LINKAGES BETWEEN STOCK AND BOND MARKETS: EVIDENCE FROM RUSSIA

by

Liliia Murzaieva

A thesis submitted in partial fulfillment of
the requirements for the degree of

MA in Financial Economics

Kyiv School of Economics

2013

Thesis Supervisor: _________________________ Professor Olesia Verchenko

Approved by ____
Head of the KSE Defense Committee, Professor Wolfram Schrettl

____

____

____

Date ____________________________________

Kyiv School of Economics

Abstract

LINKAGES BETWEEN STOCK AND BOND MARKETS: EVIDENCE FROM RUSSIA

by Liliia Murzaieva

Thesis Supervisor: Professor Olesia Verchenko

In this thesis the linkages between stock and bond markets in Russia are examined by testing the hypothesis of time-varying correlation between stock and bond returns. Data for this study comes from the Moscow Exchange and covers daily and biweekly returns on stocks and government bonds during the period of 2003-2013. Dynamic conditional correlation version of the multivariate GARCH model, allowing for asymmetric responses of volatility to positive and negative shocks, is applied to quantify the conditional stock-bond correlations.

Findings indicate significant time variability in correlation between stock and bond returns on the Russian market. The conditional correlations, estimated for daily returns, are mostly positive, but exhibit noisy behavior over time. The correlation between biweekly returns reveal decreasing trend in the co-movements between stocks and bonds during 2003-2007. In 2008, this trend reversed indicating strengthening in significance of positive stock-bond correlation during the crises period. This way, the hypothesis of flight-to-quality existence on the Russian market is rejected.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I wish to express sincere gratitude to my thesis supervisor Professor Olesia Verchenko for her highly valuable guidance and support as well as for the inspirational Financial Economics courses she taught that helped me to work through and complete this thesis.

I also would like to thank all the Research Workshop professors for their useful comments and advice on this research. Besides, I am very grateful to all the professors of Kyiv School of Economics for their enormous efforts to provide excellent knowledge I have got at the KSE.

Special words of appreciation are directed to the contributors of the KSE Alumni Scholarship 2011/2012 for their generous donations that have helped me a lot.

In addition, I wish to express my thankfulness to my classmates, particularly Ievgen Gavrysh, Ruslan Gibaiev and Mykhailo Oliinyk for their continuous help, fruitful teamwork and friendship. Besides, I am especially grateful to Sergii Kiiashko for his encouragement to enter the KSE and valuable advice throughout my studies.

Finally, I thank my family and close friends from Kharkiv for their unconditional belief, inspiration and support.

GLOSSARY

AIC. Akaike Information Criteria

BIC. Bayesian Information Criteria

ARMA. Autoregressive Moving-average Model

DCC. Dynamic Conditional Correlation

EGARCH. Exponential GARCH Model

GARCH. Generalized Autoregressive Conditional Heteroscedasticity Model

TGARCH. Threshold GARCH model

C h a p t e r 1

INTRODUCTION

The empirical linkages between markets of different asset classes are of great importance to economists and policymakers, financial institutions and investors. Stylized facts about cross-asset correlations are challenged by ongoing changes in the world financial landscape occurring due to globalization of capital markets, invention of sophisticated financial instruments and implementation of new risk-management techniques. Emergence of new financial markets amid rapid development in Latin America, East Asia and Central and Eastern Europe (CEE) opens new opportunities for investors, simultaneously raising a question about patterns that those markets follow.

Since equities and fixed income securities, primarily corporate and government bonds, remain major publicly traded financial instruments, accounting for more than a half of financial assets allocated all over the world (as McKinsey Global Institute shows in its 2011 report on global capital markets), the relationship between stock and bond markets takes one of the top spoken topics during the last two decades. This research is devoted to the investigation of the nature and dynamics of linkages between stock and government bond price movements on the Russian market, the largest market in the CEE region.

Financial institutions and investors are those who primarily interested in understanding the linkages between stock and bond markets while making asset allocation and risk management decisions. Following the modern portfolio theory, introduced by Markowitz (1952, 1959), the correlation between price movements on different securities markets is a crucial indicator taken into account by investors seeking diversification opportunities. In particular, diversification is inversely related to correlation: the lower the correlation between assets included in a portfolio is, the better the diversification and, thus, the higher the reward-to-risk ratio. The fact of inverse relation between correlation across assets in the portfolio and its riskiness is also intensively used in financial modeling and risk management by financial institutions. In particular, risk management divisions of commercial banks utilize correlation measures in building risk assessment models.

Understanding of cross-market relations is also important for economists and policymakers when evaluating the monetary policy effects on the economy. The monetary policy transmission mechanism describes how changes in the nominal money stock and the nominal interest rate affect real variables, primarily aggregate output and employment. According to Mishkin (1995), who summarizes the ways through which the transmission mechanism works, there is a separate group of asset price transmission channels.

Asset price channels are highlighted by Tobin's q-theory of investment and Modigliani's life-cycle theory of consumption. Both of these theories, in turn, rely on the monetarist view under which contractionary monetary policy results in lower stock prices. Decrease in money supply forces public to spend less, including spending on the stock market. Decline in demand for equities causes their prices to fall. Likewise, increase in short-term nominal interest rate makes bonds more attractive to investors in comparison with equities lowering prices of the latter.

Then, according to Tobin's q-theory, firms face lower value of q, the ratio of firm's market value to the replacement cost of the physical capital it owns. As a result, firms have relatively lower capacities to invest since more additional stocks should be issued to finance new investment projects. Thus, investments fall inducing contraction in output and employment. Modigliani's life-cycle theory of consumption, meanwhile, argues that stock prices decrease translates in lower financial wealth of households forcing them to consume less. Lower consumption, in turn, drives output and employment down.

Thus, classical view on monetary transmission mechanism assumes negative correlation between interest rate and stock prices. Since bond prices are inversely related to interest rate as well, the correlation between bond and stock prices should be positive. Clearly, any deviation from the suggested equilibrium relation across securities markets, which, as shown hereafter, takes place in practice, would have different implications for the outcomes of the particular monetary policy.

The theoretical argument of negative correlation between equities and interest rates is also supported by the so called Fed Model. Formulated by Yardeni (1997, 1999) and backed by empirical evidence prior 1997, it states that the forward earning yield of the stock market (earnings-to-price ratio) is roughly equal to the 10-year Treasury bond's yield to maturity. This relationship, therefore, implies negative correlation between stock prices and treasury yields, i.e. positive correlation between stock and bond prices.

Furthermore, movement of the stock and bond prices in the same direction is consistent with the present value models of asset pricing. If stock and bond prices are considered as the discounted sums of their future cash flows, then, apparently, factors affecting the discount rates are likely to move stock and bond prices in the same direction. Both theoretical and empirical support for that idea is provided by Shiller and Beltratti (1992). Using annual US and UK data over 1871-1989 and 1918-1989 respectively, in the framework of present value models authors have found strong positive correlation between the actual excess returns in the stock market and the actual excess return in the bond market.

Other early empirical studies, such as Fama and Schwert (1977) and Campbell and Ammer (1993), also confirm inverse relationship between stock returns and bond yields (i.e. positive relation between prices of stocks and bonds). Most of these studies are performed for developed financial markets, primarily US and UK, due to availability of long history of time series data.

However, starting from early 2000's, some studies conducted for developed countries (including Gulko (2002) and Ilmanen, 2003) reveal positive correlation between stock returns and bond yields (i.e. negative correlation between prices of stocks and bonds) appearing mostly around crisis periods. Such phenomenon is called "flight-to-quality" indicating investors' intention to give up more risky equity in favor of less risky bonds in times of uncertainty. Baur and Lucey (2009) provide detailed discussion of terminology on the topic and define flight-to-quality as a significant decrease in the correlation coefficient in a crisis period compared to a benchmark period resulting in a negative correlation level. It is worth to mention, that flight-to-quality is a particular case of decoupling – a term used to describe the situation when two different asset classes that typically rise and fall together move in opposing directions.

In general, despite the fact that linkages between stock and bond markets are intensively studied, there are no unified conclusions on strength and the direction of this relationship. Conflicting results among studies, obtained occasionally even for the same markets, can be explained by different time periods covered as well as different methodologies applied. Both academic (including most recent studies by Andersson et al. (2008), and Baele and Inghelbrecht, 2010) and commercial (for instance, J.P.Morgan report on cross-asset correlations of 2011) research on the topic, however, unanimously confirm the fact of significant changes in the sign and the magnitude of stock-bond correlation over time.

As was already mentioned, most existing studies concerning stock-bond relations, particularly flight-to-quality phenomenon, are devoted to developed markets. Rapid growth of emerging economies and their financial markets, accompanied by market data accumulation, gives raise to the study of cross-market relations on those markets as well. Nevertheless, to our best knowledge, the number of such studies is limited. Among them the largest coverage of different countries is provided by Boyer et al. (2006), who briefly examine stock-bond correlations for 20 emerging markets within the study on how stock market crises spread. Other studies perform analysis for individual countries. For instance, Li and Zou (2008), Ahmed and Joher (2009), Venkateshwarlu and Babu (2011) consider stock-bond relations in China, Malaysia and India respectively. Apparently, conclusions made in these works are country-specific. However, studies which, inter alia, look at assets' behavior around financial crises, including Boyer et al. (2006), Li and Zou (2008) as well as Ahmed and Joher (2009), found that correlation between stock and bond returns do not become negative in times of economic turbulence. This way, the hypothesis of flight-to-quality, confirmed for many developed markets, is not supported for considered emerging markets. One of possible explanations for non-decreasing stock-bond correlation, provided by Boyer et al. (2006), is foreign investors' behavior on the markets of developing countries. Authors suggest that foreign investors withdraw capital from both equity and bond markets in times of economic crisis. Local investors, meanwhile, do not have sufficient power to arbitrage away the price impact of foreign trades due to wealth constraints. In sum, prices of stocks and bonds move in the same direction ensuring positive correlation between their returns.

While little has been done in the context of Latin American and Asian emerging markets, academic research on linkages between stock and bond markets for transition countries in CEE region is virtually missing. Taking into account the importance of intrinsic cross-market mechanism we initiate the examination of return and volatility linkages between stock and government bond markets for Russia – the major market in the region.

According to the World Federation of Exchanges, the volume of transactions on the Russian equity market grew 8 times over the recent decade – from $41 billion in 2002 to $337 billion in 2012. By now it is one of the largest stock markets in the emerging world with the total market capitalization over $880 billion as of January 2013. Russian market of debt securities, meanwhile, became 10th largest market in the world in 2012 with annual volume of bonds traded of $334 billion.

Distinctive feature of the Russian financial market is its high accessibility to foreign investors. There are no restrictions to enter the market as well as easy procedure of revenues repatriation. Currently, depository receipts are available for 65 Russian stocks, or 22% of all traded equities. According to the Moscow Exchange, in the beginning of 2012 share of international investors in equity trading turnover on the stock market amounted to 37%. Openness for international investment community is expected to grow further in light of the Moscow's attempts to become one of the world financial centers along with New-York, London and Tokyo.

Relying on existing knowledge about cross-asset relations and taking into account Russian market specifics we impose two hypotheses which we are attempting to test in this study. Firstly, in line with previous research, we believe that a stock-bond correlation on the Russian market changes over time. Secondly, contrary to findings for developed markets but similar to conclusions made for emerging countries, we hypothesize that the flight-to-quality across domestic stock and government bond markets is not typical for Russia. The last argument relies on the suggestion that foreign investors, which hold considerable amounts of domestic stocks and fixed income instruments in "good" times, leave less developed and, thus, more vulnerable markets at times of economic uncertainty. It pushes both stock and bond prices down, which is not consistent with the flight-to-quality phenomenon.

Similarly to the most recent studies on the topic, we apply the Dynamic Conditional Correlation (DCC) version of the multivariate GARCH model by Engle (2002) to verify our initial hypotheses. This approach provides a convenient way to account for specific features of asset returns, including dynamic nature of both conditional volatilities and conditional correlations between returns. However, in contrast to most studies on stock-bond co-movements where simple GARCH (1,1) parameterization is used, we pay considerable attention to the modeling of volatility processes typical for stock and bond returns. Particularly, along with ordinary GARCH model we consider two ARCH specifications allowing for the asymmetric responses of volatilities to positive and negative shocks, particularly the EGARCH and TGARCH models.

There are a number of contributions this study makes. Firstly, we supplement existing knowledge on cross-asset relationships providing an insight into stock-bond co-movements on one of the largest emerging market. Secondly, we perform thorough examination of volatility features of stock and bond returns in Russia that enable us to obtain accurate estimates of the correlation between them. Thirdly, we provide analysis of the most recent developments of the Russian market, which allows drawing conclusions about its behavior during 2008 financial crises and testing for flight-to-quality phenomenon.

The next section of this study discusses the existing literature on the stock-bond relationships. Sections 3 presents research methodology. Data description is summarized in Section 4. Section 5 provides empirical results. The last section concludes.

C h a p t e r 2

LITERATURE REVIEW

The empirical relation between two main financial asset classes, namely stocks and government bonds, has been actively studied during the last two decades. Nevertheless, there is no consensus about the nature and determinants of the linkages between stock returns and bond yields. Different time spans used in research primarily stand for diverse, occasionally opposite, conclusions about stock-bond returns correlation. Lack of clear evidence of interaction between two asset classes, together with recent shifts in financial markets landscape, induces ongoing academic discussion on the topic.

The very first question that academic literature addresses is actual existence of correlation between stock and bond returns and the direction of this relation (correlation sign). A classical paper by Fama and Schwert (1977) documents negative correlation between returns: it reveals negative slope coefficient in the regression of stock returns on Treasury bill returns. This conclusion finds support in numerous studies of the late 1980's devoted to the issue of predictability of asset returns. In particular, stock-bond relation is extensively discussed by Keim and Stambaugh (1986), Campbell (1987), Breen et al. (1989), Ferson (1989), Shiller and Beltratti (1992) and Campbell and Ammer (1993).

Almost all early studies in this line of research are done using ordinary least squares regressions (OLS) based on U.S. monthly data. Among above mentioned studies only Shiller and Beltratti (1992) consider also U.K. data and use annual returns for the analysis. Campbell and Ammer (1993), in turn, have been the only authors who have used linear vector-autoregressive (VAR) approach instead of OLS.

Besides data coverage, the common feature of the early studies is the assumption (implicitly implied by the methods used) that the correlation between returns in two markets does not change over time. In this regard, the second question that has been raised in this line of research is whether stock-bond correlation is time dependent.

Virtually all studies starting from late 1990's reject the hypothesis of time-invariant co-movement between returns in two markets. For instance, Li (2002) uses both monthly (for the period from 1958 till 2001) and daily (for the period from 1980-1991 till 2001 depending on the country) data to detect the growing correlation of stock-bond price changes across G7 countries till mid 1990's, followed by reversion to almost zero values till 2001. Studies by Jones and Wilson (2004) and Yang et al. (2009), that are done only for US and UK markets but cover longest periods of time (1871-2000 of monthly and annual data and 1855-2001 of monthly data respectively), confirm the dynamic nature of the relation between markets. Academicians that use more recent data reveal strengthening of fluctuations in correlation between stock and bond returns over time both in the US market (Chou and Liao, 2008; Aslanidis and Christiansen, 2012)) and the markets of several European countries (Baur and Lucey, 2009; Kim et al., 2006).

Growing amount of literature on the time-varying nature of stock-bond returns correlation, in turn, can be separated into two main groups depending on the driving forces that researchers suggest may explain such variance.

One group of studies tries to connect changes in stock-bond correlation with macroeconomic factors, primarily inflation uncertainty. Following the paper by David and Veronesi (2001), Li (2002) and Ilmanen (2003) employ monthly data on developed countries to show that greater concerns about future inflation result in stronger co-movements between stocks and bonds. More recent study by

Andersson et al. (2008), performed using daily data on U.S. and German stock and bond returns, confirms that expected inflation is positively related to the time-varying correlation between returns on two markets.

Another group of studies focuses on stock market uncertainty associated with economic crises as a main source of time-variability in stock-bond relation. Among first Gulko (2002) gave attention to the patterns of the stock and bond returns dependency on market shocks. Particularly, using returns on U.S. stocks and Treasury bonds the author shows that the unconditional positive correlation between stocks and bonds switches sign during stock market crashes confirming flight-to-quality. Further this phenomenon finds support in works of Jones and Wilson (2004), Hartmann et al. (2004), Connolly et al. (2005), Cappiello et al. (2006), Baur and Lucey (2009).

All above studies deal primarily with developed markets. The number of studies performed directly for emerging world is limited. Addressing somewhat different questions and applying different techniques researchers come to country-specific conclusions that not always can be compared with each other.

Brief examination of stock-bond correlations around crisis periods for 20 emerging countries, including Russia, is performed by Boyer et al. (2006) within the study on how stock market crashes spread. Using regime-switching model the authors show that during 1989-2002 correlation between stock and government bond returns, on average, does not decreases during crisis periods on emerging markets, while there is an evidence of decrease in stock-bond co-movement on all developed markets. Authors' explanation for increase in correlations between risky (stocks) and safe (government bonds) assets is that investors withdraw capital from both equity and bond markets and wealth-constrained local investors are unable to arbitrage away the price impact of foreign trades. In this study we apply the same suggestion when hypothesize that there is no flight-to-quality on the Russian market.

More recent study by Li and Zou (2008) confirms that conclusion for Chinese market. Addressing the question of policy and information shocks impacts on the correlation between government bond and stock daily returns they have found that the tendency of stock and bond prices to move in the same direction amplifies when investors are hit concurrently by bad news. Similarly, utilizing both weekly and monthly data, Ahmed and Joher (2009) have documented strengthening in significance of positive stock-bond correlation during the crisis period in Malaysia. However, during the recovery period the correlation became negative, but insignificant.

To our best knowledge, there are no profound studies on cross-asset linkages we are considering that deal with transition economies in CEE region. In this thesis we aim to fill the existing gap by performing analysis of stock-bond relations on the largest financial market among former Soviet Union countries, namely Russia. Understanding of the intrinsic relations and mechanisms typical for this market is of the growing importance due to the country's strategic goal to compete with leading financial centers in the world. Therefore, this study is meant to supplement the existing knowledge on the relationships between stock and bond markets on one of the largest emerging markets that is expected to increase its role in the nearest future.

Chapter 3

METHODOLOGY

Dynamic Conditional Correlation (DCC) version of the multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, developed by Engle and Sheppard (2001) and Engle (2002), is applied to give an insight into time-varying stock-bond relationship.

We start this section by providing the reason why the DCC-GARCH approach is an appropriate tool to use in this research. Then we proceed to the description of the basic model's setup and its assumptions. Finally, we consider the estimation procedure envisaged by the model introducing additional volatility model specifications that allow accommodating for the asymmetry in volatility, namely the Exponential GARCH (EGARCH) and the Threshold GARCH (TGARCH) models.

A number of studies conducted for developed countries, as was described in the previous parts of this thesis, have shown that strength and direction of linkages between stock and bond markets changes over time. Thus, simple static correlation coefficients cannot provide information sufficient for understanding the true nature of the relationship between markets. As a consequence, an approach that allows for time-varying evolution of that relationship is required.

Taking into account the stylized facts of conditional heteroscedasticity in asset returns, it is reasonable to utilize DCC-GARCH approach that provides a convenient way to account for the dynamic nature of both conditional volatilities and conditional correlations between asset returns.

The main outcome of the DCC-GARCH model we are interested in is the conditional covariance matrix that allows estimating conditional correlation between two series, namely stock and bond returns, evolving over time.

To illustrate the model's setup, let $r_t = [r_t^1 \ r_t^2]'$ be the (2x1) vector containing two series of returns. In the general specification of DCC-GARCH conditional returns are assumed to be multivariate normally distributed with zero mean and conditional variance-covariance matrix Ht:

$$r_t = \mu_t + \varepsilon_t, \tag{1}$$

where μ_t is a (2x1) vector of the expected value of the conditional returns, i.e. $\mu_t = E(r_t | \Omega_{t-1})$, and ε_t is a (2x1) vector of zero mean return innovations conditional on the information Ω_{t-1} available at t-1, i.e. $\varepsilon_t \ | \Omega_{t-1} \sim N\ (0, H_t)$.

The residual returns ε_t are represented as:

$$\varepsilon_t = D_t \nu_t \sim N\ (0, H_t), \tag{2}$$

where $D_t = \text{diag}\{\sqrt{h_{it}}\}$ is a (2x2) diagonal matrix of time-varying standard deviations from the univariate GARCH models, estimated for each series, and ν_t is a (2x1) vector of standardized residuals calculated as $\nu_{it} = \varepsilon_{it} / \sqrt{h_{it}}$.

Then the conditional variance-covariance matrix $H_t = \{h_{it}\}_t \ \forall$ i=1,2 can be decomposed as:

$$H_t = D_t R_t D_t, \tag{3}$$

where $R_t = \{\rho_{ij,t}\}_t$ for i,j = 1,2 is a (2x2) conditional correlation matrix of the standardized disturbances.

The covariance matrix H_t is positive-definite by construction. From the fact that H_t is the quadratic form based on R_t it follows that correlation matrix R_t should also be positive definite. Moreover, by definition of correlation matrix all elements of R_t should not to exceed unity. To insure that both of these requirements are met, R_t is decomposed as follows:

$$R_t \; = \; Q_t^{*-1} Q_t \; Q_t^{*-1}, \tag{4}$$

where Q_t^* is a (2x2) diagonal matrix composed of the square root of the diagonal elements of the $Q_t \; = \{q_{ij,t}\}$ and the last one follows the GARCH process:

$$Q_t \; = (1-\alpha-\beta)\bar{Q} + \alpha(\nu_t'\nu_t) + \beta Q_{t-1} \tag{5}$$

where α and β are scalars such that α≥0, β≥0, α+β<1 and $\bar{Q}$ is unconditional covariance matrix of the standardized residuals from the univariate GARCH models, i.e. $\bar{Q} = \mathrm{E}[\nu_t'\nu_t]$.

For this study, the matrix of interest is the conditional correlation matrix R_t, particularly its element $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$ for i,j = 1,2, which represents the conditional correlation between returns on stocks and bonds.

In practice, there is a three-step procedure to follow in order to estimate conditional correlation coefficients using DCC-GARCH. Firstly, estimation of mean equations is performed for each time series. Secondly the residuals from the first step are used to estimate volatility, or GARCH, model for each series. Finally, the transformed residuals from the second step are employed to obtain a conditional correlation estimates. These steps are described further in details for the case of two time series of returns which is applicable for this research.

The first step in building the DCC-GARCH model is to obtain residuals ε_t from mean equation for each time series. In line with other studies of financial time series behavior, we specify the conditional mean using autoregressive moving-average (ARMA) process to capture possible autocorrelation in returns caused by market microstructure effects (e.g., spread effect) or non-trading effects. Specifically, we impose an assumption (which we will test when implementing estimation procedure) that returns follow an ARMA (p, q) process described as:

$$r_t^i = \phi_0^i + \sum_{k=1}^{p} \phi_k^i r_{t-k}^i + \varepsilon_t^i + \sum_{k=1}^{q} \theta_k^i \varepsilon_{t-k}^i, \ i = 1,2 \tag{6}$$

On the second step the residuals from the mean equations are used to get estimates of time-varying standard deviations from the volatility equation. In the basic version of DCC-GARCH volatility is modeled with the simple univariate GARCH (m, n) process as:

$$h_t^i = \omega_0^i + \sum_{k=1}^{m} \omega_k^i \varepsilon_{t-k}^i + \sum_{k=1}^{n} \eta_k^i h_{t-k}^i, \ i = 1,2 \tag{7}$$

The standard GARCH model suggests symmetric response of returns' volatility to positive and negative shocks on the market. However, many empirical studies, beginning with Black (1976), reveal strong asymmetry in volatility meaning that negative returns are followed by larger increases in volatility than equally large positive returns. This phenomenon is also called the leverage effect. To capture its probable presence on the Russian stock and bond markets, in addition to symmetric GARCH we estimate two asymmetric versions of volatility models that account for different effects of positive and negative shocks.

The first specification is the Exponential GARCH (EGARCH), introduced by Nelson (1991), which model conditional volatility as:

$$\log(h_t^2) = \omega_0 + \sum_{i=1}^{s} \omega_i \left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right| + \sum_{i=1}^{t} \sigma_j \frac{\varepsilon_{t-j}}{h_{t-j}} + \sum_{k=1}^{n} \eta_k \log(h_{t-k}^2) \qquad (8)$$

The log of the conditional variance implies that the asymmetry effect is exponential. Positive (ε_{t-j}>0) and negative (ε_{t-j}<0) shocks affect volatility differently if σ_j is not equal to zero.

The second asymmetric volatility model is the Threshold GARCH (TGARCH) by Rabemananjara and Zakoian (1993) and Zakoian (1994):

$$h_t = \omega_0 + \sum_{i=1}^{s} \omega_i \varepsilon_{t-i} + \sum_{j=1}^{t} \gamma_j \varepsilon_{t-j} I_{t-j}(.) + \sum_{k=1}^{n} \eta_k h_{t-k}, \qquad (9)$$

where I(.) is the indicator function such that I(.)=1 if ε_{t-j}<0 and I (.)=0 otherwise. Then the leverage effect is evident if γ_j is positive.

In sum, statistically significant values of σ and γ parameters in above equations indicate the leverage effect. In this case ordinary GARCH parameterization may be misleading when modeling volatility process. Thus, one of the asymmetric specifications should be utilized to estimate conditional volatility model for assets' returns.

From the conditional volatility equations, estimated for each series, the elements of matrix D_t, i.e. the diagonal matrix of time-varying standard deviations of residual returns, are obtained.

The third and last step in DCC-GARCH implementation is estimation of DCC parameters, particularly elements of conditional correlation matrix R_t. Following Engle (2002) the model can be estimated utilizing quasi-maximum likelihood method (QMLE) with the following log-likelihood function:

$$L = -0.5 \sum_{t=1}^{T} (n \log(2\pi) + \log|H_t| + r_t' H_t r_t) =$$

$$= -0.5 \sum_{t=1}^{T} (n \log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t) =$$

$$= -0.5 \sum_{t=1}^{T} \left(n \log(2\pi) + 2 \log|D_t| + \log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t\right) = \tag{10}$$

$$= -0.5 \sum_{t=1}^{T} (n \log(2\pi) + 2 \log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t' \varepsilon_t + \log|R_t|$$

$$+$$

$$+ \varepsilon_t' R_t^{-1} \varepsilon_t) = L_1 + L_2,$$

where $L_1 = -0.5 \sum_{t=1}^{T} (n \log(2\pi) + 2 \log|D_t|^2 + r_t' D_t^{-2} r_t)$ is the volatility term and $L_2 = -0.5 \sum_{t=1}^{T} (\log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t)$ is the correlation component.

The parameters of correlation model in (5), estimated with above procedure, are employed to calculate conditional correlation between returns on two series at each point of time. Then, using graphical analysis, we can draw conclusions about the validity of our initial hypotheses. In particular, from the plot of correlation series we will be able to identify whether the stock-bond correlation varies over time. Covering the period of the financial crisis of 2008, we also will obtain the picture of stock-bond relationship behavior around the period of economic distress. This will enable us to make inferences about presence of flight-to-quality phenomenon on the Russian market.

Despite all advantages of DCC approach, mentioned above, it is important to note that it does not provide any precise information about causality in stock-bond comovements or presence of long-run equilibrium relationships between markets. It also sheds no light on possible sources of correlation dynamics. Nevertheless, DCC-GARCH is a powerful tool for our research since we are not aiming to get answers to above questions, but focus on quantifying the conditional correlation between returns and analyzing its evolution over time.

Chapter 4

DATA DESCRIPTION

The data on the Russian stock and bond markets used in this study comes from the Moscow Exchange – the largest exchange in Russia created after the merger of country's two leading exchanges MICEX and RTS in 2011.

The MICEX Index is used to evaluate stock market performance. MICEX is a free-float capitalization-weighted composite index denominated in Russian rubles. It was introduced in September 1997. As of March 2013, the index constituents are the 50 most liquid Russian stocks traded on the Moscow Exchange.

Bond market dynamics is estimated utilizing the Russian Government Bond Index (RGBI). RGBI is a weighted average price bond index designed according to the clean price methodology, i.e. any interest that has accrued since the bond's issue or the most recent coupon payment is excluded when calculating the bond price. The clean-price approach helps to get rid of coupon payments effect on bond prices and, thus, to obtain price changes that occurred purely due to market factors.

RGBI constituents are both short term and long-term government bonds issues denominated in rubles. The list of constituents is reviewed each month to insure that the index tracks the actual government bond market conditions. RGBI is calculated starting from December 31, 2002.

Daily and biweekly returns on stock and bond indexes are employed for the analysis. Particularly, we use continuous log returns computed as $\ln(P_t/P_{t-1})$, where P_t is the closing value of the index on period t.

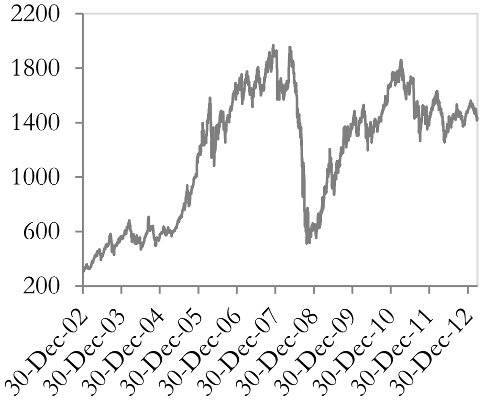
Since stock and bond returns will be analyzed together, time series of index levels is constructed starting from January 2003 – the earliest date available for the index with shorter history, i.e. RGBI. As a result, time period covered in this study is 10 years and 3 months: from January 1, 2003 till March 29, 2013.

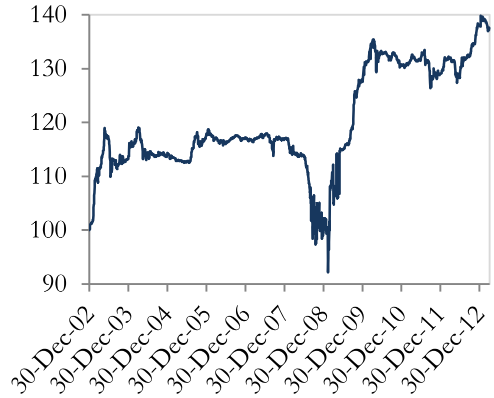
Final sample includes 2530 observations of stock and bond daily returns and 257 observations of stock and bond biweekly returns for each time series. The descriptive statistics for the returns, presented in Table 1, confirms stylized facts about assets returns. As expected, the stock market provides, on average, higher returns and is associated with higher risk as compared to the bond market. Returns distributions on both markets are not normal (as Jarque-Bara test indicates) and characterized by negative skewness and notable excess kurtosis. The last one indicates that the probability distribution for both returns exhibits fatter tails than the normal distribution.

Table 1. Descriptive statistics of stock and bond returns (in annual terms)

Period	Obs.	Mean	St. dev.	Min	Max	Skewn.	Kurt.	JB (p-value)
Daily returns								
MICEX	2 530	0.152	5.687	-50.609	61.804	-0.190	18.793	26 308 (0.00)
RGBI	2 530	0.034	1.373	-19.129	17.545	-0.158	77.134	579 365 (0.00)
Biweekly returns								
MICEX	257	0.214	1.763	-9.244	5.161	-1.178	7.961	3 179 (0.00)
RGBI	257	0.026	0.344	-1.021	2.97	3.021	27.753	68 436 (0.00)

p-value in brackets

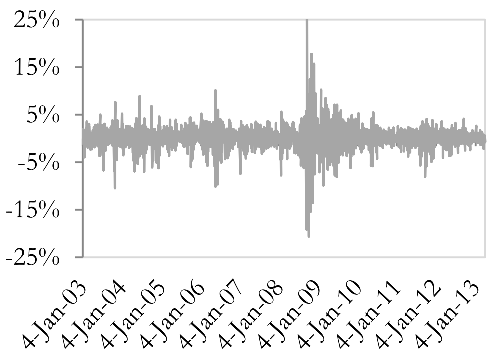


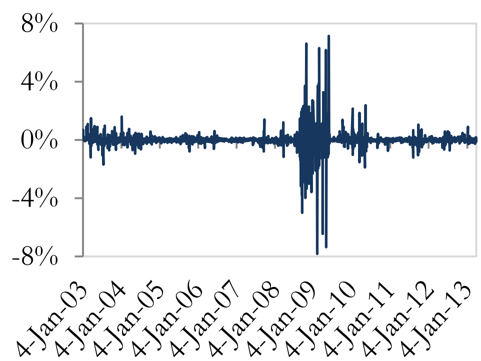


(1a) MICEX

(1b) RGBI

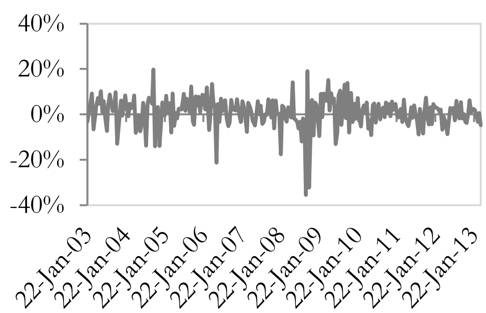
Figure 1. MICEX and RGBI dynamic, January 2003 – March 2013

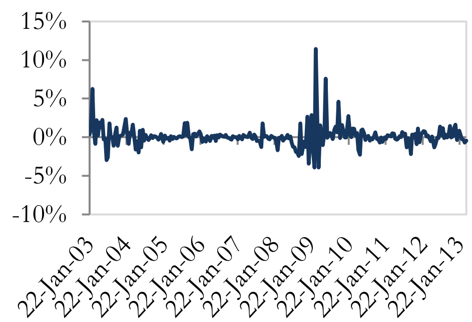




(2a) Daily stock returns

(2b) Daily bond returns





(2c) Biweekly stock returns

(2d) Biweekly bond returns

Figure 2. Stock and bond returns dynamic, January 2003 – March 2013

From the graphs of the indices dynamics (in levels), illustrated in Figure 1, we suspect that index levels are non-stationary. By contrast, returns on indexes, whose evolutions are depicted on Figure 2, look like stationary process. Formal unit-root tests confirm these observations. As can be seen from test statistics in Table 2, both Dicky-Fuller and Phillips-Perron tests reject the hypothesis of stationarity in stock and bond index levels at the 95% confidence level, but indicate that returns on both markets are stationary. Thus, the data in samples for both markets are found to be I(1) in levels.

Table 2. Augmented Dickey – Fuller (DF) and Phillips – Perron (PP) unit-root test statistics for the time series of stock and bond index levels and returns

Index	Model with intercept		Model with intercept and trend	
	DF	PP	DF	PP
Index levels				
MICEX	-1.903 (0.331)	-1.884 (0.340)	-1.820 (0.695)	-1.777 (0.716)
RGBI	-1.740 (0.411)	-1.491 (0.538)	-2.386 (0.387)	-2.006 (0.598)
Daily returns				
MICEX	-49.813 (0.000)	-49.842 (0.000)	-49.837 (0.000)	-49.872 (0.000)
RGBI	-53.420 (0.000)	-54.435 (0.000)	-53.410 (0.000)	-54.424 (0.000)
Biweekly returns				
MICEX	-17.787 (0.000)	-17.675 (0.000)	-17.918 (0.000)	-17.788 (0.000)
RGBI	-16.925 (0.000)	-54.435 (0.000)	-17.675 (0.000)	-16.886 (0.000)

Values in parentheses are MacKinnon approximate p-values for test statistics

Plots of returns dynamics in Figure 2 show an evidence of another well-known property of financial asset returns, namely volatility clustering, when high returns (of either sign) are followed by high returns and, similarly, low returns are followed by low returns. The most evident example of clusters existence in our sample is returns behavior in during the second half of 2008 when the word financial crisis was at its peak.

According to Black (1976), volatility clustering in returns manifests itself as autocorrelation in squared and absolute returns or in the residuals from the estimated conditional mean equation for financial series. Such evidence of conditional heteroscedasticity suggests that the GARCH process might be appropriate to model returns behavior.

Careful examination of the evolutions of stock and bond returns together also allows to conclude that association between volatility clusters on the markets are fairly close during certain periods (as in 2008-2009), but not all the time. This observation provides support for the idea of time-varying correlation between stock and bond returns.

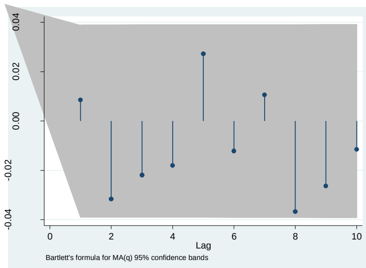
C h a p t e r   5

EMPIRICAL RESULTS

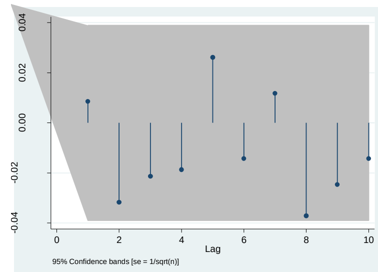
We start our analysis with thorough examination of each return series separately in order to obtain univariate conditional heteroscedasticity models that describe volatility properties of stock and bond returns. The residuals from those models will be used as inputs for the multivariate DCC-GARCH model which, in turn, will allow us to end up with estimates of conditional stock-bond correlations.

The first step in our analysis is to find the conditional mean equation that captures serial correlation in returns if any is present. From autocorrelation and partial autocorrelation functions for stock (Figure 3) and bond (Figure 4) returns we conclude that there is no statistically significant association between daily stock returns and their lagged values, whereas serial correlation in daily bond returns is evident. In order to test these initial suggestions and determine precise ARMA specifications we use the Akaike (AIC) and the Bayesian (BIC) information criteria.

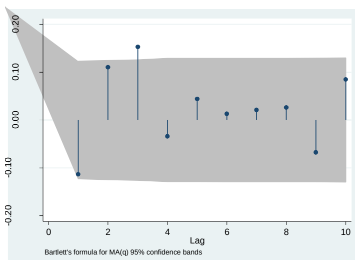
Both the AIC and the BIC, estimated for different (in terms of *p* and *q*) specifications of the ARMA (p, q) process (see tables A1 and A2 in the Appendix), select ARMA (0, 0) and ARMA (1, 4) models for daily stock and bond returns respectively. However, information criteria pick different orders for assets' biweekly returns. The AIC selects the highest among considered orders, namely ARMA (2, 2) and ARMA (4, 4) for biweekly stock and bond returns accordingly, while the BIC indicates no lags for biweekly stock returns and chooses ARMA (1, 1) for bond returns. Our findings are consistent with the fact that the BIC penalizes additional parameters more severely.



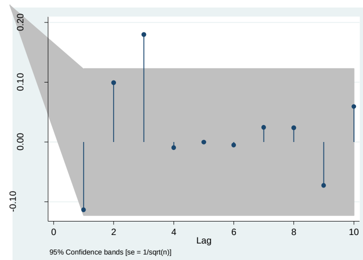
(3a) ACF, daily returns



(3b) PACF, daily returns

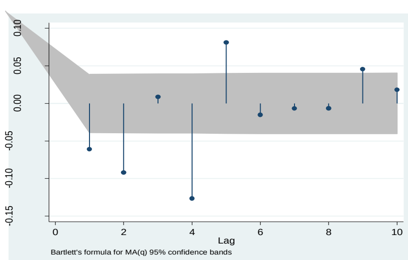


(3c) ACF, biweekly returns

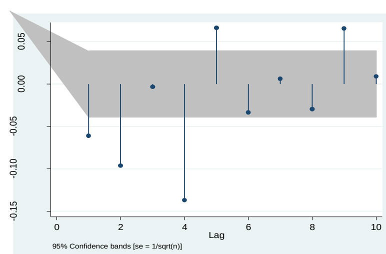


(3d) PACF, biweekly returns

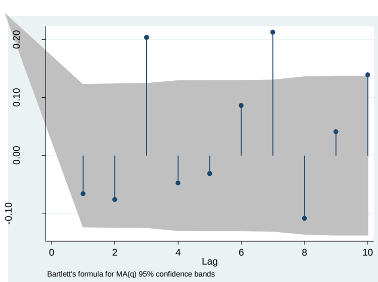
Figure 3. Sample autocorrelation (ACF) and partial autocorrelation (PACF) functions for stock returns



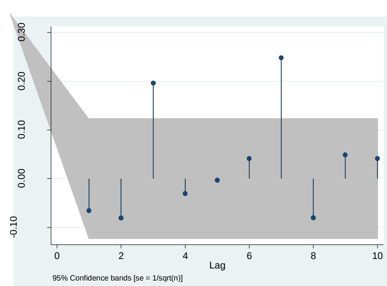
(4a) ACF, daily returns



(4b) PACF, daily returns



(4c) ACF, biweekly returns



(4d) PACF, biweekly returns

Figure 4. Sample autocorrelation (ACF) and partial autocorrelation (PACF) functions for bond returns

In order to estimate more parsimonious models we prefer to use specifications selected by the Bayesian information criteria. Thus, for further modeling of daily and biweekly stock returns we use mean equations containing constant terms only. To model bond returns behavior we incorporate AR term of first order and MA term of order 4 into the mean equation for daily bond returns and AR and MA terms both of order one for biweekly bond returns.

To test for conditional heteroscedasticity in returns, or ARCH effects, we perform the Ljung-Box (LB) and the Lagrange multiplier (LM) tests for the squared residuals from the mean equations. Test statistics, displayed in Table 3, reject the null hypothesis of no conditional heteroscedasticity for each series confirming that GARCH parameterization is appropriate to model returns behavior.

Table 3. Tests for ARCH effects in stock and bond returns

	LB	LM		LB	LM
Daily returns					
MICEX	2624.0 (0.00)	48.22 (0.00)	RGBI	910.35 (0.00)	14.29 (0.00)
Biweekly returns					
MICEX	71.75 (0.00)	5.67 (0.00)	RGBI	55.00 (0.00)	4.10 (0.00)

Values in parentheses are p-values for test statistics

The next step in our analysis is to determine the most appropriate variance equation that captures volatility properties of each returns' series. We start with estimation of univariate GARCH (m, n) models for each series. Then, using the residuals from the estimated GARCH equations, we perform a Sign and Size Bias (SSB) test to determine whether positive and negative shocks have a different impact on volatility. For the returns series that exhibit the leverage effect estimation of the different asymmetric GARCH models will follow.

Since a GARCH model can be treated as an ARMA model for squared residuals, traditional AIC and BIC information criteria can be used to select the right order of conditional volatility model. Tables A.3 and A.4 in the Appendix provides AIC and BIC values for different orders of GARCH (m, n), estimated for stock and bond returns taking into account underlying ARMA processes. Relying heavily on the Bayesian information criteria we select GARCH (1, 1) and GARCH (2, 2) models for daily and biweekly stock returns respectively and GARCH (1, 1) models for both daily and biweekly bond returns.

The p-values of the SSB test, performed for residual from each of above specified GARCH models (see Table 4), indicate that the null hypothesis of no bias is rejected for each series under consideration. Therefore, incorporation of the asymmetry effects into GARCH models seems to be meaningful. The Bayesian information criteria, obtained from estimated EGARCH and TGARCH models (see Tables A5 and A6 in the Appendix), picks TGARCH (2, 1) and EGARCH (2, 2) specifications for daily stock and bond returns and EGARCH (1, 2) and TGARCH (1, 1) models for biweekly stock and bond returns accordingly.

Table 4. Sign and Size Bias(SBB) test for asymmetry in volatility of returns

Daily returns				Biweekly returns			
MICEX	71.45 (0.00)	RGBI	124.23 (0.00)	MICEX	12.74 (0.01)	RGBI	37.84 (0.01)

Values in parentheses are p-values for test statistics

According to the Q-test statistics, presented in Table 5, the standardized residuals from the conditional volatility models, estimated under the above mentioned specifications, appear to be a white noise for each series at 5% significance level. Consequently, we may conclude that these models provide adequate descriptions of the volatility behavior of stock and bond returns.

Table 5. The Portmanteau (Q) test for white noise in the standardized residuals from the conditional volatility models

Daily returns				Biweekly returns			
MICEX	32.89 (0.78)	RGBI	53.15 (0.08)	MICEX	41.93 (0.39)	RGBI	45.70 (0.25)

Values in parentheses are p-values for test statistics

Finally, specifications for mean equations and volatility models are used to estimate the DCC-GARCH parameters. Tables 6 and 7, that can be found in the end of this section, display estimation results for the mean, variance and correlation models for daily and biweekly returns.

All parameters of the variance models predicted for bond returns are statistically significant reviling existence of volatility clustering on the government bond market. Nonzero and significant values of σ and γ terms in TGARCH and EGARCH, performed for daily and biweekly bond returns accordingly, confirm asymmetric volatility response to positive and negative shocks.

The results of models estimated for daily and biweekly stock returns are controversial. While the TGARCH model confirms the leverage effect in the daily stock returns, the EGARCH performed for biweekly stock returns provides statistically insignificant value of the asymmetry parameter σ. Nevertheless, we proceed with asymmetric GARCH model for biweekly returns relying on the SB test performed earlier and results of previous research that confirm different effects of positive and negative shocks on volatility of financial asset returns.

Plots of estimated conditional volatilities, illustrated in Figure 5 and 6, reveal clear distinction between assets behavior on two markets. Stock returns exhibit significantly higher conditional variation than bond returns, which is consistent with the difference in the assets' risk profiles. Nevertheless, spikes in volatility, recorded on both markets in September 2008, were much far above the average on the market of government bonds.

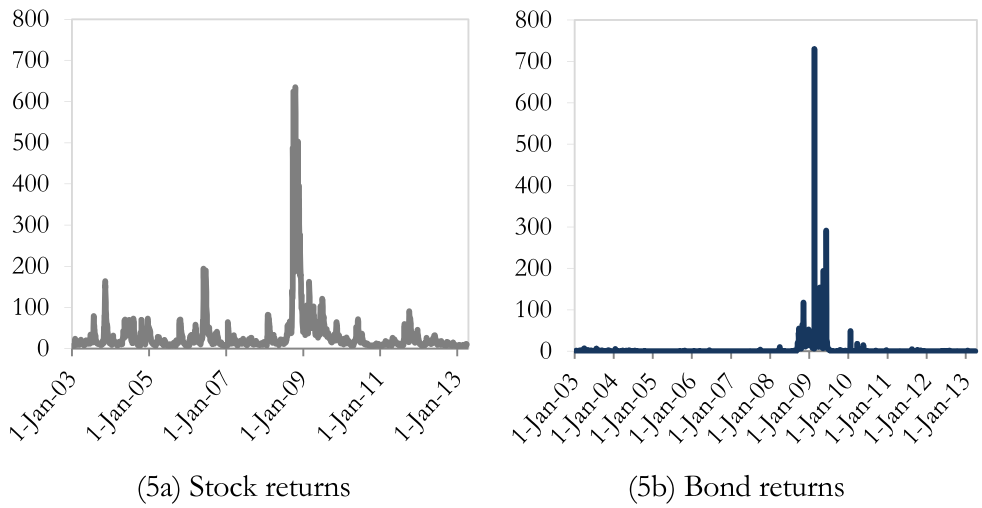


Figure 5. Estimated conditional variance of daily stock and bond returns

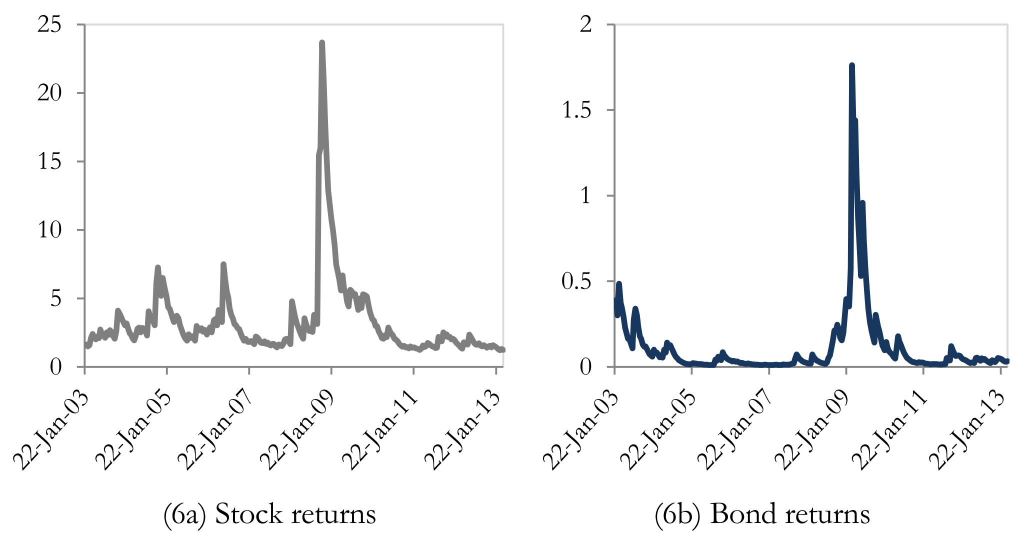
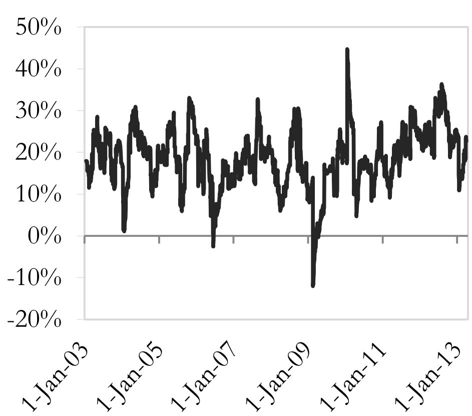


Figure 6. Estimated conditional variance of biweekly stock and bond returns

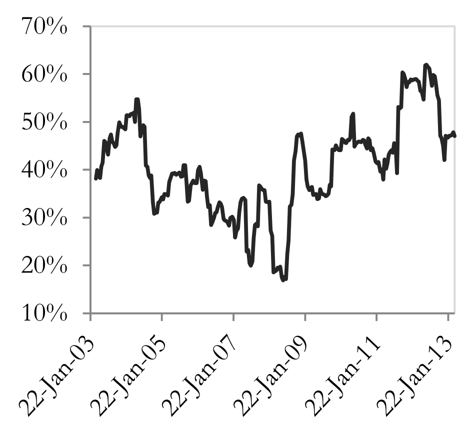
The parameters of the correlation equation, estimated for daily returns, are highly significant rejecting the hypothesis that cross-asset correlation is constant over time. Moreover, the sum of the DCC parameters α and β is almost unity indicating persistence in conditional correlation between daily stock and bond returns. From the model for biweekly asset returns the same conclusions can be derived except for the fact that the hypothesis of insignificance of α parameter in the DCC cannot be rejected at 5% level.

Evolution of the estimated conditional correlations, highlighted by Figure 6, reveals the time-varying nature of co-movements between stock and bond markets in Russia, which is in line with the conclusions of studies made for developed and developing countries.

Dynamics of the correlations estimated utilizing daily returns indicates that over the past 10 years, stock-bond conditional correlations on the Russian market estimated for daily returns have been fluctuating primarily in the range of 0% to 30%. Despite the fact that correlations are persistent, returns of daily frequency provide quite noisy picture of correlation evolution with no clear time trend over the considered period.



(6a) Daily returns



(6b) Biweekly returns

Figure 7. Dynamics of the estimated correlation between stock and bond returns

Whereas for most of the decade the daily correlations were positive, there was a substantial drop below zero value during the recent financial crisis when the correlation fell from almost 30% in August 2008 to -12% in February 2009. Thus, results based on daily returns on stocks and government bonds reveal negative stock-bond correlation in times of economic turbulence which is consistent with the flight-to-quality.

The correlation between biweekly asset returns is, on average, higher than the correlation between daily returns. Biweekly correlation also varies considerably over time, but some trends in its development are evident. Particularly, the correlation has decreased from more than 50%, observed in the beginning of 2004, to approximately 20% in the beginning of 2008. In the middle of 2008, however, the co-movement between stock and bond prices has strengthened considerably, followed by further increase in returns correlations.

Thus, the analysis performed for the returns of biweekly frequency does not provide any support for flight-to-quality on the Russian market. In contrast to the results obtained for daily returns, the biweekly correlation dynamics reveals strengthening in significance of positive stock-bond correlation during the crisis. This conclusion coincides with the results obtained for a number of emerging countries, where no flight-to-quality between stock and government bond markets was documented. In particular, our findings are similar to Ahmed and Joher (2009), who have detected increase in correlations between weekly and monthly stock and bond returns during the crisis in Malaysia.

Taking into account the fact of high noise in the dynamics of correlation between daily stock and bond returns we tend to rely mostly on the results of the analysis performed for biweekly returns and conclude that there the flight-to-quality is no typical for the Russian market

Table 6. Specifications and estimated parameters of mean, variance and correlation models for daily returns

Models' specifications

Mean models:

stocks – ARMA (0, 0): $r_t \; = \; \phi_0 \; + \varepsilon_t$;

bonds – ARMA (1, 4): $r_t \; = \; \phi_0 \; + \phi_1 \; r_{t-1} + \varepsilon_t \; + \sum_{k=1}^{4} \theta_k \; \varepsilon_{t-k}$

Variance models:

stocks – TGARCH (2, 1):

$$h_t \; = \; \omega_0 \; + \omega_1 \; \varepsilon_{t-1} + \gamma \varepsilon_{t-1} I_{t-1}(.) + \; \omega_2 \; \varepsilon_{t-2} + \eta_1 \; h_{t-1};$$

bonds – EGARCH (2, 2):

$$\log(h_t^2) = \omega_0 \; + \omega_1 \; \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \omega_2 \; \left|\frac{\varepsilon_{t-2}}{h_{t-2}}\right| + \sigma \frac{\varepsilon_{t-1}}{h_{t-1}} + \eta_1 \; \log(h_{t-1}^2) + \eta_2 \; \log(h_{t-2}^2)$$

Correlation model:

$$Q_t \; = (1 - \alpha - \beta)\bar{Q} + \alpha(v_t' v_t) + \beta Q_{t-1}$$

Mean models' parameters

	ϕ_0	ϕ_1	θ_1	θ_2	θ_3	θ_4
Stocks	0.418 (0.00)	–	–	–	–	–
Bonds	0.008 (0.03)	-0.533 (0.01)	0.720 (0.00)	0.159 (0.00)	0.043 (0.02)	0.046 (0.00)

Variance models' parameters

	ω_0	ω_1	ω_2	η_1	η_2	γ	σ
Stocks	0.416 (0.00)	0.113 (0.00)	0.091 (0.00)	0.852 (0.00)	–	-0.119 (0.00)	–
Bonds	-0.480 (0.00)	0.439 (0.00)	0.316 (0.00)	0.023 (0.00)	0.988 (0.00)	–	0.010 (0.00)

Correlation model parameters

	α	β
Stocks versus bonds	0.020 (0.01)	0.959 (0.00)

Values in parentheses are p-values for test statistics

Table 7. Specifications and estimated parameters of mean, variance and correlation models for biweekly returns

Models' specifications

Mean models:

stocks – ARMA (0, 0): $r_t \ = \phi_0 \ + \varepsilon_t$;

bonds – ARMA (1, 1): $r_t \ = \phi_0 \ + \phi_1 \ r_{t-1} + \varepsilon_t \ + \theta_1 \ \varepsilon_{t-1}$

Variance models:

stocks – EGARCH (1, 2):

$$\log(h_t^2) = \omega_0 \ + \omega_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \sigma \frac{\varepsilon_{t-1}}{h_{t-1}} + \eta_1 \log(h_{t-1}^2) + \eta_2 \log(h_{t-2}^2)$$

bonds – TGARCH (1, 1):

$$h_t \ = \omega_0 \ + \omega_1 \ \varepsilon_{t-1} + \gamma \varepsilon_{t-1} I_{t-1}(.) + \ \eta_1 \ h_{t-1};$$

Correlation model:

$$Q_t \ = (1 - \alpha - \beta)\bar{Q} + \alpha(v_t' v_t) + \beta Q_{t-1}$$

Mean models' parameters

	ϕ_0	ϕ_1	θ_1
Stocks	0.264 (0.01)	–	–
Bonds	-0.006 (0.70)	0.722 (0.00)	-0.658 (0.01)

Variance models' parameters

	ω_0	ω_1	η_1	η_2	γ	σ
Stocks	-0.217 (0.02)	0.424 (0.00)	0.080 (0.15)	0.797 (0.00)	–	0.045 (0.39)
Bonds	0.0002 (0.00)	0.142 (0.00)	0.764 (0.00)	–	0.161 (0.01)	–

Correlation model parameters

	α	β
Stocks versus bonds	0.028 (0.34)	0.953 (0.00)

Values in parentheses are p-values for test statistics

CONCLUSIONS

In this thesis the linkages between stock and bond markets in Russia are examined by testing the hypothesis of time-varying correlation between stock and bond returns. Using daily and biweekly returns on stock index MICEX and government bond index RGBI we document evolution of stock-bond correlations over 2003-2013.

The Dynamic Conditional Correlation version of the multivariate GARCH model is applied to quantify the conditional stock-bond correlations. To account for the asymmetry in volatility responses to positive and negative shocks, asymmetric versions of GARCH, in particular EGARCH and TGARCH, are used to estimate volatility models for stock and bond returns.

Our findings reveal significant time variability in correlation between stock and bond returns on the Russian market, which is in line with the conclusions of many studies performed for developed and developing countries. The conditional correlations, estimated for daily returns, are mostly positive, but exhibit noisy behavior and show no clear tendencies over the considered period.

The conditional correlations between biweekly returns, meanwhile, indicates decreasing trend in the co-movements between stocks and bonds during 2003-2007. In 2008 this trend reversed signifying strengthening in significance of positive stock-bond correlation during the crises period. This way, the hypothesis of flight-to-quality existence on the Russian market is rejected.

For further research on the topic we suggest to investigate the causality relationships between Russian stock and bond markets and shed some light on possible sources of the correlation dynamics.

WORKS CITED

Ahmed, Ali and Huson Joher. 2009. The Equilibrium Relations between Stock Index and Bond Index: Evidence from Bursa Malaysia. *International research journal of finance and economics* 30: 7-17.

Andersson, Magnus, Elizaveta Krylova, and Sami Vähämaa. 2008. Why Does the Correlation between Stock and Bond Returns Vary Over Time? *Applied Financial Economics* Vol. 18, No. 2.

Aslanidis, Nektarios, and Charlotte Christiansen. 2012. Smooth Transition Patterns in the Realized Stock-Bond Correlation. *Journal of Empirical Finance*

Baele, Lieven, Geert Bekaert, and Koen Inghelbrecht. 2010. The Determinants of Stock and Bond Return Comovements. *The Review of Financial Studies* Vol. 23, No. 6: 2374-2428.

Baur, G. Dirk and Brian M. Lucey. 2009. Flights and Contagion – An Empirical Analysis of Stock-bond Correlations. *Journal of Financial Stability* 5: 339-352.

Black, Fisher. 1976. Studies in stock price volatility changes. *Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section, American Statistical Association*: 177-181.

Boyer, Brian, Tomomi Kumagai, and Kathy Yuan. 2006. How Do Crises Spread? Evidence from Accessible and Inaccessible Stock Indices. *Journal of Finance* 61: 957–1003.

Breen, William, Lawrence R. Glosten, and Ravi Jagannathan. 1989. Economic Significance of Predictable Variations in Stock Index Returns. *The Journal of Finance* Vol. 44, No. 5 (December): 1177-1189.

Campbell, John. 1987. Stock Returns and the Term Structure. *Journal of Financial Economics* 18: 373-400.

Campbell, John and John Ammer. 1993. What moves the stock and bond markets? A variance decomposition for long-term asset returns. *Journal of Finance*, 48: 3-37.

Cappiello, Lorenzo, Robert F. Engle, and Kevin Sheppard. 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics* 4: 537–572.

Chou, Y. Ray and Wei-Yi Liao. 2008. Explaining the Great Decoupling of the Equity-Bond Linkage with a Modified Dynamic Conditional Correlation Model. *Working paper, National Chiao Tung University.*

Connolly, Robert, Chris Stivers, and Licheng Sun. 2005. Stock Market Uncertainty and the Stock - Bond Return Relation. *Journal of Financial and Quantitative Analysis*. 40: 161- 194.

David, Alexander and Pietro Veronesi. 2001. Inflation and Earnings Uncertainty and the Volatility of Asset Prices: An Empirical Investigation. *Manuscript, Graduate School of Business, University of Chicago.*

De Goeij, Peter, and Wessel Marquering. 2004. Modeling the Conditional Covariance between Stock and Bond Returns: A Multivariate GARCH Approach. *Journal of Financial Econometrics* 2, no. 4: 531-564.

Engle, Robert. 2002. Dynamic Conditional Correlation: A Simple Class of Multivariate GARCH Models. *Journal of Business and Economic Statistics* 20: 339 - 350.

Engle, Robert and Kevin Sheppard. 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. *NBER Working Paper* No. 8554.

Fama, F. Eugene and William G. Schwert. 1977. Asset Returns and Inflation. *Journal of financial economics* 5(2): 115-146.

Ferson, E. Wayne. 1989. Changes in Expected Security Returns, Risk and Level of Interest Rates. *Journal of Finance* 44: 1191-1217.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. 1993. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance* 48, no. 5: 1779-1801.

Gulko, L. 2002. Decoupling. *Journal of Portfolio Management* 28: 59-67.

Hansen, Peter R. and Asger Lunde. 2005. A forecast comparison of volatility models: does anything beat a GARCH (1, 1)? *Journal of applied econometrics* 20.7: 873-889.

Hartmann, Philipp, Stefan Straetmans, and CG de Vries. 2004. Asset market linkages in crisis periods. *Review of Economics and Statistics* 86, no. 1: 313-326.

Ilmanen, A. 2003. Stock-bond correlations. *Journal of Fixed Income* 13: 55-66.

Jones, P. Charles and Jack W. Wilson. 2004. The changing nature of stock and bond volatility. *Financial Analysts Journal* 60: 100-113.

Keim, B. Donald and Robert F. Stambaugh. 1986. Predicting returns in the stock and bond markets. *Journal of Financial Economics* 17: 357-390.

Kim, Suk-Joong, Fari Moshirian, and Eliza Wu. 2006. Evolution of International Stock and Bond Market Integration: Influence of the European Monetary Union. *Journal of Banking & Finance* 30: 1507–1534.

Kolanovic, Marko. 2011. Rise of Cross-Asset Correlations. Asset Class Roadmap for Equity Investors. *J.P. Morgan, Global Equity Derivatives & Delta One Strategy*

Li, Lingfeng. 2002. Macroeconomic Factors and the Correlation of Stock and Bond Returns. *Yale ICF Working Paper* 02-46.

Li, Xiao-Ming and Li-Ping Zou. 2008. How Do Policy and Information Shocks Impact Comovements of China's T-bond and Stock Markets? *Journal of Banking and Finance* 32: 347–359.

Markowitz, Harry. 1952. Portfolio Selection. *The journal of finance* 7(1): 77-91.

Markowitz, Harry. 1959. Portfolio Selection: Efficient Diversification of Investments. *Cowles Foundation Monograph* No. 16.

Mishkin, Frederic. 1995. Symposium on the Monetary Transmission Mechanism. The Journal of Economic Perspectives 9(4): 3-10.

Nelson, Daniel B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica: Journal of the Econometric Society*: 347-370.

Rabemananjara, Roger, and Jean-Michel Zakoian. 1993. Threshold ARCH Models and Asymmetries in Volatility. *Journal of Applied Econometrics* 8, no. 1: 31-49.

Roxburgh, Charles, Susan Lund, and John Piotrowsky. 2011. Mapping Global Capital Markets 2011. *McKinsey Global Institute*

Shiller, Robert and Andrea Beltratti. 1992. Stock Prices and Bond Yields: Can Their Comovements Be Explained in Terms of Present Value Models? *Journal of Monetary Economics* 30: 25-46.

Venkateshwarlu, M. and Ramesh Babu. 2011. Stock and Bond Price Dynamics-Evidence From An Emerging Economy. *International Business & Economics Research Journal (IBER)* 10(9): 93-104.

Yang, Jian, Yinggang Zhou, and Zijun Wang. 2009. The Stock-Bond Correlation and Macroeconomic Conditions: One and a Half Centuries of Evidence. *Journal of Banking & Finance* 33(4): 670-680.

Yardeni, Ed. 1997. Fed's Stock Market Model Finds Overvaluation. *US Equity Research, Deutsche Morgan Grenfell.* Topical Study #38.

Yardeni, Ed. 1999. New, Improved Stock Valuation Model. *US Equity Research, Deutsche Morgan Grenfell.* Topical Study #44.

Zakoian, Jean-Michel. 1994. Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control* 18, no. 5: 931-955.

APPENDIX

Table A1. Model selection criteria for estimated ARMA (p, q) models for daily and biweekly stock returns

	Daily		Biweekly	
(p, q)	AIC	BIC	AIC	BIC
(0, 0)	6.31528*	6.31759*	3.9740	3.9879*
(1, 0)	6.31600	6.32061	3.9697	3.9975
(2, 0)	6.31599	6.32061	3.9719	3.9997
(1, 1)	6.31610	6.32302	3.9753	4.0170
(2, 1)	6.31578	6.32271	3.9685	4.0101
(1, 2)	6.31576	6.32269	3.9578	3.9995
(2, 2)	6.31602	6.32526	3.9569*	4.0124

* minimum value

Table A2. Model selection criteria for estimated ARMA (p, q) models for and biweekly bond returns

	Daily		Biweekly	
(p, q)	AIC	BIC	AIC	BIC
(0, 0)	3.473822	3.476132	0.710446	0.724412
(1, 0)	3.470882	3.475501	0.714017	0.741949
(2, 0)	3.470010	3.474630	0.713551	0.741483
(3, 0)	3.461560	3.468489	0.721199	0.763097
(4, 0)	3.462381	3.469310	0.713888	0.755786
(1, 1)	3.459390	3.466319	0.717769	0.710928*
(2, 1)	3.460423	3.469662	0.655065	0.759667
(1, 2)	3.445634	3.454873	0.659604	0.715468
(2, 2)	3.443365	3.454913	0.662199	0.732029
(3, 1)	3.463161	3.472400	0.674817	0.730681
(1, 3)	3.460014	3.469253	0.685473	0.741337
(3, 2)	3.461036	3.472585	0.660677	0.730506
(2, 3)	3.445919	3.457468	0.655428	0.725258
(3, 3)	3.443226	3.457084	0.688516	0.772312
(4, 1)	3.443536	3.457394	0.663320	0.747116
(1, 4)	3.439253*	3.455421*	0.685862	0.783624
(4, 2)	3.445037	3.456585	0.682027	0.751857
(2, 4)	3.444773	3.456322	0.671520	0.741350
(4, 3)	3.438062	3.451921	0.655666	0.739462
(3, 4)	3.436124	3.449982	0.661359	0.745155
(4, 4)	3.437505	3.453673	0.662211*	0.759972

* minimum value

Table A3. Model selection criteria for estimated GARCH (m, n) models for stock and bond returns

(m, n)	Stock returns		Bond returns	
	AIC	BIC	AIC	BIC
	Daily returns			
(1, 1)	5.8360	5.8452*	1.6184	1.6392
(1, 2)	5.8352	5.8467	1.6008	1.6239
(2, 1)	5.8338*	5.8453	1.5709	1.5940
(2, 2)	5.8344	5.8483	1.5649*	1.5903*
	Biweekly returns			
(1, 1)	3.8431	3.8973*	-0.0668	0.0163*
(1, 2)	3.8298	3.8989	-0.0748*	0.0222
(2, 1)	3.8283	3.8983	-0.0665	0.0305
(2, 2)	3.8235*	3.9064	-0.0742	0.0366

* minimum value

Table A4. Model selection criteria for estimated EGARCH and TGARCH models for daily stock and bond returns

(m, n)	Stock returns		Bond returns	
	AIC	BIC	AIC	BIC
	EGARCH			
(1, 1)	5.8197	5.8312	1.8120	1.8351
(1, 2)	5.8180	5.8319	1.9638	1.9892
(2, 1)	5.8155	5.8293	1.7818	1.8072
(2, 2)	5.8162	5.8324	1.6207*	1.6484*
	TGARCH			
(1, 1)	5.8166	5.8281	1.8174	1.8405
(1, 2)	5.8141	5.8280	1.8134	1.8388
(2, 1)	5.8123*	5.8261*	1.8189	1.8442
(2, 2)	5.8125	5.8286	1.8140	1.8417

* minimum value

Table A5. Model selection criteria for estimated EGARCH and TGARCH models for biweekly stock and bond returns

(m, n)	Stock returns		Bond returns	
	AIC	BIC	AIC	BIC
	EGARCH			
(1, 1)	3.847	3.916	-0.022	0.074
(1, 2)	3.807*	3.890*	-0.017	0.094
(2, 1)	3.833	3.915	-0.016	0.095
(2, 2)	3.813	3.909	-0.016	0.109
	TGARCH			
(1, 1)	3.8498	3.9188	-0.0724	0.0245*
(1, 2)	3.8365	3.9193	-0.0765*	0.0343
(2, 1)	3.8361	3.9189	-0.0542	0.0566
(2, 2)	3.8313	3.9279	-0.0575	0.0671

* minimum value