VOLATILITY MODELLING AND FORECASTING VALUE-AT-RISK:

EVIDENCE FROM NEW AND CANDIDATE EUROPEAN UNION COUNTRIES

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VOLATILITY MODELLING AND FORECASTING VALUE-AT-RISK:

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ABSTRACT

VOLATILITY MODELLING AND FORECASTING VALUE-AT-RISK:
EVIDENCE FROM NEW AND CANDIDATE EUROPEAN UNION COUNTRIES

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A uniform risk measurement methodology called Value-at-risk (VaR) has become one of the most commonly used tools for measuring, managing and reporting market risk in recent years. It is well documented that a crucial parameter in the implementation of parametric VaR calculation methods is the estimation or forecast of a volatility parameter that describes the asset or a portfolio. The objective of this thesis is to determine the best performing method for VaR estimation by evaluating the performances of different volatility models, by using data from new European Union member countries from the Central and Eastern Europe (CEE) and three official candidate countries (Turkey, Croatia and Macedonia).

This thesis also analyzes the volatility behavior for closing prices of the stock indices of new and candidate European Union countries using short (GARCH) and long memory (FIGARCH and HYGARCH) models based on the normal, Student-*t* and skewed Student-*t* distributional assumptions. Then, the performance of value-at-risk numbers are tested by the estimated volatility models using Kupiec LR test.

The empirical results indicate the presence of dual long memory property in the returns and volatility of six of the fourteen EU new member and candidate countries. The presence of long memory volatility in most of the new and candidate EU stock markets enables us to rank the degree of market inefficiency, which also leads to the rejection of efficiency market hypothesis in these markets.

Consequently, when the stable and long memory models are compared it is observed that the long memory models capture temporal pattern of volatility better than the stable GARCH models in most of the cases. The volatility estimation results also indicate that the Student-*t* and skewed Student-*t* distributions outperform the normal distribution.

The estimated in-sample and out-of-sample VaR values based on Kupiec LR test shows that the models with skewed Student-*t* model outperforms the models generated by the normal distribution in describing the return series of the transition countries.

Keywords: *Long memory, Value-at-risk, FIGARCH, HYGARCH*

ÖZET

VOLATİLİTE MODELLEMESİ ve RİSKE MARUZ DEĞER TAHMİNLEMESİ: AVRUPA BİRLİĞİ'NE YENİ ÜYE ve ADAY ÜLKELER ÜZERİNE BİR UYGULAMA

TUNÇ, GÖKÇE

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Riske maruz değer (VaR) yöntemi son yıllarda yaygın olarak kullanılan bir risk ölçüm, yönetim ve raporlama aracı haline gelmistir. Ancak bu yöntemin kullanımında karşılaşılan en önemli sorun volatilitenin doğru tahmin edilmesidir. Bu nedenle, bu çalışmanın amacı farklı volatilite tahmin yöntemleri kullanarak en iyi performans gösteren VaR ölçüm yöntemini Avrupa Birliği'ne (AB) yeni üye ve aday ülke hisse senedi endeks verileri kullanarak belirlemektir.

Bu çalışma, örneklemdeki ülkelerin hisse senedi piyasalarının davranışını ve karakteristiğini kısa (GARCH) ve uzun (FIGARCH,HYGARCH) hafıza volatilite modelleri yardımıyla tespit etmeye çalışmaktadır. Model parametreleri normal, Student-*t* ve çarpık Student-*t* dağılım varsayımı altında tespit edilmiştir. Günlük hisse senedi endeks getirileri için belirlenen en uygun volatilite modelleri çerçevesinde hesaplanan riske maruz değerlerin performansı Kupiec LR testi kullanılarak ölçülmüştür.

Elde edilen sonuçlara göre, AB'ye yeni üye ve aday ondört ülkenin altısında endeks verilerinin hem getiri hem volatilitesinin uzun hafıza özelliği gösterdiği gözlemlenmektedir. Bu sonuç, bu ülkelerin hisse senedi piyasalarında piyasa etkinliği hipotezini desteklemediğini göstermektedir. Ayrıca çarpık Student-t dağılımının volatilitenin tahminlenmesinde en uygun varsayım olması, endeks getiri serilerinin çarpıklık ve şişman kuyruk özelligi gösterdiğini ispatlar niteliktedir. Örneklem içi ve örneklem dışı bulunan VaR değerlerinin fiyat hareketlerinin tahminlenmesinde son derece başarılı olduğu gözlemlenmiştir. Dağılım olarak da yine çarpık Student-t varsayımı altında yapılan analizler en iyi tahmin sonuçlarını vermektedir.

Anahtar Kelimeler: *Uzun hafiza, riske maruz deger, FIGARCH, HYGARCH*

To My Husband and My Parents

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CHAPTER 1

INTRODUCTION

The remarkable trading losses of well known financial institutions, recent crises in emerging markets, and the international stock market crashes of 1987 and 2008 have increased the regulatory demand for reliable quantitative risk management tools. Hence, there has been intensive research carried out by financial institutions, regulators and researchers to better develop sophisticated models for market risk estimation. A uniform risk measurement methodology called Value-at-Risk (VaR hereafter) has become one of the most commonly used tools for measuring, managing and reporting market risk. It is simply referred to a portfolio's worst outcome that is expected to occur over a predetermined period and at a given confidence level.

The need to estimate VaR has become especially relevant following the amendment of Basel Capital Accord, which obliged member countries' banks to calculate capital requirements based on the measurement of their market risk by modeling VaR. While VaR becomes a standard tool for risk management, its technique has undergone significant refinement since it originally appeared. The results of recent empirical papers have shown that a crucial parameter in the implementation of parametric VaR calculation methods is the forecast of volatility parameter that describes the level of risk of an asset or a portfolio. As discussed by many papers, the estimated VaR can be sensitive to the assumed volatility model (see Huang and Lin, 2004; Tang and Shieh, 2006; Wu and Shieh, 2007). This is an important problem because of the increasing demand on relying VaR for risk management decisions by the market agents and regulators. The accuracy of volatility forecasts is a crucial issue for the estimation of VaR which involves calculation of the expected losses that might result from changes in the market prices of particular securities.

Growth in financial markets and the continual development of new and more complex financial instruments has led to a growing need for theoretical and empirical knowledge of the volatility in financial time series. It is widely known that the daily returns of financial assets, especially of stocks, were predicted using more traditional volatility modeling statistical approaches based upon averaging and smoothing techniques or simple regression models. However, the properties that characterize financial markets (volatility clustering, integrated conditional variance, asymmetries in the response of volatility to the sign of returns etc.) have created a new path in volatility modeling techniques. In a study of the time varying conditional variances of economic variables, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model. Since then, ARCH has become very influential upon both theoretical and applied financial econometrics and has led to an explosive growth in the ARCH development, resulting in numerous variations and modifications of the ARCH-class of model, more significant examples of which include GARCH (Bollerslev, 1986), EGARCH (Nelson, 1991), and IGARCH (Engle and Bollerslev, 1986).

Several methods have been developed for measuring VaR. The most popular approach for evaluating VaR is to use parametric RiskMetrics^{TM} approach, developed by researchers at investment bank JP Morgan in 1994. It is defined as a set of financial models that are used by investors to measure portfolio risk. This model has a very simple form and assumes that the return of a portfolio has a conditional normal distribution and variance is given recursively by an exponentially weighted moving average (EWMA). However, this model has two weaknesses. First, it was well known that a return distribution usually has a heavier tail than a normal distribution. Assuming conditional normality may generate substantial bias in VaR estimation which mainly concerns the tail properties of the return distribution. Second, recent empirical studies found that many financial return series may exhibit long memory or long-term dependence on market volatility (Ding *et al.* 1993; So, 2000). Such long term dependence was found to have significant impact on the pricing of financial derivatives as well as forecasting market volatility. Besides the GARCH model and its variants which can only capture short-run dependencies, several long memory GARCH models such as FIGARCH and HYGARCH were proposed to incorporate the long memory volatility property in financial time series (Baillie *et al.,* 1996; Baillie *et al.,* 2000; Bollerslev and Mikkelsen, 1996a). It is of interest to see whether these models can affect the measurement of market risk in the context of VaR.

The objective of this thesis is to determine the best method for VaR estimation by evaluating the performances of different volatility models, using data from new European Union member countries from the Central and Eastern Europe (CEE hereafter) and three official candidate countries (Turkey, Croatia and Macedonia). Moreover, it seeks to extend previous research concerned with the evaluation of alternative volatility forecasting methods like long memory models under VaR modeling in the context of the Basel Committee criterion for determining the adequacy of the resulting VaR estimates. This thesis contributes to the literature in three-folds. First, we extend the scope of previous research through evaluative application and comparison of these methods for 11 new and 3 candidate European Union countries' daily stock market index data. It is worthwhile to investigate European Union countries, as the EU has gone through a period of extraordinary economic, monetary, and financial integration, and the structure of the financial markets in the European region has changed fundamentally in order to adhere to the Maastricht Treaty since the 1990s. Also, the CEE countries have undergone major changes in their economic and political systems during the transition to market economies. Therefore this would be an especially useful and important exercise for the eleven transition countries that recently became members of the European Union. Second, we broaden the class of GARCH models under consideration by including more recently proposed models such as the FIGARCH and HYGARCH representations, which takes long memory characteristics of return volatility into account in the estimation of VaR of market indices by using more sophisticated distributions than normal distribution, such as student-t and skewed student-t distribution. Third, we use longer time periods than other related studies in the literature, and this is particularly important for transition economies in European Union. The findings are likely to have direct theoretical and practical relevance for the assessment and management of risk associated with transition economies.

The rest of the thesis is organized as follows. Section 2 gives the institutional background to VaR. This part discusses risk and uncertainty concepts, financial disasters that give rise regulatory demand for reliable quantitative risk management tools, and the importance of risk management. Also, the chronology of events in risk management leading to VaR from a regulatory point of view is presented in the same part.

Section 3 gives a relevant literature overview of volatility models used in VaR forecasting. Section 4 discusses the main characteristics of the Central and Eastern European countries’ stock markets. Section 5 outlines the econometric methodology used in this thesis, followed by the empirical results of the analysis. Finally, section 7 contains concluding remarks and number of policy implications.

CHAPTER 2

INSTITUTIONAL BACKGROUND

2.1. Risk and Uncertainty

Financial institutions and corporations are in the business of managing many sources of risk. However, failures in risk management procedures have caused a number of financial disasters after the increase of financial uncertainty in the 1990s. Therefore, understanding the concepts of risk, uncertainty and volatility is an important part of assessing a portfolio's margin of safety levels.

Risk can be defined simply as the variability of unexpected outcomes associated with a given asset. In other words, risk is the degree of uncertainty about future net returns. It is significant that investors recognize the difference between risk and uncertainty, how the difference can change the way an opportunity is assessed, and the tools required to properly quantify the downside potential of any investment.

Knight (1921) made an important distinction between uncertainty and risk. Variability that can be quantified in terms of probabilities is thought of as "risk" whereas variability that cannot be quantified at all is best thought of simply as "uncertainty" in his famous thesis. In simple terms, while taking on risk occurs when an investor is not sure what might happen among a list of scenarios, taking on uncertainty occurs when an investor does not know what can happen with an unknown range of possible outcomes (Jean-Jacques, 2002).

Knight (1921) also discusses that this distinction is important in financial markets. If risk were the only relevant characteristic of randomness, well-organized financial institutions should be able to price and market insurance contracts that only depend on risky phenomena. Uncertainty, on the other hand, generates frictions that these institutions may not be able to accommodate. Ellsberg (1961) proposes a more specific definition of uncertainty, in which an event is uncertain or ambiguous if it has an unknown probability. Particularly, Ellsberg's paradox demonstrates important consequences of this distinction by showing that individuals may prefer gambles with precise probabilities to gambles with unknown odds. Uncertainty and risk are distinct characteristics of random environments, and they can also affect individuals' behavior very differently. Such behavior is conflicting with the expected utility model, and this observation has recently stimulated a significant amount of research in economics and finance.

According to Epstein and Wang (1994), the principle of using the term “risk” to describe decision-situations in which probabilities are available to guide choice and “uncertainty” to describe decision-situations in which information is too imprecise to be summarized by probabilities is deeply embedded in both economic theory and decision theory. Situations of risk and uncertainty can be summarized as follows;

1. Situations of Risk. Situations in which the decision-maker assigns probabilities to events on the basis of known chances, where chances are shown as numerical proportions

2. Situations of Uncertainty. Situations in which the decision-maker is unable to assign probabilities to events because it is not possible to calculate chances.

2.2 Types of Risks

Corporations are subject to various types of risks, which can be classified basically into unsystematic and systematic risk. Unsystematic risk represents the part of an asset's risk that is related with random causes that can be eliminated through diversification. In contrast, systematic or nondiversifiable risk is attributable to economic, political, social and market factors that affect all firms and markets. This kind of risk can not be eliminated through diversification by investors or portfolio managers.

Types of risks are also classified more specifically according to the fundamental sources of uncertainty about future outcomes. In Basel II, risk concepts are divided into four categories; credit, operational, liquidity and market risk. Credit risk is defined as the risk of losses due to a counterpart's inability to fulfill its contractual obligations. Jorion (2007) defines operational risk as "*the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events.*" Liquidity risk is the risk that an investment can not be easily liquidated at a reasonable price in the market to prevent a loss. It is caused by an unplanned decrease in the cash flow over a short period. Liquidity risk can take two forms, asset-liquidity risk and funding-liquidity risk. Asset-liquidity risk arises from the failure to recognize changes in market conditions that affect the ability to liquidate assets quickly and with minimal loss in value. It becomes important if the company is interested in trading its assets due to cash flow needs but cannot because of lack of demand for the asset in the market. Funding-liquidity risk includes the firm's inability to meet its payment obligations when they fall due, which may force early liquidation of its assets. Market risk is the risk of losses in the value of a portfolio due to the movements in the market conditions.

The most familiar of all risk in trading is market risk, since it reflects the exposure to potential loss that would result from changes in market prices. As with other forms of risk, the potential loss amount due to market risk can be measured in a number of ways. Value-at-Risk (VaR) has become the standard measure to quantify market risk on a daily basis.

2.3. Lessons from Financial Disasters

Following the globalization of financial markets, which has led to exposure to more sources of risk, a number of financial disasters occurred due to the lack of proper risk management procedures. The most important financial losses took place in Orange County in 1994, Barings Bank in 1995 and in Metallgesellschaft in 1993.

Orange County has an investment pool that supports various pension liabilities. The county treasurer, Robert Citron, who controlled $7.5 billion funds in this pool had riskily invested the funds in a leveraged portfolio of mainly interest-linked securities. His expectation was that interest rates would not rise and the funds were highly leveraged for rising interest rates. However, beginning in February 1994, the Federal Reserve Bank started to increase the US interest rates, causing many securities in Orange County's investment pools to fall in value. All through the year, paper losses on the fund led to margin calls from Wall Street brokers that had provided short-term financing. As news of the loss spread, investors tried to withdraw their money. This created a liquidity trap and brokers started to liquidate their collateral and Orange County declared bankruptcy. When the remaining securities were liquidated, the net loss of the county was $1.8 billion. Citron's mistake was to report his portfolio at cost instead of the market value. If his holdings had been measured in their market value, the treasurer and members of the board of supervision may have recognized how risky his investments actually were. Orange County was the victim of market and liquidity risk and the great losses were the result of poor risk measurement as well as ineffective communication of the risks involved to the investors.

Barings Bank, a respected 233-year-old bank in London, went bankrupt in 1995 after one of the bank's trader, Nick Leeson, lost $1.3 billion from derivatives trading. The loss was caused by a large exposure to the Japanese stock market, which was achieved through the futures and options market. Leeson took accumulating positions in stock index futures on the Nikkei 225 and his positions on the Singapore and Osaka exchanges added up to $7 billion. Since the market decreased more than 15 percent at the beginning of 1995, Barings' futures suffered huge losses. These losses were made worse by the sale of options with the expectation of a stable market. Following this, the bank failed to make the cash payments required by the exchanges and went bankrupt. The Barings' board and management claim to have been unaware of Leeson's activities. As a conservative bank, Barings revealed the lack of effective internal control systems and the bankruptcy served as a warning for financial institutions all over the world.

Metallgesellschaft was one of the Germany's largest industrial groups with 58,000 employees. The problems of the company arose from the idea of offering long-term contracts for oil products. The marketing of these contracts was successful because the customers could lock in fixed prices over long periods. To hedge against the possibility of price increases, Metallgesellschaft entered into a short-term futures contract on oil to supply oil products to customers. However oil prices fell from $20 to $15 in 1993, leading to approximately one billion dollar of margin calls that had to be met in cash. The company liquidated the remaining contracts, which led to a reported loss of $1.4 billion. The auditors' report stated that the losses were caused by the size of the trading exposures.

The common lesson from these disasters is that billions of dollars can be lost due to lack of proper supervision and management of financial risks.

2.4. Importance of Risk Management

Risk management is an evolving concept and has its roots in the corporate insurance industry. Its focal point was the possibility of accidental losses to the assets and income of the organization. However, actual practice of risk management is as old as the civilization itself. In a broad sense, Kloman (1990) described risk management as "*a discipline for living with possibility that future events may cause adverse effects*".

The current understanding of the risk management developed after series of financial disasters occurred without warning during 1990s. According to Jorion (2001), this new financial risk management idea refers to "*the design and implementation of procedures for identifying, measuring, controlling and managing financial risks*". Although it is well documented that systematic risk cannot be totally eliminated, through good risk management it can be

- Transferred to another party who is willing to take risk, for example through buying an insurance policy or future contract,
- Reduced by having good internal controls,
- Avoided by not entering into risky businesses
- Retained to either avoid the cost of trying to reduce risk or anticipate higher profits by taking on more risks
- Shared by following a middle path between retaining and transferring risk.

Risk management can be applied to the entire organization, across its many areas and levels at any time, as well as to specific functions and activities. Risk management consists of identifying the appropriate level of risk that a firm should have, determining the level of risk that a firm currently has, and adjusting the actual level of risk to the desired level of risk. Risk management helps to increase the value of the firm in the presence of bankruptcy costs, because it makes bankruptcy less possible. It can be beneficial to shareholders because firms can have better access to capital markets and adjust risk levels better than their shareholders, it can lessen the possibility of underinvestment (wherein firms in near bankruptcy avoid taking on value creating projects because the benefits go to the bondholders or creditors), and risk management can help firms be sure that sufficient cash is available to fund investments (Chance and Brooks, 2010).

2.5. Regulatory Mechanisms for Risk Management

The regulatory bodies have recognized the need for adequate risk measurement, management techniques and approaches in response to the financial disasters of the early 1990s. Much of the regulatory drive that considered increased importance of risk on an international basis originated from the Basel Committee of Banking Supervision. This Committee was established by the Central Bank Governors of the Group of Ten (G-10)[1] at the end of 1974. The Basel Committee does not possess any formal supervising authority, and thus its conclusions do not have a legal force. Relatively, it prepares supervisory standards and guidelines and suggests statements of best practice in the expectation that individual authorities will take steps to implement them through detailed arrangements which are best suited to their own national system. The first Basel Accord of 1988 on Banking Supervision (Basel I) took an important step towards setting an international minimum capital standard. The Accord highlighted credit risk which is the most significant type of risk in the banking industry and determined a standard ratio of capital to risk weighted assets to be maintained. However, the determined ratio was failed to establish a sufficient protection against credit risk and the treatment of derivatives was considered unsatisfactory.

[1] The Group of Ten is made up of eleven industrial countries (Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States) which consult and co-operate on economic, monetary and financial matters.

In 1993, the Global Derivatives Study Group commissioned by the Group of Thirty (G-30)[2] published a report dealing with off-balance-sheet products in a systematic way for the first time. Article 5 about measuring market risks in the report declared that "*Market risk is best measured as 'value at risk' using probability analysis upon a common confidence interval and time horizon*". This report appears to be the first publication that use the phrase 'value at risk' and prompted the use of VaR by derivatives. In 1994, J.P. Morgan initiated its free RiskMetrics™ service that was intended to promote the use of VaR among the firm's institutional clients. The service consisted of a technical document describing how to implement a VaR measure and a covariance matrix for several hundred key factors updated on the internet. Around the same time, the banking industry clearly saw the need for a proper risk management and began to seek ways to measure their risk levels. Subsequently, VaR as a market risk measure was born and RiskMetrics™ set an industry-wide standard.

After the initial Basel Accord, banks had increased their proprietary trading activities sharply, which initially were not assigned a capital charge. To remedy this omission, the Basel Accord was amended to add a charge for market risks in 1996. In respect of the amendment, banks will be required to measure and apply capital charges according to their market risks in addition to credit risks. Market risk capital requirements for banks based upon a crude VaR measure, but the Committee also approved, as an alternative, the use of banks' own proprietary VaR measures in certain circumstances.

[2] The Group of Thirty, established in 1978, is a private, nonprofit, international body composed of very senior representatives of the private and public sectors and academia.

Moreover, the US Federal Reserve, the US Securities and Exchange Commission, and regulators in the European Union have converged on VaR as a benchmark risk measure (Jorion, 2001). Because VaR provides a risk-sensitive measure of risk, it helps to deal with moral hazard problems that are so prevalent in financial markets.

After a while, VaR has become the main tool for financial institutions and regulators use to forecast market risk exposures and to set capital requirement standards (Jorion, 2001; Berkowitz and O'Brien, 2002; Lopez, 1999). It has begun to be used for risk reporting, risk limits, regulatory capital, internal capital allocation and performance measurement. Wide usage of VaR occurs due to the fact that it is an easily interpretable summary measure of risk. This measure actually aggregates the several components of price risk into a single quantitative measure of the maximum possible loss within a known confidence level over a given holding period. The usage of VaR models are appealing because they are common metrics that can be applied across all risk positions and portfolios and convey the market risk of the entire portfolio in one number (currency) that is meaningful at all levels of management. Therefore, it provides risk comparability at levels within the institution.

Moreover, VaR is calculated in currency units and is designed to cover most of the losses that a business risk might face. For this reason, VaR is assumed to be the relevant measure for determining capital that must be held to support a particular level of risky business activity (Zheng, 2006).

CHAPTER 3

LITERATURE REVIEW

Variation in market returns and other sources of risk factors has prompted researchers, practitioners and regulators to design and develop more sophisticated risk management tools. These tools play a crucial role in portfolio choice, security pricing, option pricing and risk management decisions. VaR has become the standard measure of the risk exposure associated with a particular portfolio of assets and used to quantify market risk (Jorion, 2001; Bessis, 2002). VaR is an estimation of the probability of likely losses which could arise from changes in market prices. More precisely, it is defined as the maximum loss in a value of a portfolio due to adverse market movements that is expected to occur over a pre-determined period and with a pre-determined degree of confidence.

The term VaR did not enter the financial terminology until the early 1990s, but the origins of VaR measures go further back. Early VaR measures developed along two parallel lines, portfolio theory and capital adequacy computations.

VaR measures are directly or indirectly influenced by portfolio theory. Markowitz was the first financial theorist who explicitly includes risk in the portfolio and diversification discussion. He linked terms such as return and utility with the concept of risk. Markowitz (1952) and Roy (1952), who are early users of VaR, adopted a VaR metric of single period variance of return and used this to support portfolio optimization. In these years Markowitz's ideas initiated theoretical works of researchers in this field. Specifically, Sharpe (1963) described Markowitz's VaR measure that employed a diagonal covariance matrix and this measure helped to motivate Sharpe's (1964) Capital Asset Pricing Model. Because of limited variability of processing power, VaR measures from this period were largely theoretical, and were published in the context of the emerging portfolio theory. Papers by Tobin (1958), Treynor (1961), Lintner (1965) and Mossin (1966) contributed to the emerging portfolio theory. The VaR measures employed by those researchers were best suited for equity portfolios. Therefore, VaR or portfolio risk concepts were used in earlier studies, but systematic application of VaR to many sources of financial risk has become a new concept.

VaR measures have many applications, and are used both for risk management and regulatory purposes. In the early 1980s, the US Securities and Exchange Commission adopted a crude VaR measure for use in assessing the capital adequacy of broker/dealer's non-exempt trading securities. A few years later, Bankers Trust implemented a VaR measure for use with its risk adjusted return on capital allocation system. More recently, Basel Committee on Banking Supervision (1996) at the Bank for International Settlements (BIS) implemented market risk capital requirements that allowed financial institutions to calculate their capital requirements based on their VaR calculations. In this and other ways, regulatory initiatives helped motivate the development of VaR measures.

Volatility, as measured by the standard deviation or variance of returns, is often used as a crude measure of the total risk of financial assets. Many VaR models for measuring market risk require the estimation or forecast of a volatility parameter. VaR estimates can only be produced with accurate forecasts of volatility. However, despite extensive research on volatility modeling, there exists no consensus on the appropriate model to provide the best forecast of volatility. The vast majority of earlier studies focused upon average equity returns and used traditional statistical measures for volatility modeling based on averaging and smoothing techniques or simple regression models. It has long been recognized that returns volatility exhibits clustering such that large returns (of either sign) are expected to follow large returns, and small returns (of either sign) to follow small returns. The seminal papers of Engle (1982) and Bollerslev (1986) have paved the way for the development of numerous time-varying volatility models that have been recently begun to be considered in the VaR context for researchers and practitioners. Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model in a study of the conditional variances of economic variables and Bollerslev (1986) generalized it to the GARCH model. Since then ARCH/GARCH has become a very influential econometric tool when extracting time varying volatility process from a financial data and the model has been extended to include many variations and modifications. While early generations of GARCH models have the ability to capture several characteristics of financial time series such as fat tails and volatility clustering, they do not allow leverage effect, which is also known as asymmetric volatility effect. Leverage effect means that volatility tends to rise in response to lower than expected returns and to fall in response to higher than expected returns. Failing to capture this fact, GARCH model may not produce accurate forecasts. This limitation has been overcome by the introduction of exponential GARCH (EGARCH) of Nelson (1991), the asymmetric models of Glosten *et al.* (GJR) (1993) and Engle and Ng (1993), threshold GARCH model (TGARCH) of Zakoian (1994) and quadratic GARCH (QGARCH) of Sentana (1995), which are used to capture the asymmetric volatility effect. The development of other special cases of the GARCH models includes Integrated GARCH (IGARCH) (Engle and Bollerslev, 1986), and asymmetric power ARCH (APARCH) (Ding *et al.*, 1993).

While majority of the studies found that ARCH-type models outperform the simpler volatility forecasting approaches, some studies reported poor forecast of the ARCH-type models. Cumby *et al.* (1993), Jorion (1995, 1996), Figlewski (1997) pointed out that implied volatility outperforms both moving average and GARCH forecasts. Furthermore, Tse (1991) showed that ARCH/GARCH models are slow to react to rapid changes in volatility than Exponentially Weighted Moving Average (EWMA hereafter) model using Topix Nikkei stock average daily data for one-year period. Also, Tse and Tung (1992) and Franses and Van Dijk (1996) reported superiority of simpler volatility models such us EWMA and random walk model than GARCH model.

Several recent studies, however, have reported more new results in favor of the GARCH class models. For instance, Akgiray (1989) indicated that GARCH produces the best and least biased forecast especially in high volatility periods. Andersen *et al.* (1999a) showed that GARCH (1,1) models improve forecast accuracy in high-frequency data. A similar result concerning the apparent superiority of GARCH model observed by Bera and Higgins (1997), Andersen *et al.* (1999b), McMillan and Speight (2004) on various foreign exchange rates. Also, using the US monthly stock market data, Pagan and Schwert (1990) compared the volatility forecasting performance of GARCH, EGARCH, Markov switching regimes and three non-parametric models in US stock returns from 1834 to 1925. They observed that non-parametric models produce poor predictions, and considered that the EGARCH model appears to be the best because of its ability to capture volatility asymmetry. Brailsford and Faff (1996) examined predicting performance of linear regression, historical mean, GARCH, GJR, moving average, EMWA, exponential smoothing models on Australian stock index volatility and argued that GJR and GARCH models were considerably more effective than the other models. These researches strengthened the appropriateness of GARCH models in providing accurate volatility predictions. Moreover, Hansen and Lunde (2005) compared a number of volatility models in terms of out-of-sample predictive ability and found that GARCH (1, 1) was inferior to other models in the analysis of IBM returns. Also, the articles of Degiannakis and Xekalaki (2004), Poon and Granger (2003, 2005), and Engle (2002, 2005) are dedicated to reviews of GARCH class models.

Predictive ability of volatility forecasts is also significant for pricing and hedging derivatives. Thus, Heynen and Kat (1994) investigated whether there were any differences in the ability of GARCH, EGARCH and stochastic volatility models to predict volatility of derivatives differs over the period of 1980-1992. They observed that the best forecasts come from GARCH model for currencies. Also, Day and Lewis (1993) compared the performance of similar models in crude oil futures. Christoffersen and Jacobs (2004) examined the performance of various GARCH models explicitly for the purpose of option valuation. They concluded that the performance of option valuation models with conditional heteroscedasticity could be improved by including leverage effect (results in negatively skewed returns) in line with the results of Nandi (1998) and Chernov and Ghysels (2000). Likewise, Gonzalez-Rivera *et al.* (2004) used loss functions to compare predictive performance of volatility models using call options on the S&P 500 index. They found that some simple volatility models often perform equally as well as more complex models, while their relative performance varies with users' evaluation criteria.

For S&P 100 index option, Canina and Figlewski (1993) documented that implied volatility is such a poor forecast that it is dominated by the historical volatility rate. Lamoureux and Lastrapes (1993) found that the implied volatility contains useful information in forecasting volatility, but also that time-series models contain information incremental to the implied volatility by using individual equity options.

Asymmetric behavior of financial markets is also taken into consideration in stock markets. Black (1976) and Christie (1982) were among the first who attempted to identify asymmetric volatility behavior of stock return in U.S. stock market. They explained this phenomenon by leverage effect hypothesis, which designates that a fall in stock prices increases financial leverage, leading to an increase in stock return volatility. Glosten *et al.* (1993) found a strict asymmetry in monthly stock returns in the sense that negative (positive) innovations increase (decrease) volatility. Their model presented an important application in asset pricing settings, known as GJR model. Wu (2001) verified leverage effect contributes more to the negative correlation between return and its volatility by using weekly and monthly CRSP value weighted index. Moreover, Ericsson *et al.* (2007) investigated leverage and feedback effect simultaneously at the firm level. Although they confirmed the leverage effect hypothesis, their fixed-effects panel vector autoregression model revealed that leverage effect accumulates over time.

Most models used in finance suppose that investors should be rewarded by higher return for taking additional risk. This concept is used in Engle *et al.*'s (1987) GARCH-in-mean model (GARCH-M) where the conditional variance of asset returns enters into the conditional mean equation. French *et al.* (1987) examined the relationship between monthly and daily stock returns and the predicted/unpredicted volatility in US equity index. They found evidence that there is a positive relation between the expected market risk premium and the predictable volatility of stock returns, unlike a negative relation between unexpected stock market returns and the unexpected change in volatility of stock returns. Campbell and Hentschel (1992) confirmed that an increase in volatility raises the required rate of return on common shares and hence lowers stock prices. Also, Bali and Peng (2006) provided evidence in support of GARCH-M model by employing the CRSP value-weighted index, S&P 500 cash index and S&P 500 index futures data.

Simpler GARCH models also fail to account for long memory behavior in the volatility of financial time series returns (Ding *et al.* 1993). The presence of long memory in returns and volatility implies that there exist dependencies between distant observations. In recent years, several models have been proposed to incorporate the long memory property of volatility in financial time series in order to deal with the shortcomings of simpler GARCH models. The flexibility in the structure of these models allows capturing slow decaying autocorrelation reasonably well. To allow for fractional integrated processes of the conditional variance, and therefore, provide a useful model for series in which the conditional variance is persistent, Baillie, *et al.* (1996) and Chung (1999) proposed the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model by generalizing the IGARCH model to allow for persistence in the conditional variance. Much effort has been made to explain long memory properties in returns, for example, Ding and Granger (1996), Bollerslev and Mikkelsen (1996a), and Müller *et al.* (1997). Also, Davidson (2004) developed a new long memory model, which is called as hyperbolic GARCH (HYGARCH).

Papers that have tested long memory behavior and analyzed volatility of return in developed financial markets include among others: Lo (1991), Cheung and Lai (1995), Crato (1994), Barkoulas *et al.* (2000), and Herzberg and Sibbertsen (2004). Lo (1991) tested long-run memory in U.S. stock market returns and found no support for long-term dependence in stock returns. In a similar study, Cheung and Lai (1995) and Crato (1994) explored stochastic long memory behavior in stock markets of several countries and the empirical results showed little evidence of long memory. Barkoulas *et al.* (2000) found evidence in favor of long memory in the Greek stock market using spectral regression method, which contradicts evidence of absence of long memory in other stock markets. Recently, Vougas (2004) extended the work of Barkoulas *et al.* (2000). He analyzed long memory of returns in the Athens Stock Exchange using ARFIMA-GARCH model, but found little support in favor of long memory. Furthermore, Evans and McMillan (2007) observed that GARCH-class models that account for long-memory dynamics provided the best forecasts in volatility modeling. Also, amongst others, Granger and Joyeux (1980), Geweke and Porter (1983), and Herzberg and Sibbertsen (2004) showed that price forecasting performance increases within a time-series framework in the presence of long memory.

Despite the vast literature examining long memory behavior of developed stock markets' prices, relatively few academic studies have addressed the time series properties of emerging markets. One exception is the study of Kasman *et al.* (2009) which investigated long memory property in both conditional mean and variance for Central and Eastern European countries' stock markets. The long memory parameters were statistically significant, indicating that dual long memory property is prevalent in the returns and volatility of the sampled stock markets. Besides this study, Kang and Yoon (2009) found that FIGARCH model was found to provide a good volatility representation for Hungary, Poland, Russia and Slovakia and this model provided more accurate performance in one-day-ahead volatility forecasts than other volatility models. Also, Assaf (2006) examined long memory behavior of the stock markets in MENA region by employing the modified rescaled range statistic[3] and rescaled variance statistic[4]. All markets displayed strong persistence in their volatility measures. The results of Badhani (2008) do not show long memory in stock returns of India, but their volatility show robust presence of long-range dependence.

Alternative volatility modeling techniques are also used in researches of emerging markets. In the study of four emerging markets in Central Europe, Kasch-Haroutounian and Price (2001) considered both univariate and multivariate GARCH models. Asymmetric volatility models were conducted among univariate models and weak evidence of asymmetries were found in the emerging markets. Ortiz and Arjona (2001) examined volatility in six emerging markets of Latin America. They employed several GARCH models over the time period 1988-1994. However, they noticed that best fit models differed across markets. In an earlier study, Chong *et al.* (1999) utilized volatility forecasting models including GARCH-M, stationary

[3]See Lo (1991)
[4] See Giraitis et al. (2003)

GARCH, unconstrained GARCH, non-negative GARCH, EGARCH and IGARCH to explain the characteristics of distribution of daily stock returns in the Kuala Lumpur Stock Exchange. They found that the IGARCH model underperformed other GARCH models in one-step ahead forecasting.

Recently, Balaban and Bayar (2005) attempted to investigate the relationship between stock market returns and their forecast volatility derived from the symmetric and asymmetric conditional heteroscedasticity models in fourteen countries, including developed and emerging countries. They found evidence that expected volatility have a significant positive or negative effect on country returns in a few cases. They also illustrated that the leverage effects of fourteen countries derived from the EGARCH model did not matter significantly, whereas Li (2007) concluded the presence of leverage effect in the Hong Kong stock market.

The difficulty of VaR estimation is not limited to the issue of volatility forecasting. Another important component in VaR estimation is to model the distribution of portfolio returns. When estimating VaR, a researcher chooses parametric and non-parametric models. Recently, alternative methods of estimating VaR have been proposed, called semi-parametric models, such as Extreme Value Theory (EVT hereafter), Filtered Historical Simulation which was presented by Hull and White (1998) and Barone-Adesi *et al.* (1999), and applications of regression quantile techniques such as in Engle and Manganelli (1999). While parametric methods estimate volatility parameter conditioned upon an assumption of normality, nonparametric methods require the adoption of a modeling process that makes no assumption about the distribution of the data return series. Under the framework of nonparametric models, Historical Simulation has been thoroughly examined by several authors. Hendriks (1996), Vlaar (2000) and Danielsson (2002) argued that sample size affects the accuracy of VaR forecasts and concluded that average size of the VaR on the basis of historical simulation must be relatively large. In contrast, Hoppe (1998), Lambadiaris *et al.* (2003) and Degiannakis *et al.* (2003) supported the use of smaller sample sizes in order to capture structural changes over time due to changes in trading behavior.

To overcome some limitations of Historical Simulation model, Barone-Adesi *et al.* (1998) and Barone-Adesi *et al.* (1999) introduced Filtered Historical Simulation (FHS hereafter). They take into account changes in past and current volatilities of historical returns, and make fewest assumptions about the statistical properties of future. The empirical performance of this model has been examined by Barone-Adesi and Giannopoulos (2001), Pritsker (2006) and Kuester *et al.* (2006) among others. Variations on the FHS model include Hull and White (1998) and McNeil and Frey (2000). In fact, the Hull and White model is identical with FHS model when the VaR time horizon is one period. However, McNeil and Frey (2000) combined FHS model with extreme value theory in their research.

Recent applications of univariate time series models of the GARCH type to VaR problems are conducted mostly in developed markets in several papers. Beltratti and Morana (1999) evaluated VaR measurements that can be obtained from GARCH and FIGARCH models by using daily and half-hour data of Deutsche Mark-US dollar exchange rate. Moreover, Burns (2002) forecasted VaR by employing univariate GARCH models in S&P 500 index. He compared these forecasts with other several approaches of VaR calculation and indicated that GARCH models performed relatively well in terms of the accuracy and consistency of probability level.

So and Yu (2006) compared the performance of seven GARCH models, including RiskMetrics and two long-memory GARCH models in estimating VaR of twelve market indices and four foreign exchange rates. In the models, both normal and conditional t-distributions are considered. They reported evidence in favor of the GARCH approach in estimating 1% VaR. Likewise, McMillan and Kambouroudis (2009) attempted to answer the question of whether RiskMetrics volatility model can provide superior forecasts of volatility in a VaR setting in comparison GARCH models. They detected that APARCH model outperforms other models in calculating 1% VaR while in calculating 5% VaR the RiskMetrics is adequate using a selection of G7, developed thirteen European stock markets and eleven Asian stock markets.

Giot and Laurent (2004) assessed the performance of a daily ARCH type model and daily-realized volatility when the one-step ahead VaR measure is calculated by employing two stock indices and two exchange rates from France and the US. The results showed that ARCH type model provides accurate VaR forecasts and performs as well as VaR model based on the realized volatility.

Although the variety of studies based on artificial portfolios, surprisingly little research carried out using real portfolio data. Berkowitz and O'Brien (2002) examined the performance of VaR forecasts for large U.S. commercial banks. They concluded that banks' reported VaR perform poorly and they do not outperform estimates based on GARCH type econometric models that are applied to banks' profit and loss.

Several recent papers attempted to investigate the predictive performance of various VaR methods and have shown that different methods of computing VaR generate widely varying results. Manganelli and Engle (2001) also provide a comprehensive review of recent developments in VaR modeling. They evaluate the performance of these methods by using Monte Carlo simulation and show that the conditional autoregressive VaR (CaViaR) model produced the best estimates. Billio and Pelizzon (2000) introduced multivariate switching regime model to estimate VaR that gives rise to a non-normal return distribution in a simple and intuitive way using data from Italian stocks and several portfolios generated by them. They suggested that multivariate switching regime specification is preferred to RiskMetrics and GARCH (1, 1) models. Likewise, Guermat and Harris (2002) estimated an exponentially weighted maximum likelihood model for three representative equity portfolios for the US, UK and Japan. The proposed model improved the daily VaR measures at higher confidence interval levels compared to GARCH (1,1) specification.

While Pritsker (1997), Hendriks (1996) and Andersen *et al.* (2005) examined the advantages and disadvantages of most popular VaR methods used to forecast market risk and evaluated their accuracy and computational time requirement, Alexander and Leigh (1997) analyzed the performance of equally weighted, exponentially weighted moving average (EWMA) and GARCH volatility forecasting approaches using standard statistical and operational adequacy criteria. The GARCH model is found to be preferable to EWMA in terms of minimizing the number of outliers in a backtest, although the simple unweighted average is superior to both.

Angelidis and Benos (2008) attempted to analyze parametric, semi-parametric and non-parametric models to forecast daily VaR for Greek stocks and indices by employing different distributions (normal, student-t and skewed student-t). However, they were unable to identify a unique model by using backtesting measures.

Applications of VaR models to financial futures include Brooks *et al.* (2005), Benavides (2007), Wu and Shieh (2007) as well as Cotter (2005). Above all, Brooks *et al.* (2005) compared different extreme value theory models for three LIFFE futures contract. The empirical results showed that semi-nonparametric and the small sample tail index techniques yield superior results. Also, Wu and Shieh (2007) used FIGARCH model to calculate daily VaR for T-bond interest rate futures of long and short positions based on normal, student-t and skewed student-t distributions. The empirical evidence showed that VaR values calculated using FIGARCH model with skewed student-t distributions are more accurate than those generated using traditional GARCH (1, 1) model.

Technical aspects of bank risk management also have attracted attention in the academic literature due to VaR's obvious importance. For instance, Hsieh (1993) and Merton and Perold (1993) discussed issues related to bank risk management and market risk measurement. In addition, Dimson and Marsh (1995) compared several methods proposed by regulators for computing risk capital for equity portfolios.

Despite the extensive research on the estimation of VaR in the well-developed financial markets, less is known about it in other markets. Su and Knowles (2006) performed volatility modeling by mixture switch, exponentially weighted moving average and GARCH models to implement VaR measure in Asian Pacific countries. They found that Indonesia and Korea exhibits the highest VaRs and VaR sensitivity. In addition, McMillan and Speight (2007) employed both asymmetric and long memory models in the evaluation of risk exposure in eight Asia and Pacific emerging markets. With respect to the range of forecasting models considered in the research, the results reported that asymmetric and long memory features improves VaR estimates. Furthermore, Bao *et al.* (2006) examined the performance of different VaR approaches by employing data from five Asian emerging stock markets which suffered from the 1997-1998 financial crises. While a number of distributional modeling techniques are compared, only GARCH model is used as a volatility forecasting model in their study. Asian crisis present a type of stress test for VaR estimators. The results of stress tests indicate that the RiskMetrics model works reasonably well before and after the crises, whereas some EVT models do better during the crisis period. Ho *et al.* (2000) and Gencay and Selcuk (2004) applied EVT to emerging stock markets which have been affected by a recent financial crisis. In particular, Gencay and Selcuk (2004) investigated the relative performance of VaR models with the daily stock market returns of nine different emerging markets. They reported that EVT dominates other well-known modeling approaches, such as the variance–covariance method and historical simulation for more extreme tail quantile. Gencay *et al.* (2003) reached similar results for Istanbul Stock Exchange Index (ISE-100) and S&P-500 returns.

To sum up, the choice of an adequate model for volatility forecasting is far from resolved. This study sheds light on the volatility forecasting models under a risk management framework, since it puts together the performance of the best known techniques for sophisticated distributions in several Central and Eastern European countries.

CHAPTER 4

CHARACTERISTICS of CENTRAL and EASTERN EUROPEAN COUNTRIES' STOCK MARKETS

4.1. Introduction

A new area of political and economic transformation began in all of the Central and Eastern European (CEE hereafter) countries since the start of transitional process from the former centrally planned system to market economy. The intention of most CEE countries to join the European Union (EU hereafter) has given additional influence to the transition process, but has also increased the pressure to adjust rapidly (Lannoo & Salem, 2001). The EU Enlargement involves three main conditions to be satisfied by the acceding and candidate countries; political, economic, and adoption of the *Community Acquis*[5]. The Copenhagen economic criteria force acceding and candidate countries to execute reform programs to obtain capacity to cope with market forces, have a sound market economy, and competitive pressures within the EU and ability to take on the obligations of membership including Economic and Monetary Union (EMU hereafter). Thus, these countries have to adjust their monetary and fiscal policies to satisfy Maastricht convergence

[5] The term *Community Acquis* is used in European Union law to refer to the total body of EU law accumulated thus far.

criteria[6] in the areas of inflation, long term interest rates, exchange rate stability and GDP deficits before entering into the Euro area. CEE countries consecutively engaged in implementing various liberalization and privatization programs to allow market forces to play a significant role on the economy, though at different paces and intensity. Transformation from a centrally planned to a market economy is a multifaceted process of political, economic, social and institutional changes (Havrylyshyn, 2001). These changes typically involved the liberalization of product and financial markets, and restructuring and privatization of state owned enterprises to open their markets to global competition (Yildirim, 2003). There were positive consequences in the form of stabilizing currencies, higher rate of economic growth and bringing inflation under control in most of the countries. Market-oriented economy brought new opportunities and the EU has opened negotiations for EU membership. Eight of the CEE countries (the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia) joined the EU at the recent enlargement of the European Union on 1 May 2004. It has opened up further possibilities for trade and investment in acceding countries, with far reaching implications for their growth and the development of their financial market. On 1 January 2007, Romania and Bulgaria became the EU's newest members. Croatia, as a CEE country is expected to join the EU by 2010, and Turkey, which is not a

[6] The euro convergence criteria (also known as the Maastricht criteria) are the criteria for European Union member states to enter European Economic and Monetary Union (EMU) and adopt the Euro as their currency. The purpose of setting the criteria is to maintain the price stability within the Eurozone even with the inclusion of new member states. These are the criteria that is set by the EU:

a) Inflation rate should be no more than 1.5% higher than the average three best performing member states of the EU.

b) The ratio of the annual government deficit to gross domestic product (GDP) must not exceed 3% at the end of the preceding fiscal year. If not, it is at least required to reach a level close to 3%. The ratio of gross government debt to GDP must not exceed 60% at the end of the preceding fiscal year.

c) Applicant countries should have joined the exchange-rate mechanism (ERM II) under the European Monetary System (EMS) for two consecutive years and should not have devaluated its currency during the period

d) The nominal long-term interest rate must not be more than 2 percentage points higher than in the three lowest inflation member states.

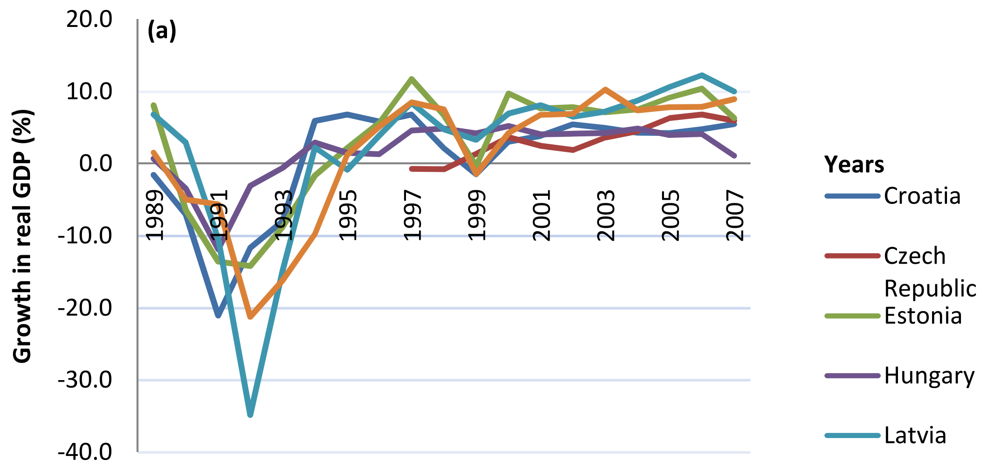
transition economy but included in our sample, is hoping to be a member in the near future.

The joining countries have to adopt legislative framework common to all EU members. All the way through the transition process, the restructuring and strengthening of the financial sectors, as well as improving the supervision and regulation of banking and financial services, received a strong emphasis to tackle with market forces and maintain economic stability and growth. Young and Reynolds (1995) and Ibrahim and Galt (2002) found an evidence that establishing appropriate financial and economic institutions is an important feature of successful transition from centrally planned to market economy. Well-functioning capital markets are essential in order to enhance economic performance because they facilitate price discovery, hedging and the allocation of capital (Harrison & Paton, 2004). Growing companies require funds and capital markets provide a way to raise capital at lower costs. As the capital markets are an important determinant of this study and essential part of the transition process, it is of major interest to analyze//the determinants of stock market development such as macroeconomic conditions, legal framework and institutional investors in the integration process into the EU.

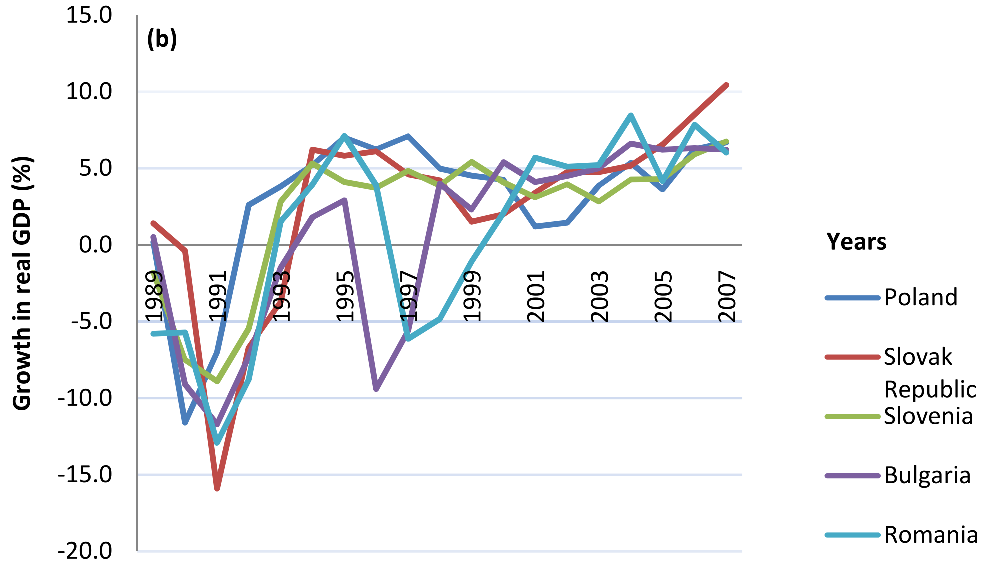
4.2. Macroeconomic Conditions of the CEE Countries

The behavior of major macroeconomic factors is important for the development and the performance of national capital markets. Actually, these factors determine the domestic demand and supply of capital and influence capital inflows from foreign countries. The collapse of the Soviet Union allowed the CEE countries to abandon central planning and to adopt free market policies. All of the centrally planned economies suffered from transformation recession after the political changes in 1989. Most of the CEE countries have showed a remarkable negative real economic performance at the beginning of the transition in the early 1990s as shown in Figure 1. The common reason for this downturn included the transformation of economic system, the economic disintegration after the dissolution of the Council for Mutual Economic Assistance [7](CMEA), and the adaptation of new production structures (Skosples, 2006). Also, political circumstances such as the military conflicts due to rise in nationalism depressed output levels. Initial decrease in GDP combined with a rapid increase in inflation and a depreciation of the real exchange rate have forced CEE countries' government to introduce a reform program.

Figure 1a-b: Real GDP Growth in CEE countries, 1989-2007



[7] CMEA. Free trade agreement between the countries of the Soviet bloc (1949-1991) which are the Soviet Union, Bulgaria, Czechoslovakia, East Germany, Hungary, Poland, Romania, Cuba, Mongolia and Vietnam.



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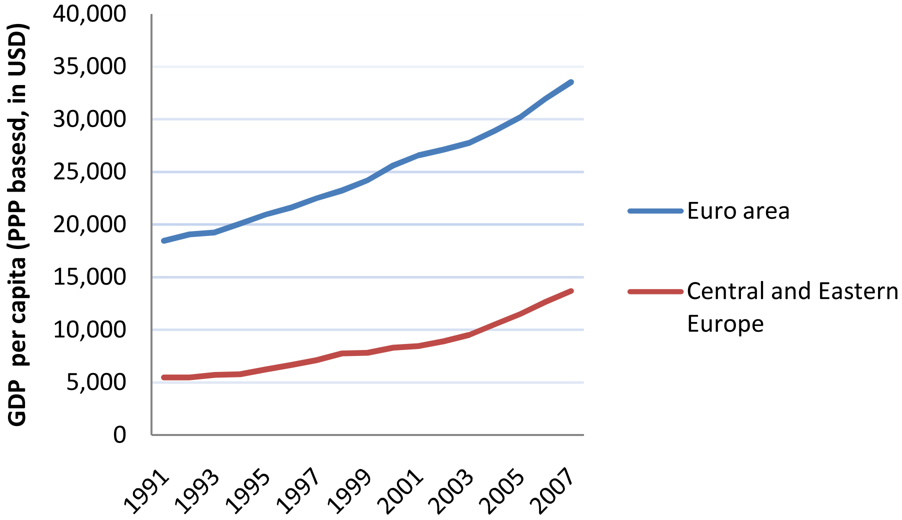
Source: IMF, World Bank, Eurostat

The major reforms in most of the countries consists of currency and exchange rate convertibility, full price liberalization, reduction of income and wages control, stricter budgetary policies, sounder monetary policies and comprehensive liberalization of foreign trade (Skosples, 2006). By the second half of the nineties, the effects of restructuring began to take place and output started to grow. After an initial fall, the CEE economies quickly regained momentum and sustained consistent and robust growth rates in real GDP. Only in Bulgaria and Romania, there were two strong several year-long recessions during the transition period. They experienced decline in economic growth due to banking crisis. Thus, GDP in CEE countries have surpassed their pre-transition output levels in 2007. Actually, the region as a whole is growing more rapidly that the EU average, and since the beginning of the restructuring process, productivity is also catching up especially in manufacturing (Syriopoulos, 2005). However, in terms of per capita income the gap between CEE countries and Euro area countries is still very high, as shown in Figure 2.

Figure 2: GDP per capita based on PPP



Source: International Monetary Fund, World Economic Outlook Database, October 2009

One of the major components that determines the degree of confidence in the long run performance of international capital markets is the stability of monetary conditions (Schroder, 2001). Main macroeconomic problem in all transition countries were high inflation and output collapse. Low and stable inflation rates are a precondition for stable exchange rates and capital inflows from abroad. All CEE countries were struggling with hyperinflation at the beginning of the transition process due to an enormous monetary overhang. Subsequently, they presented distorted price controls and were faced with serious price liberalization issues. Beginning with Poland in 1990, comprehensive stabilization packages were adopted in all CEE countries by 1993 and significant progress was achieved in the process of bringing inflation under control as indicated in Table 1. As an outcome, the interest rates also declined on average in these countries, whereas real interest rates increased to relatively high levels during the process of disinflation due to tighter monetary policies. According to a reform index developed by Havrylyshyn *et al.* (1998), Romania is lagging behind and Czech Republic leading the group in terms of the strength of the reform process.

Table 1: Consumer Prices (annual percentage)

	1990	1993	1996	1999	2002	2005	2007
Croatia	609.5	1,517.50	3.5	4	1.7	3.3	2.9
Czech Rep.	na	na	na	2.1	1.8	1.9	3
Estonia	23.1	89.8	23.1	3.3	3.6	4.1	6.6
Hungary	28.9	22.5	23.6	10	5.3	3.6	8
Latvia	10.5	109.2	25	4.7	1.9	6.7	10.1
Lithuania	8.4	410.4	24.6	0.8	0.3	2.7	5.7
Poland	585.8	35.3	19.9	7.3	1.9	2.2	2.4
Slovakia	10.8	23.2	5.8	10.6	3	2.5	2.8
Slovenia	551.6	32.9	9.9	6.2	7.5	2.5	3.6
Bulgaria	26.3	73	123	0.7	5.9	5	8.4
Romania	5.1	256.1	38.8	45.8	22.5	9.5	4.8

Source: Eurostat Database

Moreover, the stabilization process in CEE countries included the choice of exchange rate regime. It is a major concern for transition countries, because they need to establish credibility when moving from a planned regime to a market-based one. Most of the CEE countries introduced tight monetary and credit policies, wage control policies, and monetary reforms (Illieva, 2003) at the time when price controls were removed. They have gone through frequent exchange rate regime adjustments, from am fixed exchange rate regime with varying bands to managed or full floating rate systems (Wang & Moore, 2009), which gave them some control over their exchange rates and monetary policies.

One of the main features of centrally planned economies was that almost all productive capacity was state owned; therefore a major challenge during transition is privatization. Privatization is a key part of reforms for the efficient functioning of market economy (Stirbock, 2001). It is defined as the deliberate sale by a government of state-owned enterprises or assets to private economic agents. While this is important for sustainable private sector growth and efficient capital markets, the functioning of financial markets and a positive and liberalized macroeconomic climate are also necessary for the success of privatization process. The objectives set for the British privatization program by the Conservatives since 1979 are the same as those described by many governments in CEE countries. These goals as described in Price Waterhouse (1989a, 1989b), are to:

(1) raise revenue for the state,

(2) promote economic efficiency,

(3) reduce government interference in the economy,

(4) promote wider share ownership,

(5) provide the opportunity to introduce competition

(6) subject state owned enterprises to market discipline.

(7) develop the national capital market.

The difference in privatization performance among transition countries is the result of the success in privatizing the large state owned enterprises. According to the data indicated in the EBRD Transition Report 2002, Romania and Slovenia have the lowest degree of privatization, while Czech Republic and Hungary quickly privatized the majority of their large-state owned enterprises and increased the share of private sector on the economic growth (Table 2).

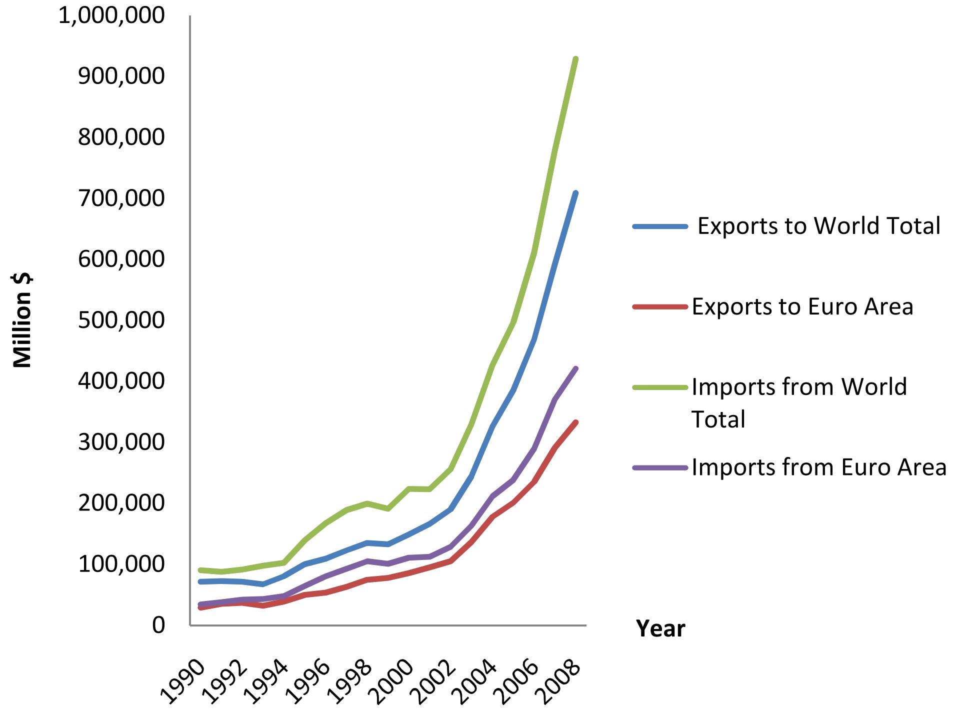
Table 2: Private sector share of GDP (%)

	1992	1994	1996	1998	2000	2001	2002
Croatia	30	65	75	75	80	80	80
Hungary	40	55	70	80	80	80	80
Poland	45	55	60	65	70	75	75
Slovakia	30	55	70	75	80	80	80
Slovenia	30	45	55	60	65	65	65
Estonia	25	55	70	70	75	75	80
Latvia	25	40	60	65	65	65	70
Lithuania	20	60	70	70	70	70	75
Bulgaria	25	40	55	65	70	70	75
Romania	25	40	55	60	60	65	65

Source: EBRD Transition Report 2002

Trade has always been the vehicle of economic growth in CEE countries. Figure 3 shows that CEE countries exhibit high degree of trade openness since the second half of 1990s. This openness means that these countries' vulnerability to external shocks has dramatically increased. The economies of CEE experienced a reorientation of trade away from the members of CMEA towards the European Union countries accounting for as much as 60-70% of total trade in may CEE countries. Actually, a large amount of their GDP depends on exports to the EU. The implication of this is that the EU is the single most important partner for all CEE countries and as a result these countries' competitive position has strengthened. Although all CEE countries suffer from substantial current account deficits due to trade deficits, they are not immediate concern as their financing is secured via capital inflows.

Figure 3: Exports of CEE countries to the World and Euro area



Source:Eurostat

The liberalization of financial capital flows are of special interest for the understanding of the capital markets in CEE countries. While domestic savings are the main source of financing, foreign capital contributes significantly to the financial markets of CEE countries and helps to finance equity capital and budget deficit. At the beginning of the transition period, there were several restrictions on all capital flows. However, while most of the limitations on foreign direct investments (FDI hereafter) were lifted in almost all countries, other capital flows were subject to various restrictions (Feldman *et al.*, 1998). Net financial flows to CEE countries have increased enormously over the past years. The structure of financial account in these countries showed that FDI dominated net portfolio investments in the late 1990s which represents foreign capital that is invested for a medium or long term period.

The considerable capital inflows of FDI have resulted to restructuring of corporate and banking sectors, and reform of the legal and regulatory framework (Nord, 2000).

Table 3: Exports of goods and services in % of GDP

	1995	1997	1999	2001	2003	2005	2007
Bulgaria	44.7	58.3	44.6	55.6	53.3	60.2	63.4
Czech Republic	50.7	52.1	55.5	65.4	61.8	72.2	80.1
Latvia	41.9	46.2	40.4	41.6	42.1	47.8	42.2
Lithuania	47.5	51.6	38.7	49.8	51.2	57.5	54.1
Hungary	44.9	54.5	63.4	71	61.1	66	80.5
Poland	23.2	23.4	24.2	27.1	33.3	37.1	40.8
Romania	na	na	27.8	33.1	34.8	33.1	29.3
Slovenia	49.9	51.7	47.6	55.5	54	62.1	69.5
Slovakia	57.8	56.4	61.2	72.7	75.9	76.3	86.5

Source: Eurostat Database

4.3. Development of Financial Sector in CEE Countries

The macroeconomic conditions prevailing in any country as well as the situation of the banking system, determines the origin and development of the capital markets (Reininger, 2001). It is also well documented that an efficiently-functioning banking and financial sector enhances a country's economic growth (Levine, 1997) through facilitating price discovery, risk hedging and the allocation of capital to its most efficient use.

CEE countries' capital markets were underdeveloped in the beginning of transition despite the success in price, trade and exchange rate liberalization and this denoted that restructuring enterprises had to rely on self-financing or on bank lending. Hence, banks had to fulfill a very important function in the overall financial system and were expected to be a driving force for economic restructuring. Since the beginning of covering the deficits of the state budget the transition process, the CEE countries acted to create a true banking system through privatization of their state owned banks and to establish functioning financial markets. In the framework of communism, the banking system in CEE countries had the following characteristics: state-owned banking, single-tier banking system[8], and they were not run as profit maximizing units (e.g. loans were granted on the basis of criteria not related to market performance). The monobank was responsible for issuing currency, collecting household deposits, providing financing to enterprises, and managing the payment system among enterprises. In fact, the functions of central bank and the commercial banks were not separated. Risk and return principles were not considered during valuation of investment projects and bankruptcy law did not exist. Therefore, when borrowers were unable to pay their loans, they were not threatened with bankruptcy and liquidation.

The progress made in the banking system was structural and reforms started with the creation of two-tier banking system that broke up the monobank into a central bank and a number of commercial banks in each country through new regulatory frameworks. However, some of the assets of single-tier banking system were transferred to new commercial banks. Therefore, they were left with bad loans without the resources to measure credit risk, and were overstaffed (Skosples, 2006). In fact, they were technically insolvent from the date of their establishment. Initially, commercial banks maintained close ties with state-owned enterprises. Furthermore, the new banking system did not focus on effective and efficient functioning of the system and were managed by administrative decisions rather than market forces.

[8] Monolithic central bank plus a limited number of specialized banks (e.g. for foreign trade, agriculture, national savings, investment etc.) Monobank performed the simultaneous roles of central bank and commercial bank. Specialized banks were organizationally dependent upon and regulated by central banks.

Also, the new banking system had little motivation to pursue efficient behavior due to the lack of competitive pressure. Thus, some governments relaxed the restrictions on the establishment of new banks and encouraged the free entry of *de novo* private banks[9] (Yildirim, 2003). While the number of commercial banks increased in the early 1990s and brought a certain degree of competition to the banking sector in these years, they soon became financially distressed and insolvent. Because, the banking sector contained excessive numbers of small unhealthy banks and they were expected to support unproductive enterprises. Kraft and Tirtiroglu (1998) found that newer banks were less cost and scale efficient than older banks, and these undercapitalized banks did not improve overall efficiency of financial intermediation.

The banking sector in most of the CEE countries has been subjected to a number of crises over the years of restructuring. Banking crises were experienced in Estonia in 1992, in Latvia and Lithuania in 1995 and in Bulgaria and Czech Republic in 1996. The causes of these crises were mainly accumulation of bad loans, insufficient regulation and supervision of the banking system and corporate distress. It became apparent that the transition countries needed a new approach to restructuring their banks. Therefore, bank regulation and supervision became particularly important for the more liberalized banking system in all CEE countries to ensure banking stability. Supervision aims to ensure well functioning risk management system for the banks through identifying, measuring and monitoring the risks they take. Banking system supervision was executed by central banks in all CEE countries except for Hungary and Slovenia, where some supervisory authorities helped central banks. Each CEE country was able to determine banks' capital adequacy and the reserve requirement

[9] De novo implies that a new bank was not created through privatization process of an already existing bank, but that it was established as a new entity.

and enforce stricter loan provision (Skosples, 2006). As for capital adequacy, all countries seem to comply with the Bank for International Settlements (BIS thereafter) recommendation to keep the required minimum risk weighted capital to asset ratio of 8 % (Yildirim, 2003). Regulations included general portfolio assessment and loan classification to ensure transparency and to give auditors the necessary warning signals. After the implementation of EU compatible financial legislation and regulations, governments initiated large scale privatization programs that considerably reduced state ownership. The key idea behind privatization was to improve competition and efficiency through increased foreign and domestic competition. Foreign participation accelerated following the banking crises and it helped the establishment of a sound banking sector in CEE. Currently, more than half of all CEE banks are fully or substantially foreign owned and foreign ownership of bank assets is above 70% and is rising every year. Most of the CEE banks' assets were sold to EU banks to facilitate coordination of monetary policy with the EU. The size of state owned had declined dramatically between 1996 and 2001. The increased foreign ownership brought foreign capital and know-how, raised competition among banks and protected the sector from emerging market crises[10] experienced in Russia and Asia. Also, the amounts of non-performing assets reduced and asset quality improved after enacting the new regulations and bailing out of bad loans by governments.

Simultaneously, the success of privatization and the development of government debt market have enormously affected the growth of security markets in the CEE countries. Secondary public debt markets provide liquidity to investors that are incentives for financial market development and support interest rate liberalization.

[10] See World Bank Development Report (2002).

The Community *acquis* in the area of securities markets is composed of measures regarding operations on market, rules governing the markets themselves and the intermediaries active on these markets and free provision of unit trusts (Lannoo & Salem, 2001). Stock exchanges that had closed during the socialist period were reopened with mass privatization programs in the early 1990s. For instance, the Budapest Stock Exchange (Hungary) was reopened in June 1990, the Bratislava Stock Exchange (Slovakia) in March 1991, the Warsaw Stock Exchange (Poland) in April 1991, and the Prague Stock Exchange (Czech Republic) in April 1993. The stock markets were characterized by the lack of a sufficient regulatory framework and the dominance of a small number of companies (Wang & Moore, 2009) in the reopening stage. Also, the firms were not encouraged to be listed in stock exchanges due to the requirement of disclosure and higher costs of raising funds through the market compared to bank credit.

The privatization method has actually influenced the number of listed companies. The basic feature of stock markets in Bulgaria, Czech Republic, Lithuania, Romania and Slovakia was the transfer of ownership rights to mass-privatized companies. At the beginning, large number of stocks was listed in these stock markets, which were illiquid. Conversely, the stock markets in Croatia, Estonia, Hungary, Latvia, Poland and Slovenia began operations with a small number of stocks that were offered by voluntary initial public offerings (IPO, hereafter). Since illiquid companies are removed from the system due to avoidance of paying taxes and low cost of bank credit, the number of listed companies declined in mass privatized stock markets in the late 1990s. In contrast, as seen in Table 4, the number of listed companies increased in IPO-type markets such as in Poland and Hungary.

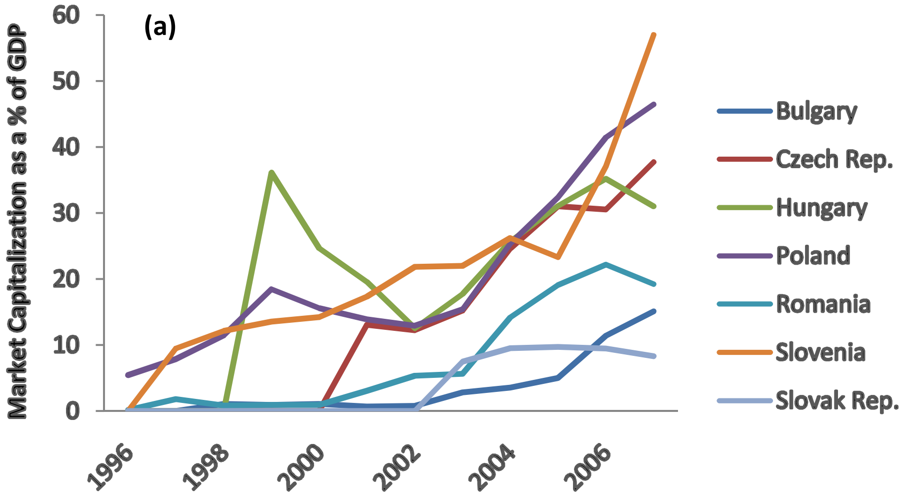
Table 4: Number of listed companies in transition economies by market origin, 1994-2000

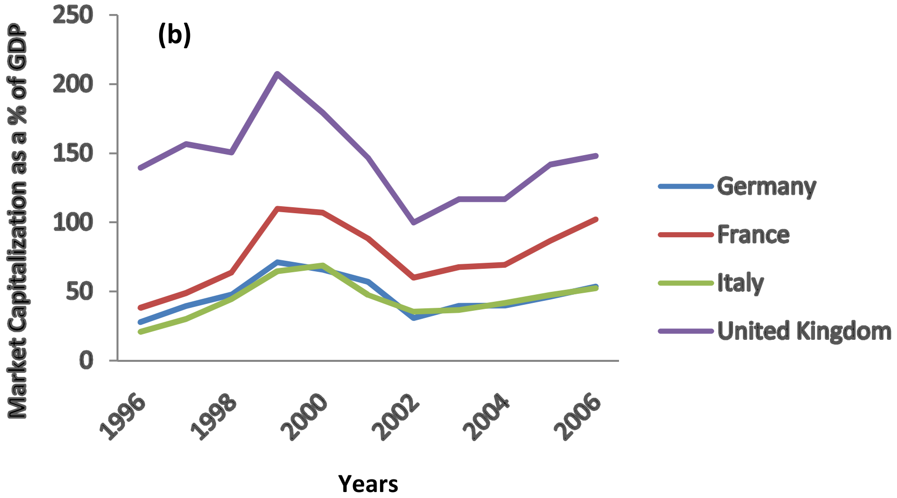
	1994	1995	1996	1997	1998	1999	2000
Czech Republic	1028	1716	1670	320	304	195	151
Hungary	40	42	45	49	55	66	60
Estonia	0	0	19	31	29	24	21
Latvia	0	17	34	51	68	67	63
Lithuania	183	351	460	667	1365	1250	1188
Poland	44	65	83	143	198	221	225
Romania	0	9	17	75	126	126	115
Slovakia	521	850	970	918	833	830	866
Slovenia	-	-	-	85	92	134	154

Source: Stock exchange websites

Countries with more stable macroeconomic environment, better regulations and accounting rules and stronger disclosure requirements are expected to have larger stock markets in terms of market capitalization. Figure 4a shows the market capitalization of transition economies. The market capitalization has increased outstandingly for Hungary and Poland, whereas Slovakia has shown the lowest level of market capitalization in absolute value and percentage of GDP. Despite the rapid growth in their market capitalization, these stock markets are relatively small when compared to developed stock markets in EU, as shown Figure 4b. Developed stock markets denote a smooth pattern when compared with unsteady movements in the transition stock markets. This can be interpreted as an indication of unstable economic conditions in CEE countries.

Figure 4: a) Market capitalization of CEE stock markets as a share of GDP (b) Market capitalization of developed stock markets as a share of GDP





Source: Eurostat

Another important characteristic of stock markets is liquidity, which is often measured as the market turnover ratio. It is calculated by dividing the total value of shares traded during the period to the average market capitalization for the period. It is an indicator of market depth and higher ratio designates higher liquidity of the market. The most liquid stock market is in Hungary, induced by foreign trade activities. Also, turnover ratio has risen in all CEE stock markets with the exception of Slovakia and Bulgaria due to the poor economic development and weak regulatory environment (Pajuste, 2002). A small number of companies dominated the stock markets of transition countries and thus there is a high concentration of turnover in these markets.

Table 5: Market turnover (equity market), in % of market capitalization

	1995	1996	1997	1998	1999	2000
Czech Republic	23	47	55	40	36	58
Hungary	15	31	50	114	175	204
Estonia	0	40	148	210	27	33
Latvia	0	8	25	12	5	47
Lithuania	10	4	11	8	10	7
Poland	61	66	66	44	80	132
Romania	0	8	52	54	31	23
Slovakia	na	na	na	na	14	17
Slovenia	67	60	34	33	32	21

Source: Homepages of national stock exchanges, author's calculations

The liquidity of stock markets also depends on the development of a class of well governed institutional investors. However, institutional investors, i.e. investment funds, mutual funds, pension funds and insurance companies are very small in size with assets accounting for an average of 7% of GDP. Mutual funds are immature in transition economies and the size of the assets of pension funds, which have only recently been set up, is insignificant. Also, the insurance industry started to develop after 1996 with the exception of Czech Republic.

Corresponding to the market capitalization of equity markets, it would be remarkable to compare the ownership structure of the total capital of all listed companies in CEE stock markets. The share of foreign equity financing is relatively high in many large and listed companies in transition countries. The Czech Republic, Estonia, Hungary and Slovakia exhibit foreign investment ratios that are comparable with Euro area countries. On the contrary, foreign stock holdings are significantly lower in Poland but still much higher than in Latvia, Lithuania and Slovenia.

Despite their small size, these CEE markets have become more attractive in the last few years due to a combination of greater perceived economic and political stability in comparison to some other emerging markets and much higher returns than those of the developed EU markets (Gilmore et al. 2008). However, they experienced higher volatility changes and unstable macroeconomic conditions due the growth of market capitalization and trading volumes. Also, they are more sensitive to shifts in regional and worldwide portfolio adjustments of large investment funds due to the small size of the market compared to the stock exchanges of the more developed and larger markets.

CHAPTER 5

METHODOLOGY

5.1. Modelling Volatility

Modelling and forecasting stock market volatility has been the subject of vast empirical and theoretical investigation by market professionals and academic researchers over the past decade. Volatility, usually measured by standard deviation or variance of portfolio returns, is uniquely vital in financial markets, for it is often taken as a crude measure of the total risk of financial assets. Many value at risk models for measuring market risk require the estimation or forecast of a volatility parameter.

In this thesis, the volatility modelling techniques cover a wide range of simple pre-ARCH to post-ARCH class of models. As for the ARCH class models, this study take into consideration the first generation of model (GARCH or other symmetric model), asymmetric models (e.g. Nelson, 1991; Glosten *et al.* 1993) and long memory models (e.g. Baillie *et al.* 1996; Engle & Lee, 1999). The forecasting performance of these models compared to simpler benchmark models based upon smoothing and averaging techniques is also considered in the scope of this study.

The next sections will discuss various models that are appropriate to capture the stylized features of volatility that have been observed in the literature.

5.1.1. Averaging and Smoothing Models

In order to establish notation and models in simpler averaging and smoothing models to forecast volatility, consider the return process is given by

$$r_t = \mu + \varepsilon_t \tag{1}$$

where μ is the conditional mean process, ε_t is the error term and decomposed of $\varepsilon_t = \sigma_t z_t$ with z_t an idiosyncratic zero mean constant variance noise term and σ_t is the volatility process to be estimated with forecast values denoted by h_t^2. The sample data is split between the in sample period $t = 1,2, \dots, T$ and the out of sample period $t = T, \dots, \tau$

5.1.1.1. Historical Average

Historical average in volatility process is perhaps the most apparent way of forecasting future volatility. Moreover, if the conditional expectation of volatility is assumed to be constant, all variation in estimated volatility could be attributed to measurement error and the optimal forecast of future volatility would be the historical average computed as follows

$$h_{t+1}^2 = \frac{1}{\tau - T} \sum_{t=1}^{T} \sigma_t^2 \tag{2}$$

where h_t^2 is the forecast of volatility at time t, σ_t^2 is the actual volatility at time t.

5.1.1.2. Random Walk Model

Random walk model assumes volatility fluctuates randomly in all period. Hence, the best forecast of next period's volatility is simply current period's actual volatility. It is defined as:

$$h_{t+1}^2 = \sigma_t^2 \tag{3}$$

This model suggests that the optimal forecast of volatility is for no change since the last observed observation (Evans & McMillan, 2007).

5.1.1.3. Exponential smoothing

Exponential smoothing is another one-step-ahead volatility forecasting technique that uses weighted function of the immediate preceding volatility forecast and actual volatility. The equation of the model is

$$h_{t+1}^2 = (1-\alpha)h_t^2 + \alpha\sigma_t^2 \tag{4}$$

where h_t^2 is the forecast of volatility at time t, σ_t^2 is the actual volatility at time t and α is the smoothing constant constrained to lie between zero and one. For α=1 the exponential smoothing model reduces to the random walk model, while as α=0 major weight is given to the prior period forecast. By repeated substitution, the recursive can be written as

$$h_{t+1}^2 = \alpha\sum_{i=0}^{T}(1-\alpha)^i\sigma_{t-i}^2 \tag{5}$$

This can be an explanation of why this method is called as exponential smoothing. Because Eq. (5) shows that the forecast of volatility is a weighted average of the past values of σ_{t-i}^2, where the weights decline exponentially with time (Yu, 2002). The value of α is chosen to produce best fit by minimizing the sum of squared in-sample forecast errors.

5.1.1.4. Exponentially weighted moving average (EWMA)

The exponentially weighted moving average (EWMA hereafter) model allows more recent observations to have a stronger effect on the forecast of volatility than older data points. The weighting for each older data point decreases exponentially, giving much more importance to recent observations while still not discarding older observations entirely. According to EWMA model, the forecast is obtained by

$$h_{t+1}^2 = (1-\lambda)\sum_{i=1}^{N} \lambda^{i-1}\, r_{t+1-i}^2 \tag{6}$$

Where r_t is the observed return on day t with squared returns typically used as an estimate of the ex-post daily variance and λ is the decay factor that determines how much weight is given to recent versus older observations. The decay factor could be estimated, however in many researches it is set as 0.94 as recommended by RiskMetrics, producers of popular risk measurement software.

5.1.2. Linear Time Series Models

5.1.2.1. Autoregressive Moving Average (ARMA) Models

Yule (1926) first introduced autoregressive (AR) models and they were supplemented with the work of Slutsky (1937) who presented moving average (MA) schemes. Wold’s (1938) autoregressive moving average (ARMA) model of order (*p*,*q*) is obtained by combining autoregressive (AR) model of order *p* and moving average (MA) model of order q. This model can be used to model a large class of stationary time series. The AR models are used in time series analysis to describe stationary time series. The current value of y_t, $t=1\ldots T$, given by

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{7}$$

$$\varepsilon_t = z_t \sigma_t, \quad z_t \sim N(0,1)$$

is called an autoregressive process of order p and is denoted by AR(p). In Eq. (7), μ is a constant term which relates to the mean of the stochastic process and ε_t is a sequence of independently and identically distributed (i.i.d) error term with zero mean and constant variance. y_t is generated by its own past values together with an error term (ε_t) . AR(p) process can also be expressed more compactly using sigma notation

$$y_t = \mu + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t \tag{8}$$

Moreover, lag operator notation can be used to write Eq. (8). L is lag operator which imposes a one period time lag each time it is applied to a variable. $Ly_t = y_{t-1}$ is used to denote that y_t is lagged once. In order to show ith lag of y_t is being taken, the notation would be $L^i y_t = y_{t-i}$. Then AR(p) process would be written as

$$y_t = \mu + \sum_{i=1}^{p} \phi_i L^i \, y_t + \varepsilon_t \tag{9}$$

In the moving average model of order q, general series y_t can be modeled as a combination of current and previous values of white noise[11] disturbance term going back q periods. This process is denoted as MA(q) and is written as

$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-q} \tag{10}$$

This can also be expressed as sigma or lag operator notation

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i} + \varepsilon_t \tag{11}$$

$$y_t = \mu + \sum_{i=1}^{q} \theta_i L^i \, \varepsilon_t + \varepsilon_t \tag{12}$$

An ARMA(p,q) model is one which combines AR(p) and MA(q) models. The model states that series of y_t depends on its past observations going back p periods together with current and previous values of random disturbances going back q periods. This model can be written as

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-q} + \varepsilon_t$$

with $E(\varepsilon_t)=0$; $E(\varepsilon_t^2)=\sigma^2$; $E(\varepsilon_t \varepsilon_s)=0$, $t \neq s$

or it can be expressed using lag operator as

$$\phi(L) y_t = \mu + \theta(L) \varepsilon_t \tag{13}$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_p L^p$$

[11] White noise process has a constant mean and variance, and zero covariances except at lag zero. Last condition means that each observation is uncorrelated with all other values in the sequence.

5.1.2.2. Autoregressive Integrated Moving Average (ARIMA) Models

Subclass of ARMA models are built on stationary data. The stationarity reflects certain time-invariant properties of time series and is somehow a necessary condition for making statistical inference (Fan and Yao, 2003). On the other hand, real time series data often contains time trends or random shifts that are beyond the capacity of stationary ARMA models. Box and Jenkins (1970) suggest preprocessing the data to remove those unstable components. It is achieved by taking the difference more than once if necessary to obtain stationary series that has a constant mean, constant variance and constant autocovariances for each given lag. Then, the new series can be modeled by a stationary ARMA model. Since the original series is the integration of the differenced series, this process is called as an autoregressive integrated moving average (ARIMA) process. Briefly, an ARMA (*p*,*q*) model in the variable differenced *d* times is equivalent to an ARIMA(*p*,*d*,*q*) model on the original data.

If the difference of the series y_t is taken to obtain new stationary series x_t , then ARMA model can be used. It is shown as

$$x_t = \Delta^d y_t, \qquad d \geq 1$$

where Δ denotes differencing and *d* is the order of differencing need to be an integer. ARIMA*(p,d,q)* process is written as

$$\phi(L)\Delta^d \mathrm{y_t} = \mu + \theta(\mathrm{L})\varepsilon_\mathrm{t} \qquad (14)$$

5.1.2.3. Autoregressive Fractionally Integrated Moving Average (ARFIMA) Models

Granger and Joyeux (1980), Hosking (1981) and Geweke and Porter-Hudak (1983) were the early contributors who proposed the use of ARFIMA processes to test the long memory property in the asset returns. Autoregressive fractionally integrated moving average (ARFIMA) models generalizes the ARIMA models by allowing differencing parameter to take on real value, rather than restricting it to be an integer. They allow for series to exhibit stationary ARMA behavior after being fractionally differenced (Koop *et al.* 1997). The fractional difference operator $(1\text{-}L)^{\xi}$ is used for the ARFIMA(p,ξ,q) process, where ξ denotes the degree of fractional integration. For the observed series y_t ,the ARFIMA(p,ξ,q) process can be expressed as:

$$\phi(L)(1-\mathrm{L})^{\xi}(\mathrm{y_t}-\mu)=\theta(\mathrm{L})\varepsilon_{\mathrm{t}} \qquad (15)$$

$$\varepsilon_t = z_t\sigma_t, \qquad z_t \sim N(0,1)$$

where μ denotes the unconditional mean and ε_t symbolizes iid error term. $\phi(L)$ and $\theta(L)$ are the usual AR and MA lag polynomials with roots outside the unit circle, respectively. The major difference between ARIMA and ARMA models is, here differencing parameter ξ need not to be an integer. The integer values of differencing parameter leads to traditional ARIMA model and zero value of this parameter corresponds to ARMA model. The properties of the process depend on the value of the differencing parameter ξ. The process exhibits long memory when$\xi \, \epsilon \, (0,0.5)$, intermediate memory when $\xi \, \epsilon \, (-0.5,0)$ and short memory when $\xi = 0$. Following Hosking (1981), when $\xi \, \epsilon \, (0.5,-0.5)$, the y_t process is stationary and invertible and the effects of ε_t on y_t decays slowly to zero. Specifically for $\xi \, \epsilon \, (0,0.5)$, the autocorrelation function of an ARFIMA process can be shown to be positive and exhibit more persistence with the autocorrelation decaying at a hyperbolic rate which is much slower than the usual exponential rate associated with stationary ARMA process when $\xi = 0$. In the case of $\xi \, \epsilon \, (-0.5,0)$, inverse autocorrelations decay hyperbolically.

5.1.3. Nonlinear Time Series Models

The basic assumption of classical linear regression model is that the variance of the errors is constant at any given point in time. This assumption is known as homoscedasticity and it is the focus of ARCH/GARCH models. In many cases, especially in financial time series data that display periods of unusually large volatility followed by periods of relative tranquility, the assumption of homoscedasticity might be unreasonable. If the variance of the errors is not constant, time series data are said to suffer from heteroscedasticity. In the presence of this problem, the regression coefficients will be still unbiased, whereas standard error estimates could be wrong. Therefore, it makes sense to use a model that does not assume constant variance especially for financial time series data.

Moreover, most of the financial time series data exhibit volatility clustering which is described as the tendency of large changes in asset prices of either sign to follow large changes and small changes of either sign follow small changes. In other words, there is a degree of autocorrelation in the riskiness of financial returns. The ARCH and GARCH[12] time- varying models are appropriately designed to deal with this set of issues. Specifically, Engle (1982) and Sumel and Engle (1994) among other studies state that the ARCH appropriately accounts for volatility clustering in the error terms that are serially uncorrelated and have fat tailed distributions. As Bollerslev *et al*. (1992) point out; such evidence proposes that the ARCH process and its generalizations due to Bollerslev (1986) can well represent time-varying stock return volatility and fat tailed-distribution parsimoniously, while incorporating autocorrelation.

[12] It stands for autoregressive conditional heteroscedasticity and generalized autoregressive conditional heteroscedasticity.

This study proceeds with the description of the family of ARCH and GARCH models that will be used in volatility modeling.

5.1.3.1. ARCH Models

The autoregressive conditional heteroscedasticity (ARCH) model is proposed by Engle (1982) and is known as the accurate estimators of time varying volatility. ARCH class models involve joint estimation of the conditional mean and the conditional variance processes. Initially, the definition of conditional variance of a random variable, ε_t, is needed to understand how the model works. The conditional variance of ε_t symbolized by σ_t^2 can be written as

$$\sigma_t^2 = var(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) = E[(\varepsilon_t - E(\varepsilon_t)^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots] \tag{16}$$

Because it is assumed that the error term has a zero mean, $E[\varepsilon_t]=0$, then

$$\sigma_t^2 = var(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) = E[\varepsilon_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots] \tag{17}$$

Eq. (17) verify that the conditional variance of a zero mean normally distributed random variable ε_t is equal to the conditional expected value of the square ε_t. The autocorrelation in ε_t^2 can be captured by an AR(q) process,

$$\varepsilon_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \tag{18}$$

Using Eq. (17) and (18), ARCH(q) model can be shown as a moving average of past error terms

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{19}$$

where ε_{t-i}^2 lagged squared prediction errors, σ_t^2 is conditional variance and the coefficients α_i must be estimated from empirical data. The error term have the form of $\varepsilon_t = \sigma_t z_t$ where z_t is defined as standardized residual that have zero mean and unit variance and assumed to be normally distributed. It is mentioned that ARCH class models are estimated using conditional mean and conditional variance equations. Thus far, conditional variance is modeled, but nothing has been said about conditional mean. Under ARCH, the conditional mean equation which describes how the dependent variable y_t varies over time could take almost any form that the researcher wishes (Brooks, 2002). Therefore, using one example of conditional mean equation, the full model can be expressed as

$$r_t = \mu + \varepsilon_{t\,,} \qquad \varepsilon_t |\, \Omega_{t-1} \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \qquad (20)$$

where Ω_{t-1} denotes the information up to time t-1 and r_t is the daily return. The formulation in the mean equation implies that the conditional distribution of the returns is normal with mean zero. ARCH(q) model can be explained as error variance depends on q lags of squared errors. In the previous equation, squares of lagged errors will not be negative, whereas coefficients could be negative. Therefore, in order to ensure that the conditional variance is always nonnegative, all coefficients would be required to be nonnegative, $\omega \geq 0$, $\alpha_i \geq 0$ $\forall i = 0,1,2, \dots, q$. The value of q, the number of lags of the squared residual, should be decided carefully in order to have the correct model. In this study, likelihood ratio test is used to determine the number of lags of squared residuals.

In the ARCH specification, while the conditional variance is changing, the unconditional variance of ε_t is constant and expressed as $\sigma_t^2 = \frac{\omega}{1-\sum_{i=1}^{q}\alpha_i}$. As long as $\sum_{i=1}^{q}\alpha_i < 1$, the ARCH process is weakly stationary with constant unconditional variance.

5.1.3.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Bollerslev (1986) extended Engle's original work by overcoming some of the limitations of the ARCH model. Bollerslev indicated that the number of lags of the squared errors that are required to capture all of the dependence in the conditional variance might be very large in empirical applications. This will result in a large conditional variance model that was not parsimonious. Besides that, nonnegativity constraints might be violated when there are more parameters in the conditional variance equation. Elaborating on these weaknesses, Bollerslev developed a more parsimonious model would entail fewer coefficient restrictions which is called as generalized autoregressive conditional heteroscedasticity (GARCH) model. The general specification of GARCH (*p*,*q*) model is given by;

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \tag{21}$$

$$= \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$$

where α(L) and β(L) are polynomials of order p and q, respectively expressed in terms of lag operator. The main difference between GARCH and ARMA processes is that the former allows volatility shocks to persist over time. The key feature of GARCH models is that both AR and MA components are included in the heteroscedastic variance (Baillie et al., 1996; Bollerslev, 1989, 1990; Bollerslev and

Mikkelsen, 1996b). Using GARCH (*p*,*q*) models, forecasts of volatility are generated as a weighted function of a long-term average value, ω, information about volatility during the previous periods and the fitted variance from the model during the previous periods. Alternatively, the estimate of ARCH coefficient α_i shows the impact of current news on the conditional variance process and β_i indicates the persistence of volatility of a shock or the impact of old news on volatility. In other words α implies the existence of volatility clustering within the data and β presents the level of volatility memory. Hence, the combined value of $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_i$ provides a general indication of the persistence of volatility in any given time series data. The stationarity of the process is achieved only if $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_i < 1$ restriction is satisfied. As the mentioned sum converges to unity, the persistence of shocks to volatility becomes permanent and unconditional variance moves towards infinity. In Eq. (21), nonnegativity conditions of parameters ω, α_i and β_i are sufficient for the conditional variances to be strictly positive.

Using Eq. (21) the following expression can be derived

$$[1 - \alpha(L) - \beta(L)]\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \tag{22}$$

where $v_t = \varepsilon_t^2 - \sigma_t^2$. The GARCH (*p*,*q*) model is covariance stationary if all the roots of $1 - \alpha(L) - \beta(L)$ lie outside the unit circle. It means, $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_i < 1$ condition is necessary to satisfy covariance stationarity of the conditional variance. For $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_i > 1$, the unconditional variance of ε_t[13] is not defined and this would be termed non-stationarity in variance. This is representative of a case in which a shock to volatility during the current period results in even greater volatility

[13]It is expressed as $\sigma_t^2 = \frac{\omega}{1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_i}$

during the next period. The case when $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_i = 1$ would be known as a unit root in variance and referred to as an Integrated GARCH (IGARCH) model. Engle and Bollerslev (1986) defined the IGARCH (*p,q*) model as

$$\phi(L)[1-L]\varepsilon_t^2 = \omega + [1-\beta(L)]v_t \tag{23}$$

where $\phi(L) = [1-\alpha(L)-\beta(L)](1-L)^{-1}$. In this situation, the past information (shocks) is persistent indefinitely for forecasts of the conditional variance for all horizons. Hence, the unconditional variance of IGARCH model does not exist.

5.1.3.3 Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

Many of extensions to the GARCH model have been proposed as a consequence of some limitations of traditional GARCH (*p,q*) model. One of the primary restrictions of GARCH model is that to it imposes a nonnegativity condition on all parameters to ensure the conditional variance is positive. However, Nelson and Cao (1992) argued that this condition may be violated because stock return and volatility can be negatively correlated based on some empirical research.[14] While GARCH models proved successful in considering main features of return series, namely volatility clustering and leptokurtosis, they fail to account for asymmetry in the conditional variance. The shocks to the traditional GARCH (*p,q*) model have the symmetric (same) effect on the conditional variance whether the shocks are negative or positive. This actually arises since the conditional variance in Eq. (21) is a function of the magnitudes of lagged residuals and not their signs. In the case of equity returns, asymmetries are attributed to leverage effects, whereby large negative shocks or innovations result in higher observed volatility than a positive shocks of the same

[14] See for example, Black (1976), Christie (1982), and French *et al*.(1987).

magnitude. The existence of this asymmetric effect implies that a symmetric specification on the conditional variance function as in the GARCH (*p,q*) model is theoretically inappropriate. The exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model proposed by Nelson (1991) showed that the nonnegative constraints are too restrictive and introduced asymmetry into the conditional variance.

The EGARCH model developed by (Nelson, 1991) can be written as follows:

$$\ln(\sigma_t^2) = \omega + \alpha \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \tag{24}$$

The model has several advantages over the traditional GARCH model. First of all, the logarithmic form of the conditional variance function provides that the variance will be positive even if the parameters are negative. Hence, there is no need for nonnegativity constraints for the parameters of the EGARCH model. This feature of the model is useful in which it significantly simplifies the estimation of the parameters and avoids a number of possible difficulties in a negative estimation of GARCH models. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ, will be negative (Brooks, 2002). Also, Eq. (24) allows good and bad news to affect volatility in different ways. The only restriction on the parameters in the EGARCH model is that the sum of the terms must not exceed unity in order to guarantee the stationarity of the process (Kasman and Kasman, 2008).

5.1.3.4. The GJR Model

The GJR model is proposed by Glosten *et al.* (1993) which is a simple extension of GARCH model with an additional term included to account for possible asymmetries. Its generalized version is given by

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i}\varepsilon_{t-i}^2) + \sum_{j=1}^{p}\beta_j\, \sigma_{t-j}^2 \qquad (25)$$

where I_{t-i} is a dummy variable that take the value 1 if ε_{t-i} is negative and 0 when it is positive. In this model, the impact of squares of lagged errors on conditional variance is different when lagged error term is negative or positive. Basically using GJR (1,1) model, good news or shocks has an impact of α while bad news or shocks has an impact of α+γ on the conditional variance.

5.1.3.5. Fractionally Integrated GARCH (FIGARCH) Model

In order to capture long memory property in financial market volatility, Baillie *et al.* (1996) introduced the fractionally integrated GARCH (FIGARCH) process. The model also fills the gap between short and complete persistence. Actually, the model is an extension of IGARCH model and is formed by replacing the first difference operator *(1-L)* in Eq. (23) by fractional differencing operator $(1-L)^d$ with $0<d<1$. In contrast to an *I(0)* time series in which shocks die out at an exponential rate , or an *I(1)* series in which there is no mean reversion , shocks to an *I(d)* time series decay at a slow hyperbolic rate.

The FIGARCH (*p*,*d*,*q*) model can be defined as

$$\phi(L)(1-L)^d\varepsilon_t^2 = \omega + [1-\beta(L)]v_t \qquad (26)$$

where $v_t = \varepsilon_t^2 - \sigma_t^2$ and all the roots of $\phi(L)$ and [1-$\beta(L)$] lie outside the unit circle. When $d=1$, a FIGARCH model is reduced to an IGARCH model; and when $d=0$; it is reduced to a GARCH model. Alternatively, for $0<d<1$ the FIGARCH model implies a long memory behavior. To better understand the conditional variance equation, one can rearrange Eq. (26) and can write the FIGARCH model as follows

$$[1-\beta(L)]\sigma_t^2 = \omega + [1-\beta(L)-\phi(L)(1-L)^d]\varepsilon_t^2 \tag{27}$$

The conditional variance of ε_t^2 is obtained by

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_t^2 \tag{28}$$

That is

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \lambda(L)\varepsilon_t^2 \tag{29}$$

where $\lambda(L) = 1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d]$. The conditions of $\omega > 0, \beta(L) - d \leq \phi(L) \leq \frac{2-d}{3}$, and $d\left(\phi(L) - \frac{1-d}{2}\right) \leq \beta(L)(\phi(L) - \beta(L) + d)$ are sufficient to ensure that the conditional variance of FIGARCH model is positive almost surely for all t.

In the FIGARCH model, the effect of a given shock on the conditional variance will die out at a hyperbolic rate, reflecting the highly persistent nature of these shocks. For noninteger values of d when $0<d<1$ the autocorrelations of series will decline very slowly to zero. Since, series is weakly stationary for $d<0.5$, it is nonstationary for $d \geq 0.5$. This makes a clear difference from GARCH ($d=0$) and IGARCH ($d=1$) models where the effect of past squared errors on the current conditional variance dies out exponentially in GARCH and remains important for all lags in IGARCH.

Thus, FIGARCH model can be a good compromise of GARCH and IGARCH in capturing long term dynamics in volatility.

5.1.3.6. Fractionally Integrated Exponential GARCH (FIEGARCH) Model

The FIGARCH model assumes that the conditional volatility symmetrically responds to the magnitude of both positive and negative shocks. Therefore, the idea of fractional integration has been extended to the fractionally integrated exponential GARCH (FIEGARCH) model of Bollerslev and Mikkelsen (1996b) which incorporated the asymmetric dynamics of the EGARCH model. The FIEGARCH model is given by

$$\ln(\sigma_t^2) = \omega + \phi(L)^{-1}(1-L)^{-d}[1+\psi(L)]g(z_{t-1}) \quad (30)$$

where $g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$. The parameter θ measures the leverage effect while d is the long memory parameter as discussed above. If d=0, the short memory EGARCH model is obtained. The log form of FIEGARCH model allows estimation of the model without imposing any nonnegativity conditions. The FIEGARCH model is stationary only if $|d|$<1 and $|d|$<0.5.

5.1.3.7. Hyperbolic GARCH (HYGARCH) Model

Davidson (2004) proposed a generalized version of FIGARCH model that is labeled as hyperbolic GARCH (HYGARCH) model with hyperbolic convergence rates. The HYGARCH (p,d,q) model is given by Eq.(29) when $\lambda(L)$ in Eq. (29) is replaced by

$$\lambda(L) = 1 - [1-\beta(L)]^{-1}\phi(L)\{1+\alpha[(1-L)^d - 1]\} \quad (31)$$

The HYGARCH model nests the FIGARCH model when $\alpha=1$ and if the GARCH component satisfies the usual covariance stationarity restrictions, then this process is stationary with $0<\alpha<1$ and if $\alpha>1$ the process is nonstationary.

5.1.3.8 ARCH/GARCH Models with Different Distributional Assumptions

It is widely known that the distribution of financial time series exhibit fat tails and excess kurtosis rather than the normal distribution. In a VaR context, assuming normality when returns are fat tailed or leptokurtic will result a systematic underestimation or overestimation of the riskiness of the portfolio. Hence, an extension of ARCH/GARCH models are also employed in the analysis by substituting the conditional normal density by alternative distributions like student-*t* (Blattberg and Gonedes, 1974) or skewed student-*t* (Fernandez and Steel, 1998; Lambert and Laurent, 2001) in order to allow excess kurtosis or fat tails in the conditional distribution. Since it may be expected that excess kurtosis and skewness presented by the residuals of conditional heteroscedasticity models will be reduced when a more appropriate distribution is used, this study considers normal, student-*t* and skewed student-*t* distributional assumptions in the models. For example, the GARCH model can also be estimated under student-*t* distributional assumption and can be shown as

$$r_t = \mu + \varepsilon_t , \qquad \varepsilon_t |\, \Omega_{t-1} \sim T_v(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (32)$$

where $T_v(0, \sigma_t^2)$ denotes the student's t distribution with mean zero, variance σ_t^2 and *v* degrees of freedom. The degrees of freedom parameter determines the kurtosis of the conditional distribution.

Under the assumption that the error term has a normal distribution($\varepsilon_t \sim N(0,1)$), the log likelihood of normal distribution can be expressed as,

$$L_{normal} = -\frac{1}{2}\sum_{t=1}^{T}[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2] \tag{33}$$

where z_t is the standardized residual expressed as $z_t = \varepsilon_t/\sigma_t$, σ_t^2 is the conditional variance and T is the number of observations.

If ε_t follows a heavy tailed distribution such as a Student-*t* distribution, the log likelihood function for the conditional *t* distribution is

$$L_{St} = \sum_{t=1}^{T}\left[log\left(\Gamma\left(\frac{v+1}{2}\right)\right) - \log\left(\Gamma\left(\frac{v}{2}\right)\right) - \frac{1}{2}log\left((v-2)\sigma_t^2\right)\right] \tag{34}$$

Where Γ(.) is the gamma function and *v* is the degree of freedom (*v*>2). When innovations are t-distributed, fat tails can be modeled easily. The fatness increases when *v* decreases since the conditional kurtosis can be expressed as 3(*v*-2) / (*v*-4).

To capture excess kurtosis and skewness, the skewed Student-t distribution is considered in the analysis. If ε_t has a skewed student-*t* distribution ($\varepsilon_t \sim SkST(0,1,k,v)$), the log likelihood of the skewed Student-t distribution is as follows,

$$L_{SkSt} = T\left\{ln\Gamma\left(\frac{v+1}{2}\right) - ln\Gamma\left(\frac{v}{2}\right) - \frac{1}{2}ln[\pi(v-2)] + ln\left(\frac{2}{k+1/k}\right) + \ln(s)\right\} -$$

$$\frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+v)ln\left[1 + \frac{(sz_t+m)^2}{v-2}k^{-2I_t}\right]\right] \tag{35}$$

where $I_t = 1 \; if \; z_t \geq -\frac{m}{s} or \; I_t = -1 \; if \; z_t < -m/s,$ k is an asymmetry parameter, *m* and *s* are the mean and standard deviation of the skewed Student-*t* distribution.

5.1.4 Diagnostics Check for Volatility Models

The adequacy of the models that are used in the analysis is tested by Ljung-Box statistics for both standardized and squared standardized residuals. Furthermore, ARCH-LM test of Engle (1982) is employed to check the presence of ARCH effects. On the other hand, the adjusted Pearson chi-squared goodness-of-fit is applied on the residuals of the estimated models to compare the empirical distribution of the standardized residuals with theoretical distribution.

5.1.4.1 Ljung-Box Q statistics

The Q-statistic developed by Box and Pierce (1970) is used to test whether the group of correlation coefficients are equal to zero. The Q-statistic is computed as follows:

$$Q = T \sum_{j=1}^{m} \tau_j^2 \tag{36}$$

where T is the sample size, m is the maximum lag length and τ_j is the *j*th lag autocorrelation of the time series. The correlation coefficients are squared so that positive and negative coefficients do not cancel out each other. The Q-statistic is asymptotically distributed as chi-square (χ^2) distribution with *m* degrees of freedom under the assumption that error terms are serially uncorrelated. If the sum of the autocorrelation coefficients exceeds the critical value, the null hypothesis of no autocorrelation is rejected.

However, the Box-Pierce test has poor performance and leads to wrong decision frequently in small samples since it has poor small sample properties. Therefore, another portmanteau test developed by Ljung and Box (1978) is preferred which is better for all sample sizes. This study also employs the Ljung-Box Q-statistic test which is shown as

$$Q = T(T+2)\sum_{j=1}^{m}\frac{\tau_j^2}{T-j} \tag{37}$$

The null hypothesis of the Ljung-Box Q-statistic is there is no series autocorrelation and this Q-statistic is also treated as a $\chi^2$with *m* degrees of freedom. Rejection of the null hypothesis that the sequence of error terms is serially uncorrelated is equivalent to rejection of the null hypothesis of no ARCH or GARCH errors.

5.1.4.2 ARCH-LM test

The purpose of the heteroscedasticity test is to examine the null hypothesis of constant variance in random variables. The ARCH-LM test of Engle (1982) is chosen to test the presence of additional ARCH effects in the squared residuals. The testing problem can be formulated as the test of the null hypothesis that the ARCH coefficient is higher than zero which is shown below;

$$H_0\colon \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0$$

$$H_1\colon \alpha_i > 0\ for\ at\ least\ one\ i = 1,2,\ldots,q$$

ARCH-LM test is performed by first obtaining the residuals from the ordinary least squares regression of the conditional mean equation and then regressing the squared residuals on its own lags and saving the regressed R square. The test result is found by multiplying number of observations by the R^2 and this number is evaluated under χ^2 distribution with the lag number as degree of freedom. If the value exceeds the critical value, it indicates that the null hypothesis can be rejected meaning the series appear to be nonstationary stochastic process with the variance that is changing through time.

5.1.4.3 Pearson chi-squared goodness-of-fit test

The appropriateness of the model is checked by performing Pearson chi-squared goodness-of-fit test on the residuals of the estimated models. The Pearson goodness-of-fit test compares the empirical distribution of the standardized residuals with theoretical distribution. Vlaar and Palm (1993) classify the residuals in cells according to their magnitude. For a i.i.d. process, the Pearson goodness-of-fit statistics can be shown by

$$P(g) = \sum_{i=1}^{g} \frac{(n_i - En_i)^2}{En_i} \sim \chi^2(g-1) \tag{38}$$

where g is the number of cells, n_i is the number of observations in each cell and En_i is the expected number of observations. The Pearson goodness-of-fit statistic is distributed as $\chi^2(g-1)$ for a model with a null hypothesis of a correct distribution, Although there is no consensus on the proper choice of g in the literature, 60 is used for the analyzed sample size.

5.2. Forecasting Value at Risk

Value at risk (VaR, hereafter) is widely used as a standard measure of the market risk for financial risk management by institutions including banks, regulators and portfolio managers. It is formally defined by Jorion (2001) as “the worst loss over a target horizon with a given level of confidence”. In other words, VaR is quantile measure of risk expressing expected loss resulting from potential market movements with a specified probability over a period of time. VaR is therefore a statistical measure of variability in the value of a portfolio of positions or earnings from economic activity arising from the changes in the market prices of the commodities or other variables underlying the portfolio or activity. The advantage of VaR is that exposure to downside risk can be summarized as a single number and can be applied easily by financial managers.

Accordingly, VaR is the value for which $[abs(loss)] < \alpha$, where α denotes the confidence level. For instance, a portfolio with one-day VaR value of $10 million at a confidence level 99% indicates that the loss in the value of portfolio under consideration will not exceed $10 million 99 out 100 days.

To calculate the VaR of a portfolio, let W_o as the initial portfolio investment and R as its rate of return. The expected value of portfolio at the end of a chosen time horizon is

$$W = W_0(1 + R) \qquad (39)$$

Also, assume that expected return and volatility of R is shown by μ and σ. Since the lowest portfolio value at a particular confidence level *c* is considered, the rate of return R^* resulting in lowest portfolio value W^* is calculated as

$$W^* = W_0(1 + R^*) \quad (40)$$

The estimate of VaR relative to mean is defined as

$$VaR = E(W) - W^* = W_0(1 + \mu) - W_O(1 + R^*) \quad (41)$$

Simply,

$$VaR = -W_O(R^* - \mu)$$

An accurate estimate of VaR is provided by identifying cutoff return R^* associated with the portfolio W^*. Many methodologies have been developed to estimate these cutoff returns. However, no consensus has been reached on the best way to implement VaR analysis. Most of the methodological approaches based on estimation of the statistical distributions of the asset returns. The main approaches to VaR calculation fall into three groups that are[15]:

- Parametric Models (Variance-Covariance Method, RiskMetrics and GARCH)
- Nonparametric Models (Historical Simulation)
- Semiparametric Models (Extreme Value Theory, Conditional Value at Risk and Quasi-Maximum Likelihood GARCH)

The parametric approach obliged a specific distributional assumption on conditional asset returns. This approach involves estimate of the variance-covariance matrix of asset returns, using historical time series asset returns to calculate standard deviations and correlations. A representative member of this class of models is the conditional

[15] The number and types of approaches to VaR estimation is growing exponentially and it’s impossible to take all of them into account. In particular,Monte Carlo simulation and stress testing are commonly used methods that will not be discussed here.

normal case with time-varying volatility, where volatility is estimated from recent past data. However, nonparametric approach uses historical data directly without imposing a specific set of distributional assumptions. Historical simulation is the simplest and most prominent representative of this class of models. Moreover, semiparametric models combine both approaches in one model.

5.2.1. Parametric Models

The VaR calculation can be simplified considerably if the distribution can be assumed to belong to a parametric family, such as the normal distribution. When this is the assumption, the VaR figure can be derived directly from the portfolio standard deviation using a multiplicative factor that depends on the confidence level. This method is simple and convenient and produces more accurate results.

VaR of the portfolio can be expressed as

$$VaR = W_O \alpha \sigma \sqrt{\Delta t} \tag{42}$$

where W_O is the initial portfolio investment, α stands for the critical value for a required confidence level, σ is the volatility forecast of the portfolio return and Δt is the time interval. In other words, the VaR is simply a multiple of the standard deviation of the distribution times an adjustment factor that is directly related to the confidence level and time horizon. Therefore, parametric models involve a good estimation of volatility parameter that describes the asset or the portfolio.

Most of the researchers focused on the computation of the VaR for negative returns.[16] In fact, it is assumed that investors have long positions and are concerned about decreases in the value (price) of the asset. However, investors also have short

[16] See for example van den Goorbergh and Vlaar, 1999 and Jorion, 2001.

trading positions when they borrow the asset and sell in the market and expect a price fall in order to buy the asset at a lower price and give it back to the lender. In the long trading positions, the risk arises from a decrease in the price of the assets, while the investor with a short position loses money when the price increases. The long side of the daily VaR is defined as the VaR level for traders having long positions in the relevant equity index. This is the common VaR where traders incur losses when negative returns are observed. Correspondingly, the short side of the daily VaR is the VaR level for traders who incur losses when stock price increases. The performance of a model at predicting short VaR is thus related to its ability to model positive returns, while its performance regarding the long side of the VaR is based on its ability to take into account large negative returns. Therefore, I will also focus on modeling VaR for portfolios defined on long and short trading positions.

Under a probabilistic framework, we are interested in the risk of a financial position at time t. Let R_t be the change in the value of assets from time t-1 to t. By the definition of VaR for long and short trading positions

$$\alpha = P\left(R_t, VaR_{t,Long}\right) = P\left(\frac{R_t - \mu_t}{\sigma_t} < \frac{VaR_{t,Long} - \mu_t}{\sigma_t}\right) \tag{43}$$

$$\alpha = P\left(R_t, VaR_{t,Short}\right) = P\left(\frac{R_t - \mu_t}{\sigma_t} > \frac{VaR_{t,Short} - \mu_t}{\sigma_t}\right) \tag{44}$$

In this study, models are estimated under three different distributional assumptions including normal, Student-*t* and skewed Student-*t*. The one-step-ahead VaRs of α quantile for long and short trading position are estimated as:

Under normal distribution,

$$VaR_{Long} = \widehat{\mu_t} - z_\alpha \widehat{\sigma_t} \tag{45}$$

$$VaR_{Short} = \widehat{\mu_t} + z_\alpha \widehat{\sigma_t} \tag{46}$$

where $\widehat{\mu_t}$ is the conditional mean and $\widehat{\sigma_t}$ is the conditional variance at time t and z_α is the left or right quantile at $\alpha\%$ for the normal distribution Under Student-*t* distribution,

$$VaR_{Long} = \widehat{\mu_t} - st_{\alpha,v} \widehat{\sigma_t} \tag{47}$$

$$VaR_{Short} = \widehat{\mu_t} + st_{\alpha,v} \widehat{\sigma_t} \tag{48}$$

where $st_{\alpha,v}$ is the left or right quantile at $\alpha\%$ for the Student-*t* distribution.
Under skewed Student-*t* distribution,

$$VaR_{Long} = \widehat{\mu_t} - skst_{\alpha,v,k} \widehat{\sigma_t} \tag{49}$$

$$VaR_{Short} = \widehat{\mu_t} + skst_{\alpha,v,k} \widehat{\sigma_t} \tag{50}$$

where $skst_{\alpha,v,k}$ is the left or right quantile at $\alpha\%$ for the skewed Student-*t* distribution with *v* degrees of freedom and asymmetry coefficient *k*. If $k<1$, the VaR value for long trading position will be bigger than that of short trading position, and vice versa.

5.2.2. Measure of accuracy for VaR estimates

The effectiveness and accuracy of the computed VaR estimates are tested by computing their empirical failure rate both for the left and right tails of the distribution of the returns and then performing the Kupiec likelihood ratio (LR) test (Kupiec, 1995). It attempts to prove whether the observed frequency of exceptions conforms to the frequency of true exceptions according to the model and chosen confidence interval. The failure rate is defined as the proportion of the number of times the return exceed the forecasted VaR in the sample (x) to the number of all sample (N). The number of exceptions x follows a binomial distribution and the probability of experiencing x or more exceptions is

$$P(x, f, N) = C_x^N (1-f)^{N-x} f^x \tag{51}$$

where C_x^N signifies the binomial coefficient of N objects taken x at a time. The failure rate is defined as $\hat{f}$, where:

$$\hat{f} = \frac{x}{N} \tag{52}$$

The Kupiec LR test is employed to assess the difference between the prescribed VaR confidence level α and failure rate. Preferably, the failure rate should be equal or very close to the prescribed VaR level α to conclude that VaR is specified very well. Thus, null and alternative hypotheses are:

$$\mathrm{H_0: f = \alpha} \quad \text{and}$$

$$\mathrm{H_1: f \neq \alpha}$$

where f is the failure rate, the probability of a failure on any one of the independent trials, estimated by the empirical failure rate $\hat{f}$, and α is the model's prescribed probability. The statistic of Kupiec LR test is given by

$$LR = -2log \frac{\alpha^x (1-\alpha)^{N-x}}{\hat{f}^x (1-\hat{f})^{N-x}} \tag{53}$$

Under the null hypothesis that f is the true failure rate, the LR test statistic is asymptotically distributed as chi-square (χ^2) with 1 degree of freedom.

CHAPTER 6

EMPIRICAL RESULTS

6.1 Data Analysis and Descriptive Statistics

This section presents a comprehensive analysis of the statistical and time series properties of the data that is used in the research. The raw data set is composed of daily stock price indices of eleven new European Union members namely Malta (MALTEX), Slovenia (SVSM), Estonia (TALSE), Latvia (RIGSE), Lithuania (NSEL30), Poland (WIG20), the Czech Republic (PX), Slovakia (SKSM), Hungary (BUX), Romania (BET), Bulgaria(SOFIX)[17], and three candidate countries, Croatia (CROBEX), Macedonia (MBI10) and Turkey(XU100)[18]. Data for each of the series are obtained from Datastream and Bloomberg database in US dollars. The daily stock returns are calculated as the logarithmic difference of the daily closing index values as $r_t = lnI_t - lnI_{t-1}$, where I_t is the index value for date t.

The descriptive statistics for these seventeen stock indices are reported in Table 6.[19] In particular, the table reports the first four moments of each return series namely mean, standard deviation, skewness and excess kurtosis; the Jarque Bera statistics for normality, sample size, sample period and Ljung-Box Q-statistics for detecting serial correlation in standardized residuals and standardized squared residuals. The huge

[17] Cyprus which is also a new EU country is not included in the analysis because of the data availability constraints.
[18] The descriptions of stock indices that are used in the analysis are shown in Appendix A.
[19] The plots of the stock indices and the respective return series are presented in Appendix B.

magnitudes of Jarque-Bera statistics show that there are significant departures from normality by referring to *p-values* for all return series. Thus, all return series do not correspond with the normal distribution assumption. The highest averages of daily returns are in Macedonia (0.10%) and Turkey (0.07%). Not surprisingly, Turkey has the highest standard deviation (3.34%) of the daily stock returns which is a characteristic of emerging markets. Also, Poland and Romania have higher standard deviation than the other markets despite lower returns. This could be explained by the fact that low liquidity of the stock markets of these countries. According to the sample excess kurtosis estimates, the daily rate of returns are far from being Gaussian. The highest kurtosis estimates are 12.0 (the Czech Republic) and 11.8 (Latvia), while the lowest estimates are 3.1 (Poland) and 4.0 (Slovenia). Based on the sample kurtosis, it could be argued that residuals appear to be leptokurtic or fat-tailed and peaked about the mean.

The sample skewness shows that daily returns have an asymmetric distribution. Most of the series are negatively skewed with an exception of Croatia, Estonia, Malta and Slovenia. This indicates that the asymmetric tail extends more towards negative values than positive ones in most of the series. The negative skewness, high kurtosis and the rejection of the normality test by the Jarque-Bera test for most of the series corroborate the general empirical finding that daily returns are far from being normally distributed.

The hypothesis of a white noise process for the sample return series is also examined by employing Ljung-Box Q statistic for return residuals (Q (20)) and squared return residuals (Q_s(20)). The test statistics are distributed as a chi-square distribution with 20 degrees of freedom under the null hypothesis of white noise. Q statistics for return residuals and squared return residuals reveal that there is a significant serial correlation among residuals up to 20^{th} lag which also shows conditional heteroscedasticity in the return series. In particular, Q statistics affirm that these return and squared return residuals are autocorrelated and fail to be an independently and i.i.d. process.

6.2. Stationarity

Before performing time series analysis, the stationarity of the series must be determined because the stationarity or otherwise of a series can strongly influence its behavior and properties. A stationarity of the series can be defined as "*one with a constant mean, constant variance and constant autocovariances for each given lag*" (Brooks, 2002, p.367). For a stationarity process, the effect of shocks is temporary and will gradually die away. However, in nonstationarity series time dependence exists and the persistence of shocks will always be infinite. Therefore, stochastic trends in the autoregressive representation of each individual time series should be tested using unit root tests. For robustness purposes, both Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and KPSS tests (Kwaitkowski *et al*., 1992) are used to check whether or not the return series are stationary. These tests differ in their null hypothesis. While the null hypothesis of ADF test is that the time series contain a unit root, the KPSS test has the null hypothesis of stationarity. An important issue for the implementation of the ADF and KPSS tests is the specification of the lag length. If the lag length is too small, it will not remove the autocorrelation in the errors and bias the test. Otherwise, if the lag length is too large, it will increase the coefficient standard errors and the test will suffer. Therefore, Schwarz information criterion

Table 6: Descriptive statistics of sample return series

	Mean	SD	Skewness	Excess Kurtosis	JB	Sample size	Sample period[a]	Q(20)	Qs(20)
Bulgaria	0.0001	0.0169	-0.6071	5.7533	770.46*	2033	1/2/2002	38.21*	635.02*
Croatia	0.0006	0.0184	0.1092	10.3680	8074.90*	1802	6/17/2002	70.55*	1167.81*
Czech Republic	0.0004	0.0177	-0.1271	12.0140	20938.00*	3480	1/8/1996	107.08*	4376.39*
Estonia	0.0006	0.0142	0.4213	7.7710	7046.70*	2768	1/4/1999	115.31*	510.38*
Hungary	0.0006	0.0213	-0.4353	9.6146	14496.00*	3733	1/1/1995	87.29*	2251.84*
Latvia	0.0005	0.0173	-0.6861	11.8730	14957.00*	2513	1/3/2000	164.86*	3927.33*
Lithuania	0.0005	0.0145	-0.2641	18.992	35705.0*	2374	4/2/2000	158.48*	780.24*
Macedonia	0.0010	0.0202	-0.6930	7.3188	2760.4*	1194	12/30/2004	325.08*	251.50*
Malta	0.0005	0.0109	0.5483	5.0662	3023.9*	3333	1/4/1999	214.17*	488.97*
Poland	0.0001	0.0224	-0.1671	3.1058	1564.90*	3849	6/6/1994	75.03*	2492.04*
Romania	0.0000	0.0228	-0.3106	7.8858	7771.8*	2981	9/22/1997	75.59*	911.81*
Slovakia	0.0005	0.0166	1.6797	32.302	9049.1*	3836	9/14/1993	215.12*	1209.84*
Slovenia	0.0004	0.0122	0.3820	4.0368	1518.4*	2685	1/5/1999	125.09*	125.54*
Turkey	0.0007	0.0334	-0.2252	4.6491	4280.10*	4696	1/2/1991	55.99*	1641.88*

Notes: SD indicates standard deviation. Jarque-Bera normality test statistic has a chi-square distribution with 2 degrees of freedom.
* denotes significance at 1% level. Q(20) and Qs(20) are the Ljung-Box statistics for returns and squared returns, respectively.
[a] The end of sample period is 12/09/2009 for all return series except Slovakia. Slovakia's sample period ends at 05/27/2008 due to data availability.

developed by Schwarz (1978) is used in order to determine optimum number of lags of the dependent variable for ADF test and Newey and West's (1994) bandwidth selection procedure is applied for KPSS test. Table 7 summarizes the results of the ADF and KPSS tests for the sample return series that are performed based on a regression with and without a time trend. The null hypothesis of a unit root in the ADF test is strongly rejected for all of the series while the KPSS test statistics are insignificant to reject the null of stationarity, indicating that all return series are stationary, I(0). Thus, the return series are suitable for the further analysis.

Table 7: ADF and KPSS unit root results

	ADF		KPSS	
	η_μ	η_τ	η_μ	η_τ
Bulgaria	-43.525*(0)	-43.527*(0)	0.163(10)	0.135(10)
Croatia	-22.816*(2)	-22.860*(2)	0.397(11)	0.088(10)
Czech Republic	-56.460*(0)	-56.500*(0)	0.425(5)	0.107(3)
Estonia	-46.130*(0)	-46.150*(0)	0.328(21)	0.105(21)
Hungary	-57.903*(0)	-57.902*(0)	0.091(7)	0.066(7)
Latvia	-30.659*(1)	-30.728*(1)	0.366(16)	0.088(18)
Lithuania	-45.763*(0)	-45.824*(0)	0.392(27)	0.092(27)
Macedonia	-20.544*(1)	-20.737*(1)	0.364(11)	0.053(10)
Malta	-41.378*(0)	-41.407*(0)	0.296(19)	0.085(19)
Poland	-55.086*(0)	-55.082*(0)	0.085(2)	0.058(2)
Romania	-50.583*(0)	50.610*(0)	0.295(19)	0.078(19)
Slovakia	-16.397*(7)	-16.427*(7)	0.301(33)	0.133(32)
Slovenia	-42.443*(0)	-42.454*(0)	0.441(15)	0.038(15)
Turkey	-64.371*(0)	-64.370*(0)	0.055(16)	0.029(16)

Note: η_μ and η_τ refer to the test statistics with and without trend, respectively. Numbers in parenthesis are the optimum number of lags determined according to Schwarz information criterion for ADF and Newey and West's (1994) bandwidth selection procedure for KPSS. The critical values of ADF test based on Davidson and MacKinnon (1993) values are -2.565 (99%), -1.940 (95%) and -3.961 (99%), -3.411 (95%) with no trend and with trend, respectively. Critical values for KPSS are 0.739 and 0.463, for the model without trend; 0.216 and 0.146 for the model with trend and for 1% and 5% respectively (Kwiatkowski et al., 1992).
* and ** denotes rejection of null hypothesis at 1% and 5% level respectively

6.3. Empirical Results for Volatility Modelling

6.3.1. Long Memory in Returns

In this section, some specifications of the ARFIMA model with different orders of autoregressive and moving average terms *(p,q)* are estimated and the performance of these specifications are compared in order to determine the optimum lag order in detecting the long memory property in the index return series. Sowell's (1992) maximum likelihood method is used to estimate the long memory parameter in return equation. This method estimates not only the long memory parameter but simultaneously estimates the components of the ARMA process (short-memory).

Therefore, the ARFIMA model by Sowell (1992) maximum likelihood method requires the correct specification of the ARMA order to obtain the final ARFIMA specification. All of the possible combinations for ARMA *(p,q)* are considered with a maximum of two autoregressive and two moving average terms ($p \in (0.2) and\ q \in (0,2)$) for each sample return series following the study of Cheung (1993). An ARFIMA (p,ξ,q) process is specified for the conditional mean equation using a conventional model selection criterion, Akaike's information criterion[20] (AIC) and log likelihood value that eliminates serial correlation from residuals. The estimation results and diagnostic statistics are reported in Tables 8a and 8b. The best models that describe the data are reported in the top row of the tables.

The *t-statistics* are used with the purpose of testing the null hypothesis of nonfractional process (H_0: $d = 0$) beside the alternative hypothesis of fractional process (H_1: $d \neq 0$). The results show that estimates of long memory parameter (ξ)

[20] If ΰ is the value of maximized likelihood, the AIC statistics is defined as -2(ΰ/n)+(2(p+q+2))/n where n is the number of estimated parameters. Note that a lowest AIC corresponds to a better fit.

are different from zero and statistically significant for sample index return series except for Bulgaria, Croatia, Latvia, Malta and Poland. Therefore, the ARFIMA models support the evidence of long memory in nine of the fourteen new EU member and candidate countries' index returns. Since the estimated significant d values for the eight countries are in the stationary region *($0< \xi <0.5$)*, the value of ξ is negative only for Lithuania indicating the presence of negative persistence or antipersistence in the returns. Having long memory in the stationary region implies that the market would return to its long-term trend sometime in the future and stock prices follow a predictable behavior (Assaf, 2006; Kasman *et al.,* 2009) In other words, the correlations between price movements of the stock indices and any shock will have a lasting impact (Henry, 2002) and die out very slowly.

The existence of long-term dependence in financial time series has important implications for the measurement of efficiency in financial markets. The traditional efficient market hypothesis (EMH, hereafter) of Fama (1970) implies that stock prices fully reflect all available information. In support of this hypothesis, stock returns show a random walk causing it impossible to make a prediction from past returns. Even in weak-form efficiency future prices can not be predicted by analyzing prices from the past and changes in stock prices are white noise processes. However, if series exhibits long-term dependence, the arrival of new information can not be arbitraged away (Mandelbrot, 1971) and this will not support even the existence of weak-form efficiency. Hence, the results support that most of the transition stock markets namely the Czech Republic, Estonia, Hungary, Macedonia, Romania, Slovakia, Slovenia and Turkey indicates a strict long memory process which would be a radical departure from the random walk hypothesis. Besides this outcome, the studies of Cajueiro and Tabak (2006), Chow et al. (1996), Henry (2002) found

Table 8a: Estimation results of ARFIMA models

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania
	(1,ξ,0)	(0,ξ,0)	(1,ξ,0)	(2,ξ,0)	(0,ξ,0)	(2,ξ,2)	(1,ξ,1)
μ	0.0002	0.0014*	0.0003	0.0010**	0.0008***	0.0010*	0.0012*
	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
Φ_1	0.0420	-	0.0868*	0.0174	-	1.5022*	0.9720*
	(0.0389)		(0.0287)	(0.0383)		(0.0561)	(0.0160)
Φ_2	-	-	-	-0.0441***	-	-0.8307*	-
				(0.0261)		(0.0439)	
ξ	0.0371	-0.0109	0.0381***	0.0774**	0.0641*	-0.0497	-0.0779**
	(0.0304)	(0.0207)	(0.0221)	(0.0324)	(0.0136)	(0.0307)	(0.0344)
θ_1	-	-	-	-	-	-1.3534*	-0.9347*
						(0.0727)	(0.0313)
θ_2	-	-	-	-	-	0.7369*	-
						(0.0462)	
ln(L)	4919.39	3753.55	9565.80	6744.24	9380.64	5562.11	5709.35
AIC	-5.5074	-5.7612	-5.7256	-5.9429	-5.18	-5.5192	-6.0879
Skewness	-0.3940	0.9256	-0.2168	0.6658	-0.58	-0.6192	-0.1458
Excess kurtosis	5.39	19.04	1.84	9.28	9.31	14.04	40.59
JB	727.26*	2305.90*	283.48*	1686.30*	2838.00*	16657.00*	8994.00*
Q(20)	31.59**	31.07**	33.82**	25.32***	52.19*	61.55*	15.47
ARCH(5)	23.59*	47.07*	57.60*	5.09*	94.10*	132.55*	59.69*

Notes: Standard errors are reported in the parentheses below corresponding parameter estimates. *ln*(L) is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria. The Q(20) is the Ljung-Box test test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(5) denotes the ARCH statistic with lag 5. The skewness and excess kurtosis are also based on standardized residuals.

*,**, and *** indicate significance levels at the 1%, 5% and 10% respectively.

Table 8b: Estimation results of ARFIMA models

	Macedonia	Malta	Poland	Romania	Slovakia	Slovenia	Turkey
	(2,ξ,2)	(2,ξ,0)	(0,ξ,1)	(1,ξ,0)	(2,ξ,2)	(2,ξ,1)	(0,ξ,0)
μ	0.0028	0.0007**	0.0004	0.0004	0.0005	0.0010	0.0003
	(0.0029)	(0.0003)	(0.0004)	(0.0007)	(0.0015)	(0.0006)	(0.0007)
Φ_1	1.1158*	0.2214*	-	-0.7394*	0.8178**	0.7126*	-
	(0.1459)	(0.0376)		(0.1730)	(0.6324)	(0.0748)	
Φ_2	-0.4387*	0.0217	-	-	-0.3521**	-0.1098*	-
	(0.1368)	(0.0231)			(0.1639)	(0.0322)	
ξ	0.2754***	0.0246	-0.0045	0.0812*	0.2313*	0.2005**	0.0376*
	(0.1433)	(0.0309)	(0.0205)	(0.0177)	(0.0418)	(0.0791)	(0.0124)
θ_1	-0.8429*	-	0.1325*	0.7098*	-1.0189	-0.7232*	-
	(0.2642)		(0.0256)	(0.1825)	(0.6243)	(0.1178)	
θ_2	0.1140	-	-	-	0.4135	-	-
	(0.1772)				(0.3054)		
ln(L)	1964.11	6950.04	8292.15	6139.61	8806.54	7132.03	8298.30
AIC	-5.6401	-6.3108	-4.9496	-4.9453	-5.2771	-6.5167	-3.9548
Skewness	-0.0042	0.5812	-0.1541	-0.1020	1.1524	0.3352	-0.1826
Excess kurtosis	3.24	4.87	2.58	11.84	24.84	3.97	4.6763
JB	161.36*	654.92*	503.11*	3092.00*	7376.7*	584.09*	1513.60*
Q(20)	20.32	42.04*	20.87	22.21	36.23*	17.72	31.55**
ARCH(5)	21.67*	31.13*	115.52*	74.47*	64.34*	35.81*	112.49*

Notes: See Table 8a.

evidence of long memory in stock returns of small and underdeveloped markets that is consistent with this study.

Diagnostic statistics reveal that the standardized residuals display large skewness and excess kurtosis statistics representing departure from normality assumption. Most of the residuals are negatively skewed confirming nonsymmetrical distribution. The residuals also exhibit large value of kurtosis statistics indicating that they are sharply peaked about the mean which is also termed as fat tailed when compared with the Gaussian distribution. In addition, rejection of the normality tests by Jarque-Bera implying that the residuals appear to be leptokurtic. Moreover, highly significant ARCH test statistics show the presence of ARCH effects in the standardized residuals. The hypothesis of no autocorrelation is strongly rejected according to Ljung-Box Q statistics in most of the series indicating that the residuals are not independent. Hence, these diagnostic statistics imply that modelling only the level of returns does not provide a clear picture on the presence of long memory property in the new EU member and candidate countries.

Table 9a: Estimation results of AR(FI)MA-GARCH models

	Bulgaria			Croatia			Czech Republic		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0009*	0.0008*	0.0006***	0.0014*	0.0013*	0.0014*	0.0008*	0.0009*	0.0007**
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Φ_1	0.0674**	0.0360	0.0340	-	-	-	0.0805*	0.0647**	0.0637**
	(0.0275)	(0.0245)	(0.0246)				(0.0308)	(0.0279)	(0.0280)
Φ_2	-	-	-	-	-	-	-	-	-
ξ	-	-	-	-	-	-	0.0480**	0.0507**	0.0518**
							(0.0243)	(0.0214)	(0.0215)
θ_1	-	-	-	-	-	-	-	-	-
θ_2	-	-	-	-	-	-	-	-	-
ω	0.0399***	0.0448**	0.0462**	0.5147*	0.4149*	0.4091*	0.0526*	0.0440*	0.0460*
	(0.0235)	(0.0192)	(0.0195)	(0.1508)	(0.1182)	(0.1156)	(0.0182)	(0.0140)	(0.0146)
α_1	0.0801*	0.0909*	0.0892*	0.1679*	0.1500*	0.1501*	0.1039*	0.1081*	0.1095*
	(0.0268)	(0.0237)	(0.0235)	(0.0472)	(0.0388)	(0.0388)	(0.0157)	(0.0163)	(0.0167)
β_1	0.9061*	0.8944*	0.8946*	0.5165*	0.5968*	0.6005*	0.8710*	0.8732*	0.8704*
	(0.0320)	(0.0265)	(0.0267)	(0.1040)	(0.0876)	(0.0861)	(0.0212)	(0.0199)	(0.0207)
v	-	4.8093*	4.8371*	-	4.7272*	0.0457*	-	8.2799*	8.6043*
		(0.5737)	(0.5770)		(0.5850)	(0.5901)		(1.0912)	(1.1662)
ln(k)	-	-	-0.0546***	-	-	0.0404	-	-	-0.0596**
			(0.0312)			(0.0457)			(0.0248)
ln(L)	5093.69	5186.56	5187.99	3877.35	3946.21	3946.69	9817.72	9865.29	9868.17
AIC	-5.70	-5.80	-5.81	-5.95	-6.05	-6.05	-5.88	-5.90	-5.90
Q(20)	26.24	30.51**	31.60**	19.43	19.70	19.70	24.61	25.03	25.09
Qs(20)	7.50	7.39	7.37	16.61	16.45	16.44	15.43	15.41	15.71
ARCH(5)	0.40	0.35	0.36	1.92***	1.90***	1.86***	0.50	0.44	0.44
P(60)	160.04*	67.20	49.12	94.59*	58.37	62.42	80.86**	59.41	52.55

Notes: Standard errors are reported in the parentheses below corresponding parameter estimates. ln(L) is the value of the maximized Gaussian log likelihood and AIC is the Akaike information criterion. The Q(20) and $Q_s(20)$ are the Ljung-Box test statistics with 20 degrees of freedom on the standardized residuals and squared residuals, respectively. ARCH(5) represents the t-statistics of ARCH test statistic with lag 5. P(60) is the Pearson goodness-of-fit test statistic for 60 cells. *, ** and ** indicate significance levels at 1%, 5% and 10%, respectively.

Table 9b: Estimation results of AR(FI)MA-GARCH models

	Estonia			Hungary			Latvia		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0010**	0.0009**	0.0010**	0.0009***	0.0010*	0.0008**	0.0012*	0.0008*	0.0011*
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Φ_1	0.0210	0.0139	0.0142	-	-	-	-	-	-
	(0.0561)	(0.0383)	(0.0383)						
Φ_2	-0.0397	-0.0458***	-0.0457***	-	-	-	-	-	-
	(0.0302)	(0.0267)	(0.0267)						
ξ	0.0880***	0.0910*	0.0913*	0.0830*	0.0575*	0.0571*	-	-	-
	(0.0507)	(0.0323)	(0.0323)	(0.0176)	(0.0155)	(0.0154)			
θ_1	-	-	-	-	-	-	-	-	-
θ_2	-	-	-	-	-	-	-	-	-
ω	0.0204	0.0475*	0.0475*	0.2128*	0.1399*	0.1414*	0.1005***	0.1072**	0.1077**
	(0.0141)	(0.0164)	(0.0164)	(0.0802)	(0.0400)	(0.0407)	(0.0607)	(0.0444)	(0.0420)
α_1	0.0587*	0.0865*	0.0867*	0.1618*	0.1438*	0.1445*	0.1395**	0.1645*	0.1713*
	(0.0129)	(0.0185)	(0.0185)	(0.0390)	(0.0236)	(0.0239)	(0.0625)	(0.0516)	(0.0508)
β_1	0.9311*	0.8827*	0.8824*	0.7774*	0.8172*	0.8160*	0.8032*	0.7782*	0.7722*
	(0.0209)	(0.0254)	(0.0254)	(0.0509)	(0.0306)	(0.0310)	(0.0909)	(0.0692)	(0.0661)
v	-	5.5216*	5.5269*	-	5.4233*	5.4405*	-	4.4434*	4.5332*
		(0.6928)	(0.6911)		(0.5277)	(0.5295)		(0.4703)	(0.4825)
ln(k)	-	-	0.0149	-	-	-0.0384***	-	-	0.0718**
			(0.0320)			(0.0223)			(0.0282)
ln(L)	6884.43	7018.33	7018.45	9821.41	10004.21	10005.61	6086.60	6221.27	6224.13
AIC	-6.06	-6.18	-6.18	-5.42	-5.52	-5.52	-6.04	-6.18	-6.18
Q(20)	17.82	16.78	16.70	33.65**	41.62*	41.85*	22.77	22.91	23.04
Qs(20)	6.34	4.81	4.80	7.89	6.89	6.96	21.20	18.08	17.44
ARCH(5)	0.44	0.33	0.33	0.26	0.29	0.30	0.92	0.57	0.50
P(60)	106.39*	57.40	60.78	149.98*	65.12	60.88	166.64*	72.87	42.65

Notes: See Table 9a

6.3.2. Estimation Results of ARFIMA-GARCH and dual long memory models

In this section, we model the conditional mean as a ARFIMA *(p, ξ,q)* process and the conditional variances as a GARCH, EGARCH[21], FIGARCH and HYGARCH processes[22]. The performances of these specifications in modeling volatility are compared and the best fitting orders are determined under three different distributional assumptions: the normal, Student-t and skewed Student-t. For each of the fourteen stock indices, the models with best fitting orders are estimated for ARFIMA-GARCH, ARFIMA-FIGARCH and ARFIMA-HYGARCH models.

For conditional mean equations, ARFIMA *(p, ξ,q)* models are used that is specified in the previous section using a conventional model selection criterion, Akaike's information criterion (AIC) that eliminates serial correlation from residuals. The same ARFIMA (*p*,*d*,*q*) specification is used for a given sample when estimating GARCH and its variants' parameters. The *p* and *q* parameters in GARCH type models are also specified based on lowest AIC and highest log likelihood value and simultaneously pass the Ljung-Box Q-statistics are used for the conditional variance equations.

[21] Numerical maximization of the log-likelihood function for the EGARCH model is failed to converge in most of the series. Therefore, EGARCH model is excluded from the estimation results.
[22] The presence of long memory in the conditional variance equations are also examined by using GARCH, FIGARCH and HYGARCH models. However, using ARFIMA in the conditional mean equation provides better results for modeling the volatility process.

Table 9c: Estimation results of AR(FI)MA-GARCH models

	Lithuania			Macedonia			Malta			Poland		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0011**	0.0005	0.0007	0.0031	0.0033	0.0036	0.0005**	0.0005**	0.0005**	0.0009*	0.0008*	0.0009*
	(0.0004)	(0.0008)	(0.0008)	(0.0028)	(0.0028)	(0.0028)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Φ_1	-	0.6391*	0.6422*	1.5361*	1.5363*	1.5357*	0.1497*	0.1435*	0.1436*	-	-	-
		(0.0710)	(0.0726)	(0.1530)	(0.1017)	(0.0990)	(0.0262)	(0.0233)	(0.0233)			
Φ_2	-	-	-	-0.7127*	-0.7267*	-0.7265*	0.0567**	0.0449**	0.0447**	-	-	-
				(0.0887)	(0.0744)	(0.0730)	(0.0248)	(0.0212)	(0.0213)			
ξ	0.0625**	0.2793*	0.2751*	0.5094*	0.5160*	0.5128*	-	-	-	-	-	-
	(0.0279)	(0.0748)	(0.0765)	(0.1057)	(0.0822)	(0.0833)						
θ_1	0.0872***	-0.8028*	-0.8016*	-1.6563*	-1.6514*	-1.6489*	-	-	-	0.1287*	0.1185*	0.1186*
	(0.0455)	(0.0422)	(0.0426)	(0.2236)	(0.1207)	(0.1186)				(0.0189)	(0.0186)	(0.0186)
θ_2	-	-	-	0.7362*	0.7471*	0.7448*	-	-	-	-	-	-
				(0.1925)	(0.1108)	(0.1087)						
ω	0.6285*	0.5528*	0.5497*	0.1941**	0.1929**	0.1871**	0.0605	0.1308*	0.1306*	0.1546*	0.1027*	0.1030*
	(0.1912)	(0.1530)	(0.1573)	(0.0888)	(0.0884)	(0.0919)	(0.0381)	(0.0360)	(0.0361)	(0.0667)	(0.0374)	(0.0376)
α_1	0.1671*	0.2283*	0.2280*	0.2379*	0.2353*	0.2324*	0.1180*	0.1632*	0.1627*	0.1044*	0.0867*	0.0869*
	(0.0448)	(0.0522)	(0.0525)	(0.0642)	(0.0644)	(0.0663)	(0.0326)	(0.0293)	(0.0294)	(0.0281)	(0.0178)	(0.0179)
β_1	0.3033**	0.2021	0.2053	0.6753*	0.6841*	0.6901*	0.8289*	0.0293*	0.7190*	0.8559*	0.8873*	0.8870*
	(0.1459)	(0.1684)	(0.1738)	(0.0903)	(0.0869)	(0.0919)	(0.0670)	(0.0539)	(0.0543)	(0.0417)	(0.0249)	(0.0251)
v	-	4.7161*	4.7120*	-	5.9248*	5.8958*	-	5.4476*	5.4596*	-	10.2409*	10.2085*
		(0.6460)	(0.6438)		(1.2560)	(1.2291)		(0.6739)	(0.6730)		(1.7694)	(1.7489)
ln(k)	-	-	0.0160	-	-	0.0207	-	-	0.0071	-	-	0.0049
			(0.0363)			(0.0591)			(0.0282)			(0.0231)
ln(L)	5884.50	6170.33	6170.44	2047.53	2063.65	2063.72	7086.55	7162.30	7162.32	8601.74	8630.64	8630.66
AIC	-6.27	-6.58	-6.58	-5.87	-5.92	-5.92	-6.43	-6.50	-6.50	-5.13	-5.15	-5.15
Q(20)	17.40	14.17	14.12	20.69	21.05	21.07	30.49**	33.93**	33.98**	12.13	13.47	13.44
Qs(20)	2.29	1.22	1.21	20.03	21.11	21.25	10.02	7.87	7.86	17.35	25.94	25.83
ARCH(5)	0.36	0.16	0.15	0.93	0.94	0.98	0.36	0.36	0.36	1.12	2.34**	2.32**
P(60)	191.42*	60.60	61.37	58.85	47.27	45.71	116.37*	32.52	35.08	72.79	52.94	52.30

Notes: See Table 9a

Table 9d: Estimation results of AR(FI)MA-GARCH models

	Romania			Slovakia			Slovenia			Turkey		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0012	0.0001	0.0008	-0.0004	0.0004	-0.0000	0.0011*	0.0005	0.0004	0.0010	0.0015*	0.0013**
	(0.0009)	(0.0008)	(0.0009)	(0.0006)	(0.0003)	(0.0004)	(0.0004)	(0.0013)	(0.0013)	(0.0007)	(0.0005)	(0.0006)
Φ_1	0.7416*	0.7533*	0.7535*	0.1143	0.1109	0.1305	0.7968*	0.6486*	0.6470*	-	-	-
	(0.0590)	(0.0720)	(0.0720)	(0.4048)	(0.1398)	(0.1315)	(0.1454)	(0.0961)	(0.0960)			
Φ_2	-	-	-	0.0574	0.0375	0.0343	-0.4136*	-0.0468	-0.0468	-	-	-
				(0.0557)	(0.0676)	(0.0673)	(0.1444)	(0.0542)	(0.0536)			
ξ	0.1717*	0.1761*	0.1726*	0.1495*	0.0999*	0.1019*	0.1265*	0.4004**	0.4022**	0.0550*	0.0420*	0.0410*
	(0.0514)	(0.0450)	(0.0454)	(0.0457)	(0.0355)	(0.0359)	(0.0387)	(0.1588)	(0.1583)	(0.0162)	(0.0142)	(0.0142)
θ_1	-0.8282*	-0.8199*	-0.8179*	-0.2896	-0.2308	-0.2520	-0.7061*	-0.8540*	-0.8543*	-	-	-
	(0.0462)	(0.0619)	(0.0625)	(0.4237)	(0.1501)	(0.1416)	(0.1681)	(0.0731)	(0.0723)			
θ_2	-	-	-	-0.0937	-0.0734	-0.0684	0.2939**	-	-	-	-	-
				(0.1361)	(0.0707)	(0.0693)	(0.1469)					
ω	0.3568**	0.6882*	0.6755*	0.1370**	0.1887*	0.1930*	0.1713*	0.0577	0.0593	0.3178*	0.3256*	0.3269*
	(0.1387)	(0.1991)	(0.1960)	(0.0588)	(0.0684)	(0.0667)	(0.0580)	(0.1672)	(0.1853)	(0.0980)	(0.0882)	(0.0886)
α_1	0.2706*	0.3461*	0.3427*	0.1019*	0.0977*	0.1007*	0.1426*	0.0650	0.0659	0.1218*	0.1297*	0.1297*
	(0.0580)	(0.0578)	(0.0576)	(0.0290)	(0.0265)	(0.0262)	(0.0421)	(0.1027)	(0.1121)	(0.0213)	(0.0213)	(0.0213)
β_1	0.6711*	0.5241*	0.5305*	0.8511*	0.8429*	0.8388*	0.6542*	0.8650*	0.8622**	0.8526*	0.8454*	0.8450*
	(0.0746)	(0.0841)	(0.0839)	(0.0430)	(0.0433)	(0.0420)	(0.0973)	(0.3041)	(0.3353)	(0.0269)	(0.0255)	(0.0256)
v	-	4.1790*	4.1739*	-	3.5102*	3.5241*	-	9.1392*	9.1227*	-	6.0787*	6.1143*
		(0.3656)	(0.3613)		(0.2311)	(0.2328)		(1.6619)	(1.6571)		(0.5430)	(0.5446)
ln(k)	-	-	0.0421	-	-	-0.0421**	-	-	-0.0083	-	-	-0.0178
			(0.0278)			(0.0208)			(0.0340)			(0.0215)
ln(L)	6491.56	6651.09	6652.27	9214.19	9495.23	9497.05	7220.98	7244.36	7244.40	8809.46	8931.92	8932.25
AIC	-5.23	-5.36	-5.36	-5.52	-5.69	-5.69	-6.60	-6.62	-6.62	-4.20	-4.26	-4.26
Q(20)	31.75**	23.91	24.05	19.56	25.42	24.97	13.11	14.00	14.00	21.86	26.14	26.55
Qs(20)	15.63	16.75	16.41	30.10**	36.78*	37.27*	19.32	35.36*	35.23*	26.70***	27.05***	27.02***
ARCH(5)	0.76	0.78	0.76	0.58	0.54	0.53	1.92***	4.85*	4.85*	2.01***	1.75	1.75
P(60)	183.93*	70.61	73.22	418.16*	217.12*	211.76*	72.01	59.06	58.29	156.70*	48.46	47.46

Notes: See Table 9a

The results of ARFIMA-GARCH models are reported in Tables 9a, 9b, 9c and 9d under three distributional assumptions. The parameters denoted by ω, α_1 and β_1 satisfy the set of conditions to guarantee the nonnegativity of the conditional variance for all cases. Coefficients of ARCH and GARCH terms are highly significant for all indices confirming the presence of heteroscedasticity in daily returns in line with the results of Kang and Yoon (2009) and Kasch-Haroutounian and Price (2001). The sum of the estimates of α_1 and β_1 is very close to unity in most of the series except Croatia and Lithuania suggesting that return generating process is characterized by a high degree of persistence in the conditional variance. The GARCH parameter β_1 is greater than ARCH parameter α_1 for all cases indicating that these volatilities are influenced by random shocks for long-periods.

The Student- t and skewed Student- t distributions are found to outperform the normal distribution according to higher log likelihood *(ln(L))* and lower Akaike information criteria (*AIC*) values. Also it is evident that the t-statistics of the parameter v is highly significant for all series and the asymmetric parameters *ln(k)* are unequal to zero and statistically significant for five of the fourteen return series. ARFIMA-GARCH skewed student-t distribution model confirming that the densities of five stock return series are skewed. Since the density of Bulgaria, the Czech Republic, Hungary and Slovakia returns is skewed to the left side as a result of their negative parameter, the asymmetric parameter for Latvia returns is significantly positive so that the density is skewed to the right side.

Since long memory dynamics are commonly observed in conditional mean and conditional variance, ARFIMA-FIGARCH and ARFIMA-HYGARCH models with different orders are also estimated under the normal, Student-t and skewed Student-t distributions to analyze the dual long memory property in the series. The estimated results of the ARFIMA-FIGARCH and ARFIMA-HYGARCH models with three different distributional assumptions are collected in Tables 10a, 10b, 10c and 11a, 11b, 11c[23]. Estimated parameters are significant at standard levels for the conditional mean and conditional variance equations in the models. Moreover, the nonnegativity condition of the conditional variance is satisfied for all cases. In the estimates of the models, both long memory parameters ξ and d are significantly different from zero, implying the presence of dual long memory property in the returns and volatility of six of the fourteen EU member and candidate countries. Long memory process is not observed in the conditional variance of Croatia, Latvia, Lithuania, Macedonia and Slovakia stock markets which mean their volatility follow a short memory. Also, I drop the long memory parameter in the conditional mean equations of Bulgaria, Malta and Poland which are found to be insignificant in the ARFIMA models. Actually, it is seen that dual long memory is observed in most of the CEE countries' stock markets in accordance with the prior results of Kasman *et al.* (2009). The parameter d ranging from *0.2265* to *0.4667* significantly rejects the validity of GARCH null hypothesis $(d=0)$ and IGARCH null hypothesis $(d=1)$ for nine out of the fourteen return series. The values of d which are lower than 0.5 confirms that the shock in the series are persistent, but it ends eventually. Consequently, when the stable and long memory models are compared it is observed that the long memory models capture temporal pattern of volatility better than the stable GARCH models in most of the cases.

[23] The presence of dual long memory in conditional mean and variance are also examined for Croatia, Latvia, Lithuania, Macedonia, and Slovenia. However, the long memory parameter d is found to be insignificant for these countries. Therefore, the estimation results are not reported in the tables.

Table 10a: Estimation results of AR(FI)MA-FIGARCH models

	Bulgaria			Czech Republic			Estonia		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0008*	0.0008*	0.0006**	0.0008**	0.0012**	0.0007	0.0010***	0.0009**	0.0010**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0007)	(0.0005)	(0.0004)	(0.0004)
Φ_1	0.0684**	0.0383	0.0367	0.0774**	0.7289*	0.7185*	0.3094	0.7931**	0.7791**
	(0.0275)	(0.0247)	(0.0249)	(0.0312)	(0.0753)	(0.0733)	(0.2123)	(0.3320)	(0.3285)
Φ_2	-	-	-	-	-	-	-0.5789	-0.6252*	-0.6248*
							(0.4047)	(0.2010)	(0.1845)
ξ	-	-	-	0.0541**	0.2126*	0.2240*	0.0952*	0.0914*	0.0920*
				(0.0248)	(0.0586)	(0.0605)	(0.0335)	(0.0238)	(0.0236)
θ_1	-	-	-	-	-0.8309*	-0.8307*	-0.3045	-0.7880**	-0.7738**
					(0.0362)	(0.0335)	(0.2209)	(0.3265)	(0.3238)
θ_2	-	-	-	-	-	-	0.5433	0.6072*	0.6064*
							(0.4379)	(0.2110)	(0.1947)
ω	0.3327**	0.0595***	0.0616***	0.0675**	0.0526*	0.0539*	0.0514	0.3172*	0.3162*
	(0.1334)	(0.0329)	(0.0344)	(0.0298)	(0.0195)	(0.0198)	(0.0464)	(0.0927)	(0.0928)
α_1	-0.4050***	0.4252*	0.4279*	0.2601*	0.2856*	0.2956*	0.4365*	-0.4416**	-0.4415**
	(0.2149)	(0.1300)	(0.1323)	(0.0683)	(0.0619)	(0.0630)	(0.1297)	(0.1885)	(0.1899)
β_1	-0.2654	0.7005*	0.6940*	0.5643*	0.6065*	0.6017*	0.7017*	-0.3405***	-0.3393***
	(0.1988)	(0.1051)	(0.1103)	(0.0903)	(0.0691)	(0.0693)	(0.1927)	(0.1930)	(0.1945)
d	0.2976*	0.4575*	0.4466**	0.4352*	0.4667*	0.4587*	0.3777**	0.2265*	0.2268*
	(0.0556)	(0.1221)	(0.1221)	(0.0887)	(0.0695)	(0.0681)	(0.1602)	(0.0305)	(0.0304)
v	-	4.8886*	4.8981*	-	8.1377*	8.4321*	-	5.6200*	5.6287*
		(0.5687)	(0.5744)		(1.0696)	(1.1362)		(0.6735)	(0.6710)
ln(k)	-	-	-0.0507	-	-	-0.0694*	-	-	0.0205
			(0.0314)			(0.0250)			(0.0329)
ln(L)	5104.84	5186.70	5187.92	9820.46	9874.76	9878.60	6885.34	7026.30	7026.52
AIC	-5.72	-5.81	-5.81	-5.86	-5.91	-5.91	-6.06	-6.19	-6.19
Q(20)	25.76	30.02***	31.02**	25.83	25.27	25.19	18.43	18.54	18.46
Qs(20)	10.53	8.23	8.24	15.65	15.24	15.67	7.65	5.61	5.60
ARCH(5)	0.48	0.29	0.28	0.50	0.56	0.60	0.53	0.35	0.35
P(60)	120.13*	60.87	53.40	84.78**	48.06	41.34	108.35*	44.70	44.38

Notes: See Table 9a

Table 10b: Estimation results of AR(FI)MA-FIGARCH models

	Hungary			Poland			Romania		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0009***	0.0010*	0.0007***	0.0009*	0.0009*	0.0009*	0.0011	0.0001	0.0009
	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0009)	(0.0008)	(0.0009)
Φ_1	-	-	-	-	-	-	0.7329*	0.7281*	0.7303*
							(0.0618)	(0.0738)	(0.0747)
Φ_2	-	-	-	-	-	-	-	-	-
ξ	0.0801*	0.0586*	0.0584*	-	-	-	0.1721*	0.1818*	0.1742*
	(0.0174)	(0.0153)	(0.0152)				(0.0538)	(0.0467)	(0.0473)
θ_1	-	-	-	0.1256*	0.1176*	0.1178*	-0.8183*	-0.8026*	-0.7997*
				(0.0189)	(0.0183)	(0.0183)	(0.0518)	(0.0630)	(0.0658)
θ_2	-	-	-	-	-	-	-	-	-
ω	0.2605***	0.1544*	0.1536*	0.2592**	0.1940**	0.1955**	0.6421*	0.4051	0.3894
	(0.1377)	(0.0540)	(0.0536)	(0.1250)	(0.0878)	(0.0879)	(0.1879)	(0.2469)	(0.2576)
α_1	0.1687	0.2677*	0.2792*	0.3193**	0.3118*	0.3094*	-0.3891*	0.7030*	0.6926*
	(0.1453)	(0.0876)	(0.0876)	(0.1395)	(0.1013)	(0.1017)	(0.1283)	(0.2004)	(0.2278)
β_1	0.3828***	0.4847*	0.4929*	0.4494*	0.5091*	0.5068*	-0.2883*	0.5136**	0.5176***
	(0.1997)	(0.1119)	(0.1120)	(0.1587)	(0.1207)	(0.1210)	(0.1239)	(0.2468)	(0.2775)
d	0.4340**	0.4123*	0.4132*	0.2907*	0.3334*	0.3336*	0.4239*	0.1993***	0.2137***
	(0.1851)	(0.0896)	(0.0915)	(0.0514)	(0.0628)	(0.0625)	(0.0872)	(0.1191)	(0.1273)
v	-	5.3486*	5.3564*	-	10.5572*	10.4801*	-	4.1826*	4.1728*
		(0.5195)	(0.5223)		(1.8831)	(1.8492)		(0.3863)	(0.3831)
ln(k)	-	-	-0.0409***	-	-	0.0096*	-	-	0.0494***
			(0.0229)			(0.0231)			(0.0282)
ln(L)	9821.81	10012.12	10013.66	8611.16	8635.33	8635.41	6504.62	6656.52	6658.10
AIC	-5.42	-5.52	-5.52	-5.14	-5.15	-5.15	-5.24	-5.36	-5.36
Q(20)	35.38**	42.09*	42.23*	12.11	13.43	13.39	27.85	22.29	22.41
Qs(20)	6.97	6.34	6.33	5.93	8.02	8.00	12.14	15.61	15.35
ARCH(5)	0.17	0.13	0.13	0.02	0.18	0.17	0.55	1.12	1.12
P(60)	163.49*	54.06	61.25	72.40	53.05	45.38	179.92*	67.42	54.74

Notes: See Table 9a

Table 10c: Estimation results of AR(FI)MA-FIGARCH models

	Malta			Slovakia			Turkey		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0005**	0.0005**	0.0006**	-0.0004	0.0005	0.0001	0.0012***	0.0015*	0.0014**
	(0.0002)	(0.0002)	(0.0002)	(0.0007)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0006)
Φ_1	0.1486*	0.1435*	0.1435*	0.1387	0.1215	0.1365	-	-	-
	(0.0278)	(0.0231)	(0.0232)	(0.1725)	(0.1358)	(0.1288)			
Φ_2	0.0532**	0.0416**	0.0409***	0.0538	0.0356	0.0334	-	-	-
	(0.0245)	(0.0210)	(0.0211)	(0.0405)	(0.0690)	(0.0688)			
ξ	-	-	-	0.1654*	0.1062*	0.1082*	0.0539*	0.0420*	0.0413*
				(0.0463)	(0.0356)	(0.0361)	(0.0160)	(0.0140)	(0.0141)
θ_1	-	-	-	-0.3317***	-0.2461***	-0.2627***	-	-	-
				(0.1937)	(0.1454)	(0.1383)			
θ_2	-	-	-	-0.0828	-0.0729	-0.0693	-	-	-
				(0.0539)	(0.0726)	(0.0715)			
ω	0.0565	0.1247*	0.1240*	0.1216**	0.4110*	0.4079*	0.4296**	0.5383*	0.5382*
	(0.0638)	(0.0481)	(0.0477)	(0.0547)	(0.1504)	(0.1458)	(0.1945)	(0.2031)	(0.2037)
α_1	0.3326***	0.1902***	0.1893***	0.3580*	0.1096	0.1065	0.2547***	0.1509	0.1502
	(0.1981)	(0.1091)	(0.1091)	(0.0993)	(0.1167)	(0.1124)	(0.1326)	(0.1348)	(0.1359)
β_1	0.5333	0.2880**	0.2878**	0.6172*	0.4536**	0.4669*	0.4638*	0.3838**	0.3817**
	(0.3454)	(0.1241)	(0.1231)	(0.1316)	(0.1862)	(0.1809)	(0.1641)	(0.1653)	(0.1666)
d	0.3515***	0.2598*	0.2581*	0.4210*	0.4456*	0.4649*	0.3825*	0.4039*	0.4029*
	(0.2024)	(0.0733)	(0.0710)	(0.1535)	(0.1463)	(0.1507)	(0.0673)	(0.0620)	(0.0621)
v	-	5.4428*	5.4887*	-	3.1801*	3.1766*	-	6.1862*	6.2151*
		(0.6740)	(0.6800)		(0.2198)	(0.2198)		(0.5498)	(0.5522)
ln(k)	-	-	0.0210	-	-	-0.0362***	-	-	-0.0156
			(0.0285)			(0.0212)			(0.0216)
ln(L)	7089.06	7165.26	7165.52	9219.17	9493.91	9495.21	8829.74	8942.05	8942.30
AIC	-6.44	-6.50	-6.50	-5.52	-5.69	-5.69	-4.21	-4.26	-4.26
Q(20)	29.33**	32.08**	32.27**	16.71	21.78	21.37	24.58	28.46***	28.77***
Qs(20)	7.84	7.32	7.27	23.51	38.86*	38.63*	27.02***	30.99**	30.94**
ARCH(5)	0.29	0.32	0.31	0.25	1.04	1.04	1.55	1.64	1.64
P(60)	118.34*	48.06	48.33	389.23*	201.40*	204.46*	141.28*	61.08	54.15

Notes: See Table 9a

The relevance of the Student-*t* distribution and skewed Student-*t* distribution is verified as seen in the tables. Asymmetry and tail parameters t-statistics are highly significant in most of the return series. The Student-*t* distribution is found to outperform the normal distribution, since the estimates of the degrees of freedom parameter *v* are significantly different from zero for all of the series, validating the existence of leptokurtosis in the returns conditional distribution. For the skewed Student-*t* distribution, the asymmetric parameters $ln(k)$ are statistically significant for five of the selected countries. The lower values of P(60) test statistics reconfirm the relevance of Student-*t* and skewed Student-*t* distribution for all return series. Moreover, the AIC and log likelihood are used to evaluate the in sample goodness of fit of the models. According to these measures, the long memory models under skewed Student-*t* distribution provide a better fit to the data.

Box-Pierce Q statistics, ARCH-LM test of Engle (1982), residual based diagnostic test (RBD) of Tse (1992), Pearson chi-squared goodness-of-fit of Vlaar and Palm (1993) are used to ensure that the standard residuals are not autocorrelated, no remaining ARCH effect left in the series and to compare the empirical distribution of the standardized residuals with theoretical distribution.

Table 11a: Estimation results of AR(FI)MA-HYGARCH models

	Bulgaria			Czech Republic			Estonia		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0007**	0.0008*	0.0006**	0.0008**	0.0009*	0.0007**	0.0010***	0.0009**	0.0011**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0004)
Φ_1	0.0653**	0.0378	0.0363	0.0774**	0.0618**	0.0604**	0.3104	0.7867**	0.7721**
	(0.0273)	(0.0248)	(0.0249)	(0.0314)	(0.0281)	(0.0282)	(0.2250)	(0.3357)	(0.3243)
Φ_2	-	-	-	-	-	-	-0.5735	-0.6163*	-0.6166*
							(0.4217)	(0.2149)	(0.1943)
ξ	-	-	-	0.0535**	0.0557**	0.0573*	0.0933*	0.0918*	0.0925*
				(0.0248)	(0.0217)	(0.0218)	(0.0341)	(0.0240)	(0.0237)
θ_1	-	-	-	-	-	-	-0.3045	-0.7823**	-0.7674**
							(0.2353)	(0.3297)	(0.3193)
θ_2	-	-	-	-	-	-	0.5380	0.5977*	0.5974*
							(0.4561)	(0.2261)	(0.2055)
ω	0.0132	0.0679	0.0741***	0.0977***	0.0478	0.0514	0.0152	0.1001	0.0926
	(0.0437)	(0.0434)	(0.0448)	(0.0501)	(0.0391)	(0.0391)	(0.0626)	(0.1625)	(0.1634)
α_1	0.6230*	0.4134*	0.4092*	0.2318*	0.2833*	0.2890*	0.5032***	-0.5215*	-0.5235*
	(0.1723)	(0.1376)	(0.1372)	(0.0685)	(0.0663)	(0.0673)	(0.2635)	(0.1625)	(0.1630)
β_1	0.7584*	0.7099*	0.7070*	0.6194*	0.6024*	0.6001*	0.6692**	-0.4532*	-0.4549*
	(0.1178)	(0.1001)	(0.1029)	(0.1056)	(0.0830)	(0.0830)	(0.2991)	(0.1662)	(0.1667)
d	0.3090**	0.4858*	0.4882*	0.5425*	0.4614*	0.4610*	0.2372**	0.1190***	0.1168***
	(0.1394)	(0.1485)	(0.1485)	(0.1538)	(0.1144)	(0.1157)	(0.1029)	(0.0692)	(0.0691)
$log(\alpha)$	0.0860	-0.0171	-0.0255	-0.0492	0.0066	0.0020	0.1728	0.4577	0.4734
	(0.1514)	(0.0547)	(0.0530)	(0.0505)	(0.0548)	(0.0549)	(0.2563)	(0.4155)	(0.4254)
v	-	4.9263	4.9602*	-	8.2743*	8.6156*	-	5.5138*	5.5185*
		(0.6035)	(0.6084)		(1.1114)	(1.1898)		(0.6828)	(0.6802)
$ln(k)$	-	-	-0.0525***	-	-	-0.0623**	-	-	0.0241
			(0.0312)			(0.0250)			(0.0336)
ln(L)	5108.80	5189.96	5191.26	9821.26	9871.32	9874.42	6886.56	7027.74	7028.04
AIC	-5.72	-5.81	-5.81	-5.88	-5.91	-5.91	-6.06	-6.19	-6.19
Q(20)	27.19	30.26**	31.27**	25.60	26.39	26.43	18.38	18.69	18.61
Qs(20)	8.86	8.22	8.20	16.00	15.54	15.96	7.92	6.25	6.26
ARCH(5)	0.16	0.29	0.29	0.48	0.53	0.57	0.43	0.31	0.31
P(60)	116.08*	65.59	55.03	95.56*	68.22	46.66	113.85*	45.60	51.10

Notes: See Table 9a

Table 11b: Estimation results of AR(FI)MA-HYGARCH models

	Hungary			Poland			Romania		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0010***	0.0010*	0.0007**	0.0009*	0.0009*	0.0009*	0.0011	0.0001	0.0009
	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0009)	(0.0008)	(0.0009)
Φ_1	-	-	-	-	-	-	0.7326**	0.7298*	0.7315*
							(0.0619)	(0.0738)	(0.0745)
Φ_2	-	-	-	-	-	-	-	-	-
ξ	0.0805*	0.0580*	0.0577*	-	-	-	0.1738*	0.1805*	0.1737*
	(0.0177)	(0.0155)	(0.0154)				(0.0544)	(0.0464)	(0.0468)
θ_1	-	-	-	0.1244*	0.1175*	0.1177*	-0.8184*	-0.8036*	-0.8007*
				(0.0192)	(0.0184)	(0.0184)	(0.0519)	(0.0633)	(0.0659)
θ_2	-	-	-	-	-	-	-	-	-
ω	0.3574*	0.2021*	0.2027*	0.3216**	0.2637**	0.2643**	0.7686**	0.3881	0.3749
	(0.1372)	(0.0750)	(0.0742)	(0.1372)	(0.1053)	(0.1056)	(0.3404)	(0.2386)	(0.2460)
α_1	0.1673***	0.2577*	0.2672*	0.3225*	0.2988*	0.2976*	-0.3711*	0.7097*	0.7018*
	(0.1017)	(0.0803)	(0.0804)	(0.1112)	(0.0851)	(0.0857)	(0.1278)	(0.1958)	(0.2166)
β_1	0.5383*	0.5264*	0.5356*	0.5304*	0.5664*	0.5640*	-0.2640**	0.5962**	0.6004**
	(0.1303)	(0.1069)	(0.1056)	(0.1443)	(0.1133)	(0.1142)	(0.1222)	(0.2417)	(0.2579)
d	0.6364*	0.4838*	0.4889*	0.4089*	0.4374*	0.4358*	0.4452*	0.3357**	0.3425**
	(0.1589)	(0.1151)	(0.1158)	(0.1093)	(0.1017)	(0.1019)	(0.0964)	(0.1542)	(0.1506)
log(α)	-0.1269**	-0.0579	-0.0604	-0.1016****	-0.0789	-0.0782	-0.0547	-0.2062	-0.1876
	(0.0526)	(0.0534)	(0.0526)	(0.0591)	(0.0488)	(0.0493)	(0.1197)	(0.1838)	(0.1737)
v	-	5.4814*	5.4995*	-	10.8529*	10.7871*	-	4.2316*	4.2283*
		(0.5394)	(0.5417)		(1.9654)	(1.9271)		(0.3714)	(0.3680)
ln(k)	-	-	-0.0414***	-	-	0.0076	-	-	0.0491***
			(0.0227)			(0.0231)			(0.0280)
ln(L)	9828.22	10012.60	10014.20	8612.19	8636.12	8636.17	6504.99	6656.88	6658.46
AIC	-5.42	-5.52	-5.52	-5.14	-5.15	-5.15	-5.24	-5.36	-5.36
Q(20)	34.33**	41.85*	42.00*	12.28	13.48	13.44	27.56	22.08	22.18
Qs(20)	7.89	6.54	6.53	6.41	8.97	8.94	11.95	15.66	15.44
ARCH(5)	0.16	0.13	0.13	0.03	0.23	0.22	0.55	1.16	1.16
P(60)	146.37*	51.71	63.80	81.43**	58.14	58.42	180.16*	69.54	69.69

Notes: See Table 9a

Table 11c: Estimation results of AR(FI)MA-HYGARCH models

	Malta			Slovakia			Turkey		
	Normal	Student-t	Skewed	Normal	Student-t	Skewed	Normal	Student-t	Skewed
μ	0.0005**	0.0005**	0.0005**	-0.0004	0.0005	0.0000	0.0012***	0.0015*	0.0014**
	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0006)
Φ_1	0.1452*	0.1426*	0.1427*	0.1220	0.1192	0.1366	-	-	-
	(0.0282)	(0.0232)	(0.0232)	(0.3059)	(0.1390)	(0.1318)			
Φ_2	0.0549**	0.0427**	0.0421**	0.0535	0.0368	0.0336	-	-	-
	(0.0249)	(0.0211)	(0.0212)	(0.0354)	(0.0687)	(0.0689)			
ξ	-	-	-	0.1531	0.1033*	0.1052*	0.0539*	0.0421*	0.0414*
				(0.0466)	(0.0355)	(0.0360)	(0.0160)	(0.0141)	(0.0141)
θ_1	-	-	-	-0.3037	-0.2417	-0.2605***	-	-	-
				(0.3265)	(0.1486)	(0.1413)			
θ_2	-	-	-	-0.0862	-0.0731	-0.0683	-	-	-
				(0.0908)	(0.0719)	(0.0712)			
ω	0.0922	0.1801*	0.1782*	0.2190**	0.4667*	0.4581*	0.4389***	0.6079**	0.6148**
	(0.0721)	(0.0602)	(0.0619)	(0.0885)	(0.1434)	(0.1409)	(0.2546)	(0.2389)	(0.2392)
α_1	0.2747*	0.1816***	0.1827***	0.2720**	0.0969	0.0891	0.2558***	0.1619	0.1624
	(0.1035)	(0.1019)	(0.1022)	(0.1137)	(0.0758)	(0.0754)	(0.1318)	(0.1202)	(0.1197)
β_1	0.6286**	0.3981*	0.3914*	0.6828*	0.5534*	0.5652*	0.4674*	0.4114*	0.4121*
	(0.2672)	(0.1200)	(0.1201)	(0.1048)	(0.1256)	(0.1254)	(0.1797)	(0.1566)	(0.1560)
d	0.5697***	0.4617**	0.4482**	0.6167*	0.6384*	0.6603*	0.3862*	0.4291*	0.4306*
	(0.2915)	(0.1893)	(0.1909)	(0.1913)	(0.1297)	(0.1344)	(0.1079)	(0.0786)	(0.0785)
$log(\alpha)$	-0.1109	-0.2035***	-0.1996***	-0.1070***	-0.1757**	-0.1705**	-0.0035	-0.0246	-0.0271
	(0.1079)	(0.1086)	(0.1147)	(0.0632)	(0.0705)	(0.0691)	(0.0690)	(0.0474)	(0.0471)
v	-	5.5601*	5.5920*	-	3.5301*	3.5417*	-	6.2494*	6.2859*
		(0.6918)	(0.6952)		(0.2327)	(0.2341)		(0.5693)	(0.5717)
$ln(k)$	-	-	0.0168	-	-	-0.0384***	-	-	-0.0163
			(0.0289)			(0.0210)			(0.0216)
ln(L)	7090.47	7166.10	7166.26	9224.23	9498.30	9499.80	8829.75	8942.16	8942.44
AIC	-6.44	-6.50	-6.50	-5.53	-5.69	-5.69	-4.21	-4.26	-4.26
Q(20)	29.61**	32.53**	32.64**	18.11	23.60	23.24	24.54	28.22	28.53***
Qs(20)	8.24	7.27	7.24	25.74	47.48*	47.67*	27.06	31.55**	31.56**
ARCH(5)	0.30	0.32	0.32	0.20	1.06	1.05	1.55	1.62	1.62
P(60)	123.90*	45.44	47.08	397.79*	216.55*	209.89*	143.40*	61.94	60.99

Notes: See Table 9a

6.3.3. Forecast evaluation measures

In order to evaluate the performance of GARCH type models in forecasting volatility, four different metrics are conducted all of which are well-known and well-established in the literature. The last 500 observations are chosen for the out-of-sample period over which one-step ahead forecasts will be obtained. More specifically, we use the mean error (ME) that measures the difference between the true value and forecasted value, mean squared error (MSE) which measures the average of the squared distance of the true value and forecasted value, and root mean squared error (RMSE) that measures square root of the MSE. These measures are defined as follows:

$$ME = \frac{1}{m}\sum_{t=1}^{m}\left(\widehat{\sigma_t^2} - \sigma_t^2\right)$$

$$MSE = \frac{1}{m}\sum_{t=1}^{m}\left(\widehat{\sigma_t^2} - \sigma_t^2\right)^2$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(\widehat{\sigma_t^2} - \sigma_t^2\right)^2}$$

where m is the number of out-of-sample data, $\widehat{\sigma_t^2}$ is the forecasted variance and σ_t^2 is the actual variance.

Table 12a: Forecast performance

	Bulgaria		Czech Republic		Estonia		Hungary		Malta	
	ARMA-FIGARCH	ARMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH	ARMA-FIGARCH	ARMA-HYGARCH
MSE	1.57E-06	1.60E-06	8.83E-06	8.83E-06	9.77E-07	9.83E-07	8.89E-06	8.99E-06	7.63E-08	7.55E-08
ME	0.0002776	0.0003408	0.0008143	0.00081	0.0002727	0.0002826	0.000779	0.0008365	4.93E-05	4.25E-05
RMSE	0.001251	0.001266	0.002972	0.002971	0.0009886	0.0009916	0.002982	0.002999	0.0002762	0.0002748

Table 12b: Forecast performance

	Poland		Romania		Slovakia		Turkey	
	ARMA-FIGARCH	ARMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH	ARFIMA-FIGARCH	ARFIMA-HYGARCH
MSE	4.74E-06	4.74E-06	4.09E-06	4.20E-06	7.90E-08	6.30E-08	5.89E-06	5.88E-06
ME	0.0007154	0.0007138	0.0002862	0.0004434	0.0002207	0.0001856	6.68E-05	9.54E-05
RMSE	0.002178	0.002177	0.002023	0.00205	0.0002811	0.0002509	0.002427	0.002425

The out-of sample return forecast volatility errors are performed using the last 500 observations and are summarized in Tables 12a and 12b[24]. As seen in tables, the forecast error statistics are in favor of the FIGARCH model for Bulgaria, Estonia, Hungary, and Romania with the highest forecast accuracy, whereas the HYGARCH model gives the lowest forecast errors for the Czech Republic, Malta, Poland, Slovakia and Turkey. It is noticed that, different from other candidates, Turkey's stock market show similar characteristics with transition countries when we compare volatility behavior of all candidate countries with new EU countries. As a result, the ARFIMA-HYGARCH model outperforms the ARFIMA-FIGARCH model for most of the sample return series.

6.4. Empirical results for VaR computations

The volatility models that best fits the return series are used in VaR computations. Although, we used in-sample VaR values to examine the selected model's goodness-of-fit ability, out-of-sample VaR values are also computed to evaluate the forecasting capability of the selected models. All models tested with a VaR level α which ranges from 5% to 0.25% and their performance is then evaluated by computing the failure rate for the return series. If the VaR model is specified correctly, the failure rate will equal to the prescribed VaR level α. More specifically, the more the failure rate approaches to the determined confidence level α, the more the VaR model helps investors to forecast their possible trading losses correctly. In practice, VaR inherently focuses on the left-hand tail of the distribution of possible returns because a key aspect of management is to minimize the loss of negative events, supposing the

[24] The distributional assumption which has the lowest forecast error measures are reported for ARFIMA-FIGARCH and ARFIMA-HYGARCH models in the tables.

investors have a long position. Throughout this section, both long and short positions in the financial market are analyzed.

Table 13: In-sample VaR calculated by ARMA-FIGARCH for Bulgaria

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9546	0.8177	0.3659	0.0500	0.0549	0.8867	0.3464
0.9750	0.9770	0.3062	0.5800	0.0250	0.0325	3.7778***	0.0519
0.9900	0.9877	0.9122	0.3395	0.0100	0.0174	8.0360*	0.0046
0.9950	0.9938	0.4536	0.5006	0.0050	0.0112	10.2070*	0.0014
0.9975	0.9972	0.0631	0.8017	0.0025	0.0101	23.2510*	0.0000
Student-t distribution							
0.9500	0.9518	0.1222	0.7266	0.0500	0.0617	4.7682**	0.0290
0.9750	0.9815	3.3963***	0.0653	0.0250	0.0286	0.9009	0.3425
0.9900	0.9950	5.4082**	0.0200	0.0100	0.0118	0.5350	0.4645
0.9950	0.9972	2.0601	0.1512	0.0050	0.0062	0.4536	0.5006
0.9975	0.9978	0.0493	0.8243	0.0025	0.0017	0.5420	0.4616
Skewed Student-t distribution							
0.9500	0.9496	0.0075	0.9308	0.0500	0.0555	1.0961	0.2951
0.9750	0.9765	0.1585	0.6906	0.0250	0.0230	0.3062	0.5800
0.9900	0.9933	2.1824	0.1396	0.0100	0.0107	0.0746	0.7848
0.9950	0.9972	2.0601	0.1512	0.0050	0.0050	0.0007	0.9786
0.9975	0.9978	0.0493	0.8243	0.0025	0.0017	0.5420	0.4616

Note: Quantile indicates ideal failure rate. Failure rate indicates the actual failure rate estimated by the model. * ,** and *** denotes 1%, 5% and 10% level, respectively

Table14: In-sample VaR calculated by ARMA-GARCH for Croatia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9555	0.8448	0.3580	0.0500	0.0392	3.4620***	0.0628
0.9750	0.9716	0.5980	0.4393	0.0250	0.0223	0.4120	0.5210
0.9900	0.9839	4.1670**	0.0412	0.0100	0.0131	1.1210	0.2897
0.9950	0.9846	18.0570*	0.0000	0.0050	0.0092	3.7209***	0.0537
0.9975	0.9885	22.4520*	0.0000	0.0025	0.0069	6.8420*	0.0089
Student-t distribution							
0.9500	0.9493	0.0130	0.9091	0.0500	0.0445	0.8448	0.3580
0.9750	0.9731	0.1847	0.6674	0.0250	0.0223	0.4120	0.5210
0.9900	0.9862	1.7191	0.1898	0.0100	0.0077	0.7690	0.3805
0.9950	0.9939	0.3194	0.5720	0.0050	0.0038	0.3827	0.5361
0.9975	0.9977	0.0206	0.8860	0.0025	0.0031	0.1592	0.6899
Skewed Student-t distribution							
0.9500	0.9524	0.1578	0.6912	0.0500	0.0461	0.4314	0.5113
0.9750	0.9762	0.0769	0.7815	0.0250	0.0223	0.4120	0.5210
0.9900	0.9869	1.1210	0.2897	0.0100	0.0092	0.0829	0.7734
0.9950	0.9939	0.3194	0.5720	0.0050	0.0054	0.0362	0.8492
0.9975	0.9985	0.5630	0.4530	0.0025	0.0031	0.1592	0.6899

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 15: In-sample VaR calculated by ARFIMA-HYGARCH for the Czech Republic

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9569	3.4903***	0.0617	0.0500	0.0515	0.1561	0.6928
0.9750	0.9787	2.0202	0.1552	0.0250	0.0308	4.3528**	0.0369
0.9900	0.9913	0.6128	0.4338	0.0100	0.0168	12.8360*	0.0003
0.9950	0.9952	0.0299	0.8627	0.0050	0.0123	25.2280*	0.0000
0.9975	0.9970	0.3073	0.5794	0.0025	0.0096	38.8510*	0.0000
Student-t distribution							
0.9500	0.9557	2.3622	0.1243	0.0500	0.0548	1.5670	0.2106
0.9750	0.9808	5.0732**	0.0243	0.0250	0.0305	3.9310**	0.0474
0.9900	0.9949	9.9196*	0.0016	0.0100	0.0126	2.0679	0.1504
0.9950	0.9973	4.2905**	0.0383	0.0050	0.0078	4.4458**	0.0350
0.9975	0.9982	0.7356	0.3911	0.0025	0.0045	4.2869**	0.0384
Skewed Student-t distribution							
0.9500	0.9518	0.2295	0.6319	0.0500	0.0515	0.1561	0.6928
0.9750	0.9761	0.1526	0.6961	0.0250	0.0269	0.5063	0.4767
0.9900	0.9919	1.3256	0.2496	0.0100	0.0120	1.2391	0.2657
0.9950	0.9961	0.8922	0.3449	0.0050	0.0075	3.5941***	0.0580
0.9975	0.9979	0.2316	0.6303	0.0025	0.0030	0.3073	0.5794

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 16: In-sample VaR calculated by ARFIMA-FIGARCH for Estonia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9603	5.4531**	0.0195	0.0500	0.0388	6.4674**	0.0110
0.9750	0.9784	1.1233	0.2892	0.0250	0.0207	1.8056	0.1790
0.9900	0.9899	0.0045	0.9463	0.0100	0.0128	1.6349	0.2010
0.9950	0.9912	5.4091**	0.0200	0.0050	0.0084	4.3179**	0.0377
0.9975	0.9930	12.5840*	0.0004	0.0025	0.0062	8.6790*	0.0032
Student-t distribution							
0.9500	0.9511	0.0538	0.8165	0.0500	0.0472	0.3872	0.5338
0.9750	0.9762	0.1340	0.7144	0.0250	0.0220	0.8452	0.3579
0.9900	0.9921	1.0497	0.3056	0.0100	0.0093	0.1289	0.7196
0.9950	0.9947	0.0379	0.8457	0.0050	0.0053	0.0379	0.8457
0.9975	0.9965	0.8504	0.3564	0.0025	0.0031	0.2909	0.5897
Skewed Student-t distribution							
0.9500	0.9515	0.1083	0.7421	0.0500	0.0494	0.0183	0.8925
0.9750	0.9780	0.8452	0.3579	0.0250	0.0229	0.4108	0.5216
0.9900	0.9925	1.5732	0.2098	0.0100	0.0097	0.0208	0.8853
0.9950	0.9952	0.0103	0.9190	0.0050	0.0062	0.5833	0.4450
0.9975	0.9965	0.8504	0.3564	0.0025	0.0031	0.2909	0.5897

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 17: In-sample VaR calculated by ARFIMA-FIGARCH for Hungary

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9627	13.5220*	0.0002	0.0500	0.0400	8.1268*	0.0044
0.9750	0.9801	4.1978**	0.0405	0.0250	0.0232	0.5015	0.4788
0.9900	0.9890	0.3833	0.5358	0.0100	0.0144	6.1105**	0.0134
0.9950	0.9926	3.8031***	0.0512	0.0050	0.0119	24.7460*	0.0000
0.9975	0.9956	4.3362**	0.0373	0.0025	0.0094	40.2360*	0.0000
Student-t distribution							
0.9500	0.9523	0.3916	0.5315	0.0500	0.0491	0.0580	0.8097
0.9750	0.9790	2.5424	0.1108	0.0250	0.0237	0.2410	0.6235
0.9900	0.9923	2.0486	0.1523	0.0100	0.0124	1.9912	0.1582
0.9950	0.9975	5.6617**	0.0173	0.0050	0.0061	0.7835	0.3761
0.9975	0.9989	3.5837***	0.0584	0.0025	0.0036	1.5146	0.2184
Skewed Student-t distribution							
0.9500	0.9500	0.0001	0.9909	0.0500	0.0444	2.4472	0.1177
0.9750	0.9757	0.0758	0.7831	0.0250	0.0221	1.3174	0.2511
0.9900	0.9906	0.1416	0.7067	0.0100	0.0108	0.2087	0.6478
0.9950	0.9975	5.6617**	0.0173	0.0050	0.0055	0.1907	0.6624
0.9975	0.9989	3.5837***	0.0584	0.0025	0.0033	0.8689	0.3513

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 18: In-sample VaR calculated by ARMA-GARCH for Latvia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9558	1.4746	0.2246	0.0500	0.0397	4.7826**	0.0287
0.9750	0.9707	1.4546	0.2278	0.0250	0.0209	1.4953	0.2214
0.9900	0.9821	10.2410*	0.0014	0.0100	0.0104	0.0375	0.8466
0.9950	0.9866	19.5590*	0.0000	0.0050	0.0075	2.1118	0.1462
0.9975	0.9901	25.3690*	0.0000	0.0025	0.0070	10.7530*	0.0010
Student-t distribution							
0.9500	0.9419	2.6630	0.1027	0.0500	0.0477	0.2295	0.6319
0.9750	0.9707	1.4546	0.2278	0.0250	0.0184	3.9790**	0.0461
0.9900	0.9861	2.7707***	0.0960	0.0100	0.0075	1.4484	0.2288
0.9950	0.9940	0.3521	0.5529	0.0050	0.0030	1.9306	0.1647
0.9975	0.9960	1.4858	0.2229	0.0025	0.0015	0.9632	0.3264
Skewed Student-t distribution							
0.9500	0.9478	0.1953	0.6586	0.0500	0.0517	0.1162	0.7332
0.9750	0.9737	0.1434	0.7049	0.0250	0.0209	1.4953	0.2214
0.9900	0.9901	0.0008	0.9767	0.0100	0.0079	0.9206	0.3373
0.9950	0.9940	0.3521	0.5529	0.0050	0.0050	0.0004	0.9836
0.9975	0.9965	0.6868	0.4072	0.0025	0.0020	0.2286	0.6326

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 19: In-sample VaR calculated by ARFIMA-GARCH for Lithuania

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9691	16.4710*	0.0000	0.0500	0.0261	26.9820*	0.0000
0.9750	0.9829	5.4226**	0.0199	0.0250	0.0155	8.0538*	0.0045
0.9900	0.9909	0.1684	0.6815	0.0100	0.0085	0.4258	0.5141
0.9950	0.9936	0.6812	0.4092	0.0050	0.0069	1.2604	0.2616
0.9975	0.9957	1.9371	0.1640	0.0025	0.0048	3.1314***	0.0768
Student-t distribution							
0.9500	0.9482	0.1210	0.7280	0.0500	0.0422	2.5583	0.1097
0.9750	0.9787	1.0799	0.2987	0.0250	0.0192	2.7972***	0.0944
0.9900	0.9936	2.8064***	0.0939	0.0100	0.0085	0.4258	0.5141
0.9950	0.9963	0.6606	0.4164	0.0050	0.0048	0.0149	0.9029
0.9975	0.9979	0.1057	0.7451	0.0025	0.0032	0.3397	0.5600
Skewed Student-t distribution							
0.9500	0.9498	0.0010	0.9747	0.0500	0.0443	1.3354	0.2478
0.9750	0.9803	2.2866	0.1305	0.0250	0.0213	1.0799	0.2987
0.9900	0.9936	2.8064***	0.0939	0.0100	0.0085	0.4258	0.5141
0.9950	0.9968	1.3970	0.2372	0.0050	0.0048	0.0149	0.9029
0.9975	0.9979	0.1057	0.7451	0.0025	0.0037	0.9945	0.3187

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 20: In-sample VaR calculated by ARFIMA-GARCH for Macedonia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9510	0.0150	0.9027	0.0500	0.0432	0.7009	0.4025
0.9750	0.9755	0.0073	0.9320	0.0250	0.0274	0.1562	0.6927
0.9900	0.9856	1.1993	0.2735	0.0100	0.0159	2.0371	0.1535
0.9950	0.9914	1.5205	0.2175	0.0050	0.0144	8.1706*	0.0043
0.9975	0.9942	2.1597	0.1417	0.0025	0.0086	6.3854**	0.0115
Student-t distribution							
0.9500	0.9438	0.5402	0.4623	0.0500	0.0461	0.2268	0.6339
0.9750	0.9770	0.1106	0.7395	0.0250	0.0288	0.3960	0.5292
0.9900	0.9914	0.1348	0.7135	0.0100	0.0144	1.1993	0.2735
0.9950	0.9957	0.0671	0.7957	0.0050	0.0086	1.5205	0.2175
0.9975	0.9971	0.0387	0.8441	0.0025	0.0043	0.7579	0.3840
Skewed Student-t distribution							
0.9500	0.9452	0.3209	0.5711	0.0500	0.0461	0.2268	0.6339
0.9750	0.9798	0.7096	0.3996	0.0250	0.0303	0.7388	0.3901
0.9900	0.9914	0.1348	0.7135	0.0100	0.0144	1.1993	0.2735
0.9950	0.9957	0.0671	0.7957	0.0050	0.0086	1.5205	0.2175
0.9975	0.9971	0.0387	0.8441	0.0025	0.0043	0.7579	0.3840

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 21: In-sample VaR calculated by ARMA-HYGARCH for Malta

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9473	0.3330	0.5639	0.0500	0.0463	0.6347	0.4256
0.9750	0.9682	3.8538**	0.0496	0.0250	0.0254	0.0176	0.8944
0.9900	0.9836	7.5356*	0.0060	0.0100	0.0109	0.1766	0.6744
0.9950	0.9882	14.8200*	0.0001	0.0050	0.0073	1.9970	0.1576
0.9975	0.9927	13.2120*	0.0003	0.0025	0.0055	5.7371**	0.0166
Student-t distribution							
0.9500	0.9432	2.0519	0.1520	0.0500	0.0518	0.1476	0.7009
0.9750	0.9687	3.3732***	0.0663	0.0250	0.0200	2.4299	0.1190
0.9900	0.9886	0.3931	0.5307	0.0100	0.0073	1.8315	0.1760
0.9950	0.9955	0.0952	0.7577	0.0050	0.0036	0.9116	0.3397
0.9975	0.9982	0.4548	0.5001	0.0025	0.0009	2.9624***	0.0852
Skewed Student-t distribution							
0.9500	0.9437	1.7913	0.1808	0.0500	0.0532	0.4531	0.5009
0.9750	0.9696	2.5022	0.1137	0.0250	0.0214	1.2618	0.2613
0.9900	0.9891	0.1766	0.6744	0.0100	0.0082	0.7869	0.3751
0.9950	0.9955	0.0952	0.7577	0.0050	0.0041	0.3916	0.5315
0.9975	0.9982	0.4548	0.5001	0.0025	0.0009	2.9624***	0.0852

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 22: In-sample VaR calculated by ARMA-HYGARCH for Poland

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9495	0.0151	0.9023	0.0500	0.0487	0.1255	0.7231
0.9750	0.9731	0.4710	0.4925	0.0250	0.0293	2.3688	0.1238
0.9900	0.9881	1.2034	0.2726	0.0100	0.0152	7.9717*	0.0048
0.9950	0.9940	0.5985	0.4392	0.0050	0.0102	13.7410*	0.0002
0.9975	0.9967	0.7518	0.3859	0.0025	0.0048	5.4868**	0.0192
Student-t distribution							
0.9500	0.9486	0.1290	0.7194	0.0500	0.0514	0.1290	0.7194
0.9750	0.9746	0.0198	0.8881	0.0250	0.0275	0.8132	0.3672
0.9900	0.9916	0.9627	0.3265	0.0100	0.0122	1.5877	0.2077
0.9950	0.9970	3.1934***	0.0739	0.0050	0.0045	0.1894	0.6634
0.9975	0.9997	10.5110*	0.0012	0.0025	0.0030	0.2984	0.5849
Skewed Student-t distribution							
0.9500	0.9489	0.0787	0.7791	0.0500	0.0517	0.1916	0.6616
0.9750	0.9749	0.0009	0.9757	0.0250	0.0284	1.4934	0.2217
0.9900	0.9916	0.9627	0.3265	0.0100	0.0125	2.0214	0.1551
0.9950	0.9970	3.1934***	0.0739	0.0050	0.0051	0.0039	0.9503
0.9975	0.9997	10.5110*	0.0012	0.0025	0.0030	0.2984	0.5849

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

6.4.1. In-sample VaR Analysis

The in-sample VaR results computed under the three distributions: the normal, Student-*t*, and skewed Student-*t*. The models that are selected according to the forecast evaluation measures are used in in-sample VaR computations. The empirical results for the new and candidate EU countries' return index series are presented from Table 13 to Table 26. These tables show the failure rates and computed and their corresponding Kupiec's LR values. Ideally, the failure rate should be equal to the prescribed VaR level α and the null hypothesis of the Kupiec's LR test should not be rejected in order to estimate accurate VaR models.

Table 23: In-sample VaR calculated by ARFIMA-FIGARCH for Romania

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9496	0.0076	0.9304	0.0500	0.0391	6.6904*	0.0097
0.9750	0.9742	0.0638	0.8005	0.0250	0.0222	0.8479	0.3572
0.9900	0.9871	1.9284	0.1649	0.0100	0.0149	5.2563**	0.0219
0.9950	0.9907	7.2557*	0.0071	0.0050	0.0117	16.1750*	0.0001
0.9975	0.9944	7.2245*	0.0072	0.0025	0.0105	35.0870*	0.0000
Student-t distribution							
0.9500	0.9444	1.5958	0.2065	0.0500	0.0439	2.0005	0.1573
0.9750	0.9730	0.3990	0.5276	0.0250	0.0206	2.1376	0.1437
0.9900	0.9932	2.7917***	0.0948	0.0100	0.0101	0.0015	0.9695
0.9950	0.9960	0.5021	0.4786	0.0050	0.0064	0.9589	0.3275
0.9975	0.9968	0.4781	0.4893	0.0025	0.0028	0.0987	0.7534
Skewed Student-t distribution							
0.9500	0.9468	0.5258	0.4684	0.0500	0.0484	0.1406	0.7076
0.9750	0.9774	0.6202	0.4310	0.0250	0.0230	0.4290	0.5125
0.9900	0.9936	3.6145***	0.0573	0.0100	0.0113	0.3978	0.5282
0.9950	0.9968	1.7993	0.1798	0.0050	0.0069	1.5324	0.2158
0.9975	0.9968	0.4781	0.4893	0.0025	0.0040	1.9635	0.1611

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 24: In-sample VaR calculated by ARFIMA-HYGARCH for Slovakia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9574	4.0630**	0.0438	0.0500	0.0456	1.4136	0.2345
0.9750	0.9745	0.0323	0.8574	0.0250	0.0300	3.1995***	0.0737
0.9900	0.9886	0.6267	0.4286	0.0100	0.0201	26.5270*	0.0000
0.9950	0.9919	5.4062**	0.0201	0.0050	0.0153	45.7340*	0.0000
0.9975	0.9931	17.4170*	0.0000	0.0025	0.0114	56.2190*	0.0000
Student-t distribution							
0.9500	0.9472	0.5309	0.4662	0.0500	0.0510	0.0663	0.7969
0.9750	0.9763	0.2396	0.6245	0.0250	0.0303	3.5837***	0.0584
0.9900	0.9931	3.6405***	0.0564	0.0100	0.0120	1.2591	0.2618
0.9950	0.9973	4.2674**	0.0389	0.0050	0.0054	0.1031	0.7481
0.9975	0.9982	0.7286	0.3933	0.0025	0.0018	0.7286	0.3933
Skewed Student-t distribution							
0.9500	0.9442	2.2586	0.1329	0.0500	0.0492	0.0480	0.8266
0.9750	0.9742	0.0839	0.7721	0.0250	0.0279	1.0992	0.2944
0.9900	0.9922	1.7704	0.1833	0.0100	0.0111	0.3897	0.5325
0.9950	0.9973	4.2674**	0.0389	0.0050	0.0036	1.4605	0.2269
0.9975	0.9982	0.7286	0.3933	0.0025	0.0015	1.5651	0.2109

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

The results show that the VaR models with skewed Student-*t* distribution assumption predict critical loss more accurate than the models with normal and Student-*t* distribution. It is observed that the normal models underestimate or overestimate the in-sample VaR values for both long and short trading positions. However, gauss distribution perform well for all of the α quantiles for the short position of Bulgaria Macedonia and Poland. That gives strong evidence that the return series of these countries are skewed to the left rather than to the right. The volatility models under skewed Student-*t* distribution performs better in all cases for the negative returns (long VaR) except for the Czech Republic, Malta and Slovenia.

Consequently, the empirical results indicate that the determined models in the previous section with skewed Student-*t* distribution can describe the fat-tail behavior exhibited in the stock index series.

Table 25: In-sample VaR calculated by ARFIMA-GARCH for Slovenia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9552	1.2830	0.2574	0.0500	0.0462	0.6880	0.4069
0.9750	0.9803	2.7561***	0.0969	0.0250	0.0229	0.4219	0.5160
0.9900	0.9899	0.0008	0.9777	0.0100	0.0146	4.1472**	0.0417
0.9950	0.9918	3.8355***	0.0502	0.0050	0.0096	7.3239*	0.0068
0.9975	0.9936	9.2950*	0.0023	0.0025	0.0046	3.0197***	0.0823
Student-t distribution							
0.9500	0.9502	0.0012	0.9726	0.0500	0.0471	0.3955	0.5294
0.9750	0.9840	8.3069*	0.0039	0.0250	0.0224	0.6256	0.4290
0.9900	0.9904	0.0354	0.8507	0.0100	0.0114	0.4325	0.5108
0.9950	0.9931	1.3600	0.2435	0.0050	0.0046	0.0827	0.7736
0.9975	0.9963	1.0279	0.3107	0.0025	0.0018	0.4358	0.5092
Skewed Student-t distribution							
0.9500	0.9497	0.0041	0.9492	0.0500	0.0471	0.3955	0.5294
0.9750	0.9840	8.3069*	0.0039	0.0250	0.0219	0.8711	0.3506
0.9900	0.9895	0.0580	0.8097	0.0100	0.0114	0.4325	0.5108
0.9950	0.9931	1.3600	0.2435	0.0050	0.0041	0.3663	0.5450
0.9975	0.9963	1.0279	0.3107	0.0025	0.0018	0.4358	0.5092

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 26: In-sample VaR calculated by ARFIMA-HYGARCH for Turkey

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9559	3.1836***	0.0744	0.0500	0.0467	0.9623	0.3266
0.9750	0.9762	0.2336	0.6288	0.0250	0.0284	1.8781	0.1706
0.9900	0.9871	3.2114***	0.0731	0.0100	0.0160	12.8040*	0.0003
0.9950	0.9909	11.1910*	0.0008	0.0050	0.0110	22.3610*	0.0000
0.9975	0.9940	14.4670*	0.0001	0.0025	0.0086	37.9430*	0.0000
Student-t distribution							
0.9500	0.9521	0.3850	0.5349	0.0500	0.0532	0.8707	0.3508
0.9750	0.9783	1.9627	0.1612	0.0250	0.0274	0.9775	0.3228
0.9900	0.9912	0.6120	0.4340	0.0100	0.0114	0.8451	0.3579
0.9950	0.9962	1.2898	0.2561	0.0050	0.0064	1.5969	0.2063
0.9975	0.9981	0.6434	0.4225	0.0025	0.0045	5.5781**	0.0182
Skewed Student-t distribution							
0.9500	0.9506	0.0367	0.8480	0.0500	0.0515	0.1974	0.6569
0.9750	0.9778	1.4271	0.2322	0.0250	0.0258	0.0961	0.7565
0.9900	0.9909	0.3860	0.5344	0.0100	0.0112	0.5935	0.4411
0.9950	0.9960	0.8079	0.3688	0.0050	0.0060	0.7330	0.3919
0.9975	0.9981	0.6434	0.4225	0.0025	0.0041	3.4113***	0.0648

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

6.4.2. Out-of-sample VAR Analysis

In the previous subsection, the estimated best models are used to calculate the VaR values. By comparing the VaR values using different models, we only know the past performance of the VaR models. However, the contribution of VaR calculations is its forecasting ability that provides information to investors or financial institutions about the biggest loss they will incur (Tang and Shieh, 2006). Hence, it is important to evaluate the forecasting ability of the VaR models.

Table 27: Out-of-sample VaR calculated by ARMA-FIGARCH for Bulgaria

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9640	2.2765	0.1314	0.0500	0.0520	0.0416	0.8384
0.9750	0.9820	1.1120	0.2917	0.0250	0.0320	0.9247	0.3362
0.9900	0.9880	0.1899	0.6630	0.0100	0.0200	3.9136**	0.0479
0.9950	0.9980	1.1719	0.2790	0.0050	0.0200	12.8400*	0.0003
0.9975	1.0000	.NaN	1.0000	0.0025	0.0140	12.6850*	0.0004
Student-t distribution							
0.9500	0.9620	1.6469	0.1994	0.0500	0.0560	0.3654	0.5455
0.9750	0.9820	1.1120	0.2917	0.0250	0.0280	0.1778	0.6733
0.9900	0.9960	2.3530	0.1250	0.0100	0.0160	1.5383	0.2149
0.9950	0.9980	1.1719	0.2790	0.0050	0.0100	1.9441	0.1632
0.9975	1.0000	.NaN	1.0000	0.0025	0.0040	0.3811	0.5370
Skewed Student-t distribution							
0.9500	0.9540	0.1729	0.6776	0.0500	0.0480	0.0426	0.8364
0.9750	0.9780	0.1923	0.6610	0.0250	0.0280	0.1778	0.6733
0.9900	0.9880	0.1899	0.6630	0.0100	0.0140	0.7187	0.3966
0.9950	0.9980	1.1719	0.2790	0.0050	0.0060	0.0944	0.7586
0.9975	1.0000	.NaN	1.0000	0.0025	0.0020	0.0538	0.8165

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

The out-of-sample VaR is a one-step-ahead forecast based on the available information. 500 out-of-sample VaRs are calculated for each series using the best volatility model that is determined in Section *6.3.3* under three distributional assumptions, and the performances of the models will be evaluated by the Kupiec's

LR test. As in the in-sample VaR calculations, these out-of-sample VaR values are calculated with observed returns and results are recorded for evaluation of performance of VaR models. Moreover, if the value of the Kupiec LR test appears to be NaN, it means the model captures all the characteristics of the series perfectly. The empirical results of the out-of-sample VaR calculations are given in Tables 27-40.

Table 28: Out-of-sample VaR calculated by ARMA-GARCH for Croatia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9526	0.0690	0.7929	0.0500	0.0515	0.0242	0.8764
0.9750	0.9711	0.2835	0.5944	0.0250	0.0289	0.2835	0.5944
0.9900	0.9856	0.8467	0.3575	0.0100	0.0186	2.8644***	0.0906
0.9950	0.9959	0.0796	0.7778	0.0050	0.0165	8.0124*	0.0046
0.9975	0.9959	0.4281	0.5129	0.0025	0.0082	3.9900**	0.0458
Student-t distribution							
0.9500	0.9505	0.0027	0.9584	0.0500	0.0515	0.0242	0.8764
0.9750	0.9732	0.0633	0.8014	0.0250	0.0247	0.0013	0.9710
0.9900	0.9918	0.1600	0.6891	0.0100	0.0165	1.7281	0.1887
0.9950	0.9979	1.0825	0.2981	0.0050	0.0062	0.1274	0.7212
0.9975	1.0000	.NaN	1.0000	0.0025	0.0021	0.0397	0.8420
Skewed Student-t distribution							
0.9500	0.9423	0.5827	0.4453	0.0500	0.0474	0.0690	0.7929
0.9750	0.9670	1.1561	0.2823	0.0250	0.0227	0.1104	0.7396
0.9900	0.9897	0.0046	0.9457	0.0100	0.0144	0.8467	0.3575
0.9950	0.9959	0.0796	0.7778	0.0050	0.0041	0.0796	0.7778
0.9975	0.9979	0.0397	0.8420	0.0025	0.0000	.NaN	1.0000

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

The results show that for both of the positions, the Student-*t* and skewed Student-*t* perform better than the normal distribution for all sample return series. However, the performance of normal models improve considerably in out-of-sample VaR forecasting. The findings are similar to those of Giot and Laurent (2003) and Sriananthakumar and Silvapulle (2003) who document that non-normal distributions perform better than the normal one.

Obviously, when the confidence level is more conservative (as α quantile gets smaller), the performance of all models is better than other situations by a lower failure rate or higher success rate. It is worth noting that zero failure rates appearing in 99.75% quantile meaning the VaR model performs perfectly since the model captures all the characteristics of the indices.

All of the models with the Student-*t* and skewed Student-*t* innovations are not rejected the null hypothesis f=α. In contrast to the findings of Grau (2002) and Giot and Laurent (2003) we found that good in-sample VaR estimation of a model also perform well for out-of-sample VaR forecasting. The results also confirm that long memory models provide efficient results when analyzing risk that requires variance series.

Overall, the empirical results are encouraging in that they suggest that the proposed long memory models with Student-t or skewed student-t distributional assumptions are useful techniques for forecasting VaR in CEE stock markets.

Table 29: Out-of-sample VaR calculated by ARFIMA-HYGARCH for the Czech Republic

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9573	0.5823	0.4454	0.0500	0.0508	0.0068	0.9342
0.9750	0.9736	0.0401	0.8412	0.0250	0.0244	0.0076	0.9307
0.9900	0.9858	0.7853	0.3755	0.0100	0.0142	0.7853	0.3755
0.9950	0.9919	0.8139	0.3670	0.0050	0.0102	2.0260	0.1546
0.9975	0.9919	3.9099**	0.0480	0.0025	0.0061	1.8160	0.1778
Student-t distribution							
0.9500	0.9431	0.4744	0.4910	0.0500	0.0508	0.0068	0.9342
0.9750	0.9736	0.0401	0.8412	0.0250	0.0183	0.9999	0.3173
0.9900	0.9919	0.1856	0.6666	0.0100	0.0102	0.0013	0.9712
0.9950	0.9919	0.8139	0.3670	0.0050	0.0041	0.0924	0.7612
0.9975	0.9980	0.0461	0.8300	0.0025	0.0020	0.0461	0.8300
Skewed Student-t distribution							
0.9500	0.9472	0.0824	0.7741	0.0500	0.0549	0.2392	0.6248
0.9750	0.9776	0.1460	0.7024	0.0250	0.0224	0.1460	0.7024
0.9900	0.9919	0.1856	0.6666	0.0100	0.0102	0.0013	0.9712
0.9950	0.9919	0.8139	0.3670	0.0050	0.0061	0.1113	0.7387
0.9975	0.9980	0.0461	0.8300	0.0025	0.0020	0.0461	0.8300

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 30: Out-of-sample VaR calculated by ARFIMA-FIGARCH for Estonia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9532	0.1051	0.7458	0.0500	0.0489	0.0131	0.9090
0.9750	0.9613	3.2461***	0.0716	0.0250	0.0326	1.0598	0.3033
0.9900	0.9878	0.2283	0.6328	0.0100	0.0102	0.0017	0.9675
0.9950	0.9898	2.0364	0.1536	0.0050	0.0061	0.1135	0.7362
0.9975	0.9959	0.4089	0.5225	0.0025	0.0041	0.4089	0.5225
Student-t distribution							
0.9500	0.9532	0.1051	0.7458	0.0500	0.0570	0.4892	0.4843
0.9750	0.9674	1.0598	0.3033	0.0250	0.0265	0.0431	0.8355
0.9900	0.9898	0.0017	0.9675	0.0100	0.0061	0.8715	0.3505
0.9950	0.9959	0.0905	0.7635	0.0050	0.0041	0.0905	0.7635
0.9975	0.9980	0.0451	0.8317	0.0025	0.0000	.NaN	1.0000
Skewed Student-t distribution							
0.9500	0.9532	0.1051	0.7458	0.0500	0.0591	0.8045	0.3698
0.9750	0.9695	0.5801	0.4463	0.0250	0.0265	0.0431	0.8355
0.9900	0.9919	0.1819	0.6698	0.0100	0.0061	0.8715	0.3505
0.9950	0.9980	1.1181	0.2903	0.0050	0.0041	0.0905	0.7635
0.9975	0.9980	0.0451	0.8317	0.0025	0.0000	.NaN	1.0000

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 31: Out-of-sample VaR calculated by ARFIMA-FIGARCH for Hungary

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9512	0.0155	0.9008	0.0500	0.0589	0.7854	0.3755
0.9750	0.9695	0.5688	0.4508	0.0250	0.0305	0.5688	0.4508
0.9900	0.9878	0.2238	0.6362	0.0100	0.0102	0.0013	0.9712
0.9950	0.9959	0.0924	0.7612	0.0050	0.0061	0.1113	0.7387
0.9975	0.9980	0.0461	0.8300	0.0025	0.0041	0.4057	0.5241
Student-t distribution							
0.9500	0.9492	0.0068	0.9342	0.0500	0.0589	0.7854	0.3755
0.9750	0.9695	0.5688	0.4508	0.0250	0.0264	0.0401	0.8412
0.9900	0.9939	0.8794	0.3484	0.0100	0.0102	0.0013	0.9712
0.9950	0.9959	0.0924	0.7612	0.0050	0.0061	0.1113	0.7387
0.9975	0.9980	0.0461	0.8300	0.0025	0.0020	0.0461	0.8300
Skewed Student-t distribution							
0.9500	0.9512	0.0155	0.9008	0.0500	0.0610	1.1697	0.2795
0.9750	0.9695	0.5688	0.4508	0.0250	0.0305	0.5688	0.4508
0.9900	0.9939	0.8794	0.3484	0.0100	0.0102	0.0013	0.9712
0.9950	0.9959	0.0924	0.7612	0.0050	0.0061	0.1113	0.7387
0.9975	0.9980	0.0461	0.8300	0.0025	0.0041	0.4057	0.5241

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 32: Out-of-sample VaR calculated by ARMA-GARCH for Latvia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9552	0.2885	0.5912	0.0500	0.0407	0.9451	0.3310
0.9750	0.9756	0.0064	0.9364	0.0250	0.0244	0.0064	0.9364
0.9900	0.9817	2.7616***	0.0966	0.0100	0.0143	0.7939	0.3729
0.9950	0.9878	3.6594***	0.0558	0.0050	0.0061	0.1135	0.7362
0.9975	0.9939	1.8232	0.1769	0.0025	0.0041	0.4089	0.5225
Student-t distribution							
0.9500	0.9552	0.2885	0.5912	0.0500	0.0407	0.9451	0.3310
0.9750	0.9756	0.0064	0.9364	0.0250	0.0224	0.1407	0.7076
0.9900	0.9857	0.7939	0.3729	0.0100	0.0041	2.2449	0.1341
0.9950	0.9939	0.1135	0.7362	0.0050	0.0041	0.0905	0.7635
0.9975	0.9939	1.8232	0.1769	0.0025	0.0000	.NaN	1.0000
Skewed Student-t distribution							
0.9500	0.9593	0.9451	0.3310	0.0500	0.0468	0.1051	0.7458
0.9750	0.9817	0.9862	0.3207	0.0250	0.0285	0.2380	0.6256
0.9900	0.9919	0.1819	0.6698	0.0100	0.0143	0.7939	0.3729
0.9950	0.9939	0.1135	0.7362	0.0050	0.0041	0.0905	0.7635
0.9975	0.9939	1.8232	0.1769	0.0025	0.0041	0.4089	0.5225

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 33: Out-of-sample VaR calculated by ARFIMA-GARCH for Lithuania

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9592	0.8891	0.3457	0.0500	0.0429	0.5157	0.4727
0.9750	0.9785	0.2516	0.6160	0.0250	0.0236	0.0379	0.8457
0.9900	0.9914	0.0992	0.7528	0.0100	0.0129	0.3568	0.5503
0.9950	0.9957	0.0494	0.8242	0.0050	0.0107	2.3111	0.1285
0.9975	0.9957	0.4932	0.4825	0.0025	0.0064	2.0126	0.1560
Student-t distribution							
0.9500	0.9528	0.0777	0.7804	0.0500	0.0515	0.0219	0.8823
0.9750	0.9807	0.6700	0.4131	0.0250	0.0215	0.2516	0.6160
0.9900	0.9957	1.9518	0.1624	0.0100	0.0107	0.0245	0.8757
0.9950	0.9957	0.0494	0.8242	0.0050	0.0064	0.1774	0.6736
0.9975	0.9957	0.4932	0.4825	0.0025	0.0043	0.4932	0.4825
Skewed Student-t distribution							
0.9500	0.9549	0.2468	0.6193	0.0500	0.0579	0.5897	0.4425
0.9750	0.9828	1.3154	0.2514	0.0250	0.0279	0.1547	0.6941
0.9900	0.9957	1.9518	0.1624	0.0100	0.0107	0.0245	0.8757
0.9950	0.9957	0.0494	0.8242	0.0050	0.0064	0.1774	0.6736
0.9975	0.9957	0.4932	0.4825	0.0025	0.0043	0.4932	0.4825

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 34: Out-of-sample VaR calculated by ARFIMA-GARCH for Macedonia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9500	0.0000	1.0000	0.0500	0.0417	0.7421	0.3890
0.9750	0.9729	0.0832	0.7729	0.0250	0.0271	0.0832	0.7729
0.9900	0.9875	0.2808	0.5962	0.0100	0.0188	2.9522***	0.0858
0.9950	0.9917	0.8920	0.3449	0.0050	0.0146	5.8306**	0.0158
0.9975	0.9917	4.0482**	0.0442	0.0025	0.0104	6.7014*	0.0096
Student-t distribution							
0.9500	0.9458	0.1710	0.6792	0.0500	0.0500	0.0000	1.0000
0.9750	0.9771	0.0879	0.7669	0.0250	0.0208	0.3621	0.5473
0.9900	0.9938	0.7868	0.3751	0.0100	0.0104	0.0083	0.9274
0.9950	0.9979	1.0532	0.3048	0.0050	0.0083	0.8920	0.3449
0.9975	1.0000	.NaN	1.0000	0.0025	0.0021	0.0354	0.8507
Skewed Student-t distribution							
0.9500	0.9396	1.0311	0.3099	0.0500	0.0479	0.0444	0.8330
0.9750	0.9729	0.0832	0.7729	0.0250	0.0208	0.3621	0.5473
0.9900	0.9938	0.7868	0.3751	0.0100	0.0104	0.0083	0.9274
0.9950	0.9958	0.0710	0.7898	0.0050	0.0063	0.1396	0.7087
0.9975	1.0000	.NaN	1.0000	0.0025	0.0021	0.0354	0.8507

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 35: Out-of-sample VaR calculated by ARMA-HYGARCH for Malta

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9569	0.5078	0.4761	0.0500	0.0472	0.0802	0.7770
0.9750	0.9672	1.1234	0.2892	0.0250	0.0329	1.1234	0.2892
0.9900	0.9856	0.8289	0.3626	0.0100	0.0164	1.7019	0.1920
0.9950	0.9918	0.8458	0.3577	0.0050	0.0062	0.1227	0.7262
0.9975	0.9959	0.4217	0.5161	0.0025	0.0062	1.8524	0.1735
Student-t distribution							
0.9500	0.9487	0.0181	0.8929	0.0500	0.0513	0.0181	0.8929
0.9750	0.9754	0.0026	0.9594	0.0250	0.0267	0.0561	0.8127
0.9900	0.9918	0.1672	0.6826	0.0100	0.0103	0.0035	0.9530
0.9950	0.9980	1.0944	0.2955	0.0050	0.0041	0.0832	0.7730
0.9975	1.0000	.NaN	1.0000	0.0025	0.0021	0.0415	0.8386
Skewed Student-t distribution							
0.9500	0.9466	0.1153	0.7342	0.0500	0.0493	0.0053	0.9419
0.9750	0.9733	0.0561	0.8127	0.0250	0.0267	0.0561	0.8127
0.9900	0.9918	0.1672	0.6826	0.0100	0.0103	0.0035	0.9530
0.9950	0.9980	1.0944	0.2955	0.0050	0.0041	0.0832	0.7730
0.9975	1.0000	.NaN	1.0000	0.0025	0.0021	0.0415	0.8386

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 36: Out-of-sample VaR calculated by ARMA-HYGARCH for Poland

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9552	0.2885	0.5912	0.0500	0.0489	0.0131	0.9090
0.9750	0.9796	0.4612	0.4971	0.0250	0.0285	0.2380	0.6256
0.9900	0.9857	0.7939	0.3729	0.0100	0.0163	1.6504	0.1989
0.9950	0.9980	1.1181	0.2903	0.0050	0.0122	3.6594***	0.0558
0.9975	0.9980	0.0451	0.8317	0.0025	0.0061	1.8232	0.1769
Student-t distribution							
0.9500	0.9552	0.2885	0.5912	0.9500	0.9552	0.2885	0.5912
0.9750	0.9796	0.4612	0.4971	0.9750	0.9796	0.4612	0.4971
0.9900	0.9898	0.0017	0.9675	0.9900	0.9898	0.0017	0.9675
0.9950	0.9980	1.1181	0.2903	0.9950	0.9980	1.1181	0.2903
0.9975	1.0000	.NaN	1.0000	0.9975	1.0000	.NaN	1.0000
Skewed Student-t distribution							
0.9500	0.9511	0.0131	0.9090	0.0500	0.0489	0.0131	0.9090
0.9750	0.9796	0.4612	0.4971	0.0250	0.0224	0.1407	0.7076
0.9900	0.9837	1.6504	0.1989	0.0100	0.0143	0.7939	0.3729
0.9950	0.9980	1.1181	0.2903	0.0050	0.0081	0.8202	0.3651
0.9975	0.9980	0.0451	0.8317	0.0025	0.0020	0.0451	0.8317

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 37: Out-of-sample VaR calculated by ARFIMA-HYGARCH for Romania

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9592	0.9257	0.3360	0.0500	0.0571	0.5041	0.4777
0.9750	0.9837	1.7203	0.1897	0.0250	0.0327	1.0755	0.2997
0.9900	0.9939	0.8637	0.3527	0.0100	0.0163	1.6632	0.1972
0.9950	0.9959	0.0887	0.7659	0.0050	0.0122	3.6740***	0.0553
0.9975	0.9959	0.4121	0.5209	0.0025	0.0082	3.9326**	0.0474
Student-t distribution							
0.9500	0.9633	1.9915	0.1582	0.0500	0.0592	0.8238	0.3641
0.9750	0.9837	1.7203	0.1897	0.0250	0.0286	0.2453	0.6204
0.9900	0.9959	2.2330	0.1351	0.0100	0.0122	0.2328	0.6295
0.9950	0.9959	0.0887	0.7659	0.0050	0.0061	0.1158	0.7337
0.9975	0.9980	0.0442	0.8334	0.0025	0.0041	0.4121	0.5209
Skewed Student-t distribution							
0.9500	0.9510	0.0108	0.9172	0.0500	0.0531	0.0949	0.7581
0.9750	0.9816	0.9726	0.3240	0.0250	0.0265	0.0462	0.8298
0.9900	0.9939	0.8637	0.3527	0.0100	0.0122	0.2328	0.6295
0.9950	0.9959	0.0887	0.7659	0.0050	0.0061	0.1158	0.7337
0.9975	0.9980	0.0442	0.8334	0.0025	0.0041	0.4121	0.5209

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 38: Out-of-sample VaR calculated by ARFIMA-HYGARCH for Slovakia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9660	3.0215***	0.0822	0.0500	0.0560	0.3654	0.5455
0.9750	0.9720	0.1778	0.6733	0.0250	0.0300	0.4825	0.4873
0.9900	0.9860	0.7187	0.3966	0.0100	0.0240	7.1107*	0.0077
0.9950	0.9900	1.9441	0.1632	0.0050	0.0160	7.6714*	0.0056
0.9975	0.9940	1.7590	0.1848	0.0025	0.0120	9.3688*	0.0022
Student-t distribution							
0.9500	0.9640	2.2765	0.1314	0.0500	0.0640	1.9027	0.1678
0.9750	0.9780	0.1923	0.6610	0.0250	0.0320	0.9247	0.3362
0.9900	0.9920	0.2169	0.6414	0.0100	0.0160	1.5383	0.2149
0.9950	0.9940	0.0944	0.7586	0.0050	0.0060	0.0944	0.7586
0.9975	0.9980	0.0538	0.8165	0.0025	0.0000	.NaN	1.0000
Skewed Student-t distribution							
0.9500	0.9440	0.3654	0.5455	0.0500	0.0520	0.0416	0.8384
0.9750	0.9740	0.0203	0.8868	0.0250	0.0280	0.1778	0.6733
0.9900	0.9900	0.0000	1.0000	0.0100	0.0120	0.1899	0.6630
0.9950	0.9960	0.1079	0.7425	0.0050	0.0040	0.1079	0.7425
0.9975	0.9960	0.3811	0.5370	0.0025	0.0000	.NaN	1.0000

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 39: Out-of-sample VaR calculated by ARFIMA-GARCH for Slovenia

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9612	1.4038	0.2361	0.0500	0.0490	0.0108	0.9172
0.9750	0.9816	0.9726	0.3240	0.0250	0.0306	0.5916	0.4418
0.9900	0.9918	0.1781	0.6730	0.0100	0.0204	4.1208**	0.0424
0.9950	0.9939	0.1158	0.7337	0.0050	0.0061	0.1158	0.7337
0.9975	0.9980	0.0442	0.8334	0.0025	0.0041	0.4121	0.5209
Student-t distribution							
0.9500	0.9633	1.9915	0.1582	0.0500	0.0449	0.2777	0.5982
0.9750	0.9816	0.9726	0.3240	0.0250	0.0306	0.5916	0.4418
0.9900	0.9918	0.1781	0.6730	0.0100	0.0122	0.2328	0.6295
0.9950	0.9939	0.1158	0.7337	0.0050	0.0041	0.0887	0.7659
0.9975	0.9980	0.0442	0.8334	0.0025	0.0020	0.0442	0.8334
Skewed Student-t distribution							
0.9500	0.9612	1.4038	0.2361	0.0500	0.0449	0.2777	0.5982
0.9750	0.9816	0.9726	0.3240	0.0250	0.0306	0.5916	0.4418
0.9900	0.9918	0.1781	0.6730	0.0100	0.0102	0.0020	0.9639
0.9950	0.9939	0.1158	0.7337	0.0050	0.0041	0.0887	0.7659
0.9975	0.9980	0.0442	0.8334	0.0025	0.0020	0.0442	0.8334

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

Table 40: Out-of-sample VaR calculated by ARFIMA-HYGARCH for Turkey

Short position				Long position			
Quantile	Failure rate	Kupiec	P-value	Quantile	Failure rate	Kupiec	P-value
Normal distribution							
0.9500	0.9420	0.6421	0.4229	0.0500	0.0480	0.0426	0.8364
0.9750	0.9720	0.1778	0.6733	0.0250	0.0220	0.1923	0.6610
0.9900	0.9880	0.1899	0.6630	0.0100	0.0160	1.5383	0.2149
0.9950	0.9900	1.9441	0.1632	0.0050	0.0120	3.5303***	0.0603
0.9975	0.9940	1.7590	0.1848	0.0025	0.0060	1.7590	0.1848
Student-t distribution							
0.9500	0.9420	0.6421	0.4229	0.0500	0.0500	.NaN	1.0000
0.9750	0.9740	0.0203	0.8868	0.0250	0.0200	0.5499	0.4584
0.9900	0.9900	.NaN	1.0000	0.0100	0.0100	.NaN	1.0000
0.9950	0.9960	0.1079	0.7425	0.0050	0.0060	0.0944	0.7586
0.9975	0.9980	0.0538	0.8165	0.0025	0.0020	0.0538	0.8165
Skewed Student-t distribution							
0.9500	0.9440	0.3654	0.5455	0.0500	0.0540	0.1643	0.6852
0.9750	0.9760	0.0208	0.8854	0.0250	0.0220	0.1923	0.6610
0.9900	0.9900	.NaN	1.0000	0.0100	0.0140	0.7187	0.3966
0.9950	0.9960	0.1079	0.7425	0.0050	0.0060	0.0944	0.7586
0.9975	0.9980	0.0538	0.8165	0.0025	0.0040	0.3811	0.5370

Note: * ,** and *** denotes 1%, 5% and 10% level, respectively

CHAPTER 7

CONCLUSION

The incredible trading losses of well known financial institutions, recent crises in emerging markets, and international stock market crash of 1987 and 2008 have motivated the need for an effective risk measurement methodology for measuring and managing market risk. To respond these needs, VaR has especially emerged as the most widely used and uniform risk measurement tool in all of the EU and G10 countries since its adoption by the Basel Committee on Banking Supervision. As a risk management technique, VaR describes the maximum loss that can occur over a given period, at a given confidence level, to a given portfolio due to exposure to market risk.

The results of recent empirical studies have revealed that forecast of the volatility parameter that describes level of riskiness of the asset or a portfolio is a crucial parameter in the implementation of parametric VaR calculation methods. Therefore, the estimated VaR is highly sensitive to the assumed volatility model. This is an important problem because of the increasing demand on relying VaR for risk management decisions by market agents and regulators. The accuracy of volatility forecasts is a very critical issue in the estimation of VaR that involves calculation of the expected losses that might result from changes in the market prices of particular securities. Henceforth, it is rather unclear which forecasting model is the most appropriate. Therefore, the objective of this thesis is to determine the best method for VaR estimation by evaluating the performances of different volatility models, by using data from new European Union member countries from the Central and Eastern Europe (CEE hereafter) and three official candidate countries (Turkey, Croatia and Macedonia). Moreover, it seeks to extend previous research concerned with the evaluation of alternative volatility forecasting methods such as long memory models under VaR modeling.

As a contribution to the current literature, this thesis firstly extends the scope of previous research through evaluative application and comparison of volatility forecasting methods for 11 new and 3 candidate European Union countries' daily stock market index data. It is found worthwhile to investigate European Union countries, as it has gone through a period of extraordinary economic, monetary, and financial integration, and the structure of the financial markets in the European region has changed fundamentally in order to adhere to the Maastricht Treaty since 1990s. Secondly, we broaden the class of GARCH models under consideration by including more recently proposed models such as the FIGARCH and HYGARCH representations, which takes long memory characteristics of return volatility in the estimation of VaR of market indices. In this context, we are using hybrid method in the sense that we combine ARFIMA time series models with FIGARCH and HYGARCH models to examine the dual long memory property in the returns and volatility of the sample index series. While many applications assume that financial asset returns are normally distributed, it is widely documented that they are leptokurtic and fat-tailed resulting in an underestimation or overestimation of true VaR. Hence, we implement volatility models under more sophisticated distributions than normal distribution such as student-t and skewed student-t distribution. Third, we will investigate longer time periods than done other studies in the literature, and this especially for transition economies in European Union. The findings have a direct theoretical and practical relevance for the assessment and management of risk associated with transition economies.

The empirical results show that long memory parameters ξ and d are significantly different from zero, implying the presence of dual long memory property in the returns and volatility of six of the fourteen EU member and candidate countries. Long memory process is not observed in the conditional variance of Croatia, Latvia, Lithuania, Macedonia and Slovakia stock markets which mean their volatility follow a short memory. It is also found that, unlike other candidates, Turkey's stock market show similar characteristics with transition countries when we compare volatility behavior of all candidate countries with new EU countries. The presence of long memory volatility in most of the new and candidate EU stock markets enables us to rank the degree of market inefficiency, which also leads to the rejection of efficiency market hypothesis in these markets.

Consequently, when the stable and long memory models are compared it is observed that the long memory models capture temporal pattern of volatility better than the stable GARCH models in most of the cases. The volatility estimation results also indicate that the Student-*t* and skewed Student-*t* distribution outperforms the normal distribution. This indicates that the return series of all sample indices are skewed distributed and have fat tails by the significant coefficient of $ln(k)$ and v in the results of model estimation.

Comparing the estimated in-sample and out-of-sample one-step-ahead VaR numbers based on Kupiec LR test, the skewed Student-*t* model outperforms the normal distribution in describing the return series of the transition countries.

In summary, long memory models provide more efficient results in risk analyzing, such as VaR, when variance series of the returns is filtered by the long memory model, rather than short memory model. Moreover, non-normal distributional assumptions of portfolio returns like Student-*t* and skewed Student-*t* should be taken into consideration when forecasting VaR. Therefore, these findings would be helpful to the financial managers, investors, bankers and fund managers whose success depend on the ability to forecast stock price movements in the transition countries.

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APPENDIX A: Description of Stock Indices

Country	Index - Abbreviation	Description
Bulgaria	Sofix Index (SOFIX)	The Bulgaria Stock Exchange Sofix Index is a free float market capitalization weighted index representing the most liquid companies listed on the exchange. The market capitalization of each company should not be less than BGN 50 million.
Croatia	Croatia Zagreb CROBEX Index (CROBEX)	CROBEX is a capitalization-weighted index, capped at a maximum 20% weighting of the index capitalization. The index was designed to measure price movements of shares listed on the Zagreb Stock Exchange
Czech Republic	Prague Stock Exchange PX Index (PX)	The PX index is the official index of the Prague Stock Exchange. The index was calculated for the first time on March 20, 2006 when it replaced the PX50 and PX-D indices. The index took over the historical values of the PX50 index. ThePX Index is a price index and dividend yields are not considered in the calculation
Estonia	OMX Tallinn Index (TALSE)	OMX Tallinn is a capitalization weighted chain-linked total return index which includes all the shares listed on the Main & Secondary lists on the Tallinn Stock Exchange
Hungary	Budapest Stock Exchange Index (BUX)	The Budapest Stock Exchange Index is a capitalization-weighted index adjusted for free float. The index tracks the daily price only performance of large, actively traded shares on the Budapest Stock Exchange. The shares account for 58% of the domestic equity market capitalization.
Latvia	OMX Riga Index (RIGSE)	OMX Riga is an all-share index consisting of all the shares listed on the Main & Secondary lists on the Riga Stock Exchange with exception of the shares of the companies where a single shareholder controls at least 90% of the outstanding shares
Lithuania	Lithuania NSEL 30 Index (NSEL30)	NSEL 30 Index is a cap-weighted index composed of 30 stocks with the largest free-float based market capitalization that are listed on the Vilnius Stock Exchange. NSEL 30 Index is rebalanced quarterly. Index is adjusted for splits, distributions, breakups, spinoffs, exchanges, and it includes dividends
Macedonia	MBI 10 Index (MBI10)	MBI 10 is a price index weighted with market capitalization and consists of up to 10 listed ordinary shares, chosen by the Macedonia Stock Exchange Index Commission

Malta	Malta Stock Exchange Index (MALTEX)	The Malta Stock Exchange index is a capitalization weighted index encompassing all shares traded on the Stock Exchange of Malta. Index is the current market value of all shares listed
Poland	Warsaw Stock Exchange WIG 20 index (WIG20)	The WIG20 index is a modified capitalization-weighted index of 20 Polish stocks which are listed on the main market. The index is the underlying instrument for futures transactions listed on the Warsaw Stock Exchange.
Romania	Bucharest Exchange Trading Index (BET)	Bucharest Exchange Trading Index is a capitalization weighted index, comprised of the most liquid 10 stocks listed on the BSE tier 1.
Slovakia	Slovak Share Index (SKSM)	The Slovak share index is a capital-weighted total return index that compares the market capitalization of a selected set of shares with the market capitalization of the same set of shares as of a given reference day.
Slovenia	Slovenia Stock Market Index (SVSM)	The SVSM Index is the Ljubljana Stock Exchange total market index, measuring the performance of the entire Slovene organized securities market. It is aimed primarily at providing accumulated credible information on the price movements.
Turkey	Istanbul Stock Exchange National 100 Index (XU100)	The Istanbul Stock Exchange National 100 Index is a capitalization-weighted index composed of National Market companies except investment trusts. The constituents of the ISE National 100 Index are selected on the basis of pre-determined criteria directed for the companies to be included in the indices.

APPENDIX B : Plots of The Stock Indices and The Respective Return Series

Figure 5a) Price series for Bulgaria

Figure 5b) Return series for Bulgaria

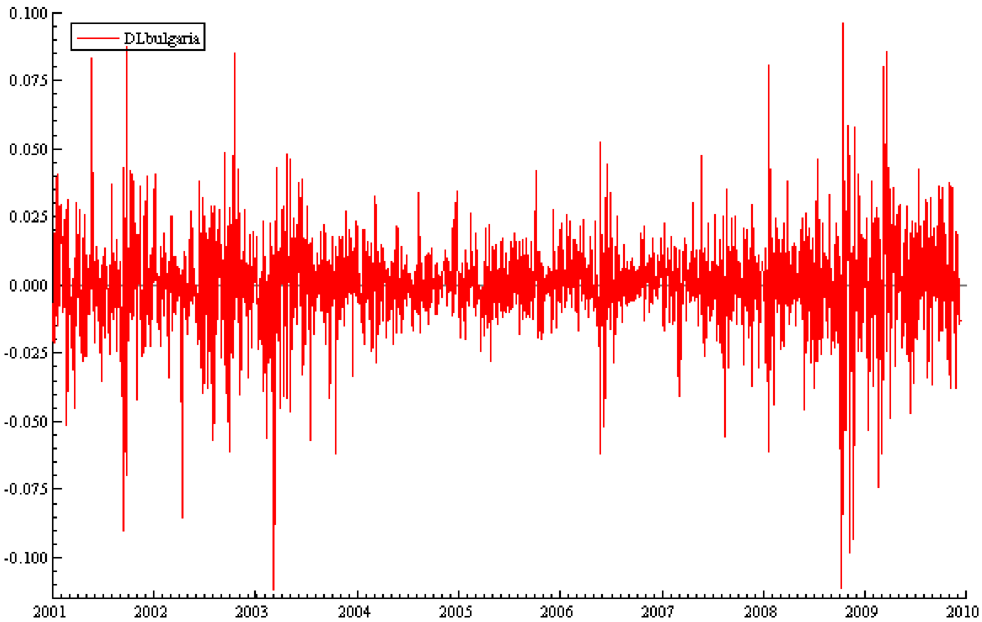


Figure 6a) Price series for Croatia

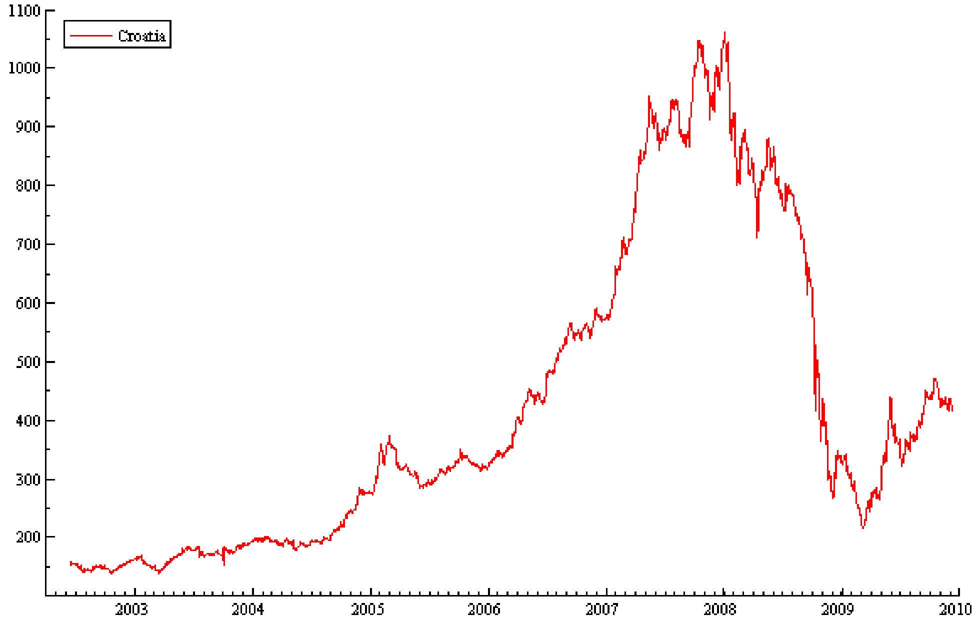


Figure 6b) Return series for Croatia

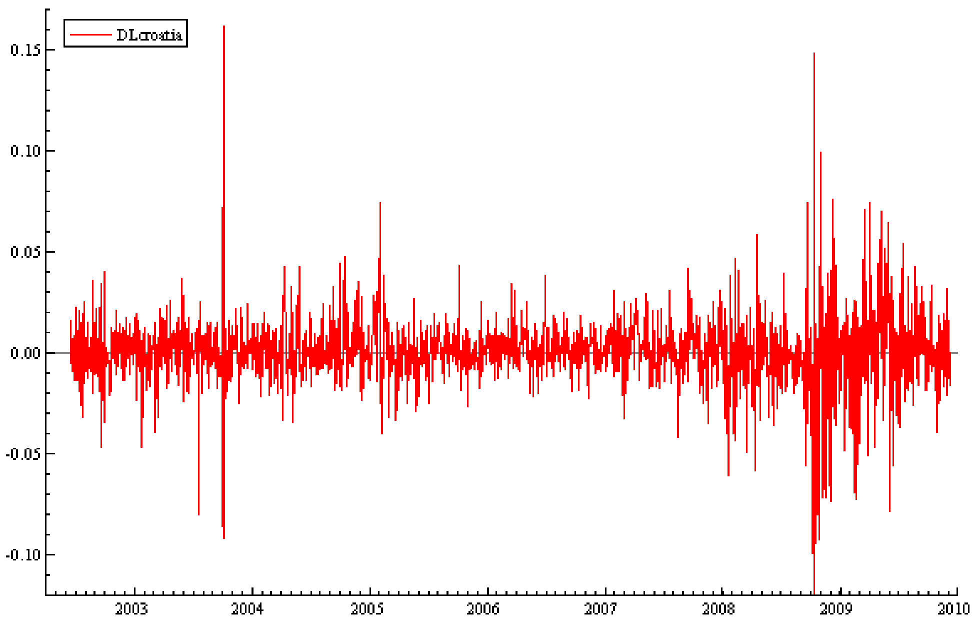


Figure 7a) Price series for the Czech Republic

Figure 7b) Return series for the Czech Republic

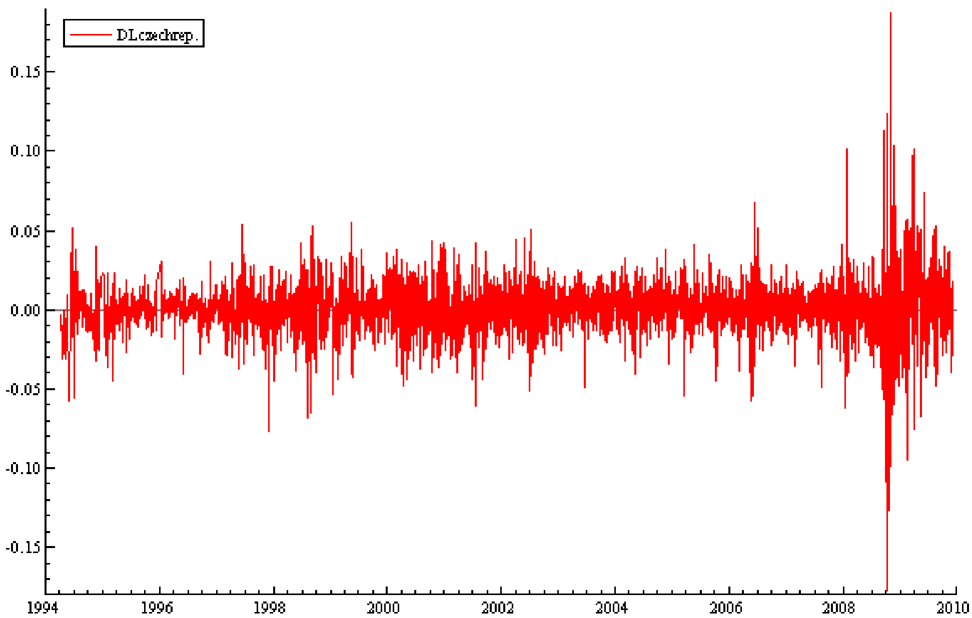


Figure 8a) Price series for Estonia

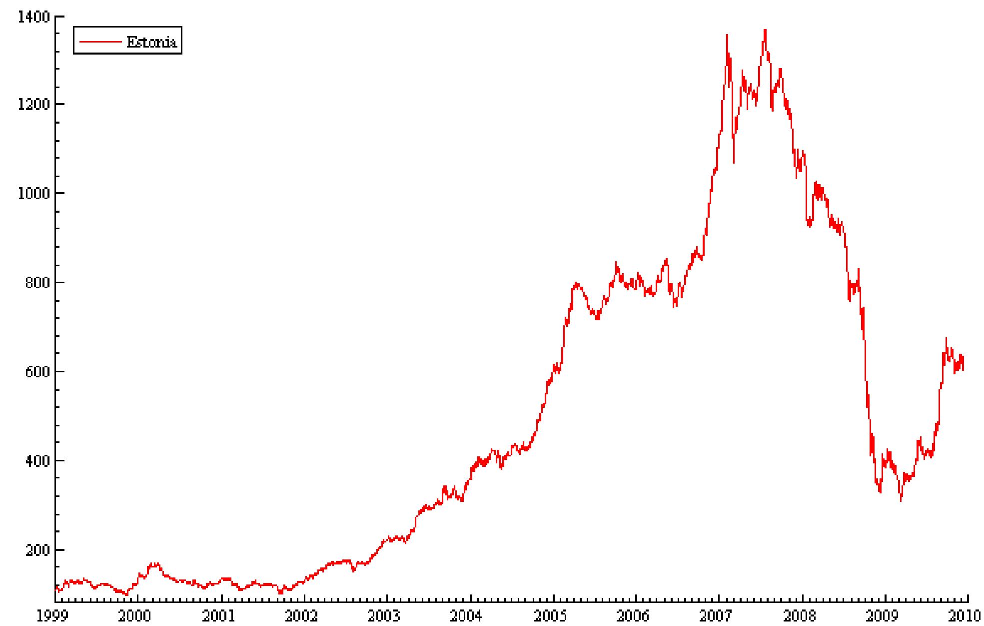


Figure 8b) Return series for Estonia

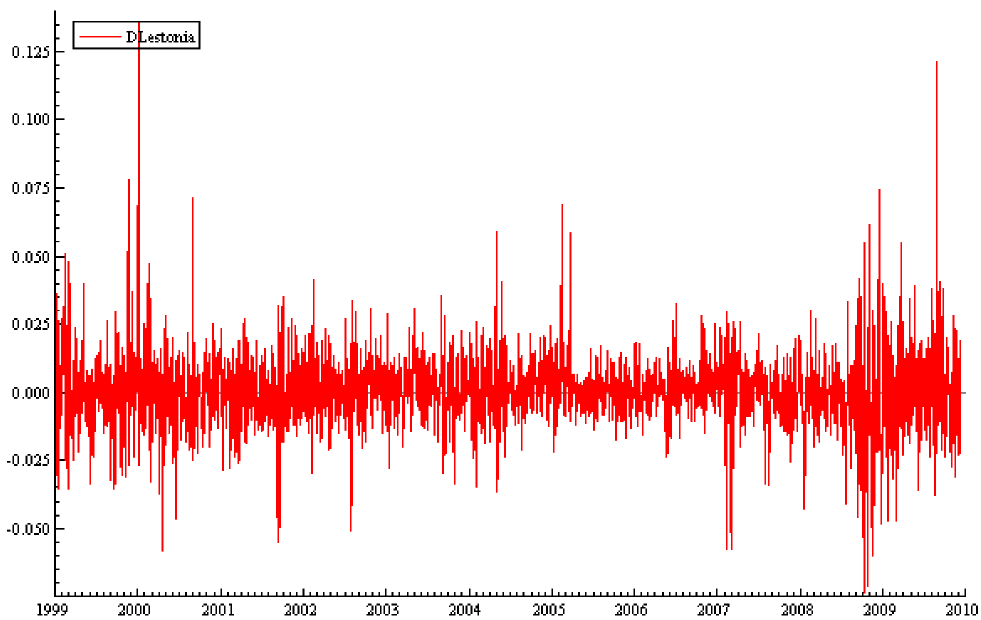


Figure 9a) Price series for Hungary

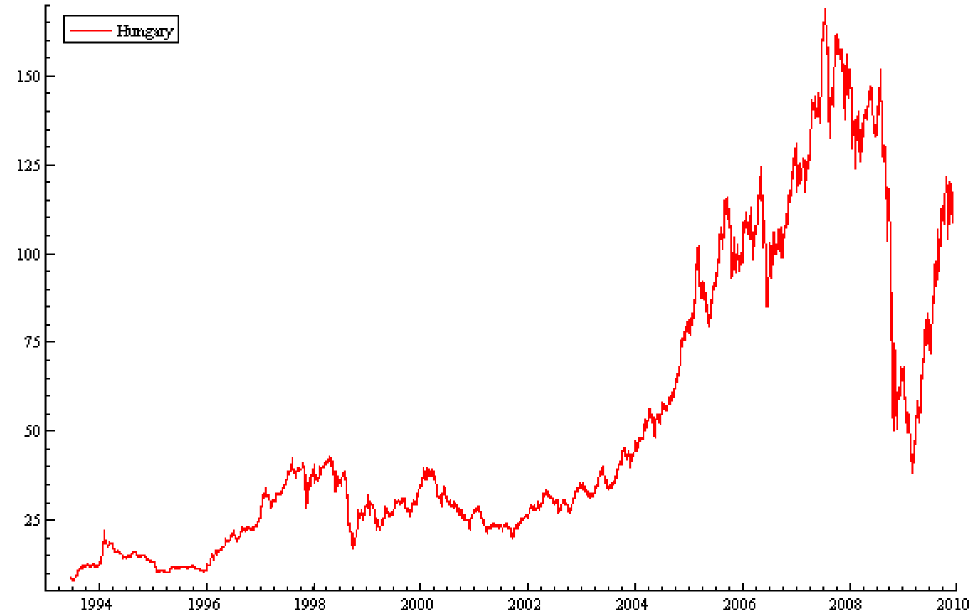


Figure 9b) Return series for Hungary

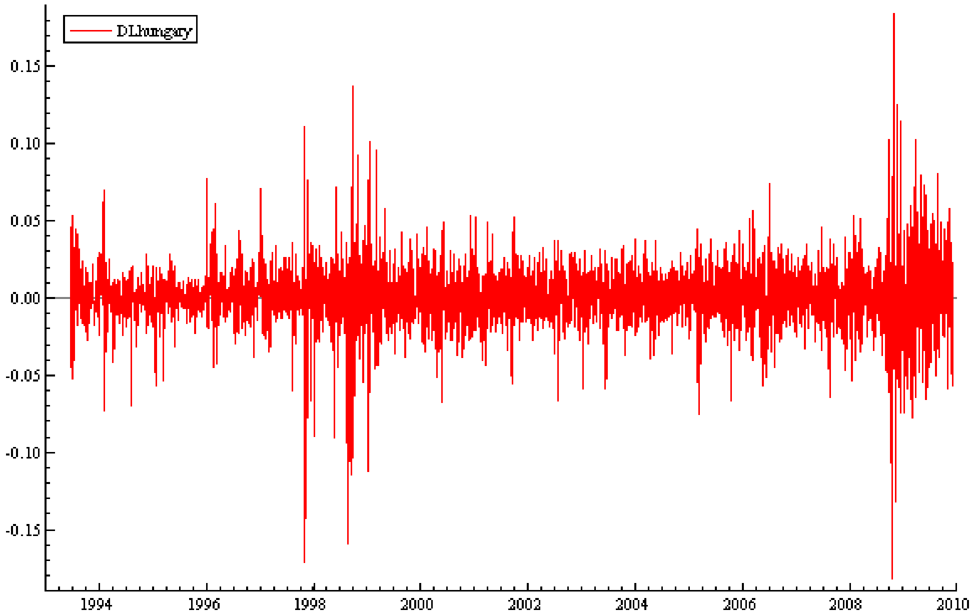


Figure 10a) Price series for Latvia

Figure 10b) Return series for Latvia

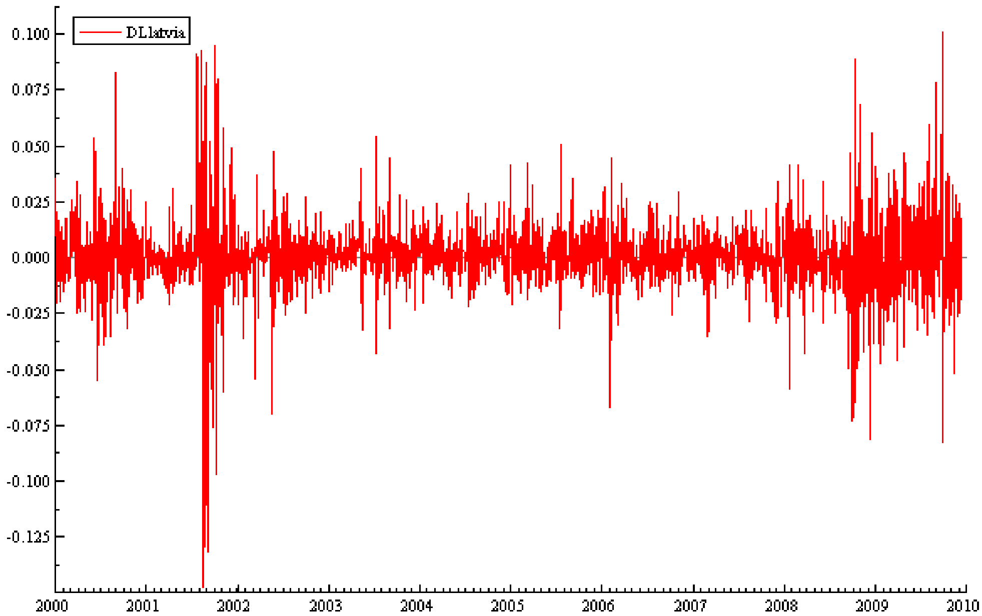


Figure 11a) Price series for Lithuania

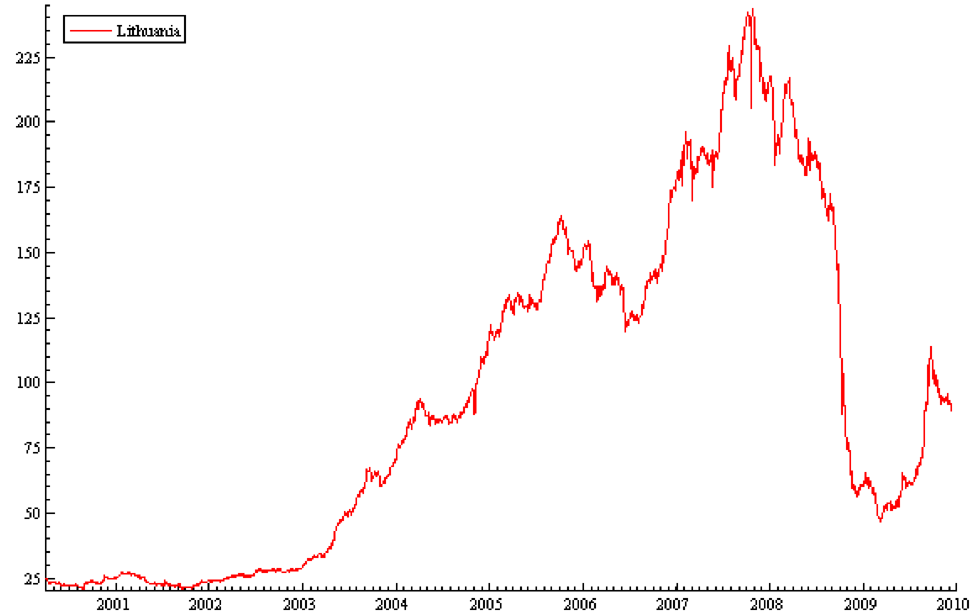


Figure 11b) Return series for Lithuania

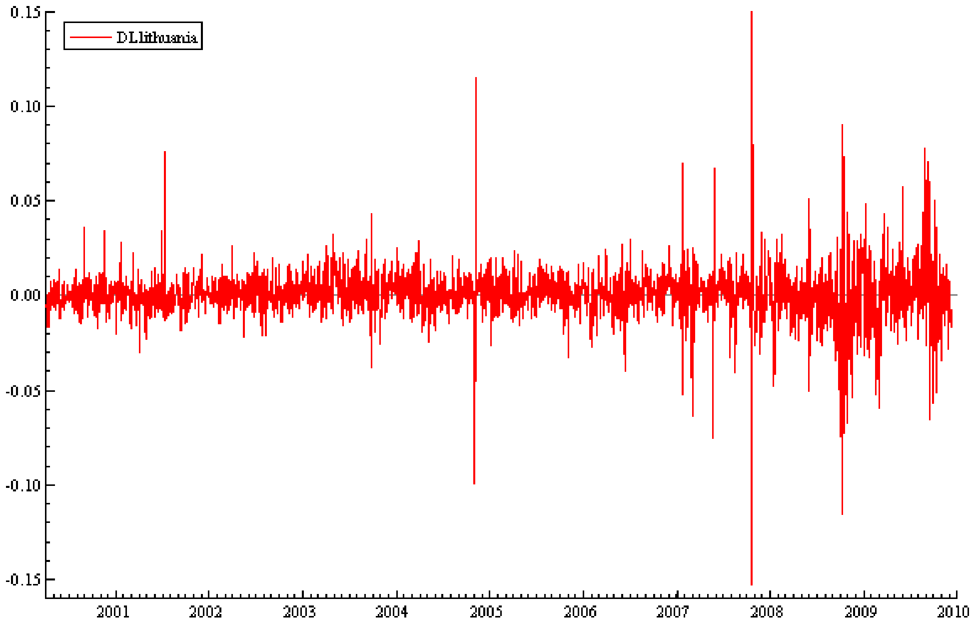


Figure 12a) Price series for Macedonia

Figure 12b) Return series for Macedonia

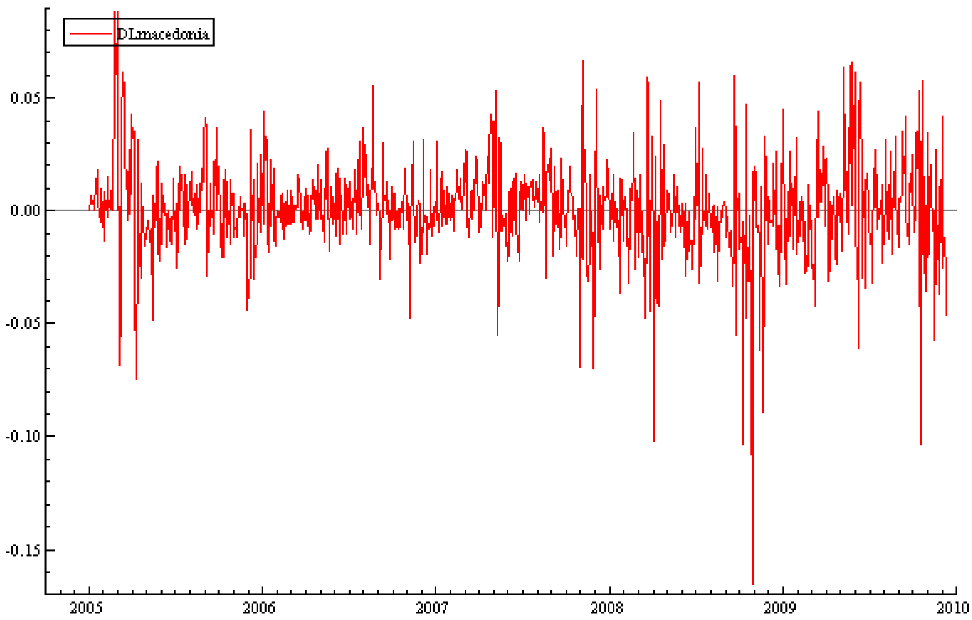


Figure 13a) Price series for Malta

Figure 13b) Return series for Malta

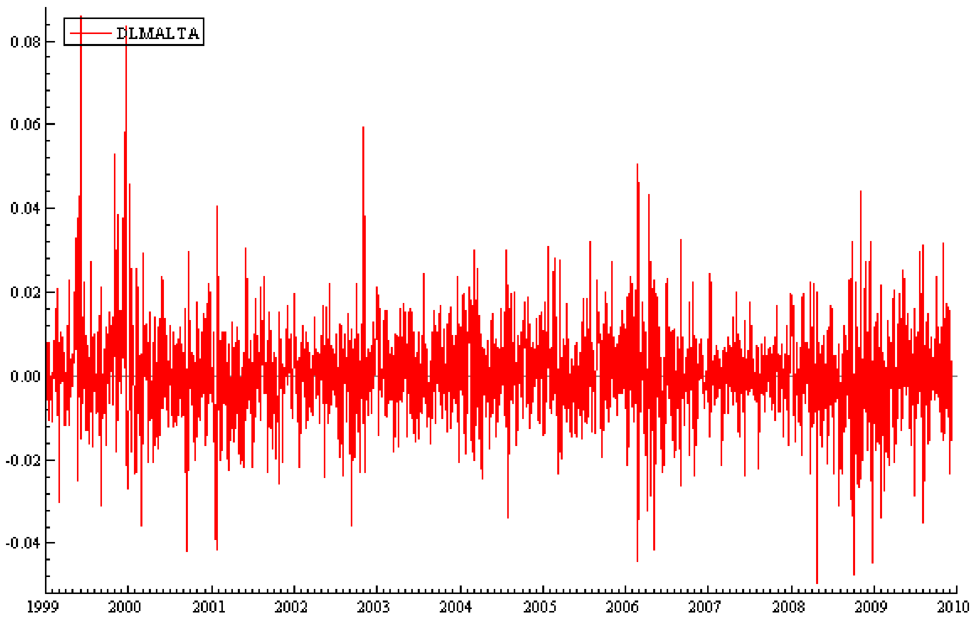


Figure 14a) Price series for Poland

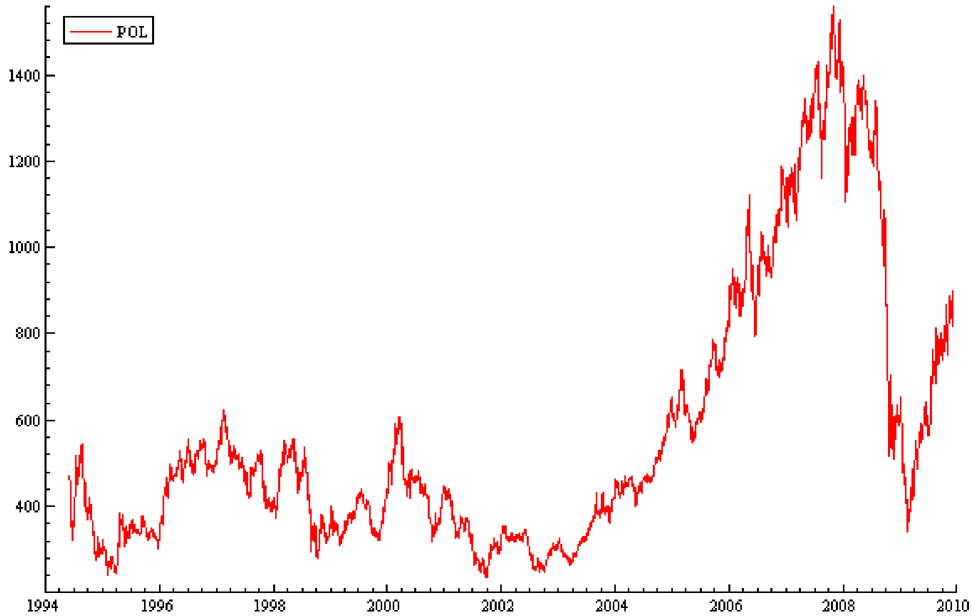


Figure 14b) Return series for Poland

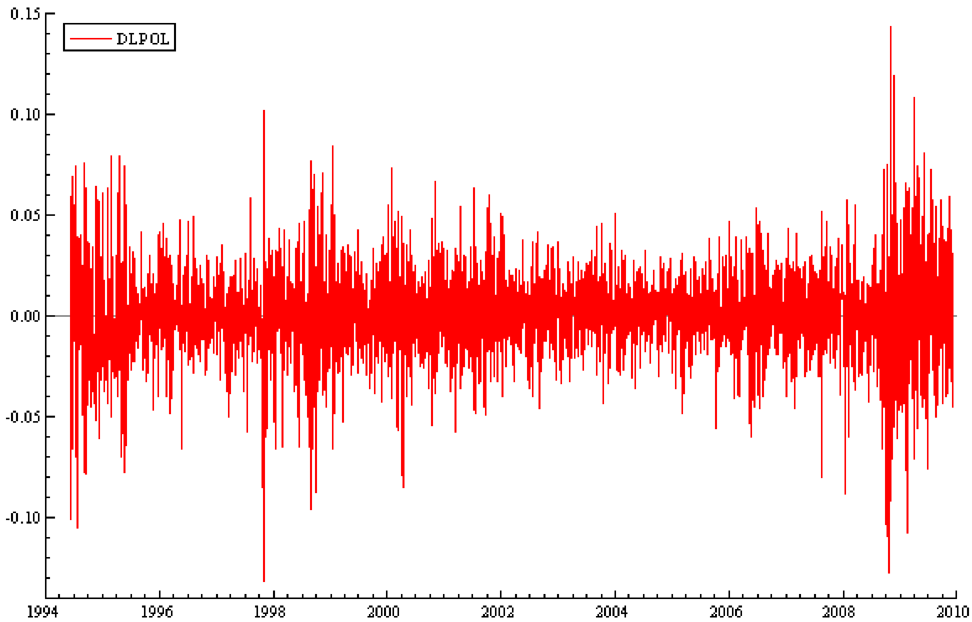


Figure 15a) Price series for Romania

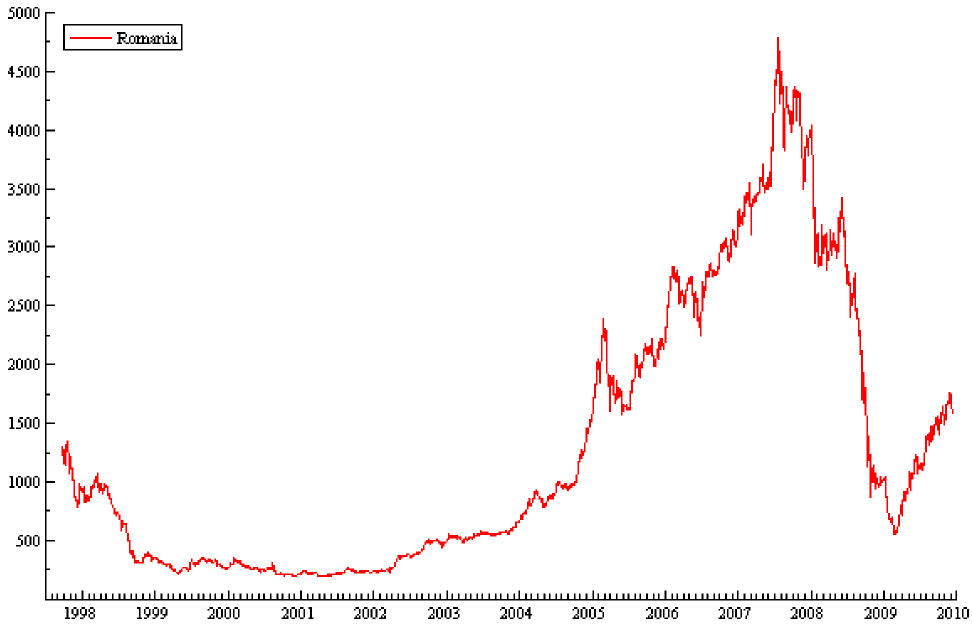


Figure 15b) Return series for Romania

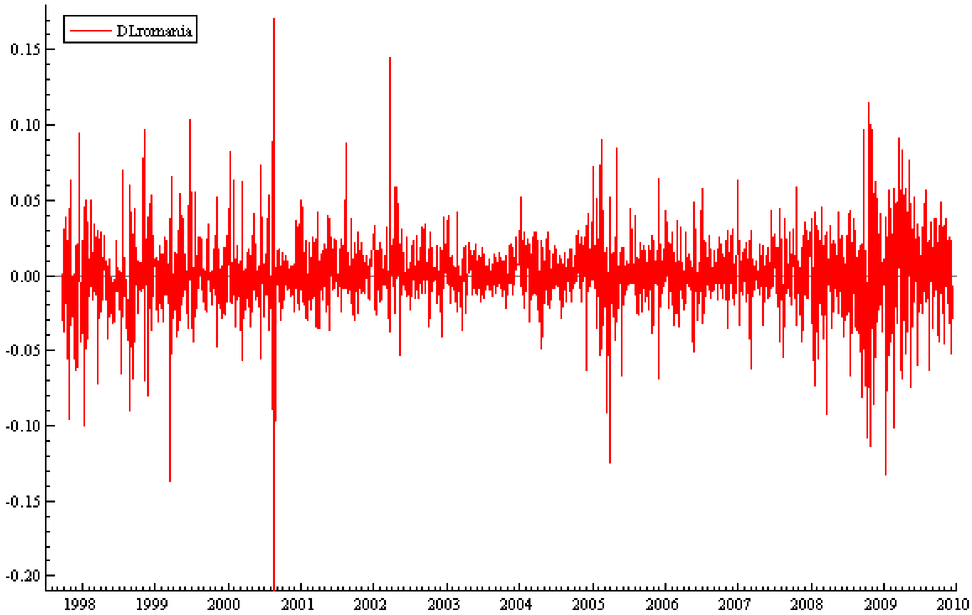


Figure 16a) Price series for Slovakia

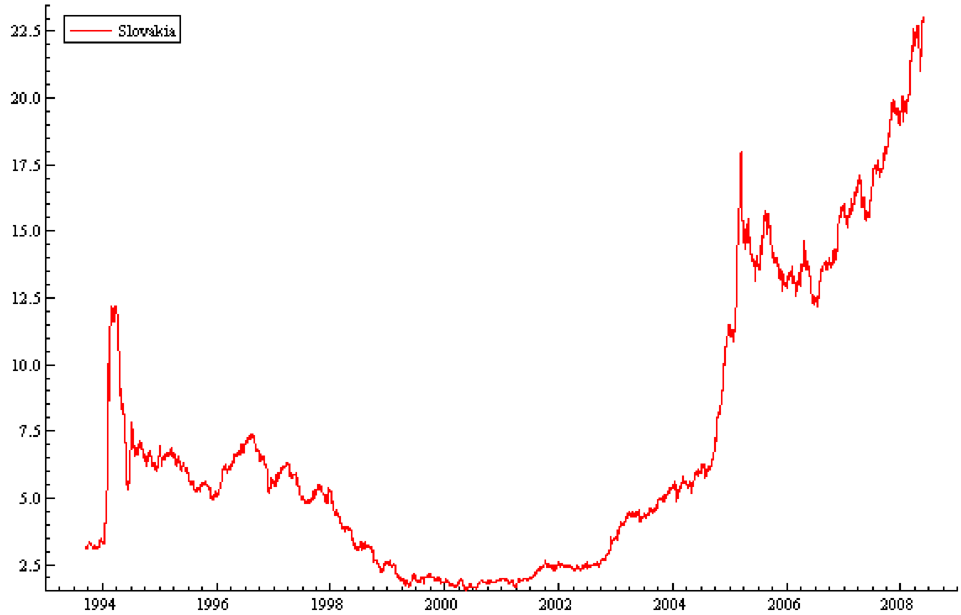


Figure 16b) Price series for Slovakia

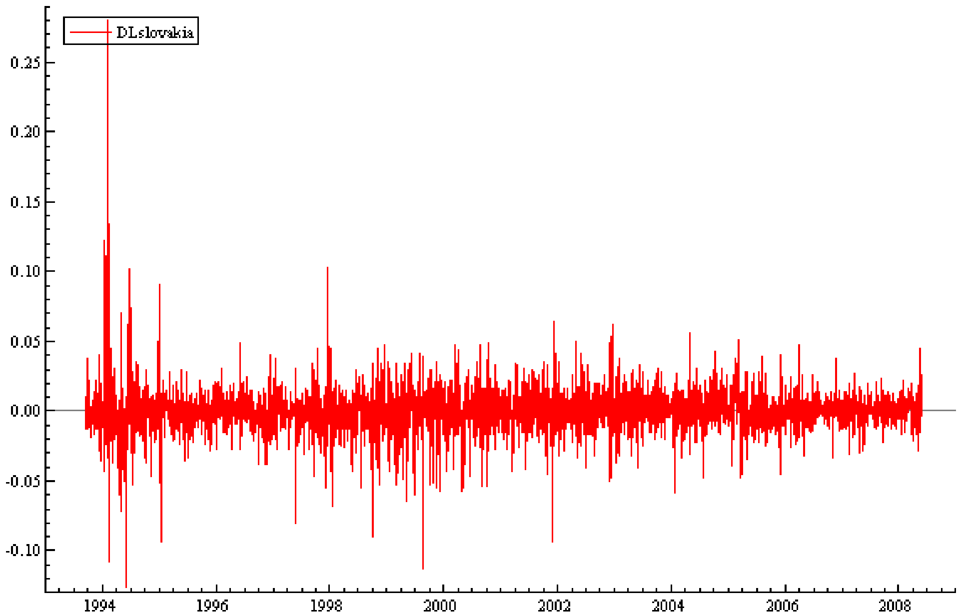


Figure 17a) Price series for Slovenia

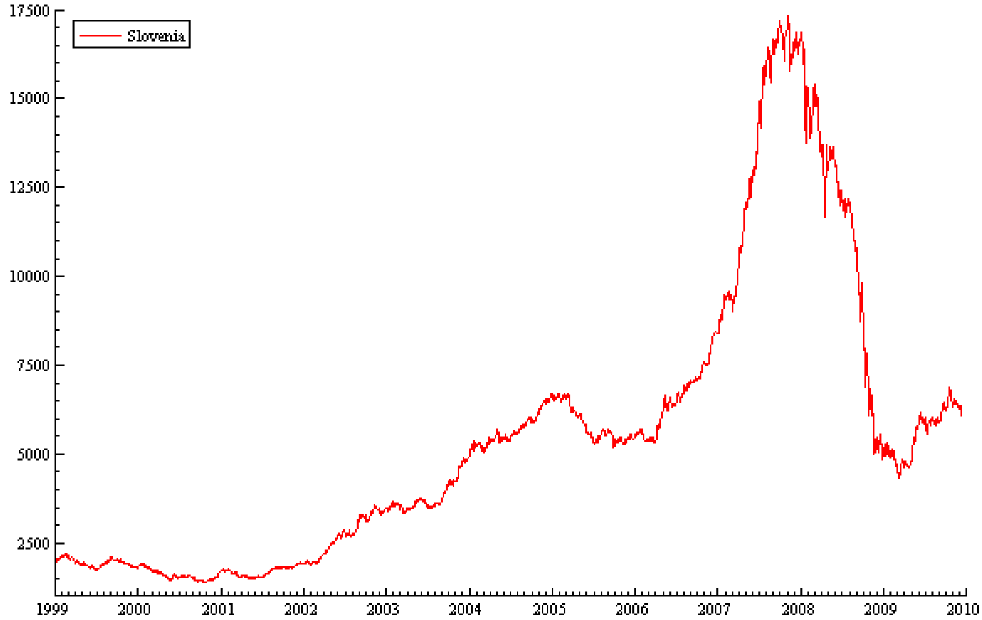


Figure 17b) Return series for Slovakia

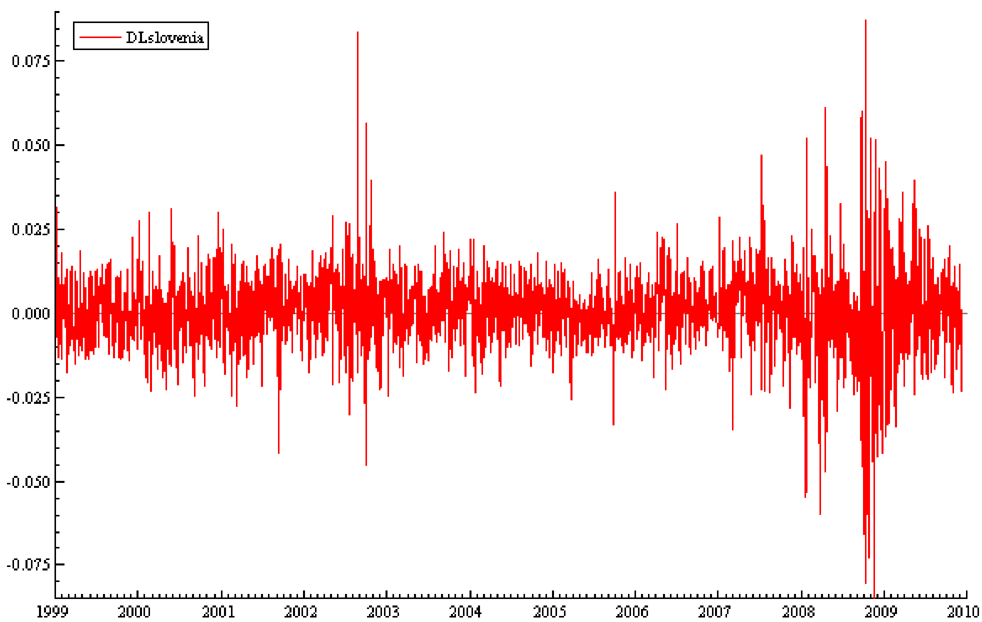


Figure 18a) Price series for Turkey

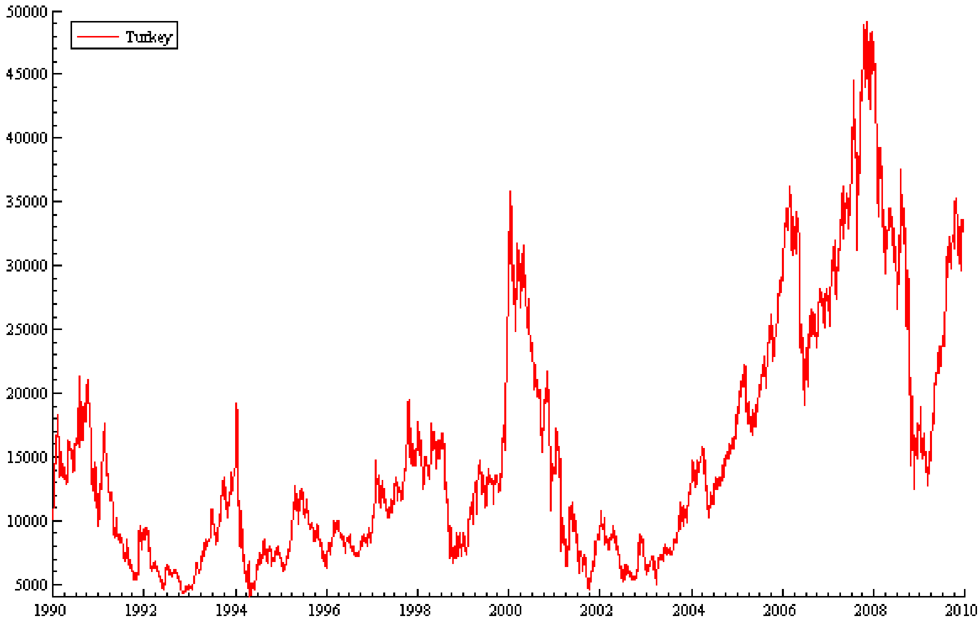
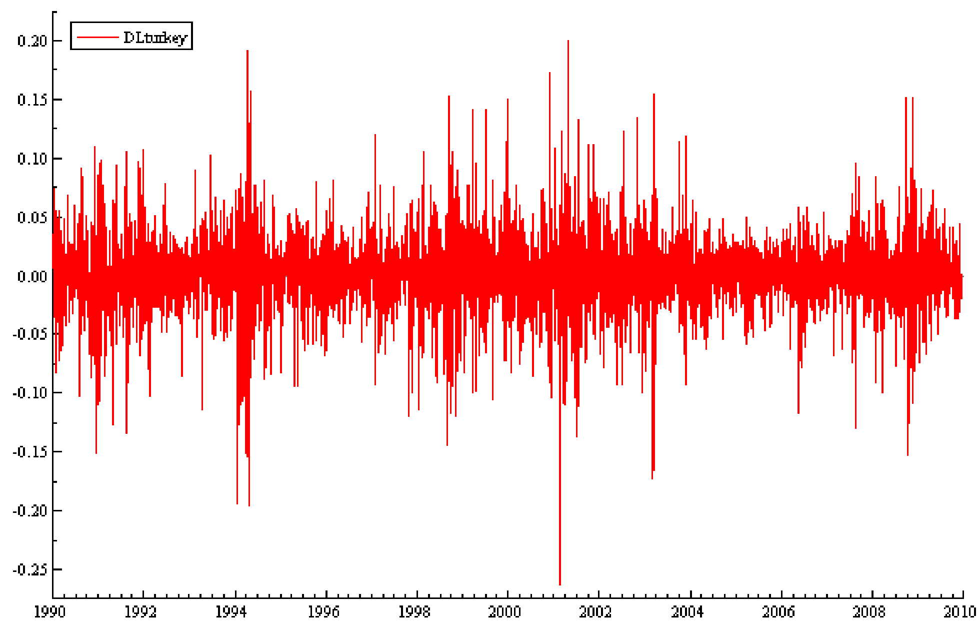


Figure 18b) Price series for Turkey



VITA

Gökçe Tunç was born in Izmir on August 28, 1982. She completed her undergraduate work in the Department of Business Administration of Faculty of Business in Dokuz Eylül University in June 2004. She started her PhD in the Department of Business Administration in a major field of finance at Izmir University of Economics in 2004. At the same year, she started to work as a research assistant at the Department of International Trade and Finance. Since 2007, she has been working as an instructor in the Department of International Trade and Finance at Izmir University of Economics. She teaches business finance and risk management courses. Her research is focused on stock and derivatives market and banking. Her academic papers have been published in peer-reviewed journals such as *Economic Modelling, İktisat, İşletme ve Finans, Review of Middle East Economics and Finance and European Journal of Economics, Finance and Administrative Sciences.*