaviour. It was found 21 out of 30 unit trusts exhibited time varying beta. Surprisingly there were eight trusts which do not exhibit any time-varying characteristics.

Another important issue in the area of time varying beta is how the instability in beta is to be modelled. Wells (1994) investigated the performance of modelling techniques used to estimate time-varying beta. In addition to the constant coefficient model, three models were considered namely the mean reverting model, the random coefficient model and the random walk model. He examined the performance of conditional beta series of 10 individual stocks on the Stockholm exchange and of the equally weighted portfolio of all 10 stocks from January 1971 to December 1989. The relative performance among all modelling techniques is compared using the mean absolute error and the mean square error. Although there was no conclusive evidence as to which model is the best but he proposed the random walk model as it forecasts on the average slightly better than other models.

Brooks et.al. (1998) also examined the performance of modelling techniques used to estimate time-varying beta. In particular, three models were employed in their study namely multivariate generalised ARCH (M-GARCH model), the Schwert and Seguin model and the Kalman Filter technique. For the later technique, in this study Brooks et.al only applied the random walk model. They investigated monthly returns data for 24 Australian industry indices from January 1974 to March 1996. Based on in-sample and out-of-sample forecasting, it was found that the random walk model was superior as compared to M-GARCH model and the Schwert and Seguin model.

Faff et.al (2000) investigated the performance of modelling techniques used to estimate time-varying beta. As in Brooks et.al (1998), three models were used namely

GARCH type models, the Schwert and Seguin model and the Kalman Filter techniques. However in this study more models were employed. Within GARCH type models, Faff et.al (2000) used three variant of ARCH specification namely GARCH (1,1), EGARCH (1,1) and TARCH (1,1) whereas within the Kalman Filter they used Autoregressive order one, random coefficient and random walk. They investigated daily returns data for 32 different UK industry sectors from 1 January 1969 to 30 April 1998. The relative performance among all modelling techniques is compared by using two steps or procedures. In the first step the in-sample forecast errors of each conditional beta series are generated. In the second step the relative performance of each model is compared using the mean square error (MSE) and the modified Diebold and Mariano test statistic. Based on the results of MSE and the modified Diebold and Mariano test statistic it was found that the performance of the Kalman Filter models were superior as compared to the other two main models. More specifically, their results were in favour of the random walk model.

Brooks et.al (2002) proposed the use of time-varying beta as a representative of country risk. In this study, their aim is to compare the performance of modelling techniques used to estimate time-varying beta. In particular they focused on three models, namely the multivariate generalised ARCH (M-GARCH) model introduced by Bollerslev (1990), the Schwert and Seguin model and the random walk Kalman filter model. They investigated monthly US dollar value weighted indices from the Morgan and Stanley Capital International (MSCI) database from January 1970 to May 1995. There were 17 developed countries sample used in this study. The stability in the beta coefficients were tested using the CUSUM square test, the White test for unconditional heteroscedasticity and the LM test for conditional heteroscedasticity. It was found that 11 out of 17 countries exhibited time-varying betas based on the results of the stability tests. The relative performance among all modelling techniques used in this study are compared using two metrics namely mean absolute error and mean square error. Furthermore, in order to determine whether the differences between forecast errors of each model are statistically significant they used the approach suggested by Ashley et.al (1980). In general, it was found that M-GARCH was the best technique to be used for generating the conditional beta series in developed countries. Although it should be noted here that when the performance of M-GARCH and Schwert and Seguin model are compared using the Ashley et.al (1980) testing procedure, the results are not statistically significant different.

Other studies have been conducted to explain the relation between the systematic risk and some underlying variables. For example, Shanken (1990) modelled beta as a function of different state variables. There are three state variables included in his model namely, (1) the monthly Treasury bill rate (TB); (2) TBV, which measures the volatility of Treasury bill, and (3) a January dummy variable. The main reason to include the final variable is motivated by previous evidence which suggests that the distribution of returns is different in January than in the rest of the year. It was found that over the period 1953 to 1982 there is a negative relation between the expected stock return and the one-month T-bill rate whereas expected stocks returns was found to be positively related to a measure of rate volatility.

Faff and Brooks (1998) modelled time varying beta models for Australian industry portfolios using an approach similar to Abell and Krueger (1989) and Shanken (1990). In this study the beta was modelled as such to describe the influences of two main variables namely the realised excess return on a market index and RFV as a measure of the volatility of the risk free rate. In addition to these two variables, the beta was also modelled to incorporate the effect of two different regimes including the deregulation of Australian financial markets in late 1983 and the introduction of the Imputation system of taxation on 1 July 1987. There were 23 industry portfolios examined for the period of January 1974 to December 1992. In general it was found that industry betas were reasonably successfully described by the proposed model.

Gangemi, Brooks and Faff (2000) modelled the Australia's time varying beta based on nine different economic variables including Australian government's net overseas borrowing; the rate of interest on 90-day bank accepted bills; the rate of interest on 10-year treasury bills; the price of wool; the trade-weighted index; the manufacturers price index; retail trade; the balance on current account; and the Australian money supply. The choice of these set of economic variables was justified on the basis of previous studies conducted by Bekaert et.al (1996) and Erb et.al (1996). In this study, Gangemi et.al investigated monthly return from the Morgan Stanley Capital International (MSCI) for the Australian and World stock market indices from January 1974 to December 1994. The stability in the beta coefficients were tested using the CUSUM test and the CUSUM of square tests. Based on the CUSUM of square tests it was found that the beta parameter indicated instability but not with the CUSUM test. The results of the estimated time varying model showed that the explanatory variable that has significant influence to the Australia's country beta (or country risk) is only the trade-weighted index of exchange rate.

2.2.1. Conclusions

The overall findings from the literature review support the notion that beta value is time varying. The standard tests used to examine the variability in beta values are the CUSUM test, CUSUM squares test, the White test and the LM test for conditional heteroscedasticity. One of the important issues with regard to time varying beta that is what is the best model to be used. Prior studies compare the performance of different modelling techniques to estimate time varying beta by including the GARCH model, the Schwert and Seguin model and the Kalman Filter model. The relative performance of each model is then assessed using several metrics such as the mean square error and the modified Diebold and Mariano test statistic.

Wells (1994) proposed the random walk model as the most appropriate model for the Stockholm exchange. The same findings were also found by Brooks et.al (1998) and Faff et.al (2000) in Australian industry indices and UK industry sectors respectively. On the contrary, Brooks et.al (2002) find that the multivariate GARCH model is the best technique for generating time varying beta in developed countries. However, there is no research has been carried out to study the best model to forecast time varying beta in emerging stock markets. In this thesis, we will use the same methodology as outlined in Brooks (2002) paper by adding two more distributions under the GARCH (1,1) model namely the t-distribution and the GED distribution.

2.3. THIRD EMPIRICAL STUDY

An important type of risk facing stock investors is equity risk (or market risk of stock). According to Jorion (2003), equity risk arises from potential movements in the value of stock prices. For investors who invest their money in investment funds which adopt passive investment strategies such as indexation, they can simply look at the equity risk of the particular index in which the investment funds try to track (or use as a benchmark). This is because large movements in indices may expose an index fund to risk.

When modelling equity risk, the assumption drawn from the behaviour of asset return is the major factor in the consideration of model specification. The most commonly used measure of risk used in the equity markets is the standard deviation of a security's price (or index) over a number of periods. In this case, the frequency (or the behaviour) of asset returns are approximated by the normal distribution, i.e. the frequency distributions are bell-shaped. From the point of view of risk, the greater the dispersion of actual values around the mean, the greater the potential volatility and hence the greater the risk. Thus, the idea behind standard deviation is very simple whereby the dispersion of return is the key source of risk. The main disadvantage of the standard deviation is that it is symmetrical and cannot distinguish between large losses or gains (Jorion, 2003). Despite its simplicity and drawback, the standard deviation plays an important role for calculating value at risk (VAR); a relatively new idea for measuring equity risk. The most popular approach to calculate VAR is the variance-covariance approach which also known as the correlation method, parametric method or analytical method. The model assumes that the distribution of investment returns is normal. This variance-covariance of VAR concept has gained popularity since its introduction by JP Morgan in 1996. Because variance-covariance VAR also assumes normal distribution of investment returns, VAR could not describe the worst loss (or extreme risks). This is because extreme events occur when a risk takes values from the tail of its distribution whereby the tails of the normal distribution are too thin to address the extreme loss. (McNeil, 1999).

One direction to overcome the drawback of VAR is to introduce the extreme value approach. The extreme value theory addresses the issue of non normality distribution of asset returns so that we can have a better forecast for the tail estimation. In the following section we will provide a summary of the existing literature which discusses the application of extreme value theory for measuring risk in finance.

Danielson and de Vries (1997) used a semiparametric approach based on the Hill-estimator of the tail index. In this study, Danielson and de Vries proposed an automatic procedure to determine the number of observations in the tail (or m) where they used a double subsample bootstrap to eliminate reliance on the initial α and assumption of β. They used the Olsen data set comprises one year of data on three forex contracts: yen-DM, yen/USD and DM/USD. In particular, they used logarithmic middle prices quotation of each currency and there were two types of data frequency, i.e. ten minutes data interval and one second data interval. It was found that the tail index estimations for either exchange rate drift around four at the ten minutes aggregation level but are closer to three at the one second frequency. Thus, the findings are consistent with previous work that used much lower frequency data and concluded that the fourth unconditional moment is probably just unbounded, i.e. $\alpha < 4$.

Danielsson and Vries (2000) compared the performance of the extreme value theory with the other modelling techniques including the GARCH based RiskMetrics method and the historical simulation method. Danielsson and Vries extended the historical simulation approach by obtaining empirical distribution function via historical simulation and using EVT to fit a smooth curve through the tail of this distribution. In this study, they used data on six randomly selected US stocks in addition to the J.P. Morgan bank stock price as the basis for portfolio analysis. The data set for each VaR estimation was set to 1500 trading days. For each of these portfolios, VaR was calculated by applying 500 random portfolio weights to 1500 days of returns for the individual stocks to obtain 1500 days of returns for the portfolios, as in the method of historical simulation, and using the EVT-derived estimator. The VaR estimate was compared to the realized portfolio return on the following day, and this procedure was repeated for 1000 different consecutive days. The total number of trading days required for this back-test was therefore 2500. It was found that RiskMetrics approach was the most accurate VaR estimates at the lowest confidence level, but consistently underpredicted VaR at subsequent levels. Historical simulation performed well until its probability limit (1/1500), and the EVT-based estimator is impressive in its agreement with the expected number of violations, especially at the higher confidence levels. Therefore based on these results it can be concluded that for the data set employed the Danielsson and Vries (2000) estimator seems appropriate.

Ho et.al (2000) applied the block maxima extreme value approach in order to capture the financial turmoil in the Asian Markets. There were six Asian stock market indices examined in this study and this data was obtained from Datastream. Daily returns were used in this study since they dealt with indices. The most important factor in terms of characterising the limiting extreme distribution of the tail is the tail indices. To estimate the tail indices, they employed the generalised extreme value distribution as provided by Jenkinson (1955) and it was estimated using the maximum likelihood estimation. It was found that all tail indices values are negative and confirmed the Frechet distribution. Therefore the results are consistent with the findings of other studies including Danielson and De Vries (1997), Longin (1996, 1997) and Mc Neil (1998). Furthermore, Ho et.al (2000) compared the performances between extreme value and traditional measures (the variance-covariance and historical method) for estimating value at risks. The performance of the different VAR estimates is compared on the basis of the number of times that the actual returns exceed the VAR estimate. They found that in general, the VAR values obtained from the extreme value method outperformed the traditional methods by two or more times higher. Notwithstanding the superiority of the extreme value theory, in this study they noted that since Basle requires three times the VaR (99% confidence level, 10-day horizon) estimated by a Bank's internal models it appears that banks have little incentive to use extreme value theory for this purpose.

Cotter (2004) used another method of applying extreme value theory based on a semi parametric tail estimator, the moments based Hill estimator, to estimate the tail index of five European equity indices. The data includes the daily returns of ISEQ (Ireland), FTSE 100 (UK), CAC40 (France), DAX100 (Germany), and IBEX35 (Spain). It was found that all tail indices values verified the Frechet distribution and exhibit GARCH characteristics. Furthermore, in this study the performance between extreme value theory and the other two approaches, value at risk and the excess loss probability estimator, to estimate the tail are compared. Cotter (2004) found that in general extreme value theory dominates alternative approaches in tail estimation as it avoids model risk.

Longin (2000) applied a parametric method (block maxima) of extreme value theory. The database consists of daily returns on the S&P 500 index over the period January 1962 to December 1993. There are four different time periods examined in this study including one week (T=5), one month (T=21), one quarter (T=63), and one semester (T=125). It was found that the tail index value for all different time periods is always negative and is between -0.148 and -0.465, implying that the limiting distribution is a Frechet distribution. Furthermore, Longin (2000) also investigated whether difference in the holding period (or frequency) will have an impact on the tail index. For this purpose, three different frequencies are used including one day, five days and ten days. As before, it was found that the tail index value for all different frequency is always negative and therefore confirmed the Frechet distribution. The performance of extreme value method in generating the value at risk (the VaR) was compared with the other methods including the VaR based on the historical distribution of returns, the VaR based on the normal distribution of returns, the VaR based on the conditional GARCH process and the VaR based on the exponentionally weighted moving average process. Longin (2000) concluded that the extreme value method presents three main advantages over the other four methods. First, out-of-sample VaR for high probability values can be calculated by the extreme value but not with the historical method. Second, the extreme value method has lower model risk as compared with the other four models since the extreme value method does not assume a particular model for return. Third, large unexpected market movements are taken into account by the extreme value method but not with the other four models under consideration.

Gencay et.al (2003) compared the performance of the extreme value theory with the other modelling techniques including GARCH (1,1), GARCH (1,1) with student t distribution, variance-covariance approach and historical simulation approach. The extreme value parameters in this study were estimated by the GPD approach. More specifically there are two types of GPD approaches used in this study namely adaptive GPD and non adaptive GPD. The difference between non adaptive GPD and the other models is that while the other models adopt a sliding window approach (500, 1000 and 2000 days), non adaptive GPD uses all the available data. The relative performance of each model is compared on the basis of the violation ratio. The violation ratio is defined as the total number of violation divided by the total number of one-period forecasts. The data used in this study include daily returns of the Istanbul Stock Exchange (ISE-100) Index from 2 November 1987 to 8 June 2001. Based on the violation ratio, the GPD models (adaptive and non-adaptive) performed best whereby the second best model is GARCH (1,1) with student t distribution.

Danielson and Morimoto (2000) compared the performance among different models in forecasting value at risk including the GARCH (1,1) with normal distribution, GARCH (1,1) with t distribution and EVT based on Hill estimator. The data used in this study are The TOPIX Index (consists of over 1,500 of the most prestigious Japanese companies which are listed on the Tokyo Stock Exchange), oil price index WTI (West Texas Intermediate), SP-500 index, JPY/USD exchange rate and Tokyo Stock Exchange. The estimation window was 1000 observations and the model is re-estimated each day. To obtain objective result (or to avoid data snooping) they did not look at the data before applying each model. It was found that the EVT was the best model followed by GARCH (1,1) with student t distribution whereas the normal GARCH (1,1) has the worst performance. As a conclusion, Danielson and Morimoto (2000) recommended the uses of EVT for value at risk prediction for Japanese financial institutions and other users of Japanese market data.

McNeil and Frey (2000) examined the performance of several models in estimating value at risk (or market risk). In particular they fit GARCH (1,1) to return data using maximum likelihood estimation and use a GPD approximation to model the tail of the distribution of the innovation. This model is referred to as the conditional EVT. The other models are the GARCH (1,1) model with normal distribution, the GARCH (1,1) model with student t-innovations and the unconditional EVT. McNeil and Frey (2000) proposed the use of the GPD approach to tail estimation because of several reasons as follows: (1) In finite samples of the order of 1000 points from typical return distributions EVT quantile estimators are more efficient than the historical simulation method; (2) The GPD based quantile estimator is more stable in terms of mean squared error) with respect to choice of k than the Hill quantile estimator; (3) For high quantiles with confidence interval (or q) equals or higher than 0.99 the GPD method is at least as efficient as the Hill method; (4) The GPD method allows effective estimates of expected shortfall to be constructed; and (5) the GPD method is applicable to light-tailed data or even short-tailed data; whereas the Hill method is design specifically for the heavy-tailed case. The size of the data set used to fit the GARCH models was 1000 days and the method was tested on individual assets. The returns of assets used in this study are: S&P index, DAX index, BMV, USDGBP, and price of Gold. The performance of all models is evaluated using dynamic backtesting based on the 1000 rolling windows estimation. To backtest the method, they compared the estimated quantile with the actual return.

VaR was calculated at the 95, 99, and 99.5% confidence levels for the purposes of the back-test. A violation is said to occur whenever the actual return is greater than the estimated quantile. It was found that the conditional EVT performed the best followed by GARCH (1,1) with t distribution. The unconditional EVT and GARCH (1,1) with normal distribution are considered to share the same ranking. It was also concluded that the GPD approximation was preferable because it can deal with asymmetries in the tails.

Seymour and Polakow (2003) compared the performance between historical simulation and the extreme value theory in estimating value at risk for nine stocks of the South African Market. More specifically, for extreme value theory, they applied two methods namely the method suggested by Danielson and De Vries (2000) and the method suggested by McNeil and Frey (2000). Initially, Seymour and Polakow constructed 500 random portfolios. Because it is impossible to analyse all data for back testing purposes as a result only two portfolios were arbitrarily chosen for further analysis. It was found that all three methods provide similar value at risk estimation at the lower confidence levels. However, the difference becomes substantial at the highest confidence levels between the value at risk predicted by the Danielson and De Vries method and by McNeil and Frey method. It was concluded that based on the backtest results and the magnitudes of the VaR estimates provided by the methods, McNeil and Frey (2000) performed the best.

Fernandez (2003) adopted the conditional extreme value approach as suggested by McNeil and Frey (2000). In addition to all models used in McNeil and Frey (2000) paper, in this study Fernandez (2003) also examined the performance of empirical quantile in computing VaR; the issue that is not addressed by McNeil and

Frey. The data of the study include daily returns of the Index Price of Selective Stocks (IPSA), the Chilean peso/US dollar exchange rate, the spot price of copper, and a proxy for a one-year zero coupon bond traded domestically. The performance of each model is evaluated using dynamic backtesting based on the different rolling windows estimation depending on the type of data. It was found that the GARCH (1,1) with t distribution and the conditional EVT outperformed the other models. The next best performers are the unconditional EVT and the empirical quantiles approaches. Finally the GARCH (1,1) with normal distribution was placed at the bottom of the performance ranking.

2.3.1. Conclusions

Based on the literature review it can be concluded that there are two principal types of model for extreme values. The first one is the block maxima model and the second one is the peaks-over-threshold (POT) model. Within the POT class of models, we can further distinguish two styles of analysis. There are the semi-parametric models built around the Hill estimator and its relatives and the fully parametric models based on the Generalised Pareto Distribution or GPD. Furthermore there have been two significant modified models developed by Danielsson and Vries (2000) and McNeil and Frey (2000). The later model is also referred to as the conditional EVT. The results showed that the performance of McNeil and Frey outdoes the Danielsson and Vries method and the other models.

Previous studies compared the performance of different models in generating VAR using either data on a particular country (or an index) or several indices. The general finding across studies is that the EVT or the conditional EVT ranks as the best model. Although with the exception in which in Fernandez (2003), the conditional

EVT and the t distribution share similar performance. However, there was no prior study tries to compare the performance of different models in producing VAR for a comprehensive sample in emerging stock markets. In this paper we will use exactly the same models as in Fernandez (2003) to investigate what is the best model to use to capture the extreme risk in emerging stock markets.

2.4. FOURTH EMPIRICAL STUDY

In an analysis of the empirical properties of returns on assets, three properties or stylized facts emerge which are important from a risk perspective, namely non-normality of returns, volatility clustering and asymmetry in return distributions. The most relevant property of non-normality of returns for risk purposes is that the tails of the return distribution are higher than normal distribution (i.e. fat tailed). The fat tailed property has been discussed in the previous chapter and the focus of this chapter is to provide a summary of the existing literature which discusses the application of asymmetry model of volatility. In addition to that a summary of literature of long term memory in volatility will also be presented. The existence of asymmetry in return distributions implies that usually one of the tails is fatter than the other. In the case of equity, the lower tail is commonly thicker than the upper tail and as a result the GARCH (1,1) model tends to under predict losses relative to gains. It is argued that for emerging stock markets, shocks to volatility persist for a very long time affecting significantly stock prices (Camargo and Martinez, 2003). The presence of long memory volatility in asset returns has important implications for pricing contingent claims in emerging markets.

Extensive research has been conducted on the relation between the stock market index and its volatility. In general the main finding is that the stock market index and its volatility is negatively correlated, for instance a decrease in the level of the stock price leads to an increase in its volatility. Furthermore, it was found that the relation is asymmetric. There are two main hypotheses (or explanations) for the asymmetric nature of the volatility response to stock returns, namely the leverage effect and time-varying risk premium (Chen et.al, 2005). The first study which examined the asymmetric property in the stock returns in the light of the leverage effect was conducted by Black (1976). Using a sample of 30 stocks (basically the Dow Jones Industrials), he constructed monthly estimates of stock return volatility over the period 1962-1975 by summing squared daily returns and taking the square root of the results. The estimated model on this research is as follows:

$$\frac{\sigma_{i,t+1} - \sigma_{i,t}}{\sigma_{i,t}} = \alpha_0 + \lambda_0 r_{i,t} + \varepsilon_{i,t+1} \tag{1}$$

It was found that the coefficient λ_0 was always negative and usually less than -1. Therefore he concluded that if the stock price today fell then the volatility on the following day would, on average, be higher than if the stock price rose by the same amount. Black (1976) explains this as follows. When the price of a company's stock falls, the market value of its equity also falls and hence increases the debt-to-equity ratio. As a consequences the financial risk (or the riskiness) of the company rises causing higher volatility in its stock return. In other words, the firm's return on equity and volatility are negatively correlated. The findings of Black were subsequently confirmed by Christie (1982), French et al (1987), Nelson (1991), and Glosten et al (1993).

Christie (1982) tested Black's explanation by looking at the relationship between the asymmetry in equity volatility and the debt-to-equity ratio of firms. More specifically he did this by testing the leverage hypothesis and analyzing cross section of a sample of large firms. The leverage hypothesis assumes that, under Modigliani and Miller framework, the volatility of log changes in a firm's net asset value (debt plus equity) is constant over time. The volatility of log changes in the firm's equity varies over time with the firm's debt to equity ratio. If the value of the firm's assets falls then it is estimated that the value of equity will fall (almost) entirely and as a result the ratio debt to equity increases which will lead to rise in the future volatility of stock returns. According to this hypothesis, λ_0's (slope in equation 1) for firms with large debt to equity ratios should be lower than for firms with small debt to equity ratios. It was found that stock price changes and volatility are inversely related i.e., the elasticity of volatility with respect to the value of equity is negative. He argues that this finding implies that volatility is an increasing function of financial leverage. Although he found that there is actually strong relationship between the leverage effect and the debt-to-equity ratio but the leverage itself is not sufficient to explain the asymmetric effects. On page 425 he suggested '......leverage is a dominant, although probably not the only, determinant......' of λ_0. Furthermore it is found that the riskless interest rate has a strong positive effect on volatility. This finding is consistent with the fact that the value of the firm is an inverse function of the interest rate.

Schwert (1990) examined the issue of leverage effect with regard to the stock market crash of 1987. In this study the presence of the leverage effect is represented by 22 days lag variable of unexpected returns. The idea is that, similar to Black (1976) and Christie (1982), an unexpected negative return is associated with an unexpected increase in volatility. Thus, we expect that the coefficient of lag variable of unexpected returns to be negative. There was evidence of the leverage effect during the period under study. All the lag variables of unexpected returns are negative. Moreover a negative return shock increases volatility by more than 2.5 times as compared to a positive return shock. Schwert (1990) notes that the relatively higher volatility was due to recessions and the major banking panics in the nineteenth and early twentieth centuries. However this was not the case for the stock market 1987 crash as there was no major crisis or recession prior to the crash.

Cheung and Ng (1992) analyze the relation between stock price dynamics and firm size. The data include daily return of American and New York Stock Exchange (AMEX-NYSE) and NASDAQ-National Market System (NMS) security returns. In order to examine the asymmetric effect, in this study they used EGARCH model with the logarithm of lagged stock price to 251 firms with no missing returns on the Center for Research in Security Prices between July 1962 and December 1989. The presence of leverage effect is indicated by the coefficient of the log of lagged stock price which, according to Black (1976) and Christie (1982), should have negative value. It was found that conditional future volatility of equity returns is negatively related to the level of stock price for both sets of market data (for over 95% of the firms), which implies the existence of leverage effect. Furthermore the leverage effect is stronger for smaller firms and with higher financial leverage (or debt to equity ratio). This conclusion is based on the results of the Spearman rank correlations between the coefficient of the log of lagged stock price and the firms' average debt to equity ratio and between debt to equity ratio and firm size. Both of the Spearman rank correlations have negative value which implies the higher the ratio debt to equity the larger the negative value of the coefficient of the log of lagged stock price.

All previous studies above show that volatility tends to react more to negative returns than to positive return. Asymmetric effects of good news (or unexpected increase in price) and bad news (or unexpected drop in price) was successfully modelled firstly by Nelson (1991). To allow for asymmetric volatility Nelson (1991) introduce the exponential GARCH process (EGARCH). Recall that in an EGARCH model, the conditional volatility depends on lagged volatility, lagged absolute returns and lagged returns. Using daily data, he showed that negative shocks have a more impact on stock return volatility than positive ones.

Unlike the previous studies, Glosten et.al (1993) find both a positive and a negative relation between risk and return depending on the method used. More specifically, when the standard GARCH-M was used it was found that the relation between the conditional mean and conditional volatility of the excess return on stocks is positive but insignificant. On the other hand, the modified model of GARCH-M which allow positive and negative unanticipated returns to have different impacts on the conditional variance resulted in a negative relation between the conditional mean and the conditional variance of the excess return on stock. More specifically, Glosten et.al (1993) report a strong negative relation between the market risk premium and conditional market variance when the nominal one-month Treasury Bill yield is included in the conditioning information set. Glosten et.al (1993) explained this phenomenon as follows. If all assets carry risk and investors want to save more in volatile times, prices may be bid up, thereby reducing the risk premium. In their paper, they proposed a new model which is referred to as the GJR model. The same model was also proposed by Zakoian (1991) which refers to as the TGARCH model.

Bae and Karolyi (1994) investigate the return and volatility spill over effect between the United States and Japan. This sample was intraday open and closing prices from the Standard and Poor's 500 stock index and the Nikkei Stock Average over the period 1988 to 1992. In order to allow for asymmetric effects of negative ("bad news") and positive ("good news"), in this study they used the EGARCH model. They report that the volatility spillovers between the New York and Tokyo stock markets are significant in both directions for the post-crash period. Furthermore they found that the volatility transmission between the two markets is asymmetric which implies bad news from domestic and foreign markets to have a much larger impact on subsequent return volatility than good news. In this case, they find that if the asymmetric effect of good and bad news on the volatility of the domestic market is ignored then the magnitude and the persistence of volatility surprises from one country to the other, from Japan to New York vice versa, are significantly understated. It should be noted here that they could not offer substantive explanation for the importance of asymmetry in international stock return volatility processes. Nevertheless they recognised the main factor that could explain the phenomenon was trading volume.

Duffee (1995) examined the presence of leverage effect at a firm level. The approached adopted by Duffee is simple in that he decomposed the estimated equation in Black (1976) and Christie (1982) into two following equations as follows:

$$\begin{aligned} \log(\sigma_t) &= \alpha_1 + \lambda_1 r_t + \varepsilon_{t,1}, \\ \log(\sigma_{t+1}) &= \alpha_2 + \lambda_2 r_t + \varepsilon_{t+1,2.} \end{aligned} \qquad (2)$$

The data used in this study include daily and monthly stock returns of almost 2,500 firms that were traded on either the Amex or NYSE from 1977 through 1991 (or until the firm disappeared from the AMEX/ NYSE Center for Research in Security Prices tape). There was evidence to support the findings of Black (1976) and Christie (1982) in which the relation between current stock returns and future volatility is negative.

However Duffee (1995) finds positive relation between the debt to equity ratio and the coefficient of leverage effect which is contrary evidence to Christie (1982) and Cheung and Ng (1992). His main finding, which is contradictory with Black's (1976) proposition, is that at the firm level, stock returns and volatility are contemporaneously positively correlated. In other words the relation between current stock return and current volatility is positive. This conclusion is confirmed for both daily and monthly data. However it should be noted that at the monthly horizon, Duffee (1995) find no clear pattern between a firm's stock returns and future volatility. Duffee (1995) explains the reason behind the difference between his finding with Black (1976) and Christie (1982) hypothesis is because the leverage effect hypothesis focuses on the relation between returns and future volatility not with the current volatility.

Braun, Nelson and Sunier (1995) examined the issue of asymmetric nature not only for volatility but also beta coefficient. The intuition to scrutinize the beta of the firm's equity is that leverage increases the risk of equity. There are two main reasons for expecting asymmetric behaviour in beta coefficient. Firstly we might expect that an exogenous shocks to the value of a firm's assets that raises (lowers) the firm's financial leverage will raise (lower) the beta of the firm's equity. Alternatively a persistent shock to the riskiness or conditional beta of a firm's equity, ceteris paribus, will manifest itself in a change in the price of equity. In this study they used bivariate exponential ARCH (EGARCH) model. For this empirical analysis they use monthly returns from the Center for Research in Security Prices (CRSP) for the period July 1926-December 1990. The performance between the EGARCH model and rolling regression approach to estimating betas are compared by using mean square error (MSE) and mean absolute error (MAE). It was found that the EGARCH outperformed rolling regression in estimating the beta coefficient. They found strong evidence of asymmetric response of market volatility but found no evidence of asymmetric response in conditional betas. Based on this finding, they conclude that betas were not responsive enough to explain for the differing return performances of "winners" and "losers".

Koutmos and Saidi (1995) examined the issue of asymmetric effect for individual stocks which they believe was the first attempt in this area. In this study they use the EGARCH model to test for asymmetric volatility (leverage effect) in individual stock returns. In further analysis, they investigate whether financial leverage as measured by ratio of debt to equity has an influence to the variations in the asymmetric response of volatility to shocks. In this case they run cross section regression in which the absolute value of the degree of asymmetry treated as dependent variable and the independent variables are the debt to equity ratio and the asset size. To calculate the ratio of debt to equity they use book value and market value of equity. Since there are three different definitions of debt and two measures of market value of equity, in total there are nine debt to equity ratios used in this study. This data included dividend-adjusted daily stock returns for the thirty companies that constitute the Dow Jones Industrial Index. It was found that all stocks, except one, exhibited asymmetric volatility in which negative innovations increase volatility more than positive innovations with an average difference of 2.13 times. Furthermore, based on the cross section analysis the degree of asymmetry can be explained by the degree of leverage. Thus this finding is in line with previous studies such as Christie (1982) and Black (1976).

Koutmos and Booth (1995) examined asymmetric volatility transmission in international stock markets including New York, Tokyo and London. Previous studies on the first moment interdependencies (or price spillovers) and second moment interdependencies (or volatility spillovers) put the emphasise only on quantifying the news (i.e. the size of an innovation). Therefore they try to fill the gap in the literature by examining not only the quantity of the news but also the quality of the news (or the sign of the innovation). In order to allow for asymmetric effect in the volatility transmission mechanism, in this study they used multivariate EGARCH model. The data used in this study was the daily opening and closing figures of the S&P 500 for the USA, the Financial Times 100 Share Index for the UK and the Nikkei 225 Stock Index for Japan. There was significant evidence of volatility sipllovers between the three stock markets in both directions. Furthermore they found that the volatility transmission is asymmetric in which bad news (or negative innovations) in a given market increases volatility in the next market to a greater extent to good news (or positive innovations). In addition, they also analysis the pre and post the October 1987 crash. The results show that the volatility transmission was significantly asymmetric only after the crash took place.

Bekaert and Harvey (1997) examined volatility of twenty emerging markets. In this study they use data of 20 emerging markets from the International Finance Corporation (IFC) of the World Bank for the period beginning January 1976 to December 1992. In this study they use GARCH specification as suggested by Glosten, Jagannathan and Runkle (1993) and Zakoian (1994). They found, at monthly frequency, that ten out of twenty emerging stock markets exhibit time varying volatility. Furthermore, in seven of these ten cases the asymmetry parameter is positive, implying negative shocks increase volatility by more than positive shocks.

Excessive volatility in these markets during the Asian crisis of 1997-1998, and the turnmoil in Russia, Brazil, Turkey and Argentina afterwards showed that volatility is an inherent part of these economies. In other words, in contrast to the mature markets, Bekaert and Harvey (1997) show that volatility in emerging markets are primarily determined by the local information variable.

Fraser and Power (1997) examined the issue of leverage effect in five Pacific Rim markets (Hong Kong, Japan, Singapore, Malaysia, and Australia) as well as the U.S. and U.K. To test for asymmetry in volatility, they extended the vanilla GARCH model by adding a lagged dummy variable which has value of one if ex post returns at previous period is less than one or otherwise. It was found that leverage effect existed significantly for the UK, Japan and Malaysia. In particular, bearish market conditions would appear to increase future volatility. They also find ex ante volatility parameter for Malaysia, from GARCH in mean model, is significantly negative which they interpret as showing that investors in Malaysia are predominantly risk-lovers. Furthermore they propose that the result of this finding suggest that information on the weekly market performance for these countries may be useful in forecasting volatility.

Booth et al. (1997) provide evidence of price and volatility spillovers among the Danish, Norwegian, Swedish, and Finnish stock markets. The KFX, OBX, OMX and FOX indexes are used as a proxy of the stock price behaviour of Denmark, Norway, Sweden and Finland, respectively. The raw data consist of 1,574 daily observations of the natural logarithms of the closing values of the price indexes for each market for the period beginning 2 May 1988 and ending 30 June 1994. In order to examine the impact of good news (market advances) and bad news (market retreats), Booth et al. (1997) employed a multivariate EGARCH model. It was found that volatility transmission is asymmetric in which spillovers being more pronounced for bad than good news. More specifically, with the exception of Denmark, the asymmetric effect exists for Norway, Sweden and Finland. Numerically, bad news for Norway, Sweden and Finland have 2.12, 1.92 and 1.49 times the impact of good news, respectively.

Shields (1997) discusses asymmetry in stock market return volatility of Emerging Eastern European Markets (ESMs). The country samples are Poland and Hungary. There was no evidence of asymmetry in the two countries sample and she suggests the possibility of 'non-rational investor behaviour' and 'a comparatively lower level of understanding' of the market in ESMs. Another plausible explanation maybe that information dissemination is slower in these markets as compared to those in developed markets, and/or that investors in general may be less responsive to negative news because dramatic fluctuations during the recent transition process have posited them to view current fluctuation as insignificant.

Koutmos (1999) examined the issue of asymmetric price and volatility adjustments in five emerging markets including Korea, Malaysia, Philippines, Singapore and Taiwan. The data used in this study are the stock price indices of six emerging stock markets namely those of Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand. The time period under investigation extends from January 2, 1986 to December 1, 1995 for a total of 2,584 observations. To detect the asymmetries in the conditional variance, Koutmos used the diagnostics test as proposed by Engle and Ng (1993). The results of this test show that each market fails at least two of the individual tests and all markets fail the joint test. Therefore

Koutmos (1999) concluded that the conditional variances in the five markets under study are likely to be asymmetric. In this study the EGARCH model is used and to deal with the problem of leptokurtic the generalised error distribution (GED) was employed. The results show that there is asymmetric response of stock returns to past information.

Ng (2000) examines the size and the impact of volatility spillover from Japan (regional shocks) and the U.S. (the world) by constructing four different correlation specifications. She conducts her investigation on a sample of weekly national stock index returns complied by DataStream International from January 1980 to December 1996, including the Hang Seng Index (Hong Kong), the Korean Composite Stock Price Index, the Kuala Lumpur Stock Exchange Composite Index (Malaysia), the Stock Exchange of Singapore All Share Index, the Taiwan Stock Exchange Weighted Price Index, the Stock Exchange of Thailand Index, the Tokyo Stock Price Index, and the Standard and Poor's 500 Index. These indices are value weighted. Weekly returns are employed in order to avoid problems associated with nonsynchronous trading and day-of-the-week effects. The research conducted by Ng (2000) consists of two basic steps. The first step entails the estimation of a bivariate GARCH (1,1) model describing the joint dynamics of U.S. and Japanese conditional returns and variance/covariances. Four different specifications are considered for this stage but the most general one, the general asymmetric dynamic covariance (ADC) model with asymmetry originally proposed by Kroner and Ng (1995) is retained given its superior fit. In the second stage, a univariate volatility spillover model for each Pacific-Basin country is estimated in which volatility surprises from Japan and the U.S. manifest themselves through that country's error term. The findings from this study may be summarized as follows: first, both regional and world factors are found to play an important role for market volatility in the Pacific-Basin region, although the world market influence tends to be greater. Second, the relative importance of the regional and world market factors is influenced by important liberalization events (such as the introduction of country funds and changes in foreign investment restrictions), fluctuations in currency returns, number of DR listings, sizes of trade, and closed-end country fund premium but the effects vary from country to country and from liberalization event to liberalization event. Third, the proportions of the Pacific-Basin market volatility captured by the regional and world factors are generally small. For instance, the U.S. accounts for 5.84% of Hong Kong volatility while Japan accounts for 2.16%.

Brooks, Faff, McKenzie and Mitchell (2000) examined the issue of leverage effect in equity indices for ten mature markets using the power ARCH models. This data included daily stock price index of Australia, Canada, France, Germany, Hong Kong, Japan, New Zealand, Singapore, the United Kingdom and the United States from February 1989 to December 1996 for a total of 2062 observations. There are two asymmetric ARCH models considered in this paper namely the Leverage ARCH and the GJR-ARCH models. They find strong evidence of leverage effects in the country samples. They noted that there is very little practical difference between how the leverage ARCH and GJR-ARCH models capture the leverage effects in conditional volatility. Furthermore, the inclusion of a power term into the leverage GARCH models is found to be meaningful.

Reyes (2001) examined the issue of asymmetric volatility spillover in the Tokyo Stock Exchange, in particular he testes volatility transmission between large and small capitalisation stock indexes. Two indexes from the Tokyo Stock Exchange

(TSE) are used namely: (1) Japanese Large Companies Index (JLG), which consists of the larger half of the First Section, and (2) Japanese Smaller Companies Index (JSM), which consists of the smaller half of (1).The data used in this study consist of continuously monthly rates of return over the period starting on January 1970 and ending on March 1996. In order to allow for asymmetric effects, in this study he used a bivariate EGARCH model. There was evidence of asymmetric volatility spillover from large capitalisation stock to small capitalisation stock but not vice versa.

Lee et.al (2001) examined the issue of time varying volatility on China's stock markets. The data used in this study include the Shanghai A Index, the Shanghai B Index, the Shenzhen A Index, and the Shenzhen B Index. For all indices, two types of series are used namely value weighted index (VW) and equally weighted index (EW). To test for leverage effect, the EGARCH model was employed. It was found that leverage factor is positive for EW returns of Shanghai A-share stocks, whereas the leverage factors are negative for both EW and VW returns of Shenzhen B-share stocks. The leverage factors for other return series are mixed and not statistically significant.

Francis et al. (2001) examines dynamic interdependence, volatility transmission, and market integration across selected stock markets during the Asian financial crisis periods 1997 and 1998. In particular, this study uses data covering the aggregate stock closing price indices of three Asian stock markets: Hang Seng Index (Hong Kong), KOSPI (Korea), and SET Index (Thailand). The data set ranges from February 3, 1997 to June 30, 1998 for a total of 354 observations. The analysis was done using a vector autoregressive exponential generalized autoregressive conditional heterskedasticity (VAR-EGARCH) model. It was found that reciprocal volatility transmission existed between Hong Kong and Korea, and unindirectional volatility transmission from Korea to Thailand. This finding suggests that Hong Kong played a significant role in volatility transmission to the other Asian markets. With regard to asymmetric feature, it was found that asymmetric effect is only statistically significant and has a negative coefficient for Hong Kong. By contrast, for Thailand the asymmetric effect is positive.

The idea behind the time-varying risk premia is that an anticipated increase in volatility (or risk) raises required expected future stock returns (or risk premium) and as a result the stock price falls immediately. This hypothesis is also referred to as volatility feedback. The pioneer of this idea is Pindyck (1984) who argued that much of the decline in stock prices during the 1970s was due to increases in risk premium arising from increases in volatility.

French, Schwert and Stambaugh (1987) examine the intertemporal relation between volatility and expected returns for the U.S. and found evidence that the expected risk premium is positively related to volatility of stock returns. In addition to this they also documented a significant negative relation between the realized risk premium and the unexpected volatility of stock returns. Initially, French et al. (1987) employed a simple regression model between the excess risk premiums and the predictable of the stock market standard deviation and the model provides little evidence of a relation between expected risk premiums and predictable volatility. In other words there is weak evidence that expected risk premiums are positively related to expected stock volatility. However when the initial model is extended to include the unpredicted components of volatility the reliable evidence is obtained. It was shown that if expected risk premiums are positively related to predictable volatility, then a positive unexpected change in volatility (and an upward revision in predicted volatility) increases future expected risk premiums and lowers current stock price. They suggest however that while there is a negative relationship between stock returns and volatility, leverage is probably not the only explanation for such a finding.

Poterba and Summers (1986) investigate the degree of persistence of unexpected shocks on volatility in order to test the hypothesis whether shocks on volatility could have an important effect on the level of stock price. The idea is that if increases in volatility are expected to persist, they will have a greater impact on the discount factors applied to future cash flows and therefore on current share prices. There are three different stochastic specifications of the volatility process used in this study including an AR(1) process, an AR(12) process which designed to capture long-run persistence, and the IMA (1,3) model. The data used in this study is the daily return data of the Standard and Poor's Composite Stock Index for the period 1928-1984. It was found that shocks to the volatility are transitory but not permanent (or not highly persistent) and as a result they will have very small effect on the share price; these findings were found regardless of the stochastic specification. In other words, for the shock to volatility to have influence on the share price then it has to be persistent otherwise the share price will not be affected. Therefore Poterba and Summers (1986) concluded that their findings provide little support for the hypothesis that changes in volatility could have an important effect on the level of stock price.

Chou (1988) comes up with a difference conclusion from Poterba and Summers (1986). In this case, Chou (1988) claims that the difference is due to the methodology chosen and the frequency of the data. In particular, the monthly data used by Poterba and Summers (1986) tends to seriously underestimate the persistence parameter. The data used in Chou's study are weekly returns of the NYSE value-weighted index with dividends reinvested from Center for Research in Security Prices. The sample period starts from July 1962 through December 1985 for a total of 1225 observations. Using a GARCH-M model he found a positive relation between returns and conditional variance. Moreover, he argues that persistence of shocks to the stock return volatility is high in the US market during 1962-1985 which caused the drop in the U.S. stock market. In other words, he argues that the rise in stock market volatility is a major reason for declines in the U.S. stock market. Therefore his research findings confirmed the hypothesis raised by Malkiel and Pindyck who argued that the unforeseen rise in the investment uncertainty during 1974 that causes the market to fall.

Turner, Startz, and Nelson (1989) used a markov model of heteroskedasticity in order to explore the relation between the time-dependent variance and the risk premium in the stock market. The model allows the variance to be categorized into two states namely a high-variance state and a low-variance state. There are two types of models employed in this study whereby the difference between the two models depends upon the assumption about the agent's knowledge of the state in the variance. The first model assumes that agent knows the state whereas for the second model the agent is uncertain of the state in the variance. This sample was monthly data from Standard and Poor's composite index for the period January 1946 to December 1987. It was found that the relation between volatility and excess return both negative and positive, depending on the method used. More specifically, for the first model the relation between variance and risk premium is negative while for the second model the relation is positive. Furthermore, the result also suggests that the risk premium will move over time in response to agents' perception of the market's riskiness.

Baillie and DeGennaro (1990) examined the relation between stock returns and volatility. In this study they employed GARCH in mean model by using student t distribution in order to control for excess kurtosis. The data used in this study is daily returns of index obtained from the Center for Research in Security Prices from January 1, 1970 until December 22, 1987. They report no evidence of a relationship between mean returns on a portfolio of stocks and the variance or standard deviation of those returns. Furthermore they also investigated the impact of lower frequency in data sample to the result of mean variance hypothesis. It was found, under the assumption of the conditional t distribution, that GARCH effect in the mean is weaker when the frequency of the sample is lowered to monthly data.

Chan, Karolysi and Stulz (1992) examine the issue of time-varying risk-return relation. The main ideas of the Chan et al. research is as follows. If the U.S. capital markets are segmented from foreign markets, the risk premium on U.S. assets should be determined solely in the U.S. On the other hand, if the U.S. capital markets are integrated with foreign markets, the risk premium on U.S. assets may be determined primarily on world capital market. In addition to the S&P 500 Index, there are three indices used in this study including the Nikkei 225 Stock Average, the Morgan Stanley Japan index in yen and the Morgan Stanley EAFE index in dollars. They find no significant relation between the conditional expected excess return on the S&P 500 and its conditional variance based on a bivariate GARCH process. Instead they concluded that the U.S. excess equity returns were positively related to the conditional covariance with the return of the foreign index, in particular with the Japanese equity index.

Campbell and Hentschel (1992) use GARCH-type process (a quadratic GARCH model) to examine the relation between market risk premium and volatility. The research aims was to formally model the volatility feedback. They argue that the volatility feedback is a very useful concept to help explaining the nature of stock returns. In this case they mentioned that volatility feedback occurs when an increase in stock market volatility raise required stock returns and thus lowers stock prices. In this study they applied their model to the US stock market data. In particular, they use monthly and daily data on excess stock returns over the period 1926-1988. The data is obtained from the Center for Research in Security Prices (CRSP). It was found that there is a positive albeit mostly insignificant relation between the conditional variance and the conditional expected return. More specifically, contrary to previous findings, they noted that volatility feedback has little influence on returns although it can be important during periods of high volatility.

De Santis and Imrohoroglu (1997) study the dynamics of expected returns and volatility for emerging markets and found that the level of volatility in emerging markets is considerably higher than that of more mature markets. They also scrutinize the issue of whether liberalization would increase or decrease volatility. The main source of data for this study is the Emerging Markets Data Base (EMDB) constructed by the International Finance Corporation (IFC). They analyze weekly series from the last week of December 1988 to the second week of May 1996, for a total of 384 observations. The countries covered in this study can be grouped into three geographical regions: Europe/Mid-east (Greece, Turkey), Asia (India, Korea, Malaysia, Philippines, Taiwan/China, Thailand), and Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Venezuela). They found evidence of a statistically significant risk premium for only three of fourteen emerging markets under the assumption of fully segmented markets. It was also found that volatility decreased after liberalization in a subset of countries, such as Argentina. They also found evidence suggesting that country-specific risk does not play any role in explaining conditional expected returns.

Koutmos and Saidi (2001) examined the issue of positive feedback trading which is referred to as selling during market declines and buying during market advances in emerging capital markets. This data included daily stock price index of Hong Kong, Malaysia, the Philippines, Singapore, Taiwan and Thailand from 2 January 1990 to 9 September 1996 for a total of 1765 observations. There was strong evidence of positive feedback during market declines but weak evidence during the market advances. Therefore this finding suggests that positive feedback trading is asymmetric in up and down markets. This may be due to portfolio insurance and stop-loss order users.

The above section has been devoted to provide literature review on asymmetric volatility. It can be concluded that there are two main hypotheses or explanations for asymmetric in volatility namely leverage effect and time varying risk premium (or volatility feedback). The first hypothesis was pioneered by Black (1976) who explains this phenomenon as follows. When the price of a company's stock falls, the market value of its equity also falls and hence increases the debt-to-equity ratio. As a consequences the financial risk (or the riskiness) of the company rises causing higher volatility in its stock return. According to time varying risk premium, positive shocks to volatility increase future risk premium and if the future dividends remain the same then the stock price should fall. Several models have been proposed to account for asymmetric volatility including the EGARCH model and the TGARCH or the GJR model.

In the following section we will provide the existing literature which examines the issue of long term memory (or long term dependence) in stock market volatility. Many empirical studies have been performed to detect the presence of long memory pattern in various stocks and indices returns. While many empirical works were done on the detection of long memory in return series, very few investigations focused on the market volatility. The first study in this area was conducted by Ding et.al (1993). In this study they investigate the existence of long memory in volatility by examining the sample autocorrelations of the transformed absolute returns ($|r_t|^d$). The data used in this study is the Standard and Poor 500 stock market daily closing price index from January 3, 1928 to August 30, 1991 for a total observation of 17,055. There are various values of d used in this study including 0.125, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2, and 3 at lags 1 to 5 and 10, 20, 40, 70, 100. It was found that the power transformations of the absolute return have significant positive autocorrelations at least up to lag 100 which supports the claim that stock market returns have long-term memory. In this study they also proposed a new general class of ARCH models which they call Asymmetric Power ARCH model (or A-PARCH or PGARCH).

De Lima and Crato (1994) examine the long term dependence in the conditional variance of stock returns on five different series of U.S. stock return indices. Two of these are weekly: NYSE-stock returns as given by the New York Stock Exchange index, from 1966 to 1991; and SP500-stock returns as given by the Standard and Poor 500 index, from 1982 to 1990. The three other series are daily and for the period 2 January (1980) to 31 December 1990: SP500D-stock returns as given by the Standard and Poor 500 index; ECRSP-stock returns as given by the equal-weighted index of the CRSP; and VCRSP-stock returns as given by the CRSP value-weighted index. There are three different tests to examine long term memory in conditional variances used in this study including test proposed by Geweke and porter-Hudak (1983), the R/S statistic as proposed by Hurst (1951) and the modified R/S statistic as proposed by Lo (1991). Based on the results of the three statistics above, they found evidence of persistent long-run dependence in the squared returns series.

Bollerslev and Mikkelsen (1996) investigate the issue of long memory in stock market volatility for U.S. stock market. The data used in this study is the Standard and Poor's 500 Composite Index from January 2, 1953 through December 31, 1990. They found evidence of long term memory in volatility based on the result of autocorrelation function of the absolute returns in which the absolute return correlations for very long lags exceed the two 95% Bartlett confidence bands for no serial dependence. To account for the long memory in volatility, they examined whether the Fractionally Integrated GARCH is more appropriate for modelling conditional variance than the standard GARCH model. It was found evidence to suggest that the apparent long-run dependence in U.S. stock market volatility is best described by a mean-reverting fractionally integrated process.

Following the works of Ding et.al (1993), De Lima and Crato (1994) and Bollerslev and Mikkelsen (1996), Breidt et.al (1998) investigated the issue of long memory in volatility. To detect the existence of long memory in volatility, they used two different tests. The first test is the semi parametric test as proposed by Geweke and Porter-Hudak and the second test is the Hurst exponent. The data used in this study is obtained from the CRSP from July 1962 to July 1989. They computed returns for both the equally weighted and the value-weighted data. In addition to that, there are two others data used namely the excess returns series based on the monthly Treasury bill returns and the long series constructed by Schwert (1990). For each of the series, the long-memory tests were applied over the squared returns and the logarithms of the squared returns. There was strong evidence of long memory in volatility for all series. However they noted that in the case of the equally weighted index the tests are less significant. They argued that this result was due to the fact that the equally weighted indexes are economically much less sensible as representative of the overall financial markets' activity than the value-weighted ones. To account for presence of long term memory in volatility, in this study they proposed a new model called a long memory stochastic volatility (LMSV) model. This model is constructed by incorporating an ARFIMA process in a standard stochastic volatility scheme. An empirical example with a long time series of stock prices demonstrates the superiority of the LMSV model over existing (short-memory) volatility models.

So, Mike.K.P. (2000) examined the long-term memory in stock market volatility. To detect the existence of long-term dependence in volatility, he used two commonly used tests, the semi parametric test introduced by Geweke and Porter-Hudak and the modified rescaled-range (R/S) test of Lo. The data used in this study are the S&P 500 Index, Dow Jones Industrial Average (DJIA) index and the 30 constituent stocks of the DJIA index. There are three transformed series (or proxies of the variability of returns) considered in the study namely the square mean deviation, the absolute deviation and the logarithm of the absolute deviation. There was strong evidence of long memory found in most securities using the squared mean deviation and stronger evidence was found based on the other two transformed series. All in all, he claims that the volatility for the two indices and the 30 stocks composing the DJIA index exhibits clear long-range dependence and suggests the importance of this long-term memory feature to be included in modelling volatility.

Beran and Ocker (2001) also examined long memory in the volatility on the stock market index. In this case, they particularly apply the SEMIFAR model in order to assess the potential usefulness of SEMIFAR model for volatility analysis. The data in this study include 19 nominal stock-market closing indexes for the period January 1, 1992, to November 10, 1995. They are, according to the definition of the IFC (1997), indexes for 10 developed markets (DM's: Australia, Belgium, Canada, France, Germany, Hong Kong, Italy, Switzerland, United Kingdom, and United States) and 9 emerging markets (EM's: Brazil, Chile, Greece, Hungary, Malaysia, Mexico, Poland, South Korea, and Thailand). To study volatility, they analyze the power-transformed absolute difference $Y_t = |I_t - I_{t-1}|^{1/4}$; where I_t denotes the original index. The reason for taking the fourth root of the increments is that the marginal distribution of the resulting series is very close to normal. The approach they used is as follows. In a first step, missing values in the original index series are replaced by the closest previous closing value, resulting in zero increments. In a second step, zero values of Y_t were omitted and the series are treated as equidistant. The research findings indicate that there is evidence of long memory in the volatility of stock market indexes based on the data used. Furthermore, overall results show that the SEMIFAR model fits the long term memory feature in volatility successfully based on the normal probability plots and correlograms of the residuals.

The above empirical studies with regard literature on long term memory in stock market volatility show evidence that stock market volatility exhibit long memory. The standard tests used to examine the long term memory in volatility are the R/S statistic, the modified R/S statistic, Hurst Coefficient and GPH test. Several models have been used to model long term memory in volatility including the Fractionally Integrated GARCH (or FIGARCH), the long memory stochastic volatility (LMSV) model, and the SEMIFAR model and the asymmetric power ARCH (or PGARCH) model.

2.4.1. Conclusions

The literature review regarding volatility asymmetry is extensive. The studies show that there are evidences of leverage effects both at a micro level (firm size) and at a macro level (stock market indexes). Most of the studies employed EGARCH model proposed by Nelson (1991). Several other models also have been proposed in the literature such as threshold GARCH (TGARCH or the GJR) model and the power of GARCH (PGARCH) model. Although number of studies have appeared in the literature providing the application of the above models, however none has investigated performance ability for each model. In this case it is important to address an important research question what is the appropriate model to be used to explain asymmetry property in volatility in emerging stock markets.

Equally important is the long term memory feature in volatility. There are substantial evidences of long term memory in volatility and as a consequence the traditional short-memory ARCH for modelling volatility of stock market index may no longer be valid. Most of studies used the same statistical tests including the R/S statistic (classical and modified), Hurst Coefficient and GPH test in order to detect the existence of long term memory in volatility. In this paper we will use the R/S statistic (classical and modified) and Hurst Coefficient and apply the same approach as Beran and Ocker (2001) to examine the satisfactory fits of SEMIFAR model for capturing long term memory feature in volatility. We extend the work of Beran and Ocker (2001) by considering more country samples in emerging market.

CHAPTER 3. METHODOLOGY EMPIRICAL STUDIES

3.1. METHODOLOGY EMPIRICAL I

This chapter presents the methodologies that are going to be applied for the first empirical studies. There are three main methodologies explained here namely the term structure of interest rate, the short term interest rate modelling and the default probability model.

3.1.1. Term Structure of Interest Rates

In financial markets, the term structure of interest rates is crucial to pricing of fixed income securities and derivatives. An increasing term structure generally results from two factors: (1) increased risk of longer debt; and (2) anticipated general interest rate rises. The last thirty years have seen great advances in research in term structure of interest rates. This section will focus on the process to estimate the term structure of risk-free interest rate on emerging market bonds that will be used to estimate the default probability of emerging market bond. We apply a model of short-term interest rate developed by Cox, Ingersoll and Ross (CIR, 1985). Before presenting this short-term model, firstly we discuss the procedure of constructing zero coupon yield curve and the general form of one-factor model of interest rate.

Constructing Zero Coupon Yield Curve

The theoretical spot-rate curve is constructed from the yield curve based on the observed yields of US$ Libor and Swap rates. In this section, we derive the basic pricing formulas for interest rate swaps. Pricing for interest rates swaps is important because it provides basis information for generating term structure of interest rates (i.e. the yield to maturity of various default free pure discount bond). The market for interest rate swap must reflect the term structure that prevails in the bond market. Otherwise, arbitrage opportunities will exist in the market. (Kolb, 1997). In other words, at initiation of a swap, the swap rate must be equal to the yield of a par bond that has face value equal to the notional amount of the swap and coupon payment dates at the same dates that the swap payments must be made. The valuation of interest rate swaps uses simple interest rate. The simple interest rate i_s *(T)* over the period *T* days is given by:

$$B(0,T) = \frac{1}{1+(i_s(T)\,\mathrm{x}\,\frac{T}{365}} \qquad (1)$$

Definition 1. Time to maturity

The time to maturity T - t is the amount of time (in years) from the present time t to the maturity time T > t.

Definition 2. Interest-Rate Swap

An interest-rate swap is an agreement between two parties to exchange streams of cash flows in the same currency on the basis of LIBOR payments for fixed-rate payments, every m months, over a total period of n years, on a principal amount of A. We will define the fixed rate by K. The two cashflows that constitute the swap are called the fixed leg and floating leg respectively.

a. The Fixed Leg

Consider a swap with payment days t_1, t_2,....t_n set in the terms of the swap and define the day count fraction δ_k as the time difference $t_k - t_{k-1}$ (in years), where k = 1,....,n. For the fixed leg, the day-count conventions is actual number of days divided by 360 for USD Swaps and 365 for GBP Sterling Swaps. The fixed payment is calculated as:

$$Fixed\ payment\ at\ t_i = A.\ \delta_k\ .\ K \tag{2}$$

b. The Floating Leg

Let R be the stochastic process, defined on (Ω, P,F), for the instantaneous interest rate corresponding to the LIBOR rates. The floating leg pays the amount at time t_i:

$$A.\ \delta_k.R(t_k - t_{k-1}) \tag{3}$$

Having known the cashflows stream from each leg, we can use the principle valuation of interest rate swap to create the term structure of interest rate. The value of swap is defined as the difference between the present value of the fixed leg of the swap and the present value of the floating leg of the swap. Since there is no principal exchanged in interest rate swap, therefore the value of the swap at initiation is zero. This implies that the present value of the fixed leg equals the present value of the floating leg of the swap.

The discounted payoff of the fixed payment at initiation is

$$PV_{\text{fixed}} = A \sum_{k=1}^{n} B(0,Tk) \times Kk \times \delta k \tag{4}$$

whereas the present value of the floating rate payment is:

$$PV_{\text{floating}} = A\,x\left[1 - B(0,T_k)\right] \tag{5}$$

Equating the value of the fixed payments (equation (4)) and the value of the floating leg payments (equation (5)) gives the following solution for a one-year discount factor:

$$B(0,T1)=\frac{1}{1+K1\delta 1} \tag{6}$$

Similarly, the discount factor for two years can be derived using the following formula:

$$B(0,T2)=\frac{1-K2 \text{ x } B(0,T1) \text{ x}\delta 1}{1+K2\delta 2} \tag{7}$$

In general, we can calculate the price of zero coupon bond for maturity greater than one year using the following formula:

$$B(0,Tk)=\frac{1-Kk\left[\sum_{1}^{k-1} B(0,Tk)\text{x}\,\delta k\right]}{1+Kk\,\delta k} \tag{8}$$

However, the swap rates with maturities equal to 6, 8 and 10 years exactly are not available in the market. The approach often used by practitioners is to interpolate between the swap rates data before they are used to calculate the zero curve.

After we establish the series of discount factor of zero coupon bonds then we can use the data to generate zero coupon yield curve. If we denote the yield to maturity of zero coupon bond or the spot rate as $Y_{(0,Tk)}$, the yield of zero coupon can be calculated using the following formula:

$$Y(0,Tk)=[B(0,Tk)^{-365/(Tk-To)}-1]\times 100 \tag{9}$$

3.1.2. Interest Rate Modelling

This section describes the fundamentals of the term-structure modelling that we use to generate the term structure of risk free rate.

One-Factor Models of Interest Rate

By definition a short rate model is a term structure model that uses short rate r_t as the modelling object. In other words, the assumption underlying the model is that the only factor driving the term structure of interest rate is the short rate itself. A general model for the short rate interest rate assumes to be represented by the following time homogeneous stochastic differential equation (SDE):

$$dr = \mu(r,t)dt + \sigma(r,t)dz \qquad (10)$$

where r is the current level of the interest rate, $\mu(r,t)$ is the expected change in the short rate over the next instant or drift function, $\sigma(r,t)$ is the standard deviation of the change in the short rate and z is a the standard Brownian motion or Wiener proces.

There are four well-known interest rate processes that fit the general model of short term interest rate as outlined in the equation (1). They are the Ornstein-Uhlenbeck (OU) process, the square-root (SR) process, the log-normal (LN) process, and the binomial process. Vasicek (1977) used the OU process while Cox, Ingersoll and Ross (1985) used the SR process to model the term structure. Brennan and Schwartz (1977) used the log-normal process to model the term structure of discount bonds. Finally, Ho and Lee (1986) pioneered the use of no-arbitrage computational lattices (or binomial) for the evolution of the short interest rate by assuming that the interest rates are normally distributed. Unlike Ho and Lee (1986), Black, Derman and Toy (1990) and Black and Karasinski (1991) assumed that the interest rates are log-normally distributed.

3.1.3. The Cox, Ingersoll and Ross (1985) Model

The CIR model probably is the most famous and widely used term structure model in the literature. Basically, Cox, et.al modified the mean reverting diffusion of Vasicek by using a square root process to represent the behaviour of the short term interest rate. Due to the presence of the square root in the diffusion coefficient takes only positive value; it can reach zero, but it never becomes negative. CIR model therefore solves the problem of possible negative interest rates imposed in the Vasicek model. The CIR model is based on the following stochastic process for the short rates:

$$dr = a(b - r_t)dt + \sigma r_t^{1/2} dz \tag{11}$$

where r_t is the interest rate, t is time; a, b, and σ are positive constants and represent rate of revision of the short-term interest rate r toward its long-term average value, long-term average value of the short-term interest rate r and volatility component respectively; and dz is a standard Brownian motion. Because of the drift term a(b-rt), the short rate process is mean reverting; the current value of the short rate process is pulled towards the long-run mean b with a speed proportional to the difference from the mean. The volatility term $\sigma\sqrt{r}$, approaches zero as r approaches zero, ensuring that the short rate stays positive. Also, the volatility increases as the short rate increases.

Like Vasicek's model, the CIR model also has a closed form solution for the yield-to-maturity. The price of zero coupon bond is calculated using the following formula:

$$P(t,T)=A(t,T)e^{-B(t,T)r}$$

Where $$B(t,T)=\frac{2(e^{\gamma(T-t)}-1)}{(\gamma+a)(e^{\gamma(T-t)}-1)+2\gamma}$$

and $$A(t,T)=\left[\frac{2\gamma e^{(a+\gamma)(T-t)/2}}{(\gamma+a)(e^{\gamma(T-t)}-1)+2\gamma}\right]^{2a\mu/\sigma^2} \tag{12}$$

$$\gamma=\sqrt{a^2+2\sigma^2}$$

CIR provide a characterization of the shape of the yield curve as a function of the current spot rate. They claim that when $r \leq \frac{2ab}{\gamma+a}$, the yield curve is uniformly rising and if $r \geq \frac{ab}{\gamma+a}$ the yield curve is falling whereby for $\frac{2ab}{\gamma+a} < r < \frac{ab}{\gamma+a}$, the yield curve is humped.

The main drawback of this model, like that of Vasicek, is that it does not fit the current term structure but rather provides the current term structure. As a result the price resulted from the models will deviate from the market price.

From the above explanations, we can conclude that CIR model encompasses mean reverting short rates. Also the model generates arbitrage-free yield curves. In both models, the parameters are time invariant. The main difference is that while Vasicek permits negative rates, CIR does not. Furthermore, Vasicek is more mathematically tractable.

Chan, Karolyi, Longstaff, and Sanders (hereafter CKLS) in their seminal paper (1992) proposed the following general model for short-term interest rate:

$$dr = (\alpha + \beta r_t)dt + \sigma r_t^{\gamma} dz \qquad (13)$$

where r is the short-term interest rate which follows geometric Brownian motion process. It implies that, both the drift ($\alpha+\beta r_t$) and conditional variance $\sigma^2 r_t^{2\gamma}$ depend upon the level of interest rate.

The specification in (13) encompasses several models studies in previous literature. The specification of each different models are summarized in the Table 1. Model 1 is used in Merton (1973) to derive a model of discount bond prices. This stochastic process for the riskless rate is simply a Brownian motion with drift. Model 2 is the Ornstein-Uhlenbeck process used by Vasicek (1977) in deriving an equilibrium model of discount bond prices. This Gaussian process has been used extensively by others in valuing bond options, future options, and other types of contingent claim. Examples include Jamshidian (1989) and Gibson and Schwartz (1990). The Merton model can be nested within the Vasicek model by the parameter restriction $\beta = 0$. Both of these models imply that the conditional volatility of changes in the riskless rate is constant. Model 3 is the square root (SR) process which appears in the Cox, Ingersoll and Ross (CIR) (1985) single-factor general-equilibrium term structure model. This model has also been used extensively in developing valuation models for interest-rate-sensitive contingent claims. Examples include the mortgage-backed security valuation model in Dunn and McConnel (1981), the discount bond option model in CIR (1985), the futures and futures option pricing models in Ramaswamy and Sundaresan (1986), the swap pricing model in Sundaresan (1989), and the yield option valuation model in

Longstaff (1990). The CIR SR model implies that the conditional volatility of changes in r is proportional to r.

Model 4 is used by Dothan (1978) in valuing discount bonds and has also been used by Brennan and Schwartz (1977) in developing numerical models of savings, retractable, and callable bonds. Model 5 is the familiar Geometric Brownian Motion (GBM) of Black and Scholes (1973). Geometric Brownian motion is also one of the interest rate models considered by Marsh and Rosenfeld (1983). Model 6 is used by Brennan and Schwartz (1980) in deriving a numerical model for convertible bond prices. This process is also used by Courtadon (1982) in developing a model of discount bond option prices. The GBM model is nested within the Brennan-Schwartz model by the parameter restriction $\alpha = 0$. In turn, the Dothan model is nested within the GBM model by the parameter restriction $\beta = 0$. All three of these models imply that the conditional volatility of changes in the riskless rate is proportional.

Model 7 is introduced by CIR (1980) in their study of variable-rate (VR) securities. A similar model is also used by Constantinides and Ingersol (1984) to value bonds in the presence of taxes. Finally, model 8 is the constant elasticity of variance (CEV) process introduced by Cox (1975) and by Cox and Ross (1976). The application of this process to interest rates is discussed in Marsh and Rosenfeld (1983). Table 1 shows that the CEV model nests the Dothan, Brennan-Schwartz, and CIR VR models.

Table 1. The Interest Rate Models Specifications of CKLS

This Table presents short term interest rate models which are nested according to CKLS's specification. The nested model implies restriction according to CKLS's specification.

No.	Model	Specifications	Restrictions
1	Merton (1973)	$dr = \alpha d_t + \sigma dz$	$\beta = 0; \gamma = 0$
2	Vasicek (1977)	$dr = (\alpha+\beta r_t)d_t + \sigma dz$	$\gamma = 0$
3	Cox, Ingersoll and Ross SR (1985)	$dr = (\alpha+\beta r_t)d_t + \sigma r_t^{1/2} dz$	$\gamma = ½$
4	Dothan (1978)	$dr = \sigma r_t dz$	$\alpha = 0\ \beta = 0\ \gamma = 1$
5	Geometric Brownian Motion	$dr = \beta r_t d_t + \sigma r_t dz$	$\alpha = 0\ \gamma = 1$
6	Brennan-Schwartz (1980)	$dr = (\alpha+\beta r_t)d_t + \sigma r_t dz$	$\gamma = 1$
7	Cox, Ingersoll and Ross VR (1980)	$dr = \sigma r_t^{3/2} dz$	$\alpha = 0\ \beta = 0\ \gamma = 3/2$
8	Cox (1975)	$dr = \beta r_t d_t + \sigma r_t^{\gamma} dz$	$\alpha = 0$

Following CKLS, we estimate the parameters of the continuous-time model of CIR in Equation (11) using a discrete-time specification as follows:

$$r_{t+1} = \alpha + (1+\beta) r_t + \varepsilon_{t+1} \tag{14}$$

$$E(\varepsilon_{t+1}) = 0 \text{ and } E(\varepsilon^2_{t+1}) = \sigma^2 r^{2\gamma}_t \tag{15}$$

where:

$\alpha = k.\mu_t$

$(1+\beta) = (1 - k)$

$\gamma = ½$

The parameterisations above are obtained through the following identities.

Recall that the continuous form of the CIR equation is given as:

$$dr = k(\mu - r_t)dt + \sigma r_t^{1/2} dz \tag{16}$$

The discrete-time econometric form of the continuous CIR equation above is specified by CKLS as follows:

$$r_{t+1} - r_t = \alpha + \beta r_t + \varepsilon_{t+1} \tag{17}$$

which can be written in the other form, based on the continuous CIR as follows:

$$r_{t+1} - r_t = k\,\mu - k\,r_t + \varepsilon_{t+1} \tag{18}$$

rearranging to yield

$$r_{t+1} = k\,\mu + r_t - k\,r_t + \varepsilon_{t+1} \tag{19}$$

If we connect the equation (14) we equation (19) clearly we can obtain the parameterisations imposed by the discrete time form of CIR model.

Following CKLS, we used the Generalized Method of Moments (GMM) of Hansen (1982) to estimate the discrete model of CIR. We now present a brief discussion of the GMM methodology provided by Christiaan Heij et.al (2004). Basically the GMM technique is an extension of the method of moments estimation. The basic assumption is that we can formulate a set of *moment conditions* involving the parameter vector such that the expected value of these conditions at the true parameter vector is zero. In instrumental variable estimation, the key idea is to find a set of instruments that is correlated with regressors but uncorrelated with the error terms. In the GMM, the moment conditions are also referred to as orthogonality conditions.

More formally, the GMM estimation framework is as follows: Suppose that the parameter vector of interest, θ, contains p unknown parameters and let vector $f_t(\theta)$ be a q x 1 vector of disturbances that satisfies *m* distinct moment conditions (or orthogonality conditions)-these conditions are usually restrictions on the moments of the errors in the model:

$$E[g_t(\theta)] = 0 \tag{20}$$

The GMM estimator $\hat{\theta}$ is defined as the solution of the *m* equations obtained by replacing the population mean E in (10) by its sample counterpart, $f_t(\theta)$, using the T observations where:

$$f_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} f_t(\theta)$$

and then choosing parameter estimates that minimize the quadratic form,

$$J_T(\theta) = f_T'(\theta) W_T(\theta) f_T(\theta)$$

where $W_T(\theta)$ is a positive-definite symmetric weighting matrix.

The parameter set is $\theta = (\alpha, \beta, \sigma^2, \gamma)'$ and if we set $\varepsilon_{t+1} = r_{t+1} - \alpha - (1+\beta) r_t$, we have the vector moment condition of θ as follows:

$$g_t(\theta) = \begin{pmatrix} \varepsilon_{t+1} \\ \varepsilon_{t+1} r_t \\ \varepsilon^2_{t+1} - \sigma^2 r^{2\gamma}_t \\ (\varepsilon^2_{t+1} - \sigma^2 r^{2\gamma}_t) r_t \end{pmatrix}$$

Under the null hypothesis that the restrictions implied by (4) and (5) are true, $E[g_t(\theta)] = 0$. Then the efficient GMM estimator selects the values of the parameter vector θ that minimize the quadratic form as defined by the criterion function:

$$\theta_{GMM} = \arg\min (g_t \theta^1 W_T \, g_t \theta)$$

GMM offers several advantages for the estimation of the continuous-time interest rate processes. First, unlike the other techniques it does not require that the distribution of interest rate changes follows normal process. Second, the GMM estimators and their standard errors are consistent even if the disturbances, ε_{t+1}, are conditionally heteroscedastic.

Valuation Framework

In this section we describe the method that we use to calculate default probability. Several models for the pricing of defaultable bonds have been proposed in the literature. The three main approaches are categorised into three models as follows.

(i) The first category of credit risk models are the ones based on the original framework developed by Merton (1974) using the principles of option pricing (Black and Scholes, 1973) which computes the payoff at maturity as the face value of the defaultable bond minus the value of a put option on the issuer's market value with an exercise price equal to the face value of the bond. The weakness of this approach is that default can only occur at maturity of the debt when the issuer's assets are no longer sufficient to face its obligations toward bondholders. The payment to the bondholders at the maturity of the debt is therefore the smaller of two quantities: the face value of the bond or the market value of the firm's assets.

(ii) Structural models assume that default may occur at any time between issuance and maturity of the debt and that default is triggered when the issuer's assets reach a lower threshold level (Black and Cox (1976), Longstaff and Schwartz (1995), Saa-Requejo and Santa-Clara (1997)). These models generally assume that debtholders, in case of default, get a fraction of debt's face value back named the "recovery rate", and that the latter is known as a priori.

(iii) Reduced-form models, which do not condition default explicitly on issuer's value, and therefore are easier to implement. They are also more general than structural models as they can easily accommodate defaults that came as surprises (see, for example, Jarrow, Lando and Turnbull (1997), Duffie and Singleton (1997, 1999), Lando (1998) Schonbucher 91998), Duffee (1999)). Reduced-form models for pricing sovereign debt have recently been adopted by Merrick (2001) and Duffie, Pedersen and Singleton (2002).

We followed the procedures in Trova (2000), which assumes that under no arbitrage conditions, the market price of a risk free asset, at each point in time, should equal the present value of all future cash flows.

$$v_t = \sum_{i=1}^{N} c_{ti} \exp\{-r_f t_i\}\left[q\left(1-(1-p)^i\right)+(1-p)^i\right] \qquad (21)$$

where $t_i = 1, \ldots, N$, indicates the time to i-th maturity, c_{ti} the i-th cash flow, r_{ti} the risk-free interest rate for the i-th maturity, $p = 1, \ldots, N$, the risk-neutral probability that default occurs between t_{i-1} and t_i and q the recovery ratio.

Equation (21) is explained theoretically in the following section.

Theoretical Background

The bond value would be expressed at the discounted sum of terminal values when a default takes place and when there is no default. Assuming no arbitrage opportunity, the expected value of a risky bond must be equal to the expected value of risk-free return. Therefore we can write the following equation (equation (22)) for the future value of the bond in discrete time (assuming a single cash flow):

$$v_t = \left[v_0\, pq\,(1+r)\right] + \left[v_0\,(1-p)(1+r)\right] \qquad (22)$$

Whereby the expected value of risk-free return is represented by the following equation (equation (23))

$$v_t = \left[v_0(1+rf)\right] \qquad (23)$$

As mentioned earlier that equation (22) must be satisfied equation (23), therefore:

$$v_0 = \frac{v_t}{[pq(1+r)]+[(1-p)(1+r)]} = \frac{v_t}{(1+rf)} \qquad (24)$$

Rearranging the above equation yields the following:

$$\frac{v_t}{(1+r)} = \frac{v_t[(pq)+(1-p)]}{(1+r_f)} \tag{25}$$

In general we can write the today's value of a defaultable bond as follows:

$$\text{Value today} = \sum_{i=1}^{N} c_{ti}\left(1+r_f\right)^{-ti}\left[\left(p_{t_i}q\right)+\left(1-p_{t_i}\right)\right] \tag{26}$$

Where c_{t_i} denotes a set of cash flows to be received at dates t_1, t_2,....,t_N. Using continuous compounded return the value of a defaultable bond can be written as follows:

$$\text{Value today} = \sum_{i=1}^{N} c_{ti}\,(e)^{-r_f ti}\left[\left(p_{t_i}\times q\right)+\left(1-p_{t_i}\right)\right] \tag{27}$$

Following Ciraolo et.al (2002) we make the following assumptions:

2. We assume that the default probability is constant throughout the life of the bonds.
3. We assume as in Duffee (1999) that the bondholders will receive a fraction (equal to the recovery rate) of both coupon and principal if the issuers of the bonds default.
4. We also assume that the recovery rate to be constant over time. For the sake of simplicity we fix the recovery rate equal to 20 percent as in Ciraolo et.al (2002).

Based on the three assumptions outlined above, we can derive the following equilibrium relationship between the market price of a defaultable bond and its expected cash flows as follows:

$$v_t = \sum_{i=1}^{N} c_{ti} x(e)^{-r_f ti} x\left[q\left(1-\left(1-p_{t_i}\right)^i\right)+\left(1-p_{t_i}\right)^i\right] \tag{28}$$

Notes:

p_{t_i} = probability of default

1-p = probability of no default

r_f = the risk-free interest rate

q = recovery rate

3.1.4. Summary

In this section, we have set out the empirical background to the tests I will conduct on the first empirical study. The main methodologies used in the first empirical study encompass the constructing spot rate, the estimation of discrete version of CIR parameters using the GMM model and the discrete version default probability model.

3.2. METHODOLOGY EMPIRICAL II

This chapter presents the methodologies that are going to be applied for the second empirical studies. There are six main methodologies explained here namely the basic international market model, tests for varying parameter, the multivariate GARCH model, the Schwert and Seguin model, the Kalman Filter approach and the performance metrics evaluation.

3.2.1. Basic International Market Model

The standard approach to estimate beta (or unconditional beta) is the market model regression, as developed by Sharp (1964) and Lintner (1965), which is defined as:

$$R_{it} = \alpha_i + \beta_i R_{wt} + \varepsilon_{it} \qquad t=1,\ldots\ldots,T. \tag{29}$$

where :

R_{it} is the return on country i for period t,

R_{wt} is the return on the world index for period t,

ε_{it} is the disturbance vector.

In this study we used raw return and all returns are measured in the same currency, i.e. US Dollars. The error term, ε_{it}, is assumed to have zero mean and a serially independent and homoscedastic variance-covariance matrix. Under this specification the intercept and slope coefficient are assumed to be constant (or fixed) over time. The slope coefficient β_i is a measure of the relative nondiversifiable risk or systematic risk of country i. To classify a country according to its systematic risk we have to compare its international beta value with the beta value of the world market index, which has the value of unity. In this case, we can define a country that has an international beta greater (less) than unity has greater (less) systematic risk than that of the benchmark global market index.

However, beta estimation generated from the model (29) is backward looking. And what we need to concern more is the forward looking beta that gives estimation of future risk, which will be useful for evaluating country risk or portfolio in the emerging market. In section 3 we will discuss the more appropriate technique that can be used to estimate conditional (or time-varying) beta that is the multivariate-GARCH.

3.2.2. Tests for Varying Parameter

Having generated the international standard beta value the next step is to test the validity of the assumption that the beta value for each country is constant over time. The assumption of fixed parameters means that these effects are the same for all observations. We carry out different tests to examine a time invariant behaviour of the beta values.

1) Rolling Regression

For the linear regression model, rolling analysis may be used to assess the stability of the model's parameters and to provide a simple "poor man's" time varying parameter model. For a window of width n<T, the rolling linear regression model may be expressed as:

$$y_t(n) = X_t(n)\beta_t(n) + \varepsilon_t(n),\ t = n, \ldots\ldots, T \qquad (30)$$

where $y_t(n)$ is an (n x 1) vector of observations on the response, $X_t(n)$ is an (n x k) matrix of explanatory variables, $\beta_t(n)$ is an (k x 1) vector of regression parameters and

$\varepsilon_t(n)$ is an (n x 1) vector of error terms. The n observations in $y_t(n)$ and $X_t(n)$ are the n most recent values from times $t - n+1$ to t. It is assumed that $n>k$.

2) The CUSUMSQ test for the variance

The CUSUM of square test (Brown, Durbin, and Evans, 1975) is based on the test statistic:

$$S_r = \frac{\sum_{t=k+1}^{r} w_t^2}{\sum_{t=k+1}^{n} w_t^2}, \; r = k+1, \ldots\ldots, n. \tag{31}$$

where the sum of the squared recursive residuals to period r divided by the total sum of squared recursive residuals. Note that the values always run from $S_k = 0$ (for $r = k$) to $S_n = 1$ (for $r = n$) for the expected value of S under the hypothesis of parameter constancy which is:

$$\mathrm{E}[S_t] = (r - k)/(n-k).$$

This test will be carried out in Eviews, which provides the graph to identify the departure of S from its expected value. If the cumulative sum of squares lie within the 5 percent critical value it can be argued that the parameters of the single market model are constant over time. This test has been used previously by various researchers in similar contexts including, Izan (1985), Bos and Fetherston (1992, 1995), Wells (1994) and Bos et al (1995).

3) Heteroscedasticity-based tests of international beta stability

Another test to check a constant parameter in the unconditional model is the Lagrange Multiplier (LM) test introduced by Engle (1982). The basic idea of the test is to examine the homoskedasticity assumption of simple linear regression that the variance of error term is the same for the entire sample. Thus the LM test actually uses the same concept as the CUSUMSQ test. The difference between these two tests is that CUSUMSQ test is likely to perform well when the parameters experience a discrete jump whereas the LM test investigate the heteroscedasticity characteristics in the data, assuming that the changing variance follows an autoregressive conditional heteroscedasticity model. There are three steps involved in the LM test for general an ARCH (*p*) process as follows:

1. Retrieve the residual value (ε_{it}) from the estimated unconditional market model.

2. Run the following regression model:

$$\varepsilon_t^2 = \alpha_0 + \sum_{s=1}^{p} \alpha_s \varepsilon_{t-s}^2 + \upsilon$$

3. Test the null hypothesis of homoskedasticity H_0 : $\alpha_1 = \alpha_2 = \alpha_3 = ... = \alpha_p = 0$ against the alternative hypothesis that at least one $\alpha_s \neq 0$ by using $(n-p)R^2$ as test statistic where R^2 is the coefficient determination of the regression model in step 2. This test statistic follows the χ^2 (or Chi-squared) distribution with p degrees of freedom. If the LM statistic evaluated under the null hypothesis is greater than $\chi^2_{\alpha(p-1)}$, the null hypothesis is rejected at level $\alpha \neq 0$.

If we do not reject the null hypothesis, then we conclude that the variance of error term is constant and there is no ARCH effect. In other words if the LM test indicates the absence of an ARCH term in the residual series, we can infer that the beta of the unconditional market model is stable over time.

The White test can also be used to examine the heteroscedasticity in the error term. The idea of the white test is to examine whether the disturbance term is related with their explanatory variables (x_j), the square of explanatory variables (x_j^2), and the cross products of explanatory variables ($x_i\ x_j;\ i \neq j$). In this study we test the unconditional heteroscedasticity in the form of the square of explanatory variables (or the squared of the global market index return), i.e. $\sigma_t^2 = f(R_{wt}^2)$.

3.2.3. The Multivariate Generalised ARCH (M-GARCH) model

Before presenting the theoretical background of multivariate GARCH model we firstly discuss briefly the univariate ARCH (Autoregressive Conditional Heteroscedasticity) model. The ARCH model was introduced by Engle in 1982 to capture the volatility clustering of financial time series by assuming that today's conditional variance is a linear function of the squares of past shocks (or unexpected return). The general form of ARCH(p) model is as follows:

$$\sigma_t^2 = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots\dots + \alpha_p \varepsilon_{t-p}^2 \tag{32}$$

From the above equation it is very obvious that the (conditional) variance σ_t^2 needs to be nonnegative. In order to guarantee that this is the case the parameters in the equation above have to satisfy the conditions that $\omega_0 > 0$, and $\alpha_1 \dots\dots \alpha_p \geq 0$.

ARCH model mostly was applied to economic data and is not often used in financial markets because the simple GARCH models (introduced by Bollerslev in 1986) perform much better (Alexander, 2001). The general GARCH (p,q) model is given by:

$$\sigma_t^2=\omega_0+\alpha_1\varepsilon_{t-1}^2+.......+\alpha_p\varepsilon_{t-p}^2+\beta_1\sigma_{t-1}^2+..........+\beta_q\sigma_{t-q}^2 \qquad (33)$$

where $\omega_0 > 0$ and $\alpha_1......\alpha_p, \beta_1.........\beta_q \geq 0$.

To estimate the order of GARCH model is very challenging task however it is sufficient to use the GARCH (1,1) model (Alexander, 2001; Tsay, 2002). The GARCH (1,1) where the conditional volatility estimated as follows:

$$\sigma_t^2=\omega_0+\alpha_1\varepsilon_{t-1}^2+\beta_1\sigma_{t-1}^2 \qquad (34)$$

The conditional variance equation above is the one period ahead forecast variance based on past information. The conditional variance equation is a function of the constant, ω, news about volatility from the previous period, ε^2_{t-1} (ARCH term), and last periods forecast variance σ^2_{t-1} (GARCH term). The sum $\alpha + \beta$ must be less than 1 if the returns process is to be stationary. Otherwise the weight applied to the long-term variance is negative.

The GARCH model discussed above is univariate. As mentioned earlier, to describe the characteristics of the conditional beta is more appropriate to use multivariate GARCH model. This is because the multivariate GARCH models can be used to model the time-varying behaviour of conditional covariances such as in the CAPM (Franses, Philip and Dick van Dijk, 2000).

A general multivariate GARCH model for the k-dimensional process ε_t = $(\varepsilon_{1t},......, \varepsilon_{kt})'$ is given by:

$$\varepsilon_t=z_t H_t^{1/2} \qquad (35)$$

where $\mathbf{z}_t$ is a k-dimensional i.i.d. process with mean zero and covariance matrix equal to the identity matrix I_k. From these properties of zt and $\varepsilon_t = \mathbf{z}_t \mathbf{H}_t^{1/2}$, it follows that $E[\varepsilon_t | \Omega_{t-1}] = \mathbf{0}$ and $E[\varepsilon_t \varepsilon_t' | \Omega_{t-1}] = \mathbf{H}_t$. To complete the model, a parameterization for the conditional covariance matrix $\mathbf{H}_t$ needs to be specified. We need to determine the order on lagged shocks (q) and the order on lagged conditional covariance matrices (p). In this study we use simple bivariate GARCH (1,1).

Following Brooks et.al, 2002, we specify the functional form of the conditional mean as:

$$R_{it}' = \varepsilon_{it}' \qquad i = 1,2$$

where:

$$R_{it}' = \begin{bmatrix} R_{1t} \\ R_{2t} \end{bmatrix}$$

and

$$\varepsilon_{it}' = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

which may be described as $\varepsilon_{it} | \Omega_{t-1} \sim N(0, H_t)$, that is, ε_{it} is conditioned by the complete information set at time t-1, Ω_{t-1}, and is normally distributed with zero mean and a conditional covariance matrix H_t, which may be described as:

$$\mathbf{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}$$

As mentioned earlier, we choose a bivariate GARCH (1,1) model to specify the function of conditional variance matrix $\mathbf{H}_t$. Therefore the conditional variance equations take the form in vector as follows:

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} \omega_{11} \\ \omega_{12} \\ \omega_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11}\alpha_{12}\alpha_{13} \\ \alpha_{21}\alpha_{22}\alpha_{23} \\ \alpha_{31}\alpha_{32}\alpha_{33} \end{bmatrix} \text{x} \begin{bmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11}\beta_{12}\beta_{13} \\ \beta_{21}\beta_{22}\beta_{23} \\ \beta_{31}\beta_{32}\beta_{33} \end{bmatrix} \text{x} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \qquad (36)$$

or

$$(\text{vech})\, \mathbf{H}_t = \text{W} + \text{A}\,\varepsilon + \text{BH}_{t-1}$$

where H_t, W, A and B represent their respective matrices in the above equation. This simple bivariate GARCH (1,1) model contains 21 parameters which have to be estimated (W has 3 elements, A and B each has 9 elements). Thus estimating this general model becomes a very excessive task especially as the order of GARCH increases. To overcome this problem, we may use the approach proposed by Bollerslev (1990) by setting the off-diagonals in the coefficient matrices (i.e. matrices A and B) equal to zero. More specifically, it is assumed that the conditional correlations between the elements of ε_t are time-invariant. This implies that the conditional covariance $h_{ij,t}$ between ε_{it} and ε_{jt} is proportional to the product of their conditional standard deviations. Furthermore, it is assumed that the individual variances follow univariate GARCH (1,1) model. The general form of the diagonal model is given by:

$$h_{ii,t} = \omega_{ii} + \alpha_{ii}\, \varepsilon^2_{1,t-1} + \beta_{ii}\, \text{h}_{ii,t-1} \quad \text{for } i = 1,\ldots\ldots, \text{k}.$$

$$h_{ij,t} = \rho_{ij}\, \sqrt{h_{ii,t}}\,\sqrt{h_{jj,t}} \quad \text{for all } \text{i} \neq \text{j} \qquad (37)$$

Thus the conditional variance and covariance for bivariate GARCH (1,1) may be specified as:

$$h_{11,t} = \omega_{11} + \alpha_{11}\ \varepsilon^2_{1,t-1} + \beta_{11}\, h_{11,t-1}$$

$$h_{22,t} = \omega_{22} + \alpha_{33}\ \varepsilon^2_{2,t-1} + \beta_{33}\, h_{22,t-1}$$

$$h_{12,t} = \rho_{12}\sqrt{h_{11,t}}\sqrt{h_{22,t}} \tag{38}$$

From these three equations we have reduced the number of parameters to be estimated from 21 to 7. To ensure a positive conditional variances, the values of α, β, and ω are restricted to zero or greater. Following Bollerslev, in order to estimate the a time series of conditional betas under bivariate GARCH (1,1) model, we need to assume that there is a constant correlation between the return of a country stock market index with the return of the world stock market index. The time series of conditional beta is then obtained by using the standard formula to estimate the beta, which is based on the formula to calculate the slope coefficient of a simple regression as follows:

$$\beta = \text{cov}\,(R_{it}, R_{wt}) / \text{var}\,(R_{wt}) \tag{39}$$

where R_{it} and R_{wt} represent the return of country *i* and return of the world stock index respectively. The variance series of the world stock index is directly obtained from the equation (38) whereas the covariance series between country *i* and the world stock index is provided in the form of $h_{12,t}$. In addition to the GARCH (1,1) under normal distribution, in this study we will also model GARCH (1,1) with t-distribution and generalised error distribution. Nelson (1991) proposed to use the generalised error distribution (GED) to capture the fat tails usually observed in the distribution of financial time series.

3.2.4. Schwert and Seguin model (1990)

Schewert and Seguin model is referred to as the heteroscedastic market model. Under this model the return generating process for each market is described as follows:

$$R_{it} = \alpha_i + \beta_{i,t} R_{wt} + \varepsilon_{it} \qquad t=1,\ldots\ldots,T. \tag{40}$$

where R_{it} is the stock market return for country i during week t, R_{wt} is the return for the world market index, and ε_{it} is an error term. The coefficient $\beta_{i,t}$, is a time-varying beta and measures systematic risk in country i. The conditional covariance of returns in stock markets i and j, given Φ_{t-1}, is specified as:

$$\sigma_{i,j,t} \equiv \operatorname{cov}(R_{i,t}, R_{j,t} \mid \Omega_{t-1})$$

$$= c_{0,i,j} + c_{1,i,j}\, \sigma^2_{w,t}$$

where $\sigma^2_{w,t}$ is the conditional variance of returns for the world market portfolio. The time-varying coefficient $\beta_{i,t}$ is equal to:

$$\beta_{i,t} = \operatorname{cov}(R_{i,t}, R_{j,t} \mid \Omega_{t-1}) / \sigma^2_{w,t}$$

$$=\sum_{j=1}^{N} X_j \sigma_{i,j,t} / \sigma_{w,t}^2$$

$$=\sum_{j=1}^{N} X_j c_{0,i,j} / \sigma_{w,t}^2 + \sum_{j=1}^{N} X_j c_{1,i,j}$$

$$=\beta_i + \delta_i / \sigma_{w,t}^2 \qquad (41)$$

where is the world portfolio weight for the *j* th market, and N = 8. According to equation , the time-varying beta consists of a constant term

According to equation above, the time-varying beta consists of a constant term β_i and a time-varying term $\delta_i / \sigma_{w,t}^2$. A positive δ_i implies that systematic risk for country *i* varies inversely with the world stock market index volatility, whereas a negative δ_i implies that systematic risk and the world stock market index volatility are positively related.

If we substitute equation of the time-varying coefficient beta into the standard market model, we will get the Schwert and Seguin model as shown in the equation below:

$$R_{i,t} = \alpha_i + \beta_i \, Rw,t + \delta i \, Rw,t / \sigma^2_{w,t} + ei,t, \text{ for } t = 1,\ldots\ldots, T. \qquad (42)$$

In order to obtain the varying beta coefficient using this approach, the first step we need to do is to estimate the regression equation of the Schwert and Seguin model and after that we plug in the regression coefficients into the time varying beta equation. The conditional variance of the market index in this estimation procedure is obtained from the bivariate GARCH (1,1) model.

3.2.5. The Kalman Filter Approach

In calculating the time varying beta using the technique, the fundamental concept comes from the notion of the state space. The state space formulation assumes that the forecast variable Y_t can be expressed as a linear function of unobserved state variables and exogenous variables. It also assumed that the state variables depend on the previous state. Thus we can write

$$y_t = A'x_t + H'z_t + w_t \tag{43}$$

$$z_t = F z_{t-1} + v_t$$

where:

- y_t is the observable variable and z_t is the unobservable variable.
- The first equation, the y_t equation, is called the "space" or the "observation" equation whereas the second equation, the z_t equation, is called the "state" (or transition) equation.
- x_t is a vector of exogenous (or predetermined) variables.
- w_t and v_t are iid and assumed to be uncorrelated at all lags. Formally this states as follows: $E(w_t, v_t') = 0$; $E(w_t, w_t') = \text{var}(w_t) = R$; and $E(v_t, v_t') = \text{var}(v_t) = Q$.

Together the two equations (y_t and z_t) form a state space model. State space models are estimated using a powerful recursive algorithm known as the Kalman Filter. In particular, we estimate three different model of time varying beta:

1) Random Walk : $\beta^{RW} = \beta_{it-1} + v_{it-1}$
2) Random Coefficient : $\beta^{RC} = \text{average } \beta + v_{it-1}$

3) Autoregressive (1) : $\beta^{AR} = \varnothing\,(\beta_{it-1} - \text{average } \beta) + \text{average } \beta + v_{it-1}$

All the three models described above share the main assumption is that the resultant estimation error is a random variable following Gaussian distribution with zero mean and a fixed variance. According to the random walk model the current period's beta is simply a function of the last period's beta. Under this model, shocks to the conditional beta are assumed to persist indefinitely. The random coefficient approach imposes the current period's beta fluctuates randomly about a mean value. In other word, shocks to the conditional beta have no persistence from period to period. Finally, the autoregressive process claims that the difference between the current period's beta and the long-term mean is a function of the difference between the immediate past value of beta and the long-term mean. In this model, shocks to the conditional beta have some persistence.

There are several reasons why state space models are useful:

1. Kalman (1960) and Kalman and Bucy (1961) developed a general set of recursive equations to handle the forecasting. These are usually called the "Kalman recursion equations" or the "Kalman Filter". The equations also enable easy calculation of the one-step forecast errors and the likelihood. So provided a model can be written in state space form, the calculations can all be carried out using the Kalman recursion equations. This unified framework for computation simplifies the development of forecasting packages because a wide range of models can be handled within the same code.

2. State space models are easy to generalize. For example, we generalized simple exponential smoothing to allow the parameters to be changing over time (the

adaptive response model). This can also be handled in the state space framework and can be done for any sate space model. So, for example, it would be possible to use a dynamic regression model where the parameter of the ARIMA error changed over time.

3. The state space formulation makes it easier to handle missing values within a time series.

3.2.6. Assessing the relative performance of the alternative time-varying beta techniques

To determine which model performed better than the others, we employ the following methodology. Firstly, we obtain in-sample forecast of stock market index return on each country using the standard market model as follows:

$$\hat{R}_{it} = \alpha_i + \beta_{it} R_{wt} \tag{44}$$

where : β_{it} = beta coefficient generated from three different techniques as previously described

R_{wt} = the return on the world market index.

The next step is to estimate a conditional intercept coefficient series for each technique. In order to obtain the α_i coefficient, we run the following equation:

$$\alpha_i = \bar{R}_{it} - \bar{\beta}_{it} \bar{R}_{wt}$$

where α_i is equal to the mean country return less the mean conditional beta times the mean world market index.

After estimating the alpha coefficient, the final step is to identify the accuracy of each model. By definition the accuracy of a forecasting model depends on how close the forecast values are to the actual values. Generally the difference between the actual and the forecast values is defined as the forecast error as follows:

$$\varepsilon_t = (Y_t - \hat{Y}_t)$$

The accuracy of the forecast $\hat{R}_{it}$ generated from each of the conditional beta series may be assessed using the mean absolute forecasting error (MAE) where:

$$\text{MAE} = \frac{\sum_{t=1}^{n} |\varepsilon_t|}{n} \tag{45}$$

Therefore, the MAE is defined by first making each error positive by taking its absolute value and then averaging the results. The main drawback of this measure of forecast accuracy is that it gives all errors equal weighs. Alternatively, the forecast accuracy can be evaluated using the following statistical measure:

$$\text{MSE} = \frac{\sum_{t=1}^{n} \varepsilon_t^2}{n} \tag{46}$$

where MSE stands for the mean square forecasting error. This measure uses the same idea as MAE whereby the errors are made positive by squaring each one and then the squared errors are averaged. However the use of a squared term in the equation places a heavier penalty on outlier than the MAE measure. In order to determine the best model to explain the time variant beta we select the one that yields the smallest MAE and MSE.

Although the use of MAE and MSE give information towards the relative superiority of a particular model, yet we need to have a formal testing procedure in order to determine whether the differences between two forecasted series are significant. To do so, we employ the modified Diebold-Mariano statistic as proposed by Harvey et.al (1997). The modified Diebold-Mariano statistic tests the following hypothesis and alternative:

$$H_0 : MSFE_0 = MSFE_P \tag{47}$$

versus

$$H_1 : MSFE_0 > MSFE_P$$

The test statistic is using the differences in the loss function of the forecasts (in this case, the MSFE) defined as: dt $\cong [MSFE_0 - MSFE_P]$. For a h step ahead forecast in an n row forecast vector, the test statistic is:

$$\text{MDM} = \sqrt{\frac{n+1-2h+n^{-1}h(h-1)}{n}} \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}} \tag{48}$$

Where $\bar{d} = n^{-1} \sum_{t=1}^{n} d_t$

$$\hat{V}(\bar{d}) = n^{-1} (r_0 + 2\sum_{i=1}^{h-1} r_i)$$

and where the i th order auto-correlation r_i is calculated by:

$$r_i = n^{-1} \sum_{t=i+1}^{n} (d_t - \bar{d})(d_{t-i} - \bar{d})$$

The statistic MDM is distributed under a Student's t-distribution with (n-1) degrees of freedom.

3.2.7. Summary

In this section, we have set out the empirical background to the tests I will conduct on the second empirical study. The main methodologies used in the second empirical study encompass the basic international market model, tests for varying parameter, the multivariate GARCH model, the Schwert and Seguin model, the Kalman Filter approach and the performance metrics evaluation.

3.3. METHODOLOGY EMPIRICAL III

This chapter presents the methodologies that are going to be applied for the first empirical studies. We begin with a review of extreme value theory in the statistical literature.

We take X_1, X_2,....,X_n to be an identically distributed and independent (iid) sequence of random variables that represent risks or losses with an unknown cumulative distribution function (cdf), $F(x)=\Pr(X_i \leq x)$. Examples of random risks are negative returns on financial assets or portfolios, operational losses, catastrophic insurance claims, credit losses, natural disasters such as floods, service life of items exposed to corrosion, traffic prediction in telecommunications, etc (see Coles, 2001; Reiss and Thomas, 2001; McNeil and Frey 2000).

As a convention, a loss is treated as a positive number and extreme events take place when losses come from the right tale of the loss distribution F. Let M_n = $\max(X_1, X_2, \ldots X_n)$ be the worst-case loss in a sample of n losses. For a sample of iid observations, the cdf of M_n is given by

$$\Pr(Mn \leq x) = \Pr(X_1 \leq x, X_2 \leq x, \ldots\ldots X_n \leq x) = \prod_{i=1}^{n} F(x) = F^n(x) \qquad (49)$$

An asymptotic approximation to F^n (x) is based on the Fisher-Tippet theorem. Given that x<x+, where x+ is the upper end-point of F (that is, the smallest value of x such that F(x)=1), $F^n(x) \rightarrow 0$ as $n \rightarrow \infty$, the asymptotic approximation is based on the standardized maximum value

$$Z_n = \frac{M_n - \mu_n}{\sigma_n} \qquad , \sigma_n > 0 \qquad (50)$$

where σ_n and μ_n are a scale and location parameters, respectively. The Fisher-Tippet theorem states if Z_n converges to some non-degenerate distribution function, this must be a generalized extreme value (GEV) of the form:

$$G_\xi(z) = \begin{cases} \exp(-(1+\xi z)^{-1/\xi} & \xi \neq 0, 1+\xi z > 0 \\ \exp(-\exp(-z)) & \xi = 0, -\infty < z < \infty \end{cases} \qquad (51)$$

The parameter ξ is a shape parameter and determines the tail behavior of $G_\xi(z)$. If Z_n converges to $G_\xi(z)$, then Zn is said to be in the domain of attraction of $G_\xi(z)$. The shape of parameter ξ is in turn determined by the tail behavior of the cdf of the underlying data, F. If the tail of F declines exponentially, then $G_\xi(z)$ is of the Gumbel type and $\xi = 0$. In this case, distributions in the domain of attraction of $G_\xi(z)$ are of the thin-tailed type, such as the normal, log-normal, exponential, and gamma. If the tail of F declines by a power function instead, then $G_\xi(z)$ is of the Frechet type and $\xi > 0$. Distributions in the domain of attraction of $G_\xi(z)$ are called fat tailed distributions, which include the Pareto, Cauchy, Student-t, and mixture models. Lastly, if the tail of F is finite then $G_\xi(z)$ is of the Weibull type and $\xi < 0$. Distributions in the domain of attraction of $G_\xi(z)$ include distributions with bounded support, such as the uniform and beta distributions.

In practice, modeling all block maxima is inefficient if other data on extreme values are available. Therefore, a more efficient approach is to model the behavior of extreme values above a high threshold. This method is usually referred to as the peaks over threshold (POT). The POT method is a method to estimate a tail or a quantile based on the extreme observations of a sample. The POT method provides advantages over block maxima model in which the common risk measures like Value-at-Risk and expected shortfall (ES) can easily be obtained. As we know, VaR (i.e., the qth quantile of F) and ES (ie., the average loss given that VaR has been exceeded), are commonly used risk measures. Figure (1) serves as an illustration of the background of POT method.

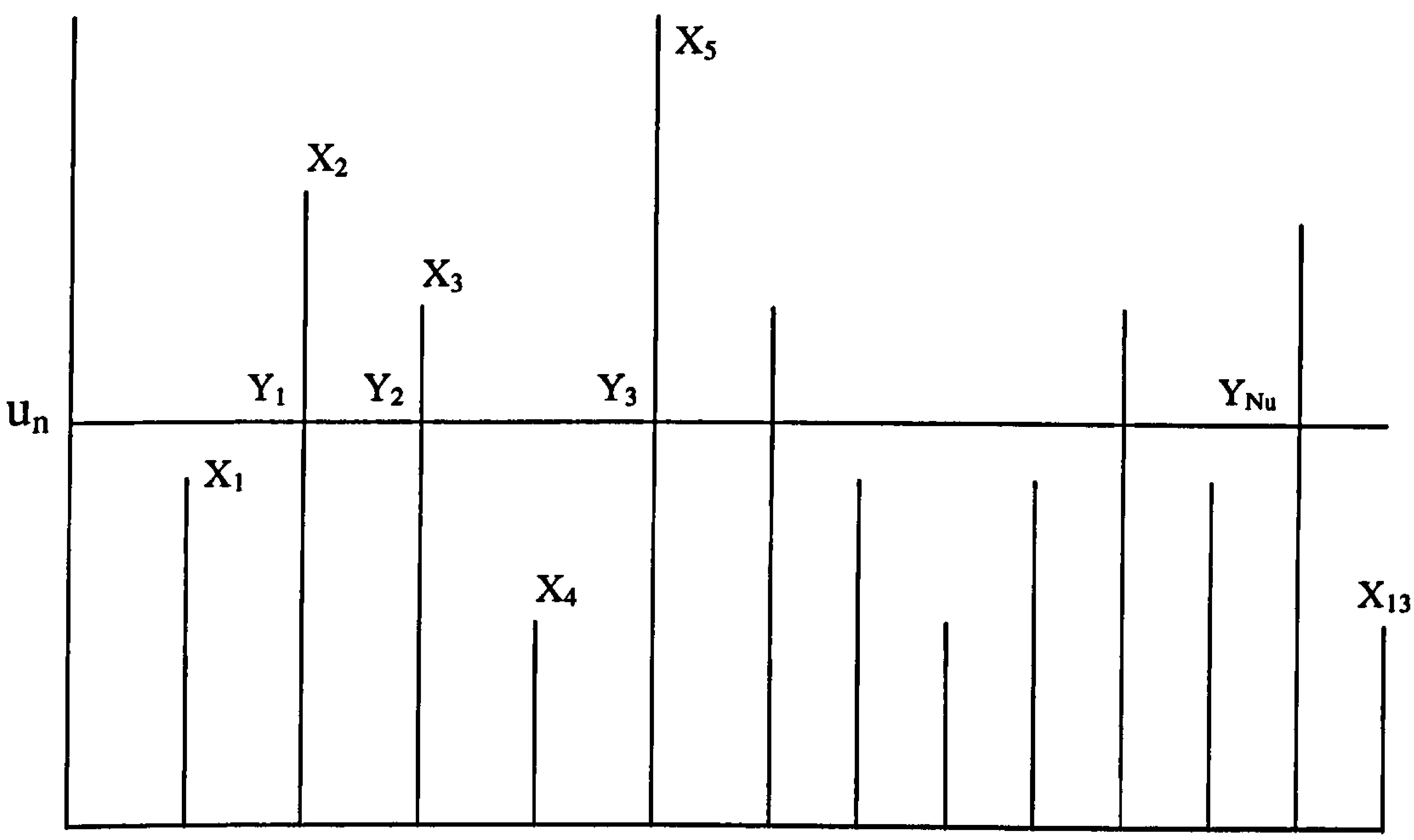


Figure 1. Data $X_1, \ldots, X_{13}$

We will now derive a limit process for the point process of exceedances of high thresholds. Given a high threshold u_n we index each observation of the sample $X_1,\ldots,X_n$, exceeding u_n. (In Figure (1), these are observations 2,3, 5,6, 10, and 12). To obtain a limit result, we let the sample size n tend to infinity and, simultaneously, the threshold u_n increases, and this in the correct proportion.

Let us define the excess distribution above the threshold u as the conditional probability

$$F_u(y) = \Pr(X-u \le y \mid X > u) = \frac{F(y+u) - F(u)}{1 - F(u)}, \; y > 0 \qquad (52)$$

For those distributions F that satisfy that the cdf in (50) converges to (51), it can be shown that for large enough u there exists a positive function $\beta(u)$, such that (52) is well approximated by the generalized Pareto distribution (GPD)

$$H_{\xi,\beta(u)}(y) = \begin{cases} 1 - \left(1 + \dfrac{\xi y}{\beta(u)}\right)^{-1/\xi} & \xi \neq 0 \\ 1 - \exp\left(-\dfrac{y}{\beta(u)}\right) & \xi = 0 \end{cases} \qquad (53)$$

where $\beta(u) > 0$, and $y \ge 0$ when $\xi \ge 0$ and $0 \le y \le -\beta(u)/\xi$ when $\xi < 0$.

For a given value of u, the parameter ξ, μ and σ of the GEV distribution determine the parameters ξ and $\beta(u)$. In particular, the shape parameter ξ is independent of u, and it is the same for both the GEV and GDP distributions. If $\xi>0$, F is in the Fréchet family and $H_{\xi,\beta(u)}$ is a Pareto distribution; if $\xi = 0$, F is in the Gumbell family and $H_{\xi,\beta(u)}$is an exponential distribution; and, if $\xi<0$, F is in the Weibull family and $H_{\xi,\beta(u)}$is a Pareto type II distribution. In most applications of risk management, the data comes from a heavy-tailed distribution, so that $\xi>0$. In this case, $E(X^k) = \infty$ for $k \geq 1/\xi$. For example, if $\xi = 0.5$ the distribution of losses has an infinite variance.

We estimate the parameters ξ and $\beta(u)$ in expression (52) by the method of maximum likelihood (ml). In particular, let x1, x2, ..., xn be an iid sample of losses with unknown cdf F. For a given high threshold u, extreme values are those xi such that xi-u>0. Let us denote these values as x(1), x(2),....., x(k), and define the threshold excesses as y_i- $x_i - u$, i=1,2,....,k. If u is large enough, then y1, y2, ..., yk may be thought of as a random sample of a GPD distribution with unknown parameters ξ and β. (Hereafter, for simplicity the argument of β is omitted). For the log-likelihood for an iid sample is given by:

$$L(\xi,\beta) = -k\ln(\beta) - \left(1+\frac{1}{\xi}\right)\sum_{i=1}^{k}\ln\left(1+\frac{\xi y_i}{\beta}\right) \qquad (54)$$

provided $y_i \geq 0$ when $\xi > 0$ and $0 \leq y_i \leq -\beta/\xi$. For $\xi = 0$, the log-likelihood function simplifies to

$$L(\xi,\beta) = -k\ln(\beta) - \frac{1}{\beta}\sum_{i=1}^{k} y_i$$

The asymptotic properties of ml estimates apply here as usual.

Our next aim is to estimate the tails of the loss distribution. To do this, we use the result that, for a sufficiently high threshold u, $F_u(y) \approx G_{\xi,\beta(u)}(y)$ and by setting x=u+y, an approximation of F(x), for x>u, can be obtained from equation (4)

$$F(x) = (1-F(u))G_{\xi,\beta(u)}(y) + F(u) \qquad (55)$$

The value of F(u) can be estimated non-parametrically by means of the empirical cdf

$$\hat{F}(u)=\frac{n-k}{n} \tag{56}$$

Where k represents the number of exceedences over the threshold u. After substituting (55) into (56), we get the following estimate for F(x)

$$\hat{F}(x)=1-\frac{k}{n}\left(1+\hat{\xi}\frac{(x-u)}{\hat{\beta}}\right)^{-\frac{1}{\hat{\xi}}} \tag{57}$$

Where $\hat{\xi}$ and $\hat{\beta}$ are the ml estimates of ξ and β respectively.

As mentioned earlier, two commonly used risk measures are the value at risk (VAR) and the expected shortfall risk (ES). Both are usually computed for confidence levels between 95 and 99.5 percent. That is, for $0.95 \leq q < 1$, VaRq is the qth quantile of the distribution F

$$\text{VaRq} = F^{-1}(q) \tag{58}$$

Where F^{-1} is the inverse function of F. For q>F(u), an estimate of (58) can be obtained from (57) by solving for x

$$\hat{VaR}_q = u + \frac{\hat{\beta}}{\hat{\xi}}\left(\left(\frac{1-q}{k/n}\right)\right)^{-\hat{\xi}} - 1 \tag{59}$$

The expected shortfall is the expected loss, given that VaRq is exceeded

$$ES_q = E(X|X > VaR_q = E(X - VaR_q|X > VaR_q) \tag{60}$$

The expression E(X-VaRq|X>VaRq) is the mean of the excess distribution over the threshold VaRq. It can be shown that (see, for example, Coles, 2001)

$$E(X - VaR_q|X > VaR_q) = \frac{\beta + \xi(VaR_q - u)}{1-\xi} \tag{61}$$

Provided that $\xi<1$. From equation (59) through (61), we obtain an approximation to ESq

$$\hat{ES}_q = \frac{\hat{VaR}}{1-\hat{\xi}} + \frac{\hat{\beta}-\hat{\xi}u}{1-\hat{\xi}} \tag{62}$$

In this study, we follow McNeil and Frey (2000)'s two-step estimation procedure called conditional EVT. The steps required to estimate conditional EVT are as follows:

Step1: Fit a GARCH-type model to the return data by quasi-maximum likelihood. That is, maximize the log-likelihood function of the sample assuming normal innovations.

Step 2: Estimate the tails of the innovations using extreme value theory by considering standardized residuals computed in step (1) as a white noise process. Next, we compute the quantiles of the innovations for $q \geq 0.95$.

Mc Neil and Frey further assume that the dynamics of log-negative returns can be represented by

$$r_t = \mu + \sigma_t Z_t \tag{63}$$

where μ is a constant term and Z_t are iid innovations with zero mean and unit variance, and marginal distribution $F_z(z)$.

The conditional variance of the mean-adjusted series $\varepsilon_t = r_t - \mu$ follows a GARCH (1,1) process

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \tag{64}$$

where $\beta_0>0$, $\beta_1>0$ and $\gamma>0$. Strictly stationarity is ensured by $\beta_1 + \gamma < 1$.

Under the assumption of normally distributed innovations, the log-likelihood function of a sample of iid observations becomes

$$L(\theta)=-\frac{n}{2}\log(2\pi)-\frac{1}{2}\sum_{t=1}^{n}\log(\sigma_t)-\frac{1}{2}\sum_{t=1}^{n}\frac{(r_t-\mu)^2}{\sigma_t} \quad (65)$$

Standardized residuals can be computed after maximizing (17) with respect to the unknown parameters μ, β_0, β_1, γ

$$(z_{t-n+1}, z_{t-n+2}, \ldots z_t)=\left(\frac{r_{t-n+1}-\hat{\mu}}{\hat{\sigma}_{t-n+1}}, \frac{r_{t-n+2}-\hat{\mu}}{\hat{\sigma}_{t-n+2}}, \ldots, \frac{r_t-\hat{\mu}}{\hat{\sigma}_t}\right) \quad (66)$$

where $\hat{\mu}$ and $\{\hat{\sigma}_{t-n+1}, \hat{\sigma}_{t-n+2}, \ldots \hat{\sigma}_t\}$ are the pseudo-maximum likelihood estimates. The natural 1-step forecast for the conditional variance in t+1 is given by

$$\hat{\sigma}_{t+1}^2=\hat{\beta}_0+\hat{\beta}_1\hat{\varepsilon}_t^2+\hat{\gamma}\hat{\sigma}_t^2 \quad (67)$$

where $\hat{\varepsilon}_t=r_t-\hat{\mu}$.

For a one-day horizon, estimates of the dynamic risk measures are

$$\hat{VaR}_q^t=\hat{\mu}+\hat{\sigma}_{t+1}\hat{VaR}(Z)_q$$

$$\hat{ES}_q^t=\hat{\mu}+\hat{\sigma}_{t+1}\hat{ES}(Z)_q \quad (68)$$

where $\hat{VaR}_q$ and $\hat{ES}_q$ are given by equations (59) and (62), respectively, and

$$\hat{\sigma}_{t+1}=\sqrt{\hat{\beta}_0+\hat{\beta}_1\hat{\varepsilon}_t^2+\hat{\gamma}\hat{\sigma}_t^2}.$$

It is important to mention that, even if Z_t is not truly normally distributed, the maximization of (65) still provides consistent and asymptotically normal estimates (see, for example, Engle and Gonzalez-Rivera, 1991). This result is the one on which McNeil and Frey's approach relies upon.

Once the VaRs have been estimated, it needs to be established the accuracy of each method. In order to do that we backtested the method on the 28 return series described earlier by the following procedure. Let $r_1, r_2, \ldots, r_m$ be a historical return series. The conditional quantile $\hat{r}_q^t$ is computed on t days in the set of T = {n,.......,m-1} using an n-day window each time. We use the same n, in this case equals 1000, for all the return data cycle. Following McNeil and Frey (2000)'s approach, the constant k which defines the number of exceedences above the threshold u, was set so that the 90^{th} percentile of the innovation distribution is estimated by historical simulation.

On each day $t \in T$, we fitted a new GARCH (1,1) model and estimated a new generalized Pareto distribution to losses, which were computed from the series of standardized residuals. This procedure is called conditional EVT. In addition, we estimated the unconditional EVT quantile, which corresponds to expression (11).

The conditional normal quantile is simply given by $z_q = \Phi^{-1}(q)$, where $\Phi(.)$ is the cdf of a standard normal. In turn the quantile of a Student-t distribution (scaled to have variance 1) is given by $z_q = \sqrt{(\upsilon-2)/\upsilon}\ F_T^{-1}(q)$, where T follows a t-distribution with υ degress of freedom (υ>2). On each day t, we estimated a GARCH (1,1) model with Student-t innovations and estimated a new υ and new quantiles. The value at risk was computed according to formula (20) for both the normal and t conditional cases.

If Zt is assumed to be distributed as t with υ degrees of freedom in equation (15), the log-likelihood function of the sample becomes (see, for example, Hamilton 1994, chapter 21)

$$L(\theta)=n\log\left(\frac{\Gamma(\upsilon+1)/2}{\pi^{1/2}\Gamma(v/2)}(v-2)^{-1/2}\right)-\frac{1}{2}\sum_{t=1}^{n}\log(\sigma_t)-\frac{(\upsilon+1)}{2}\sum_{t=1}^{n}\log\left(1+\frac{(r_t-\mu)^2}{\sigma_t(v-2)}\right)$$

Where n is the sample size. This is a better approximation to the data generating process in case observed returns appear to come from a (symmetric) fat-tailed distribution.

To backtest the methods, we compare the quantile estimate in t $\hat{r}_q^t$ is compared in each case with r_{t+1}, the log-negative return in t+1 for $q \in \{0.95, 0.99, 0.995\}$. A violation is said to occur whenever $r_{t+1} > \hat{r}_q^t$. To test whether the number of violation is statistically significant we use the following statistic based on the binomial distribution

$$\frac{\frac{Y}{n}-p}{\sqrt{\frac{p(1-p)}{n}}}\xrightarrow{d}N(0,1) \tag{69}$$

Where n is the sample size and Y is the number of violations, so that Y/n is the actual proportion of violations. The proportion p is the expected number of violations, under the assumption that the indicator function $I_t \equiv 1_{\{r_{t+1}>r_q^t\}} = 1_{\{z_{t+1}>z_q\}} \sim Be(p)$. This is a one-tailed test that is asymptotically distributed as N(0,1) (see, for example, Larsen and Marx, 1986, chapter 5). If Y/n<p, we test the null hypothesis of estimating correctly the conditional quantile against the alternative that the method systematically underestimates the conditional quantile. Otherwise, we test the null against the alternative that the method systematically overestimates the conditional quantile.

3.3.1. Summary

In this section, we have set out the empirical background to the tests I will conduct on the third empirical study. The main methodologies used in the third empirical study encompass the unconditional EVT, the conditional EVT and the back testing method.

3.4. METHODOLOGY EMPIRICAL IV

3.4.1 Introduction

This chapter presents the research method used for the fourth empirical study. The empirical analysis is separated into two parts. The first part studies the asymmetrical volatility in emerging markets. The analysis begins with examining up market and down market volatility and testing asymmetry condition in the volatility of emerging markets stocks using Engle and Ng (1993) approach. Having found evidence of asymmetry in volatility of emerging markets the last section of the first study will investigate the best model to use. We will examine the models of among EGARCH, TGARCH and PGARCH, using three main criteria namely likelihood ratio, Bayesian Information Criteria (BIC) and Akaike's Information Criterion (AIC). The second part of the empirical study examines whether the emerging stock markets exhibited long term memory and considers the satisfactory fit of SEFIMAR in modelling long term memory in emerging stock markets. In order to examine the long memory feature we employ classical R/S statistic, the modified R/S statistic and Hurst Coefficient.

3.4.2 Up Market and Down Market Volatility

The first step in the analysis is to explore whether the volatility of emerging stock markets is different in upstates compared with downstates. Therefore, we subdivide the entire history of stock returns for each country into up markets and down markets. A month or a week is classified as upmarket if the respective return is above average; the reverse is true for down markets. Given the series of m up and n down markets, we compute the following up and downvolatility measures, σ_{up} and σ_{down}:

$$\sigma_{up} = \sqrt{\frac{1}{m-1}\sum_{t=1}^{m}\left(r_{up,t} - mr_{full}\right)^2} \tag{70}$$

$$\sigma_{down} = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(r_{down,t} - mr_{full}\right)^2} \tag{71}$$

The mean of the full sample, denoted as mr_{full}, is substracted from the up- and down returns of the two subsamples, not their individual means. The reason is that we want to compare two volatility measures with respect to a common mean. This procedure also guarantees that the volatility of the full sample always falls between up-and downvolatility.

3.4.3 Testing for Asymmetry in Volatility

Asymmetry in volatility may be detected using the Engle and Ng (1993) sign and size bias tests. These tests are commonly used to differentiate the effect of good and bad news on the predictability of stock returns volatility (see Engle and Ng, 1993, Henry, 1998, Kroner and Ng, 1998, Brooks and Henry, 2002, *inter alia*). Engle and Ng (1993) (Engle-Ng, hereafter) develop a test for size and sign bias in conditionally heteroscedastic models. Consider a GARCH model of the form

$$x_t = \mu + \varepsilon_t, \varepsilon_t|\Omega_{t-1} \sim N(0, h_t) \tag{72}$$

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{73}$$

Define I_{t-1}^- as an indicator dummy that takes the value of 1 if $\varepsilon_{t-1} < 0$ and the value zero otherwise. The test for sign bias is based on the significance of ϕ_1 in

$$v_t^2 = \phi_0 + \phi_1 \mathrm{I}_{t-1}^- + e_t \tag{74}$$

Where v_t^2 is the squared standardised residuals and e_t is a white noise error term. If positive and negative innovations to ε_t impact on the conditional variance of x_t differently to the prediction of the model, then ϕ_1 will be statistically significant. It may also be the case that the source of bias is caused not only by the sign, but also the magnitude or the size of the shock. The negative size bias test is based on the significance of the slope coefficient ϕ_1 in

$$v_t^2 = \phi_0 + \phi_1 \varepsilon_{t-1} \mathrm{I}_{t-1}^- + e_t \tag{75}$$

The test statistics for the individual sign and size bias tests are distributed asymptotically with a t-distribution. Likewise, define $\mathrm{I}_{t-1}^+ = 1 - \mathrm{I}_{t-1}^-$, then the Engle-Ng joint test for asymmetry in variance is based on the regression

$$v_t^2 = \phi_0 + \phi_1 \mathrm{I}_{t-1}^- + \phi_2 \varepsilon_{t-1} \mathrm{I}_{t-1}^- + \phi_3 \varepsilon_{t-1} \mathrm{I}_{t-1}^+ + e_t \tag{76}$$

Where e_t is a white noise disturbance term. Significance of parameter ϕ_1 indicates the presence of sign bias. That is positive and negative realisations of ε_{t-1} affect future volatility differently to the prediction of the model. Similarly significance of ϕ_2 and ϕ_3 would suggest size bias, where not only the sign but also the magnitude of innovation in x_t is important. A joint test for sign and size bias may be performed based on F test.

3.4.4 Models for Asymmetry in Volatility

The next step of the analysis is to fit GARCH models to account for asymmetry in the conditional volatility. In this study we use three models of asymmetric GARCH including EGARCH, TGARCH and PGARCH. The following section describes the definitions of the three models.

(i) EGARCH Model

The EGARCH (Exponentional GARCH) was proposed by Nelson (1991). The model has several advantages over the basic GARCH model. Firstly, since the model specifies conditional variance in logarithmic form, this ensures variance is always positive. Thus there is no need to impose estimation constraint in order to avoid negative variance. Secondly, asymmetries are allowed for under the EGARCH formulation, since if the relation between volatility and returns is negative, γ would be negative (Brooks, 2002).

$$h_t = a_0 + \sum_{i=1}^{p} \frac{a_1 |\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} b_j h_{t-j} \qquad (77)$$

Note that the left hand side of the conditional variance specification is exponential. This implies that the leverage effect is exponential rather than quadratic and that forecasts of the conditional variance are guaranteed to be non negative. The most important is that the coefficient γ captures possible asymmetries in the conditional variance. In Finmetrics the surprises on the stock market is defined as ε_{t-i}. It is further assumed that good news and bad news have different effects on the conditional volatility.

If ε_{t-i} is positive or there is "good news", the total effect of ε_{t-i} is $(1+\gamma_i)|\varepsilon_{t-i}|$ whereas if is negative or there is "bad news" the total effect of ε_{t-i} is $(1-\gamma_i)|\varepsilon_{t-i}|$. Intuition suggests that bad news can have a stronger impact on the conditional volatility and hence the value of γ_i would be expected to be negative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

(ii) TGARCH Model

Another model that can be used to capture leverage effects is the threshold GARCH (TGARCH) model. The threshold GARCH was introduced independently by Zakoian (1990) and Glosten, Jaganathan, and Runkle (1993). The TGARCH model has the following form:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \gamma_i s_{t-i} \varepsilon_{t-1}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \qquad (78)$$

where
$$s_{t-i} = \begin{cases} 1 & \text{if } \varepsilon_{t-i} < 0 \\ 0 & \phantom{\text{if }} \varepsilon_{t-i} \geq 0 \end{cases}$$

In this model, as in the EGARCH model, good news occurs when ε_{t-i} is positive and bad news occurs when ε_{t-i} is negative. If there is good news the total effects are given by $a_i\ \varepsilon^2_{t-i}$ whereas for bad news the total effects are given by $(a_i + \gamma_i)\ \varepsilon^2_{t-i}$. Therefore for bad news to have larger impact on volatility, the value of γ_i would be expected to be positive. In other words, the presence of leverage effect is indicated by the positive value of coefficient γ. If $\gamma \neq 0$, the news impact is asymmetric. This model is also known as the GJR model because Glosten, Jagannathan and Runkle (1993) proposed essentially the same model.

(iii) PGARCH Model

The other variant of GARCH that is capable of modelling leverage effects is the power GARCH (PGARCH) model proposed by Ding, Granger and Engle (1993). The specification of the model is as follows:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \left(|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}\right)^d + \sum_{j=1}^{q} b_j \sigma_{t-j}^d \tag{79}$$

Where d is a positive exponent and γ_i denotes the coefficient of leverage effects.

3.4.5 Criteria for Model Selection

The criteria for model selection will be based mainly on the likelihood parameter. The model with the largest likelihood is chosen. In addition to the likelihood parameter, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) will be examined in order to take into account parsimony.

3.4.6 Statistical Tests for Long Memory

In this section we provide explanation of three parameters which are used to tests for long memory in the volatility of emerging market stocks as follows:

(i) Hurst Coefficient

The Hurst coefficient can vary from zero to one. The higher the value of the Hurst coefficient the higher is the intensity of long memory. A Hurst coefficient of 0.5 implies a random series or no persistence in a process or the absence of long memory. A value significantly less than 0.5 implies "anti-persistent". In other words, if the series has been up in the previous period, it is more likely to be down in the next period. When a value significantly greater than 0.5 we have positive persistent or trend reinforcing series. In other words, if the series has been up (down) the last period, then the changes will continue to be positive (negative) in the next period.

(ii) R/S Statistic

The most commonly used test for long memory or long range dependence probably is the rescaled range, or range over standard deviation, or simply R/S Statistic. The test was originally proposed by Hurst (1951) and later refined by Mandelbrot and his co-authors. The classical R/S statistic is the range of partial sums of deviations of a time series from its mean, rescaled by its standard deviation. Specifically, consider a time series y_t, for $t = 1, \ldots,$ T. The R/S statistic is defined as:

$$Q_T = \frac{1}{s_T}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y}) - \min_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y})\right] \tag{11}$$

where $\bar{y} = 1/T\sum_i^T y_i$ is the sample mean and $s_T = \sqrt{1/T\sum_{i=1}^{T}(y_i - \bar{y})^2}$ is the sample standard deviation. If y_t's are i.i.d normal random variables, then

$$\frac{1}{\sqrt{T}}Q_T \Rightarrow V$$

where $\Rightarrow$ denotes weak convergence and V is the range of a Brownian bridge on the unit interval.

(iii) Modified R/S Statistic

According to Lo (1991) the main drawback of the R/S statistic is that it biases to short range dependence. In particular, if y_t is autocorrelated (has short memory) then to remove the bias the denominator ST is replaced by $\hat{\sigma}_T(q)$ where:

$$\hat{\sigma}_T(q)^2 = s^2 + 2\sum_{j=1}^{q} w_j(q)\gamma_j \tag{80}$$

$$w_j(q) = 1 - \frac{j}{q+1}$$

and γj is the sample autocovariance at lag j.

The modified R/S statistic is then specified as follows:

$$\overline{Q}_T = \frac{1}{\hat{\sigma}_T(q)}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y}) - \min_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y})\right] \tag{81}$$

3.4.7 SEMIFAR Model

Andersen, Bollerslev, Diebold and Labys (1999) suggested use if FARIMA models to forecast daily volatility based on logarithmic realised volatility. However the FARIMA model chosen by BIC suggests that the underlying series may be non-stationary. To overcome this drawback, Beran, Feng and Ocker (1998), Beran and Ocker (1999), and Beran and Ocker (2001) proposed the semiparametric fractional autoregressive (SEMIFAR) model. SEMIFAR model allows for a possible deterministic trend in a time series, in addition to a stochastic trend, long memory and short memory components. The model basically an extension to the FARIMA(p,d,0) model and is specified as follows:

$$\varnothing(L)\,(1\text{-}L)^{\delta}\,[(1\text{-}L)^{m}\,yt - g(i_t)] = \varepsilon_t$$

where the term $g(i_t)$ represents a smooth trend function on [0,1].

CHAPTER 4. DATA

For the first empirical study, following Ciraolo et.al (2002), we focus on the Global Bond market, which has clear advantages to other types of risky bonds. The data is gathered from the Datastream for eleven emerging markets namely Argentina, Brazil, Columbia, Mexico, Russia, Venezuela, Panama, South Africa, Turkey, Philippines and South Korea. Each bond series starts from the issuance date (5/12/1997) until end of December 2002. In particular we use weekly market values of Global bond prices. Since we only work on US dollar denominated emerging markets Global Bond, USD Libor and swap rates are used to generate the risk-free term structure. As for the Libor rates, we use US Interbank with maturities between overnight and 12 months, whereas for the swap rates we include all maturities between 2 and 10 years and the 12, 15, 20, 25 and 30 years maturities. Data for explanatory variables is also obtained from the Datastream including short and long term interest rates in local currency, J.P. Morgan and Lehman Brothers local indexes, log changes in exchange rates, interest rate spreads with respect to US rates, ratio of international reserves to GDP, inflation rate and real rate of annual GDP growth rate.

The data used in the second empirical study, the third empirical study and the fourth empirical study is the US dollar value weighted indices from the Morgan and Stanley Capital International (MSCI) price index and Datastream Market Index which covers 28 countries in emerging markets. Due to the availability of MSCI data for Mexico, Indonesia, Malaysia, Philippines, Thailand and Greece we use DataStream Market Index instead.[2] This replacement however is justifiable given the fact that all data series in each region exhibit the same pattern. Details of the countries included in this study are given in the tables. We use weekly data ranging from 12 January 1995 to 28 April 2005 for a total of 538 observations. The choice of weekly data is important for two reasons. First, the effect of nonsynchronous trading induces spurious autocorrelation into the index return, but the lower the data frequency the less important this effect is. Thus to mitigate this effect we choose to use weekly rather than daily data. Second, almost all statistical inferences drawn in the subsequent section require a sufficient number of observations to be reliable. Using monthly data would therefore not be appropriate due to the short history of most of the stock markets under study. The return series for each market between period t-1 and t is defined in the usual way by $R_{it} = \ln(P_{it}/P_{it-1})]$, where P_{it} denotes the level of the stock market index for each country at time t and ln is the natural logarithm.

4.1. Data and Preliminary Findings

The data used in this study include the US dollar value weighted indices from the Morgan and Stanley Capital International (MSCI) price index and DataStream Market Index which cover 28 countries in emerging markets. Due to the availability of MSCI data for Mexico, Indonesia, Malaysia, Philippines, Thailand and Greece we use DataStream Market Index instead. This replacement however is justifiable given the fact that all data series in each region exhibit the same pattern. Details of the countries included in this study are given

[2] Recent research by Ince and Porter (2006) have identified several problems with using TDS (Thomson Datasteram). One of them is the data issues. An important problem is the discreteness of the TDS return index in which the return index is reported to the nearest tenth. To avoid the problem they suggested the use of price index to calculate return.

in the tables. We use weekly data ranging from 12 January 1995 to 28 April 2005 for a total of 538 observations. The choice of weekly data is important for two reasons. First, the effect of non-synchronous trading induces spurious autocorrelation into the index return, but the lower the data frequency the less important this effect is. Thus to mitigate this effect we choose to use weekly rather than daily data. Second, almost all statistical inferences drawn in the subsequent section require a sufficient number of observations to be reliable. Using monthly data would therefore not be appropriate due to the short history of most of the stock markets under study. The return series for each market between period t-1 and t is defined in the usual way by $R_{it} = \ln(P_{it}/P_{it-1})]$, where P_{it} denotes the level of the stock market index for each country at time t and ln is the natural logarithm.

Table 2 presents descriptive statistics for return data indices of the 28 countries. It can be seen that most of all the sample means of the 28 countries, except Indonesia, Malaysia, Philippines, Singapore, Taiwan, Thailand, and Pakistan, are positive. Hungary provided the highest mean return. Philippines provided the lowest mean return, although its variance was higher than that of Morocco which exhibited the lowest variance. It is interesting to note that mean and variance of Morocco is nearly the same as of the world index return.

It is clear from Table 2 that none of the series of log returns of all the indices follows the normal distribution as indicated by the Skewness and Kurtosis statistic. Skewness is a measure of asymmetry of the distribution of the series around its mean. The skewness coefficient is computed as follows:

$$S = \frac{1}{N}\sum_{i=1}^{n}\left[\frac{y_i - \bar{y}}{\sigma}\right]^3$$

The skewness of a symmetrical distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail. As can be seen from Table 2, most of the series are negatively skewed or have a long left tail, with the exception of the Philippines, Taiwan, Thailand, Greece, Egypt, and Morocco series. This means that there is a higher probability for investors to get negative returns.

Another measurement to check whether the series follow a normal distribution is kurtosis. Kurtosis measures the peakedness or flatness of the distribution of the series and is computed as follows:

$$K = \frac{1}{N}\sum_{i=1}^{n}\left[\frac{y_i - \bar{y}}{\sigma}\right]^4$$

The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

Table 2 shows that the kurtosis statistic of all of the country indices of the emerging markets exceeds 3. The kurtosis values range from the minimum value of 3.5 to the maximum value of 38. This means that the distribution of each index is peaked (leptokurtic) relative to the normal.

Alternatively, a testing of normality can be examined by using the Jarque-Bera statistic which is calculated as:

$$JB = \frac{N-k}{6}\left[S^2 + \frac{1}{4}(K-3)^2\right]$$

Where S is the skewness coefficient, K is the kurtosis, and k represents the number of estimated coefficients used to create the series. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as ε^2 with 2 degrees of freedom. In Eviews, the reported probability is the probability that a Jarque-Bera Statistic exceeds (in absolute value) the observed value under the null – a small probability value leads to the rejection of the null hypothesis of a normal distribution. As would be expected, the probability value of all emerging market return indices is less than 5 percent. This implies that none of the return indices are normally distributed at 5 percent significant level.

Table 2. Data summary statistics for weekly raw returns data for country indices and the world market portfolio covering the period from 12 January 1995 to 28 April 2005.

Country	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Beta Estimate (std.error)
Argentina	0.0001	0.0576	- 0.1822	8.5843	702.0	1.038 [a] (0.114)
Brazil	0.0007	0.0591	- 0.6588	9.6459	1,029.0	1.309 [ab] (0.113)
Chile	0.0001	0.0320	- 0.2570	8.1515	600.8	0.667 [ab] (0.062)
Colombia	0.0008	0.0419	- 0.0694	5.7170	165.9	0.327 [ab] (0.088)
Mexico	0.0014	0.0418	- 0.5160	6.3851	280.7	1.116 [ab] (0.075)
Peru	0.0013	0.0375	- 0.1876	7.4516	447.4	0.561 [ab] (0.076)
Venezuela	0.0006	0.0665	- 3.0266	38.4202	28,945.1	0.735 [ab] (0.138)
Hong Kong	0.0006	0.0371	- 0.8600	9.2591	944.5	0.988 [a] (0.066)
Indonesia	-0.0016	0.0690	- 2.0887	29.6976	16,368.9	0.703 [ab] (0.144)
Korea	0.0004	0.0616	- 0.8427	13.0678	2,335.8	1.332 [ab] (0.118)
Malaysia	-0.0007	0.0478	- 1.5905	23.0734	9,259.4	0.471 [ab] (0.099)
Philippines	-0.0019	0.0405	0.2405	10.2737	1,191.2	0.601 [ab] (0.082)
Singapore	-0.0003	0.0346	- 0.2067	7.4182	441.4	0.852 [ab] (0.064)
Taiwan	-0.0007	0.0419	0.1953	4.4122	48.1	0.757 [ab] (0.083)
Thailand	-0.0018	0.0539	0.1226	5.9550	197.1	0.914 [a] (0.108)
Czech	0.0020	0.0363	- 0.2259	3.9777	26.0	0.627 [ab] (0.073)
Greece	0.0022	0.0389	0.1231	5.2541	115.3	0.730 [ab] (0.077)
Hungary	0.0036	0.0467	- 0.7079	8.6058	749.4	1.069 [a] (0.088)
Poland	0.0009	0.0471	- 0.1054	4.4326	47.0	1.049 [a] (0.089)
Portugal	0.0012	0.0287	- 0.4525	5.5177	160.5	0.676 [ab] (0.054)
Turkey	0.0019	0.0787	- 0.9702	9.5038	1,032.6	1.297 [ab] (0.158)
Egypt	0.0029	0.0361	0.3185	5.1589	113.6	0.194 [ab] (0.076)
India	0.0005	0.0370	- 0.0639	3.5603	7.4	0.463 [ab] (0.076)
Israel	0.0015	0.0375	- 0.5124	5.2098	133.0	1.056 [a] (0.066)

Table 2. Data summary statistics for weekly raw returns data for country indices and the world market portfolio covering the period from 12 January 1995 to 28 April 2005 (continued)

Country	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera	Beta Estimate (std.error)
Morocco	0.0012	0.0202	0.2605	4.8465	82.5	0.018[b] (0.043)
Pakistan	-0.0006	0.0452	- 0.5994	5.2240	143.1	0.146[b] (0.096)
South Africa	0.0004	0.0354	- 0.7995	6.1639	281.7	0.958[a] (0.063)
Russia	0.0030	0.0844	- 0.1601	9.6637	997.7	1.519[ab] (0.168)
World	0.0011	0.0203	- 0.2969	4.6191	66.7	

Note:

a) Significantly different from zero

b) Significantly different from unity

CHAPTER 5. FIRST EMPIRICAL STUDY: IMPLIED DEFAULT PROBABILITY OF EMERGING MARKET BONDS

5.1. Introduction

The main objective of this chapter is to estimate the default probability of emerging market bonds. Apart from interest rate, there are three main factors that influence the value of a risky bond: the nominal value and coupon of the bond, the recovery rate and the default probability. The recovery rate represents the proportion of the face value of the bond that is recovered in the case of default. Bonds with high recovery rate indicate low possibility of default and hence pay low interest as compared to riskier bonds. The default probability indicates the likelihood that the company, who issues the bond, will be unable to meet the contractual obligations (interest and or principal) on the various payment dates. The bond rating is one of the most important indicators of a corporation's credit quality and therefore its default probability. A change in a rating reflects the assessment that the company's credit quality has improved (upgrade) or deteriorated (downgrade). The bond rating was first developed by Moody's in 1914 and by Standard & Poor's Corporation in 1922 and it is generally assigned by external agencies to publicly traded debts.

Despite their widespread acceptance and use, bond ratings have some limitations. The two agencies may disagree on their evaluations. Furthermore, because most bonds are in the top four categories, it seems safe to argue that not all issues in a single category (such as A) can be equally risky. Finally, it is extremely important to remember that bond ratings are a reflection of the relative probability of default, which says little or nothing about the absolute probability of default (Jones, 2002).

Therefore it is important to model default probability for at least for two reasons. First, we may expect that high yields offered by emerging market bonds are associated with the high degree of default probability. Thus, fundamentally default probability model can provide insight to the probability of default of emerging market bonds. Second, by extracting default probability we will be able to examine the relationship between default probability and other factors. In this chapter we address both of these issues. Moreover credit rating is traditionally based on financial statement information whereas implied default probability is a market-based measure.

As stated earlier in the methodology of empirical 1 section, in this study we adopt the approach in Ciraolo et.al (2002) and extend it in three ways. Firstly, we extend Ciraolo's sample to include more recent data in order to investigate the power of the model in explaining the default probability of emerging market bonds and particularly to capture South American Economic Crisis of 2002. Secondly, while Ciraolo used Kalman Filter to fit the term structure of interest rate, we use GMM method to estimate the term structure of interest rate. Finally, we try to elaborate several other economic factors which have influence on default probability. This task will be presented in this chapter.

5.2. Empirical Results of Implied Default Probability

Figure 1 demonstrates the implied risk-neutral default probabilities estimated for the countries considered in the sample. It can be seen from the figure 1 that the estimated risk-neutral default probabilities reflect the changes of both the political and macroeconomic situations of different countries over the period of 1997 to 2002. These include period of deep financial and economic crisis as follows: the Asian's banking system crises in 1997, Russia's default in 1998, the Turkish and Argentina's crises in 2001-2002, and South American economic crisis of 2002.

From the Figure 1 (Panel A and Panel B) it is clear that, although not too dramatically, all countries experienced an increase in default probability during the financial turmoil in Asia. Argentina's and Brazil's implied default probability almost doubled from 2.2 percent to 4 percent. The default probability of Mexico and Venezuela increased by 1 percent and 2.4 percent respectively. Nevertheless the Asian crisis is one of the many developing-country financial crises. The first major blow to the international financial system took place in August 1982, when Mexico announced that it could not meet its regularly scheduled payments to international creditors. The second major crisis came on December 20, 1994, when the Mexican government announced it would devalue the peso against the dollar by 14 percent.

As mentioned previously, the crisis in Asia subsequently followed by another huge crisis as a result of Russian default in 1998. By July 1998, Russian government was unable to rollover treasury bills maturing before the end of 1999. The IMF had approved a financial rescue package of $11 billion to support Russia. However, within a month, on August 17, 1998, Russia declared unilateral default on $40 billion in short-term domestic treasury debt, of which about one third was held by foreign investors. Nonetheless the crisis in 1998 was also triggered to some extent by the Asian's banking crisis. This was pointed out by International Monetary Fund's 1998 World Economic Outlook (WEO), which indicates that the impact of the Asian crisis was the main factor contributing to a full 1 percent slowing of growth in the world economy in 1998. In fact, the Asian crisis had pushed one-third of the globe into recession during 1998. The default probability of Venezuela was the highest during this period, reached 27 percent, and then followed by Brazil and Columbia whose default probabilities are 14 percent and 8.8 percent respectively. While Argentina's and Mexico's default probability stood at 8.3 percent and 6.1 percent correspondingly.

We can see that from 2001 to 2002 all countries in the sample exhibited increase in the default probability; with the exception of Russia whose default probability was relatively stable. In addition Turkey also showed different pattern of default probability in comparison to the others. Turkey's default probability increased, although fluctuated, quite dramatically from 3.7 percent on 26 January 2001 to 7.6 percent on 5 October 2001. After that there was a sudden decrease of the default probability of Turkey and the figure rose again on 5 July 2002 to 7.3 percent. However it should be noted here that because the market value of global bond issued by Argentina dropped significantly after July 2001 then it becomes impossible to obtain the default probability figure using the algorithm process.

As stated earlier there was a recent crisis happened in South American. From the Figure 1 (Panel A to B) there was clear evidence to support that the South American economic crisis impacts countries within its region including Argentina, Brazil, Columbia, Mexico, Panama and Venezuela. The default probability of these countries suddenly increased on 15 November 2002. Columbia's default probability jumped from 5.5 percent on January 2002 to 13 percent whereas Mexico's default probability also doubled from 3 percent to 6 percent.

FIGURE 1 (Panel A)
Estimated Default Probabilities

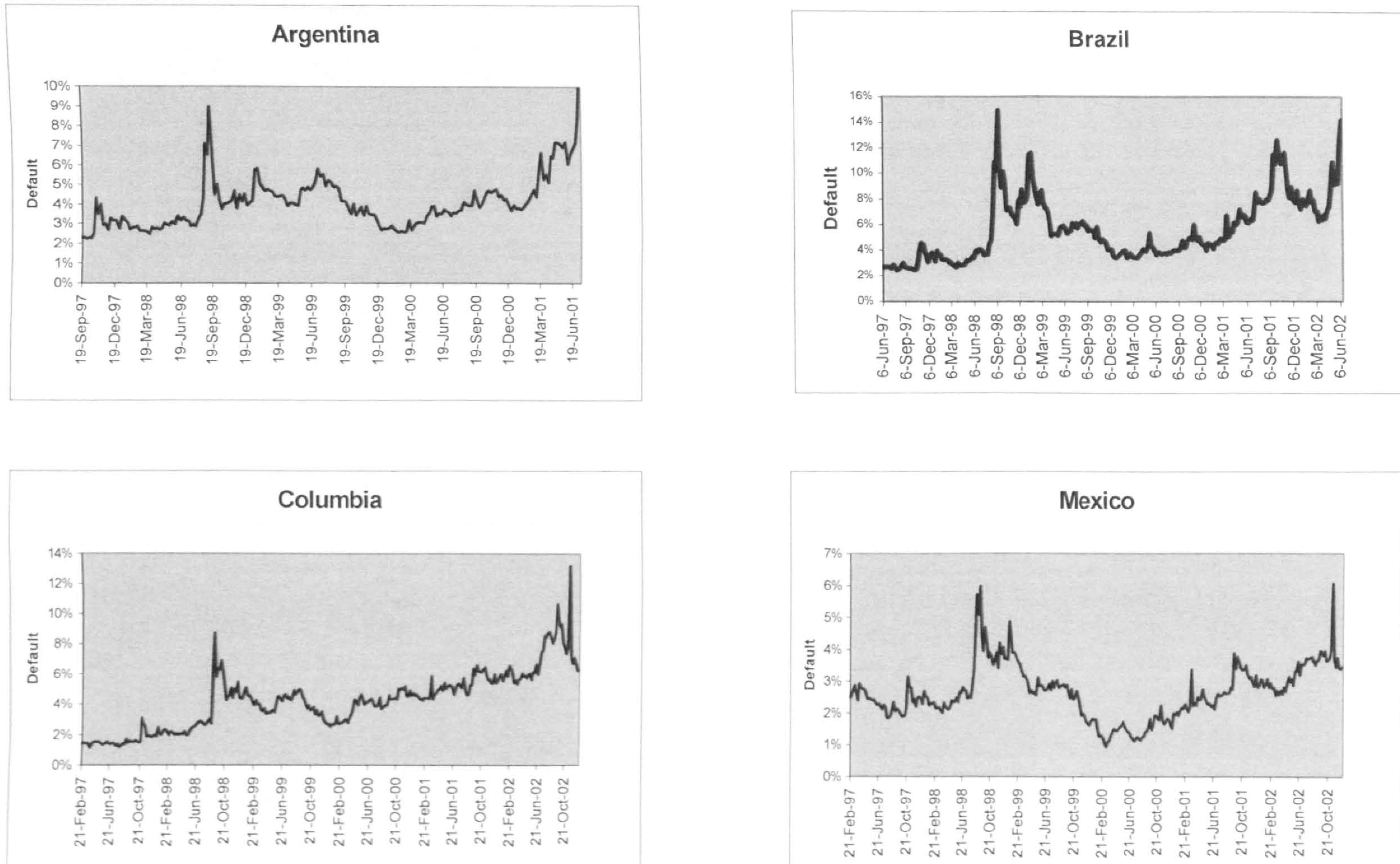
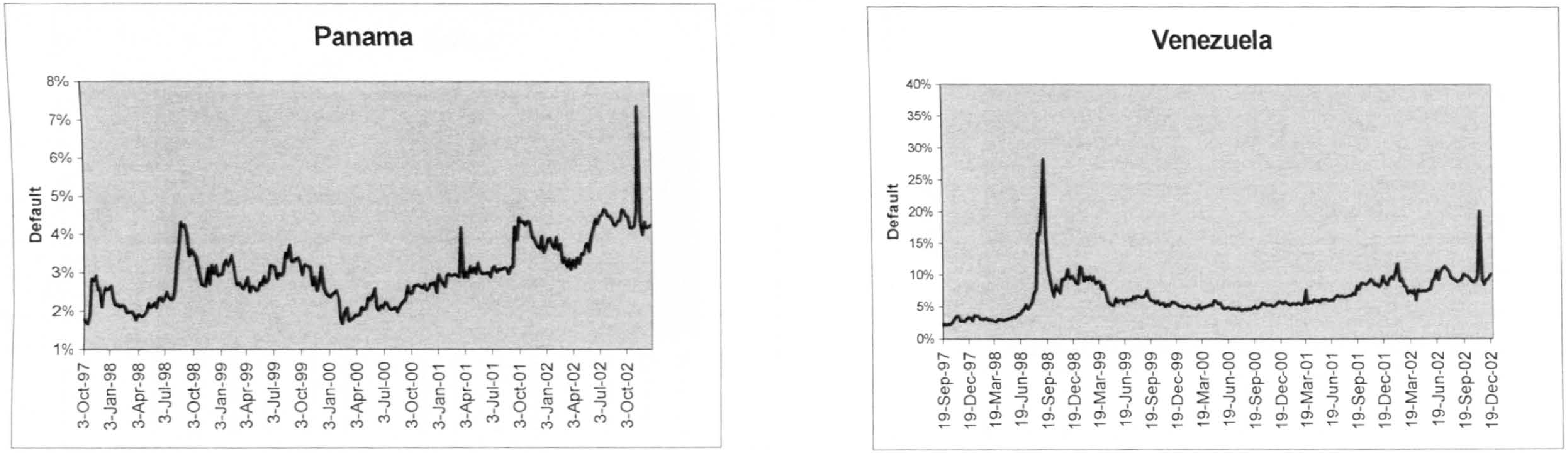


FIGURE 1 (Panel B)
Estimated Default Probabilities



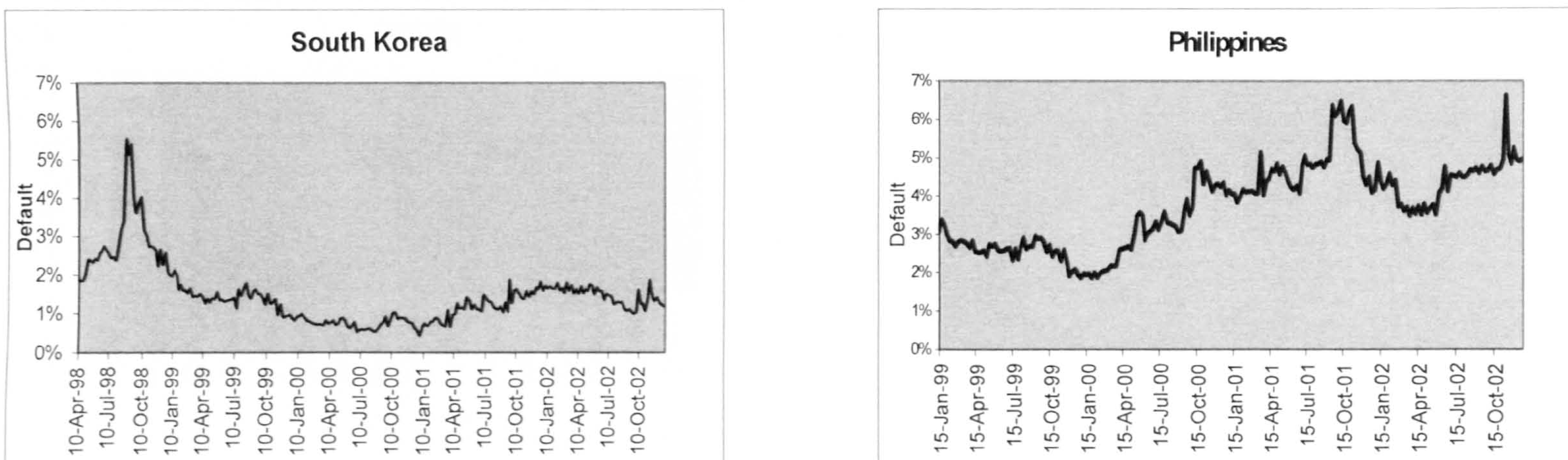
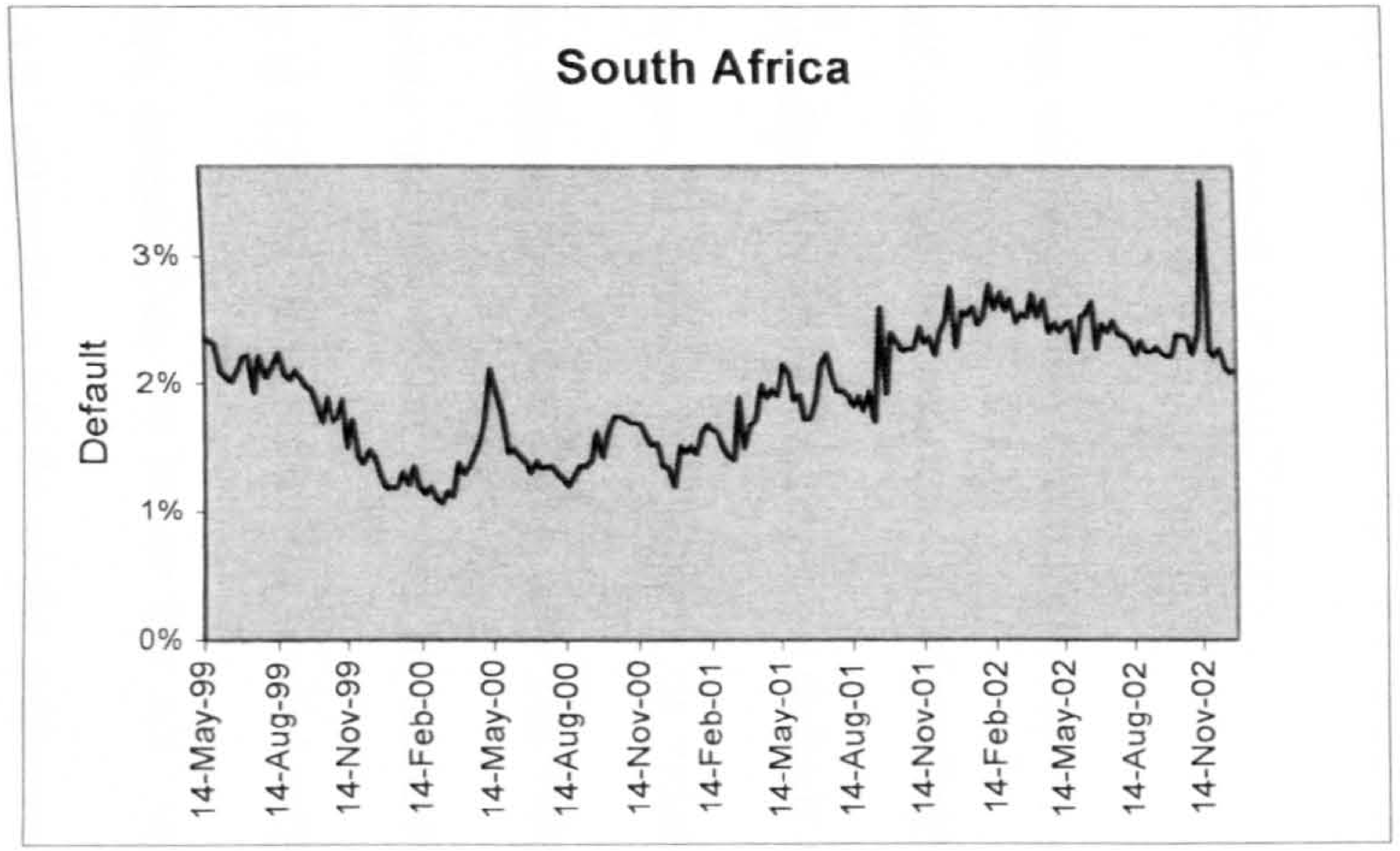
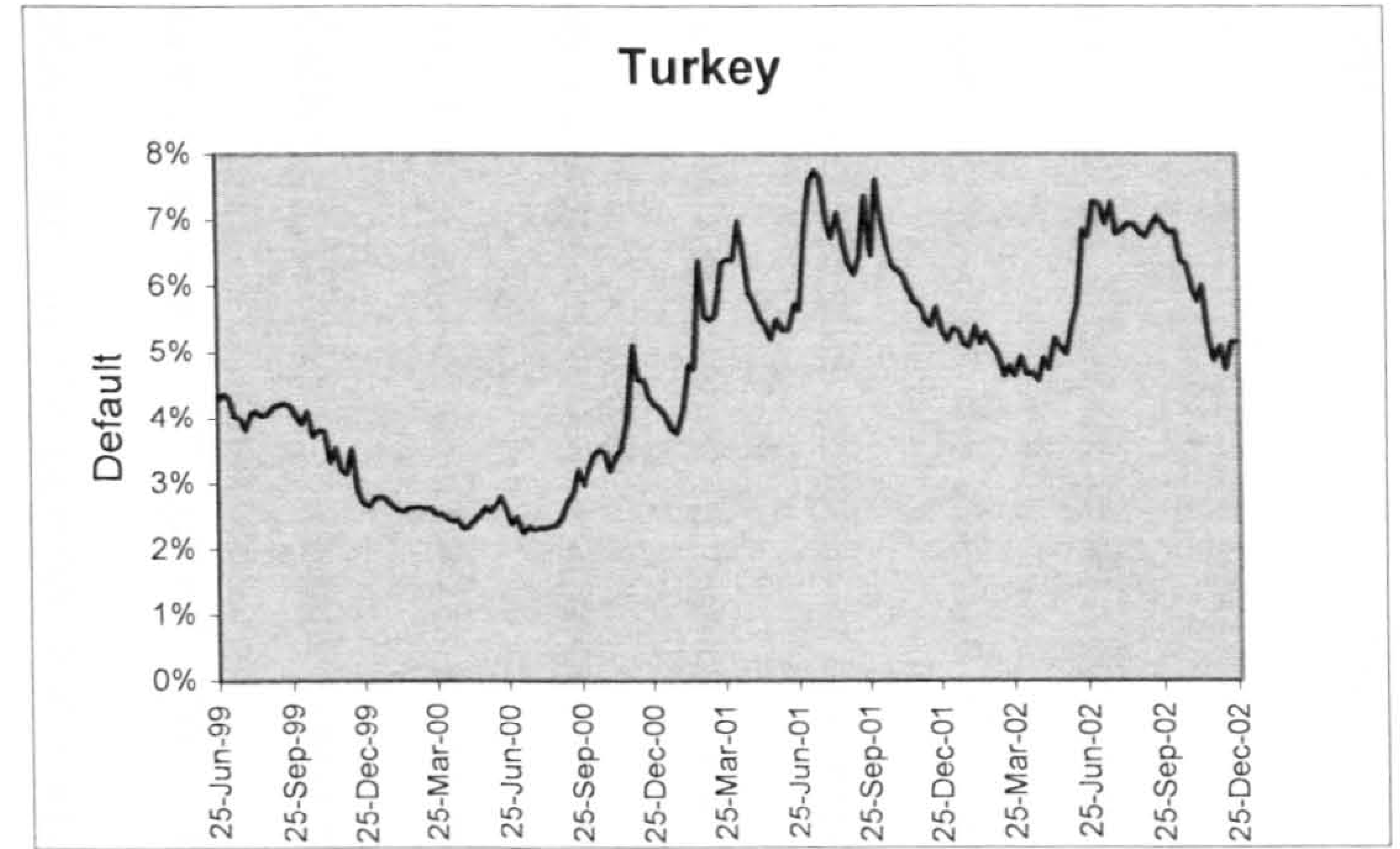
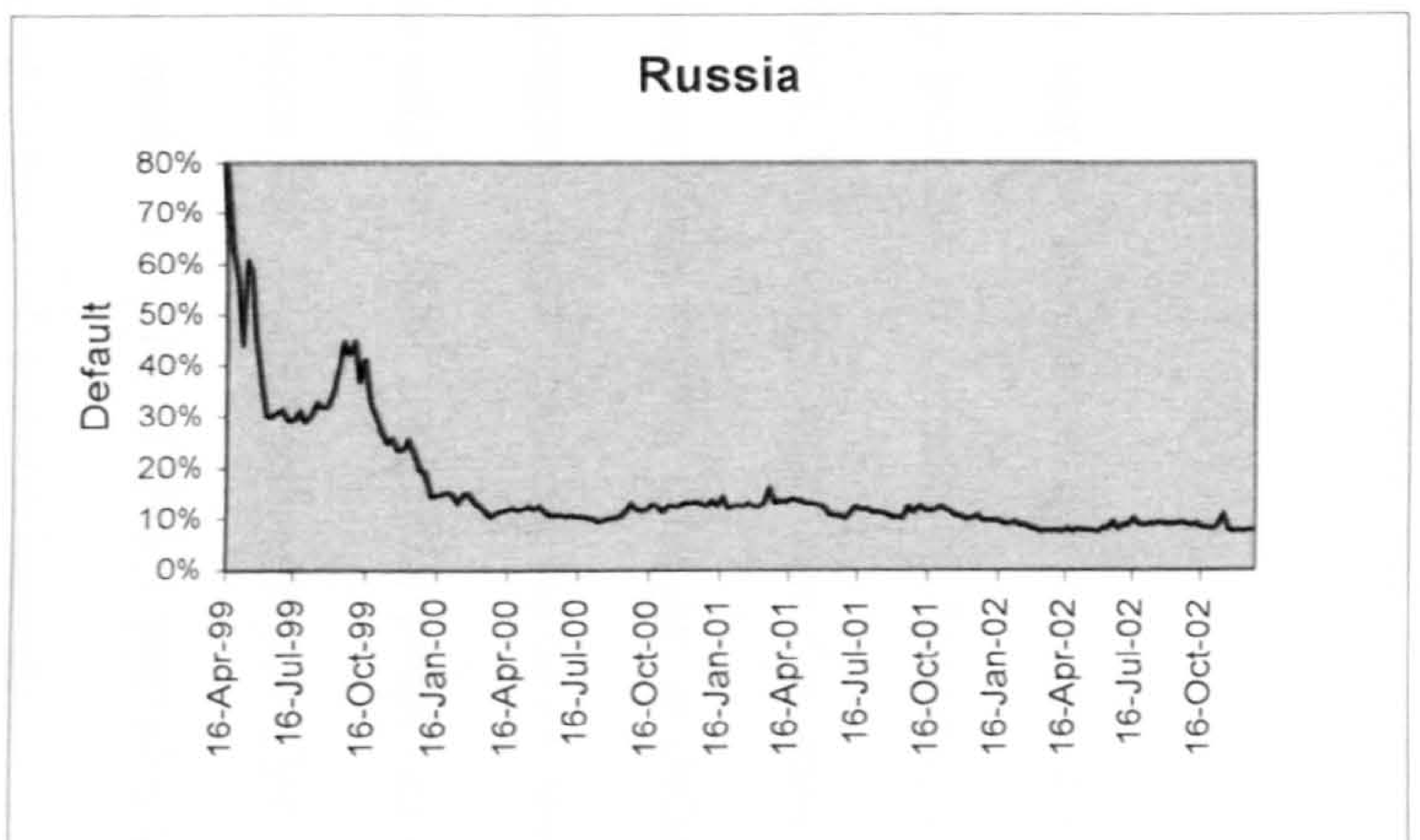


FIGURE 1 (Panel C)

Estimated Default Probabilities







In the following section we discuss the results obtained from the logit model. As we have already mentioned on the introductory section of this chapter, we extend the original model proposed by Ciraolo, et.al (2002) by adding five other macroeconomic variables. However since the data on external debt is not fully available for all country samples therefore we exclude this variable in our analysis. The other variable that we do not include in our analysis is the change in the spot rate. The reason for this is because the short term interest rate in local currency will arguably have identical features to the change in the spot rate. The first step in our analysis is to check whether there is multicollinearity among the three candidate explanatory variables (ratio of international reserves to GDP, inflation rate and real rate of annual GDP growth rate). To check for multicollinearity we examine the cross correlation among the independent variables for each country sample. Table 3 presents the result of the cross correlation analysis. Based on the correlation matrix analysis we find no evidence of multicollinearity and thus the inclusion the three additional independent variables has a statistical justification[3].

After analysing the multicollinearity, the next step is to decide the best model to choose that can explain market downgrading (weekly increase in default probability) and market upgrading (weekly decrease in default probability). We assign value one for positive weekly changes in default probability or value zero for negative weekly changes in default probability. Since there are three new candidate explanatory variables then we have seven other possible models to be chosen in addition to the original logit model as proposed by Ciraolo, et.al (2002). The selection model will based upon the Akaike Information Criteria (AIC) which asserts that the lower the AIC value, the model is better. Table 4 provides the results of AIC estimation for the eight different logit models for each country sample.

[3] The correlation matrix is not a multicollinearity test per se. However, it can be used to detect the presence of multicollinearity (Brooks, 2002). Gujarati (1995) suggests the rule of thumb of 0.8 as an indicator of a high correlation among regressors

Table 3. Correlation matrix analysis for additional explanatory variables.

This table reports the results of the multicollinearity analysis based on the correlation matrix for each country sample. There are three variables were analysed including ratio of international reserve to GDP, inflation rate and GDP growth.

Argentina	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	0.366298	0.052197
Inflation rate	0.366298	1	0.060949
GDP growth	0.052197	0.060949	1
Brazil	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	0.002434	-0.03342
Inflation rate	0.002434	1	0.087781
GDP growth	-0.03342	0.087781	1
Mexico	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	-0.062608	-0.023434
Inflation rate	-0.062608	1	-0.100514
GDP growth	-0.023434	-0.100514	1
Russia	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	-0.130631	-0.276567
Inflation rate	-0.130631	1	0.055971
GDP growth	-0.276567	0.055971	1
Turkey	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	-0.566993	-0.422359
Inflation rate	-0.566993	1	-0.111162
GDP growth	-0.422359	-0.111162	1
Philippines	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	-0.088799	-0.272795
Inflation rate	-0.088799	1	0.032632
GDP growth	-0.272795	0.032632	1
Korea	Ratio of IR to GDP	Inflation rate	GDP growth
Ratio of IR to GDP	1	-0.149535	-0.114916
Inflation rate	-0.149535	1	0.072445
GDP growth	-0.114916	0.072445	1

Table 4. Estimation Results of Akaike Information Criterion (AIC) for each country sample for all different eight models.

This table presents the results of AIC estimations for eight different models for each country sample together with the rank value. Original refers to the original model proposed by Ciraolo (2002), new refers to the original model plus ratio of international reserve to gdp (inrs), inflation rate (infl), and gdp growth (gdp). The first model adds inrs only, the second model adds inrs and infl, the third model adds inrs and gdp, the fourth model adds infl and gdp, the fifth model adds infl only, the sixth model adds gdp only.

Model / Country	Original	new	1	2	3	4	5	6
Argentina	1.42	1.45	1.43	1.44	1.44	1.44	1.43	1.43
Rank	**1**	8	**2**	6	5	7	4	3
Brazil	1.33	1.35	1.34	1.34	1.34	1.34	1.34	1.34
Rank	**1**	8	**2**	7	5	6	3	4
Mexico	1.31	1.31	1.31	1.32	1.31	1.30	1.31	1.30
Rank	7	4	6	8	3	2	5	**1**
Russia	1.38	1.38	1.37	1.37	1.37	1.40	1.39	1.39
Rank	4	5	**1**	2	3	8	7	6
Turkey	1.29	1.33	1.31	1.32	1.32	1.31	1.30	1.30
Rank	**1**	8	4	7	6	5	3	2
Philippines	1.41	1.42	1.41	1.42	1.41	1.41	1.42	1.40
Rank	2	8	3	7	5	4	6	**1**
Korea	1.41	1.42	1.41	1.42	1.41	1.42	1.41	1.41
Rank	**1**	7	**2**	6	5	8	3	4
Average	1.37	1.38	1.37	1.37	1.37	1.38	1.37	1.37
	1	8	**2**	6	4	7	5	3

Due to data restrictions on the explanatory variables, the analysis is restricted to seven countries including Argentina, Brazil, Mexico, Russia, Turkey, South Korea and Philippines. It can be seen that the original model outperforms the other models in four cases (Argentina, Brazil, Turkey and Korea). The second best model is where the original model is combined with a variable of GDP growth. Therefore in this case we might conclude that the original model as proposed by Ciraolo et.al (2002) is still the best model to use for describing the default probability feature in emerging markets even though the data sample has been expanded and it has included recent financial crisis.

The final step of the analysis is to examine the accuracy of the selected model in predicting default probability. Table 5 provides the results of in sample prediction of the original model for each country samples. In general the ability of the model to predict the future default probability is not symmetrical. As can be seen from Table 5, the model predicts more accurately for one week ahead decrease in default probability than for increase in default probability; except for Philippines. By a similar token, the model's ability to predict future changes in bond prices is more successful for upgrade. Comparing our results with the results obtained by Ciraolo et.al (2002) we find surprising finding in which Ciraolo et.al (2002) get successful results for both upgrading and downgrading. Our explanation for differences most probably lies on the sample selection bias because in our study we try to include more recent sample in order to capture the South American economic crisis.

Table 5. Percentage of correct in-sample predictions

This table presents the percentage of correct in-sample predictions of a market downgrading (weekly increase in default probability or decrease in bond price) or upgrading (weekly decrease in default probability or increase in bond price) in the underlying bonds. The sample period varies for each country and ranges between 21 February 1997 and 27 December 2002. Values are expressed in percentage terms.

		Change in default probability		Change in bond price	
Country	**No. obs**	**Downgrade**	**Upgrade**	**Downgrade**	**Upgrade**
Argentina	200	55.45	58.16	41.05	70.19
Brazil	263	50.41	81.29	51.54	75.76
Mexico	306	57.14	70.25	42.86	83.80
Russia	194	37.50	72.38	11.27	94.26
Turkey	138	56.45	77.33	19.23	95.29
Philippines	202	75.93	33.33	45.45	78.76
South Korea	244	31.53	78.03	34.38	89.80

5.3. Conclusion

The primary focus of this chapter is on modelling implied default probability of emerging stock markets. Our study is based on the original model proposed by Ciraolo et.al (2002) and differs in three respects, especially by trying to include several other economic factors which have influence on default probability. With regard to the model's ability to generate default probability, the model generated successfully the implied default probability for all countries samples. Although it should be noted here that for Argentina the estimated default probability can not go beyond July 2001 because of the significant drop of its bond value and as a result the algorithm process in gauss fails to produce the result.

In testing the new candidate for explanatory variables we follow two steps. The first one is to check whether there is evidence of multicollinearity. And the second one is the selection of the best model among eight available models (including the original model as proposed by Ciraolo (2002)) using the Akaike Information Criteria. With respect to the first step, we find no evindence of multicollinearity. Based on the Akaike Information Criteria we find that the original model still outperforms the other models as it produces the lowest value of AIC. Finally we have shown that weekly changes of the estimated default probabilities can be predicted quite successfully by the logit model.

CHAPTER 6. SECOND EMPIRICAL STUDY: TIME VARYING COUNTRY RISK IN EMERGING MARKETS

6.1. Introduction

The main objective of the present chapter is to investigate three different techniques for estimating a time-varying beta. Previous studies that focus on emerging markets have investigated only limited countries and techniques. This study, which we believe for the first time, provides a comprehensive outlook of emerging market countries. In particular we examine 28 countries in emerging markets which cover four regions, i.e. Emerging Market Latin America, Emerging Market East Asia, Emerging Market Europe and Other Emerging Markets. In testing the time varying characteristic of beta we employed a multivariate generalised ARCH (M-GARCH) model introduced by Bollerslev (1990), the Schwert and Seguin model (1990), and the Kalman Filter method. We also contribute to the literature by examining the other two distributions, t-distribution and Generalised Error Distribution (GED), under GARCH (1,) model. The main reasons underlying the inclusion of t distribution and GED are the facts that most financial time series exhibit non-normal distribution and the presence of fat tails in financial time series. Hence our research objectives are to answer the following two main questions: (1) which distribution of GARCH (1,1) model that the best for modelling time varying beta and (2) which model is the best to use to modelling country risk in emerging markets. This chapter is organized in the following way. We start this chapter by providing a brief introduction to the theoretical foundation of systematic risk (beta). Then, the findings and results of each methodology used in the second empirical study are presented in the next section. The methodology used in this chapter is explained in the section of methodology empirical 2. We end this chapter by providing a summary and conclusion.

6.2. Systematic Risk (Beta)

In this thesis, we use the international version of CAPM. According to Erb, Harvey and Viskanta (1999), by using international version of the CAPM one can infer the beta value as indicator of country risk. Thus a similar conclusion can also be established in the international investment is that if the beta value is relatively stable investors with international perspective can predict the returns more accurately. The main assumptions underlying the use of beta as a proxy of country risk are the global economy will become fully integrated and that most emerging markets will become open and efficient (Copeland, et al. 2000).

However, there has been a substantial amount of evidence in support that security beta coefficients have time varying characteristic over time. Early attempts on this area of study were conducted by Blume (1968), Fisher (1970) and Gonides (1973). More recent studies provide evidence that security betas are not only time varying but can also be better described by some type of stochastic model. For example of this literature are Blume (1971), Fabozzi and Francis (1978), Sunder (1980), Alexander and Benson (1982), Rosenberg and Ohlson (1976) and Bos and Newbold (1984).

Roll (1988), Harvey and Zhou (1993), Giannopolous (1995), Erb, Harvey and Viskanta (1996), Gangemi, Brooks, and Faff (1999a, 1999b), Brooks, Faff and Mckenzie (2002) examined the beta coefficient within the framework of country risk. Giannopolous (1995) used a bivariate GARCH model to calculate betas for weekly stock returns data for 13 developed countries. Brooks, Faff and McKenzie (2002) also used a bivariate GARCH model to calculate betas for 17 developed countries. The existing studies around time varying country risk have largely focused on the set of developed countries and put less emphasis on emerging markets. Thus this paper tries to contribute by focusing on studying the time varying country risk of 28 countries in emerging markets.

6.3. Unconditional International Beta Estimates

The results of the market model specified in equation (1) for each of the countries included in our sample are presented in Table 6. All the beta coefficients are positive and significantly different from zero (except for Morocco and Pakistan) at one percent significant level. The highest (lowest) betas are 1.5185 and 0.0178 respectively. Further investigation reveals that most of the countries samples (75 percent) have beta values less than unity. Thus it implies the systematic risks of the majority countries sample are less than that of the benchmark-world index. This also may suggest that these countries on average will underperform the world market index if the overall market is in bullish condition.

Interestingly, each region of emerging markets has a representative country that has a beta value greater than one. This can be interpreted that these countries have a higher systematic risk than that of the benchmark-world index. It also implies that on average a portfolio consists of securities that tracking the indices from these countries will outperform the return of world index in bullish market.

However it seems that we cannot make a general conclusion about the use of unconditional country beta risk to explain the risk-return trade off in emerging market. By examining the mean return (Table 2 in the data section) with the value of the beta coefficient in Table 6 we find mixed results. For example, the mean return and the beta coefficient of Brazil are higher than Chile. In contrast, Hong Kong has higher mean return as compared to Korea although the Hong Kong's beta is lower than Korea. Furthermore, this consistency in relationship between beta and return exist in each region of emerging markets. For instance, we have a case in Emerging Markets Latin America between Brazil and Mexico, in Emerging

Markets Europe between Turkey and Hungary and in Other Emerging Markets between Egypt and Israel. This fact is also supported by relatively low value of R-square of the market model. As Table 6 shows, the values R-square range from 0.03 percent to 32 percent. This means that in general the ability of the world market return to explain the variability of return in particular market is very weak.

Table 6. Estimates of Emerging Stock Market Point Betas

This table presents the beta point estimates reproduced from table 2. The value of R-squared of the market model together with the value of LM test and the value of White test are presented in the third, fourth and fifth column respectively. The correlation coefficient between the country's return and the world's stock return is presented in the last column.

Country	Beta Estimate (std.error)	OLS R^2	LM test [c]	White test [c]	correlation
Argentina	1.038 [a] (0.114)	0.1334	71.71 **(0.00)**	1.78 (0.41)	0.37
Brazil	1.309 [ab] (0.113)	0.2017	102.57 **(0.00)**	6.54 **(0.04)**	0.45
Chile	0.667 [ab] (0.062)	0.1778	98.13 **(0.00)**	0.58 (0.75)	0.42
Colombia	0.327 [ab] (0.088)	0.0250	37.36 **(0.00)**	2.00 (0.37)	0.16
Mexico	1.116 [ab] (0.075)	0.2924	82.92 **(0.00)**	0.20 (0.90)	0.54
Peru	0.561 [ab] (0.076)	0.0920	41.83 **(0.00)**	3.27 (0.19)	0.30
Venezuela	0.735 [ab] (0.138)	0.0502	0.37 (1.00)	0.29 (0.87)	0.22
Hong Kong	0.988 [a] (0.066)	0.2911	8.71 (0.12)	3.52 (0.17)	0.54
Indonesia	0.703 [ab] (0.144)	0.0427	25.47 **(0.00)**	0.24 (0.89)	0.21
Korea	1.332 [ab] (0.118)	0.1917	138.58 **(0.00)**	1.72 (0.42)	0.44
Malaysia	0.471 [ab] (0.099)	0.0399	31.10 **(0.00)**	0.59 (0.74)	0.20
Philippines	0.601 [ab] (0.082)	0.0906	22.49 **(0.00)**	0.23 (0.89)	0.30

Table 6. Estimates of Emerging Stock Market Point Betas (continued)

Country	Beta Estimate (std.error)	OLS R^2	LM test [c]	White test [c]	correlation
Singapore	0.852 [ab] (0.064)	0.2497	63.60 **(0.00)**	0.54 (0.76)	0.50
Taiwan	0.757 [ab] (0.083)	0.1341	45.90 **(0.00)**	1.01 (0.60)	0.37
Thailand	0.914 [a] (0.108)	0.1181	56.69 **(0.00)**	0.47 (0.79)	0.34
Czech Republic	0.627 [ab] (0.073)	0.1221	11.89 **(0.04)**	5.27 (0.07)	0.35
Greece	0.730 [ab] (0.077)	0.1443	42.62 **(0.00)**	1.00 (0.61)	0.38
Hungary	1.069 [a] (0.088)	0.2152	30.97 **(0.00)**	19.99 **(0.00)**	0.46
Poland	1.049 [a] (0.089)	0.2035	18.97 **(0.00)**	5.15 (0.08)	0.45
Portugal	0.676 [ab] (0.054)	0.2283	53.42 **(0.00)**	35.77 **(0.00)**	0.48
Turkey	1.297 [ab] (0.158)	0.1115	30.55 **(0.00)**	21.02 **(0.00)**	0.33
Egypt	0.194 [ab] (0.076)	0.0118	54.23 **(0.00)**	5.88 (0.05)	0.11
India	0.463 [ab] (0.076)	0.0645	30.37 **(0.00)**	0.97 (0.62)	0.25
Israel	1.056 [a] (0.066)	0.3257	20.42 **(0.00)**	1.77 (0.41)	0.57
Morocco	0.018 [b] (0.043)	0.0003	14.40 **(0.01)**	1.08 (0.58)	0.02
Pakistan	0.146 [b] (0.096)	0.0043	33.65 **(0.00)**	1.40 (0.50)	0.07
South Africa	0.958 [a] (0.063)	0.3005	27.65 **(0.00)**	13.71 **(0.00)**	0.55
Russia	1.519 [ab] (0.168)	0.1329	67.85 **(0.00)**	42.66 **(0.00)**	0.36

Note : [a] significantly different from zero,

[b] significantly different from unity,

[c] *p*-values are in parenthesis

6.4. International Beta Stability Test Results

As mentioned earlier, the first test used to examine the stability in the beta coefficient is by running rolling regression. In particular since we use weekly data, we choose rolling windows of size 52 weeks. Appendix 1 provides the results of the rolling beta coefficients of some of the sample countries used in the study. From the computation (although not all shown in appendix 1), all countries exhibited time variation in their beta coefficients. Furthermore, most of countries exhibited jump in their country risk in 1997 reflected the Asian crisis.

Following McKenzie et al. (2000), the second test used to investigate whether the beta resulted from the market model is stable over time is the recursive residuals of the cumulative sum of the recursive residuals square (or CUSUMSQ) test. The interpretation of this test is relatively straightforward. As mentioned earlier, by looking at the graph we can see whether the cumulative sum of the squared recursive residuals is inside or outside the significance level. If the cumulative sum of the squared recursive residuals crosses the bounds of 5% critical line, one can deduce instability of the parameters of the market model.

The results of the CUSUMQ test are depicted in Appendix 2. It is clear that from the Appendix 2, only Columbia and Czech Republic, which have the recursive residuals within the 5 percent bound of significance while the rest of the countries in the sample have the recursive residuals across the boundary level. This suggests that in general the parameters of the market model are not stable over time. Uniquely, countries in Emerging Market East Asia exhibited almost the same pattern for the CUSUMQ test. The boundary is breached during the 1997, suggesting the Asian crisis.

Alternative tests to check for varying parameters used this study are the LM test for conditional heteroscedasticity in the form of ARCH effects and the White test for unconditional heteroscedasticity. The results of the LM test and the White test, together with their respective p values, are summarized in Table 6. As noted before, a finding of heteroscedasticity from these two tests can be interpreted as evidence of unstable international betas. With regard to the LM test the results are consistent with the CUSUMSQ results is that heteroscedasticity is found for 26 of 28 countries as the test statistics are rejected at the 5% level. Nonetheless it should be stressed here for CUSUMSQ test the only country who has relatively stable parameter is Columbia, Czech Republic and Pakistan whereas for the LM test is Venezuela and Hong Kong. Unlike the two other tests, based on the White test we only found six countries that have heteroscedasticity namely Brazil, Hungary, Portugal, Turkey, South Africa and Russia.

Although it obvious that the three tests do not provide the same results, we may conclude that in general the parameters of the market models of the countries sample are not stable over time. This leads us to the conclusion that the test of parameter stability applied to our data confirms the general findings in the literature that the betas coefficients of the standard market model is time varying in most cases. Thus this fact will justify us to use other models that allowing time varying characteristics of parameter. Later in the subsequent sections we will examine three different techniques: (1) Bivariate GARCH; (2) Schwert and Seguin; and (3) Kalman Filter to estimate the time-varying beta and determine a better model to use than a simple market model.

6.5. GARCH Conditional Beta Results

In this section we estimate the GARCH (1,1) based on three different distributions previously described. As discussed earlier, the estimated variance based on GARCH (1,1) is important input to estimate GARCH conditional beta; the other two necessary inputs are a conditional volatility series for the global market index and a correlation coefficient between the country return and the global market return. Table 7, 8 and 9 present the results of bivariate GARCH (1,1) model for all countries based on the normal distribution, t-distribution and GED respectively.

The ARCH and GARCH coefficients for every country are highly significantly different from zero at the 5 percent and the 1 percent level; the p-value corresponding to its t-statistic is less than 0.05 under the three distributions. All three estimated coefficients in the variance equation are positive for each country under normal distribution and under generalised error distribution, thus the coefficient restrictions to ensure that the variance is positive are satisfied. However, under the t-distribution we have one case, i.e. Venezuela, where the GARCH term is negative thereby violated the positivity assumption underlying the conditional covariance matrix. The significance of GARCH parameter implies that a considerable part of the current volatility of each country stock market index returns can be explained by past volatility.

We found different results for the volatility persistence which measures the stability of the GARCH (1,1) model under three different distributions. Under the normal distribution, there are four countries namely Venezuela, Indonesia, Singapore and Egypt that have the volatility persistence greater than one. However, under t-distribution and generalised error distribution only Egypt remains having the volatility persistence greater than one.

Having generated the conditional variances series for each of the GARCH (1,1) models and the correlation coefficients, we then estimate the value of the beta (β_{it}^{G}) using the standard formula to calculate slope coefficient of simple regression model. The mean value of beta along with the highest and lowest value (in brackets) is presented in Table 10. As can be seen from Table 10, the beta values derived from the GARCH (1,1) models form the three distributions do not deviate from the point of estimates of the market model. Moreover the correlation coefficient between beta series generated from the market model and beta series generated from the GARCH (1,1) under the three different distributions is considerably high 0.994 . This finding is consistent with other research on the time varying beta [e.g. Brooks, Faff and Mckenzie (2002)]. However, we cannot directly draw a solid conclusion that there is a strong relationship between the two series. This is because we have to take into account the information concerning the variability of the risk measure itself.

If we look at Table 10 again, we can see that the values of β_{it}^{G} for each country vary significantly. It is interesting to note the countries with the highest and the lowest range for the three different distributions are the same. The country which has the highest range of beta values is Venezuela whereas the country which has the lowest range of beta values is Morocco. In particular for the highest range, the t-distribution ranks first and then followed by the normal distribution and generalised error distribution. Likewise, GED ranks first for the lowest range value of the beta series generated by GARCH (1,1) model and then followed by the normal distribution and the t-distribution.

Table 7. GARCH Model Estimation (Normal Distribution) for Each Country

This table presents GARCH parameters for models fitted to each country return series and the world index (standard errors in parentheses). The sum of the GARCH parameter estimates is an indication of the persistence of shocks in the model and should be less than unity.

Country	ω	α	β	$\alpha + \beta$
Argentina	0.00037[a] (0.00005)	0.32806 [a] (0.06029)	0.60385 [a] (0.04572)	0.93190
Brazil	0.00017 [a] (0.00004)	0.23407 [a] (0.03535)	0.73958 [a] (0.02632)	0.97365
Chile	0.00007 [a] (0.00002)	0.12354 [a] (0.02038)	0.80639 [a] (0.02682)	0.92994
Colombia	0.00063 [a] (0.00012)	0.37635 [a] (0.05935)	0.31593 [a] (0.09133)	0.69229
Mexico	0.00003 [a] (0.00001)	0.11480 [a] (0.01845)	0.86960 [a] (0.02082)	0.98440
Peru	0.00012 [a] (0.00003)	0.13191 [a] (0.01863)	0.77842 [a] (0.03309)	0.91033
Venezuela	0.00024 [a] (0.00005)	0.40428 [a] (0.05062)	0.68017 [a] (0.02445)	**1.08445**
Hong Kong	0.00002 (0.00002)	0.12516 [a] (0.02289)	0.87262 [a] (0.03035)	0.99778
Indonesia	0.00004 [b] (0.00002)	0.17158 [a] (0.02083)	0.84322 [a] (0.02006)	**1.01481**
Korea	0.00006 [b] (0.00003)	0.13875 [a] (0.02166)	0.85032 [a] (0.02289)	0.98907
Malaysia	0.00001 [a] (0.00000)	0.09761 [a] (0.01152)	0.89948 [a] (0.01046)	0.99709
Philippines	0.00004 [a] (0.00002)	0.13653 [a] (0.02145)	0.84328 [a] (0.02362)	0.97980
Singapore	0.00001 (0.00000)	0.09786 [a] (0.01652)	0.90393 [a] (0.01619)	**1.00179**
Taiwan	0.00009 [a] (0.00003)	0.10546 [a] (0.02795)	0.84884 [a] (0.03854)	0.95429
Thailand	0.00002 (0.00002)	0.10565 [a] (0.03049)	0.88680 [a] (0.03045)	0.99246
Czech Republic	0.00018 [b] (0.00008)	0.16531 [a] (0.04085)	0.70507 [a] (0.08627)	0.87039
Greece	0.00001 [b] (0.00000)	0.08863 [a] (0.02287)	0.90386 [a] (0.02407)	0.99248
Hungary	0.00038 [a] (0.00011)	0.23688 [a] (0.04836)	0.58284 [a] (0.09099)	0.81973
Poland	0.00009 [b] (0.00006)	0.05820 [a] (0.01874)	0.89708 [a] (0.040471)	0.95528
Portugal	0.00001 [b] (0.00000)	0.07899 [a] (0.01974)	0.91008 [a] (0.02272)	0.98906
Turkey	0.00020 [a] (0.00008)	0.06903 [a] (0.01635)	0.90110 [a] (0.02319)	0.97013
Egypt	0.00002 [b] (0.00000)	0.18564 [a] (0.02845)	0.82578 [a] (0.02390)	**1.01142**
India	0.00005 (0.00003)	0.06894 [a] (0.02350)	0.89660 [a] (0.03949)	0.96553

Israel	0.00003 [a] (0.00001)	0.06168 [a] (0.01341)	0.91324 [a] (0.01542)	0.97492
Morocco	0.00005 [b] (0.00002)	0.08732 [a] (0.02596)	0.79118 [a] (0.06708)	0.87849
Pakistan	0.00049 [a] (0.00012)	0.21503 [a] (0.05572)	0.55329 [a] (0.09181)	0.76832
South Africa	0.00006 [a] (0.00001)	0.10473 [a] (0.02006)	0.85175 [a] (0.02259)	0.95648
Russia	0.00023 [a] (0.00009)	0.13428 [a] (0.02265)	0.83417 [a] (0.02919)	0.96844
World	0.00001 (0.00000)	0.09982 [a] (0.02876)	0.88900 [a] (0.03345)	0.98883

Note: a indicates significantly different from zero at the 1% level.

b indicates significantly different from zero at the 5% level

Table 8. GARCH Model Estimation (t-Distribution) for Each Country

This table presents GARCH parameters for models fitted to each country return series and the world index (standard errors in parentheses). The sum of the GARCH parameter estimates is an indication of the persistence of shocks in the model and should be less than unity.

Country	ω	A	β	$\alpha + \beta$
Argentina	0.00030 [b] (0.00013)	0.22612 [a] (0.07333)	0.70667 [a] (0.07629)	0.93279
Brazil	0.00020 [a] (0.00008)	0.19816 [a] (0.05338)	0.74802 [a] (0.05679)	0.94619
Chile	0.00010 [b] (0.00004)	0.11860 [a] (0.03883)	0.77415 [a] (0.06486)	0.89274
Colombia	0.00053 [a] (0.00018)	0.36720 [a] (0.11765)	0.41379 [a] (0.13415)	0.78100
Mexico	0.00002 (0.00001)	0.10065 [a] (0.02811)	0.88777 [a] (0.02817)	0.98842
Peru	0.00010 [b] (0.00005)	0.12647 [a] (0.04387)	0.81228 [a] (0.05906)	0.93875
Venezuela	0.00216 [a] (0.00031)	0.51512 [a] (0.13925)	**-0.01422** (0.02446)	0.50090
Hong Kong	0.00001 (0.00001)	0.07237 [a] (0.02814)	0.91678 [a] (0.03183)	0.98915
Indonesia	0.00005 [b] (0.00003)	0.13319 [a] (0.03681)	0.86229 [a] (0.03217)	0.99548
Korea	0.00008 [b] (0.00005)	0.11400 [a] (0.03368)	0.85985 [a] (0.03584)	0.97386
Malaysia	0.00001 (0.00000)	0.07678 [a] (0.02282)	0.91625 [a] (0.02026)	0.99303
Philippines	0.00007 [b] (0.00003)	0.09758 [a] (0.03652)	0.85606 [a] (0.04782)	0.95365
Singapore	0.00001 (0.00000)	0.07295 [a] (0.02247)	0.92343 [a] (0.02262)	0.99638
Taiwan	0.00007 (0.00004)	0.10663 [a] (0.03506)	0.85529 [a] (0.04666)	0.96193
Thailand	0.00002 (0.00002)	0.10324 [a] (0.03416)	0.88861 [a] (0.03354)	0.99185
Czech Republic	0.00017 [b] (0.00009)	0.15257 [a] (0.04672)	0.72237 [a] (0.09681)	0.87494
Greece	0.00001 (0.00000)	0.08993 [a] (0.02705)	0.90382 [a] (0.02786)	0.99375
Hungary	0.00025 [b] (0.00011)	0.16780 [a] (0.05344)	0.71318 [a] (0.08740)	0.88098
Poland	0.00009 (0.00007)	0.07000 [b] (0.03120)	0.88786 [a] (0.05277)	0.95786
Portugal	0.00001 (0.00000)	0.07954 [a] (0.02665)	0.91451 [a] (0.02771)	0.99405
Turkey	0.00012 (0.00008)	0.05306 [a] (0.01971)	0.92705 [a] (0.02655)	0.98011
Egypt	0.00003 [b] (0.00001)	0.32268 [a] (0.07625)	0.73255 [a] (0.04493)	**1.05523**
India	0.00005 [b] (0.00004)	0.06554 [a] (0.02473)	0.89584 [a] (0.04383)	0.96139

Israel	0.00004 (0.00002)	0.07981 [a] (0.02898)	0.88978 [a] (0.03732)	0.96959
Morocco	0.00005 (0.00003)	0.08968 [a] (0.04217)	0.79489 [a] (0.10099)	0.88457
Pakistan	0.00044 [a] (0.00016)	0.20786 [a] (0.06836)	0.58534 [a] (0.11591)	0.79321
South Africa	0.00003 [b] (0.00002)	0.10421 [a] (0.03389)	0.87787 [a] (0.03597)	0.98208
Russia	0.00029 [b] (0.00015)	0.12354 [a] (0.04023)	0.84031 [a] (0.04499)	0.96385
World	0.00001 (0.00000)	0.08936 [a] (0.02996)	0.89863 [a] (0.03459)	0.98799

Note: a indicates significantly different from zero at the 1% level.

b indicates significantly different from zero at the 5% level

Table 9. GARCH Model Estimation (GED) for Each Country

This table presents GARCH parameters for models fitted to each country return series and the world index (standard errors in parentheses). The sum of the GARCH parameter estimates is an indication of the persistence of shocks in the model and should be less than unity.

Country	ω	α	β	$\alpha+\beta$
Argentina	0.00027 [a] (0.0001)	0.21909 [a] (0.06977)	0.70572 [a] (0.07376)	0.92482
Brazil	0.00018 [a] (0.00007)	0.20463 [a] (0.05288)	0.74734 [a] (0.05015)	0.95197
Chile	0.00008 [a] (0.00003)	0.11781 [a] (0.03195)	0.79621 [a] (0.04521)	0.91402
Colombia	0.00054 [a] (0.00019)	0.35105 [a] (0.10273)	0.37640 [a] (0.14577)	0.72745
Mexico	0.00003 (0.00002)	0.10973 [a] (0.02850)	0.87497 [a] (0.03016)	0.98470
Peru	0.00010 [b] (0.00005)	0.11950 [a] (0.03655)	0.80235 [a] (0.05959)	0.92185
Venezuela	0.00063 [a] (0.00024)	0.33807 [a] (0.10743)	0.55918 [a] (0.09657)	0.89725
Hong Kong	0.00002 (0.00002)	0.10629 [a] (0.03727)	0.88677 [a] (0.04044)	0.99307
Indonesia	0.00005 (0.00003)	0.14415 [a] (0.03678)	0.85456 [a] (0.03355)	0.99871
Korea	0.00007 [b] (0.00004)	0.12647 [a] (0.03203)	0.85442 [a] (0.03209)	0.98089
Malaysia	0.00001 (0.00000)	0.08214 [a] (0.02053)	0.90756 [a] (0.01988)	0.98970
Philippines	0.00006 [b] (0.00003)	0.11953 [a] (0.03787)	0.84248 [a] (0.04445)	0.96202
Singapore	0.00001 (0.00000)	0.08458 [a] (0.02425)	0.91337 [a] (0.02401)	0.99794
Taiwan	0.00009 [b] (0.00005)	0.10335 [a] (0.03489)	0.84934 [a] (0.05013)	0.95269
Thailand	0.00002 (0.00002)	0.10239 [a] (0.03182)	0.88965 [a] (0.03144)	0.99203
Czech Republic	0.00016 [b] (0.00009)	0.13930 [a] (0.04549)	0.74522 [a] (0.09718)	0.88452
Greece	0.00001 (0.00000)	0.08924 [a] (0.02670)	0.90433 [a] (0.02774)	0.99357
Hungary	0.00030 [b] (0.00012)	0.18548 [a] (0.05487)	0.66594 [a] (0.10429)	0.85142
Poland	0.00008 (0.00006)	0.06095 [b] (0.02686)	0.89987 [a] (0.04929)	0.96082
Portugal	0.00001 (0.00000)	0.07707 [a] (0.02643)	0.91325 [a] (0.02956)	0.99032
Turkey	0.00015 (0.00011)	0.05691 [a] (0.02315)	0.91578 [a] (0.03372)	0.97268
Egypt	0.00003 [b] (0.00015)	0.28383 [a] (0.07001)	0.75068 [a] (0.04838)	**1.03451**
India	0.00004 (0.00003)	0.06640 [a] (0.02370)	0.90090 [a] (0.03957)	0.96731

Israel	0.00003 [b] (0.00002)	0.06741 [a] (0.02069)	0.90635 [a] (0.02530)	0.97377
Morocco	0.00005 (0.00003)	0.08355 [b] (0.03926)	0.79952 [a] (0.10124)	0.88307
Pakistan	0.00047 [a] (0.00018)	0.20794 [a] (0.07470)	0.57126 [a] (0.12924)	0.77919
South Africa	0.00004 [b] (0.00002)	0.10010 [a] (0.03073)	0.86903 [a] (0.03575)	0.96914
Russia	0.00026 [b] (0.00017)	0.12124 [a] (0.03555)	0.83575 [a] (0.04726)	0.95699
World	0.00001 (0.00000)	0.09427 [a] (0.03088)	0.89460 [a] (0.03559)	0.98887

Note: a indicates significantly different from zero at the 1% level.

b indicates significantly different from zero at the 5% level

Table 10. GARCH Betas for the Three Distributions

This table the beta point estimate reproduced from table 3. The mean conditional beta together with their high/low values using the GARCH based on normal distribution, t-distribution and GED are presented in columns 2,3 and 4 respectively.

Country	Normal Distribution (high/low)	T Distribution (high/low)	Generalised Error Distribution (high/low)	Point Estimates of Beta
Argentina	1.0455 (4.50/0.39)	1.0516 (3.84/0.43)	1.0194 (3.83/0.41)	1.038
Brazil	1.2832 (6.79/0.57)	1.2643 (6.11/0.60)	1.2573 (6.30/0.58)	1.309
Chile	0.6934 (2.79/0.28)	0.6914 (2.64/0.30)	0.6901 (2.69/0.29)	0.667
Colombia	0.3564 (1.20/0.13)	0.3663 (1.21/0.14)	0.3541 (1.18/0.13)	0.327
Mexico	1.1427 (3.69/0.49)	1.1449 (3.44/0.51)	1.1386 (3.60/0.50)	1.116
Peru	0.5932 (2.09/0.23)	0.6137 (2.03/0.24)	0.5922 (1.99/0.23)	0.561
Venezuela	0.8445 (9.27/0.26)	0.7254 (10.27/0.28)	0.7637 (8.45/0.28)	0.735
Hong Kong	1.0150 (3.09/0.51)	0.9964 (2.45/0.48)	1.0135 (2.90/0.51)	0.988
Indonesia	0.6421 (2.94/0.22)	0.6312 (2.65/0.24)	0.6284 (2.73/0.23)	0.703
Korea	1.2629 (4.58/0.63)	1.2485 (4.25/0.64)	1.2553 (4.41/0.63)	1.332
Malaysia	0.3964 (1.33/0.12)	0.4011 (1.26/0.13)	0.3870 (1.26/0.12)	0.471
Philippines	0.6007 (1.43/0.21)	0.6027 (1.25/0.23)	0.5949 (1.35/0.22)	0.601
Singapore	0.8433 (2.25/0.43)	0.8413 (2.11/0.44)	0.8376 (2.17/0.43)	0.852
Taiwan	0.7991 (1.52/0.45)	0.7957 (1.49/0.47)	0.7966 (1.51/0.46)	0.757
Thailand	0.9016 (2.35/0.31)	0.9005 (2.29/0.32)	0.9031 (2.32/0.31)	0.914
Czech Republic	0.6776 (2.07/0.30)	0.6788 (1.98/0.31)	0.6778 (1.94/0.31)	0.627
Greece	0.7321 (1.61/0.31)	0.7300 (1.58/0.31)	0.7309 (1.59/0.31)	0.730
Hungary	1.1006 (2.92/0.47)	1.1021 (2.63/0.49)	1.0907 (2.68/0.47)	1.069
Poland	1.1213 (2.28/0.45)	1.1309 (2.36/0.46)	1.1212 (2.30/0.45)	1.049
Portugal	0.6838 (1.25/0.44)	0.6864 (1.25/0.46)	0.6822 (1.24/0.44)	0.676
Turkey	1.3446 2.29/0.55	1.3258 (2.11/0.58)	1.3164 (2.13/0.55)	1.297
Egypt	0.2090 (0.66/0.05)	0.2157 (0.74/0.05)	0.2121 (0.72/0.05)	0.194

India	0.5059 (0.93/0.17)	0.5012 (0.91/0.18)	0.5047 (0.92/0.17)	0.463
Israel	1.0897 (1.65/0.50)	1.0791 (1.76/0.51)	1.0815 (1.65/0.51)	1.056
Morocco	0.0196 (0.04/0.01)	0.0197 (0.04/0.01)	0.0194 (0.04/0.01)	0.018
Pakistan	0.1578 (0.50/0.06)	0.1573 (0.49/0.06)	0.1579 (0.49/0.06)	0.146
South Africa	0.9884 (2.33/0.54)	0.9929 (2.36/0.58)	0.9781 (2.31/0.55)	0.958
Russia	1.5366 (4.57/0.54)	1.5702 (4.47/0.59)	1.5183 (4.39/0.56)	1.519

6.6. Schwert and Seguin Conditional Beta Results

Table 11, 12, 13 display the results of the Schwert and Seguin model for normal distribution, t-distribution and generalised error distribution respectively. The estimated coefficient values for α_i, β_i and δ_i, their respective statistics, the regression equation R^2 and standard error of estimate are presented in these tables.

As mentioned before, in order to generate Schwert and Seguin conditional beta series, we need firstly to estimate the conditional volatility of the market return. Thus, the series of variance of the world stock market index derived from the GARCH (1,1) model is needed in order to generate the beta series (β_{it}^{SS}) using the equation $\beta^{SS}{}_{it} = \beta_i + \delta_i / \sigma^2_{wt}$.

It can be seen from the Table 11, with the exception of Peru and Greece, the δ coefficients are not statistically significant. Thus we can conclude that in general the statistical significance of coefficient δ is weak. This finding confirms the results of previous research conducted by Episcopos (1996) and Brooks et.al (1998, 2002), among others, who also found insignificance of the δ coefficient. As a result, the value of R square for each country is mostly similar to the market model. On the other hand, as shown in Table 12 and Table 13, there are 13 countries which have significance of their δ coefficient under t-distribution and generalised error distribution. Nevertheless the values of R square among the Schwert and Seguin models under the three distributions are very similar. In fact the average differences in the value of R square are zero. Thus we may conclude that as in the case of normal distribution that the inclusion of coefficient δ is not significant under the other two distributions.

The value of R square of the Schwert and Seguin model ranges from 0.3 percent (Morocco) to 32.7 percent (Israel) under the normal distribution and these range values are similar to those under t-distribution and generalised error distribution. This implies that the inclusion of the δ_i term to the original market model does not increase the ability of the model to explain the variability of return. Furthermore, under the normal distribution there are 17 countries in which the δ coefficients are positive. This means that in general there is an inverse relationship between systematic risk and the world stock market index volatility under the normal distribution. By contrast, under the t-distribution and generalised error distribution it is found that there are 22 countries that have negative δ coefficients.

Since the δ coefficient is not significant, the mean of β_{it}^{SS} is similar to those of market model as indicated by the correlation coefficient between the two series which is very high at 0.99. However like the previous discussion in the GARCH section, we cannot draw a conclusion solely based on the correlation parameter. Likewise if we observe that the value of β_{it}^{SS} vary considerably this suggest that there is information contained in the time series. Unlike the beta series for GARCH (1,1) models, the range values for the Schwert and Seguin models are different under the three distribution. As can be seen from Table 14, the highest range value of β_{it}^{SS} (1.36) is Indonesia whereas the lowest range value (0.06) is South Africa under the normal distribution. For t-distribution and generalised error distribution the pair countries with the highest and the lowest ranges are Thailand-Israel and Thailand-Morocco. Comparing these ranges with those of M-GARCH might lead us to the conclusion that the the Schwert and Seguin model yields a better beta prediction since the range is quite narrow. However we have to use more trustworthy methodologies for evaluating forecasting performance namely MAE and MSE.

Table 11. Schwert and Seguin Augmented Market Model Estimation for Emerging Market Countries Based on Normal Distribution

This table present the estimated coefficient values and descriptive statistics using the Schwert and Seguin (1990) Market Model. The last two columns present the value of R-squared and Standard Error of Regression.

Country	α_i	β_i	δ_i	R^2	SEE
Argentina	-0.0011 (0.47)	0.8741 (3.96)	0.0001 (0.87)	0.135	0.054
Brazil	-0.0008 (0.33)	1.2045 (5.54)	0.0000 (0.57)	0.202	0.053
Chile	-0.0006 (0.50)	0.7111 (5.94)	-0.0000 (0.43)	0.178	0.029
Colombia	0.0004 (0.21)	0.2299 (1.35)	0.0000 (0.67)	0.026	0.041
Mexico	0.0001 (0.07)	0.9642 (6.66)	0.0001 (1.23)	0.294	0.035
Peru	0.0005 (0.33)	0.2324 (1.59)	**0.0001** **(2.63)**	0.104	0.036
Venezuela	-0.0003 (0.10)	0.4969 (1.86)	0.0001 (1.04)	0.052	0.065
Hong Kong	-0.0005 (0.39)	0.8864 (6.89)	0.0000 (0.92)	0.292	0.031
Indonesia	-0.0026 (0.89)	0.3204 (1.15)	0.0002 (1.61)	0.047	0.067
Korea	-0.0010 (0.41)	1.6435 (7.21)	-0.0001 (1.60)	0.195	0.055
Malaysia	-0.0014 (0.67)	0.2566 (1.33)	0.0001 (1.30)	0.043	0.047
Philippines	-0.0027 (1.62)	0.3493 (2.20)	0.0001 (1.86)	0.096	0.039
Singapore	-0.0012 (0.95)	0.9387 (7.61)	-0.0000 (0.82)	0.251	0.030
Taiwan	-0.0015 (0.87)	0.9161 (5.71)	-0.0001 (1.16)	0.136	0.039
Thailand	-0.0029 (1.32)	0.8532 (4.09)	0.0000 (0.34)	0.118	0.051
Czech Republic	0.0014 (0.95)	0.7872 (5.62)	-0.0001 (1.34)	0.125	0.034
Greece	0.0016 (1.00)	1.0591 (7.19)	**-0.0001** **(2.61)**	0.155	0.036
Hungary	0.0024 (1.36)	1.1315 (6.64)	-0.0000 (0.42)	0.216	0.041
Poland	-0.0003 (0.15)	0.9916 (5.73)	0.0000 (0.39)	0.204	0.042
Portugal	0.0005 (0.47)	0.7834 (7.55)	-0.0000 (1.20)	0.230	0.025
Turkey	0.0005 (0.15)	1.4528 (4.75)	-0.0001 (0.60)	0.112	0.074
Egypt	0.0027 (1.71)	0.0405 (0.27)	0.0001 (1.21)	0.015	0.036
India	-0.0001 (0.09)	0.2540 (1.73)	0.0001 (1.67)	0.069	0.036

Israel	0.0004 (0.32)	1.1712 (9.24)	-0.0000 (1.06)	0.327	0.031
Morocco	0.0011 (1.32)	-0.0731 (0.88)	0.0000 (1.28)	0.003	0.020
Pakistan	-0.0009 (0.44)	-0.1263 (0.68)	0.0001 (1.71)	0.010	0.045
South Africa	-0.0006 (0.49)	0.9733 (7.98)	-0.0000 (0.15)	0.301	0.030
Russia	0.0013 (0.39)	1.4828 (4.58)	0.0000 (0.13)	0.133	0.079

Note: Absolute values of t-statistics are in parenthesis.

Table 12. Schwert and Seguin Augmented Market Model Estimation for Emerging Market Countries Based on T-Distribution

This table present the estimated coefficient values and descriptive statistics using the Schwert and Seguin (1990) Market Model. The last two columns present the value of R-squared and Standard Error of Regression.

Country	α_i	β_i	δ_i	R^2	SEE
Argentina	-0.0010 (0.42)	1.1756 (6.10)	-0.0003 (0.89)	0.135	0.054
Brazil	-0.0006 (0.26)	1.6282 (8.61)	**-0.0008** **(2.09)**	0.208	0.053
Chile	-0.0006 (0.47)	0.8163 (7.84)	-0.0004 (1.78)	0.183	0.029
Colombia	0.0004 (0.22)	0.2412 (1.62)	0.0002 (0.72)	0.026	0.041
Mexico	0.0003 (0.18)	1.3419 (10.66)	**-0.0005** **(2.23)**	0.299	0.035
Peru	0.0007 (0.44)	0.6368 (4.96)	-0.0002 (0.73)	0.093	0.036
Venezuela	-0.0002 (0.06)	0.7644 (3.28)	-0.0001 (0.16)	0.050	0.065
Hong Kong	-0.0004 (0.29)	1.2294 (11.02)	**-0.0006** **(2.69)**	0.301	0.031
Indonesia	-0.0023 (0.80)	0.8962 (3.70)	-0.0005 (0.99)	0.044	0.068
Korea	-0.0010 (0.41)	1.6940 (8.54)	**-0.0009** **(2.27)**	0.199	0.055
Malaysia	-0.0012 (0.58)	0.7253 (4.32)	-0.0006 (1.89)	0.046	0.047
Philippines	-0.0025 (1.50)	0.8374 (6.06)	**-0.0006** **(2.12)**	0.098	0.039
Singapore	-0.0012 (0.92)	1.0475 (9.78)	**-0.0005** **(2.26)**	0.257	0.030
Taiwan	-0.0015 (0.89)	0.8387 (5.99)	-0.0002 (0.73)	0.135	0.039
Thailand	-0.0026 (1.21)	1.5426 (8.63)	**-0.0015** **(4.36)**	0.148	0.050
Czech Republic	0.0014 (0.95)	0.7712 (6.31)	-0.0003 (1.47)	0.126	0.034
Greece	0.0015 (0.95)	0.9191 (7.12)	-0.0005 (1.83)	0.150	0.036
Hungary	0.0026 (1.44)	1.4307 (9.70)	**-0.0009** **(3.04)**	0.229	0.041
Poland	-0.0001 (0.08)	1.3337 (8.87)	**-0.0007** **(2.35)**	0.212	0.042
Portugal	0.0005 (0.49)	0.8364 (9.27)	**-0.0004** **(2.20)**	0.235	0.025
Turkey	0.0004 (0.12)	1.2611 (4.73)	0.0001 (0.17)	0.112	0.074
Egypt	0.0027 (1.73)	0.1063 (0.82)	0.0002 (0.84)	0.013	0.036
India	-0.0001 (0.07)	0.3361 (2.62)	0.0003 (1.23)	0.067	0.036

Israel	0.0004 (0.29)	1.0756 (9.71)	-0.0000 (0.22)	0.326	0.031
Morocco	0.0012 (1.35)	-0.0037 (0.05)	0.0001 (0.37)	0.001	0.020
Pakistan	-0.0008 (0.43)	-0.1143 (0.71)	**0.0006** **(2.00)**	0.012	0.045
South Africa	-0.0005 (0.41)	1.2374 (11.74)	**-0.0007** **(3.29)**	0.314	0.029
Russia	0.0016 (0.46)	2.0693 (7.36)	**-0.0013** **(2.43)**	0.142	0.078

Note: Absolute values of t-statistics are in parenthesis.

Table 13. Schwert and Seguin Augmented Market Model Estimation for Emerging Market Countries Based on Generalised Error Distribution

This table present the estimated coefficient values and descriptive statistics using the Schwert and Seguin (1990) Market Model. The last two columns present the value of R-squared and Standard Error of Regression.

Country	α_i	β_i	δ_i	R^2	SEE
Argentina	-0.0010 (0.42)	1.1486 (6.13)	-0.0003 (0.75)	0.134	0.054
Brazil	-0.0006 (0.26)	1.6014 (8.70)	**-0.0007 (2.00)**	0.208	0.053
Chile	-0.0006 (0.47)	0.8080 (7.97)	-0.0003 (1.76)	0.182	0.029
Colombia	0.0004 (0.22)	0.2464 (1.70)	0.0002 (0.71)	0.026	0.041
Mexico	0.0003 (0.17)	1.3165 (10.74)	**-0.0005 (2.06)**	0.298	0.035
Peru	0.0007 (0.44)	0.6270 (5.02)	-0.0002 (0.67)	0.093	0.036
Venezuela	-0.0002 (0.06)	0.7551 (3.33)	-0.0000 (0.11)	0.050	0.065
Hong Kong	-0.0004 (0.29)	1.2142 (11.18)	**-0.0005 (2.63)**	0.300	0.031
Indonesia	-0.0023 (0.80)	0.8826 (3.74)	-0.0004 (0.96)	0.044	0.068
Korea	-0.0010 (0.41)	1.6752 (8.68)	**-0.0008 (2.24)**	0.199	0.055
Malaysia	-0.0012 (0.58)	0.7095 (4.35)	-0.0006 (1.85)	0.046	0.047
Philippines	-0.0025 (1.50)	0.8160 (6.06)	**-0.0005 (2.01)**	0.097	0.039
Singapore	-0.0012 (0.92)	1.0387 (9.96)	**-0.0004 (2.25)**	0.257	0.030
Taiwan	-0.0015 (0.89)	0.8385 (6.15)	-0.0002 (0.76)	0.135	0.039
Thailand	-0.0026 (1.21)	1.5028 (8.63)	**-0.0014 (4.26)**	0.147	0.050
Czech Republic	0.0014 (0.95)	0.7639 (6.42)	-0.0003 (1.45)	0.126	0.034
Greece	0.0015 (0.95)	0.9064 (7.22)	-0.0004 (1.78)	0.149	0.036
Hungary	0.0026 (1.43)	1.4007 (9.75)	**-0.0008 (2.90)**	0.227	0.041
Poland	-0.0001 (0.08)	1.3091 (8.94)	**-0.0006 (2.24)**	0.211	0.042
Portugal	0.0005 (0.49)	0.8274 (9.42)	**-0.0003 (2.17)**	0.235	0.025
Turkey	0.0004 (0.12)	1.2258 (4.72)	0.0002 (0.35)	0.112	0.074
Egypt	0.0027 (1.73)	0.1089 (0.87)	0.0002 (0.85)	0.013	0.036
India	-0.0001 (0.07)	0.3463 (2.77)	0.0003 (1.18)	0.067	0.036

Israel	0.0004 (0.29)	1.0777 (10.00)	-0.0000 (0.25)	0.326	0.031
Morocco	0.0012 (1.35)	0.0023 (0.03)	0.0000 (0.28)	0.000	0.020
Pakistan	-0.0008 (0.43)	-0.1003 (0.64)	**0.0006** **(1.97)**	0.011	0.045
South Africa	-0.0005 (0.41)	1.2199 (11.89)	**-0.0006** **(3.22)**	0.314	0.029
Russia	0.0016 (0.46)	2.0306 (7.42)	**-0.0012** **(2.36)**	0.142	0.078

Note: Absolute values of t-statistics are in parenthesis.

Table 14. Schwert and Seguin Betas for the Three Distributions

This table presents the beta point estimate reproduced from table 2. The mean conditional beta together with their high/low values estimated using the Schwert and Seguin model based on normal distribution, t-distribution and GED are presented in columns 2,3, and 4 respectively.

Country	Normal Distribution (high/low)	T Distribution (high/low)	Generalised Error Distribution (high/low)	Point Estimates of Beta
Argentina	1.0960 (1.50/0.92)	0.9965 (1.17/0.61)	1.0027 (1.15/0.65)	1.038
Brazil	1.3471 (1.61/1.23)	1.2140 (1.62/0.32)	1.2172 (1.59/0.28)	1.309
Chile	0.6512 (0.70/0.54)	0.6221 (0.81/0.20)	0.6222 (0.80/0.17)	0.667
Colombia	0.3620 0.60/0.25	0.3532 (0.59/0.24)	0.3530 (0.61/0.25)	0.327
Mexico	1.1703 1.54/1.00	1.0484 1.34/0.42	1.0527 1.31/0.41	1.116
Peru	0.6779 1.49/0.32	0.5383 0.63/0.33	0.54016 0.63/0.33	0.561
Venezuela	0.8195 1.40/0.56	0.7260 0.76/0.64	0.7285 0.75/0.66	0.735
Hong Kong	1.0240 1.27/0.91	0.9153 1.22/0.24	0.9161 1.21/0.19	0.988
Indonesia	0.8396 1.78/0.42	0.6456 0.89/0.11	0.6467 0.88/0.07	0.703
Korea	1.2212 1.56/0.46	1.2231 1.68/0.21	1.2231 1.67/0.12	1.332
Malaysia	0.5468 1.07/0.31	0.3942 0.72/-0.32	0.3950 0.70/-0.37	0.471
Philippines	0.6909 1.31/0.41	0.5304 0.83/-0.13	0.5333 0.81/-0.15	0.601
Singapore	0.8219 0.92/0.61	0.7939 1.04/0.25	0.7935 1.03/0.20	0.852
Taiwan	0.7004 0.88/0.31	0.7324 0.84/0.50	0.7311 0.84/0.47	0.757
Thailand	0.9361 1.09/0.87	0.7256 1.52/-1.03	0.7278 1.49/-1.16	0.914
Czech Republic	0.5699 0.75/0.18	0.5834 0.77/0.18	0.5834 0.76/0.14	0.627
Greece	0.6123 0.97/-0.20	0.6725 0.91/0.14	0.6734 0.90/0.11	0.730
Hungary	1.0479 1.12/0.90	0.9614 1.42/-0.05	0.9649 1.39/-0.09	1.069
Poland	1.0690 1.21/1.01	0.9631 1.33/0.17	0.9662 1.30/0.13	1.049
Portugal	0.6386 0.76/0.38	0.6286 0.83/0.18	0.6288 0.82/0.15	0.676
Turkey	1.2418 1.41/0.86	1.3079 1.41/1.26	1.3197 1.55/1.23	1.297
Egypt	0.2484 0.63/0.08	0.22019 0.46/0.11	0.2208 0.49/0.11	0.194
India	0.5378 1.05/0.31	0.5016 0.86/0.34	0.5005 0.88/0.35	0.463

Israel	1.0156 1.14/0.73	1.0506 1.08/0.99	1.0496 1.08/0.98	1.056
Morocco	0.0501 0.27/-0.05	0.0242 0.08/-0.003	0.0227 0.07/0.003	0.018
Pakistan	0.2422 0.91/-0.06	0.2237 0.95/-0.11	0.2235 1.01/-0.10	0.146
South Africa	0.9524 0.97/0.91	0.8739 1.23/0.09	0.8748 1.21/0.04	0.958
Russia	1.5312 1.62/1.49	1.35301 2.05/-0.18	1.3562 2.02/-0.28	1.519

6.7. Kalman Filter Conditional Beta Results

The final model used to generate conditional betas in this paper is the Kalman Filter Model. More specifically we use three different techniques, random walk, autoregressive and random coefficient. The mean, the highest and the lowest beta values of these three techniques for each country in the sample are summarized in Table 15. If we compare the results of the beta series generated with the three Kalman Filter models, with those of market models, it appears that these series are similar as indicated by the average correlation coefficient of 0.938. Nonetheless there is a wide range of mean betas for each country indicating that the alternative models provide additional information over the market model beta.

Unlike the beta series for GARCH (1,1) models, the range values for the beta series are different within the class of Kalman Filter models. As can be seen from Table 15, the highest range value of random walk model (22.96) is Venezuela whereas the lowest range value (1.55) is Colombia[4]. For autoregressive and random coefficient the pair countries with the highest and the lowest ranges are Venezuela-Egypt and Indonesia-Egypt respectively.

Table 15. Kalman Filter Mean Model Parameter of Emerging Stock Market Betas

This table presents the Random Walk, the AR(1) and the Random Coefficient conditional beta estimates.

Country	Random Walk Parameterisation Mean Beta (high/low)	AR(1) Parameterisation Mean Beta (high/low)	Random Coefficient Parameterisation Mean Beta (high/low)	Point Estimates of Beta
Argentina	1.0911 2.26/-0.12	1.2744 2.31/1.02	1.2805 8.48/-4.74	1.038
Brazil	1.3592 2.60/0.49	1.4176 2.96/-0.01	1.4190 4.95/-1.27	1.309
Chile	0.6669 1.82/-0.16	0.9444 1.61/0.81	0.6840 1.57/0.17	0.667
Colombia	0.3904 1.29/-0.26	0.8664 1.29/0.51	0.4768 0.80/0.30	0.327

[4] The relatively high value of beta estimated from a model (such as Random Walk in the case of Venezuela) implies an extreme condition and as a consequence one has to be cautious in implementing the model because the estimation result will be very sensitive.

Mexico	1.1247 2.05/0.49	1.0230 2.34/0.36	1.1971 2.32/0.20	1.116
Peru	0.6983 2.36/-0.49	0.7164 1.27/0.16	0.6640 1.72/0.19	0.561
Venezuela	0.8191 8.14/-14.82	0.6437 11.00/-26.17	0.6719 2.83/-2.14	0.735
Hong Kong	1.0197 2.61/-0.14	1.0492 2.28/-0.05	1.1276 6.97/-1.32	0.988
Indonesia	0.7786 2.48/-0.14	0.9253 3.16/-0.54	0.9169 26.57/-7.80	0.703
Korea	1.2336 2.46/0.39	1.8884 3.03/0.77	1.9677 3.29/1.93	1.332
Malaysia	0.5036 2.19/-0.08	0.6993 2.85/-1.27	0.5701 9.84/-6.62	0.471
Philippines	0.6768 1.91/-0.17	0.7292 1.59/0.08	0.6819 1.27/0.51	0.601
Singapore	0.8227 2.47/0.05	1.0697 1.93/0.56	0.9625 4.27/-0.68	0.852
Taiwan	0.7444 1.52/-0.25	0.7942 1.54/0.54	0.6421 1.38/0.41	0.757
Thailand	0.9420 3.51/-1.04	1.0432 1.95/0.99	1.0717 5.02/-1.18	0.914
Czech Republic	0.5718 2.04/-0.93	0.7599 2.72/0.62	0.7604 1.31/0.53	0.627
Greece	0.6178 1.69/-0.41	0.6956 1.41/0.60	0.7812 1.49/0.59	0.730
Hungary	0.9870 3.14/-0.11	1.0110 3.97/-0.32	1.2545 2.22/0.80	1.069
Poland	1.0589 2.35/0.10	1.2852 3.87/0.93	1.1471 2.02/0.84	1.049
Portugal	0.5723 1.64/-0.30	0.6415 1.32/0.12	0.3883 1.07/0.21	0.676
Turkey	1.1995 2.97/-0.29	1.3384 10.74/-4.97	1.6206 11.13/-5.97	1.297
Egypt	0.2154 1.61/-0.32	0.3980 0.60/0.39	0.4264 0.63/0.36	0.194
India	0.5123 1.42/-0.41	0.4335 1.88/-1.08	0.3947 1.29/-0.52	0.463
Israel	1.0055 2.65/0.08	1.0388 2.35/0.43	1.1079 2.19/0.97	1.056
Morocco	0.0750 0.92/-0.63	0.0022 1.06/-0.85	-0.0137 1.03/-0.75	0.018
Pakistan	0.2417 1.71/-0.72	0.2314 1.06/-0.72	0.1126 0.68/-0.49	0.146
South Africa	0.9036 2.46/-0.32	0.8716 2.58/-0.03	1.0224 1.99/0.63	0.958
Russia	1.4442 4.68/-8.8E-05	2.4914 2.98/2.00	2.2992 3.82/2.30	1.519

6.8. An assessment of the relative superiority of the GARCH, Schwert and Seguin and Kalman approaches to estimating conditional beta

The first tool used in this study to verify whether the time varying betas estimated from the three different techniques are similar or not is the correlation coefficient. By examining the value of correlation coefficient we can deduce the degree of relationship between two different series. Table 16 shows the correlation coefficients between the conditional beta estimates. The correlation coefficients are all positive between all models used to predicting country risk. The highest correlation was found to exist between Schwert Seguin under t distribution and Schwert Seguin under generalised error distribution with ρ = 0.999, although a strong correlation was also found to exist within the GARCH (1,1) models are high with an average correlation coefficient of 0.991. The lowest level of association (correlation nearest zero) were found between Schwert Seguin normal distribution and Kalman Filter Random Coefficient, ρ = 0.0347. Furthermore, combined with the information provided in Table 10, Table 14 and Table 15, we can see that the higher the correlation coefficient the lower the difference between each method.

Figure 2.a. to Figure 2.d. presents graphical illustration of the conditional beta series generated by the three estimation techniques (GARCH normal distribution, SS normal distribution and Random Walk) for Colombia, Thailand, Czech Republic, and Russia as a representative country in each Emerging Market Region.

Table 16. Average Correlations of Conditional Beta Series

This table presents average correlation between each conditional beta estimation method. The correlation coefficients are measured for each country pair and averaged over the full sample.

	$\beta_{it}^{G\text{-}n}$	$\beta_{it}^{G\text{-}t}$	$\beta_{it}^{G\text{-}GED}$	$\beta_{it}^{SS\text{-}n}$	$\beta_{it}^{SS\text{-}t}$	$\beta_{it}^{SS\text{-}GED}$	β_{it}^{KFRW}	β_{it}^{KFAR}	β_{it}^{KFRC}
$\beta_{it}^{G\text{-}n}$	1	0.984	0.997	0.099	0.065	0.058	0.340	0.156	0.075
$\beta_{it}^{G\text{-}t}$		1	0.991	0.117	0.059	0.052	0.348	0.116	0.077
$\beta_{it}^{G\text{-}GED}$			1	0.106	0.059	0.052	0.342	0.158	0.075
$\beta_{it}^{SS\text{-}n}$				1	0.047	0.047	0.181	0.057	0.035
$\beta_{it}^{SS\text{-}t}$					1	0.999	0.224	0.068	0.044
$\beta_{it}^{SS\text{-}GED}$						1	0.218	0.065	0.042
β_{it}^{KFRW}							1	0.382	0.305
β_{it}^{KFAR}								1	0.454
β_{it}^{KFRC}									1

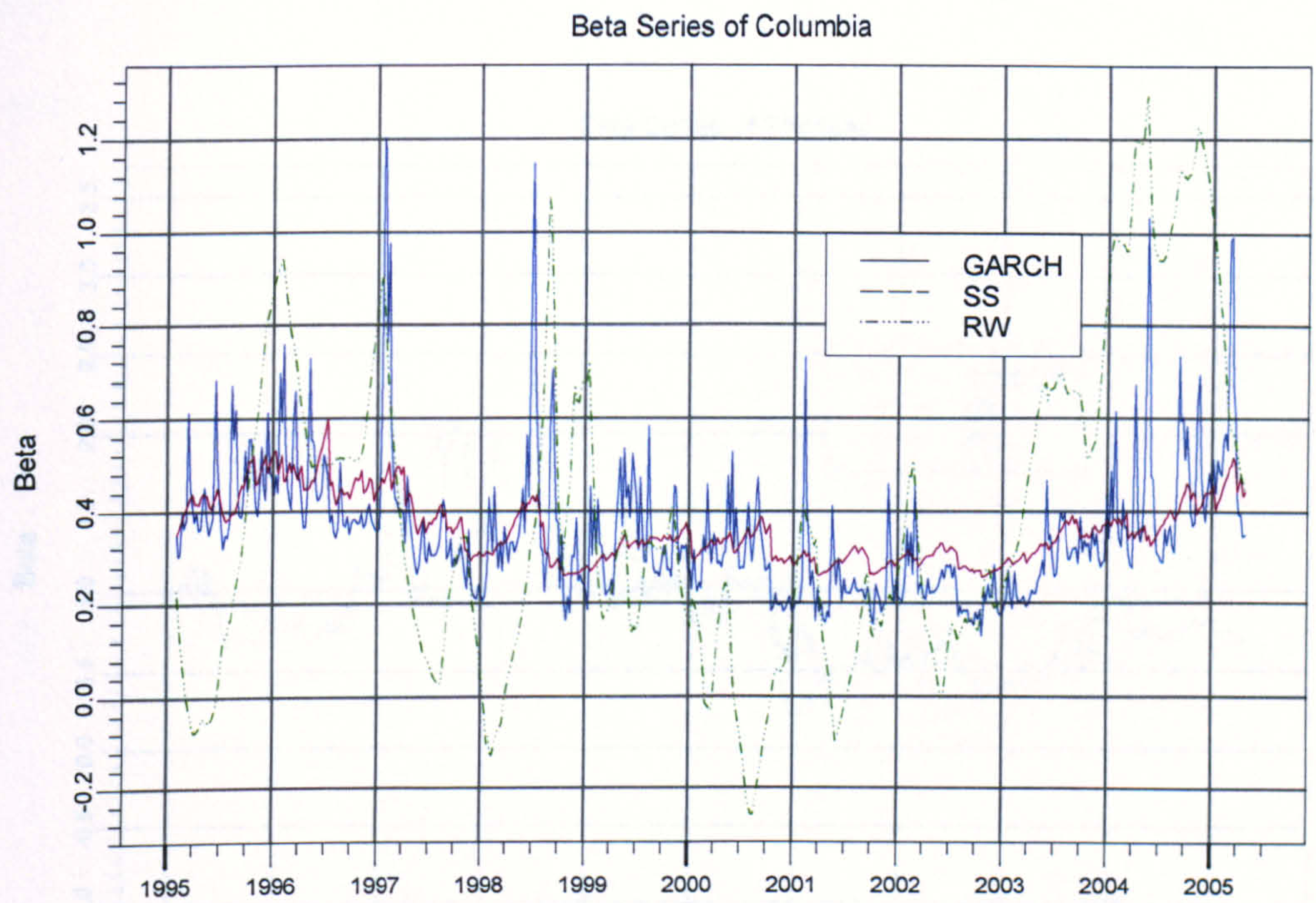


Figure 2.a. Plot of the GARCH normal, Schwert and Seguin normal and Kalman Random Walk generated conditional beta series for Colombia

We can see from the four graphs that the conditional beta series generated using Schwert and Seguin (SS) model for both countries are relatively stable. This is not surprising given the fact that the R-squares of the market model and SS model are similar which implies that the inclusion of the δ_i term to the original market model does not increase the ability of the model to explain the variability of return. In general, Kalman Filter beta exhibits most sensitivity to changes in beta.

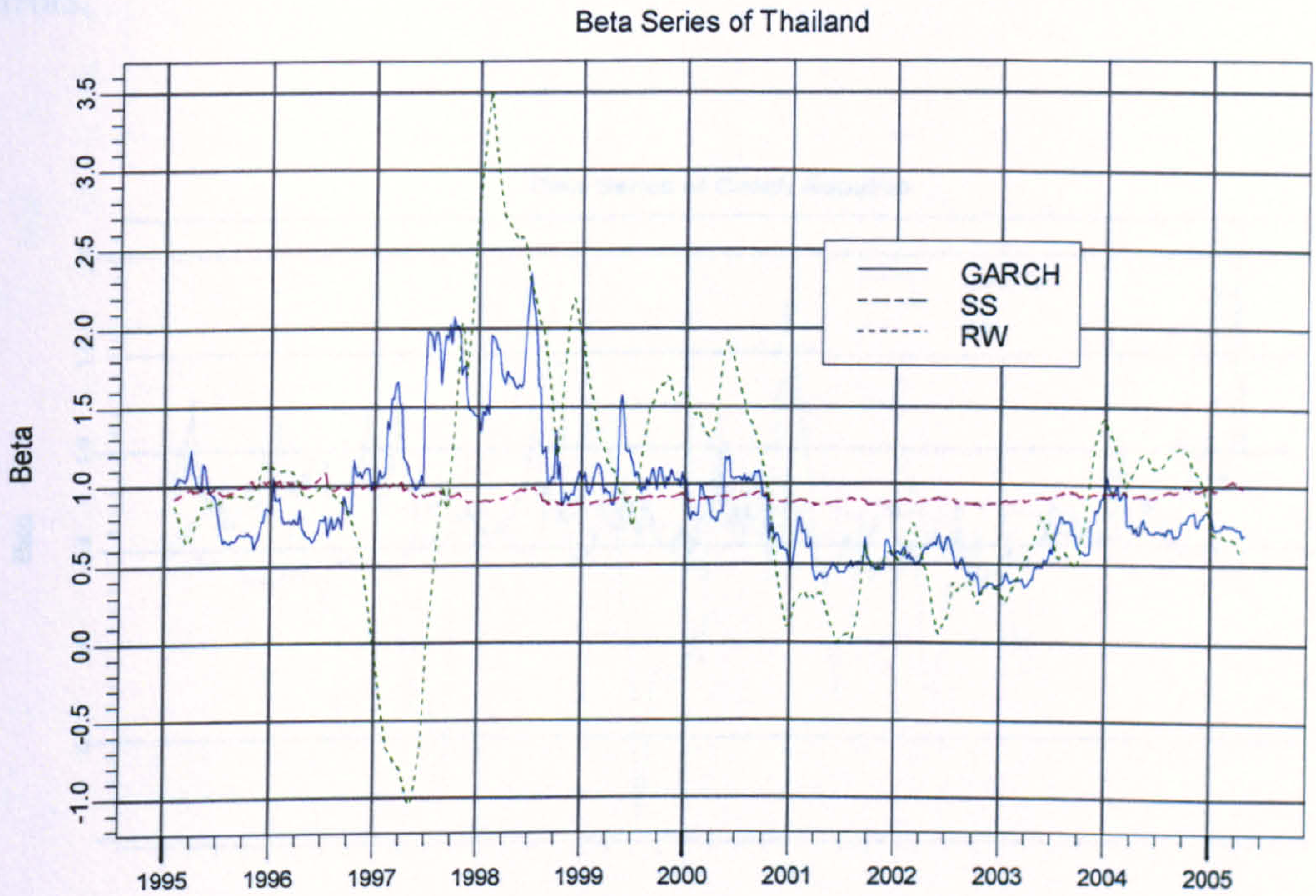


Figure 2.b. Plot of the GARCH normal, Schwert and Seguin normal and Kalman Random Walk generated conditional beta series for Thailand

Figure 2.b. portrays the conditional beta series for Thailand. It can be seen clearly that the Random Walk model "explains" the Asian Crisis better than the other two models. With regard to the Russian Crisis in 1998, as indicated by Figure 3, the Random Walk explains the crisis better than the other two models. Similarly with regard to the recent crisis in South American, it can be seen from the figure 1 that the random walk model describes the crisis better than the other models. The conditional beta series of random walk increased significantly from May 2002 onwards. Although correlation coefficient gives informative results however this technique should be used with caveat. This is because it provides no

indication regarding ranking of each models. Therefore we need to use more reliable statistic tools. As noted before in this study we will employ mean absolute error and mean squared errors.

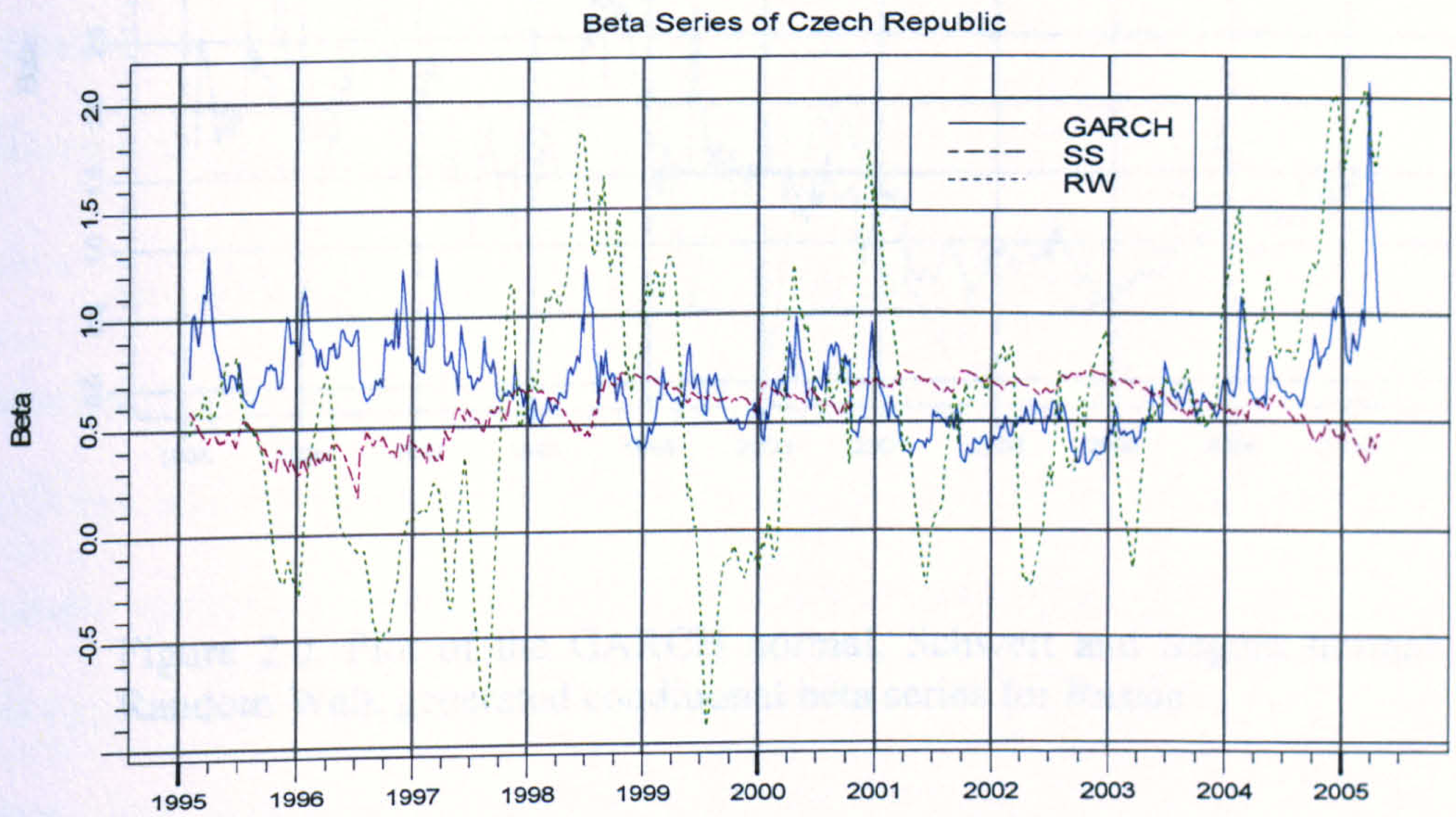


Figure 2.c. Plot of the GARCH normal, Schwert and Seguin normal and Kalman Random Walk generated conditional beta series for Czech Republic

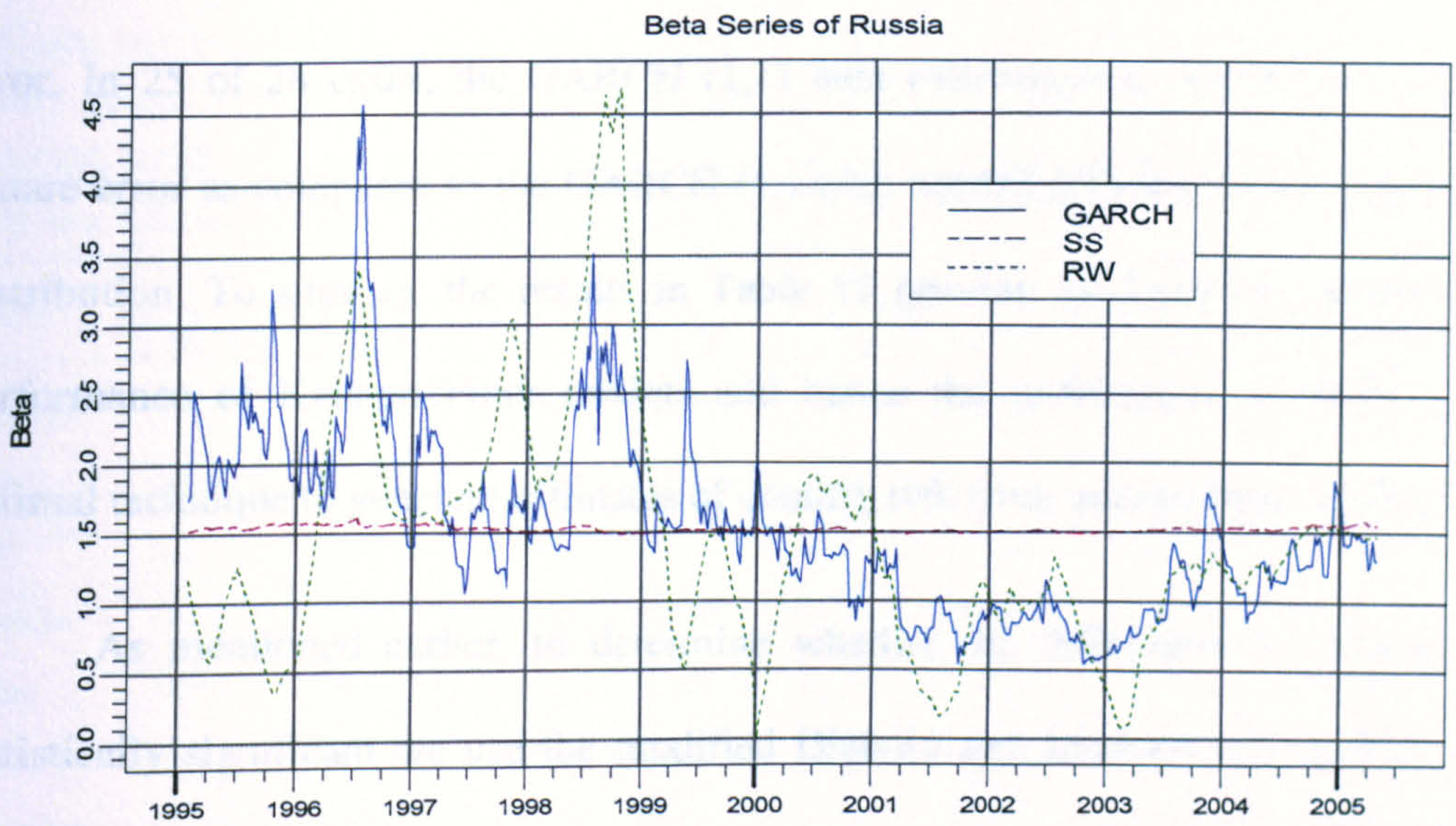


Figure 2.d. Plot of the GARCH normal, Schwert and Seguin normal and Kalman Random Walk generated conditional beta series for Russia

Table 17 summarizes the results of mean square error of all the models used in the study for each country. The results presented in Table 17 reveal that the Kalman filter technique dominates the other two techniques. In particular, within the class of Kalman Filter model the Random Walk technique produced the lowest MSE in 14 of 28 cases and then followed by Random Coefficient (10 cases) and Autoregressive 4 cases. Our results are in line with the findings of other researchers for example Brooks, Faff and McKenzie (1998) and Faff, Hillier and Hillier (2000). However using the same source of data, i.e. MSCI database, but a different sample set (developed countries), Brooks et.al. (2002) found GARCH model was superior as compared to the other two models.

Within the GARCH (1,1) models the t-distribution provided the lowest mean square error. In 25 of 28 cases, the GARCH (1,1) with t-distribution produced the lowest mean square error as compared to the GARCH (1,) with normal distribution and generalised error distribution. To sum up, the results in Table 17 provide evidence of superior forecasting performance of Kalman Filter models and hence the justification of their usage as the optimal technique to generate estimates of country risk from among those models tested.

As mentioned earlier, to determine whether the difference in forecast errors are statistically significant we use the modified Diebold and Mariano test statistic of Harvey, Leyborne and Newbold (1997). Table 18 presents the results of the modified Diebold and Mariano specifically it provides information on the proportion of countries that rejected the null hypothesis of equal mean square error. An interesting feature emerges. Only the Kalman Filter class models are significantly different from the other models. In particular, the Kalman Filter random walk parameterisation leads to different return forecasts from other models in over 90 percent of the countries tested, except one case between Random Walk and Schwert Seguin where the percentage of rejection only 67.86 percent. This finding supports the previous argument to favour Kalman Filter as the best model to predict country risk.

Table 17. Mean Square Errors of In-Sample Forecasts (x 10^{-5})

This table reports mean square error estimates between the observed country returns series and the in-sample forecast country returns series. The beta representations are GARCH(1,1) normal beta,GARCH(1,1) t distribution beta, GARCH(1,1) GED beta, Schwert and Seguin (SS) normal beta, SS t distribution beta, SS GED beta, Kalman Filter Random Walk beta, Kalman Filter AR(1) beta, and Kalman Filter Random Coefficient beta.

Country	GARCH			SS			Kalman		
	Normal	T-Dist	GED	Normal	T-Dist	GED	RW	AR(1)	RCoeff
Argentina	28.96	29.05	29.06	28.72	28.71	28.72	25.94	28.74	13.40
Brazil	28.36	28.19	28.23	27.93	27.70	27.72	25.17	24.33	18.78
Chile	8.50	8.49	8.50	8.46	8.41	8.41	7.12	8.63	7.13
Colombia	17.10	17.12	17.11	17.11	17.11	17.11	15.87	17.24	16.59
Mexico	12.19	12.16	12.18	12.42	12.32	12.34	10.93	10.26	9.82
Peru	12.34	12.32	12.34	12.60	12.73	12.74	9.65	12.37	10.75
Venezuela	41.60	41.51	41.47	41.84	41.91	41.91	22.35	15.25	35.09
Hongkong	10.04	9.83	9.96	9.80	9.67	9.68	7.83	8.67	4.22
Indonesia	45.00	44.94	44.97	45.31	45.43	45.43	42.52	41.30	14.51
Korea	30.69	30.67	30.68	30.62	30.47	30.48	28.79	31.17	32.34
Malaysia	21.34	21.33	21.35	21.81	21.73	21.73	20.20	19.27	9.01
Philippines	14.50	14.50	14.50	14.82	14.77	14.78	13.05	13.60	14.58
Singapore	9.03	9.01	9.02	8.98	8.91	8.91	7.37	8.71	4.70
Taiwan	15.33	15.33	15.34	15.15	15.18	15.18	13.81	14.58	14.63
Thailand	24.72	24.71	24.71	25.63	24.73	24.77	21.36	25.45	16.76
Czech	11.66	11.65	11.65	11.56	11.56	11.56	9.22	11.27	11.01
Greece	13.12	13.10	13.11	12.79	12.88	12.88	11.34	12.63	12.33
Hungary	16.26	16.27	16.29	17.17	16.87	16.90	13.57	12.64	15.52
Poland	17.66	17.62	17.64	17.72	17.53	17.55	15.54	16.67	16.11
Portugal	6.38	6.37	6.37	6.35	6.31	6.31	5.09	5.85	5.99
Turkey	55.00	54.96	54.98	55.02	55.07	55.06	49.10	24.05	20.61
Egypt	12.67	12.67	12.68	12.82	12.84	12.84	11.59	13.05	12.95
India	12.62	12.63	12.62	12.72	12.75	12.75	11.47	10.57	10.52
Israel	9.46	9.44	9.44	9.52	9.55	9.55	7.71	8.39	9.18
Morocco	4.05	4.05	4.05	4.04	4.05	4.05	3.43	2.84	2.96
Pakistan	20.36	20.36	20.36	20.23	20.19	20.20	18.76	18.28	18.34
SouthAfrica	8.61	8.60	8.60	8.82	8.63	8.64	6.73	8.71	7.62
Russia	58.64	58.59	58.69	61.84	61.12	61.16	51.67	65.33	64.06

Table 18. Percentage of Industries that Reject Null Hypothesis of No Difference in Forecast Error

This table presents the proposition of countries that reject the null hypothesis of no difference in MSE forecasts for each conditional beta estimation method. The statistic is the Modified Diebold and Mariano test statistic of Harvey, Leyborne and Newbold (1997). The beta representations are $\beta_{it}^{G\text{-}n}$ = GARCH (1,1) normal beta, $\beta_{it}^{G\text{-}t}$ = GARCH (1,1) t distribution, $\beta_{it}^{G\text{-}GED}$ = GARCH (1,1) GED distribution, $\beta_{it}^{SS\text{-}n}$ = Schwert and Seguin normal distribution, $\beta_{it}^{SS\text{-}t}$ = Schwert and Seguin t distribution, $\beta_{it}^{SS\text{-}GED}$ = Schwert and Seguin GED distribution, β_{it}^{KFRW} = Kalman Filter Random Walk, β_{it}^{KFAR} = Kalman Filter AR(1), and β_{it}^{KFRC} = Kalman Filter Random Coefficient.

	$\beta_{it}^{G\text{-}t}$	$\beta_{it}^{G\text{-}GED}$	$\beta_{it}^{SS\text{-}n}$	$\beta_{it}^{SS\text{-}t}$	$\beta_{it}^{SS\text{-}GED}$	β_{it}^{KFRW}	β_{it}^{KFAR}	β_{it}^{KFRC}
$\beta_{it}^{G\text{-}n}$	3.57	3.57	3.57	3.57	3.57	100	71.43	85.71
$\beta_{it}^{G\text{-}t}$		7.14	3.57	7.14	7.14	100	71.43	85.71
$\beta_{it}^{G\text{-}GED}$			3.57	7.14	7.14	100	71.43	85.71
$\beta_{it}^{SS\text{-}n}$				3.57	100	67.86	60.71	92.86
$\beta_{it}^{SS\text{-}t}$					0	100	67.86	92.86
$\beta_{it}^{SS\text{-}GED}$						100	67.86	96.43
β_{it}^{KFRW}							92.86	92.86
β_{it}^{KFAR}								85.71
β_{it}^{KFRC}								

6.9. Conclusions

The primary focus of this paper is on modelling country risk using time varying beta. The models which were tested included GARCH (1,1), the Schwert and Seguin model and the Kalman Filter model. In addition to normal distribution, GARCH (1,1) with t-distribution and generalised error distribution has been examined. We address two main questions: (1) which distribution of GARCH (1,1) model that the best for modelling time varying beta and (2) which model is the best to use to modelling country risk in emerging market.

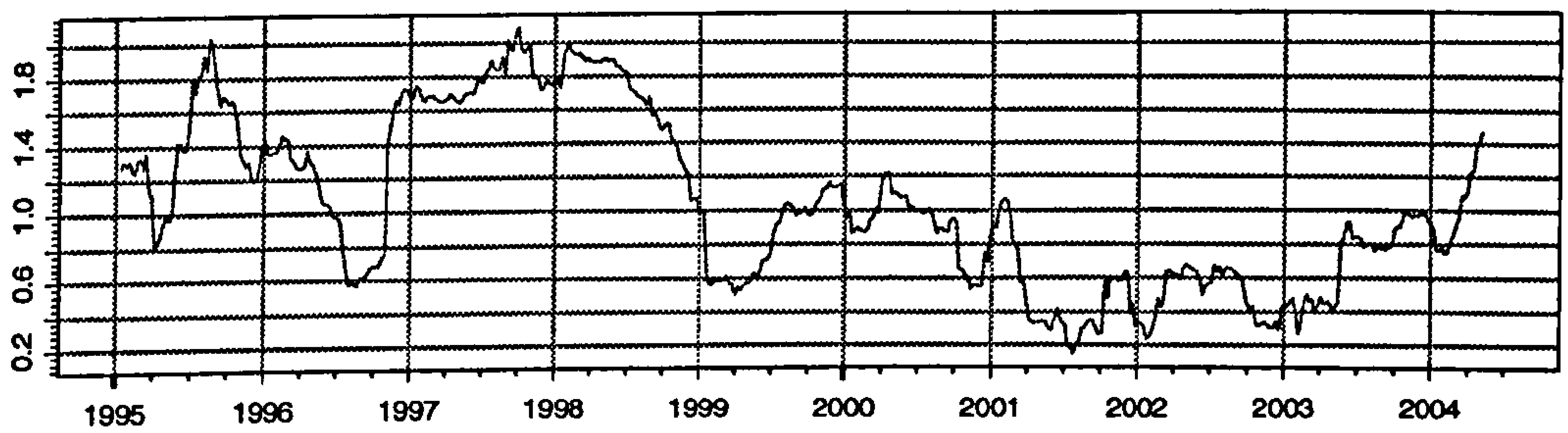
Using rolling regression, CUSUMSQ test, LM test and White test we find that in general emerging market countries exhibited time varying in their beta values. Based on in sample forecasts, the GARCH (1,1) under t-distribution was shown to generate the lowest forecast errors as compared to GARCH (1,1) under normal distribution and generalised error distribution, although these differences were insignificant when tested using the Modified Diebold and Mariano test statistics.

Finally, based on in sample forecasts and the Modified Diebold and Mariano test statistics we find that the Kalman Filter models outperform the other two classes of models. Specifically, we argue that the Random Walk model is the optimal forecasting technique within the Kalman Filter models. The implication of this finding for investor in emerging market is that Random Walk should be used as the method to estimate time varying country risk.

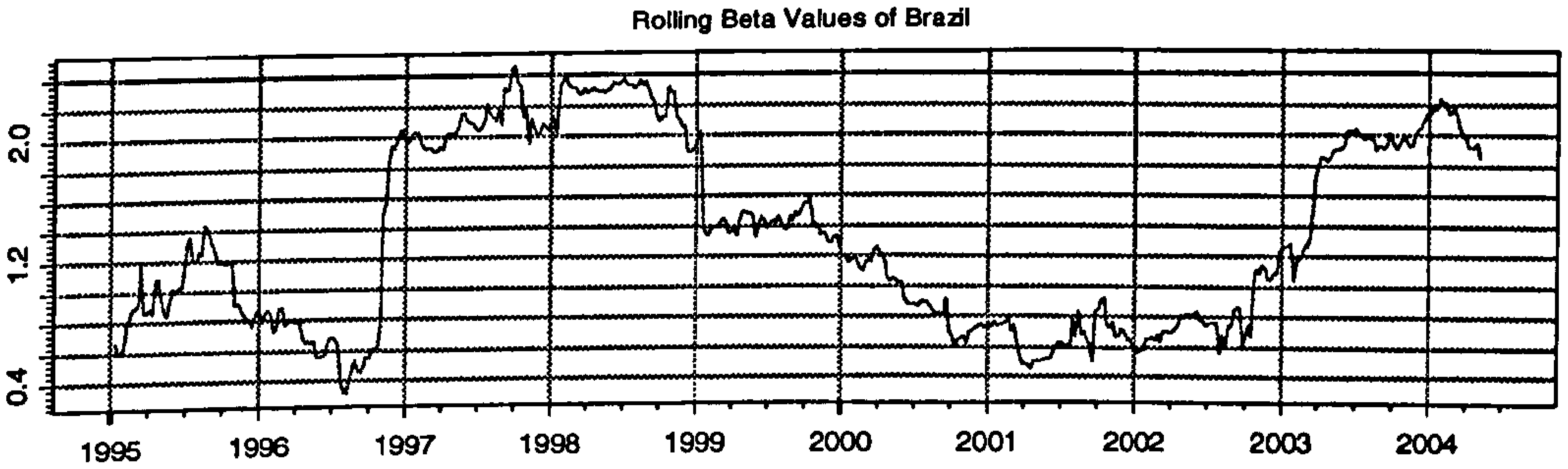
Appendix 1. Rolling Beta Values for Each Country Sample

This appendix provides the graphs of rolling beta values for each of emerging market country sample. We use 52 week sample rolling regression by incrementing factor of 1 week.

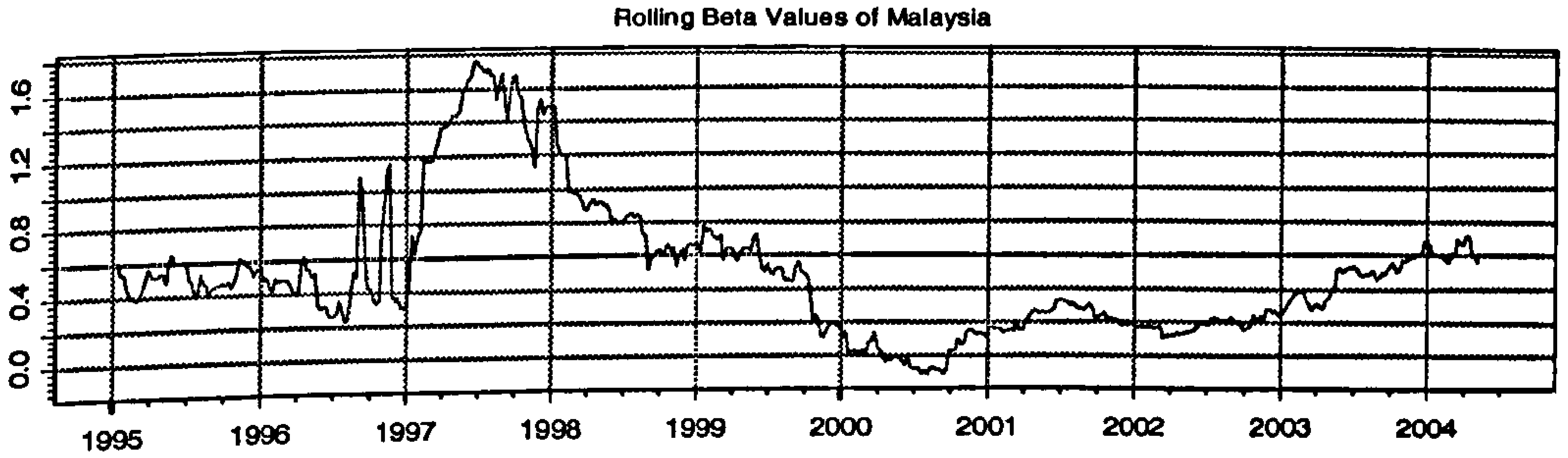
Rolling Beta Values of Argentina



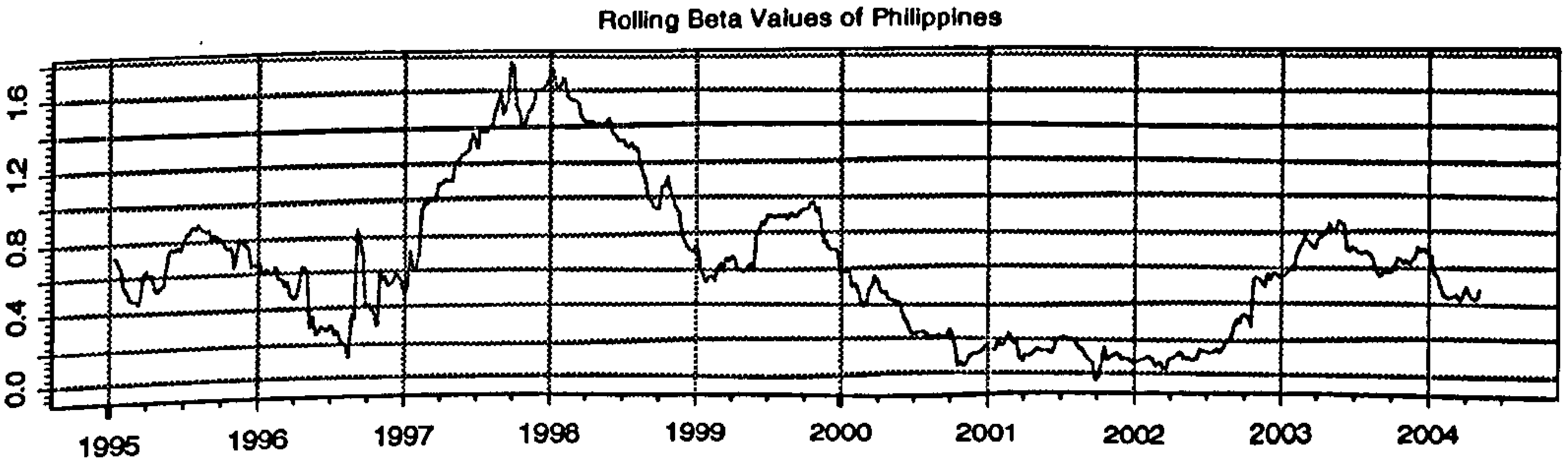
Rolling Beta Values of Brazil



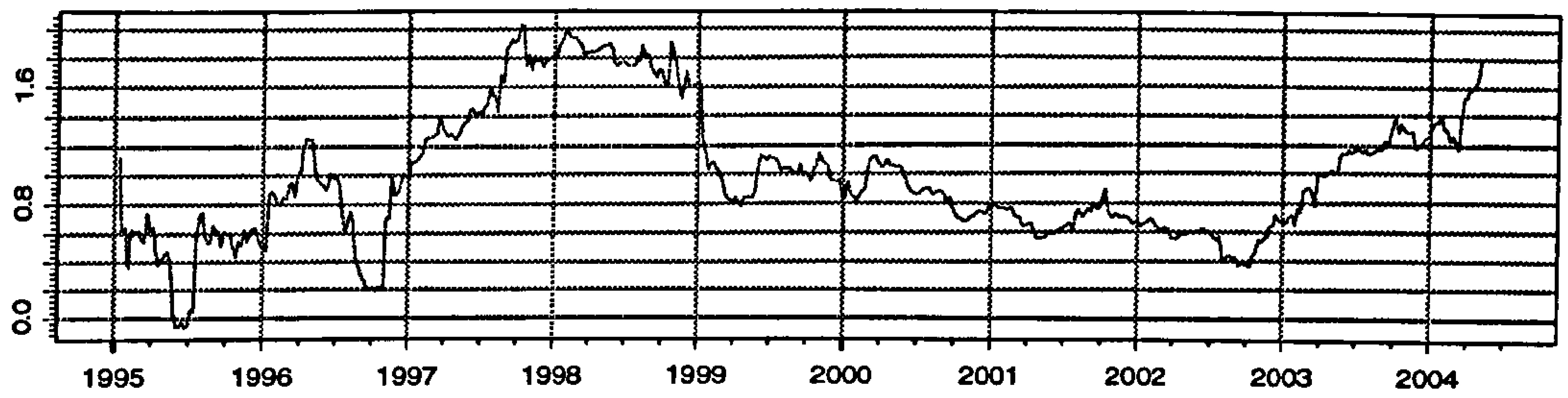
Rolling Beta Values of Malaysia



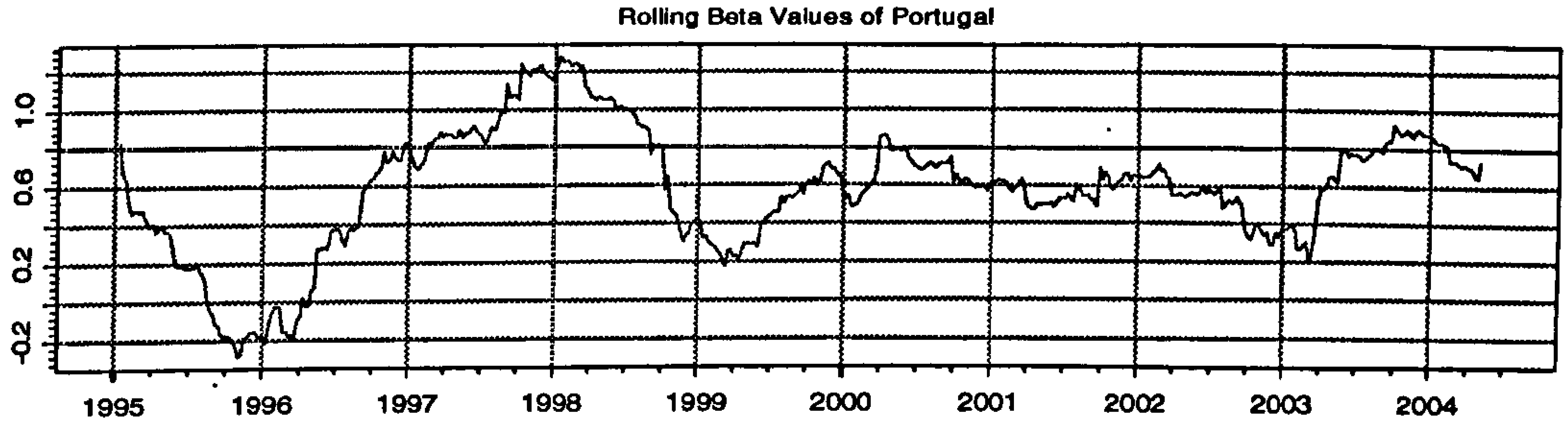
Rolling Beta Values of Philippines



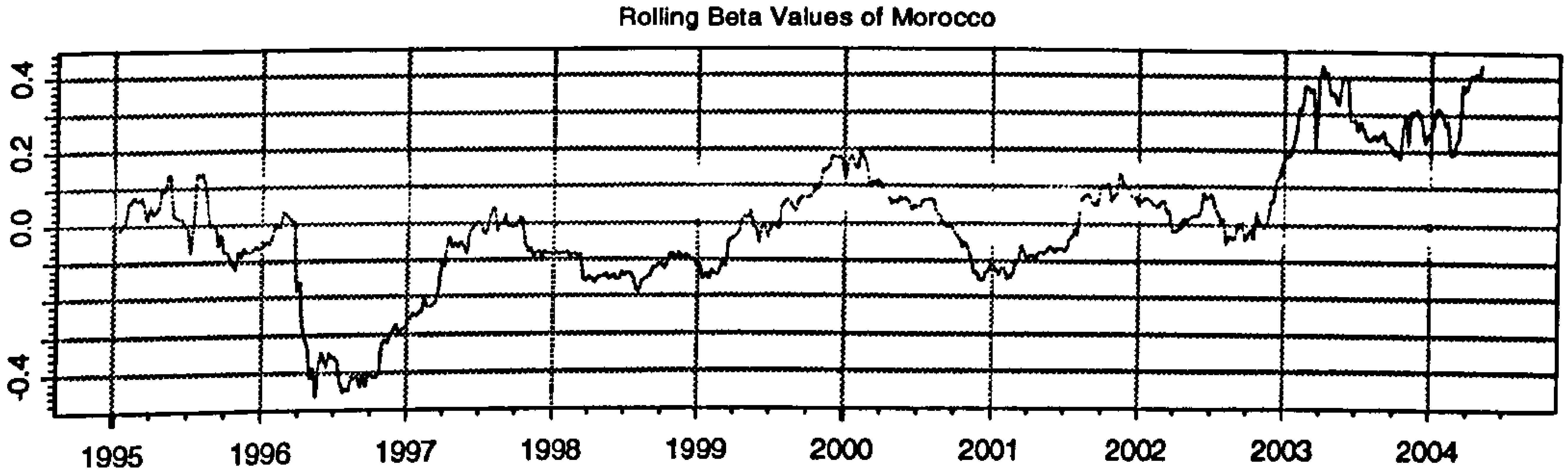
Rolling Beta Values of Poland



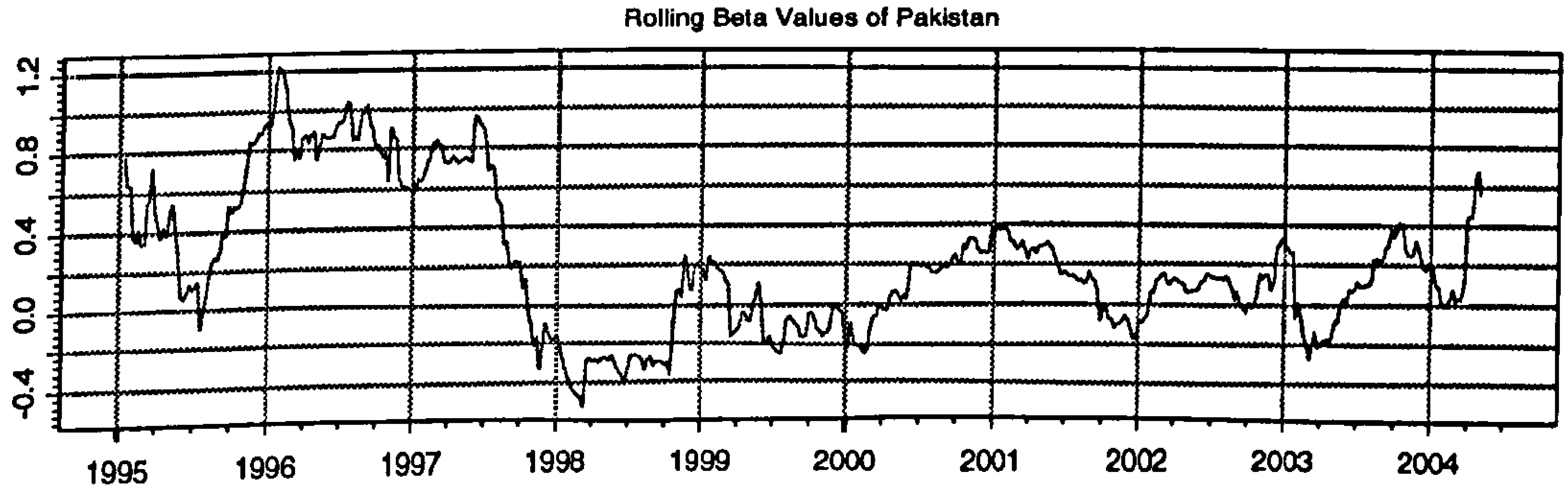
Rolling Beta Values of Portugal



Rolling Beta Values of Morocco



Rolling Beta Values of Pakistan



Appendix 2. Cumulative sum of squares from the recursive residuals

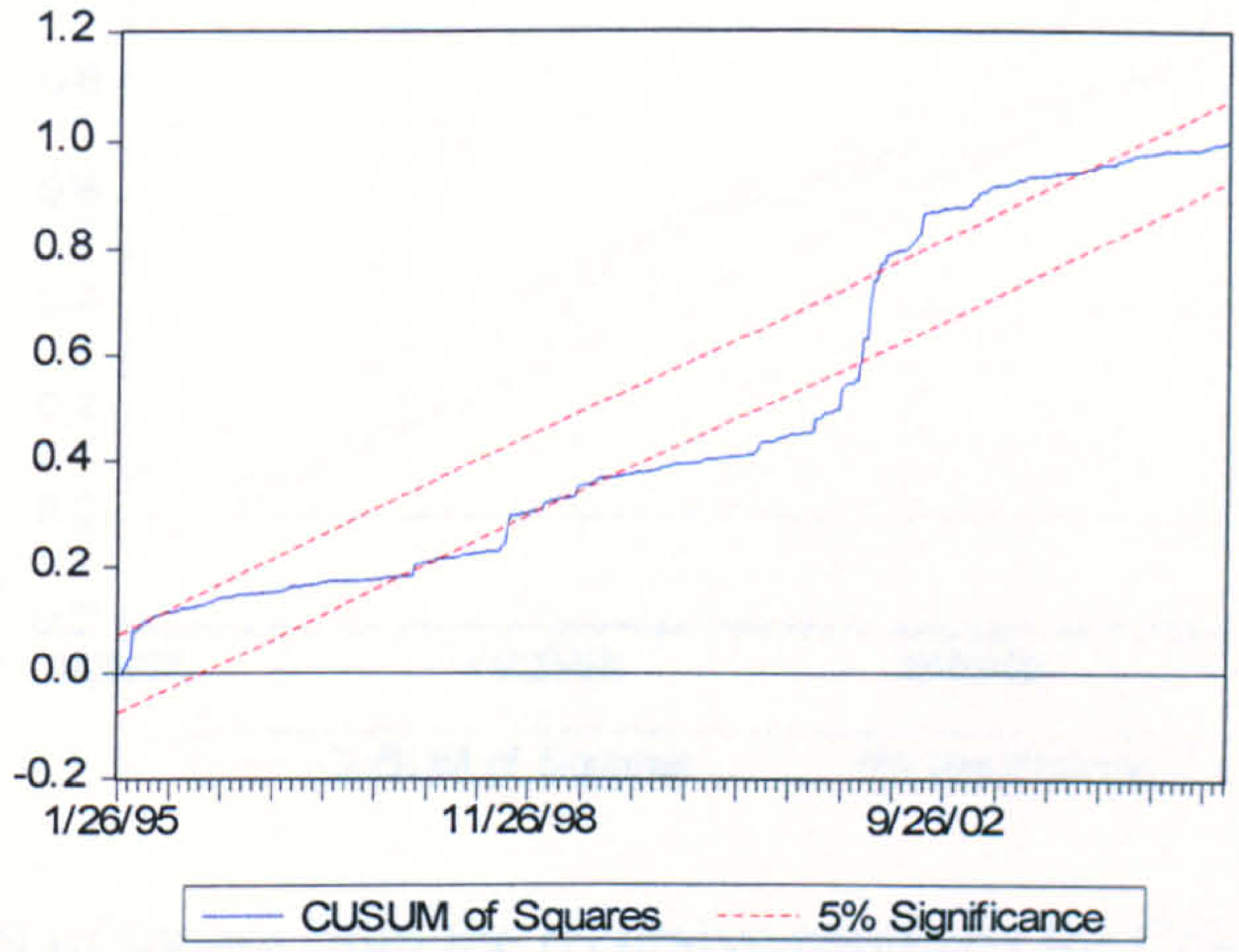


Fig. 1. Cumulative sum of square from the recursive residuals for Argentina

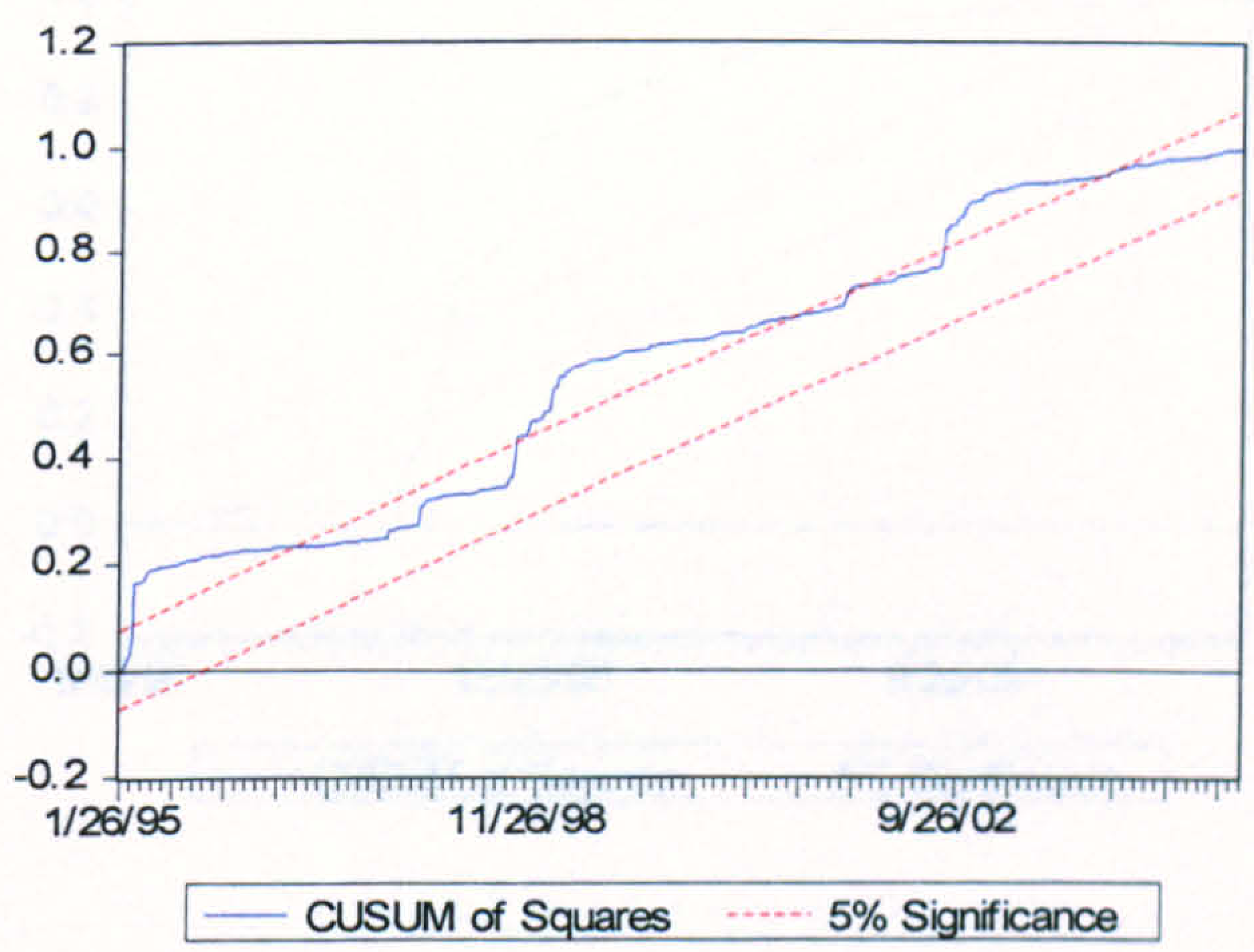


Fig. 2. Cumulative sum of square from the recursive residuals for Brazil

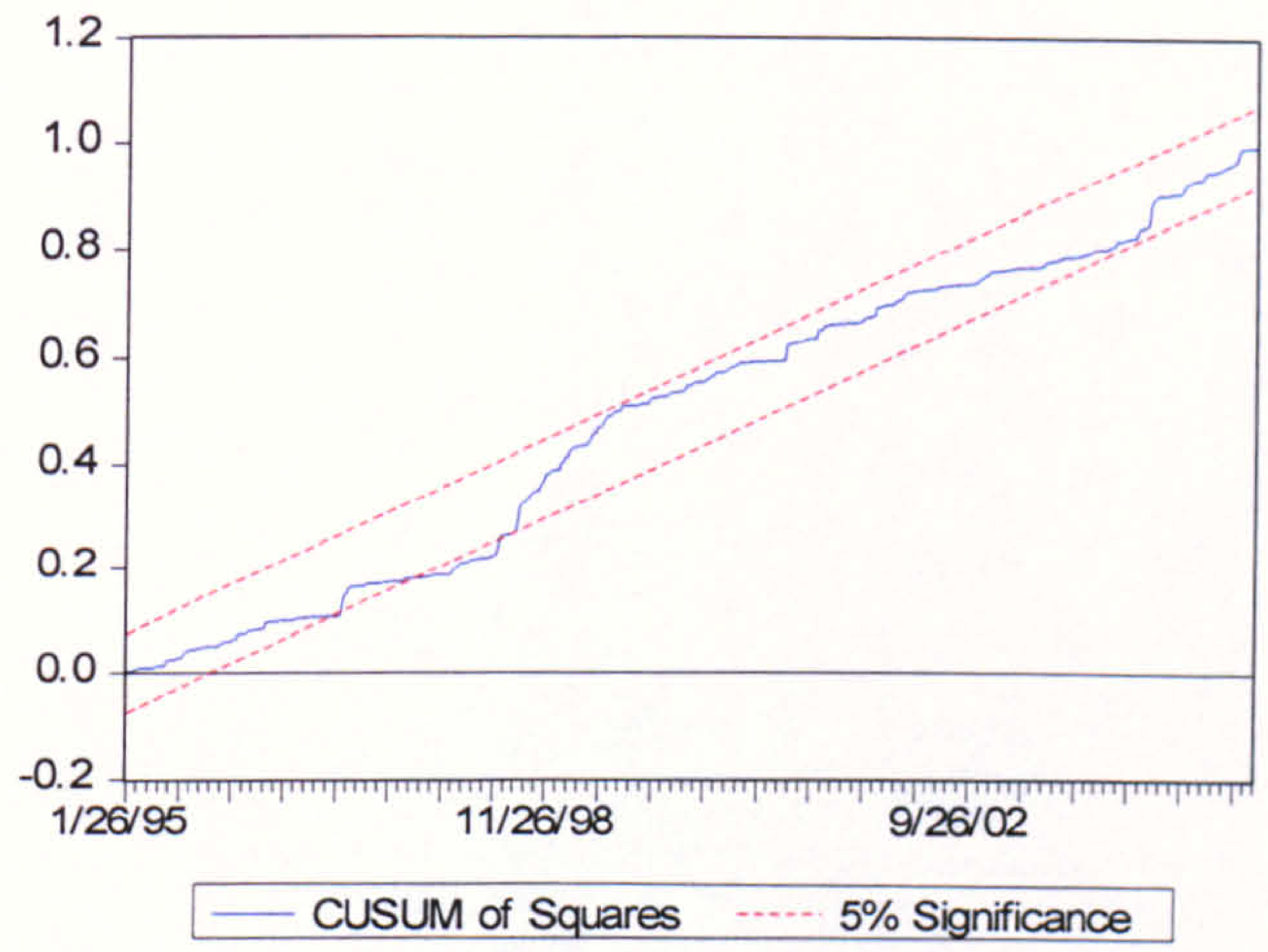


Fig. 3. Cumulative sum of square from the recursive residuals for Colombia

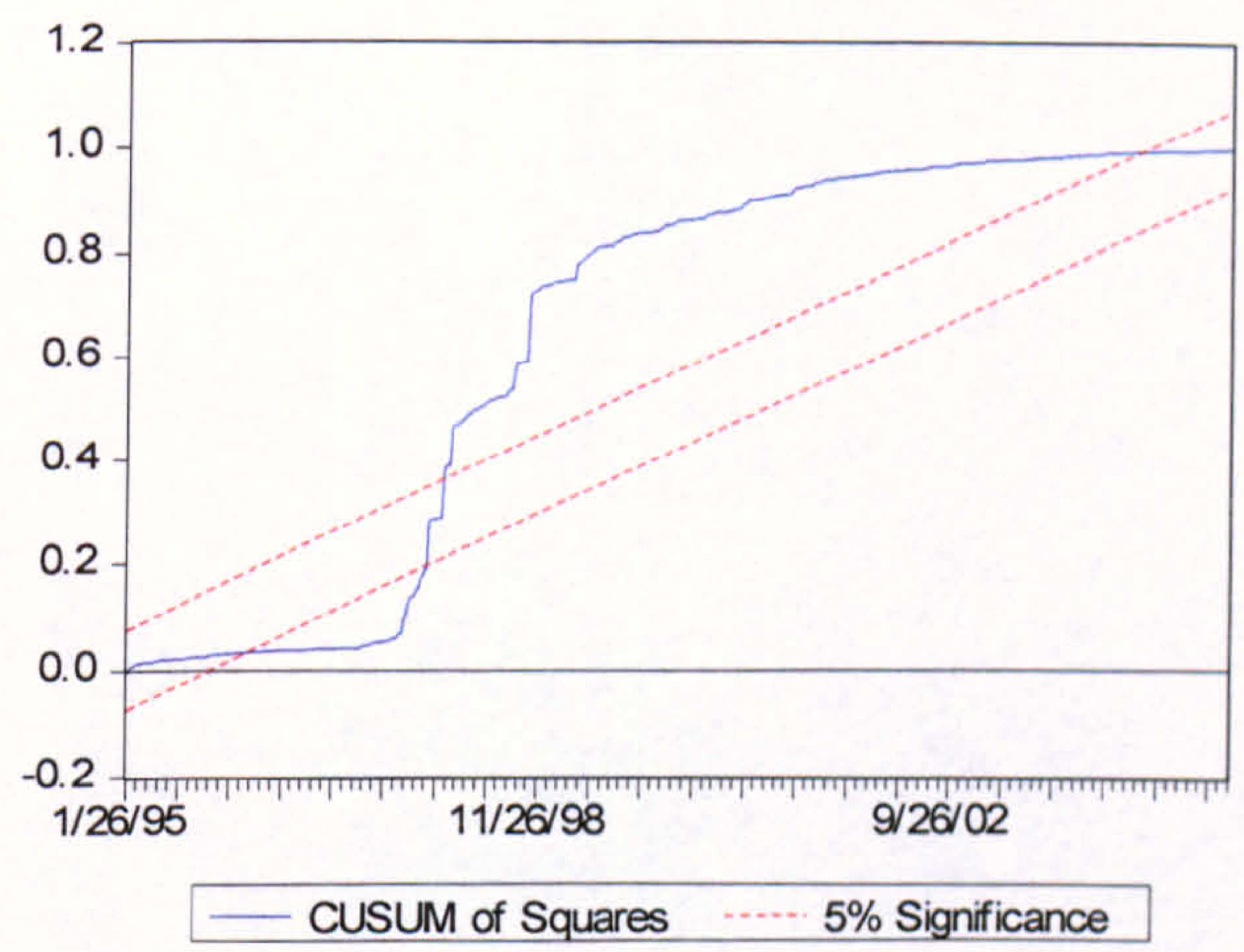


Fig. 4. Cumulative sum of square from the recursive residuals for Malaysia

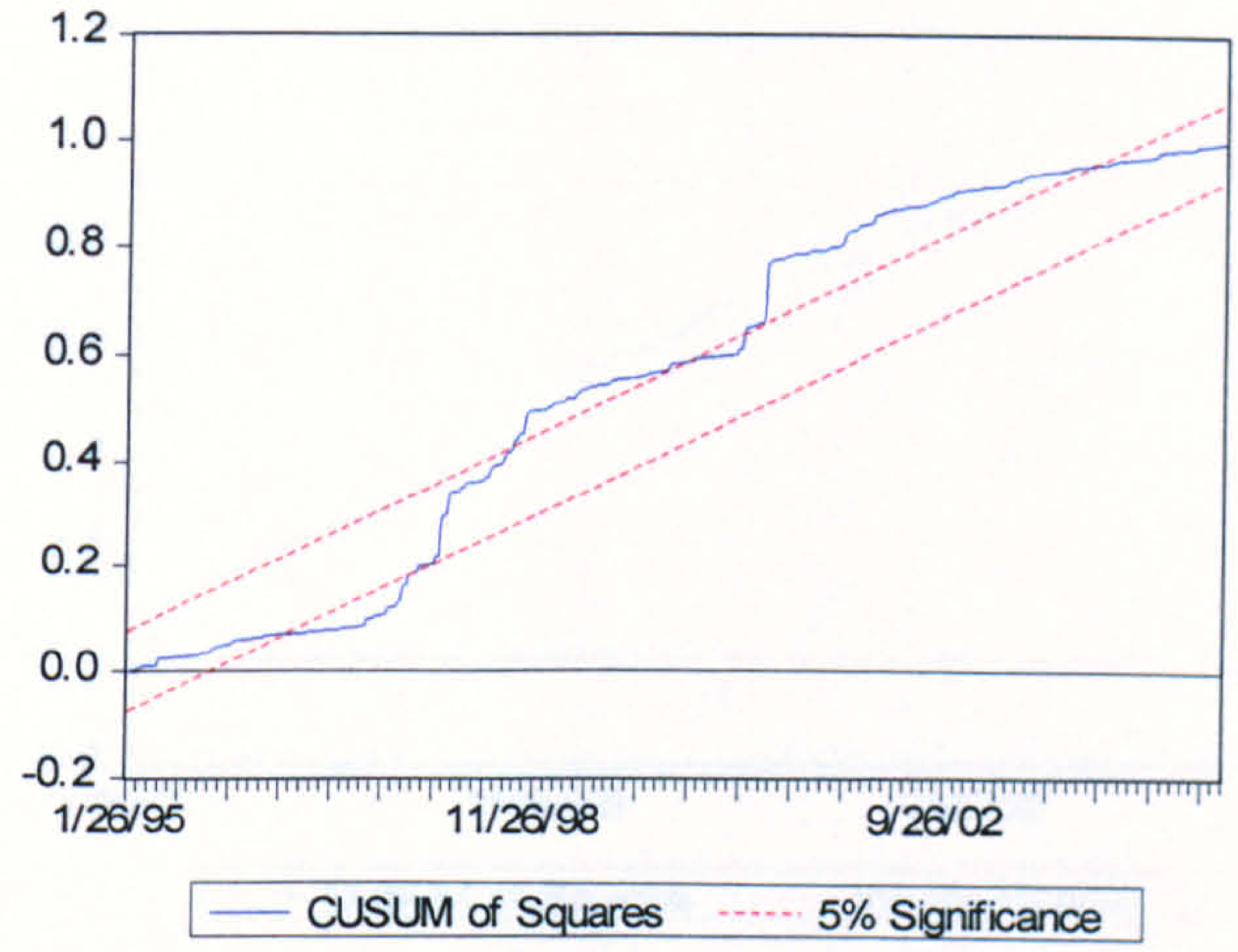


Fig. 5. Cumulative sum of square from the recursive residuals for Philippines

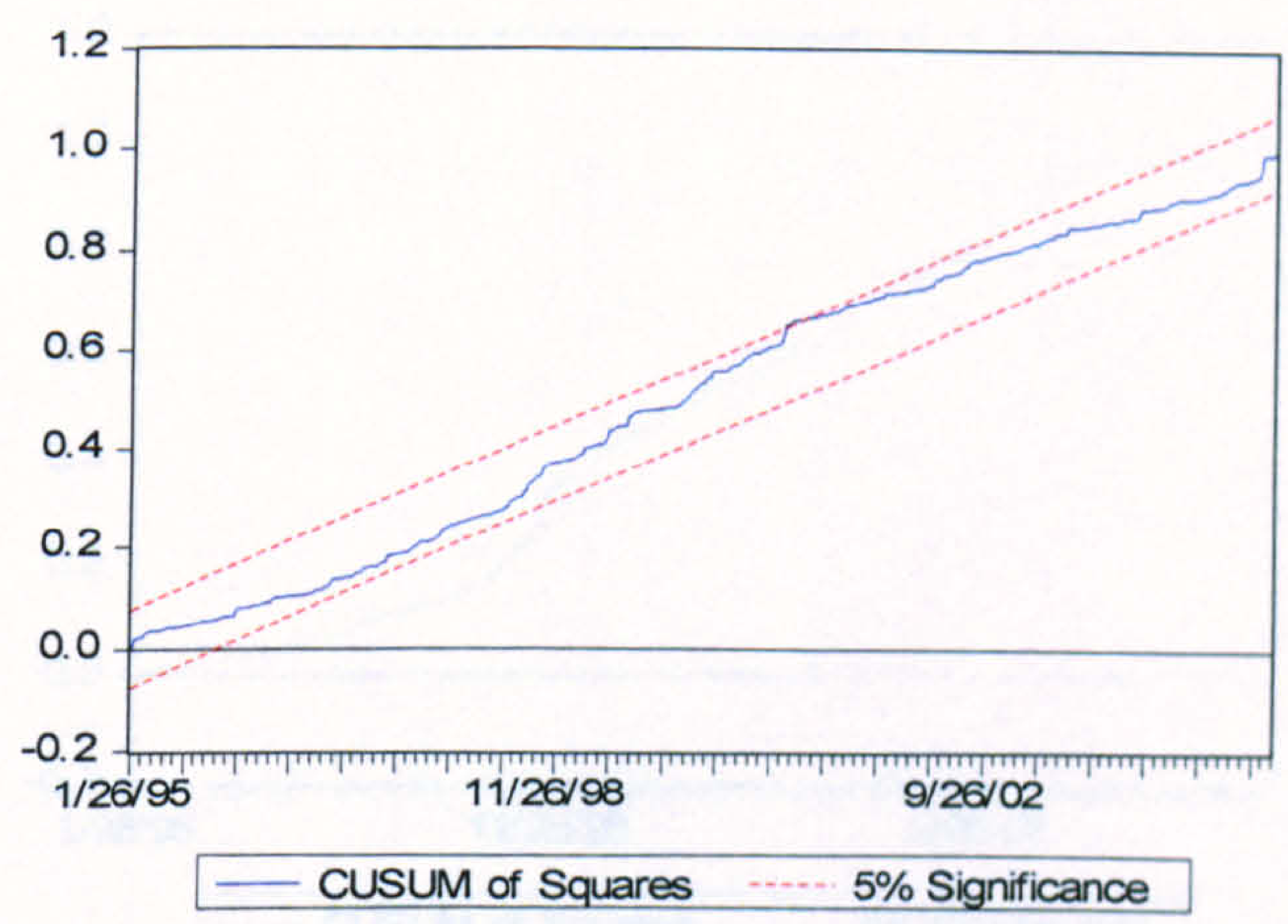


Fig. 6. Cumulative sum of square from the recursive residuals for Czech Republic

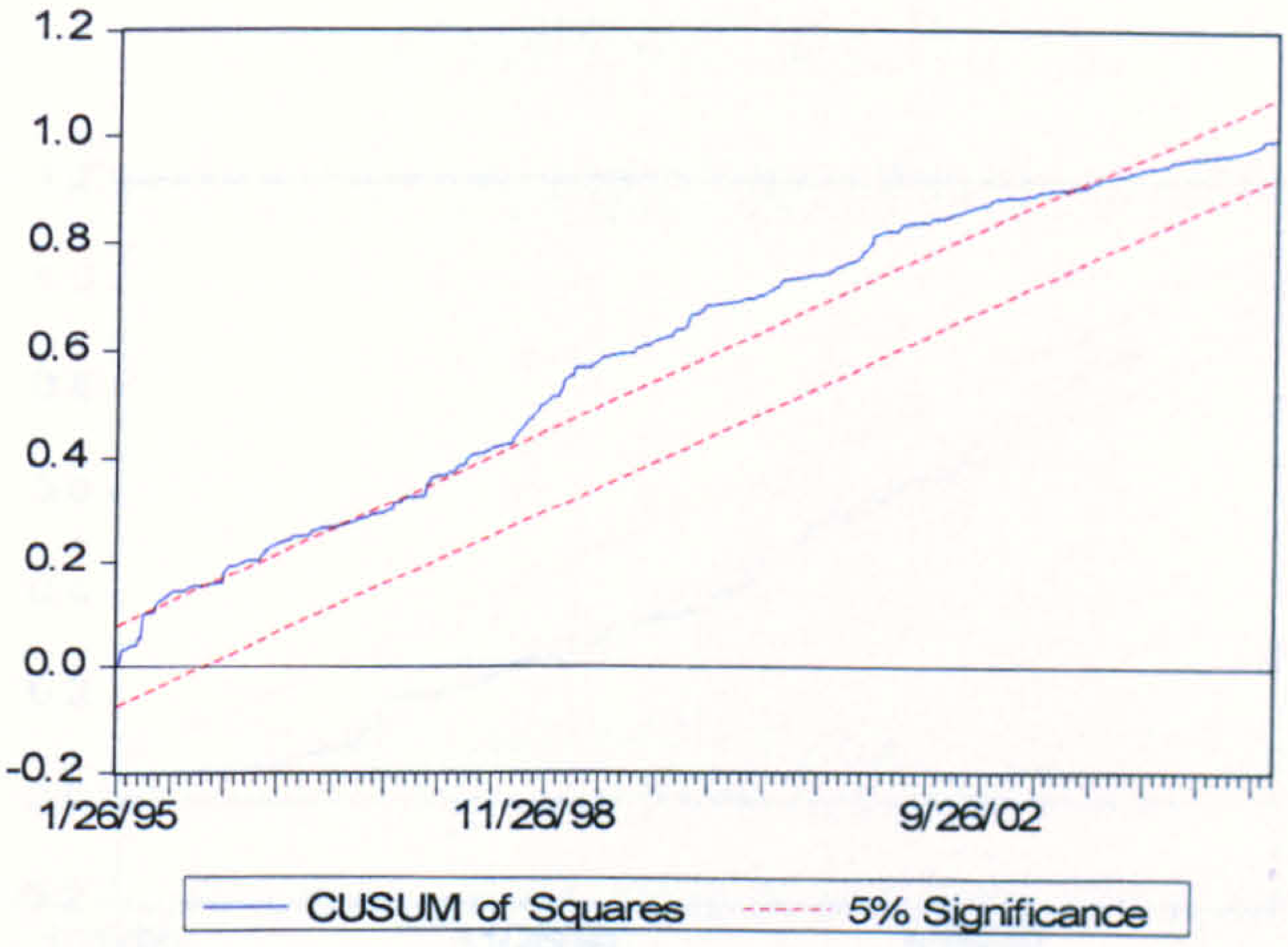


Fig. 7. Cumulative sum of square from the recursive residuals for Poland

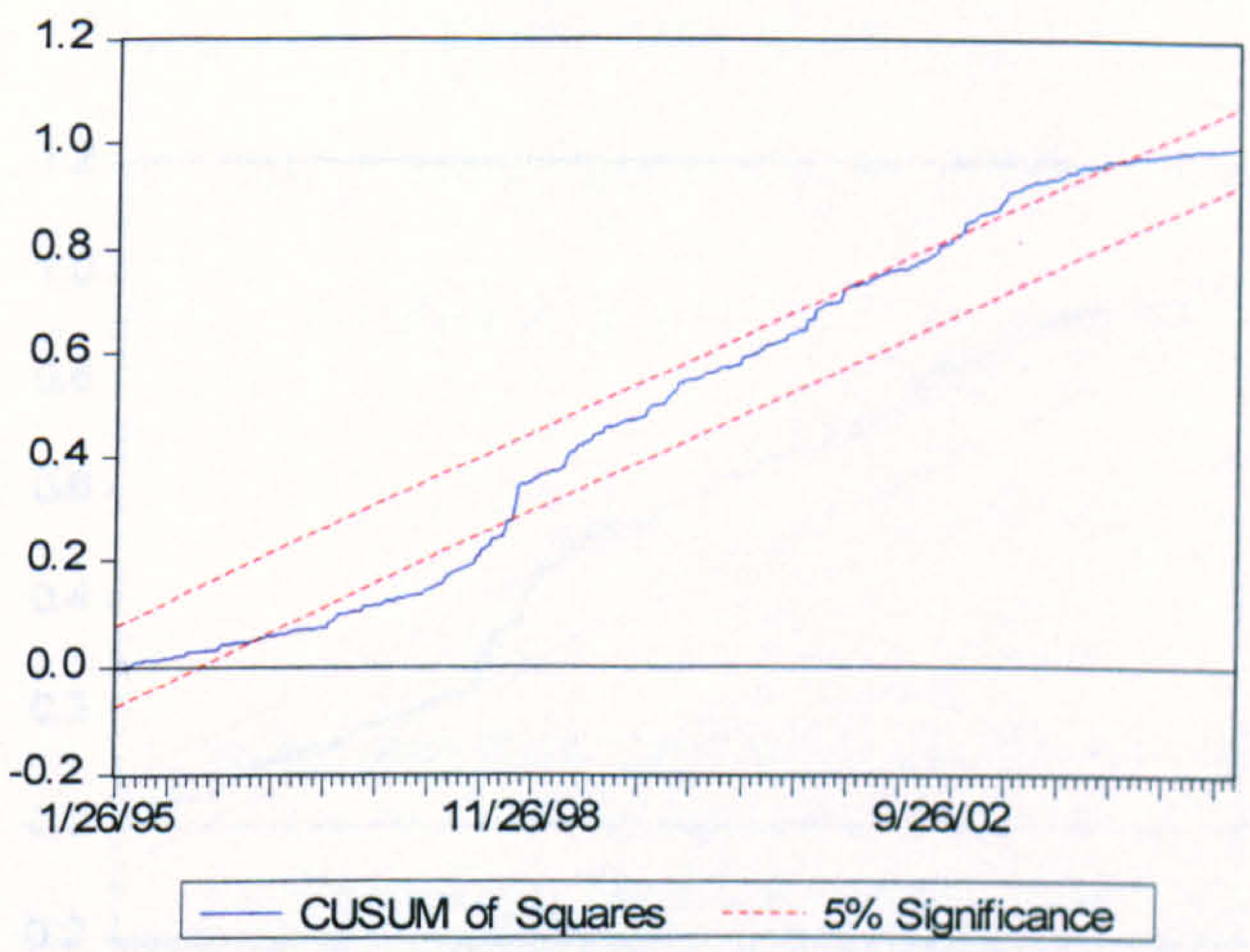


Fig. 8. Cumulative sum of square from the recursive residuals for Portugal

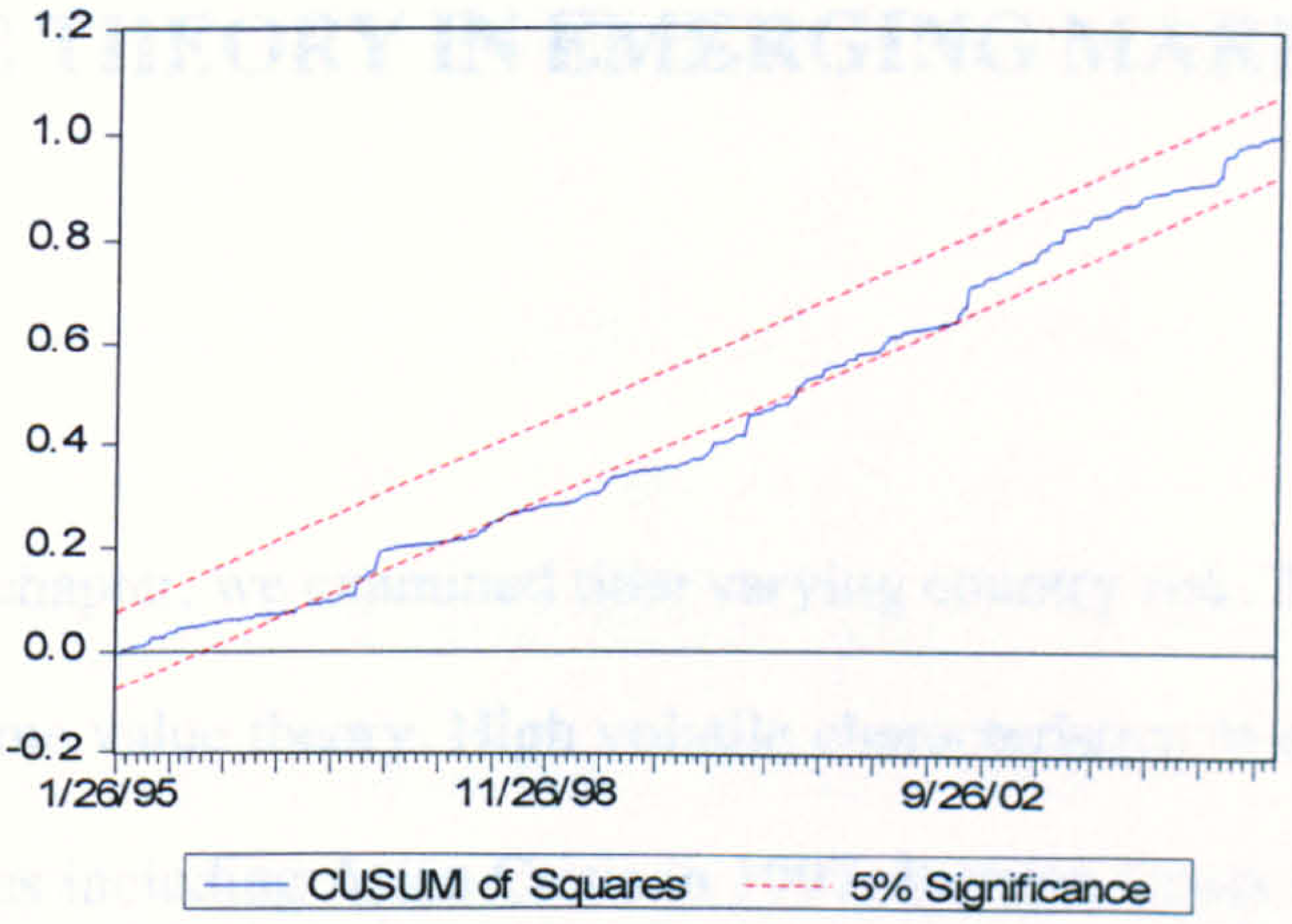


Fig. 9. Cumulative sum of square from the recursive residuals for Morocco

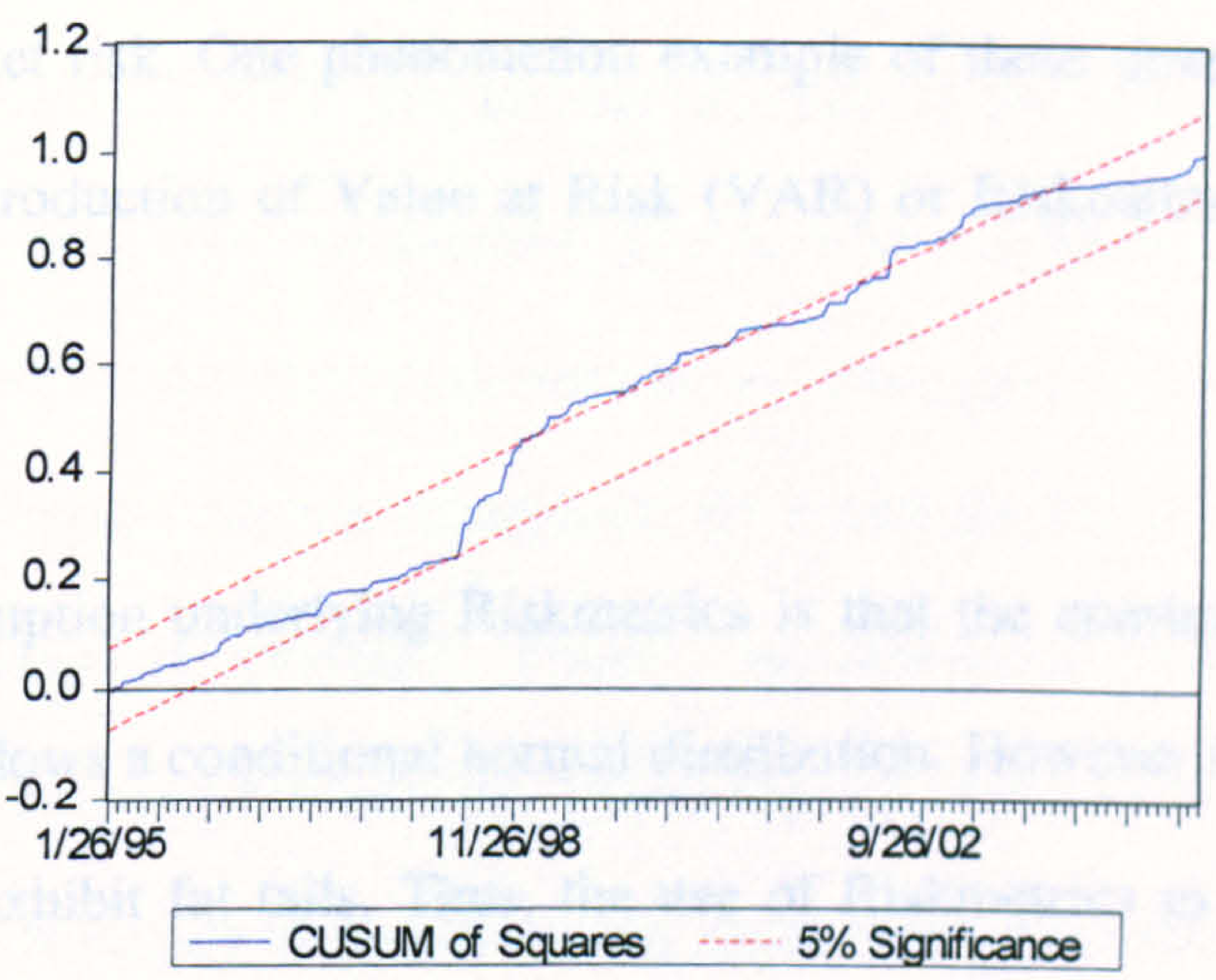


Fig. 10. Cumulative sum of square from the recursive residuals for Pakistan

CHAPTER 7. THIRD EMPIRICAL STUDY: EXTREME VALUE THEORY IN EMERGING MARKETS

7.1. Introduction

In the previous chapter, we examined time varying country risk. This chapter presents the application of extreme value theory. High volatile characteristics of emerging markets as indicated by recent crises including Asian Crisis in 1997, Russian Crisis in 1998, the Turkish and Argentina Crisis in 2001-2002, and South American Crisis in 2002 gives a reasonable basis to modelling market risk. Therefore in response to the increased volatility in financial markets, banks and other financial institutions have all developed market risk in order to be able to capitalise market risk. One phenomenon example of these developments of market risk model was the introduction of Value at Risk (VAR) or Riskmetrics by JP Morgan in 1994.

The main assumption underlying Riskmetrics is that the continuously compounded return of a portfolio follows a conditional normal distribution. However it is well known that most of asset returns exhibit fat tails. Thus, the use of Riskmetrics to estimate VAR will contain some degree of error. Extreme value theory (EVT) offers a potential solution to the problem of estimating the tails. This paper examines the application of extreme value theory (EVT) on 28 countries in emerging markets. We follow McNeil and Frey (2002) approach and estimate assets volatility with GARCH (1,1) model. In particular we focus the analysis on the tail of innovations. We compare the VAR estimated by EVT with other alternatives including t-distribution, conditional normal and empirical distribution using dynamic backtesting. As starting point of analysis we adopt the approach suggested by Engle (2001). This paper differs from the two papers by examining the performance of empirical distribution.

Two major reasons may be advanced as to why it is important to modelling extreme value theory for emerging market stocks. Firstly, as explained in the introductory chapter, that emerging markets provide good diversification benefits for investors and as a result more investment flows go to emerging markets. Secondly, investing in emerging markets is associated with high risk. Therefore a model that can deal with market risk, especially rare but large events in stock market, is of concern to investors and regulators alike.

Based on the first analysis, it is found that the estimations of the 99-percent VAR out of sample using the conditional EVT give successful results as the percentage of log negative returns exceed VAR is less than one percent. The second empirical results show that the GARCH (1,1) model with t innovation is superior as compared to the other models. The second best alternative model are the conditional EVT and the GARCH (1,1) model with non-parametric estimation of quantiles. Finally, unconditional EVT and the normal distribution provide the poorest performance. The superior performance of the GARCH (1,1) model with t innovation is mainly attributable to its ability to capture the fat tail distribution.

We present the results of the empirical study in four sections. The first section provides the result of general extreme value distribution and the estimation the tail of innovations. The analyses of estimated VAR in-sample and out of sample are discussed in the next section. The third section discusses the result of the dynamic back testing. Finally, the last section presents the conclusions of the empirical findings.

7.2. Estimation of GEV parameter

We begin the discussion of our results with the maximum likelihood method estimation of the parameters of a GEV distribution using annual block maxima. Table 19 presents the results of GEV parameter for each country.

Table 19. Parameter ξ of GEV Distribution for Each Country

No	Country	ξ	No	Country	ξ
1	Argentina	0.4718061	15	Thailand	0.3241245
2	Brazil	-0.05444098	16	Czech Republic	-0.4999781
3	Chile	0.3097655	17	Greece	0.8072804
4	Colombia	-0.3166922	18	Hungary	0.3697296
5	Mexico	0.7783499	19	Poland	0.9126802
6	Peru	0.343757	20	Portugal	-0.1352691
7	Venezuela	0.9823735	21	Turkey	0.299645
8	Hong Kong	0.2883615	22	Egypt	-0.3321462
9	Indonesia	0.7560764	23	India	1.090715
10	Korea	0.519836	24	Israel	-0.08777595
11	Malaysia	0.7215147	25	Morocco	0.05389355
12	Philippines	0.4993312	26	Pakistan	0.01684379
13	Singapore	0.02610274	27	S. Africa	0.3143473
14	Taiwan	-0.1332431	28	Russia	0.1580693

It can be seen from Table 19 that most, but not all, countries have positive ξ parameter. This means that in general, the return series of emerging market countries have fatter tails than the normal distribution and suggests the Frechet family of GEV distribution.

Nonetheless there are seven countries that have negative value of their ξ parameter, which suggests finite tail and a Weibull type as opposed to most financial time series. As stated earlier, modelling only block maxima data is inefficient if other data on extreme values are available. Therefore the following sections will be devoted to discuss the results of Peak Over Threshold estimations.

We now turn to modelling conditional heteroskedasticity in the index returns. In particular, following Fernandez (2004), we assume the GARCH (1,1) model has superior performance in comparison to other GARCH specifications. We estimate the GARCH (1,1) model by the method of maximum likelihood and compute the standardized residuals for every return series according to expression (66). To support the model specification, we firstly tested for ARCH effects. Table 20 summarizes the ARCH-LM test for the null hypothesis of no conditional heteroskedasticity in the residuals and the Ljung-Box Q-test for the null hypothesis of no serial correlation. The Ljung-Box statistics ($Q^2(20)$) which are calculated from the first 20 autocorrelation coefficients of the squares of the standardized residuals indicate that the null hypothesis of no autocorrelation is accepted for most countries except for Thailand, Greece, Poland, Portugal, Turkey, Egypt and Israel. Likewise, the Langrange multiplier test applied to each series cannot reject the null hypothesis of "no residual ARCH" for most countries.

Table 20. Specification Tests for GARCH (1,1) Models

No	Country	Lagrange multiplier test (TR^2) for serial correlation (20 lags)	Test for ARCH effects (20 df)
1	Argentina	16.1225 (0.7090)	15.7704 (0.7308)
2	Brazil	28.3403 (0.1016)	27.9760 (0.1100)
3	Chile	20.7835 (0.4100)	18.3281 (0.5658)
4	Colombia	20.2047 (0.4452)	20.4374 (0.4309)
5	Mexico	22.4316 (0.3176)	22.3764 (0.3204)
6	Peru	10.4371 (0.9595)	10.1805 (0.9648)
7	Venezuela	0.0606 (1.0000)	0.0601 (1.0000)
8	Hong Kong	13.8219 (0.8394)	13.7737 (0.8418)
9	Indonesia	19.4100 (0.4953)	18.7881 (0.5356)
10	Korea	8.1879 (0.9906)	8.1189 (0.9911)
11	Malaysia	7.6216 (0.9941)	7.0775 (0.9964)
12	Philippines	1.9966 (1.0000)	1.9556 (1.0000)
13	Singapore	24.5483 (0.2193)	23.9795 (0.2433)
14	Taiwan	17.2839 (0.6345)	16.7418 (0.6697)
15	Thailand *)	35.0510 (0.0198)	33.1518 (0.0325)
16	Czech Republic	14.3422 (0.8127)	14.0537 (0.8278)
17	Greece *)	35.6210 (0.0170)	34.5417 (0.0227)
18	Hungary	24.4693 (0.2225)	24.1119 (0.2375)
19	Poland *)	35.6589 (0.0169)	37.4891 (0.0102)
20	Portugal *)	34.0928 (0.0255)	33.3713 (0.0307)
21	Turkey *)	33.0840 (0.0330)	31.8667 (0.0447)
22	Egypt *)	96.8089 (0.0000)	83.7558 (0.0000)
23	India	17.3012 (0.6333)	16.8757 (0.6610)
24	Israel *)	77.9364 (0.0000)	64.4276 (0.0000)
25	Morocco	25.7079 (0.1757)	24.6302 (0.2159)
26	Pakistan	34.7424 (0.0215)	32.0568 (0.0427)
27	S. Africa	23.8157 (0.2505)	21.7938 (0.3518)
28	Russia	27.5985 (0.1193)	27.6088 (0.1190)

From Table 20 we can conclude that in general the both tests do not indicate presence of conditional heteroskedasticity in the estimated residuals for most countries in the sample. This suggests that the selected specification, i.e. GARCH (1,1), explains the data quite well.

Since the GARCH (1,1) specification almost was not rejected at any case, we now determine a threshold u for each individual series and assume that the standardized residuals exceeding u follow a generalised Pareto Distribution (GPD). To implement POT method, determination of the threshold value u is crucial. There are several methods available to determine the threshold level including QQ-plot (also called eye ball method), Hill plot (suggested by Reiss and Thomas (1997)), and Bootstrap Method (suggested by Danielson, et.al (1996)). In this study, we follow Mc Neil and Frey (2000) and Fernandez (2004) whereby the threshold level is set to make the number of points above the threshold equals 10 percent of the number of the observations in each tail. As stated earlier our aim firstly is to obtain the estimated GPD for the tail of innovations. Since we treat, as a convention, a loss as a positive number then tail for losses is represented by positive residuals whereas tail for gains is represented by negative residuals.

Table 21 reports GPD estimates for both tails of the innovations for each of the 28 return series. It can be seen from the Table 21 that for the majority of the returns of emerging market countries, the shape parameter ξ for losses and gains turns out to be statistically insignificant. This implies that tail distributions do not deviate substantially from the Gumbel type (thin tailed distributions). This can be also measure by the ratio of the expected shortfall to VaR. For the 99-percent quantile, this ratio is 1.15 for a standard normal (see McNeil and Frey, op.cit). It can be seen from the Table 21 the expected shortfall to VaR is around 1.2

for losses and gains. This number is not considerably greater than that of a N(0,1) distribution.

Table 21. Tails of Innovations of Emerging Market Countries

Argentina									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.619	0.075	0.077	0.729	0.083	1436	3.441	4.376	1.27
Gains	1.503	0.153	0.099	0.568	0.076	1259	3.057	4.008	1.31
Brazil									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.700	0.024	0.095	0.649	0.083	1407	3.227	3.928	1.217
Gains	1.527	0.060	0.104	0.453	0.062	1288	2.637	3.190	1.209
Chile									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.579	0.049	0.076	0.623	0.071	1415	3.089	3.821	1.237
Gains	1.641	-0.109	0.091	0.515	0.065	1280	2.686	3.048	1.134
Colombia									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.604	-0.006	0.076	0.666	0.076	1404	3.120	3.774	1.209
Gains	1.684	0.086	0.103	0.595	0.081	1291	3.193	3.986	1.248
Mexico									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.684	0.148	0.099	0.586	0.076	1387	3.283	4.249	1.294
Gains	1.548	0.038	0.074	0.540	0.062	1308	2.839	3.452	1.216
Peru									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.497	0.344	0.121	0.502	0.073	1435	3.248	4.931	1.518
Gains	1.643	0.100	0.076	0.600	0.070	1260	3.193	4.033	1.263

Table 21. Tails of Innovations of Emerging Market Countries

Venezuela									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.270	0.415	0.105	0.451	0.059	1431	3.002	5.005	1.667
Gains	1.419	0.228	0.101	0.551	0.073	1264	3.077	4.281	1.391
Hong Kong									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.606	0.148	0.091	0.568	0.069	1450	3.160	4.098	1.297
Gains	1.657	0.228	0.101	0.551	0.073	1245	3.077	4.281	1.391
Indonesia									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.595	0.092	0.089	0.756	0.093	1417	3.523	4.552	1.292
Gains	1.471	0.097	0.099	0.700	0.093	1278	3.265	4.234	1.297
Korea									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.668	0.063	0.077	0.532	0.061	1403	2.980	3.636	1.220
Gains	1.687	0.075	0.101	0.466	0.062	1292	2.852	3.450	1.210
Malaysia									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.531	0.238	0.101	0.579	0.075	1465	3.297	4.608	1.398
Gains	1.565	0.199	0.107	0.616	0.085	1230	3.355	4.567	1.361
Philippines									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.536	-0.113	0.088	0.737	0.089	1488	3.024	3.535	1.169
Gains	1.557	0.265	0.104	0.467	0.064	1207	3.024	4.187	1.385

Table 21. Tails of Innovations of Emerging Market Countries

Singapore									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.613	-0.056	0.092	0.705	0.089	1350	3.132	3.719	1.187
Gains	1.554	-0.011	0.096	0.596	0.077	1345	2.902	3.477	1.198
Taiwan									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.569	0.021	0.080	0.645	0.074	1474	3.083	3.774	1.224
Gains	1.713	-0.088	0.074	0.609	0.071	1221	2.979	3.438	1.154
Thailand									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.586	-0.038	0.098	0.592	0.077	1418	2.885	3.408	1.181
Gains	1.728	-0.038	0.077	0.663	0.078	1277	3.181	3.766	1.184
Czech Republic									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.695	0.035	0.093	0.633	0.080	1369	3.204	3.915	1.222
Gains	1.640	0.001	0.100	0.493	0.066	1326	2.770	3.264	1.178
Greece									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.572	-0.016	0.101	0.613	0.081	1373	2.953	3.536	1.197
Gains	1.656	0.123	0.097	0.528	0.069	1322	3.055	3.852	1.261
Hungary									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.540	0.229	0.101	0.593	0.078	1373	3.330	4.632	1.391
Gains	1.555	0.184	0.111	0.503	0.070	1322	2.991	3.932	1.315

Table 21. Tails of Innovations of Emerging Market Countries

Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Poland									
Losses	1.680	-0.085	0.064	0.626	0.067	1376	2.982	3.456	1.159
Gains	1.611	-0.123	0.078	0.646	0.076	1319	2.899	3.332	1.149
Portugal									
Losses	1.642	0.123	0.106	0.474	0.064	1381	2.900	3.618	1.248
Gains	1.593	0.076	0.089	0.568	0.071	1314	3.015	3.747	1.243
Turkey									
Losses	1.616	0.161	0.097	0.578	0.074	1397	3.217	4.211	1.309
Gains	1.583	-0.04	0.113	0.661	0.095	1298	3.028	3.608	1.191
Egypt									
Losses	1.356	0.149	0.093	0.628	0.077	1599	3.071	4.111	1.338
Gains	1.842	0.011	0.098	0.913	0.125	1096	3.956	4.903	1.239
India									
Losses	1.626	0.100	0.089	0.548	0.067	1414	3.039	3.806	1.252
Gains	1.514	0.086	0.092	0.573	0.073	1281	2.968	3.732	1.257
Israel									
Losses	1.651	0.031	0.105	0.713	0.097	1407	3.345	4.135	1.236
Gains	1.584	-0.054	0.083	0.709	0.086	1288	3.109	3.703	1.191

Table 21. Tails of Innovations of Emerging Market Countries

Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Morocco									
Losses	1.57	0.073	0.087	0.558	0.068	1378	2.977	3.689	1.239
Gains	1.634	0.118	0.099	0.604	0.079	1317	3.221	4.119	1.278
Pakistan									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.594	0.076	0.095	0.765	0.097	1440	3.512	4.497	1.281
Gains	1.573	0.065	0.098	0.573	0.076	1255	2.988	3.699	1.238
South Africa									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.657	0.140	0.089	0.575	0.071	1383	3.212	4.135	1.287
Gains	1.543	0.057	0.088	0.496	0.061	1312	2.758	3.356	1.217
Russia									
Tail	U	ξ	s.e.	β	s.e.	Obs	Quantile	Sfall	Sfall/q
Losses	1.607	0.036	0.088	0.698	0.085	1398	3.271	4.056	1.240
Gains	1.558	0.146	0.109	0.591	0.083	1297	3.165	4.132	1.306

7.3. Estimation VaR In-Sample and Out of Sample

In the previous section, we simply looked at the shape parameter ξ. The following section turns to the empirical estimation of value at risk based on an approach suggested by Engle (2001), but in particular we model the behaviour of tails according to the EVT approach described earlier. To estimate the 99-percent VaR in-sample we use all observations except for the last three years. The last three years of the data were used for back testing. Panels (a) through (j) of Figure (3) show the results of VaR in-sample and VaR out of sample estimations of some of the sample countries used in this study.

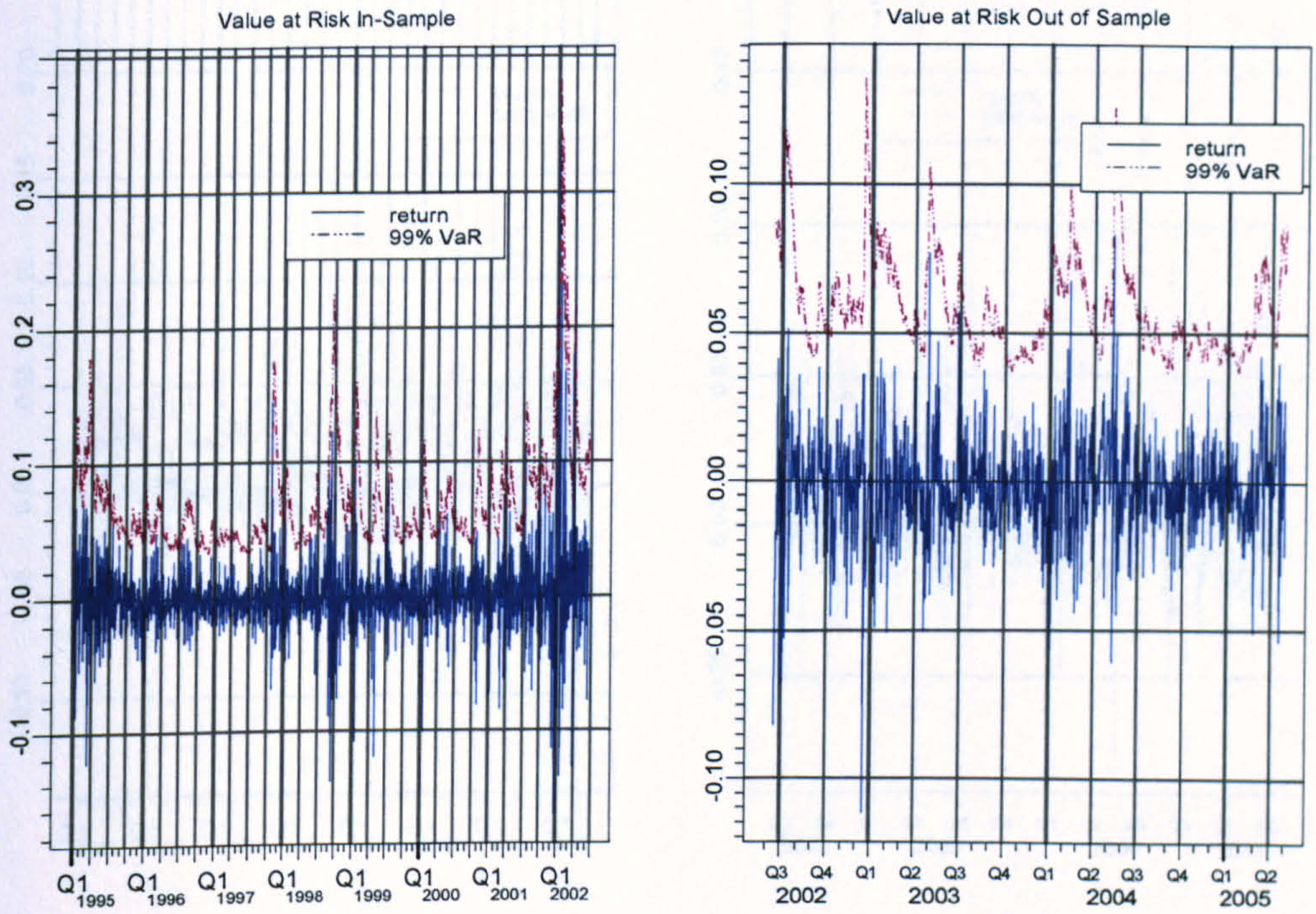
As we use 99 percent confidence level, by definition the expected in-sample error is 1 percent. In general the log negative returns tended to exceed VaR as expected. More specifically, only in the cases of Chile, Mexico, Indonesia, Philippines, Singapore, Greece, Portugal, Egypt, Israel, Pakistan and South Africa we have VaR in sample were exceeded by log negative returns. Thus for every sub emerging market region we have representative country in which the log negative returns exceeded VaR. Singapore and Israel have in sample error of 1.285347 percent and 1.182519 percent respectively. The log negative returns of Chile, Philippines, Greece, Portugal, Egypt and Pakistan exceed VaR 1.079692 percent of the time. Finally, there are three countries namely Mexico, Indonesia and South Africa that have the smallest in sample error of 1.028278 percent.

Unlike in sample estimation, the results of VaR out of sample estimation were exceeded exactly as expected for all countries. To estimate the 99-percent VaR out of sample we did not update the GARCH (1,1) parameters previously obtained from in-sample estimation. Likewise, the 99-percent quantile of the innovation distribution for each series is not recalculated either. It is found that 16 out of 28 countries have zero out of sample error. Countries in which their log negative returns exceed VaR above zero percent but below one percent out of times are Venezuela, Hong Kong, Korea, Malaysia, Singapore, Taiwan, Thailand, Czech Republic, Portugal, Turkey, Egypt and India. The Value at Risk is exceeded by the log-negative returns on Venezuela, Hong Kong, Singapore, Czech Republic, Turkey and India by 0.1335 percent. Log negative returns of Malaysia, Taiwan and Egypt exceeded the Value at Risk by 0.2670 percent whereas Korea and Thailand log negative returns exceeded the Value at Risk by 0.4005 percent. Finally, the log negative returns of Portugal exceeded the Value at Risk by 0.8011 percent.

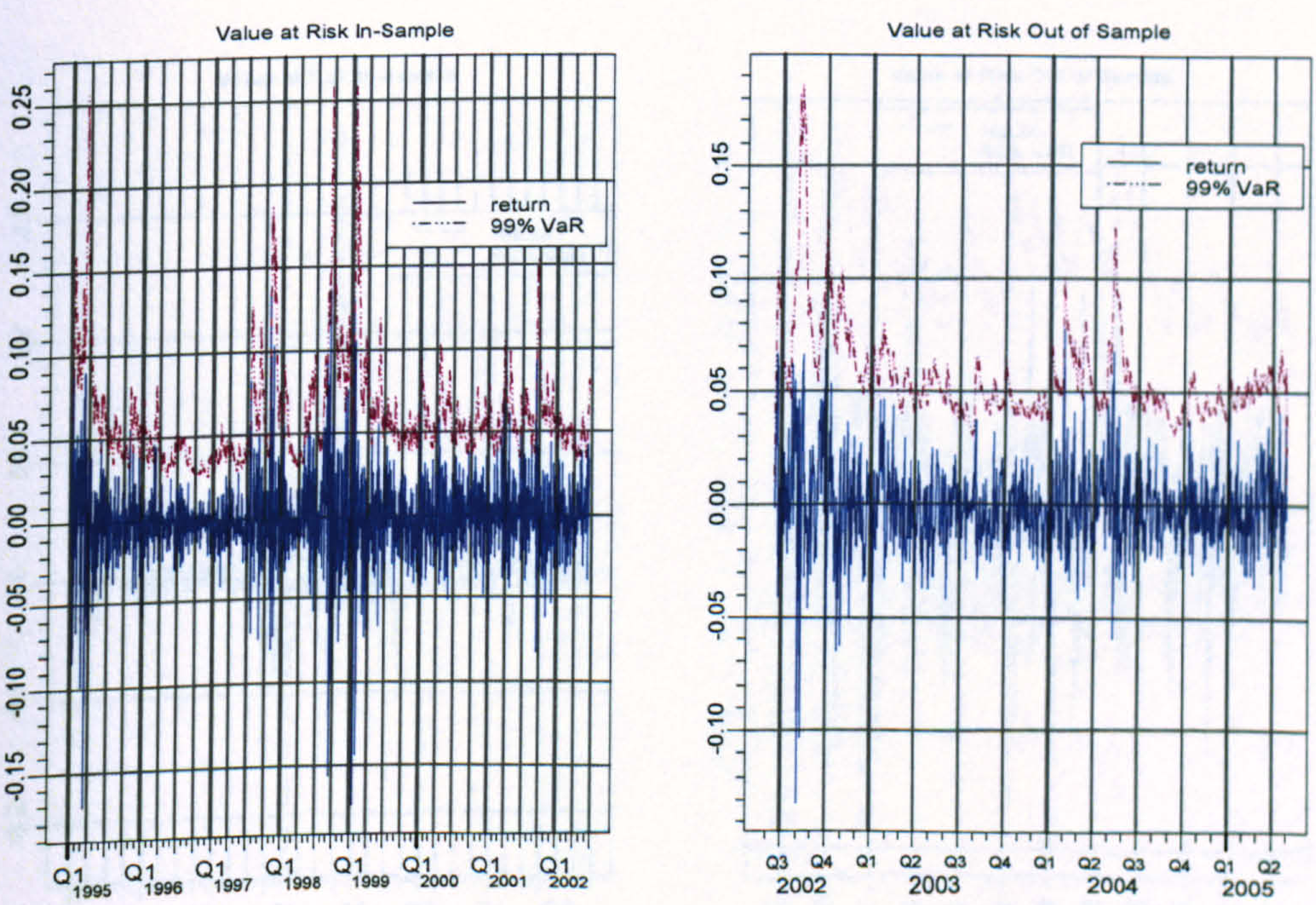
Although it would be convenient to model Value at Risk out of sample however, as Engle points out, it is not easy to assess its accuracy. This is because, in particular, the new information that becomes available in the back testing period is not incorporated either by parameter estimated or by quantiles. Thus, the next section is devoted to apply dynamic back testing which can lead us to conclusions which is the best VaR model to use.

Figure 3. Conditional 99% VaR and Log-Negative Returns In-Sample and Out of Sample

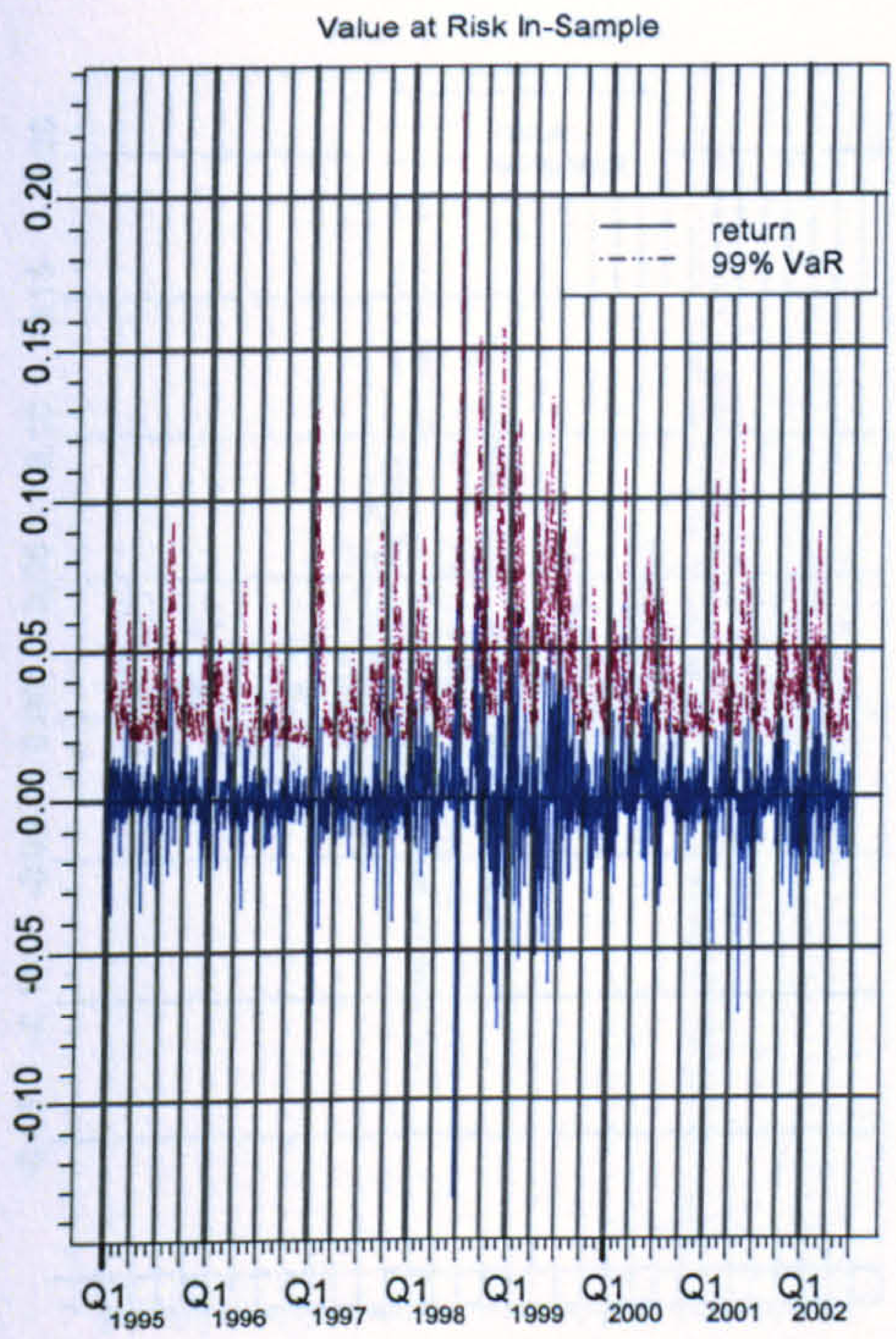
a. Argentina

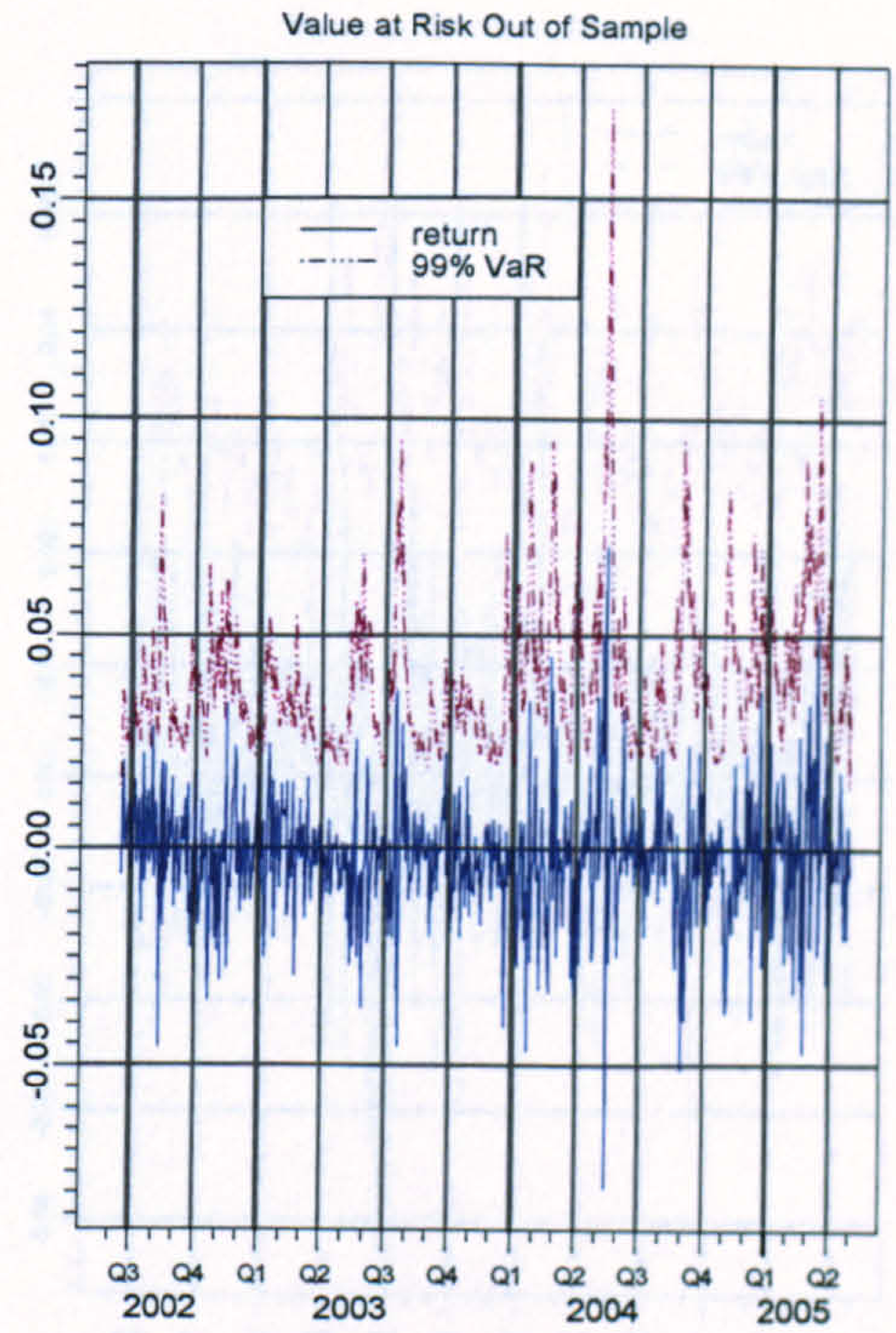


b. Brazil

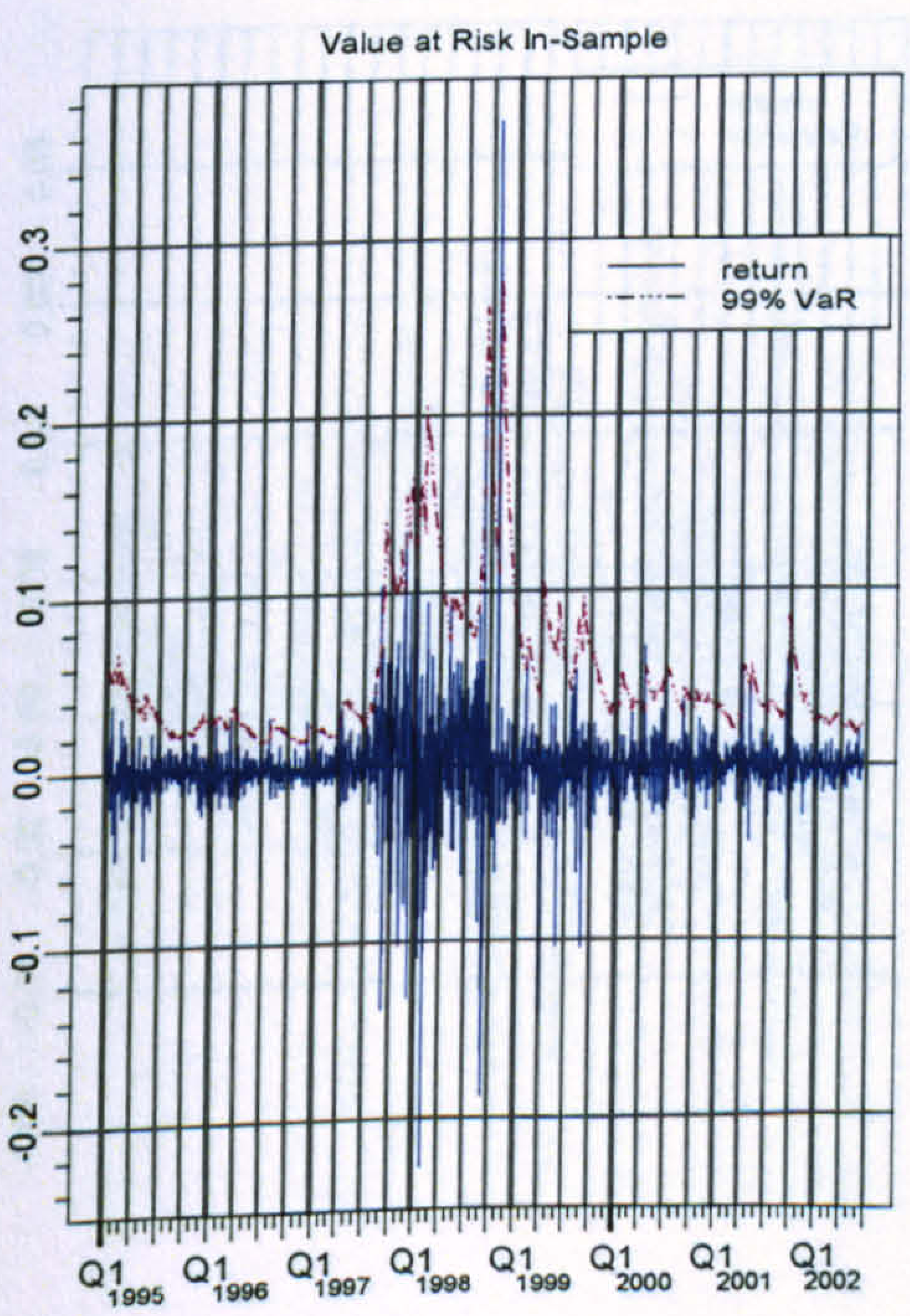


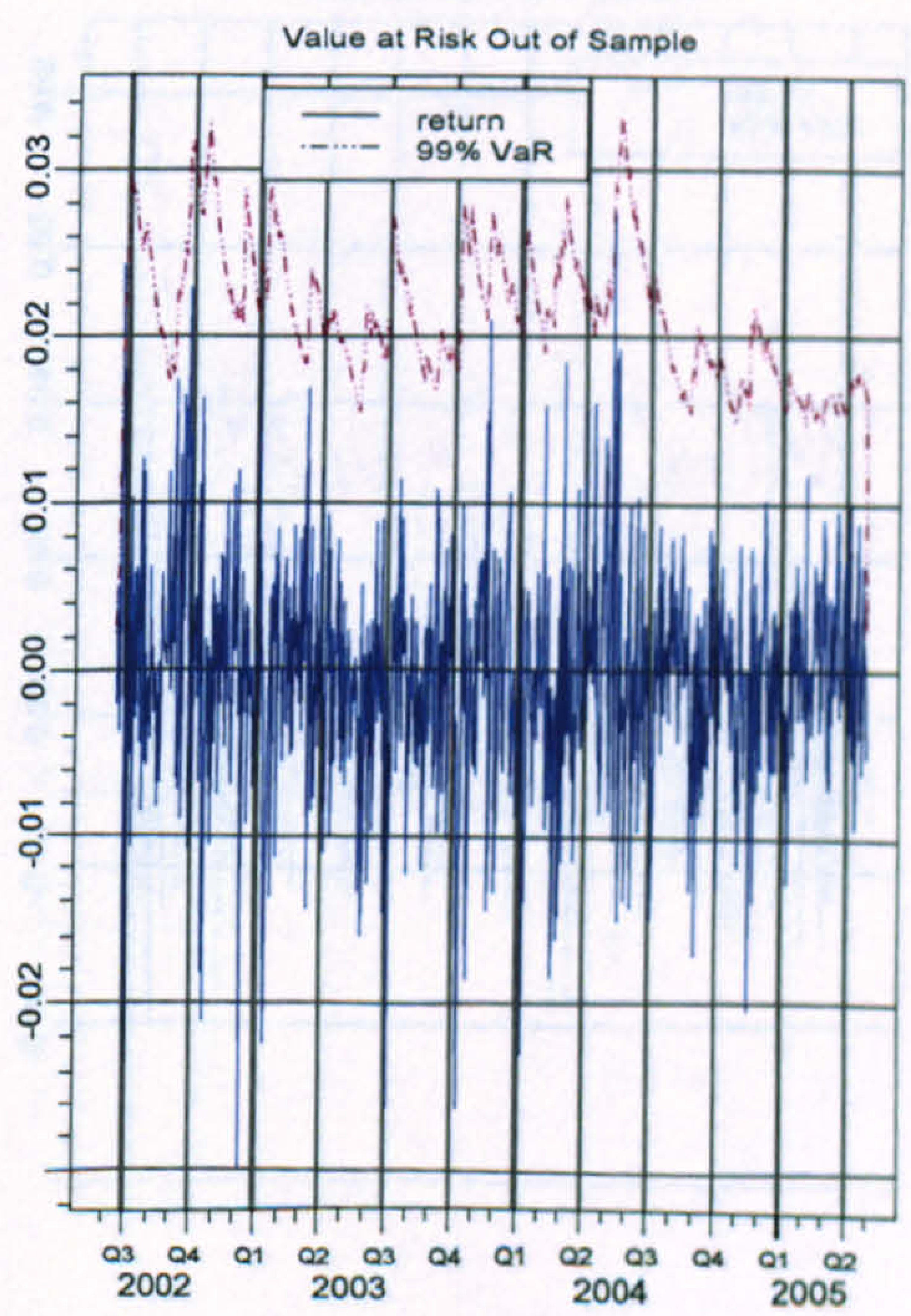
c. Colombia



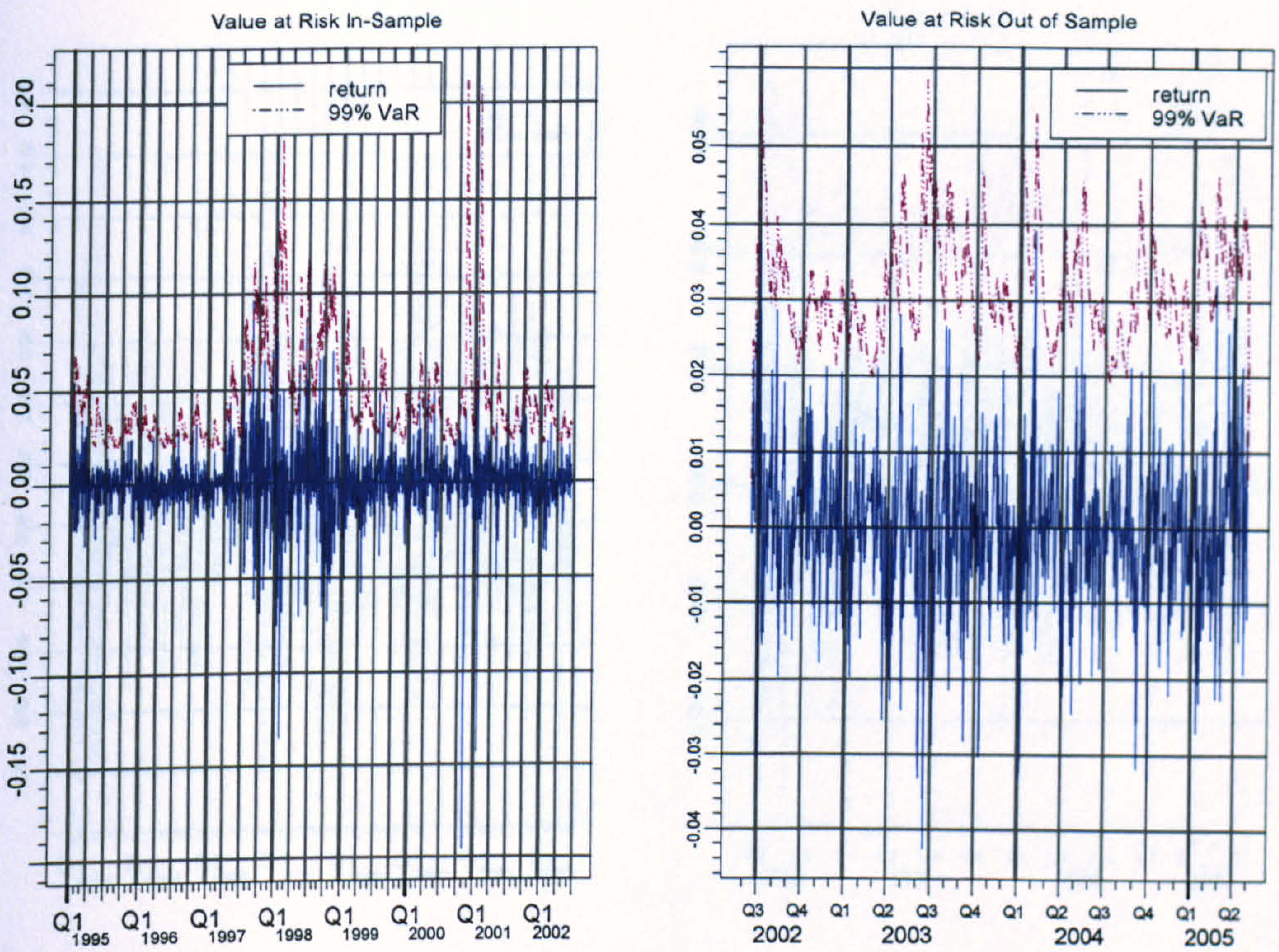


d. Malaysia

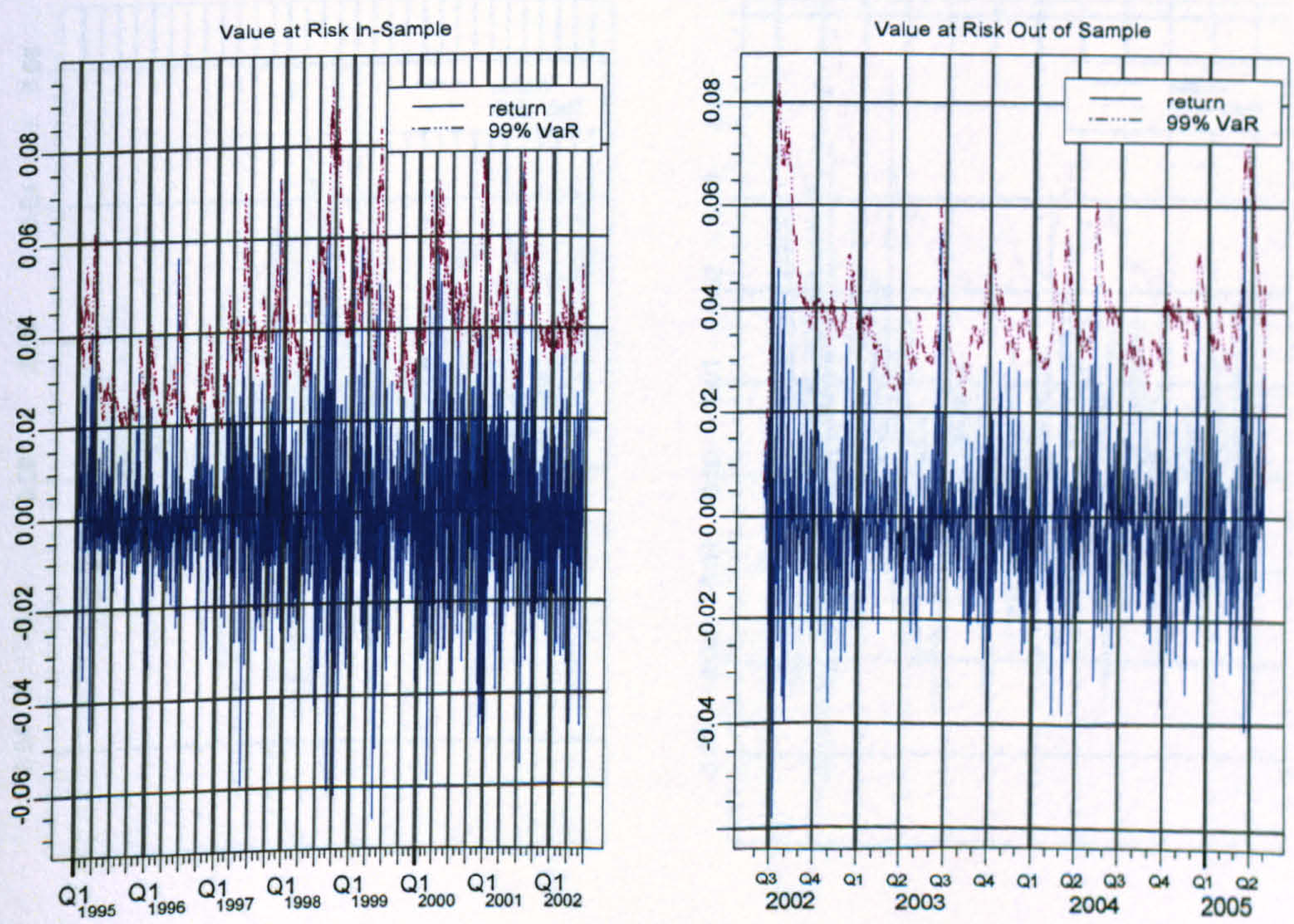




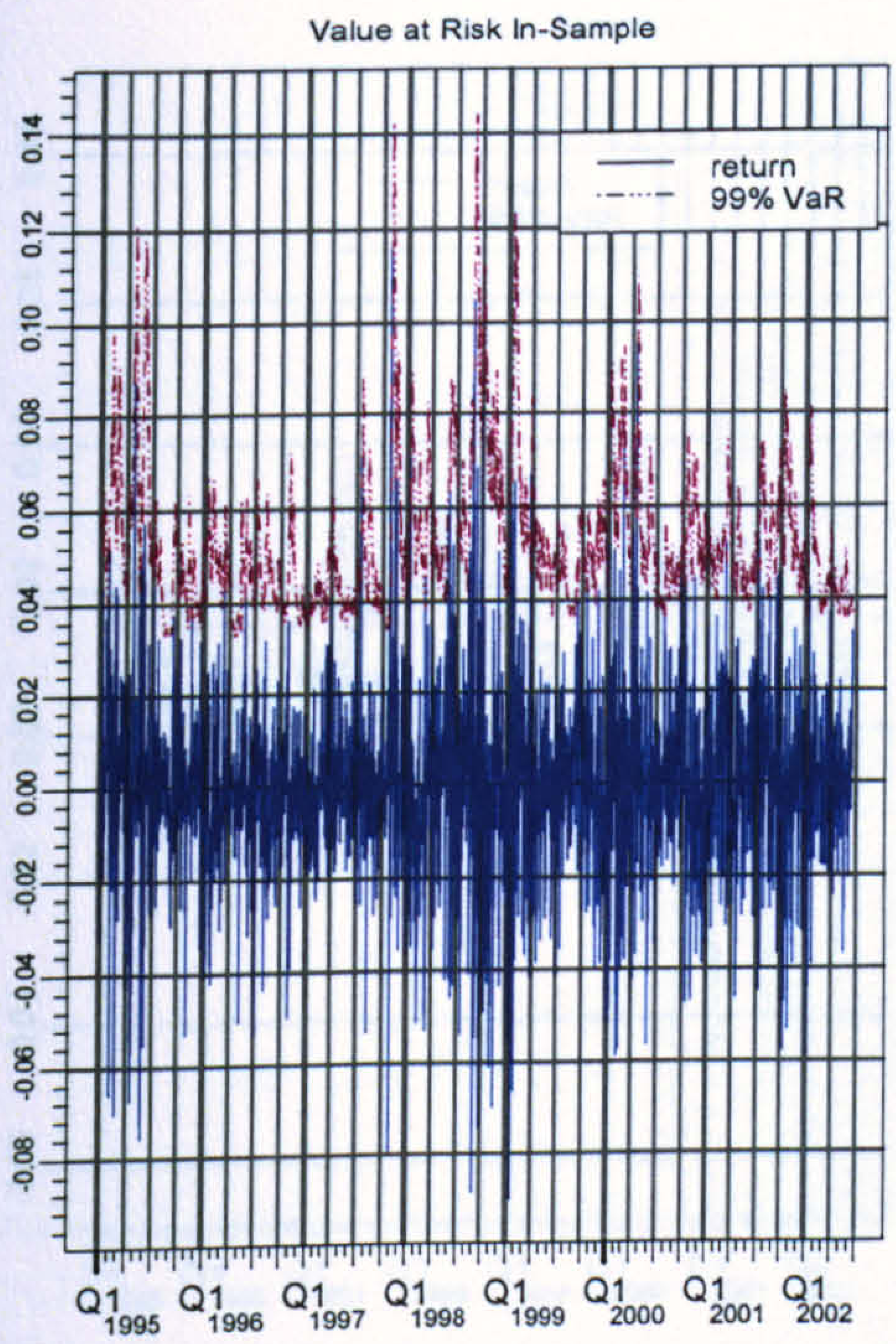
e.Philippines

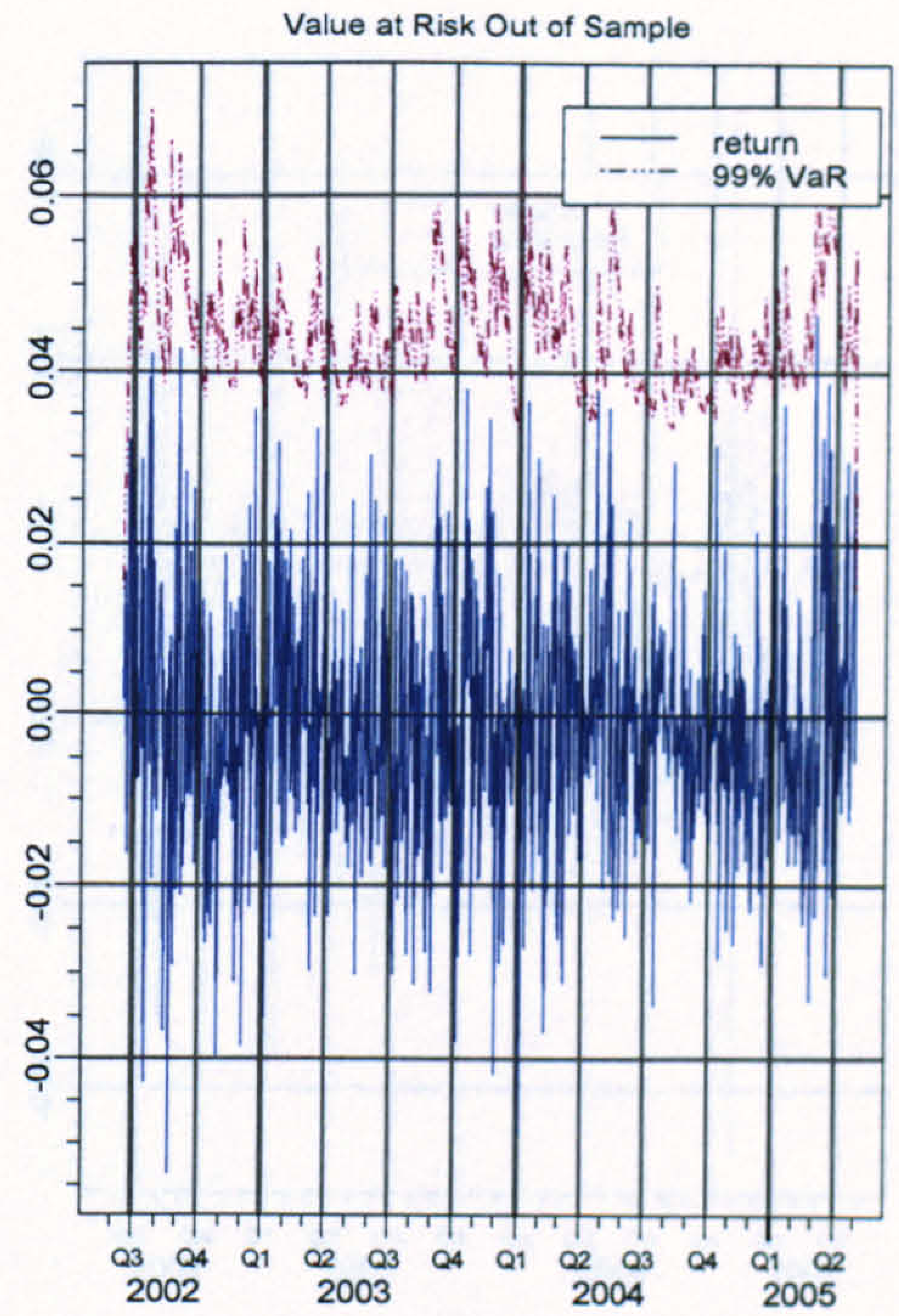


f. Czech Republic

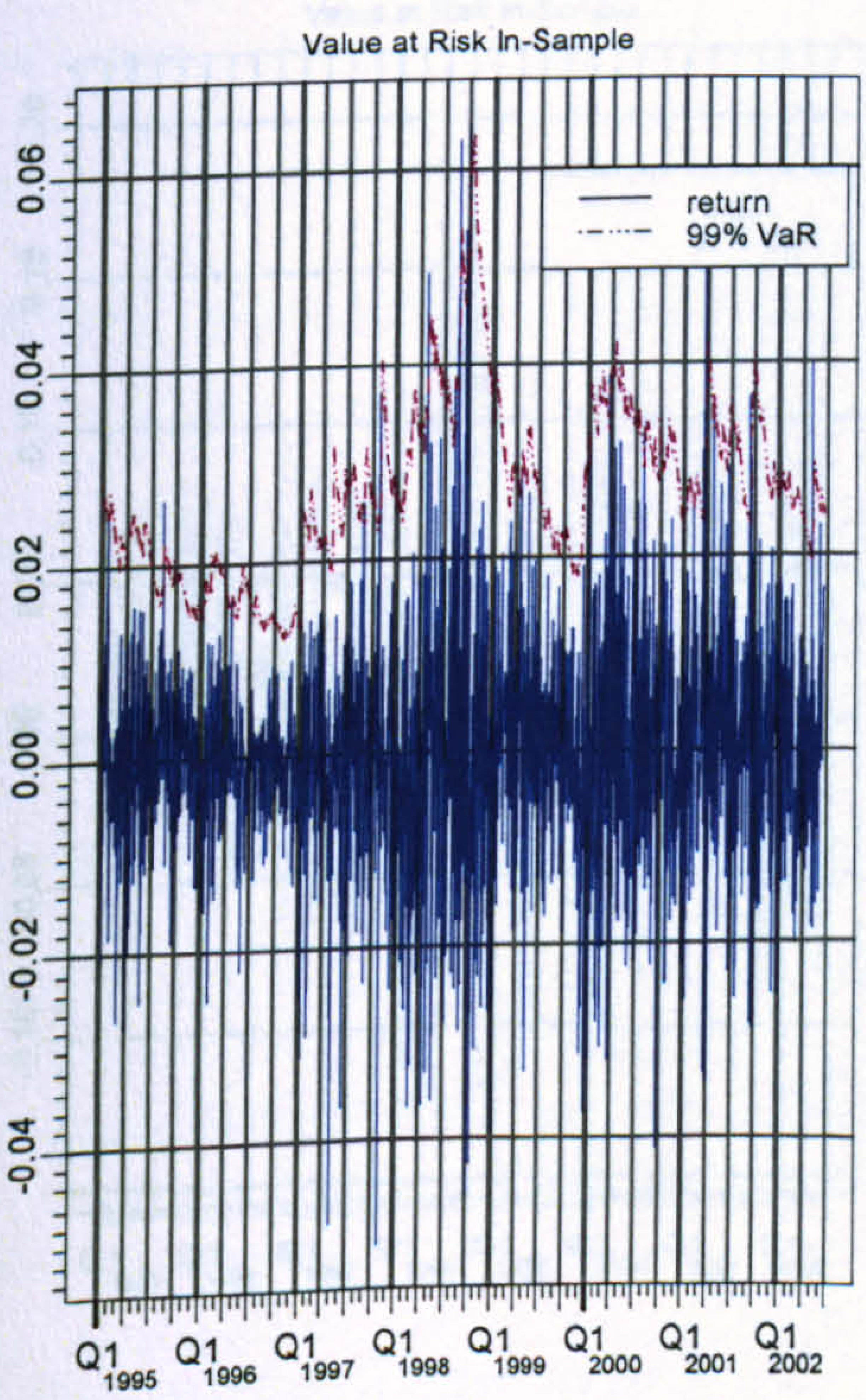


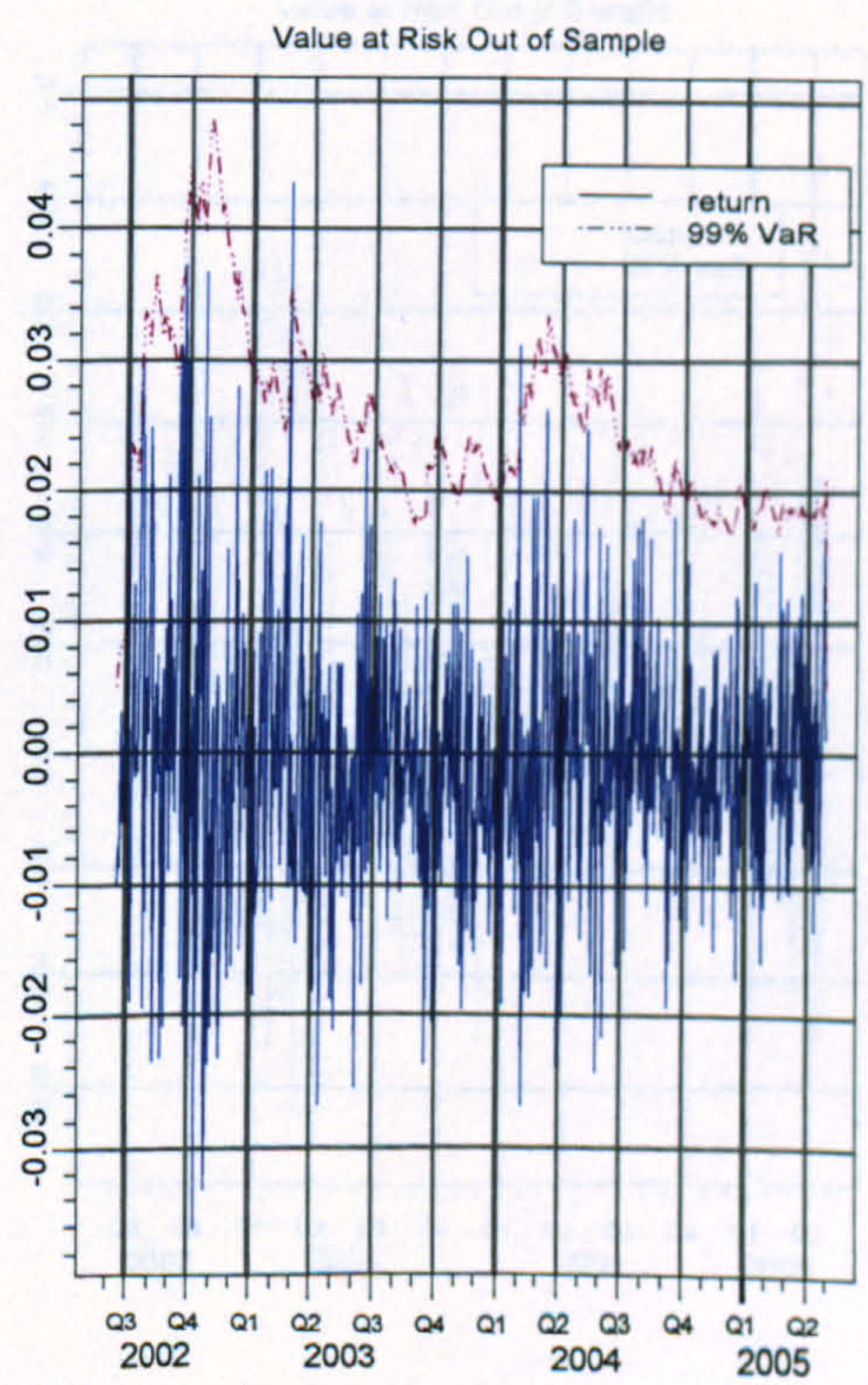
g. Poland



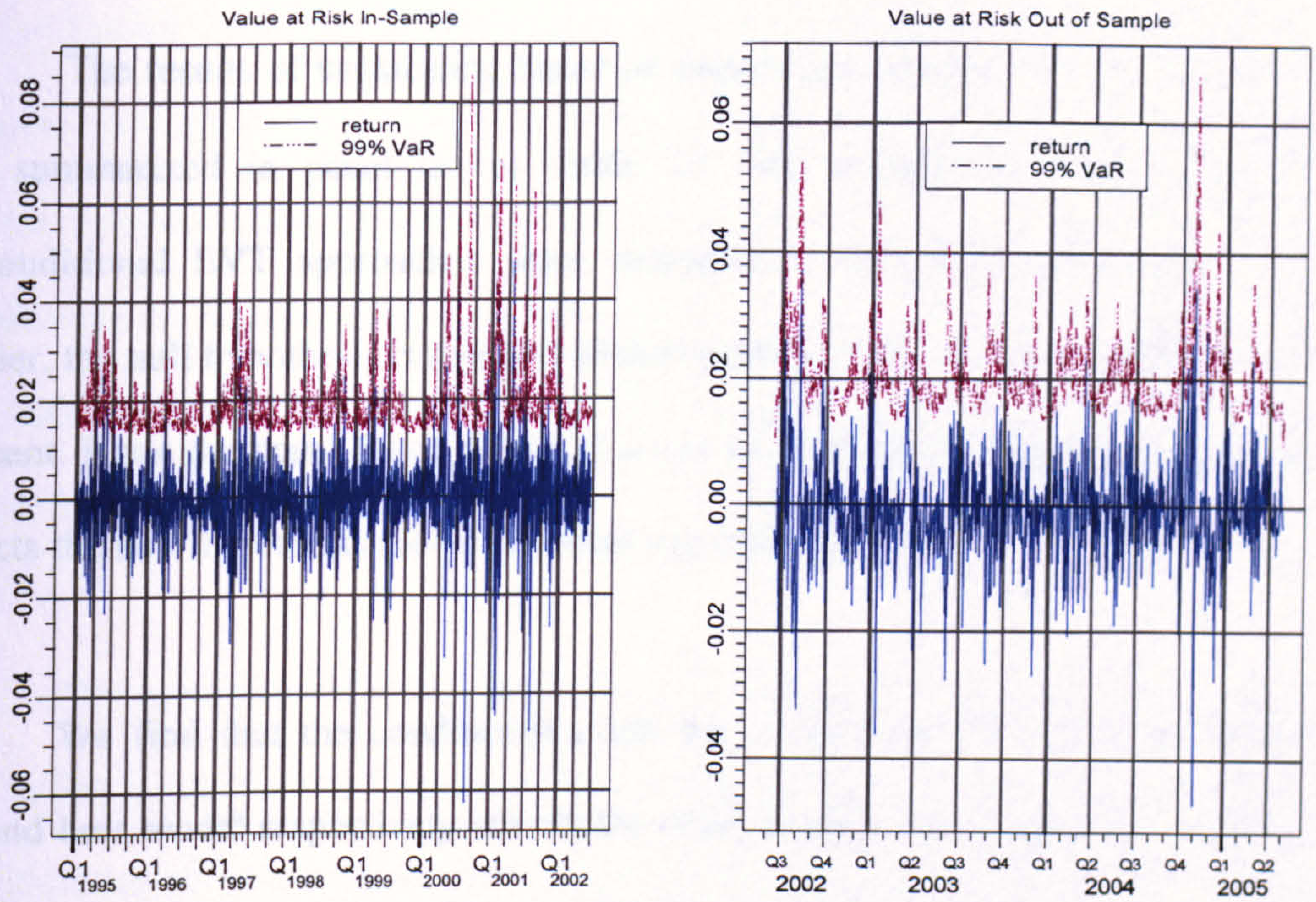


h. Portugal

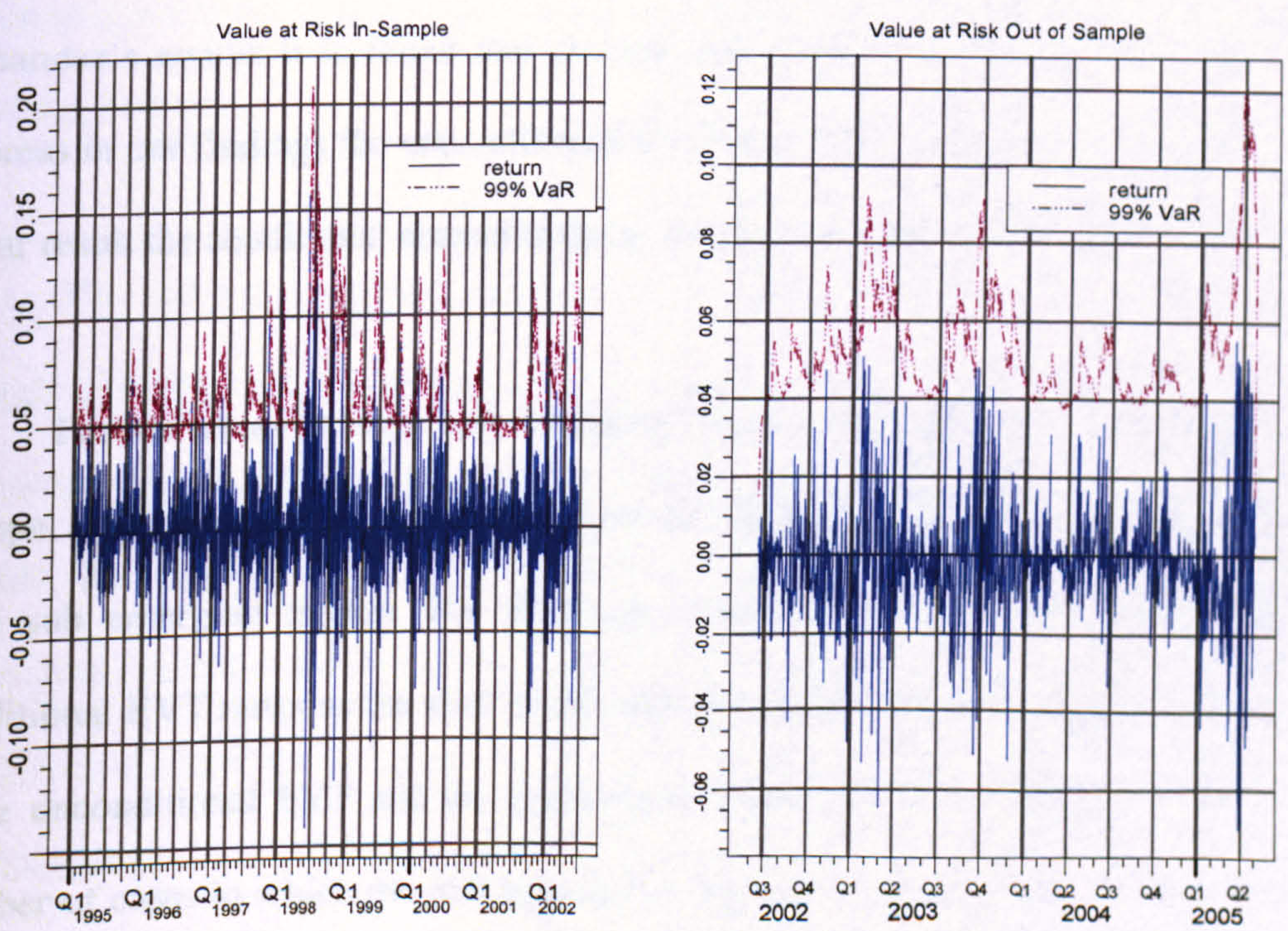




i. Morocco



j. Pakistan



7.4. Dynamic Backtesting

The results of backtesting based on population quantiles of 95, 99, and 99.5 percent are summarized in panel (a) of Table 22. The conditional t, normal, EVT and the unconditional EVT approaches were computed as previously described. As mentioned earlier, the null hypothesis is rejected whenever the p-value of the binomial test is less than 5 percent. From the panel (a) of Table 22 it can be seen that the conditional normal approach rejects the null hypothesis most often than any other models (48 out of 84 cases).

We find that the conditional t and the conditional EVT rank as the first and the second best model respectively among the other models. The number of cases in which the null hypothesis rejected were 16 cases for the conditional t and 17 cases for the conditional EVT. Our results are in line with the findings of Fernandez (2003). In particular, in Fernandez's results it is found that the unconditional EVT ranks as the third best model whereas in our findings the unconditional EVT also ranks as the third best model. Likewise, in our result the conditional normal ranks as the worst model as in Fernandez's result.

Further analysis into sub emerging market regions (Latin America, East Asia, Europe, and Other Emerging Markets) reveals different superiority among the models for each sub emerging market. For Emerging Market Latin America, it is found that the conditional EVT ranks as the first model and then followed subsequently by the conditional t, the unconditional EVT and the conditional normal. These findings are indicated by the number of cases in which the null hypothesis rejected were 0, 1, 5 an 15 for the conditional EVT, the conditional t, the unconditional EVT and the conditional normal respectively.

Unlike Emerging Market Latin America, the most successful models to explain extreme risk in East Asia Emerging Market are the conditional t and the conditional normal as the number cases in which the null hypothesis rejected are the same, i.e.11. The conditional EVT ranks as the third best model and then followed by the unconditional EVT. The null hypothesis was rejected in 12 cases and 19 cases by the conditional EVT and the unconditional EVT respectively.

The conditional t also is found to be the most successful model to capture extreme risk in Emerging Market Europe. In addition to the conditional t, the conditional EVT also considered as the most successful model as both models have the same numbers rejection of the null hypothesis, i.e. 2. The third and the fourth models were the unconditional EVT and the conditional normal as the number rejection of the null hypothesis were seven and eight cases respectively.

The last sub emerging market is the other emerging market. This another sub emerging market whereby the rank of the models matches with the findings of Fernandez Fernandez (2003). The conditional t was the most superior model as compared to the other models. The null hypothesis was rejected twice by the conditional t. Models which rank as the second, the third and the fourth model are the conditional EVT, the unconditional EVT and the conditional normal respectively. The number of cases in which the null hypothesis rejected were 3, 14 and 14 for the conditional EVT, the unconditional EVT and the conditional normal respectively. Conditional and unconditional EVT estimates along with log-negative returns of some of the sample countries used in this study are depicted in panels (a) through (j) of Figure 4.

Following Fernandez (2003) we also investigate the performance of the empirical quantile in computing VaR. This issues was not addressed by McNeil and Frey. As mentioned earlier in the methodology section, basically the procedure to obtain VaR based on the empirical quantile is similar to the other models, except that instead of parameterizing the tails of the innovation distribution, quantiles are computed from the empirical distribution of standardized residuals each time a new GARCH model is fitted to the data. We find that the empirical quantile perform quite well as the number of cases in which the null hypothesis rejected were 28. Thus, in general the performance of the empirical quantile is very similar to the conditional EVT. Panel (b) of Table 22 summarizes the results of backtesting for the empirical quantile.

A final observation, as before, is the breakdown analysis into each emerging market region. The null hypothesis for the empirical quantile was rejected in most cases by Emerging Market East Asia (10 cases). Emerging Market Latin America, Other Emerging Market region and Emerging Market Europe reject the null hypothesis by 8, 6 and 4 cases respectively. Therefore, it can be concluded that the empirical quantile performs very well in the Emerging Market Europe.

Table 22. Backtesting Results

(a) Population quantiles

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Argentina												
% error	5.25%	4.66%	5.01%	4.42%	1.18%	1.89%	1.24%	0.77%	0.47%	1.59%	0.47%	0.53%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.47	-0.65	0.02	-1.09	0.74	3.67	0.99	-0.97	-0.17	6.38	-0.17	0.18
p-value	0.32	0.26	0.49	0.14	0.23	0.00	0.16	0.17	0.43	0.00	0.43	0.43
rejection of null	0	0	0	0	0	1	0	0	0	1	0	0
Brazil												
% error	5.78%	5.31%	4.89%	4.42%	1.42%	1.95%	0.77%	0.65%	0.59%	1.24%	0.29%	0.35%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	1.47	0.58	-0.20	-1.09	1.72	3.91	-0.97	-1.45	0.52	4.31	-1.20	-0.85
p-value	0.07	0.28	0.42	0.14	0.04	0.00	0.17	0.07	0.30	0.00	0.12	0.20
rejection of null	0	0	0	0	1	1	0	0	0	1	0	0
Chile												
% error	5.19%	4.83%	5.19%	5.13%	1.06%	1.47%	0.94%	0.59%	0.47%	1.00%	0.35%	0.12%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.36	-0.31	0.36	0.24	0.25	1.96	-0.23	-1.70	-0.17	2.93	-0.85	-2.23
p-value	0.36	0.38	0.36	0.40	0.40	0.02	0.41	0.04	0.43	0.00	0.20	0.01
rejection of null	0	0	0	0	0	1	0	1	0	1	0	1
Colombia												
% error	5.72%	4.83%	4.78%	4.66%	0.71%	1.65%	0.94%	1.36%	0.24%	1.24%	0.47%	0.65%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	1.36	-0.31	-0.42	-0.65	-1.21	2.69	-0.23	1.47	-1.54	4.31	-0.17	0.87
p-value	0.09	0.38	0.34	0.26	0.11	0.00	0.41	0.07	0.06	0.00	0.43	0.19
rejection of null	0	0	0	0	0	1	0	0	0	1	0	0

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Mexico												
% error	5.13%	4.72%	4.66%	3.30%	1.24%	1.77%	1.00%	0.59%	0.65%	1.18%	0.53%	0.12%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.25	-0.53	-0.65	-3.21	0.99	3.18	0.01	-1.70	0.87	3.97	0.18	-2.23
p-value	0.40	0.30	0.26	0.00	0.16	0.00	0.50	0.04	0.19	0.00	0.43	0.01
rejection of null	0	0	0	1	0	1	0	1	0	1	0	1
Peru												
% error	4.72%	4.13%	4.83%	4.72%	0.88%	1.42%	1.00%	0.94%	0.59%	1.12%	0.65%	0.53%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.53	-1.65	-0.31	-0.53	-0.48	1.72	0.01	-0.23	0.52	3.62	0.87	0.18
p-value	0.30	0.05	0.38	0.30	0.32	0.04	0.50	0.41	0.30	0.00	0.19	0.43
rejection of null	0	1	0	0	0	1	0	0	0	1	0	0
Venezuela												
% error	5.37%	3.77%	5.42%	5.19%	0.88%	1.36%	0.83%	0.94%	0.41%	0.83%	0.53%	0.47%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.69	-2.32	0.80	0.36	-0.48	1.47	-0.72	-0.23	-0.51	1.90	0.18	-0.17
p-value	0.24	0.01	0.21	0.36	0.32	0.07	0.24	0.41	0.31	0.03	0.43	0.43
rejection of null	0	1	0	0	0	0	0	0	0	1	0	0
Hong Kong												
% error	4.60%	4.07%	3.83%	2.30%	0.47%	0.88%	0.59%	0.29%	0.24%	0.65%	0.24%	0.24%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.76	-1.76	-2.21	-5.10	-2.19	-0.48	-1.70	-2.92	-1.54	0.87	-1.54	-1.54
p-value	0.22	0.04	0.01	0.00	0.01	0.32	0.04	0.00	0.06	0.19	0.06	0.06
rejection of null	0	1	1	1	1	0	1	1	0	0	0	0
Indonesia												
% error	4.54%	4.01%	3.95%	2.42%	0.59%	1.59%	0.41%	0.18%	0.12%	1.18%	0.12%	0.18%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.87	-1.87	-1.98	-4.88	-1.70	2.45	-2.43	-3.41	-2.23	3.97	-2.23	-1.89
p-value	0.19	0.03	0.02	0.00	0.04	0.01	0.01	0.00	0.01	0.00	0.01	0.03
rejection of null	0	1	1	1	1	1	1	1	1	1	1	1

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Korea												
% error	4.95%	4.13%	4.13%	3.18%	0.65%	0.94%	0.77%	0.18%	0.24%	0.71%	0.41%	0.06%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.09	-1.65	-1.65	-3.43	-1.45	-0.23	-0.97	-3.41	-1.54	1.21	-0.51	-2.58
p-value	0.46	0.05	0.05	0.00	0.07	0.41	0.17	0.00	0.06	0.11	0.31	0.01
rejection of null	0	1	1	1	0	0	0	1	0	0	0	1
Malaysia												
% error	2.89%	2.71%	3.60%	1.59%	0.35%	1.18%	0.59%	0.00%	0.12%	0.65%	0.29%	0.00%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-3.99	-4.32	-2.65	-6.44	-2.67	0.74	-1.70	-4.14	-2.23	0.87	-1.20	-2.92
p-value	0.00	0.00	0.00	0.00	0.00	0.23	0.04	0.00	0.01	0.19	0.12	0.00
rejection of null	1	1	1	1	1	0	1	1	1	0	0	1
Philippines												
% error	5.01%	3.66%	3.89%	2.65%	0.88%	1.18%	0.83%	0.29%	0.24%	0.88%	0.29%	0.18%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.02	-2.54	-2.09	-4.43	-0.48	0.74	-0.72	-2.92	-1.54	2.24	-1.20	-1.89
p-value	0.49	0.01	0.02	0.00	0.32	0.23	0.24	0.00	0.06	0.01	0.12	0.03
rejection of null	0	1	1	1	0	0	0	1	0	1	0	1
Singapore												
% error	3.60%	3.54%	3.77%	3.07%	0.59%	1.18%	0.65%	0.53%	0.35%	0.59%	0.35%	0.24%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-2.65	-2.76	-2.32	-3.65	-1.70	0.74	-1.45	-1.94	-0.85	0.52	-0.85	-1.54
p-value	0.00	0.00	0.01	0.00	0.04	0.23	0.07	0.03	0.20	0.30	0.20	0.06
rejection of null	1	1	1	1	1	0	0	1	0	0	0	0
Taiwan												
% error	4.95%	4.54%	4.60%	5.07%	0.77%	1.36%	0.94%	1.00%	0.41%	0.94%	0.47%	0.47%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.09	-0.87	-0.76	0.13	-0.97	1.47	-0.23	0.01	-0.51	2.59	-0.17	-0.17
p-value	0.46	0.19	0.22	0.45	0.17	0.07	0.41	0.50	0.31	0.00	0.43	0.43
rejection of null	0	0	0	0	0	0	0	0	0	1	0	0

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Thailand												
% error	3.83%	3.48%	3.95%	2.89%	0.47%	0.88%	0.59%	0.47%	0.18%	0.53%	0.41%	0.12%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-2.21	-2.87	-1.98	-3.99	-2.19	-0.48	-1.70	-2.19	-1.89	0.18	-0.51	-2.23
p-value	0.01	0.00	0.02	0.00	0.01	0.32	0.04	0.01	0.03	0.43	0.31	0.01
rejection of null	1	1	1	1	1	0	1	1	1	0	0	1
Czech												
% error	5.66%	5.31%	5.42%	4.48%	1.30%	1.65%	0.94%	1.06%	0.59%	1.24%	0.47%	0.41%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	1.25	0.58	0.80	-0.98	1.23	2.69	-0.23	0.25	0.52	4.31	-0.17	-0.51
p-value	0.11	0.28	0.21	0.16	0.11	0.00	0.41	0.40	0.30	0.00	0.43	0.31
rejection of null	0	0	0	0	0	1	0	0	0	1	0	0
Greece												
% error	3.83%	3.36%	3.42%	3.48%	0.77%	1.30%	0.88%	0.53%	0.18%	0.83%	0.29%	0.35%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-2.21	-3.10	-2.99	-2.87	-0.97	1.23	-0.48	-1.94	-1.89	1.90	-1.20	-0.85
p-value	0.01	0.00	0.00	0.00	0.17	0.11	0.32	0.03	0.03	0.03	0.12	0.20
rejection of null	1	1	1	1	0	0	0	1	1	1	0	0
Hungary												
% error	4.30%	3.42%	4.36%	2.89%	0.71%	1.18%	0.77%	0.65%	0.65%	0.83%	0.59%	0.24%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-1.31	-2.99	-1.20	-3.99	-1.21	0.74	-0.97	-1.45	0.87	1.90	0.52	-1.54
p-value	0.09	0.00	0.11	0.00	0.11	0.23	0.17	0.07	0.19	0.03	0.30	0.06
rejection of null	0	1	0	1	0	0	0	0	0	1	0	0
Poland												
% error	4.78%	4.78%	4.42%	3.36%	0.77%	1.24%	0.71%	0.29%	0.29%	0.71%	0.35%	0.12%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.42	-0.42	-1.09	-3.10	-0.97	0.99	-1.21	-2.92	-1.20	1.21	-0.85	-2.23
p-value	0.34	0.34	0.14	0.00	0.17	0.16	0.11	0.00	0.12	0.11	0.20	0.01
rejection of null	0	0	0	1	0	0	0	1	0	0	0	1

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Portugal												
% error	4.95%	4.66%	4.83%	5.19%	0.71%	1.12%	0.77%	0.53%	0.35%	0.71%	35.38%	0.24%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.09	-0.65	-0.31	0.36	-1.21	0.50	-0.97	-1.94	-0.85	1.21	203.64	-1.54
p-value	0.46	0.26	0.38	0.36	0.11	0.31	0.17	0.03	0.20	0.11	-	0.06
rejection of null	0	0	0	0	0	0	0	1	0	0	1	0
Turkey												
% error	4.89%	4.25%	4.72%	4.78%	1.12%	1.47%	0.94%	0.94%	0.59%	1.06%	0.53%	0.47%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.20	-1.43	-0.53	-0.42	0.50	1.96	-0.23	-0.23	0.52	3.28	0.18	-0.17
p-value	0.42	0.08	0.30	0.34	0.31	0.02	0.41	0.41	0.30	0.00	0.43	0.43
rejection of null	0	0	0	0	0	1	0	0	0	1	0	0
Egypt												
% error	5.54%	4.25%	4.89%	6.90%	0.53%	1.65%	1.06%	1.52%	0.24%	1.24%	0.59%	1.00%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	1.03	-1.43	-0.20	3.59	-1.94	2.69	0.25	2.15	-1.54	4.31	0.52	2.93
p-value	0.15	0.08	0.42	0.00	0.03	0.00	0.40	0.02	0.06	0.00	0.30	0.00
rejection of null	0	0	0	1	1	1	0	1	0	1	0	1
India												
% error	5.19%	4.78%	4.66%	4.66%	1.06%	1.42%	0.88%	1.24%	0.65%	1.00%	0.59%	0.65%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.36	-0.42	-0.65	-0.65	0.25	1.72	-0.48	0.99	0.87	2.93	0.52	0.87
p-value	0.36	0.34	0.26	0.26	0.40	0.04	0.32	0.16	0.19	0.00	0.30	0.19
rejection of null	0	0	0	0	0	1	0	0	0	1	0	0
Israel												
% error	6.25%	5.84%	5.37%	5.31%	1.24%	2.36%	1.12%	0.94%	0.24%	1.65%	0.47%	0.47%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	2.36	1.58	0.69	0.58	0.99	5.62	0.50	-0.23	-1.54	6.72	-0.17	-0.17
p-value	0.01	0.06	0.24	0.28	0.16	0.00	0.31	0.41	0.06	0.00	0.43	0.43
rejection of null	1	0	0	0	0	1	0	0	0	1	0	0

	95%	95%	95%	95%	99%	99%	99%	99%	99.5%	99.5%	99.5%	99.5%
	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT	Cond. t	Cond. normal	Cond. EVT	Unc. EVT
Morocco												
% error	5.72%	4.89%	6.43%	6.43%	1.18%	1.83%	1.42%	1.42%	0.59%	1.36%	0.94%	0.94%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	1.36	-0.20	2.70	2.70	0.74	3.43	1.72	1.72	0.52	5.00	2.59	2.59
p-value	0.09	0.42	0.00	0.00	0.23	0.00	0.04	0.04	0.30	0.00	0.00	0.00
rejection of null	0	0	1	1	0	1	1	1	0	1	1	1
Pakistan												
% error	4.83%	3.95%	4.30%	4.19%	0.71%	1.59%	0.71%	0.41%	0.35%	0.88%	0.35%	0.12%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.31	-1.98	-1.31	-1.54	-1.21	2.45	-1.21	-2.43	-0.85	2.24	-0.85	-2.23
p-value	0.38	0.02	0.09	0.06	0.11	0.01	0.11	0.01	0.20	0.01	0.20	0.01
rejection of null	0	1	0	0	0	1	0	1	0	1	0	1
S.Africa												
% error	5.37%	5.13%	4.95%	4.13%	0.88%	1.42%	0.71%	0.53%	0.41%	0.77%	0.24%	0.18%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	0.69	0.25	-0.09	-1.65	-0.48	1.72	-1.21	-1.94	-0.51	1.56	-1.54	-1.89
p-value	0.24	0.40	0.46	0.05	0.32	0.04	0.11	0.03	0.31	0.06	0.06	0.03
rejection of null	0	0	0	1	0	1	0	1	0	0	0	1
Russia												
% error	4.72%	4.60%	4.36%	2.65%	1.24%	1.89%	0.83%	0.41%	0.59%	1.36%	0.53%	0.18%
expected	5.00%	5.00%	5.00%	5.00%	1.00%	1.00%	1.00%	1.00%	0.50%	0.50%	0.50%	0.50%
Binomial test	-0.53	-0.76	-1.20	-4.43	0.99	3.67	-0.72	-2.43	0.52	5.00	0.18	-1.89
p-value	0.30	0.22	0.11	0.00	0.16	0.00	0.24	0.01	0.30	0.00	0.43	0.03
rejection of null	0	0	0	1	0	1	0	1	0	1	0	1
rejection of null	5	12	9	15	7	16	5	17	4	20	3	13
by quantile												
	Cond-t	Cond-normal	Cond-EVT	Unc-EVT								
	16	48	17	45								

Table 22. Backtesting Results Continued

(b) Empirical Quantiles

Quantile	95%	99%	99.5%
Argentina			
% error	6.37%	1.59%	0.65%
expected	5.00%	1.00%	0.50%
Binomial test	2.58	2.45	0.87
p-value	0.00	0.01	0.19
rejection of null	1	1	0
Brazil			
% error	6.13%	1.59%	0.83%
expected	5.00%	1.00%	0.50%
Binomial test	2.14	2.45	1.90
p-value	0.02	0.01	0.03
rejection of null	1	1	1
Chile			
% error	5.19%	1.24%	0.71%
expected	5.00%	1.00%	0.50%
Binomial test	0.36	0.99	1.21
p-value	0.36	0.16	0.11
rejection of null	0	0	0
Colombia			
% error	5.31%	0.77%	0.24%
expected	5.00%	1.00%	0.50%
Binomial test	0.58	-0.97	-1.54
p-value	0.28	0.17	0.06
rejection of null	0	0	0
Mexico			
% error	5.37%	1.42%	0.94%
expected	5.00%	1.00%	0.50%
Binomial test	0.69	1.72	2.59
p-value	0.24	0.04	0.00
rejection of null	0	1	1
Peru			
% error	3.77%	1.00%	0.65%
expected	5.00%	1.00%	0.50%
Binomial test	-2.32	0.01	0.87
p-value	0.01	0.50	0.19
rejection of null	1	0	0
Venezuela			
% error	4.95%	0.77%	0.24%
expected	5.00%	1.00%	0.50%
Binomial test	-0.09	-0.97	-1.54
p-value	0.46	0.17	0.06
rejection of null	0	0	0
Hong Kong			
% error	4.66%	0.65%	0.29%
expected	5.00%	1.00%	0.50%
Binomial test	-0.65	-1.45	-1.20
p-value	0.26	0.07	0.12
rejection of null	0	0	0

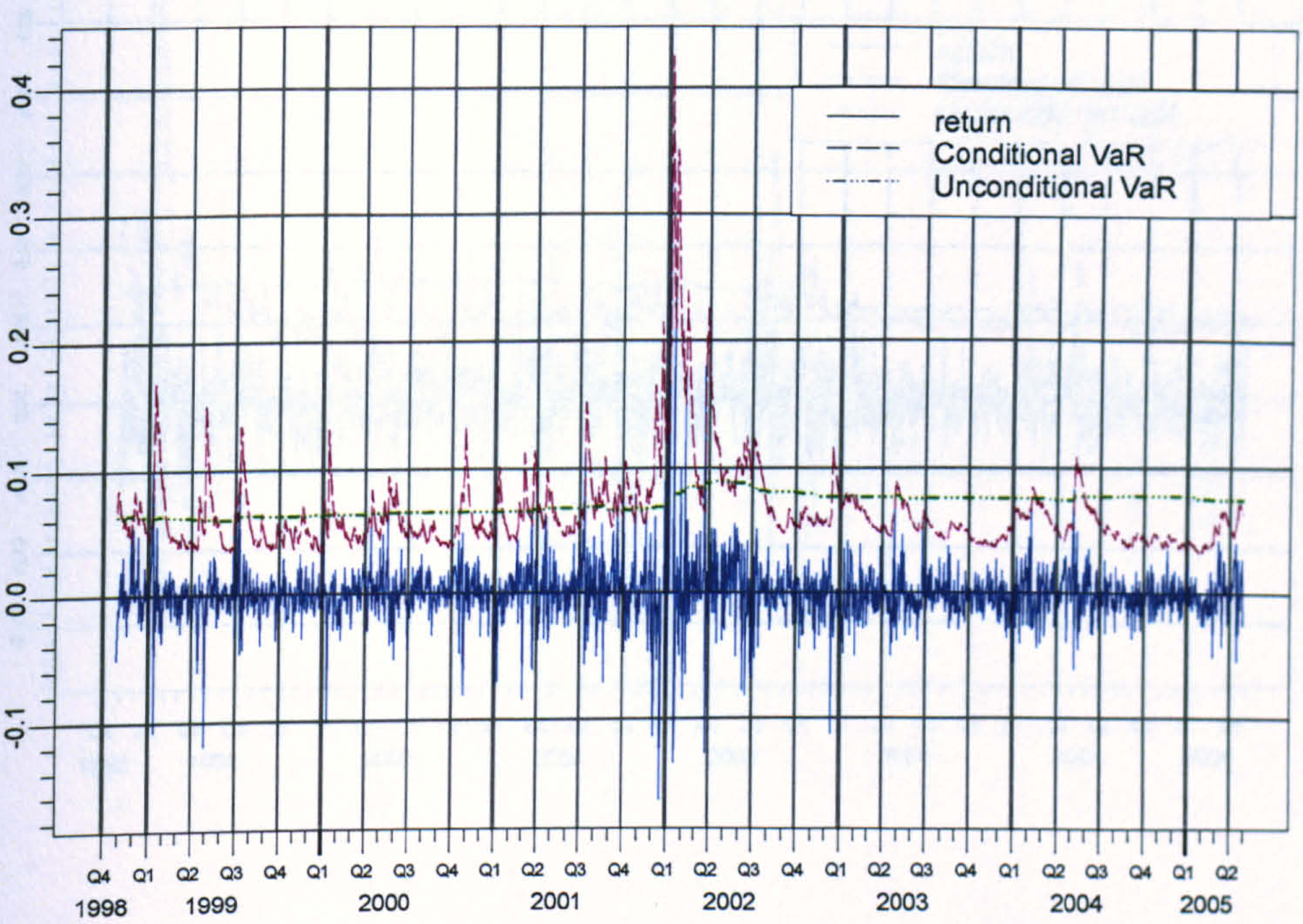
Quantile	95%	99%	99.5%
Indonesia			
% error	4.89%	1.06%	0.12%
expected	5.00%	1.00%	0.50%
Binomial test	-0.20	0.25	-2.23
p-value	0.42	0.40	0.01
rejection of null	0	0	1
Korea			
% error	3.71%	0.65%	0.35%
expected	5.00%	1.00%	0.50%
Binomial test	-2.43	-1.45	-0.85
p-value	0.01	0.07	0.20
rejection of null	1	0	0
Malaysia			
% error	3.60%	0.47%	0.18%
expected	5.00%	1.00%	0.50%
Binomial test	-2.65	-2.19	-1.89
p-value	0.00	0.01	0.03
rejection of null	1	1	1
Philippines			
% error	4.72%	0.83%	0.29%
expected	5.00%	1.00%	0.50%
Binomial test	-0.53	-0.72	-1.20
p-value	0.30	0.24	0.12
rejection of null	0	0	0
Singapore			
% error	3.89%	0.59%	0.29%
expected	5.00%	1.00%	0.50%
Binomial test	-2.09	-1.70	-1.20
p-value	0.02	0.04	0.12
rejection of null	1	1	0
Taiwan			
% error	4.30%	0.88%	0.53%
expected	5.00%	1.00%	0.50%
Binomial test	-1.31	-0.48	0.18
p-value	0.09	0.32	0.43
rejection of null	0	0	0
Thailand			
% error	3.30%	0.35%	0.12%
expected	5.00%	1.00%	0.50%
Binomial test	-3.21	-2.67	-2.23
p-value	0.00	0.00	0.01
rejection of null	1	1	1
Czech			
% error	5.07%	1.42%	0.83%
expected	5.00%	1.00%	0.50%
Binomial test	0.13	1.72	1.90
p-value	0.45	0.04	0.03
rejection of null	0	1	1

Quantile	95%	99%	99.5%
Greece			
% error	3.66%	0.65%	0.18%
expected	5.00%	1.00%	0.50%
Binomial test	-2.54	-1.45	-1.89
p-value	0.01	0.07	0.03
rejection of null	1	0	1
Hungary			
% error	4.60%	0.83%	0.47%
expected	5.00%	1.00%	0.50%
Binomial test	-0.76	-0.72	-0.17
p-value	0.22	0.24	0.43
rejection of null	0	0	0
Poland			
% error	4.89%	0.83%	0.24%
expected	5.00%	1.00%	0.50%
Binomial test	-0.20	-0.72	-1.54
p-value	0.42	0.24	0.06
rejection of null	0	0	0
Portugal			
% error	5.01%	0.94%	0.29%
expected	5.00%	1.00%	0.50%
Binomial test	0.02	-0.23	-1.20
p-value	0.49	0.41	0.12
rejection of null	0	0	0
Turkey			
% error	4.54%	1.00%	0.41%
expected	5.00%	1.00%	0.50%
Binomial test	-0.87	0.01	-0.51
p-value	0.19	0.50	0.31
rejection of null	0	0	0
Egypt			
% error	3.95%	0.59%	0.41%
expected	5.00%	1.00%	0.50%
Binomial test	-1.98	-1.70	-0.51
p-value	0.02	0.04	0.31
rejection of null	1	1	0
India			
% error	5.25%	1.00%	0.47%
expected	5.00%	1.00%	0.50%
Binomial test	0.47	0.01	-0.17
p-value	0.32	0.50	0.43
rejection of null	0	0	0
Israel			
% error	6.54%	1.53%	0.59%
expected	5.00%	1.00%	0.50%
Binomial test	2.92	2.21	0.52
p-value	0.00	0.01	0.30
rejection of null	1	1	0

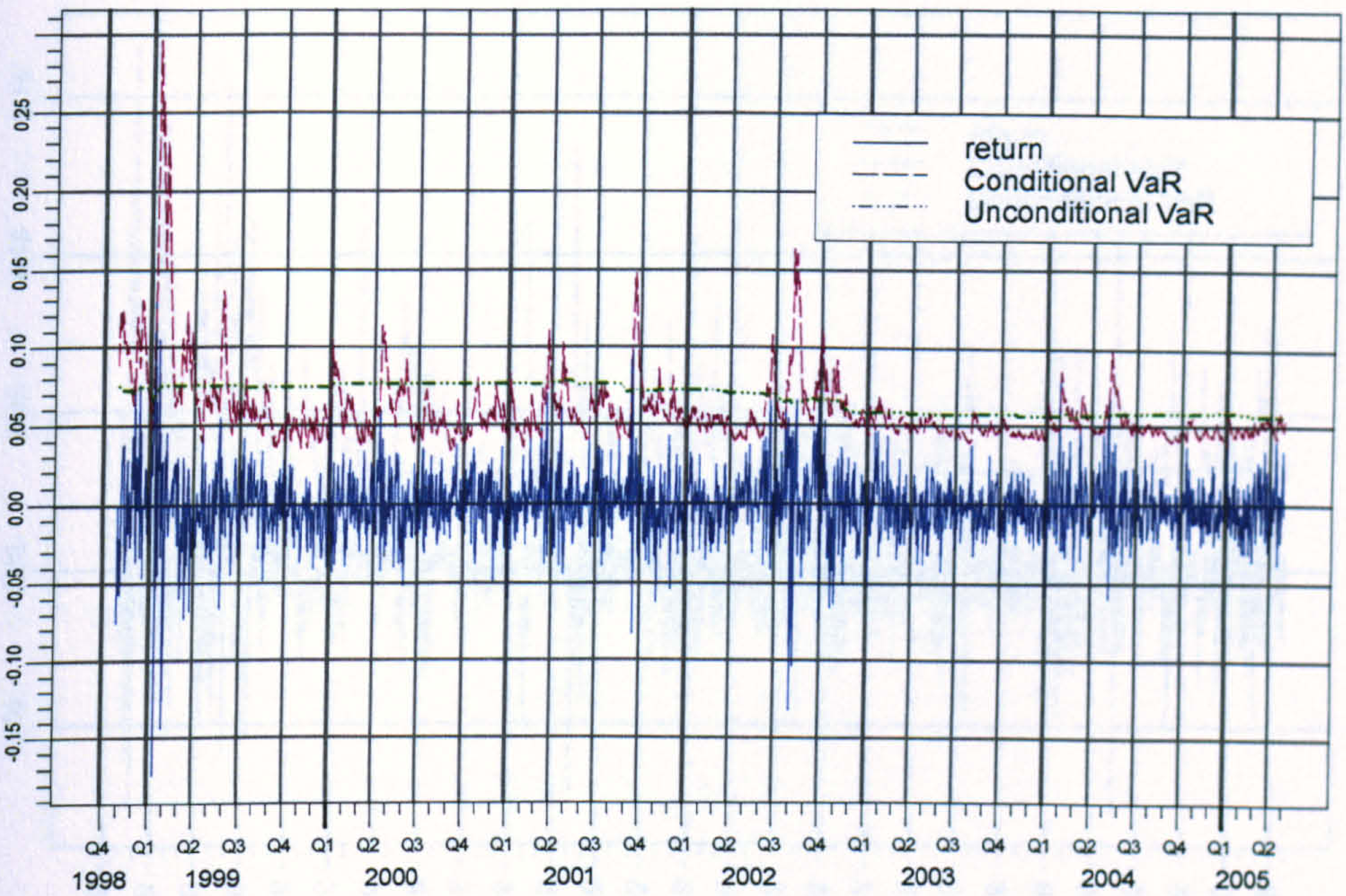
Quantile	95%	99%	99.5%
Morocco			
% error	5.66%	0.88%	0.41%
expected	5.00%	1.00%	0.50%
Binomial test	1.25	-0.48	-0.51
p-value	0.11	0.32	0.31
rejection of null	0	0	0
Pakistan			
% error	4.66%	0.83%	0.41%
expected	5.00%	1.00%	0.50%
Binomial test	-0.65	-0.72	-0.51
p-value	0.26	0.24	0.31
rejection of null	0	0	0
S.Africa			
% error	5.96%	1.24%	0.65%
expected	5.00%	1.00%	0.50%
Binomial test	1.80	0.99	0.87
p-value	0.04	0.16	0.19
rejection of null	1	0	0
Russia			
% error	5.25%	94.34%	0.47%
expected	5.00%	1.00%	0.50%
Binomial test	0.47	386.33	-0.17
p-value	0.32	-	0.43
rejection of null	0	1	0
rejection of null by quantile	11	10	7
Empirical quantile	28		

Figure 4. Backtesting: Conditional and Unconditional 99% VaR according to EVT approach

a) Argentina

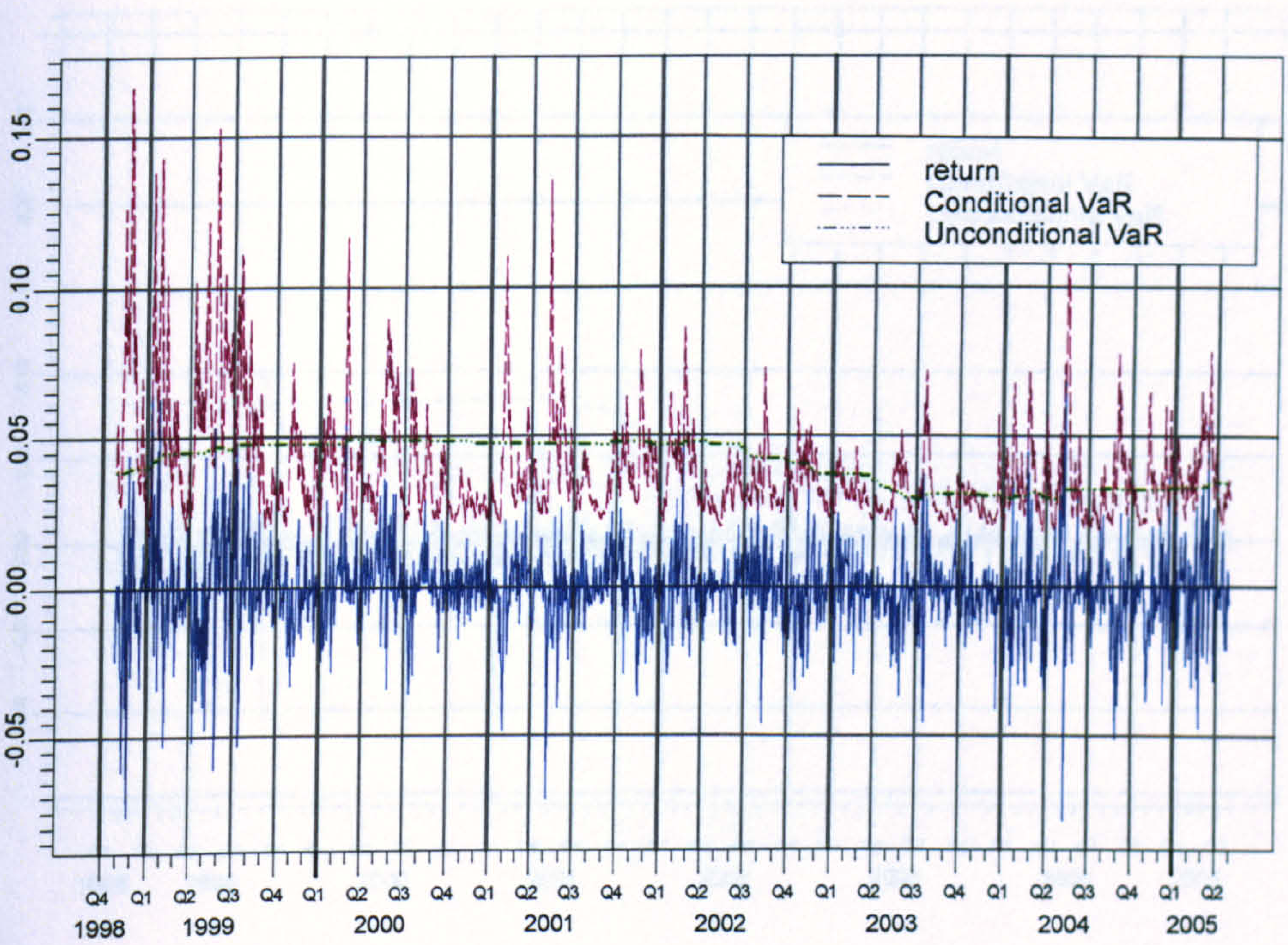


b) Brazil



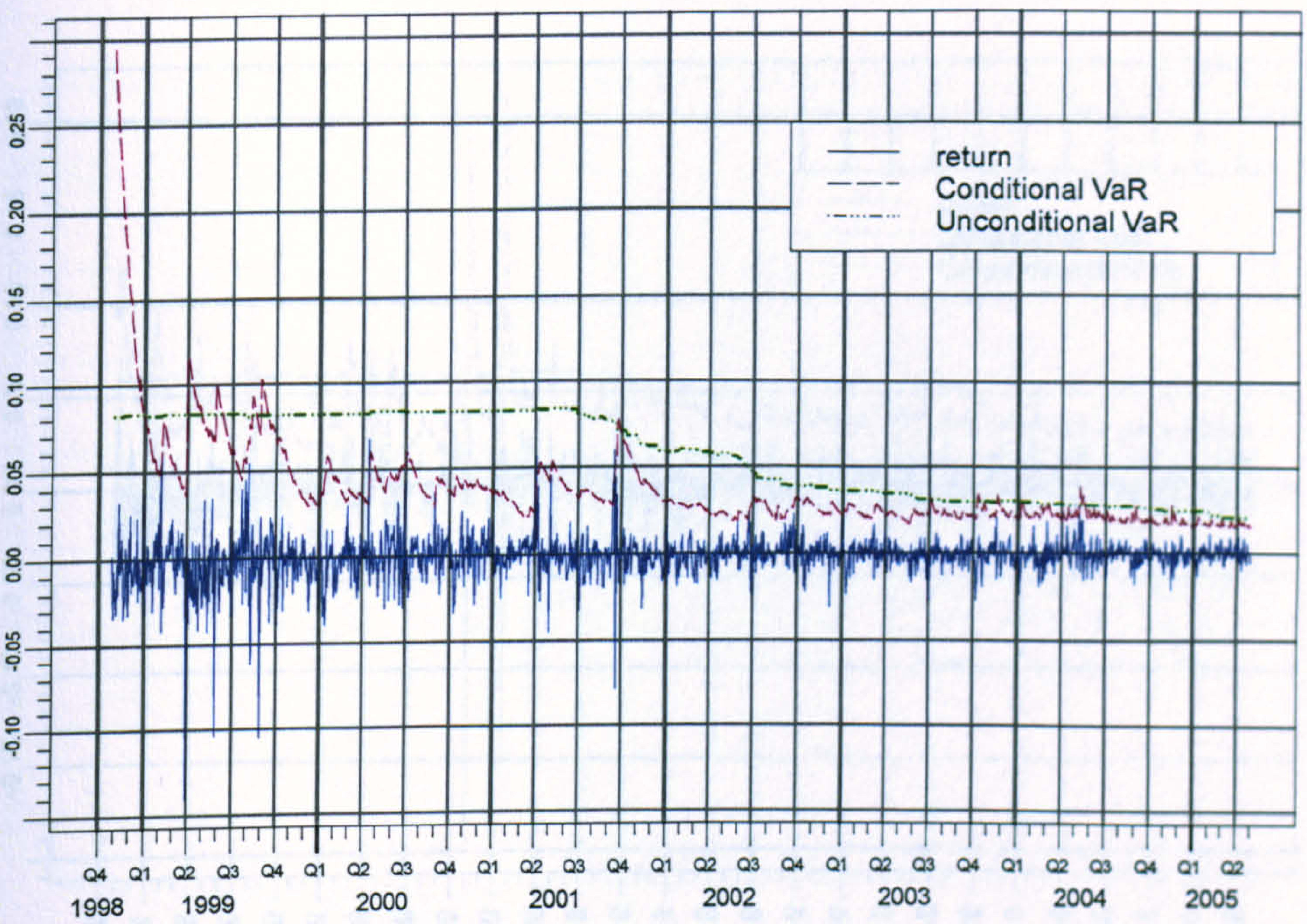
return
Conditional VaR
Unconditional VaR
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
-0.15
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

c) Colombia



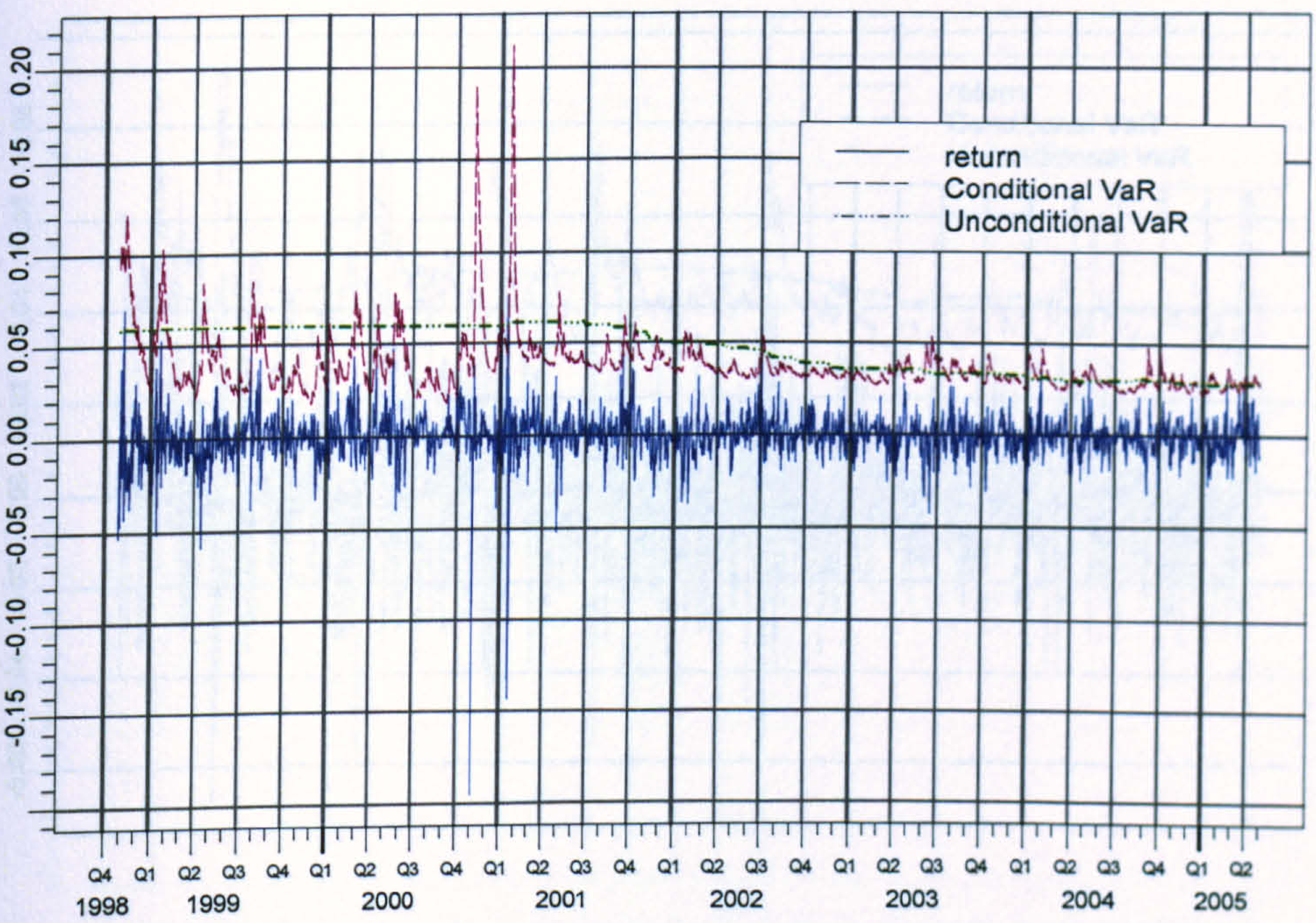
return
Conditional VaR
Unconditional VaR
0.15
0.10
0.05
0.00
-0.05
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

d) Malaysia

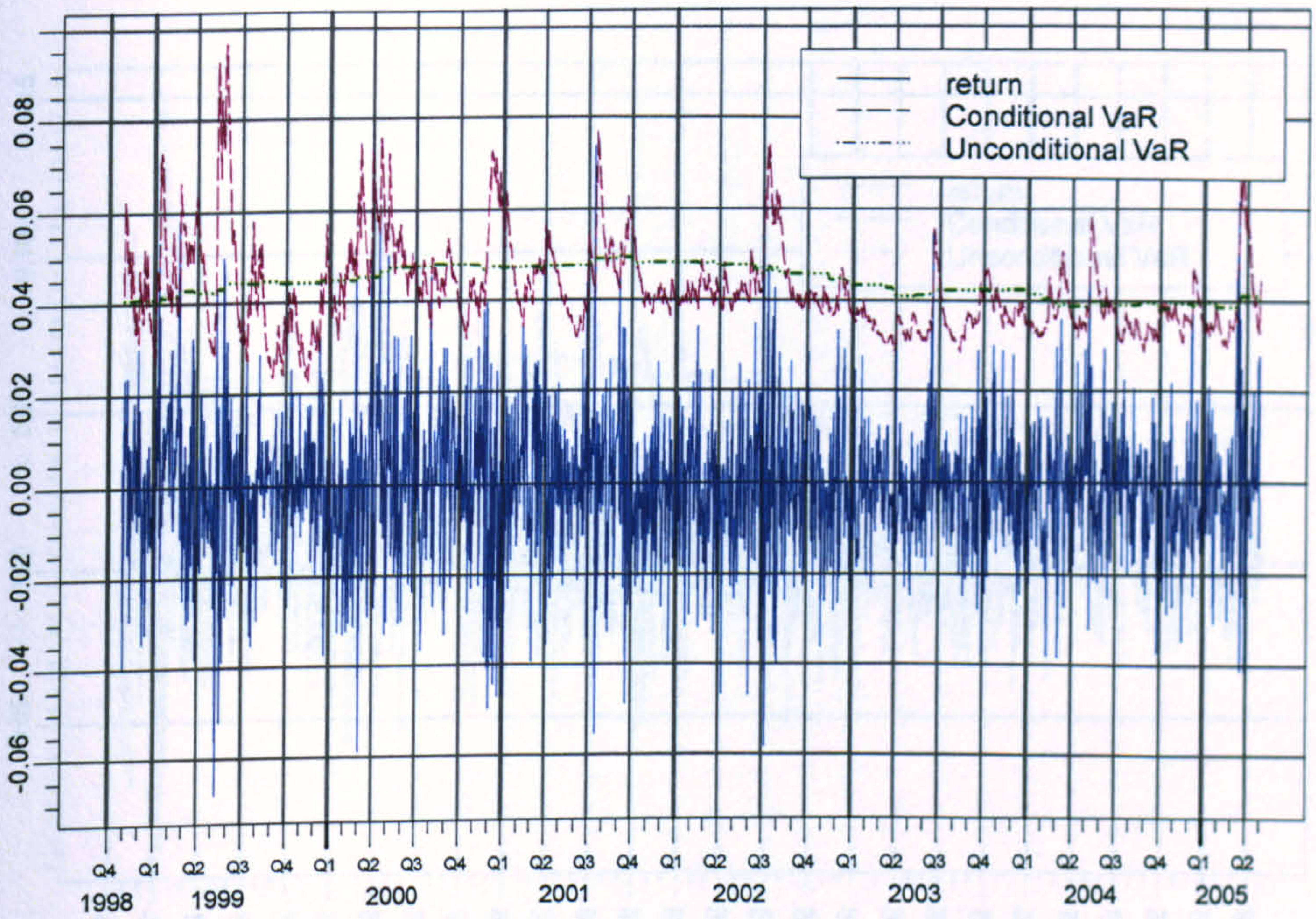


return
Conditional VaR
Unconditional VaR
0.25
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998
1999
2000
2001
2002
2003
2004
2005

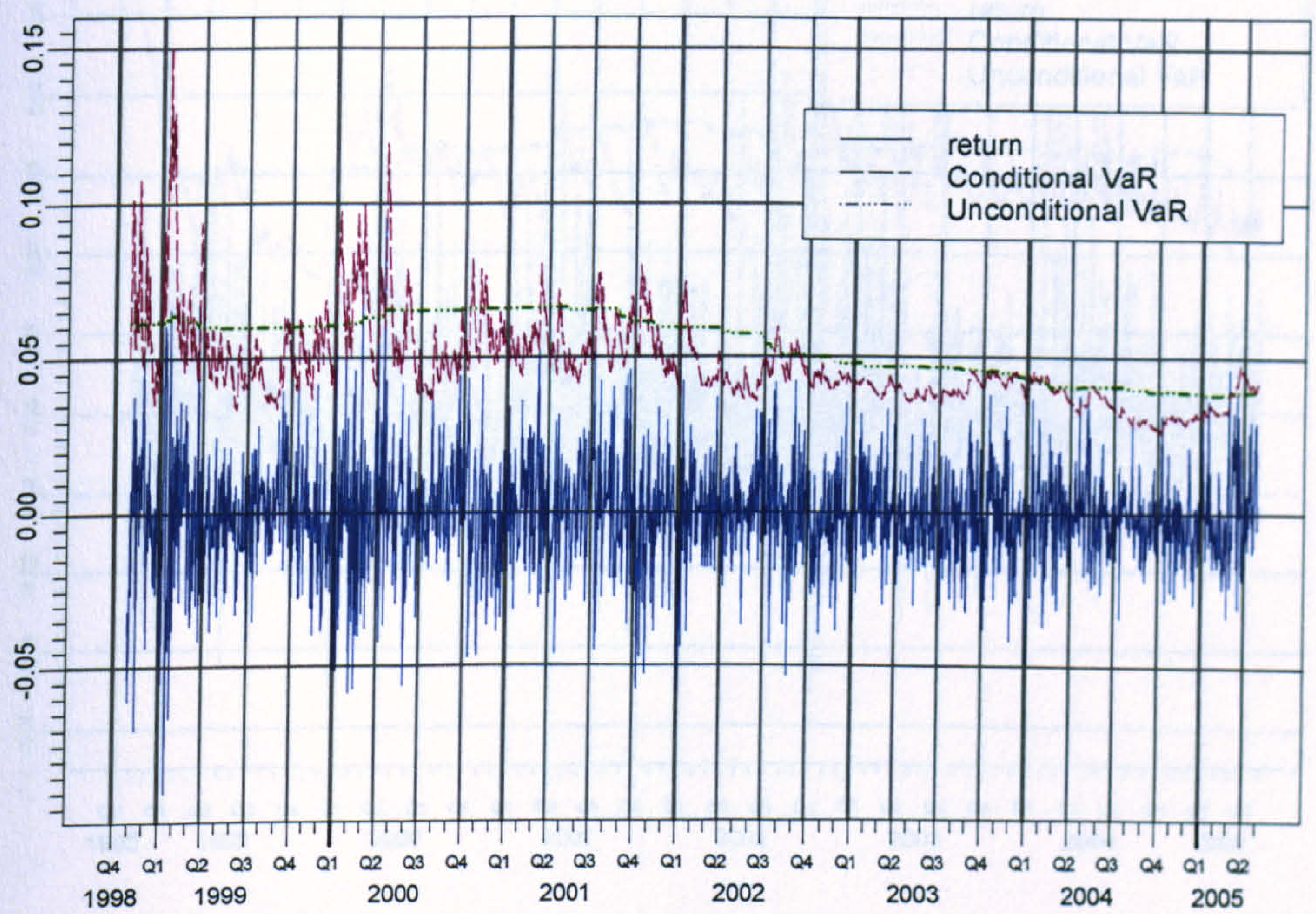
e) Philippines



f) Czech Republic

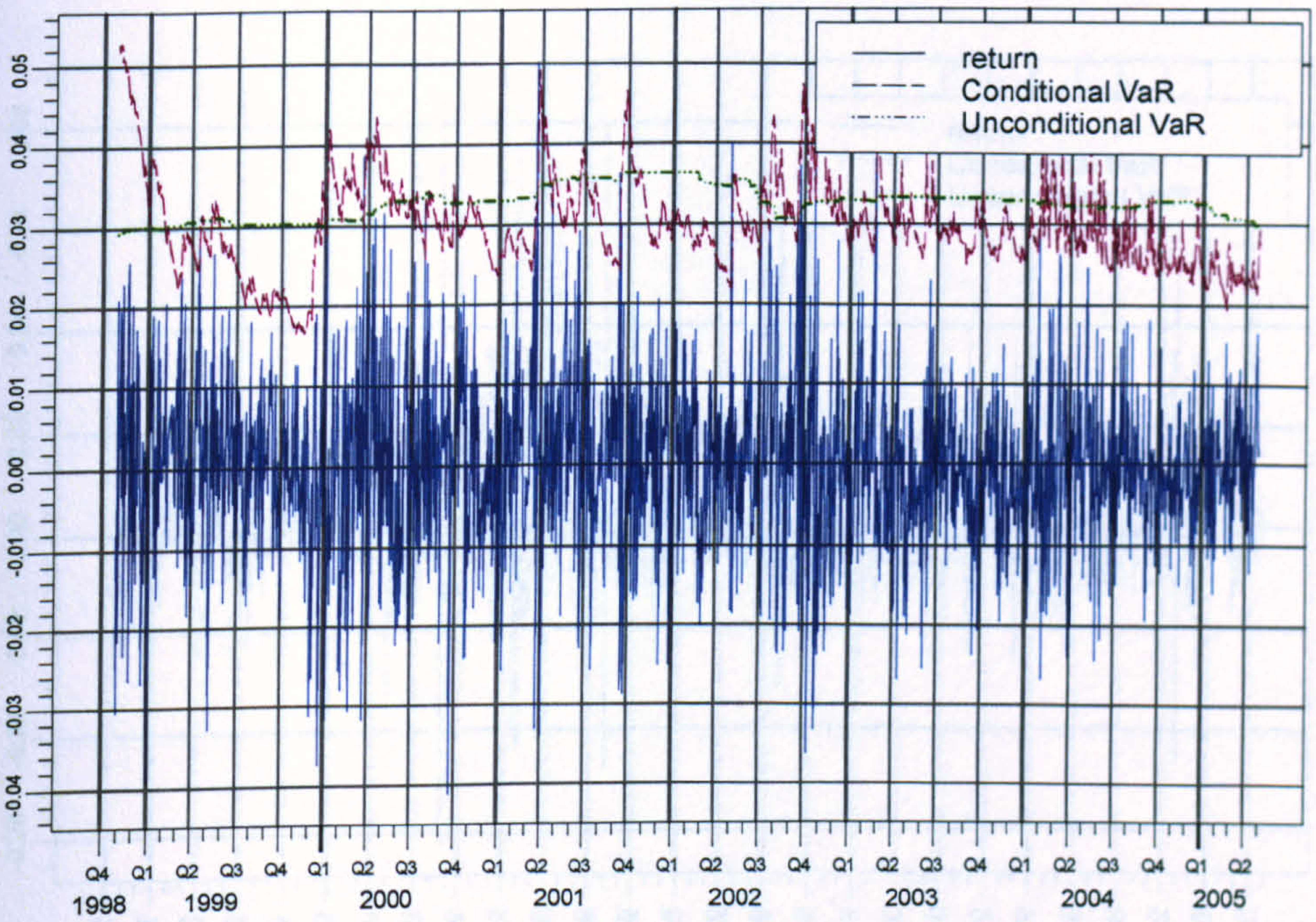


g) Poland

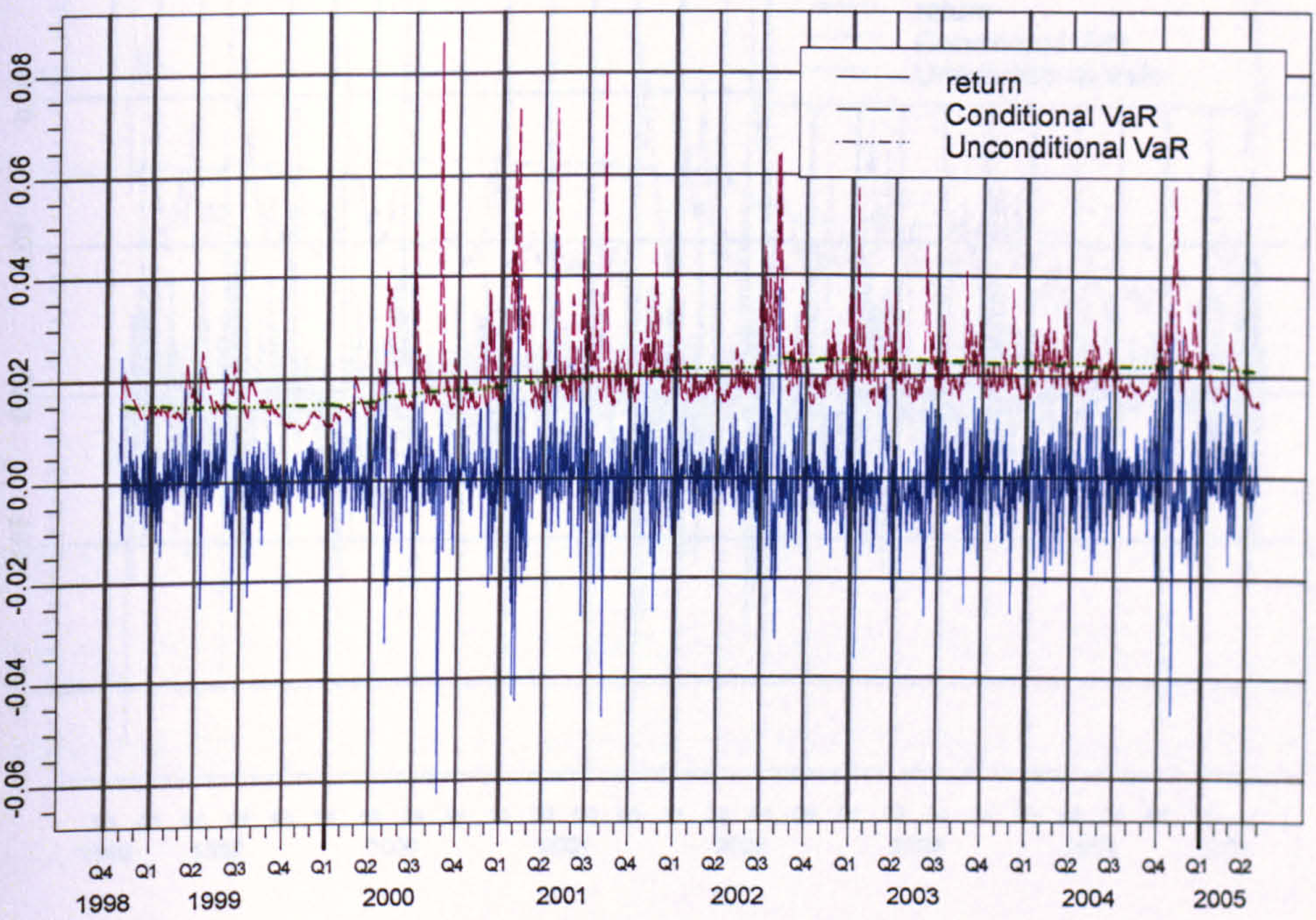


return
Conditional VaR
Unconditional VaR
0.15
0.10
0.05
0.00
-0.05
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

h) Portugal

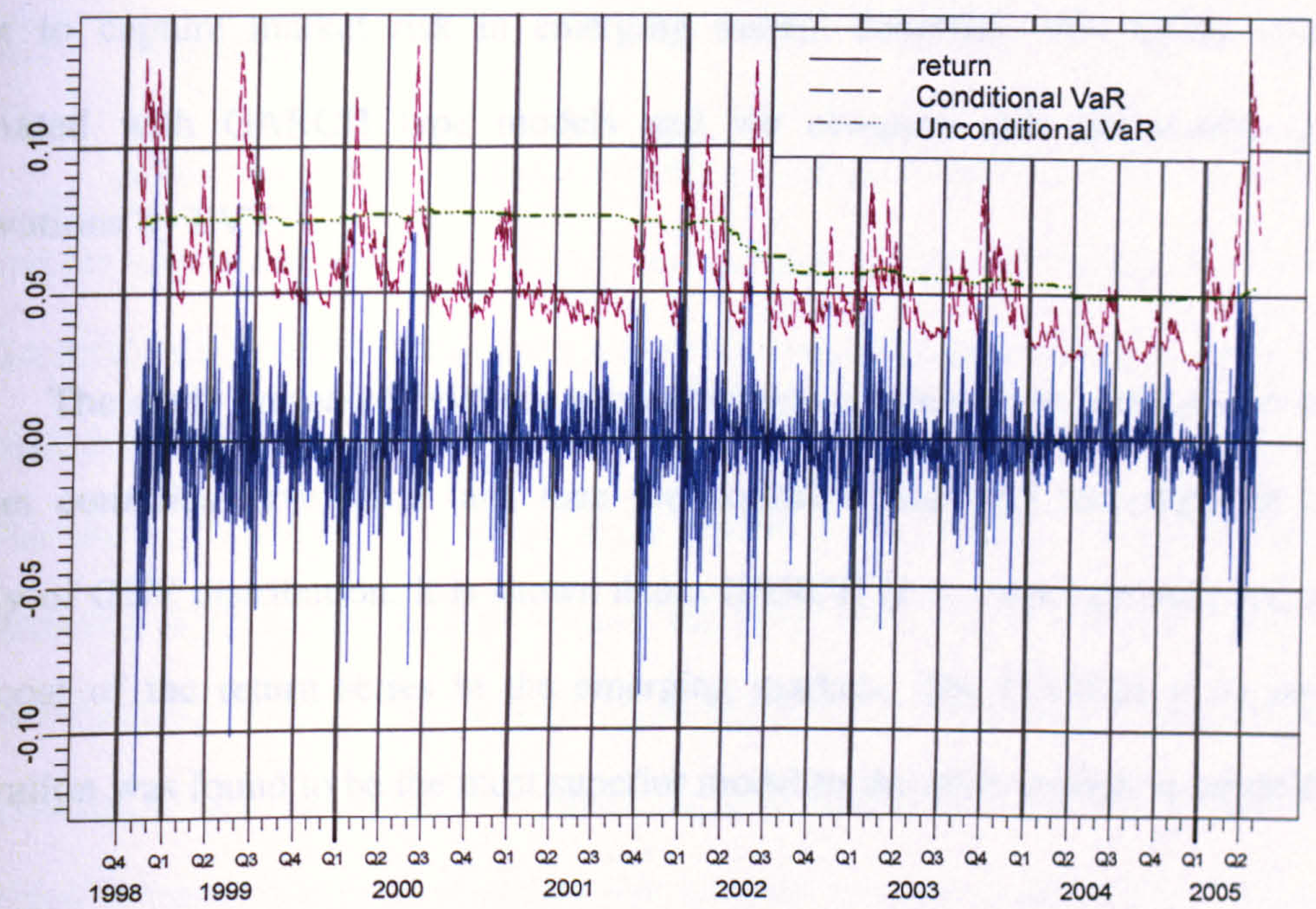

return
Conditional VaR
Unconditional VaR
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
-0.04
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

i) Morocco



return
Conditional VaR
Unconditional VaR
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

j) Pakistan



return
Conditional VaR
Unconditional VaR
0.10
0.05
0.00
-0.05
-0.10
Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2
1998 1999 2000 2001 2002 2003 2004 2005

7.5. Conclusion

The chapter attempted to evaluate the application of extreme value techniques in order to capture market risk in emerging market countries. The assets volatility were estimated with GARCH type models and we compute tails distribution of GARCH innovations by EVT.

The study presented evidence suggesting that in general the return series of emerging market countries have fatter tails than the normal distribution and suggests the Frechet family of GEV distribution. It is shown that a GARCH (1,1) model provides an adequate fit for most of the return series in the emerging markets. The GARCH (1,1) model with t innovation was found to be the most superior model to the other models in modelling market risk.

The second best model was the conditional EVT. We found that non-parametric estimation of quantiles also give more accurate VaR estimates than the assumption of conditional normality. Furthermore, they have the advantage of being easy to compute. Nonetheless, it should be noted that this general conclusion does not hold when we breakdown the analysis into sub emerging market.

CHAPTER 8. FOURTH EMPIRICAL STUDY: ANATOMY OF VOLATILITY AND LONG TERM MEMORY OF VOLATILITY IN EMERGING MARKETS

8.1. Introduction

In the two previous empirical studies we use the basic GARCH (1,1) by assuming that the specification of GARCH (1,1) has superior performance in comparison to other GARCH specifications. This assumption is also supported by the results of specification tests using Lagrange multiplier test and test for ARCH effects (Table 20 on page 228). The use of GARCH (1,1) specification implies a symmetrical model of conditional volatility (i.e., upstate and downstate volatility are treated as equal in the basic specification). However it was well documented that stock returns exhibit asymmetric conditional heteroskedasticity in which negative returns are typically associated with higher volatility than positive returns. For instance, research conducted by Koutmos and Booth (1995) found evidence to support that volatility spillover is asymmetric i.e., bad news in a given market increase volatility in the next market more than good news. Asymmetric volatility in emerging markets has been identified at the aggregate level in the Asian stock market by Chiang and Doong (2001).

In addition to asymmetric feature, many empirical studies have been conducted to investigate long memory characteristic in financial volatility series. However it should be noted here that the results are mixed. Research by Lo (1991), Cheung and Lai (1995), Chow et.al (1995), Barkoulas and Baum (1996), Chow et. al (1996) and Jacobsen (1996) found weak or no evidence of long memory in returns, on the other hand research by Lobato and Savin (1998) and Ray and Tsay (2000) found strong evidence for long term memory in financial volatility series.

Based on the above explanation, our research objectives are to answer the following two main questions: (1) is there any symmetrical evidence in the volatility of emerging stock markets and what is the best model to capture the phenomenon and (2) is there any long memory feature in the volatility of emerging stock markets and whether the SEMIFAR model is successful at modelling the long memory in the volatility of emerging stock markets.

We present the results of the empirical study in third section. The first section provides the result of up market and down market volatility, testing for asymmetry in volatility and the best asymmetric volatility model to use based on the model selection criteria including likelihood parameter, AIC and BIC. The second section discusses the results of testing long memory characteristics based on the classical R/S statistic and the modified R/S statistic as proposed by Lo (1991). The final section presents the results of SEMIFAR model.

8.2. Testing of Asymmetric Condition in Volatility

We begin our empirical analysis by examining the up-and down volatility. By so doing, we obtain a basis for understanding asymmetric volatility of emerging market in the individual country samples. Table 23 presents a summary of the up-and down volatility for our sample of emerging stock markets. It is shown in Table 23 that the volatility of up returns in general is smaller than the volatility of down returns for all emerging stock markets, except for Colombia, Philippines, Taiwan, Greece, Egypt and Morocco. The average up volatility is 4.37 percent, while the average down volatility is 4.89 percent. The difference is especially quite distinct in Brazil (5.24% vs 6.63%), Venezuela (5.81% vs 7.41%), Indonesia (6.10% vs 7.73%), Turkey (7.16% vs 8.58%), and Russia (7.87% vs 9.08%). This finding suggests that stock markets are more sensitive to bad news than to good news and implies the existence of asymmetric response of volatility in the country samples. This result is consistent with Black (1976) who argued that a drop in stock price (or negative return) would lead to a higher volatility than an increase in stock price (or positive) return by the same amount.

Although the result above is very intuitive, we need to obtain more robust evidence based on further statistical testing. As mentioned in the research method for the fourth empirical study, Engle and Ng (1993) specification tests can be used to detect potential asymmetries in the volatility process. Table 24 reports volatility specification tests for the daily and weekly returns. It can be seen from Panel B Table 24 that based on the numbers of rejection of the null hypothesis that the volatility of daily returns is symmetric (the sign bias: 11; the negative size:14, the positive size: 7; and the joint test: 16) we can deduce that the inclusion of the volatility model which accounts for the asymmetric impact of past residuals on volatility has to be examined. It should be noted however that for weekly returns (Panel A) the rejections are fewer. Thus, this result is consistent with previous empirical findings that at lower frequencies stock returns are closer to being normally distributed, while volatility clustering and asymmetric effects become less severe (Booth and Koutmos, 1998).

The next step of the analysis is to develop a statistical model of volatility that can explain this asymmetric pattern. As explained in the chapter of methodology on section 4 that there are three models used in this study namely EGARCH, TGARCH, and PGARCH. Note that since the daily data generates more robust results than weekly data for further analysis we will use daily data instead. The parameter estimates for each model are obtained with the Finmetrics S-Plus 6.1 module.

Table 25a reports the results of the EGARCH (1,1) model. The log-likelihood statistics are very large. This result implies that the EGARCH model is an attractive representation of daily return behaviour that successfully captures the temporal dependence of return volatility (Chen, et.al, 2001). The coefficients a1 and b1 that links current volatility to past shock and past volatility respectively are statistically significant for all countries. This implies that current volatility is a function of past innovation and past volatility. The estimated degree of volatility persistence is measured by b1. The b1 values in Table 25a are less than 1–results necessary for the unconditional variance to be finite. For EGARCH (1,1) model, the presence of asymmetric effect is tested by the hypothesis that $\gamma \neq 0$. The leverage effect exists if $\gamma < 0$. It is shown in Table 25a that the asymmetric relation between shocks (innovation) in returns and changes in variance (volatility), as represented by parameter γ, is highly significant at the 1 percent level of significance for stock markets of most countries sample (except stock markets of Colombia and Morocco). Moreover, most of all γ coefficients are negative, except for

Venezuela and Egypt, which implies that bad news, has a stronger impact on the conditional variance ("leverage effects") than good news. Generally γ coefficient was found to be negative in empirical work. However some studies reported positive leverage factors. For example, Lee, Chen and Rui (2001) reported positive leverage factor for Shanghai A-share stocks. Francis In et.al (2001) also found positive γ coefficient for Thailand (although not statistically significant) using the VAR-EGARCH model.

The results of TGARCH (1,1) estimation are presented in Table 25b. As the TGARCH (1,1) (or GJR) model is a simple extension of GARCH (1,1) with an additional term that takes into account possible asymmetric, the coefficient a1 measures the symmetric impact of new information on volatility. It can be seen in Table 25b that coefficient a1 is statistically significant for all countries indicating that unexpected information increase volatility. For TGARCH (1,1), the estimated degree of volatility persistence is measured by $a1 + \frac{1}{2}\gamma + b1$ and is often used to characterize the volatility process. When the volatility persistence equals one the volatility process behaves like a random walk. Most of countries sample have volatility persistence less than one; except for Indonesia, Malaysia and Egypt. Recall that under the TGARCH model, the presence of asymmetric effect is tested on the basis of the alternative hypothesis being that $\gamma \neq 0$ and leverage effect is tested by the hypothesis that $\gamma > 0$. Similar results with regard to γ coefficient are also obtained from TGARCH model. As shown in Table 25b, 26 of 28 country samples have a significant positive value of γ coefficient (except for Colombia). The other two countries namely Venezuela and Egypt have negative γ coefficient. As γ is estimated with only one constraint, $a + \gamma \geq 0$, it is possible that γ is negative, which is contrary to the theoretical leverage effect (Blair et.al, 2002). As a result for Venezuela and Egypt we expect that bad news would not have larger impact on volatility. Therefore, the estimation results of TGARCH (1,1) model are consistent with the common results from estimating EGARCH (1,1) model.

Table 25c presents the results of the PGARCH (1,1,1) model and from this table it can be seen that all of the ARCH and GARCH coefficients are statistically significant at the 1 percent level. The value of γ coefficient under PGARCH model would be expected to be negative for the bad news to have larger effect on the conditional volatility. The results shown in Table 25c are consistent with the previous findings when we use EGARCH model in which most of all countries sample have negative γ coefficient as expected except for Venezuela and Egypt. Having generated the parameters for all asymmetric models, the next step is to examine the relative superiority for each model using the likelihood test, AIC and BIC.

The results of the model selection criteria are summarized in Table 26. It can be seen that in general the TGARCH model is the most appropriate model to be used for explaining asymmetry in volatility in emerging markets. Based on the likelihood test and BIC, the TGARCH model outperforms the EGARCH and the PGARCH models in 23 countries (cases). On the other hand, the PGARCH model is superior to the EGARCH and the TGARCH model in the case of Peru, Malaysia and Czech Republic. Finally, the EGARCH model is the most suitable model for Morocco and Russia. In a related study, Panagiotidis (2005) also investigated whether the EGARH and TGARCH were better at capturing the asymmetric feature in the Athens Stock Exchange. He concluded that TGARCH model is found to be more successful than EGARCH model.

Table 23. Up- and Down volatility

This table presents three volatility numbers for each stock market: for up markets or down markets. Up- and down markets are classified on the basis of whether returns are above or below their average value in a specified week.

Country	Full Sample Volatility (%)	Up-Volatility (%)	Down-Volatility (%)	Number of Upstates	Number of Downstates	Difference Up and Down Volaltility
Argentina	5.75	5.49	6.05	282	256	0.55
Brazil	5.90	5.24	6.63	293	245	**1.39**
Chile	3.20	3.13	3.28	269	269	0.15
Colombia	4.19	4.26	4.14	264	274	0.11
Mexico	4.18	3.80	4.60	291	247	0.79
Peru	3.74	3.68	3.82	265	273	0.13
Venezuela	6.64	5.81	7.41	270	268	**1.6**
Hong Kong	3.71	3.32	4.13	291	247	0.81
Indonesia	6.89	6.10	7.73	287	251	**1.62**
Korea	6.16	5.79	6.54	277	261	0.75
Malaysia	4.77	4.27	5.25	273	265	0.98
Philippines	4.04	4.05	4.06	275	263	0.01
Singapore	3.45	3.44	3.47	268	270	0.03
Taiwan	4.18	4.26	4.12	268	270	0.14
Thailand	5.38	5.39	5.40	270	268	0.01
Czech Republic	3.63	3.39	3.91	289	249	0.52
Greece	3.89	4.01	3.79	262	276	0.22
Hungary	4.67	4.39	4.99	276	262	0.59
Poland	4.71	4.49	4.95	283	255	0.45
Portugal	2.87	2.72	3.02	276	262	0.30
Turkey	7.86	7.16	8.58	277	261	**1.42**
Egypt	3.61	3.96	3.32	245	293	0.64
India	3.69	3.58	3.82	278	260	0.24
Israel	3.75	3.48	4.03	278	260	0.54
Morocco	2.01	2.09	1.95	265	273	0.14
Pakistan	4.52	4.12	4.94	284	254	0.82
South Africa	3.54	3.18	3.90	281	257	0.72
Russia	8.43	7.87	9.08	289	249	**1.21**
Average	4.62	4.37	4.89			

Table 24. Volatility specification tests for returns.

This table presents the results of Engle and Ng (1993) sign test, size bias tests and join test. Panel A and Panel B use weekly returns and daily returns of each emerging stock market indexes respectively. All returns are continuously compounded and denominated in US dollars.

Panel A. Weekly returns

Country	Sign bias		Negative size bias		Positive size bias		Join test	
	t-stat-2	p-value	t-stat-2	p-value	t-stat-2	p-value	F-test	p-value
Argentina	1.3702194	0.1711920	1.1882299	0.2352691	1.7185698	0.0862702	1.1158582	0.3422288
Brazil	**2.0763599**	0.0383366	1.7922932	0.0736499	1.7498623	0.0807143	1.6768666	0.1716315
Chile	0.0546080	0.9564711	1.0948491	0.2740745	0.8882469	0.3748064	1.2117680	0.3050042
Colombia	0.9455791	0.3447894	0.2056468	0.8371449	0.5072855	0.6121632	0.3700147	0.7742037
Mexico	**2.0415881**	0.0416815	1.9157634	0.0559269	1.8319874	0.0675080	1.7366681	0.1591541
Peru	0.9071898	0.3647141	1.2049541	0.2287528	1.6782526	0.0938807	1.1890069	0.3134947
Venezuela	0.1248599	0.9006812	0.7252725	0.4686014	0.6668528	0.5051531	0.3823997	0.7652530
Hong Kong	0.7446347	0.4568189	1.6145003	0.1070074	1.2534184	0.2105999	1.2679459	0.2849282
Indonesia	0.2203474	0.8256845	0.2331193	0.8157578	0.5001938	0.6171439	0.1521387	0.9280734
Korea	0.1560245	0.8760725	0.5096842	0.6104825	0.8393214	0.4016632	0.5572443	0.6430069
Malaysia	1.0330575	0.3020429	0.3930558	0.6944345	1.6626960	0.0969579	0.9379609	0.4219206
Philippines	0.0489654	0.9609651	1.6990045	0.0898986	1.1360595	0.2564393	2.1767150	0.0906411
Singapore	1.8334831	0.0672851	0.9572587	0.3388682	**2.0786599**	0.0381237	1.5758523	0.1948348
Taiwan	**2.6827741**	0.0075269	**2.5271456**	0.0117858	**2.2447366**	0.0251921	**2.8948340**	0.0354717
Thailand	0.8303540	0.4067084	1.8260786	0.0683946	0.7169053	0.4737448	1.2176414	0.3028471
Czech Republic	0.2285310	0.8193206	0.0137918	0.9890012	0.0137177	0.9890603	0.0448664	0.9873198
Greece	1.4506409	0.1474648	1.2377191	0.2163621	0.4467450	0.6552396	0.9120956	0.4347281
Hungary	0.4190097	0.6753769	0.8901124	0.3738049	0.4288743	0.6681870	0.7771272	0.5068098
Poland	0.1389862	0.8895133	0.5254070	0.5995176	1.1338360	0.2573702	0.9714408	0.4058138
Portugal	0.8228117	0.4109810	0.3545986	0.7230298	0.8158910	0.4149249	0.2811348	0.8386204
Turkey	0.3565079	0.7216006	0.3119443	0.7552042	0.7493996	0.4539452	0.5693708	0.6349248
Egypt	**2.3933043**	0.0170404	0.6096101	0.5423785	**2.5855466**	0.0099853	**3.0708962**	0.0281161
India	1.7076818	0.0882745	**2.2065007**	0.0277722	1.3474675	0.1783990	1.6648477	0.1742487
Israel	**2.4247737**	0.0156474	**2.4426742**	0.0149008	1.5492670	0.1219078	2.4480830	0.0637265
Morocco	0.1408792	0.8880183	0.2120635	0.8321381	0.0776173	0.9381615	0.0288769	0.9933570
Pakistan	0.3787000	0.7050606	0.2492608	0.8032545	0.1141038	0.9091983	0.1827542	0.9078322
South Africa	1.1268997	0.2602891	1.8832496	0.0602077	**1.9632177**	0.0501375	2.0602843	0.1053192
Russia	1.6288348	0.1039356	0.7794420	0.4360634	0.7290303	0.4663015	0.9425179	0.4196972

Table 24. Volatility specification tests for returns.

This table presents the results of Engle and Ng (1993) sign test, size bias tests and join test. Panel A and Panel B use weekly returns and daily returns of each emerging stock market indexes respectively. All returns are continuously compounded and denominated in US dollars.

Panel B. Daily returns

Country	Sign bias		Negative size bias		Positive size bias		Join test	
	t-stat-2	p-value	t-stat-2	p-value	t-stat-2	p-value	F-test	p-value
Argentina	**2.6797940**	0.0074116	**2.2398142**	0.0251843	1.3725157	0.1700173	**2.7125991**	**0.0436097**
Brazil	**3.7055278**	0.0002152	**3.9497826**	8.023E-05	**3.8392740**	0.0001262	**7.2851188**	**7.548E-05**
Chile	1.7416411	0.0816855	**3.3968247**	0.0006916	0.1876673	0.8511516	**4.5027279**	**0.0037567**
Colombia	0.4546563	0.6493931	0.0095529	0.9923787	1.6037968	0.1088761	1.9701635	0.1164809
Mexico	**2.3569279**	0.0184980	**3.6037716**	0.0003193	1.3760196	0.1689300	**4.3496325**	0.0046462
Peru	0.7188298	0.4723082	1.6854916	0.0920096	0.9231370	0.3560185	1.9051502	0.1267373
Venezuela	0.4162616	0.6772518	0.0110176	0.9912102	0.0047110	0.9962416	0.0909955	0.9649944
Hong Kong	1.7398129	0.0820061	1.7897615	0.0736046	**2.8545873**	0.0043422	**3.0440060**	**0.0278903**
Indonesia	**2.6446207**	0.0082257	**2.5632937**	0.0104223	1.8499020	0.0644372	**2.9638085**	**0.0310882**
Korea	1.8380384	0.0661668	1.6462558	0.0998278	1.6603020	0.0969701	1.4154021	0.2364248
Malaysia	**2.5005620**	0.0124586	**3.0295675**	0.0024723	0.3463240	0.7291263	**4.0777777**	**0.0067693**
Philippines	1.1563976	0.2476211	0.1222784	0.9026877	0.2651544	0.7909108	0.6635237	0.5743646
Singapore	1.0886107	0.2764230	0.9293042	0.3528147	1.5945609	0.1109278	0.8846989	0.4481957
Taiwan	1.8401442	0.0658570	**2.0308507**	0.0423682	**2.3179435**	0.0205270	2.3374753	0.0719171
Thailand	0.4970918	0.6191649	0.1219728	0.9029297	0.3260403	0.7444192	0.1002634	0.9598440
Czech Republic	1.0054498	0.3147706	1.4873202	0.1370473	0.1834923	0.8544255	1.1273900	0.3366036
Greece	1.6315704	0.1028870	1.7076563	0.0878154	**2.0151924**	0.0439837	1.6809806	0.1690899
Hungary	**2.0560016**	0.0398786	**2.7277327**	0.0064185	0.7453430	0.4561294	**2.7306402**	**0.0425661**
Poland	1.6356546	0.1020288	**3.0638350**	0.0022068	0.1296015	0.8968914	**3.6419640**	**0.0123370**
Portugal	1.5935761	0.1111484	**5.2491121**	1.647E-07	1.1463536	0.2517507	**10.736082**	**5.626E-07**
Turkey	0.0585223	0.9533369	1.0932449	0.2743841	0.3993296	0.6896820	0.7089982	0.5464911
Egypt	**4.5112922**	6.719E-06	0.2042614	0.8381647	0.9121290	0.3617825	**10.435130**	**8.632E-07**
India	**3.7848327**	0.0001572	**3.4638264**	0.0005409	**2.5083084**	0.0121894	**5.5329153**	**0.0008915**
Israel	**3.4026973**	0.0006770	**2.0138844**	0.0441210	**2.5528472**	0.0107393	**3.9799919**	**0.0077479**
Morocco	1.2678681	0.2049546	0.6744957	0.5000541	1.0396412	0.2986000	2.3088669	0.0746917
Pakistan	**2.8230210**	0.0047923	0.8277864	0.4078648	**2.2421600**	0.0250321	**2.9298055**	**0.0325502**
South Africa	**2.1401926**	0.0324288	**2.2584373**	0.0239981	0.2234264	0.8232206	**3.3157712**	**0.0192759**
Russia	1.8247994	0.0681420	**2.8601206**	0.0042674	1.1094712	0.2673260	**2.7334129**	**0.0424079**

Table 25a. Estimate of EGARCH (1,1) Model Parameters for Each Country

This table reports the results of the EGARCH specification. Daily returns of each emerging stock market indexes are used. All returns are continuously compounded and denominated in US dollars.

Country	a0	a1 (ARCH)	b1 (GARCH)	γ (Asymmetric)
Argentina	-0.406*	0.222*	0.968*	-0.283*
Brazil	-0.670*	0.230*	0.937*	-0.488*
Chile	-0.967*	0.263*	0.915*	-0.219*
Colombia	-1.622*	0.524*	0.859*	-0.034
Mexico	-0.446*	0.178*	0.963*	-0.485*
Peru	-0.715*	0.238*	0.937*	-0.218*
Venezuela	-0.527*	0.114*	0.937*	0.400*
Hong Kong	-0.329*	0.155*	0.975*	-0.452*
Indonesia	-0.310*	0.229*	0.981*	-0.217*
Korea	-0.167*	0.138*	0.992*	-0.263*
Malaysia	-0.087*	0.097*	0.998*	-0.388*
Philippines	-0.604*	0.274*	0.953*	-0.238*
Singapore	-0.394*	0.216*	0.974*	-0.278*
Taiwan	-0.673*	0.160*	0.932*	-0.493*
Thailand	-0.282*	0.186*	0.982*	-0.134*
Czech Republic	-0.672*	0.231*	0.942*	-0.169*
Greece	-0.426*	0.229*	0.970*	-0.103*
Hungary	-1.510*	0.419*	0.852*	-0.162*
Poland	-0.859*	0.233*	0.915*	-0.150*
Portugal	-0.450*	0.144*	0.963*	-0.149*
Turkey	-0.447*	0.204*	0.957*	-0.144*
Egypt	-0.296*	0.178*	0.979*	0.165*
India	-0.958*	0.267*	0.910*	-0.298*
Israel	-0.609*	0.199*	0.945*	-0.314*
Morocco	-1.341*	0.305*	0.887*	-0.042
Pakistan	-0.588*	0.232*	0.947*	-0.136*
South Africa	-0.620*	0.310*	0.945*	-0.077*
Russia	-0.550*	0.209*	0.955*	-0.353*

Note: * denotes statistical significance at the 1 percent level of significance.

Table 25b. Estimate of TGARCH (1,1) Model Parameters for Each Country

This table reports the results of the TGARCH specification. Daily returns of each emerging stock market indexes are used. All returns are continuously compounded and denominated in US dollars.

Country	$a_0 \times 10^{-6}$	a_1 (ARCH)	b_1 (GARCH)	γ (Asymmetric)
Argentina	12.73*	0.068*	0.868*	0.095*
Brazil	17.51*	0.031*	0.852*	0.149*
Chile	8.08*	0.075*	0.823*	0.093*
Colombia	15.01*	0.300*	0.644*	0.043
Mexico	5.56*	0.031*	0.892*	0.109*
Peru	11.61*	0.070*	0.841*	0.077*
Venezuela	519*	0.182*	0.168*	-0.115*
Hong Kong	3.41*	0.022*	0.916*	0.098*
Indonesia	5.98*	0.097*	0.870*	0.075*
Korea	2.36*	0.033*	0.941*	0.048*
Malaysia	0.48*	0.028*	0.948*	0.051*
Philippines	5.29*	0.064*	0.868*	0.110*
Singapore	2.48*	0.063*	0.889*	0.079*
Taiwan	10.62*	0.028*	0.893*	0.094*
Thailand	4.14*	0.062*	0.912*	0.039*
Czech Republic	6.10*	0.080*	0.879*	0.035*
Greece	4.55*	0.086*	0.877*	0.050*
Hungary	33.92*	0.133*	0.726*	0.107*
Poland	17.68*	0.080*	0.849*	0.048*
Portugal	0.90*	0.037*	0.945*	0.022*
Turkey	35.49*	0.081*	0.866*	0.046*
Egypt	0.78*	0.073*	0.939*	-0.019*
India	17.68*	0.081*	0.791*	0.118*
Israel	7.56*	0.045*	0.888*	0.069*
Morocco	4.30*	0.121*	0.794*	0.043*
Pakistan	16.31*	0.100*	0.846*	0.034*
South Africa	23.76*	0.123*	0.843*	0.039*
Russia	4.39*	0.053*	0.884*	0.085*

Note: * denotes statistical significance at the 1 percent level of significance.

Table 25c. Estimate of PGARCH (1,1) Model Parameters for Each Country

This table reports the results of the PGARCH specification. Daily returns of each emerging stock market indexes are used. All returns are continuously compounded and denominated in US dollars.

Country	a_0*10^{-4}	a_1 (ARCH)	b_1 (GARCH)	γ (Asymmetric)
Argentina	5.51*	0.114*	0.893*	-0.294*
Brazil	10.74*	0.112*	0.860*	-0.567*
Chile	6.88*	0.116*	0.852*	-0.244*
Colombia	13.66*	0.278*	0.699*	-0.049
Mexico	4.01*	0.087*	0.908*	-0.507*
Peru	8.01*	0.122*	0.856*	-0.233*
Venezuela	12.53*	0.058*	0.917*	0.363*
Hong Kong	2.10*	0.072*	0.933*	-0.477*
Indonesia	2.76*	0.116*	0.906*	-0.246*
Korea	1.05*	0.066*	0.947*	-0.288*
Malaysia	0.10	0.053*	0.962*	-0.374*
Philippines	5.02*	0.138*	0.866*	-0.247*
Singapore	1.69*	0.095*	0.916*	-0.292*
Taiwan	5.66*	0.067*	0.918*	-0.455*
Thailand	1.64*	0.079*	0.933*	-0.130*
Czech Republic	4.86*	0.106*	0.887*	-0.151*
Greece	2.51*	0.108*	0.902*	-0.108*
Hungary	23.03*	0.205*	0.723*	-0.230*
Poland	12.11*	0.116*	0.847*	-0.189*
Portugal	1.86*	0.071*	0.929*	-0.148*
Turkey	9.29*	0.099*	0.898*	-0.129*
Egypt	1.47*	0.082*	0.937*	0.195*
India	10.27*	0.126*	0.837*	-0.308*
Israel	5.68*	0.090*	0.895*	-0.324*
Morocco	5.12*	0.140*	0.828*	-0.078*
Pakistan	7.65*	0.109*	0.883*	-0.140*
South Africa	12.46*	0.142*	0.854*	-0.095*
Russia	3.86*	0.107*	0.890*	-0.353*

Note: * denotes statistical significance at the 1 percent level of significance.

Table 26. Model Selection Criteria Results

This table reports the results of the model selection criteria. Three metrics are used in order to compare the performance of EGARCH, TGARCH, PGARCH models namely AIC, BIC and Likelihood ratio. The best model will be chosen based on the one which generates the highest likelihood ratio or the lowest BIC and AIC. The best model is indicated by bold font.

Country	Model Selection Criteria	Models considered		
		em.egarch	em.tgarch	em.pgarch
Argentina	AIC	-13236	-13304	-13217
	BIC	-13207	**-13275**	-13188
	Likelihood	6623	**6657**	6614
		em.egarch	em.tgarch	em.pgarch
Brazil	AIC	-13533	-13535	-13531
	BIC	-13503	**-13506**	-13502
	Likelihood	6771	**6773**	6771
		em.egarch	em.tgarch	em.pgarch
Chile	AIC	-16607	-16642	-16605
	BIC	-16577	**-16612**	-16575
	Likelihood	8308	**8326**	8307
		em.egarch	em.tgarch	em.pgarch
Colombia	AIC	-16133	-16140	-16130
	BIC	-16104	**-16111**	-16100
	Likelihood	8072	**8075**	8070
		em.egarch	em.tgarch	em.pgarch
Mexico	AIC	-15164	-15182	-15169
	BIC	-15135	**-15152**	-15139
	Likelihood	7587	**7596**	7589
		em.egarch	em.tgarch	em.pgarch
Peru	AIC	-15606	-15609	-15620
	BIC	-15577	-15580	**-15591**
	Likelihood	7808	7810	**7815**
		em.egarch	em.tgarch	em.pgarch
Venezuela	AIC	-11513	-11523	-11489
	BIC	-11484	**-11494**	-11460
	Likelihood	5762	**5767**	5750
		em.egarch	em.tgarch	em.pgarch
Hong Kong	AIC	-15261	-15282	-15269
	BIC	-15232	**-15253**	-15239
	Likelihood	7636	**7646**	7639
		em.egarch	em.tgarch	em.pgarch
Indonesia	AIC	-13360	-13364	-13361
	BIC	-13331	**-13335**	-13331
	Likelihood	6685	**6687**	6685
		em.egarch	em.tgarch	em.pgarch
Korea	AIC	-13034	-13063	-13033
	BIC	-13004	**-13034**	-13003
	Likelihood	6522	**6537**	6521

Table 26. Model Selection Criteria Results (continued)

This table reports the results of the model selection criteria. Three metrics are used in order to compare the performance of EGARCH, TGARCH, PGARCH models namely AIC, BIC and Likelihood ratio. The best model will be chosen based on the one which generates the highest likelihood ratio or the lowest BIC and AIC. The best model is indicated by bold font.

Country	Model Selection Criteria	Models considered		
		em.egarch	em.tgarch	em.pgarch
Malaysia	AIC	-16079	-16078	-16096
	BIC	-16049	-16048	**-16066**
	Likelihood	8044	8044	**8053**
		em.egarch	em.tgarch	em.pgarch
Philippines	AIC	-15578	-15605	-15584
	BIC	-15548	**-15576**	-15555
	Likelihood	7794	**7808**	7797
		em.egarch	em.tgarch	em.pgarch
Singapore	AIC	-16075	-16098	-16074
	BIC	-16045	**-16069**	-16045
	Likelihood	8042	**8054**	8042
		em.egarch	em.tgarch	em.pgarch
Taiwan	AIC	-14331	-14352	-14341
	BIC	-14301	**-14322**	-14311
	Likelihood	7170	**7181**	7175
		em.egarch	em.tgarch	em.pgarch
Thailand	AIC	-13814	-13841	-13817
	BIC	-13784	**-13811**	-13788
	Likelihood	6912	**6925**	6914
		em.egarch	em.tgarch	em.pgarch
Czech Republic	AIC	-15289	-15267	-15291
	BIC	-15259	-15237	**-15261**
	Likelihood	7649	7638	**7650**
		em.egarch	em.tgarch	em.pgarch
Greece	AIC	-15162	-15175	-15159
	BIC	-15133	**-15146**	-15130
	Likelihood	7586	**7593**	7585
		em.egarch	em.tgarch	em.pgarch
Hungary	AIC	-14162	-14198	-14136
	BIC	-14132	**-14169**	-14106
	Likelihood	7086	**7104**	7073
		em.egarch	em.tgarch	em.pgarch
Poland	AIC	-13960	-13989	-13959
	BIC	-13931	**-13959**	-13930
	Likelihood	6985	**6999**	6985
		em.egarch	em.tgarch	em.pgarch
Portugal	AIC	-17011	-17035	-17022
	BIC	-16982	**-17005**	-16993
	Likelihood	8511	**8522**	8516

Table 26. Model Selection Criteria Results (continued)

This table reports the results of the model selection criteria. Three metrics are used in order to compare the performance of EGARCH, TGARCH, PGARCH models namely AIC, BIC and Likelihood ratio. The best model will be chosen based on the one which generates the highest likelihood ratio or the lowest BIC and AIC. The best model is indicated by bold font.

Country	Model Selection Criteria	Models considered		
		em.egarch	em.tgarch	em.pgarch
Turkey	AIC	-11216	-11262	-11204
	BIC	-11187	**-11233**	-11174
	Likelihood	5613	**5636**	5607
		em.egarch	em.tgarch	em.pgarch
Egypt	AIC	-15656	-15668	-15645
	BIC	-15626	**-15639**	-15616
	Likelihood	7833	**7839**	7828
		em.egarch	em.tgarch	em.pgarch
India	AIC	-15087	-15103	-15081
	BIC	-15058	**-15074**	-15052
	Likelihood	7549	**7557**	7546
		em.egarch	em.tgarch	em.pgarch
Israel	AIC	-15326	-15336	-15333
	BIC	-15296	**-15307**	-15304
	Likelihood	7668	**7673**	7672
		em.egarch	em.tgarch	em.pgarch
Morocco	AIC	-18828	-18826	-18825
	BIC	**-18798**	-18796	-18795
	Likelihood	**9419**	9418	9417
		em.egarch	em.tgarch	em.pgarch
Pakistan	AIC	-13932	-13958	-13926
	BIC	-13903	**-13929**	-13897
	Likelihood	6971	**6984**	6968
		em.egarch	em.tgarch	em.pgarch
South Africa	AIC	-11595	-11639	-11585
	BIC	-11565	**-11610**	-11555
	Likelihood	5802	**5825**	5797
		em.egarch	em.tgarch	em.pgarch
Russia	AIC	-15772	-15761	-15760
	BIC	**-15743**	-15731	-15730
	Likelihood	**7891**	7885	7885

8.3. Long-term memory in volatility and SEMIFAR model

Having discussed the anatomy of volatility in emerging markets, we will turn our attention to the analysis of the long-memory characteristics of emerging stock markets. We will begin our examination by providing the statistic estimations to detect the existence of dependence in volatility in emerging markets. Table 27 presents the results for the classical R/S statistic and the modified R/S statistics as proposed by Lo (1991). The estimated test statistics are obtained with the Finmetrics S-Plus 6.1 module. Table 27 also provides the bias of the classical R/S when compared to the modified R/S. The bias is defined to be: ((classical R/S)/(modified R/S)-1) x 100.

The statistics computed in Table 27 have a distribution with critical values given in Lo (1991, pg 1288, Table 11). Using these values, we can test the null hypothesis at the 99 percent and the 95 percent level of confidence. We also provide the results of the Hurst coefficient in Table 5.

It can be seen in Table 27 that the value of the Hurst coefficients ranges from 0.6238386 (Portugal) to 0.8546383 (Russia). Peters (1981) applies R/S analysis to individual stocks and to the S&P return's using monthly data over a 38-year period, from January 1950 to July 1988. He found the Hurst exponent ranges from 0.64 (Anheuser-Busch) to 0.78 (S&P 500). These findings suggest that the stock market of emerging markets countries used in this study are considered fractal (i.e. they have long-memory) since all the value of the Hurst coefficients are greater than 0.5. One of usefulness of long term memory analysis is that it can be used to assess efficiency in the stock market. In this case the market efficiency can be judged by the amount of noise in the data. Because Russia has the highest Hurst coefficient this would suggest a very strong inefficiency in the Russian stock market. The rather more efficient of Portugal stock market (as indicated by its lower Hurst coefficient as compared to Russia) could be due to the fact that the Lisbon stock exchange was established earlier (1891) than the Russian stock exchange (1995).

Further evidence of long-memory using classical R/S test is reported in Table 27. In this case we test the null hypothesis of no long-term dependence. As with the Hurst coefficients, all countries sample demonstrate evidence of long-memory. The null hypotheses are all rejected, mostly at one percent level. As can be seen from Table 27, the highest value of classical R/S (8.9187) is for Greece whereas the lowest value (1.995) is for Venezuela. The above findings are supported by the graphs of R/S estimate of Long Memory Parameter. Appendix 1 provides the results of the graphs of R/S estimate of Long Memory Parameter of some of the countries in the study. From the appendix 1 we can see that all the solid lines are far away from the dotted line, which is substantial evidence for long-memory. One possible explanation of this result is that investors in emerging markets responded slowly to the new information during the period under consideration.

Unlike the three previous tests or parameters, based on the results of modified R/S statistic it was found for 26 of 28 countries exhibited long-memory as the test statistic of no long-term dependence was rejected at either the one percent or five percent level. More specifically, the null hypothesis of no long-term dependence cannot be rejected for Chile and Venezuela. The acceptance of the null hypothesis for Venezuela is understandable given the feature of the modified R/S statistics which essentially produces lower value than the classical R/S statistics. As a result, Chile which has the second lowest value for its classical R/S statistic also rejects the null hypothesis based on the modified R/S statistic. From Table 27 we can see that the highest value of modified R/S (5.2437) is for Greece whereas the lowest value (1.4849) is for Venezuela. Thus there is a strong relation between the classical and the modified R/S statistic. That is the classical R/S and the modified R/S statistics give the same pair countries for their lowest and highest test statistics.

The fourth column of numbers in Table 27 shows the bias as defined earlier. The bias ranges from 34.35 percent (Venezuela) to 95.59 percent (Indonesia). It should be noted that however we cannot find the clear pattern between the bias and the modified R/S. In other words the size of the bias is not associated with the value of modified R/S or the rejection of null hypothesis of no long-term dependence.

In summary, results of the Hurst coefficient, the classical R/S statistic, and the modified R/S statistic suggest that the assumption of no long-term dependence (or no long-term memory) in stock volatilities is invalid for the majority of countries. Therefore in the next section we will apply SEMIFAR model to explain the long-memory behaviour of emerging stock markets.

Table 27. Classical R/S, Modified R/S Statistics and Hurst Coefficient for the Countries under Analysis

This table reports the results of the Classical R/S, Modified R/S and Hurst Coefficient. We also provide the bias which is defined as ((classical R/S)/(modified R/S)-1)x100.

No.	Country	Classical R/S	Modified R/S	Bias (%)	Hurst Coefficient
1	Argentina	3.681 **	2.421 **	52.04	0.798
2	Brazil	4.034 **	2.225 **	81.30	0.798
3	Chile	2.822 **	1.810	55.91	0.770
4	Colombia	3.853 **	2.337 **	64.87	0.749
5	Mexico	5.500 **	3.179 **	73.01	0.717
6	Peru	3.539 **	2.222 **	59.27	0.724
7	Venezuela	1.995 *	1.485	34.34	0.702
8	Hong Kong	7.176 **	4.157 **	72.62	0.688
9	Indonesia	8.723 **	4.459 **	95.63	0.711
10	Korea	8.194 **	4.609 **	77.78	0.754
11	Malaysia	8.819 **	4.658 **	89.33	0.689
12	Philippines	6.936 **	3.937 **	76.17	0.682
13	Singapore	7.964 **	4.590 **	73.51	0.746
14	Taiwan	5.107 **	3.539 **	44.31	0.683
15	Thailand	8.478 **	4.834 **	75.38	0.749
16	Czech Republic	5.709 **	3.667 **	55.69	0.741
17	Greece	8.919 **	5.244 **	70.08	0.694
18	Hungary	4.708 **	2.983 **	57.83	0.699
19	Poland	4.983 **	3.186 **	56.40	0.669
20	Portugal	6.734 **	4.415 **	52.53	0.624
21	Turkey	5.714 **	3.612 **	58.19	0.759
22	Egypt	5.993 **	4.071 **	47.21	0.778
23	India	5.723 **	3.621 **	58.05	0.674
24	Israel	7.106 **	4.458 **	59.40	0.700
25	Morocco	4.512 **	3.062 **	47.35	0.742
26	Pakistan	4.521 **	2.770 **	63.21	0.703
27	South Africa	7.359 **	4.152 **	77.24	0.822
28	Russia	5.561 **	3.348 **	66.10	0.855

Note: ** indicates statistically significant at the 1% level.

* indicates statistically significant at the 5% level.

The most crucial step in applying the SEMIFAR model is how the original data series (or stock index in our case) is transformed to represent the volatility or variance. In this study, the testing of volatility is analysed based on the power-transformed absolute which is defined as $Y_t = |I_t - I_{t-1}|^{1/4}$; where I_t denotes the original index. Following Beran and Ocker (2001), we take a simple pragmatic approach. In a first step, missing values in the original index series are replaced by the closest previous closing value, resulting in zero increments. In a second step, zero values of Y_t were omitted and the series are treated as equidistant. The use of the fourth root of the increments is based on the fact that the marginal distribution of the resulting series is very close to normal. A similar methodology was used by Ding et.al (1993).

The results of the long memory parameter (d) as specified in SEMIFAR model for the daily volatility series are presented in Table 28. The SEMIFAR model was estimated by Finmetrics S-Plus 6.1 module and it uses BIC to choose the short memory autoregressive order p. Table 28 also provides the corresponding 95% confidence intervals for each long memory parameter.

Based on the estimated values of d and the confidence intervals, it is found that all values of d are less than 0.5. Therefore we might conclude that the stochastic part of all emerging stock market is stationary. This also implies that there is long-range dependence in the stochastic component of daily volatility series in emerging stock markets.

With respect to the short memory dependence, there are 14 countries that have the short memory autoregressive order. In particular Argentina, Indonesia, Korea, Taiwan, Thailand, Greece, Egypt, Israel, Morocco, Pakistan, South Africa and Russia have autoregressive of order 1 whereas Brazil and Peru have autoregressive of order 2.

A final observation is that all emerging stock markets (except for Brazil) demonstrated significant deterministic trend. In Appendix 2, we present SEMIFAR decomposition of daily volatility series of some of the sample countries of emerging stock markets used in this thesis. As can be seen in the Appendix 2 the smooth trend component is plotted with a confidence band. If the trend falls outside the confidence band, it indicates that the trend component is significant. In general, there are evidences of high and low volatility (or up and down volatility) pattern in the form of a significant deterministic trend.

With regard to the capability of SEFIMAR model at modelling the long memory, based on the ACF plot of residuals and normal probability plots (or QQ plots) of residuals we might conclude that the SEMIFAR model seems to be very successful at modelling the long memory. The results of the ACF plot of residuals and normal probability plots of residuals of some of the sample countries used in this thesis are presented in appendix 3 and appendix 4 respectively.

Table 28. Estimation Results of d and Significant trend.

This table reports the results of the estimated value of d generated by SEMIFAR model together with its SE and its confidence interval. The results of significant trend are also provided.

No.	Country	d	SE	Confidence Interval Low	Confidence Interval Up	Significant trend
1	Argentina	0.187	0.023	0.1424	0.2314	Yes
2	Brazil	0.272	0.027	0.2193	0.3251	No
3	Chile	0.131	0.015	0.1010	0.1610	Yes
4	Colombia	0.208	0.015	0.1777	0.2381	Yes
5	Mexico	0.116	0.015	0.0866	0.1462	Yes
6	Peru	0.242	0.028	0.1875	0.2965	Yes
7	Venezuela	0.147	0.015	0.1171	0.1775	Yes
8	Hong Kong	0.075	0.015	0.0452	0.1048	Yes
9	Indonesia	0.232	0.023	0.1869	0.2763	Yes
10	Korea	0.135	0.022	0.0910	0.1788	Yes
11	Malaysia	0.104	0.015	0.0743	0.1343	Yes
12	Philippines	0.145	0.015	0.1149	0.1749	Yes
13	Singapore	0.062	0.015	0.0320	0.0916	Yes
14	Taiwan	0.154	0.023	0.1099	0.1981	Yes
15	Thailand	0.176	0.022	0.1329	0.2195	Yes
16	Czech	0.141	0.015	0.1108	0.1704	Yes
17	Greece	0.186	0.022	0.1420	0.2294	Yes
18	Hungary	0.141	0.015	0.1114	0.1710	Yes
19	Poland	0.111	0.015	0.0813	0.1409	Yes
20	Portugal	0.087	0.015	0.0568	0.1164	Yes
21	Turkey	0.141	0.015	0.1107	0.1707	Yes
22	Egypt	0.215	0.024	0.1682	0.2626	Yes
23	India	0.128	0.015	0.0983	0.1583	Yes
24	Israel	0.131	0.022	0.0876	0.1746	Yes
25	Morocco	0.203	0.022	0.1590	0.2468	Yes
26	Pakistan	0.227	0.024	0.1804	0.2734	Yes
27	S.Africa	0.237	0.023	0.1926	0.2820	Yes
28	Russia	0.208	0.022	0.1642	0.2512	Yes

8.4. Conclusion

The primary focus of this chapter is on the issue of asymmetric volatility and long term memory characteristic of volatility of emerging stock markets. In particular we attempted to seek the most appropriate asymmetric volatility model and to examine the robustness of SEMIFAR in modelling long term memory of volatility. We examined the asymmetric condition in volatility firstly by using the simple analysis, i.e. up and down volatility and finally by employing framework suggested by Engle and Ng (1993). For modelling asymmetry in volatility we employ three models namely EGARCH, TGARCH and PGARCH. The selection of the best model is based on the likelihood ratio, BIC and AIC. In order to identify the long memory feature in volatility of emerging stock markets we utilize three parameters, classical R/S statistic, the modified R/S statistic and Hurst coefficient. The final part of the analysis is to test the robustness of SEMIFAR model.

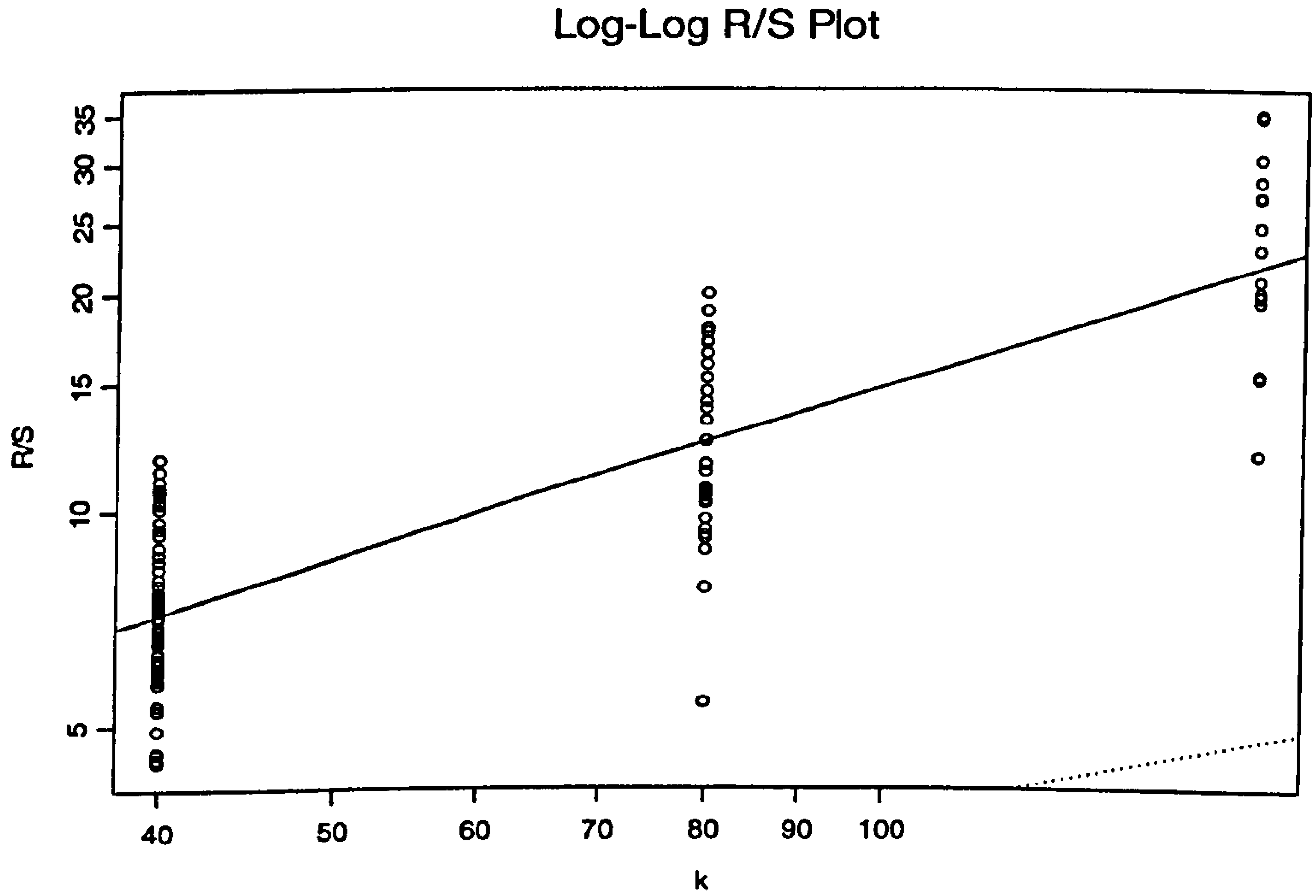
With respect to asymmetry feature, based on the result of Engle and Ng (1993) we find evidence (although considered to be weak) to propose that emerging stock markets volatility exhibited asymmetric pattern. It should be noted here that our conclusion is based on daily data while for the weekly data we did not find any such evidence. Based on the result of likelihood ratio, BIC and AIC it is found that the best model to use for modelling asymmetric in volatility of emerging stock markets is TGARCH.

Using classical R/S statistic, the modified R/S statistic and Hurst coefficient, we find evidence of long term memory feature in volatility of emerging stock markets. Based on the ACF plot of residuals and normal probability plots (or QQ plots) of residuals we might conclude that the SEMIFAR model seems to be very successful at modelling the long memory. The existence of long memory in volatility of emerging stock markets has three implications. First, the long-term dependence in volatility means that it is problematic to use short memory models, such as ARMA models, in assessing volatility forecasting. Second, as the volatility dynamic plays a very important role in derivative pricing, it may be beneficial to incorporate the long-term volatility structure in deriving pricing formulas (So, 2000). Finally, the presence of persistence in volatility implies the market is relatively inefficient and the volatility pattern is dependent on previous volatility. Therefore the findings will also be useful for investors and fund managers in implementing trading strategy based on volatility such as positive feedback and negative feedback trading.

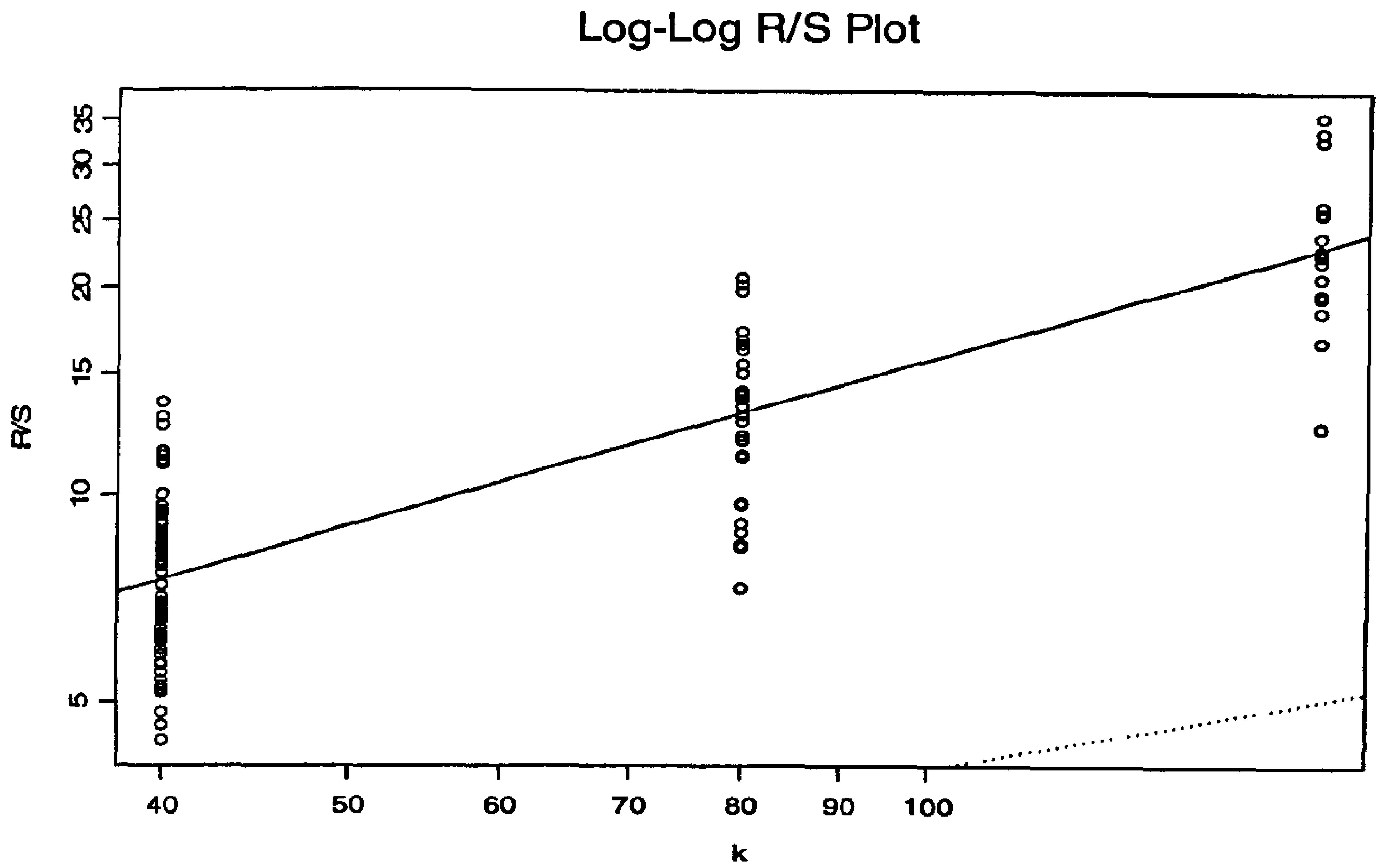
Appendix 1. Plot of Log-Log R/S for Each Country Sample.

This appendix provides the result of Log-Log R/S Plot. If the dotted line (no long memory) is far away from the solid line there is evidence of long memory. K represents the number of observations in the sample.

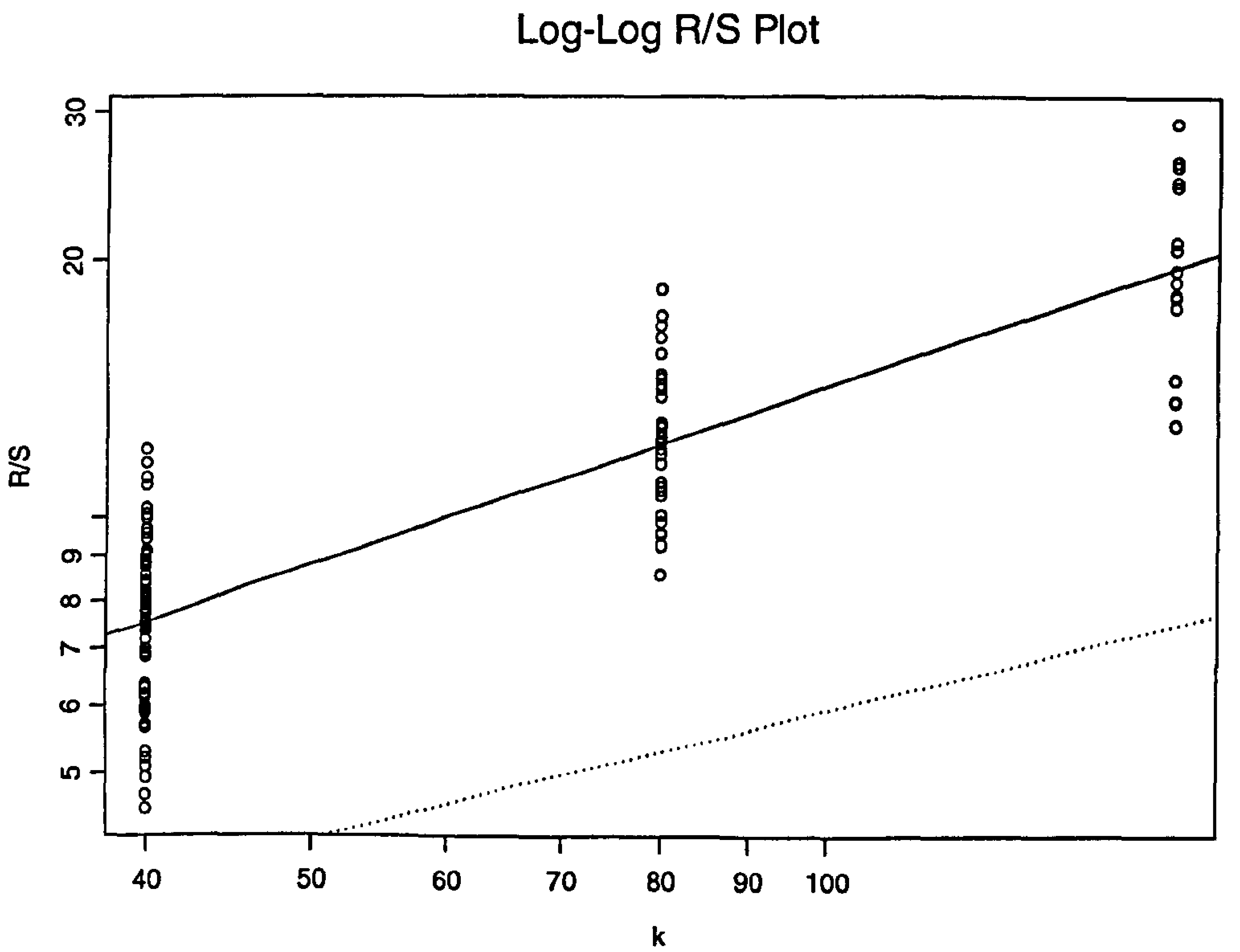
Argentina



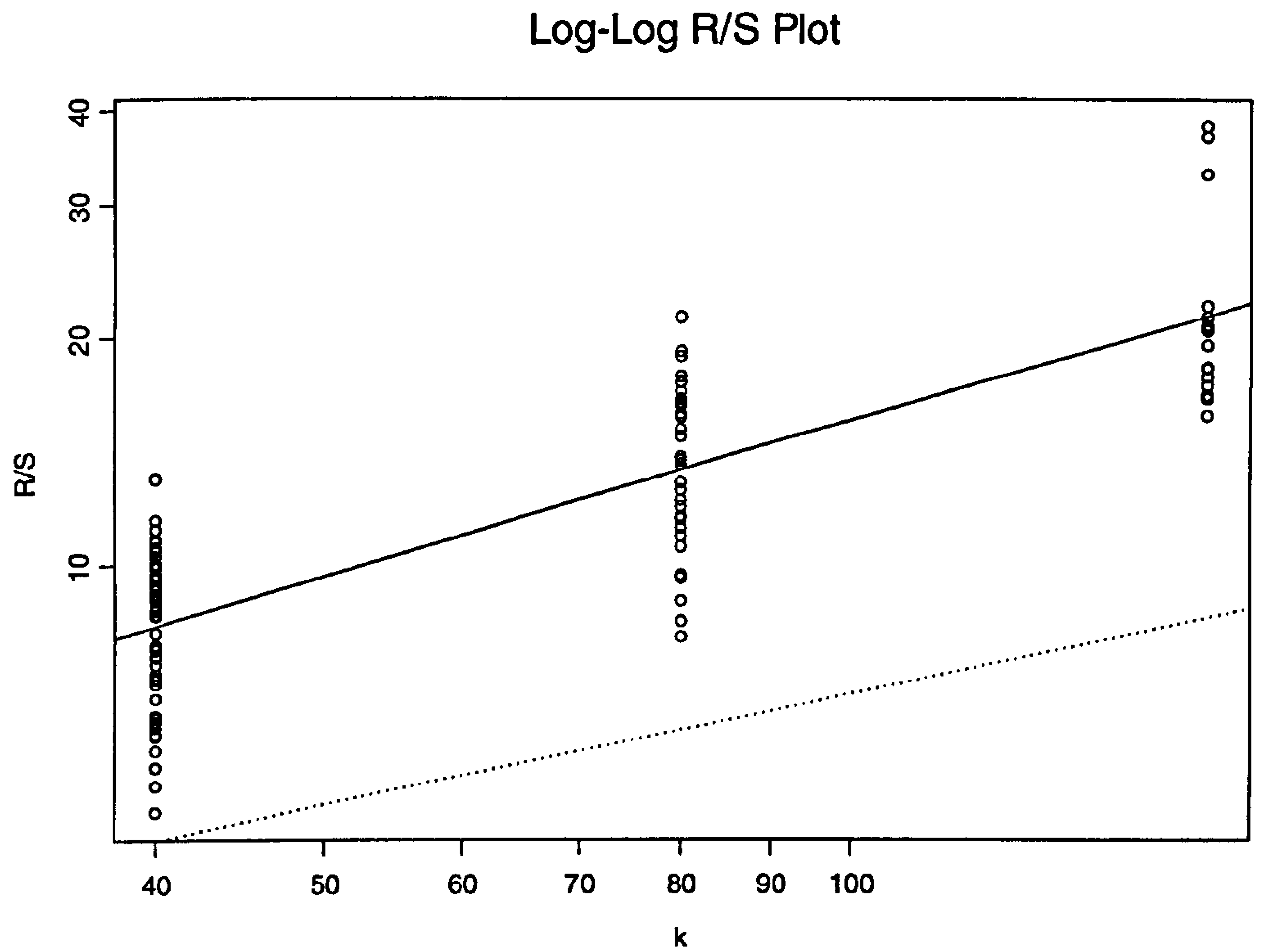
Brazil



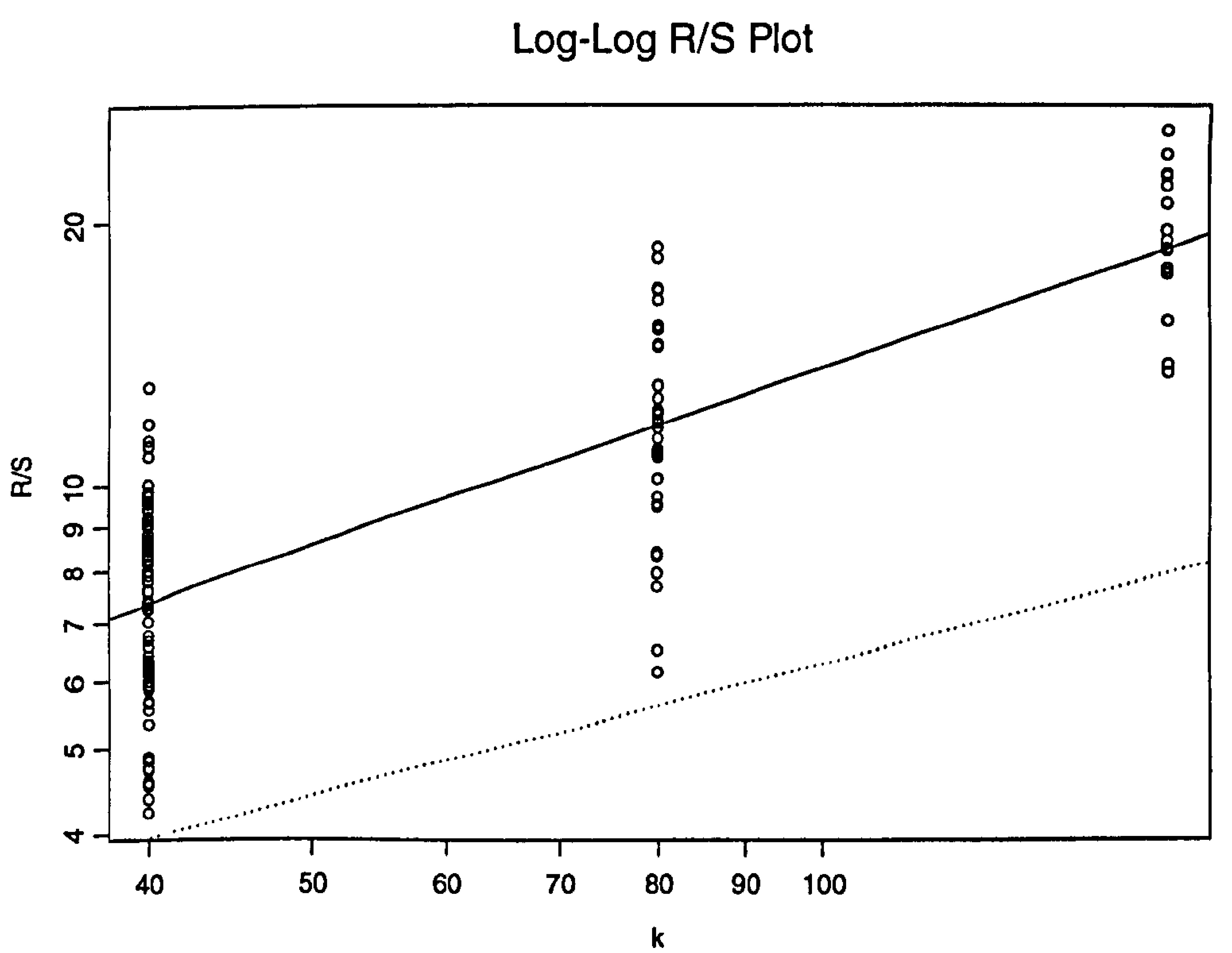
Malaysia



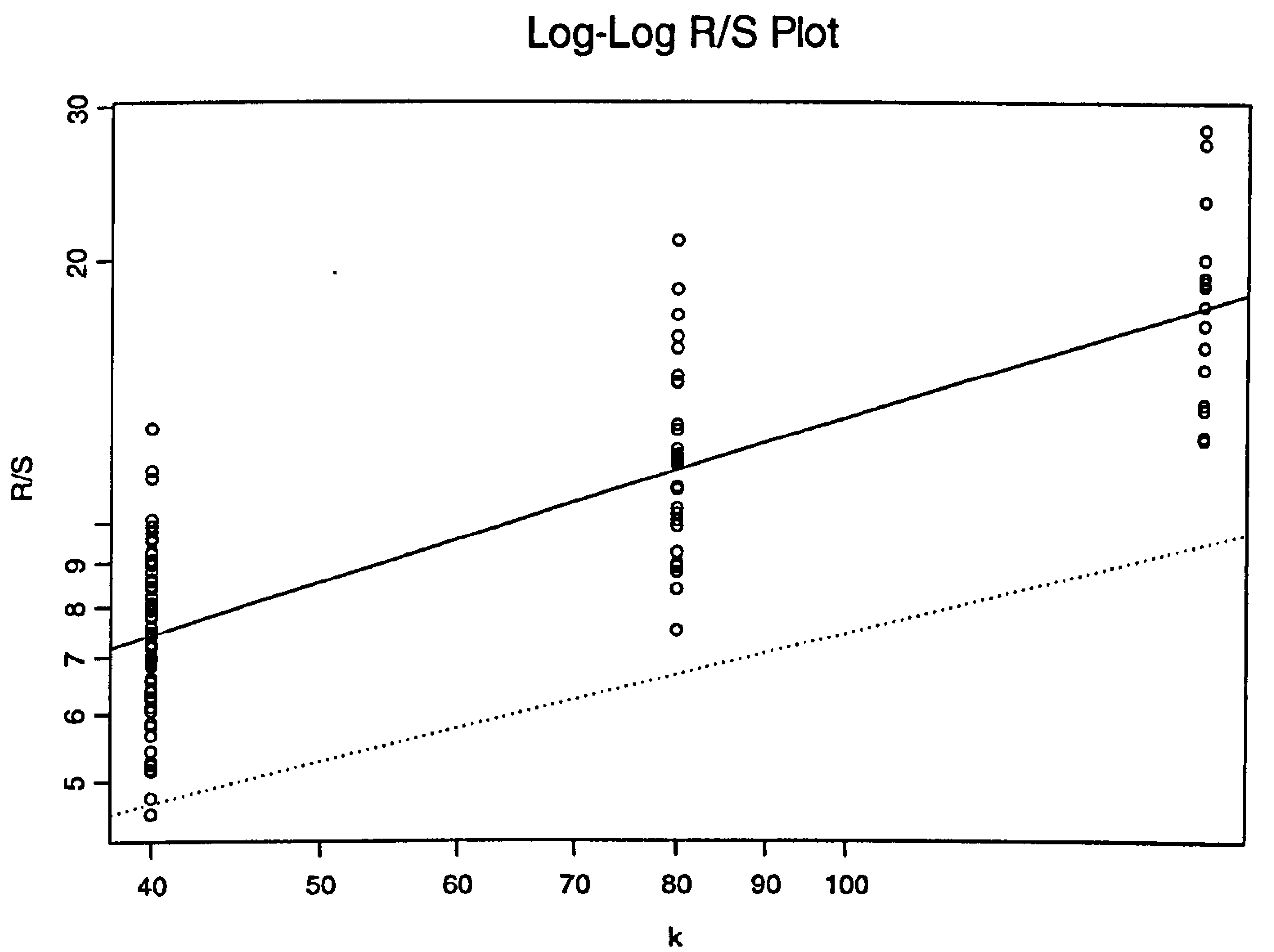
Philippines



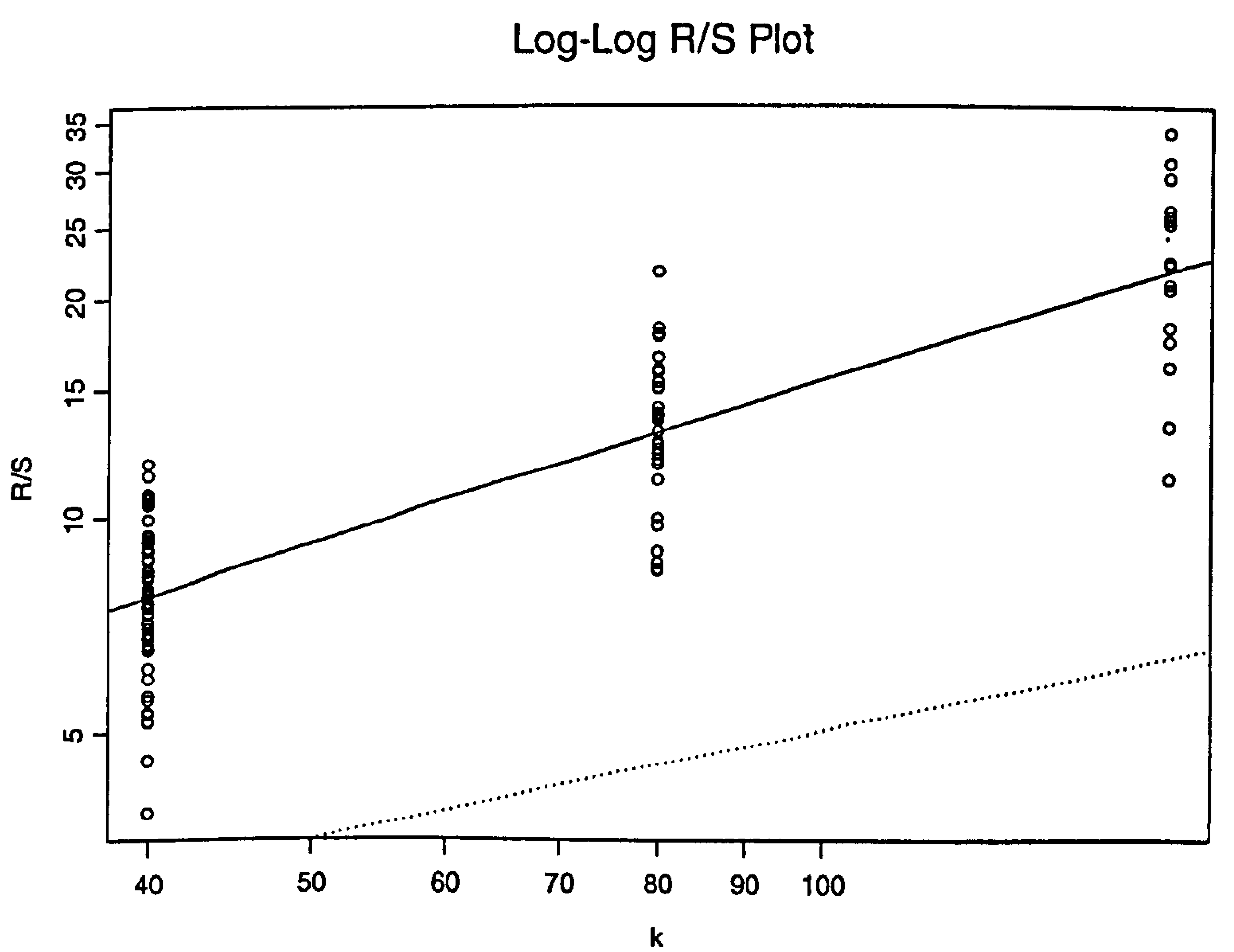
Poland



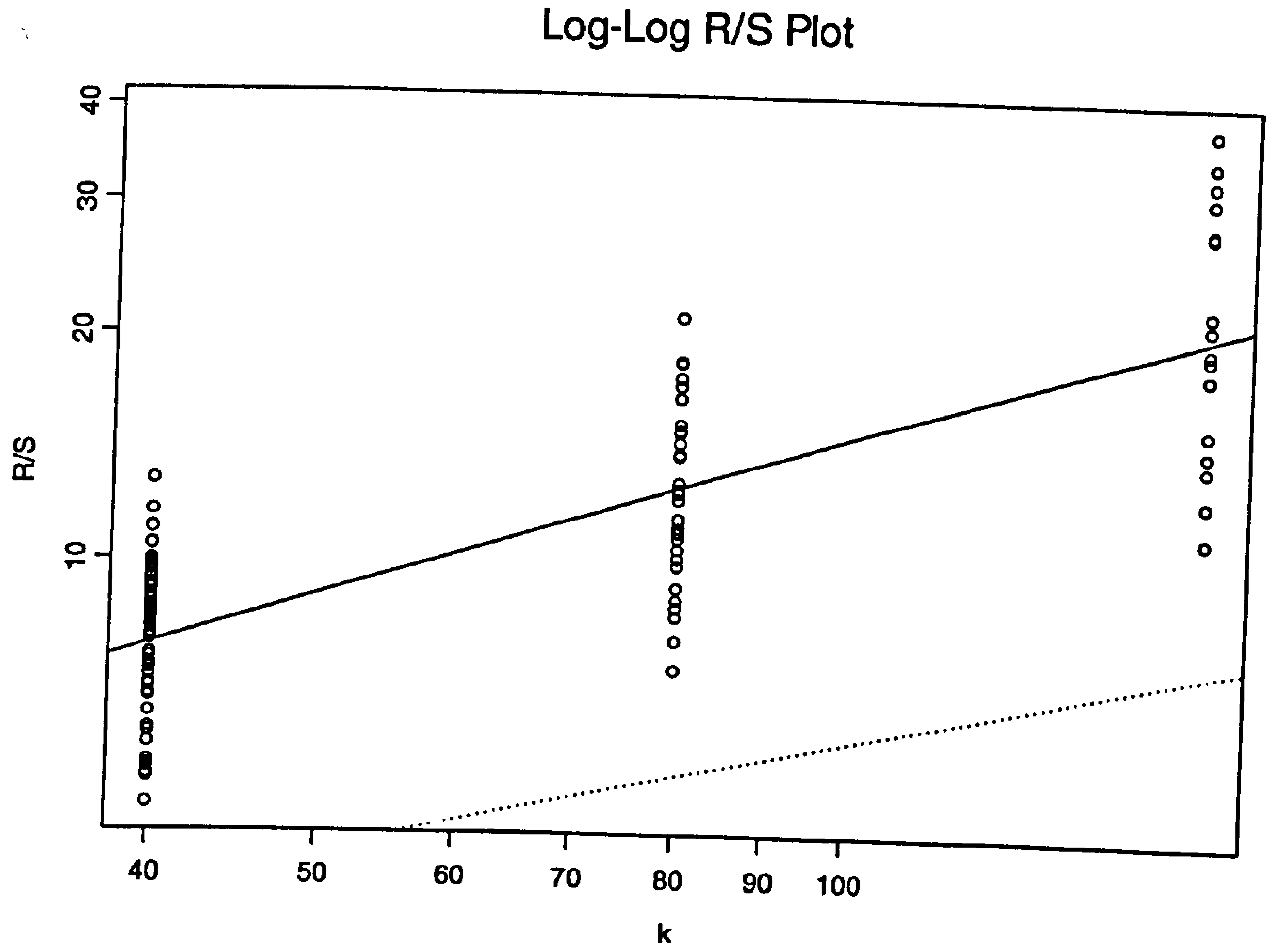
Portugal



Morocco



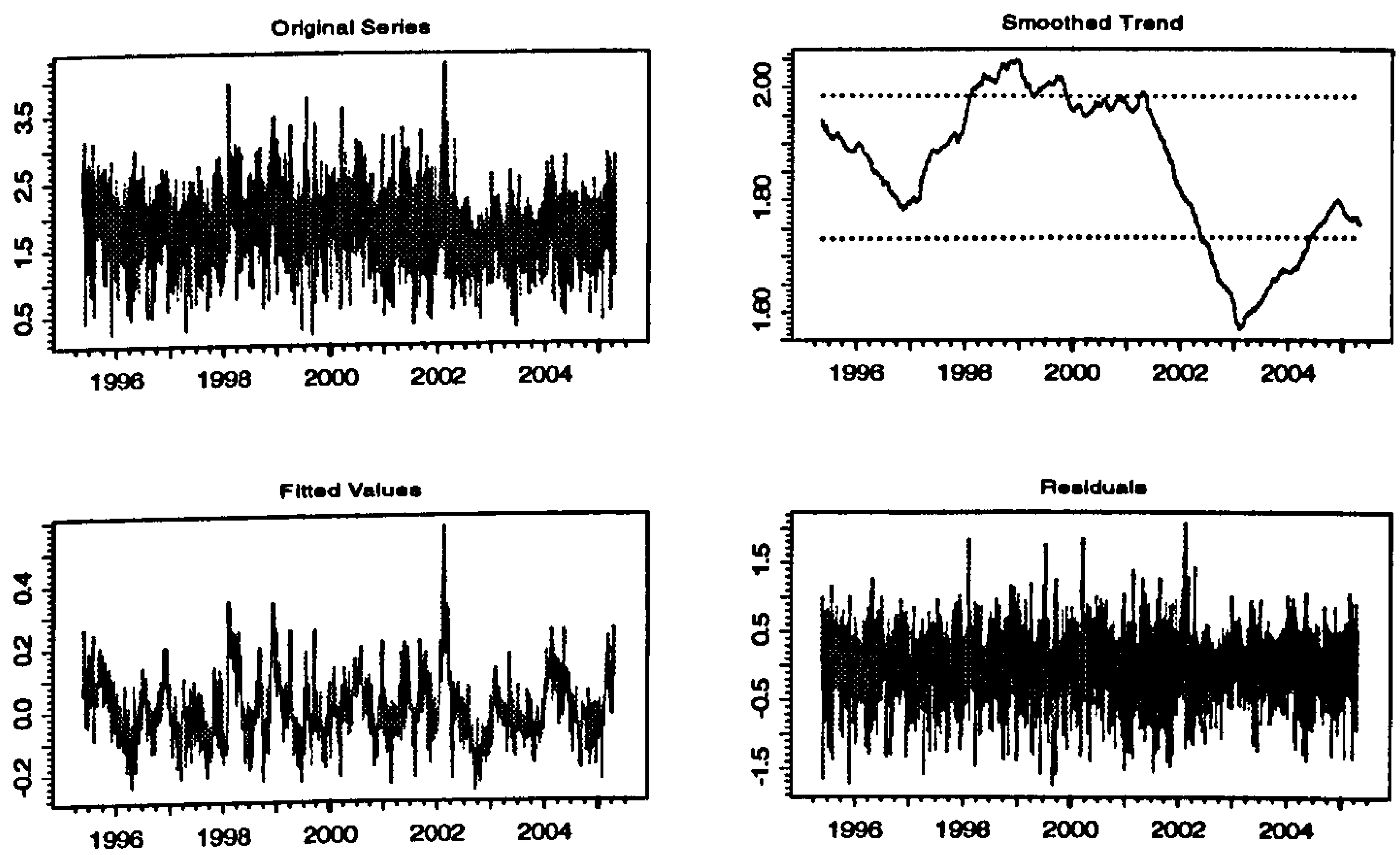
Pakistan



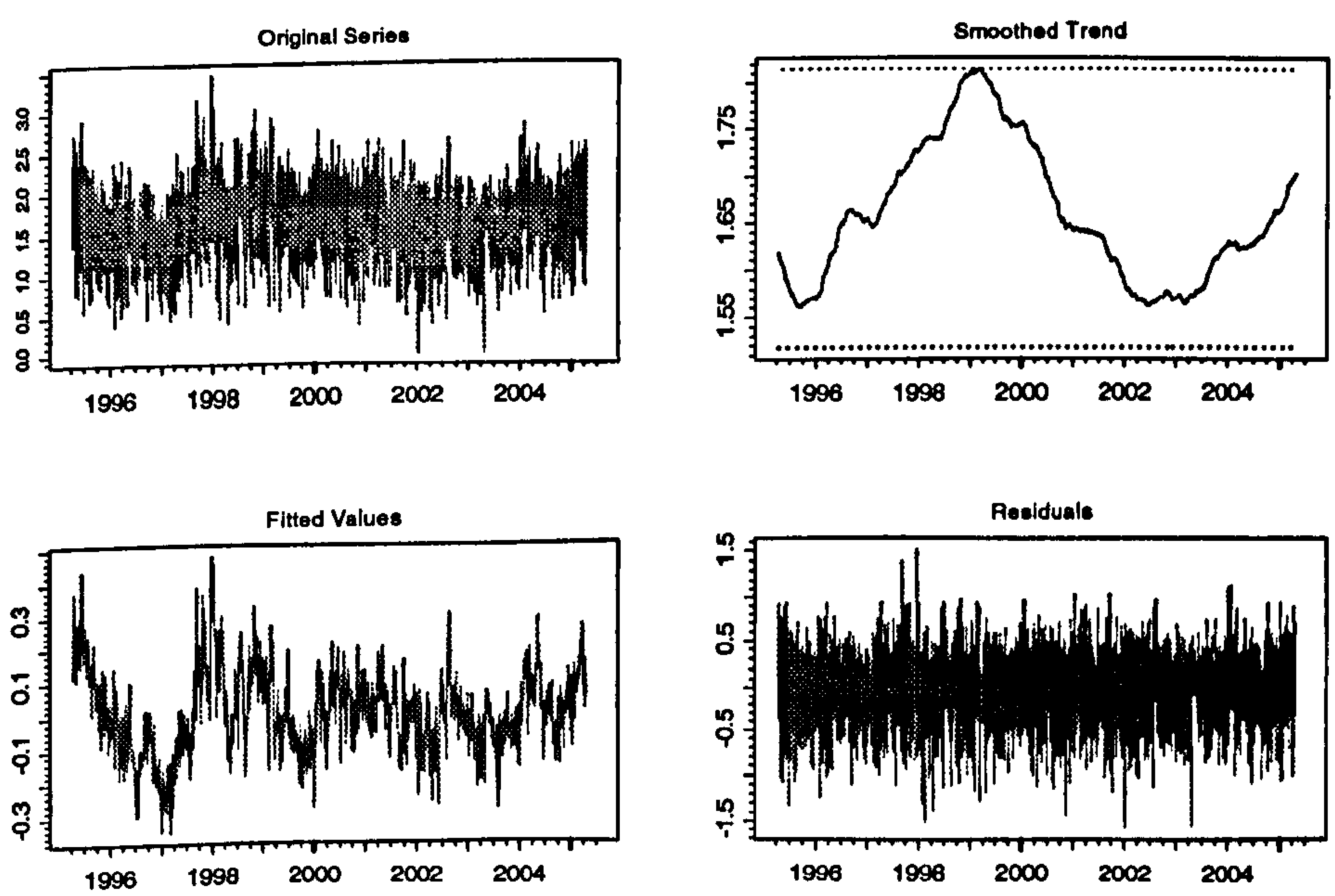
Appendix 2. SEMIFAR Decomposition for Each Country Sample.

This appendix provides the graphs of original series, smoothed trend, fitted value and residuals of SEMIFAR model. If the smoothed trend falls outside the confidence band it indicates that the trend component is significant.

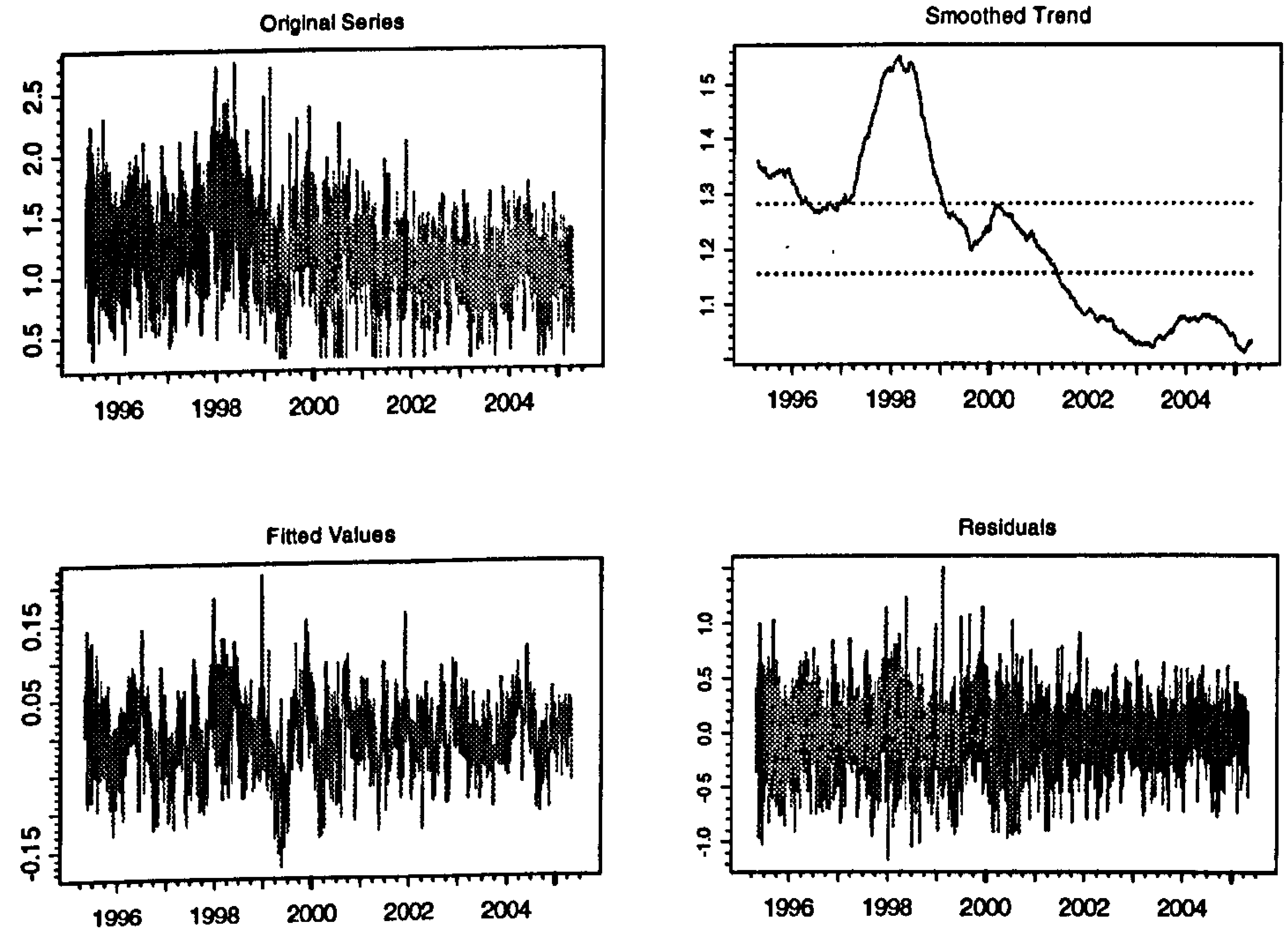
Argentina



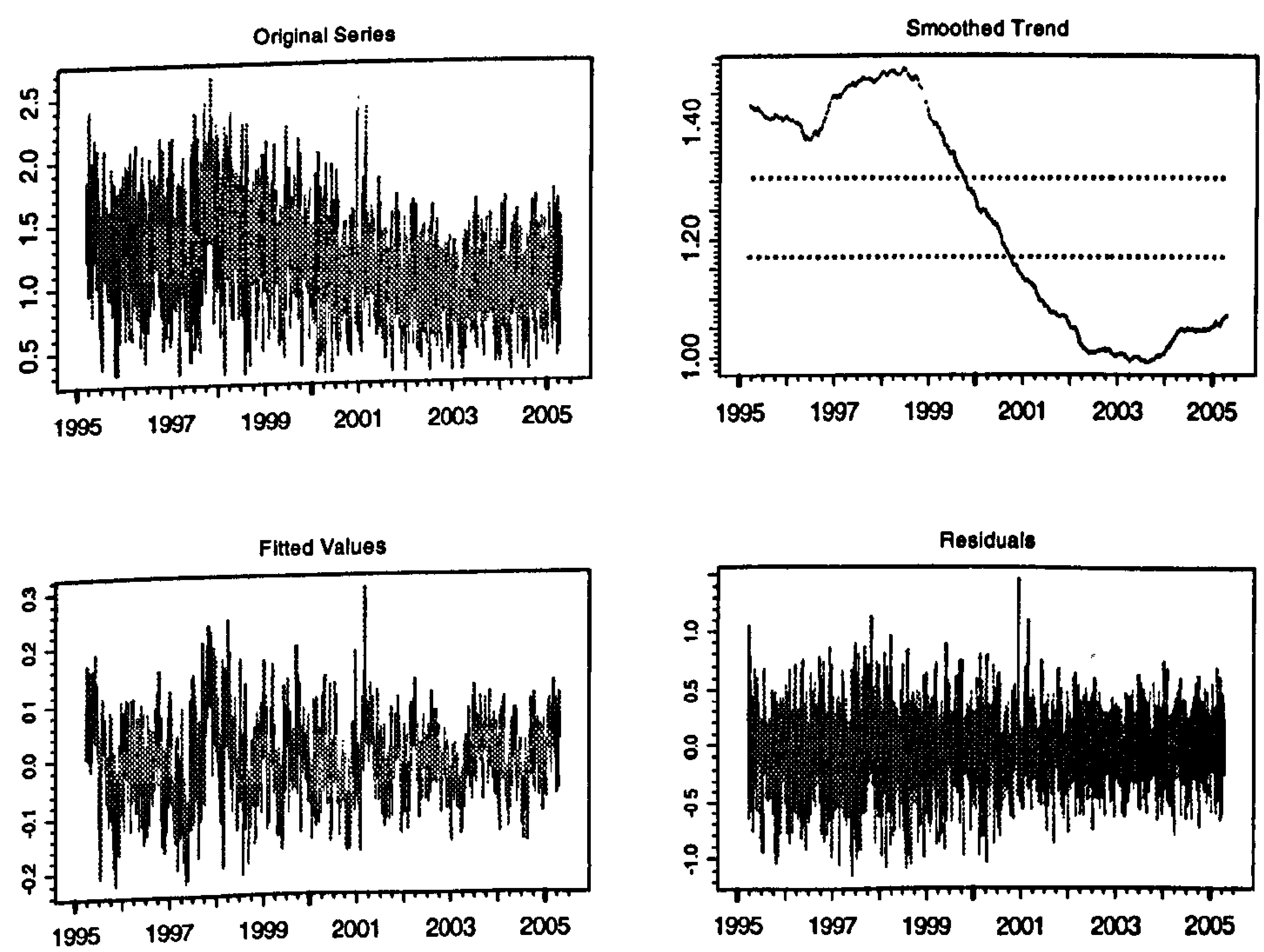
Brazil



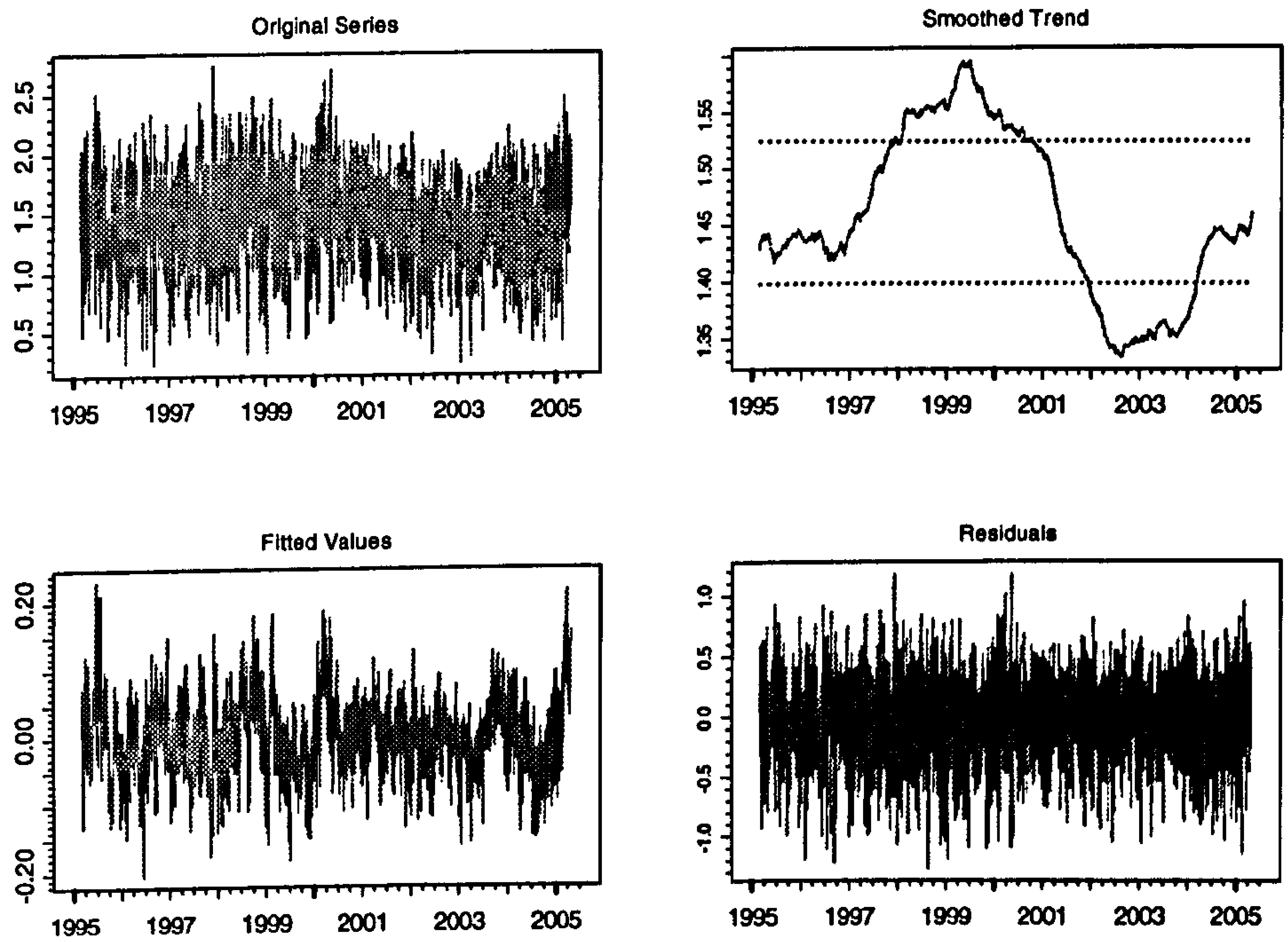
Malaysia



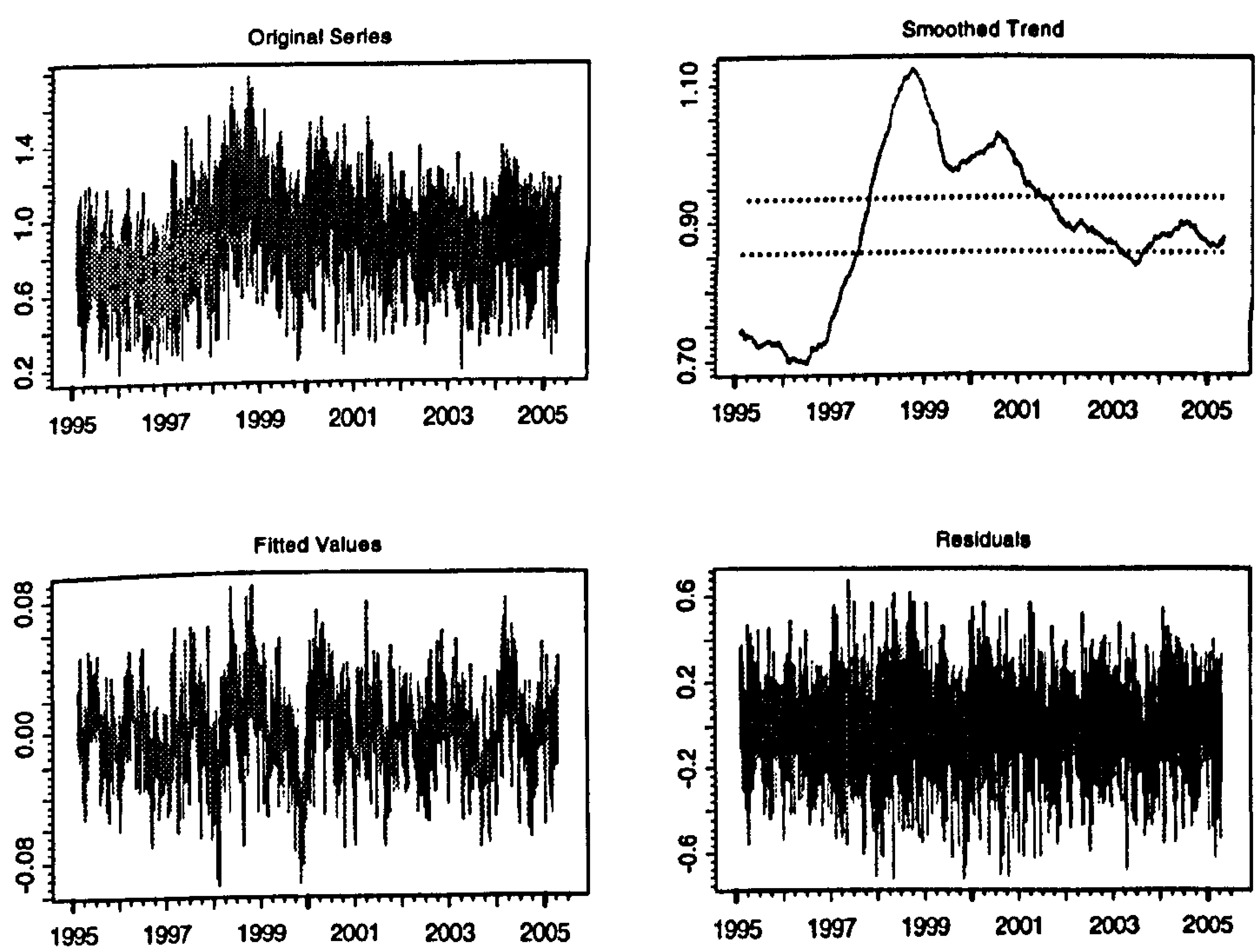
Philippines



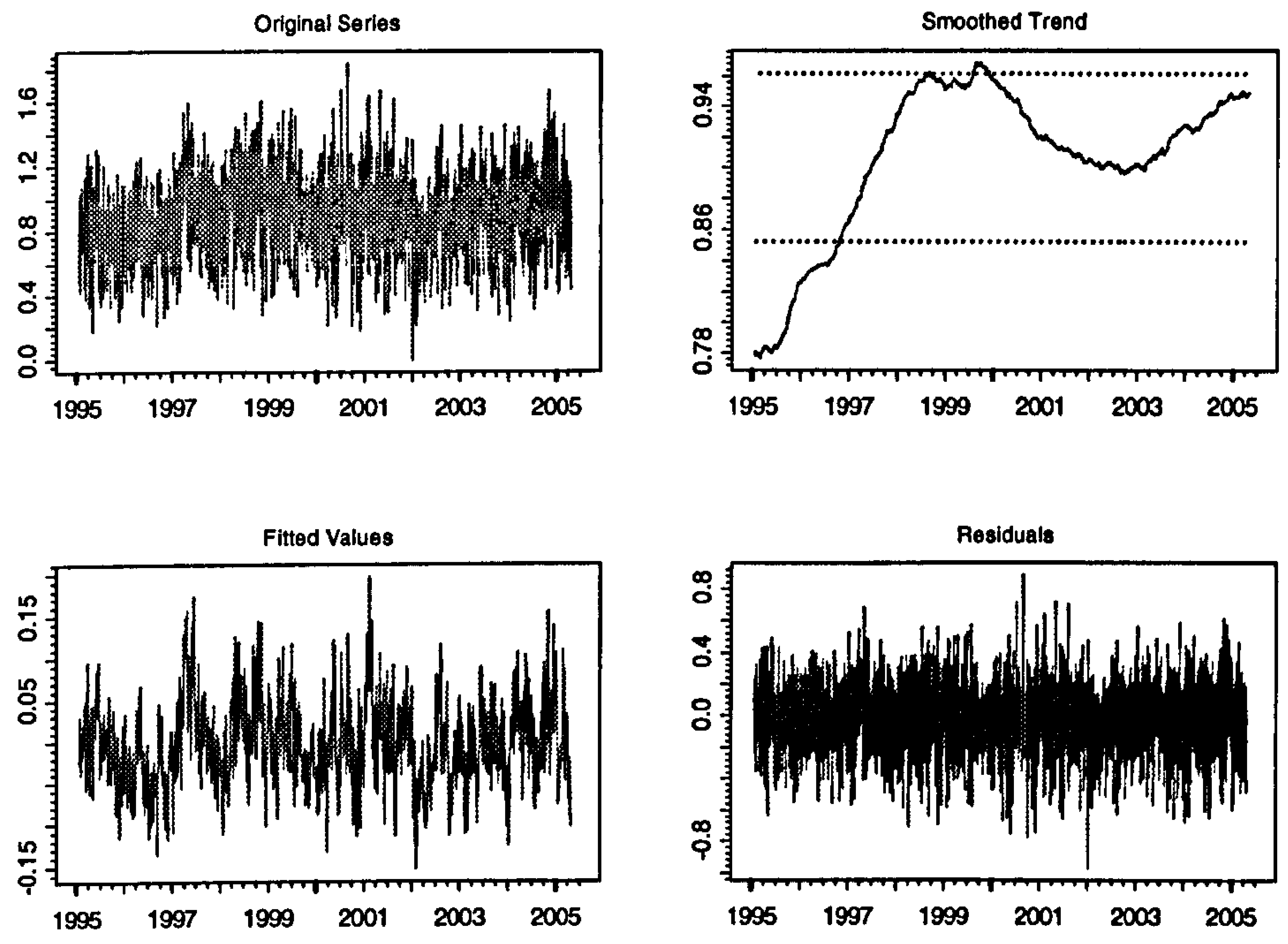
Poland



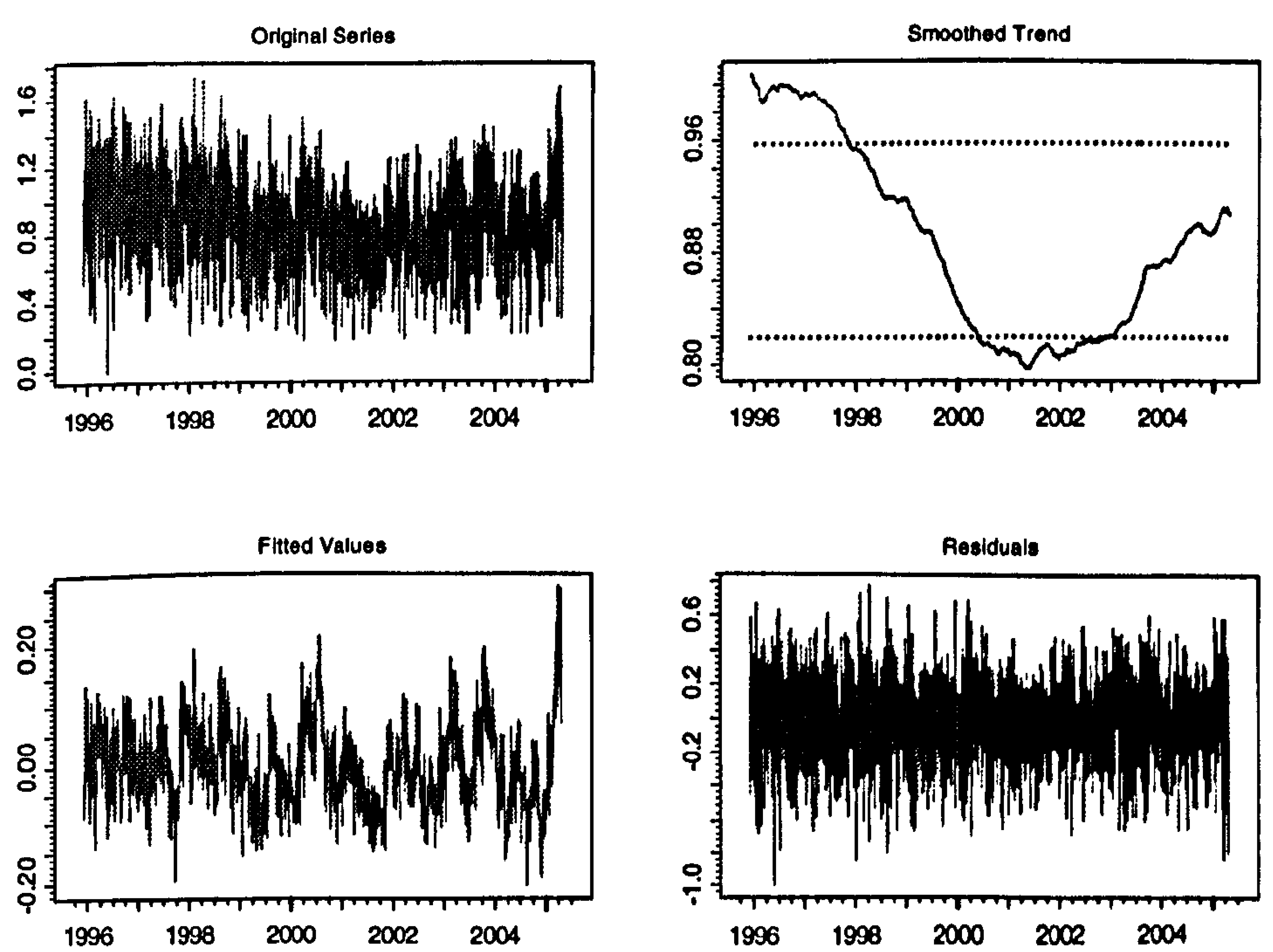
Portugal



Morocco



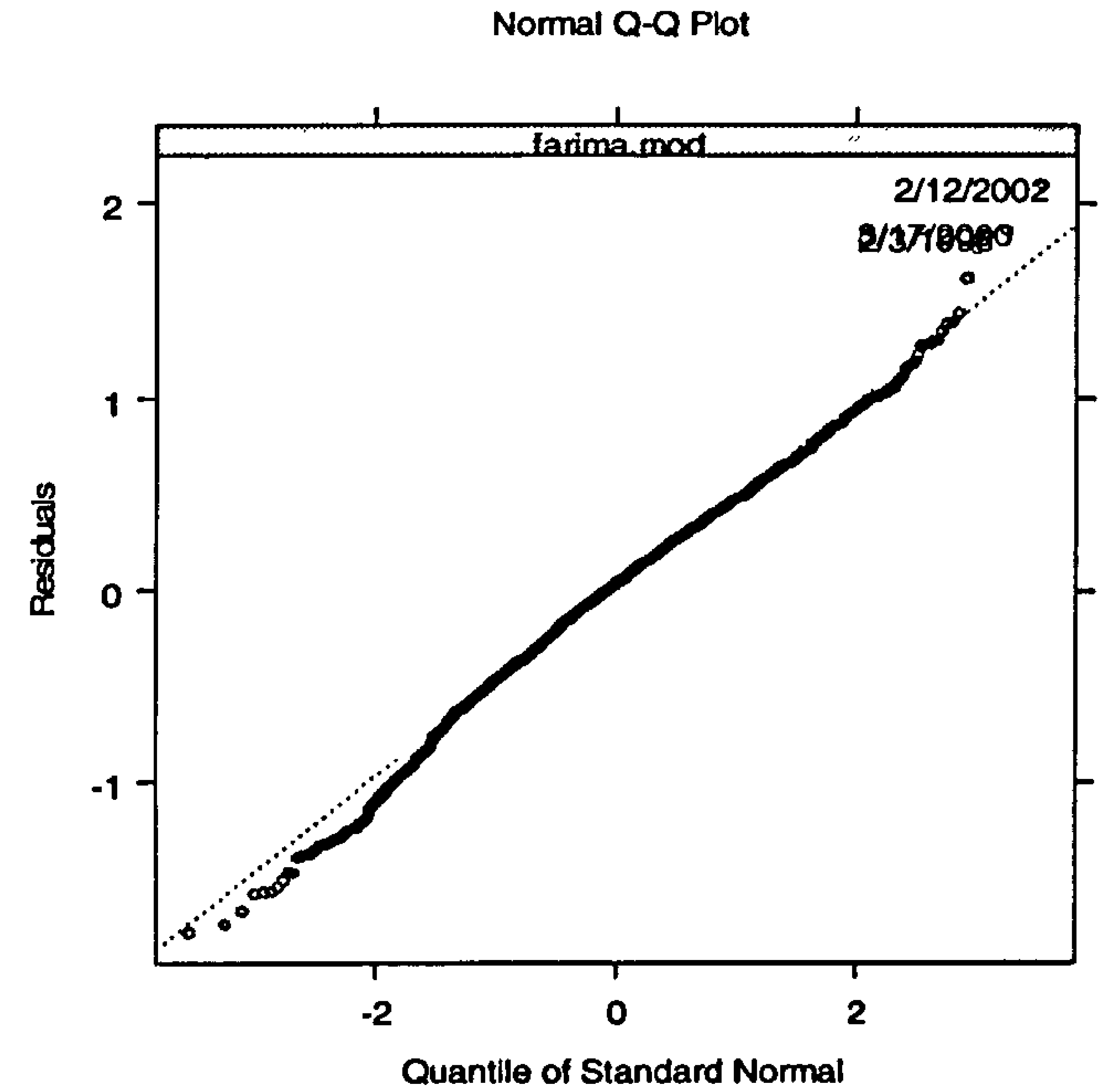
Pakistan



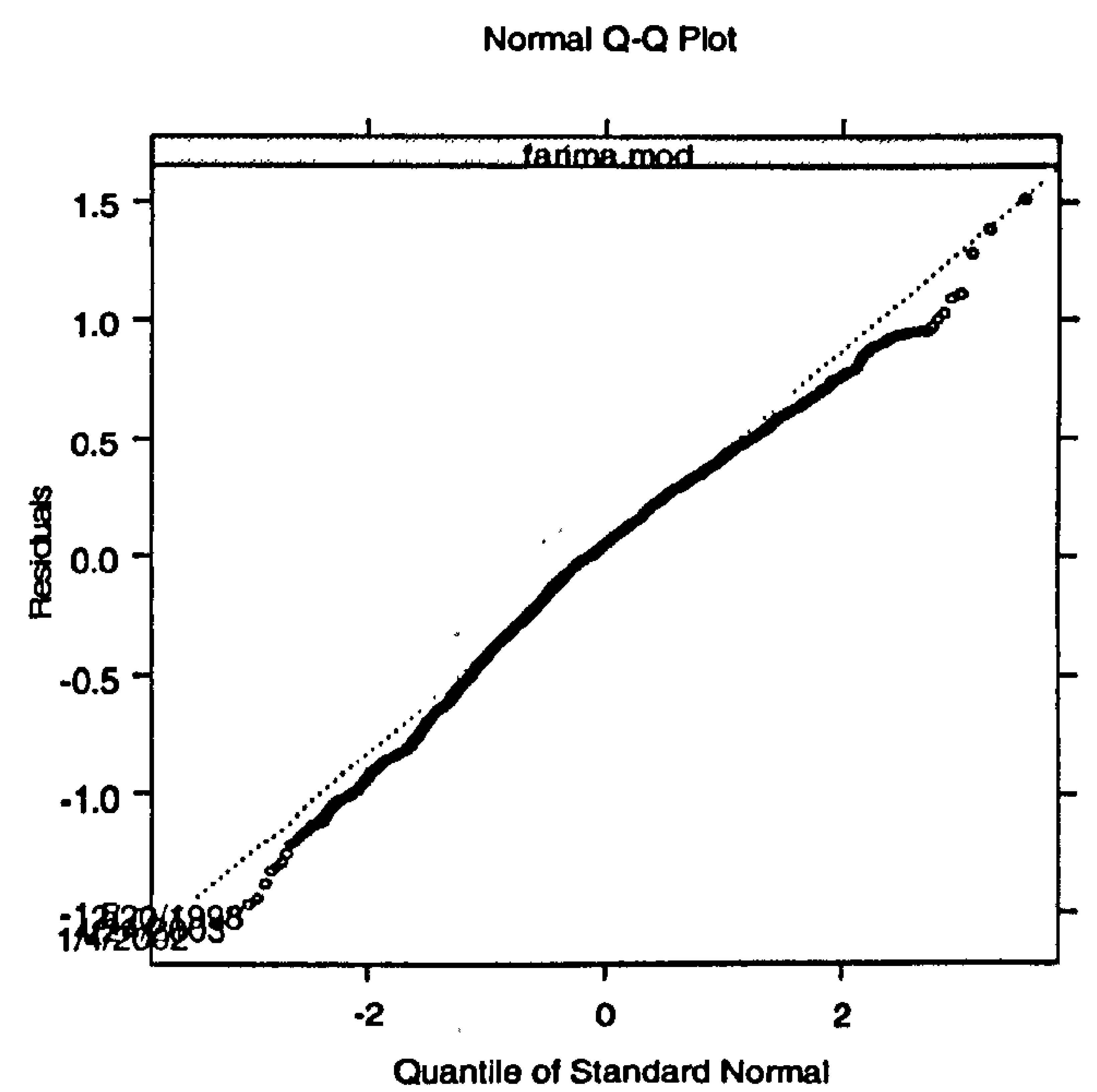
Appendix 3. Normal Probability Plots of the Residuals for Each Country Sample.

This appendix provides the graphs of Normal Probability Plots (or QQ Plots) of the residuals of SEMIFAR model.

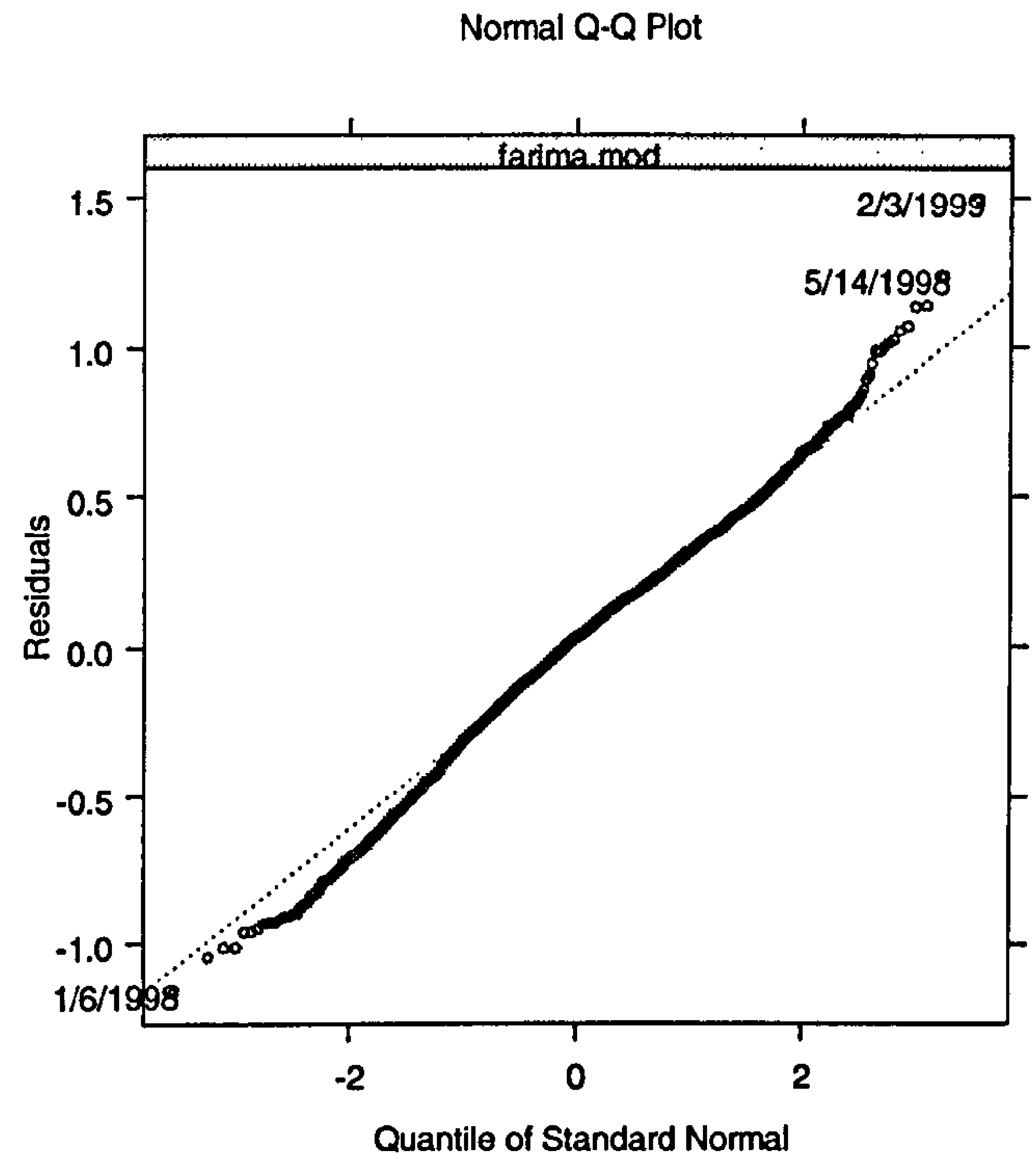
Argentina



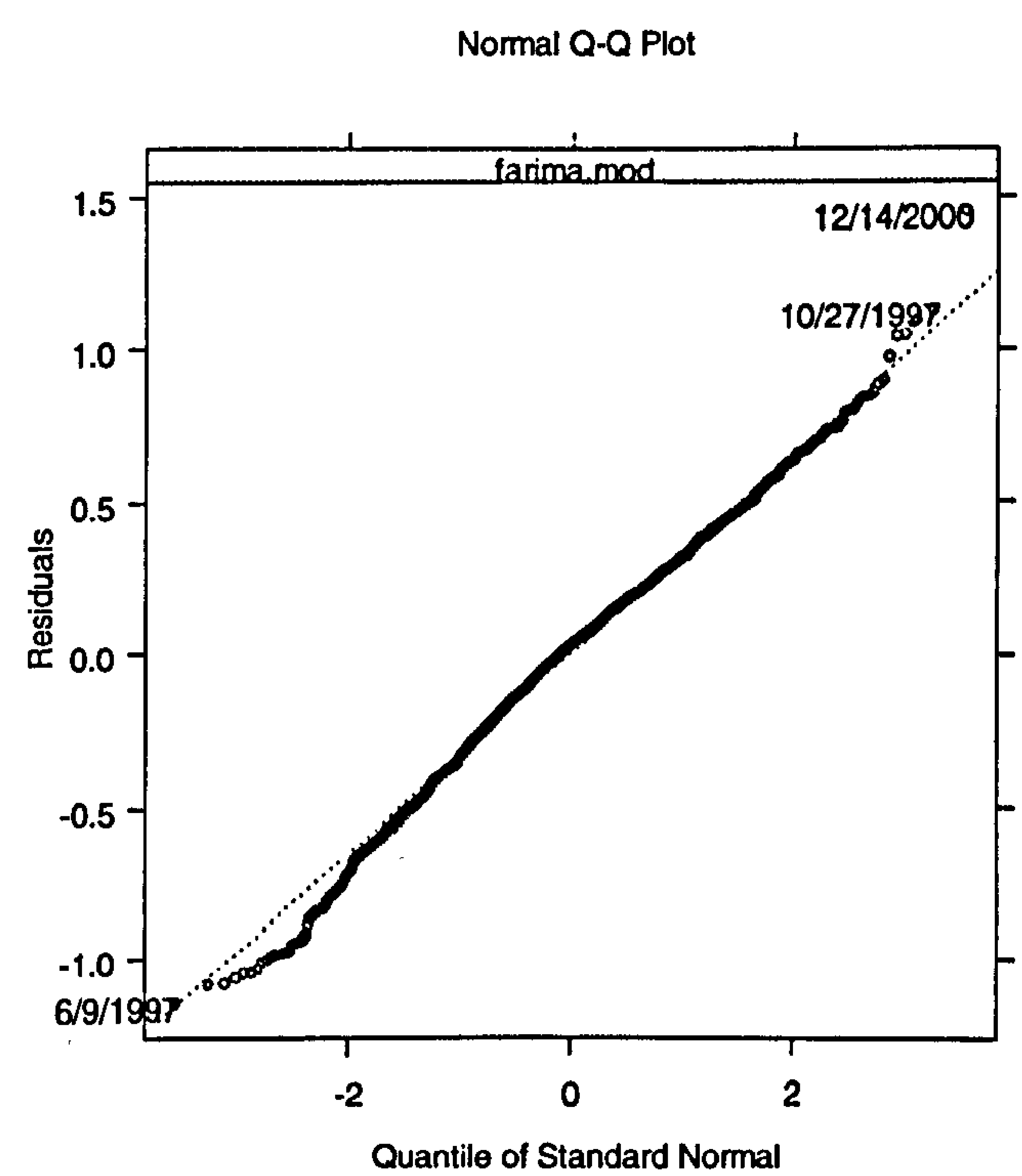
Brazil



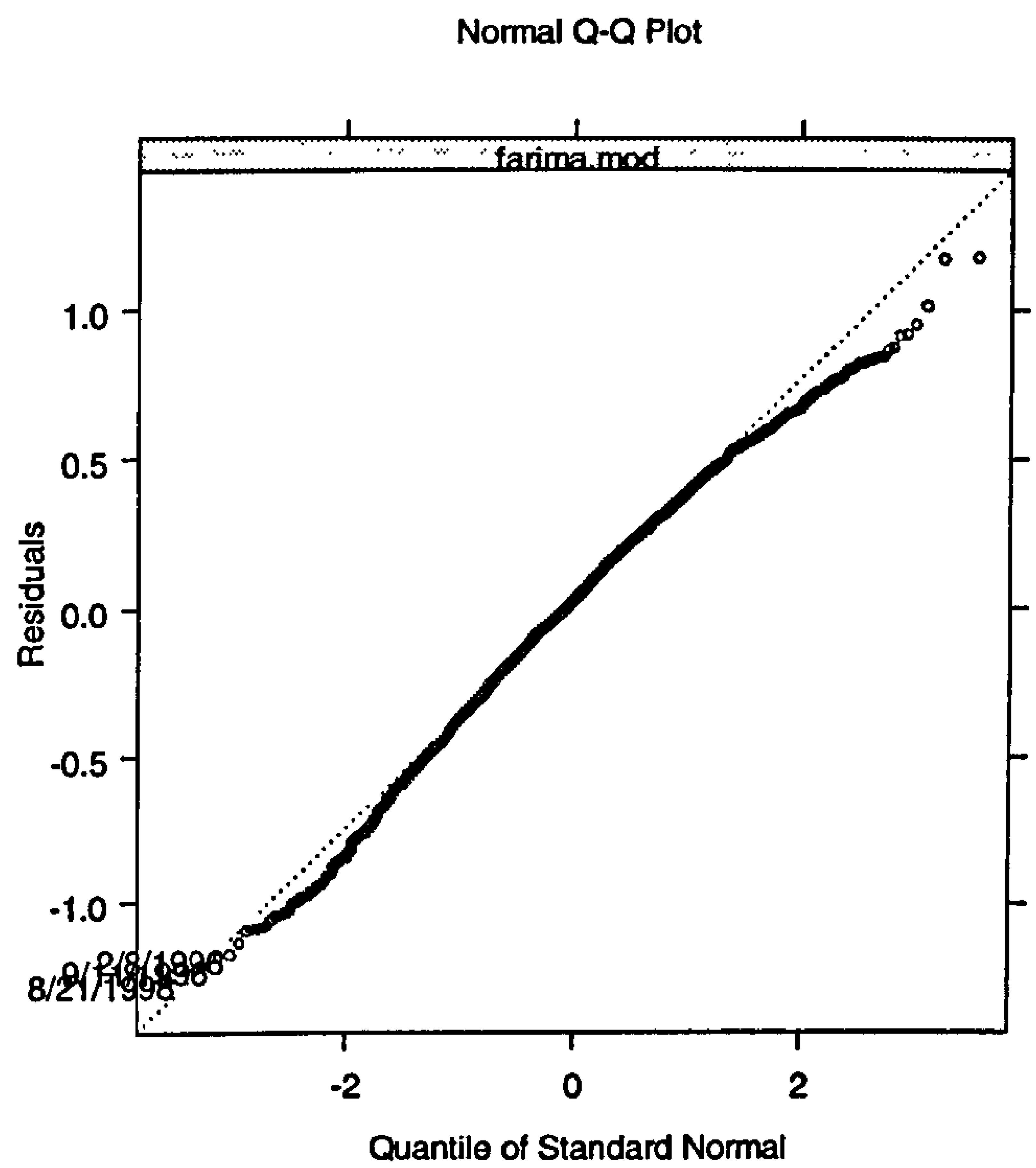
Malaysia



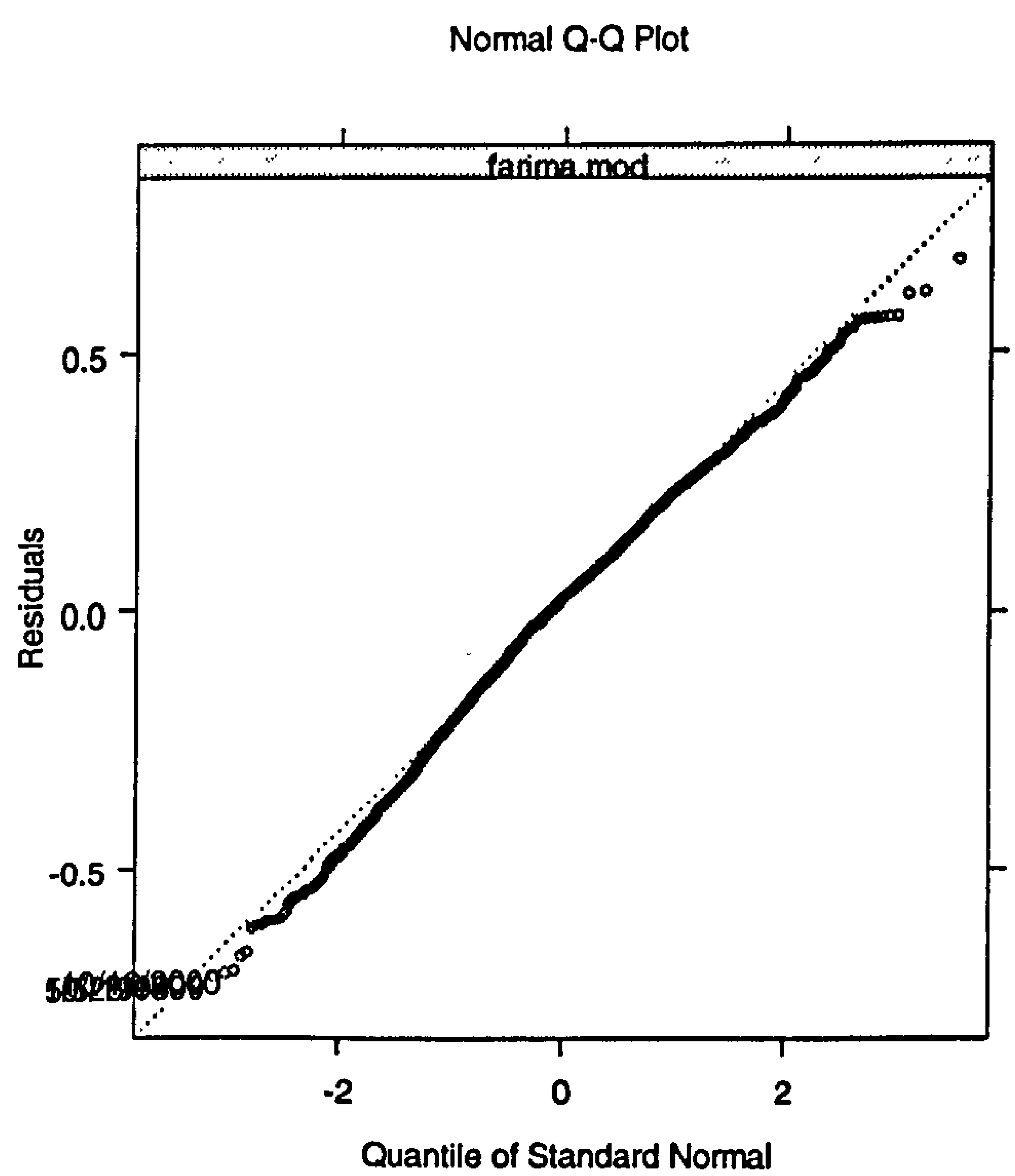
Philippines



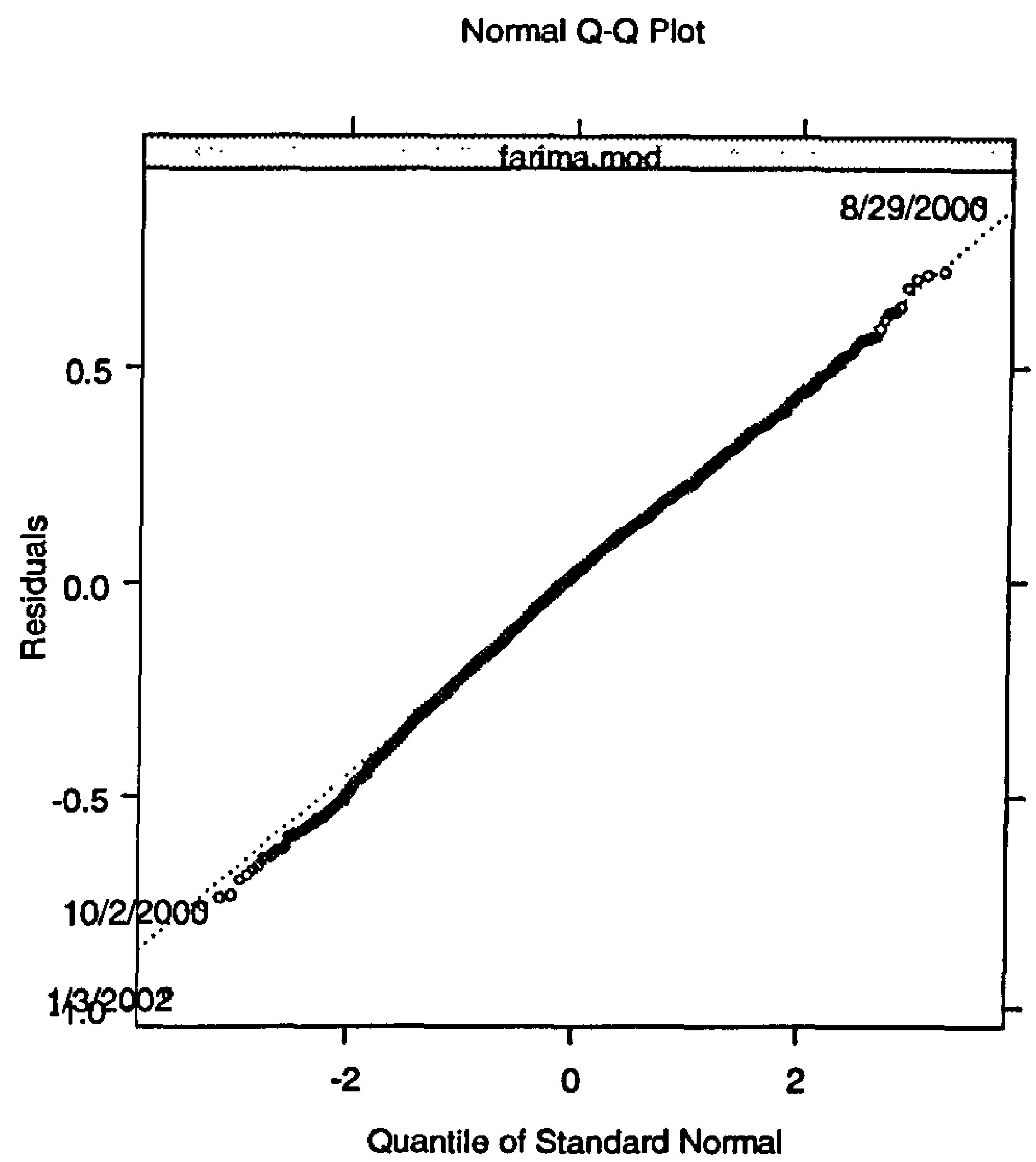
Poland



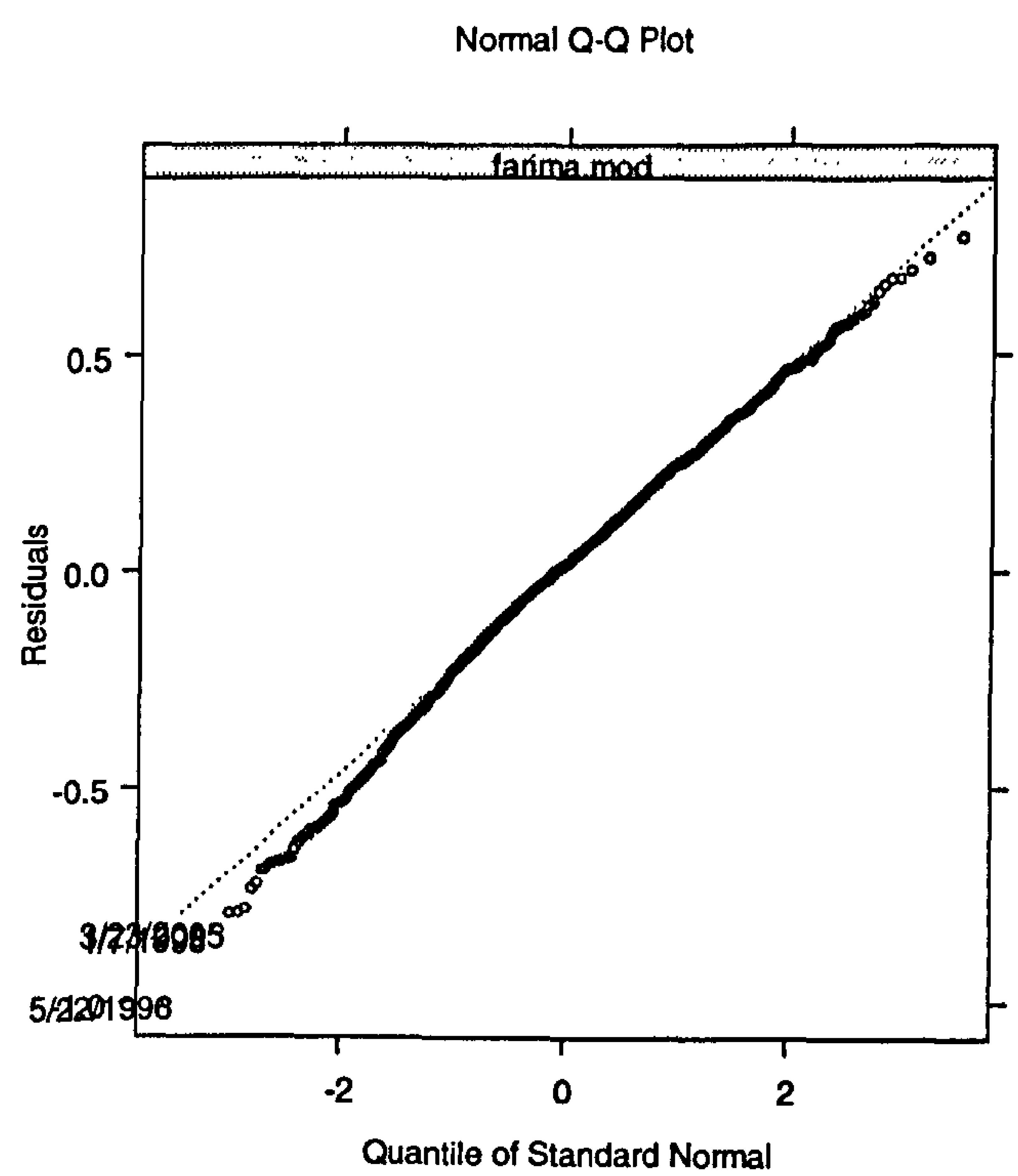
Portugal



Morocco



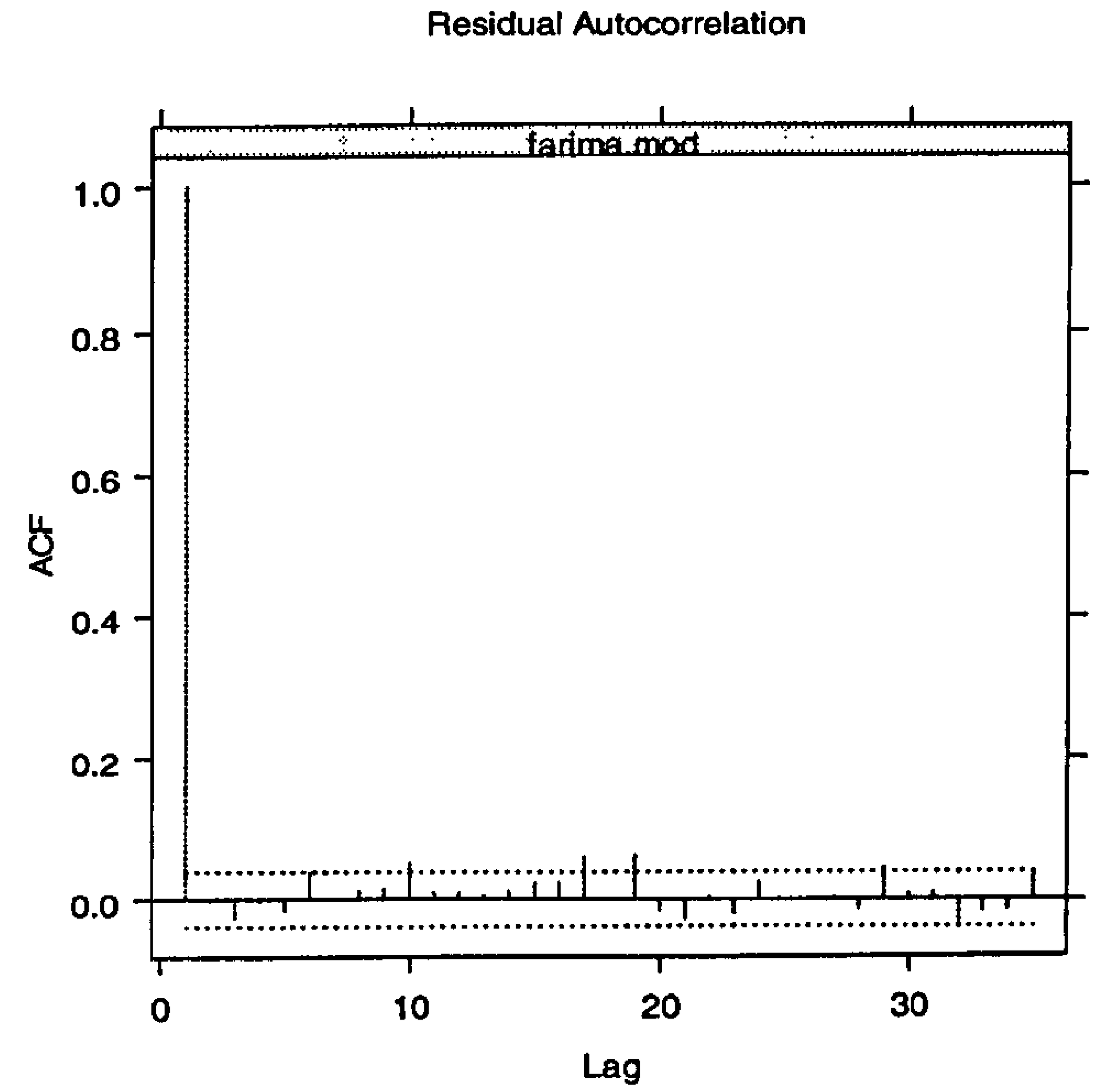
Pakistan



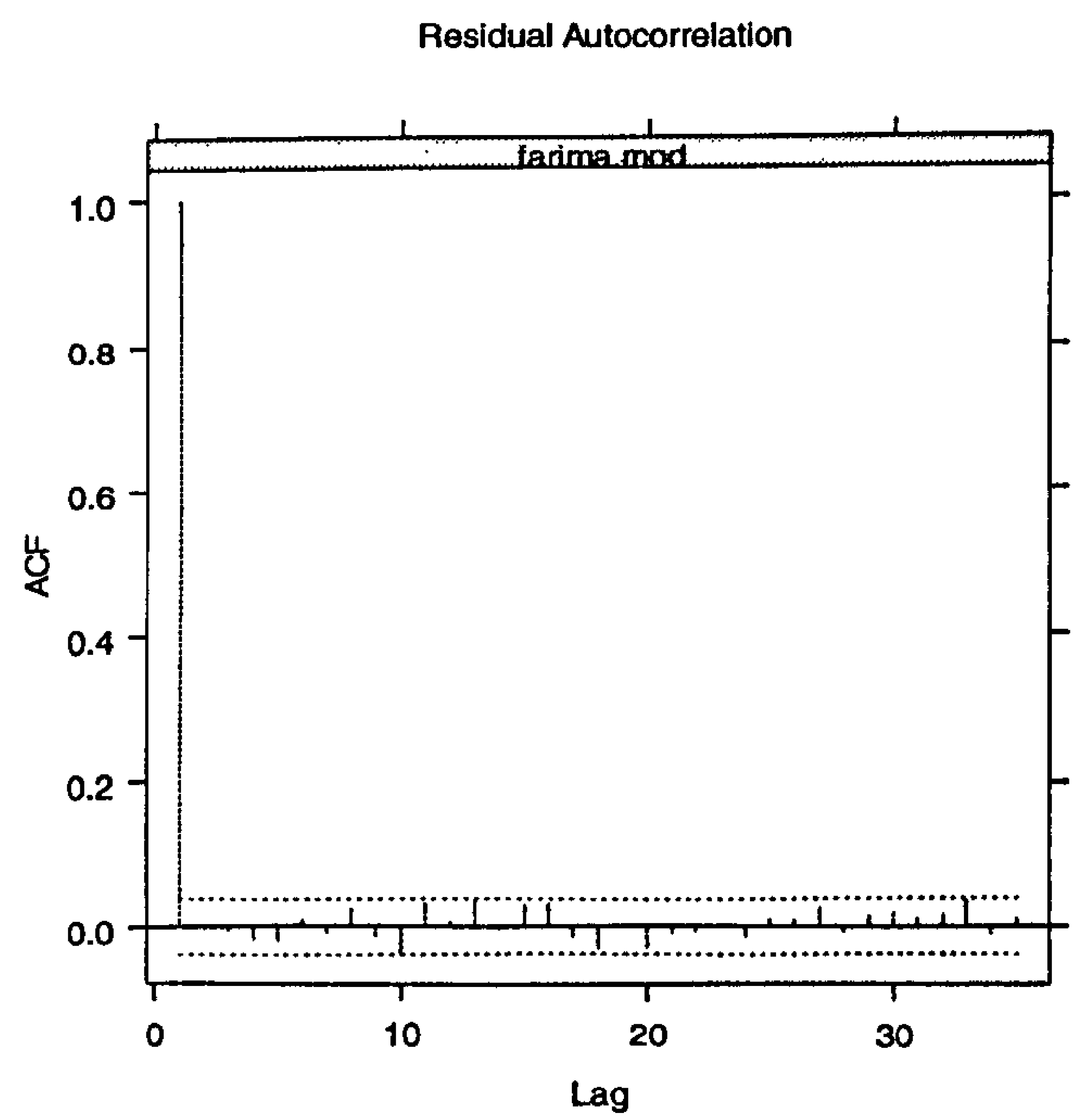
Appendix 4. Plots of Residual Autocorrelation for Each Country Sample.

This appendix provides the graphs of residual autocorrelation function (ACF) of SEMIFAR model. The model is successful in modelling long term memory if the residuals ACF are within the boundary range.

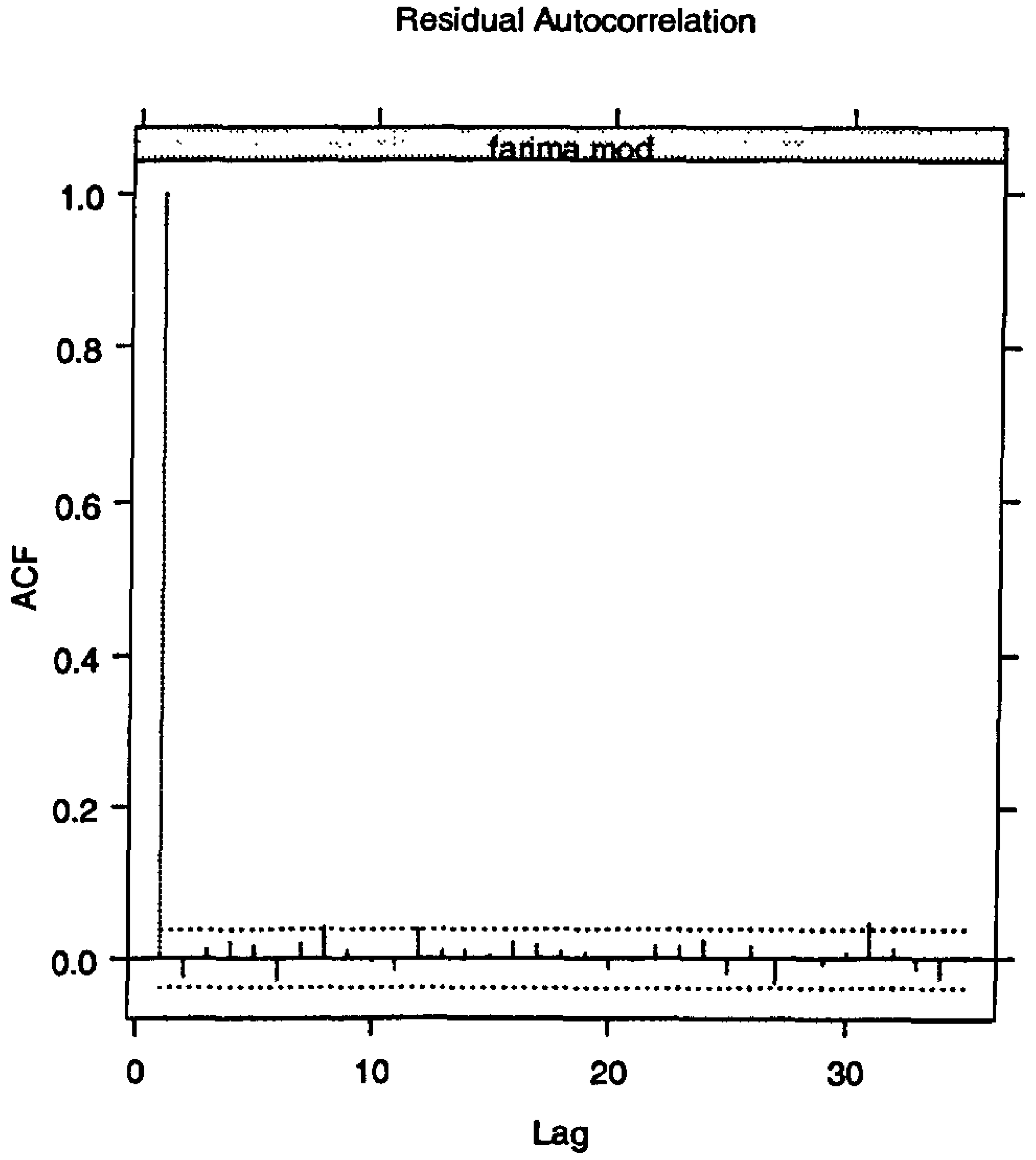
Argentina



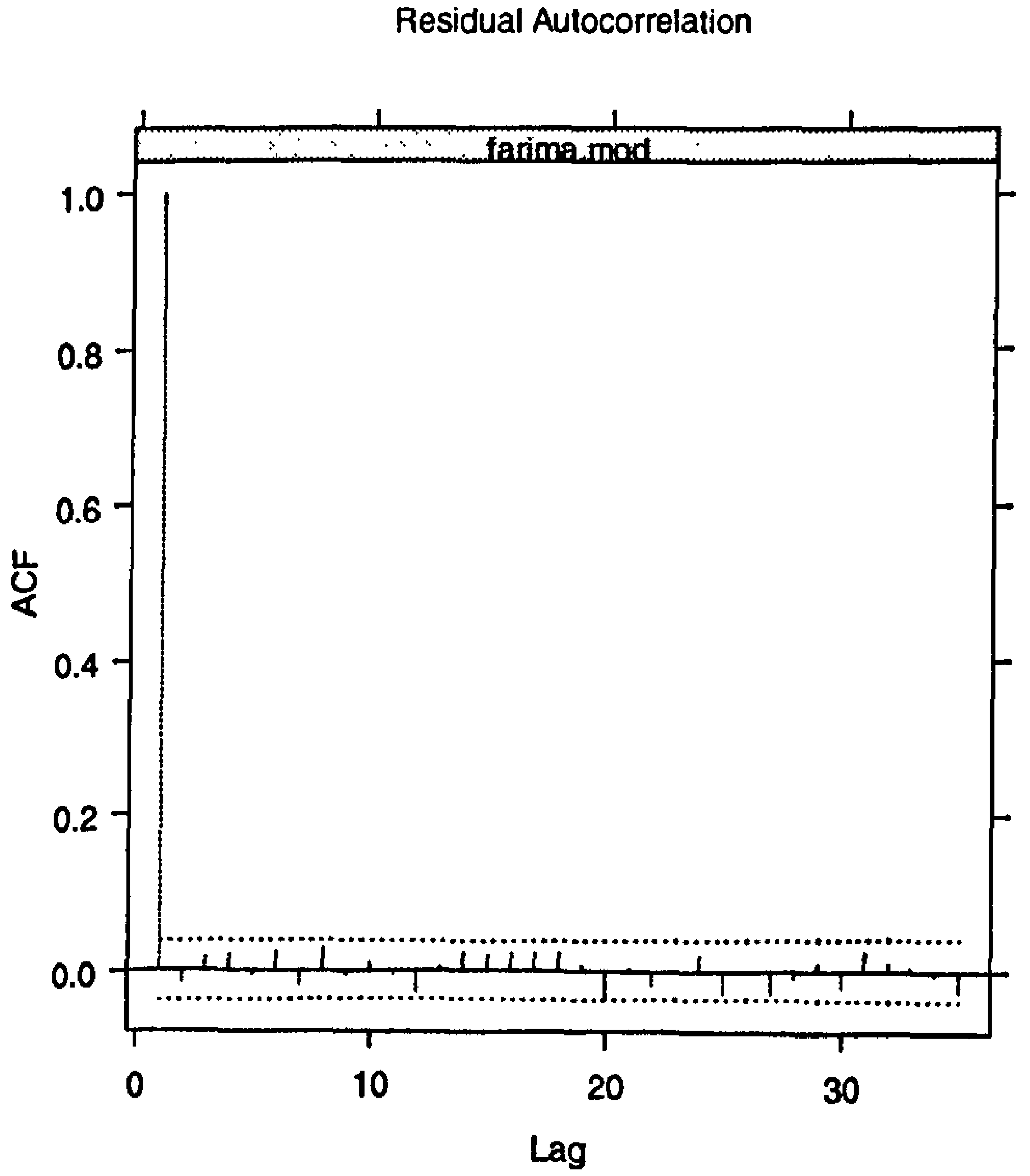
Brazil



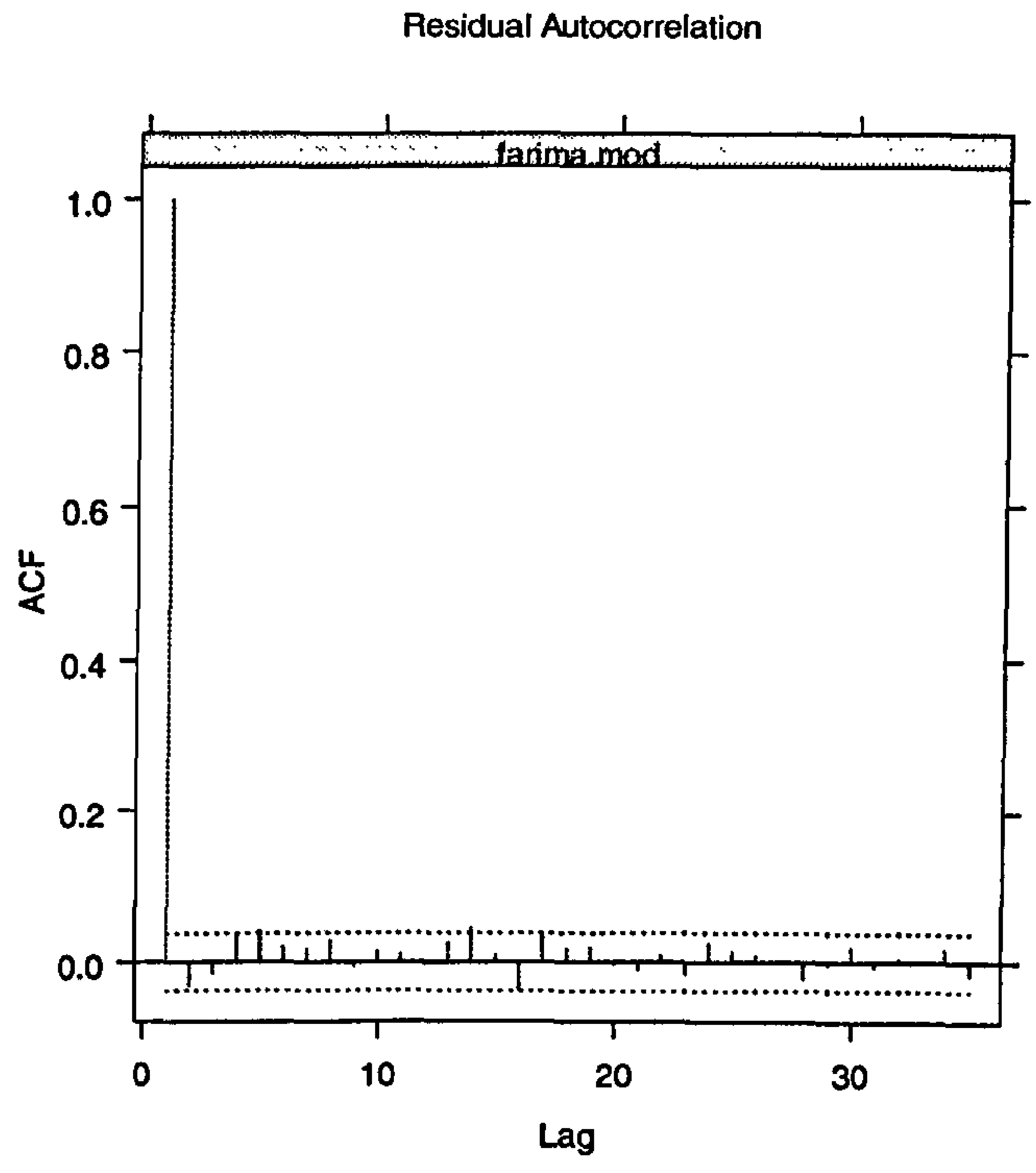
Malaysia



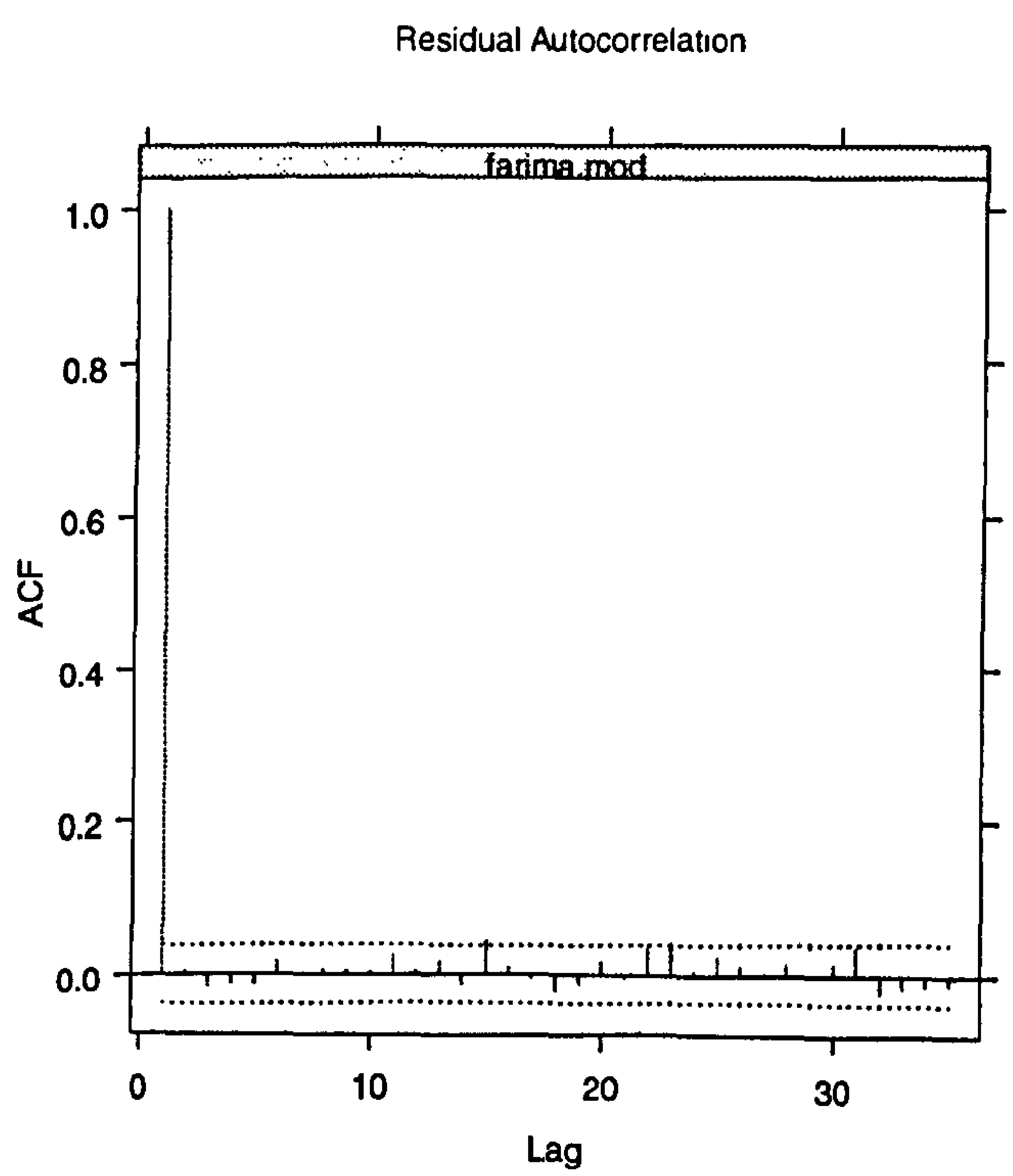
Philippines



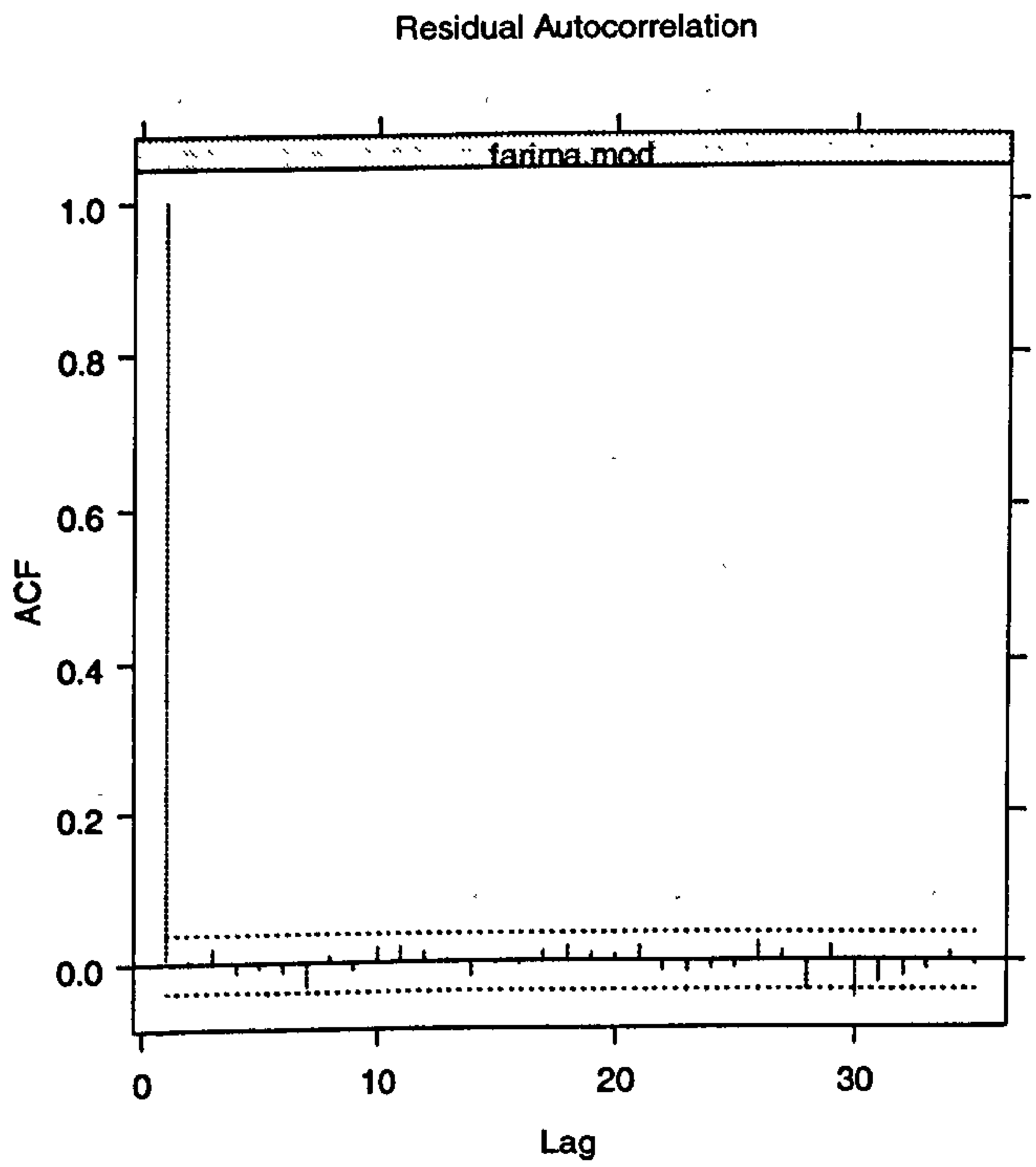
Poland



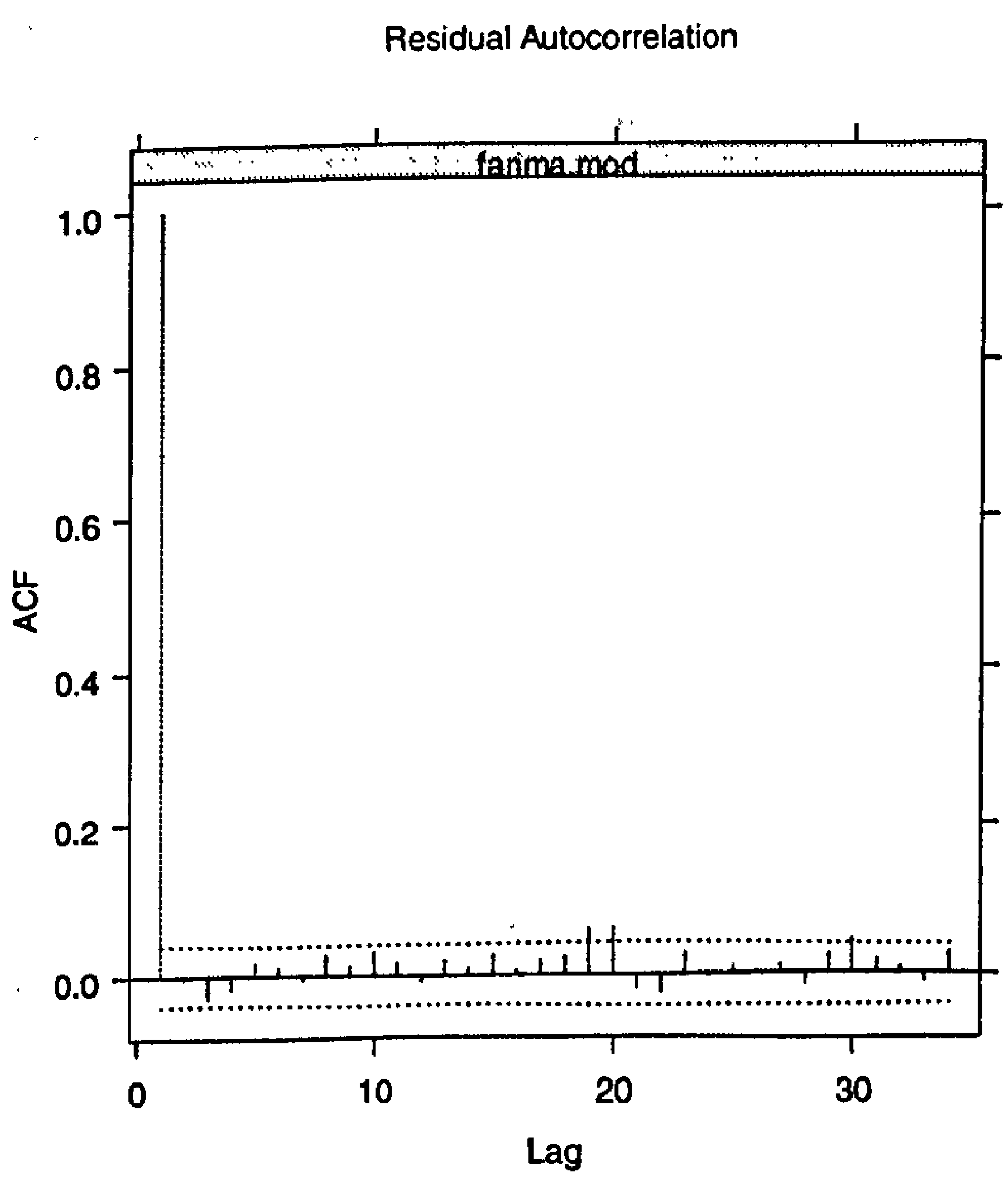
Portugal



Morocco



Pakistan



CHAPTER 9. CONCLUSIONS

9.1. MOTIVATION AND RESEARCH QUESTIONS

This chapter provides a summary of the main results of the thesis and identifies the contribution to the literature. The chapter also points out the limitations of the present study and suggests several areas in which it could be extended. Why study emerging markets? Research on emerging markets is important because emerging markets offer high growth potential and returns. In addition to that emerging markets also offer diversification benefits due to low correlation with developed markets (Cadle, 2000). The literature on emerging markets indicates that emerging markets exhibit high expected returns as well as high volatility. For instance, Harvey (1995) shows that equities in emerging markets promise U.S. investors both higher expected returns and risk than in developed markets. Harvey (1995) and Aggarwal et.al (1999) found that volatility in emerging markets is higher than that of developed markets. Although emerging market equity returns are highly volatile, they are relatively less correlated with equity returns in the developed world, making it possible to construct low risk portfolio. Studies by Divecha et al. (1992), De Santis (1993) and Harvey (1995) all show very significant diversification benefits for emerging market investments.

Risk management is an integral part of an investment process. In the context of emerging markets, risk management process encompass several processes including measurement of risk or modeling risk. Recent financial crises in emerging markets such as Asian financial crisis, Russian financial crisis and Mexico financial crisis has triggered off the implementation of a comprehensive risk management framework by financial institutions, most notably are credit risk and market risk. For the same reason, research on risk management especially in order to accurately model risk has also been developed. A number of recent papers recently have focused on emerging markets and risk which indicates the importance of the topic of emerging markets as well as risk to finance research. In particular, two main topics of risk have been discussed, country risk and the credit risk.

The main findings of these recent papers can be summarized as follows: (1) the variation in the conditional variance and country spillover effect can be modelled using a model of conditional volatility; (2) the extension version of the BSM option pricing model can be used as an early warning system for Argentina's debt crisis and Thailand's currency crisis; (3) the warning signals for crises in developing countries can be estimated using the RiskMonitor CDM model; and (4) the creditworthiness of Argentina, Brazil, Mexico and Venezuela can be measured by distance-to-default which extracted form the extension version of structural model and prices of Brady bonds. Distance-to-default is largely explained by regional and global factors. All in all, these research papers show that modeling risk becomes one of the significant issues in empirical research in emerging market. The thesis considered various different aspects of modeling risks in emerging stock market, with particular emphasis being placed on selection of the best models for examining credit risk, country risk, market risk and asymmetric volatility model.

The research questions of this thesis are as follows: (1) what are the main factors determine and what is the best model to explain default probability in emerging bond market?; (2) which model is the best to use to modelling country risk in emerging markets?; (3) what is the best model to be used for explaining market risk in emerging stock markets?; (4) what is the best asymmetric model to be used in emerging stock markets and is the SEMIFAR model successful at modelling long memory in the volatility of emerging stock markets? The basis argument to construct these research questions is explained in the following section.

Although literature on credit risk is enormous there is still gap whereby only a few studies put emphasis on examining default probability. According to Fabozi (2001), credit risk also consists of default risk or default probability. Credit risk modeling discussed in the first empirical study explores implied default probability. To generate implied default probability we use the pricing model as proposed by Ciraolo et.al (2002). This pricing model can be considered as a discrete time version of the Duffie and Singleton (1999) reduced form model. There are at least two main reasons why modeling default probability is important. Firstly, we may expect that high yields offered by emerging market bonds are associated with the high degree of default probability. Secondly, by extracting default probability we will be able to examine the relation between default probability and the other factors. The later reason is the major objective of the first empirical study.

For international investors, country risk assessment is important element in the investment process. The most obvious source for assessing country risk is global country risk rating provided by rating agencies such as the Political Risk Services (PRS), International Country risk Guide (ICRG) and the Economist Intelligence Unit (EIU). Another approach which addresses country risk from a portfolio investment perspective is based on the Capital Asset Pricing Model (Bouchet et al., 2003). In fact, according to Erb et.al (1999), by using international version of the CAPM one can infer the beta value as indicator of country risk. Following the approach proposed by Brooks et al (2002), the objective of the second empirical study is to find what the best country risk model for emerging markets.

In recent years, Value at Risk (VAR) has received many attentions both among researchers and practitioners. The most common approach to estimate VAR is referred to as variance covariance approach. The merit of this approach is simplicity of its calculation. Despite its simplicity this approach also has main drawback is that the assumption of normal distribution of asset returns which subsequently ignores the fact that asset returns may exhibit fait tail. This contrast with a relatively new approach so called extreme value theory which would be more relevant for calculating VAR for emerging stock markets as this approach takes into account extreme events. Therefore the objective of the third empirical study is to find what the best market risk model for estimating VAR in emerging markets.

The estimation of VAR in the third empirical study is based on the assumption that volatility of asset returns can be best described by GARCH (1,1) model. The GARCH (1,1) by far is the most common approach to estimate asset volatility. This approach assumes that shock to volatility is symmetrical. However empirical studies suggest that a negative shock to stock prices will generate more volatility than a positive shock, implying that the assumption of symmetric volatility is invalid. This issue raises the objective of the fourth empirical study that is to find what the best asymmetric volatility model in emerging stock markets. Furthermore, the GARCH (1,1) implies short memory. Camargo and Martinez (2003) found that shocks to volatility for emerging stock markets persist for a very long time which subsequently affect stock prices. In this case, another objective of the fourth empirical study is to examine the existence of long term memory in emerging stock markets and to examine the robustness of the SEMIFAR model as long term volatility model.

9.2. RESULTS AND CONTRIBUTIONS

We examine credit risk modeling in the first empirical study. This chapter extends the previous study by estimating the term structure interest rate under the Cox and Ingersol model using the GMM estimation, by expanding the data sample in order to capture the recent South American crisis, and by including additional explanatory variables into the logit model. For the later, we compare the performances between the original model used by Ciraolo et.al (2002) and the over seven models. Therefore these extensions can be regarded as the contributions of the first empirical study.

It is found that the pricing model can successfully produce the implied default probability. Based on the literature review we propose five candidate explanatory variables to be added into the original model which leads to eight different models including the original model. These variables are external debt, change in the spot rate, ratio of international reserves to GDP, inflation rate and real rate of annual GDP growth rate. Due to the availability of data we exclude the external debt from the analysis whereas the change in the spot rate is also excluded as we argue that it will have identical features to short term interest rate in local currency. Based on the Akaike Information Criteria, the best model to be used is still the original model as proposed by Ciraolo et.al (2002). It should be noted here that our results differ from the results obtained by Ciraolo et.al (2002) in which the ability of the logit model to estimate in sample forecast is not symmetric. The main reason for this difference mainly is due to the sample selection bias.

The issue of country risk was examined in the second empirical study. Following the definition of the beta value under international CAPM as an indicator of country risk as proposed by Erb, Harvey and Viskanta (1999), in this study we also proposed the same approach as in Brooks et al (2002). To the best of our knowledge, this is the first research study which examines country risk in emerging markets. There are 28 countries were examined in this study which comprises four regions, i.e. Emerging Market Latin America, Emerging Market East Asia, Emerging Market Europe and Other Emerging Markets. Therefore this can be regarded as the contribution of the research. The aims of the research are to answer two main questions: (1) which distribution of GARCH (1,1) model that the best for modeling time varying beta and (2) which model is the best to use to modeling country risk in emerging markets. To answer the first question, in addition to normal distribution, we explore the appropriateness of the generalized error distribution and t-distribution. The main reasons to include the other two distributions is that financial time series generally exhibit fat tails in comparisons to the normal distribution. The second research question is answered by examining the results of mean square errors of in-sample forecasts and the Modified Diebold and Mariano test statistics.

There are three different main models used in the second empirical study including GARCH (1,1), Schwert Seguin and Kalman Filter. For the later we investigate three further different types of model including the Random Walk model, Autoregressive order one (AR (1)) and Random Coefficient model. There is evidence that the beta coefficients for each country samples exhibit time varying characteristics. The results of rolling regressions of size 52 weeks rolling windows, the CUSUMQ test, the LM and the White test show that the common notion that the beta coefficient is constant is invalid. Based on in sample forecasts, the GARCH (1,1) under t-distribution was shown to generate the lowest forecast errors as compared to GARCH (1,1) under normal distribution and generalized error distribution.

The results, in general, suggest that the Kalman Filter technique dominates the other two techniques. In particular, within the class of Kalman Filter model the Random

Walk technique produced the lowest MSE in 14 of 28 cases and then followed by Random Coefficient (10 cases) and Autoregressive 4 cases. Our results are in line with the other research findings for example Brooks, Faff and McKenzie (1998) and Faff, Hillier and Hillier (2000). Therefore, it can be concluded that the optimal technique to generate estimates of country risk is the Random Walk model. This finding is also supported by the result from the modified Diebold and Mariano test statistic. In particular, the Kalman Filter random walk parameterization leads to different return forecasts from other model in over 90 percent of the countries tested, except one case between Random Walk and Schwert Seguin where the percentage of rejection only 67.86 percent.

The third empirical study addresses the application of extreme value theory in emerging stock markets in order to describe market risk. The aim of the empirical work in this chapter has been to examine the best model for estimating VAR in emerging stock markets. Our findings contribute to the understanding of return characteristics of emerging stock markets. Furthermore, this empirical study contribute, by the first time, by implementing the same methodology as outlined in Viviana (2003) research paper for a comprehensive sample of emerging stock markets. The estimated of general extreme value (GEV) distribution indicate that most country samples have positive ξ parameter. This implies that in general, the return series of emerging market countries have fatter tail than the normal distribution and suggests the Frechet family of GEV distribution which in turn gives more relevance for risk management purposes.

As in the second empirical study, the asset volatility were estimated with GARCH (1,1) model. The choice of GARCH (1,1) is supported by the test for autocorrelation (Ljung-Box) and test for ARCH effects. Based on the results of both tests, it can be inferred that the GARCH (1,1) can explain the data quite well since the null hypothesis of no serial correlation and the null hypothesis of no conditional heteroskedasticity are accepted in 21 cases. We also point out the GDP estimation for both tails of the innovations. The results reveal that tail distributions do not departure substantially from the Gumbel type (thin tailed distribution) which is also supported by the ratio of the expected shortfall to VAR which the majority has value of around 1.2.

The first analysis in the third empirical study follows the approach as proposed by Engle (2001) with the modification by applying the conditional extreme value theory (EVT). The relative accuracy of the model is assessed by estimating value at risk (VaR) in-sample and out of sample for 99 percent confidence level. The results for in sample and out of sample forecast show that in general the model performs quite well. However, as Engle (2001) points out, it is not easy to assess its accuracy. To overcome this drawback, the next step of the analysis is to perform dynamic backtesting on the conditional EVT. Following Fernandez (2003), the performance of the conditional EVT is then compared with the other models including the conditional normal, the conditional t distribution and the unconditional EVT. It is found that the conditional t outperform the other three models. In other words, the conditional t is the most successful model to capture extreme risk in emerging markets. The second best model is the conditional EVT. These findings are in line with the findings of Fernandez (2003).

The fourth (or the last) empirical study attempted to examine the best asymmetric volatility model as well as to examine whether the SEMIFAR model is successful at modeling the long memory in the volatility of emerging stock markets. We believe that this is the first study which tries to implement the SEMIFAR model for a comprehensive sample of emerging stock market and therefore is regarded as our contribution. As a starting point of analysis, we use the up-and down volatility measure to examine whether emerging stock markets exhibit asymmetric volatility. The up-and down volatility analysis indicate the existence of asymmetric volatility in emerging stock markets. The average downvolatility is 4.89 percent whereas the average upvolatility is 4.37 percent. This finding suggests that emerging stock markets are more sensitive to bad news than to good news. This result is consistent with the finding of Black (1976) who argued that a drop in stock price (or negative return) would lead to a higher volatility than an increase in stock price (or positive return) by the same amount. Furthermore, the results of Engle and Ng (1993) specification tests also reveal the evidence of the asymmetric volatility in emerging stock markets. Overall, our findings support the notion that volatility is asymmetric and it also true for emerging stock markets. In the next analysis, to examine the best asymmetric volatility model for emerging stock markets, three competing asymmetric volatility models are applied including the exponential GARCH (EGARCH), the threshold GARCH (TGARCH) and the power GARCH (PGARCH).

The results of the Akaike information criterion (AIC), Bayesian information criterion (BIC) and the likelihood test applied for the three different asymmetric volatility models suggest that the TGARCH model is the most appropriate model to be used for explaining asymmetry in volatility in emerging stock markets. Our results are in line with the finding of Panagiotidis (2005) who found that the TGARCH model is more successful than EGARCH model for capturing the asymmetric feature in the Athens Stock Exchange. The issue of long term memory in volatility of emerging stock markets was examined by using classical R/S statistic, the modified R/S statistic and Hurst coefficient. The results of these three statistics show that there is evidence of long term memory in volatility in emerging stock markets. The application of SEMIFAR model is based on an approach proposed by Beran and Ocher (2001). It was found that all values of the long memory parameter (or d) are less than 0.5 which implies that there is long-range dependence in the stochastic component of daily volatility series in emerging stock markets. Based on the autocorrelation function (or ACF) plot of residual and normal probability plots (or QQ plots) of residuals, it can be concluded that the SEMIFAR model seems to be very successful at modeling the long term memory in volatility.

9.3. LIMITATION AND FURTHER STUDY

There are a number of limitations. The first constraint is data availability. In the first empirical study, data of global bond is weekly data while data of three macro economic variables namely international reserves and gross domestic product are on a quarterly basis whereas consumer price index is available on monthly basis. As a consequence we come up with the crude approximate figure for these three variables which subsequently have an effect on the whole analysis. In other words, if more reliable source of data with the same time interval is available then the different conclusion with regard to the best model used for explaining default probability in emerging stock markets could be obtained. We also faced a data constraint for the other three empirical studies. More specifically as we use the same set of data the limitations lie on the fact that the MSCI data is not available for the whole country samples.

The second constraint is the limited models available in the software used in this study. In the second empirical study, we only compare three classes of models namely GARCH (1,1), Kalman Filter model and Schwert and Seguin model. The comparison would be broadening if more models are included in the study. Examples are the bivariate stochastic volatility model and regime switching models. Likewise, the results of the third empirical study can be extended by examining the performance of the conditional EVT under different volatility models for example stochastic volatility model or regime switching volatility model. One example of such models is the Switching ARCH (SWARCH) model of Hamilton and Susmel (1994). In the fourth empirical study, there are only three asymmetric volatility models examined namely the EGARCH model, the TGARCH (or the GJR) model and the PGARCH model. If for example, the other asymmetric volatility model such as the Trend-GARCH model and Threshold Autoregressive GARCH (1,1) are available, the comparison then could be rich and we could come up with different finding or conclusion about the best asymmetric volatility models for emerging stock markets.

The third constraint is related to the assumption used in the study. In the first empirical study, we assume that the recovery rate to be deterministic rather than stochastic, more specifically we fix the recovery rate equal to 20 percent. If this assumption is relaxed then the possibility to obtain different value of default probability under different recovery rate will be useful for a comparison purpose. One approach to estimate recovery rate is to apply a statistical method called Bayesian technique. This method depends on historical data of recovery rate (Beloreshki, 2002). In the second empirical study, the multivariate GARCH model has been restricted to a constant mean assumption. This assumption can be relaxed by using a more general model with a vector ARM structure and optional inclusion of weakly exogenous variables in the conditional mean which allows different estimation for volatility and subsequently will enrich the performance comparison among different models used in the first empirical study for estimating beta coefficient.

The fourth limitation is the theory underlying the empirical studies in this thesis and method used in this thesis. Another possible direction for further research for the first empirical study is to examine factors that might influence recovery rate. Previous research has examined the relation between recovery rate and business cycle. The results for a potential correlation between business cycle indicators and recovery rates are mixed. Whereas Asarnow and Edwards (1995) and Altman and Brady (2002) observe only a weak dependence of recovery rates on macroeconomic variables, the work by Gupton et.al (2000) and Frye (2003) suggests that recovery rates are more closely linked to the business cycle. Therefore the first study can be extended by examining the relation between recovery rates of emerging market bonds with macroeconomic variables.

The second empirical study use beta coefficient as a proxy of country risk. According to Bos and Newbold (1984) the variation in the stock's beta may be due to the influence of macroeconomic factors. Following studies conducted by Cantor and Packer (1996) and Erb, Harvey and Viskanta (1996), Beng (2002) examined the relation between time varying betas in seven countries in East Asian Equity Markets with six country-specific macroeconomic factors. Therefore the second empirical study can be extended by examining the relation between the time varying betas with country-specific macroeconomic variables in emerging stock markets. The first study uses the international version of CAPM (ICAPM) which specifically assumes that the emerging stock markets are integrated with world equity market. A variant of ICAPM whereby exchange rate risk included in the model was proposed by Solnik (1983). Therefore another possible extension of the second empirical study is by comparing the performance of a single factor model of ICAPM with the model proposed by Solnik (1983).

In the third empirical study, the VAR estimate obtained from extreme value method is based on univariate approach. This study can be extended by adopting a multivariate approach of EVT as in Hacksson et.al (2000) in order to have a complete picture of the risk and reward in the emerging stock markets. Multivariate EVT provides the theoretical background to model and analyze joint extreme events by concentrating on dependence in extreme observations. A recent approach to analyze multivariate EVT is the copula method.

The fourth empirical study can be expanded by implementing the long term memory based on the extension of GARCH model namely FIGARCH model. By so doing, we can analyze whether the long term component of the conditional variance has an impact on the mean of the term premium. To achieve this objective, the variant of FIGARCH model namely FIGARCH-M model can be adopted. Another possible extension for the fourth empirical study is to examine the impacts of current information flow on conditional volatility. To achieve this objective the original model of TGARCH or EGARCH can be extended by including one explanatory variable namely trading volume as a proxy of current information flow. The use of trading volume as a proxy variable for the daily information had been used by Schwert (1989), Lamoureux, and Lastrapes (1990), Gallant, Rossi, and Tauchen (1992), and Jones, Kaul, and Lipson (1994).

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