TWO ESSAYS ON

RETURN AND VOLATILITY SPILLOVERS
&
FEEDBACK TRADING STRATEGIES

IN TWELVE BALKAN, SLAVIC AND ORIENTAL COUNTRIES

Dimitrios Angelidis

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Department of Balkan, Slavic and Oriental Studies
University of Macedonia

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knowledge is wealth for poor

jewel for rich

supply for young

and consolation for old…

Diogenes of Sinope 412 – 323 BC

Prologue

In this research an attempt is taken place to broaden the horizons around the themes of return and volatility spillovers, and in parallel about feedback trading strategies. These are two related to each other subjects, but not overlapping. They are objects of continuous and growing scientific research as the economic integration at a global level and the advancement of technology turned the attention of many scientists on such areas.The scientific interest is reinforced by the potential practical use of findings by individual and institutional investors. However, as the limits of knowledge and science can be considered -if not without borders- at least vast, there is always available space for deeper exploration.The ambition of this study is to contribute into relative literature expanding the applied methodology to a number of countries which have not received much attention from scholars until now.

The aim of the dissertation is to examine return and volatility spillovers, and feedback trading strategies phenomena for a range of Balkan, Oriental and Slavic countries. Often, such countries that are considered peripherals do not attract the attention of researchers and their importance is neglected. However, real life teaches, sometimes in the hard way, that every cycle of the global chain has its significance. A typical example is the financial crisis in Greece that churned violently not only the country itself or the neighboring countries, but had important consequences in the worldwide economic system, causing nervousness at the four corners of the globe.

Through this prism, empirical results of such a study become of great interest. In order to spotlight the behavior of spillover effects and also to detect whether some kind of feedback trading strategy is followed by traders on stock exchanges, twelve representative markets were selected from Balkan, Slavic and Oriental countries. The choice was based on the specific area of interest of University’s School. These states, in alphabetical order, are: Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Study aspires to cover a decennial time period, by selecting daily data for each one of the aforementioned countries and handle this information according to the preferred methodology. Specifically, time period under investigation is from 2006 till 2015, which includes the great crisis episodes of 2007-2008 and the global economic recession.

As far as the first essay -the one about return and volatility spillovers- is concerned, study is focused on the way that spillover effects influence demand and supply for shares. These findings have both theoretical significance and practical implications. Research explores not only the relationships among returns, but moreover evaluates the volatility spillover phenomenon, since the latter is used as a measurement of the overall risk of financial assets. The volatility spillover effect can be considered as quite important as it is a main factor to spread the financial risk from one spot to another. This effect can be mostly visible during periods of intense fluctuations, where the advantages that stock holders get by international portfolio diversification are limited -if not reversed-. Another question is the possible existence of the leverage effect. According to this, spillover volatility is asymmetric, which means that “bad news” (price drop) have a bigger impact on volatility than “good news” (rise in prise).

Of course, there are some second thoughts about return and volatility spillovers’ negative impact on optimal formation of a rational portfolio which is based on fundamentals. The decoding and therefore the knowledge of transmission mechanisms may provide the prospect to predict the behavior of a given market by using the necessary information and the suitable methodology, leading into successful trading strategies.

In order to achieve that and to shape a model as reliable as possible, present study tries to contribute towards this direction by enriching the analysis of return and volatility spillovers with some extra explanatory variables. As potential extensions of the basic spillover model, this research adds not only the trading volume effect, but furthermore two additional explanatory variables are tested; these are i) the exchange rates of each country's domestic currency related to the US dollar, and ii) the behaviour of S&P 500 index. These variables are used not only independently, but combined as well, with and without the liquidity factor. Hence, analysis is composed of eight parallel equations. As far as we are aware, this method is pioneer, since it is the first time that such a combined formula is formed. It will be quite interesting to discover the ability of these approaches to improve the performance of the basic model in terms of predicting the behavior of return and volatility spillovers.

In parallel, the second essay is related to feedback trading. According to the theory, there are two dissimilar groups of investors. On one side active the so-called "rational" traders who decide by perusing firms' balance sheets and fundamentals. On the other side there are the notorious "noise" speculators that ignore companies' fundamentals and base their transactions on a kind of feedback trading strategy. The idea behind feedback trading is about a behavior of herd mentality. More specifically, feedback strategy is a pattern of investment that causes investors to buy (sell) stocks when prices rise and sell (buy) stocks when prices fall. This is the positive (negative) feedback trading strategy. To test whether feedback strategies are present in the examined stock markets during period under investigation, two equations are formed and employed simultaneously. Firstly, the Sentana and Wadhani (1992) formula and secondly the LeBaron (1992) exponential model.

Positive feedback trading can be considered as a main reason why some times markets falls can lead into a further depreciation of shares' values. In the same sense, a market rise may cause a self-perpetuating spiral, resulting into even further increases. Whenever a considerable number of speculators adopt positive feedback trading strategies, stocks prices may move away from the value that could be regarded as fair according to fundamentals. Consequently, positive feedback can be thought as a possible source of increased volatility in markets. Even more, every time that a cycle of positive feedback trading strategies lasts too long, it is likely a "bubble" of stocks prices to be created or in some extreme situations a market violent crash.

A possible explanation, at least on an individual level, may come from psychological factors such as excessive enthusiasm or fear, or even greed. Furthermore, the completion of a successful transaction can provide too much confidence to the investor, who will proceed to less-studied transactions. In addition, well-experience traders and institutions may enhance positive feedback, not because of ignorance, but because of intentions to speculate by exploiting the individual investors who will be naive enough to follow them, and then jump off the train at the right moment. As an antidote, investors should adopt a rational trading plan and to follow it faithfully, remaining calm, confident and stoic, even during the inevitable losing periods.

Concluding, the doctoral dissertation consists of two parts that investigate phenomena such as spillovers and feedback strategies in a number of selected stock markets. The relevant established literature is adopted and adapted to the needs of this research. In addition, attempts are made to develop further the models in order to achieve a more rigorous analysis of investors' patterns. The "food" for these formulas is the information of daily closing prices of each country's major stock exchange index. We look forward to seeing if the empirical results will verify the existence of return and volatility spillovers and also the presence of feedback trading strategies, for which of the markets, and moreover the form of each phenomenon. Besides, we are going to find out whether the formulas introduced by this paper "run" satisfactorily and produce statistically significant results that help to understand better the phenomena.

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List of Acronyms

AIC	Akaike Information Criterion
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving-Average
EAR	Exponential Autoregressive
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ER	Exchange Rates
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
IGARCH	Integrated Generalized Autoregressive Conditional Heteroskedasticity
(LB)	Ljung-Box statistic
MoU	Memorandum of Understanding
NFT	Negative Feedback Trading
PFT	Positive Feedback Trading
QGARCH	Quadratic Exponential Generalized Autoregressive Conditional Heteroskedasticity
S&P	Standard & Poor
TV	Trading Volume
VAR	Vector Autoregression

UNIVERSITY OF MACEDONIA

PhD THESIS

RETURN AND VOLATILITY SPILLOVERS IN TWELVE BALKAN, SLAVIC AND ORIENTAL COUNTRIES

Author: Dimitrios Angelidis, PhD Candidate

Supervisor: Athanasios Koulakiotis, Assistant Professor

Department of Balkan, Slavic and Oriental Studies

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RETURN AND VOLATILITY SPILLOVERS IN TWELVE BALKAN, SLAVIC AND ORIENTAL COUNTRIES

Synopsis

This study investigates return and volatility spillovers on stock markets of twelve selected Balkan, Slavic and Eastern countries. Research focuses on a decennial period, from 2006 till 2015. Analysis, which employs an augmented univariate AR-EGARCH model, is based on a "bouquet" of eight parallel equations. Two additional explanatory variables are tested; namely, the change of exchange rates of each country's domestic currency to the US dollar, and the return of S&P 500 index during the previous period. They are used not only separately, but in combination as well, with and without the liquidity factor. According to the empirical results, return and volatility spillovers are confirmed for the majority of the cases, no matter the different approaches. Furthermore, the positive sign for the coefficients about the exchange rates and about the S&P 500 index is verified for most of the occasions. Moreover, the leverage effect is present in several cases. In addition, outcomes illustrate that trading volume's coefficient mainly carries a positive sign and also that this variable accounts for spillovers effects in return and volatility. Overall, it can be concluded that the formed univariate AR-EGARCH models, capture successfully the effects of volatility transmission in the examined stock markets.

Keywords: Return and volatility spillovers, leverage effect, capital markets in Balkan, Slavic and Eastern countries

JEL Classification: G12, C22

Dimitrios Angelidis, d.angelidis@hotmail.com

1. Introduction

Generally, “spillover effect” is defined as a secondary effect that follows from a primary effect, and may be far removed in time or place from the event that caused the primary effect. In science of economics the term “spillover effects” is used to describe economic events that take place in one frame because of something else in an apparently unrelated or at least not directed related frame. As an example, the economic benefits of increased revenues from tourist industry in a particular country may be considered as spillover effects originated to risen social and political instability in an antagonistic country. Focusing on a more financial paradigm, we suppose that some markets fail to be considered as diaphanous enough. Such failure may influence in one or another way the demand and/or the supply behavior of affected participants not only in these countries but in others closely related markets as well. This phenomenon will have as a result, the observed demand and/or supply to differ at least up to a level than their -let’s name it- notional demand and supply.

Economic spillover effects among countries have been increased significantly in recent decades, with the share of world trade in global gross product to rise from an average of 26 percent in the 1960s to 42 percent in the 1990s (Arora and Vamvakidis, 2005). It is a common belief, that as countries become more integrated they are increasingly influenced by each other’s economic development or recession. According to the theory, economic conditions abroad such as growth rates and income levels influence a home country’s improvement. This is because an augment in partners’ trading, leads to a boost in their total demand for imports, which then contributes directly to an increase in the net exports of the home country. Arora and Vamvakidis found that the importance of growth spillover effects had been increased with the expansion of world trade, as estimated coefficients for 1980–99 were larger compared with the corresponded estimates for 1960–99.

Of course, spillover effects do not refer always to positive influences but to negative as well. For example, the spillover effects of the global crisis on the economic activity of emerging market countries. Moriyama (2010) estimated the spillover effects of the global crisis to emerging market economies in the Middle East and North Africa countries and discovered that nearly two-thirds of the increased financial stress in these countries after the Lehman shock was attributable to direct or indirect spillovers of financial stress in advanced economies. Moreover, researcher claimed that the estimated models showed that the increased financial stress and slowdown in economic activity in advanced economies could explain about half of the drop in real GDP growth in emerging market economies of the Middle East and North Africa countries after the Lehman shock.

Beyond the fields of real economy, spillover effects are also present in other markets, where brokers and traders can buy and/or sell shares, bonds, derivates and other securities, commonly known as stock exchanges. In fact, spillovers among stock markets can be considered that are more easily and widely extended than spillovers among other forms of markets, due to the economic integration of international stock markets that has taken place especially over the last decades. The considerable increased flows of capitals among countries, the collapse of restricts into international commerce, in addition with the important development of technology can be thought as the main factors for this globalization process. As a consequence, it is a matter of great significance for portfolio managers and financial institutions to comprehend the relationships amongst various financial markets.

When referring to the international equity markets integration, researchers explore not only the return causality linkages, but they also evaluate volatility spillover effects. Volatility, as it measured by the variance or alternative by the standard deviation of shares' returns, is usually utilized as a basic parameter of the overall risk of financial assets. Information about volatility spillover effects can be assumed as substantial helpful for the application of value especially at high risk and hedging strategies.

The volatility spillover effect is the main procedure to spread the financial risk from one place to another. A financial crisis is often characterized by sudden and significant decreases in asset prices and in parallel increases in markets volatility. Exactly this kind of financial phenomena can be transmitted from one market to others with the speed of fire in a dry grass field, due to markets integrating and the various spillover channels. Therefore, when individual investors and professionals seek to construct the optimum portfolio, they have to keep in mind the systematic hazard that travels tirelessly among different markets.

Over the last years, as developing markets strengthened and their role in global economy became more and more important, economists had to focus not only on developed countries, but on a plethora of emerging markets as well. This is because, especially for the case of shares markets, the degree of the spillover effects between the emerging stock market exchanges and the developed stock market exchanges has important implications for both the developing and the developed countries' investors. Nevertheless, although spillover effects can be considered up to an extent as a mutual process, it does not mean that they are isobaric too. In real life developed markets influence developing markets in a larger scale than developing markets influence developed markets.

The intensity of transmission effects for each case can be proved as a crucial matter for investors' decisions. More specific, whether a given emerging stock market exchange is only weakly integrated with the developed markets, this means that external shocks will have less influence on that emerging markets. In this way, the developed markets investors can benefit via including the emerging market stocks in their portfolio as this diversification should reduce their risk. On the other hand, whether the emerging stock markets are highly or even fully integrated with the developed stock markets, the volatility in the emerging markets will decrease as it will be mainly determined by the developed markets' volatilities, which can be considered generally as more moderate. Of course, in this case a potential depreciation in equities of developed stock markets will unavoidably influence negatively the developing stock markets.

The spillover effects between stock market exchanges can be considered not only among developed and emerging markets, but also among exchanges of similar importance that are located in a specific area and their economies are under a kind of interdependence. In this case, a potential economic recession in one country is expected to impact not merely on this particular country's stock market but to neighboring countries' markets as well. As a typical example of such situation can be considered the Asian financial crisis, which although it started in Thailand during July 1997, gripped much of East Asia due to financial contagion. This crisis is well known in history of economics as "Asian tigers' crisis". Earlier, in the 1980s, the Latin American debt crisis occurred when countries such as Argentina, Brazil and Mexico reached a point where their foreign debt was so high that they were not able to repay it. This crisis underlined how intense was and may still be the effects of banking and financial systems between Latin American countries.

Beyond spillover effects from one stock market to another, these phenomena can be referred to the effects from one period to the next into the very same market or to the asymmetric behavior of volatility. In particular, stock market volatility may change more or less after a fall in price (which is interpreted as bad news), than a respective rise in price (which is considered as good news). In other words, the asymmetric volatility phenomenon can be considered as a market dynamic which illustrates that there are higher or lower market volatility levels in market downswings than in market upswings. As possible explanations about asymmetric behavior of volatility can be regarded a range of factors such as the volatility feedback, the different psychological profiles of investors, and perhaps the most important of all, the effects of leverage in the markets.

This study aims to spotlight the behavior of spillover effects that take place on the stock markets of selected Balkan, Slavic and Oriental countries. These are (in alphabetical order): Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Table 1.1 shows the percent change of Gross Domestic Product (GDP) of these twelve countries over the years under investigation, from 2006 till 2015. It is noteworthy that for the years 2006 and 2007 all countries managed to boost their GDPs. This trend continued in 2008 as well, except for Greece. However, 2009 proved to be a bad year for the global economy as world GDP met its unique negative figure (-1.701%) since 1960. The bankruptcy of financial services firm Lehman Brothers in late 2008, the fourth biggest investment bank in the US, played certainly a protagonist role. Only Israel and Poland from the countries of Table 1.1 achieved to maintain a positive sign for the change of their GDP. Moreover, these two countries, achieved higher GDP than the previous year for the whole period under investigation. The greatest single increase of GDP was for Turkey in 2010 (9.157%), while the most negative single change was for Ukraine in 2009, 14.8%. The second worst performance was again for Ukraine in 2015, -9.87%. Nevertheless, this was not the country with the overall highest decrease of GDP. As it can be seen by the last column of Table 1.1 which illustrates the total fluctuation of GDPs during the ten years, Greece met a dramatic drop in its domestic wealth up to almost one fifth (-19.72%). Diametrically antithetic was the icon for countries such as Israel, Poland and Turkey, having an increase over 40%. Actually, ten out of twelve countries augmented their GDPs, in a higher or more moderate way.

Based on the above evidences, it can be claimed that patterns of countries' GDPs have on one hand some similarities as the recession in 2009, and in parallel several differentiations in total changes during the overall period from 2006 until 2015. Hence, it would be interesting to explore the correlations among these figures into the economies under investigation. Table 1.2 shows the relevant results. Correlation coefficients are statistically significant at 10% level of significance or more for 51 out of 66 cases. This can be interpreted as that these economies are generally quite interrelated. Of course, that does not mean necessary that one economy determines the route of another, but maybe they follow the mainstream of the global economy. To test it, the correlation coefficients between each country's GDP and the US' GPD on one hand, and the global gross product on the other, are calculated. The last columns of Table 1.2 reveal that less than half of the countries presented statistically important correlation with the US, while basically only Cyprus and Greece seems to follow a separated route than global trends. This is probably due to the financial crisis that stormed these countries and the imposed Memorandums of Understanding (MoU). In conclusion, findings suggest that regional influence is stronger than the dependence on the hegemony of the world economy, i.e. the US.

Table 1.1 Percentage changes of GDPs

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2006-2015
Croatia	4.785%	5.15%	2.053%	-7.384%	-1.701%	-0.281%	-2.187%	-1.064%	-0.36%	1.645%	0.05%
Cyprus	4.51%	4.821%	3.864%	-1.772%	1.318%	0.321%	-3.158%	-5.953%	-1.531%	1.679%	3.592%
Czech Republic	6.877%	5.529%	2.7115	-4.842%	2.295%	2.005%	-0.8%	-0.484%	2.715%	4.536%	21.927%
Greece	5.652%	3.274%	-0.335%	-4.301%	-5.479%	-9.132%	-7.3%	-3.241%	0.353%	-0.219%	-19.72%
Israel	5.802%	6.135%	3.059%	1.269%	5.517%	5.062%	2.382%	4.376%	3.163%	2.508%	46.821%
Poland	6.18%	7.035%	4.25%	2.82%	3.607%	5.017%	1.607%	1.391%	3.283%	3.941%	46.592%
Romania	8.056%	6.864%	8.459%	-7.067%	-0.798%	1.056%	0.641%	3.532%	3.076%	3.663%	29.906%
Russia	8.153%	8.535%	5.248%	-7.821%	4.504%	4.264%	3.518%	1.279%	0.706%	-3.727%	26.129%
Serbia	4.904%	5.889%	5.367%	-3.116%	0.584%	1.401%	-1.015%	2.572%	-1.831%	0.758%	16.151%
Slovenia	5.656%	6.942%	3.3%	-7.797%	1.238%	0.649%	-2.689%	-1.087%	3.106%	2.317%	11.349%
Turkey	6.893%	4.669%	0.659%	-4.826%	9.157%	8.773%	2.127%	4.193%	3.02%	3.972%	45.053%
Ukraine	7.3%	7.9%	2.3%	-14.8%	4.2%	5.466%	0.239%	-0.027%	-6.553%	-9.87%	-6.401%

Table 1.2 Correlation coefficients among GDPs

Country	Croatia	Cyprus	Czech Republic	Greece	Israel	Poland	Romania	Russia	Serbia	Slovenia	Turkey	US	World
Croatia												0.584 (0.076)***	0.766 (0.003)*
Cyprus	0.472 (0.168)											0.111 (0.759)	0.431 (0.161)
Czech Republic	0.944 (0.001)*	0.746 (0.026)**										0.683 (0.029)**	0.823 (0.001)*
Greece	0.700 (0.004)*	0.589 (0.074)***	0.671 (0.053)***									0.178 (0.621)	0.306 (0.333)
Israel	0.655 (0.077)***	0.449 (0.323)	0.663 (0.029)**	0.290 (0.281)								0.550 (0.099)***	0.845 (0.001)*
Poland	0.737 (0.067)***	0.898 (0.001)*	0.756 (0.052)***	0.578 (0.244)	0.637 (0.055)***							0.170 (0.639)	0.497 (0.1002)
Romania	0.931 (0.001)*	0.547 (0.136)	0.819 (0.001)*	0.672 (0.033)**	0.494 (0.054)***	0.519 (0.192)						0.488 (0.152)	0.636 (0.026)**
Russia	0.750 (0.024)**	0.513 (0.231)	0.672 (0.012)**	0.302 (0.154)	0.810 (0.004)*	0.563 (0.150)	0.712 (0.003)*					0.531 (0.113)	0.817 (0.001)*
Serbia	0.850 (0.001)***	0.643 (0.052)***	0.694 (0.007)*	0.559 (0.030)**	0.670 (0.011)**	0.652 (0.047)**	0.853 (0.001)*	0.762 (0.002)*				0.244 (0.496)	0.577 (0.049)**
Slovenia	0.956 (0.001)***	0.713 (0.046)**	0.962 (0.001)*	0.683 (0.0104)**	0.693 (0.008)*	0.740 (0.001)*	0.874 (0.001)*	0.746 (0.007)*	0.756 (0.007)*			0.625 (0.053)***	0.816 (0.001)*
Turkey	0.518 (0.016)**	0.261 (0.373)	0.636 (0.024)**	-0.025 (0.920)	0.819 (0.004)*	0.378 (0.303)	0.366 (0.009)*	0.641 (0.016)**	0.380 (0.019)**	0.581 (0.009)*		0.802 (0.005)*	0.889 (0.001)*
Ukraine	0.664 (0.044)**	0.443 (0.310)	0.586 (0.037)**	0.147 (0.343)	0.868 (0.001)*	0.531 (0.205)	0.604 (0.017)**	0.967 (0.001)*	0.752 (0.002)*	0.642 (0.034)**	0.718 (0.006)*	0.493 0.147	0.798 (0.001)*

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

Returning to the spillover effects, the twelve Balkan, Slavic and Oriental countries will be studied as subject to the influence of their own past returns. The interactions between previous and present period's returns are the main purposes of the present study. The employed econometric model will be augmented with the trading volume variable for each case. Moreover, two additional variables are going to be employed into the model, namely the change of exchange rates of the domestic currency to the US dollar and also the return of the S&P 500 index of the previous period, both with and without the trading volume effect. Finally, all variables will be combined in a single model. By implementing this procedure we aspire to shape a comprehensive image about the behavior of the twelve stock exchanges and the role of spillover effects.

The paper proceeds as follows: section 2 presents a brief but comprehensive selected literature review around study's subject, section 3 describes the data and in section 4 is displayed the following methodology. Section 5 illustrates the empirical results, while section 6 summarizes and concludes.

2. Literature review

This section illustrates some selected studies that refer to spillover effects related to stock market exchanges of several countries. As usually happens, researches for this particular scientific subject initially began for developed economies and Western Europe. Western Europe can be considered as a very interesting area for studying spillover effects among stock market exchanges, due to its economic magnitude. Baele (2005) investigated to what extent globalization and regional integration led to increasing equity market interdependence. Researcher focused on Western Europe, as this region had gone through a unique period of economic, financial, and monetary integration. More specifically, he quantified the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU) and U.S. market to 13 local European equity markets. To account for time-varying integration, writer used a regime-switching model to allow the shock sensitivities to change over time. Results revealed regime switches to be both statistically and economically important. Both the EU and U.S. shock spillover intensity increased substantially over the 1980s and 1990s, though the rise was more pronounced for EU spillovers. Shock spillover intensities increased most strongly in the second half of the 1980s and the first half of the 1990s. According to findings, increased trade integration, equity market development and low inflation contributed to the increase in EU shock spillover intensity. Finally, there were evidences for contagion from the U.S. market to a number of local European equity markets during periods of high world market volatility.

Angkinand et al. (2009) examined the degree of interdependence between national stock market returns for 17 advanced economies such as Germany, France, Switzerland and Japan that represented almost the 30% of global stock market capitalization, and the United States for various sub-periods from January 1973 to February 2009. The examination was based on time-series techniques including both single equation (ordinary least squares and generalized method of moments) and system approaches (structural vector autoregressive process). They found an increasing degree of interdependence between national stock market returns over time as well as spillover effects from a shock to U.S. stock market returns to the advanced economies. They claimed that the main focus of their paper was to examine interdependence and spillover effects for the pre- and post-turmoil periods that characterized the U.S. financial crisis. Their findings indicated that the degree of interdependence and spillover effects were greatest after the emergence of the U.S. subprime mortgage meltdown in the summer of 2007, and even more so after the collapse of Lehman Brothers in September 2008. The empirical results indicated varying degrees of interdependence and spillover effects between the different advanced countries and the United States in the earlier decades. However, the results became fairly uniform across all the countries after the emergence of the U.S. financial crisis.

Regarding Eastern Europe, Egert and Kocenda (2007) analyzed interrelations between three stock markets in Central and Eastern Europe and, in addition, interconnections which may exist between Western European countries (Germany, France, United Kingdom) and Central and Eastern European countries stock markets (Hungary, Czech Republic, Poland). They used the five-minute tick intraday price data from the mid-2003 to the early 2005 for stock indices and found no robust integration relationship for any of the stock index pairs or for any of the extended specifications. There were signs of short-term spillover effects both in terms of stock returns and stock price volatility. Results showed the presence of bidirectional causality for returns as well as volatility series. The results based on a VAR framework indicated a more limited number of short-term relationships between the stock markets. In general, it appeared that spillover effects were stronger from volatility to volatility than contagion effects from return to return series.

Syriopoulos and Roumpis (2009) investigated the presence of time varying co-movements, volatility implications and dynamic correlations in major Balkan and mature equity markets, in order to provide quantified responses to international asset allocation decisions. Since asset returns and correlation dynamics were critical inputs in asset pricing, portfolio management and risk hedging, emphasis was placed on the respective (constant and dynamic) equity market correlations produced by alternative multivariate GARCH forms, the Constant Conditional Correlation and the Asymmetric Dynamic Conditional Correlation models. The Balkan stock markets were seen to exhibit time varying correlations as a peer group, although correlations with the mature markets remained relatively modest. In conjunction with sensitivity analysis on the asymmetric variance–covariance matrix, active portfolio diversification to the Balkan equity markets indicated to potentially improve investors' risk-return trade-off.

Furthermore, as far as the Balkan stock exchange markets is concerned, Kenourgios and Samitas (2011) examined long-run relationships among five Balkan emerging stock markets (Turkey, Romania, Bulgaria, Croatia, Serbia), the United States and three European markets that they characterized as developed (UK, Germany, Greece), during the period 2000–2009. Conventional, regime-switching co-integration tests and Monte Carlo simulation provided evidence in favor of a long-run co-integrating relationship between the Balkan emerging markets within the region and globally. Moreover, they applied the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) multivariate GARCH model in order to capture the impact of the 2007–2009 financial crisis on the time-varying correlation dynamics among the developed and the Balkan stock markets. Results showed that stock market dependence was heightened, supporting the herding behavior during the 2008 stock market crash period.

Abou-Zaid (2011) investigated the international transmission of daily stock index volatility movements from U.S. and U.K. to selected Middle East and North Africa emerging markets: Egypt, Israel, and Turkey. The sample period spanned from January 2, 1997, through September 25, 2007. Daily returns data was able to capture most of the possible interactions. Employing a multivariate GARCH in Mean technique, the study found that Egypt and Israel were significantly influenced by the U.S. stock market while Turkey was not. The British market had no influence whatsoever on any of the three markets. The results also indicated that the own lag return effects dominated the spillover effects for both Egypt and Israel. That is, own lag market returns were crucial indicators in explaining the current trend and return volatilities in both markets. On the other hand, spillover effects dominated own lag returns in the Turkish market.

Regarding to some countries of Middle East, Ezzati (2013) studied financial markets' volatilities spillover from one market to another, focusing on Iran. Through an analysis of the international transmission of financial volatility movements among six selected countries, writer considered unidirectional effects coming from the U.S., Germany, Japan, Saudi Arabia and Kuwait to Iran. The selection of these countries was based on the recycling of petrodollars. The analysis had been conducted using two stage procedure based on GARCH-M model; whilst data took the form of monthly financial returns derived from equity, money and foreign exchange markets of the chosen countries. Results indicated existence of significant volatility interdependencies among Iranian financial markets within the Middle East and with the rest of the world.

Alikhanov (2013) paid attention on eight Eastern European countries such as Croatia, Czech Republic, Hungary, Poland, Romania, Russia, Ukraine and Turkey, with emphasis on the mean and volatility spillover effects from the US and EU stock markets as well as oil price market for a weekly based period from 2000 till 2012. To evaluate the magnitude of volatility spillovers the variance ratios were computed. Results revealed that the individual emerging countries' stock returns were mostly influenced by the US volatility spillovers rather than EU or oil markets. Also, writer implemented asymmetric tests on stock returns of the eight markets. The stock market returns of Hungary, Poland, Russia and Ukraine were found to respond asymmetrically to negative and positive shocks in the US stock returns. A weak evidence of asymmetric effects was found in the case of Russia, but with respect to oil market shocks. Moreover, a model with dummy variable confirmed the effect of EU enlargement on stock returns only for Romania. Finally, a conditional model suggested that the spillover effects were partially explained by instrumental macroeconomic variables, out of which exchange rate fluctuations played the key role in explaining the spillover parameters rather than total trade to GDP.

Besides, Koulakiotis et al. (2016) investigated return and volatility spillovers among large, medium and small size stock portfolios in Athens stock exchange by employing an augmented univariate and multivariate VAR-EGARCH model. Their study was based on a sample of daily closing prices and aggregate trading volume for the period 5-6-2001 to 31-12-2012. Since writers were interested in capturing the effects of the financial crisis, they analyzed spillover effects in mean and volatility for two sub-periods. In the pre-crisis period, return spillovers were significant within the same index for all the three equity indices. Asymmetry was present for the three conditional volatility indices; however the only statistically significant volatility spillover was from large to medium equity index. Trading volume carried a positive sign when it was introduced in the variance equation. As for the post crisis period, return spillovers within the same stock index were statistically insignificant. Nevertheless, spillovers across indices were significant. Asymmetry in variance equation was important only for the medium stock index, while the results of volatility spillovers indicated that just the impact from small to medium index was statistically significant. Finally, when trading volume was included in the variance model, asymmetry was valid only for the medium stock index.

3. Data

This paper employs data from stock markets of twelve selected Balkan, Slavic and Eastern countries. In alphabetical order: Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Information consists of daily closing prices for the major index of each country's stock exchange. We consider that this major index represents adequately each stock market. Research covers a time period of ten years for the majority of countries, from 2006 till 2015. For Cyprus and Ukraine there are shorter periods, six and eight years respectively, as only for these years data was available. Table 3.1 illustrates the titles of indices and also provides their descriptive statistics.

Table 3.1 Descriptive statistics of indices

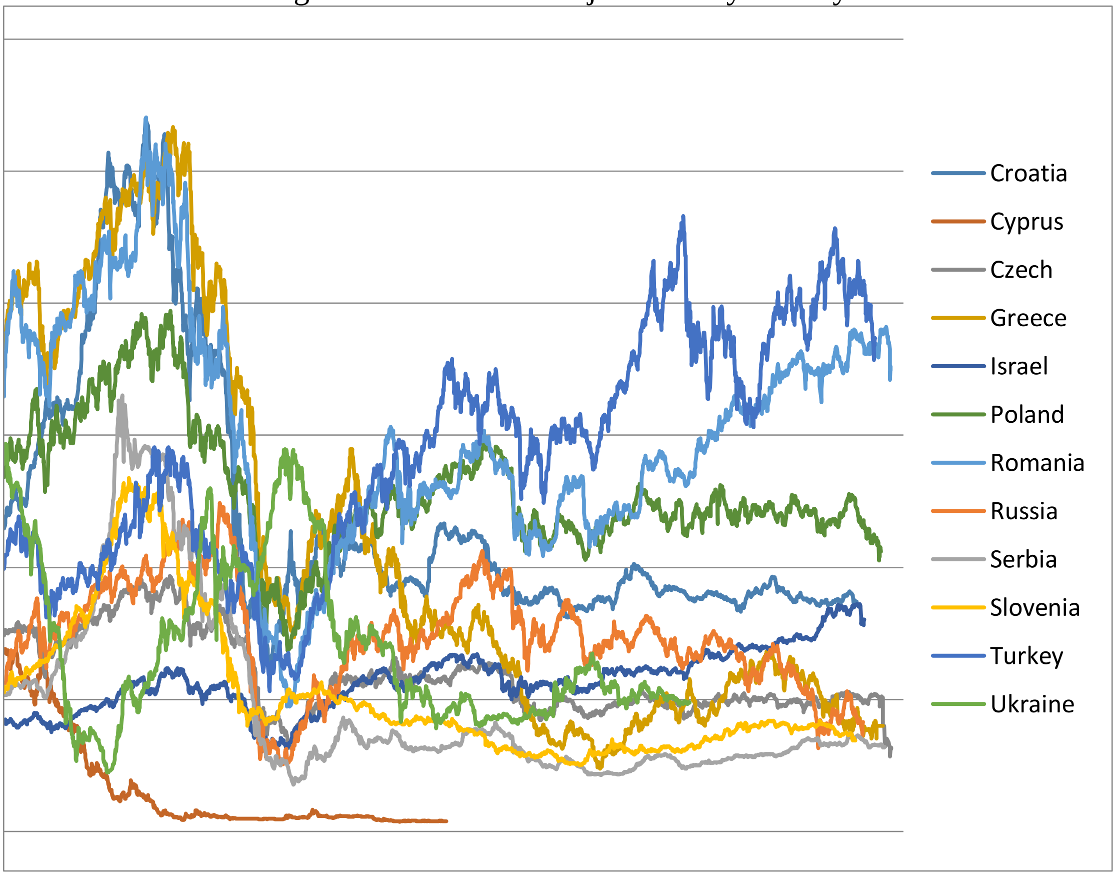
Country	Index	OBS	Mean	Median	SD	Max	Min
Croatia	CROBEX	2356	0.02	-0.001	1.286	11.36%	-13.73%
Cyprus	General Index	1215*	-0.188	-0.155	3.044	18.48%	-14.37%
Czech Republic	PX	2356	-0.005	0.022	1.559	13.16%	-14.94%
Greece	General Index	2345	-0.051	0.02	2.205	14.37%	-16.23%
Israel	TA 25	1886	-0.01	-0.058	1.293	7.51%	-7.78%
Poland	WIG 20	2356	-0.004	0.03	1.398	8.51%	-8.54%
Romania	BET 10	2356	0.012	0.022	1.65	11.14%	-12.29%
Russia	RTSI	2353	0.015	0.089	2.356	22.38%	-19.1%
Serbia	BELEX 15	2356	-0.014	-0.03	1.393	12.92%	-10.29%
Slovenia	SBITOP	2339	-0.011	0.001	1.199	8.71%	-8.08%
Turkey	BIST 100	2356	0.036	0.071	1.8	12.89%	-13.54%
Ukraine	UX	1896**	-0.028	-0.058	2.33	18.2%	-12.37%

* from 2010 to 2015
** from 2008 to 2015

As it is revealed by Table 3.1, the stock market that suffered the greatest negative mean return among the twelve countries under investigation is this of Cyprus, having a value of -0.188. In parallel, this was the market with the highest volatility as well, as the last is measured by standard deviation. The price of standard deviation of Cyprus stock exchange was 3.044. These findings cannot be considered as an unexpected thunderbolt, while during that period, and specifically in 2012, issued the domestic financial crisis which led the Cypriot economy to the Memorandum of Understanding (MoU). This turn proved to be a fairly good reason for a big number of investors to react nervously and even more for some of them to abandon the Cyprus exchange market. Of course, we have to keep in mind the fact that for Cyprus we have available data just for six years and not for ten, as for the other countries. Hence, it can be supposed that if we had available data for the period 2006-2009 as well, when there was no MoU, the total figures for both mean and standard deviation could be improved for Cyprus share market.

On the antipode, the stock index that achieved the highest mean return was Turkey's BIST 100, with a value of 0.036, following by Croatia's CROBEX which met an increase of 0.02. This is despite the great decline of the Gross Domestic Product (GDP) in these countries during 2009, which was -4.826% and -7.384%, respectively. In parallel, the most "calm" stock exchange can be regarded the Slovenian, as its index SBITOP met the lowest volatility. The figure of SBITOP for standard deviation was 1.199, while again the Croatian stock market was following, with a price of 1.286.

Figure 3.1 Returns of major index by country



In addition, Table 3.2 reports some diagnostic test statistics on the daily return data. These statistics are: skewness, kurtosis, the Kolmogorov-Smirnov test, the Ljung-Box test and the Ljung-Box squared test.

Table 3.2 Diagnostic tests on indices' returns

Country	Index	Skewness	Kurtosis	Kolmogorov-Smirnov	LB(20)	$LB^2(20)$
Croatia	CROBEX	0.365	15.848	-15.857*	153.24*	2804.95*
Cyprus	General Index	0.526	5.649	-7.097*	34.089**	259.846*
Czech Republic	PX	-0.126	13.797	-30.403*	70.161*	3309.797*
Greece	General Index	-0.07	5.646	2.79*	30.552***	627.329*
Israel	TA 25	0.438	3.475	-14.768*	29.105**	1620.076*
Poland	WIG 20	-0.355	4.102	-19.216*	39.323*	1000.864*
Romania	BET 10	-0.344	8.09	-40.018*	67.677*	1787.799*
Russia	RTSI	0.067	10.829	1.068*	67.042*	2217.461*
Serbia	BELEX 15	0.475	14.685	-41.086*	464.002*	909.803*
Slovenia	SBITOP	-0.296	6.588	8.045*	104.29*	1757.869*
Turkey	BIST 100	-0.137	5.478	5.462*	24.139	378.013*
Ukraine	UX	0.186	7.605	-1.142*	89.152*	680.012*

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

In a perfectly normal distribution the mean is equal to the mode, and both are located on the maximum point on the curve of distribution's graph, which is symmetrical and known as bell-shaped. When a distribution is skewed to the left (right) the tail on the curve's left-hand (right) side is longer than the tail on the right-hand (left) side. This is negative (positive) skewness. In other words, skewness is a measurement of the asymmetry of a given variable around its mean. Hence, a positive (negative) skewness indicates that less (more) in number and sharper (softer) in intense values are observed on the left of the mean and therefore more (less) in number and softer (sharper) in intense are appeared on the right of it. Skewness is statistically important for the majority of the cases, with the exception of Greek and Russian stock markets. For Czech Republic skewness is statistically important only at 5% level of significance. For Croatia, Cyprus, Israel, Serbia and Ukraine skewness is positive and statistically important indicating that there were fewer and more intense observations which were lower than the mean returns. These findings can be considered as a sign that these markets were more nervous during the bad days. This is a quite interesting result, as it can be received as an omen for the existence of the so-called leverage effect. This term is used to describe a situation according to which a negative shock (price drop) increases volatility more than a positive shock (price rise), or in other words that there is an asymmetric effect of shocks changes on volatility. The mechanism behind this idea is described in section 4 which presents analytically the employed methodology.

Moreover, kurtosis is a measurement of the so-called "tailedness" of the distribution of a variable. It states whether the data are heavy-tailed or light-tailed relative to a normal distribution. That is, samples with high kurtosis have more heavy tails, while samples with low kurtosis tend to have light tails. Here, an adjusted version of kurtosis is used, the excess kurtosis, which is the kurtosis minus 3, in order to provide the comparison to the normal distribution. This definition is used in order the standard normal distribution to have a kurtosis of zero. In this way, positive kurtosis indicates a heavy-tailed distribution, while negative kurtosis indicates a light tailed distribution. A distribution with a positive kurtosis value denotes that the distribution has heavier tails and a sharper peak than the normal distribution (leptokurtic curve). A distribution with a negative kurtosis value denotes that the distribution has lighter tails and a flatter peak than the normal distribution (platykurtic curve). At the present study, kurtosis was found positive and statistically important at 1% level of significance for every occasion. These results may signify the existence of some extreme values.

Hence, as the vast majority of the figures about skewness and kurtosis are statistically different than zero, some thoughts about the normality of the samples are raised. For that reason the Kolmogorov-Smirnov test is employed. This is a nonparametric test for the equality of continuous distributions which compares the empirical cumulative distribution function of a given sample data with the distribution expected if the data were normal. The main advantage of this test is that the distribution of the Kolmogorov-Smirnov test statistic itself does not depend on the underlying cumulative distribution function being tested. The Kolmogorov-Smirnov test used to compare the data of each market with a reference probability distribution. The critical value here at the 1% level of significance is $1.63/\sqrt{n}$, where n is the sample size. Whenever the observed difference between the sample of each market and the reference probability distribution is adequately large, the test will reject the null hypothesis of population normality and it can be concluded that population is non-normal. Otherwise, the null hypothesis about difference cannot be rejected, so it can be assumed that the population is normal. According to empirical results that are illustrated in Table 3.2, the Kolmogorov-Smirnov statistic rejects the null hypotheses about normality at the 1% level of significance for every stock market.

Additional, variance specification tests are also reported in Table 3.3. These tests were proposed by Engle and Ng (1993) and they are designed to investigate how well the particular model used captures the volatility dynamics. The tests are applied on the estimated squared standardized residuals. The Engle-Ng tests are: i) the Sign bias test, ii) the Negative size bias test, iii) the Positive size bias test and iv) the Joint test. The first test examines the asymmetric impact of positive and negative innovations on volatility. The test is based on the t-statistic. The Negative size bias test examines how well the model captures the impact of large and small negative innovations. The Positive size bias test examines possible biases associated with large and small positive innovations. Finally, a Joint test can be based on F-statistic of a regression involving all three above explanatory variables.

Table 3.3 Sign and size bias tests

Country	Sign bias	Negative size bias	Positive size bias	Joint test
Croatia	-4.759*	-3.528*	-7.498*	2.227**
Cyprus	1.377	-1.744***	4.796*	-0.41***
Czech	-1.717***	-1.554	-2.684*	8.827*
Greece	-0.659	0.556	-4.509*	5.7*
Israel	-0.457	0.112	0.876	2.808*
Poland	1.86***	3.033*	0.791**	8.46*
Romania	-0.747	-5.956*	2.048**	2.89*
Russia	-1.008	-5.197*	3.906*	2.301**
Serbia	2.403**	-1.203	7.913*	5.502*
Slovenia	-0.578	-1.785**	0.408	8.402*
Turkey	0.862	-3.128*	1.345	-0.714
Ukraine	2.893*	2.56**	5.345	9.008

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

This absence of normality, indicating by the above findings, may be originated, at least to some extent, to temporal dependencies in the returns. This phenomenon may be augmented in second-moment temporal dependencies. In order to test whether such dependencies are present, we employed the Ljung-Box (LB) statistic. The LB test is a diagnostic tool used to test about the lack or not of fit as regards a time series model. Instead of testing randomness at each distinct lag, LB test checks the total randomness based on a number of lags, which at the present study is twenty. The null hypothesis states that the data are independently distributed, while the alternative declares the data are not independently distributed, in other words they exhibit serial correlation. Random variables in a time series present dependence if the value at some time κ in the series is statistically dependent on the value at another time λ. In contrast, a series is serially independent if there is no dependence between any pair. The Ljung–Box statistics were estimated for twenty lags and applied to returns in order to test for first moment dependencies (linear), and furthermore applied to squared returns in order to test for second moment dependencies (nonlinear), or in other words to test about heteroskedasticity. They both are distributed as χ^2 with 20 degrees of freedom, where 20 is the number of lags.

Initially, focusing on the first moment dependencies (linear), as it can be seen by Table 3.2, the null hypothesis which states that all autocorrelations up to the 20^{th} lag are jointly zero, is rejected for eight out of twelve countries at 1% level of significance. These are: Croatia, Czech Republic, Poland, Romania, Russia, Serbia Slovenia and Ukraine. For Cyprus and Israel the null hypothesis is rejected only at 5% level of significance, while in Greece it is rejected only at 10% level of significance. The above outcomes provide some strong evidences of temporal first moment dependencies as regards the distribution of stock returns, or that the autocorrelation is present in the returns of the above markets. On the other hand, Turkish stock exchange seems to be the only exception and not to suffer by autocorrelation, as LB figure is not statistically important.

In parallel, the null hypothesis about the squared returns is emphatically rejected for every sample without any exceptions. Hence, based on the above empirical results, it can be concluded that indeed there is heteroskedasticity into samples. This absence of homoskedasticity means that there are differentiated dispersions in the examined data, or in other words there is non-constant volatility. As it is made clear by Table 3.2, the LB statistics obtained by squared returns are several times greater than the corresponding LB statistics calculated for the returns, suggesting that higher moment temporal dependencies are more distinct. Finally, a possible explanation for the existence of autocorrelation in returns -at least in the vast majority of the cases- could be that common information is impounded into stock prices not only on the disclosure day, but on the following day as well.

An uncorrelated time series can still be serially dependent due to a dynamic conditional variance process. A time series exhibiting conditional heteroscedasticity (or autocorrelation in the squared series) is said to have autoregressive conditional heteroscedastic (ARCH) effects. Table 3.4 illustrates results about ARCH effects. For every case, the null hypothesis about normality is rejected and the alternative hypothesis is accepted, i.e. there is heteroscedasticity.

Table 3.4 ARCH effect tests

Country	Lags (4) Statistic Signifant
Croatia	262.987*
Cyprus	19.159*
Czech	183.684*
Greece	72.116*
Israel	69.186*
Poland	57.800*
Romania	117.876*
Russia	90.573*
Serbia	95.892*
Slovenia	173.723*
Turkey	19.448*
Ukraine	78.463*

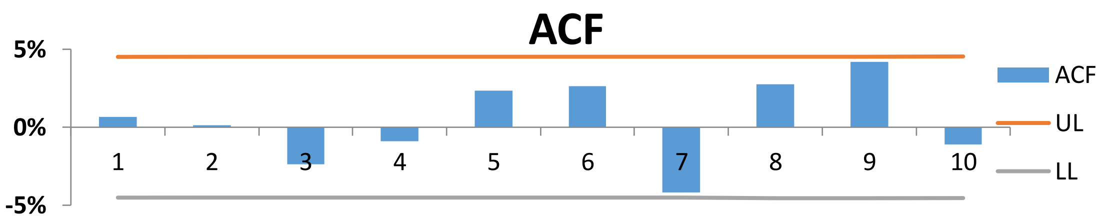
Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

Figure 3.2 illustrates the auto-correlation function (AFC) for up to ten lags of each sample, as well as the upper and the lower limit of the AFC confidence interval.

Figure 3.2 AFCs

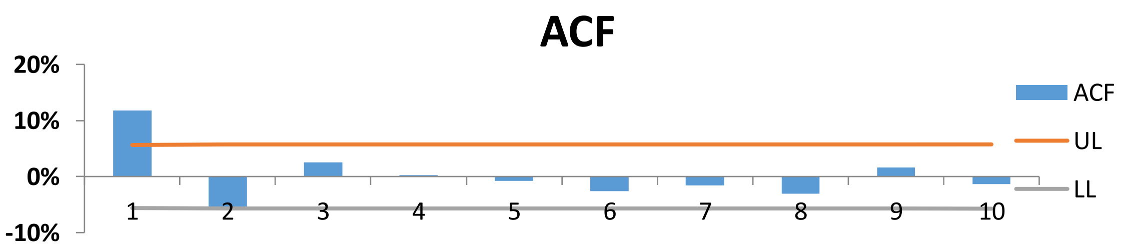
Croatia

Lag	ACF	UL	LL
1	0,65%	4,51%	-4,51%
2	0,13%	4,51%	-4,51%
3	-2,38%	4,51%	-4,51%
4	-0,88%	4,52%	-4,52%
5	2,33%	4,52%	-4,52%
6	2,65%	4,52%	-4,52%
7	-4,16%	4,52%	-4,52%
8	2,77%	4,53%	-4,53%
9	4,19%	4,53%	-4,53%
10	-1,12%	4,54%	-4,54%



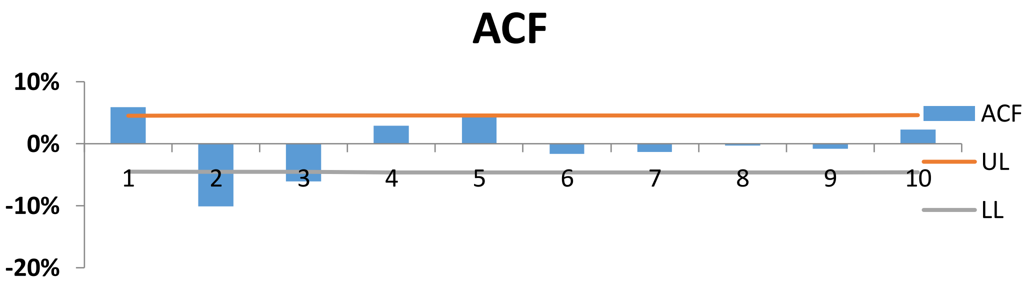
Cyprus

Lag	ACF	UL	LL
1	11,76%	5,62%	-5,62%
2	-5,65%	5,70%	-5,70%
3	2,54%	5,72%	-5,72%
4	0,20%	5,72%	-5,72%
5	-0,75%	5,72%	-5,72%
6	-2,63%	5,72%	-5,72%
7	-1,55%	5,73%	-5,73%
8	-3,07%	5,73%	-5,73%
9	1,66%	5,73%	-5,73%
10	-1,31%	5,73%	-5,73%



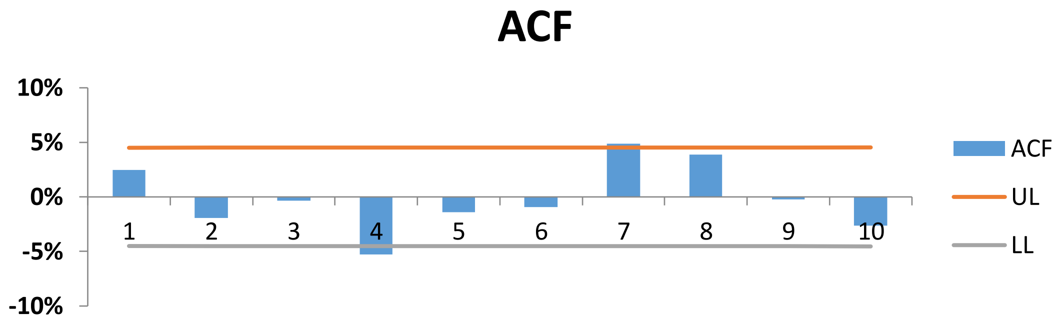
Czech

Lag	ACF	UL	LL
1	5,89%	4,51%	-4,51%
2	-10,09%	4,53%	-4,53%
3	-6,12%	4,57%	-4,57%
4	2,86%	4,59%	-4,59%
5	4,75%	4,59%	-4,59%
6	-1,64%	4,60%	-4,60%
7	-1,32%	4,61%	-4,61%
8	-0,31%	4,61%	-4,61%
9	-0,80%	4,61%	-4,61%
10	2,27%	4,61%	-4,61%



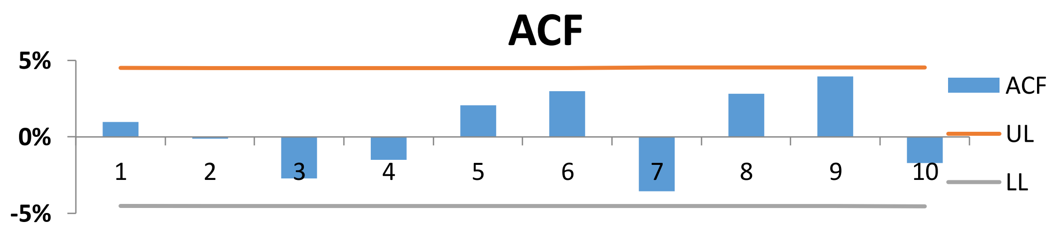
Greece

Lag	ACF	UL	LL
1	2,46%	4,50%	-4,50%
2	-1,95%	4,50%	-4,50%
3	-0,35%	4,51%	-4,51%
4	-5,25%	4,51%	-4,51%
5	-1,43%	4,52%	-4,52%
6	-0,94%	4,52%	-4,52%
7	4,87%	4,52%	-4,52%
8	3,88%	4,53%	-4,53%
9	-0,24%	4,54%	-4,54%
10	-2,62%	4,54%	-4,54%



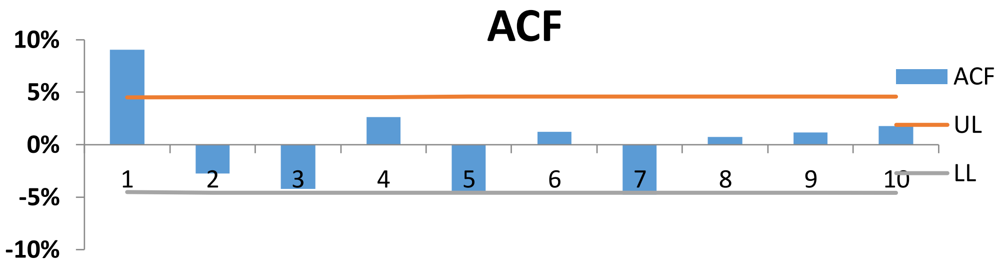
Israel

Lag	ACF	UL	LL
1	0,97%	4,51%	-4,51%
2	-0,12%	4,51%	-4,51%
3	-2,70%	4,51%	-4,51%
4	-1,48%	4,52%	-4,52%
5	2,05%	4,52%	-4,52%
6	3,00%	4,52%	-4,52%
7	-3,57%	4,52%	-4,52%
8	2,84%	4,53%	-4,53%
9	3,95%	4,53%	-4,53%
10	-1,69%	4,54%	-4,54%



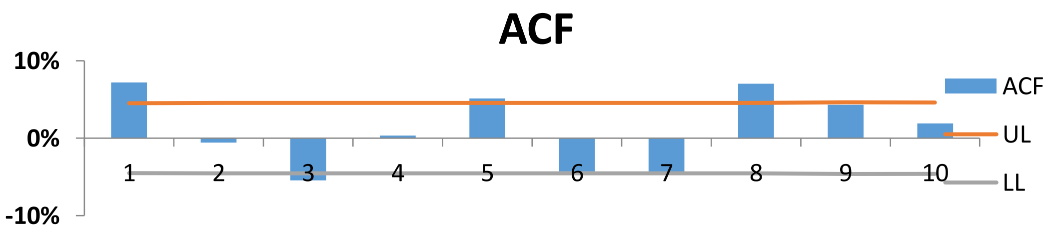
Poland

Lag	ACF	UL	LL
1	9,07%	4,51%	-4,51%
2	-2,76%	4,55%	-4,55%
3	-4,23%	4,55%	-4,55%
4	2,63%	4,56%	-4,56%
5	-4,52%	4,56%	-4,56%
6	1,22%	4,57%	-4,57%
7	-4,75%	4,57%	-4,57%
8	0,76%	4,58%	-4,58%
9	1,19%	4,58%	-4,58%
10	1,76%	4,59%	-4,59%



Romania

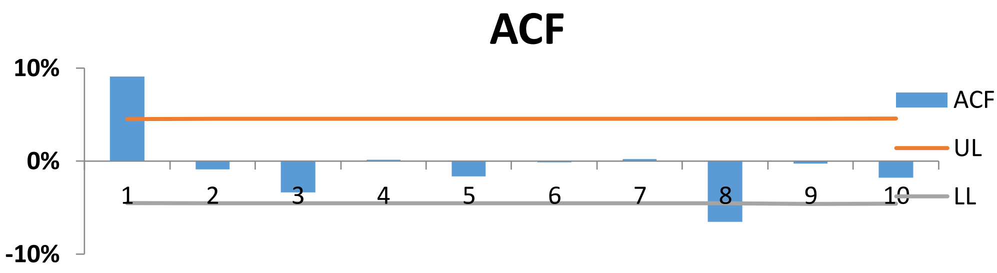
Lag	ACF	UL	LL
1	7,22%	4,51%	-4,51%
2	-0,54%	4,54%	-4,54%
3	-5,48%	4,54%	-4,54%
4	0,35%	4,55%	-4,55%
5	5,12%	4,55%	-4,55%
6	-4,29%	4,56%	-4,56%
7	-4,36%	4,57%	-4,57%
8	7,07%	4,58%	-4,58%
9	4,31%	4,60%	-4,60%
10	1,94%	4,61%	-4,61%



Russia

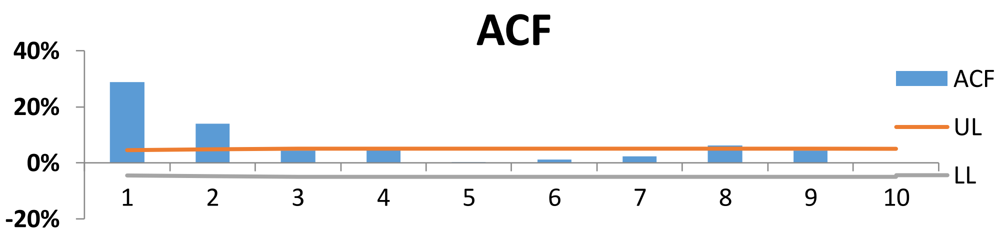
Lag	ACF	UL	LL
1	9,08%	4,51%	-4,51%
2	-0,86%	4,55%	-4,55%
3	-3,36%	4,55%	-4,55%
4	0,15%	4,56%	-4,56%
5	-1,66%	4,56%	-4,56%
6	-0,12%	4,56%	-4,56%
7	0,20%	4,56%	-4,56%
8	-6,51%	4,56%	-4,56%
9	-0,26%	4,58%	-4,58%

10	-1,81%	4,58%	-4,58%



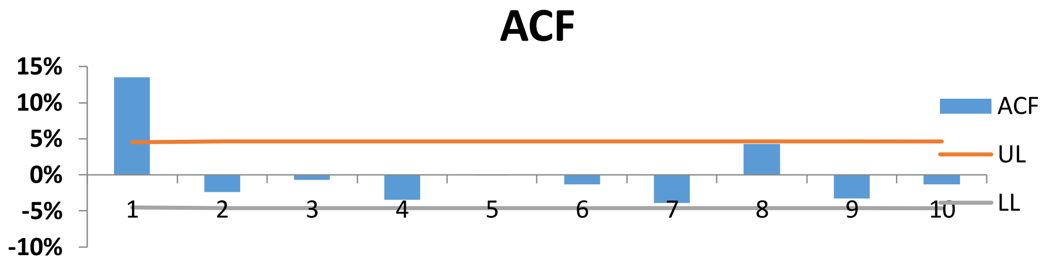
Serbia

Lag	ACF	UL	LL
1	28,79%	4,51%	-4,51%
2	14,07%	4,87%	-4,87%
3	4,30%	4,95%	-4,95%
4	4,82%	4,96%	-4,96%
5	0,07%	4,97%	-4,97%
6	1,21%	4,97%	-4,97%
7	2,25%	4,97%	-4,97%
8	6,19%	4,97%	-4,97%
9	4,46%	4,99%	-4,99%
10	-0,09%	5,00%	-5,00%



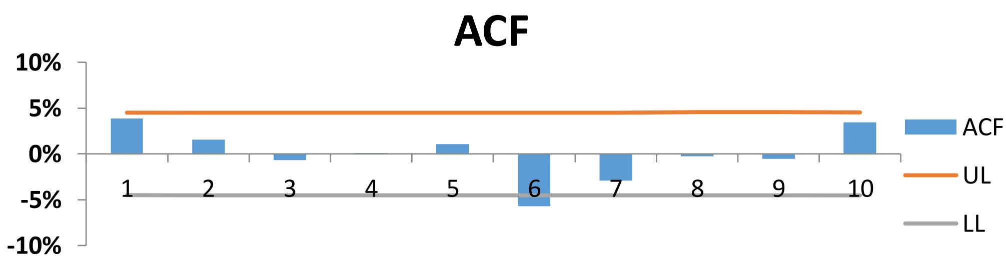
Slovenia

Lag	ACF	UL	LL
1	13,47%	4,51%	-4,51%
2	-2,38%	4,59%	-4,59%
3	-0,73%	4,60%	-4,60%
4	-3,47%	4,60%	-4,60%
5	-0,02%	4,60%	-4,60%
6	-1,32%	4,60%	-4,60%
7	-3,90%	4,60%	-4,60%
8	4,31%	4,61%	-4,61%
9	-3,31%	4,62%	-4,62%
10	-1,32%	4,62%	-4,62%



Turkey

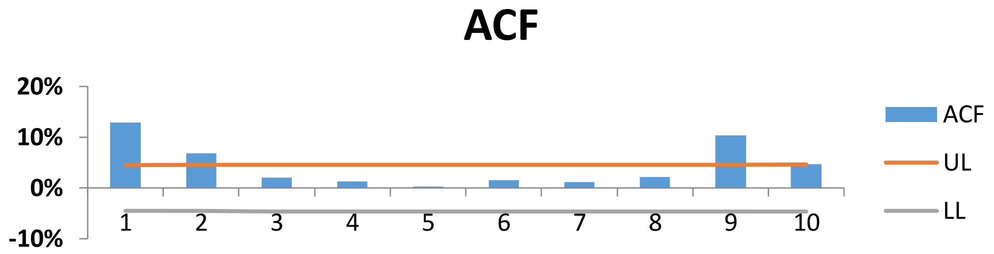
Lag	ACF	UL	LL
1	3,85%	4,50%	-4,50%
2	1,57%	4,51%	-4,51%
3	-0,66%	4,51%	-4,51%
4	0,00%	4,51%	-4,51%
5	1,05%	4,51%	-4,51%
6	-5,70%	4,51%	-4,51%
7	-2,93%	4,52%	-4,52%
8	-0,27%	4,53%	-4,53%
9	-0,51%	4,53%	-4,53%
10	3,47%	4,53%	-4,53%



Ukraine

Lag	ACF	UL	LL
1	12,84%	4,50%	-4,50%
2	6,84%	4,57%	-4,57%
3	2,04%	4,60%	-4,60%
4	1,27%	4,60%	-4,60%
5	0,30%	4,60%	-4,60%
6	1,53%	4,60%	-4,60%
7	1,22%	4,60%	-4,60%
8	2,21%	4,60%	-4,60%
9	10,40%	4,60%	-4,60%

10	4,71%	4,65%	-4,65%



4. Methodology

This section explains the econometric methodology which is employed in the present study. This methodology is based on the autoregressive conditional heteroskedasticity (ARCH) processes (Engle, 1982) which are used to characterize and shape observed time series data, such as daily stock markets returns. These kinds of models are utilized whenever it is assumed that the variance of the current error terms is a function of the actual sizes of the previous time period's error terms. For the purposes of the present study we develop the ARCH model into a more sophisticated form, that of extended univariate AR(1)-EGARCH(1,1) model, as it is explained in this chapter.

4.1 Autoregressive (AR) models

Numerous observed time series enclose serial autocorrelation, which means that a kind of linear association exists between lagged observations. This pattern implies that past results might forecast current observations. This type of process that depends on p past observations is called an autoregressive (AR) model of degree p, symbolized as AR(p). In finance, it can be assumed that the return generating process can be described by an autoregressive (AR) model, in which the dynamics of current stock returns are explained by their own lagged returns. The notation AR(p) indicates an autoregressive model of order p. In our case we adopt the AR(1) model, or in other words one step lagged returns. In statistics, an AR model is a representation of a type of random process. As such, it can describe specific time varying processes like stock markets returns. The AR model specifies that the output variable depends linearly on its own previous prices and on a stochastic term.

4.2 Autoregressive conditional heteroskedasticity (ARCH) models

Many researchers regard the ARCH model as one of the most important development in modeling volatility changes. The econometric models which are employed by the present study are based on the autoregressive conditional heteroskedasticity (ARCH) processes which are used to characterize time series data, such as daily stock markets returns. These kinds of models are utilized whenever it is assumed that the variance of the current error terms is a function of the actual sizes of the previous time period's error terms. ARCH models are applied widely for modeling financial time series that present time-variety volatility.

There is a plethora of various acronyms that are used to explain certain patterns of a specific variable and are based on ARCH models. As an initial differentiated type of the primary form can be considered the generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986). GARCH models are generally employed to investigate the stochastic behaviour of numerous financial time series, and often to describe the movements of volatility intertemporally (Theodossiou and Lee, 1993).

GARCH models approach is favored whenever an autoregressive moving-average model (ARMA) is assumed for the error variance (Whittle, 1951). ARMA models consist of two sections, one autoregressive (AR) part and one moving average (MA) part. Therefore, they are generally known as ARMA(p,q) models, where p is the order of the autoregressive part and q is the order of the moving average part. The AR(p) part can be written as:

$$R_t = c + \sum_{i=1}^{p} \varphi_i X_{t-1} + \varepsilon_t \tag{1}$$

where c is the constant factor, $\varphi_1,\varphi_2,\ldots,\varphi_3$ are the parameters of the model and ε_t are the error terms. The notation MA(q) refers, as it is mentioned above, to the moving average model of order q and can be written as:

$$R_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{2}$$

where μ is the expectation of R_t, $\theta_1,\theta_2,\ldots,\theta_3$ are the parameters of the model and ε_t are again the error terms. Hence, the ARMA(p,q) model which contains both equations (1) and (2) can be expressed by the following formula:

$$R_t = c + \sum_{i=1}^{p} \varphi_i X_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

The error terms ε_t are in general lines assumed to be independent identically distributed (i.i.d.) random variables, sampled from a normal distribution with mean equal to zero. In symbols, $\varepsilon_t \sim N(0, \sigma^2)$, where σ^2 is the variance. These assumptions in practice are not an inviolable red line, but in some cases may be weakened. However, doing so will change the properties of the model. In particular, a change to the i.i.d. hypothesis would make a rather fundamental difference.

Whenever an ARMA model is assumed for the error variance, the model is transformed into a GARCH model, as it was introduced by Bollerslev (1986). A GARCH model uses values of the past squared observations and past variances to model the variance at time *t*. If we symbolize the order of the GARCH terms σ^2 by p and the order of the ARCH terms ε_t by q, the GARCH model is written as GARCH (p,q). Following the common notation, σ_t^2 is given by:

$$\sigma_t^2 = \alpha_0+\alpha_1\varepsilon_{t-1}^2+\ldots+\alpha_q\varepsilon_{t-q}^2+\beta_1\sigma_{t-1}^2+\ldots+\beta_\rho\sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i\sigma_{t-i}^2 \tag{4}$$

where $\alpha_0 > 0$, α_i, $\beta_i \geq 0$, $i > 0$

As it is known, when testing for heteroskedasticity in econometric models, a suitable test is the White test. However, when dealing with time series data, as this study does, it is better to test for ARCH and GARCH errors. The general process for the lag length p of a GARCH(p, q) model involves three steps. The first is to estimate the best-fitting AR(q) model, secondly to compute autocorrelations of the error term and finally to test for significance. The null hypothesis states that there are no ARCH or GARCH errors. Rejecting the null thus means that such errors exist in the conditional variance.

4.3 Exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models

For the aims of the present research we prefer to employ a more advanced version of GARCH models, namely the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model, introduced by Nelson (1991), which allows for the estimation of volatility interactions in one-step ahead while, at the same time, incorporates the impact of any of asymmetric news on volatility spillovers. Formally, an EGARCH(p,q) model can be written as:

$$\log \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_1 \left(|z_{t-i}| - E|z_{t-i}|\right) + \alpha_2 z_{t-i} + \sum_{j=1}^{q} \alpha_3 \log \sigma_{t-j}^2 \qquad (5)$$

where σ_t^2 is the conditional variance, α_0, α_1, α_2 and α_3 are coefficients, and z_t may be a standard normal variable or come from a generalized error distribution. The above formulation allows the sign and the magnitude of z_{t-i} to have separate effects on the volatility. This is particularly practical in an asset pricing procedure (St. Pierre, 1998). Of course, as long as $\log \sigma_t^2$ may be negative, there are no limitations on the parameters.

Alternative to EGARCH model, there is the quadratic exponential generalized autoregressive conditional heteroskedasticity (QGARCH) model, which was introduced by Sentana (1995) and it is employed to catch asymmetric effects of positive and negative changes. Similar to the QGARCH model, there is the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model, which was introduced by Glosten, Jagannathan and Runkle (1993) and it is also used to model asymmetry in the ARCH process.

However, for the purposes of the present study we are going to employ, as it is mentioned, an extended AR-EGARCH model. This kind of model is superior compared to the QGARCH model and the GJR-GARCH model as well. This is because, the first approach tends to under predict volatility associated with negative innovations (Engle and NG, 1993), while the second one does not account for the difference between positive and negative innovations as the EGARCH model does (Nelson, 1991).

4.4 The extended univariate AR(1)-EGARCH(1,1) model

As indicated above, the GARCH models are commonly employed to investigate the stochastic behavior of a plethora of financial time series and more specific to enlighten the behavior of volatility over time (Theodossiou and Lee, 1993). Following Koutmos (1996), we use the AR-EGARCH model which allows for the estimation of volatility interactions in one-step ahead and at the same time tests the impact of asymmetric news on volatility spillovers. Next, we are going to present extensively the preferred methodology as far as the mean and the variance is concerned.

4.4.1 Mean

An AR model describes the behaviour of a set of endogenous variables over the same period as a linear function of only their past values, or it can be said that each variable is a linear function of past lags of itself and past lags of the other variables. The AR model of order 1, denoted as AR(1), is as follows:

$$\omega_t = \beta_0 + \beta_1 \omega_{t-1} + \varepsilon_t \qquad (6)$$

In order to achieve the goals of the current study we assume as dependent variable the returns of a given stock index, symbolized by R, and as independent variable the one step lagged returns of that index.

Return of a given stock index is calculated by the following formula:

$$[(P_t - P_{t-1})/P_{t-1})]*100 \qquad (6.a)$$

Accepting the model proposed by Nelson (1991), equation (6) takes the following form:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t \qquad (7)$$

where R_t stands for the percentage return at time t for each individual market and ε_t is the innovation at time t for that market. Note that $\varepsilon_t = R_t - \mu_t$, where μ_t is the conditional mean.

Equation (7) describes the returns of stock indices of each market as an autoregressive (AR) process, where, as it is said, the conditional mean for each of the stock indices is a function of past own prices.

4.4.2 Variance

Beyond the estimation about the means of stock indices returns, as they are captured by equation (7), we should focus as well on the variance of data, in order to complete the exploration of the AR(1)-EGARCH(1,1) model. So, in order to describe the variance too, we shall employ the conditional variance of ε_t, symbolized by σ_t^2. Hence, the AR(1)-EGARCH(1,1) model, combining both the conditional mean and the conditional variance, takes the following form:

Mean: $$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t \qquad (7)$$

The conditional variance of ε_t is given as:

$$\sigma_t^2 = \exp\{\alpha_0 + \alpha_1[(|z_{t-1}| - E|z_{t-1}|) + \alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2\} \qquad (8)$$

where σ_t^2 symbolizes the conditional variance, z is the standardized innovation, i.e. $z_t = (\varepsilon_t - \mu_t) / \sigma_t^2$, where μ_t is the conditional mean.

Equation (8) analyzes the conditional (time varying) variance of returns in prices of each particular stock index under examination. Specifically, conditional variance is an exponential function of past own standardized innovations. Terms $[(|z_{t-1}| - E|z_{t-1}|) + \alpha_2 z_{t-1}]$ in equation (8) refer to the functional type of the standardized residuals. This function is asymmetric and for $z_{t-1} < 0$ the slope of f (.) function is equal to $-1 + \alpha_2$, while in contrast for $z_{t-1} > 0$ the slope of f (.) function is equal to $1 + \alpha_2$. As a result, equation (8) allows lagged standardized innovations to affect the conditional variance of stock indices asymmetrically.

When it is assumed for a positive α_1, the impact of z_{t-1} on σ_t^2 will be positive whether the magnitude of z_{t-1} is greater than its expected value $E|z_{t-1}|$. On contrary, the impact of z_{t-1} on σ_t^2 will be negative whether the magnitude of z_{t-1} is smaller than its expected value $E|z_{t-1}|$, supposing again for a positive α_1.

Terms ($|z_{t-1}| - E|z_{t-1}|$) measure the magnitude effect, whereas term $\alpha_2 z_{t-1}$ measures the sign effect. The sign effect may enhance or offset the magnitude effect. More specific, when α_2 is negative, a decrease in stock index' price ($z_{t-1}<0$) will be followed by higher volatility, while an increase in stock value ($z_{t-1}>0$) will be followed by a more moderate volatility. A negative and statistically significant α_2 indicates that the leverage effect exists. The leverage effect refers to the generally negative correlation between an asset's returns and an asset's volatility. Typically, rising asset prices are accompanied by declining volatility, and vice versa. Besides, it has been stated (Engle and Ng, 1993), that the leverage effect is generally asymmetric, i.e., *ceteris paribus*, decrease in shares prices are accompanied by greater increases in volatility, than the decrease in volatility which is connected with rising stock markets. This effect is measured by the ratio $|-1 + \alpha_2|/(1 + \alpha_2)$, which is greater than one for negative α_2 and less than one for a positive α_2. In the same sense, if α_2 is positive, decreases in stock prices index will be followed by lower volatility than stock index advances.

Volatility spillovers in own past stock observations are captured by the coefficient α_1. The asymmetric volatility transmission mechanism is interpreted as follows: A statistically significant α_1 with a negative α_2 at the same time means that negative innovations in the stock price index have a higher influence than positive innovations. On the opposite, a positive α_2 means that positive innovations in the stock price index have a higher influence than negative innovations.

The persistence of volatility implied by equation (8) is measured by the factor α_3. If α_3 is less than one, the conditional variance is finite, while if α_3 is statistically equal to one then the conditional variance follows an integrated process of order 1.

Given a sample of n observations and conditional normality for the stock returns in each index, the log-likelihood function for the univariate EGARCH can be written as:

$$L(\Theta) = (-0.5n)\ln(2\pi) - 0.5\sum_{t=1}^{T}\ln(\sigma_t^2) \qquad (9)$$

where Θ is the parameter vector to be estimated.

4.5 Explanatory variables

Next, we are going to enrich the conditional asymmetric volatility equation (8) by adding some explanatory exogenous variables such as the trading volume (TV) in order to discover their ability to explain additionally the transmission mechanism process in each stock market. In order to achieve that, and by following Hasan and Francis (1998), the coefficient φ is nested in equation (8) to capture the potential relationship between stock index returns of each market with the impact of trading volume. In symbols:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \varphi TV_t\} \qquad (10)$$

Beyond the use of the TV variable, this paper seeks to contribute to scientific literature on volatility spillovers by focusing on some extra independent variables such as the exchange rates fluctuations (ER) of each Balkan, Slavic and Oriental country's domestic currency related to the US dollar, or the return from a major stock index of the US exchange market of the previous day. The idea for considering these variables arises from the notion that numerous investors in emerging markets may perceive the route of global financial centre as a signal from lighthouse about their very own decisions for local transactions. Moreover, whenever the value of the domestic currency meets a drop (raise), the real price of shares becomes cheaper (more expensive) for international investors and as a consequence some may see it as a bargain (obstacle) to acquire stocks. The theory is adjusted for shares selling as well. Thus, as domestic money meets greater variances, it is expected the number and the intense of transactions to increase and therefore we suppose for a positive relationship between the exchange rates variable and the conditional variance. In any case, the price of the previous period is preferred, not only for the percentage change of the exchange rates but for the major stock index of the US market too, as it is considered that some time is needed for the dispersion of information. Furthermore, these variables are going to be tested without and with the influence of the TV variable.

Based on the above, equation (8) is expanded as follows, to include the ER effect as well:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \chi ER_{t-1}\} \qquad (11)$$

where χ is the coefficient for the ER variable. This factor is employed to analyze whether it is able to capture deeper the transmission mechanism process than the simple model of equation (8) does. In an analogous way that equation (8) leads into equation (10) when the trading volume variable is enclosed, equation (11) is morphing as:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \chi ER_{t-1} + \varphi TV_t\} \qquad (12)$$

since the trading volume of the current period is added.

Returning back to the basic equation number (8), another variable can be used in the model to evaluate the influence of the US stock exchange into each separate examined domestic market. For this purpose, the S&P 500 index is selected as a representative one of the American stock market, since it is based on 500 large companies that have common shares listed on NYSE or NASDAQ. It differs from other U.S. stock market indices, such as the Dow Jones Industrial Average or the NASDAQ Composite index, because of its diverse synthesis chosen by a team of analysts and economists and its weighting methodology. S&P 500 index is considered enough representative of the market because it includes a significant portion of the total value of the market. Hence, in order to capture the S&P 500 effect, an augmented form of equation (8) is shaped as below:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \psi SP_{t-1}\} \quad (13)$$

here ψ is the coefficient for the S&P 500 index return (SP). Note that for the SP variable, just as for the exchange rates previously, the observations of the previous period are employed. We expect for rather a positive relationship between the S&P 500 index fluctuations of the previous period and the conditional variance of the domestic markets, in other words a positive ψ, as behaviors on the other side of Atlantic Ocean may travel and influence through the spillover effects the variance of the examined stock exchanges. Similarly to equation (12), the price of the trading volume for the current period is included, to test if it helps to shed more light into spillovers' mechanism process or not. In symbols:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \psi SP_{t-1} + \varphi TV_t\} \quad (14)$$

Finally, a composite model of the previous equations will be employed, by combining into a single mathematical sentence the fluctuation of exchange rates, and the returns of S&P 500 index, with and without the trading volume level. Particularly, equations (11) and (13) will be merged in a new single model. This is:

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \chi ER_{t-1} + \psi SP_{t-1}\} \quad (15)$$

and for the inclusion of the liquidity effect, equations (12) and (14) are merged into equation (16):

$$\sigma_t^2 = \exp\{\alpha_0+\alpha_1[(|z_{t-1}|-E|z_{t-1}|)+\alpha_2 z_{t-1}] + \alpha_3 \ln\sigma_{t-1}^2 + \chi ER_{t-1} + \psi SP_{t-1} + \varphi TV_t\} \quad (16)$$

These comprehensive approaches may help to get a more spherical view about the powers that drive conditional variance in a given stock market by counting in for more financial variables. As far as we are aware, this is the first time that such a combined formula is shaped and it will be quite interesting to test whether such an approach can strengthen the ability of model to predict future volatility.

In any case, the likelihood estimation method will be employed to estimate the function of the parameters for each econometric model and for each country. The likelihood function indicates how likely the observed sample is a function of possible parameter values. For the purposes of the current study, the natural logarithm of the likelihood function is used, called the log-likelihood. This approach is preferred as the logarithm is a monotonically increasing function, so it achieves its maximum value at the same point as the function itself. Thus, the log-likelihood function can be estimated instead of the classical likelihood. In other words, the log-likelihood is an expression of optimal values of estimated coefficients.

The log-likelihood values are a function of sample size, so they are used to compare the fit of different coefficients. Hence, it is meaningful to compare the log-likelihood values of same size samples, i.e. to compare the results of the various models for each country separately. Higher values of log-likelihood are better than lower, as these kinds of results indicate that independent coefficients are able to express more reliably the endogenous variable.

5. Empirical results

This sector presents the empirical results about return and volatility spillovers in the twelve Balkan, Slavic or Eastern countries under examination and for the corresponding periods. Results are based on the methodology which was analyzed intently in Chapter 4, by employing the collected data. Table 5.1 (i, ii) shows the findings for the coefficients β_0 and β_1 about the mean, and about the factors α_0, α_1, α_2 and α_3 of equations (8) and (10) for the conditional variance. The first line for each country refers to the basic model (8), while the line titled "TV" shows outcomes when trading volume variable enters into the model (10). Therefore, the coefficient φ for variable trading is added. Below each figure, in parenthesis there are the corresponded p-values, which state whether parameters are statistically important or not. Also, Table 5.1 illustrates the maximum log-likelihood estimations for equations (8) and (10).

According to Table 5.1, the return spillover coefficients of β_1 are positive for eleven out of twelve countries, with the exception of Turkey, when the trading volume effect is not considered. Thus, there is positive first order autoregressive process, as it is specified by the mean equation. This relationship is statistically significant at 1% level for Greece, Romania, Russia, Serbia, Slovenia and Ukraine, at 5% level for Croatia, and at 10% level for Cyprus and Czech Republic. For the rest countries, including the negative sign of Turkey, the return spillovers coefficients are not significant. When the trading volume effect is entered into the model, coefficients become significant even at 1% level for Croatia, Cyprus and Czech Republic, while it loses its significance for Greece. For the rest of the cases there are not remarkable changes, except for Romania where coefficient is now statistically significant at 5% level.

As far as the volatility coefficient α_1 and the magnitude effect for variance is concerned, it is positive and statistically important at 1% level for every occasion, except for Czech Republic where it is positive but not statistically significant. Thus, the impact of z_{t-1} on σ_t^2 is positive whether the magnitude of z_{t-1} is greater than its expected value $E\left|z_{t-1}\right|$. There are no dramatic changes around the coefficient of volatility's magnitude when the liquidity effect is added in the model, as it stills positive and statistically important for the same eleven markets. The only exception is again for Czech Republic where the coefficient is negative. However, some evidences of a pattern can be detected as coefficient is increased for eight cases: Croatia, Cyprus, Czech Republic |in absolute terms|, Israel, Romania, Serbia, Slovenia and Ukraine.

The leverage effect parameter α_2 is found to be negative and statistically significant for all indices, except for Cyprus and Slovenia where it is positive. In the latter case, the coefficient is not statistically important. Such results indicate that the leverage effect indeed exists in these markets. These findings are in line with previous research which found a leverage effect in the stock returns of other indices (Karpoff, 1987). As α_2 is less than zero, a negative shock increases volatility more than a positive shock. This is the way that parameter α_2 captures the asymmetric effect of shocks on volatility. When the trading volume is taken into account, it seems to mitigate these outcomes, as coefficient is no more statistically significant for Greece and Ukraine. Yet, there is not a clear pattern about the influence of trading volume variable on the size of coefficients, as they are increased in half of cases, while they are decreased for the rest.

Table 5.1i Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for basic models {(8) & (10)}

	β_0	β_1	α_0	α_1	α_2	α_3	φ	**Log-likelihood**
Croatia	0.003	0.033	0.005	0.188	-0.045	0.99	-	-672.913
	(0.807)	(0.049)**	(0.055)***	(0.001)*	(0.001)*	(0.001)*	-	
TV	-0.001	0.068 ↑	-0.426	0.467 ↑	-0.066 ↑	0.689	0.001	-698.4912
	(0.824)	(0.004)*	(0.001)*	(0.001)*	(0.013)**	(0.001)*	(0.001)*	
Cyprus	-0.012	0.059	0.033	0.308	0.042	0.984	-	-965.9422
	(0.717)	(0.069)***	(0.001)*	(0.001)*	(0.033)**	(0.001)*	-	
TV	-0.015	0.063 ↑	0.02	0.357 ↑	0.041 ↓	0.955	0.001	-952.7145
	(0.637)	(0.001)*	(0.054)***	(0.001)*	(0.135)	(0.001)*	(0.001)*	
Czech Republic	-0.077	0.153	0.003	0.026	-0.23	0.962	-	-70.5218
	(0.299)	(0.064)***	(0.852)	(0.603)	(0.001)*	(0.001)*	-	
	-0.063	0.092 ↓	-0.019	-0.129 ↑	-0.063 ↓	0.991	0.008	-65.9112
TV	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	
Greece	0.003	0.084	0.067	0.201	-0.041	0.966	-	-1514.4441
	(0.919)	(0.001)*	(0.001)*	(0.001)*	(0.017)**	(0.001)*	-	
TV	-0.004	0.043 ↓	1.832	0.135 ↓	-0.04 ↓	-0.368	0.006	-1533.1553
	(0.95)	(0.144)	(0.001)*	(0.0102)**	(0.276)	(0.021)**	(0.001)*	
Israel	0.034	0.025	0.008	0.133	-0.07	0.982	-	-1330.828
	(0.051)***	(0.202)	(0.002)*	(0.001)*	(0.001)*	(0.001)*	-	
TV	0.033	0.028 ↑	0.05	0.142 ↑	-0.085 ↑	0.973	-0.001	-1325.6284
	(0.08)***	(0.172)	(0.004)*	(0.001)*	(0.001)*	(0.001)*	(0.012)**	
Poland	-0.025	0.021	0.007	0.113	-0.074	0.991	-	-1275.02
	(0.313)	(0.382)	(0.021)**	(0.001)*	(0.001)*	(0.001)*	-	
TV	-0.03	0.019 ↓	-0.009	0.086 ↓	-0.086 ↑	0.987	0.001	-1269.6595
	(0.153)	(0.216)	(0.086)***	(0.001)*	(0.001)*	(0.001)*	(0.002)*	

Table 5.1ii Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for basic models {(8) & (10)}

	β_0	**β_1**		**α_0**	**α_1**		**α_2**		**α_3**	**φ**	**Log-likelihood**
Romania	0.001	0.095		0.006	0.261		-0.079		0.931	-	-745.5649
	(0.95)	(0.001)*		(0.16)	(0.001)*		(0.001)*		(0.001)*	-	
TV	0.005	0.061	↓	-0.427	0.447	↑	-0.09	↑	0.51	0.024	-716.2735
	(0.803)	(0.035)**		(0.001)*	(0.001)*		(0.009)*		(0.001)*	(0.001)*	
Russia	0.042	0.068		0.046	0.151		-0.079		0.9701	-	-3092.5115
	(0.178)	(0.001)*		(0.001)*	(0.001)*		(0.001)*		(0.001)*	-	
TV	0.041	0.066	↓	0.049	0.142	↓	-0.082	↑	0.9709	-0.001	-3090.9607
	(0.209)	(0.001)*		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.086)***	
Serbia	0.004	0.192		0.025	0.418		-0.027		0.961	-	-1281.6866
	(0.758)	(0.001)*		(0.001)*	(0.001)*		(0.032)**		(0.001)*	-	
TV	0.001	0.194	↑	0.001	0.419	↑	-0.032	↑	0.954	0.001	-1275.7352
	(0.825)	(0.001)*		(0.235)	(0.001)*		(0.017)**		(0.001)*	(0.001)*	
Slovenia	0.009	0.155		-0.047	0.324		0.06		0.898	-	-95.9113
	(0.793)	(0.002)*		(0.07)***	(0.001)*		(0.146)		(0.001)*	-	
TV	0.004	0.166	↑	-0.105	0.336	↑	0.05	↓	0.876	0.001	-94.54
	(0.883)	(0.001)*		(0.028)**	(0.001)*		(0.236)		(0.001)*	(0.121)	
Turkey	0.059	-0.006		0.059	0.132		-0.083		0.928	-	-1489.2759
	(0.075)	(0.798)		(0.001)*	(0.001)*		(0.001)*		(0.001)*	-	
TV	0.052	-0.028	↑	-0.065	0.117	↓	-0.068	↓	-0.445	0.002	-1488.6461
	(0.131)	(0.258)		(0.59)	(0.008)*		(0.033)**		(0.001)*	(0.001)*	
Ukraine	-0.014	0.12		0.09	0.358		-0.045		0.95	-	-1863.8668
	(0.711)	(0.001)*		(0.001)*	(0.001)*		(0.009)*		(0.001)*	-	
TV	-0.043	0.145	↑	0.308	0.63	↑	-0.029	↓	0.73	0.001	-1919.4194
	(0.287)	(0.001)*		(0.001)*	(0.001)*		(0.377)		(0.001)*	(0.001)*	

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

The degree of volatility persistence, as it measured by coefficient α_3, is quite close to one for almost all cases. It peaks for Poland, having a value of 0.991. Maybe the only exception is for Slovenia where the value of coefficient α_3 is just 0.898. Hence, it can be concluded that the conditional variance rather follows an integrated process of order 1 for the majority of the countries. Testing for α_3=1 indicates that hypothesis cannot be rejected for Croatia, Cyprus, Israel, Poland and Russia. However, the inclusion of trading volume variable in the conditional variance equation has as a result the values of the coefficient α_3 to be declined for many countries, implying that this variable accounts for some of the volatility persistence in these markets. Indicatively, figures of coefficient α_3 become 0.51 for Romania and 0.689 for Croatia. Such outcomes let to assume that according to this approach the conditional variance is finite in these markets.

The penultimate column of Table 5.1 illustrates the values of φ coefficient for the trading volume variable. This coefficient is found to be statistically significant at 5% level for Israel, at 10% level for Russia and at 1% level for the rest countries, with the exception of Slovenia where coefficient φ is not statistically important. The sign of coefficient φ is positive for ten out of twelve cases, except for Israel and Russia. Note that for these two countries the significance of coefficient φ was more moderate, as it was not statistically important at 1% level. So, it can be concluded that there is a rather positive relationship between the height of trading volume and the conditional variance. This can be interpreted as that more transactions may lead into greater fluctuations.

After that, it is tested in which way the addition of trading volume variable influences the log-likelihood values for each country. Of course, the higher values of log-likelihood are superior to the lower for a given sample as it is used to compare the fit of different coefficients. According to Table 5.1 the log-likelihood values for equation (10) are increased compared to those of equation (8) for nine out of twelve occasions. These countries are: Cyprus, Czech Republic, Israel, Poland, Romania, Russia, Serbia, Slovenia and Turkey. On the contrary, the log-likelihood values are higher for the model without the trading volume observations only for Croatia, Greece and Ukraine. Thus, it can be concluded that, in general, the inclusion of trading volume variable may help to understand deeper the transmission mechanisms between the returns and volatilities into stock exchange markets.

Next, research focuses on the equations which take into account the influence of exchange rates variable into the model for each country, according to the methodology that has been analyzed in Chapter 4. Table 5.2 (i, ii) illustrates the outcomes for coefficients β_0 and β_1 about the mean, and also for factors α_0, α_1, α_2 and α_3 of equations (11) and (12) about the conditional variance. Again, the first line for each country refers to the model (11) with the exchange rates variable but without the trading volume variable, whereas the second line titled "TV" presents the outcomes when trading volume enters into the model. Of course, this is equation (12). Consequently, parameter χ refers to the exchange rates variable and parameter φ refers to the trading volume variable. Below each figure and inside the parenthesis is laid its corresponded p-value, which states whether the figure is statistically important at a given level of significance. Besides, Table 5.2 shows the maximum likelihood estimates which determine optimal values of the estimated coefficients of equations (11) and (12).

Table 5.2i Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for exchange rates models {(11) & (12)}

	β_0	β_1		α_0	α_1		α_2		α_3	χ	φ	**Log-likelihood**
Croatia	0.001	0.034		-0.01	0.178		-0.042		0.985	0.027	-	-666.3331
	(0.904)	(0.021)**		(0.059)***	(0.001)*		(0.001)*		(0.001)*	(0.001)*	-	
TV	0.001	0.056	↑	-0.068	0.177	↓	-0.036	↓	0.957	0.042	0.001	-644.1103
	(0.698)	(0.016)**		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.001)*	(0.001)*	
Cyprus	-0.013	0.057		0.041	0.311		0.04		0.982	-0.021	-	-965.6499
	(0.682)	(0.078)***		(0.003)*	(0.001)*		(0.062)***		(0.001)*	(0.459)	-	
TV	-0.016	0.06	↑	0.034	0.337	↑	0.044	↑	0.959	-0.048	0.001	-956.2435
	(0.358)	(0.001)*		(0.037)**	(0.001)*		(0.091)***		(0.001)*	(0.156)	(0.005)*	
Czech	-0.077	0.153		0.003	0.026		-0.23		0.962	0.001	-	-70.5218
Republic	(0.324)	(0.041)**		(0.906)	(0.642)		(0.001)*		(0.001)*	(0.995)	-	
	0.023	0.195	↑	-0.107	-0.138	↑	-0.17	↓	0.29	0.343	-0.02	-67.0585
TV	(0.763)	(0.035)**		(0.351)	(0.616)		(0.208)		(0.292)	(0.037)**	(0.287)	
Greece	0.007	0.085		0.067	0.193		-0.041		0.956	0.043	-	-1513.1782
	(0.912)	(0.001)*		(0.001)*	(0.001)*		(0.018)**		(0.001)*	(0.115)	-	
TV	-0.003	0.043	↓	1.821	0.135	↓	-0.04	↓	-0.362	0.005	0.006	-1533.1534
	(0.952)	(0.118)		(0.001)*	(0.007)*		(0.25)		(0.042)**	(0.944)	(0.001)*	
Israel	0.037	0.025		0.001	0.141		-0.078		0.972	0.021	-	-1325.5199
	(0.007)*	(0.024)**		(0.61)	(0.001)*		(0.001)*		(0.001)*	(0.005)*	-	
TV	0.035	0.027	↑	0.061	0.144	↑	-0.1	↑	0.957	0.029	-0.001	-1317.483
	(0.047)**	(0.198)		(0.002)*	(0.001)*		(0.001)*		(0.001)*	(0.001)*	(0.002)*	
Poland	-0.026	0.021		0.004	0.102		-0.076		0.988	0.004	-	-1273.4118
	(0.329)	(0.391)		(0.194)	(0.001)*		(0.001)*		(0.001)*	(0.08)***	-	
TV	-0.03	0.019	↓	-0.009	0.084	↓	-0.086	↑	0.986	0.001	0.001	-1269.4473
	(0.261)	(0.413)		(0.082)***	(0.001)*		(0.001)*		(0.001)*	(0.509)	(0.004)*	

Table 5.2ii Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for exchange rates models {(11) & (12)}

	β_0	β_1	α_0	α_1	α_2	α_3	χ	φ	**Log-likelihood**
Romania	0.006	0.099	-0.05	0.3	-0.079	0.883	0.116	-	-733.68
	(0.779)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	-	
TV	0.013	0.063 ↓	-0.593	0.451 ↑	-0.081 ↑	0.421	0.282	0.025	-685.9563
	(0.513)	(0.012)**	(0.001)*	(0.001)*	(0.011)**	(0.001)*	(0.001)*	(0.001)*	
Russia	0.042	0.074	0.057	0.131	-0.086	0.95	0.003	-	-3082.9931
	(0.146)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	-	
TV	0.04	0.073 ↓	0.06	0.124 ↓	-0.088 ↑	0.952	0.001	-0.001	-3081.9855
	(0.25)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.136)	
Serbia	0.042	0.073	0.059	0.133	-0.088	0.95	0.003	-	-2987.6127
	(0.188)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	-	
TV	0.039	0.072 ↓	0.062	0.125 ↓	-0.09 ↑	0.951	0.001	-0.001	-2986.5136
	(0.247)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.003)*	(0.167)	
Slovenia	0.007	0.153	-0.114	0.305	0.059	0.87	0.132	-	-94.2552
	(0.796)	(0.001)*	(0.018)**	(0.001)*	(0.102)	(0.001)*	(0.07)***	-	
TV	0.001	0.165 ↑	-0.214	0.306 ↑	0.043 ↓	0.835	0.173	0.002	-92.4953
	(0.98)	(0.001)*	(0.003)*	(0.001)*	(0.291)	(0.001)*	(0.018)**	(0.063)***	
Turkey	0.06	-0.007	0.061	0.133	-0.083	0.921	0.009	-	-1488.9837
	(0.045)*	(0.765)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.421)	-	
TV	0.052	-0.031 ↑	-0.09	0.095 ↓	-0.065 ↓	-0.452	0.063	0.002	-1484.4439
	(0.116)	(0.177)	(0.435)	(0.023)**	(0.018)**	(0.001)*	(0.004)*	(0.001)*	
Ukraine	-0.013	0.12	0.09	0.358	-0.046	0.95	0.001	-	-1864.7347
	(0.71)	(0.001)*	(0.001)*	(0.001)*	(0.013)**	(0.001)*	(0.211)	-	
TV	-0.019	0.1206 ↑	0.086	0.363 ↑	-0.054 ↑	0.945	0.001	0.001	-1860.3065
	(0.645)	(0.001)*	(0.001)*	(0.001)*	(0.009)*	(0.001)*	(0.162)	(0.036)**	

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

Based on Table 5.2, it can be seen that the return spillover coefficients of β_1 are positive for eleven out of twelve countries when the trading volume effect is not considered. The only exception is for Turkey. Hence, it can be concluded that mainly there is a positive first order autoregressive process. This relationship is statistically significant at 1% level for Greece, Romania, Russia, Serbia, Slovenia and Ukraine, at 5% level for Croatia, Czech Republic and Israel, and at 10% level for Cyprus. For Poland and Turkey (remember the negative sign of β_1 for this country), the return spillovers coefficients are not statistically significant. These results are quite similar to the corresponding findings for equation (8) where the exchange rates variable is not included. Thus, it can be said that the use of exchange rates variable does not affect the behavior of return spillover coefficient β_1 whether trading volume effect is absent from the model.

As the liquidity is introduced in the conditional variance equation number (11), the return spillover coefficients β_1 become insignificant even at 10% level for Greece and Israel, and in parallel its level of significance is changed for Cyprus (from 10% to 1%) and for Romania (from 1% to 5%). For the rest occasions there are not remarkable differentiations. If these findings are compared with the corresponding results of equation (10), in which the exchange rates variable is not included, it is revealed that for Romania coefficient β_1 is not statistically important according to the first approach (10), whereas it turns to be statistically important at 5% level according to the second approach (12). Apart from that, the trading volume equations (10) and (12) do not present remarkable inconsistency because of the exchange rates variable.

The volatility coefficient α_1, which refers to the magnitude effect for the conditional (time varying) variance, is positive and statistically important at 1% level, except for Czech Republic where it is not statistically significant. These results are exactly the same with the equation (8) where the exchange rates variable is not concerned. Thus, the entry of this variable seems to keep stable the outcomes for the magnitude effect of the conditional variance. Regarding the size of the volatility coefficient α_1, it becomes greater in four occasions (Cyprus, Israel, Romania and Turkey), and lower in six cases (Croatia, Greece, Poland, Russia, Serbia and Slovenia).

Empirical results about the statistical significance of coefficient α_1 as the trading volume values are entered into model reveal that there are no differences at levels where it is important, with the exception of Turkey where now it is statistically significant only at 5% level and not at 1% level as previously. Moreover, coefficient α_1 seems to keep its positive sign for every time it was statistically significant. However, no evidences of a particular pattern can be detected about the size of volatility's coefficient when the liquidity effect is added in the model, as it is increased |in absolute terms| for six cases and it is decreased for six cases as well. Comparing these outcomes with the analogous results of equation (10), where the exchange rates variable is not included, it is revealed that the levels of significance of coefficient α_1 become statistically important from 5% level to 1% level for Greece, whereas follows the opposite route for Turkey (from 1% to 5%). In respect to the size of coefficient α_1, the inclusion of the exchange rates variable seems to reduce its volume as it becomes higher only for two cases; namely, Israel and Romania.

Coefficient α_2 tests for asymmetry in the conditional variance index, and Table 5.2 reports its figures for each country when the exchange rates variable is taken into account. The figures of coefficient α_2 that come from the equation (11) are negative and statistically significant at the 1% significance level in Croatia, Czech Republic, Israel, Poland, Romania, Russia, Serbia and Turkey, while they are statistically significant at the 5% significance level in Greece and Ukraine. To the contrary, figures are positive only in Cyprus and Slovenia. However, it is noteworthy that for these two occasions figures are not statistically important (at the 5% significance level). Thus, it can be concluded that the leverage effect was present for the large majority of the examined markets. Table 5.2 shows that almost all spillovers are asymmetric. Specifically, “bad news” had a greater effect on the conditional variance of the markets than “good news”. A comparison of these results with those obtained by the basic model of equation (8), where the exchange rates variable is not included, indicates that the results are in general lines very similar under both methodologies.

If the trading volume is included into the model (11), then the equation (12) arises. According to the results of that model, there is no a change to the sign of coefficient α_2, i.e. it stays negative for Croatia, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Turkey and Ukraine, and positive for Cyprus and Slovenia. For these two countries, as well as for Czech Republic and Greece, coefficient is not statistically significant at 5% level. As far as the influence of the trading volume variable on the size of the coefficient α_2 is concerned, it is increased |in absolute terms| in Cyprus, Israel, Poland, Romania, Russia Serbia and Ukraine, while it is decreased |in absolute terms| for the rest countries.

Comparing these results with the outcomes of equation (10), in which the exchange rates variable is missing, it comes out that there is not a single change for the sign of the coefficient. Furthermore, the coefficient α_2 is now statistically significant at 1% level for Ukraine, while it was not statistically important before the entrance of the exchange rates variable into the model. Finally, the size of coefficient α_2, if the exchange rates variable is entered into the models with the trading volume variable, is risen |in absolute terms| for six cases (Croatia, Cyprus, Israel, Russia, Serbia and Ukraine), while it is reduced |in absolute terms| for four cases as well (Czech Republic, Romania, Slovenia and Turkey). For Greece and Poland there are not remarkable changes.

As it shown in Table 5.2, the values of coefficient α_3 that has to do with the degree of volatility persistence range from 0.988 for Poland till 0.87 for Slovenia. These two countries had the most extreme values for this particular coefficient for the equation (8) as well, where the exchange rates variable was not included. Testing for α_3=1 indicates that hypothesis can be accepted for four occasions: Croatia, Cyprus, Israel and Poland. It is remarkable that for none of the twelve occasions the value of coefficient α_3 for the model with exchange rates variable (11) is higher than the corresponding value of the model without exchange rates variable (8). These results are consistent with the remarks of Kanas (1998) who found that the entrance of spillover effect variables in the conditional variance equation explains some of the degree of the volatility persistence in stock markets.

Since the trading volume variable is entered into model (11), the figures of coefficient α_3 meet again a decline for every market, with the exceptions of Russia and Serbia where there is a slight increase. However, in general, the inclusion of an explanatory variable such as the trading volume seems to move the conditional variance away from an integrated process of order 1. The conclusion is the same when the trading volume was added in the model where the exchange rates variable is not used. In addition, the comparison between the models that include the trading volume variable with the exchange rates variable on the one hand (12) and without this variable on the other hand (10), underlines that the first approach provides lower numbers for a plethora of countries. As a synopsis, the basic conclusion is that the insertion of some extra variables into the models rather weakens shock’s persistence in volatility.

When the exchange rates fluctuations of each country's domestic currency to the US dollar is included in the variance equation it is anticipated that some more light is going to be shed on the process. Specifically, we expected a positive relationship between the fluctuation of exchange rates variable and the conditional variance. Table 5.2 reports the results about the coefficient χ of the exchange rates variable without and with trading volume. The positive relationship between the exchange rates variable and the conditional variance is confirmed for almost any case, with the only exception of Cyprus. The highest value of coefficient χ is for Slovenia and it is equal to 0.132. The coefficient is found to be statistically significant at the 1% significance level for Croatia, Israel, Romania, Russia and Serbia, at the 10% significance level for Poland and Slovenia, whereas the null hypothesis cannot be rejected for Cyprus (sign was negative), Czech Republic, Greece, Turkey and Ukraine.

Employing the trading volume variable into the model does not seem to influence the size of exchange rates coefficient in a particular pattern as it becomes higher just for half of cases. Also, there is no change about the signs of coefficient χ as it remains negative only for Cyprus. However, coefficient χ which was not statistically important for Turkey and Czech Republic without trading volume parameter turns to be statistically significance at the 1% significance level and significance at the 5% significance level, respectively, and moreover coefficient χ is now statistically important even at 5% level for Slovenia. Nevertheless, for Poland coefficient χ is considered no more statistically significant at the 10% significance level.

The next column of Table 5.2 reports the values of coefficient φ for the trading volume variable. This coefficient is found to be statistically significant at the 1% significance level for Croatia, Cyprus, Greece, Israel, Poland, Romania and Turkey, at the 5% significance level for Ukraine, at the 10% significance level for Slovenia, while it is not statistically important for Czech Republic, Russia and Serbia. Based on the above results, it is revealed that when the exchange rates are included in the variance equation the influence of trading volume seems to be mitigated since the coefficient of the latter variable was statistically important for eleven stock markets in the model without the usage of the exchange rates variable. About the sign of coefficient φ, it is changed from positive to negative for Czech Republic and Serbia, but as it is written previously, neither of them is statistically important. For the remaining cases there are no changes about the sign of coefficient φ. So, it can be concluded that rather there is a positive relationship between the height of trading volume and the conditional variance when the exchange rates variable is included, although this connection seems to be less strong when this variable enters the model.

Finally, the last column of Table 5.2 mentions the log-likelihood values for each country as exchange rates variable is including in the model. Of course, it is meaningful to compare the results before and after the addition of trading volume variable for each country separately. Based on the empirical results, it can be seen that the log-likelihood figures are boosted for eleven cases. Hence, as higher log-likelihood value is superior to lower for a specific sample, it is obvious that the use of trading volume variable into the model with the exchange rates variable underlines that the observed sample is more likely to be a function of possible parameter values. Greece is the only exception.

Measuring results of equation (11) against the results of equation (8) where not only the trading volume variable, but the exchange rates variable as well, is out of the model, it is revealed that the log-likelihood values are greater according to the first approach for nine markets: Croatia, Czech Republic, Greece, Israel, Poland, Romania, Russia, Slovenia and Russia. Hence, the use of these particular variables manages to produce superior outcomes for the majority of the cases and it can be considered that their employment contributes to the analysis of the conditional variance. Lastly, if we put in parallel the two models which mutually contain the trading volume variable, but the first is without the exchange rates variable (10) and the second one is with the exchange rates variable (12), it can be confirmed that the log-likelihood prices are higher for the approach with both factors for nine countries, Croatia, Greece, Israel, Poland, Romania, Russia, Slovenia, Turkey and Ukraine. To conclude, the use of these extra explanatory variables is able, in general, to shed some more light on conditional variance's behavior.

Afterwards, research will be involved in the potential way that the US stock exchange may influence the conditional mean and variance of the examined markets. For this purpose, the typical index of S&P 500, which is shaped by the market capitalizations of 500 large companies of the American stock market, is employed. As it is described in the methodology Chapter, it is expected a positive relationship between the S&P 500 index innovations of the previous period and the conditional variance of the domestic markets. Table 5.3 (i, ii) illustrates the results for coefficients β_0 and β_1 about the conditional mean, and also for factors α_0, α_1, α_2 and α_3 of equations (13) and (14) about the conditional (time varying) variance. In addition, the first line for each country refers to the model (13) where the S&P 500 variable is included but the trading volume variable is not, whereas the second line titled "TV" presents the findings when trading volume enters in the model. This is equation (14). So, parameter ψ refers to the S&P 500 variable and parameter φ refers to the trading volume variable. Under each price about the coefficients, and inside the parenthesis, there is the corresponded p-value, which indicates the statistically significance for every occasion. Furthermore, Table 5.3 reports the maximum log-likelihood values for equations (13) and (14).

According to Table 5.3, the spillover coefficient β_1 about return is positive for eleven out of twelve countries when the trading volume effect is not considered. The only exception is for Turkey. Hence, it can be concluded that mainly there is a positive first order autoregressive process, as it is specified by the mean equation, or in other words, that for the majority of the markets, the returns of US' exchange influence their own returns towards the same direction in the following period. This relationship is statistically significant at the 1% significance level for Croatia, Greece, Romania, Russia, Serbia, Slovenia and Ukraine, at the 5% significance level for Israel, and at the 10% significance level for Cyprus. For Czech Republic, Poland and Turkey (where is the only occasion with negative sign of β_1), the return coefficients are not statistically significant. These results are similar in many ways to the corresponding findings for equation (8) where the S&P variable is not included. This is the case as well when the model with the S&P variable (13) is compared to the model with the exchange rates variable (11).

When the liquidity factor enters the conditional variance equation number (13), the return spillover coefficients β_1 still positive for every country, except for Turkey. However, it is not statistically significant anymore for Israel, while they are not statistically significant any longer at the 1% significance level for Croatia and Greece. Based on these changes, it can be supported that the inclusion of trading volume variable into the model with the S&P parameter mitigates the significance of coefficient β_1 about the return spillover.

Table 5.3i Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for S&P 500 index models {(13) & (14)}

	β_0	**β_1**	**α_0**	**α_1**	**α_2**	**α_3**	**ψ**	**φ**	**Log-likelihood**
Croatia	0.002	0.033	-0.001	0.185	-0.038	0.985	0.002	-	-668.9807
	(0.829)	(0.003)*	(0.901)	(0.001)*	(0.001)*	(0.001)*	(0.04)**	-	
TV	0.001	0.06 ↑	-0.078	0.209 ↑	-0.025 ↓	0.94	0.001	0.001	-646.3995
	(0.628)	(0.012)**	(0.002)*	(0.001)*	(0.076)***	(0.001)*	(0.012)**	(0.001)*	
Cyprus	-0.011	0.057	0.041	0.301	0.024	0.983	-0.007	-	-956.0171
	(0.722)	(0.076)***	(0.001)*	(0.001)*	(0.226)	(0.001)*	(0.409)	-	
TV	-0.01	0.06 ↑	0.036	0.327 ↑	0.027 ↑	0.96	-0.019	0.001	-947.6874
	(0.748)	(0.081)***	(0.011)**	(0.001)*	(0.234)	(0.001)*	(0.097)***	(0.002)*	
Czech	0.024	0.126	-0.179	-0.118	-0.205	-0.122	0.264	-	-72.6681
Republic	(0.763)	(0.138)	(0.217)	(0.524)	(0.062)***	(0.624)	(0.031)**	-	
	0.032	0.122 ↓	-0.225	-0.133 ↑	-0.204 ↓	-0.164	0.269	0.011	-72.6229
TV	(0.712)	(0.127)	(0.268)	(0.466)	(0.06)***	(0.524)	(0.043)**	(0.755)	
Greece	-0.002	0.082	0.061	0.194	-0.054	0.976	-0.015	-	-1512.0706
	(0.967)	(0.005)*	(0.002)*	(0.001)*	(0.003)*	(0.001)*	(0.036)**	-	
TV	0.005	0.049 ↓	1.518	0.12 ↓	-0.019 ↓	-0.18	0.05	0.006	-1531.6716
	(0.932)	(0.095)***	(0.001)*	(0.03)**	(0.622)	(0.334)	(0.064)**	(0.001)*	
Israel	0.037	0.025	0.001	0.141	-0.078	0.972	0.021	-	-1325.5199
	(0.007)*	(0.024)**	(0.61)	(0.001)*	(0.001)*	(0.001)*	(0.005)*	-	
TV	0.035	0.027 ↑	0.061	0.144 ↑	-0.1 ↑	0.957	0.029	-0.001	-1317.483
	(0.047)**	(0.198)	(0.002)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.002)*	
Poland	-0.021	0.022	0.003	0.106	-0.068	0.977	0.007	-	-1267.8064
	(0.42)	(0.334)	(0.384)	(0.001)*	(0.001)*	(0.001)*	(0.004)*	-	
TV	-0.027	0.021 ↓	-0.014	0.083 ↓	-0.08 ↑	0.974	0.006	0.001	-1263.1167
	(0.303)	(0.359)	(0.037)**	(0.001)*	(0.001)*	(0.001)*	(0.023)**	(0.007)*	

Table 5.3ii Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for S&P 500 index models {(13) & (14)}

	β_0	β_1		α_0	α_1		α_2		α_3	ψ	φ	Log-likelihood
Romania	0.024	0.075		-0.154	0.33		-0.048		0.707	0.126	-	-662.4339
	(0.06)***	(0.001)*		(0.001)*	(0.001)*		(0.065)***		(0.001)*	(0.001)*	-	
TV	0.022	0.064	↓	-0.345	0.398	↑	-0.045	↓	0.62	0.074	0.012	-616.293
	(0.117)	(0.001)*		(0.001)*	(0.001)*		(0.139)		(0.001)*	(0.001)*	(0.001)*	
Russia	0.043	0.067		0.055	0.153		-0.0874		0.958	0.003	-	-3089.045
	(0.207)	(0.001)*		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.021)**	-	
TV	0.041	0.066	↓	0.056	0.146	↓	-0.0878	↑	0.961	-0.001	-0.001	-3087.0134
	(0.047)**	(0.001)*		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.056)***	(0.3)	
Serbia	0.01	0.198		0.01	0.441		-0.009		0.939	0.008	-	-1273.5997
	(0.472)	(0.001)*		(0.184)	(0.001)*		(0.503)		(0.001)*	(0.001)*	-	
TV	0.001	0.202	↑	-0.02	0.443	↑	-0.011	↑	0.923	0.011	0.001	-1264.0365
	(0.514)	(0.001)*		(0.107)	(0.001)*		(0.48)		(0.001)*	(0.001)*	(0.001)*	
Slovenia	0.008	0.143		-0.128	0.28		0.075		0.851	0.041	-	-92.6995
	(0.772)	(0.003)*		(0.015)**	(0.001)*		(0.084)***		(0.001)*	(0.041)**	-	
TV	0.003	0.155	↑	-0.214	0.284	↑	0.065	↓	0.821	0.047	0.001	-90.7845
	(0.924)	(0.002)*		(0.004)*	(0.001)*		(0.125)		(0.001)*	(0.015)**	(0.071)***	
Turkey	0.059	-0.004		0.056	0.126		-0.084		0.927	0.004	-	-1488.7955
	(0.065)***	(0.852)		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.318)	-	
TV	0.051	-0.027	↑	-0.062	0.12	↓	-0.067	↓	-0.452	-0.004	0.002	-1488.5015
	(0.121)	(0.234)		(0.588)	(0.004)*		(0.018)**		(0.001)*	(0.563)	(0.001)*	
Ukraine	-0.013	0.12		0.085	0.348		-0.039		0.946	0.008	-	-1862.5364
	(0.707)	(0.001)*		(0.001)*	(0.001)*		(0.03)**		(0.001)*	(0.094)***	-	
TV	-0.02	0.121	↑	0.084	0.356	↑	-0.047	↑	0.941	0.001	0.001	-1855.8402
	(0.624)	(0.001)*		(0.001)*	(0.001)*		(0.033)**		(0.001)*	(0.273)	(0.07)***	

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

The coefficient α_1 about the magnitude effect on the conditional (time varying) variance is positive and statistically important at the 1% significance level in every market, with the exception of Czech Republic where it is negative and not statistically significant. These results are by and large the same with those which were obtained by equation where the S&P variable is not concerned (8) and with the equation where the exchange rates variable is employed in the model (11), with the sole difference that in the case of Czech Republic the sign was positive. Thus, using exchange rates or S&P variables does not seem to influence drastically the basic characteristics of coefficient α_1, relating to its sign and significance. Concerning the size of the volatility coefficient α_1, it is greater in model (13) than it is in the basic model (8), for four occasions (Israel, Romania, Russia and Serbia), and lower for eight cases (Croatia, Cyprus, Czech Republic, Greece, Poland, Slovenia, Turkey and Ukraine).

When trading volume enters in the model with the S&P variable, there are no differences at levels where it was found to be important, with the exception of Greece where now it is statistically significant only at 5% level and not at 1% level as previously. So, coefficient α_1 remains positive and statistically important for every case, with the exception of Czech Republic where not only it is negative but it is not statistically significant as well. Furthermore, when the liquidity effect is added in the model, the size of the coefficient about volatility's magnitude is increased |in absolute terms| in eight markets: Croatia, Cyprus, Czech Republic, Israel, Romania, Serbia, Slovenia and Ukraine. If we compare these results with the parallel outcomes of equation (10), where the S&P variable is not included, it is obvious that actually there are no changes about the levels of significance and the signs of coefficients $\alpha_{1.}$ In respect to the size, the inclusion of S&P variable seems in general to decrease it, as it becomes higher only for four cases; namely, Israel, Russia, Serbia and Turkey. Such a behavior is similar when the exchange rates variable was introduced into equation (10).

Table 5.3 also reports the results for the parameter measuring asymmetric volatility spillover effects when the S&P variable is taken into account. The figures of coefficient α_2 that come from the equation (13) are negative and statistically significant at the 1% significance level in Croatia, Greece, Israel, Poland, Russia, and Turkey, and at the 5% significance level in Ukraine, at the 10% significance level in Czech Republic and Romania, while it is not statistically important for Serbia. On the other side, coefficient α_2 is found to be positive for Cyprus and Slovenia. It is noteworthy these two markets were the only ones that presented a positive coefficient α_2 for the model without the S&P influence, i.e. equation (8), as well. Nevertheless, the latter figures of equation (13) are not statistically important at the 5% significance level. Therefore, the above findings confirm the existence of the leverage effect, at least for the vast majority of the markets under examination. Specifically, news that runs from the previous period to the next is asymmetric, meaning that "bad news" has a bigger impact on volatility than "good news". On the opposite, the positive α_2 means that positive innovations in the stock price index have a higher influence than negative innovations.

The comparison between the results that were obtained from model (13) with those that came from the basic equation (8), where the S&P variable was not included, indicated that there was not a single change as far as the sign of coefficient α_2 is concerned. However, the levels of significance are lower according to the second methodology (13) for a series of countries such as Cyprus, Czech Republic, Romania, Serbia and Ukraine, while they are higher only for Greece and Slovenia. These outcomes imply that the employment of the S&P variable into the model may dull the magnitude of the sign effect variable regarding the conditional variance.

If we insert the trading volume into the model (13), then equation (14) is emerged. According to the results, there is no change to the sign of coefficient α_2, i.e. it stays negative for Croatia, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Turkey and Ukraine, and positive only for Cyprus and Slovenia. These outcomes are identical not only to the results of equations (8) and (10), but also to the results of equations (11) and (12), where the exchange rates variable is included. Such a complete agreement about coefficient of asymmetric volatility spillover effects coming from six differentiated approaches, underlines the constant behavior of that coefficient with regards to the conditional variance.

However trading volume variable seems to deaden the levels where coefficient α_2 is statistically different than zero. More specifically, the coefficients α_2 that obtained from equation (14) are statistically significant at 10% level for Croatia and at 5% level for Turkey, while they were statistically important at the 1% significance level before the entrance of the trading volume into the model (13). Furthermore, coefficients α_2 which were statistically significant at 1% level for Greece and at 10% level for Romania and Slovenia, now are found to be no more statistically important. A comparison of these results to the findings of equation (10), reveals that the inclusion of S&P factor in the model with the trading volume (14) rather mitigates the importance of coefficient α_2, as for Romania and Serbia it was statistically significant at the 1% and 5% significance levels respectively, but it is considered no more statistically important for both of them when S&P variable is taken into account. Also, coefficient α_2 is now statistically significant at 10% level for Croatia and Czech Republic, while it was statistically important at 5% and 1% levels respectively without S&P variable. On the other hand, for Ukraine coefficient becomes significant at the 5% significance level while it was not statistically important without S&P variable.

As far as the influence of S&P variable on the size of coefficient α_2 is concerned $\{(8) \rightarrow (13)\}$, it is increased |in absolute terms| in five countries. Namely: Greece, Israel, Russia, Slovenia and Turkey. In parallel, the entry of the trading volume (14) into the model with the S&P variable (13) increases |in absolute terms| coefficient α_2 in Cyprus, Israel, Poland, Russia, Serbia and Ukraine. Finally, for the models with the S&P variable (14) and without the S&P variable (10), the size of coefficient α_2 is greater for the first approach in four markets: Israel, Russia, Slovenia and Ukraine.

Additionally, Table 5.3 reports the results about the degree of volatility persistence, as it measured by coefficient α_3. According to these, coefficient α_3 is quite close to one for most of the cases. The greater value is for Croatia, presenting a price equal to 0.985. Hence, it can be concluded that the conditional variance rather follows an integrated process of order 1 for the majority of the countries. However, testing for α_3=1 indicates that hypothesis can be accepted just for five occasions: Croatia, Cyprus, Greece, Israel and Poland. It is remarkable that only for Greece the value of coefficient α_3 obtained from the model with S&P variable (13) is higher than the corresponding value of the model without S&P variable (8). Moreover, the inclusion of trading volume variable in the conditional variance equation leads to a decline of coefficient's α_3 value, except for Russia. This was the case too, when the trading volume was entered into the basic model (8) and into the model with exchange rates variable (11). Generally, the inclusion of an explanatory variable such as the trading volume seems to move the conditional variance away from an integrated process of order 1. As a synopsis, the basic conclusion is that the insertion of some extra variables into the models rather weakens shock's persistence in volatility.

When S&P 500 index return of the previous period is included in the variance equation, it is anticipated some more light to be shed on the spillovers' mechanism process. Specifically, as it is described in the methodology Chapter, it is expected a positive relationship between S&P 500 index changes of the previous period and the conditional variance of domestic markets. Table 5.3 reports the results about coefficient ψ of the S&P variable without and with trading volume. The positive relationship between the S&P variable and conditional variance is confirmed for almost any case, only with the exception of Cyprus and Greece. The expected positive relationship for Cyprus had not been confirmed for the exchange rates variable too. Coefficient ψ is found to be statistically significant at the 1% level for Israel, Poland, Romania and Serbia, at the 5% level for Croatia, Czech Republic, Greece, Russia and Slovenia, and at the 10% level for Ukraine, whereas the null hypothesis cannot be rejected for Cyprus (negative sign) and Turkey.

The inclusion of trading volume in the variance equation does not seem to influence the size of S&P coefficient in a particular pattern. However, there are some changes about the sign of coefficient ψ as it becomes positive from negative for Greece and it follows the reverse route for Russia and Turkey, i.e. from negative to positive. Moreover, coefficient ψ which was not statistically important for Cyprus without trading volume parameter turns to be statistically significance at the 10% level, while coefficient ψ is no more statistically important at the 10% significance level for Ukraine. Finally, coefficient ψ is now statistically important at 5% level and at 10% level for Poland and Russia respectively from 1% level and 5% level.

The following column of Table 5.3 reports the values of coefficient φ for the trading volume variable when S&P parameter is considered. This coefficient is found to be statistically significant at the 1% significance level for Croatia, Cyprus, Greece, Israel, Poland, Romania, Serbia and Turkey, and at the 10% significance level for Slovenia and Ukraine, while it is not statistically important for Czech Republic and Russia. Hence, it can be concluded that when the S&P variable is included in the variance equation (14), the influence of trading volume seems to be mitigated, since the coefficient of the latter variable was found to be statistically important for eleven stock markets in the model without the S&P variable (10). As far as the sign of coefficient φ is concerned, it is positive for all cases, with the exception of Israel and Russia. That was the case for the equation without the S&P variable (10) as well. Remember that for Russia coefficient φ was not found to be statistically important according to equation (14). Overall, it can be concluded that rather there is a positive relationship between the height of trading volume and the range of conditional variance when the S&P variable is included.

Last column of Table 5.3 states the log-likelihood values for each country as S&P variable is including in the models with and without the trading volume variable. Based on these results, it can be concluded that the addition of trading volume has as a result the growth of log-likelihood figures for eleven cases. Hence, as higher log-likelihood value is superior to lower for a specific sample, using trading volume variable into the model with the S&P parameter shows that the observed sample is more likely to be a function of possible parameter values. Greece is the only exception. This is exactly the same pattern when trading volume entered the model with the exchange rates variable.

A comparison between the results of equation (13) and the outcomes of equation (8) where not only the trading volume variable, but the S&P parameter as well, is out of the model reveals that the log-likelihood values are greater according to model (13) for almost every case. Thus, the use of this particular variable manages to produce superior outcomes for the majority of cases and it can be considered that its usage contributes to the analysis of conditional variance. Finally, if we put in parallel the two models which mutually contain the trading volume variable, but the former is without the S&P variable (10) and the latter is with the S&P variable (14), it can be confirmed that the log-likelihood prices are higher for the approach with both factors for eleven countries: Croatia, Cyprus, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. As a general conclusion, the use of these extra explanatory variables is able to shed some additional light on conditional variance.

The next phase of study combines all the previous models into a single scheme, with (16) and without (15) the trading volume variable. More precisely, these two blending models, which are based on the previous equations, are shaped by combining into a particular mathematical sentence the fluctuations of exchange rates as well as the returns of S&P 500 index, in order to explore in which way these parameters influence together the conditional variance of the examined markets. Table 5.4 (i, ii) illustrates the results for coefficients β_0 and β_1 about the conditional mean, and also for factors α_0, α_1, α_2 and α_3 of equations (15) and (16) about the conditional (time varying) variance. In addition, the first line for each country refers to the model (15) where the trading volume variable is not included, whereas the second line titled "TV" presents the findings when trading volume enters in the model. This is equation (16). Parameter χ refers to the exchange rates variable, parameter ψ refers to the S&P 500 variable and parameter φ refers to the trading volume variable. Under each price about the coefficients, and inside the parenthesis, there is the corresponded p-value, which indicates the statistically significance for every occasion. Furthermore, Table 5.4 reports the maximum log-likelihood values for equations (15) and (16).

According to Table 5.4, the spillover coefficient β_1 of conditional mean is positive for eleven out of twelve countries when the trading volume effect is not considered. The only exception is for Turkey. Hence, it can be concluded that there is a positive first order autoregressive process, as it is specified by the mean equation. This relationship is statistically significant at the 1% significance level for Greece, Romania, Russia, Serbia, Slovenia and Ukraine, and at the 10% significance level for Croatia. For Cyprus, Czech Republic, Israel, Poland and Turkey (where is the only occasion with negative sign of β_1), the return coefficients are not statistically significant. Regarding the size of coefficient β_1, it is revealed that is higher for the model with both variables (15) as compared with the corresponding values of the basic model (8), only in three cases: Poland, Russia and Serbia. Thus, based on the above findings, it can be supported that the inclusion of these two variables into the initial model generally mitigates the volume of return spillover coefficient.

When the liquidity factor enters the conditional variance equation number (15), the return spillover coefficients β_1 is not statistically significant anymore for Greece. In parallel, it remains positive for every country, except for Turkey. These results about the sign of coefficient β_1 obtained by models (15) and (16) are identical to the findings of the previous equations pairs, i.e. the basic model, the model with the exchange rates and the model with the S&P 500 return. As far as the size of coefficient β_1 is concerned, it is higher for the model without trading volume only in four cases; Greece, Poland, Romania and Russia.

Table 5.4i Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for combined models {(15) & (16)}

	β_0	β_1		α_0	α_1		α_2		α_3	χ	ψ	φ	**Log-likelihood**
Croatia	0.002	0.033		-0.001	0.184		-0.038		0.986	0.004	0.002	-	-670.5858
	(0.827)	(0.093)***		(0.952)	(0.001)*		(0.001)*		(0.001)*	(0.782)	(0.045)**	-	
TV	0.001	0.06	↑	-0.077	0.207	↑	-0.025	↓	0.941	0.001	0.001	0.001	-646.3727
	(0.574)	(0.013)**		(0.005)*	(0.001)*		(0.099)***		(0.001)*	(0.835)	(0.033)**	(0.001)*	
Cyprus	-0.016	0.053		0.035	0.319		0.038		0.982	-0.032	0.014	-	-918.6118
	(0.602)	(0.1001)		(0.012)**	(0.001)*		(0.064)**		(0.001)*	(0.204)	(0.044)**	-	
TV	-0.017	0.058	↑	0.029	0.336	↑	0.039	↑	0.962	-0.058	0.014	0.001	-911.6988
	(0.642)	(0.102)		(0.083)***	(0.001)*		(0.109)		(0.001)*	(0.078)***	(0.129)	(0.002)*	
Czech	0.021	0.14		-0.198	-0.127		-0.204		-0.024	0.136	0.218	-	-72.0479
Republic	(0.793)	(0.113)		(0.17)	(0.532)		(0.093)***		(0.921)	(0.471)	(0.143)	-	
	0.011	0.143	↑	-0.178	-0.116	↓	-0.203	↓	-0.006	0.153	0.213	-0.006	-72.3889
TV	(0.89)	(0.103)		(0.325)	(0.576)		(0.081)***		(0.98)	(0.451)	(0.168)	(0.834)	
Greece	-0.002	0.084		0.056	0.171		-0.06		0.968	0.066	-0.022	-	-1508.7675
	(0.966)	(0.004)*		(0.001)*	(0.001)*		(0.002)*		(0.001)*	(0.014)**	(0.001)*	-	
TV	0.001	0.048	↓	1.814	0.126	↓	-0.017	↓	-0.401	0.131	0.034	0.006	-1529.634
	(0.978)	(0.128)		(0.001)*	(0.027)**		(0.629)		(0.011)**	(0.022)**	(0.161)	(0.001)*	
Israel	0.037	0.025		0.001	0.14		-0.079		0.972	0.021	0.001	-	-1325.4933
	(0.047)**	(0.209)		(0.679)	(0.001)*		(0.001)*		(0.001)*	(0.005)*	(0.829)	-	
TV	0.035	0.027	↑	0.061	0.144	↑	-0.1	↑	0.957	0.029	-0.001	-0.001	-1317.4812
	(0.066)***	(0.223)		(0.001)*	(0.001)*		(0.001)*		(0.001)*	(0.001)*	(0.958)	(0.001)*	
Poland	-0.021	0.022		0.003	0.106		-0.068		0.978	0.001	0.007	-	-1267.783
	(0.441)	(0.329)		(0.392)	(0.001)*		(0.001)*		(0.001)*	(0.833)	(0.012)**	-	
TV	-0.027	0.021	↓	-0.016	0.078	↓	-0.079	↑	0.976	-0.005	0.008	0.001	-1261.7623
	(0.304)	(0.396)		(0.019)**	(0.001)*		(0.001)*		(0.001)*	(0.102)	(0.005)*	(0.004)*	

Table 5.4ii Univariate AR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers for combined models {(15) & (16)}

	β_0	β_1	α_0	α_1	α_2	α_3	χ	ψ	φ	Log-likelihood
Romania	0.02	0.083	-0.065	0.307	-0.046	0.823	-0.03	0.062	-	-636.6018
	(0.169)	(0.001)*	(0.007)*	(0.001)*	(0.038)**	(0.001)*	(0.294)	(0.001)*	-	
TV	0.021	0.064 ↓	-0.323	0.398 ↑	-0.045 ↓	0.63	-0.03	0.075	0.012	-615.9548
	(0.289)	(0.025)**	(0.001)*	(0.001)*	(0.11)	(0.001)*	(0.323)	(0.001)*	(0.001)*	
Russia	0.042	0.074	0.058	0.132	-0.087	0.949	0.003	0.001	-	-3082.9731
	(0.158)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.846)	-	
TV	0.04	0.073 ↓	0.06	0.123 ↓	-0.088 ↑	0.952	0.001	-0.001	-0.001	-3081.9669
	(0.253)	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.002)*	(0.866)	(0.199)	
Serbia	0.011	0.197	0.012	0.44	-0.009	0.941	-0.001	0.008	-	-1273.4774
	(0.434)	(0.001)*	(0.156)	(0.001)*	(0.509)	(0.001)*	(0.63)	(0.001)*	-	
TV	0.001	0.202 ↑	-0.023	0.444 ↑	-0.011 ↑	0.921	0.001	0.012	0.001	-1263.911
	(0.008)*	(0.001)*	(0.111)	(0.001)*	(0.429)	(0.001)*	(0.679)	(0.001)*	(0.001)*	
Slovenia	0.008	0.145	-0.165	0.284	0.075	0.834	0.089	0.036	-	-92.5486
	(0.788)	(0.002)*	(0.015)**	(0.001)*	(0.082)***	(0.001)*	(0.281)	(0.087)***	-	
TV	0.002	0.162 ↑	-0.287	0.283 ↓	0.061 ↓	0.79	0.13	0.041	0.002	-90.2443
	(0.935)	(0.001)*	(0.005)*	(0.001)*	(0.202)	(0.001)*	(0.149)	(0.069)***	(0.065)***	
Turkey	0.06	-0.005	0.057	0.127	-0.084	0.921	0.008	0.003	-	-1488.5875
	(0.071)***	(0.822)	(0.002)*	(0.001)*	(0.001)*	(0.001)*	(0.008)*	(0.369)	-	
TV	0.051	-0.031 ↑	-0.088	0.098 ↓	-0.065 ↓	-0.457	0.062	-0.003	0.002	-1484.357
	(0.109)	(0.194)	(0.447)	(0.016)**	(0.017)**	(0.001)*	(0.006)*	(0.581)	(0.001)*	
Ukraine	-0.012	0.119	0.083	0.345	-0.041	0.945	0.001	0.009	-	-1861.5554
	(0.689)	(0.001)*	(0.001)*	(0.001)*	(0.023)**	(0.001)*	(0.194)	(0.113)	-	
TV	-0.018	0.12 ↑	0.081	0.353 ↑	-0.049 ↑	0.941	0.001	0.001	0.001	-1859.3628
	(0.636)	(0.001)*	(0.001)*	(0.001)*	(0.011)**	(0.001)*	(0.136)	(0.171)	(0.048)**	

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

The coefficient α_1 about the magnitude effect on the conditional (time varying) variance is positive and statistically important at the 1% significance level in every market, with the exception of Czech Republic where it is negative and not statistically significant. These outcomes are exactly the same with the corresponding results of equation including the S&P variable (13) and quite similar with i) the basic model (8) and ii) the equation including the exchange rates variable (11), since the single difference in these cases is that the sign for Czech Republic was positive. Thus, using exchange rates or S&P variables does not seem to influence radically the fundamental characteristics of coefficient α_1 regarding its sign and significance. Concerning the size of the volatility coefficient α_1, it is greater in model (15) than it is in the basic model (8), for four occasions (Cyprus, Israel, Romania, and Serbia) while it is found to be lower for the rest countries. Thus, it can be said that the inclusion of some extra explanatory variables may mitigate the size of the coefficient about the volatility spillovers. There are no great differences in this pattern when the exchange rates and the S&P variables were used separately.

When trading volume enters the model with both variables (16), coefficient α_1 remains statistically significant at the same levels, with the exception of Greece and Turkey where now it is important at 5% level and not at 1% level as previously. So, this coefficient stays positive and statistically important for every occasion, with the exception of Czech Republic where it is negative and in parallel not statistically significant. Moreover, when liquidity effect is added in the model, there is a kind of balance around the changes of this coefficient's size, as it is increased |in absolute terms| for six markets and it is decreased in equal numbers. Comparing these outcomes with the corresponding findings of equation (10) where the extra variables are not included, it is revealed that in general there are no changes as far as the level of significance and the sign of coefficient α_1 is concerned. These results can be interpreted as an evidence of conditional variance model's stability. In respect to the size of coefficient α_1, the inclusion of the additional variables seems by and large to lessen it, as it becomes higher only for two cases. These are Israel and Serbia. Such a behavior was the same when the extra variables were employed into equation (10) each one independently, confirming once again the constancy of the model.

Besides, Table 5.4 illustrates the results for the coefficient α_2 which measures the asymmetric volatility spillover effects when the exchange rates and the S&P variables are taken together into account. The prices of coefficient α_2 according to equation (15) are negative and statistically significant at the 1% significance level in Croatia, Greece, Israel, Poland, Russia, and Turkey, and at the 5% significance level in Romania and Ukraine, at the 10% significance level in Czech Republic, while it was not statistically important for Serbia. On the other side, coefficient α_2 was found to be positive for Cyprus and Slovenia. It is remarkable that the results about the sign of coefficient α_2 are precisely the same, when liquidity is not included, for every single of the four employed approaches, i.e. the basic model (8), the equation with the exchange rates variable (11), the equation with the S&P variable (13), and the equation with both variables (15). Consequently, the above findings confirm the solidity of the preferred methodology and in parallel the existence of the leverage effect, at least for the vast majority of the markets under examination. This implies that news which runs from the previous period to the next is asymmetric, and in particular that "bad news" has a bigger impact on volatility than "good news".

Although there are not changes about the sign of coefficient α_2, the levels of significance for the model with additional variables (15) are lower than the corresponding figures obtained by the basic model (8) for some countries such as Czech

Republic, Romania, Serbia and Ukraine, while they are higher only for Greece and Slovenia. These findings mean that the utilization of the extra variables in the model may lead to the mitigation of coefficient α_2 importance about the conditional variance.

When the trading volume enters the model (15), we receive equation (16). According to these results, there are no changes about the sign of coefficient α_2, i.e. it remains negative for Croatia, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Turkey and Ukraine, and it is positive only for Cyprus and Slovenia. Such results are exactly the same with the corresponding outcomes of all previous equations where no additional variables were used, or they were employed separately. This observed absolute alignment between the results concerning the coefficient of asymmetric volatility spillover effect among various approaches emphasizes the consistency of the preferred methodology.

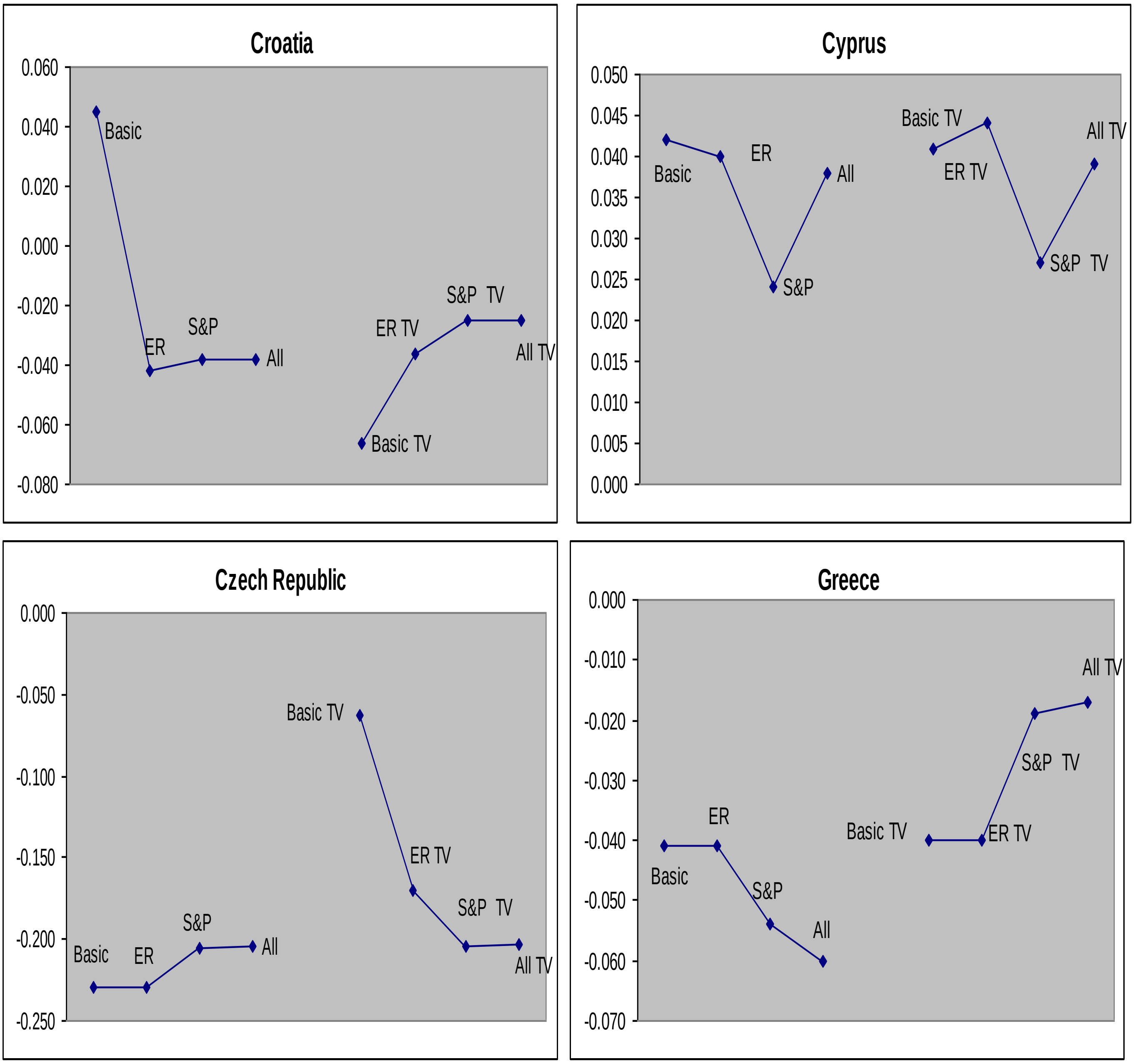
Nevertheless, the inclusion of trading volume variable in the variance equation seems to reduce the levels where coefficient α_2 is considered statistically different than zero. Analytically, the coefficients α_2 that obtained from equation (16) are now statistically significant at 10% level for Croatia and at 5% level for Turkey, while they were both statistically important at the 1% significance level before the entrance of the trading volume into the model (15). Furthermore, coefficients α_2 which were statistically significant at 1% level for Greece, at 5% level for Cyprus and Romania and at 10% level for Slovenia, were found to be no statistically important anymore. Hence, it can be supported that in these markets a positive shock has the same effect as a negative effect of the same magnitude.

A comparison between the results of basic equation (10) and the results of equation (16), where both additional variables are taken into account, reveals that the inclusion of these two variables effect in a similar way like trading volume did above. This is because coefficient α_2 is now statistically significant at 10% level for Croatia and Czech Republic, whereas it was statistically important at the 5% significance level and at 1% significance level respectively, before the entrance of these extra variables into the model. Also, at the Romanian and at the Serbian stock markets, coefficient α_2 was statistically significant at the 1% significance level and at the 5% significance level respectively, but now it is considered as no more statistically important for both cases. On the other hand, coefficient α_2 becomes significant at the 5% significance level for Ukraine, while it was not statistically important without exchange rates and S&P variables.

Regarding the influence of additional variables on the size of coefficient α_2 when the liquidity effect is isolated $\{(8) \rightarrow (15)\}$, it is increased |in absolute terms| in five countries. Namely: Greece, Israel, Russia, Slovenia and Turkey. In parallel, the entry of the trading volume (16) into the model with the extra variables (15) increases |in absolute terms| coefficient α_2 in Cyprus, Israel, Poland, Russia, Serbia and Ukraine. Finally, the comparison between models (16) and (10), i.e. with and without the additional variables respectively, reveals that the size of coefficient α_2 is greater according to the first approach in four stock markets: Israel, Russia, Slovenia and Ukraine. These results are identical to the corresponding outcomes when only the S&P variable is employed in the model and are very similar when the exchange rates variable is used separately, confirming once again the constant character of selected methodology.

Figure 5.1 (i, ii) provides a panoramic icon relating to the behavior of the leverage effect parameter α_2 through various models.

Figure 5.1i Asymmetric effect of shocks on volatility (α_2) across models



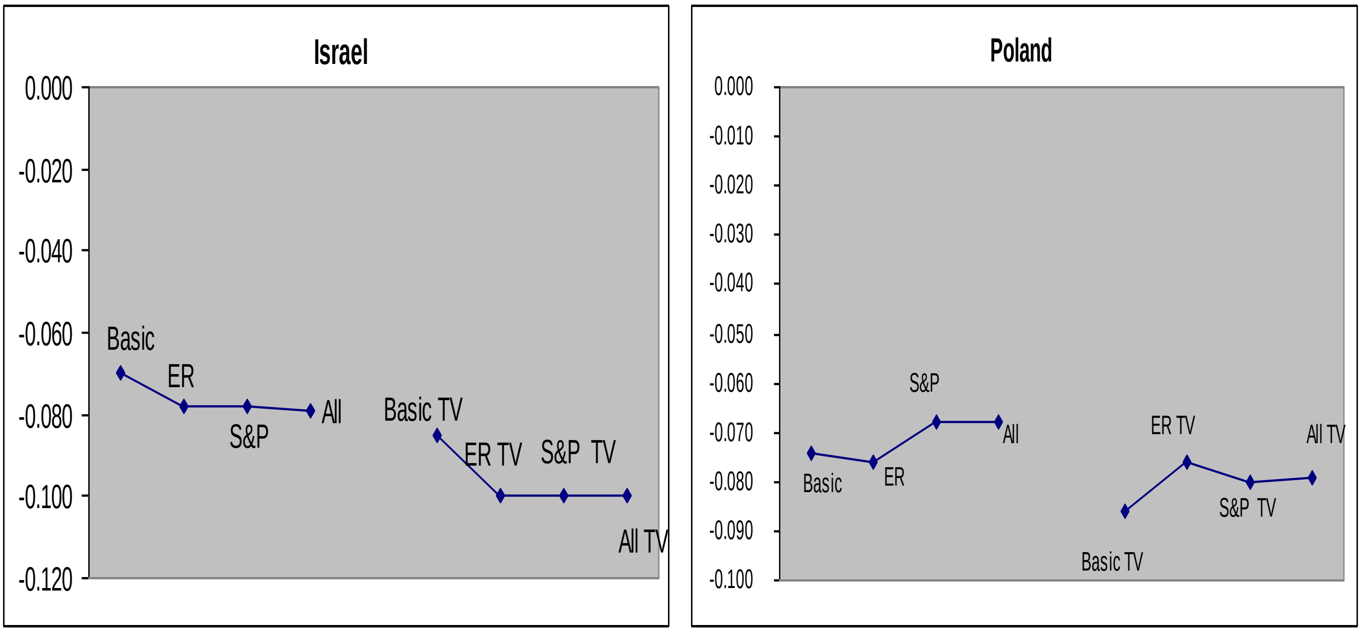
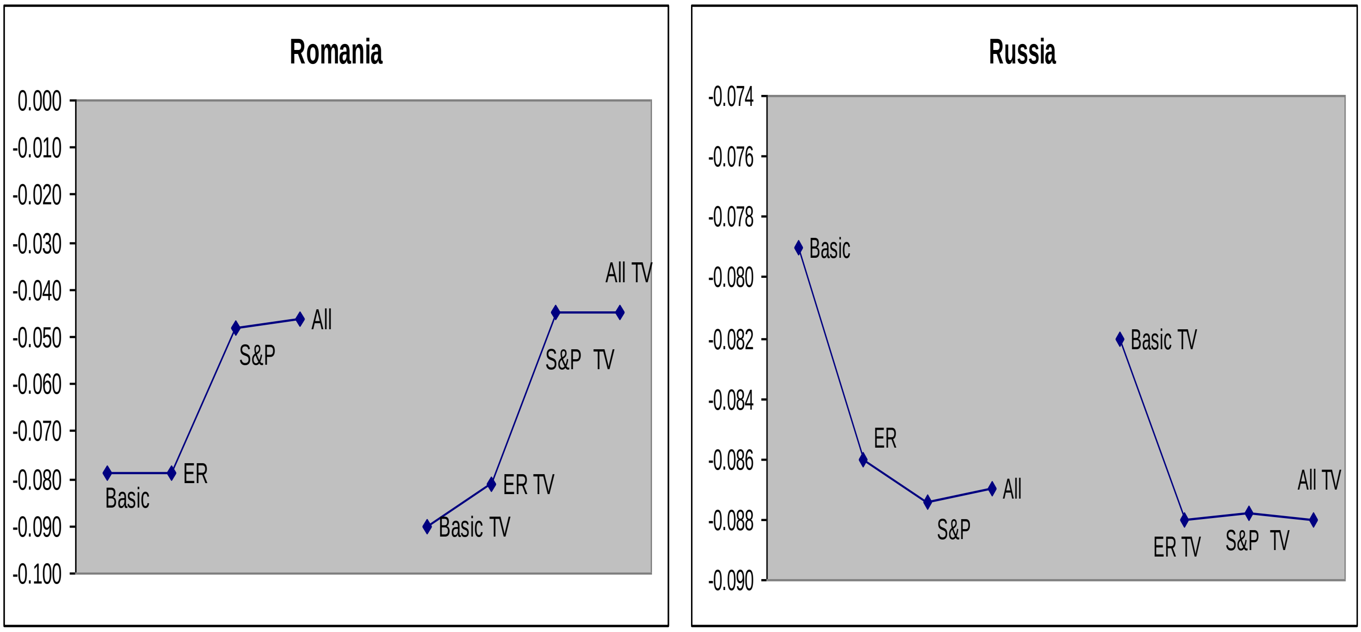
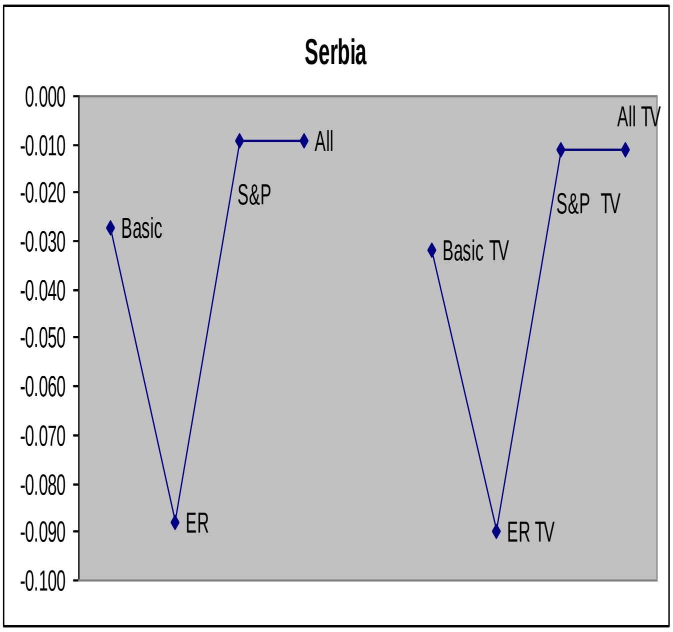


Figure 5.1ii Asymmetric effect of shocks on volatility (α_2) across models

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-0.050
-0.060
-0.070
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-0.090
-0.100
Basic
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Basic TV
ER TV
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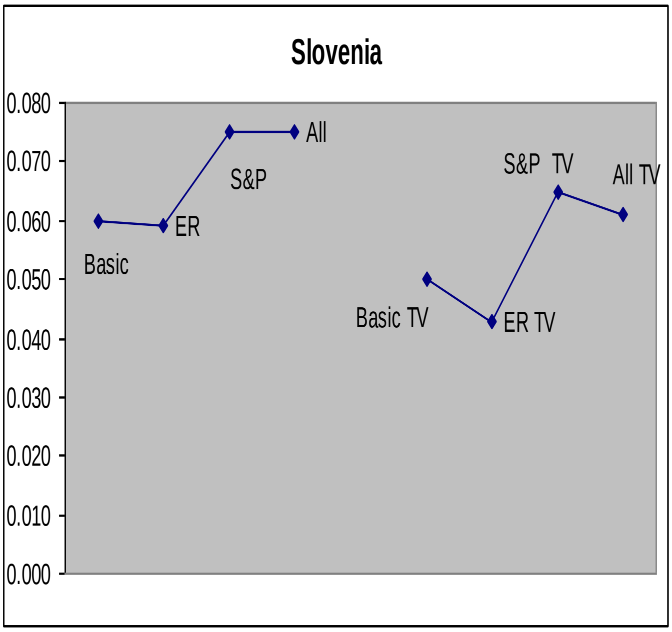
All TV


Slovenia
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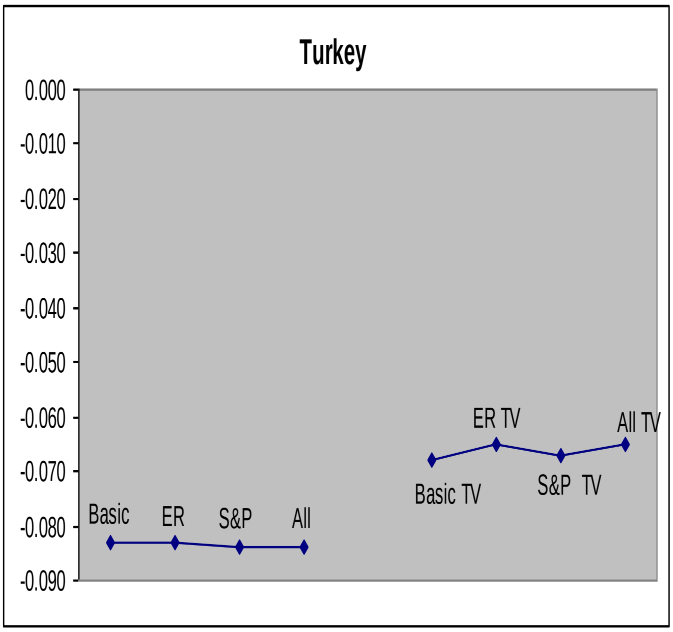
Turkey
0.000
-0.010
-0.020
-0.030
-0.040
-0.050
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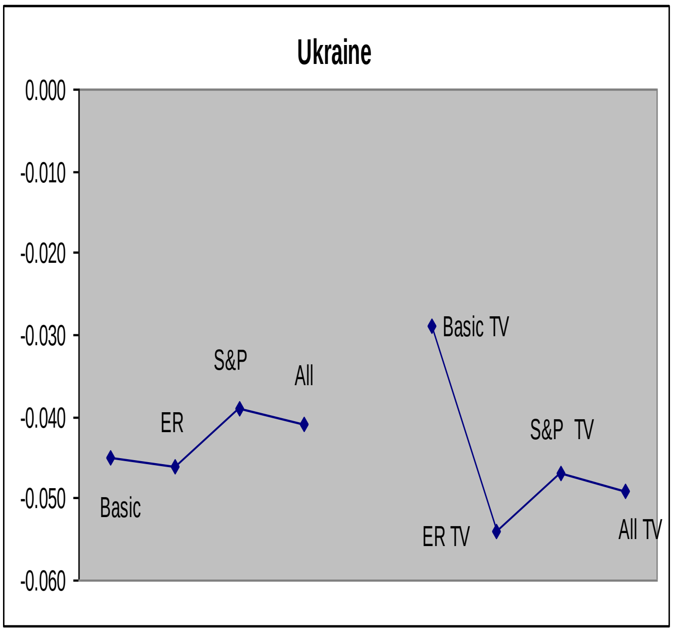
Ukraine
0.000
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Basic
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Basic TV
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All TV

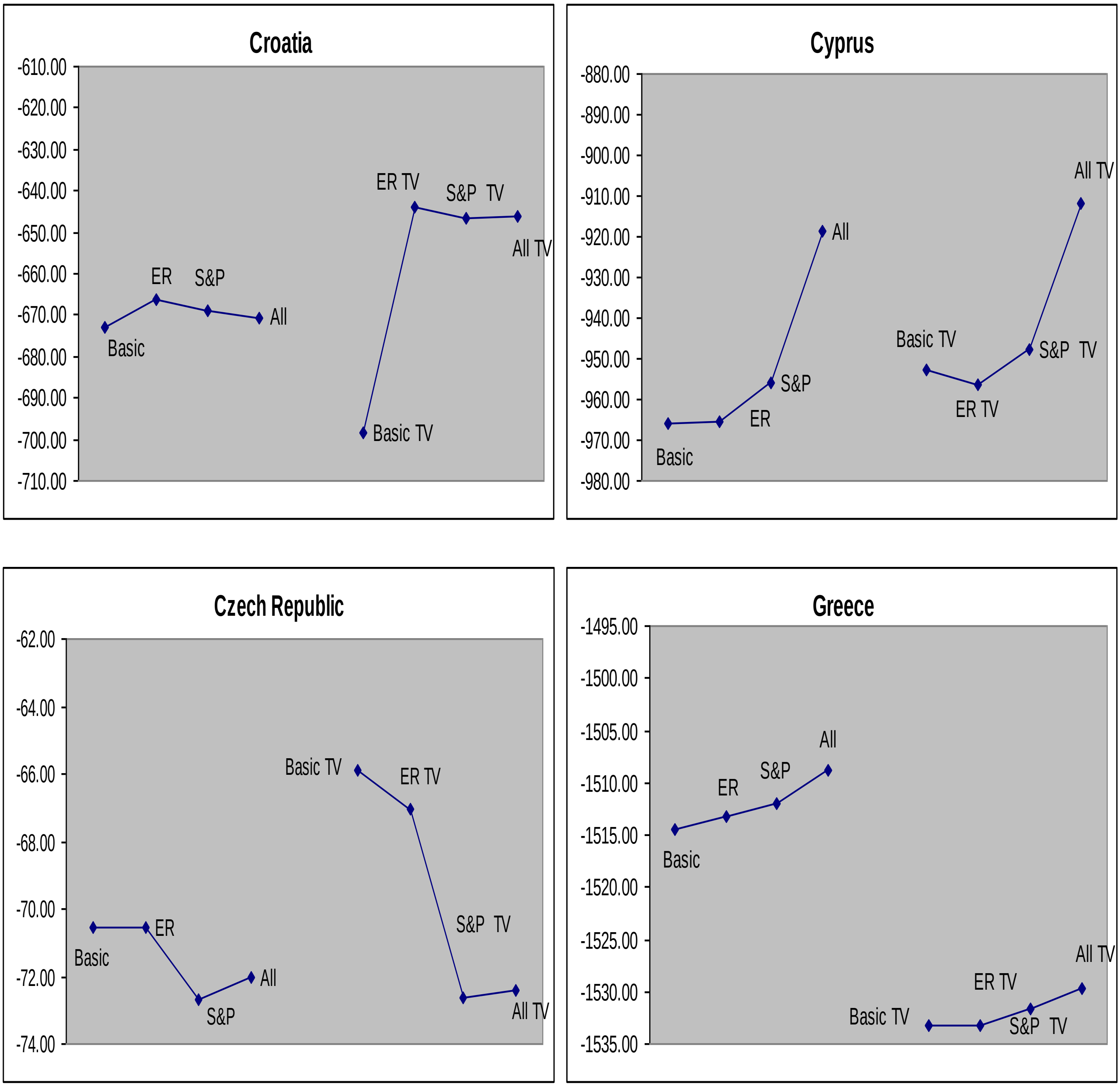
Additionally, Table 5.4 reports the results about the degree of volatility persistence, as it measured by coefficient α_3. It is revealed that when the trading volume variable is not used (15), coefficient is quite close to one for almost any market. But, testing for α_3=1 shows that hypothesis cannot be rejected only for five occasions: Croatia, Cyprus, Greece, Israel and Poland. It is remarkable that the value of coefficient α_3 which is obtained from the model with additional variables (15) is higher than the corresponding value of the model without them (8) only for Greece. As trading volume variable is included in the conditional variance equation, the value of coefficient's α_3 is reduced. This is typical for any of the formed models, since the inclusion of trading volume seems to move the conditional variance away from an integrated process of order 1. Indicatively, now the null hypothesis which states that α_3 is equal to one cannot be rejected only for Poland.

Moreover, Table 5.4 illustrates the results about the additional coefficients, i.e. χ for the exchange rates variable and ψ for the S&P 500 variable. The positive relationship for the model without the trading volume (15) is confirmed nine times for the first parameter and eleven times for the second. However, they are statistically important only for four and seven cases, respectively. These figures are considerable lower comparing with the results of the models where variables are employed separately. Specifically, coefficient χ was statistically significant in seven markets according to the model number (11) and coefficient ψ was statistically significant in ten markets according to the model number (13). The entry of trading volume variable into the model, this is equation (16), has as a result the coefficient χ to still positive for nine occasions, but coefficient ψ is now positive for fewer cases, form eleven to nine. Each of these figures is statistically important for five countries. Nonetheless, there is a clearer pattern when coefficient χ is used separately (12), as based on this approach, parameter is positive for eleven cases and statistically significant for eight cases. Also, coefficient ψ is statistically important for ten countries when it is used individually into model number (14). Hence, it can be concluded that the employment of the additional variables into a single model simultaneously, has the effect to moderate their influence on the conditional variance, compared with the influence if they are used separately. This is the conclusion for both the equations with and without trading volume variable. On the other hand, the inclusion of trading volume in the model with both additional variables does not seem to affect their parameters drastically.

The following column of Table 5.4 reports the values of coefficient φ for the trading volume variable when both the additional variables are considered. This coefficient is found to be statistically significant at the 1% level for Croatia, Cyprus, Greece, Israel, Poland, Romania, Serbia and Turkey, at the 5% level for Ukraine, and at the 10% level for Slovenia, while it is cannot be accepted as statistically important for Czech Republic and Russia. As far as the sign of coefficient φ is concerned, it is positive for all cases, with the exception of Israel, Czech Republic and Russia. We remind that for the two latter occasions the coefficient was not found to be statistically important. A comparison of these results with those obtained from the previous models (10), (12) and (14) indicates that the results are broadly similar under any methodology. Generally, it can be concluded that the trading volume variable, as it is introduced in the equations, is able to explain some of the conditional variance's behaviour and that there is a rather positive relationship between trading volume and conditional variance.

Final column of Table 5.4 reports the log-likelihood values for each country as both additional variables are including in the models with (16) and without (15) trading volume, while Figure 5.2 (i, ii) presents an overview of this parameter through the plethora of the employed models.

Figure 5.2i Log-likelihood estimations across models



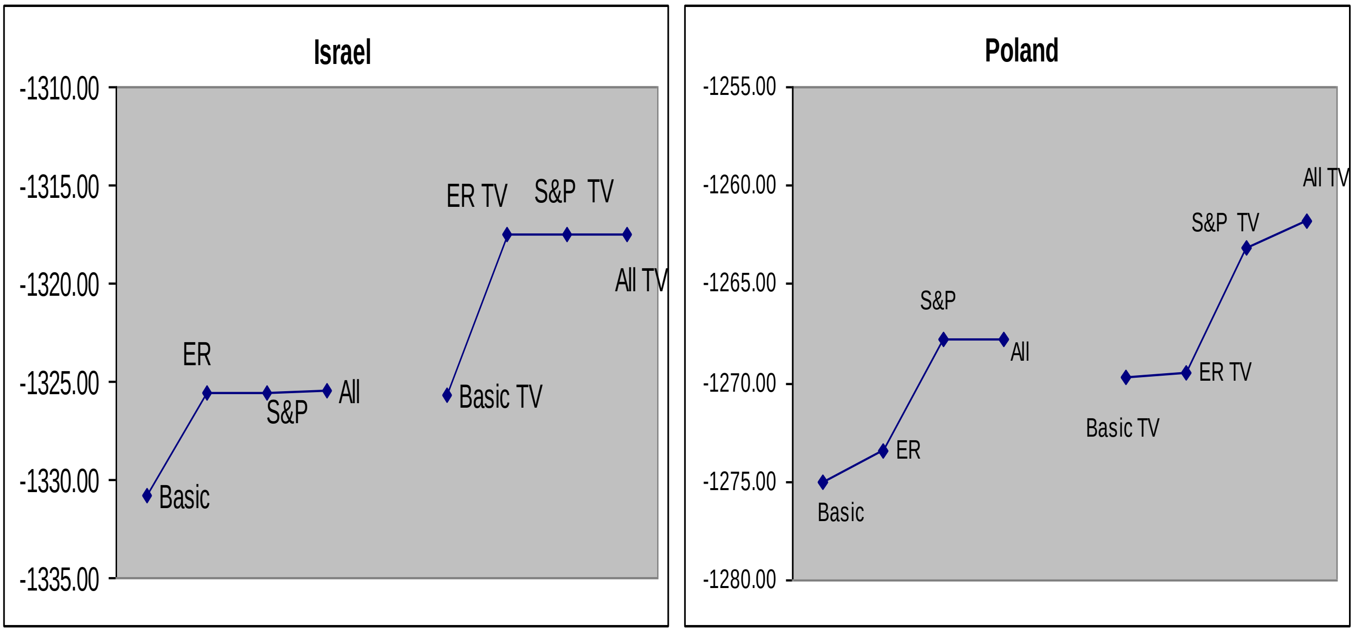
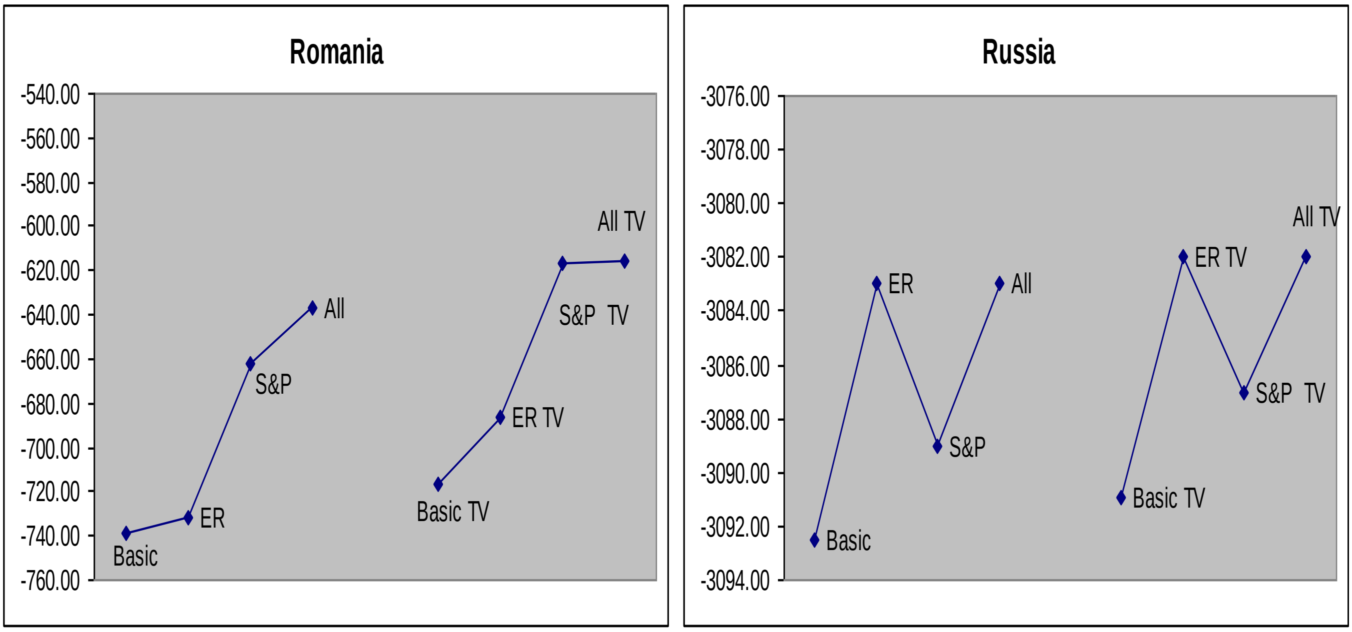
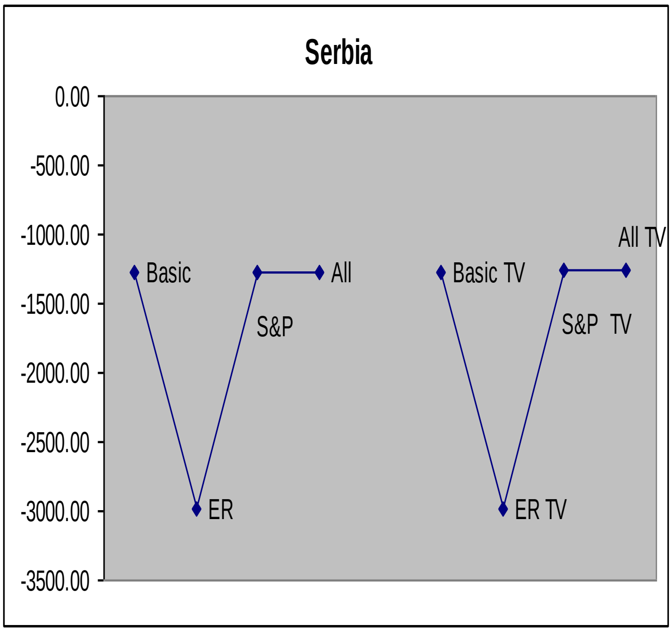


Figure 5.2ii Log-likelihood estimations across models

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-500.00
-1000.00
-1500.00
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-3000.00
-3500.00
Basic
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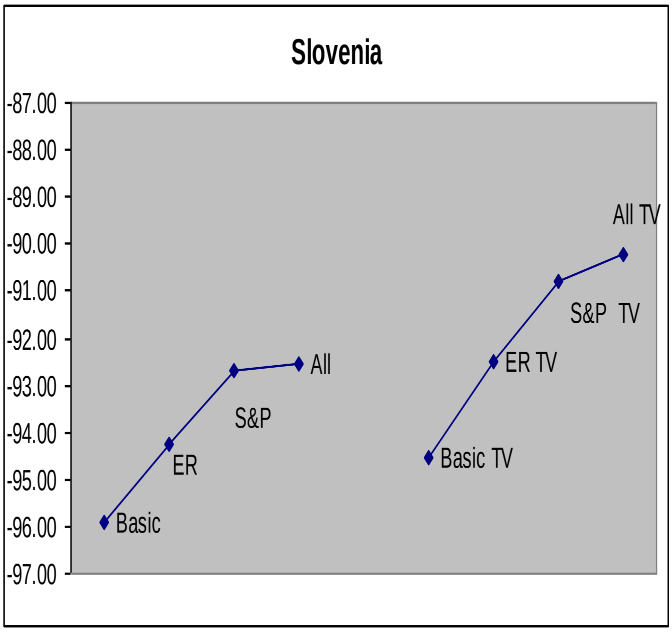
ER TV
S&P TV
All TV


Slovenia
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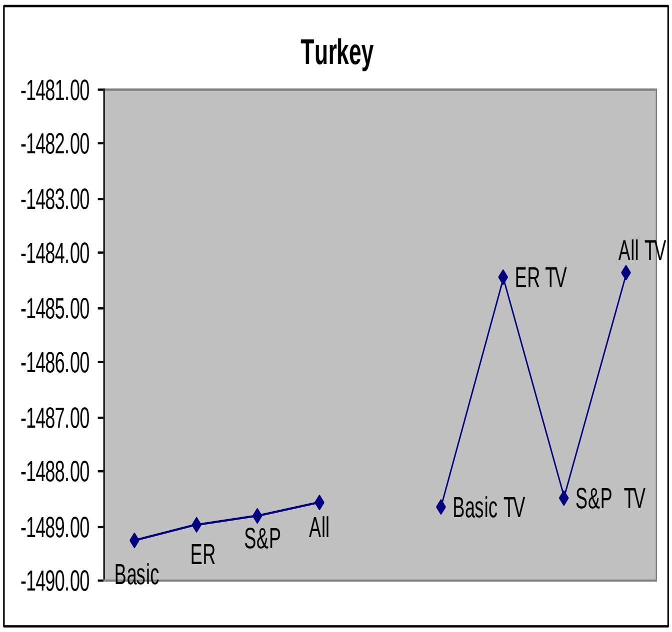
All TV


Turkey
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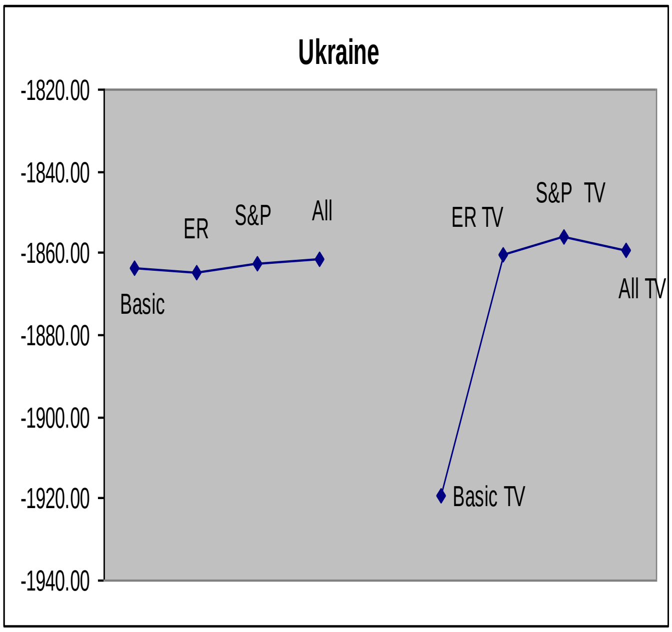
Ukraine
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-1860.00
-1880.00
-1900.00
-1920.00
-1940.00
Basic
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Based on the figures of the last column of Table 5.4, it can be concluded that the employment of trading volume leads in the growth of log-likelihood figures for ten cases. Thus, when trading volume is used in the model the observed sample is more likely to be a function of possible parameter values. A comparison between the results of equation (15) and the outcomes of equation (8) where not only the trading volume variable, but also the additional variables are out of the model reveals that the log-likelihood values are greater according to model (15) for almost every case. Hence, the use of these particular variables contributes to the analysis of conditional mean and variance. Additionally, if we put in parallel the two models which both contain the trading volume parameter, but the former is without the extra variables (10) while the latter includes them (16), it is confirmed that the log-likelihood prices are greater according to the second approach. Furthermore, the model with both extra variables (16) provides often higher figures than models (12) and (14) where extra variables are used separately. As a general conclusion, it can be supported that the explanatory variables are able to shed some additional light on the conditional mean and variance.

6. Epilogue

This research studied the return and volatility spillover phenomenon on twelve equity markets of some selected Balkan, Slavic and Eastern countries. In alphabetical order: Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Term “spillover effect” is employed to describe an event that takes place in one frame because of something else in a not directed related frame. Spillovers among stock markets are widely extended over last years due to the economic integration of international markets, the increased flows of capitals among countries, the abatement of limitations into worldwide transactions, and the remarkable improvement of technology.

Volatility is commonly used as a basic coefficient of the overall risk around financial assets and it is measured by the variance of shares’ returns. The volatility spillover effect is considered to spread the financial risk from one spot to another. Therefore, when individual investors and professionals seek to construct the optimum portfolio, they have to keep in mind this hazard as a central theme related to their decisions. However, the spillover effects can be considered not only from one stock exchange to another, but for a given market from one period to another as well. Thus, the main purpose of the present study was to explore empirically the transmission mechanisms about stock price returns and stock price volatilities for the twelve countries under examination. For that reason an augmented univariate AR(1)-EGARCH(1,1) model, initially proposed by Nelson (1991), was used, which catches both sign and size of innovations allowing to test whether shocks originating from one period can affect return and volatility of next period in an asymmetric way. The asymmetric effect of innovations on volatility refers to a situation according to which a negative shock (price drop) increases volatility more than a positive shock (price rise).

The mechanism behind this idea was described in Section 4, which presented analytically the employed methodology. The “fuel” for these models was the information of daily closing prices for the major index of each country’s stock exchange. The tests covered a time period over ten years for the majority of countries, from 2006 till 2015. In total, eight models were shaped to describe the conditional variance for each country. Analytically, beyond the basic model, the trading volume variable was firstly introduced, and subsequently the additional explanatory variables of exchange rates’ fluctuations and

S&P 500 index returns of the previous period were used separately, without and with trading volume. Moreover, a synthesis of the previous equations was employed by combining into a single mathematical sentence both extra variables, with and without liquidity.

According to the empirical results, return and volatility spillovers were confirmed for most of the cases through the different approaches. Besides, a leverage effect was found in many occasions too. More specifically, coefficient about return spillover was positive and statistically important for 64 out of 96 outcomes, while the parameter of volatility spillovers proved to be positive and statistically significant for almost every case, with the only exception of the Czech Republic market. As far as the coefficient that catches the leverage effect is concerned, it was negative and statistically important for 68 out of 96 times. Also, the volatility persistence measure was found statistically equal to one in 27 cases and less than one in 69 cases. In addition, the empirical outcomes of present study illustrated that trading volume accounts for spillovers as this variable was statistically significant for 40 out of 48 occasions; even, inside these 40 cases, the coefficient about trading volume carried a positive sign 35 times. Furthermore, the positive relationship between the exchange rates of each Balkan, Slavic and Oriental country’s domestic currency to the US dollar and the conditional variance was confirmed again for 40 out of 48 occasions; however, it was statistically significant just for 23 of them. In parallel, the coefficient of the other explanatory variable, that of S&P 500 index return, was confirmed to be positive for 39 occasions and negative just for 9. This latter parameter was found to be positive and statistically important at the same time for 28 times. Finally, the log-likelihood figure, as an expression of optimal values of estimated coefficients, was proved to be higher for the approach which includes both explanatory variables compared to the corresponding values of the initial basic model for the majority of the cases. Figure 5.2 shows that when the equation with both extra variables was preferred, the log-likelihood was greater for almost any case. Furthermore, the use of trading volume in models seems that helped to shed some further light on the mechanism of return and volatility spillovers as log-likelihood became superior for a plethora of cases, and in particular for 41 out of 48.

The sizes of return and volatility spillovers’ coefficients were affected by the employment of trading volume in various ways. In particular, return spillovers were increased |in absolute terms| 29 times (out of 48) when liquidity was taken into account. Similarly, parameters about volatility spillover met a rise at 28 cases, while asymmetry was more intense for 25 occasions. These outcomes underline rather a balanced influence of trading volume on the size of these specific coefficients. However, there was a cleaner pattern about the degree of the volatility persistence in markets, as the relevant coefficient was mitigated for 41 out of 48 cases when trading volume entered in equations.

To conclude, there were several evidences to suggest that return and volatility spillovers were present into the stock markets under examination. Moreover, results revealed that trading volume accounted up to extend for spillover effects. Also, asymmetry was found to be substantial for conditional volatility for the majority of the cases, confirming largely the leverage effect theory. In addition, the two explanatory variables that were introduced at this study were proved to be statistically significant for many occasions, underlying that scientific investigations about relevant topics could consider them too. As a field of future research, some more explanatory variables might be added into the equation models in order to achieve a further in-depth analysis about the transmission mechanisms between the returns and volatilities of stock investments.

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- https://en.wikipedia.org/wiki/Autoregressive_moving-average_model
- https://en.wikipedia.org/wiki/Spillover_effect

UNIVERSITY OF MACEDONIA

PhD THESIS

FEEDBACK TRADING STRATEGIES IN TWELVE BALKAN, SLAVIC AND ORIENTAL COUNTRIES

Author: Dimitrios Angelidis

Supervisor: Athanasios Koulakiotis, Assistant Professor

Department of Balkan Slavic and Oriental Studies

Thessaloniki, 2018

FEEDBACK TRADING STRATEGIES IN TWELVE BALKAN, SLAVIC AND ORIENTAL COUNTRIES

Synopsis

This paper examines the hypothesis that some kind of feedback trading strategy is followed by a share of participants on stock markets of twelve selected Balkan, Slavic and Eastern countries. Study covers a decennial period, from 2006 till 2015. Analysis employs a couple of parallel models. Firstly, the feedback trading model introduced by Sentana and Wadhani and secondly the exponential autoregressive model suggested by LeBaron. These theoretical frameworks, together with a FIGARCH(1,d,1) approach, allows us to draw conclusions about the presence of feedback traders in stock markets. Both models assume two different groups of traders, on one hand the so-called “rational” investors that build their portfolio by perusing firms’ fundamentals, and on the other hand the “noise” speculators that ignore fundamentals and base their decisions on a positive (negative) feedback trading strategy. In particular, they buy (sell) stocks when prices rise and sell (buy) stocks when prices fall. Empirical results reveal that feedback trading strategies indeed exist in the examined stock markets during the period considered. As far as the type of feedback is concerned, negative feedback trading prevails over positive feedback trading for the majority of cases.

Keywords: Feedback trading, FIGARCH(1,d,1) model, capital markets in Balkan, Slavic and Eastern countries

JEL Classification: G14, C22

Dimitrios Angelidis, d.angelidis@hotmail.com

1. Introduction

Stock exchange is a market where brokers and traders can buy and/or sell stocks, bonds and other securities. The basic role of a stock exchange in the economy is to provide companies with the facility to raise capital for expansion through selling shares to the investing public. Such a procedure is considered to be beneficial for an economic system, since when people draw their savings and invest in shares it usually leads to rational allocation of financial resources. This is because funds which could have been consumed or kept in idle deposits are now mobilized towards the direction of helping companies' managers to finance their organizations. This behavior may promote business activity, resulting into stronger economic growth and higher productivity levels by firms. Of course, this is the case whenever investing in stock exchanges does not influence negatively the total demand of households for goods.

Beyond this apparently “well-intentioned” function of stock markets, many people see it as a bargain for easy money through shares transactions. The idea is simple: buy low and sell high. It seems simple, but even the last one that has been involved in stock dealings knows that it is not. As everyone has the same ambition with you, the key for a profitable career in stock markets is to predict correctly the future changes of shares prices. A plethora of techniques have been developed to serve this purpose. Although there are no proofs that the Holy Grail has been discovered, some approaches are quite promising, while some others are less.

Even if the goal is common for everybody, it is clear that people’s different personalities mean they react differently to various circumstances and they adopt different strategies. By and large, the academic literature distinguishes between two types of speculators, namely, rational investors and ‘‘noise’’ speculators. The first group (smart money) act in accordance with the standard present value model. They value assets according to the cash flows (dividends) that the asset is expected to generate and the expected selling price in the next period. The name of the second group is used to describe traders who make their decisions, regarding buy and sells transactions, without the use of fundamental data. These speculators generally follow trends and overreact both to good and bad news. This behavior is known as positive feedback trading and can induce autocorrelation in securities returns and enhance volatility. Whenever a big number of speculators adopt feedback trading strategies, securities prices may move away substantially and persistently from fundamentals.

Here, raises the question up to which level do rational investors effect on asset prices. Short-term, one can provide the easy answer that it is a matter of speculators’ numbers from each group and also the amount of money that they invest. But long-term, we have to consider the classical answer of Friedman, back in 1953. According to him, rational investors stabilize asset prices. This is because ‘‘noise’’ speculators, and specifically positive feedback traders, destabilize asset prices by buying when prices are high and selling when prices are low. That’s the safest way to loose your money and get out of market. Antithetically, investors that make profits, trade against less rational investors who move prices away from fundamentals. So, such speculators rationally counter the deviations of prices from fundamentals and as a result they stabilize them. Of course, the previous assumptions concern mostly mature markets.

However, de Long et al. (1990) described a rather more complex relationship. According to them, when rational investors receive some good news they accept that the initial price increase will stimulate buying by positive feedback traders tomorrow. As a result, informed rational investors buy more today and so drive prices higher than fundamentals. On next day, positive feedback traders buy more securities in response to previous day's increase and in this way keep prices above fundamentals, even if rational investors are selling off. The bottom line is that although price increase is to some extent rational, part of it results from rational investors' anticipatory trades and part of it results from positive feedback traders' reaction to such trades.

Beyond theory, the notion of rational speculation has been part of well known speculator George Soros' investment strategy. He claimed that his apparent success over decades was based on betting not on fundamentals but on future crowd behavior. He saw a number of poorly informed investors becoming excited about rises in the reported annual earnings of companies. The truly informed investment strategy was not to sell short in anticipation of the eventual collapse of shares but instead to buy in anticipation of further buying by uniformed investors. The initial price rice in stocks caused in part by speculators like him and then this stimulated the appetites of uninformed investors. As a result**,** a stream of increasing prices was created. While uninformed investors bought more, prices rose further and further. Unavoidably, one day, price increases stopped and stock prices collapsed. Analytically, disinvestment just before the end and perhaps short sales at the beginning by some smart money, brought stock prices down to fundamentals. On antipode, the initial buying by smart money, by raising the expectations of uniformed investors about future returns, may have enhanced the total move of prices away from fundamental. To cut a long story short, the above strategy can be titled as: "self-feeding bubbles".

Koulakiotis (2015) mentioned that feedback traders (buy-shell shortly), base their decisions on the response to price changes and on the historical past return trading, rather than on the expected fundamental return series. These feedback trading strategies, positive or negative, end up to a reverse relationship between volatility and autocorrelation. This reversal sign in stock return autocorrelation is consistent with the fact that traders follow feedback (buy-shell) strategies. In particular, positive traders buy (sell) when prices rise (fall). Thus, positive feedback trading produces negative first order autocorrelation in stock returns. This impact, in turn, increases proportional to the level of volatility. Furthermore, negative feedback trading cause positive first order autocorrelation in stock returns, as traders sell (buy) when prices rise (fall). This impact, in turn, decreases proportional to the level of volatility.

Nonetheless, among the researchers there is a plethora of various feedback trading models which present different implications for the autocorrelation pattern of stock returns. For example, Cutler et al. (1990) implied positive correlations of short-term returns. Their analysis focused on long-horizon U.S. securities returns and they assumed that investors do not learn from past experience.

More recent researches suggest that the autocorrelation pattern of share returns is quite further complex. Sentana and Wadhani (1992) used data from U.S. stock exchange and they found evidences that during low volatility periods, daily stock returns are positively autocorrelated, while during high volatility periods they tend to be negatively autocorrelated. LeBaron (1992) used a GARCH model with an exponential time-varying first order autocorrelation to describe the short run dynamics of several U.S. indices stock returns and individual stock returns as well. He reported significant nonlinear first moment dependencies as autocorrelation and volatility were inversely connected. In other words, first order autocorrelations of stock prices returns were higher during calm periods and lower during volatile periods. For the purposes of the present paper we employ both models by two above approaches in order to run our data.

Making a step further from developed markets, we shift our interest in emerging markets and on technical trading strategies. For the purposes of present paper we employ twelve, mostly emerging, Balkan, Slavic and Eastern markets. The term “emerging markets” dates back to 1981, recalls the man who invented it, Antoine van Agtmael. An emerging market is a country that has some characteristics of a developed market, but does not meet standards to be a developed market. However, according to “The Economist”, many people find the term outdated, but no new term has gained traction yet. Table 1.1 contains countries in alphabetical order, the main index of stock market which is going to be used, the per capita nominal GPD in US dollars and stock market capitalization in billions of US dollars. Institutions as IMF and S&P, classify these countries as “emerging”, with the exception of Israel, although some of them, like Russia and Turkey, belong to G20.

Table 1.1 Countries under examination

Country	Index	Per capita nominal GPD in US $*	Stock market capitalization in billions of US $**
Croatia	CROBEX	11.551	22
Cyprus	General Index	21.531	2
Czech Republic	PX	17.330	37
Greece	General Index	17.657	45
Israel	TA 25	35.702	148
Poland	WIG 20	12.662	178
Romania	BET 10	8.807	16
Russia	RTSI	8.447	875
Serbia	BELEX 15	5.102	7
Slovenia	SBITOP	20.712	6
Turkey	BIST 100	9.290	309
Ukraine	UX	2.109	21

* International monetary fund, 2015
** 2012

Previous researches acknowledge the existence of feedback trading strategies in emerging markets. Ratner and Leal (1999) examined the potential profit of such strategies among ten emerging markets of Latin America and Asia: Argentina, Brazil, Chile, Mexico, India, Korea, Malaysia, Philippines, Taiwan and Thailand. They used daily returns for the January 1982 to April 1995 period and ten different variable moving average trading models which were assessed through a bootstrapping simulation. The average buy-sell returns difference for each strategy and country were compared to a buy and hold strategy. Taiwan, Mexico and Thailand emerged as markets where technical trading strategies might be profitable. Writers found no strong evidence of profitability for the other markets. Bohl and Siklos (2004) examined daily returns not only for mature stock markets but for some emerging as well, such as Czech Republic, Poland and Russia. The time period under investigation covered a phase over ten years from 1994 till 2003 and the empirical results showed that positive and negative feedback trading strategies existed in both types of markets but were more pronounced in emerging stock markets than in their mature counterparts. Hence, non-fundamental trading strategies seemed to play a more important role in emerging relative to mature stock markets. Malyar (2005) investigated the behaviour of stock markets in a number of transition economies. The analysis was carried out in the context of Sentana-Wadhwani framework with two kinds of traders in the market, rational ones and feedback traders. She modelled the conditional volatility using EGARCH model. The findings provided strong evidence of positive feedback trading in the stock markets of Hungary, Lithuania, Estonia, Slovenia, Bulgaria, Romania, Poland, and Russia. She did not find sufficient evidence for the presence of such traders in Latvia, Czech Republic, Slovakia, and Ukraine. Writer argued that this absence of feedback traders in these markets could be explained by relative small size of stock markets and low liquidity of assets. Koutmos et al. (2006) investigated the short-dynamics of returns in the Cyprus stock exchange and they found an inverse relationship between volatility and autocorrelation, consistent with the findings from other mature stock markets. Altay (2006) studied the possible causes of the autocorrelation problem in Istanbul stock exchange. The evidence got from the autocorrelation problem supported the existence of positive feedback trading. Returns provided negative autocorrelation when the volatility was high. Results also supported the idea of stronger positive feedback effect in down markets relative to up markets.

The aim of present paper is to explore whether the phenomenon of positive or negative feedback trading strategies exists in the stock exchanges of Table 1.1. In order to serve this goal we are going to employ two models; firstly, the Sentana and Wadhwani (1992) approach and secondly the LeBaron (1992) exponential equation. The sign of coefficients and the importance of them at certain levels of significance will let to reach into conclusions about the presence or not of feedback trading strategies in each market separately. Our ambitious is the empirical results to add a piece of knowledge to the fields of science and theory, and in parallel to be proven as a useful and practical tool for transactors to their daily decisions.

The paper proceeds as follows. Section 2 presents some information and historic elements about the stock markets under investigation. Section 3 describes the data. In Section 4 we discuss the methodology. Section 5 illustrates the empirical results. Section 6 summarizes and concludes.

2. Information and historic elements

In this section we present some information and historic elements about the stock markets under investigation in an attempt to get a more spherical view about these institutions. The idea of financial transactions back to the ancient world, as clay tablets recording interest-bearing loans were found in archaic Mesopotamian. However, there is little unanimity about the period that corporate stock was first traded. Some theoreticals see the key event as the Dutch East India Company's founding in 1602, while others point to earlier developments. For example, there are some evidences that a share market existed as far back as ancient Rome.

Closer to modern times, the oldest formal exchange was founded –as we mention above- in Amsterdam in 1602. Besides, the first exchange of the Habsburg monarchy was established in Rijeka. After the Habsburg monarchy was divided into the Austrian and the Hungarian part in 1867, another exchange was also established in Budapest. Croatian regions were split between the Austrian and Hungarian part. After World War I, the Zagreb Exchange opened first its securities department on 4th June, 1919. The commodities department began to operate on 1st August, 1919. Since the exchange as a speculative institution had no place in the socialist society, its operations were suspended in 1945. Croatia's exchange did not see its revival until as late as 1991, when 25 banks and 2 insurance companies established the Zagreb stock exchange as the central place of securities trading in Croatia. At the very beginning, trading took place at the exchange head office with all brokers actually physically present. In 1994, an electronic trading system was introduced, enabling member brokers to trade on the exchange via a telecommunications link throughout Croatia. The outcome of rapid development of share ownership and trading in Croatia is best illustrated by the fact that in the first five years following the introduction of the electronic trading system, between 1995 and 2000, the Zagreb stock exchange market capitalization grew almost 10 times (982.6%).

The Cyprus stock exchange was established as a legal entity in the form of a public corporate body under the Cyprus securities and stock exchange laws and regulations which were passed by the House of Representatives in 1993 and 1995, respectively. The first trading session on the Cyprus stock exchange was held on March 29, 1996. The Stock exchange operates a regulated market and a market in the form of multilateral trading facility, also known as the emerging companies market, which operates under the Cyprus securities and stock exchange law and the investment services and activities and regulated markets law. Main participants of the stock exchange are brokerage offices, listed issuers and investors

Efforts to create a stock exchange in Prague date back to the reign of the empress Maria Theresa, but success was not achieved until one year after her death in 1871. Initially, both securities and commodities were traded at the Prague exchange. The Prague exchange enjoyed great success in the sugar trade, becoming a key market for the whole Austro-Hungarian Empire. After World War I, however, this type of transaction declined, so thereafter only securities were traded. For the Prague exchange, the interwar period became the era of its greatest boom. This period of prosperity was interrupted by the arrival of World War II, bringing an end to trading at the Prague exchange for more than 60 years. Not until after the fall of communism was it possible to follow up on the exchange's heritage. With the first trades made on the floor of the renewed exchange on 6 April 1993, the Prague stock exchange began to write its modern history.

The Athens stock exchange started trading in 1876. In 1918 Athens stock exchange was transformed into a public entity. The first electronic trading system was put into operation in 1991, abolishing the open outcry method. In February of the same year, the central securities depository was founded, for the clearing of transactions. In 1995, as part of the efforts to modernize the capital market, Athens stock exchange was transformed into a societe anonyme (public limited company), with the Hellenic state as the sole shareholder. The derivatives market started trading in August 1999. In 2002 the Athens stock exchange and the Athens derivatives exchange merged to form the Athens stock exchange. The Athens stock exchange was closed on 27 June 2015 because of the Greek government-debt crisis. It reopened on 3 August 2015 and on that particular trading day many stocks plummeted 30%, the daily change limit.

The Tel Aviv stock exchange fulfils a major role in the Israeli economy and is a key player in the nation's economic growth. Local trade in securities began in the 1930s, years before the formation of the state of Israel. Trade was carried out through the exchange bureau for securities, founded by the Anglo-Palestine bank in 1935. With the formation of the state of Israel in 1948, a pressing need arose to formalize trade in securities. In September 1953, a number of banks and brokerages joined forces and established the Tel Aviv stock exchange. Since the mid-1990s the Tel Aviv stock exchange had been adapting to meet the standards of the most advanced exchanges in the world. Physical trading floors, long abolished, had been replaced by a computerized system, allowing transaction orders to flow in real time. Financial activities cover all forms of securities: stocks, convertible securities, corporate and government bonds, index options and futures, currency options and futures and a variety of securities derivatives.

Polish capital market traditions go back to 1817, when the Warsaw mercantile exchange was established. Following the overthrow of Poland's former communist regime in 1989, Warsaw mercantile exchange was created as a joint-stock company on April 12, 1991, and held its first trading session on April 16, 1991 with five listed companies, all of which were formerly state-owned companies that had been privatized. In 1999, Poland reformed its pension system, which contributed to an increase in domestic institutional investment, and in 2004 it joined the European Union. These developments helped to boost trading volume in subsequent years. In 2015, 471 companies listed on its main market, including 51 foreign companies, and 431 companies listed on the so-called "NewConnect", an alternative stock exchange allowing smaller companies to float shares run by the Warsaw stock exchange. In addition, a trading platform for derivatives has grown, helping Warsaw stock exchange to be enlarged.

With history tracing back to 1839, when commodities-trade exchanges were established on December 1, the Bucharest stock exchange activity was affected throughout its existence by the social and political events of the time. Bucharest capital market was re-established as a public interest institution on April 21**,** 1995, after almost 50 years of suspension following the establishment of the communist regime, having its first trading session on November 20 of the same year. In 2002, some of Romania's most important companies were listed on Bucharest stock exchange. As a result, market capitalization grew almost four times and the turnover doubled. In 2007 Romania became a European Union member, with a significant positive effect on capital markets. Indeed, 2007 became the best year in Bucharest stock exchange's history, both for traded value and market indices which reached new historical highs.

Moscow exchange is the largest exchange group in Russia, operating trading markets in equities, bonds, derivatives, the foreign exchange market, money markets and precious metals. Moscow exchange was established by merging the two largest Moscow-based exchanges, the Moscow interbank currency exchange (MICEX) and the Russian trading system (RTS), hence the name "Moscow Exchange MICEX-RTS. Both organizations had been formed in the 1990s and were the leading Russian exchanges for two decades with their MICEX index and RTS index, respectively The merger created a single entity and advanced Russia's plans to turn Moscow into an international financial centre.

The initial ideas about establishing an institution which would control the movement of the value of money appeared in Serbia in the 1830s. The Serbian trading association initiated the passing of the stock exchange law. Several years later, on 21 November 1894, the Belgrade stock exchange held its founding assembly and selected the management and exchange intermediaries. In the beginning of 20th century, various securities were listed on the exchange. Between the two world wars, after a four-year break and in a difficult economic situation, the exchange resumed its business. The capital market lasted until 1953, when it was formally abolished. With a change in the general climate and the beginning of the economic reforms, the Belgrade stock exchange was established in 1992. It is remarkable that the operation of the Belgrade stock exchange had not been interrupted not even in the time of bombings in 1999. During 2003 remote trading was introduced. The first index of the Belgrade stock exchange was published in late 2004.

The first stock exchange in Ljubljana existed as early as in the period between 1924 and 1942. In 1922, industrialists and businessmen decided to set up another stock exchange beside the one in Zagreb. They chose Ljubljana as the venue. It was only on 6 August 1923 that the first general meeting of the Ljubljana stock exchange was held. The exchange officially began to officiate only after lengthy preparations, on 16 August 1924, whereas the first trading deals were carried out. During the second world war the trading on the exchange was suspended. After the war also officially banned by a decree. Slovenians were thus left without a stock exchange for almost half a century. The present Ljubljana stock exchange was established in December 1989. In October 1997, the Ljubljana stock exchange became the 50th full member of the world federation of stock exchanges. Today, the brokers' open outcry method has been replaced by electronic computer trading on the majority of stock exchanges.

The origin of an organized securities market in Turkey has its roots in the second half of the 19th century. The first securities market in the Ottoman Empire was established in 1866. Following the proclamation of the Turkish Republic, a new law was enacted in 1929 to reorganize capital markets. In 1981, another capital market law was voted, which led to the inauguration of the Istanbul stock exchange on December 26, 1985. Today, the Borsa Istanbul capital market aspires to bring together all the exchanges operating in the Turkish capital markets under one single roof. Actually, the Borsa Istanbul is the sole exchange entity of Turkey, combining the former Istanbul stock exchange, the Istanbul gold exchange, and the derivatives exchange of Turkey, under one umbrella. It was established on April 3, 2013, and began to operate on April 5, 2013. Its logo is the traditional Ottoman mark for Constantinople, the tulip.

The first Ukrainian stock exchange was created in 1991 with the help of $5 million grant from the French government. Stock exchange in Ukraine is the less common type of exchange, comparing to the commodity market, and also is the youngest. In 1996 there was created electronic trade system, but it was not until the orange revolution (late November 2004 to January 2005) when stock market in Ukraine showed a noticeable growth. On March 26, 2008 the Ukrainian exchange launched UX index, the first real time cash equities index in Ukraine, which is widely recognized as the main benchmark for the Ukrainian securities market. Numbers of stock exchanges in Ukraine belong to Russian owners.

3. Data

Empirical analysis of present study is based on data for twelve Balkan, Slavic and Eastern countries. In alphabetical order: Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Information is continuously compounded and consists of daily returns about a major index for each country. It is considered that this major index represents sufficiently every stock market. Research covers a period over ten years from 2006 till 2015. Table 3.1 illustrates some descriptive statistics about these indices.

Table 3.1 Descriptive statistics of indices

Country	Index	OBS	Mean	Median	Std.	Max	Min
Croatia	CROBEX	2356	0.02	-0.001	1.286	11.36%	-13.73%
Cyprus	General Index	1215*	-0.188	-0.155	3.044	18.48%	-14.37%
Czech Republic	PX	2356	-0.005	0.022	1.559	13.16%	-14.94%
Greece	General Index	2345	-0.051	0.02	2.205	14.37%	-16.23%
Israel	TA 25	1886	-0.01	-0.058	1.293	7.51%	-7.78%
Poland	WIG 20	2356	-0.004	0.03	1.398	8.51%	-8.54%
Romania	BET 10	2356	0.012	0.022	1.65	11.14%	-12.29%
Russia	RTSI	2353	0.015	0.089	2.356	22.38%	-19.1%
Serbia	BELEX 15	2356	-0.014	-0.03	1.393	12.92%	-10.29%
Slovenia	SBITOP	2339	-0.011	0.001	1.199	8.71%	-8.08%
Turkey	BIST 100	2356	0.036	0.071	1.8	12.89%	-13.54%
Ukraine	UX	1896**	-0.028	-0.058	2.33	18.2%	-12.37%

* from 2010 to 2015
** from 2008 to 2015

It is revealed that Cyprus stock market suffered the lowest mean return and in parallel met the highest volatility, as the last is measured by standard deviation. This is not a bolt from the blue, since during period under investigation, and specifically in 2012, issued the domestic financial crisis which led to the Cypriot Memorandum of Understanding (MoU). This was a good reason for investors to act nervously and/or leave the Cyprus exchange market. On the other hand, Turkey’s BIST 100 achieved the highest mean return, while Slovenian SBITOP met the lowest volatility. Table 3.2 reports some diagnostic test statistics on the daily return data, such as skewness and kurtosis.

Table 3.2 Diagnostic tests on indices' returns

Country	Index	Skewness	Kurtosis	Kolmogorov-Smirnov	LB(20)	$LB^2(20)$
Croatia	CROBEX	0.365	15.848	-15.857*	153.24*	2804.95*
Cyprus	General Index	0.526	5.649	-7.097*	34.089**	259.846*
Czech Republic	PX	-0.126	13.797	-30.403*	70.161*	3309.797*
Greece	General Index	-0.07	5.646	2.79*	30.552***	627.329*
Israel	TA 25	0.438	3.475	-14.768*	29.105**	1620.076*
Poland	WIG 20	-0.355	4.102	-19.216*	39.323*	1000.864*
Romania	BET 10	-0.344	8.09	-40.018*	67.677*	1787.799*
Russia	RTSI	0.067	10.829	1.068*	67.042*	2217.461*
Serbia	BELEX 15	0.475	14.685	-41.086*	464.002*	909.803*
Slovenia	SBITOP	-0.296	6.588	8.045*	104.29*	1757.869*
Turkey	BIST 100	-0.137	5.478	5.462*	24.139	378.013*
Ukraine	UX	0.186	7.605	-1.142*	89.152*	680.012*

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

Skewness is a measurement of the asymmetry of a given variable about its mean. A positive (negative) skewness indicates that less (more) in number and sharper (softer) in intense values are observed on the left of the mean and therefore more (less) in number and softer (sharper) in intense are appeared on the right of it. Skewness is absent only in Greek and Russian stock markets and in Czech at 1% level of significance. There is not a particular pattern about its sign, as half of countries have positive skewness and the rest of them negative skewness.

Kurtosis is a measurement of the so-called "tailedness" of the distribution of a variable. Here, an adjusted version of kurtosis is used, the excess kurtosis, which is the kurtosis minus 3, in order to provide the comparison to the normal distribution. Kurtosis was found statistically important at 1% level of significance for every sample. The Kolmogorov-Smirnov test is a non-parametric test of the equality of continuous distributions that is employed to compare the data of each market with a reference probability distribution. The critical value at the 1% is $1.63/\sqrt{n}$, where n is the sample size. The Kolmogorov-Smirnov statistic rejects the null hypotheses about normality at 1% level of significance,

These omens about absence of normality, as it is indicating by the above findings, may be originated, at least to some extent, to temporal dependencies in the returns. This phenomenon may be augmented in second-moment temporal dependencies. In order to test whether such dependencies are present, the Ljung-Box (LB) statistic is employed.

The Ljung-Box test analyses whether any of a group of autocorrelations of a time sample is different than zero. Actually, it is a diagnostic tool used to test about the lack or not of fit as regards a time series model. Instead of testing randomness at each distinct lag, Ljung–Box test checks the total randomness based on a number of lags, which at the present study is twenty. The null hypothesis states that the data are independently distributed, while the alternative declares the data are not independently distributed, in other words they exhibit serial correlation. The Ljung–Box statistics were estimated for twenty lags and applied to returns in order to test for first moment dependencies (linear), and furthermore applied to squared returns in order to test for second moment dependencies (nonlinear), or in other words to test about heteroscedasticity. They both are distributed as χ^2 with 20 degrees of freedom, where 20 is the number of lags.

As far as for the first moment dependencies (linear) is concerned, the null hypothesis that all autocorrelations up to the 20th lag are jointly zero is rejected for eight out of twelve samples at 1% level of significance. For Cyprus and Israel the null hypothesis is rejected at 5% level of significance, while in Greece it is rejected only at 10% level of significance. This provides evidence of temporal dependencies in the first moment of the distribution of spot returns, or that the autocorrelation is present in the returns of the above markets. Turkish stock exchange seems to be the only exception. In parallel, the null hypothesis about the squared returns is emphatically rejected without exception. Hence, there are evidences about heteroscedasticity. Furthermore, the Ljung–Box statistics obtained by squared returns are several times higher than the corresponding LB statistics calculated for the returns, suggesting that higher moment temporal dependencies are more distinct. A possible explanation for the existence of autocorrelation in the returns -at least for the vast majority of cases- could be that common information is impounded into stock prices not only on the disclosure day but on the following day as well.

4. Methodology

This section illustrates the econometric models that are used in this study. These models are based on the autoregressive conditional heteroskedasticity (ARCH) processes (Engle, 1982) which are employed to characterize and shape observed time series data, such as daily stock markets returns. This kind of models is utilized whenever it is assumed that the variance of the current error terms is a function of the actual sizes of the previous time period's error terms. ARCH models are applied widely for modeling financial time series that present time-variety volatility. Hence, this type of tools may be considered as ideal to interpret the behavior of current research's data. For the purposes of the present study we combine the ARCH volatility process according the following specifications for the conditional mean: i) the FIGARCH(1,d,1) equation according the positive feedback trading model introduced by Sentana and Wadhani (1992), and ii) the FIGARCH(1,d,1) equation according to the exponential autoregressive model suggested by LeBaron (1992).

4.1 FIGARCH(1,d,1) approach

There is a plethora of other acronyms that are employed to explain particular structures of a given variable and they have an analogous to ARCH model basis. A first variation type of the principal form is the generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986). GARCH models are generally used to explore the stochastic behaviour of several financial time series, and in many cases to explain the activity of volatility over time (Theodossiou and Lee, 1993). This approach is preferred whether an autoregressive moving-average model (ARMA) is assumed for the error variance (Whittle, 1953). The ARMA model consists of two sections, one autoregressive (AR) part and one moving average (MA) part. As a consequence, it is usually known as the ARMA(p,q) model where p is the order of the autoregressive part and q is the order of the moving average part. The AR(p) part can be written as:

$$R_t = c + \sum_{i=1}^{p} \varphi_i X_{t-1} + \varepsilon_t \quad (1)$$

where c is the constant factor, $\varphi_1,\varphi_2,\ldots,\varphi_3$ are the parameters of the model and ε_t are the error terms. The MA(q) part can be written as:

$$R_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (2)$$

where μ is the expectation of R_t, $\theta_1,\theta_2,\ldots,\theta_3$ are the parameters of the model and ε_t are again the error terms. Hence, the ARMA(p,q) model nests both two above equations and can be expressed by the following formula:

$$R_t = c + \sum_{i=1}^{p} \varphi_i X_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (3)$$

Based on the previous, the GARCH model is shaped as GARCH(p,q), where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ε^2. In symbols:

$$\sigma_t^2 = \alpha_0+\alpha_1\varepsilon_{t-1}^2+\ldots+\alpha_q\varepsilon_{t-q}^2+\beta_1\sigma_{t-1}^2+\ldots+\beta_\rho\sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i\sigma_{t-i}^2 \quad (4)$$

where $\alpha_0 > 0$, α_i, $\beta_i \geq 0$, $i > 0$

A step further than the GARCH model is the so-called IGARCH model. Integrated generalized autoregressive conditional heteroskedasticity IGARCH is a restricted version of the GARCH model, where the total amount of the persistent parameters is equal to one. Mathematically:

$$\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i = 1 \quad (5)$$

However, for the purposes of this study, we prefer the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) approach. This is because, due to its long memory nature, this model is appropriate to describe in a proper way the persistence in the volatility of a time series measurement, such as stock market returns. FIGARCH was introduced by Baillie et al. (1996) in an effort to overcome some imperfections linked to IGARCH model, as it may show extreme dependence on the initial conditions and presents long memory in the autocorrelations of squared returns of time series variables. Hence, the ambition of the FIGARCH model was to build up a more elastic class of processes for the conditional variance, which would be able of explaining in a more effective way the observed temporal dependencies in financial markets volatilities. In particular, the FIGARCH model permits only a slow hyperbolic rate of decline for the lagged squared in the conditional variance function. This approach can nest the time dependence of the variance and a leptokurtic unconditional distribution for the returns with a long memory behavior for the conditional variances.

A GARCH(p,q) process may also be expressed as an ARMA process by writing:

$$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1\text{-}\beta L\text{-}(1\text{-}eL)]\ \varepsilon_t^2 \tag{6}$$

Therefore, an IGARCH process can be written as:

$$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1\text{-}\beta L\text{-}(1\text{-}eL)(1\text{-}L)]\ \varepsilon_t^2 \tag{7}$$

Finally, a FIGARCH(1,d,1) model is obtained by replacing the first difference operator $(1 - L)$ with the fractional differencing operator $(1 - L)^d$, where d is a fraction $0 < d < 1$. Thus, the FIGARCH model can be obtained by considering:

$$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1\text{-}\beta L\text{-}(1\text{-}eL)(1\text{-}L)^d]\ \varepsilon_t^2 \tag{8}$$

The FIGARCH(p,d,q) model involves the covariance-stationary GARCH(p,q) model for d=0 and the IGARCH model for d=1. It should be allowed for prices of d between 0 and 1, modeling long-term dependence in the conditional variance. Whenever 0<d<0.5, the series are covariance stationary, while if 0.5<d<1 the series are no longer stationary but they are mean reverting with the effect of shocks fade in the long-run. For the FIGARCH approach all series can be estimated in terms of “d” parameter with d higher than 0 and lower than 1. As a result, series can be either stationary (0<d<0.5) or mean reverting (0.5<d<1), in other words returns will tend to move to the average price over time.

4.2 Positive feedback trading model

The positive feedback trading (PFT) model that was introduced by Sentana and Wadhani (1992) is based on the hypothesis that market traders consist of two heterogeneous to each other groups. Namely, risk averse expected maximum utility investors on the one hand, and positive feedback traders on the other. Focus on the first group the demand for shares is given by the following equality:

$$D_{1,t} = (E_{t-1}(r_t) - \beta_0) / \beta_1\sigma_t^2 \tag{9}$$

where $D_{1,t}$ stands for stocks demand at time t, E_{t-1} is the expectation of return at t-1 time, r_t is the ex-post shares’ return at time t, β_0 is the rate of return on the risk-free assets, σ_t^2 represents the conditional variance as a measurement of risk at time t, and the coefficient β_1 symbolizes the risk aversion. Note, that according to (9), whether all the investors had the same demand behavior, then the function would be transformed as $E_{t-1}(r_t) - \beta_0 = \beta_1\sigma_t^2$, which actually is the dynamic capital asset pricing (CAPM) model by Merton (1973).

Risk averse utility maximizers respond rationally to expected returns subject to their wealth limitation. Antithetically, the second group of traders prefer a positive (or negative) feedback strategy and base their choices on the response to shares variations and on historical past return, rather than on the fundamental return series.

Whether feedback trading is of the positive kind (speculators buy stocks when prices rise and sell if prices fall), stock prices overshoot levels based on fundamentals and exhibit excess volatility. Hence, the activities of positive feedback traders may potentially destabilize stock prices. In contrast, negative feedback traders buy when prices are low and sell when prices are high and thereby may stabilize stock markets (Bohl and Siklos, 2004).

According to Sentana and Wadhwani (1992) approach, when stock return volatility is low, stock returns exhibit positive autocorrelation, while during periods of high volatility the autocorrelations of stock returns turns negative. The reversal in the sign of stock returns and autocorrelations is consistent with the presence of positive feedback traders in the stock market.

So, the demand function for positive feedback traders is given by:

$$D_{2,t} = \rho r_{t-1} \tag{10}$$

where $D_{1,t}$ stands for stocks demand at time t-1, r_{t-1} is the ex-post shares' return at time t-1, and ρ is a coefficient grater than zero. Note, that whether $\rho < 0$ there would be negative feedback trading. It should not be considered that positive feedback trading is in any case an irrational pattern adopted by traders. It may be an outcome of a specific portfolio insurance strategy and the employment of stop-loss orders.

In balance, all stocks must be held, so the sum of $D_{1,t}$ and $D_{2,t}$ will be equal to one. Thus, $D_{1,t} = 1 - D_{2,t}$ or $D_{1,t} = 1 - \rho r_{t-1}$. Following equality (9) the new form can be written as: $1 - \rho r_{t-1} = (E_{t-1}(r_t) - \beta_0) / \beta_1\sigma_t^2$, and by isolating the expectation of return at t-1 time on the left part, the equation becomes:

$$E_{t-1}(r_t) = \beta_0 + \beta_1\sigma_t^2 - \beta_1\sigma_t^2 \rho r_{t-1} \tag{11}$$

The term $-\beta_1\sigma_t^2\rho$ in equation (11) implies that the presence of positive (negative) feedback trading will induce negative (positive) autocorrelation in returns. Also, the higher the volatility the more negative (positive) the autocorrelation. By defining the ex-post shares' return at time t equal to $E_{t-1}(r_t)$ plus a stochastic error term, equation (11) is transformed into a regression equation, namely the positive feedback trading model.

The positive feedback trading model that was proposed by Sentana and Wadhani (1992) can be formed according to the following type:

$$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2)r_{t-1} + \varepsilon_t \tag{12}$$

where r_t is the stock return at time t, β_0 is the constant factor, r_{t-1} is the stock return in the previous period, $\beta_1\sigma_t^2$ is the risk premium, modelled as a positive function of the conditional variance of stock price, β_2 pickups the possibility of constant correlation in the model. Parameter β_3, that links autocorrelation to volatility, should be negative and statistically important for the presence of positive feedback trading. Note that where $-\beta_1\rho = \beta_3$. The advantage of this model is that can capture not only the feedback trading strategies but also the relation between autocorrelation and long-memory volatility. At low volatility, β_2 plays a more important role in determining autocorrelation. With a rising volatility, the impact of β_3 on return autocorrelation increases (compared to β_2) and will induce negative autocorrelation due to the dominance of positive feedback trading at high volatility level. The higher the volatility, the more negative the autocorrelation.

Coefficient β_1 is a measurement of rational investors' impact on stock prices. At this point, it should be noted again that positive feedback trading is not necessarily illogical. As an example, it may be the outcome of particular insurance defence strategies and the use of stop-loss orders. Portfolio insurance may be considered as a rational tactic when risk aversion declines rapidly with wealth (Sentana and Wadhani, 1992).

The infancy of positive and/or negative feedback strategy may be originated in various conflict psychological profiles of investors. In particular, when stocks are rising, one pack of investors believe that further rises are probable and therefore this is an incentive for them to buy. In this way, the rise is reinforced and the positive feedback trading phenomenon is appeared. Synchronously, another pack of investors believe that there must be a peak after which the market falls, which ends up to sceptical buyers or even to some imminent sellers. Thus, the negative feedback trading phenomenon takes place, stabilizing the rise. Antithetically, when stocks are falling regularly, the first pack of investors may expect further losing days and refrain from buying or start selling. In this way the fall is reinforced and the positive feedback trading phenomenon is emerging again. Following previous, the second pack of investors may decide to buy as stocks become more and more of a bargain. Now, the negative feedback trading phenomenon is happened again and thereby stock markets may be stabilized.

4.3 Exponential autoregressive model

According to the exponential autoregressive (EA) model, it is considered that the yield of shares is connected to their previous results in a nonlinear pattern. Based on LeBaron (1992) a specific equilibrium is employed as follows:

$$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\exp\{-\sigma_{t-1}^2\})r_{t-1} + \varepsilon_t \quad (13)$$

The conditional return, given by the above equation, is an exponential autoregressive process of order one [EAR(1)] along with a FIGARCH effect. The autocorrelation of returns is an exponential function of the conditional variance.

5. Empirical results

5.1 Positive feedback trading

Table 5.1 (i, ii, iii) shows the maximum likelihood estimates for equations (12) and (8) using daily returns, as far as the positive feedback trading and the FIGARCH(1,d,1) model is concerned, for all the twelve samples. Also, Table 5.1 reports the skewness, the kurtosis and the Ljung-Box (LB) statistic for standardized residuals and also the Ljung-Box (LB) statistic for squared standardized residuals.

Table 5.1i PFT-FIGARCH(1,d,1) for Croatia, Cyprus, Czech Republic and Greece

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2)r_{t-1} + \varepsilon_t$ (12)

$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Croatia	Cyprus	Czech	Greece
β_0	0.032 (0.001)*	-0.215 (0.001)*	0.035 (0.001)*	-0.062 (0.001)*
β_1	-0.035 (0.001)*	-0.033 (0.001)*	-0.007 (0.001)*	0.004 (0.001)*
β_2	0.053 (0.001)*	0.005 (0.001)*	0.001 (0.001)*	-0.002 (0.006)*
β_3	0.014 (0.001)*	0.007 (0.001)*	-0.011 (0.001)*	0.009 (0.001)*
c	-0.016 (0.001)*	2.288 (0.001)*	0.076 (0.001)*	-0.022 (0.001)*
b	0.342 (0.001)*	0.275 (0.001)*	0.426 (0.001)*	0.481 (0.001)*
ε	-0.064 (0.001)*	0.22 (0.001)*	-0.004 (0.001)*	-0.03 (0.001)*
d	0.484 (0.001)*	0.689 (0.001)*	0.594 (0.001)*	0.511 (0.001)*
Log-likelihood	-3933.74	-3074.157	-4497.147	-5179.592
Skewness	2.334	0.44	-0.444	-0.084
Kurtosis	45.931	6.959	15.034	5.837
LB(20)	233.901*	48.355*	58.342*	30.535***
LB^2 (20)	903.495*	353.2*	3107.705*	604.023*

Notes: Asterisks (*) (***) indicate significance at the (1%) (10%) level, respectively

Table 5.1ii PFT-FIGARCH(1,d,1) for Israel, Poland, Romania and Russia

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2)r_{t-1} + \varepsilon_t$ (12)

$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Israel	Poland	Romania	Russia
β_0	-0.008	0.029	0.016	0.014
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_1	-0.013	-0.045	-0.019	0.003
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_2	-0.029	-0.031	0.026	0.003
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_3	-0.012	0.036	0.003	0.009
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
c	-0.1	0.123	0.053	3.598
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
b	0.063	0.471	0.216	0.368
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
ε	0.021	0.093	0.006	0.257
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
d	0.262	0.493	0.483	0.561
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
Log-likelihood	-3159.27	-4244.152	-4691.644	-5353.629
Skewness	0.582	-0.394	-0.218	-1.007
Kurtosis	3.653	4.381	8.812	23.241
LB(20)	46.033*	27.366	50.921*	215.23*
LB^2 (20)	1920.302*	804.077*	1440.29*	1500.721*

Notes: Asterisks (*) indicate significance at the (1%) level

Table 5.1iii PFT-FIGARCH(1,d,1) for Serbia, Slovenia, Turkey and Ukraine

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2)r_{t-1} + \varepsilon_t$ (12)

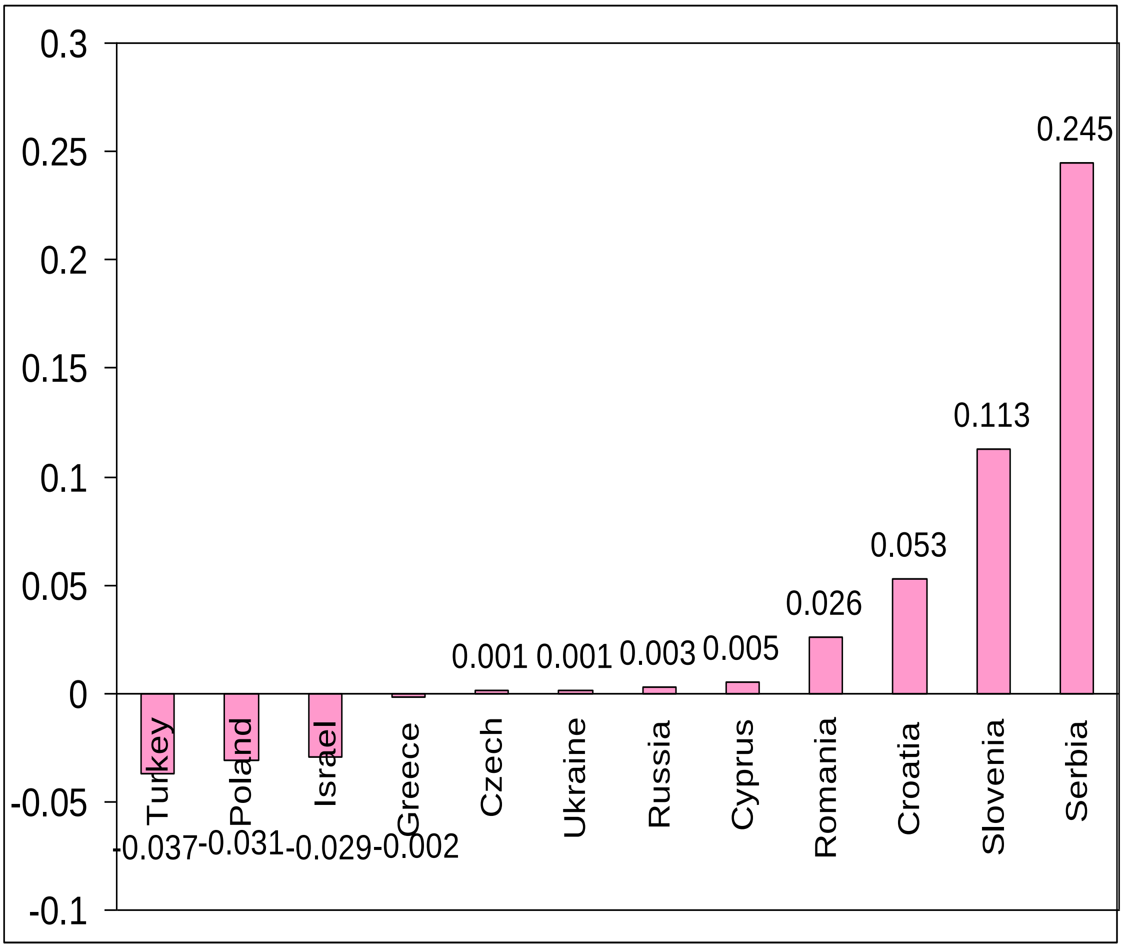
$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Serbia	Slovenia	Turkey	Ukraine
β_0	-0.008	-0.012	0.153	-0.03
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_1	0.018	-0.009	-0.032	0.025
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_2	0.245	0.113	-0.037	0.001
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_3	0.004	0.012	0.012	0.01
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
c	0.073	0.112	0.053	0.367
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β	-0.08	0.353	0.373	0.372
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
ε	-0.103	-0.02	0.407	0.057
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
d	0.399	0.674	0.002	0.538
	(0.001)*	(0.001)*	(0.854)	(0.001)*
Log-likelihood	-4223.321	-3743.343	-4787.682	-4292.357
Skewness	0.403	-0.544	-0.124	-0.401
Kurtosis	17.405	11.198	5.593	12.093
LB(20)	96.952*	57.091*	20.923	72.925*
LB^2 (20)	667.902*	1312.898*	340.48*	839.97*

Notes: Asterisks (*) (**) indicate significance at the (1%) (5%) level, respectively

Initially, research focuses on these parameters that govern the autocorrelation of returns, as equation (12) shows, i.e. β_2 and β_3. The constant component of the autocorrelation, β_2, is statistically significant in all twelve markets, even at 1% level of significance. It is possible that the basis of this particular type of autocorrelation is related to asynchronous trading (Lo and Mackinlay, 1990). Of course, it could be that time variation in ex ante returns causes autocorrelation in ex post returns (Conrad and Kaul, 1998). Atchison et al. (1987) estimated the theoretical portfolio autocorrelation due solely to nonsynchronous trading. Parameters were calculated based upon a random sample of 280 NYSE firms with known trading frequencies over a period of time. They revealed that the theoretical autocorrelation due solely to nonsynchronous trading was much lower than that observed empirically. The above can be considered as markets' inefficiencies. Figure 5.1 presents the values of β_2 coefficient from lower to higher.

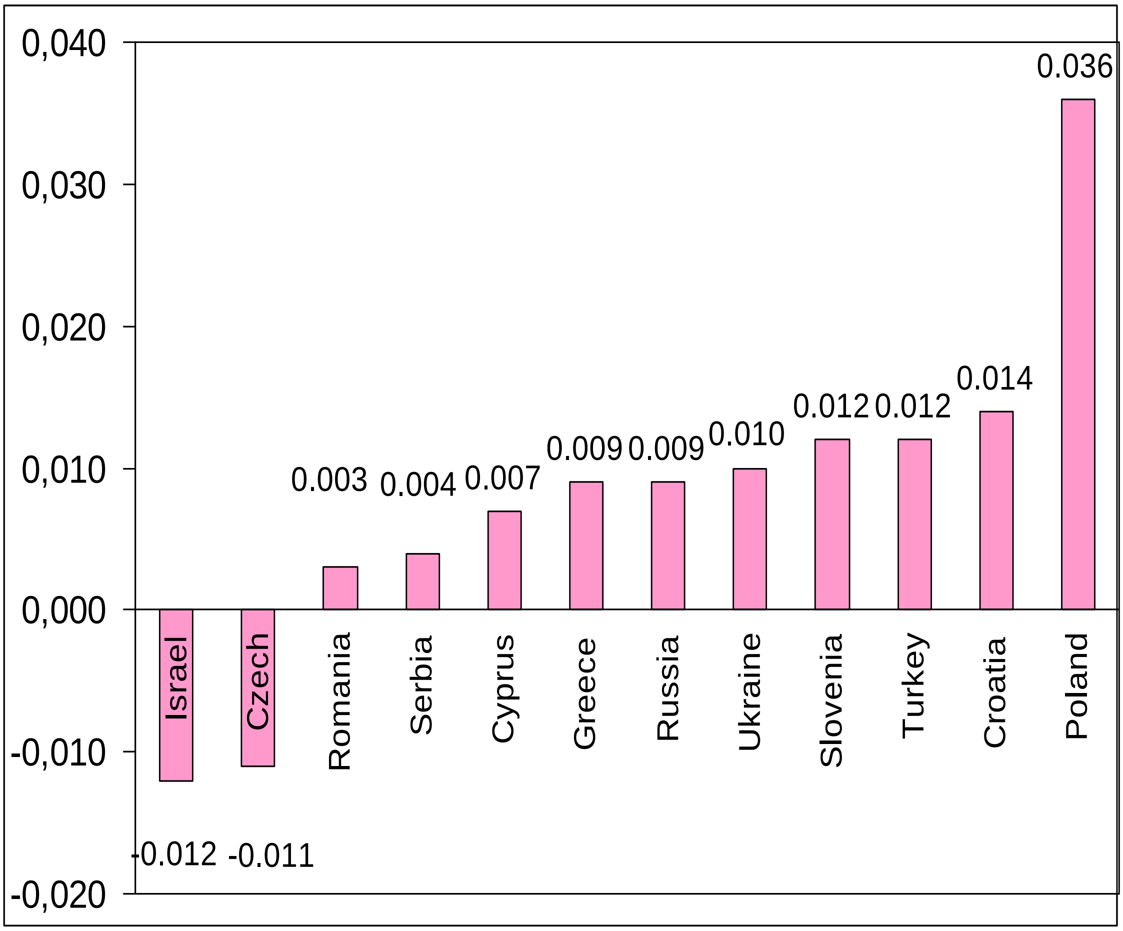
Figure 5.1 Coefficient β_2 in the PFT model



According to Figure 5.1, eight out of twelve markets present positive sign for the parameter of constant correlation β_2, while sign is negative for the remaining of them, having a value from -0.037 for Turkey till 0.245 for Serbia. Thus, serial correlation is positive for the first group of markets and negative for the second one.

Next, the outcomes of coefficient β_3 that links autocorrelation to volatility are analyzed.

Figure 5.2 Coefficient β_3 in the PFT model



As it is revealed by Table 5.1 (i, ii, iii) the coefficient β_3 is statistically important for all markets at 1% level of significance, so it can be concluded that feedback trading is present, being an important determinant of short-terms movements. Of course, positive feedback trading causes negative autocorrelation that rises |in absolute terms| with the level of volatility. Hence, β_3 should be both negative and statistically significant for the presence of positive feedback trading. This is the case only for Israel and Czech Republic, where there is a negative relationship between volatility and autocorrelation into stock returns. According to this, investors buy stocks when prices rise, and sell if prices fall. As it is mentioned above, that negative autocorrelation raises |in absolute terms| with the level of volatility and this inverse relationship is consistent with the fact that traders adopt positive feedback strategy.

However, coefficient β_3 is positive and statistically important for ten out of twelve stock markets. This means that there is the phenomenon of negative feedback trading. In particular, traders buy stocks when prices fall and sell when prices rise. This is because, when stocks are rising, investors believe that there must be a peak near, after which the market falls, which ends up to reluctant buyers and willing sellers. On the other hand, when stocks are falling, investors may decide to buy as stocks become more and more of a bargain. Again, the negative feedback trading strategies take place. Also, as it is seen by equation (13), whether volatility is high the magnitude of autocorrelation is low, while if volatility is low the magnitude of autocorrelation is high.

These findings are mostly consistent with the study of Bohl and Siklos (2004), who analyzed daily returns for three indices for mature stock markets and four indices for emerging capital markets in Central and Eastern European Countries. The stock markets indices were the DAX (Germany), the FTSE (UK) and the S&P500 (US). The PX50 (Czech Republic), the BUX (Hungary), the WIG (Poland) and the RTS (Russia) were the indices for the emerging stock markets. The time period under investigation covered a phase over ten years from 1994 till 2003, by and large a decade before present study. Empirical results supported the existence of both positive and negative as well trading strategies in stock markets. Stock returns remained essentially positively autocorrelated in all emerging markets, except Poland (WIG), while they turned significantly negative in mature markets, except for the FTSE100. Writers concluded that they had a little bit of preliminary evidence that positive feedback trading is particularly a phenomenon of mature markets.

The implication for this phenomenon is that traders do not trust in the long run stock markets, but rather behave as speculators by buying stocks when prices fall and selling when prices rise, aspiring a fast and modest profit and detesting potential losses. This practice may have as its source the lack of confidence in a given market in the long run. In turn, the absence of confidence could be originated from a plethora of various factors. For example, many of the countries under investigation that present negative feedback trading, such as Croatia, Poland, Romania, Russia, Serbia, Slovenia and Ukraine, overthrew relatively recently their former communist regimes in the late 80s. So, some may consider as reasonable, citizens and local investors not to have developed yet strong relationships of faith with financial institutions like stock market exchange, as traders have done in mature markets throughout the past many decades or even centuries in some cases. In parallel, for Cyprus and Greece story seems to be quite different. Here, the lack of confidence seems to emerge out of the financial crisis and the imposition of Memorandum of Understanding. As main factors that connect Memorandum of Understanding with this kind of traders pattern we consider the negative influence of macroeconomics on listed companies, the limited available incomes of households that result into weak market demand which again presses companies' fundamentals, the reluctance of individuals for long-term investments as they need cash to respond to their daily obligations and finally the capital controls that these countries has had to impose. To reinforce our opinion, we mention the empirical results of Koutmos et al. (2006) that found positive feedback trading of stock returns in the Cyprus stock exchange for a period some years before the financial crisis.

On the other hand, the coefficient β_3 is negative and statistically important for Israel and Czech Republic, confirming the existence of positive feedback trading at these stock markets. As far as the case of Israel is concerned, it is not characterized as emerging market for most of independent evaluation institutions such as IMF and S&P. Local trade in securities has strong roots in the area as it began in the 1930s, years before the formation of the state of Israel. With the formation of the state of Israel, a number of banks and brokerages joined forces and established the Tel Aviv stock exchange in September 1953. Since the mid-1990s the Tel Aviv stock exchange had been adapting to meet the standards of the most advanced exchanges in the world. As a result, there was enough time for market to develop different patterns from the ex-communist countries. Finally, it seemed that the Prague stock exchange followed its own route, since, after a fifty-year break caused by world war II and the communist regime, it was reopened in 1993. Country quickly became one of the most stable and prosperous of the post-communist states of Europe, a fact that helped itself to differentiate from the most of ex Soviet and ex Yugoslavian republics.

At this point, markets are classified by the various values of coefficients β_2 and β_3, shaping four different groups.

Table 5.2 Markets classified by coefficients β_2 and β_3

Negative β_2 and negative β_3	Negative β_2 and positive β_3
Israel	Greece, Poland, Turkey
Positive β_2 and negative β_3	**Positive β_2 and positive β_3**
Czech Republic	Croatia, Cyprus Romania, Russia Serbia, Slovenia, Ukraine

As it is revealed by equation (12), when volatility tends to infinity first-order autoregression tends to β_2, while when volatility tends to zero first-order autoregression tends to the sum of $\beta_2 + \beta_3$. Based on the results of Table 5.1, Table 5.3 shows figures for first-order autocorrelation during high and low volatility periods. As risk increases, first-order autocorrelation becomes negative for Greece, Israel, Poland and Turkey. Thus, investors follow a feedback strategy according to which they buy stocks after prices increase and sell shares after prices decrease. The explanation for this pattern may have two different origins. Firstly, traders realize a raise as an opportunity for profits, and/or they are afraid for big losses when a fall begins. Also, as risk decreases, first-order autocorrelation is negative for Czech Republic, Israel and Turkey.

Table 5.3 First-order autocorrelation during high and low volatility

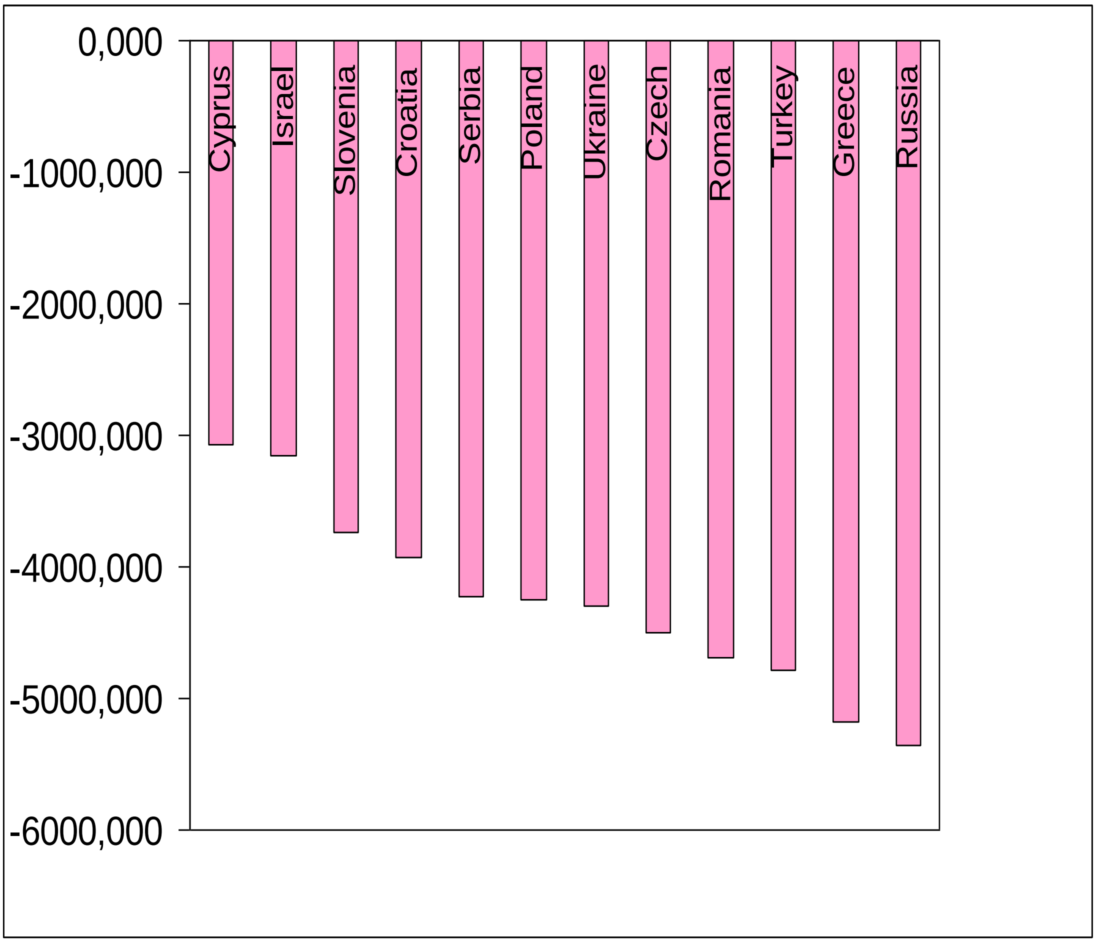
	High volatility (β_2)	Low volatility ($\beta_2 + \beta_3$)
Croatia	0.053	0.067
Cyprus	0.005	0.012
Czech Republic	0.001	-0.01
Greece	-0.002	0.007
Israel	-0.029	-0.041
Poland	-0.031	0.005
Romania	0.026	0.029
Russia	0.003	0.012
Serbia	0.245	0.249
Slovenia	0.113	0.125
Turkey	-0.037	-0.025

Ukraine	0.001	0.011

A likelihood function is a function of the parameters of a statistical model. For the purposes of current study, the natural logarithm of the likelihood function is preferred. This is the so-called log-likelihood. This approach preferred, since the logarithm is a monotonically increasing function, so it achieves its maximum value at the same point as the function itself. Hence, the log-likelihood can be used instead of the classical likelihood for the cases of maximum likelihood estimations. In other words, the log-likelihood is an expression of optimal values of estimated coefficients. Thus, it is desirable to maximize the log-likelihood, as the higher value is better.

Figure 5.3 illustrates the results about the log-likelihood estimations as they are reported in Table 5.1, with the higher to the lower form left to right. The highest price is for Cyprus (-3074.157) and the lowest for Russia (-5353.629).

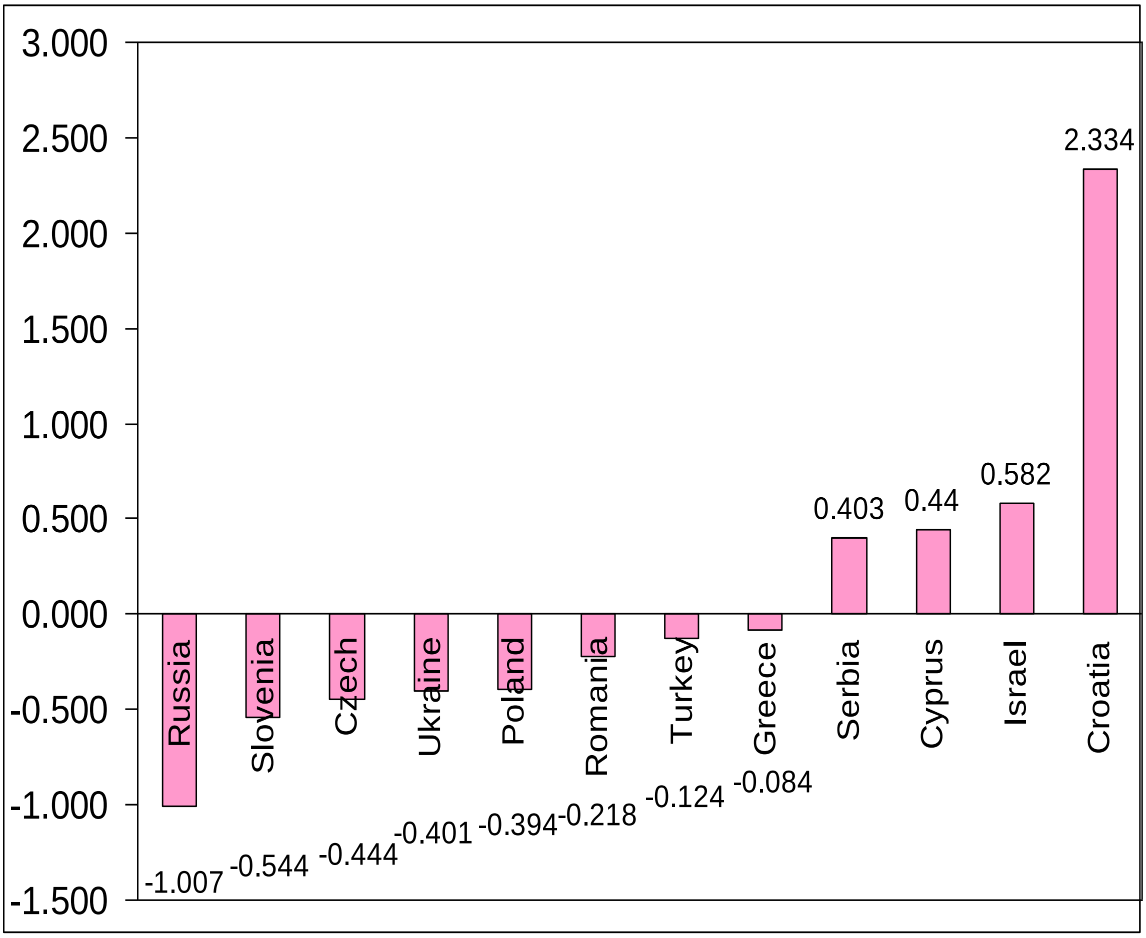
Figure 5.3 Log-likelihood estimation in the PFT model



Next research focuses on parameters connected with distribution, namely skewness and kurtosis. As it mentioned above, skewness is a measurement of the asymmetry of a given variable about its mean. Negative skewness indicates that the mean of the data values is less than the median, and the data distribution is left-skewed. Positive skewness would indicate that the mean of the data values is larger than the median and the data distribution is right-skewed. As it is shown by Figure

5.4, four countries, namely Croatia, Israel, Cyprus and Serbia, present a positive skewness, indicating that less in number and sharper in intense values of returns are observed on the left of the returns' mean and therefore more in number and softer in intense are appeared on the right of it. Contrary to this, eight stock markets, Russia, Slovenia, Czech Republic, Ukraine, Poland, Romania, Turkey and Greece, appear a negative skewness, implying that more in number and softer in intense values of returns are observed on the left of the returns' mean and so less in number and sharper in intense are appeared on the right of it.

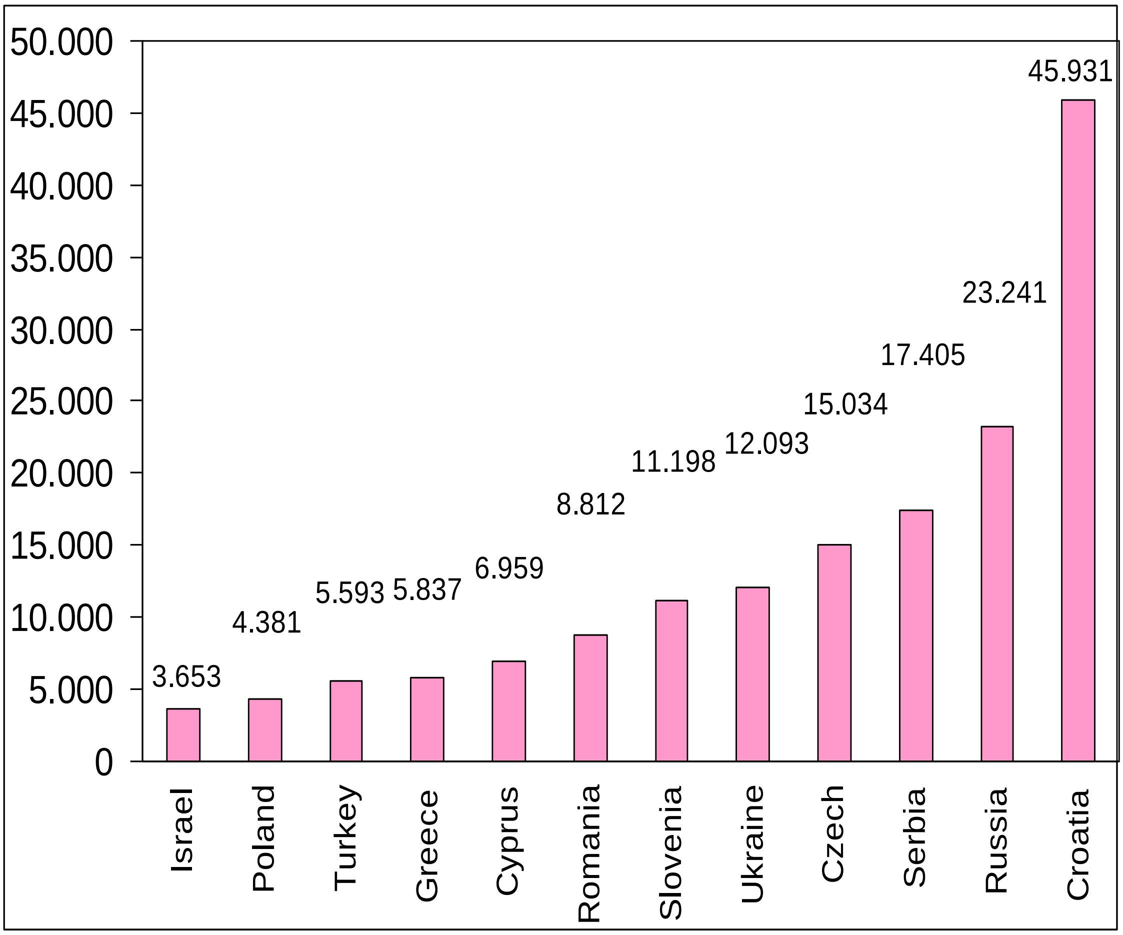
Figure 5.4 Skewness of residuals in the PFT model



Croatia has the higher positive skewness with a value of 2.334, while Russia marks the greater |in absolute terms| negative skewness with a value of -1.007. Based on these results, it can be considered that traders in Croatia are the more frightened in falls and the more moderate in raises. At the same time, investors in Russia seems to be the more moderate in falls and the more enthusiastic in rises. The lowest |in absolute terms| skewness was found for Greece (-0.084) underlying the greater symmetry of returns about their mean. This underlines that traders in Greece present some kind of stoicism, comparing with the other markets. It is important at this point to mention that Greece's coefficient for skewness is the only one among the samples of this study that is statistically significant just for the 10% level, while the remaining coefficients are statistically important even at 1% level of significance, with the exception of Turkey, which has the second smallest |in absolute terms| coefficient for skewness (-0.124). The last one is statistically significant at the 5% level.

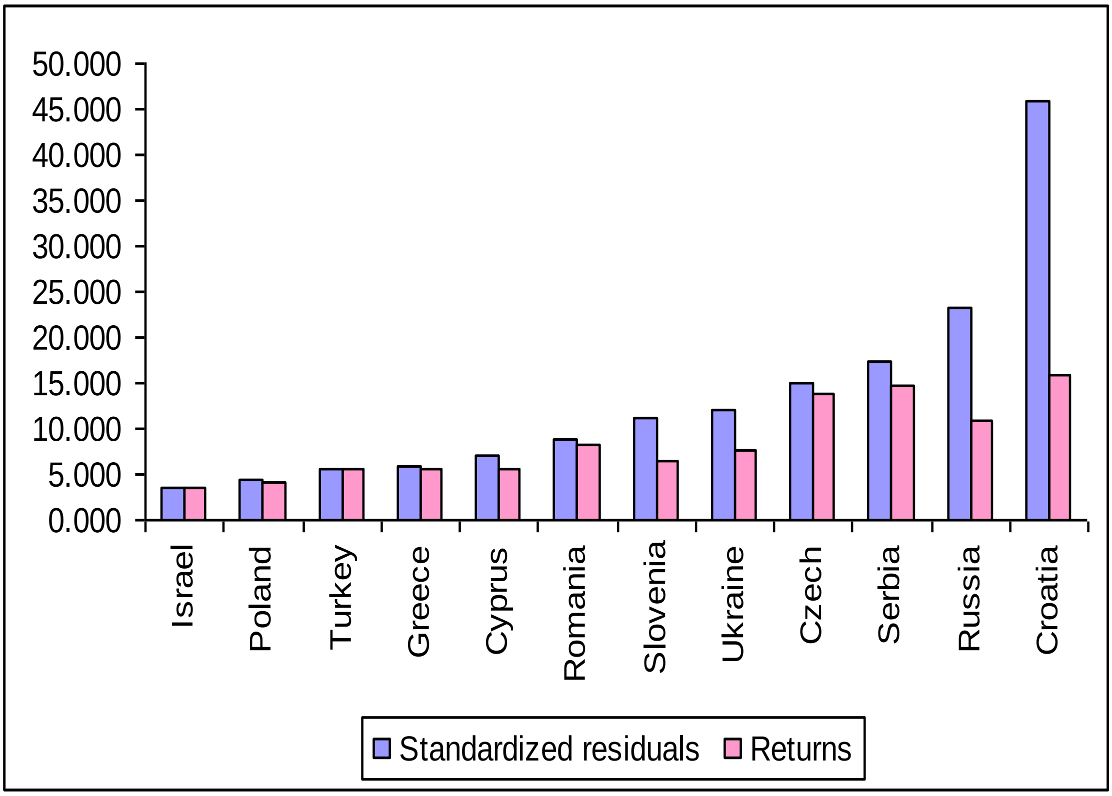
As far as the kurtosis is concerned, it is a measurement of the so-called "tailedness" of the distribution of a variable. Kurtosis indicates how the peak and tails of a distribution differ from the normal distribution. A distribution with a positive kurtosis value indicates that the distribution has heavier tails and a sharper peak than the normal distribution. A distribution with a negative kurtosis value indicates that the distribution has lighter tails and a flatter peak than the normal distribution. According to Table 5.1 the null hypothesis of kurtosis absence about the standardized residuals obtained from each sample cannot be accepted even at 1% level of significance for the totality of the occasions. Kurtosis is lower for Israel (3.653) and higher for Croatia (45.931). Analytically, figure 5.5 illustrates the results for each market.

Figure 5.5 Kurtosis of residuals in the PFT model



For the purposes of this study we have calculated the kurtosis of returns according to an adjusted version of it, the excess kurtosis, which actually is the kurtosis minus 3. As it is illustrated by Table 3.2, the null hypotheses about normality cannot be accepted even at 1% level of significance for the totality of samples. Hence, as we receive parallel outcomes for "returns" and "standardized residuals obtained by PFT", it would be very interesting to provide a comparison between the kurtosis measures of returns' values and their residuals in order to examine whether modeling of nonlinearities can lead into kurtosis' reduction. As it is obvious by Figure 5.6, the kurtosis measures of the standardized residuals got by the feedback model are not lower than the respective excess kurtosis measures of stock returns. Actually, prices for kurtosis obtained by standardized residuals are greater from the corresponding prices of returns' kurtosis for every case. This means that modeling of nonlinearities could not lead into kurtosis' reduction.

Figure 5.6 Kurtosis of returns and their standardized residuals (PFT)



Ljung and Box (1978) introduced the homonym test as a more quantitative way to test for autocorrelation at multiple lags jointly. This means that the Ljung-Box statistic is used to test whether a series of observations over time are random and independent. The calculated Ljung-Box statistics (Table 5.1) for twenty lags in the residuals for the present study, underline that the null hypothesis about the absence of linear dependence can not be rejected for Turkey and Poland at 1% level of significance and for Greece at 10% level of significance, while the null hypothesis is rejected for the remaining markets. In other words, autocorrelation is statistically equal to zero for the first group at the mentioned levels of significance, meaning that observations are independent and random over time. On the opposite, autocorrelation is not statistically equal to zero for the second group and observations are not independent and random over time.

We can also test for conditional heteroscedasticity by conducting a Ljung-Box test on the squared residual of daily returns. The estimated Ljung-Box statistics for twenty lags in the squared residuals test for nonlinear or in other words second-moment temporal dependencies. The null hypothesis declares the existence of homoscedasticity. Based on the results of Table 5.1, the null hypothesis is clearly rejected for 1% level of significance without exception. Hence, we can conclude for heteroscedasticity. Analytically, results about Ljung-Box (20) statistics are presented in Figure 5.7 and results about Ljung-Box (20) statistics for squared residuals are presented in Figure 5.8

Figure 5.7 Ljung-Box (20) statistics for residuals in the PFT model

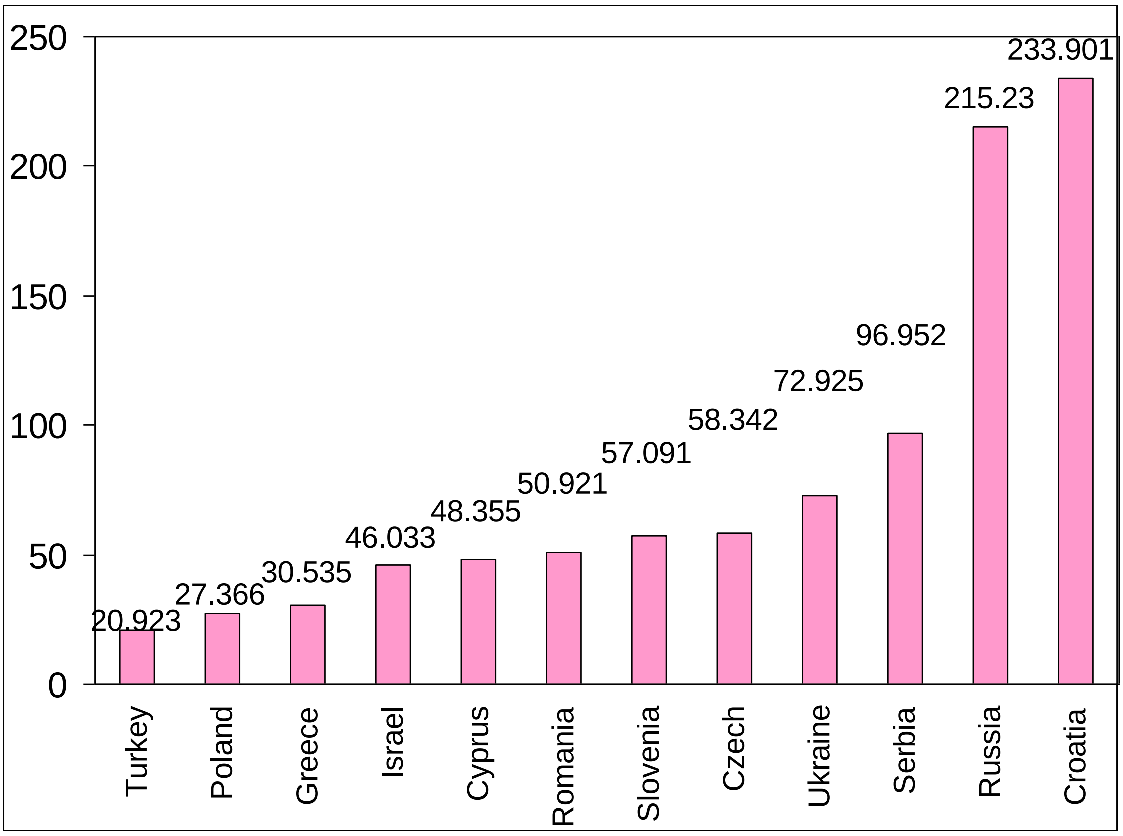
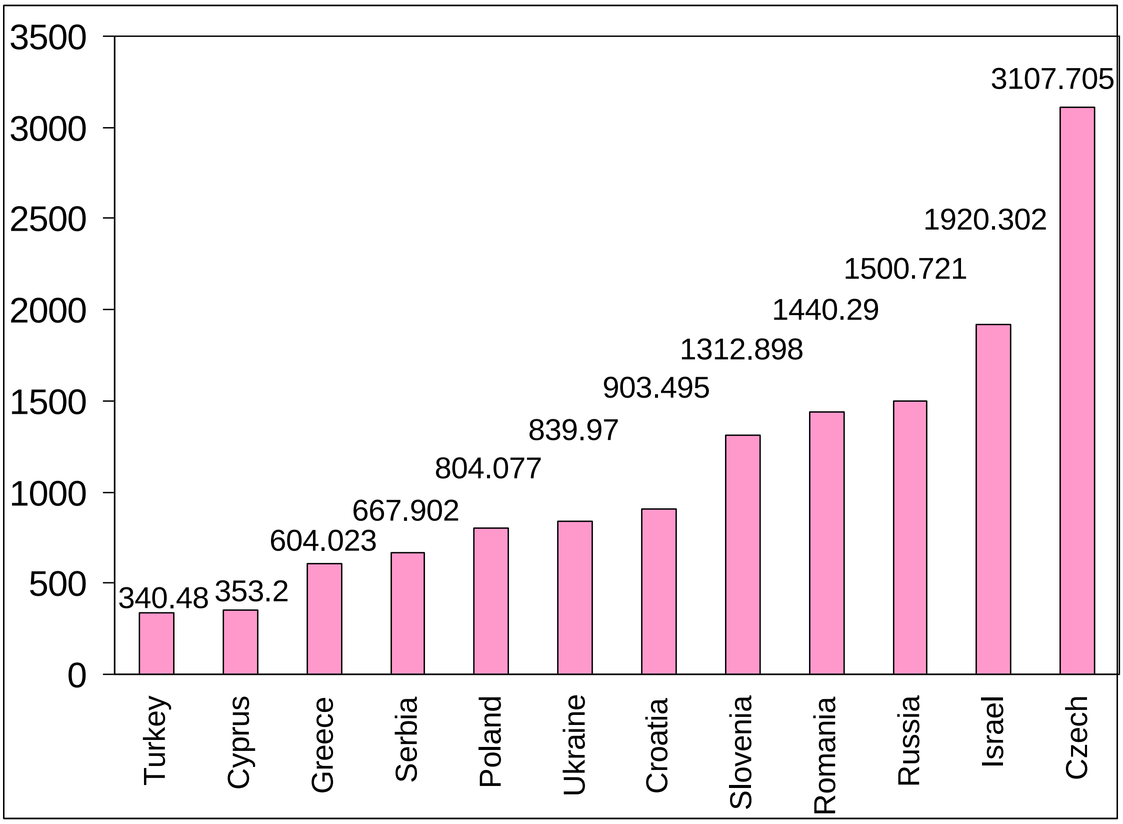
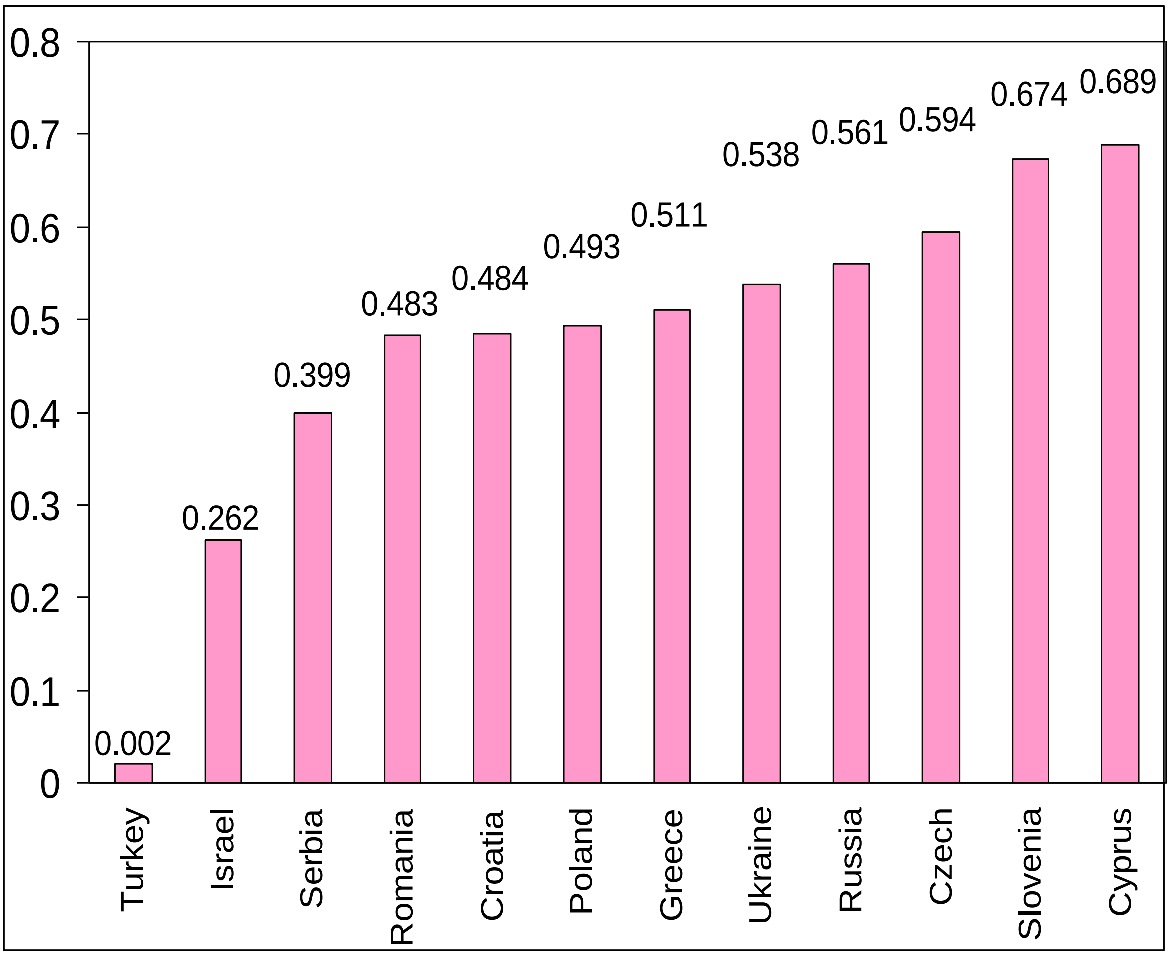


Figure 5.8 Ljung-Box (20) statistics for squared residuals in the PFT model



Regarding the FIGARCH(1,d,1) model attention is being paid on the coefficient d as it is set at equation (8). Values of d should be allowed between 0 and 1 when modeling long-term dependence in the conditional variance. As long as $0<d<0.5$, it is considered that the series are covariance stationary, while whether $0.5<d<1$ the series are no longer stationary but they are mean reverting, with the effect of shocks dying away in the long-run. As it can be seen by Figure 5.9, half of countries have a price between 0 and 0.5 (Turkey, Israel, Serbia, Romania, Croatia and Poland) for the coefficient d, while the remaining six samples present a value higher than 0.5 and less than 1. Thus, there is not a specific pattern, as the first group series can be considered as stationary while the second group series are mean reverting which means that shocks to the conditional variance are ultimately die out. Notice that parameter d is statistically important at 1% level of significance for all cases, apart from Turkey where the null hypothesis supporting that d is statistically equal to zero cannot be rejected.

Figure 5.9 Coefficient “d” in the PFT-FIGARCH(1,d,1) model



5.2 Exponential Autoregressive (EA) model

In parallel with the feedback trading model introduced by Sentana and Wadhani (1992), present study employs the exponential autoregressive model as it was introduced by LeBaron (1992). The exponential autoregressive model assumes that stock returns are related to their past in a nonlinear way. Table 5.4 (i, ii, iii) shows the results about equations (13) and (8) regarding the exponential autoregressive approach and the FIGARCH(1,d,1) model, based on the daily returns for every one of the twelve samples. Also, Table 5.4 reports the skewness, the kurtosis and the Ljung-Box (LB) statistic for standardized residuals and also the Ljung-Box (LB) statistic for squared standardized residuals.

Table 5.4i EA-FIGARCH(1,d,1) for Croatia, Cyprus, Czech Republic and Greece

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\exp\{-\sigma_{t-1}^2\})r_{t-1} + \varepsilon_t$ (13)

$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Croatia	Cyprus	Czech	Greece
β_0	0.311	-0.25	0.092	0.135
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_1	-0.009	0.001	-0.025	-0.025
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_2	-0.008	0.076	-0.042	-0.014
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_3	0.013	0.124	0.017	0.274
	(0.001)*	(0.001)*	(0.54)	(0.001)*
c	0.726	-0.237	0.08	-0.144
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β	0.306	0.001	0.662	0.392
	(0.001)*	(0.012)**	(0.001)*	(0.001)*
ε	0.295	-0.086	0.03	-0.02
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
d	0.666	0.355	0.796	0.431
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
Log-likelihood	-3933.74	-2974.542	-4491.389	-5179.592
Skewness	0.498	0.496	0.383	0.005
Kurtosis	16.106	5.526	13.362	5.678
LB(20)	168.852*	20.525	86.749*	31.096***
LB^2 (20)	2642.005*	197.365*	3143.765*	621.101*

Notes: Asterisks (*) (**) (***) indicate significance at the (1%) (5%) (10%) level, respectively

Table 5.4ii EA -FIGARCH(1,d,1) for Israel, Poland, Romania and Russia

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\exp\{-\sigma_{t-1}^2\})r_{t-1} + \varepsilon_t$ (13)

$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Israel	Poland	Romania	Russia
β_0	-0.012	0.106	0.117	0.278
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_1	-0.027	-0.078	0.002	-0.055
	(0.001)*	(0.001)*	(0.819)	(0.001)*
β_2	-0.037	0.051	-0.001	0.023
	(0.001)*	(0.001)*	(0.451)	(0.001)*
β_3	0.008	0.008	-0.001	-0.644
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
c	0.106	0.11	2.691	-0.713
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β	0.562	0.428	0.079	0.09
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
ε	0.051	0.094	0.296	-0.071
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
d	0.627	0.484	0.494	0.228
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
Log-likelihood	-3159.27	-4244.152	-4691.644	-5289.786
Skewness	0.556	-0.225	-0.279	0.724
Kurtosis	3.533	4.001	8.253	11.648
LB(20)	36.311**	26.377	68.141*	67.572*
LB^2 (20)	1775.086*	876.511*	1791.872*	1781.245*

Notes: Asterisks (*) (**) indicate significance at the (1%) (5%) level, respectively

Table 5.4iii EA -FIGARCH(1,d,1) for Serbia, Slovenia, Turkey and Ukraine

$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\exp\{-\sigma_{t-1}^2\})r_{t-1} + \varepsilon_t$ (13)

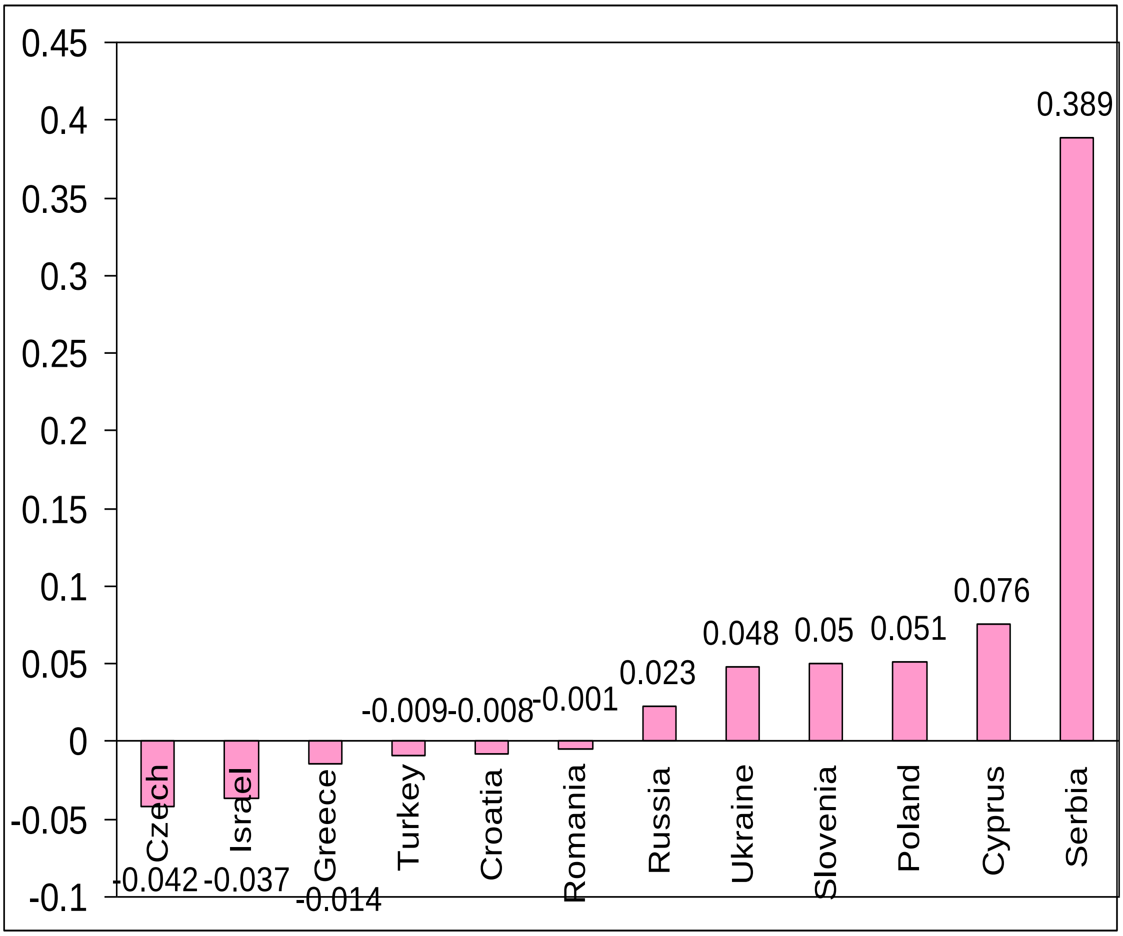
$\sigma_t^2 = c + \beta\sigma_{t-1}^2 + [1-\beta L-(1-eL)(1-L)^d]\,\varepsilon_t^2$ (8)

Variables	Serbia	Slovenia	Turkey	Ukraine
β_0	0.025	-0.01	0.045	0.048
	(0.118)	(0.001)*	(0.001)*	(0.001)*
β_1	-0.008	0.023	-0.016	-0.021
	(0.476)	(0.001)*	(0.001)*	(0.001)*
β_2	0.389	0.05	-0.009	0.048
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β_3	-0.462	0.015	-0.002	0.031
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
c	0.086	0.136	1.619	0.362
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
β	0.343	0.124	0.04	0.485
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
ε	0.001	0.011	0.124	0.054
	(0.908)	(0.001)*	(0.001)*	(0.001)*
d	0.622	0.52	0.659	0.671
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
Log-likelihood	-4182.731	-3743.343	-4787.682	-4292.357
Skewness	0.897	-0.538	-0.096	0.391
Kurtosis	18.646	7.126	5.493	7.502
LB(20)	66.426*	87.859*	26.985	63.402*
LB^2 (20)	442.177*	1796.243*	369.811*	648.069*

Notes: Asterisks (*) (***) indicate significance at the (1%) (10%) level, respectively

Initially, as it was committed with the first feedback trading model, the analysis about the results of exponential autoregressive model is started from these parameters that rule the autocorrelation of returns, as equation (13) shows, i.e. β_2 and β_3. As it is obvious by Figure 5.10, half markets present positive sign for the parameter of constant autocorrelation β_2 and half markets present negative sign. Values are moving into a range from -0.042 for Czech Republic till 0.389 for Serbia.

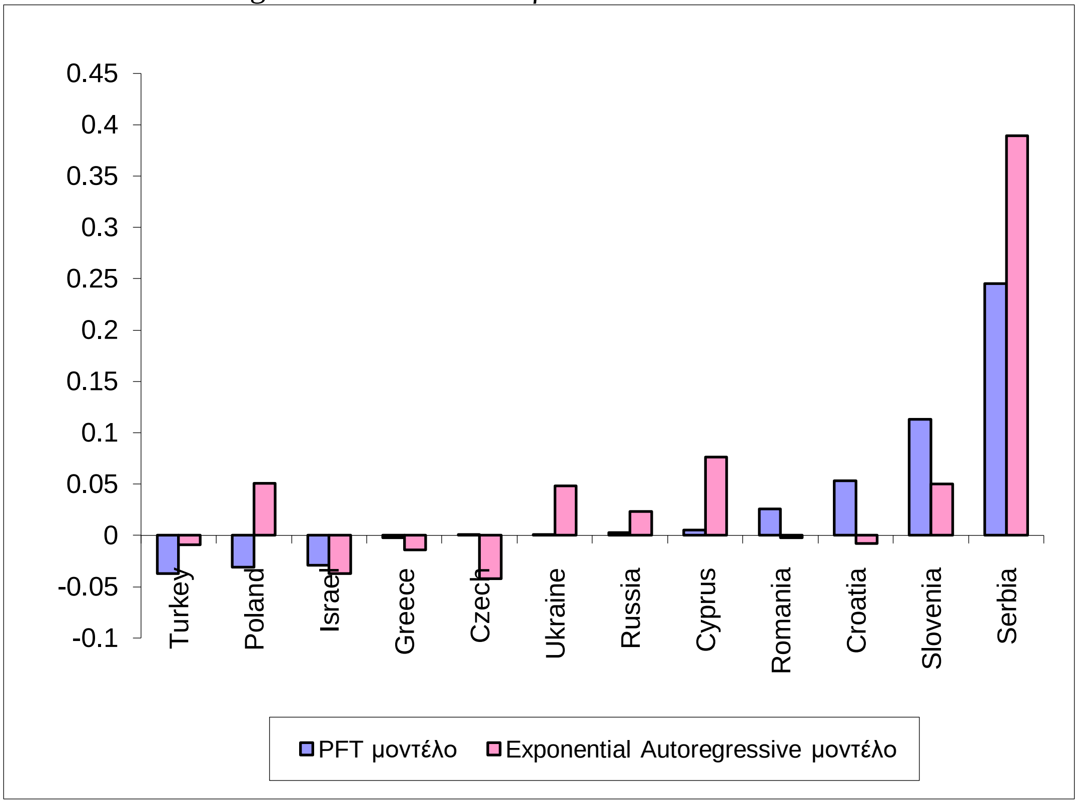
Figure 5.10 Coefficient β_2 in the EA model



Coefficient β_2 is statistically important at 1% level of significance, except for Romania. This is the only exception not only among the exponential autoregressive model, but for the PFT model as well. The above outcomes can be considered as markets' inefficiencies. As we mentioned before, it is possible that the basis of this particular type of autocorrelation is related to asynchronous trading.

A comparison between results that arose by each model is illustrated in Figure 5.11. According to this, the sign of coefficient β_2 remains constant for eight cases, i.e. negative for Turkey, Israel and Greece, and positive for Ukraine, Russia, Slovenia, Cyprus and Serbia. Sign turns from positive to negative, or vice versa, when the exponential autoregressive approach is employed for Poland, Czech Republic, Croatia and Romania. For the last case the coefficient β_2 is not statistically important in the exponential autoregressive model. Hence, it can be concluded that the behavior of the coefficient β_2 remains relatively stable in general among the two approaches.

Figure 5.11 Coefficient β_2 in PFT and EA models



After coefficient β_2, the results about coefficient β_3 that links autocorrelation to volatility are examined. As Table 5.4 illustrates, coefficient β_3 is statistically important for all markets at 1% level of significance, with the exception of Czech Republic. Hence, it can be inferred that a feedback strategy is present in the vast majority of stock markets as an essential factor for short-terms movements. In other words, share returns of the above eleven stock exchange markets seem to be connected to their past history in a nonlinear way, meaning that past returns can be employed to improve the techniques of forecasting.

Of course, β_3 should be both negative and statistically significant for the presence of positive feedback trading. This means that investors buy stocks after prices increase and they sell after prices decrease. These conditions are confirmed for four countries: Russia, Serbia, Turkey and Romania. On the other hand, coefficient β_3 is positive and statistically important for seven share markets: Israel, Poland, Croatia, Slovenia, Ukraine, Cyprus and Greece. This means positive autocorrelation in daily stock returns and negative feedback trading. So, investors buy stocks after prices decrease and they sell after prices increase. These results concur with the findings of Koutmos et al. (2006) for Cyprus, where researchers noticed a positive and statistically important β_3 coefficient by using the LeBaron model. Furthermore, as it is revealed by equation (13), whenever volatility is high the magnitude of autocorrelation is degraded, while during periods of lower volatility the magnitude of autocorrelation is enhanced.

Figure 5.12 shows the values of coefficient β_3 according to the exponential autoregressive model. They present a range from -0.644 for Russia till 0.274 for Greece.

Figure 5.12 Coefficient β_3 in the EA model

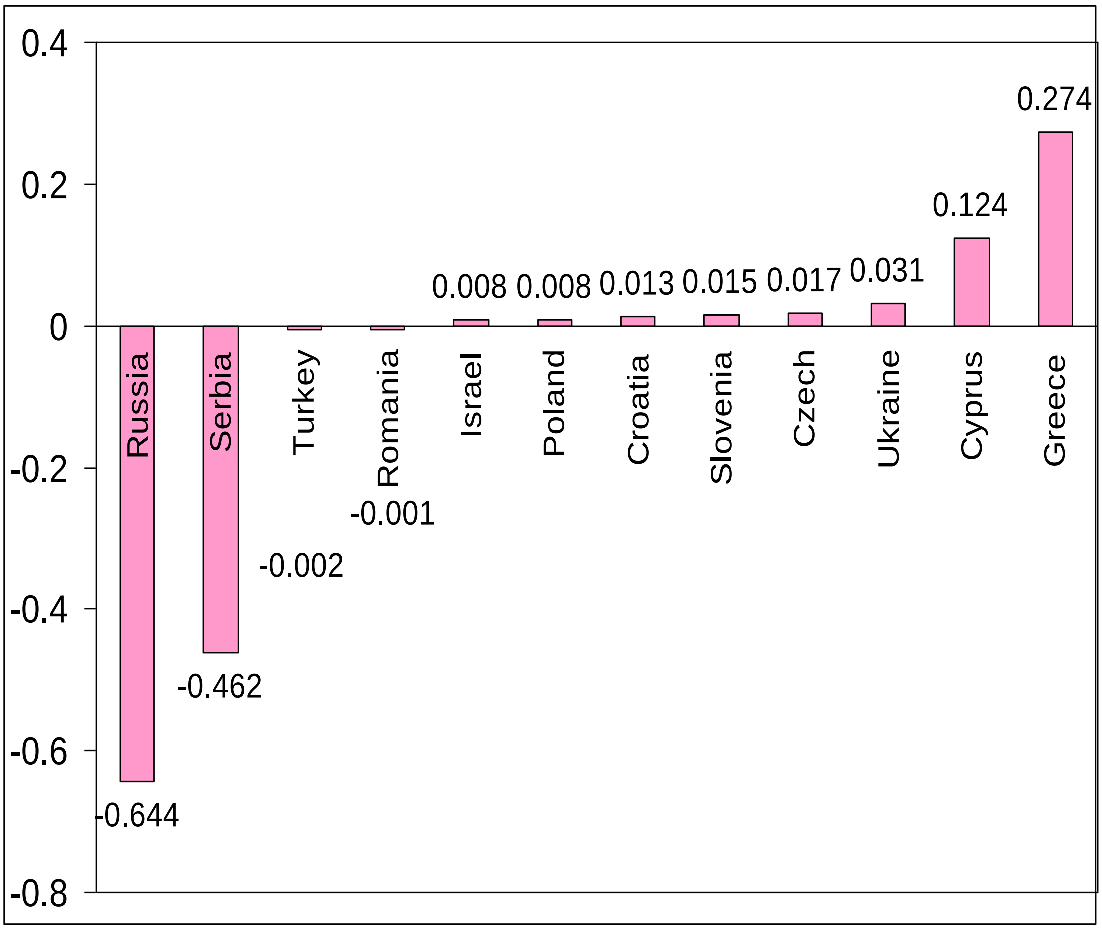


Table 5.5 organizes markets by the signs of coefficients β_2 and β_3 for both approaches, which for reasons of simplicity we call as feedback trading model and exponential autoregressive model, forming four groups.

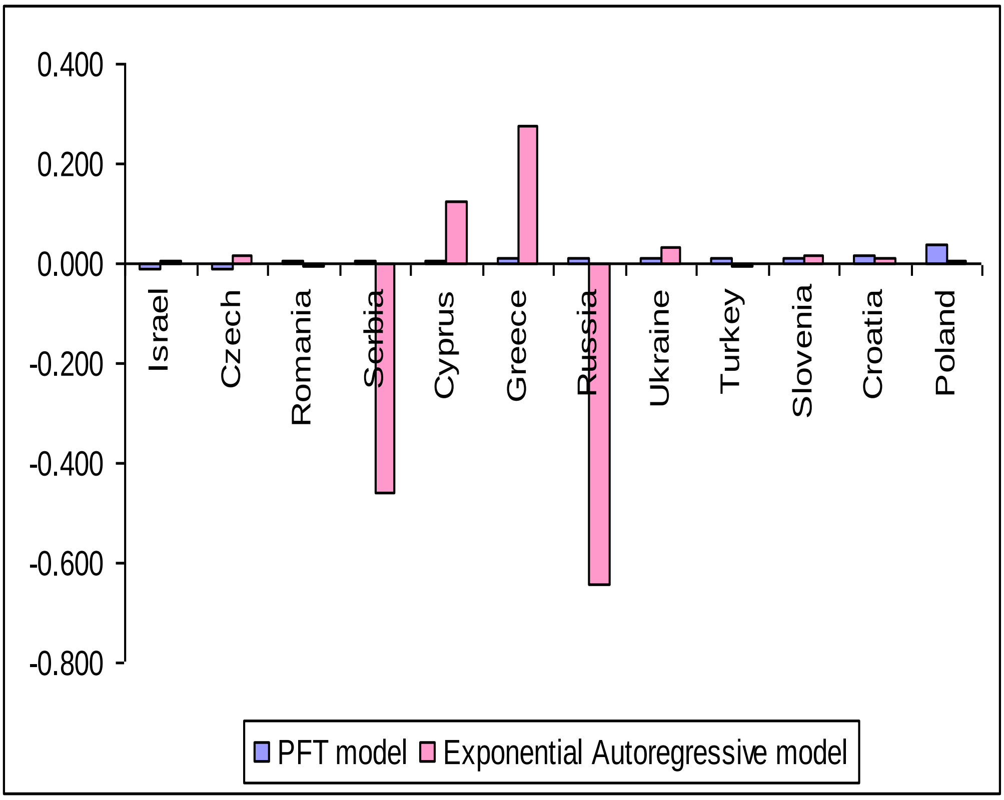
Table 5.5 Markets classified by coefficients β_2 and β_3

Negative β_2 and negative β_3	Negative β_2 and positive β_3
Israel *Romania, Turkey*	Greece, Poland, Turkey *Croatia, Czech, Greece, Israel*
Positive β_2 and negative β_3	Positive β_2 and positive β_3
Czech Republic *Russia, Serbia*	Croatia, Cyprus, Romania, Russia Serbia, Slovenia, Ukraine *Cyprus, Poland, Slovenia, Ukraine*

Feedback trading
Exponential autoregressive

As it can be seen in Table 5.5, four countries, namely Cyprus, Greece, Slovenia and Ukraine, remain into the same "box" (quadrant) for both approaches. For the remaining of them at least one out of two coefficients has different sign in each model. These results mean that (as data is the same for each sample) a researcher can reach into different conclusions by using the one or the other model. The icon of Figure 5.13 about coefficient β_3 is helpful to realize this disunion.

Figure 5.13 Coefficient β_3 in PFT and EA models



As it can be seen by Figure 5.13, feedback strategy turns from negative to positive –or vice versa– for Israel, Romania, Serbia, Russia and Turkey, being at the same time statistically important. So, the one model denotes for positive feedback strategy, while the other indicates for negative feedback strategy, for the same sample data. These mixed results presented by Table 5.5 and Figure 5.13 unavoidably raise the question which of the two models can describe reality in a more appropriate manner. In order to reach into a conclusion, we employ the Akaike Information Criterion (AIC). AIC is a measure of the relative quality of statistical models for a given set of data. It will estimate the quality of feedback trading model and exponential autoregressive model, relative to each other for the same sample of data for each country. AIC provides a comparative estimate of the information lost when the one or the other model is used to represent the process that generates the outcomes from a particular data base.

Following Akaike (1974) the AIC values are calculated for each model and for each sample by employing the next formula:

$$AIC = -2\text{Log-likelihood} + 2k \qquad (14)$$

where k is the number of estimated parameters in the model. The preferred model is the one with the minimum AIC value. This is because the lower the price is, the fewer the lost information. To apply AIC in practice, the values for every case are calculated according to equation (14). Then the outcome of $\exp[(AIC_{min} - AIC_{max})/2]$ can be interpreted as the relative probability that the AIC_{max} model minimizes the (estimated) information loss. Results are shown in Table 5.6

Table 5.6 AIC for the PFT model and for the exponential autoregressive model

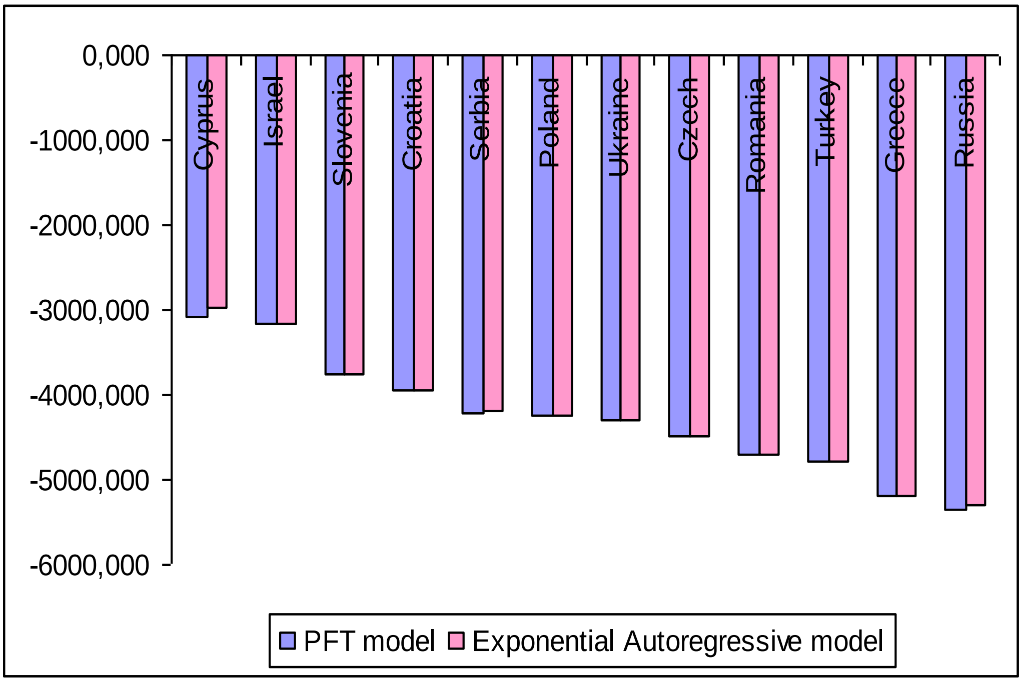
Country	AIC_{PFT}	AIC_{EA}	$\exp[(AIC_{min} - AIC_{max})/2]$
Croatia	7873.48	7873.48	1.000
Cyprus	6154.314	5955.084	0.001
Czech Republic	9000.294	8988.778	0.003
Greece	10365.18	10365.18	1.000
Israel	6324.54	6324.54	1.000
Poland	8494.304	8494.304	1.000
Romania	9389.288	9389.288	1.000
Russia	10713.26	10585.57	0.001
Serbia	8452.642	8371.462	0.001
Slovenia	7492.686	7492.686	1.000
Turkey	9581.364	9581.364	1.000
Ukraine	8590.714	8590.714	1.000

AIC values are equal for a given country, no matter the employed model, for eight out of twelve occasions, while the exponential autoregressive model appears lower values for the remaining of them. This means that regarding Cyprus for example, the feedback trading model is 0.001 times as probable as the exponential autoregressive model to minimize the information loss. For Serbia and Russia, where there are converse results about the sign of the coefficient β_3, AIC is lower for exponential autoregressive model, since this approach achieves to minimize the information loss. In this sense, exponential autoregressive model is the preferred one. However, it is noteworthy that while for Israel, Romania and Turkey feedback strategy turns from negative to positive –or the other way around– the AIC value remains unchanged between the two approaches.

Beyond the Akaike Information Criterion, the likelihood function is used in addition. The likelihood function indicates how likely the observed sample is as a function of possible parameter values. As was the case for the feedback trading model, the natural logarithm of the likelihood function, called the log-likelihood, is employed. This approach is preferable as the logarithm is a monotonically increasing function, so it achieves its maximum value at the same point as the function itself. It is reminded that higher price of log-likelihood is better than lower.

Consistent with the findings of Akaike information criterion, log-likelihood values obtained by each model are equal to the corresponding of the very same eight samples. Values are different only for the remaining four countries, i.e. Cyprus, Czech Republic, Russia and Serbia. Actually, prices of the exponential autoregressive model are superior for both criterions, as they are lower for the Akaike information and higher for the log-likelihood function. Figure 5.14 illustrates the outcomes about the log-likelihood for both models as they are reported in Tables 5.1 and 5.4

Figure 5.14 Log-likelihood estimations in PFT and EA models



Skewness characterizes the degree of asymmetry of a distribution around its mean. In other words, it is the degree of departure from symmetry of a distribution. A positively skewed distribution has a "tail" to the right, while a negatively skewed distribution has a "tail" to the left. Figure 5.15 illustrates that skewness is positive for eight countries. Namely: Greece, Czech Republic, Ukraine, Cyprus, Croatia, Israel, Russia and Serbia. Thus, less in number and sharper in intense values are observed on the left of the returns' mean and therefore more in number and softer in intense values are on the right of it. Antithetically, Slovenia, Romania, Poland and Turkey present negative skewness implying that more in number and softer in intense prices are observed on the left of the mean, while less in number and sharper in intense are appeared on the right of it. Of course, normal distributions produce a skewness statistic of zero. So, as the null hypothesis about skewness cannot be rejected for Greece at 1% level of significance (Table 5.4), it can be concluded for normal distribution. The null hypothesis is not rejected as well, but at 10% level of significance this time, for Turkey. Finally, null hypothesis about zero skewness is rejected for the remaining occasions.

These results about skewness for the exponential autoregressive model are not quite similar to those for the first feedback strategy model. In particular, for Russia, Czech Republic, Greece and Ukraine skewness was negative according to positive feedback trading model, while it is changed to positive according to exponential autoregressive model. However, the sign of skewness remains unaffected for the majority of data sets. Also, although the sign for Greece is changed, the price of skewness (as we have mentioned above) is not statistically important. Moreover, at both approaches, skewness for Greece remains |in absolute terms| the lowest among the samples.

Another pattern that one can detect is that skewness in exponential autoregressive model tends to be lower |in absolute terms| than the corresponding in the positive feedback trading model. This is the case for nine out of twelve occasions, with the exceptions only of Romania, Serbia and Cyprus. Thus, it can be concluded that the exponential autoregressive approach "normalizes" the distribution. Figure 5.16 presents the results about skewness for the two models, simultaneously.

Figure 5.15 Skewness of residuals in the EA model

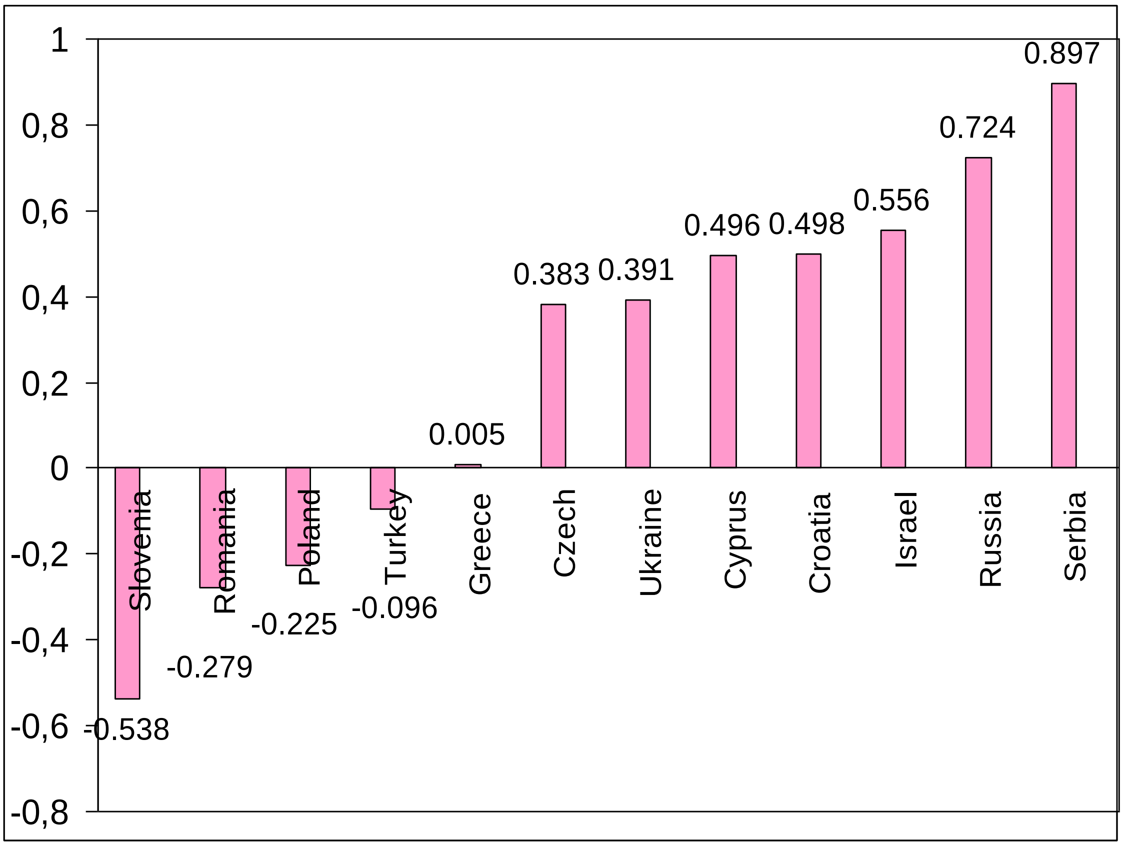
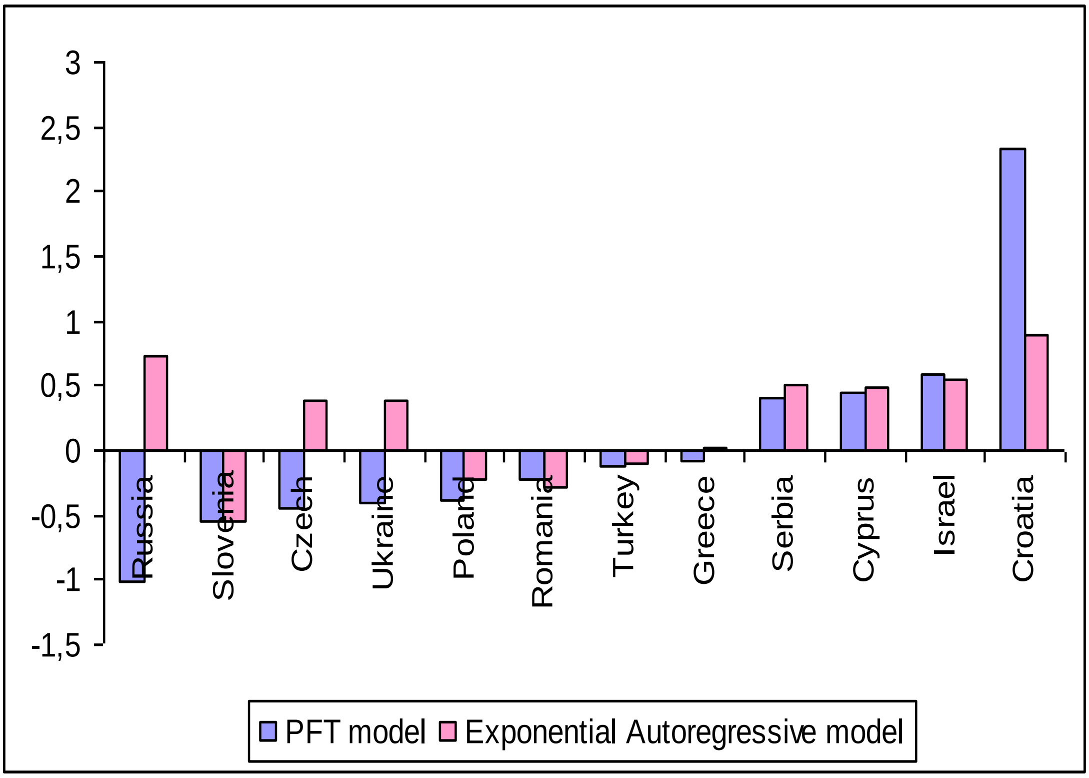


Figure 5.16 Skewness in PFT and EA models



As deviations from normality may display combinations of both skewness and kurtosis presences, it would be appropriate to extend the study by examining for kurtosis as well, in order to get a more spherical view. Kurtosis is the degree of "peakedness" of a distribution. A normal distribution is a mesokurtic distribution. A pure leptokurtic distribution has a higher peak than the normal distribution and has heavier tails. A pure platykurtic distribution has a lower peak than a normal distribution and lighter tails. According to Table 5.4 the null hypothesis is rejected at 1% level of significance for every case. So, we cannot conclude about normality as far as the kurtosis measure is concerned. Israel presents the lowest kurtosis, with a value of 3.533. It is noteworthy that the smallest kurtosis for the positive feedback trading model was for Israel, as well. In contrast, kurtosis meets its highest price for Serbia. In particular, for this case kurtosis is equal to 18.646. Analytically, Figure 5.17 illustrates the results for each market.

It is remarkable that kurtosis prices that are obtained by the exponential autoregressive model are lower than the corresponding values which are received by the first feedback trading model for eleven out of twelve occasions, with the unique exception of Serbia. Hence, adopting the exponential autoregressive model may heal the abnormality of distribution, at least up to an extent. Figure 5.18 provides a picture about kurtosis for both formulas at the same time.

Figure 5.17 Kurtosis of residuals in the EA model

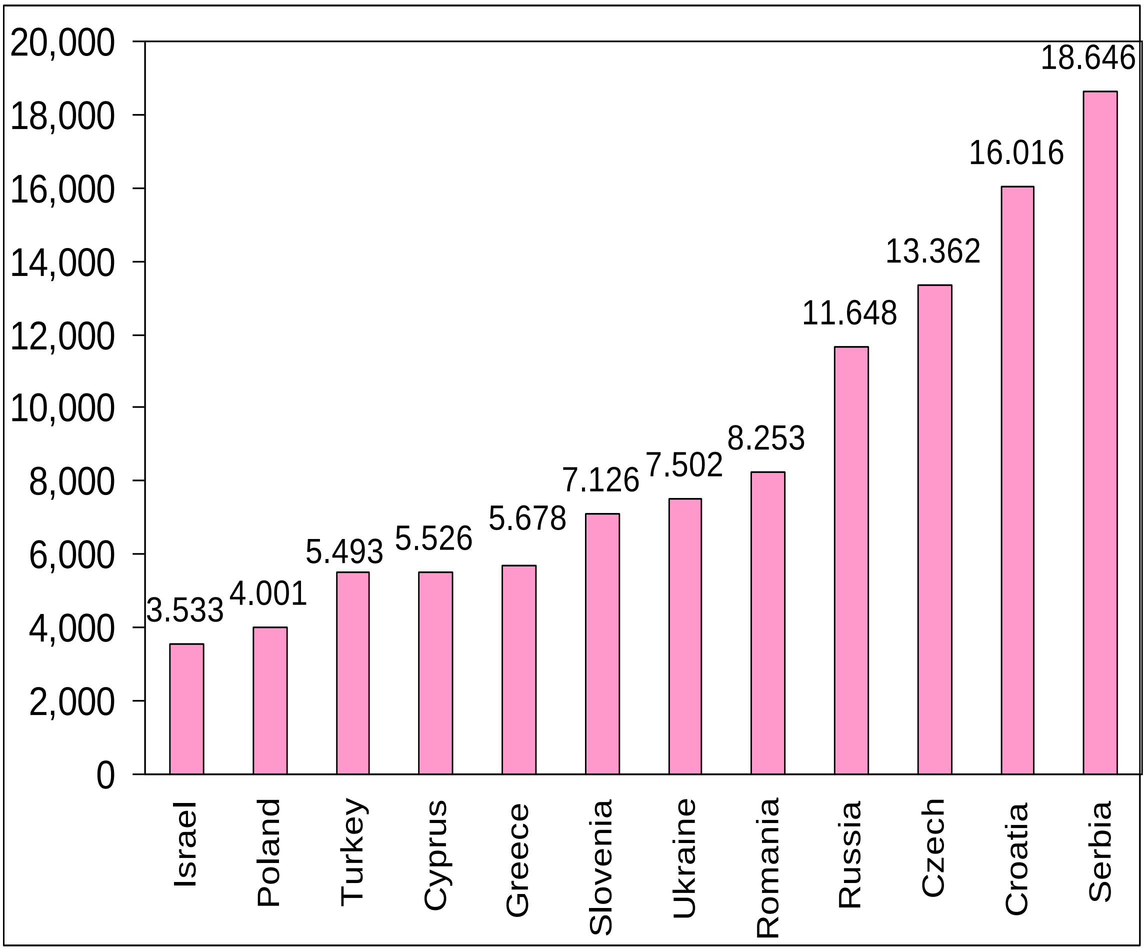
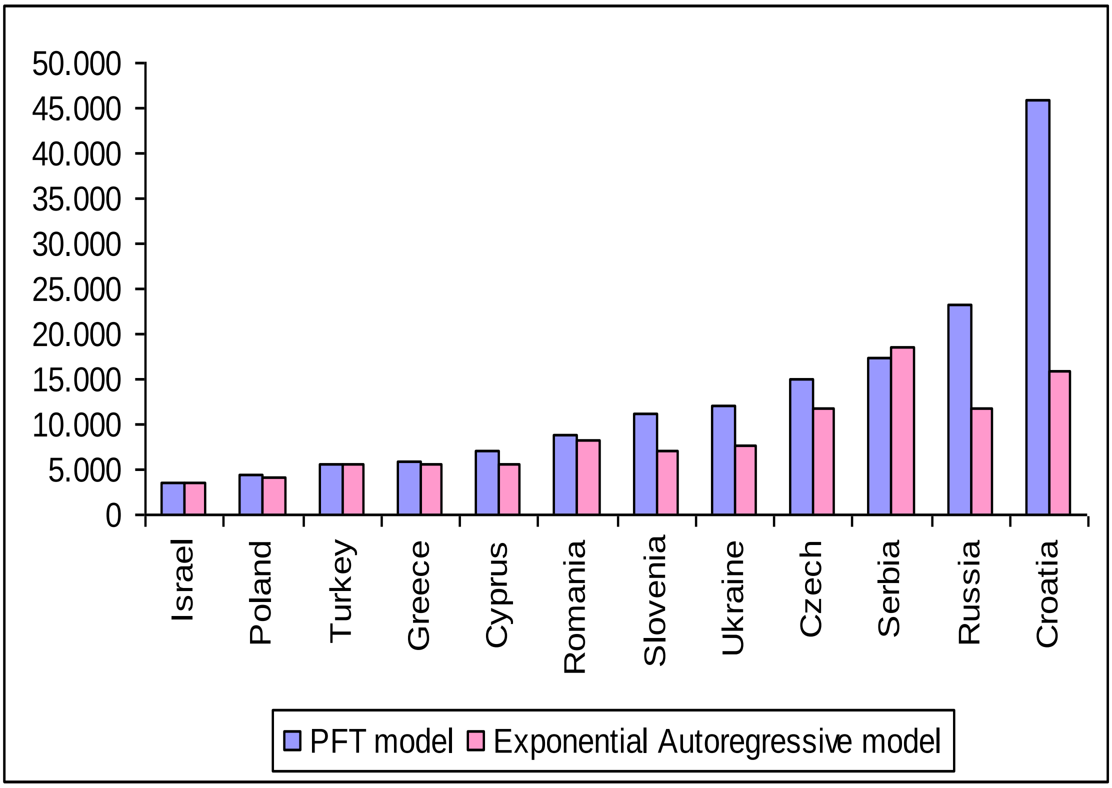
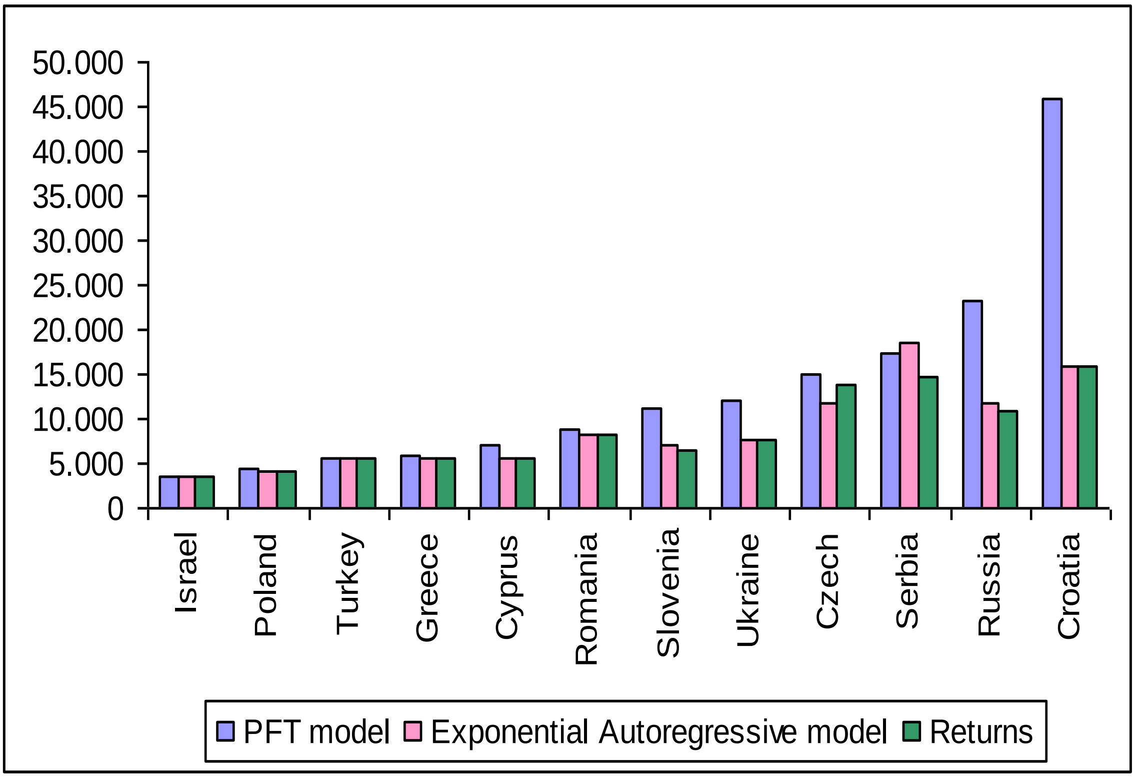


Figure 5.18 Kurtosis in PFT and EA models



Enriching Figure 5.6, results about kurtosis are compared not only for "returns" and "standardized residuals obtained by the PFT model", but for "standardized residuals obtained by the exponential autoregressive model" as well. It is reminded that, the kurtosis measures of the standardized residuals obtained by the feedback model were not lower than the respective excess kurtosis measures of stock returns. However, as it seen by Figure 5.18, the "standardized residuals obtained by the exponential autoregressive model" are firmly smaller than those of the PFT model. This brings up the question whether kurtosis of the "standardized residuals obtained by the exponential autoregressive model" is more moderate than the corresponding kurtosis of "returns". This hypothesis is confirmed only for four cases: Poland, Cyprus, Ukraine and Czech Republic. The greater reduced price is presented for Czech Republic, which is equal to 2.149. Thus, modeling of nonlinearities could lead into kurtosis' reduction for these samples. On the other hand, for Israel, Turkey, Greece, Romania, Slovenia, Serbia, Russia and Croatia kurtosis about "returns" remains lower than the corresponding kurtosis about "standardized residuals" obtained by any of the two models. These outcomes underline that modeling of data did not manage in general to lead distribution closer to normality. The largest difference between kurtosis of "returns" and kurtosis of "standardized residuals obtained by the PFT model" is for Croatia, with a value of 30.083. In parallel, the biggest difference between kurtosis of "returns" and kurtosis of "standardized residuals obtained by the exponential autoregressive model" is for Serbia, with a value of 3.961. Closest differences |in absolute terms| for both formulas are observed in Turkish stock market: -0.115 for the first feedback trading model and -0.015 for the exponential autoregressive model. Figure 5.19 involves kurtosis for every occasion.

Figure 5.19 Kurtosis of returns and standardized residuals in PFT and EA models



In order to test whether the series of observations of each sample are random and independent over time, we employ the Ljung-Box test for the exponential autoregressive model, as we did for the initial feedback trading model. If observations are not independent, of course there is autocorrelation. The Ljung-Box statistic tests the null hypothesis that autocorrelations up to a chosen lag equal zero. That is, the data values are random and independent up to a certain number of lags, in our case 20. When the Ljung-Box price is greater than a specific critical value, autocorrelations for lags may be considered as significant different from zero, indicating that values are not independent and random over time.

According to Table 5.4 the null hypothesis (for twenty lags in the residuals) cannot be rejected for Cyprus, Poland and Turkey at 1% level of significance, for Israel at 5% level of significance and for Greece at 10% level of significance. So, for these cases and for the corresponding levels of significance, there are no evidences about autocorrelation existence, supposing random and independent series of observations over time. In contrast, the null hypothesis is rejected for seven out of twelve cases, concluding that autocorrelation is statistically different than zero and the series of observations of each sample are not random and independent over time. The Ljung-Box coefficients range from 20.525 for Cyprus till 168.852 for Croatia. Results are illustrated in Figure 5.20

The above results about the Ljung-Box test for twenty lags as far as the exponential autoregressive model is concerned, are quite similar to the corresponding outcomes obtained by the feedback trading model. The null hypothesis cannot be rejected for Poland and Turkey at 1% level of significance and for Greece at 10% level of significance for both approaches. The exponential autoregressive formula allows for reduced Ljung-Box statistics in seven countries (Poland, Israel, Cyprus, Ukraine, Serbia, Russia and Croatia), while for the remaining five countries the feedback trading model marks lower prices, signifying that the first group of markets present less autocorrelation according to the exponential autoregressive model, while the latter group appear less autocorrelation according to the feedback trading model. Figure 5.21 displays outcomes of both models in parallel.

Figure 5.20 Ljung-Box (20) statistics for residuals in the EA model

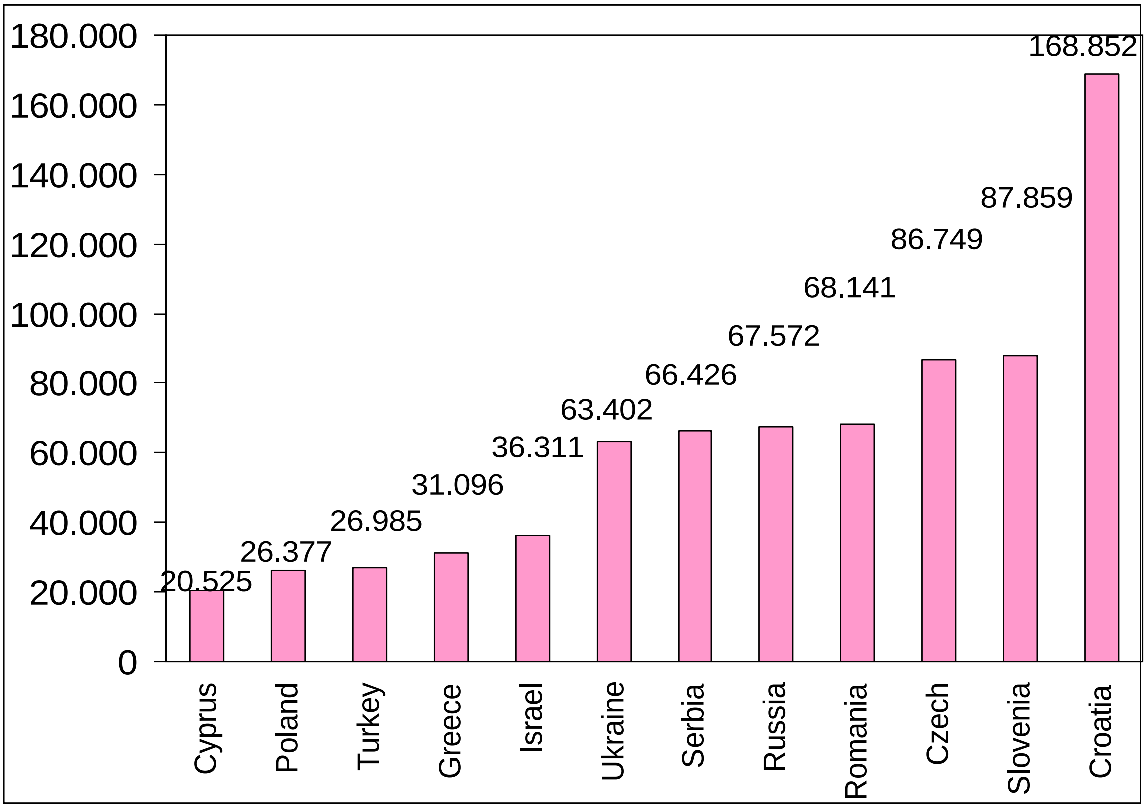
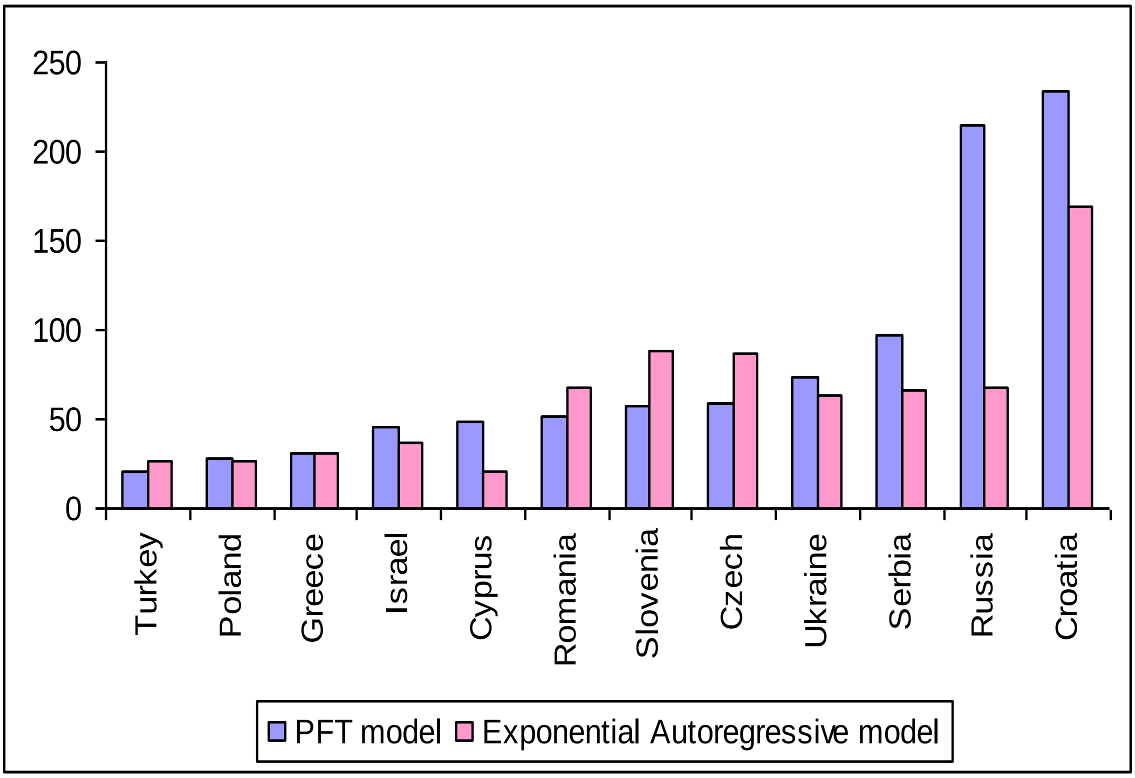


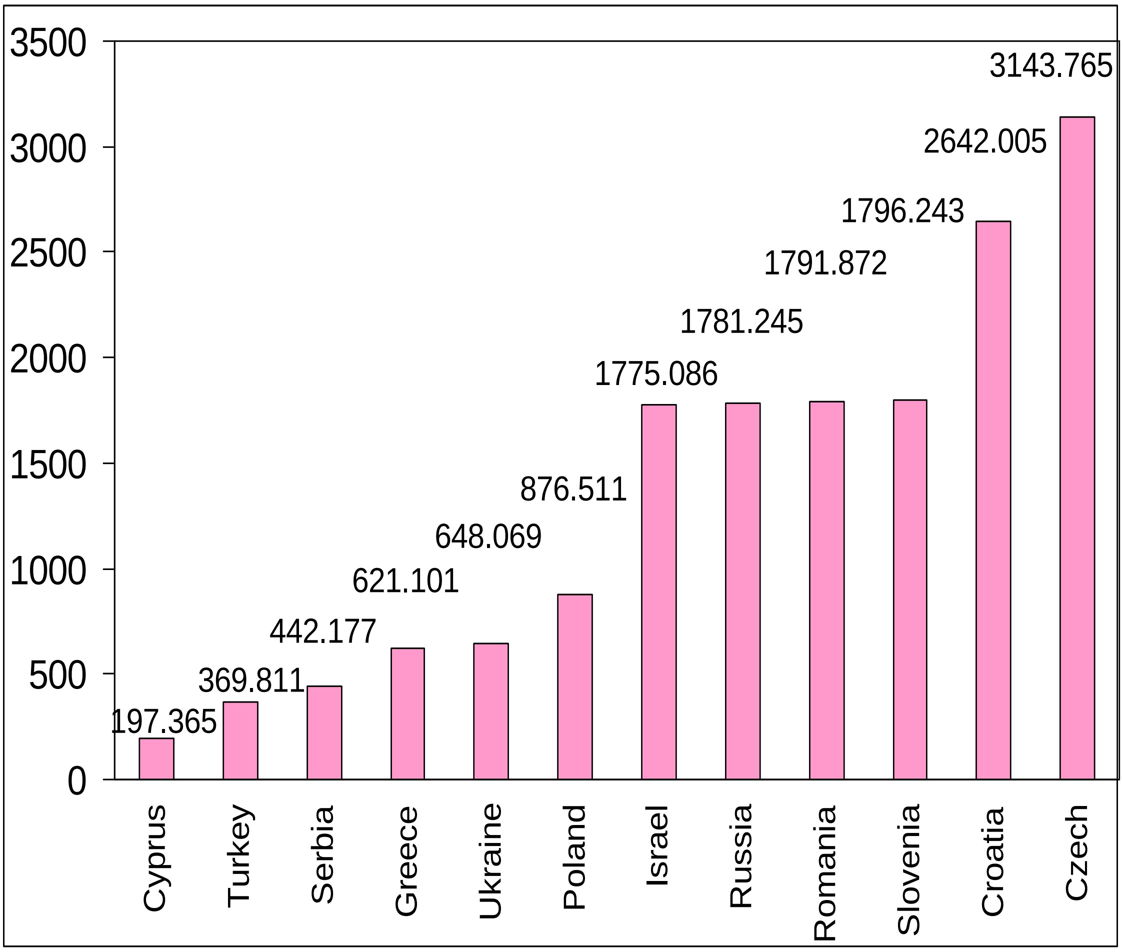
Figure 5.21 Ljung-Box (20) statistics for residuals in PFT and EA models



Beyond testing for autocorrelation, the Ljung-Box test can be used for checking conditional heteroscedasticity. This can be achieved by conducting a Ljung-Box test on the squared residual of observations. The estimated Ljung-Box statistics for twenty lags in the squared residuals test for nonlinear or in other words for second-moment temporal dependencies. The null hypothesis states about the existence of normality and homoscedasticity into the sample under examination. That is, that all autocorrelations up to the 20th lag are jointly statistically equal to zero. The alternative hypothesis declares the absence of homoscedasticity and therefore the presence of heteroscedasticity. That is, that all autocorrelations up to the 20th lag are jointly statistically different than zero.

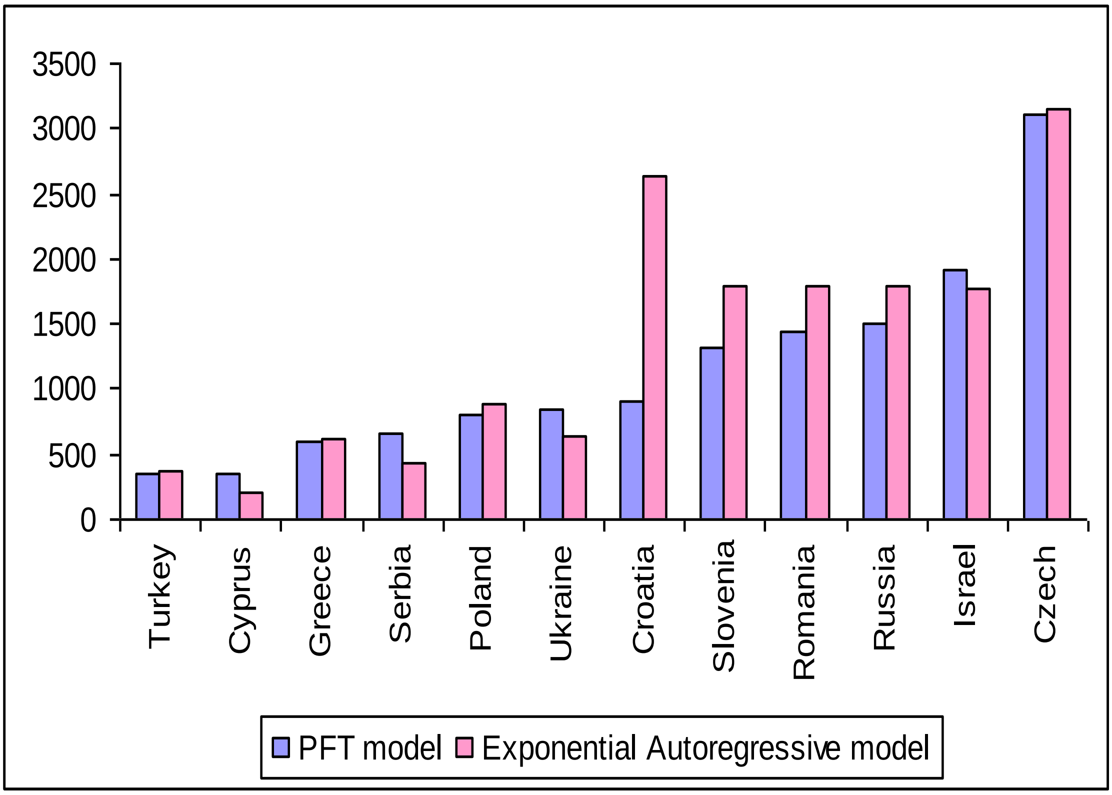
As it can be seen by Table 5.4, the null hypothesis is distinctly rejected at 1% level of significance for all cases with no exceptions. Results about squared Ljung-Box (20) statistics are presented in Figure 5.22.

Figure 5.22 Ljung-Box (20) statistics for squared residuals in the EA model



Based on the above results, it can be concluded that the null hypothesis about the existence of normality and homoscedasticity is rejected at 1% level of significance for every country by both models. However, values of the Ljung-Box statistic for twenty lags as far as the squared residuals is concerned, differ among the two different approaches. Specifically, the exponential autoregressive approach achieves lower Ljung-Box statistics for four cases. Namely: Cyprus, Serbia, Ukraine and Israel. At the same time, prices obtained by the initial feedback trading model are lower for the remaining eight samples. These results underline that first group of countries illustrate less heteroscedasticity for the exponential autoregressive model, while the second one show less heteroscedasticity for the Sentana - Wadhwani feedback trading model. Figure 5.23 presents results for both formulas synchronously.

Figure 5.23 Ljung-Box (20) statistics for squared residuals in PFT and EA models



Focus on coefficient d, as it is set by equation (8), allows checking for long-term dependence on the conditional variance. For the FIGARCH(1,d,1) approach all series can be estimated in terms of parameter “d”, allowing for prices higher than zero and lower than one. As a result, series can be either stationary as long as d is between 0 and 0.5, or mean reverting whether d is higher than 0.5 and lower than 1, with the effect of shocks dying away in the long-run. As it can be seen by Figure 5.24, d values are between 0 and 0.5 for stock markets of five countries. Specifically, these countries are Russia, Cyprus, Greece, Poland and Romania. This implies for stationery series. However, these results stay in harmony with the corresponding of the PFT model only for Poland and Romania. In parallel, d is greater than 0.5 for Slovenia, Serbia, Israel, Turkey, Croatia, Ukraine and Czech Republic. Hence, for this group of samples, series are mean reverting, which means that shocks to the conditional variance are ultimately die out. Again, these outcomes are in agreement with the corresponding results of the feedback trading model only for three cases: Ukraine, Slovenia and Czech Republic. Consequently, for seven countries (Cyprus, Greece, Russia, Israel, Turkey, Serbia and Croatia) the selection of different formulas leads into contradictory conclusions about interpretation of d parameter. Finally, d coefficient is statistically important at 1% level of significance for every case and method, with the exception of Turkey for the feedback trading model. Figure 5.25 presents mixed results about d coefficient for both approaches.

Figure 5.24 Coefficient “d” in the EA-FIGARCH(1,d,1) model

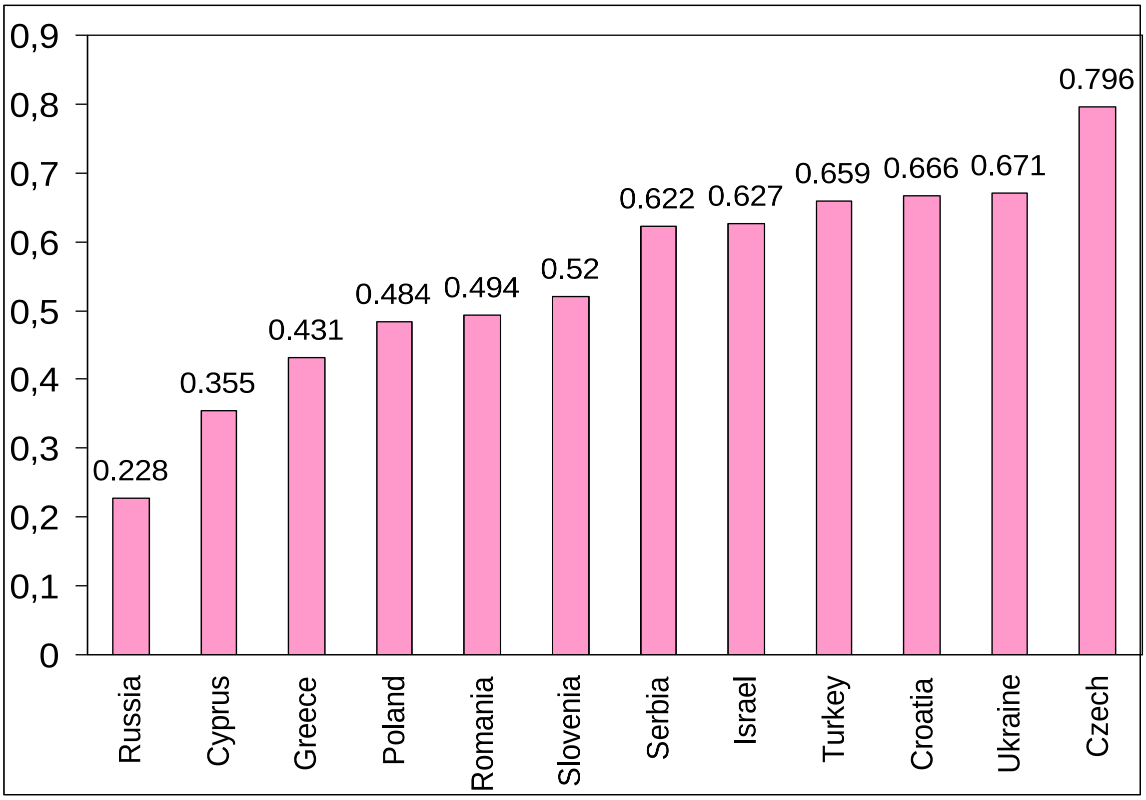
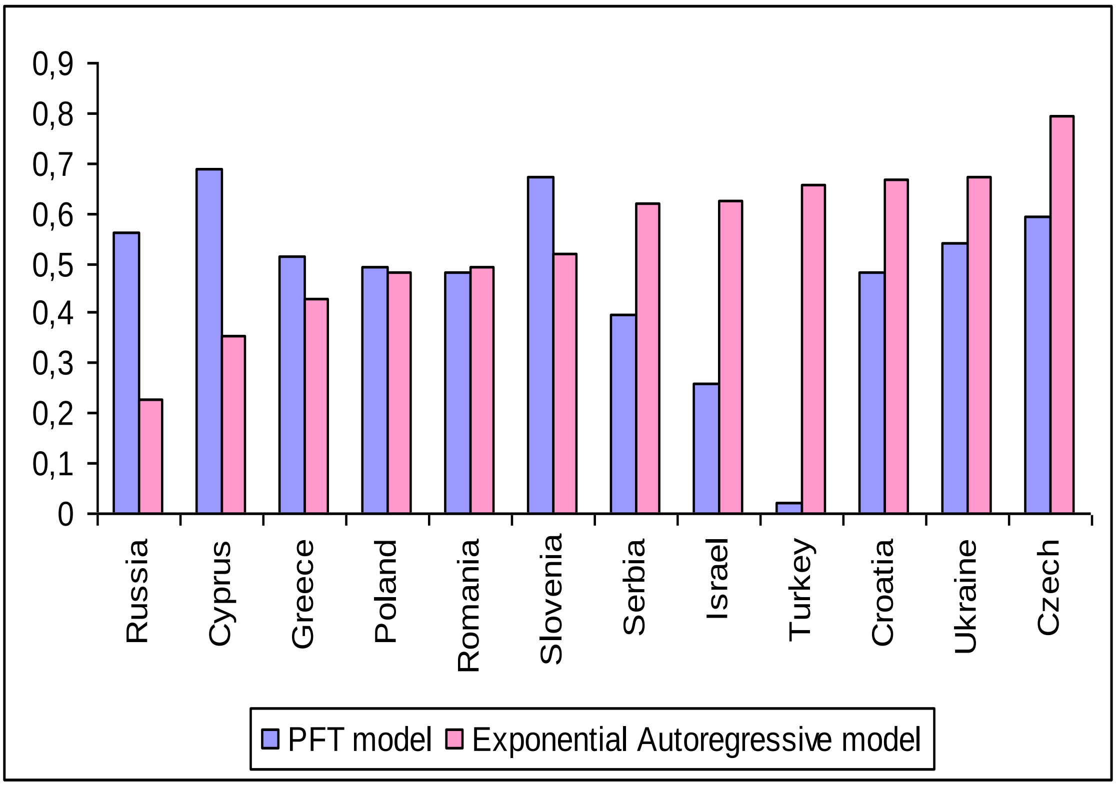


Figure 5.25 Coefficient “d” in PFT and EA models



6. Epilogue

This paper examined the behaviour of traders on twelve stock markets from some chosen Balkan, Slavic and Eastern countries. Alphabetically: Croatia, Cyprus, Czech Republic, Greece, Israel, Poland, Romania, Russia, Serbia, Slovenia, Turkey and Ukraine. Specifically, it was investigated whether feedback strategies were popular among speculators. The main idea behind traders who adopt feedback strategies is that this kind of speculators does not base their decisions on firms’ fundamentals –as “rational” investors do– but rather on current tendencies of stock prices.

Feedback trading method can be divided into two categories, the positive feedback trading approach and the negative feedback approach. Speculators’ movements that follow the one or another approach are determined (in any case) by stock prices returns, but in a different way. Particularly, positive feedback traders walk according to last patterns, while negative feedback traders prefer to stand contrary to these trends. The first group buy stocks when prices rise and sell when prices fall. In contrast, the second group buy stocks when prices fall and sell when prices rise. In this way, the one set augment the destabilization and the removal from fundamentals, while the second set contributes to stabilization. Despite the apparent antithesis, actually the two groups address two aspects of the same situation, as both sets of speculators base their transactions not on companies’ balance sheets, promising dividends and bad or good news, but on prices changes.

The authentic other side of feedback traders are the so-called rational investors, who analyse companies’ fundamentals. They plan on a certain proportion of return via stock price increase and/or dividend policy of listed firms, with limitation to their available amount for investment. Theoretically, the first pack of speculators adopt short-term decision horizon and the second group of investors are long-term. In any case, only ex-post analysis can answer which approach is more successful each time.

In order to test whether feedback strategies were present in the examined stock markets during period under investigation, two equations were formed in parallel: firstly, the Sentana and Wadhani (1992) formula as it is expressed by equation (12), and secondly the LeBaron (1992) exponential model as it is described by equation (13). Both approaches should produce a negative and statistically important β_3 coefficient as evidence for the existence of positive feedback trading phenomenon.

Empirical results revealed that coefficient β_3 was statistically different than zero for almost any case, with the only exception of Czech Republic and just for the exponential model. This means that feedback trading strategies existed in the examined stock markets. As far as the sign of coefficient β_3 is concerned, it was negative for Czech Republic and Israel according to the first approach, while for the second approach it was negative for Romania, Russia, Serbia and Turkey. Thus, feedback trading was positive for these occasions, whereas it can be considered as negative for the remaining cases where coefficient β_3 was not only over zero but statistically important too.

Trying to provide an explanation for the above findings, it can be stated the obvious, i.e. traders in these markets do not trust generally long-term investments and they do not pay great attention on fundamentals. It is logical, the background for such a behaviour to have different sources among various markets. One reasonable explanation could be that citizens of these countries prefer to invest long-term in assets like houses and real estate rather than shares as perhaps people in Central and Western Europe do. Also, these markets can be characterised as quite “shallow” relatively to mature markets and thereby stock prices are easier to be manipulated. This is therefore good reason for rational investors to avoid shares’ acquisition, letting room for feedback strategies to dominate in markets. In parallel, macroeconomic domestic recession, instable tax environment about listed companies and received dividends, and lack of investing culture may enhance feedback trading.

Moreover, the direction of feedback strategy was another interesting finding of this study. In particular, negative feedback trading dominated positive feedback trading for the majority of cases (18 out of 24). Thus, speculators buy when prices fall and -maybe the most important- sell without hesitation after prices rise. This is probably an omen of lack of belief on stock markets long-term. In other words, as negative feedback prevails over positive feedback, it can be concluded that cautiousness prevails over enthusiasm. Needless to say that, every stock market is a different case. Nevertheless, in general terms, financial stability and a constant law frame could gradually strengthen the confidence of local traders in stock exchange organizations and in parallel attract international institutional investors, who by and large select shares based on fundamentals.

However, it is essential to underline that rational investors are not a priori more successful than feedback traders. This is because sometimes predicting crowd’s future reactions is more important than studying fundamentals, especially when a big number of poorly informed and inexperienced traders act in the market. Hence, adopting a (let’s name it) pro-feedback trading strategy or in other words an adjusted to potential feedback demand and supply strategy, may ensure more profits than traditional rational investment. Needless to say that if the one or another strategy leads in systematic losses, the followers of that particular strategy unavoidably will be ostracized out of market.

Focusing on some more technical matters, it was revealed that the exponential autoregressive model seems to perform better than the first feedback trading model, in the sense that prices of the exponential autoregressive model were lower for some cases for the Akaike information criterion and in parallel higher for the log-likelihood function. This means that prices of the exponential autoregressive model may be considered as preferable as first feedback trading model failed to produce superior results.

Results about coefficient d, as it was set by equation (8) in order to check for long-term dependencies on the conditional variance, revealed that using one or other model can lead into contradictory conclusions about the interpretation of d parameter. These findings may cast a shadow over the reliability of the employed mathematical tools, as it is not clarified if series were stationary or mean reverting.

In conclusion, we found evidences about mainly negative feedback trading strategies into the stock markets under examination. Our hope is present research to contribute into academic bibliography and in addition to prove a useful tool for financial institutions and individual traders. A field of future investigation could be the test whether feedback trading strategies are still “alive” during more recent years. In addition, it would be interesting to explore the actual (ex-post) return of, on the one hand a typical rational investor that purchases and holds a portfolio for a certain long-term time period, and on the other hand of two average feedback traders for the very same time period, one that follows positive feedback strategy and one that adopts negative feedback trading, to ascertain after all which methodology can lead into higher yields for each stock market.

Concluding remarks

The research reported in this thesis has investigated the return and volatility spillover effects as well as the feedback trading strategies phenomenon on twelve equity markets of some selected Balkan, Slavic and Eastern countries. This final segment summarizes some of the most distinctive points and underlines the main conclusions drawn from the empirical investigation. Besides, includes suggestions for future work, in order the formulas it introduces to be further developed.

One basic aim of present study was to explore empirically the transmission mechanisms about stock price returns and stock price volatilities for the twelve countries under examination. For that purpose, an augmented univariate AR(1)-EGARCH(1,1) model was applied, initially proposed by Nelson (1991).This formula catches both sign and size of innovations, allowing to check whether shocks originating from one period can affect return and volatility of next period in an asymmetric way.

Undoubtedly, an obvious contribution of the thesis is the introduction into the basic model about spillover effects of not only the trading volume variable, but also of two additional explanatory variables. Namely, the exchange rates’ fluctuations and the S&P 500 index returns. Furthermore, a combination of the mentioned above parameters was employed by merging into a single mathematical sentence both extra variables, with and without liquidity.

Empirical results revealed that indeed there were return and volatility spillovers, at least for most of the cases through the various approaches. In detail, coefficient about return spillovers proved to be positive and statistically important for two-thirds of cases, while the parameter of volatility spillovers was positive and statistically significant for almost every occasion, with only one exception.

Another contribution of the thesis is the knowledge derived from the empirical tests about the behavior of the leverage effect not only into basic formulas but also in the prototype models with the additional variables. Outcomes showed up that the leverage effect was widely present, since coefficient that catches asymmetry was negative and statistically important for 68 out of 96 equations.

In addition, findings revealed that liquidity accounted for spillovers according to newly modeled models, since trading volume variable proved to be statistically important in 40 of the 48 cases; even, the coefficient was significant with a positive sign 35 times.

As far as the extra explanatory variables is concerned, the exchange rates of each Balkan, Slavic and Oriental country's domestic currency related to the US dollar was found positive in 40 of the 48 cases and in parallel it was positive as well as statistically significant for 23. The other explanatory variable, that of S&P 500 index return, was confirmed as positive 39 times and additionally statistically important 28 times. Thus, the general concept is that since coefficients are mainly statistically different than zero, the inclusion of the additional variables -as they are introduced by this paper- improves the capability of the basic model to describe the spillovers patterns more accurately.

To confirm the above, the log-likelihood function was employed as a tool to compare the fit of different coefficient sets. As was evident from the findings, log-likelihood values, as an expression of optimal values of estimated coefficients, were greater when the trading volume variable was included in the models for most cases, and in particular at 41 out of 48. Furthermore, whenever one of the two extra explanatory variable was added in the models, log-likelihood prices were rising for almost every occasion. Moreover, models that included both explanatory variables and liquidity provided higher figures than models that extra variables were used separately. Hence, since higher numbers mean that the observed sample is more likely to be a function of possible parameter values, the conclusion that can be drawn is that utilization of these extra explanatory variables can shed some additional light on the conditional mean and variance and to contribute to spillovers analysis.

The next phase of the PhD was the examination of feedback trading strategies for the same pack of countries and for the same time period. Such a plethora of countries for so many years is another contribution of this study. For the purposes of the research, a pair of parallel models was employed. On the one hand, the feedback trading model introduced by Sentana and Wadhani (1992) and on the other the exponential autoregressive model suggested by LeBaron (1992). This theoretical background, together with a FIGARCH(1,d,1) approach allowed conclusions to be drawn about the possible presence of feedback traders in the stock markets which were investigated.

Empirical evidence obtained by these formulas revealed that coefficient which catches the potential feedback trading phenomenon was statistically different from zero for almost any case. These findings confirm that feedback trading strategies actually existed in stock markets under examination. Regarding the sign of the coefficient, it was positive for the majority of cases under both approaches. In view of these findings, it is concluded that primarily there was negative feedback trading. On the contrary, for rest of the cases this coefficient was less than zero and statistically important declaring the existence of positive feedback strategy. Generally, it can be argued that negative feedback trading prevailed over the positive feedback in the majority of cases. Hence, speculators mainly bought when prices were falling and -perhaps the most important- they sold without hesitation after a rising on prices.

The above findings may prove to be particularly useful for both individual and institutional investors. Results mainly highlight the lack of patience and the absence of confidence among shareholders in these stock markets. A rise in prices is likely to be followed soon by some form of decline. Speculators have to adapt to this environment in order to protect their investment.

A comparison between the two employed models, shows that the exponential autoregressive model managed to deliver more accurate results in the sense that prices of log-likelihood function were higher or equal according to this approach in relation to the corresponding results of Sentana and Wadhani equation. These findings can also be seen as a sign that researchers may need to prefer the exponential method.

The ambition of this study was to contribute into academic literature and in parallel to prove a useful tool for financial organizations and individual investors. Thesis also suggested other avenues for future research involving the enlargement of the sample of countries for more recent time periods, to test whether the phenomena under consideration have been preserved and in what form. A potential proposal about the part of return and volatility spillovers is to extend this study by adding some more extra explanatory variables into the equation models in order to reach a deeper analysis around the transmission mechanisms. Regarding the feedback trading strategies, it would be interesting to form two virtual portfolios, on the one hand a portfolio of a typical rational trader who acquires and maintains a number of shares for a certain period of time based on the foundations of the companies, and on the other hand two groups of feedback strategies speculators for the same amount of time. From these two groups, one will follow positive feedback trading, while the other will adopt negative feedback strategy. All three groups will invest the same amount of money, so that an ex post analysis of the empirical observed performance can be made about each approach and for each stock market. Generally, modern developments such as admirable advances in technology, lifting restrictions on capital movements internationally and increasingly growing interaction between markets will keep the themes of the present study constantly interesting.

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