An Empirical Analysis of the Russian Financial Markets' Liquidity and Returns*

Karina LEBEDEVA
MS in Global Finance (RANEPA), BA (Hons) Finance and Investment Management (Northumbria University), BS in World Economics (Financial University, Moscow)
kmlebede@gmail.com

Abstract. The study aims to identify whether illiquidity and returns in the Russian stock and bond markets may be forecasted with the help of local macroeconomic variables, internet queries, global factors as well as the fundamental asset classes' characteristics. To address these questions we use the correlation analysis, the VAR analysis and Granger causality tests. Despite the structural instability of the Russian financial markets, the market microstructure variables influence each other and are affected by the characteristics of other asset types. In highly volatile markets dynamic models should be applied. Stock and bond returns may be used for forecasting liquidity and volatility in the Russian market. Stock illiquidity is not useful for forecasting returns in the Russian market as opposed to the US and UK markets. In the Russian market investors rely on risk factors rather than on illiquidity measures in decision-making process. Bond maturity in the Russian market has a significant impact on the bonds' characteristics and implicitly on switching between different asset classes similarly to the US market. Increase in the number of internet queries may serve as an indicator of higher volatility and illiquidity in the Russian stock market in the future, but Google Trends should be used only in combination with other forecasting tools such as macroeconomic measures and political situation analysis.

Аннотация. Целью работы является исследование возможностей прогнозирования неликвидности и доходности на российских рынках акций и облигаций с помощью макроэкономических переменных, данных по запросам в сети Интернет, глобальных факторов, а также фундаментальных характеристик различных классов активов. Для изучения данного вопроса используются корреляционный анализ, система векторных авторегрессий и тест причинности Грейнджера. Несмотря на структурную нестабильность российских финансовых рынков, переменные микроструктуры рынка влияют друг на друга и подвержены влиянию характеристик других классов активов. Для анализа рынков с высокой степенью волатильности необходимо использовать динамические модели. Доходность акций и облигаций может быть использована для прогнозирования ликвидности и волатильности на российском рынке. В отличие от рынков США и Великобритании фактор неликвидности акций не эффективен для прогнозирования доходности на российском рынке. В процессе принятия решений инвесторы на российском рынке в большей степени руководствуются факторами риска, чем показателями индикаторов неликвидности. Срок погашения облигаций на российском рынке имеет значительное влияние на характеристики облигаций и косвенно на переключение инвесторов между классами активов, что соответствует ситуации на рынке США. Увеличение количества интернет-запросов по российскому фондовому рынку может служить индикатором повышения волатильности и неликвидности в будущем, но Google Trends может быть использован только в комбинации с другими инструментами прогнозирования, такими как макроэкономические индикаторы и анализ политической ситуации.

Key words: Russia, financial market microstructure, Google Trends as a forecasting tool, illiquidity spillovers, macroeconomic indicators, dynamic modeling.

INTRODUCTION

Every time a crisis happens, analysts address the questions of market efficiency, asset pricing or corporate finance. In the recent years liquidity has gained an enormous importance in each of these areas. In times of globalization and well-developed electronic trading platforms investors may quickly transfer their funds between different jurisdictions, and negative political or economic news may have

* Эмпирический анализ ликвидности и доходности российского фондового рынка.

a significant impact on stock and bond markets' liquidity and returns.

This study focuses on returns, liquidity that is calculated with the help of quotes and volumes as well as on the trading behavior. As such the research may be attributed to the field of market microstructure that focuses on the process and outcomes of trading assets under certain rules. Many economic studies describe the mechanics of trading, whereas microstructure theory explains how specific trading mechanisms influence the price formation process (O'Hara, 1995). In other words, the research in the given area examines factors influencing transaction costs, prices, quotes, volume, trading behavior, insider trading and market manipulation.

Financial crises of the last two decades have demonstrated that in unfavorable economic conditions liquidity may decrease significantly or even completely disappear. This fact may serve as an explanation of how liquidity shocks affect asset prices. There is a discussion in the contemporary literature on the causes of liquidity shortages and its contribution to financial crises. Brunnermeier (2008), Brunnermeier and Pedersen (2009) explain the concept of "liquidity spiral" that is a consequence of mutual reinforcing of market liquidity and funding liquidity that occurred during subprime mortgage crisis in the USA, and after that took place in many countries all over the world. The process of liquidity spiral starts when asset prices drop, which deteriorates financial institutions' capital. This results in tightening lending standards and margins. Both effects cause fire — sales and additional wave of price decreases. Adrian and Shin (2009) state that in the market-based financial systems the banking sector and capital markets are interconnected, and a contraction of broker-dealer balance sheets may be an indicator of a negative trend in economic growth. The description of the mechanism of liquidity shocks' influence on asset prices is presented in the studies of Amihud and Mendelson (1986) and Jacoby, Fowler and Gottesman (2000). Pastor and Stambaugh (2003) demonstrate that expected stock returns are linked to liquidity. Jones (2001) and Amihud (2002) state that liquidity is useful for expected returns prediction, however in their research liquidity is viewed in the context of transaction costs. Additional market microstructure elements examined in our research are return and volatility. Volatility or risk of the asset, typically measured as a standard deviation of returns is one of the factors that influence the willingness of investor to transfer funds between asset classes or assets. Returns are calculated on the basis of asset prices, either as differences or differenced logged prices.

Technological development has a growing influence on the society's everyday life. People rely on the online information sources not only in such life aspects as health and entertainment, but also in the personal finance area. Internet search tools help investors get information for free and in a timely manner. This information is likely to affect traders' decision making. According to MICEX (2015), individuals account for 53 per cent of all investors in the total shares trading turnover on the exchange. The abovementioned dominance of individual investors in Russia to some extent supports the usefulness of internet searches for investment decision-making. The rationale behind the internet search influence on the financial markets' liquidity is based on the fact that investors have limited cognitive resources, because of the information tracking and processing costs (Grossman & Stigliz, 1980; Merton, 1987). Due to these constraints market participants are likely to limit their choice to assets that attract their attention first. Information on the assets, which investors search in the internet, may serve as a proxy for macroeconomic announcements as well as company-specific or asset-specific news considered in the investment decision-making. Thus, it is probable that people tend to trade heavily relying on the news available online.

Efficient financial market concept has been introduced in Fama (1970) seminal paper and defined as "one in which prices fully reflect available information". Following Fama (1970) this issue has been addressed by dozens of scholars: Basu (1977), Rosenberg, Reid, and Lanstein (1985). This study explores the influence of publicly available online information on the fundamental characteristics of assets or asset classes. As such, it relies on weak-form market efficiency that assumes that "fundamental analysis may still provide excess returns". The Mixture of Distributions Hypothesis states that price volatility and trading volume are determined by the same information arrival rate (Luu & Martens, 2002). Renowned examples of MDH investigations are due to Clark, (1973), Epps and Epps (1976), Tauchen and Pitts (1983) and Andersen (1996). A common result of the Mixture of Distributions Hypothesis is that certain market activity patterns such as volatility persistence are determined by the same type of information flow (Vlastakis & Markellos, 2012).

One of the possible consequences of the economic news online availability for the international investment community decisions is an almost 250 percent net capital outflow increase which Russia experienced in 2014 as compared with 2013 (Bank of Russia, 2015). The Ministry of Economic Development of Russia (2015) forecasts that in 2015 investment is expected to fall by 13 percent. The initial forecast for the net capital outflow has been also increased by approximately

30 percent. Probable additional reasons for the investment outflow from Russia are economic slowdown and unfavorable environment of economic and political sanctions. At the moment the stock market experiences gradual recovery due to wider choice of investment contracts as well as market infrastructure improvement. Bond market suffered more from the sanctions, but the situation is likely to become better in the near future, because of the expansionary monetary policy of the Bank of Russia (*Vedomosti*, 2015). Dynamically changing patterns mentioned above as well as the unique character of the Russian market environment represent a particular interest for research.

The Russian market has been examined before with the focus and approach different from those in the given study. There are some similarities in the techniques employed, but no research exists, where particular models and tools are applied to the main research objects of the given master thesis with the same focus. It is necessary to mention that there are studies analyzing the relationship of stock and bond markets' microstructure parameters, research focusing on stock market parameters and Google Trends, but, to the best of our knowledge, there is no study that would have provided dynamic models for stock and bond market microstructure parameters with the participation of internet search query factors for the emerging market, and there is no research, where Granger causality test is performed on the recent data for the individual assets or asset classes characteristics, internet search parameters and macroeconomic variables for the Russian Federation. These models will be an innovation introduced in the given research. This study contributes to the literature by building and interpreting such models as well as by testing the effectiveness of modern forecasting tools that may be used by investment community in the future.

1. LITERATURE REVIEW

The studies of stock and bond markets illiquidity have developed in separate literature strands. According to Chorida, Sarkar, and Subrahmanyam (2005), the early studies of liquidity focus solely on the stock market due to the data availability issues. Among the earliest research in the given field one could mention Benston and Hagerman (1974), Glosten and Milgrom (1985), Seyhun (1986) and Amihud and Mendelson (1986). Glosten and Milgrom (1985) analyze the informational properties of transaction prices and the formation of bid-ask spreads adopting the adverse selection view to the insider trading phenomenon. Seyhun (1986) investigates the effect of insider trading on stock prices behavior and abnormal returns of informed traders. Both studies emphasize that insider trading significantly influences stock market illiquidity. Butler, Grullon, and Weston (2005) is an example of a more recent work examining the stock market illiquidity from a perspective of the trading environment and frictions. The authors find that investment banks' fees are lower for companies whose stocks are liquid. In contrast to studies focusing mainly on the trading environment and institutional agreements, Naes, Skjeltorp and Odegaard (2011) examine bidirectional impact of the economic stance on the stock market liquidity. They compare the case of the USA and Norway and establish that stock market liquidity influences not only current, but also future state of the economy in the USA and Norway. The results received by the authors are robust to different liquidity proxies. Naes, Skjeltorp and Odegaard also show that there is Granger causality between liquidity and macroeconomic parameters in the given markets. Extending their idea, we investigate the bidirectional impact of the economic stance on the stock and bond market liquidity, volatility and returns in Russia. The research in this area was also performed by Kim (2013), who outlines that stock market illiquidity, in particular Amihud ratio, is an effective predictor of economic growth in Korea.

The idea of a joint analysis of volatility, liquidity and returns is not new. For instance, Andrikoupolos and Angelidis (2008) offer a pre-crisis analysis of the relations between volatility, illiquidity and returns on exchanges in advanced economies. The authors also conclude that there are volatility spillovers from large capitalization stocks to those with small capitalization and vice versa in London Stock Exchange. They establish that volatility shocks may be predicted by illiquidity shocks and return shocks. The authors also discuss illiquidity spillovers between large capitalization stocks and small capitalization stocks. Large capitalization stocks capture the effect first, while small capitalization stocks follow the pattern. Andrikoupolos, Angelidis, and Skintzi (2012) state that there are Granger-causal associations between volatility, illiquidity and returns of G-7 countries and within each country. The authors document that illiquidity and returns are negatively related in the majority of cases, and causal relationship between illiquidity and volatility is valid only for American market. Chang, Faff, and Hwang (2011) examine the dependency of liquidity, stock returns and the business cycle phase in Japan. The authors report that there is solely negative relationship between liquidity proxies and stock returns in Japanese market during the business cycle expansionary phase, while for the contractionary phase the results are ambiguous. Overconfidence hypothesis is likely to explain turnover/return relationship in Japan.

Stocks and bonds' trading activities follow completely different trading patterns due to the assets' specific features and suitability of the given assets for various strategies. Among other things, the latter yields, different speed of responsiveness of bond and stock market liquidity to changes in macroeconomic situation. For both types of assets the effect of macroeconomic variables and announcements on the market liquidity has been extensively analyzed. Brandt and Kavajecz (2002) study the dependence of liquidity, order flow and yield curve and make the conclusion that order flow imbalances explain 26% of the yield curve variation, and the impact of order flow on yields is the most evident in times of low liquidity. Fleming and Remolona (1999) and Balduzzi, Elton, and Green (2001) examine returns, spreads, and trading volume in the fixed income markets around financial announcements. Fleming and Remolona (1999) find that macroeconomic announcements have greater effect on expected future interest rate than on current short-term interest rates, and various types of announcements result in different expectations about the target rate. Balduzzi, Elton, and Green (2001) mention that adjustment of price volatility to news occurs within a minute, while bid-ask spreads widen and adjust to normal values only in 15 minutes after announcements. In addition, the authors state that the effect of macroeconomic announcements on bond market differs significantly depending on the assets' maturity; the statement is also supported by Beber, Brandt, and Kavajecz (2009), Longstaff (2004) and Goyenko and Ukhov (2009). Therefore, the analysis in this research also focuses on different bond maturities. Goyenko, Subrahmanyam and Ukhov (2011) outline that bond illiquidity influences the asset allocation efficiency and interest rate discovery. Moreover, dynamics of the bond markets' trading costs is very important for understanding investors' cost optimization. Interestingly, illiquidity becomes higher during recession periods across all maturities. However, the effect is stronger for short-term bonds. The difference between spreads of various maturity fixed income instruments also becomes more significant during the times of economic downturn for both on-the-run and off-the-run issues. The macroeconomic parameters' impact on the dealer costs has more importance in the less liquid off-the-run sector. On-the-run illiquidity is heavily influenced only by volatility, while off-the-run illiquidity is affected by inflation, monetary policy surprises, bond returns, and volatility. Off-the-run illiquidity is a key determinant for returns forecasting, and thus the liquidity premium, in the Treasury market. Nowadays, the studies of stock and bond markets illiquidity have developed in separate strands. However, there are also papers that provide combined analysis of stock and bond markets illiquidity and describe the intuition behind their comovement — Chrorida, Sarkar, Subrahmanyam (2005), Goyenko and Uhov (2009). These papers apply vector autoregression analysis for the US market.

Although the studies of stock and bond markets illiquidity to some extent still constitute two separate literature strands, some researches have attempted to bridge the gap between them and provide a combined analysis of stock and bond markets illiquidity. Chrorida, Sarkar, Subrahmanyam (2005), Goyenko and Uhov (2009) model a joint dynamics of the US stock and bond markets within a vector autoregression framework and provide the intuition behind these markets' comovement. Various authors establish the existence of an illiquidity spillover between the stock and bond market (see for instance: Chorida, Sarkar, & Subrahmanyam, 2005; Fleming, Kirby, & Ostdiek, 1998; Ho & Stoll, 1993; O'Hara & Oldfield, 1996). According to Goyenko and Ukhov (2009), there is mutual Granger causality between illiquidity of stock and Treasury bonds markets in the United States. Trading activity may result in the interaction between stock and fixed income market illiquidity (Fox, 1999; Swensen, 2000; Longstaff, 2004; Goetzman & Mazza, 2002; Agnew & Balduzzi, 2005). The impact of stock market illiquidity on those of the bond market is consistent with flight-to-quality and flight-to-liquidity episodes. At the same time, illiquidity of short-term bonds has a stronger effect on the stock market (Goyenko & Ukhov, 2009). The choice of the instruments by market participants depends heavily on the stage of economic cycle, bond maturity and date of the fixed income instrument issue (Goyenko, Subrahmanyam, & Ukhov, 2011). Amihud and Mendelson (1986) report that market participants are willing to pay for liquidity. Since illiquidity is a systematic risk factor, therefore illiquidity in one market may affect illiquidity in another market (Chorida, Roll, & Subrahmanyam, 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001; Amihud, 2002; Pastor & Stambaugh, 2003; Amihud & Mendelson, 1986, 1989; Brennan & Subrahmanyam, 1996; Warga, 1992; Boudoukh & Whitelaw, 1993; Kamara, 1994; Krishnamurthy, 2002; Goldreich, Hanke & Nath, 2005; Goyenko & Ukhov, 2009; Brunnermeier & Pedersen, 2009). Vayanos (2004) outlines that illiquid assets become riskier whereas investors' risk aversion increases over time. Interestingly, Brunnermeier and Pedersen (2009) indicate that Federal Reserve can improve market liquidity by monetary policy actions. Fleming, and Remolona (1997) and Fair (2002) report that monetary shocks are accompanied by significant changes in stock and bond prices. Lesmond (2005) mentions that weak political institutions and legal enforcement system have a negative impact on the markets' liquidity. Chorida, Sarkar, and Subrahmanyam (2005) show that expansionary monetary policy results in higher stock market liquidity during recessions, and unexpected increases (decreases) in the federal funds rate lead to increases (decreases) in stock and bond volatility. In addition, the authors state that the flows in the stock and government bonds sectors are useful for stock and fixed income markets liquidity prediction thus establishing the link between "macro" liquidity, or money flows, and "micro", or transaction-based, liquidity in the American market.

Actually, Chorida, Sarkar, and Subrahmanyam (2005) find that volatility is an important driver of liquidity. Innovation in the spreads in one market affects the spreads in another market; therefore it is possible to conclude that liquidity and volatility are driven by the common factors.

This study focuses on the liquidity, not on volatility, because liquidity belongs to a more complex field of research. Various authors offer different measures of liquidity and its explanatory factors. There is also no consensus on the best liquidity indicator. Moreover, suitability of the indicators is determined by the asset type and data frequency. In addition, there is less data available for liquidity measures' computation. The following sections provide a discussion of the most commonly employed measures of liquidity and its drivers, behavior of the Russian financial market as well as the modern financial markets' forecasting techniques based on the information available online.

1.1 LIQUIDITY MEASURES

Liquidity is a key notion in financial markets studies, but as it was mentioned above, there are some difficulties with its measurement. Low-frequency price impact proxies described by Goyenko, Holden and Trzcinka (2009) include return-to-volume ratio of Amihud (2002), Pastor and Stambaugh (2003) and Amivest Liquidity (Amihud, Mendelson & Lauterbach, 1997). Goyenko, Holden and Trzcinka (2009) outline that Amihud (2002) is effective for capturing price impact and high-frequency transaction costs benchmarks in NYSE. Florackis, Gregoriou and Kostakis (2011) introduce another low-frequency liquidity measure not mentioned by Goyenko, Holden and Trzcinka (2009) that is the return-to-turnover ratio. Florackis, Gregoriou and Kostakis (2011) notice that asset pricing is significantly influenced by trading frequency and transaction costs — the above-mentioned factors are not considered in isolation, and emphasize that return -to-turnover ratio separates size effect from illiquidity effect as compared to Amihud (2002) thus being a more accurate measure. Lesmond (2005) reports that volume and turnover-based measures are downward-biased for low-liquidity markets. This research uses low frequency price impact benchmark for stock illiquidity measurement similar to those presented by Florackis, Gregoriou and Kostakis (2011) and simplified low frequency spread benchmark as bond illiquidity proxy. The formula for the bond illiquidity proxy is provided in Methodology section.

1.2 FACTORS INFLUENCING THE RUSSIAN STOCK MARKET BEHAVIOR

Apparently, the first econometric study modeling the Russian stock market is due to Rockinger and Urga (2000) who state that the Russian market has a tendency to exhibit the market efficiency. Initially, most research has concentrated on market returns and volatility and employed models ranging from GARCH (Hayo & Kutan, 2005; Goriaev & Sonin, 2005), EGARCH (Jalolov & Miyakoshi, 2005), TGARCH (Hayo & Kutan, 2005) to non-parametric approach to event studies (Chesney, Reshetar, & Karaman, 2011). Generalized Autoregressive Conditional Heteroskedasticity or GARCH framework, an extension of ARCH model, is typically used to model time series variance (Engle, 1982; Bollerslev, 1986). EGARCH and TGARCH are examples of asymmetric GARCH models introduced by Nelson (1991) and Zakoian (1994) respectively. Goriaev and Zabotkin (2006) report high influence of "corporate governance, political risk and macroeconomic risk factors such as emerging markets performance, oil prices and exchange rates on the Russian stock market". They stress that significant sensitivity of developing markets to political events may jeopardize the growth prospects, and macroeconomic factors that have significant impact in the developed markets become significant in the volatile emerging markets only after corporate governance reaches the proper level of quality and transparency. Furthermore, investors' over-reaction or under-reaction to certain events in highly volatile markets additionally contributes to the risk of the assets in addition to country- and firm-specific risks. Therefore, static models are not suitable for markets with high level of risk, and dynamic models should be applied. Anatolyev (2005) emphasizes a structural — not depending on the financial crises — instability of the Russian market, and a growing importance for the Russian market of such explanatory factors as the US stock prices as well as the US and Russian interest rates. Nevertheless, according to Anatolyev the influence of the exchange rates, oil prices and monetary aggregates on the Russian stock market returns diminished in years 2003 and 2004. Interestingly, Jalolov and Miyakoshi (2005) suggest that German market is more efficient predictor for the Russian stock market monthly returns. In their view, this fact could be attributed to relatively close trade and investment relations between Germany and the Russian Federation. Surprisingly, the authors do not report a strong dependence between oil and gas prices and the Russian stock market returns. In contrast, Hayo and Kutan (2005) find that the Russian market returns may be explained by their own lagged values as well as the S&P 500 return and oil index return and thus reject the EMH for the Russian stock market. The authors also establish a direct volatility link between the Russian and US markets.

1.3 GOOGLE TRENDS AND OTHER TYPES OF ONLINE INFORMATION AS MODERN FORECASTING TOOLS

In the world of advanced technological development people tend to resort to the online information sources in many aspects of their life, including investment decision making. With a growing role of internet searches a valid research question is whether internet searches can help predict market behavior and what would be the rationale behind their forecasting capacity. Preis, Moat, and Stanley (2013) argue that Google Trends data may reflect the current state of the economy and provide some insights to the future behavior of the economic actors. The authors state that there is an increase in the search for key words connected with the financial market before the financial market falls, so it is possible to construct trading strategies based on the volume of internet queries. Financial relevance of each term is calculated as a frequency of each term in the online edition of *Financial Times* newspaper normalized by the number of Google hits. In addition, Preis, Moat, and Stanley (2013) determine that Google search volume in the US is a better predictor for the US market price dynamics as compared with global Google search volume. Vlastakis and Markellos (2012) use Google Trends as information demand quantification and empirically confirm that information demand is positively related to investors' risk aversion. The authors also obtain that demand for idiosyncratic information influences individual stock trading volume and excess stock returns. The usefulness of the Google search volume is not solely confined to the US market. Arouri *et al.* (2013) indicate that Google Trends tool is useful for the liquidity forecasting in French stock market. Adding information demand variables to their model helps improve it. In addition to Google Trends variables the authors use the following parameters as liquidity forecasting factors: absolute returns, firm size, information supply, risk and trading costs.

Apart from the liquidity forecasting, the Google search volumes have been examined with respect to their applicability in the market volatility and price dynamics prediction. Da *et al*. (2011), Dzielinski (2011) outline that internet search volume data may be effectively used for stock market volatility forecasting. Dimpfl and Jank (2011) state that Google Trends may be efficiently employed for forecasting volatility in the UK, US, French and German markets. They show that adding internet search queries variables to the model leads to more precise in- and out-of-samples forecasts. Moreover, Dimpfl and Jank find strong co-movement of stock indexes' volatilities and internet queries for their names. In their models volatility is an exogenous factor owing to the fact that first and subsequent internet queries are considered as a consequence of the strong primary fundamental volatility shock following the logic of Lux and Marchesi (1999). Our empirical strategy relies on all the market microstructure variables being endogenous and the global factors being exogenous both for microstructure variables and internet queries.

2. METHODOLOGY AND MODEL SELECTION

This study aims to assess the impact of the asset characteristics and internet searches on the returns and liquidity in the Russian stock and bond markets. The purpose of the research is to determine whether market microstructure parameters are useful for forecasting liquidity, volatility and return and if internet searches may be successfully employed to forecast the market microstructure characteristics. In particular, the following hypotheses are examined:

Ho (1): Individual asset or asset classes' characteristics are irrelevant for the Russian financial markets' liquidity and returns forecasting.

Ho (2): Internet search time series is irrelevant for the Russian stock market liquidity and returns forecasting.

Ho (3): Changes in macroeconomic variables do not influence the Russian stock and bonds' market return, liquidity and volatility.

Our empirical strategy involves the correlation analysis, the Granger causality tests and the vector autoregression models built for daily, weekly and monthly data. For correlation analysis Spearman method is used, because the data might not be normally distributed which is typical for the given type of research. In order to demonstrate non-normal distribution of data the Empirical Distribution Function Test for Normality is performed. The testing procedure is based on the statistics of Lilliefors (1967, 1969), Cramer — von Mises (1928) and Anderson and Darling (1952, 1954). The null hypothesis is that data is normally distributed.

3. DATA DESCRIPTION

This study uses daily, weekly and monthly data for the period between 2006 and 2015. The data has been obtained from Bloomberg database, MICEX official website, Google, *Yahoo!* Finance, Bank of Russia and Federal Service of State Statistics web sites.

4. CHARACTERISTICS OF INDIVIDUAL ASSETS OR ASSET CLASSES

In weekly data model the following variables are analyzed: stock market return measure (RETURN), stock market illiquidity measure -the higher the factor is, the less liquid the market is (LIQUIDITY), stock market volatility measure (VOLATILITY). RETURN, VOLATILITY and LIQUIDITY are calculated based on time series for MICEX closing prices from the 21st of April 2006 to the 27th of February 2015. The data sources are MICEX official web site and Bloomberg.

In daily data analysis the following variables are used: stock market return measure (RETS), short-term bonds return (RETBS), medium-term bonds return (RETBM), long-term bonds return (RETBL), stock market volatility (VOLS), short-term bonds volatility (VOLBS), medium-term bonds volatility (VOLBM), long- term bonds volatility (VOLBL), stock illiquidity (ILLIQS), short-term bonds illiquidity (ILLIQBS), medium-term bonds illiquidity (ILLIQBM), long-term bonds illiquidity (ILLIQBL).

RETS, VOLS, ILLIQS are calculated based on the MICEX time series closing prices for the period from the 1st of August 2012 to the 27th of February 2015. The data sources are MICEX official website and Bloomberg.

The period for bond microstructure parameters is from the 1st of August 2012 to the 27th of February 2015. RETBS, VOLBS, ILLIQBS are calculated for closing prices time series for 7.5% federal loan bonds (OFZ) with maturity on the 15th of March 2018 (approximately 3 years to maturity). The data source is Bloomberg. RETBM, VOLBM, ILLIQBM are calculated for closing prices time series for 7.6% federal loan bonds (OFZ) with maturity on the 20th of July 2022 (approximately 7 years to maturity). The data source is Bloomberg. RETBL, VOLBL, ILLIQBL are calculated for closing prices time series for 10% federal loan bonds (OFZ) with maturity on the 20th of August 2025 (approximately 10 years to maturity). The data source is Bloomberg.

In monthly data analysis the following market microstructure parameters are used: stock return (RETS), stock volatility (VOLS), stock illiquidity (ILLIQS) that are calculated based on the MICEX closing prices time series from April 2011 to February 2015. The data sources are MICEX official web site and Bloomberg data base.

Short term bonds return (RETBS), short term bonds volatility (VOLBS), short term bonds illiquidity (ILLIQBS) are calculated for closing prices time series for 7.5% federal loan bonds (OFZ) with maturity on the 15th of March 2018 (approximately 3 years to maturity). The data source is Bloomberg data base.

As in Goyenko and Ukhov (2009) the bond illiquidity measure is calculated as:

$$\frac{(ASK - BID)}{0.5\,(ASK + BID)}$$

Following Amihud (2002), Florackis, Gregoriou and Kostakis (2011), the stock illiquidity measure is defined as:

$$\frac{1}{number\ of\ valid\ observation\ days} * \frac{Absolute\ vaue\ of\ return}{Turnover}, \text{ where}$$

$$Turnover = \frac{Total\ number\ of\ shares\ traded\ during\ the\ period}{Average\ number\ of\ shares\ outstanding\ during\ the\ period}$$

The stock volatility and bond volatility are measured as standard deviation of their returns. For the convenience of work with data natural log of turnover time series is taken (return data is expressed in percentage terms, and turnover in 8-digit numbers). Volatility is calculated as a standard deviation for the previous 22 observations for daily data (number of working days per month), and as a standard deviation for the previous 4 observations for weekly data. Return for monthly data is calculated as averages of daily returns for a specified month. For volatility and liquidity the last observations for a specified month are taken.

4.1 INTERNET SEARCH PARAMETERS

Internet search measures included in the weekly data model are stock market internet queries in English language (GOOGLE_MICEX) and stock market internet queries in Russian language (GOOGLE_MMVB). GOOGLE_MICEX gives the number of searches done for a term "MICEX" relative to the total number of searches done on Google over time from the 21st of April 2006 to the 27th of February 2015. GOOGLE_MMVB gives the number of searches done for a term "ММВБ" (MICEX name in the Russian language) in the relative to the total number of searches done on Google over time from the 21st of April 2006 to the 27th of February 2015. The data source is Google Trends — the statistics available online for weekly data. Unfortunately, there is no open access to daily data. Monthly GOOGLE_MMVB and GOOGLE_MICEX are calculated as monthly average of weekly time series for the period from April 2011 to February 2015.

Google Trends shows a percentage of Google searches to define the number of queries made for selected terms as compared to the total quantity of Google searches done during that period. The data is normalized with respect to total searches in order to avoid variable's effect and to allow comparisons across regions. Therefore it is expressed in relative terms. Data is presented on a scale from 0–100 (Google, 2015).

From the given chart it is possible to make the conclusion that the query "ММВБ" was more common in Google than the query "MICEX".

The interest for the Russian stock market is demonstrated not only in Moscow and Saint Petersburg, but also in top two global financial centers London and New York (Z/Yen, 2015). The absence of interest

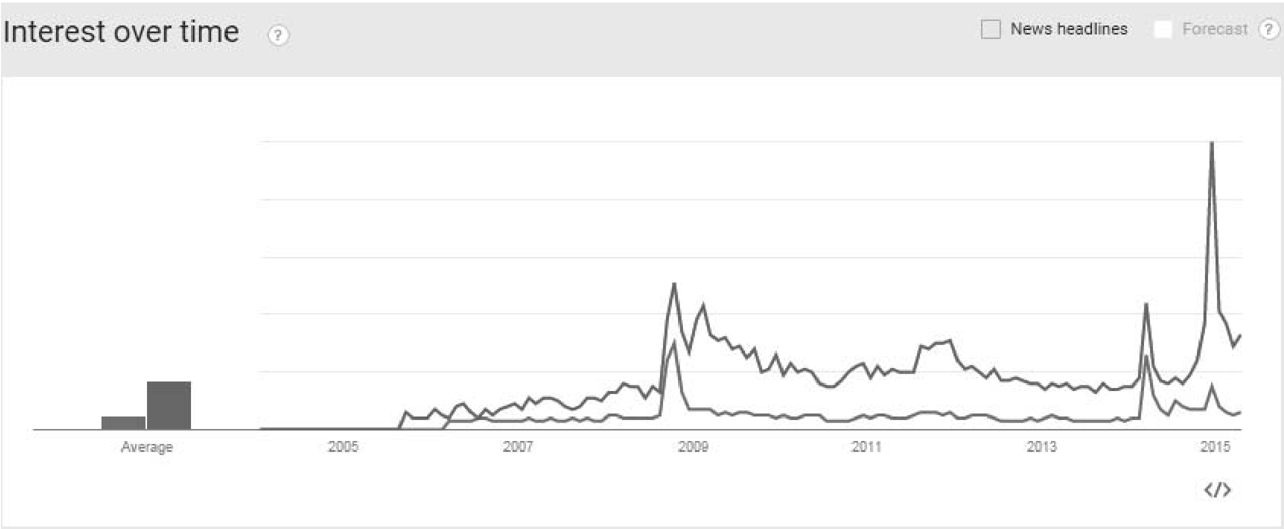


Figure 4.2.1. Interest over Time — MICEX Query (Lower graph) vs. ММВБ Query (Upper graph) in Google Trends.

Source: Google (2015).

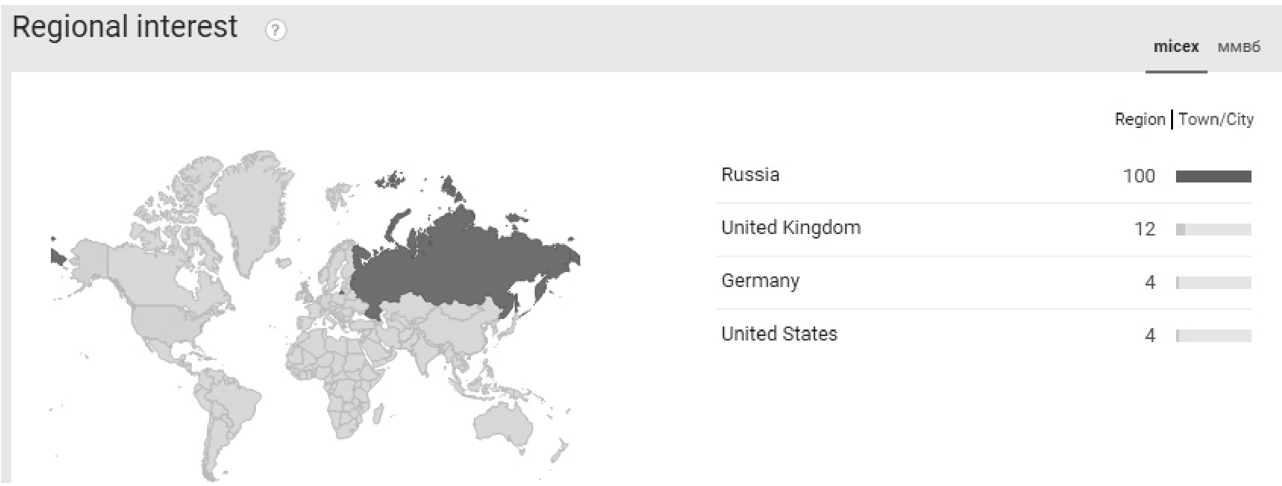


Figure 4.2.2. Regional Interest for "MICEX" by Country (End of April 2015).

Source: Google (2015).

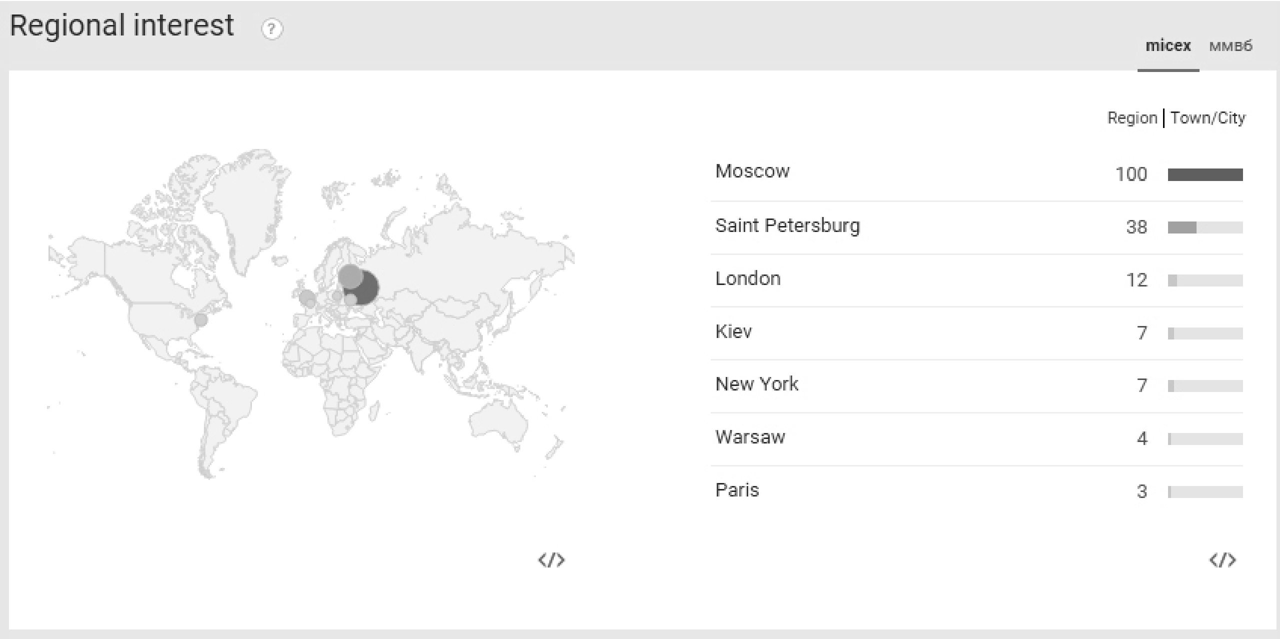


Figure 4.2.3. Regional Interest for "MICEX" by City (End of April 2015).

Source: Google (2015).

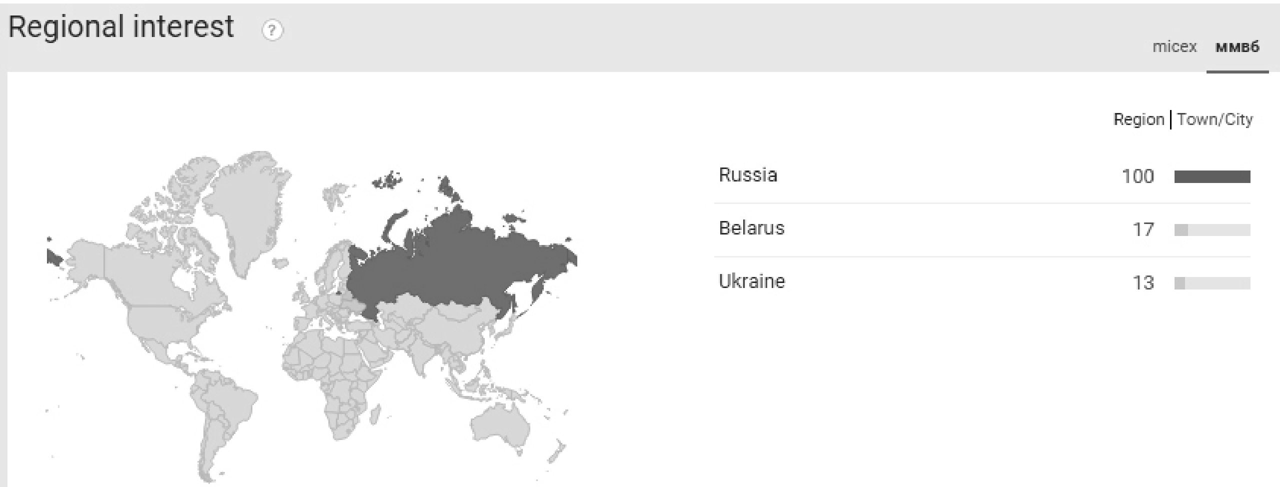


Figure 4.2.4. Regional Interest for "ММВБ" by Country (End of April 2015).

Source: Google (2015).

in Asia, in particular in China, may be explained by the fact that Google cannot gather statistics from the given markets due to political reasons.

High interest for the Russian version of "MICEX" query in the analyzed period was demonstrated in Moscow, St. Petersburg, Kaliningrad, Siberia and Central Russia cities, as well as in CIS countries such as Ukraine and Belarus. The latter may be explained by the high share of the Russian-speaking population living there.

4.2 GLOBAL FACTORS

In order to control for the global factors affecting the Russian bond and stock markets, the daily, weekly and monthly models are augmented by the oil prices, as well as S&P 500 returns (prices). The choice of the control variables is based on Anatolyev (2005), Hayo and Kutan (2005), Goriaev and Zabotkin (2006). In weekly data analysis OIL stands for United States Oil ETF quotes from the 21st of April 2006 to the 27th of February 2015. The investment traces "the performance, less expenses, of the spot price of West Texas Intermediate (WTI) light, sweet crude oil". (*Yahoo!* Finance, 2015). USA means S&P 500 quotes from the 21st of April 2006 to the 27th of February 2015 — American stock market index including 500 companies with the highest market capitalization (*Yahoo!* Finance). USCHANGE is S&P 500 return calculated as log-difference of S&P 500 time series from the 21st of April 2006 to the 27th of February 2015.

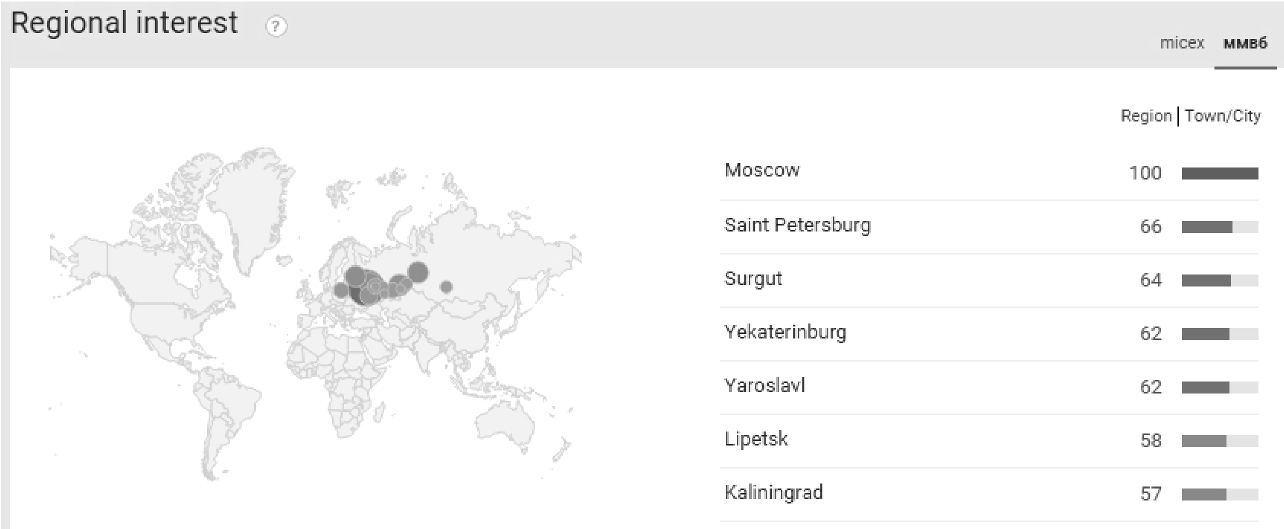


Figure 4.2.5. Regional Interest for "ММВБ" by City (End of April 2015).

Source: Google (2015).

Global factors used in daily data analysis are OIL and USA. OIL stands for United States Brent Oil ETF from the 1st of August 2012 to the 27th of February 2015. The investment "reflects, net of expenses, the daily changes in percentage terms of the spot price of Brent crude oil" (*Yahoo!* Finance, 2015). By USA we denote S&P 500 quotes from the 1st of August 2012 to the 27th of February 2015 (*Yahoo!* Finance).

The global factor used in the monthly data model is the S&P 500 monthly return (USCHANGE) from April 2011 to February 2015.

4.3 MACROECONOMIC VARIABLES

The choice of macroeconomic parameters used in weekly and daily data analysis follows Goriaev and Zabotkin (2006). RUB/USD stands for exchange rates for the period from the 21st of April 2006 to the 27th of February 2015 (Bank of Russia). RUB/EUR describes exchange rates for the period from the 21st of April 2006 to the 27th of February 2015 (Bank of Russia). In daily data analysis macroeconomic variables such as RUB/USD that is exchange rates for the period from the 1st of August 2012 to the 27th of February 2015 (Bank of Russia), and RUB/EUR describing exchange rates for the period from the 1st of August 2012 to the 27th of February 2015 (Bank of Russia), are employed.

The monthly data analysis covers the period from April 2011 to February 2015. The choice of macroeconomic variables follows Goyenko and Ukhov (2009) that performed similar analysis in the US market. Inflation is calculated as log-differences of CPI (consumer price index). The source of CPI data is Federal Service of State Statistics. Industrial Production (IP) change is calculated as log-differences of Industrial Production. IP is the index of goods and services output for basic types of economic activities. It is calculated on the basis of the data on the physical output change in the following spheres: agriculture, mining (natural resources extraction), manufacturing, production and distribution of electricity, gas and water, construction, transport, wholesale and retail trade — calculated as a ratio of two considered periods in the base period prices. The data source is Federal Service of State Statistics. International reserves change (INT_RES_DIF) is calculated as first differences of International Reserves. International Reserves are defined as the sum of currency reserves and monetary gold. Source of data is Bank of Russia. MIBOR is the first-difference of 1-day Moscow Interbank Offered Rate. MIBOR is an indicative rate of the ruble loan provision in Moscow Interbank Market. MIBOR is chosen for the analysis as it is sensitive to changing environment and reflects the macroeconomic situation in Russia.

5. RESULTS

We first present the outcome of tests examining the features of the employed time series, and then discuss the core results of our analysis.

5.1 TESTING TIME SERIES FEATURES

5.1.1 Unit Root Tests

In the given study stationarity term is used in the weak stationarity context. Weakly stationary random process requires only autocovariance and the first moment not to vary over time (Enders, 2010). The stationarity of time series is tested using so-called unit root tests. The Augmented Dickey-Fuller test, despite being criticized, continues to be the most widely used unit root test. Therefore, stationarity of the time series analyzed in this study is tested with the help of the Augmented Dickey Fuller statistic (Dickey & Fuller, 1979; MacKinnon, 1991, 1996). The conclusions are drawn at the 5% significance level. The below given tables summarize the outcome of the ADF tests.

For weekly data GOOGLE_MICEX, VOLATILITY, RETURN and USCGHNAGE are stationary time series, while GOOGLE_MMVB and LIQUIDITY are level stationary S&P 500 prices and exchange rates time series are not stationary, therefore vector autoregression analysis and Granger causality test cannot be applied on them. For daily data ILLIQS, AMERICA and VOLBS are level stationary. As we can see, global oil prices (OIL) and exchange rates time series are not stationary. In such a case, the Granger causality test cannot be applied, and at the same time it is not advisable to conduct vector autoregression analysis for non-stationary data. Although, it is typically possible to eliminate the stochastic trend by first-differencing the data. Sims (1980) does not recommend it for the VAR effectiveness purposes. The rest of the variables are stationary. For monthly data S&P 500 return, GOOGLE_MICEX, VOLBS and VOLS are level stationary, GOOGLE_MMVB is stationary, the rest of the variables are stationary.

5.2 CORRELATION ANALYSIS

Prior to proceeding with the correlation analysis we test whether the data is normally distributed. The type of data determines the type of correlation test which needs to be employed. For all weekly and daily time series employed in this study the null hypothesis of normally distributed data is rejected at the 5% significance level. Among monthly time series only the change of international reserves (IR change), the change of industrial production (IP change) and the stock returns (RETS) are normally distributed. For the return of the short-term bonds (RETBS) the null hypothesis is not rejected at the 5% significance level in accordance with Lilliefors p-value only. The rest of the variables prove to be not normally distributed at the 5% significance level. What follows, in order to detect the dependency between data, we employ robust to non-normality Spearman's rank correlation test.

The significance of the correlation coefficients is also tested. Below we present the discussion of statistically significant correlation relationships.

As we can see from the table, there is a very high positive correlation between internet search queries for MICEX both in Russian (GOOGLE_MMVB) and in English (GOOGLE_MICEX) languages (. Both types of the internet queries are positively correlated with volatility and to lesser extent with illiquidity. This may be an indicator of investors' higher interest in the financial instrument in times of uncertainty, when it experiences significant price fluctuations. Internet queries are negatively correlated with oil prices and positively with exchange rates. It means that the general public demonstrates a higher interest in the Russian economy in times, when the economy experiences problems (falling oil prices as well as ruble depreciation). Interestingly, the absolute values for correlation coefficients are higher for GOOGLE_MICEX despite the fact that MMVB ("ММВБ") is a more popular query in Google than "MICEX". This may suggest that stock market professionals, who actually make transactions in the market, use tickers with the names in English, or that the English-speaking (possibly Western) investment community has more influence on the Russian market performance.

Oil price dynamics shows almost no correlation with the US market. There is a strong negative correlation between the global oil prices and the exchange rates. As expected, the exchange rates RUB/USD and RUB/EUR demonstrate a strong positive correlation.

Table 5.2.1. The Results of Correlation Analysis for Weekly Time Series on the Russian Stock Market and Internet Queries in the Period from 2006 to 2015.

	GOOGLE_MMVB	GOOGLE_MICEX	LIQUIDITY	OIL	RETURN	VOLATILITY	USA	RUBUSD	RUBEUR
GOOGLE_MMVB	1,00	0,70	0,15	-0,50	0,01	0,26	-0,28	0,51	0,62
GOOGLE_MICEX	0,70	1,00	0,18	-0,44	-0,09	0,27	-0,12	0,50	0,59
LIQUIDITY	0,15	0,18	1,00	0,09	0,07	0,24	-0,23	-0,07	-0,03
OIL	-0,50	-0,44	0,09	1,00	-0,05	0,08	-0,04	-0,82	-0,70
RETURN	0,01	-0,09	0,07	-0,05	1,00	0,08	-0,01	0,08	0,07
VOLATILITY	0,26	0,27	0,24	0,08	0,08	1,00	-0,41	-0,07	-0,03
USA	-0,28	-0,12	-0,23	-0,04	-0,01	-0,41	1,00	0,25	0,19
RUBUSD	0,51	0,50	-0,07	-0,82	0,08	-0,07	0,25	1,00	0,86
RUBEUR	0,62	0,59	-0,03	-0,70	0,07	-0,03	0,19	0,86	1,00

Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!* Finance and the Bank of Russia.

In accordance with the correlation matrix above, there is less interest in the Russian market in times of American market positive price dynamics. We can observe a negative correlation between the US market and the following indicators: Russian market illiquidity and volatility, positive correlation with the exchange rates. There is almost no correlation of the US market and oil price dynamics. When the ruble depreciates against the American and the European currencies, the Russian market becomes more liquid and less volatile, and demonstrates better returns. It may be explained by the fact that MICEX includes high share of the natural resources' exporters that benefit from the national currency depreciation.

Illiquidity is positively correlated with volatility. The logic behind such a phenomenon could be the following: in highly volatile times people tend to make less transactions, because risk averse investors usually feel uncertainty about the assets, while the number of speculators that realize their strategies in expectation of higher returns is not too high. In times of increasing returns the majority of investors that already owned the asset tend to keep it, whereas the general public usually purchases the asset. Of course, there are also value investors using sophisticated models, very experienced technical analysts or people having inside information that act against the market, but their share is quite low. These arguments partially draw upon Dow Theory that originates from 255 Wall Street Editorials written by C.H. Dow (1851–1902) and discusses the phases of market trends.

The US market (S&P 500 price dynamics) demonstrates a positive correlation with the Russian short-term and medium-term bonds' illiquidity and to a lesser extent with the illiquidity of the Russian stocks and long-term bonds. Returns of the Russian medium term bonds market are negatively correlated with the American market. The correlation between the exchange rates and American market is very close to one, which suggests that the dynamics identified for the weekly data has become more evident in the recent years. The volatility of the Russian medium-term and short-term bonds' markets as well as the Russian stock market volatility are positively correlated with the American market. It may be explained by the fact that American market performance is a leading indicator for the majority of the economies. The US market is well developed, and many financial innovations appear in America. Improper use of the innovative financial tools such as speculation and fraud may lead to the financial crisis. One example of such phenomenon is the subprime mortgage crisis of 2007–2010 that originated in the USA, and then had strong negative impact on large number of countries all over the world. It is worth to mention that Russian long-term bonds' market volatility has zero correlation with the US market. The oil price has an evident negative correlation with the illiquidity of the Russian bonds, especially long-term, and volatility of the Russian stocks and medium-term bonds. The situation with the exchange rates is similar to those identified on weekly data, but herein the trend is less evident. Still, such a result supports the well-established belief that an increase in oil prices contributes to the stability of the Russian economy. Oil prices have also a negative correlation with the US market, but not too strong. The correlation of the oil prices with the rest of the variables is close to zero. Illiquidity of the Russian long-term bonds is positively correlated with all variables apart from the oil price, but the absolute values of the correlation coefficients are not very high. It could suggest that this asset is relatively insensitive to external shocks. Illiquidity of the Russian short-term and medium-term bonds demonstrate relatively strong correlation with each other. The given variables also have an evident positive correlation with the American market, the exchange rates as well as the medium-term and short-term bond vola-

Table 5.2.2. The Results of Correlation Analysis for Daily Time Series on the Russian Stock and Bond Markets in the period from 2012 to 2015.

	AMERICA	ILLIQBS	ILLIQS	ILLIQBM	ILLIQBL	OIL	RETBL	RETBM	RETBS	RETS	RUBEUR	RUBUSD	VOLBL	VOLBM	VOLBS	VOLS
AMERICA	1,00	0,42	0,16	0,50	0,12	-0,10	-0,03	-0,09	-0,08	0,06	0,93	0,92	0,00	0,58	0,63	0,46
ILLIQBS	0,42	1,00	0,18	0,45	0,09	-0,17	0,01	-0,02	0,01	0,07	0,50	0,49	0,10	0,47	0,42	0,39
ILLIQS	0,16	0,18	1,00	0,19	0,12	-0,13	0,04	-0,04	0,05	0,04	0,18	0,19	0,02	0,24	0,17	0,32
ILLIQBM	0,50	0,45	0,19	1,00	0,12	-0,21	-0,03	0,00	0,00	0,03	0,56	0,58	0,06	0,56	0,41	0,45
ILLIQBL	0,12	0,09	0,12	0,12	1,00	-0,40	0,03	0,06	0,02	0,02	0,13	0,11	0,09	0,21	0,11	0,27
OIL	-0,10	-0,17	-0,13	-0,21	-0,40	1,00	0,01	0,00	0,02	-0,01	-0,14	-0,20	-0,08	-0,32	-0,01	-0,28
RETBL	-0,03	0,01	0,04	-0,03	0,03	0,01	1,00	0,02	0,08	0,03	-0,04	-0,03	0,00	0,00	-0,01	-0,01
RETBM	-0,09	-0,02	-0,04	0,00	0,06	0,00	0,02	1,00	0,34	0,25	-0,08	-0,06	0,10	0,00	0,01	0,02
RETBS	-0,08	0,01	0,05	0,00	0,02	0,02	0,08	0,34	1,00	0,14	-0,07	-0,06	0,02	-0,01	0,00	0,01
RETS	0,06	0,07	0,04	0,03	0,02	-0,01	0,03	0,25	0,14	1,00	0,06	0,06	0,06	0,08	0,09	0,02
RUBEUR	0,93	0,50	0,18	0,56	0,13	-0,14	-0,04	-0,08	-0,07	0,06	1,00	0,97	0,08	0,66	0,72	0,51
RUBUSD	0,92	0,49	0,19	0,58	0,11	-0,20	-0,03	-0,06	-0,06	0,06	0,97	1,00	0,02	0,68	0,68	0,55
VOLBL	0,00	0,10	0,02	0,06	0,09	-0,08	0,00	0,10	0,02	0,06	0,08	0,02	1,00	0,08	0,40	-0,07
VOLBM	0,58	0,47	0,24	0,56	0,21	-0,32	0,00	0,00	-0,01	0,08	0,66	0,68	0,08	1,00	0,60	0,67
VOLBS	0,63	0,42	0,17	0,41	0,11	-0,01	-0,01	0,01	0,00	0,09	0,72	0,68	0,40	0,60	1,00	0,41
VOLS	0,46	0,39	0,32	0,45	0,27	-0,28	-0,01	0,02	0,01	0,02	0,51	0,55	-0,07	0,67	0,41	1,00

Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!*Finance and the Bank of Russia.

Table 5.2.3. The Results of Correlation Analysis for Monthly Time Series on the Russian Stock and Bond Markets and Macroeconomic Variables for the Period from 2011 to 2015.

	GOOGLE_MICEX	INT_RES_DIF	GOOGLE_MMVB	ILLIQBS	ILLIQS	INFLATION	RETBS	RETS	VOLS	VOLBS	IPCHANGE	MIBOR CHANGE	USCHANGE
GOOGLE_MICEX	1,00	-0,35	0,73	0,34	0,19	0,10	-0,23	-0,11	0,53	0,54	-0,10	0,17	0,10
INT_RES_DIF	-0,35	1,00	-0,30	-0,43	0,06	-0,07	0,00	-0,38	0,05	-0,47	0,36	-0,06	-0,11
GOOGLE_MMVB	0,73	-0,30	1,00	-0,01	0,30	0,20	-0,06	0,00	0,63	0,37	-0,02	0,15	0,19
ILLIQBS	0,34	-0,43	-0,01	1,00	-0,17	0,13	-0,16	0,10	-0,08	0,62	-0,08	0,11	0,06
ILLIQS	0,19	0,06	0,30	-0,17	1,00	0,05	0,05	-0,26	0,41	-0,05	0,14	-0,10	-0,03
INFLATION	0,10	-0,07	0,20	0,13	0,05	1,00	-0,02	0,14	0,23	0,32	-0,05	0,20	0,15
RETBS	-0,23	0,00	-0,06	-0,16	0,05	-0,02	1,00	0,60	-0,20	-0,05	-0,11	-0,16	-0,01
RETS	-0,11	-0,38	0,00	0,10	-0,26	0,14	0,60	1,00	-0,24	0,30	-0,31	-0,03	0,22
VOLS	0,53	0,05	0,63	-0,08	0,41	0,23	-0,20	-0,24	1,00	0,16	-0,02	0,10	0,12
VOLBS	0,54	-0,47	0,37	0,62	-0,05	0,32	-0,05	0,30	0,16	1,00	-0,06	-0,04	0,20
IPCHANGE	-0,10	0,36	-0,02	-0,08	0,14	-0,05	-0,11	-0,31	-0,02	-0,06	1,00	-0,24	0,16
MIBOR	0,17	-0,06	0,15	0,11	-0,10	0,20	-0,16	-0,03	0,10	-0,04	-0,24	1,00	-0,18
USCHANGE	0,10	-0,11	0,19	0,06	-0,03	0,15	-0,01	0,22	0,12	0,20	0,16	-0,18	1,00

Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, Yahoo!Finance and the Bank of Russia.

tilities and the stock market volatility. In addition to being positively correlated with the US market, Russian stock market illiquidity demonstrates positive correlation with the short-term, medium-term and long-term bond markets' illiquidity, exchange rates, short-term and medium term, stock market volatilities. There is a negative correlation with oil prices and almost no correlation of the Russian stock market and the other variables. RUB/USD and RUB/EUR have a positive correlation with the assets' volatilities; volatilities are also positively correlated among themselves.

For the pairs of variables describing the market microstructure daily data correlation analysis is considered primary, because of the time series' higher frequency, the absence of transformations and the focus on a more recent time period. The results for the correlation analysis of the internet searches in English (GOOGLE_MICEX) and in Russian (GOOGLE_MMVB) with the stock market microstructure parameters are consistent with the results obtained for the weekly data. GOOGLE_MICEX and GOOGLE_MMVB are also positively correlated with the short-term bonds volatility. One of the possible explanations of this phenomenon is that the queries for the main Russian stock market index result in higher interest in all assets offered in the Russian market including the short-term bonds, because Google offers the users a wide range of the market reviews in response to the given query — investors are likely to read the news related not only to one specific asset, but also to other instruments in the considered market. Certain differences in the correlation coefficients absolute values for the internet searches in English (GOOGLE_MICEX) and in Russian (GOOGLE_MMVB) may be explained by a different degree of influence of queries in various languages discussed in previous sections.

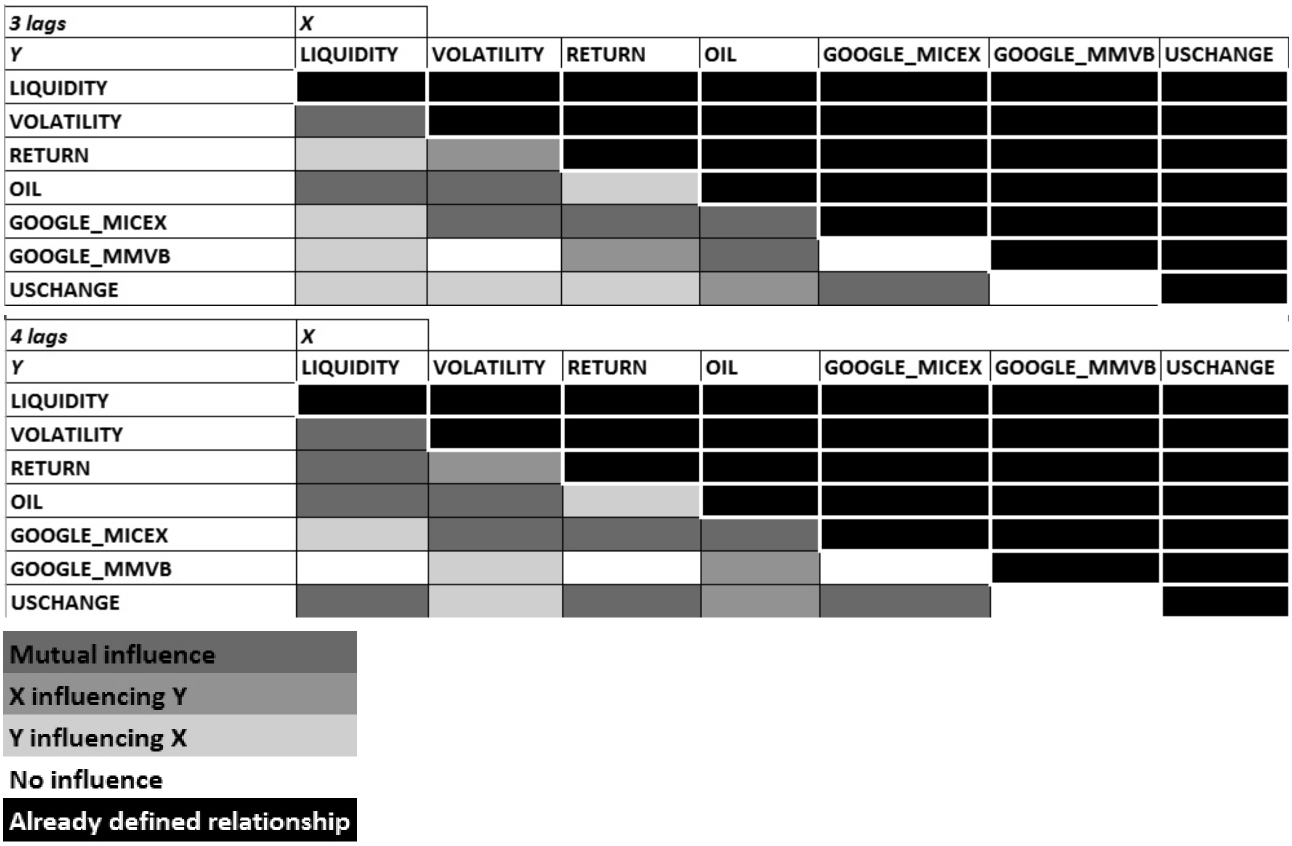
A change in international reserves is negatively correlated with the internet queries for the Russian stock market, short term bonds' illiquidity and volatility, stock return, and positively correlated with the industrial production change. We observe that the inflation is positively correlated with short term bonds' volatility. Russian stock market return shows positive correlation with S&P 500 return.

5.3 GRANGER CAUSALITY ANALYSIS

First we present the results of the Granger causality test for the weekly data. Schwarz Information Criterion (BIC) suggests choosing 3 lags, Hannan Quinn Information Criterion — 4 lags, Forecast Prediction Error — 11 lags, AIC — 12 lags, while the sequential modified LR test statistic suggests choosing 17 lags. The maximum number of lags specified for the lag selection is 20. Since each lag selection criterion suggests a different number of lags (p) to be included, we discuss various specifications. However, we pay a particular attention to SBIC and HQIC. As demonstrated by Lutkepohl (2005), choosing p to minimize SBIC or HQIC provides consistent estimates of the true lag order, while minimizing AIC or FPE tends to overestimate the true lag order with a positive probability, even with an infinite sample size.

As the impact of internet searches has not been yet tested for the Russian market, we start our discussion of the Granger causality test with the Google searches. GOOGLE_MICEX Granger causes stock market liquidity (LIQUIDITY). There is also a bidirectional causality between GOOGLE_MICEX and stock market return (RETURN). For lags 3 and 4 a bidirectional Granger causality arises for GOOGLE_MICEX and stock market volatility. It means that internet search queries in English may be used as a leading indicator for volatility and liquidity, but in case of stock market return it is difficult to determine, which factor is primary. There is a bidirectional Granger causality between GOOGLE_MICEX and oil prices. It is likely that internet queries specifically for oil

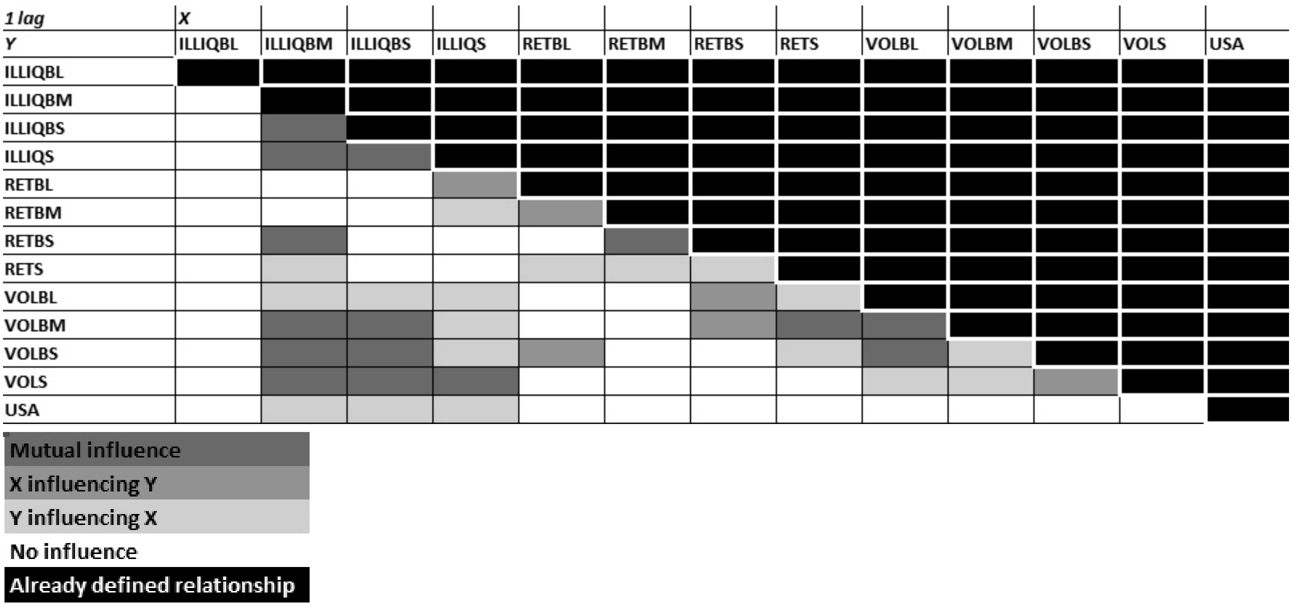
Table 5.3.1. Pairwise Granger Causality Tests for Weekly Data.



Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!*Finance and the Bank of Russia.

would be more illustrative for oil prices prediction. GOOGLE_MMVB Granger causes stock market volatility. GOOGLE_MMVB Granger causes stock market liquidity with the lag of up to 3 weeks. With lags up to 3 weeks GOOGLE_MMVB is Granger caused by stock market return. Oil prices Granger cause GOOGLE_MMVB. Summarizing, GOOGLE_MMVB is a less powerful forecasting indicator than "MICEX" query.

Table 5.3.2. Pairwise Granger Causality Tests for Daily Data.



Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, Yahoo!Finance and the Bank of Russia.

The logic behind such result confirms the arguments used for the interpretation of the correlation analysis: queries in English tend to be used more often by investment professionals and in English-speaking countries, while queries in Russian are generated by general public in Russia and CIS.

The S&P 500 index Granger causes Russian stock market liquidity and return with up to 3-week lag and stock market volatility with up to 3- and 4-week lag, while for higher lag order a mutual Granger causality arises. Finally, as in Lee and Hao (2012) we obtain that oil prices Granger cause the S&P 500 index change.

For the daily data FPE and AIC criteria suggest choosing 7 lags. SC and HQ information criteria suggest choosing 1 lag, while LR test statistic indicates 22 lags. The maximum number of lags specified for the lag selection is 25.

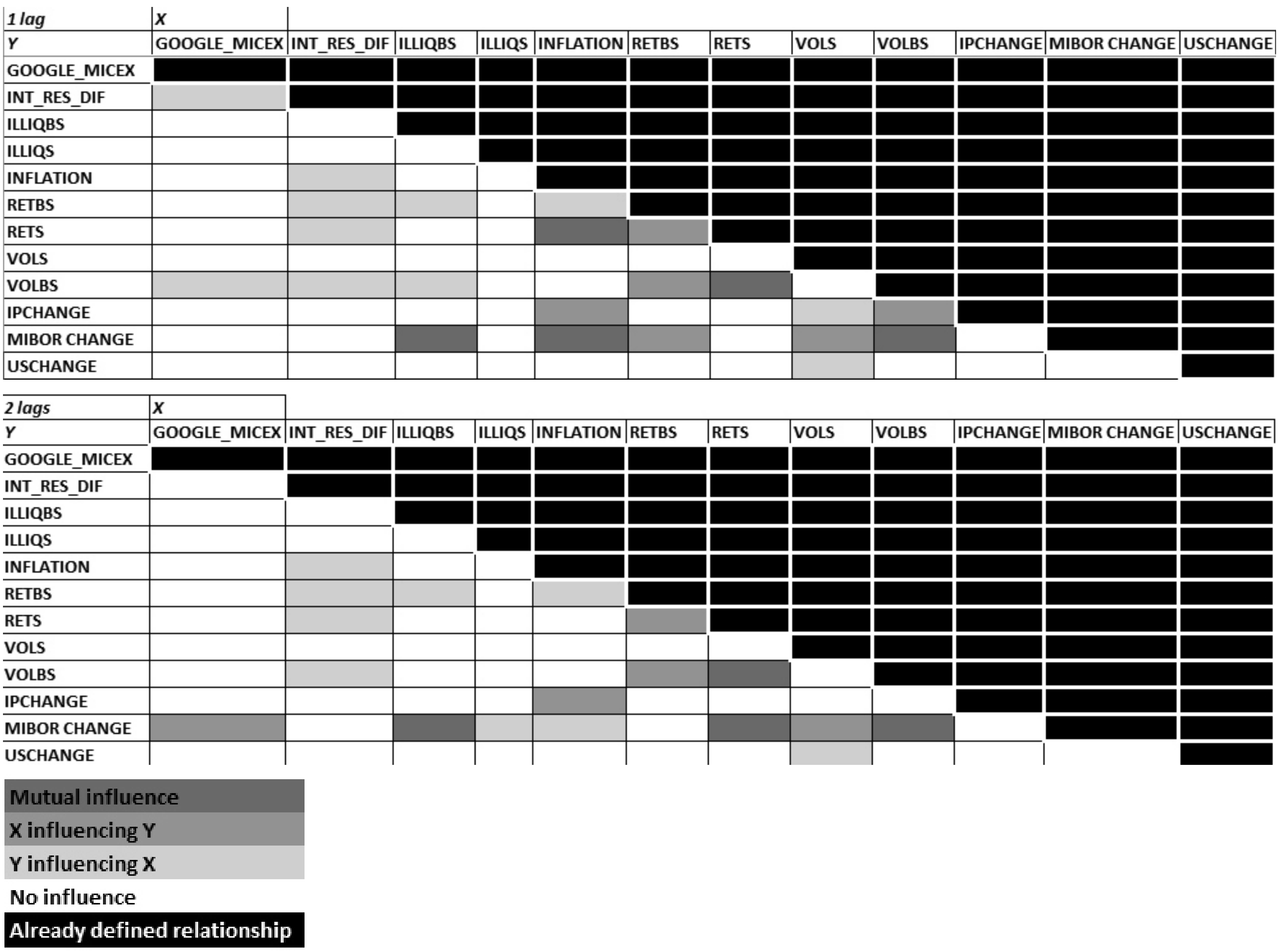
Our analysis shows that Granger causality relationships are highly sensitive to the choice of lags. We should treat our results with a caution since as shown in McCrorie and Chambers (2004) the temporal aggregation can influence Granger causality test results. Nevertheless, the obtained sensitivity to the lag choice is in line with Anatolyev (2005) conjecture saying that the Russian market is structurally unstable. It is necessary to mention that the nature of Granger causality relationships differs from those in the US market researched by Goyenko and Ukhov (2009).

For the monthly data the modified LR test statistic and Schwarz Information Criterion suggest choosing 1 lag, while FPE, AIC and HQ suggest choosing 2 lags.

5.4 VECTOR AUTOREGRESSION ANALYSIS

We start with the model incorporating the internet searches that is with the weekly data model. The model endogenous variables are internet queries in English language for MICEX index (GOOGLE_MICEX), internet queries in Russian language (GOOGLE_MMVB), stock market liquidity (LIQUIDITY), stock market return (RETURN), and stock market volatility (VOLATILITY). The exogenous variables are global oil prices (OIL), and the S&P 500 return (USCHANGE). The global factors were made exogenous from theoretical considerations. The number of lags to be selected suggested by LR-criterion is 17. VAR satis-

Table 5.3.3. Pairwise Granger Causality Tests for Monthly Data.



Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!*Finance and the Bank of Russia.

fies the stability condition and shows no significant autocorrelation in residuals of the model at the 1% significance level. Appendix 2 features the details of all diagnostic tests conducted for the discussed vector autoregession models. Next, we employ the following ordering of the variables for the Cholesky decomposition: GOOGLE_MICEX, GOOGLE_MMVB, VOLATILITY, RETURN, LIQUIDITY. We start with the 'local' shocks and forecasting tools GOOGLE_MICEX and GOOGLE_MMVB. We give the priority to GOOGLE_MICEX as Granger causes more variables than GOOGLE_MMVB. VOLATILITY, RETURN, LIQUIDITY ordering is chosen in accordance with Goyenko and Ukhov (2009) for future comparison purposes. The period for IRF-construction is 52 weeks — the approximate number of weeks in a year.

LIQUIDITY shows a series of low amplitude positive fluctuations in response to the innovation in VOLATILITY, and a series of low amplitude negative fluctuations in response to the shock in RETURN. The fluctuations last less than half a year. The results are consistent with those received by Chorida, Roll, and Subrahmanyam (2001) and Goyenko and Ukhov (2009) for the US market, however the shocks in American market last more than a year. Russian stock market liquidity also exhibits an instantaneous high amplitude positive response to its own shock followed by low amplitude fluctuations that last less than half a year.

Finding the appropriate model with stationary time series, stable and with no serial correlation in residuals posed a certain challenge for the case of daily data. It is probable that these specific features of time series reflect the rest mature nature of the Russian market as compared to the US market. The endogenous variables are medium term bonds illiquidity (ILLIQBM), short term bonds illiquidity (ILLIQBS), stock market illiquidity (ILLIQS), stock market return (RETS), and short term bonds return (RETBS). The endogenous variables are determined using the block exogeneity test with the 5% significance level. The exogenous variables are S&P 500 prices (AMERICA1). As suggested by LR-criterion, the model includes 22 lags. VAR satisfies the stability condition, and shows no significant autocorrelation in residuals of the model at the 1% significance level. The ordering of the variables for the Cholesky decomposition follows Goyenko and Ukhov (2009) and is as follows: RETBS, RETS, ILLIQS, ILLIQBM, ILLIQBS.

For daily data we consider impulse responses for up to 22 days, which is approximate number of working days per month. Similar to the result for weekly data, in case of daily data we observe that the effect of shocks in the Russian market is much shorter than in the US market. Typically shock effects last no longer than one year, and significant fluctuations are present in first several months up to half a year. Medium term bonds illiquidity shows a negative response that lasts from the seventh to eighteenth day following the shock in RETS, which is consistent with the results received by Chorida, Roll, and Subrahmanyam (2001), Goyenko and Ukhov (2009) who studied American market. Stock market illiquidity shows almost no response to the shock in medium term bonds illiquidity in the Russian market, while in the US market researched by Goyenko and Ukhov (2009) the response of stock illiquidity to innovation in medium-term bonds illiquidity is negative.

Stock illiquidity shows almost no response to the shock in short term bonds illiquidity, while in accordance with Goyenko and Ukhov (2009) the response is positive. Medium term bonds illiquidity shows evident positive response to the shock in short term bonds illiquidity in the fourth day, in the rest of the days there is almost no response. Short term bonds illiquidity shows an instantaneous positive response to its own shock that diminishes in the end of the fifth day.

Endogenous and exogenous variables for monthly VAR-model have been determined on the basis of theory and include global factors, monetary policy actions and macroeconomic variables which may have an impact on the local market microstructure. The opposite is also possible, certain policy actions may result from the market behavior. However, such situation is less likely, as monetary policy actions are usually aimed at the changing macroeconomic variables in the short run, and the market reacts to the given political decisions. As a result, the monthly VAR model features as endogenous variables stock market return (RETS), short term bonds market return (RETBS), stock market illiquidity (ILLIQS), short term bonds market illiquidity (ILLIQBS), stock market volatility (VOLS), short term bonds market volatility (VOLBS). Exogenous variables are the change in industrial production (IPCHANGE), S&P 500 return (USCHANGE), the change in international reserves (INT_RES_DIF), the change in 1 — day MIBOR (MIBOR), inflation, and monthly dummy variables which account for the seasonality. The Schwarz Information Criterion suggests to choose 1 lag. The VAR (1) satisfies the stability condition and shows no sign of autocorrelation in residuals at the 5% significance level. As the number of usable observations is not very high, the normal distribution of residuals is a very important indicator of the model quality. The null

[1] The results for the model, where US market returns are used instead of the prices are very similar.

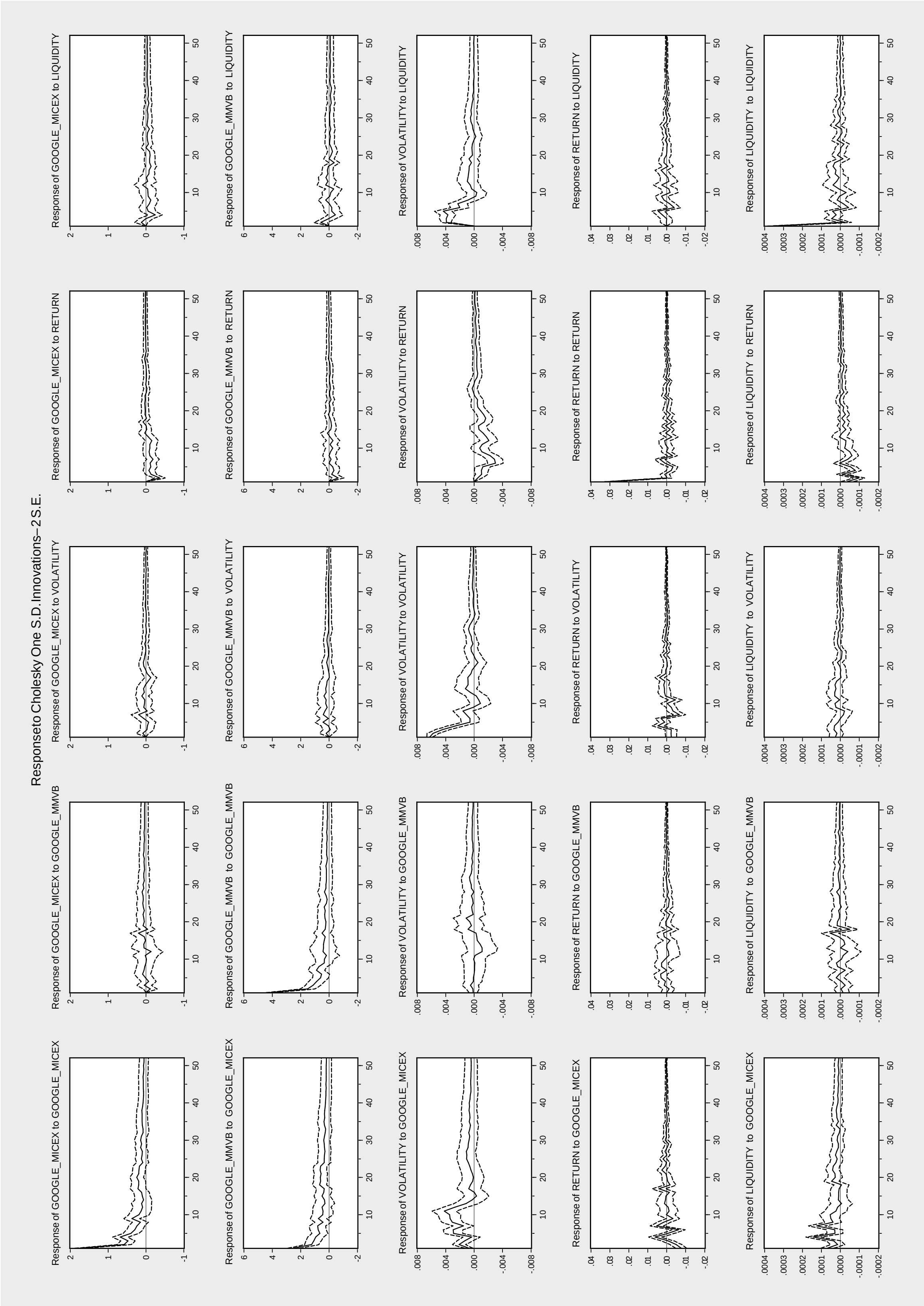


Figure 5.4.1. Impulse Response Functions for the Weekly Data VAR Model.

Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!*Finance and the Bank of Russia.

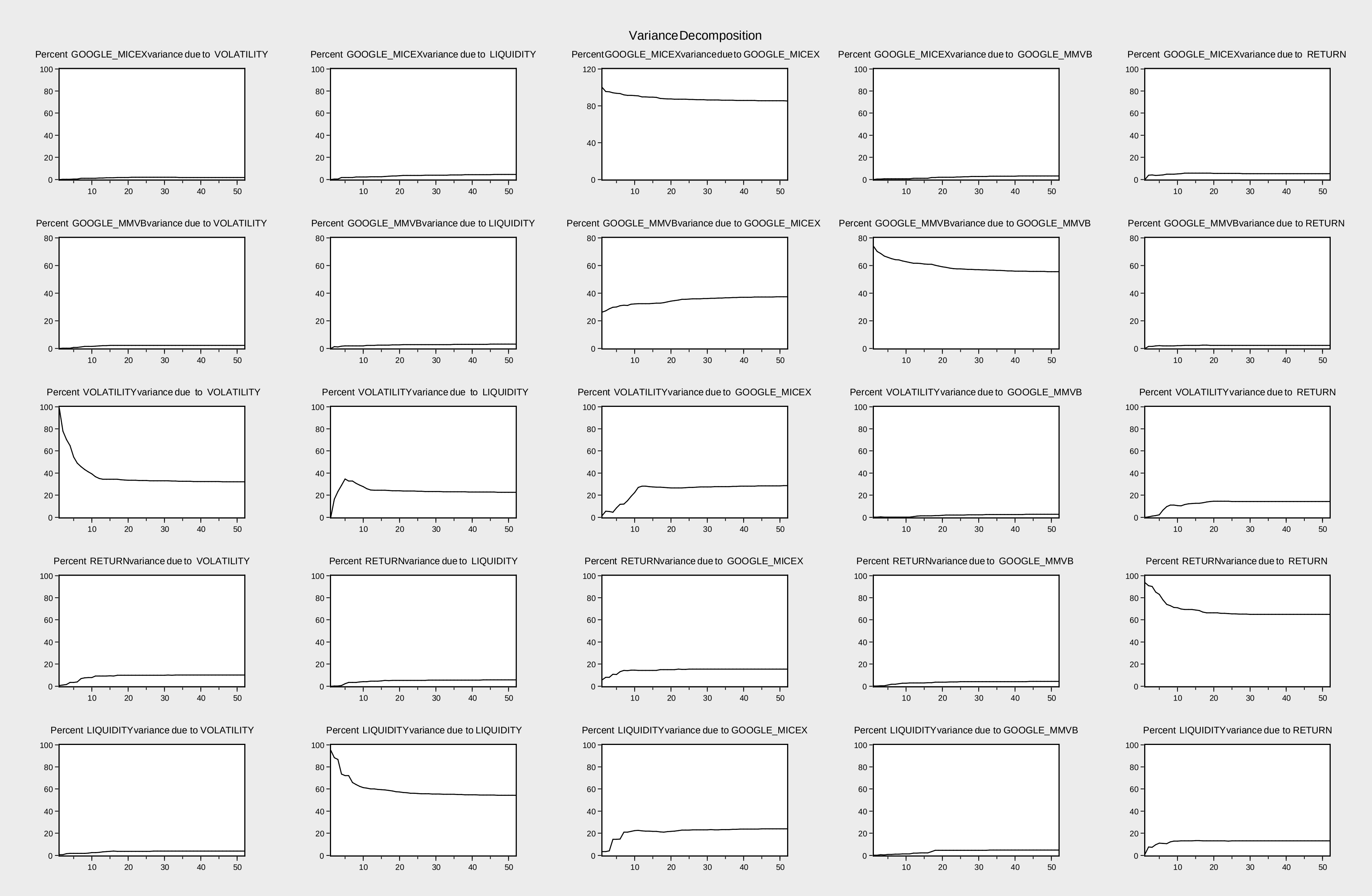


Figure 5.4.2. Forecast Error Variance Decomposition for the Weekly VAR Model..

Source: Own calculations based on the data retrieved from Google Trends, Bloomberg, *Yahoo!*Finance and the Bank of Russia.

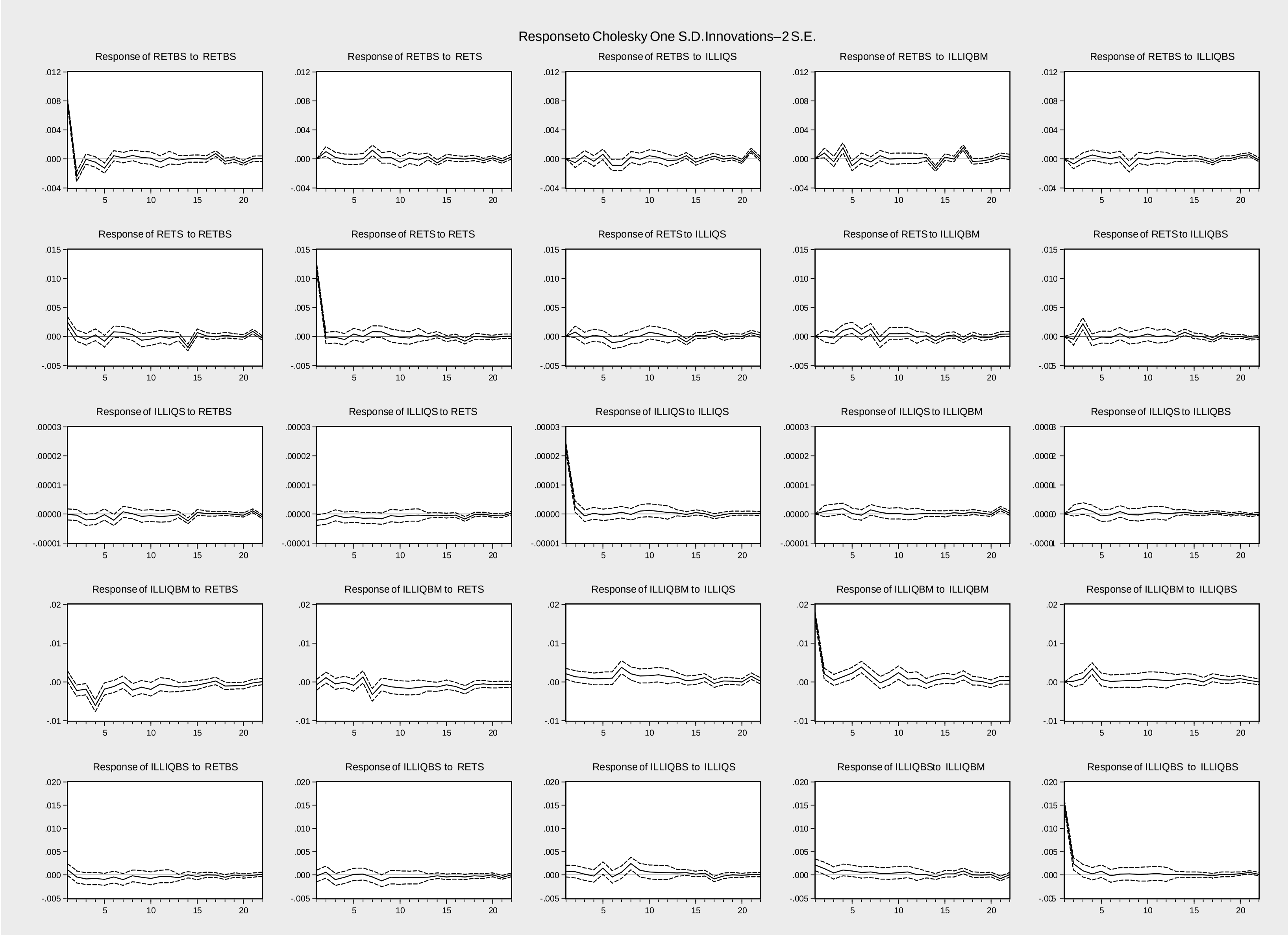


Figure 5.4.3. Impulse Response Functions for the Daily Data VAR Model.

Source: Own calculations based on the data retrieved from Bloomberg database, *Yahoo!*Finance.

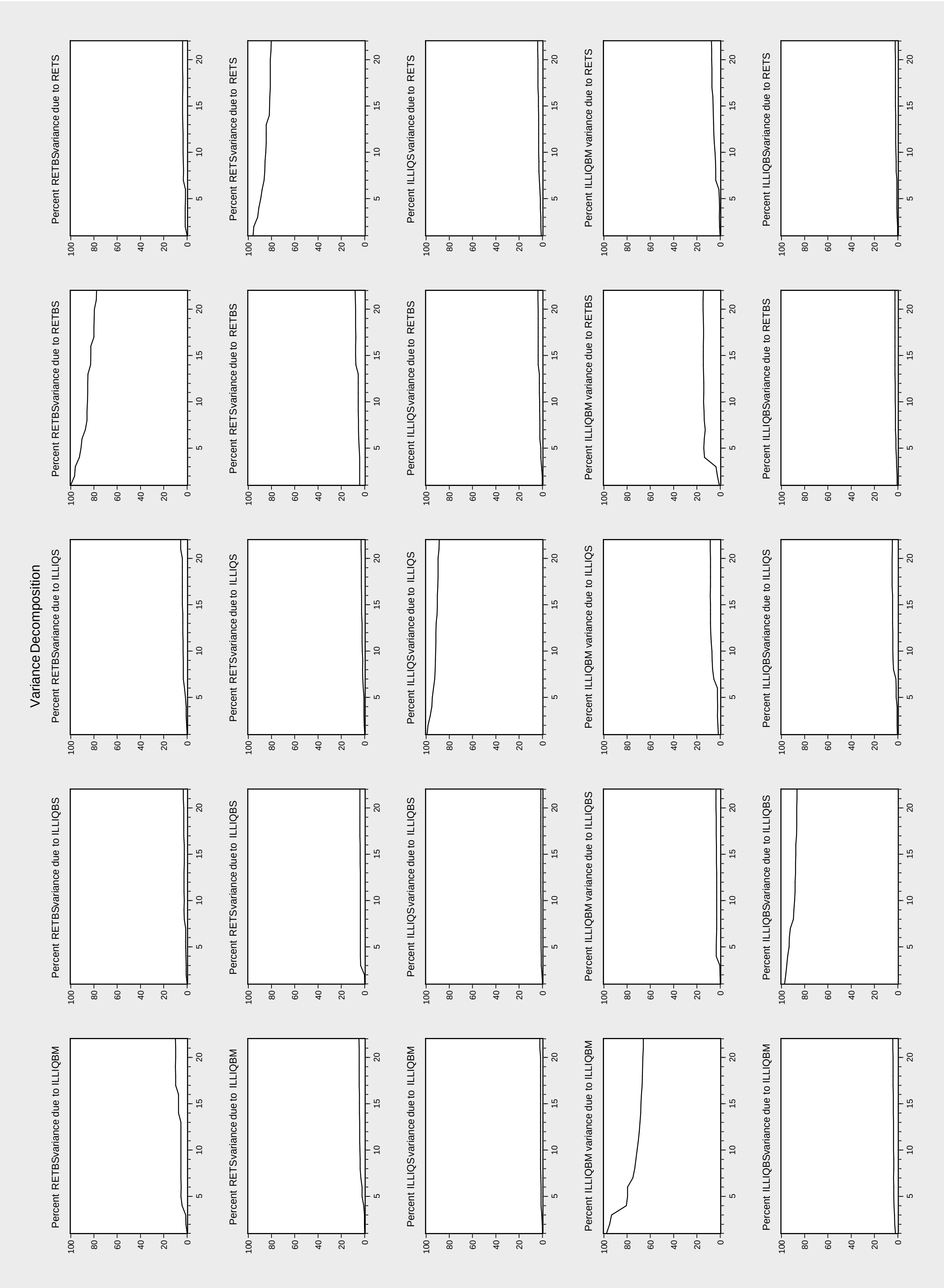


Figure 5.4.4. Forecast Error Variance Decomposition for the VAR Model for Daily Data.

Source: Own calculations based on the data retrieved from Bloomberg database, *Yahoo!*Finance.

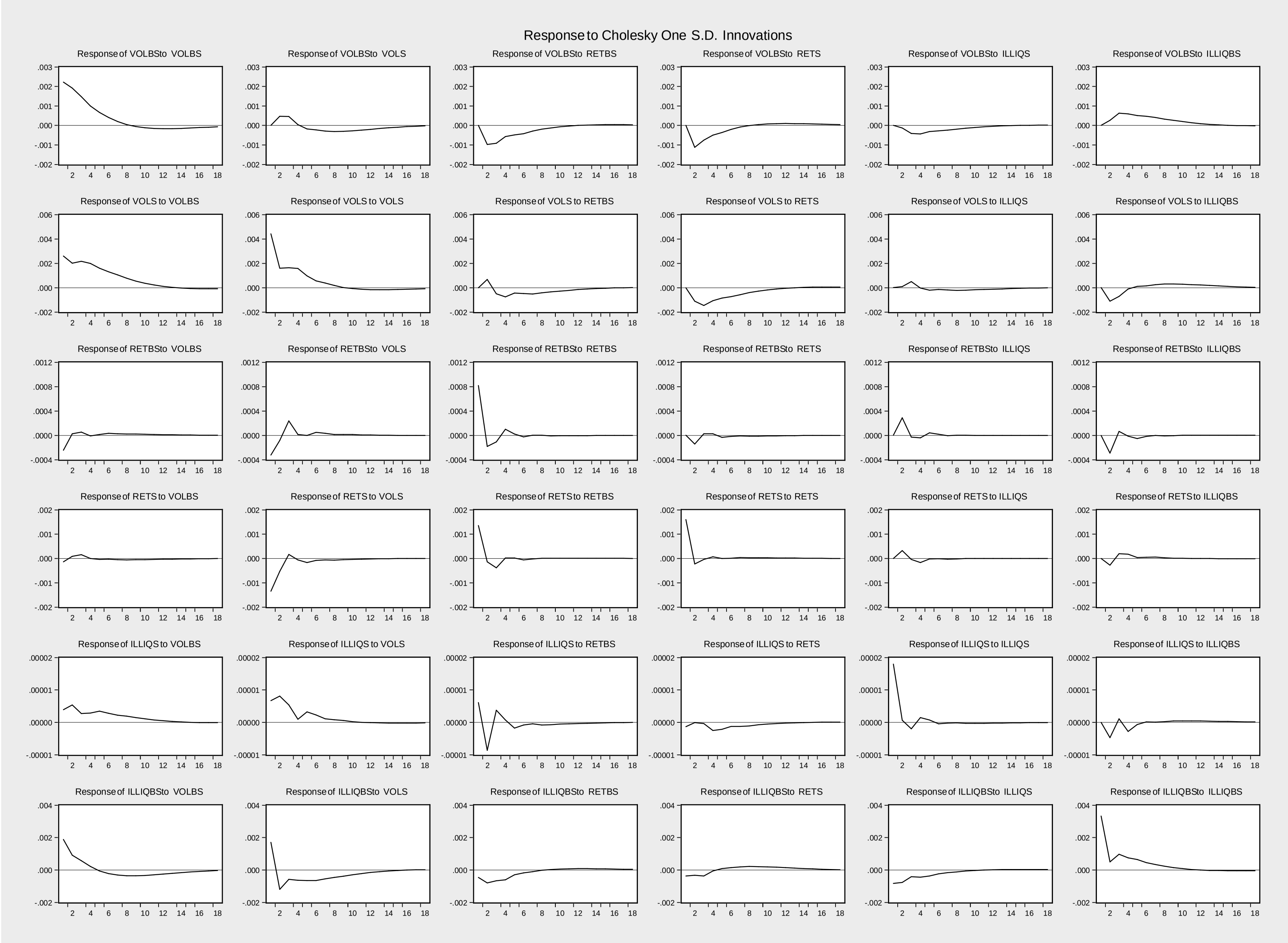


Figure 5.4.5. Impulse Response Functions for the Monthly Data VAR Model.

Source: Own calculation based on the data retrieved from Google Trends, Bloomberg database, *Yahoo!*Finance, Bank of Russia, Federal Service of State Statistics.

hypothesis for Jarques — Bera test is not rejected at the 5% significance level, and the residuals prove to be multivariate normal. The ordering of the variables for the Cholesky decomposition follows Goyenko and Ukhov (2009): VOLBS, VOLS, RETBS, RETS, ILLIQS, ILLIQBS. The chosen period for IRFs construction is 18 months.

Stock illiquidity and short term bonds illiquidity show no response to the shock in stock return, while in the US market researched by Chorida, Roll, and Subrahmanyam (2001), Goyenko and Ukhov (2009) the responses are negative. The direction of response of stock illiquidity to short term bond illiquidity is opposite to those in the US market studied by Goyenko and Ukhov (2009).

It is possible to make the conclusion that illiquidity linkages in the Russian market are present, but still much weaker than those in the US market. In both markets bond maturity category matters for market microstructure variables relationships.

5.5 SUMMARY OF RESULTS

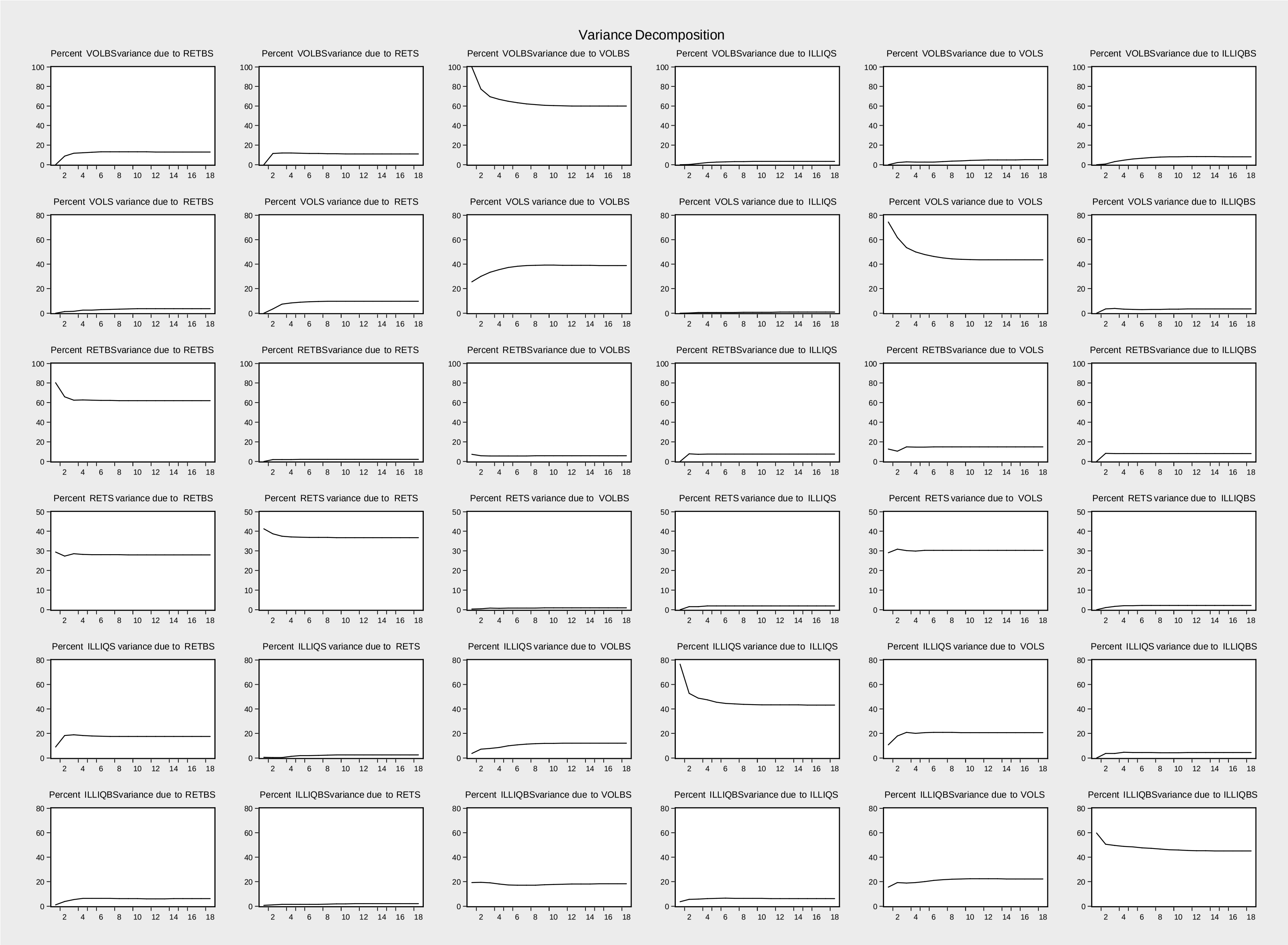
The results for weekly data Granger causality test and vector autoregression analysis do not support ***Ho (1)*** and ***Ho (2)***, which means that the market microstructure parameters and internet searches are relevant for the Russian market liquidity and returns' forecasting. However, ***Ho (2)*** is not supported by monthly data Granger causality test. The results for daily and monthly data Granger causality tests, daily and monthly vector autoregression models also reject ***Ho (1)***, which suggests that the market microstructure parameters are useful for the Russian market liquidity and returns' forecasting. The results for monthly data Granger causality test do not support ***Ho (3)*** as well. It means that macroeconomic variables may be effectively used for the Russian financial markets forecasting according to the tests with the lags of 1 or 2 months.

6. CONCLUSIONS

We find that despite the structural instability of the Russian financial markets, the market microstructure variables influence each other and are affected by the characteristics of other asset types. The nature of this influence is highly dependent on the model characteristics such as the lag selection or Cholesky ordering in case of vector autoregressions. This corroborates with the claim of Goriaev and Zabotkin (2005) about the necessity of using the dynamic models in highly volatile markets and economies heavily influenced by political news. The stock and bond returns time series may be used for forecasting liquidity and volatility in the Russian market. This is supported by the Granger causality test and vector autoregression analysis. However, the stock illiquidity is not useful for forecasting stock returns, which is in contrast to the results received by Jones (2001), Amihud (2002), Pastor and Stambaugh (2003) for the US market, and Andrikoupolos and Angelidis (2008) for the UK market. The discrepancy could be attributed not only to completely different type of the markets and their perception by the investment community, but also to differing importance of market microstructure factors. In the Western markets investors are likely to pay more attention to illiquidity, while in highly volatile markets risk is the most important factor for decision making. In accordance with the weekly VAR model, the stock illiquidity may be useful for volatility forecasting, but the stock market return and illiquidity do not Granger cause volatility. Similarly to the financial markets of G-7 countries researched by Andrikoupolos, Angelidis, and Skintzi (2012), in the Russian stock market liquidity, return and volatility in the majority of cases experience bidirectional Granger causal relationships. As opposed to the majority of G-7 countries stock markets, the Russian stock market does not demonstrate an evident negative relationship between liquidity and return. Nevertheless, there is a negative relationship between volatility and return indicating that in the Russian market investors rely on risk measures rather than on illiquidity measures in their decision-making process. Liquidity and volatility in the Russian stock market demonstrate Granger casual relationships that corroborates with the situation in the US market. The Russian market returns may be explained by their own shocks that correspond to the results received by Hayo and Kutan (2005). Bond maturity in the Russian market has a significant impact on the bonds' characteristics and implicitly on switching between different asset classes. Such a result is consistent with the conclusions made by Longstaff (2004), Beber, Brandt, and Kavajecz (2009), and Goyenko and Ukhov (2009) for the US market. There are Granger causal relationships between illiquidity of the Russian stock and bond markets that confirms the presence of illiquidity spillovers in the Russian market. This result corroborates with the patterns present in developed markets studied by Chorida, Sarkar, and Subrahmanyam (2005), Fleming, Kirby and Ostdiek (1998), Ho and Stoll (1993), O'Hara and Oldfield (1996), Goyenko and Ukhov (2009).

The correlation analysis shows that an increase in the number of internet queries may serve as an indicator of higher volatility and illiquidity in the Russian stock market in the future. GOOGLE_MICEX time series is a powerful forecasting indicator for stock market liquidity and volatility time series. Its share in

Table 5.4.6. Forecast Error Variance Decomposition for VAR Model for Monthly Data.



Source: Own calculation based on the data retrieved from Google Trends, Bloomberg database, *Yahoo!*Finance, Bank of Russia, Federal Service of State Statistics.

market microstructure factors' variance explanation is relatively high, which is consistent with the fact that individuals account for approximately a half of all investors in MICEX. The forecasts with a help of internet queries' tool should be adjusted in accordance with the proportions of each factor explained as suggested by weekly VAR model results. The results are consistent with the models' output for Western financial markets presented by Da *et al.* (2011), Dzielinski (2011), Dimpfl and Jank (2011) as well as Arouri *et al.* (2013). It is necessary to emphasize that the global factors, macroeconomic policy actions and indicators play a significant role in the Russian market. What follows, Google Trends may be used for financial analysis only in combination with other tools.

The stock and short term bonds illiquidity experience Granger causal relationship with the change in MIBOR. This conclusion differs from the results received by Naes, Skjeltorp and Odegaard (2011), who show that illiquidity indicators are useful for the economic growth forecasting in the USA and Norway. Short term bonds' volatility is a leading indicator for industrial production change. It experiences a mutual Granger causality with MIBOR as well as for short term bonds' return that is a leading indicator for inflation. Stock market return experiences mutual Granger causality with inflation and MIBOR change, and stock market volatility is Granger caused by the change in industrial production. The quality of VAR model with the participation of macroeconomic variables supports the fact that the latter help to forecast market microstructure variables.

6.1 SUMMARY OF FINDINGS

The most important implication of the study is that it was empirically shown that Google Trends, particularly the queries in English language, may be effectively used for forecasting the Russian market microstructure indicators. Another important conclusion is that the Russian market still remains structurally unstable, and the results of the models are highly sensitive to model specification and data frequency, especially when the market microstructure is analyzed. The forecasting power of different assets' liquidity, volatility and return factors varies significantly. The behavior of market microstructure parameters in the Russian market differs from those in Western markets. In addition, the influence of the global factors, macroeconomic indicators, monetary policy actions as well as market microstructure parameters on microstructure features of stocks and bonds of different maturities in the Russian market is not the same. Therefore, this study emphasizes that in the contemporary environment the analysts cannot rely only on one tool when making their forecasts. Obviously, the spillover effects from the global markets, the economic policy as well as the individual assets characteristics should be included in the analysis. Finally, internet queries may serve as a proxy of public behavior suitable for the highly volatile and unstable markets' financial analysis. The increasing availability of big data sets offers an exciting possibility to study the collective behavior of the Russian investors and the society in general.

REFERENCES

Adrian, T., & Shin, H. S. (2009). Money, liquidity and monetary policy. *Staff Report, Federal Reserve Bank of New York, № 360.*

Agnew, J., & Balduzzi, P. (2005). Rebalancing Activity in 401 (k) Plans. *Working Paper, Boston College.*

Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals of the Institute of Statistical Mathematics, 21,* 243–247.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19* (6), 716–723.

Amihud, Y., & Mendelson, H. (1986). Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics,* 17 (1986), 223–249.

Amihud, Y., & Mendelson, H. (1989). The Effect of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns. *Journal of Finance, 44* (1989), 479–486.

Amihud, Y., Mendelson, H. & Lauterbach, B. (1997). Market microstructure and securities values: evidence from the Tel Aviv Stock Exchange. *Journal of Financial Economics 45*, 365–390.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time- series effects. *Journal of Financial Markets 5*, 31–56.

Andersen, T. G. (1996). Return Volatility and Trading Volume — An Information Flow

Interpretation of Stochastic Volatility. *The Journal of Finance 51* (1), 169–204.

Anderson, T. W., & Darling, D. A. (1952). Asymptotic theory of certain "goodness-of-fit" criteria based on stochastic processes. *Annals of Mathematical Statistics 23*, 193–212.

Anderson, T. W., & Darling, D. A. (1954). A Test of Goodness-of-Fit. *Journal of the American Statistical Association 49*, 765–769.

Andrikoupolos, A., & Angelidis, T. (2008). Idiosyncratic risk, returns and liquidity in London Stock Exchange: a spillover approach. *International Review of Financial Analysis 19* (3), 214–221.

Andrikoupolos, A., Angelidis, T., & Skintzi, V. (2012). Illiquidity, return and risk in G7 stock markets: interdependencies and spillovers. *MPRA Paper 40003,* University Library of Munich, Germany.

Arouri, M., Aouadi, A., Foulquier, P., & Teulon, F. (2013). Can Information Demand Predict Stock Market Liquidity? Google it! *IPAG Business School. Working Paper 2013–024.*

Balduzzi, P., Elton, E., & Green, T. (2001). Economic News and Bond Prices: Evidence from U.S. Treasury Market. *Journal of Financial and Quantitative Analysis 36* (4), 523–543.

Bank of Russia. (2015). *Direct investments in the Russian Federation from abroad by instruments and countries- investors in 2010–2014.*

Bank of Russia. (2015). *Net capital inflow/outflow by private sector in 2005–2014.*

Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Markets Hypothesis. *Journal of Finance 32,* 663–682.

Bath University (n.d.). *Johansen Maximum Likelihood Procedure.*

Beber, A., Brandt, M., & Kavajecz, K. (2009). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *Review of Financial Studies, 22* (2009), 925–957.

Benston, G., & Hagerman, R. (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal of Financial Economics 1,* 353–364.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics 31* (3), 307–327.

Boudoukh, J., & Whitelaw, R. (1993). Liquidity as a Choice Variable: A Lesson from Japanese Government Bond Market. *Review of Financial Studies, 6* (1993), 265–292.

Brandt, M., & Kavajecz, K. (2002). Price discovery in the U.S. Treasury Market: The impact of order flow and liquidity on the yield curve. *Working paper, University of Pennsylvania*, Philadelphia, PA.

Brennan, M. & Subrahmanyam, A. (1996). Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics, 41* (1996), 441–464.

Brooks, C. (2002). *Introductory Econometrics for Finance.* Cambridge: Cambridge University Press.

Brunnermeier, M. K. (2008). Deciphering the Liquidity and Credit Crunch 2007–08. *NBER Working Paper № 14612.*

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market Liquidity and Funding Liquidity. *The Review of Financial Studies 22* (6), 2201–2238.

Butler, A. W., Grullon, G., & Weston, J. P. (2005). Stock Market Liquidity and the Cost of Issuing Equity. *Journal of Financial and Quantitative Analysis 40* (2), 331–348.

Chang, Y. Y., Faff, R., & Hwang C.-Y. (2010). Liquidity and stock returns in Japan: New evidence. *Pacific- Basin Finance Journal 18* (2010), 90–115.

Chesney, M., Reshetar, G., & Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. *Journal of Banking & Finance 35* (2), 253–267.

Chordia, T., A. Sarkar, & A. Subrahmanyam. (2005). An Empirical Analysis of Stock and Bond Market Liquidity. *Review of Financial Studies, 18* (2005), 85–129.

Chordia, T., Roll, R. & Subrahmanyam, A. (2000). Commonality in Liquidity. *Journal of Financial Economics, 56* (2000), 3–28.

Clark, P. K. (1973). A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices. *Econometrica 41*, 135–155.

Cramer, H. (1928). On the composition of elementary errors. *Scandinavian Actuarial Journal, 11*, 141–180.

Da, Z., Engelberg, J., & Gao, P. (2011). In Search of Attention. *The Journal of Finance 66* (5), 146–1499.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association 74* (366), 427–431.

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters 9*, 167–175.

Enders, W. (2010). *Applied Econometrics Time Series* (3 ed.), NY: John Wiley & Sons.

Engle, R. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U. K. inflation. *Econometrica 50* (4), 987–1008.

Engle, R. F. (1984). *Handbook of Econometrics,* Ch., 13, pp. 776–825. Elsevier Science Publishers BV.

Epps, T. W., & Epps, M. L. (1973). The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture of Distributions Hypothesis. *Econometrica*, *44*, 305–321.

Fair, R. C. (2002). Events that shook the market. *Journal of Business 75*, 713–731

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance 25* (2), 383–417.

Fleming, M., & Remolona, E. (1997). What moves the bond market? *Economic Policy Review 3* (4), 31–50.

Fleming, J., Kirby, C., & Ostdiek, B. (1998). Information and Volatility Linkages in the Stock, Bond, and Money Markets. *Journal of Financial Economics, 49* (1998), 111–137.

Fleming, M., & Remolona, E. (1999). Price formation and liquidity in the U.S. Treasury market: The response to public information. *Journal of Finance 54*, 1901–1915.

Florackis, C., Gregoriou, A., & Kostakis, A. (2011). Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance 35* (2011), 3335–3350.

Fox, S. (1999). Assessing TAA Manager Performance. *Journal of Portfolio Management, 26* (1999), 40–49.

Glosten, L., & Milgrom, P. (1985). Bid-ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*, 70–100.

Goetzmann,W., & Massa, M. Daily Momentum and Contrarian Behavior of Index Fund Investors. *Journal of Financial and Quantitative Analysis, 37* (2002), 375–389.

Goldreich, D., Hanke, B & Nath, P. (2005). The Price of Future Liquidity: Time-Varying Liquidity in the U.S. Treasury Market. *Review of Finance, 9* (2005), 1–32.

Goriaev, A., & Zabotkin, A. (2006). Risks of Investing in the Russian Stock Market: Lessons of the First Decade. *Working Paper № 77. CEFIR/NES Working Paper Series.*

Goyenko, R. Y., Holden, C. W. & Trzcinka C.A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92* (2009), 153–181.

Goyenko, R. Y & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis 44* (1), 189–212.

Goyenko, R. Y., Subrahmanyam, A., & Ukhov, A. D. (2011). The Term Structure of Bond Market Liquidity and Its Implications for Expected Bond Returns. *Journal of Financial and Quantitative Analysis, 46* (1), 111–139.

Granger, C.W. G. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica, 37* (3), 424–438.

Grossman, S. J., & Stiglitz, J. E. (1980).On the Impossibility of Informationally Efficient Markets, *American Economic Review*, *70*, 393–408.

Hannan, E. J., & Quinn, B. G. (1979). The Determination of the Order of an Autoregression. *Journal of the Royal Statistical Society*, *41*, 190–195.

Hasbrouck, J., & Seppi, D. (2001). Common Factors in Prices, Order Flows, and Liquidity. *Journal of Financial Economics, 59* (2001), 383–411.

Hasbrouck, J. (2004). Liquidity in the futures pits: inferring market dynamics from incomplete data. *Journal of Financial and Quantitative Analysis 39*, 305–326.

Ho, T., & Stoll, H. (1983). The Dynamics of Dealer Markets under Competition. *Journal of Finance, 38* (1983), 1053–1074.

Holden, C. (2009). New low-frequency liquidity measures. *Working Paper, Indiana University.*

Huberman, G., & Halka, D. (2001). Systematic Liquidity. *Journal of Financial Research, 2* (2001), 161–178.

Jacoby, G., Fowler, D. J., and Gottesman, A. A. (2000). The capital asset pricing model and the liquidity effect: a theoretical approach. *Journal of Financial Markets 3,* 69–81.

Jalolov, R., & Miyakoshi, T. (2005). Who drives the Russian financial markets? *The Developing Economies 43* (3), 374–395.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economic Letters 7* (4), 313–318.

Jarque, C. M., & Bera, A. K. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. *Economic Letters 6* (3), 255–259.

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review 55* (2), 163–172.

Jones, C. (2001). A century of stock market liquidity and trading costs. *Working paper, Columbia University*, New York, NY.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica, 59* (6), 1551–1580.

Kamara, A. (1994). Liquidity, Taxes, and Short-Term Treasury Yields. *Journal of Financial and Quantitative Analysis, 29* (1994), 403–417.

Kim, J. (2013). How does Stock Market Liquidity Forecast Economic Growth? *European Journal of Business and Management 5* (31), 155–164.

Krishnamurthy, A. (2002). The Bond/Old-Bond Spread. *Journal of Financial Economics, 66* (2002), 463–506.

Lee, Y.-H., & Hao, F. (2012). Oil and S&P 500 Markets: Evidence from the Nonlinear Model. *International Journal of Economics and Financial Issues 2* (3), 272–280.

Lesmond, D., Ogden, J. & Trzcinka, C. (1999). A new estimate of transaction costs. *Review of Financial Studies 12*, 1113–1141.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics 82*, 631–671.

Lesmond, D. A. (2005). Liquidity of Emerging Markets. *Journal of Financial Economics 77* (2005), 411–452.

Lilliefors, H. (1967). On the Kolmogorov — Smirnov test for normality with mean and variance unknown. *Journal of the American Statistical Association 62,* 399–402.

Lilliefors, H. (1969). On the Kolmogorov — Smirnov test for the exponential distribution with mean unknown. *Journal of the American Statistical Association 64,* 387–389.

Litterman, R. (1979). Techniques of forecasting using vector autoregressions. *Federal Reserve of Minneapolis Working Paper 115.*

Litterman, R. (1986). Forecasting with Bayesian vector autoregressions — Five Years of Experience. *Journal of Business and Economic Statistics 4,* 25–38.

Longstaff, F. A. (2004). The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *Journal of Business, 77* (2004), 511–526.

Lutkepohl, H. (1991). *Introduction to Multiple Time Series.* New York, NY: Springer.

Lutkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis.* New York, NY: Springer.

Luu, J. C., & Martens, M. (2002). Testing the Mixture of Distributions Hypothesis Using "Realized Volatility". Lux, T., & Marchesi, M. (1999). Scaling and criticality in a stochastic multi-agent model of a financial market. *Nature 397* (6719), 498–500.

MacKinnon, J. G. (1991). Critical values for cointegration tests. In R.F. Engle *and C.W. J.* Granger (eds), *Long-run Economic Relationships: Readings in Cointegration*, Ch. 13, pp. 267–76. Oxford: Oxford University Press.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics 11*, 601–18.

Merton, R. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance*, *42*, 483–510.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7* (1), 77–91.

McCrorie, J. R., & Chambers, M. J. (2004). Granger Causality and the Sampling of Economic Processes. *Working Paper Tilburg University, Center for Economic Research, Discussion Papers 2004–39.*

Ministry of the Economic Development of the Russian Federation. (2015). *Forecast of the socioeconomic development of the Russian Federation for the year 2015.*

Naes, R., Skjeltorp, J. A. & Odegaard, B. A. (2011). Stock Market Liquidity and the Business Cycle. *Journal of Finance 66* (1), 139–176.

Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: a new approach. *Econometrica 59* (2), 347–370.

O'Hara, M. & Oldfield, G. (1986). The Microeconomics of Market Making. *Journal of Financial and Quantitative Analysis, 21* (1986), 361–376.

O' Hara, M. (1995). *Market Microstructure Theory.* Oxford: Blackwell.

Pastor, L. & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*, 642–685.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying Trading Behavior in Financial Markets Using Google Trends. *Scientific Reports 3*, 1684.

Rockinger, M., & Urga, G. (2000). A Time Varying Parameter Model to Test for Predictability and Integration in Stock Markets of Transition Economies. *CEPR Discussion Papers 2346, C.E. P. R. Discussion Papers.*

Roll, R. (1984). A simple implicit measure of the effective bid — ask spread in an efficient market. *Journal of Finance 39*, 1127–1139.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *Journal of Portfolio Management 13,* 9–17.

Seyhun, N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics 16*, 189–212.

Shiller, R. J., & Perron, P. (1985). Testing the Random Walk Hypothesis: Power vs. Frequency of Observation. *Economic Letters 18* (1985), 381–386.

Shiller, R. J. (1989). *Market Volatility.* Cambridge, MA: MIT Press.

Schwarz, G. E. (1978). Estimating the dimension of a model. *Annals of Statistics, 6* (2), 461–464.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica 48* (1), 1–48.

Spearman, C. (1904). The proof and measurement of association between two things. *The American Journal of Psychology, 15* (1), 72–101.

Stock, J. H., & Watson, M.W. *Introduction to Econometrics.* (3d ed.) New York, NY: Addison-Wesley.

Swensen, D. (2000). *Pioneering Portfolio Management: An Unconventional Approach to Institutional Investment*. NY: Free Press, New York.

Tauchen, G. E., & Pitts, M. (1983). The Price Variability-Volume Relationship on Speculative Markets. *Econometrica* 51 (2), 485–505.

Vayanos, D. (2004). Flight to quality, flight to liquidity, and the pricing of risk. *National Bureau of Economic Research.*

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance 36* (6), 1808–1821.

Von Mises, R. E. (1928). *Wahrscheinlichkeit, Statistik und Wahrheit*. Julius Springer.

Vosen, S., & Schmidt, T. (2011). Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting 30* (6), 565–578.

Warga, A. (1992). Bond Return, Liquidity, and Missing Data. *Journal of Financial and Quantitative Analysis, 27* (1992), 605–617.

Yoo S. (2011). 'G-3 and BRICK Stock Markets: 'Co-integration and Its Forecasting Ability.' *University of Michigan.*

Zakonian, J. M. (1994). Threshold heteroscedasticity models. *Journal of Economic Dynamics and Control 18* (5), 931–955.