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"Volatility Spillovers in stock markets in emerging & developing countries".

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Abstract

This master dissertation investigates volatility spillovers in stock exchange markets of four emerging and developing countries (Kazakhstan, Turkey, Poland and Russia). The data sample consists of daily observations from January 2009 to December 2019 and the methodology is based on an augmented univariate AR-EGARCH model. Two explanatory variables are introduced to the equations i.e. the trading volume of the stock indexes and the fluctuations of exchange rates. The results of the study confirm the presence of volatility and volatility spillovers in all the examined indexes. Trading volume and exchange rate also have an impact on the indexes and their volatility spillovers in most of the cases. Finally, the presence of leverage effect is also evident in most of the cases, which means that bad news/ shocks etc. impact, to a great extent, the indexes and volatility.

Key words: volatility spillovers, leverage effect, emerging and developing markets, AR -EGARCH.

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Abbreviations

AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BIST(100)	Borsa Istanbul (100)
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ER	Exchange Rate
EU	European Union
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
IMF	International Monetary Fund
KASE	Kazakhstan Stock Exchange
MA	Moving Average
MENA	Middle East and North Africa
MOEX	Moscow Exchange
S&P	Standard and Poor
TuL	Turkish Lira
TV	Trading Volume
US	United States
USD	United States Dollar
VIF	Variance Inflation Factor Test
WIG(20)	Warszawski Indeks Giełdowy(20)[1]

[1] In English : Warsaw Stock Exchange index.

1. Introduction

Volatility is one of the analysts “favorite” words. Rarely does a market forecast do without it. However, few people understand what volatility of markets and specific instruments means. In general, we could describe it as the changeability of a price. In other words, a sharp drop or increase in the price usually leads to high volatility, while when the price fluctuates around a certain point for a long time volatility decreases ("Moscow Exchange", 2020). From another point of view, volatility is seeing as a measure of dispersion around the mean or average return of a security (Bonga,2019)

For Banumathy and Azhagaiah (2015), volatility refers to the amount of uncertainty or risk about the size of changes in a security’s value. Volatility spillover effects, on the other hand, mirror the case in which market volatility is influenced by its own early stage and by volatility coming from other markets (Xiong & Han,2015). More simply, it is a process of spreading of risk from one place (market) to another. Volatility mostly increases when occur some important events, which tend to affect the market as a whole or as a specific instrument. Such cases can be the Central banks interest rate decisions (fed, ECB, national Banks etc.) the release of statistics on supplies of oil reserves (OPEC+ deal), geopolitical and global events (pandemic - coronavirus, terrorist attacks, global financial crisis etc.) and GDP statistics ("Moscow Exchange", 2020).

In the financial industry, especially in the subdivisions of risk management, portfolio distribution and pricing of financial instruments, understanding and modeling volatility and volatility spillovers are of pragmatic significance. Volatility directly or indirectly monitors asset return series, stock prices and foreign exchange rates (Bonga,2019).When volatility persists, securities firms cannot use freely and efficiently their available capital due to the need of retaining a larger amount of cash-equivalent investments, with the purpose of encouraging creditors and regulators. Whereas, in the case of high volatility is observed a decrease in the confidence of potential investors (Ibid.). Consequently, all stakeholders in financial markets, and especially investors are alarmed at volatility, thinking of the risk of the assets they invest in.

A way to measure volatility is by using the standard deviation or variance. Although, many researchers assume that the variance, as a measure of uncertainty, is constant through time, empirical evidences reject this assumption (Bonga, 2019). In 1982, Robert F. Engle presented the fact that economic time series display periods of unusually large volatility followed by periods of relative tranquility. Banumathy and Azhagaiah (2015), also, indicated that time series depend on their own past values (autoregressive), on past information (conditional) and demonstrate non constant variance (heteroskedasticity).

1.1 Emerging and Developing markets: high expected returns and volatility

In the recent decades are observed the processes of economic integration, mutual influence of various markets (commodity, financial, labor) and their segments. Integration and influence are identified both in geographical and qualitative terms, that is to say changes in one market quickly have a significant impact on other markets and sections. This is a natural process, since the formation and strengthening of ties between different economies (in terms of development), the economic liberalization in many regions of the world, and the creation of the European Union (EU) contributed to the acceleration of commodity traffic and cash flows. All these, in accordance with the technological advances in financial markets, the innovations and shocks in dominant equity and commodity markets influence the stock prices and returns of emerging market economies. In general the processes of integration, liberalization, globalization that markets face, and particularly the interconnection among stock markets of developed and developing countries, create opportunities for international financiers to invest in stock markets in emerging and developing countries.

At this point, it is crucial to classify emerging and developing and thus their economies. Countries whose economies are classified as emerging market economies are the ones with economies characterized by lower per capita income than developed countries, liquidity in equity markets and rapid growth (Sraders, 2020). Emerging markets contributed in strengthening global economic growth, particularly after the 1997 currency crisis, which forced these markets to become more sophisticated. At the present time, around 80% of the world's economy is comprised of emerging markets - including some of the largest countries in the world like China, India, Turkey and Russia (Ibid.).

Moreover, developing countries are the ones with growing economies and growing consuming population. Developing economies and emerging markets have the common element of growing relatively fast, given their increasing labor force and their expanding markets potentials. ("Developing countries and emerging markets - Knowledge for policy European Commission", n.d.)

At present, emerging stock markets seem to be very appealing for investments since they provide higher expected returns. Besides high expected returns, other distinguishing characteristics of emerging markets are the relatively low correlations with mature capital markets and higher volatility (Alikhanov,2013).

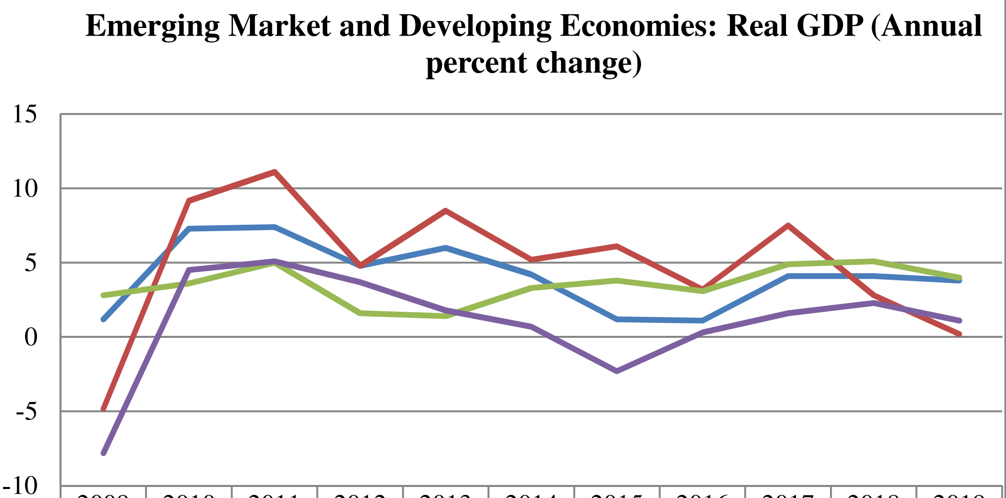
Increased volatility in these markets is manifested by regular, sudden changes in variance. Periods of high volatility, in emerging and developing markets, have generally been found from studies, to be related with significant events (global and local) like the October 1987 crash, the Gulf War, the global financial crisis etc. Furthermore, periods of increased volatility tend to be common to returns measured in local currency and dollar-adjusted returns. During the time of increased volatility, dollar-adjusted returns have higher standard deviations than local returns do, probably mirroring additional volatility in exchange rates (Aggarwal,1999).

1.2 Topic and approaches of the study

In this master dissertation are investigated the volatility spillovers in the national stock markets of Kazakhstan, Turkey, Poland and Russia, countries that are classified as emerging and developing by International Monetary Fund (hereafter referred to as IMF) (World Economic Outlook, October 2019). This classification is based on the evaluation of characteristics of national economies and specifically: "per capita income level, export diversification,[2] and degree of integration into the global financial system"("Frequently Asked Questions World Economic Outlook (WEO)", 2020). In Figure 1.0 is presented the percent of change of Gross Domestic Product (GDP) for all the above countries during the examined period (from 2009 to 2019). Aim of this "presentation" is the information for the economic progress and performance of these countries.

[2] In that way, oil exporting countries that have high per capita GDP, would not make the advanced classification because around 70% of its exports are oil

Figure 1.0:GDP change in the four examined markets



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Kazakhstan	1.2	7.3	7.4	4.8	6	4.2	1.2	1.1	4.1	4.1	3.8
Turkey	-4.826	9.157	11.1	4.8	8.5	5.2	6.1	3.2	7.5	2.8	0.2
Poland	2.82	3.607	5	1.6	1.4	3.3	3.8	3.1	4.9	5.1	4
Russia	-7.821	4.504	5.1	3.7	1.8	0.7	-2.3	0.3	1.6	2.3	1.1

Data retrieved from IMF's World Economic Outlook 2019.

Figure 1.0 reveals the significant negative consequences of the global financial crisis for all the studied economies. All countries' GDPs met surprisingly a rise in 2010-2011, maybe because the magnitudes of the financial crisis have not yet become noticeable. In the aftermath of the crisis, though, all the economies present signs of instability and vulnerability, which are indicated by the sharp declines and increases in GDP. Something very interesting in the above figure is the fact that Kazakhstan's and Russia's GDP fluctuations follow the same trend (in different values). This occurs because these two countries are major oil producers and therefore oil dependent, something that makes them more vulnerable to shocks. During the examined period these countries had to face not only the global economic crisis but also oil price crises and Russia particularly, the sanctions from European Union and United States for the annexation of Crimea in 2014. Something that is crucial and we should bear in mind, also, is the interdependence among Kazakhstani and Russian markets, with Russia being the one with the most influence. Another interesting observation is the dramatic fluctuation of Turkish GDP. We notice a meteoric rise in 2009-2010 and a sharp decrease after that and especially from 2017 until 2019. According to Aliriza and Yekeler (2018) this was the result of the fall of private consumption (negative number for first time after 2009), the decrease in net capital outflows, the depreciation of Turkish lira etc.

Returning to equity markets, the indexes (KASE, BIST100, WIG20 and MOEX) that are studied in this dissertation, are seen as subject to influence of their own past prices. The econometric model that is employed for the investigation in our research is an augmented AR(1) – EGARCH (1.1) including also the trading volume (denominated in national currency) and the exchange rate variables (value of US dollar in domestic currency).

For the investigation of the relation between trading volume and volatility in stock markets, there are two basic approaches. The first approach states that differences in investors' views and expectations are the cause of variations in trading volume and volatility. The second approach advocates that the way in which information arrives at the market "regulates" trading volume and volatility. Regardless the approach, it is generally stated in the financial literature the existence of a strong connection between contemporaneous trading volume and conditional volatility (Girard &Biswas,2007).

At a theoretical level there are links between stock prices, stock price volatility and exchange rates, which take two forms. Firstly, we have the "flow-oriented" models of exchange rates, which suggest that changes in exchange rates affect international competitiveness and trade balances (Zhao,2010 Hung,2018 Živkov et al,2015). Stock prices, generally interpreted as the present values of future cash flows of firms, react to exchange rate changes and form the link among future incomes, interest rate, innovations, current investment and consumption decisions (Ibid.). On the other hand, innovations in the stock market could affect demand through wealth and liquidity effects, thereby influencing money demand and exchange rates (Ibid.). Secondly, we have the "stock-oriented" approach, which describes exchange rate dynamics by giving the capital account an important role. Since the values of financial assets are defined by the current values of their future cash flows, prospects of relative currency values play a substantial role in their price movements. Therefore, stock price innovations may affect, or be affected by, exchange rate dynamics (Ibid.).

1.3 Aims of the study

In a whole, this research aims to examine the presence of volatility and volatility spillover effects in the four stock exchange markets, as well as to investigate and answer the question whether trading volume and exchange rate fluctuations have an impact on the volatility of stock markets. In particular, the first hypothesis states the existence of volatility spillovers in each researched market. The second hypothesis refers to the existence of leverage effect in the markets, while the third assumption denotes the presence of correlation between stock indexes and trading volume and exchange rate fluctuations separately and in combination. We test the assertion that trading volume and exchange rate fluctuations impact the examined stock indexes (KASE,BIST100, WIG20,MOEX) and their volatility spillovers. By implementing this analysis and adding more variables to the model we target to succeed a more comprehensive view of the behavior of these stock exchange markets, their volatility and spillover effects.

1.4 Contribution of the study

To the best of our knowledge, there are no studies in the literature that investigate the volatility spillovers in these four emerging and developing countries (Kazakhstan, Turkey, Poland and Russia) over the period 2009 – 2019. Something also noteworthy in this study is the examination of the impact of trading volume on the volatility in these stock indexes. So the contribution of this research could be described as two-fold: the investigation of volatility spillovers for the specific period of time and the examination of volatility spillovers under the influence of trading volume and exchange rate fluctuations.

1.5 Structure of the study

The structure of this dissertation proceeds as follows : section 2 presents a selected part of the international literature regarding the topic. In section 3 are described the data of the analysis and in section 4 follows the methodology that is employed. In Section 5 is illustrated the empirical analysis of each case study. Finally, in section 6 we have the conclusions of this master dissertation.

2. Literature Review

Stock markets obtain a significant part in the economic literature, either referring to equity returns, transmission mechanisms, volatility or spillover effects. Studies of world capital markets have typically focused on spillover effects including volatility spillovers in financial assets. On that note, many researchers have focused on the investigation of volatility in national stock markets, the volatility spillovers among markets and countries as well as the impact of several factors on spillover effects. Following this notion, the primary focus of this section is no other than a thorough view of the part of economic literature under the topics volatility spillovers and spillover effects. The structure of this section is as follows: first, the presentation of spillover effects in national stock markets, then the portrayal of spillover effects among stock assets, stock markets and countries, which is followed by the expose of the impact of various factors on spillover effects and volatility spillovers.

2.1.0. Spillover effects in equity markets

One of the pioneering papers in the field of spillover effects in financial markets is the one written by Andrew A. Christie (1982). Christie examined the relation between variance of equity returns and several explanatory variables. Aim of this paper was to record and explain the negative relationship between the volatility of return rate in equity market. For the analysis were used the price per share of equity and the number of shares outstanding that were retrieved from the Centre for Research in Security Prices (CRSP) file. In addition, the empirical results that came out showed that equity variances have a positive connection with both financial leverage and interest rates. A negative elasticity of variance though, regarding the value of equity, was found to be contributable to financial leverage. Finally, a maximum likelihood estimator that was introduced seemed to be more efficient than the extended estimation procedures in the calculation of the elasticity for that period.

In 1987 Kenneth R. French et al. studied the relation between stock returns and stock market volatility. Their analysis of inspecting the relation between stock returns and volatility consisted of two different statistical methods: at a first level, the univariate autoregressive –integrated-moving- average (hereafter referred to as ARIMA) model for the evaluation of the predictability of daily returns and monthly volatility and at a second level, the generalized autoregressive conditional heteroskedasticity (hereafter referred to as GARCH) model for the examination of measures of volatility of daily returns and the relation between risk premiums and volatility. Their research resulted in the proof of correlation between these two "assets". Specifically, it was proved a strong positive relation between the expected risk premium of common stocks and the foreseeable level of volatility and also a strong negative relation between the unforeseeable (random) characteristics of stock market volatility and the realized risk premium.

Stock returns were examined also by Eugene F. Fama and Kenneth R. French (1988). They estimated the returns on the value- and equal-weighted portfolios of New York Stock Exchange stocks for holding periods from one month to four years. For this examination they used the dividend yields ratios. Their analysis made known that the expected constituent of returns comprised a small segment of short-horizon return variances. Besides, regression analyses of returns on yields unsurprisingly explained less than 5% of monthly or quarterly return variances. Moreover it was shown that the expected component of returns constituted a larger fraction of the variation of long-horizon returns.

Cheol S. Eun and Sangdal Shim (1989) on the other hand, studied the international transmission mechanism of stock market movements. The dataset used for their examination consisted of time series of daily stock market indices at closing time (in local currency units), of the world's nine major stock markets i.e. Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the United Kingdom (UK), and the United States (US)respectively. The data covered a period of six years: from December 1979 through December 1985. Furthermore, the empirical method that was "engaged" revealed all the main channels of interactions among national stock markets and the dynamic responses of one market to innovations that took place in another market. Overall, a substantial amount of multi-lateral interaction among national stock markets was found. The novelties in the U.S., specifically, proved to be fast diffused to other markets, though no foreign market can significantly explain the U.S. market movements solely.

Moreover, Lorenzo Cappiello et al. (2003) investigated the existence of asymmetric conditional second moments in international equity and bond returns. The analysis was based on an asymmetric version of the Dynamic Conditional Correlation model, introduced by R. F. Engle (2002). The data set of their analysis included weekly observations-prices of FTSE All-World Indices- of 21 countries for a period of 15 years (1987 -2001). From the methodological investigation was made known the strong asymmetries in conditional volatility in national equity index return series, while bond index returns did not exhibit the same behavior. Nonetheless, both bonds and equities exhibited asymmetry in conditional correlation. At a global level, were studied the dynamics of volatility, having as result signs of structural breaks after the use of the Euro in January 1999. With the presence of euro and therefore a fixed exchange rate regime, an almost perfect correlation among bond returns within European Monetary Union (hereafter referred to as EMU) countries was resulted.

The asymmetric volatility spillovers between stock markets and real activity within a country was researched by Nikolaos Giannellis et al. (2010). They examined the short run relation between stock market and real activity in UK and USA (separately). They targeted in the explanation of volatility spillovers as a factor that typifies the relation between two sectors (stock market and real economic activity - productivity). Their dataset included monthly observations (stock prices, industrial production and producer price indices) for a period of almost 32 years (1970-2002). In order to investigate the abovementioned relationship they used the two-stage Cross Correlation Function (CCF) at first and univariate and bivariate Exponential GARCH model (hereafter referred to as EGARCH) later on. The results of the research stressed the existence of volatility spillovers among the two sectors within a country. Particularly, the interdependence was proved to be stronger in the case of UK rather than in USA, where in the case of USA was no evidence of asymmetric behavior.

Respectively, Mario G. Reyes (2001) examined the volatility transmissions among stock indexes, according to their size, in Tokyo Stock Exchange. He used a bivariate EGARCH model in order to assess the volatility spillover effects among small and large cap stock indexes.[3] From his analysis was proved that asymmetric volatility was directed only from large stock returns to small cap stock returns. It was also proved that the relation between large and small cap stock indexes varied over time.

More recently, Fuzuli Aliyev et al. (2019) studied the volatility of Nasdaq-100[4] by "engaging" various univariate conditional heteroskedasticity models. They examined the volatility of Nasdaq-100 index using symmetric and asymmetric

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[3] That is to say the study of stocks, which consists companies with either relatively small or large market capitalization.

[4]Nasdaq-100 is a nonfinancial, innovative and hi-tech stock.

models, i.e. GARCH, EGARCH and GJR-GARCH models and daily closing prices of the index over the period from January 2000 to March 2019. From their analysis became known that volatility shocks on the index returns are persistent. Additionally, outcomes showed that the index presents leverage effect, which indicates that the impacts of negative shocks on volatility are higher than those of positive shocks.

The case of a relatively small equity market like the Athenian Stock market was studied from Nicholas Apergis and Sophia Elepheriou (2001). They investigated the volatility of the Athens Stock Excess stock returns from 1990 to 1999. For their empirical analysis they used daily stock prices of firms traded in the Athens Stock Exchange (hereafter referred to as ASE) and the index of ASE as a proxy to measure the stock prices. Their analysis with Quadratic GARCH (hereafter referred to as QGARCH) model provided evidence for asymmetry in stock returns and volatility

On the contrary, Karunanithy Banumathy and Ramachandran Azhagaiah (2015) empirically scrutinized the volatility pattern of Indian stock market (big market) based on time series data which consisted of daily closing prices of S&P CNX Nifty Index from January 2003 to December 2012. The analysis verified that GARCH (1,1) and TGARCH (1,1) estimations were the most suitable models to capture the symmetric and asymmetric volatility respectively. The asymmetric effect (leverage)was captured by the EGARCH (1,1) and TGARCH (1,1) models, which indicated that that negative shocks had significant effect on conditional variance (volatility).

What's more, Hammoudeh et al. (2008) researched the volatility in three main divisions (Service, Industrial and Banking) in four Gulf Cooperation Countries (hereafter referred to as GCC), namely Kuwait, Qatar, Saudi Arabia and United Arab Emirates (UAE). For the empirical analysis the autoregressive moving average GARCH (VARMA-GARCH) model was employed and sector daily indices for a period of seven years (2001-2007) were used. The result of the empirical examination advocates that the Banking sector is least “vulnerable” among the sectors to past own volatility. At the same time, the Industrial sector is the most volatile to the past shocks and news. Sector volatility spillovers demonstrate that Saudi Arabia has the least intersector spillovers, while Qatar has the most. Saudi Arabia proved to be also the one of the examined countries most sensitive to geopolitics, in contrast to Kuwait.

2.1.1. Spillover effects of large and small stocks/firms

There are many studies in the literature examining the volatility spillovers among assets and participants (firms) within an equity market. In this aspect, Jennifer Conrad et al. (1992) examined the asymmetric predictability of conditional variances of the returns of large versus small firms. More specifically the writers implemented uni- and multivariate GARCH models in order to estimate the interaction between the conditional volatilities of different securities. Their data set included weekly returns on three size-based portfolios of New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stocks or the years 1962-1988. The empirical results revealed a particular asymmetry in the predictability of the volatilities of large versus small firms. To elaborate, a volatility "shock" to larger firms could be employed to forecast credibly the volatility of smaller market value firms, but not the opposite. In addition, the volatility “bombshells” to large market value firms were ascertained as crucial to the future dynamics of their own returns as well as the returns of smaller firms.

Iftekhar Hasan and Bill B. Francis (1998), also, estimated the predictability of large versus small firms. The data sample of their research included monthly portfolio returns of the largest and smallest (of twenty size based) portfolios that were comprised of New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stocks, over the period 1926–1988. By employing AR-GARCH models the authors revealed asymmetry in the capability of companies of different size to forecast conditional volatility. In particular, it was shown that volatility “shocks” of small or large companies were vital in forecasting the conditional variance of large or small companies. In addition, the results of the analysis indicated that the frame of symmetric predictability was existent in both pre- and post-war sample periods.

Return and volatility between large and small stocks within a stock market were also a case of research for Richard D. F. Harris and Anirut Pisedtasalasai (2006). Precisely, they “inspected” the return and volatility spillover effects in UK’s stock market, between the FTSE 100, FTSE 250 and FTSE Small Cap stock indices with the use of multivariate GARCH model. Their data sample constituted from daily stock returns of the examined indices for the years 1986-2002. The empirical research resulted in the finding that return and volatility transfer mechanisms between large and small stocks in the UK are asymmetric. Indeed, there were noteworthy spillover effects in both returns and volatility from the portfolios of larger stocks to the portfolios of smaller stocks. Regarding volatility exclusively, there was an indication of partial "response" from the portfolios of smaller stocks to the portfolios of larger stocks. According to the writers, the above results are reliable only in the case of a market, where information is first integrated in the prices of large stocks before being enclosed into the prices of small stocks.

2.1.2 Volatility spillovers among stock markets.

Many studies have also documented the volatility spillovers among various stock markets. Yasushi Hamao et al. (1990) studied the interconnection of price and price volatility across three major global stock markets. For the empirical evidence of the interconnection were used daily opening and closing prices of "key" stock indexes of Tokyo, London and New York stock markets from April 1985 to March 1988, and was employed the ARCH model. The study testified the existence of price change and price volatility effects from one international stock market to another. Especially, spillover effects were documented from the U.S. and the U.K. stock markets to the Japanese market, which proved an asymmetry: while the volatility spillover effects on the Japanese market were noteworthy, the spillover effects on the other two markets were sluggish.

Further, Anders C. Johansson and Christie Ljungwall (2008) examined the spillover effects among China Stock Markets in order to explore the links among the different stock markets (China, Hong Kong, Taiwan) in the greater China region. By employing MVGARCH model, their analysis reached the conclusion that in the greater region of China existed strong – long run connections among the different stock markets and additionally short run multidirectional volatility spillovers among them(from Taiwan to Hong Kong and China, and from Hong Kong to Taiwan and China). Their research also testified the presence of interdependence between the three examined internal markets of China.

From the same aspect, Gyu-Hyen Moon and Wei-Choun Yu (2010) studied the spillover effects between US Stock market and the stock market of China. Particularly, they checked the short run spillover effects from daily stock returns and volatilities between Standard & Poor's 500 Index and the Shanghai Stock Exchange by using the GARCH (GARCH-M) model. For their analysis the writers retrieved daily data for the period 1999-2007 and made evident a structural break that took place in Shanghai Stock Exchange stock return mean in the end of 2005. Became also known symmetric and asymmetric volatility spillover effects from US Stock market to the Chinese during the post-break period. A symmetric volatility spillovers from the Chinese stock market to the American stock market was also documented.

The volatility spillover effects from US Stock market towards other stock markets had previously been studied from Y. Angela Liu and Ming–Shiun Pan (1997). Mainly, they researched the mean and volatility spillover effects from US and Japanese stock market to four Asian stock markets, namely Hong Kong, Singapore, Taiwan and Thailand from 1984-1991. The results of the empirical analysis (GARCH model) revealed that the US market had a greater impact, than the Japanese one, on the other four markets. The authors also found that the volatility spillovers between these markets were time-varying. As a final point, their analysis testified that only the cross-country stock investing analysis could not describe the international transfer of return and volatility, since the market contagion was also a factor that contributed in this process.

Motivated by the idea of providing a supplementary view on the interdependence among big national stock markets, Panayiotis Theodosiou and Unro Lee (1993) "inspected" the mean and volatility spillovers in USA, Canada, UK and Germany. In their paper, the multivariate GARCH model and weekly data were used, in order to explore in which extend the conditional volatility in these markets affected the expected returns. The analysis offered a surprising result since no connection showed to exist between conditional market volatility and expected returns. At the same time though, the scholars found strong time-varying volatility in the return series of all the examined markets, with Canada and Germany having a more intense stock market volatility. USA stock market proved to be the one that affected all the others through cross-volatility spillovers, while volatility spillovers also occurred from UK stock market to the Canadian stock market and from German stock market to the Japanese stock market.

Moreover, Ramaprasad Bhar and Biljana Nikolova (2008) studied the integration and connection among BRIC countries. Aim of their paper was the confirmation of the level of regional and global integration of the BRIC countries by the documentation of the link of index stock returns and the estimation volatility spillovers from these countries (Brazil, Russia, India, and China). From their analysis with weekly data from 1995 to 2006 and the use of bivariate EGARCH model, was shown that India was the most well integrated country at all levels (regional and global) in comparison with the rest BRIC members. In a whole, no one of the BRIC countries exhibited the effect of the equity price creation process in their areas, no one had a significant influence on the conditional volatility of world market and only Russia impacted the price creation process of the world equity index price.

Besides, Abdulla Alikhanov (2013) studied the mean and volatility spillover effects from the U.S and EU stock markets along with oil price market into national stock markets of eight European countries namely Croatia, Czech Republic, Hungary, Poland, Romania, Russia, Turkey, and Ukraine. The weekly data that were used consisted of stock indexes of US, the aggregate index of EMU countries, crude oil spot prices and the stock indexes of above eight European countries over the period from September 2000 to March 2012. In order to find the mean and volatility spillover effects across financial markets GJR-GARCH model was applied. The empirical findings indicated strong signs of volatility transmission, mainly global. They presented, also, that US volatility spillovers intensities accounted for most of the amount of unexpected returns, with exception Croatia and Romania. In addition , it was revealed that the EU mean spillover effects were barely sensitive to different stock markets. Regarding oil market shocks, they showed to be noteworthy for all countries and especially in the case of Russia, where the stock returns were driven by them. While finally, the model “advocated” that spillover effects were partially clarified by instrumental macroeconomic variables, like exchange rate fluctuations.

Earlier, Bartosz Gębka and Dobromił Serwa (2006) had focused their analysis on returns and volatility spillovers between emerging capital markets of Central and Eastern Europe, Latin America, and South-East Asia. For their analysis, the writers used national equity indices for the period from April 1998 to January 2006. Their series included daily returns of indices from selected emerging markets in Asia, Central and Eastern Europe and Latin America, that was Malaysia, South Korea, Taiwan, and Thailand, Czech Republic, Hungary, Poland, Russia, Argentina, Brazil, Chile, and Mexico. The discoveries from the empirical analysis (with the use of multivariate GARCH model) indicated that linkages between emerging markets existed not only due to their common dependence on the global capital market, but also due to the common factors in intra-regional interdependencies.

Subsequently, Konstantin G. Asaturov and Tamara V. Teplova (2014i) investigated the volatility spillovers and conditional correlations between stock markets of three geographic regions (America Europe and Asia), including pre- and post-crisis periods. The paper verified the applicability of the ARMA-DCC-GARCH model, which helped in delivering a detailed examination of the dynamic correlation between 26 stock markets in the three examined regions over the period of 1995–2012. The results showed that the US market (S&P500 index) was the main volatility transmitter worldwide, while the UK, German and French markets are wellsprings of volatility for the European developed and emerging European equity markets. An unexpected finding was the fact that the German index did not have the role of a dominant volatility transmitter in the European region, although it is the continent's most significant market. The study also revealed that the role of "exporting volatility" or volatility transmitter belonged to the UK stock market regarding the European area, while together with US, Germany and France showed to be the markets that have greater impact on emerging markets rather than on developed ones. Among the two markets of the North and East European region (Russia and Poland) the main transmitter proved to be Russia.

Another Russian scientist Alexander V. Tkachev examined in 2010 the volatility and volatility spillovers as a feature of stock markets in developing countries. More specifically he studied the role of the Russian stock market in the system of developing markets, particularly its role in the union of BRIC countries. In order to analyze the volatility the writer calculated the coefficient of variation (CV) or relative standard deviation (RSD) from three MSCI group indices viz. MSCI Emerging Markets Index, MSCI BRIC Index and MSCI Russia Index for the period from 2000 to 2010. Tkachev identified the factors that influence the dynamics of stock markets and general development trends are identified. Explicitly, the research resulted in the finding that the volatility of the Russian stock market was very high, and it reached its maximum point during the years of crisis. The dynamics of MSCI index's volatility proved to be unidirectional, which indicated that the Russian stock market could be classified as developing. Among the stock markets of developing countries, the Russian market was subject to sharper fluctuations than the rest. The Russian market seemed to respond to the crisis phenomena more intensely than the other markets. In a whole, this research resulted in the verification that the volatility of MSCI Russia and MSCI BRIC indices exceeded the volatility of the MSCI Emerging Markets index during the examined period.

Yaser A. Alkulaib et al. (2007) had described earlier the dynamic relations among stock markets in MENA (Middle East and North Africa) countries. Their dataset comprised of daily closing prices of 12 MENA indices stock markets (Bahrain, Egypt, Jordan, Kuwait, Lebanon, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey and UA) and the methodology that followed was based on the state space procedure. The results of the research did not indicate any market causality or spillovers from one country to another in the North Africa region. In comparison, the results for the Levant region revealed that there were linkages between stock markets in this region. The results for the Gulf Cooperation Council (GCC) region indicated that in that area emerged more spillovers than in the North Africa and Levant regions, with the dominant stock market being UAE's (United Arab Emirates). Finally, the investigation showed strong linkages among the three regions and particularly evidences of GCC influence on the other two regions.

Likewise, in another paper, it was measured the volatility transmission for pairs of six stock markets of GCC and pairs of these markets with the three global markets (S&P 500 index, Oil-WTI prices and MSCI-world) (Khalifa et al.,2013). The writers used for their estimation weekly data –stock market indices-from January 2004 to March 2011 and employed the Multi-Chain Markov Switching (MCMS) model. The results of the analysis delivered evidence of diverse patterns of volatility transmission between the GCC markets and the international variables such as oil price, the S&P 500 index and the MSCI-World index. In a whole the results showed strong interdependence between oil and each of the Kuwait, Dubai and Abu Dhabi markets. Indications of interconnection were also shown, between Oil and each of the Saudi Arabia, Qatar and Oman markets, as well as linkages of the global market (US, Us 500Index) with Saudi Arabia, Dubai and Abu Dhabi.

2.1.3 Volatility spillovers in European stock exchange market

Several studies in modeling stock market volatility and transmission mechanisms in European market have been conducted. Ping Wang and Tomoe Moore (2009) researched the existence of sudden changes of volatility in the stock markets of the new-entered European Union (EU) members viz. Poland, Czech Republic, Slovakia and Slovenia for the period 1994-2006. Their data set was comprised of weekly closing prices of the five European markets for the examined period. The empirical investigation revealed that unexpected changes in volatility took place and rose from the evolution of emerging stock markets, the exchange rate policy changes and the financial crises. The results also made known that when unexpected changes were encompassed into the GARCH model, the persistence of volatility reduced significantly.

Earlier, Gregory Koutmos (1996) researched the first and second moment interactions among four major stock European markets namely England, France, Germany and Italy. In order to inspect the interaction and volatility between these markets Koutmos implemented a multivariate VAR-EGARCH model and used daily figures for the aggregate stock price indices of the stock markets of the examined countries from January 1986 to December 1991. From the econometric analysis became known the existence of multidirectional relationships (first moment interactions) and a notable volatility (second moment interactions). In general, the volatility transmission mechanism proved to be asymmetric, to elaborate according to Koutmos "*negative innovations in market i increase volatility in market j considerably more than positive innovations*". In a nutshell, all the "discoveries" advocated that European stock markets were integrated in terms of responding to local news and to news coming from other markets, especially when the news was unfavorable.

Additionally, the interdependence of European equity market was scrutinized by Lieven Baele (2005). The research emphasized on the way and on what degree the volatility in local equity markets is driven by common global and regional shocks. For his investigation, he used weekly stock returns from eight countries that belong to EMU i.e. Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, and Spain, three EU member countries- non –members of EMU (Denmark, Sweden, UK[*)]) and two countries non- members of EU (Norway & Switzerland). The data sample covered the period from January 1980 to August 2001(except from the cases of Sweden and Spain). By employing several GARCH models it was shown that regime switches were significant statistically and economically. The EU and US shock spillover intensity increased during 1980s and 1990s and also the impact of US stock

[*] UK is not currently an EU member state

market to local European ones was strong during that time, and the time of high world market volatility.

Dimitrios P. Louzis (2013) accordingly, researched the return prices and volatility spillovers among money, stock, foreign exchange and bond markets of the euro area. His data sample encompassed Stoxx Europe 50 index, the 3-month Euribor index, the EURO/USD exchange rate and the total return sovereign bond indices for the euro area periphery countries (Greece, Ireland, Italy, Portugal and Spain) and countries with developed economies (Austria, France, Germany and Netherlands), respectively, on weekly basis from 2000-2012. His empirical investigation (with a generalized VAR model) indicated a high degree of total return and volatility spillover effects for all the countries. The stock market was identified as the main "spreader" of both return and volatility spillovers ,still throughout the economic crisis, in the euro area. The importance of money market in volatility transfer, was recorded, during the outburst of the financial crisis.

2.1.4 Spillover effects, volatility spillovers and the impact of trading volume and information.

In 1989, Stephen A. Ross wrote about the influence of information on asset prices. In particular, he used a non-arbitrage martingale analysis to study the effect of changes in the rate of information flow on asset prices. The analysis was first employed for the development of some simple tools for asset pricing in a continuous-time setting, and later for definition of the effect of information on prices and price volatility. His investigation resulted in the disclose that the volatility of prices was directly related to the rate of flow of information to the market. In a simple model the these two (volatility and rate of flow of information) were found to be identical. This outcome linked volatility tests to efficient market hypotheses, which specified the information set that the market uses for pricing. It was also shown that changes that took place in time of uncertainty didn't affect the prices. This fact derived independently from any particular parameterization of the stochastic information flow process. In a nutshell, the resolution irrelevancy and the relation between price volatility and rate of information flow proved to be important consequences of arbitrage-free economies.

Respectively, Robert F. Engle and Victor K. NG (1993) analyzed the impact of news on volatility. Specifically they tested how information was integrated into the volatility calculation. By introducing non parametric models (the model by Glosten, Jagannathan, and Runkle (GJR)), partially various ARCH and GARCH (EGARCH)) and by having as sample daily Japanese stock returns from 1980 to 1988, the researchers demonstrated that negative shocks cause more volatility than positive shocks. This asymmetry of the volatility response to news was stressed by the introduced diagnostic tests.

In addition, Theodore E. Day and Craig M. Lewis (1992) examined the information content of the implied volatilities from call options on the S&P 100 index. For their analysis they used daily data i.e. closing prices and contract volumes for call options on the Standard and Poor's 100 index (OEX options) and daily closing prices of the underlying index from a period extending from March 1983 to December 1989. As analytical tools they applied GARCH and EGARCH models, and added volatility as an exogenous variable. The empirical results showed that implied volatilities may contain some incremental information relative to conditional volatility from GARCH and EGARCH models. Another finding was the "solid" within-sample indications of conditional volatility that demonstrated additional information relative to implied volatility. Combining the results of the analysis, the writers reached the conclusion that neither implied volatility nor the conditional volatilities described to full extent conditional stock market volatility, especially when the additional market return was expected to be a linear function of conditional market volatility.

An interesting research regarding asymmetric volatility is the one by Heitham Al-Hajieh (2015). Al-Hajieh viewed the asymmetric behavior of 17 Islamic markets (Abu Dhabi, Bahrain, Bangladesh, Dubai, Egypt, Indonesia, Jordan, Kuwait, Lebanon, Malaysia, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Tunisia, and Turkey) by using daily closing price of each stock market's index from 1995 to 2015. Objective of his paper was the assessment of the asymmetry and its pattern in the region, taking into account the distinguishing characteristics of each country's economy. For the empirical analysis he employed GARCH, EGARCH and GJR-GARCH models for capturing the dependence in the variance. The results of the GARCH family models indicated that the conditional variance exhibited long persistence of volatility for all countries, while the EGARCH and GJR GARCH models, proved that the stock market investors responded differently to bad news compared to good news in all countries. In a nutshell, it was proved that all stock index returns demonstrated asymmetry that was persistent in the studied stock markets.

Another aspect of the research of volatility is expressed in the investigation of the relation of volatility and trading volume. Eric Girard and Rita Biswas (2007) inspected this relation for developed and emerging countries. Particularly, in their paper was viewed the relation between daily information flow and the conditional volatility of stock index returns. Objective of the paper was the comparison between volume and volatility in developed and emerging markets. For the realization of this research the used dataset included daily prices and volume activity in 49 equity markets—22 developed and 27 emerging markets for the years 1985-2005. The methodological approach that was followed included GARCH models and especially the (asymmetric) Threshold GARCH (TARCH) and EGARCH. The empirical findings testified the presence of negative correlation between expected volume and volatility in numerous emerging markets, which could be attributed to the relative inefficiency in those markets. Another interesting fact that was revealed from the analysis was the decrease in volatility persistence, when trading volume was decomposed into expected and unexpected parts.

2.1.5 Volatility spillovers and the impact of exogenous factors: global, regional &local shocks -events.

There is a substantial literature on the study of different fundamental factors that explain the dynamics of stock markets and the spillover effects in and among them. These factors global, regional and local, economic or not, reflect the degree of integration of stock markets in international financial markets, and the state of the economy.

The impact of economic factors on volatility spillovers and general on equity markets was presented thoroughly in the paper of John J. Binder and Matthias J. Merges (2001). In their paper was theoretically and empirically viewed the impact of rational factors on the standard deviation of returns in a market index, like the Standard & Poor’s Composite. Using monthly data from February 1929 to April 1989 the analysis showed that generally in an “insecure” economy exist four factors of stock market volatility: uncertainty about the price level, the riskless rate of interest, the risk premium in equity and the ratio of expected profits to expected revenues. The contribution of the specific research was the indication of a way of counting the past behavior of stock market volatility and of predicting future volatility.

Eric M. E. Atengal and Mbodja Mougoué (2020) inspected the way the effect of global and regional shocks was spread to African equity markets, by using a network methodology that was introduced and developed by Diebold and Yilmaz (2009). For their analysis the writers used daily price indices denominated in local currencies for eleven African markets, five developed markets, and seven emerging markets for the period from January 2007 to September 2019. As a methodological approach they employed Autoregressive Conditional Heteroskedasticity (hereafter referred to as ARCH) model, which resulted in the reveal of the fact that international and regional market shocks affected heterogeneously and time-varyingly the African equity markets. There were also evidences of bidirectional spillovers that showed the African markets as net receivers for both return and volatility spillovers. In addition, signs of spillovers were recorded during the 2008 global financial and the 2012 European debt crisis.

A lot earlier, Reena Aggarwal et al. (1999) paid attention to the causes of large shifts in volatility of emerging stock markets. Since it is up today generally known that emerging stock markets “suffer” from high volatility, the writers examined whether global or local events (social, economic, political) were key factors for causing major shifts in emerging stock markets. Their data sample included daily closing prices of different stock markets including the ten largest emerging markets in Asia and Latin America and others like Japan Germany, Singapore, Brazil Korea, India, Malaysia and Mexico covering a period of ten years (1985-1995).Their empirical analysis, based on Iterated Cumulative Sums of Squares (ICSS) and GARCH model, showed that the majority of the events that affected the stock markets proved to be local, for instance the Mexican peso crisis, periods of hyperinflation in Latin America, the Marcos-Aquino conflict in the Philippines, and the stock market scandal in India. In addition, the 1987 crash showed to be the only global event of that period that triggered a dramatic increase in the volatility of several emerging stock markets.

In contrast to the study of Aggarwal et al., Shawkat Hammoudeh and Huimin Li (2006) found that sudden changes in volatility for five Arab Stock markets in Gulf area were more susceptible to major global events rather than local. The findings of this paper exposed the sensitivity of Gulf Arab stock markets to global events, such as the 1997 Asian crisis, the collapse of oil prices in 1998, the adoption of the price band mechanism by OPEC in 2000 etc. The GARCH model that was employed proved that sudden changes in volatility occurred almost exclusively due to global events.

In another research of Shawkat Hammoudeh together with Kyongwook Choi (2005) were inspected the relations among five GCC stock markets and their links to three global factors i.e. the WTI oil spot prices, the US 3-months Treasury bill rate, and the S&P Index. For their study, Hammoudeh and Choi they used weekly data over the period February 1994 to December 2004. They employed two unit root tests, namely the augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test, to investigate the presence of a stochastic trend in the individual series and the Zivot and Andrews test to assess the occurrence of structural breaks. The results of their analysis about the relationships between the GCC stock markets and the three global factors (the oil price, the US S&P 500 index, and the US T-bill rate) indicated that the US T-bill rate had a direct impact on some of the GCC markets (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates). The S&P 500 index and the Western Texas Intermediate (WTI) or the Brent oil prices had not such direct impact, inferring that local/ regional factors had a more significant effect on them. On the other hand, the impulse response analysis showed that the S&P 500 shocks had positive dynamic impacts on all GCC markets over a 20-week forecast horizon, under the assumption that GCC stock markets “bloomed” alongside US markets.

More recently, Agata M. Lozinskaia and Anastasiia D. Saltykova (2019) documented the impact of the essential factors on the Russian stock market changes retrospectively. They empirically tested the influence of daily values of several significant factors (indexes of foreign stock markets, oil price, exchange rate and interest rates in Russia and the USA) on the MOEX Russia Index from 2003 to 2018. In their paper were used daily data (prices) of the MOEX Russia Index (IMOEX), daily closing prices of S&P500 (S&P500) and NIKKEI 225 (NIKKEI), Brent crude oil price (BRENT) and ruble/USD official exchange rates (USDCB), 3-month US Treasury bills rate (TBILL) and 1-month Moscow interbank offer rate (MIBOR). The analysis with the ARIMA-GARCH (1, 1) model with a rolling window indicated a diversity on the way that fundamental factors affected the Russian stock market. The Quandt-Andrews breakpoint test and Bai-Perron test classified the number and likely the location of structural breaks. Multiple breaks were found related to dramatic decreases in the stock market index, like the falls of the Russian index in the spring of 2006 and the global financial crisis of 2008-2009. In addition, the results of the regression models were characterized by structural breaks, differentiated distinctly over time.

Bouri et al. (2014) investigated the time varying correlation between 12 MENA stock markets. The dataset included daily closing prices from the 12 MENA stock indexes (Morocco, Tunisia, Egypt, Israel, Lebanon, Jordan, Kuwait, Bahrain, Qatar, UAE, Saudi Arabia, and Oman) over the period July 2005 to January 2013. The analysis managed to incorporate the impact of two downturn periods i.e. the economic crisis and the Israeli – Hezbollah war. Methodologically, a multivariate framework, a MGARCH model was used, which allowed for both return asymmetry and leptokurtic distribution. The empirical results demonstrated a very strong own and cross-persistent volatility in all MENA countries' stock prices. The GARCH model exposed the presence of asymmetric volatility, indicating that the MENA markets overreact to bad news and underreact to good news. Moreover, conditional volatilities faced a rise in all MENA markets during the global financial crisis of 2008, whereas during the Israeli- Hezbollah war of 2006 the results of conditional volatility differentiated for the examined countries.

Supplementary, studies have found evidence of occasional sudden breaks in many economic time series. For example, oil prices change in response to shocks from exogenous geopolitical events or supply interruptions, and financial markets can shift unexpectedly in response to financial crises. Nader Naifar and Mohammed Saleh Al Dohaiman (2013) studied the relationship among oil price variables (changes and volatility), economic growth indicators and stock market returns under regime shifts in GCC countries. Their dataset included daily OPEC oil spot prices covering the period from July 2004 to November 2011 and the empirical model that they used, for capturing oil price volatility, was the EGARCH. The empirical investigation exposed that oil price volatility had an impact on oil exporting and oil importing countries. Furthermore, became evident that the relationships between oil price volatility and GCC stock market performance were regime-dependent and that monetary policy's sensitivity to crude oil prices was related to current market characteristics. Lastly, it was proved the dependence structure between crude oil prices and inflation rates, which appeared also asymmetric.

2.1.6 Volatility spillovers during economic crises

Another growing body of literature is the one referring to the relationship between stock markets and financial crises. Economic crises are believed to have a negative correlation to the financial markets, which means that during a period of crisis, we observe a great negative fluctuation of stock prices and generally an instability of the equity markets.

Riadh Aloui et al. (2010) inspected the degree of the recent global crisis and the negative effects of it, by examining the financial linkages of some specific emerging markets with the US market. Several copula functions additionally to the GARCH-M model were employed in this analysis , while the dataset consisted daily return data from Brazil, Russia, India, China (BRIC) and the US for the years 2004-2009. The empirical results illustrated a time-varying dependence between each of the BRIC markets and the US markets. The writers, however, clarified that the reliance was stronger for commodity-price dependent markets rather than for finished-product export-oriented markets. Lastly, they detected high degree of dependence persistence for all markets.

Similarly, Juha Kotkatvuori-Örnberg et al. (2013) explored the existent conditional and unconditional correlations around two major banking events during the recent financial crisis (2008–2009). Particularly, they researched the effects of two major banking events viz. the JP Morgan Chase's acquisition of the Bear Stearns investment bank and the collapse of the Lehman Brothers Holding Inc. investment bank, on the time-varying correlations of worldwide stock markets. Objective of the paper was the examination of the influence of these events on fifty international stock markets from six different regions (Emerging Europe, Middle East, Latin America, Developed Europe, Asia Pacific,G7).For their analysis the researchers used an augmented dynamic conditional correlation (hereafter referred to as DCC) model. The results indicated that while the JP Morgan's acquisition of Bear Stearns had a tiny impact on stock market correlations across all regions, the effect on interconnection of the Lehman Brothers' collapse was substantial. In addition, the results from both the unconditional and conditional correlation study suggested that the impact of the financial crisis on stock markets was significant for all regions. Moreover, in a two-asset distribution framework, the model showed rather low portfolio variances, suggesting considerable benefits in portfolio diversification.

Additionally, Kenji Moriyama (2010) examined the spillover effects of the recent global economic crisis on emerging economies in Middle East and North Africa (hereafter referred to as MENA). For the research of the impact of economic crisis, after the Lehman Brothers shock, he engaged the Financial Stress Index. Firstly, he estimated the spillovers of great financial stress from advanced economies to MENA countries and secondly, the effect of the economic stress and lower economic activity in trade partners on economic activity of MENA countries. The analysis resulted in the confirmation of existence of direct and indirect spillovers in advanced economies. Also, the empirical model specified that increased financial stress and slowdown in economic activity in advanced economies could enlighten a significant amount of the drop in real GDP growth in MENA countries.

MENA stock markets were a case of study also for Ahmed S. Abou-Zaid (2011). Aim of his research was, in the aftermath of the global economic crisis, the study of the international transmission of daily stock index volatility movements from U.S. and U.K. to certain MENA emerging markets (i.e. Egypt, Israel, and Turkey). The data sample consisted daily return price over the years 1997-2007and the chosen empirical method was based on multivariate GARCH -M model. The empirical study resulted in the fact that Egypt and Israel were significantly influenced by the U.S. stock market, while Turkey was not. At the same time the British market had no impact on this three MENA markets.

Athanasios Koulakiotis et al. (2016) studied the return and volatility spillovers among large, medium and small size stock portfolios and the effects of global economic crisis in Athens stock exchange. By engaging univariate and multivariate VAR-EGARCH model and by using daily data (closing prices and trading volume) from 2001 to 2012, the researchers examined the mean and volatility spillovers for two sub-periods: pre- and post-crisis period. The results from the empirical analysis showed that in the pre-crisis period (2001-2008) return spillovers were significant for all three stock indices. Asymmetry was existent for all the three indices, with the most significant spillovers being these directed from large to medium stock index. During the post-crisis period (2009-2012) though, it was showed an insignificant return spillovers but significant across the indices. In this period asymmetry was also noticeable in medium stock index, and volatility spillovers vital from small to medium indexes.

Further, James R. Barth et al. (2010) studied the spillover effects of US financial crisis. In particular, the writers examined the level of interdependence between national stock market returns for 17 advanced economies and the United States, for several sub-periods from January 1973 to February 2009 (before and after the US financial crisis). For their analysis they used weekly and monthly national stock market returns for the examined countries like France, Germany, Japan UK, US etc. The method that followed included time-series models with single equations (ordinary least squares and generalized method of moments) and system approaches (structural vector autoregressive process). The results showed strong linkages between national stock market returns over time, as well as spillover effects from a shock in U.S. stock market returns to the advanced economies. It was pointed out also the level of interconnection and spillover effects from US stock market to the stock markets of the advanced economies that got higher 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.

Kian-Ping Li and et al. (2007), also researched the impact of the 1997 economic crisis on the efficiency of eight Asian markets. The rolling bicorrelation analysis that was used in their paper proved that the crisis affected the efficiency of the examined Asian countries, with Hong Kong being the one that got affected the most. However, these markets recovered in the aftermath of the crisis, by improving their markets efficiency. In a nutshell, the empirical calculation indicated an equilibrium deviation caused by external shocks, which suggested that the markets' inefficient was connected with news happening during a crisis.

The Asian economic crisis of 1997-1998 and its impact on stock markets in Eastern Asia were viewed, as well, by Nancy Huyghebaert and Lihong Wang (2009). More specifically they investigated the integration and causality of interdependencies between seven major East Asian stock exchanges before, during, and after the crisis. For their analysis, they used daily stock market data from July 1, 1992 to June 30, 2003 in local currency and in US dollar. Regarding methodological approach that followed, the writers introduced multivariate VAR models to examine the degree of integration among these stock markets and Granger causality tests to examine their time-varying lead–lag relationships. They also employed generalized impulse response tests to decide on the short-term causal relationships in the different sub periods. Their analysis made known that the links among East Asian stock markets were time varying. Despite the fact that there were minor stock market interactions before the Asian financial crisis, the Hong Kong and Singapore reacted to shocks, more intensively than other East Asian markets, during the crisis. In the aftermath of the crisis though, shocks in Hong Kong and Singapore largely affected other East Asian stock markets, except for those in Mainland China. As a final point, the results indicated that US market significantly influenced stock returns in East Asia during all the examined periods, but that did not happen vice versa.

G. William Schwert (1989) estimated the behavior of stock return volatility from 1885 until 1987, the period before and of the stock market crash. By applying an autoregression of daily returns with a heteroskedastic error standard deviation, it was demonstrated the fact that volatility rose sharply during and after the crisis, nevertheless eventually declined.

In addition, Anastasios G. Malliaris and Jorge L. Urrutia (1992) analyzed the lead-lag relationships for six major stock market indexes i.e. New York S&P 500, Tokyo Nikkei, London FT-30, Hong Kong Hang Seng, Singapore Straits Times, and Australia All Ordinaries, for time sub periods: before, during, and after the October 1987 market crash. Specifically, the dataset included daily closing prices of the above equity market indexes, for the period May 1987 through March 1988. The researchers delivered unidirectional and bidirectional causality assessments that illustrated the non-existence of lead-lag relationships for the periods before and after the crash. Nevertheless, vital feedback relationships and unidirectional causality were noticed for the month of the crash. It was also noticed an increase in contemporaneous causality during and after the month of the crash. In general, the results advocated that the October 1987 market crash seemed to be an intercontinental crisis of the equity markets.

Likewise, Bala Arshanapalli and John Doukas (1993) “inspected” the links between stock prices in significant world stock exchanges like Germany, the United Kingdom (UK), France, Japan and the United States (US). They viewed the connections of stock price indices before and after the October crash and the impact of stock price movements in one market or from one market to another. In order to proceed with their empirical investigation the writers used daily closing data from January 1980 through May 1990 and employed the augmented Dickey-Fuller (ADF) tests and the DJIA (Dow Jones Industrial Average) as the base index. The empirical results showed weak correlation between national stock markets before the October

1987 and for the time after the October 1987 an increased degree of global movements among stock price indices, excluding Nikkei index. Besides that, the US stock market was proved to affect all the other markets in the post-crisis period, and respectively the French, German and UK markets showed to react to US stock market innovations. Finally, the Japanese equity market performance presented to not have correlations with both the US stock market and the stock markets in France, Germany and UK before and after the October crash time.

2.1.7 Volatility spillovers between stock and currency markets

The existence of an interrelationship between stock and foreign exchange markets is well known in the international financial literature. For instance, Kyung-Chun Mun (2005) examined the role of exchange rate fluctuations in international stock market fundamentals and the way and degree they (fluctuations) influence the equity market volatility and cross-market correlations. The data set was comprised of weekly data (closing exchange rates and stock market indices) of eight countries namely UK, France, Germany, Italy, Australia, Hong Kong, Japan, and Singapore for the period from January 1990 to September 2003. The empirical analysis included EGARCH model, which resulted in the indication that the higher foreign exchange rate variability, the higher local stock market volatility became, and the less the volatility in US stock market. The degree to which stock market volatility was affected by foreign exchange variability presented to be higher for local markets than for the US market, as a result of the strong interconnection between exchange rate changes and local equity market returns.

Earlier, Richard A. Ajayi et al. (1998) had examined the causal relationship between stock returns and exchange rates. For this purpose, Granger causality tests were used for the investigation of unidirectional, bidirectional causality and contemporary adjustments between stock returns and changes in exchange rates. In addition, were used daily closing market indexes and exchange rates for seven advanced markets (Germany, Canada, France, Italy, UK, USA, Japan) from April 1985 to August 1991, and eight Asian emerging markets (Taiwan, Korea, Philippines, Malaysia, Singapore, Hong Kong, Indonesia & Thailand) from December 1987 to September 1991. The empirical investigation indicated signs of unidirectional causality between the stock and currency markets in all the advanced economies, while non-reliable fundamental relations were observed in the emerging economies. In addition, the stock and currency markets proved to be well integrated in the six advanced economies with the exchange rates responding to innovations in the stock markets. While in the case of the eight emerging economies the evidences of causal relations between the two markets were mixed.

Furthermore, Sheng-Yung Yang and Shuh-Chyi Doong (2004) examined the mean and volatility transmission mechanism between stock and foreign exchange markets for the G-7 countries. They used weekly closing exchange rates and stock market indices of the G-7 countries (i.e. Toronto 300 Composite, Paris CAC 40, Frankfurt DAX, Milan Stock Index, Nikkei 225, FT-100, and S&P 500) and implemented a bivariate EGARCH model for the examination of the dynamic price and volatility spillovers between stock prices and exchange rates. The empirical results exposed the existence of asymmetric volatility spillover effects. The fact that movements of stock prices had the tendency to affect future exchange rate movements but not the opposite (changes in exchange rate showed to have less influence on future changes of stock prices), was also resulted.

Hua Zhao (2010) researched the dynamic correlation between exchange rates and stock prices in China. Objective of the paper was to deliver another scientific view that will bridge the gap in the literature of the study of the way that information is transmitted between these two economic variables through short-term price interactions and volatility spillovers. The paper, based on GARCH models, investigated the dynamic relationship between Renminbi (RMB) real effective exchange rate and stock price. The data set included data from January 1991 to June 2009 and the results of the empirical analysis “exposed” that there was not a stable long-term equilibrium relationship between RMB real effective exchange rate and stock price. There were not, also, any evidences for mean spillovers between the foreign exchange and stock markets. Regarding the cross-volatility effects between these two markets, there was a bidirectional volatility, that showed that the past novelties in stock market had significant impact on future volatility in foreign exchange market, and vice versa.

Elena Fedorova and Kashif Saalem (2010) examined the connections between the currency markets of Poland, Hungary, Russia, and the Czech Republic and the linkage between Emerging Eastern European and Russian equity and currency markets. The data sample of the analysis included weekly indexes, stock returns and exchange rate for each country from 1995 to 2008. Proceeding with the empirical analysis, they employed a bivariate GARCH-BEKK model, which showed direct bonds between the equity markets, in terms of both returns, volatility, and currency markets. Furthermore, unidirectional volatility spillovers from currency to stock markets were specified ,as well as process regional integration of Eastern European markets as well as an integration of these markets with Russia.

Later on, Walid Chkili et al. (2011) studied the link between stock price volatility and exchange rate changes in four emerging countries (Hong Kong, Singapore, Malaysia and Mexico). In order to investigate this dynamic link between stock price volatility and exchange rate changes the writers “engaged” Markov-Switching EGARCH model and their data sample included weekly closing stock market indexes denominated in local currency and exchange rates for the four emerging countries for the years 1994–2009. The results of the analysis revealed the existence of two volatility regimes regarding the conditional mean and the conditional variance of stock returns. The first regime presented a high mean-low variance and the second was characterized by low mean and a high variance. Moreover, it was proved that the connection between stock and foreign exchange markets was regime dependent and that stock price volatility replied asymmetrically to events in the foreign exchange market. In a nutshell, it was exhibited that foreign exchange rate fluctuations had a noteworthy effect on the probability of transition across regimes.

In a similar way, the properties of conditional volatilities of stock returns and exchange rates were surveyed (Chkili et al.,2012). For their investigation Chkili et al. used daily closing prices of stock market indices of the three examined European countries (France, Germany, UK) for the period from January 1999 to December 2009, and from January 4, 2010 through December 31, 2010 (for out-of-sample analysis). The results of univariate and multivariate GARCH models revealed robust evidences of asymmetry and long memory in the conditional variances of all series. The multivariate analysis, additionally, illustrated that bilateral relationships between stock and foreign exchange markets were highly significant for France and Germany and, both the univariate FIAPARCH and bivariate CCC-FIAPARCH models provided more accurate in-sample estimates and out-of-sample.

Saadet Kasman et al. (2011) paid attention to the impact of interest and exchange rate volatility on Turkish bank stock returns. The data sample comprised of daily closing prices of the bank index of thirteen Turkish commercial bank stocks listed on the Istanbul Stock Exchange (ISE), exchange rates and interest rates used for the decade 1999-2009. The estimation models that were applied in this paper were the OLS and GARCH models. The results from the empirical investigation suggested that interest rate and exchange rate changes had a negative and weighty effect on the conditional bank stock returns. Additionally, bank stock returns were found to be more sensitive to market returns than to interest rates and exchange rates. This suggested that market returns play a key role in determining the dynamics of conditional return of bank stocks.

What's more, Khalil Jebran and Amjad Iqbal (2016) explored the volatility spillover effects between stock market and foreign exchange market in selected Asian countries like Pakistan, India, Sri Lanka, China, Hong Kong and Japan. By using daily data from 1997 to 2014 and EGARCH model for their analysis, the writers found that bidirectional asymmetric volatility spillovers between stock market and foreign exchange market of Pakistan, China, Hong Kong and Sri Lanka. Regarding India, the results "manifested" unidirectional transmission of volatility from stock market to foreign exchange market.

As a final point, Ngo Thai Hung (2018) examined the volatility spillovers between stock and exchange rate market in central and eastern European countries i.e. Hungary, Poland, Czech Republic, Romania and Croatia. The data sample for the empirical analysis consisted of daily data (closing stock and exchange rate prices) for these five countries, covering the period from April 2000 to September 2017. The examined period was divided into two sub-periods: Pre-crisis period (from 1st April 2000 to 29th August 2008) and post-crisis period (from 1st September 2008 to 29th September 2017). The empirical examination, based on the EGARCH model, uncovered the existence of bidirectional volatility spillovers between stock and foreign exchange market in Hungary for all the studied years and Poland in the post-crisis time. A unidirectional volatility spillovers existed in Croatia during the pre-crisis time-space and volatility spillovers from the stock market to exchange market in the Czech Republic in general. In the aftermath of the crisis, volatility spillovers from the financial markets of Hungary and Poland towards Croatia had not been recorded .

Most of the studies presented above ,targeted in modeling volatility ,found that GARCH family models are appropriate for capturing the symmetric and asymmetric (leverage) effects in stock markets. However, the choice of the best fitted and adequate model depends on the evaluation in the study. Therefore, the present study used an augmented EGARCH model, as it has been used in several papers in this section like those of Engle & Ng (1993),Koutmos(1996), Girard and Biswas (2007), Aliyev (2019), in order to capture volatility spillovers and leverage effects .

3. Methodology

This part of this master dissertation reveals the fundamentals of the methodology that is employed in this thesis. In general the notion of this section is based on the methodology presented in several papers viz. Engle (1982,1993), Nelson(1991), Koutmos (1996), Angelidis (2018) and Aliyev(2019).

To begin with, the Auto-Regression/autoregressive (hereafter referred to as AR) model is a model that describes certain time-varying processes in different fields like in economics. The autoregressive model clarifies that the resulted variable has a linear correlation with its own former values on a stochastic term (i.e. an imperfectly predictable term), in other words a value from a time series is regressed on previous values from that same time series. In a nutshell, an AR model forecasts future behavior based on past behavior (Gandhi, 2015). Therefore, the model is in the form of a stochastic difference equation (or recurrence relation which should not be confused with differential equation). The AR (p) model can be presented as:

$$\mathrm{x_t = c + \sum_{i=1}^{p} + \varphi_1 X_{t-i} + \varepsilon_t} \qquad \text{(i)}$$

Where c in this equation is the constant factor, φ_1, φ_2, φ_3 etc. are the parameters (coefficients) of the model and ε_t are the error terms.

The AR model combined with the moving –average (hereafter referred to as MA) model, which is considered a “simple” method for framing univariate time series, creates the module of a more general autoregressive –moving average (ARMA) (Adhikari & Agrawal,2013).

The general ARMA model that was first described in the 1951 paper of Peter Whittle “Hypothesis testing in time series analysis”, provides in time series analysis a description of a (weakly) stationary stochastic process in terms of two polynomials, one for the auto-regression (AR) and the second for the MA (Mills,2019).

The notation of MA refers to the moving average model of order (mentioned above) and can be written as:

$$\mathrm{X_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t} \qquad \text{(ii)}$$

Where μ is the expectation of X_t, θ_i, θ_{ii}, θ_{iii} etc. are the parameters (coefficients) of the model and ε_t are the error terms

As it is already stated, the ARMA model is the combination of AR (i) and MA (ii) models, so the equation of the model is:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \qquad \text{(iii)}$$

The error terms are supposed to be independent, identically distributed random variables tested from a normal distribution with zero mean: $N(0,\sigma^2)$ where σ^2 is the variance. These hypotheses can be weakened but by this mean they change the properties of the model.

According to Tim Bollerslev (1986), when an ARMA model is implied for an error variance the model is transformed into a GARCH model. The GARCH model is an "extension" of ARCH model, which was introduced by Robert F. Engle in 1982. The ARCH model was developed initially for the description of the insecurity about inflation in UK, however, it was proved that the model levies an autoregressive structure on conditional variance, that lets volatility shocks to continue over time (Lamoureux and Lastrapes , 1990. Bollerslev, 1986. Bollerslev,2008). This model can capture also, according to Christopher G. Lamoureux and William D. Lastrapes (1990), the tendency of returns in time and clarify the well documented non normality and non-stability of empirical asset return distributions.

The fundamental form of ARCH is the one introduced by Engle, which provides a suitable and natural parameterization for capturing the tendency for large (small) variances to be followed by other large (small) variances (Bollerslev, 2008):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 \qquad \text{(iv)}$$

Coming back, according to Panayiotis Theodosiou and Unro Lee (1993) GARCH models are usually used for the scrutiny of the stochastic behavior of several economic time series and for framing the movements of volatility without time restrictions. The GARCH model observes the relationship between some of the residuals and also uses values of the past squared observations and past variances to model the variance at time x (Virginia et al.,2018 Engle et al.,2008). If the order of the GARCH terms is symbolized by p and the order of the ARCH terms by q, the

GARCH model is written as GARCH (p,q). Following the common notation, σ is given by:

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

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

Standard GARCH models adopt the hypothesis that positive and negative error terms have a symmetric effect on the volatility. On the other hand, financial time series in fact show an asymmetrical nonlinear behavior due to various reasons like transaction costs, market frictions and others (Aliyev et al., 2019). This implies that the effect of "bad news" or negative shocks on conditional volatility can last longer than the impact of "good news" or positive shocks. GARCH model observed to be incapable to capture this leverage effect (Ibid). The model that allows for the asymmetric effect of news is the EGARCH model proposed by Nelson (1991) in his paper "Conditional Heteroskedasticity in Asset Returns: A New Approach" (Ibid).

The EGARCH model has several advantages over standard GARCH model. In particular, a simple univariate or bivariate EGARCH model allows the test of volatility spillovers whereas testing within a multivariate GARCH specification is complicated because additional restrictions on the variance must be imposed (Reyes, 2001). In addition, parameter limitations are not required due to the fact that EGARCH models log the conditional variance, therefore securing that the variance will be positive (Ibid.). It is also confirmed that EGARCH model is in general the one of the most appropriate models for stock indexes, such as those used in our study. Finally, EGARCH model provides the best prediction of volatility (Ibid. Engle &NG,1993).

The EGARCH model formula can be written like:

$$\log\sigma_t^2 = \alpha_0 + \sum_{i=1}^{P}\alpha_1(|Z_{t-i}| - E|Z_{t-i}|) + \alpha_2 Z_{t-i} + \sum_{j=i}^{q}\alpha_3\log\sigma_{t=j}^2 \quad \text{(vi)}$$

where σ^2_t is the conditional variance, α_0, α_1, α_2 and α_3 are coefficients, and z_t can be seen as a standard normal variable or it can derive from a generalized error distribution (Pierre,1998). In the case where $\log \sigma^2_t$ ($\ln \sigma^2_t$) is negative, there are no sign restrictions for the parameters in the model (Aliyev et al.,2019).According to Eileen F. St. Pierre the EGARCH equation permits the sign and the magnitude of z_{t-i} to affect distinctively the volatility. This is mainly practical in an asset pricing procedure (Ibid.,1998).

There are several GARCH models like QGARCH, GJR-GARCH, FIGARCH and others, though for this study we will implement the EGARCH model and specifically we will use an extended AR-EGARCH model.

The extended univariate EGARCH model allows the calculation of volatility interactions in one-step ahead and simultaneously examines the impact of asymmetric news on volatility (Koutmos,1996).

In order to understand the final AR-EGARCH model first we have to “deconstruct” it and see the equations that are included in it. Initially, it is included the AR model (mentioned above), which designates the behavior of endogenous variables over the same amount of time as a linear function of past their past values or a linear function of past lags of itself and other variables. According to Yiu, Ho, and Choi (2010), the AR models are “able” to capture the conditional correlations derived from the second step. The AR model of order 1 (AR(1)) can be simply presented as:

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

This equation is transformed into the next one, if we take into account also the equation introduced by Nelson :

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

where R_t symbolizes the percentage return at time t or the daily return for day t for each individual market and ε_t is the innovation at time t for that market (Tamakoshi & Hamori,2012. Hasan &Francis, 1998). The dependent variable R represents the returns of the given stock indexes and the independent variable is the one step back returns of that index.

Concerning the variance of the data, which also has to be included in our analysis, we implement the conditional variance of ε_t indicated by σ_t^2. The formula of conditional variance is as follows:

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

where σ^2_t denotes the conditional variance, and z is the standardized innovation.

Equation (ix) examines the conditional variance of returns in values of each particular stock index under investigation. Terms ($|z_{t-1}|$ - E$|z_{t-1}|$) count the magnitude effect, while term $\alpha_2 z_{t-1}$ measures the sign effect. The sign effect may increase or balance the magnitude effect (Angelidis,2018). To elaborate, when α_2 is negative, a decrease in stock index price ($z_{t-1}<0$) is expected to be followed by higher volatility, while an increase in stock value ($z_{t-1}>0$) will be followed by a moderate volatility (Ibid.). A negative and statistically significant α_2 shows that the existence of leverage effect. Leverage effect denotes the largely negative correlation between an asset return or price and its changes of volatility (Ibid.). That denotes that a rise in asset prices, usually, is accompanied by decreasing volatility, and the opposite. As it was mentioned in Engle and Ng (1993) the leverage effect can be also asymmetric, which is translated into: decline in shares prices goes with greater increases in volatility, than the decrease in volatility which is linked with rising stock markets

Volatility spillovers in own past stock observations are captured by the coefficient α_1. According to Dimitrios Angelidis (2018) the asymmetric volatility transmission mechanism can be perceived as follows: On the one hand, a statistically significant α_1 with a negative α_2 at the same time indicates that negative novelties in the stock price index have higher influence than positive innovations. On the other hand, a positive α_2 implies that positive novelties in the stock price index influence more than negative innovations. The persistence of volatility in equation (ix) is measured by the factor α_3. If α_3 is less than one (α_3 <1), the conditional variance is limited, while if α_3 equals to one (α_3 =1) the conditional variance follows an integrated process of order 1.

Continuing, following the notion of Hasan and Francis (1998) we add in the above conditional asymmetric volatility equation (ix) some explanatory exogenous variables such as the trading volume (TV) and exchange rate (ER) with the objective to investigate their ability to explain furthermore the transmission mechanism process in each stock market. In order to make that feasible, new coefficients are inserted in the equation (ix) -the coefficient φ and the coefficient χ. Aim of the coefficient φ is to capture the possible correlation between stock index of each market with the impact of trading volume.

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

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

Where χ is the coefficient for the exchange rate (ER) variable. Therefore, the equation (xi) will reveal the correlation between stock index and exchange rate, specifically the influence of exchange rate on stock market indexes. If we combine the two above presented equations (x, xi) we end up having the bellow formula:

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

The above described methodological procedure helps us investigate the volatility spillovers in stock markets of emerging and developing economies, as well as see the impact of exchange rate and trading volume on them.

4. Data description

This section of the master dissertation describes the data that have been used for the empirical analysis. The dataset consists of daily stock price indexes for each of the four examined stock exchange markets, namely Kazakhstan Stock Exchange (Kazakhstan),Warsaw Stock Exchange (Poland), Istanbul Stock Exchange (Borsa Istanbul -Turkey) and Moscow Stock Exchange (Russia). Particularly, the sample contains daily closing prices and daily prices of exchange rate (denominated in local currencies) and trading volume given also in national currency (the value of the volume of deals on share in national currency) for a period of 11 years, from January 20, 2009 to December 31, 2019 (3998 observations in total). The rationale behind the use of daily data is to capture more information than we could have by using weekly and monthly data. Regarding the selection of the data, they are retrieved from the national exchange stock markets of each country and the global financial portal: investing.com.

In the academic and economic world is generally accepted that the below mentioned indexes represent sufficiently the stock market of each country, i.e. KASE index (Kazakhstan), WIG20 (Poland), BIST100 (Turkey) and MOEX index (Russia).

KASE Index is the ratio of shares' market prices (at a certain date), which are included into the representative list, weighted on capitalization considering free floating shares ("KASE", 2020). The index includes shares of large and significant

Kazakhstani companies like: Bank Center Credit, KAZ Minerals, Halyk Bank, Kcell, KEGOC, NAC Kazatomprom, Kazakhtelecom and KazTransOil (Ibid.).

Following, WIG 20 index is a capitalization-weighted stock market index of the twenty largest companies on the Warsaw Stock Exchange. Its composition includes: Alior Bank, Bank Pekao, CD Projekt, Dino Polska, PGE Polska Grupa Energetyczna, PKN Orlen, Play Communication, Santander Bank Polska, Tauron Polska, MBank ("GPW Main Market - Main Market", 2020).

Likewise , BIST 100 index or the Borsa Istanbul 100 index is a capitalization-weighted index, which includes constituents from National Market Companies. BIST100 is the main index of Borsa Istanbul Equity Market. It consists of 100 stocks selected among the stocks of companies traded on the Stars Market ("Borsa Istanbul", 2020). [5] Some of the companies that are included in the index are Akbank TAS, Aksa Akrilik, Aksa Enerji Uretim, Anatolu Efes Malt, Besiktas, Coca Cola Icecek, Hurriyet Gazete, ICBC Turkey, Metro Holding, Turk Telekom, Turkcell, Turk Traktor, Turkiye IS Bankasi C and Yapi ve Kredi Bankasi (investing.com., 2020).

The MOEX Russia, formerly MICEX Index, is the main ruble-denominated benchmark of the Russian stock market and has the same composition as the dollar-denominated RTS Index ("Russia Trading System").The index consists of 50 Russian stocks traded on the Moscow Exchange with some of them being AFK Sistema, Aeroflot, Rosagro, Credit Bank of Moscow, Detsky Mir , Gazprom , Norilsk, Nickel, RusHydro, Lukoil, Sberbank, Magnitogorsk Iron and Steel Works, MegaFon and Yandex ("Moscow Exchange", 2020).

In many statistical analyses, like this one, is crucial to characterize the location and variability of a data set. (*NIST/SEMATECH e-Handbook of Statistical Methods*, n.d.). In view of that, we proceed, in this section, with the visualization of our dataset that is to say the presentation of any information is contained in our sample convey.

[5] it covers automatically BIST 30 and BIST 50 stock indexes

Figure 1.0.0: KASE index

Figure 1.0.1: BIST 100 index : 2009-2019.

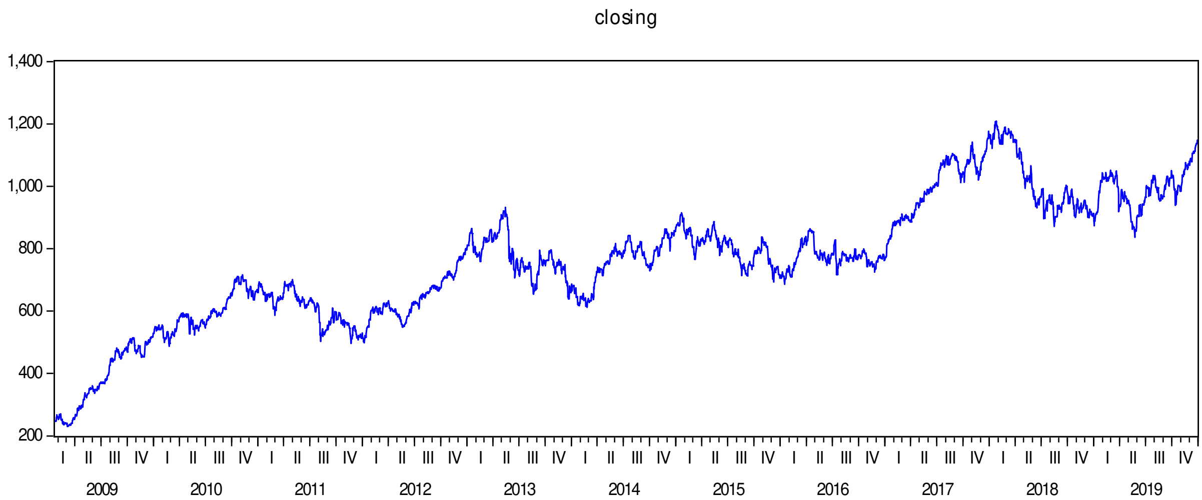


Figure 1.0.2: WIG 20 index

Figure 1.0.3: MOEX index

Figure 1.0 presents the fluctuation of KASE index, showing that during the examined period (2009-2019) the index met a rise in 2009 and rapid decline in the second quarter of 2010. A slowdown is also evident from the second half of 2011 until 2018, when we observe a "recovery" of the price -a rise. All these movements of the index could be the result of the dependencies of the index and of the impact of the global economic crisis that started in 2010 and the oil price crises that followed. Firure1.0 in the Introduction).

Regarding BIST 100 index (Figure 1.0.1) of the Turkish stock market, we observe that during the examined period, the index fluctuated in a stable (low) way, with exceptions in 2011 and 2017, when there are some picks of the price.

In the case of Polish stock index- namely WIG20, we observe a clear trend of the stock index and its volatility (see above Figure 1.0.2). WIG 20 index met a rise from 2009-2011, a balance the next years and a rapid decline from the second half of 2015 until 2017, as a result of the economic crisis.

The fluctuation of MOEX index, respectively, shows that during the examined period (2009-2019) the index overall met a rise since 2009 and then fluctuated "steadily" during the years of the global financial crisis and the oil prices crisis (2010 and after). In particular according to the descriptive and diagnostic statistics below (see Figure 1.1 & Table 1.0) the index all these years met a rise rather than a decline (the mean value of the index is positive).

In all cases the trend of the indexes follows the trend of the GDP change, only in the case of MOEX the line of the index does not quite match the one of GDP.

Continuing, after the visualization of the indexes we proceed with the descriptive and diagnostic statistics of each stock market index, as we target in obtaining more information and have a better look of the data.

Figure 1.1: KASE summary statistics: histogram

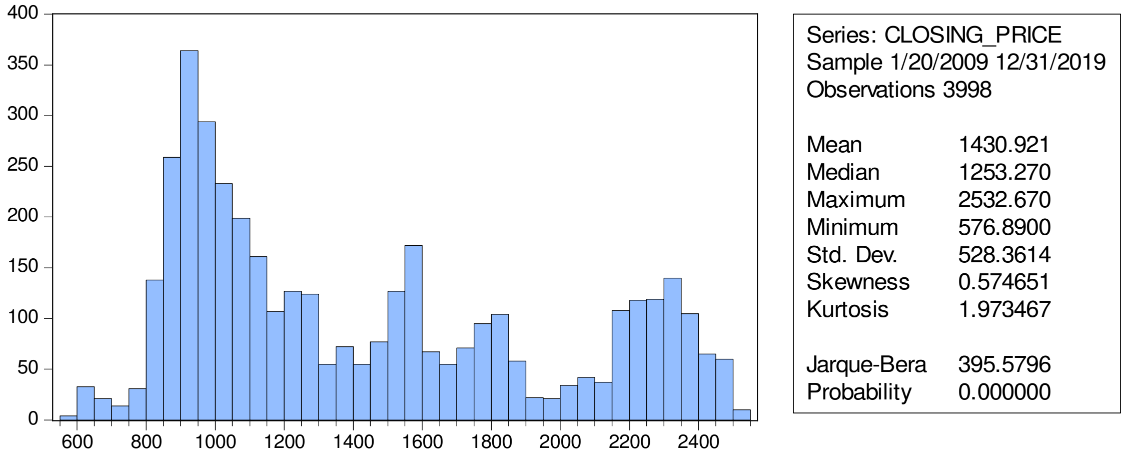


Figure1.1.1: BIST100 summary statistics: histogram

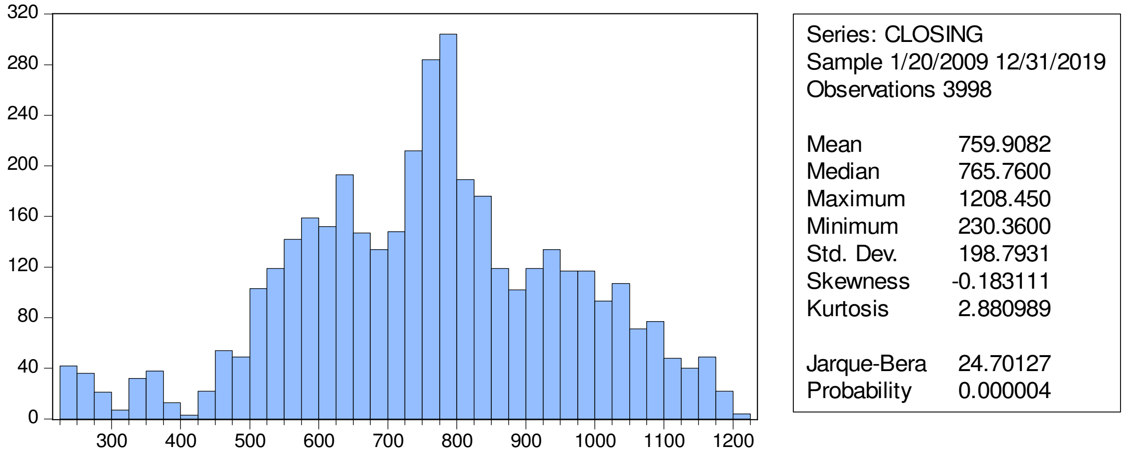


Figure 1.1.2: WIG20summary statistics: histogram

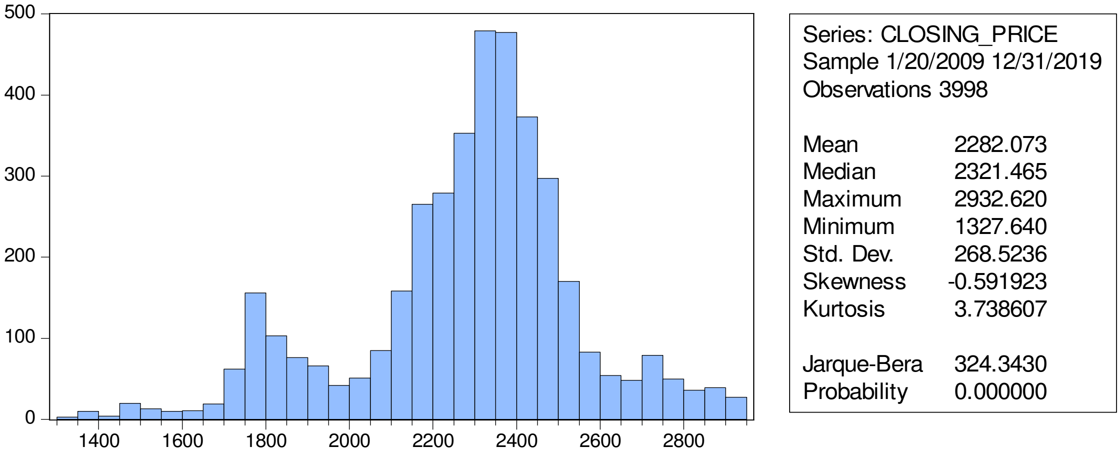
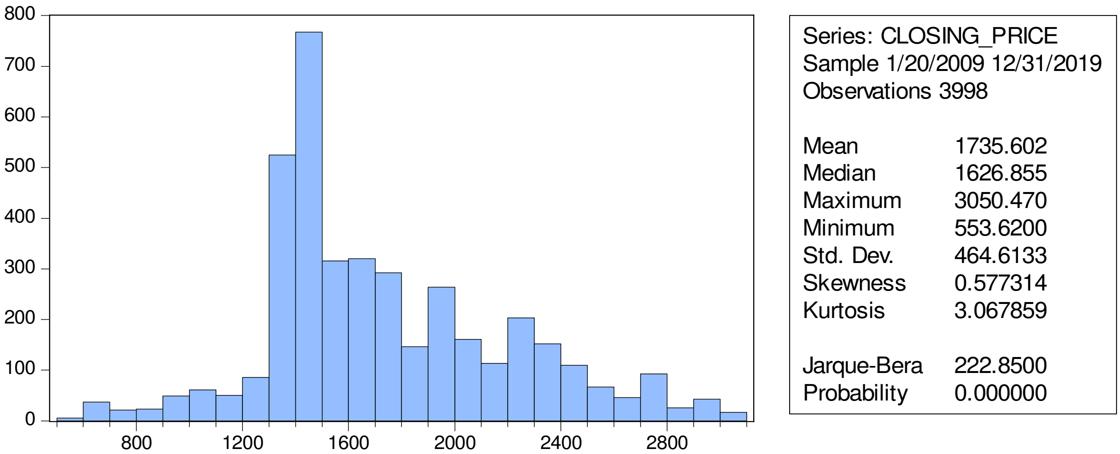


Figure 1.1.3: MOEX summary statistics: histogram



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In the Figures above, “mean” pictures the mean value of the stock index (closing prices). If mean is negative, we conclude that the price/value has declined through the years, while when is positive we have an increase of this value. Median is the middle value after shorting observations and standard deviation is how far observations are from the sample average.

Furthermore, skewness is the measurement of the asymmetry of a given variable around its mean. Normal skewness implies that the distribution is symmetric around its mean. The skewness value in this case is around 0. Positive skewness implies that the distribution has long right tail, that says that we have in our sample higher values than the sample mean, while negative skewness implies that the distribution will have long left tail and lower values than the sample mean (Dugar, 2018).

Kurtosis measures the peakness or flatness of the distribution of the series. Standard normal distribution (mesokurtic) has a kurtosis of 3, while a positive kurtosis (kurtosis >3) shows a peaked curve (leptokutic) indicating that there are more higher values than the sample mean and the opposite - negative kurtosis (kurtosis< 3) - indicates a flatted curve (platykurtic) and more lower value (Ibid., 2018).

In the case of KASE index the mean of the index is positive (1430.921), indicating the fact that price met an increase, rather than a decrease, over the examined period. Furthermore, skewness counts 0.574651 and the kurtosis is 1.973467 (< 3), which means that our sample mirrors a normal skewness although its distribution is platykurtic, in other words extreme values count less than the mean sample value. Having these results, in addition with the Jaque-Bera test,[6] which indicates significance at 1% level, we reject the null hypothesis of a normal distribution.

The descriptive and diagnostic statistics tests of BIST100 index (see Figure 1.1.1) show that the index fluctuated positively and faced an increase, since the mean value of the sample is positive (779.2745). Skewness is negative (-0.183111) implying that the distribution has long left tail and lower values than the sample mean. Kurtosis is positive and but not greater than 3 (2.880989<3), showing a more flatted curve (platykurtic). In a nutshell, our sample is asymmetric around its mean and platykurtic, in other words we reject the null hypothesis of normal distribution.

In Figure 1.1.2 are displayed the descriptive and diagnostic tests of WIG 20 stock index. The mean of the index is positive (22282.073) indicating the fact that it met an increase over the studied period. Furthermore, skewness is negative. Negative skewness denotes that the distribution will have long left tail and lower values than the sample mean. Kurtosis measures the peakness or flatness of the distribution of the series. Positive and greater than 3 kurtosis (3.738607) mirrors a slightly leptokurtic distribution. All these in combination with the Jaque-Bera test leads us to the rejection of the null hypothesis of a normal distribution

According to the descriptive and diagnostic statistics of MOEX index (see Figure 1.1.3) the index all these years met a rise (the mean value of the index is positive). From the above figure we realize that skewness values 0.57777 (positive),

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[6]Jaque – Bera test measures the difference of the skewness and kurtosis of the series with those from the normal distribution.

which shows that our distribution has long right tail or that in our sample occur higher values than the sample mean. Kurtosis, on the other hand, is almost normal since it counts 3.068, so we can argue that the distribution is slightly mesokurtic. Having these results and applying the Jaque-Bera test we reject the null hypothesis of a totally normal distribution

Many classical statistical tests and intervals depend on normality assumptions. Significant skewness and kurtosis clearly indicate that our data are not normal. A method to "solve" this problem is to transform the data in order to "correct" them. In particular, taking the log or square root of a data set is often useful for data that exhibit moderate right skewness (Dugar,2018). Following this rationale we took the natural log of the closing prices of all the indexes and we succeeded more "compact" samples, but again we reject the null hypothesis for normal distribution since after the transformation the distribution becomes leptokurtic.

Figure 1.2:KASE index- time series of logged stock's closing price

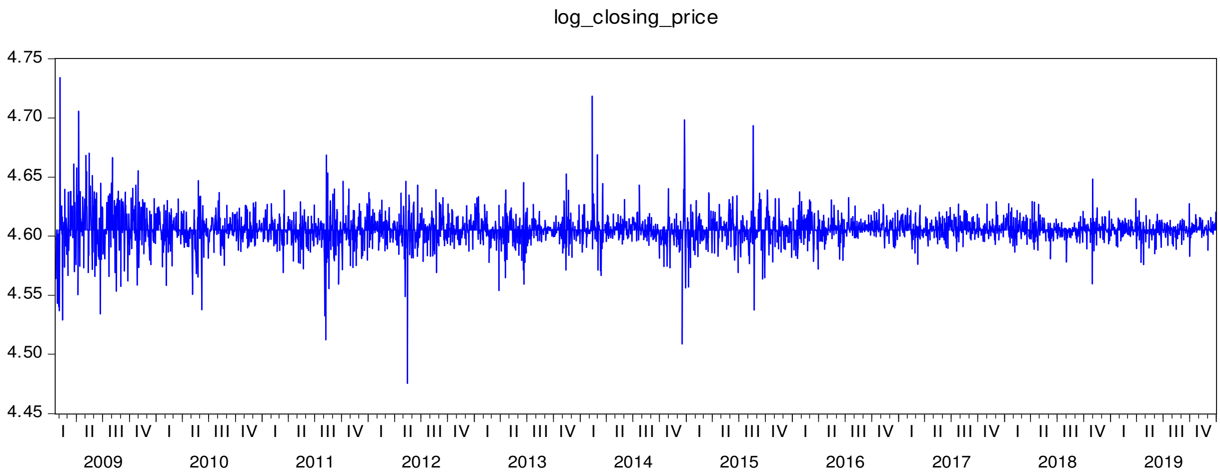


Figure1.3: KASE index summary statistics :histogram

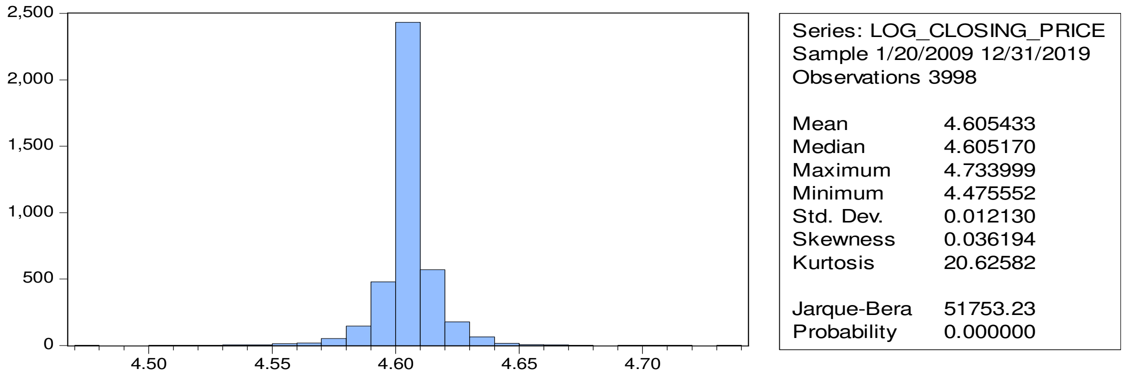


Figure 1.2.1: BIST100index time series of logged stock's closing price

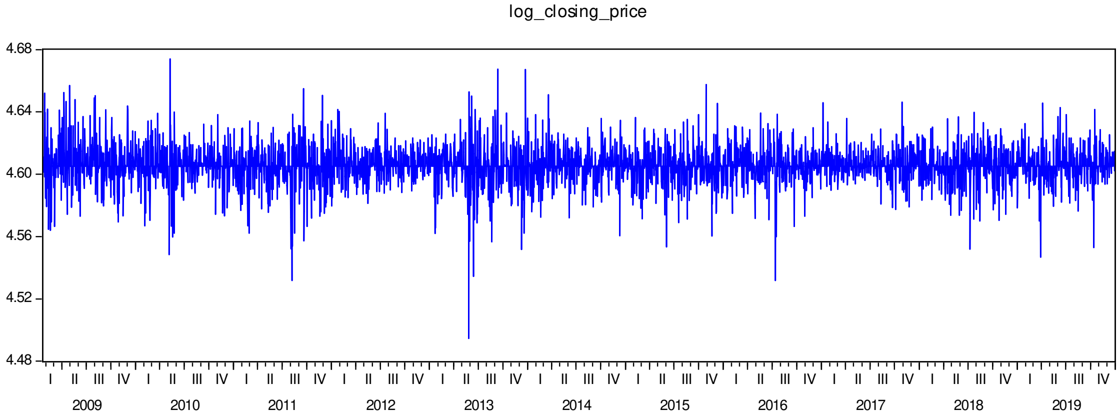
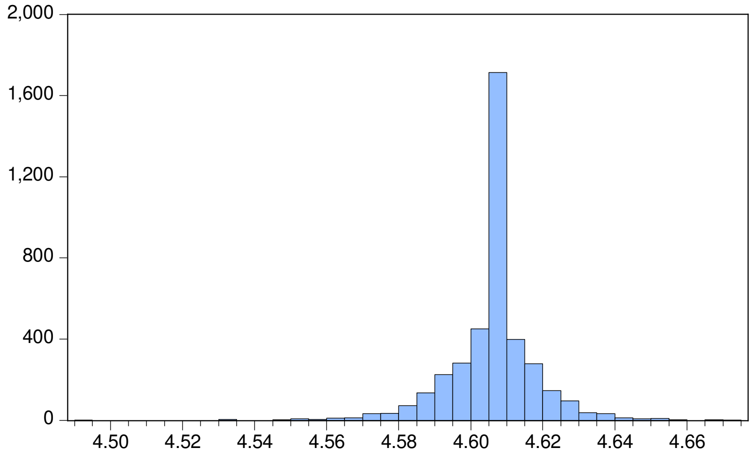


Figure 1.3.1: BIST100 index summary statistics



Series: LOG_CLOSING_PRICE
Sample 1/20/2009 12/31/2019
Observations 3998

Mean	4.605554
Median	4.605170
Maximum	4.674121
Minimum	4.494537
Std. Dev.	0.011928
Skewness	-0.436058
Kurtosis	8.978335
Jarque-Bera	6080.471
Probability	0.000000

Figure 1.2.2: WIG20 index time series of logged stock's closing price

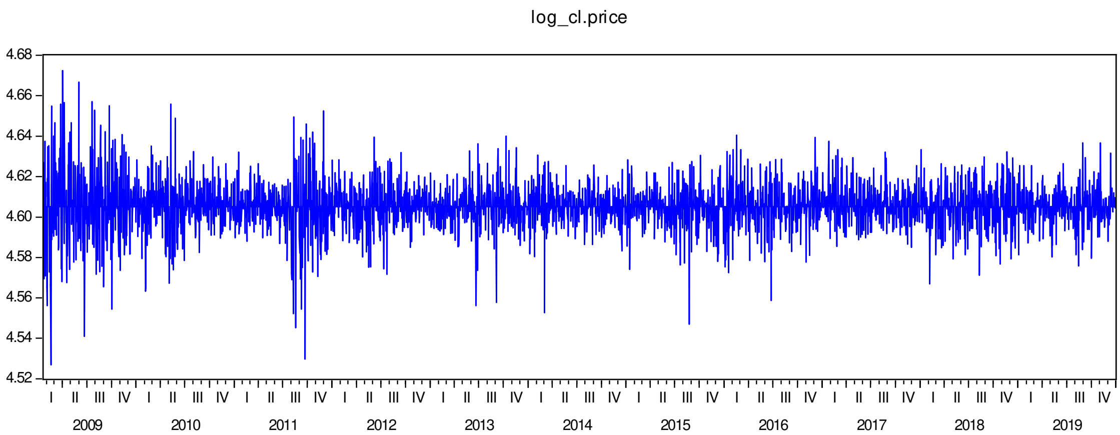


Figure1.3.2 : WIG20 index summary statistics :histogram

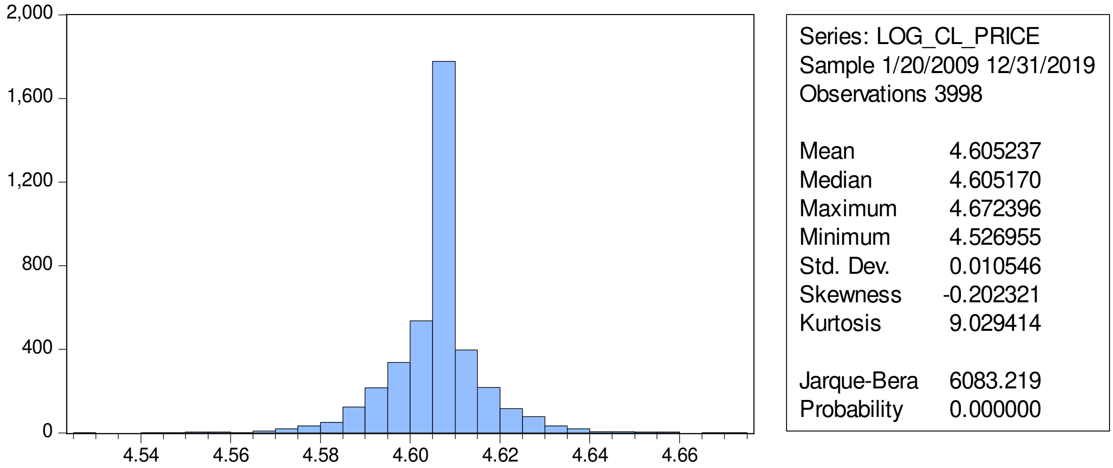


Figure 1.2.3: MOEX index time series of logged stock's closing price

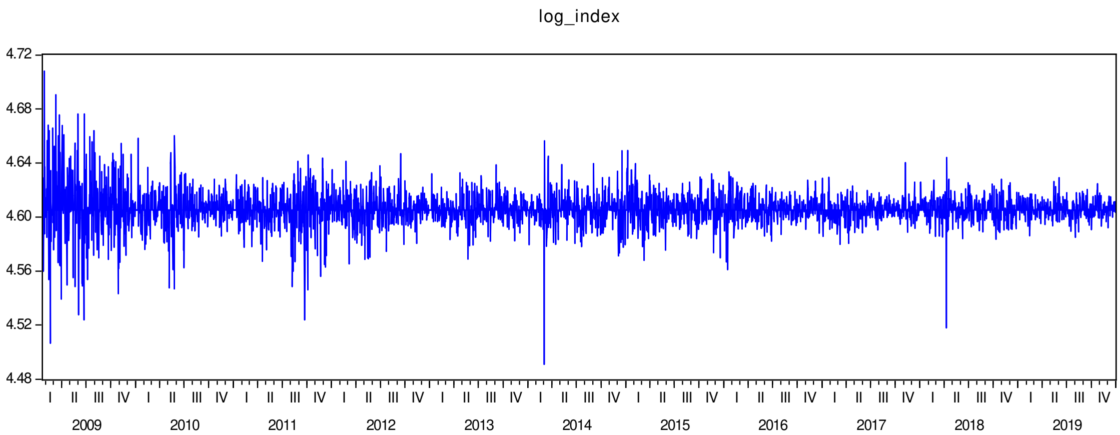


Figure1.3.3: MOEX index summary statistics :histogram

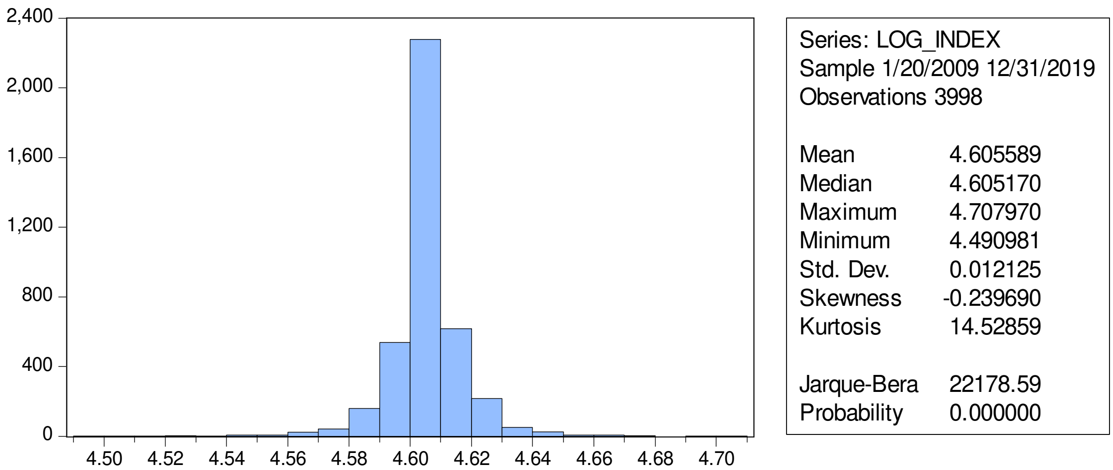


Figure1.2 presents the logged form of KASE index displaying signs of volatility clustering, that is: periods of large changes are followed by periods with

large changes and periods with small changes are followed further by periods with small changes. Of course some breaks are observed in this pattern indicating volatility “bursts”. The absence of normality (Figure 1.3), as it is revealed by the above outcomes, may be originated, at least to some extent, from temporal dependencies of the index in previous prices.

In the case of Turkey and BIST100 index, signs of volatility clustering are present (Figure 1.2.1), that is again: periods of large changes are followed by periods with large changes and periods with small changes are followed further by periods with small changes. In that case there is a break of volatility in the second quarter of 2013. By taking the natural log of the data set we succeeded a leptokurtic distribution, and again we reject the null hypothesis for normal distribution (see above Figures 1.2.1 &1.3.1).

As regards WIG20, the results in Figures 1.2.2 &1.2.3 indicate also signs of volatility clustering and non-normal distribution (leptokurtic), while MOEX index (Figures 1.2.3 &1.3.3) shows also signs of volatility clustering, and absence of normality (leptokurtic distribution). In Figure 1.2.2, in the first quarter of 2014 and 2018 are observed disruptions of the index, which can be the results of the oil price crises that took place these years. Generally, as it is known, this absence of normality is an indication of temporal dependencies of the index in previous prices.

In order to test whether such dependencies are present, we employ the Ljung-Box (LB) Q statistic, but fist, we conduct a least squares regression of the logged closing price variable with its past value.

Table 1.1: KASE index Least squares regression

Dependent Variable: LOG_CLOSING_PRICE

Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.778856	0.064238	105.5273	0.0000
LOG_CLOSING_PRICE(-1)	-0.471924	0.013947	-33.83611	0.0000

R-squared	0.222745	Mean dependent var	4.605443
Adjusted R-squared	0.222550	S.D. dependent var	0.053873
S.E. of regression	0.047502	Akaike info criterion	-3.255607
Sum squared resid	9.014321	Schwarz criterion	-3.252458
Log likelihood	6508.331	Hannan-Quinn criter.	-3.254491

F-statistic	1144.883	Durbin-Watson stat	2.268014
Prob(F-statistic)	0.000000		

Table 1.2: Ljung –Box Q-statistic
Q-statistic probabilities adjusted for 1 dynamic regressor

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>*| |</td><td>*| |</td><td>1</td><td>-0.134</td><td>-0.134</td><td>71.961</td><td>0.000</td></tr>
<tr><td>**| |</td><td>**| |</td><td>2</td><td>-0.283</td><td>-0.307</td><td>393.31</td><td>0.000</td></tr>
<tr><td>| |</td><td>*| |</td><td>3</td><td>0.001</td><td>-0.101</td><td>393.32</td><td>0.000</td></tr>
<tr><td>| |</td><td>*| |</td><td>4</td><td>-0.003</td><td>-0.123</td><td>393.36</td><td>0.000</td></tr>
<tr><td>| |</td><td>*| |</td><td>5</td><td>-0.006</td><td>-0.067</td><td>393.50</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.008</td><td>-0.049</td><td>393.74</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>0.008</td><td>-0.025</td><td>394.02</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.004</td><td>-0.023</td><td>394.10</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>-0.006</td><td>-0.018</td><td>394.23</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>0.002</td><td>-0.011</td><td>394.24</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>11</td><td>0.005</td><td>-0.004</td><td>394.34</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>12</td><td>0.003</td><td>0.001</td><td>394.39</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>13</td><td>0.001</td><td>0.002</td><td>394.39</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>14</td><td>-0.002</td><td>0.001</td><td>394.40</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>15</td><td>0.008</td><td>0.011</td><td>394.64</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>16</td><td>0.008</td><td>0.015</td><td>394.88</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>17</td><td>-0.002</td><td>0.011</td><td>394.89</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>18</td><td>0.001</td><td>0.013</td><td>394.89</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>19</td><td>0.004</td><td>0.014</td><td>394.95</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>20</td><td>-0.005</td><td>0.005</td><td>395.05</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>21</td><td>-0.000</td><td>0.007</td><td>395.05</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>22</td><td>0.003</td><td>0.006</td><td>395.09</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>23</td><td>0.002</td><td>0.007</td><td>395.10</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>24</td><td>0.000</td><td>0.006</td><td>395.10</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>25</td><td>0.001</td><td>0.006</td><td>395.11</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>26</td><td>0.002</td><td>0.006</td><td>395.12</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>27</td><td>0.002</td><td>0.007</td><td>395.13</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>28</td><td>0.007</td><td>0.013</td><td>395.32</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>29</td><td>0.005</td><td>0.014</td><td>395.41</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>30</td><td>0.001</td><td>0.014</td><td>395.42</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>31</td><td>-0.002</td><td>0.010</td><td>395.43</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>32</td><td>-0.002</td><td>0.007</td><td>395.44</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>33</td><td>0.006</td><td>0.013</td><td>395.58</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>34</td><td>0.002</td><td>0.009</td><td>395.59</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>35</td><td>-0.003</td><td>0.005</td><td>395.63</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>36</td><td>0.002</td><td>0.007</td><td>395.65</td><td>0.000</td></tr>
</table>

Table 1.1.1 : BIST 100 Least squares regression

Dependent Variable: LOG_CLOSING_PRICE
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.883517	0.063345	108.6678	0.0000
LOG_CLOSING_PRICE(-1)	-0.494612	0.013750	-35.97052	0.0000

R-squared	0.244641	Mean dependent var	4.605554
Adjusted R-squared	0.244452	S.D. dependent var	0.103513
S.E. of regression	0.089975	Akaike info criterion	-1.978059
Sum squared resid	32.34187	Schwarz criterion	-1.974910
Log likelihood	3955.151	Hannan-Quinn criter.	-1.976943
F-statistic	1293.878	Durbin-Watson stat	2.317679
Prob(F-statistic)	0.000000		

Table 1.2.1 :BIST100 index Ljung –Box Q-statistic

Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.159	-0.159	100.92	0.000
**| |	***| |	2	-0.321	-0.355	512.46	0.000
| |	*| |	3	0.001	-0.146	512.46	0.000
| |	*| |	4	-0.000	-0.177	512.46	0.000
| |	*| |	5	0.000	-0.111	512.46	0.000
| |	*| |	6	0.000	-0.106	512.46	0.000
| |	*| |	7	-0.001	-0.081	512.47	0.000
| |	*| |	8	0.001	-0.069	512.47	0.000
| |	| |	9	-0.002	-0.059	512.49	0.000
| |	| |	10	-0.001	-0.051	512.49	0.000
| |	| |	11	-0.001	-0.045	512.50	0.000
| |	| |	12	-0.002	-0.041	512.52	0.000
| |	| |	13	-0.001	-0.038	512.52	0.000
| |	| |	14	0.000	-0.033	512.52	0.000
| |	| |	15	0.004	-0.025	512.58	0.000
| |	| |	16	0.001	-0.022	512.59	0.000
| |	| |	17	0.000	-0.017	512.59	0.000
| |	| |	18	-0.001	-0.015	512.59	0.000
| |	| |	19	-0.000	-0.012	512.59	0.000
| |	| |	20	0.001	-0.009	512.60	0.000
| |	| |	21	-0.000	-0.007	512.60	0.000
| |	| |	22	0.002	-0.002	512.62	0.000
| |	| |	23	0.002	0.001	512.65	0.000

		24	-0.001	0.001	512.65	0.000
		25	0.002	0.006	512.67	0.000
		26	0.003	0.010	512.72	0.000
		27	-0.001	0.009	512.72	0.000
		28	0.005	0.018	512.81	0.000
		29	-0.006	0.008	512.94	0.000
		30	-0.008	0.003	513.21	0.000
		31	0.001	0.003	513.21	0.000
		32	0.003	0.002	513.24	0.000
		33	-0.000	0.001	513.24	0.000
		34	-0.000	0.001	513.24	0.000
		35	0.002	0.003	513.26	0.000
		36	0.003	0.006	513.29	0.000

Table 1.1.2: WIG 20 index Least squares regression

Dependent Variable: LOG_CL_PRICE

Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.530267	0.072851	62.18513	0.0000
LOG_CL_PRICE(-1)	0.016279	0.015819	1.029097	0.3035

R-squared	0.000265	Mean dependent var	4.605238
Adjusted R-squared	0.000015	S.D. dependent var	0.010547
S.E. of regression	0.010547	Akaike info criterion	-6.265433
Sum squared resid	0.444408	Schwarz criterion	-6.262284
Log likelihood	12523.47	Hannan-Quinn criter.	-6.264317
F-statistic	1.059040	Durbin-Watson stat	1.997211
Prob(F-statistic)	0.303496		

Table 1.1.2.1: WIG20 index multicollinearity test

Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.005307	190696.8	NA
LOG_CL_PRICE(-1)	0.000250	190696.8	1.000000

Table 1.2.2: WIG 20 Ljung –Box Q-statistic

Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0030	0.956
		2	-0.053	-0.053	11.347	0.003
		3	0.004	0.004	11.414	0.010
		4	-0.038	-0.041	17.088	0.002
		5	0.000	0.001	17.088	0.004
		6	0.006	0.002	17.231	0.008
		7	-0.040	-0.040	23.612	0.001
		8	-0.002	-0.003	23.624	0.003
		9	0.015	0.010	24.474	0.004
		10	0.000	0.001	24.474	0.006
		11	0.004	0.002	24.538	0.011
		12	-0.032	-0.032	28.576	0.005
		13	-0.009	-0.007	28.879	0.007
		14	0.033	0.028	33.149	0.003
		15	0.024	0.024	35.526	0.002
		16	0.007	0.009	35.744	0.003
		17	-0.015	-0.014	36.692	0.004
		18	-0.003	0.001	36.726	0.006
		19	-0.015	-0.017	37.661	0.007
		20	-0.021	-0.021	39.400	0.006
		21	-0.008	-0.008	39.656	0.008
		22	-0.014	-0.014	40.452	0.010
		23	-0.006	-0.008	40.604	0.013
		24	-0.008	-0.014	40.844	0.017
		25	0.020	0.018	42.486	0.016
		26	-0.007	-0.008	42.661	0.021
		27	0.008	0.010	42.899	0.027
		28	-0.015	-0.018	43.860	0.029
		29	0.012	0.012	44.442	0.033
		30	0.009	0.005	44.754	0.041
		31	0.008	0.009	45.027	0.050
		32	0.021	0.022	46.822	0.044
		33	0.004	0.006	46.890	0.055
		34	-0.028	-0.024	49.966	0.038
		35	0.008	0.009	50.241	0.046
		36	-0.020	-0.020	51.776	0.043

Table 1.1.3: MOEX index least squares regression

Dependent Variable: LOG_INDEX

Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.827203	0.072782	66.32399	0.0000
LOG_INDEX(-1)	-0.048118	0.015803	-3.044904	0.0023

R-squared	0.002315	Mean dependent var	4.605590
Adjusted R-squared	0.002066	S.D. dependent var	0.012127
S.E. of regression	0.012114	Akaike info criterion	-5.988375
Sum squared resid	0.586283	Schwarz criterion	-5.985226
Log likelihood	11969.77	Hannan-Quinn criter.	-5.987259
F-statistic	9.271439	Durbin-Watson stat	2.000468
Prob(F-statistic)	0.002343		

Table 1.2.3: MOEX index Ljung –Box Q-statistic

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0019	0.965
		2	-0.013	-0.013	0.6410	0.726
		3	0.043	0.043	7.9113	0.048
		4	-0.005	-0.005	7.9935	0.092
		5	-0.025	-0.024	10.525	0.062
		6	0.009	0.007	10.863	0.093
		7	-0.016	-0.016	11.883	0.104
		8	-0.022	-0.020	13.846	0.086
		9	-0.011	-0.012	14.291	0.112
		10	-0.004	-0.004	14.358	0.157
		11	-0.032	-0.031	18.571	0.069
		12	0.017	0.017	19.746	0.072
		13	0.044	0.043	27.373	0.011
		14	-0.011	-0.009	27.863	0.015
		15	0.023	0.022	29.943	0.012
		16	0.017	0.011	31.133	0.013
		17	-0.015	-0.012	32.006	0.015
		18	0.002	0.001	32.022	0.022
		19	0.015	0.012	32.935	0.024
		20	-0.036	-0.032	38.115	0.009
		21	-0.017	-0.015	39.259	0.009
		22	-0.028	-0.031	42.513	0.005
		23	-0.001	0.004	42.520	0.008
		24	-0.036	-0.033	47.846	0.003
		25	0.019	0.018	49.261	0.003
		26	-0.027	-0.028	52.120	0.002
		27	-0.010	-0.008	52.524	0.002
		28	0.003	-0.004	52.560	0.003
		29	0.022	0.020	54.488	0.003
		30	-0.007	-0.006	54.701	0.004
		31	0.008	0.002	54.983	0.005
		32	-0.009	-0.012	55.296	0.006
		33	0.006	0.008	55.453	0.009
		34	-0.043	-0.044	63.069	0.002
		35	0.008	0.009	63.334	0.002
		36	0.004	0.006	63.398	0.003

The results of the regression analysis of the KASE index show a significant negative relation between the two variables : the closing price and its past value (Table 1.1). Following that, the Correlogram (Table 1.2) displays the autocorrelation and partial autocorrelation functions of the residuals, together with the Ljung-Box Q-statistics for high-order serial correlation. The null hypothesis in that case states that the data are independently distributed, whereas the alternative hypothesis declares that the data are not independently distributed, in other words they exhibit serial correlation. In the presented matter, we accept the alternative hypothesis of serial correlation for KASE index prices, since all Q-statistics are significant at 1% level for all lags.

In the same way, the results of the regression of Turkish index (BIST100 index) show a significant negative relation between these two values (Table 1.1.1). According to the Correlogram (Table 1.2.1) we accept again the alternative hypothesis of serial correlation since all Q-statistics of all lags are significant at 1% level.

The results of the regression for the WIG20 indicate a positive but also an insignificant relation between the two variables (not even at 10% level). This means that the previous value (stock price) does not explain – affect the current one. This result could be the consequence of multicollinearity; therefore, before we continue with the intended analysis, we conduct a multicollinearity test- in our case the Variance Inflation Factor Test (hereafter referred to as VIF) (see Table 1.1.2.1). From the VIF test, we conclude that we have multicollinearity but not in a great extend since the centered Variance Inflation Factor counts less than 10. If VIF is greater or equals 10 then we have severe multicollinearity that we cannot ignore and consequently we have to reset the model. In our case, according to the outcome we proceed with our analysis by ignoring this result. Continuing, the Correlogram in Table 1.2.2 points out the acceptance of the alternative hypothesis of serial correlation since Q-statistics is significant at 5% level for almost all lags except the first one, which is insignificant at all levels (p-value = 0.956>0.10).

Last but not least, in the case of MOEX index (Russia) the regression (Table 1.1.3) indicates a significantly negative correlation. In addition, the Correlogram (Table 1.2.3) suggests the acceptance of the alternative hypothesis of serial correlation after the second lag and with exceptions lags 7, 9 and 10.

Furthermore, the Dickey- Fuller test, that is implemented, designates in accordance with the other tests that the data of this study are stationary since the t-statistics are less than the critical values for all cases (see Tables below).

Table 1.3: KASE index Dickey –Fuller test

Null Hypothesis: D(LOG_CLOSING_PRICE) has a unit root
Exogenous: Constant
Lag Length: 23 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.78978	0.0000
Test critical values:	1% level	-3.431811	
	5% level	-2.862071	
	10% level	-2.567096	

*MacKinnon (1996) one-sided p-values.

Table 1.4: KASE index Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	252.8534	Prob. F(2,3993)	0.0000
Obs*R-squared	449.3091	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.822714	0.280374	2.934340	0.0034
LOG_CLOSING_PRICE(-1)	-0.178640	0.060879	-2.934357	0.0034
RESID(-1)	-0.008175	0.058908	-0.138770	0.8896
RESID(-2)	-0.392778	0.032899	-11.93903	0.0000

R-squared	0.112412	Mean dependent var	-3.60E-15
Adjusted R-squared	0.111745	S.D. dependent var	0.047496
S.E. of regression	0.044763	Akaike info criterion	-3.373853
Sum squared resid	8.001007	Schwarz criterion	-3.367555
Log likelihood	6746.646	Hannan-Quinn criter.	-3.371621
F-statistic	168.5689	Durbin-Watson stat	2.046642
Prob(F-statistic)	0.000000		

Table 1.3.1 : BIST 100 index Dickey –Fuller test

Null Hypothesis: D(LOG_CLOSING_PRICE) has a unit root
Exogenous: Constant
Lag Length: 29 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.33724	0.0000
Test critical values:	1% level	-3.431813	
	5% level	-2.862072	
	10% level	-2.567096	

*MacKinnon (1996) one-sided p-values.

Table 1.4.1: BIST 100 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	357.3981	Prob. F(2,3993)	0.0000
Obs*R-squared	606.8742	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.054967	0.248607	4.243518	0.0000
LOG_CLOSING_PRICE(-1)	-0.229064	0.053979	-4.243576	0.0000
RESID(-1)	-0.004610	0.051777	-0.089038	0.9291
RESID(-2)	-0.471132	0.031114	-15.14190	0.0000

R-squared	0.151832	Mean dependent var	-5.32E-15
Adjusted R-squared	0.151195	S.D. dependent var	0.089964
S.E. of regression	0.082885	Akaike info criterion	-2.141735
Sum squared resid	27.43132	Schwarz criterion	-2.135437
Log likelihood	4284.258	Hannan-Quinn criter.	-2.139503
F-statistic	238.2654	Durbin-Watson stat	2.083398
Prob(F-statistic)	0.000000		

Table 1.3.2: WIG20 index Dickey –Fuller test
Null Hypothesis: D(LOG_CL_PRICE) has a unit root
Exogenous: Constant
Lag Length: 16 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.20501	0.0000
Test critical values:	1% level	-3.431808	
	5% level	-2.862069	
	10% level	-2.567095	

*MacKinnon (1996) one-sided p-values.

Table 1.4.2: WIG 20 index Breusch-Godfrey Serial Correlation LM Test
Breusch-Godfrey Serial Correlation LM Test:

F-statistic	5.805266	Prob. F(2,3993)	0.0030
Obs*R-squared	11.58847	Prob. Chi-Square(2)	0.0030

Test Equation:
Dependent Variable: RESID
Method: Least Squares

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	132.9142	260.5801	0.510071	0.6100
LOG_CL_PRICE(-1)	-28.86154	56.58343	-0.510071	0.6100
RESID(-1)	28.86205	56.58263	0.510087	0.6100
RESID(-2)	0.416602	0.921285	0.452197	0.6512

R-squared	0.002899	Mean dependent var	-4.59E-15
Adjusted R-squared	0.002150	S.D. dependent var	0.010546
S.E. of regression	0.010534	Akaike info criterion	-6.267336
Sum squared resid	0.443120	Schwarz criterion	-6.261038
Log likelihood	12529.27	Hannan-Quinn criter.	-6.265104
F-statistic	3.870177	Durbin-Watson stat	1.998168
Prob(F-statistic)	0.008907		

Table 1.3.3 : MOEX Dickey –Fuller test

Null Hypothesis: LOG_INDEX has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=30)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-66.32422	0.0001
Test critical values:	1% level	-3.431801	
	5% level	-2.862066	
	10% level	-2.567093	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG_INDEX)
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG_INDEX(-1)	-1.048118	0.015803	-66.32422	0.0000
C	4.827203	0.072782	66.32399	0.0000

R-squared	0.524059	Mean dependent var	0.000000
Adjusted R-squared	0.523940	S.D. dependent var	0.017558
S.E. of regression	0.012114	Akaike info criterion	-5.988375
Sum squared resid	0.586283	Schwarz criterion	-5.985226
Log likelihood	11969.77	Hannan-Quinn criter.	-5.987259
F-statistic	4398.902	Durbin-Watson stat	2.000468
Prob(F-statistic)	0.000000		

Table 1.4.3: MOEX index Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.631971	Prob. F(2,3993)	0.0721
Obs*R-squared	5.262278	Prob. Chi-Square(2)	0.0720

Test Equation:
Dependent Variable: RESID
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-65.78180	30.58694	-2.150650	0.0316
LOG_INDEX(-1)	14.28304	6.641264	2.150650	0.0316
RESID(-1)	-14.28326	6.641063	-2.150749	0.0316
RESID(-2)	0.674640	0.319959	2.108520	0.0350

R-squared	0.001317	Mean dependent var	-1.25E-15
Adjusted R-squared	0.000566	S.D. dependent var	0.012113
S.E. of regression	0.012109	Akaike info criterion	-5.988692
Sum squared resid	0.585511	Schwarz criterion	-5.982394
Log likelihood	11972.40	Hannan-Quinn criter.	-5.986459
F-statistic	1.754647	Durbin-Watson stat	1.999097
Prob(F-statistic)	0.153644		

Moreover, the alternative hypothesis is confirmed by the serial Breusch-Godfrey Serial Correlation LM Test for general, high-order ARMA errors (see above Tables 1.4, 1.4.1, 1.4.2 &1.4.3). The test rejects the hypothesis of no serial correlation up to 2 for all the examined indexes.

Since we have a time series that shows autocorrelation, it can also exhibit Autoregressive Conditional Heteroskedastic (ARCH) effects. For that reason, with the intention of identifying which estimation model is required (ARCH estimation method or an OLS), we employ the Heteroskedasticity Test of ARCH.

Table 1.5: KASE index Heteroskedasticity
Test: ARCH

F-statistic	399.5305	Prob. F(1,3994)	0.0000
Obs*R-squared	363.3806	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001575	0.001394	1.129576	0.2587
RESID^2(-1)	0.301556	0.015087	19.98826	0.0000

R-squared	0.090936	Mean dependent var	0.002255
Adjusted R-squared	0.090708	S.D. dependent var	0.092408
S.E. of regression	0.088117	Akaike info criterion	-2.019797
Sum squared resid	31.01199	Schwarz criterion	-2.016648
Log likelihood	4037.555	Hannan-Quinn criter.	-2.018681
F-statistic	399.5305	Durbin-Watson stat	2.071181
Prob(F-statistic)	0.000000		

Table 1.5.1: BIST 100 Heteroskedasticity
Test: ARCH

F-statistic	335.7295	Prob. F(1,3994)	0.0000
Obs*R-squared	309.8519	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005840	0.005394	1.082659	0.2790
RESID^2(-1)	0.278461	0.015197	18.32292	0.0000

R-squared	0.077541	Mean dependent var	0.008094
Adjusted R-squared	0.077310	S.D. dependent var	0.354878
S.E. of regression	0.340885	Akaike info criterion	0.685955
Sum squared resid	464.1121	Schwarz criterion	0.689105
Log likelihood	-1368.538	Hannan-Quinn criter.	0.687072
F-statistic	335.7295	Durbin-Watson stat	2.083203
Prob(F-statistic)	0.000000		

Table 1.5.2 : WIG20 index Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH

F-statistic	48.19767	Prob. F(1,3994)	0.0000
Obs*R-squared	47.64682	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.90E-05	5.25E-06	18.86156	0.0000
RESID^2(-1)	0.109180	0.015726	6.942454	0.0000

R-squared	0.011924	Mean dependent var	0.000111
Adjusted R-squared	0.011676	S.D. dependent var	0.000315
S.E. of regression	0.000313	Akaike info criterion	-13.30234
Sum squared resid	0.000390	Schwarz criterion	-13.29919
Log likelihood	26580.08	Hannan-Quinn criter.	-13.30123
F-statistic	48.19767	Durbin-Watson stat	2.007157
Prob(F-statistic)	0.000000		

Table 1.5.3: MOEX index Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH

F-statistic	58.82755	Prob. F(1,3994)	0.0000
Obs*R-squared	58.00269	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000129	8.80E-06	14.64665	0.0000
RESID^2(-1)	0.120472	0.015707	7.669912	0.0000

R-squared	0.014515	Mean dependent var	0.000147
Adjusted R-squared	0.014268	S.D. dependent var	0.000541
S.E. of regression	0.000537	Akaike info criterion	-12.22084
Sum squared resid	0.001152	Schwarz criterion	-12.21769
Log likelihood	24419.23	Hannan-Quinn criter.	-12.21972
F-statistic	58.82755	Durbin-Watson stat	2.020418
Prob(F-statistic)	0.000000		

The above analysis exposes the existence of ARCH effects for all countries since the probability value (P-value) is 0.000 (significant at 1% level).

Regarding the explanatory variables i.e. trading volume and exchange rate, as we may see from the estimations below they display an abnormal behavior, which is verified by the asymmetric features and leptokurtosis (in the case of exchange rate).

Figure 1.6: Kazakhstan's exchange rate (USD/Tenge)

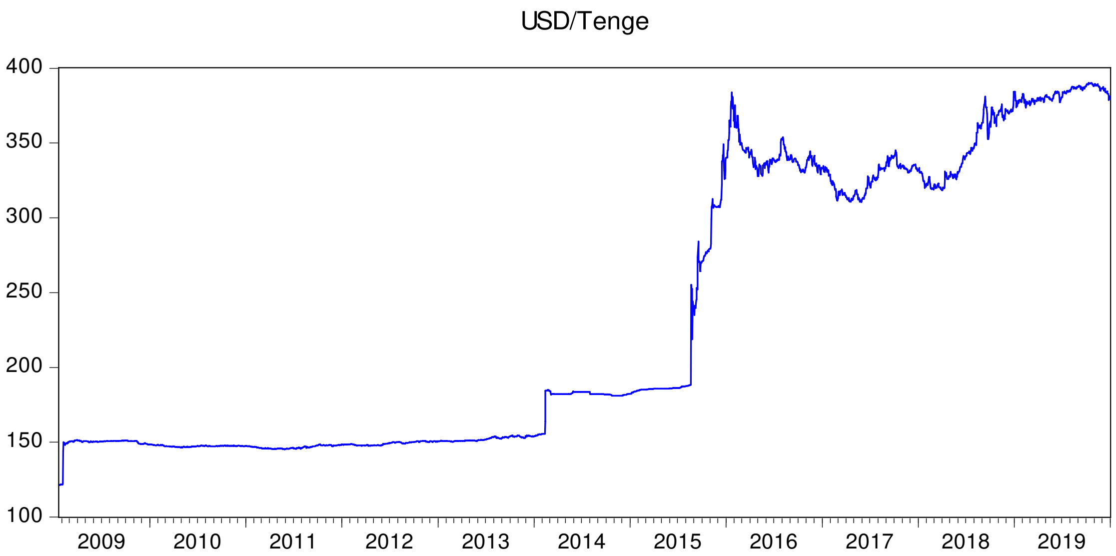


Figure 1.6.1: Turkey's exchange rate (USD/TuL)

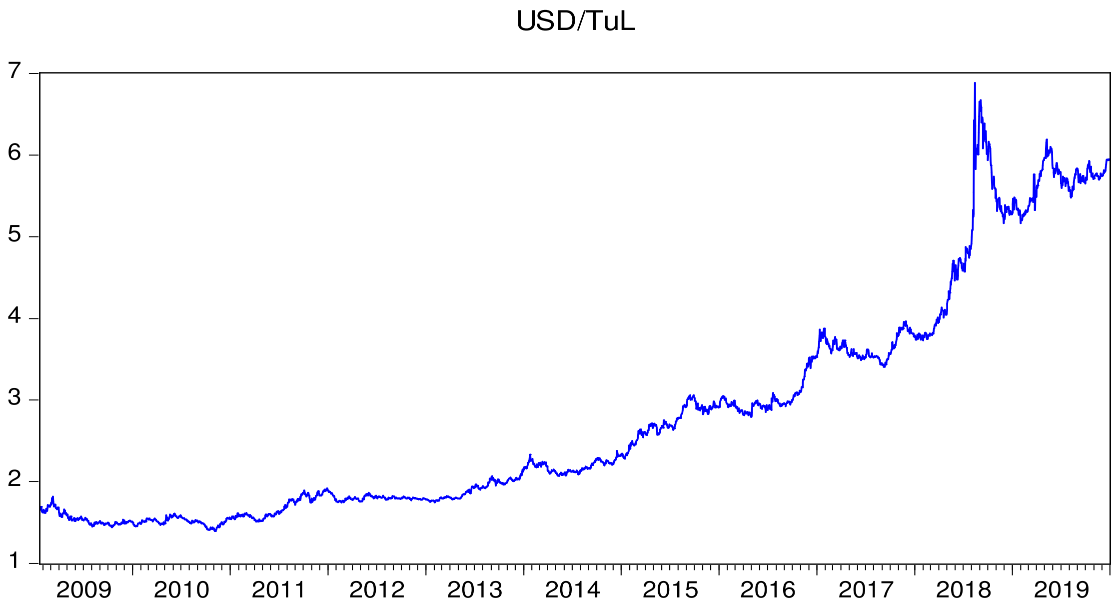


Figure 1.6.2: Poland's exchange rate (USD/Zloty)

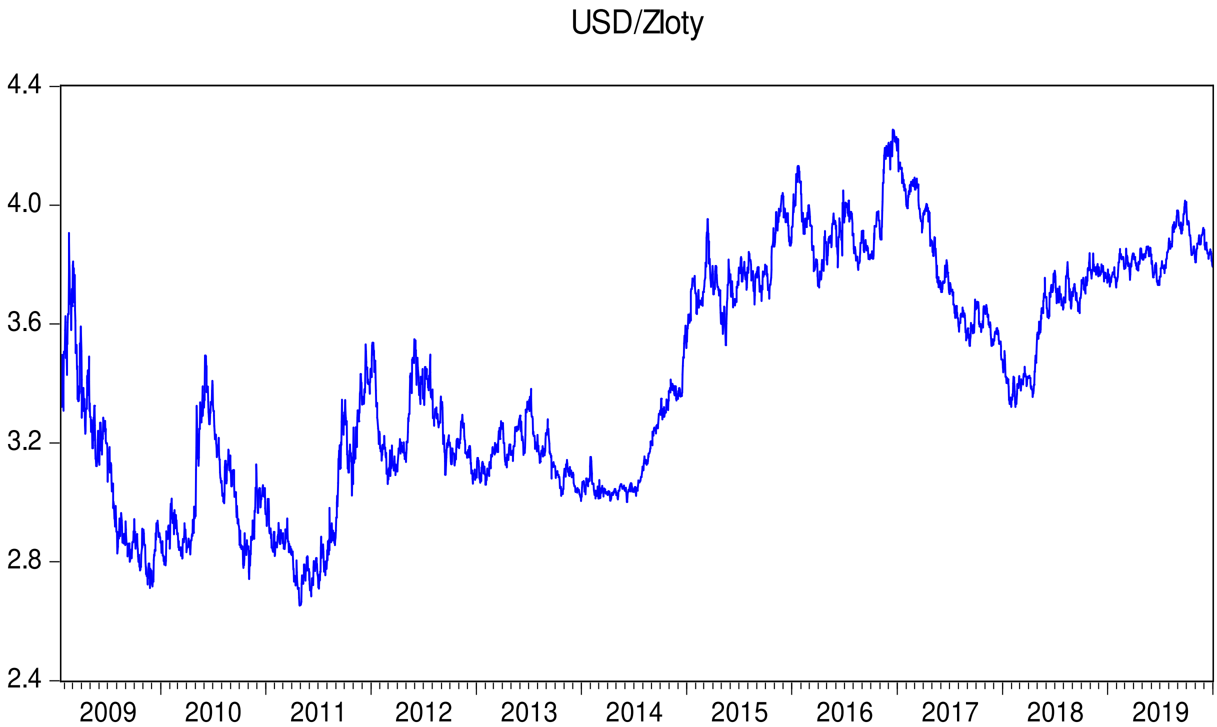


Figure 1.6.3: Russia's exchange rate (USD/Ruble)

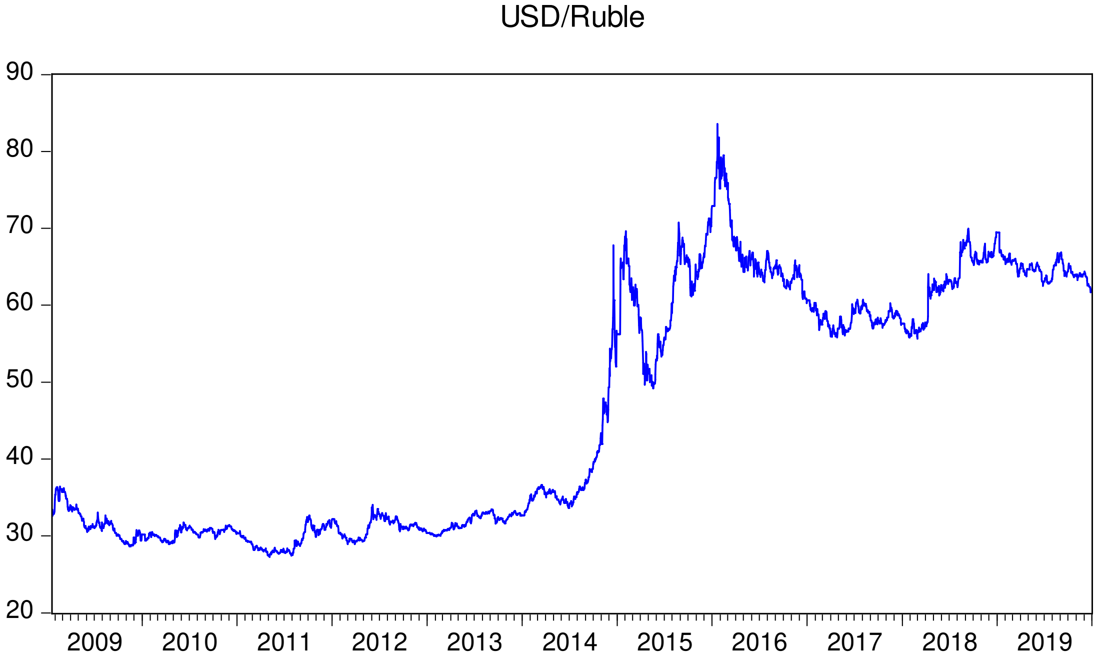


Figure 1.6.4: Kazakhstan's exchange rate descriptive statistics

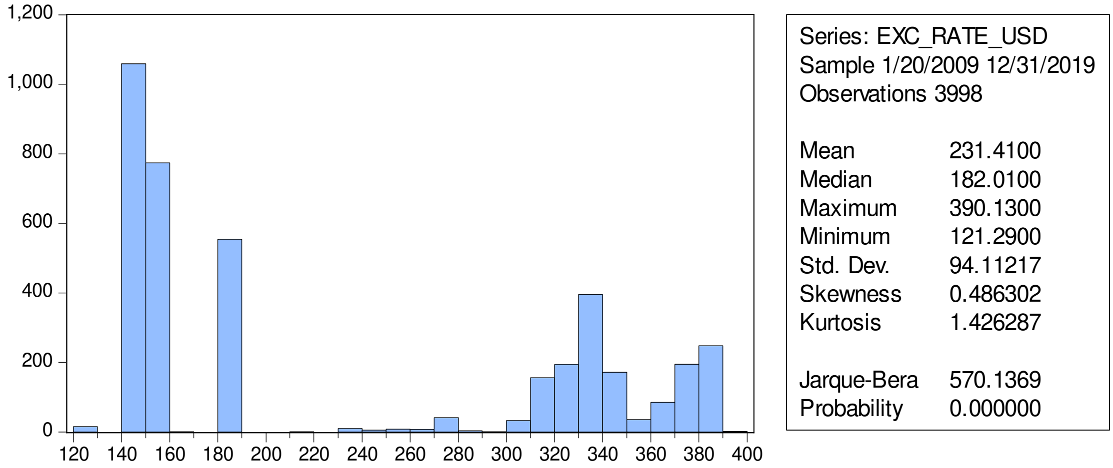


Figure 1.6.4.1: Kazakhstan's exchange rate descriptive statistics in log form

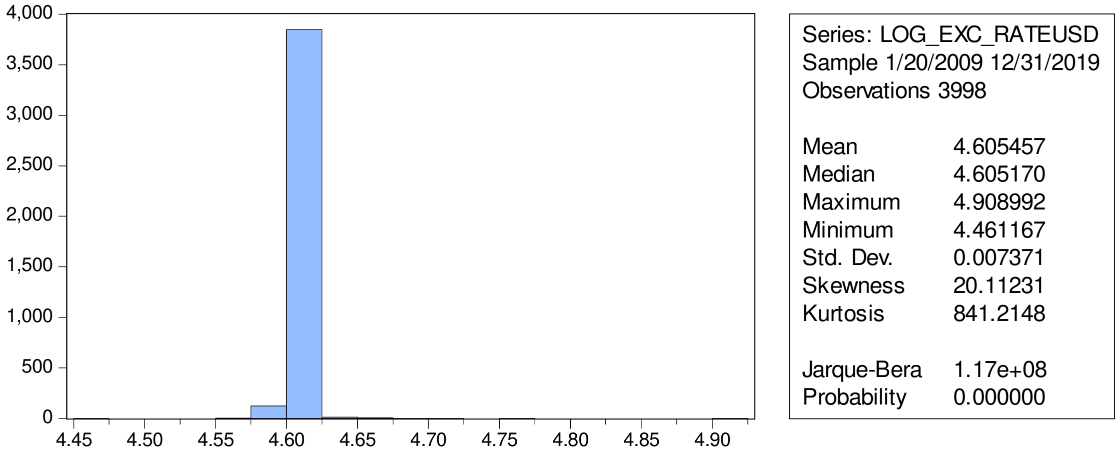


Figure 1.6.5: Turkey's exchange rate descriptive statistics

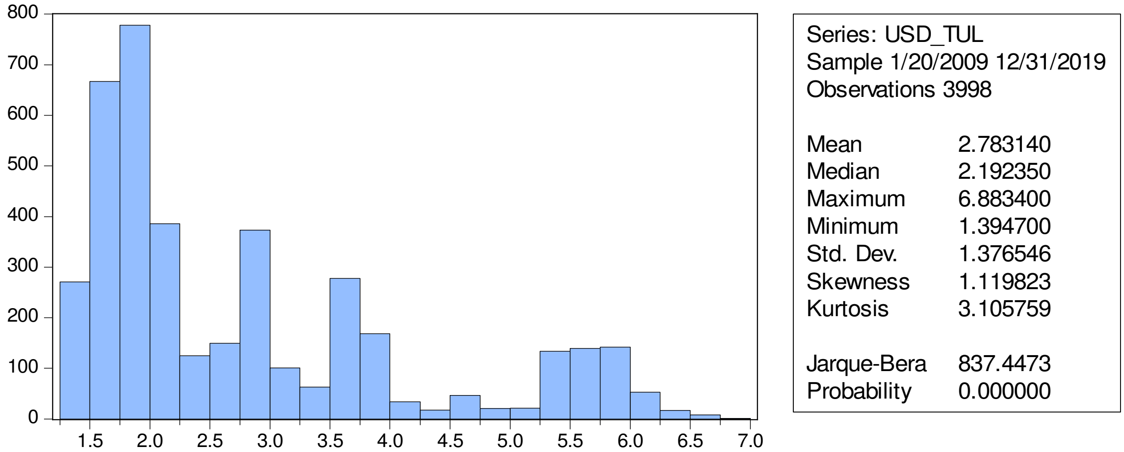


Figure 1.6.5.1 : Turkey's exchange rate descriptive statistics in log form

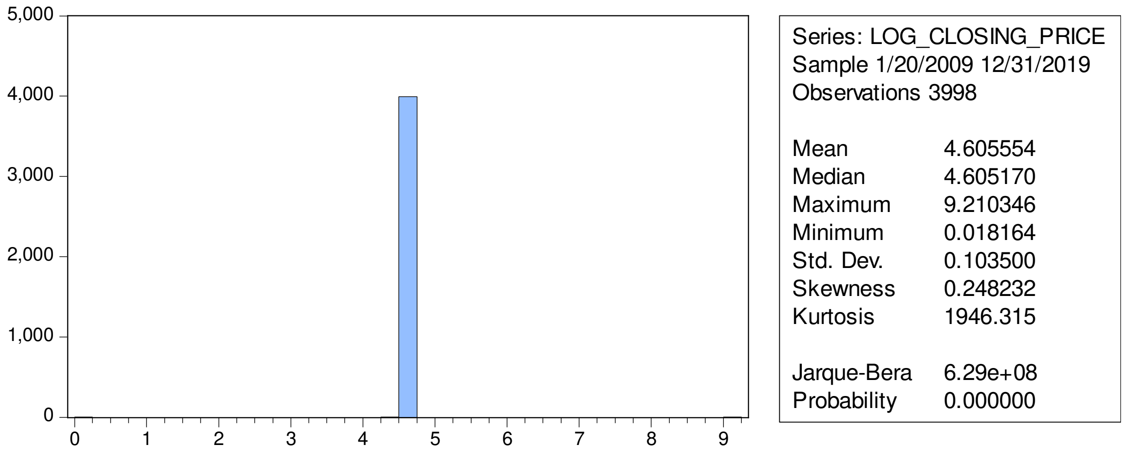


Figure 1.6.6: Poland's exchange rate descriptive statistics

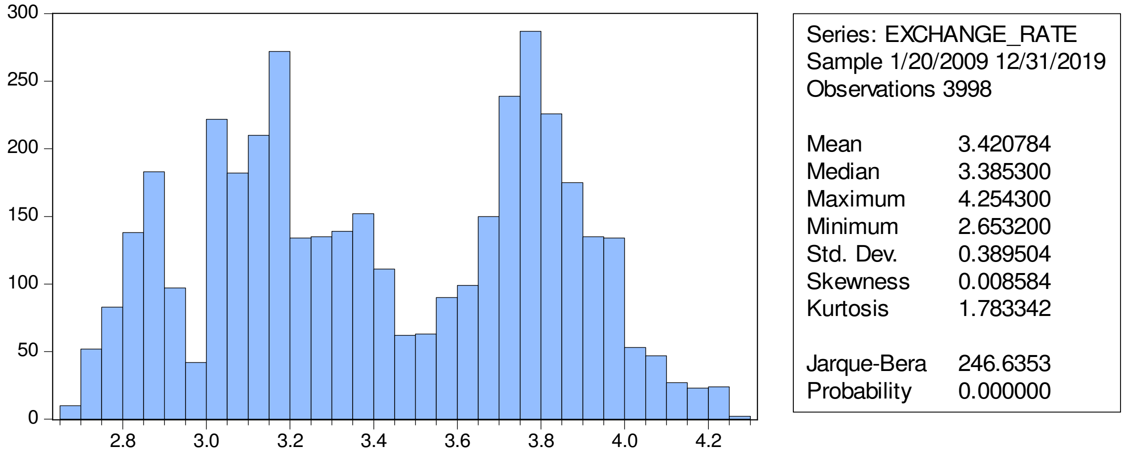


Figure 1.6.6.1: Poland's exchange rate descriptive statistics in log form

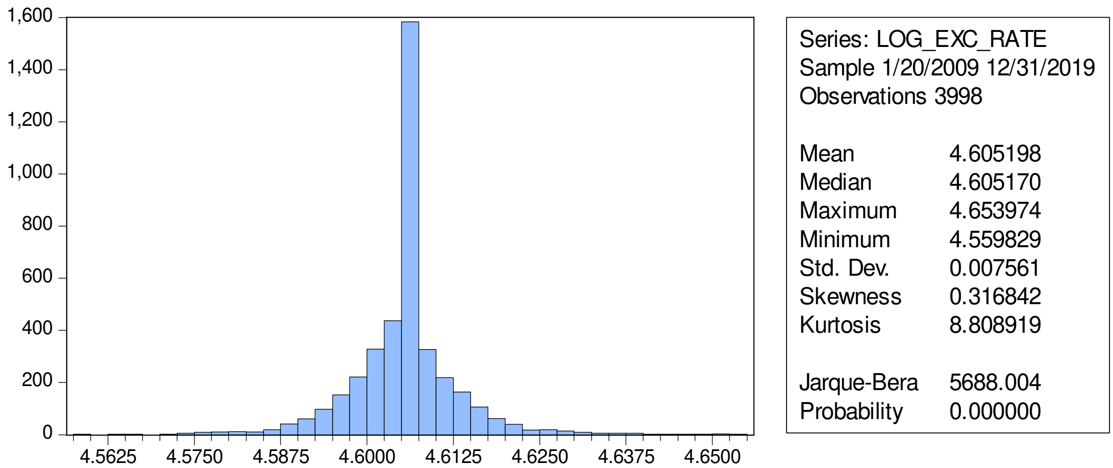
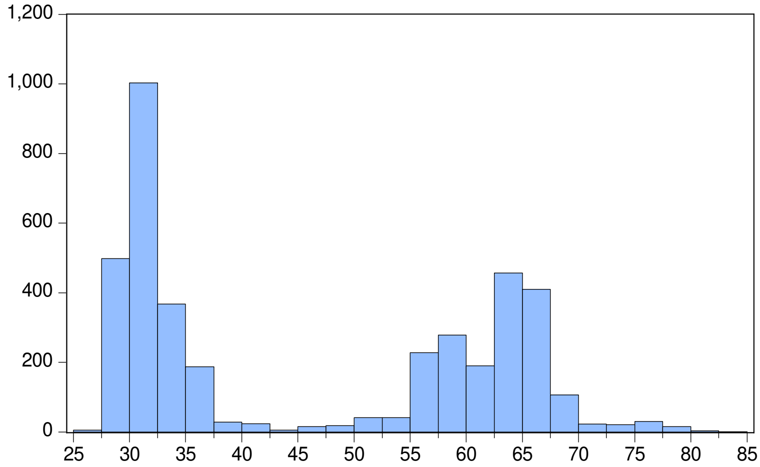
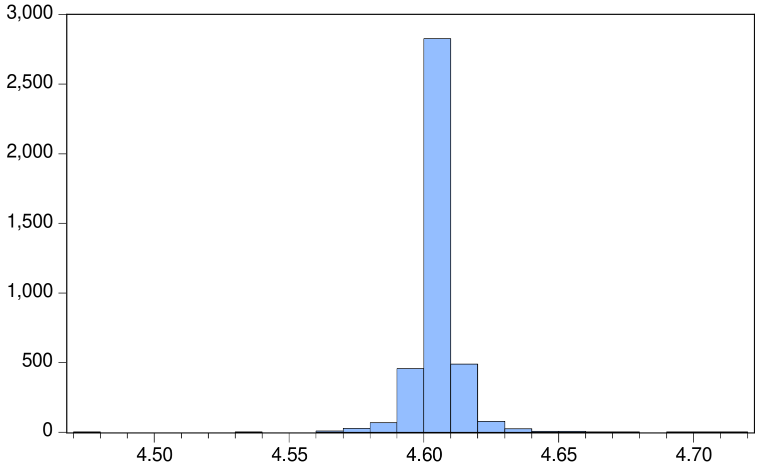


Figure 1.6.7: Russia's exchange rate descriptive statistics



Series: EXC__RATE	
Sample 1/20/2009 12/31/2019	
Observations 3998	
Mean	46.13381
Median	36.09000
Maximum	83.59130
Minimum	27.26250
Std. Dev.	15.91394
Skewness	0.238157
Kurtosis	1.304860
Jarque-Bera	516.4704
Probability	0.000000

Figure 1.6.7.1: Russia's exchange rate descriptive statistics in log form



Series: LOG_EX_RATE	
Sample 1/20/2009 12/31/2019	
Observations 3998	
Mean	4.605329
Median	4.605170
Maximum	4.714525
Minimum	4.476532
Std. Dev.	0.008508
Skewness	0.764969
Kurtosis	38.67136
Jarque-Bera	212358.2
Probability	0.000000

As we can observe from the above presented, the exchange rate variable is not normal distributed before and after the transformation (log form)for all cases. The last outcome results in a leptokurtic distribution something that coincides with the results of the stock indexes.

Referring to trading volume, which is the value of the volume of the trading in local currencies, we once again observe an non normal performance. This value is not taking a log form, so a leptokurtic distribution is not succeeded.

Figure 1.7: KASE's trading volume (Kazakhstan)

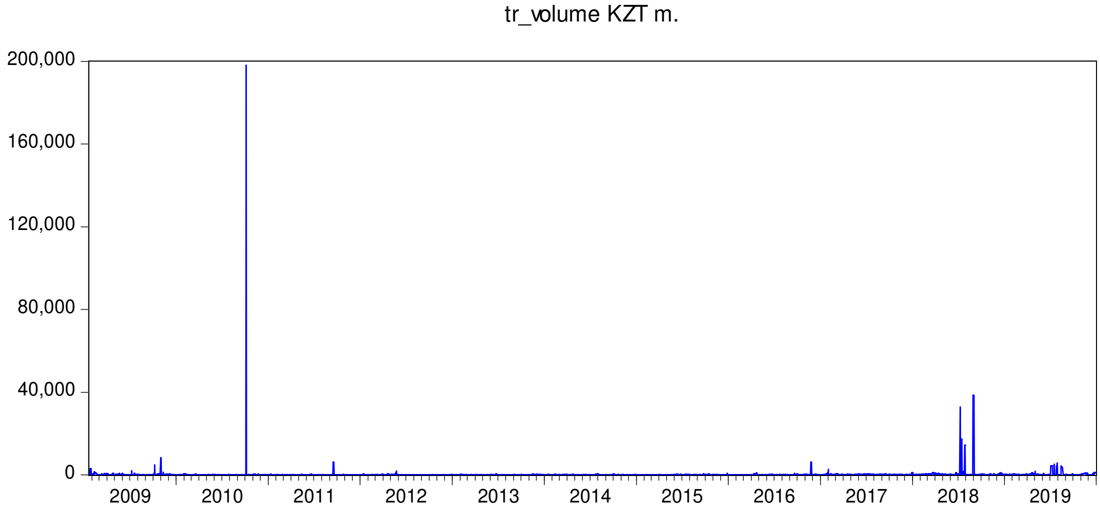
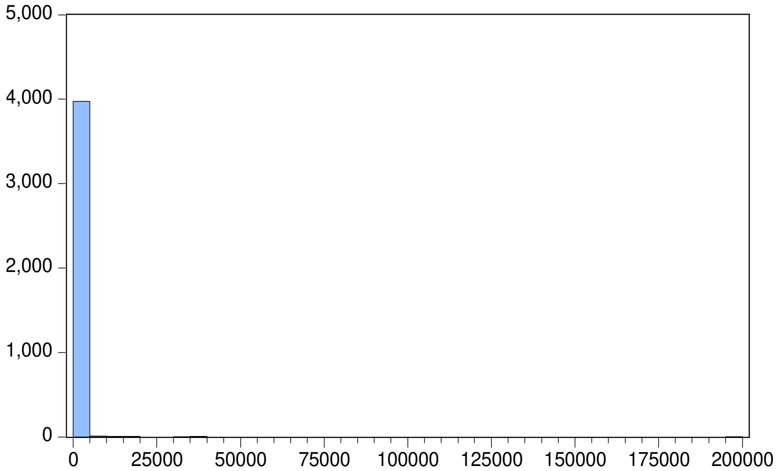


Figure 1.7.1 : KASE's trading volume – descriptive statistics



Series: TR_VOLUME_KZT_M_
Sample 1/20/2009 12/31/2019
Observations 3998

Mean	305.4883
Median	79.54000
Maximum	198075.9
Minimum	0.370000
Std. Dev.	3545.421
Skewness	45.38010
Kurtosis	2442.523
Jarque-Bera	9.93e+08
Probability	0.000000

Figure 1.7.1 : BIST100's trading volume (Turkey)

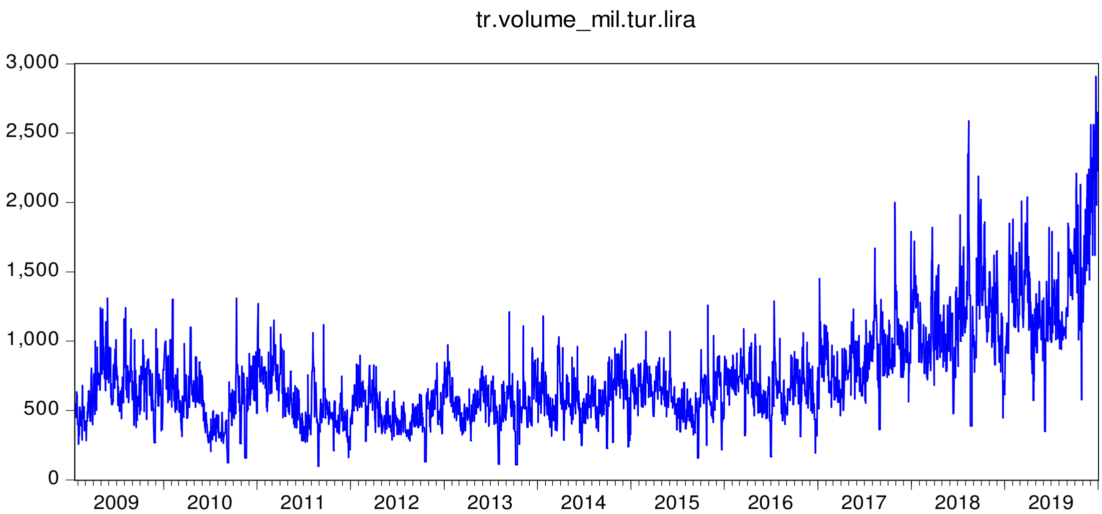
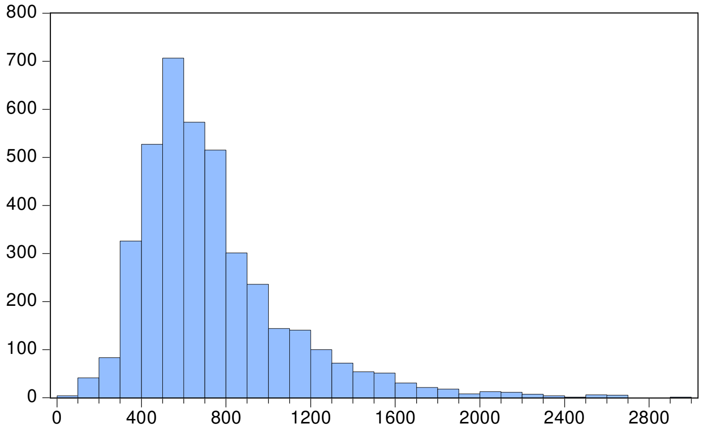


Figure 1.7.1.1 : BIST100's trading volume – Descriptive statistics



Series: TR_VOLUME_MIL_TUR_LIRA	
Sample 1/20/2009 12/31/2019	
Observations 3998	
Mean	734.2514
Median	648.7500
Maximum	2910.000
Minimum	96.94000
Std. Dev.	357.3946
Skewness	1.675748
Kurtosis	7.188250
Jarque-Bera	4793.263
Probability	0.000000

Figure 1.7.2 : WIG20's trading volume (Poland)

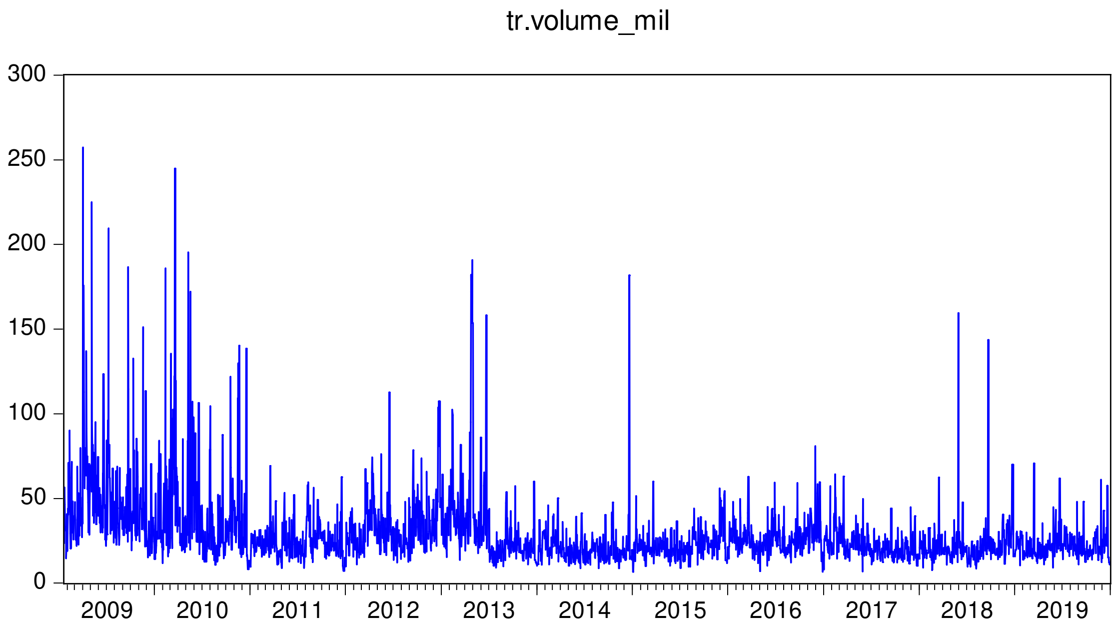


Figure 1.7.2 .1: WIG20's trading volume –Descriptive statistics

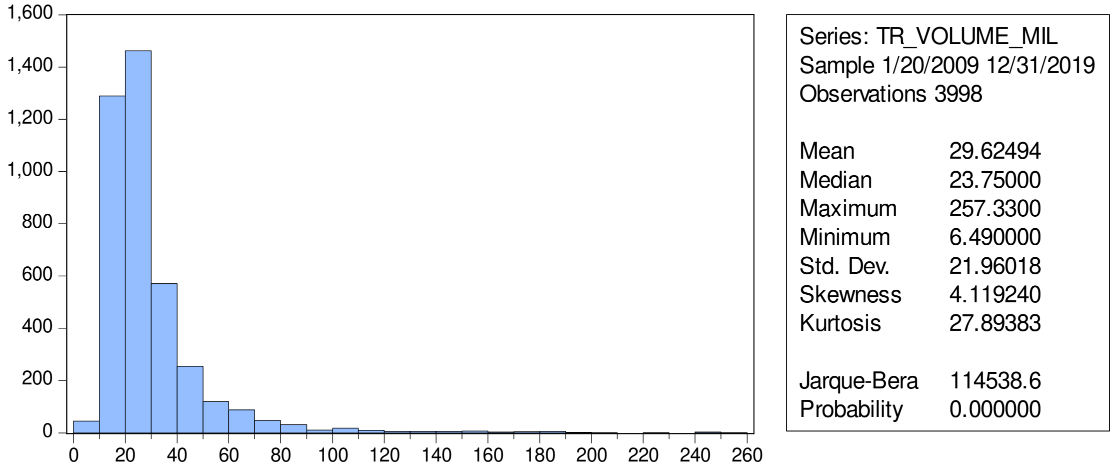


Figure 1.7.3 : MOEX's trading volume (Russia)

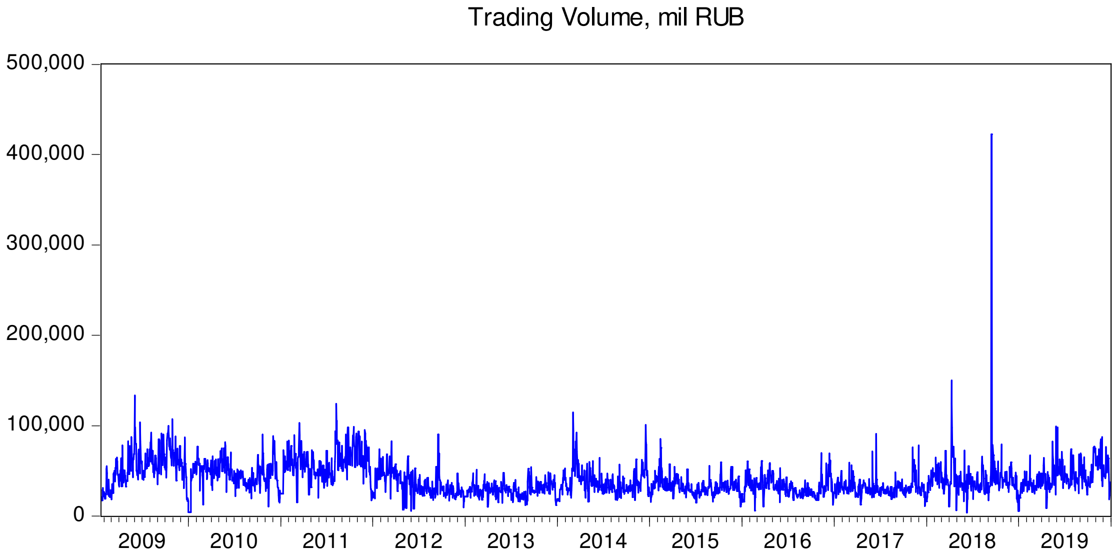
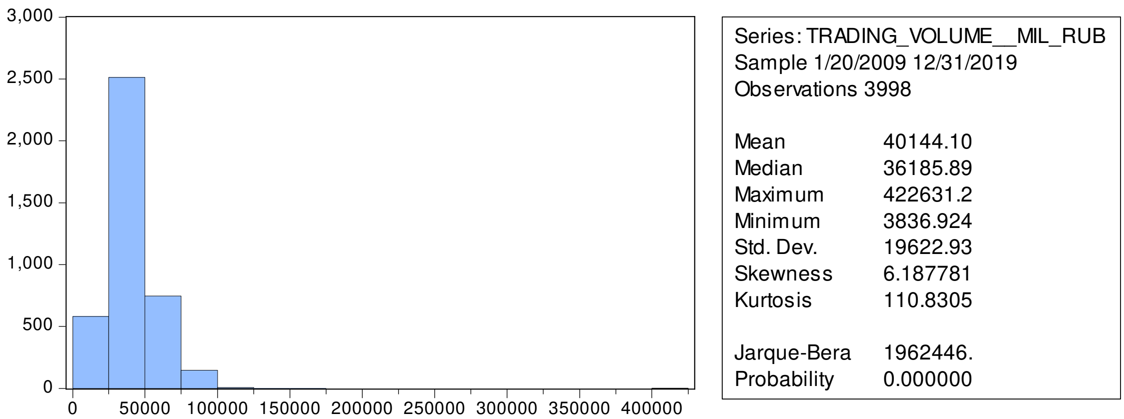


Figure 1.7.3.1 : MOEX's trading volume – Descriptive Statistics



Finally, as we observe the trading volume variable is extremely volatile for all cases. All the cases above present volatility clustering as they indexes do, and the distribution it not normal. In general, all the presented assets indicate an abnormal behavior. This is verified by the significant p-values of Jarque –Bera test for all indices, currencies and trading volume. Subsequently we continue our analysis by introducing AR(1) – EGARCH (1.1) model, which is a model that can treat heteroskedasticity and non-normal distribution.

5. Empirical results

In this section we present the empirical results of AR(1) -EGARCH (1.1) model. As we mentioned before, EGARCH model is one of the GARCH family models that threats heteroskedasticity as a variance to be modeled, captures better the leverage effect that other GARCH models and solves some of their existent weaknesses. Owing to these characteristics, we conduct our AR (1)- EGARCH (1.1) analysis on Eviews 9 statistical package, for all the indexes (KASE , BIST100, WIG20 and MOEX) separately.

5.1 Kazakhstan

Table 2.1 presents the results of selected parameters of the AR(1)-EGARCH model without the inclusion of volume in the conditional variance.

Table 2.1: AR(1) -EGARCH(1.1) (KASE INDEX)

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.815628	0.000455	14991.31	0.0000
LOG_CLOSING_PRICE(-1)	-0.479916	9.78E-05	-4906.780	0.0000
AR(1)	0.176367	0.009653	18.27081	0.0000
Variance Equation				
C(4)	-8.051041	0.070958	-113.4618	0.0000
C(5)	2.556054	0.038024	67.22142	0.0000
C(6)	2.410891	0.037728	63.90155	0.0000
C(7)	0.062507	0.008648	7.228026	0.0000

R-squared	0.163294	Mean dependent var	4.605443
Adjusted R-squared	0.162875	S.D. dependent var	0.053873
S.E. of regression	0.049291	Akaike info criterion	-4.346328

Sum squared resid	9.703815	Schwarz criterion	-4.335307
Log likelihood	8693.137	Hannan-Quinn criter.	-4.342421
Durbin-Watson stat	2.479086		
Inverted AR Roots	.18		

For a summary of the coefficients see in Appendix table 2.1.1

The above table (Table 2.1) consists of two parts: the mean equation and the variance equation. The first part involves the factor C which is the average stock price, the LOG_ CLOSING_PRICE(-1) (β_0 of mean equation) which is the past value of the C and the AR(1) - the Autoregressive process coefficient (β_1 of the mean equation). The results presented in this part indicate that the past value (past stock price) (LOG_ CLOSING_PRICE(-1)) predicts at a significant degree the current stock price. Whereas, the AR(1) coefficient is positive and significant at 1% level which means that past values have a significant impact on the current ones.

The variance equation on the other hand, contains the coefficients C(4) (a_0 constant of the equation ix, see the Methodology section), C(5) (a_1 coefficient of the equation ix), C(6) (a_2 coefficient of the equation ix) and C(7) (a_3 coefficient of the equation ix), which represent the constant, the ARCH coefficient, the asymmetric coefficient and the GARCH coefficient respectively. The C(5) or the ARCH coefficient indicates the impact of the magnitude of shock / spillover effects or volatility, while the C(6) coefficient (asymmetric coefficient) shows the impact of the sign of a shock. If C(6) is different from zero (at least at 10% level of significance) we have an asymmetric effect which means that bad news or good news/shocks of the same size have different impacts. If C6 is negative we observe leverage effect that is to say: bad news/shocks have more impact than good news/shocks of the same size. It can also be interpreted as the case of which the variance goes up more after positive residuals than after negative residuals. Lastly, the C(7) coefficient mirrors the GARCH effect. The GARCH effect (C(7)) captures the persistence of past volatility, which explains current volatility. If C(7) is less than one ($\alpha_3 <1$), the conditional variance is limited, while if C(7) equals to one ($\alpha_3 =1$) the conditional variance follows an integrated process of order 1.

The estimations of our model show the presence of volatility and asymmetry. In our case (KASE index) the C(5) coefficient is positive and significant at 1% level and the asymmetric term (C(6)) is also positive/ different from zero and significant at

1% level, which implies that positive novelties in the stock price index influence more than negative innovations. This outcome could be perceived as the situation where investors are more prone to positive than negative shocks/ news of the same magnitude. In that case we should bear in mind that the investigated period (2009-2019) is the period of the global economic crisis, therefore we could assume that this global "shock" made the markets more prone to any kind of changes – positive or negative. This indicates also that the magnitude of news plays a more significant role than its direction in influencing volatility. Moreover, the persistence of volatility (C(7) coefficient) counts less than one (0.062507), which designates that conditional variance is limited. This is also an indication of stationary persistence.

If in the above model we add the trading volume (value of the volume in Kazakhstani Tenge /national currency) we end up having the next results.

Table 2.2: AR(1)- EGARCH(1.1) with trading volume variable

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*TR_VOLUME_KZT_M_

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.761232	0.004607	1467.669	0.0000
LOG_CLOSING_PRICE(-1)	-0.470693	0.001066	-441.5268	0.0000
AR(1)	0.713513	0.042803	16.66973	0.0000
Variance Equation				
C(4)	-6.089990	1.116354	-5.455251	0.0000
C(5)	0.011476	0.004856	2.363361	0.0181
C(6)	-0.049542	0.003479	-14.23888	0.0000
C(7)	0.009969	0.180700	0.055170	0.9560
C(8)	-0.000113	1.62E-05	-6.956500	0.0000

R-squared	0.326645	Mean dependent var	4.605443
Adjusted R-squared	0.327309	S.D. dependent var	0.053873
S.E. of regression	0.062067	Akaike info criterion	-3.455351
Sum squared resid	15.38594	Schwarz criterion	-3.442755
Log likelihood	6913.519	Hannan-Quinn criter.	-3.450886
Durbin-Watson stat	2.832284		
Inverted AR Roots	.71		

For a summary of the coefficients see in Appendix table 2.1.1

As we observe, in the Table 2.2, we have the addition of another coefficient – C(8)(coefficient φ the equation x), which counts for trading volume. It is noticeable that trading volume is negatively correlated with the conditional variance and affects all the other coefficients –there is clearly a decline in the value of all the other coefficients. This result points out the fact that trading volume accounts for the volatility persistence in the market. It is also shown that the relationship between the KASE index and trading volume is inverse (decline of one of them equals rise of the other and vice versa). Tauchen and Pitts (1983) investigated this negative correlation between volume and volatility and advocated that both volatility and trading volume are strongly influenced by information flows to the market, traders' response to new information and the number of active traders. Consequently, in emerging and developing markets like Kazakhstan, which are thinly traded and highly volatile, occasionally trading can force the prices to deviate significantly from fundamentals.

At the same time we see that C(5) coefficient is positive and significant (at 10% level of significance) while C(6) coefficient obtains a negative sign (-0.049542), which is evidence of leverage effect in this model. Leverage effect demonstrates that, within the period under study, negative shocks (bad news) have higher impact on volatility than positive shocks (good news) of the same magnitude. That case reaffirms the outcomes of the research of Tauchen and Pitts, about the information flows and particularly negative information (shocks) that results in the negative relation between stock market's volatility and trading volume. In the real world, investors are more responsive to negative news rather than to positive and this assumption implies that the volatility spillovers mechanism is asymmetric. What is not quite expected form the above outcomes is the insignificance of the GARCH coefficient (C(7)) regarding the persistence of volatility.

When the exchange rate variable is added to the model, we expect to see a strong correlation between the stock prices' volatility and exchange rate fluctuations.

Table 2.3 : AR(1) -EGARCH(1.1) with exchange rate variable

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH

LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*LOG_EXC_RATEUSD

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.822632	0.017196	338.6084	0.0000
LOG_CLOSING_PRICE(-1)	-0.266711	0.003776	-70.63545	0.0000
AR(1)	0.312167	0.002169	143.9102	0.0000
Variance Equation				
C(4)	159.8997	5.717027	27.96903	0.0000
C(5)	1.733592	0.021440	80.85817	0.0000
C(6)	1.488734	0.019126	77.84024	0.0000
C(7)	-0.118166	0.001720	-68.72033	0.0000
C(8)	-36.82327	1.241682	-29.65596	0.0000

R-squared	0.068226	Mean dependent var	4.605443
Adjusted R-squared	0.068761	S.D. dependent var	0.053873
S.E. of regression	0.055694	Akaike info criterion	-4.351003
Sum squared resid	12.38889	Schwarz criterion	-4.338407
Log likelihood	8703.480	Hannan-Quinn criter.	-4.346538
Durbin-Watson stat	2.858462		
Inverted AR Roots	.31		

For a summary of the coefficients see in Appendix table 2.1.1

The above presented results point out that exchange rate fluctuation affects the whole variance model and is also negatively correlated with the conditional variance(-36.82327). This fact indicates that there is a significant (at 1% level) negative linkage between stock market changes and foreign exchange rate dynamics for Kazakhstan over the period under study. The significant negative impact of exchange rate on KASE index discloses an inverse relation between these two variables - explicitly these variables move in opposite directions (when the exchange rate decreases the KASE index increases and vice versa). In general, significant exchange rate coefficient necessarily implies that the fluctuations in exchange rates lead to a change in the stock market volatility. Moreover, the effect of the exchange rate fluctuation on the volatility becomes clear from the increase in C(5) coefficient – the volatility coefficient (1.733592). In this model we do not observe leverage effect, since C(6) coefficient is positive, which again reminds us that the magnitude of shocks and news and not only the direction of them (negative or positive) have a significant impact on markets. These findings denote that investors are very alerted and react to any sign and of great magnitude news from the exchange rate market.

By combining the two models above (including trading volume and exchange rate), we target to explain better the behavior of the conditional variance in general.

Table 2.4 : AR(1) -EGARCH(1.1) with trading volume and exchange rate variables

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*TR_VOLUME_KZT_M_ + C(9)*LOG_EXC_RATEUSD

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.751623	0.007359	917.4401	0.0000
LOG_CLOSING_PRICE(-1)	-0.468865	0.001710	-274.2474	0.0000
AR(1)	0.818484	0.028340	28.88046	0.0000
		Variance Equation		
C(4)	-6.084330	29.75391	-0.204488	0.8380
C(5)	0.007303	0.006630	1.101440	0.2707
C(6)	-0.055958	0.007195	-7.777853	0.0000
C(7)	0.010134	0.187437	0.054067	0.9569
C(8)	-0.000113	1.87E-05	-6.028374	0.0000
C(9)	0.002015	6.457406	0.000312	0.9998

R-squared	0.473246	Mean dependent var	4.605443
Adjusted R-squared	0.473984	S.D. dependent var	0.053873
S.E. of regression	0.065406	Akaike info criterion	-3.436815
Sum squared resid	17.08617	Schwarz criterion	-3.422645
Log likelihood	6877.475	Hannan-Quinn criter.	-3.431792
Durbin-Watson stat	2.857930		
Inverted AR Roots	.82		

For a summary of the coefficients see in Appendix table 2.1.1

The results of the last model (Table 2.4) show the existence leverage effect, since C(6) (asymmetric coefficient) is negative and statistically significant at the 1% level. Once more, the trading volume coefficient is negative, while an insignificant positive coefficient of exchange rate is also resulted. Therefore, 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 behavior and that there is a negative relationship between trading volume and conditional variance, while at the same time there is no specific pattern for exchange rate variable since it does not remain constant in the models. The persistence of volatility (C(7)coefficient) remains in all four models less than one and it is insignificant in half of them, which illustrates that conditional variance is steadily limited.

5.2 Turkey

In the case of Turkey and BIST100 index, the results presented indicate that the past value (past stock price) (LOG_ CLOSING_PRICE(-1)) predicts at a significant degree the current stock price. Whereas, the AR(1) coefficient is negative and significant at 1% level something that means that past values have a significant negative impact on the current ones.

Table 2.2.1: AR(1) -EGARCH(1.1) (BIST 100 index)

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.872710	0.144023	47.71942	0.0000
LOG_CLOSING_PRICE(-1)	-0.491189	0.031253	-15.71657	0.0000
AR(1)	-0.332013	0.030687	-10.81953	0.0000
Variance Equation				
C(4)	-7.428021	0.039432	-188.3766	0.0000
C(5)	3.889779	0.028504	136.4651	0.0000
C(6)	-3.733556	0.027600	-135.2749	0.0000
C(7)	0.162511	0.004858	33.45466	0.0000

R-squared	0.238132	Mean dependent var	4.605554
Adjusted R-squared	0.237750	S.D. dependent var	0.103513
S.E. of regression	0.090374	Akaike info criterion	-3.558588
Sum squared resid	32.62059	Schwarz criterion	-3.547566
Log likelihood	7118.838	Hannan-Quinn criter.	-3.554681
Durbin-Watson stat	1.895441		

Inverted AR Roots	-.33

For a summary of the coefficients see in Appendix table 2.1.1

The estimations of our model show the presence of volatility spillovers and asymmetry. C(5) coefficient -the volatility spillovers coefficient- is high and positive(3.889779) ,while the asymmetric term (C(6)) is negative and significant at 1% level. These findings indicate the presence of high volatility spillovers and leverage effect in Turkish stock index. To be precise this means that negative novelties in stock prices have greater impact than positive of the same magnitude, in other words the direction of the news is as important as its magnitude in that case. Moreover, the persistence of volatility (C(7) coefficient) is less than one (0.162511), which designates that conditional variance is limited, indicating stationary persistence.

Table 2.2.2: AR(1)- EGARCH(1.1) with trading volume variable

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6) *RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8) *TR_VOLUME_MIL_TUR_LIRA

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.203700	0.095579	54.44419	0.0000
LOG_CLOSING_PRICE(-1)	-0.129321	0.020746	-6.233453	0.0000
AR(1)	0.093409	0.019533	4.782007	0.0000
Variance Equation				
C(4)	-0.691282	0.015294	-45.19927	0.0000
C(5)	0.448268	0.004807	93.25407	0.0000
C(6)	-0.235306	0.004067	-57.86346	0.0000
C(7)	0.740781	0.003901	189.8872	0.0000
C(8)	-0.001525	1.43E-05	-106.9317	0.0000

R-squared	0.033211	Mean dependent var	4.605554
Adjusted R-squared	0.032727	S.D. dependent var	0.103513
S.E. of regression	0.101805	Akaike info criterion	-3.523072
Sum squared resid	41.39458	Schwarz criterion	-3.510476
Log likelihood	7048.859	Hannan-Quinn criter.	-3.518607
Durbin-Watson stat	2.937726		

Inverted AR Roots	.09

For a summary of the coefficients see in Appendix table 2.1.1

In table 2.2 .2 we notice that trading volume is negatively correlated with the conditional variance and affects all the other coefficients –there is clearly a decline in the value of the coefficients. This result indicates that trading volume variable accounts for the volatility persistence in the stock market. Once again the idea of Tauchen and Pitts (1983) regarding the negative correlation between trading volume and volatility in emerging markets is affirmed. Both variables are strongly influenced by information flows to the market, traders' response to new information and the number of active traders. Just as in the case of Kazakhstan, in this case, trading volume can force the prices to deviate significantly from fundamentals.

At the same time we realize that C(5) coefficient is positive (0.448268), which indicates the volatility presence and in this model, and C(6) coefficient or the asymmetric coefficient is negative (-0.235306), that is to say, that the leverage effect is also persistent. It is generally testified that the information flows and particularly negative information – shocks that can cause this negative relation between stock market's volatility and trading volume

By adding the exchange rate variable to the model, we assume that a significant correlation between the variance and the new variable will occur.

Table 2.2.3 : AR(1)- EGARCH(1.1) with exchange rate variable

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*LOG_EXC_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.868355	0.010421	659.0698	0.0000
LOG_CLOSING_PRICE(-1)	-0.490184	0.002261	-216.7799	0.0000
AR(1)	-0.503235	0.002638	-190.7947	0.0000
Variance Equation				
C(4)	-4.792347	6.082223	-0.787927	0.4307
C(5)	4.170784	0.025506	163.5204	0.0000
C(6)	-4.136987	0.031192	-132.6313	0.0000
C(7)	0.168442	0.003434	49.05155	0.0000

C(8)	-0.539601	1.320606	-0.408601	0.6828

R-squared	0.170604	Mean dependent var	4.605554
Adjusted R-squared	0.170189	S.D. dependent var	0.103513
S.E. of regression	0.094294	Akaike info criterion	-3.450959
Sum squared resid	35.51189	Schwarz criterion	-3.438363
Log likelihood	6904.742	Hannan-Quinn criter.	-3.446494
Durbin-Watson stat	1.730239		
Inverted AR Roots	-.50		

For a summary of the coefficients see in Appendix table 2.1.1

The above presented result (see Table 2.3) points out that although exchange rate fluctuation affects the whole variance model, is insignificantly negative correlated with the conditional variance (-0.539601). The insignificant negative impact of exchange rate on BIST100 index discloses that exchange rate fluctuation does not affect the stock index and its volatility. Although , in this model we observe the increase of volatility spillovers coefficient (4.170784) and the existence of leverage effect (C(6) coefficient equals to -4.136987). Overall, finding significant exchange rate coefficient points out that fluctuations in exchange rates lead to changes in stock market volatility. In that case, where we do not have a significant link between the two variables, we could assume that the relation between exchange rate and volatility may not be recorded properly. We assume this because we use exchange rate as a variable that impacts –explains the BIST100 stock index and its volatility, but we do not search for the opposite relation (stock index's impact on exchange rate). Regarding the volatility persistence (C(7) coefficient) remains constantly below 1, which means that the conditional variance is limited.

By combining the two models above, including trading volume and exchange rate variables, we target to explain better the behavior of the conditional variance in general.

Table 2.2.4: AR (1) -EGARCH (1.1) with trading volume and exchange rate variables

Dependent Variable: LOG_CLOSING_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*TR_VOLUME_MIL_TUR_LIRA + C(9)*LOG_EXC_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.278972	0.082479	64.00365	0.0000
LOG_CLOSING_PRICE(-1)	-0.145698	0.017873	-8.151866	0.0000
AR(1)	0.132512	0.011966	11.07410	0.0000
		Variance Equation		
C(4)	6.550700	3.817055	1.716166	0.0861
C(5)	0.456099	0.008951	50.95687	0.0000
C(6)	-0.254905	0.007729	-32.97906	0.0000
C(7)	0.704769	0.003277	215.0901	0.0000
C(8)	-0.001625	1.14E-05	-142.1645	0.0000
C(9)	-1.606314	0.828748	-1.938241	0.0526

R-squared	0.011920	Mean dependent var	4.605554
Adjusted R-squared	0.011426	S.D. dependent var	0.103513
S.E. of regression	0.102920	Akaike info criterion	-3.518331
Sum squared resid	42.30619	Schwarz criterion	-3.504160
Log likelihood	7040.384	Hannan-Quinn criter.	-3.513307
Durbin-Watson stat	2.955316		
Inverted AR Roots	.13		

For a summary of the coefficients see in Appendix table 2.1.1

The results in the (Table 2.4 show volatility spillovers and leverage effect, as C(5) and C(6) are statistically significant at 1% level of significance with the second being also negative. Once more, the trading volume coefficient is negative, additionally to a significant and negative exchange rate coefficient. Therefore, it can be concluded that the trading volume variable, can explain some of the conditional variance's behavior, since it remains stable in all models. The persistence of volatility (C(7)coefficient), in addition, remains in all the four models, something that illustrates that conditional variance is steadily limited.

5.3 Poland

In the case of Poland and WIG 20 index, the analysis below shows some unexpected results.

Table 2.3.1: AR(1)- EGARCH(1.1) (WIG20 index)

Dependent Variable: LOG_CL_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))

+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.534445	0.001381	3282.363	0.0000
LOG_CL_PRICE(-1)	0.015386	0.000297	51.83468	0.0000
AR(1)	-2.67E-05	0.015943	-0.001673	0.9987
		Variance Equation		
C(4)	-12.29299	0.361479	-34.00745	0.0000
C(5)	0.250363	0.016939	14.78069	0.0000
C(6)	-0.083776	0.011929	-7.022678	0.0000
C(7)	-0.328500	0.040501	-8.110822	0.0000

R-squared	0.000228	Mean dependent var	4.605238
Adjusted R-squared	0.000273	S.D. dependent var	0.010547
S.E. of regression	0.010549	Akaike info criterion	-6.297510
Sum squared resid	0.444425	Schwarz criterion	-6.286488
Log likelihood	12592.57	Hannan-Quinn criter.	-6.293603
Durbin-Watson stat	1.995397		
Inverted AR Roots	-.00		

For a summary of the coefficients see in Appendix table 2.1.1

The results presented in table 3.1 indicate that the past value (past stock price) (LOG_ CLOSING_PRICE(-1)) predicts significantly the current stock price. Whereas, the AR(1) coefficient is negative and insignificant at all levels which means that past values don't have an impact on the current ones. On the other hand, the variance equation is significant at all levels of significance and the estimations demonstrate the presence of volatility and asymmetry. We observe also the presence of leverage effect, i.e. negative shocks/news have greater impact on volatility. Continuing, the persistence of volatility is expressed by a negative coefficient (-0.328500), which designates that conditional variance is significantly limited.

Table 2.3.2: AR(1) -EGARCH(1.1) with trading volume variable

Dependent Variable: LOG_CL_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) +
C(8)
*TR_VOLUME_MIL

Variable	Coefficient	Std. Error	z-Statistic	Prob.

C	4.527916	0.001819	2489.670	0.0000
LOG_CL_PRICE(-1)	0.016775	0.000391	42.85579	0.0000
AR(1)	-0.016844	0.017601	-0.956982	0.3386
		Variance Equation		
C(4)	-11.04479	0.301621	-36.61815	0.0000
C(5)	0.190668	0.018200	10.47635	0.0000
C(6)	-0.048994	0.015081	-3.248768	0.0012
C(7)	-0.114481	0.031227	-3.666059	0.0002
C(8)	0.022527	0.001219	18.48105	0.0000

R-squared	-0.000076	Mean dependent var	4.605238
Adjusted R-squared	-0.000577	S.D. dependent var	0.010547
S.E. of regression	0.010550	Akaike info criterion	-6.363590
Sum squared resid	0.444560	Schwarz criterion	-6.350994
Log likelihood	12725.64	Hannan-Quinn criter.	-6.359125
Durbin-Watson stat	1.966178		
Inverted AR Roots	-.02		

For a summary of the coefficients see in Appendix table 2.1.1

In Table 2.2 it is evident that trading volume is positive correlated with the conditional variance and accordingly affects all the other coefficients. Positive coefficient of trading volume equals to positive relationship between the height of trading volume and conditional variance. In other words it can be described as the case where more transactions may lead to greater fluctuations- spillovers. As Tauchen and Pitts (1983) proposed, in liquid or more mature markets, where the number of traders is large the relation between trading volume and price volatility is expected to be positive. In that case, the market of Poland could be an example of the findings of Tauchen and Pitts, since it is a fast developing economy and an important member of EU. In parallel, we see that C(5) coefficient is positive and C(6) coefficient is negative (-0.048994), which makes evident the existence of volatility, volatility spillovers and leverage effect in this model. This result is translated in the situation where investors are more prone to negative shocks rather than positive of the same scale. The C(7) coefficient is negative, which shows that our variance equation is limited again. What has to be stressed here is the fact that the AR(1) in mean equation is insignificant (again) and that the R- squared is negative, something that indicates that the model does not follow/fit the trend of the data.

Table 2.3.3 : AR(1) -EGARCH(1.1) with exchange rate variable

Dependent Variable: LOG_CL_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) +
C(8)
*LOG_EXC_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.530220	0.001166	3886.483	0.0000
LOG_CL_PRICE(-1)	0.016269	0.000249	65.36306	0.0000
AR(1)	-0.010303	0.018201	-0.566084	0.5713
		Variance Equation		
C(4)	-9.139804	3.146600	-2.904660	0.0037
C(5)	0.257748	0.018642	13.82595	0.0000
C(6)	-0.061645	0.013760	-4.480074	0.0000
C(7)	0.012939	0.049434	0.261734	0.7935
C(8)	-0.007412	0.664884	-0.011147	0.9911

R-squared	0.000059	Mean dependent var	4.605238
Adjusted R-squared	0.000441	S.D. dependent var	0.010547
S.E. of regression	0.010549	Akaike info criterion	-6.295276
Sum squared resid	0.444500	Schwarz criterion	-6.282680
Log likelihood	12589.11	Hannan-Quinn criter.	-6.290811
Durbin-Watson stat	1.977523		
Inverted AR Roots	-.01		

For a summary of the coefficients see in Appendix table 2.1.1

With the addition of exchange rate variable, we observe that exchange rate fluctuation does not affect the whole variance model. There is a clear insignificant linkage between foreign exchange rate dynamics and Polish stock market over the studied period. Accordingly, we can adopt the same assumption as in the case of Turkey, that the relation between exchange rate and volatility may not be right documented . Supposing that we should search for the opposite linkage: the impact of stock price fluctuation on exchange rate in order to test if there is really some kind of correlation. Furthermore, in this model we notice the existence of volatility and leverage effect, which again demonstrates that negative shocks (bad news) have higher impact on volatility than positive shocks (good news) of the same magnitude. In comparison with the trading volume model, here the C(7) coefficient is insignificant, something that could be interpreted as the fact that the past volatility does not explain- affects current one.

Table 2.3.4 : AR(1) -EGARCH(1.1) with trading volume and exchange rate variables

Dependent Variable: LOG_CL_PRICE
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) +
C(8)
*TR_VOLUME_MIL + C(9)*LOG_EXC_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.527642	0.001683	2689.574	0.0000
LOG_CL_PRICE(-1)	0.016834	0.000360	46.79975	0.0000
AR(1)	-0.017088	0.017664	-0.967368	0.3334
Variance Equation				
C(4)	-10.18197	3.846879	-2.646814	0.0081
C(5)	0.190172	0.018606	10.22125	0.0000
C(6)	-0.048956	0.015119	-3.238031	0.0012
C(7)	-0.105447	0.031594	-3.337562	0.0008
C(8)	0.022442	0.001221	18.37939	0.0000
C(9)	-0.168620	0.835840	-0.201737	0.8401

R-squared	-0.000085	Mean dependent var	4.605238
Adjusted R-squared	-0.000586	S.D. dependent var	0.010547
S.E. of regression	0.010550	Akaike info criterion	-6.362974
Sum squared resid	0.444564	Schwarz criterion	-6.348803
Log likelihood	12725.40	Hannan-Quinn criter.	-6.357951
Durbin-Watson stat	1.965824		
Inverted AR Roots	-.02		

For a summary of the coefficients see in Appendix table 2.1.1

In the final table (Table 2.3.4) with the inclusion of trading volume and exchange rate, we reach the conclusion that WIG20 is volatile and vulnerable to negative shocks/news etc. Once more, trading volume coefficient is positive, while an insignificant negative coefficient of exchange rate is also resulted. Therefore, hypothetically, it could be concluded the positive relationship between trading volume and conditional variance, while at the same time there is no specific pattern for the exchange rate variable since it does not remain constant in the models. The C(7) coefficient does not remain constant, something that indicates that conditional variance could not follow an integrated process of order1.

Since we are interested more about the variance equation we could have ignored the “unwanted” results of AR (1) coefficient, but still we cannot ignore the negative R-squared that occurs in two models, the models where trading volume variable is introduced. A negative R-squared implies that the model doesn’t follow – fit the data. In order to find out the reason why this is happening, we conducted several tests and reached the conclusion that the model that fits better for the analysis of WIG20index is the AR(4)- EGARCH(1.1) model.

5.4 Russia

Last but not least the MOEX index attracts special interest since Russian economy is one of the most significant and maybe the most vulnerable to shocks (financial crisis, oil prices crises and the economic sanctions after 2014).

Table 2.4.1: AR(1)- EGARCH(1.1) (MOEX index)

Dependent Variable: LOG_INDEX
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.827373	0.002043	2362.535	0.0000
LOG_INDEX(-1)	-0.048144	0.000448	-107.3573	0.0000
AR(1)	0.026611	0.014930	1.782338	0.0747
Variance Equation				
C(4)	-0.095141	0.007563	-12.58042	0.0000
C(5)	0.067120	0.004235	15.84732	0.0000
C(6)	-0.039918	0.003075	-12.98003	0.0000
C(7)	0.994436	0.000725	1371.063	0.0000

R-squared	0.001557	Mean dependent var	4.605590
Adjusted R-squared	0.001057	S.D. dependent var	0.012127
S.E. of regression	0.012120	Akaike info criterion	-6.310689
Sum squared resid	0.586728	Schwarz criterion	-6.299667
Log likelihood	12618.91	Hannan-Quinn criter.	-6.306782
Durbin-Watson stat	2.052892		
Inverted AR Roots	.03		

The above presented results (Table 2.4.1) indicate that the past values (past stock prices) (LOG_ INDEX (-1)) predict at a significant degree the current stock prices. Whereas, the AR (1) coefficient is positive and significant at 10% level which means that past values have also a significant impact on the current ones.

The estimations of our model show the presence of volatility, asymmetry, and leverage effect, which denotes that bad news/shocks have greater impact than good news/shocks of the same size. Moreover, the persistence of volatility is high (C(7) coefficient is also significant at 1% level of significance),it counts almost 1 (0.994436), which designates that conditional variance could follow an integrated process of order 1.

Table 2.4.2: AR(1)- EGARCH(1.1) with trading volume variable

Dependent Variable: LOG_INDEX
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*TRADING_VOLUME__MIL_RUB

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.844876	0.004904	987.8676	0.0000
LOG_INDEX(-1)	-0.051906	0.001075	-48.28865	0.0000
AR(1)	0.021403	0.018261	1.172041	0.2412
Variance Equation				
C(4)	-6.895921	0.230443	-29.92469	0.0000
C(5)	0.297714	0.016715	17.81127	0.0000
C(6)	-0.025052	0.012475	-2.008243	0.0446
C(7)	0.243453	0.026061	9.341696	0.0000
C(8)	-1.86E-99	2.05E-07	-9.07E-93	1.0000

R-squared	0.001628	Mean dependent var	4.605590
Adjusted R-squared	0.001128	S.D. dependent var	0.012127
S.E. of regression	0.012120	Akaike info criterion	-6.037853
Sum squared resid	0.586686	Schwarz criterion	-6.025257
Log likelihood	12074.65	Hannan-Quinn criter.	-6.033388
Durbin-Watson stat	2.034549		
Inverted AR Roots	.02		

For a summary of the coefficients see in Appendix table 2.1.1

In table 2.4.2 above becomes evident that trading volume variable is negatively correlated with the conditional variance. This result can be interpreted, since the negative relationship is significant at 1% level, as an awareness of the fact that this variable (trading volume) accounts remarkably for the volatility persistence in the market and the fact of an inverse relation between the MOEX index and trading volume (decline of one of them equals rise of the other and vice versa).

At the same time we see that C(5) coefficient is positive and significant (at 10% level of significance) while C(6) coefficient obtains a negative sign (-0.025052), which is evidence of leverage effect. According to the above revealed by Tauchen and Pitts (1983) regarding the negative relation between volume and volatility, both volatility and trading volume are determined by new information flow rates to the market, traders' response to new information arrival and the number of active traders. Accordingly, in highly volatile emerging markets, sometimes trading can lead prices to deviate substantially from fundamentals. This negative correlation is also supported by the Sequential Information Hypothesis of Copeland (1976) and Jennings, Starks, and Fellingham (1981) (Girard & Biswas, 2007).Undeniably, it is highly possible that in emerging markets, distribution of information is asymmetric and only well-informed traders take positions at first place. After the transmission of information from trader to trader, less informed traders also take positions (Ibid.).

Table 2.4.3 : AR(1) -EGARCH(1.1) with exchange rate variable

Dependent Variable: LOG_INDEX
Method: ML ARCH
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)
*LOG_EX_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.826873	0.002182	2212.477	0.0000
LOG_INDEX(-1)	-0.048040	0.000478	-100.5643	0.0000
AR(1)	0.025963	0.014743	1.761112	0.0782
Variance Equation				
C(4)	-4.609760	1.489285	-3.095284	0.0020
C(5)	0.061548	0.004180	14.72454	0.0000
C(6)	-0.036166	0.003420	-10.57341	0.0000
C(7)	0.994910	0.000647	1537.400	0.0000
C(8)	0.982025	0.323296	3.037541	0.0024

R-squared	0.001597	Mean dependent var	4.605590
Adjusted R-squared	0.001097	S.D. dependent var	0.012127
S.E. of regression	0.012120	Akaike info criterion	-6.315003
Sum squared resid	0.586705	Schwarz criterion	-6.302407
Log likelihood	12628.53	Hannan-Quinn criter.	-6.310538

Durbin-Watson stat	2.051843
Inverted AR Roots	.03

For a summary of the coefficients see in Appendix table 2.1.1

As we observe after the addition to the model of the exchange rate variable the whole variance model changes. The significant positive impact of exchange rate (C(8) coefficients equals 0.982025) on MOEX index discloses an analogue/equivalent relation between these two variables, when the exchange rate decreases/increases the MOEX index decreases/increases respectively and vice versa. This is relationship is quite distinctive in emerging markets since gains or losses in the stock market expressed in hard currency could be increased (decreased) in a case of appreciation (depreciation) of the domestic currency. In general, finding significant exchange rate coefficient necessarily implies that the fluctuations in exchange rates lead to an increase or decrease in the stock market volatility. Furthermore, we confirm the presence of leverage effect, significant volatility spillovers and asymmetry in this model, which again designate the great influence of bad news or shocks on stock markets volatility and exchange rate.

By combining the two models above, including trading volume and exchange rate, we aim to enlighten the behavior of the conditional variance in general.

Table 2.4.4 : AR(1)- EGARCH(1.1) with trading volume and exchange rate variables

Dependent Variable: LOG_INDEX
Method: ML ARCH - Normal distribution
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) +
C(8)
*TRADING_VOLUME__MIL_RUB + C(9)*LOG_EX_RATE

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.852142	0.004866	997.2527	0.0000
LOG_INDEX(-1)	-0.053484	0.001066	-50.15330	0.0000
AR(1)	0.022879	0.018349	1.246868	0.2124
		Variance Equation		
C(4)	-7.884404	6.753875	-1.167390	0.2431
C(5)	0.296859	0.016779	17.69275	0.0000
C(6)	-0.025198	0.013057	-1.929767	0.0536
C(7)	0.247746	0.026457	9.364044	0.0000

C(8)	-1.83E-99	2.05E-07	-8.92E-93	1.0000
C(9)	0.223154	1.460217	0.152822	0.8785

R-squared	0.001643	Mean dependent var	4.605590
Adjusted R-squared	0.001143	S.D. dependent var	0.012127
S.E. of regression	0.012120	Akaike info criterion	-6.037737
Sum squared resid	0.586678	Schwarz criterion	-6.023567
Log likelihood	12075.42	Hannan-Quinn criter.	-6.032714
Durbin-Watson stat	2.034382		
Inverted AR Roots	.02		

For a summary of the coefficients see in Appendix table 2.1.1

The results of the last model (Table 2.4) show volatility spillovers and leverage effect (negative and significant C(6) coefficient). Once more, the trading volume coefficient(C(8)) is negative but this time insignificant, while an insignificant positive coefficient of exchange rate is also resulted. Therefore, it can be presumed that trading volume variable, as it is introduced in the equations, is able to explain some of the conditional variance's behavior. It is also obvious from the above presented that trading volume affects also the mean equation. We observe that in two models, where the trading volume variable is introduced, AR(1) coefficient becomes insignificant (p-value=0.212). [7] Referring to exchange rate variable (C(9) coefficient) it does not show any specific pattern since it does not remain constant in the models, while the persistence of past volatility (C(7)coefficient) remains constant in all four models.

6. Conclusions

Modeling and forecasting volatility of financial time series has become a fertile area for research. Volatility in financial markets is viewed by the public as a legitimate concern of government regulators, and so any increase in volatility in markets tends to lead to public demands on regulation. Policies for the reduction of volatility in the stock market are a necessity for it, in order to become a safe haven for investments. The improvement of market information systems for reducing volatility, the setting regulations to curb certain kinds of trading activities, the enforcement of institutional arrangements, designed to enable the existing market-making systems to

[7] This changes only in the case of alteration of the AR process (AR(3)- EGARCH(1.1)).

cope better with the current needs and trading strategies, and the introduction of substantial changes in the markets for the development of market liquidity, are some of the basic strategies for the reduction of volatility that have been suggested (F.R. Edwards, 1988).

In this dissertation, built on the pioneering literature about volatility and volatility spillovers in stock exchange markets, we study the volatility spillovers in KASE (Kazakhstan), BIST100 (Turkey), WIG20 (Poland) and MOEX (Russia) Indexes. The study explores the volatility in these markets by using AR(1) -EGARCH (1,1) model, which proved to be an efficient “tool” for modeling volatility and asymmetry.

Since the analysis for each country is conducted independently and the data are in the value of local currencies we cannot make any comparison between them. Although, we can draw some conclusions for each case and make some general comments regarding the empirical investigation and its outcomes, under the concept that we are referring to a group of countries / markets with common features (the IMF’s emerging and developing countries group).

In the case of Kazakhstan’s stock exchange market we observe that the results of the analysis are not constant (there is not a specific pattern). Volatility and volatility spillovers are generally manifested in every model, something that is not the case for leverage effect. The last finding (regarding leverage effect) proves that is not only the direction (positive or negative) of news/shocks that influence significantly the equity market but also the magnitude of them. Regarding the explanatory variables (trading volume and exchange rate) both affect negatively KASE index and volatility spillover effects.

Concerning Turkey, both leverage effect and volatility spillovers are recorded in the research. Trading volume variable is negatively correlated with the variance model, while the exchange rate variable is insignificantly correlated. When we introduce all the variables into one model we understand that the exchange rate coefficient changes. All these can be perceived as indications of the impact of negative novelties on Turkish stock market and exchange rate market.

Poland is a peculiar case since the results are not the expectable ones. In the half of the models R-squared is negative, something that tells us that the selected model doesn’t fit the trend of the data. The autoregressive process also, has an insignificant coefficient. These findings led us to further investigation, which resulted in the conclusion that the best fitted model for this case is AR(4)-EGARCH(1.1). Though, generally, we witness the existence of volatility spillovers and leverage effect as well as an insignificant exchange rate coefficient.

Finally, in the case of Russia we realize the existence of volatility spillovers, leverage effect, and the persistence of past volatility. Concerning the explanatory variables we see that trading volume is insignificantly negatively correlated with the MOEX index, while the exact opposite occurs with the exchange rate variable (positive and significant coefficient). The positive correlation between exchange rate variable and variance equation designates the significant positive impact of exchange rate on MOEX index and its volatility. It is a relationship, which, as we have already mentioned, is a characteristic of the emerging markets, since profits or losses in the stock market expressed in a hard currency are influenced by the appreciation or depreciation of the domestic currency (Živkov et al,2015) .

From the research above we confirmed the assumption that emerging and developing markets "suffer" from volatility. Besides, leverage effect was documented in the majority of the occasions. In the real world, it is normal for investors to be more sensitive and responsive to negative news and especially during the examined period– a decade crammed with negative events and crises (global financial crisis, oil price crises, geopolitical crises, sanctions etc.).

Furthermore, according to the empirical outcomes, it is confirmed that trading volume accounts for volatility spillovers. As we stated above, Tauchen and Pitts (1983) inspected the negative correlation between trading volume and volatility and advocated that both volatility and trading volume are strongly influenced by information flows to the market. In particular, in emerging markets, like the ones studied in this research, which are highly volatile, trading volume can push the prices to diverge significantly from fundamentals. This negative correlation is also supported by the Sequential Information Hypothesis of Copeland (1976) and Jennings, Starks, and Fellingham (1981) (Girard & Biswas, 2007).

Regarding exchange rate, its' significant impact on indexes (confirmed for half of the cases) implies that the fluctuations in exchange rates lead to a change in the stock market (volatility) ("flow"-oriented approach). On the other hand, in the cases, where we do not observe a significant link between exchange rate and stock index, we can assume that the relation between exchange rate and volatility may not be recorded right. We accept this because we use exchange rate as a variable that impacts stock index and therefore volatility, but we do not search for the opposite relation – the impact of stock index on exchange rate, the existence of which has been proved in many studies.

In a whole, the results for each case vary as it is expected and we cannot, as we said before, draw conclusions by comparing these cases. A general conclusion that we can extract, though, is the presence of volatility, volatility spillovers and asymmetry in the investigated stock markets.

6.1 Limitations of the study and future research

On the subject of potential limitations in this study, we can refer to the period under examination in this dissertation. Due to the unavailability of data for some of the indexes, we narrowed our investigated period, starting from 2009. This leads us also to the second limitation, which deals with a more narrow scope of the research, since we could not investigate thoroughly the impact of economic crisis on this markets and volatility. In addition, the study of each case individually might have limited slightly the capabilities of the research, regarding grouping and comparison of the cases.

These limitations, though, do not weaken our study, instead they set the foundations for further research. The study could be extended in several ways including the examination of cross country spillover effects, the addition of more explanatory variables, and the unidirectional, bidirectional and multidirectional analysis among markets, with the purpose of succeeding a further in-depth analysis about the transmission mechanisms between the prices and volatilities of stock markets.

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Introduction

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Appendix

Table 2.1.1 : summary of the coefficients

LoG_CLOSING PRICE/ INDEX(-1)	β0	is the past value of the C factor (C factor is the average stock price)
AR(1)	β1	the Autoregressive process coefficient
C(4)	α0	constant of the equation ix
C(5)	α1	the ARCH coefficient
C(6)	α2	asymmetric coefficient
C(7)	α3	GARCH coefficient (captures the persistence of past volatility)
C(8)	φ/χ	Trading volume or exchange rate coefficient
C(9)	χ	Exchange rate coefficient