ISSN 2313-1578 (PRINT)
ISSN 2313-6960 (ON-LINE)

RUSSIAN REVIEW
РУССКОЕ ОБОЗРЕНИЕ

SCIENTIFIC JOURNAL

VOL. 2 (3) 2015

CONTENTS

Safe Internet League

EDITORIAL

Dear colleagues,

It is my pleasure to bring to your attention an academic journal aimed at introducing well-renowned scholars and specialists to the best of their Russian colleagues' scientific papers.

Research done by Russian scholars has long remained largely unknown to the international community. Rather than the language barrier, this was due to the legacy of the ways and the self-isolation of the Soviet Academia. With a new wave of talented researchers, contemporary Russian science is undergoing a rapid transformation, and we at the Safe Internet League would like to contribute to advancing and promoting their research.

For this purpose we are presenting a choice selection of scholarly papers by Russian authors, translated into English, published, and sent to the most renowned and reputable international scholars according to SSRN (Social Science Research Network) Author Rank.

We will be delighted to receive your feedback at

chief@rusreview.com

RUSSIAN REVIEW. SCIENTIFIC JOURNAL.
WWW. RUSREVIEW.COM
FOUNDER AND PUBLISHER – THE SAFE INTERNET LEAGUE
ADRESS – 123056, MOSCOW, ОПС №56, PO BOX 124, THE SAFE INTERNET LEAGUE
TEL.: +7 (495) 989-89-91
E-MAIL: INFO@LIGAINTERNET.RU
THE JOURNAL IS REGISTERED BY THE FEDERAL SERVICE FOR SUPERVISION OF COMMUNICATIONS, INFORMATION TECHNOLOGY, AND MASS MEDIA OF RUSSIA
REGISTRATION CERTIFICATE IS ПИ № ФС77-55100 ON AUGUST 26, 2013.
THE MAGAZINE IS PUBLISHED SINCE 2014. CIRCULATION – 200 COPIES.

P2P LENDING INTEREST RATES SENSITIVITY TO SOCIOECONOMIC FACTORS

Ivan Tchemyakin,
Lomonosov Moscow State University, Faculty of Economics

Abstract. The present paper analyses how sensitive P2P credit interest rates are to the socioeconomic data declared by P2P credit users. The reasons why credit users are choosing P2P platforms as an alternative to commercial banks include: lower interest rate, shorter loan processing times, fewer document requirements and the online nature of the process. Of these, the most winning feature for the borrower is the lower interest rate. According to the study, in 94% of cases, a one-step adjustment in a user's credit rating triggers an interest rate change of 0.654%, while the length of their credit history and the purpose of their loan have no impact on the chosen interest rate.
Keywords: P2P lending, social lending, online lending, interest rate, socioeconomic factors.
JEL classification: D14, E34, G23

1. Introduction

P2P lending (People to People, Internet users directly lending money to each other) is a rapidly growing sector of *Internet finance*, an industry first articulated by Yandiev (2015). By operating as a virtual banking system, the P2P lending market plays a key role in this industry. And, like in the banking sector, its most vital question is which factors influence the rate of interest on a loan.

Therefore, the aim of this study is to find out which factors, and to what extent, are shaping the interest rate in P2P lending.

2. Review of literature

The first ever online P2P platform, called ZOPA (zone of possible agreement), was launched in 2005 in Great Britain. The company may be said to have pioneered online P2P lending. Over the last five years the practice of online P2P lending has gained scientific validity. Open access to data allows researchers in various fields to study the factors influencing the process (Bachmann, Becker et al., 2011).

The number of studies of P2P lending is growing year by year. A review by Bechmann и Becker mentions 43 papers published from 2006 to late 2010 (Bachmann, Becker et al., 2011). Yang Yang claims that 2008 to 2015 saw 70 of such papers published (Yang Yang, 2015).

One of the earlier studies of P2P lending was the paper titled *Internet Based Social Lending: Past, Present and Future* (Hulme and Wright, 2006). One of most recent ones is *Determinants of Default in P2P Lending* (Serrano-Cinca, Gutiérrez-Nietoand López-Palacios, 2015). Overall, the scope of research in P2P lending seems to begetting more narrow.

A 2008 paper, titled *Peer to Peer Banking – State of the Art* (Arne Frerichs, Matthias Schumann, 2008) describes business models of companies currently active in the P2P lending market: *Zopa, Prosper, Smava*, and even the radically different *Kiva*. The study provides a description of the industry and lays down a number of avenues for further research. (Frerichs and Schumann, 2008). Moenninghoff and Wieandt go beyond P2P lending and deals with a whole range of opportunities for avoiding middlemen afforded by P2P platforms. Particular attention is given to the risks peer-to-peer network users take unto themselves by forgoing financial middlemen (Moenninghoff and Wieandt, 2011).

A number of researchers from different countries are turning their attention to subjects like P2P lending market regulation (Verstein, 2011; Chafee and Rapp, 2012; Zeng, 2013; and Slattery, 2013). Empirical studies of direct lending market actors deal, first and foremost, with the two major subjects: risk and returns.

Studies of the risk of investing in direct lending are most often based on a binary or multivariate econometric model (Freedman and Jin, 2008; Iyer, Khwaja et al., 2009; Мальцев, 2014). Here, binary choice models help evaluate each factor's contribution to the risk total, with the latter value defined as the probability of defaulting on each individual debt.

The second avenue of empirical research in direct lending is taken by a number of publications featuring models for explaining, directly or indirectly, how an interest rate on a loan is shaped (Herzenstein, Andrews et al., 2008; Gonzalez and Loureiro, 2014; Wen and Wu, 2014; Zhang, Yang and Pan, 2014). Such models may take the shape of a regression equation (Herzenstein, Andrews et al., 2008), a game-theory model with a decision tree (Luo and Lin, 2013), and other forms. Of these, regressive equation-based models have a greater explanatory power because this type of model enables the researcher to perform factor analysis, interest rate projection, and evaluate projected forecast and overall model quality.

Reviewing prior empirical studies allows us to identify major significant factors and choose the most appropriate (in terms of significance and quality of fit) specifications for a model.

3. Econometric modeling

The present model for P2P lending interest rate was constructed using the loans data published online by LendingClub, the world's largest online retail lending platform. It allows users who have provided information about themselves and the requested loan to post loan requests. All loans are unsecured, and may vary from $1 000 to $35 000.

Using the borrower's credit rating, credit history, loan size, and a number of other factors, the platform sets the interest rate and the amount of other payments on a loan. The usual loan term is 3 years. 5-year loans are provided at a premium and at a higher interest rate. A loan may be repaid at any time with no penalty. Interest rates vary from 6.03% to 26.06%.

LendingClub makes its profit by charging credit users for its assistance in getting the loan and credit lenders for using its services. The assistance fee varies with credit user's rating from 1.1% to 5.0% of loan value. The service fee is 1% of all payments made by credit users.

4. Description of variables

With LendingClub providing the data on each provided loan – over 1 million loans annually – a year's worth of data suffices to construct a reliable model.

A total of around 200 000 observations for 2014 was made. However, more than half of that data had to be rejected because of incomplete information submitted by users. In the end, the model was constructed using 80 000 observations, with 5 000 used to test its quality.

Of the 12 initial parameters, 15 regressors and 1 dependent variable were formed. The description of these is offered below.

1) Interest rate

Interest rates, vary from 6.03% to 26.06%. However, regardless of other factors, the rate of interest on a loan cannot be lower than the key interest rate. In case of the USA, the latter is low and extremely stable, therefore, for the US market this factor is of little significance; other countries, however, set their key interest rate higher and can change it several times a year, which automatically affects all other interest rates. Therefore it would be more logical to build a model not on the interest rate itself, but on the interest rate premium. The premium is calculated as the margin between loan interest rate and key interest rate. Within the model, premium is a dependent variable expressed in fractions.

2) Loan term

LendingClub assists users in getting loans for 3- and 5-year terms. Since the variable in question can only take two discrete values, it can be classified as a dummy variable, where 3-year loans are *0*, and 5-year loans are 1. Loan term is represented by a single dummy variable *term*. Given the fact that under LendingClub rules users requesting loans for a longer term (5 years) are charged higher interest rates, the correlation between the *term* and dependent variable can be considered a direct (positive) one.

3) Credit rating

LendingClub uses its own system of calculating individual credit ratings. It uses a number of factors to allocate users into grades (A to G) and sub-grades (1 to 5), where A1 is the highest rating, and G5 is the lowest one. Associating the A1 rating with number 1, A2 with 2, and so forth creates, an ordinal variable *grade* that takes values from 1 to 35.

Higher values correspond to lower credit ratings and higher interest rates, meaning that premiums, too, are higher. That is, the correlation between *grade* and the dependent variable can be considered direct, or positive.

4) Form of residential property ownership

LendingClub recognises three forms of residential property: owned, mortgaged, and rented. In the majority of cases sampled it is the second form. This is due to the peculiarities of the US market, characterised by relatively easily available mortgages and socioeconomic stability. This parameter's values were translated into dummy variables. Given that the parameter distinguishes between three separate groups, the regression has to have two dummy variables (*home_own, home_rent*) so as to follow the premise that no independent variable can be the linear combination of one or several other independent variables.

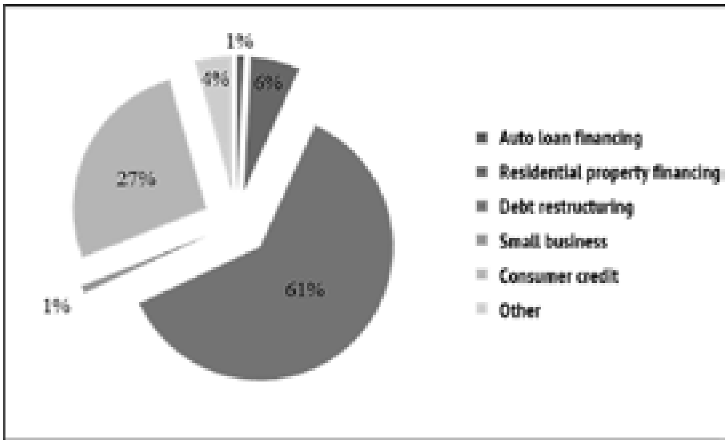
In case a borrower owns their residential property, *home_own* equals 1 and *home_rent* equals *0*. In case they are renting an accommodation, *home_own* equals *0* and *home_rent* equals 1. In case they have a mortgage, both dummy variables (*home_own* and *home_rent*) equal *0*.

5) Loan purpose

LendingClub users are seeking loans for all kinds of different purposes, like organising a wedding party, taking a trip, buying a car, covering the expense of moving house or buying a new one, restructuring a loan from a third party. However, in Russia the category is not so detailed. Therefore, 14 categories were translated into 6 dummy variables: auto loan financing (*purpose_car*), residential property financing (moving house, improving housing, buying a new house; *purpose_home*), debt consolidation (*purpose_debt_consolidation*), small business development (*purpose_small_business*), consumer credit (*purpose_cosumer_credit*), and other purposes (*purpose_other*). 6 discrete groups make 5 dummy variables (*purpose_car, purpose_home, purpose_debt_consolidation, purpose_small_business, and purpose_cosumer_credit*). In cases where a user is seeking a loan to buy a car the variable *purpose_car* equals *1*, while *purpose_home, purpose_debt_consolidation, purpose_small_business, and purpose_cnsumer_credit* equal *0*. The same logic goes for the other four groups. In cases where the individual does not fall into any one of the 5 groups (chose 'Other' as the purpose of the loan), all 5 dummy variables equal *0*.

Most LendingClub users are seeking a loan for debt restructuring. This is due to the peculiarities of the US lending market, which enjoys a high degree of development and familiarity to most Americans, so much so that there, probably, is no-one in the US who have never taken out a loan of some kind. Given that, on average, LendingClub interest rates are lower than those on the conventional market, the possibility of taking out a loan looks especially appealing, for example, to those who need to pay back a loan from a third party.

Diagram 1. Distribution of loan users by loan purpose



Source: compiled from data published on www.nsrplatform.com

6) Annual income

LendingClub users submit their annual income figures in tens of thousands of US dollars. However, not all of this income is confirmed. Average income statement of LendingClub users is $78 000 per annum.

Presumably, higher income figures translate into higher credit user reliability. However, it is not always the case. There are examples of extremely high earners prone to getting bankrupt, and extremely low earners responsible in meeting their contract obligations. Therefore it is not possible to unequivocally define the type of correlation between a borrower's income and their credit reliability.

The present analysis uses this parameter as a divisor of the *debt_to_income* index (loan size to income ratio).

7) Loan size

Loans start at $1 and are capped at $35 000, with the average loan being $14 600. Presumably, loan size must be inversely related to interest rate. That is, bigger loans must have lower interest rates. Note that the present analysis uses this parameter as a divisor of the *debt_to_income* index.

Higher debt to annual income ratios translate into higher credit risks and, consequently, higher loan interest rates and higher interest premiums. That is, the correlation between a borrower's debt to annual income ratio (*debt_to_income*) and the size of the premium on their loan is assumed to be positive.

8) Employment

LendingClub defines credit users' employment in terms of the number of years they have been/were working for their current/last employer. Longer history of continuous employment is thought to mean higher borrower reliability because it implies the ability to maintain proper contract relationship. Therefore, the level of employment must be directly correlated with interest rate, and, by extension, interest premium.

One feature of LendingClub's database is that terms of employment shorter than one year get noted as *<1*, terms over 10 years as *10+*, and everything from 1 to 10 years as an integer. Therefore this parameter cannot be represented as a continuous variable and must be transformed into an ordinal one, where *1* is any term shorter than a year, *2* is any term 1–10 years long, and *3* is any term longer than 10 years. With regard to employment, most credit users fall into the second category.

9) Credit history length

Credit history length is the number of years since a user had their first line of credit opened. It should be noted, however, that borrowers are not required to disclose any extra information about their previous loans (term, size, contract breaches etc). Credit history length may also have a positive effect on borrower reliability, that is, credit history length may be expected to be positively correlated with interest rate premium.

10) Number of loan requests over the last six months

The number of times a user has sought to take out a loan in the last six months takes the value of 1 to 6 in increments of 1. This indicator may be analysed in terms of borrower reliability. Presumably, more frequent credit users have a hard time managing their income and expenses, which makes them a greater risk for the creditor, so that they should expect a higher interest rate and, by extension, a higher premium. Therefore the correlation between this parameter and the dependent variable is assumed to be a positive one.

11) Number of years since last delinquency

Within the given sample the number of years that have passed since the user's last delinquency on a credit contract varies from 0 to 10 years. For a sample of 8 000 respondents this is a rather substantial figure. Still, in should be noted that the platform does not disclose what kinds of delinquencies get noted down. There is a possibility that this involves every kind of delinquency up to a single day's delay, which may help explain the figure. Another explanation may lie in the fact that, according to the data, the majority of loans are taken out to pay off existing debts, which means these users find themselves unable or unwilling to finance their debts out of their personal savings, and, when the latter are lacking, often find themselves in breach of their credit obligations.

This parameter, just like the 'age' of disputes, litigations etc, may be viewed as a measure of borrower reliability. That is, a longer period since the last delinquency means a longer positive credit history, hence a greater degree of borrower reliability that translates into a lower interest rate and a smaller premium. The present analysis employs this criterion as the variable *years_since_last_delinq*. Its correlation with the dependent variable is expected to be negative or inverse.

12) Rate of revolving credit use

The rate of revolving credit use is calculated as a ratio of total proceeds of credit to total amount of revolving credit lines opened to a borrower. For the reviewed sample it is less than 0.5. Higher ratio means more active use of existing credit lines, higher liabilities, hence lower borrower reliability. So that yet another credit extended to such a borrower will have to have a higher interest rate and interest premium. Therefore the correlation between this parameter and the dependent variable is assumed to be positive.

5. Choice of model

The above data represents a set of socioeconomic parameters collected under relatively fixed conditions, a set of independent data sampled from the general population. This data, therefore, can be classified as cross-sectional.

The ordinary least squares (OLS) method, provided that model preconditions are met, is a well-proven tool for analysing cross-sectional data. Meeting these preconditions is necessary for the model to produce reliable results. Failing to do so leads to a bias in coefficient estimation and, consequently, to modelling and forecasting errors.

There are two major problems analysts working with cross-sectional data have to face because of unfulfilled preconditions: multicollinearity and heteroscedasticity.

Multicollinearity occurs when the precondition of regressor independence is not met. One of the ways of identifying the problem is to build a correlation matrix. The rule of thumb is that multicollinearity occurs when the module's correlation rate is higher than 0.7. However, this rule is not absolute, since, when other correlation rates converge to zero, a rate of (module) correlation of just 0.4 can cause multicollinearity. A more reliable way of testing for this problem is comparing what the model's individual t-stats and the group's F-stat are saying about coefficient significances. A conflict between the two tests speaks of multicollinearity. This generally involves the F-statistic indicating that the regression's combined coefficients are significant, while individual t-statistics are saying their respective coefficients are not significant. The two most popular methods of solving the problem of multicollinearity are transforming or eliminating one of the variables involved, leaving the one that contributes the most to the model's quality. The most common transformation is, when theoretically justified, to merge the correlated variables into a single parameter (relation, coefficient etc). Also widespread is the logarithmic transformation, which is also useful for normalising the data.

The present model reveals that several variables (form of residential property ownership, credit history length, employment, and loan purpose) have a potential to cause multicollinearity because of their high (but not critically so[1]) correlation with other variables. Consequently, making the final conclusion requires analysing the results of the regression analysis.

Heteroscedasticity occurs when the condition of the standard deviations of regression residuals being constant is not met. The residual is the difference between the observed value of a dependent variable and its predicted (judging by the resulting coefficients) value. To test regression residuals it is necessary to make a residuals plot for each of the regressors. It is possible to say that no heteroscedasticity is present when the residuals are evenly distributed regardless of regressor values. Another precondition for the model to function properly is for the residuals' expected mean to be 0. This is also easy to check on a scatter plot. In case of heteroscedasticity, there are two methods for solving the problem: calculating the statistics with adjusted standard errors and correcting the initial coefficients by using the generalised least squares method (GLS).

6. Full regression model analysis

The regression was built using 80 000 initial observations and 15 variables (8 of them dummy).

Regression analysis has shown[2] that the model has an abnormally high rate of determination ($R^2 \approx 98.82\%$). However, also present was the previously mentioned problem of discrepancy between group F-test and individual t-tests results. The overall significance test calls for the hypothesis that all regression coefficients are 0 to be rejected (F-stat P-value being less than 0.01), while individual tests of coefficient significance say that, applied to individual coefficients, the hypothesis cannot be rejected in more than half the number of cases (t-stat's P-value being greater than 0.1). Given this and the fact that a substantial degree of correlation was detected between the problem variables and the rest, one can be fully certain that multicollinearity is indeed present. Since there is no possibility of putting the offending variables through any sort of transformation, they have to be excluded from the model.

7. Abbreviated regression model analysis

Analysis of the abbreviated regression model[3] shows that the problem of multicollinearity has indeed been successfully solved. Both tests (F and t) show all regression coefficients to have a high degree of significance (at the 5% level).

The model was further tested for heteroscedasticity by plotting the residuals for each of the regressors[4]. The error distribution plot corresponds to that of white noise distribution (errors distributed independently of the regressors, with a mean of 0), which indicates absence of heteroscedasticity.

Out of the initial 12 parameters, the reduced regression model had 1 dependent variable and 6 regressors left.

The general regression equation is as follows:

The results allow making the conclusion that the correlations defined by the model coincide with the ones

$$Premium = 0{,}052 + 0{,}000585 \cdot term + 0{,}0065376 \cdot grade + 0{,}000158 \cdot inq_{last_{6m}} -$$

that had been determined analytically.

- Borrowers seeking 5-year loans, all other things being equal, must expect a premium that is 0.000585 percentage points (0.0585%) higher than that of borrowers seeking 3-year loans;

1 See Appendix 1

2 See Appendix 2

3 See Appendix 3

4 See Appendix 4

- A one-step adjustment in a user's credit rating (e.g., being downgraded from A1 to A2), other things equal, triggers a change (a rise) in interest rate premium of 0.0065376 percentage points (0.654%);
- An increase of 1 in the number of loan requests within the current six-month period, all other things being equal, triggers a rise in interest rate premium of 0.000158 percentage points (0.0158%);
- An increase in the number of years since last credit delinquency, other things equal, triggers a fall in interest rate premium of 0.0000178 percentage points (0.00178%);
- A 0.1 increase in the rate of revolving credit use, other things equal, triggers a rise in interest rate premium of 0.000035 percentage points (0.0035%)[5];
- A 0.1 increase in the borrower's debt to income ratio, other things equal, triggers a rise in interest rate premium of 0.00012 percentage points (0.012%)[6].

Indices with the highest degree of magnitude are *credit rating* and debt to *income ratio*. The one with the lowest degree of magnitude is the n*umber of years since last delinquency*.

Indices found to have no significance are *employment, loan purpose, form of residential property ownership*, and c*redit history length*. This may be due to the fact that, as was mentioned earlier, LendingClub does not record these parameters with a sufficient degree of detail. As for *loan purpose* and f*orm of residential property ownership*, their lack of significance may be explained by a number of facts. Firstly, noone is checking each and every bit of self-reported information. Secondly, noone is checking what the borrower actually spends their money on. There is no system of accountability. Thirdly, the *loan purpose* parameter is supposed to reflect the size of the loan, but in this case all loans are capped at $35 000.

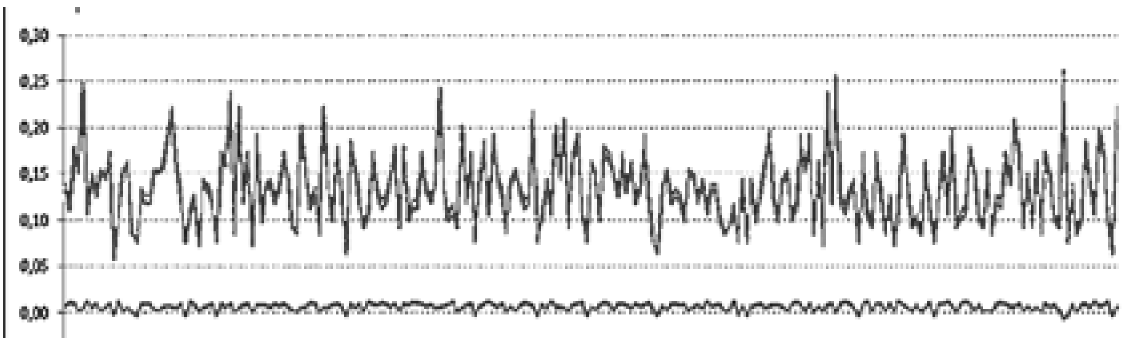
Annual income and *loan size* were merged into a single coefficient *debt to annual income ratio*.

Performing regression analysis on the model showed it to have a high rate of determination ($R^2 \approx 98.82\%$). The model has a high predictive strength.

The model correctly predicts the size of the premium in 94% of cases. This was confirmed by testing the model on the data deliberately excluded from the sample. Diagram 2 clearly shows the results of this test in three graphs: the red one (*Ypred.*) is the premium the model calculated using the resulting regression equation. The green one (*Yobs.*) is the premium set by the platform and applied when crediting its users. The blue one (*Error*) is the forecasting error, the deviation between predicted and actual values. The graph shows it to be very small. The fact that the first two graphs are virtually identical indicates that the quality of the model is very high. The fact that the blue graph (*Error*) only marginally deviates from zero is a quantitative proof of the high probability of correct forecasts of the interest rate made using this model

Diagram 2. Test of model forecasting strength

Source: own calculations



5 Here the variable cannot change in increments of 1 because it is expressed in fractions and varies between 0 and 1. Hence the coefficient gets multiplied by 0.1 instead of 1.

6 Here the variable cannot change in increments of 1 because it is expressed in fractions and varies between 0 and 1. Hence the coefficient gets multiplied by 0.1 instead of 1.

8. Conclusions

To reduce the interest rate on a loan the borrower must have the highest credit rating, a small debt to annual income ratio, a minimal rate of revolving credit use, no incidents of credit delinquency during the last 10 years, make the smallest number of loan requests in the previos six months, and be applying for a loan with a 3-year maturity.

9. References

1. Bachmann, A., Becker, A., Buerckner, D., Hilker, M. Kock, M., Lehmann, M. and Tiburtius, P. "Online peer-to-peer lending – a literature review", Journal of Internet Banking and Commerce, vol. 16, №2, 2011.

2. Binjie Luo, Zhangxi Lin. A decision tree model for herd behavior and empirical evidence from the online P2P lending market. Inf Syst E-Bus Manage, 2013.

3. Eric C. Chaffee, Geoffrey C Rapp. "Regulating Online Peer-to-Peer Lending in the Aftermath of Dodd-Frank: In Search of an Evolving Regulatory Regime for an Evolving Industry." University of Toledo Legal Studies Research Paper No. 2012-04

4. Freedman, S. and Jin, G. Z. "Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com", NET Institute Working Paper, Vol. 08-43, November 2008.

5. Frerichs, A., Schumann, M. Peer to Peer Banking – State of the Art. Gottingen, 2008

6. Herzenstein, M., Andrews, R. L., Dholakia, U. M., Lyandres, E. (2008). The Democratization Of Personal Consumer Loans? Determinants Of Success In Online Peer-To-Peer Lending Communities. 2008.

7. Hulme, M. K., Wright, C. "Internet Based Social Lending: Past, Present and Future", Social Futures Observatory: London, October 2006.

8. Iyer, R., Khwaja, A.I., Luttmer, E. F., Shue, K. "Screening peers softly: inferring the quality of small borrowers" NBER Working Paper No. 15242, August 2009.

9. Loureiro, Y.K., Gonzalez, L. "When can a photo increase credit? The impact of lender and borrower profiles on online peer-to-peer loans", International Journal of Bank Marketing, 2014.

10. Moenninghoff, S. C., Wieandt, A. "The Future of Peer-to-Peer Finance", Zeitschriftfür Betriebswirtschaftliche Forschung, August/September 2013 – pp. 466-487.

11. Serrano-Cinca, C., Gutiérrez-Nieto, B., López-Palacios, L., "Determinants of Default in P2P Lending", PLoS ONE, 2015.

12. Slattery, P. "Square Pegs in a Round Hole: SEC Regulation of Online Peer-to-Peer Lending and CFPB Alternative", Yale Journal on Regulation, vol. 30, 2013.

13. Verstein, A. "The Misregulation of Person-to-Person Lending", UC Davis Law Review, Vol. 45, No. 2, 2011.

14. Wen, X., Wu, X. "An Analysis of Factors to Influence Successful Borrowing Rate in P2P Network Lending-A Case Study of the Paipai Lending", Finance Forum, No. 3, 2014 – pp. 3-8.

15. Yandiev M. The Theory Of Finance: A Novel Finance Model Being Formed On The Internet. Russian Review (Русское обозрение), №1, 2015. – http://rusreview.com/journal/vol-1-2015/31-the-theory-of-finance-a-novel-finance-model-being-formed-on-the-internet.html

16. Yang, Y. Analysis and Assessment of Credit rating model in P2P lending, An instrument to solve information asymmetry between lenders and borrowers / Master of Science in Management Studies / 08.05.2015 – MIT Sloan School of Management

17. Zeng, R. "Legal Regulations in P2P Financing in the US and Europe", US-China Law Review, vol. 10: 229, 2013 – pp. 229-245.

18. Zhang, Y., Yang, Z., Pan, H. "Influencing Factors of Online P2P Lending Success Rate in China" the National

Natural Science Foundation of China (No.61309029, 61273293) and Ministry of Education Humanities Social Sciences Research Project (No.11YJC880163), 2015.

19. Мальцев А.И. Моделирование кредитного риска при peer-to-peer кредитовании / Выпускная квалификационная работа / Пермь, 2014 г.

10. Appendices

Appendix 1

Table 1. Regressor pair correlation matrix

	term	grade	inq_ last_ 6m	years_ since_ last_ delinq	revol_ util	debt_ to_ income	home_ own	home_ rent	credit_ history_ length	employ-ment	purpose_ car	purpose_ home	purpose_ debt_ consoli-dation	purpose_ small_ business	purpose_ cnsumer_ credit
term	1														
grade	-0.05	1													
inq_last_6m	0.01	0.22	1												
years_since_last_delinq	0.00	-0.03	0.02	1											
revol_util	-0.10	0.18	-0.11	0.00	1										
debt_to_income	-0.04	0.13	-0.09	0.03	0.07	1									
home_own	0.02	0.01	0.00	0.01	-0.04	0.04	1								
home_rent	0.10	0.01	-0.03	0.64	-0.03	-0.01	-0.02	1							
credit_history_length	0.03	0.00	-0.44	0.00	0.00	0.00	0.01	0.00	1						
employ-ment	0.53	-0.02	0.01	0.02	-0.04	0.00	-0.02	0.17	0.00	1					
purpose_car	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	-0.02	0.00	1				
purpose_home	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	-0.02	1			
purpose_debt_consoli-dation	0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.11	-0.32	1		
purpose_small_business	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	-0.30	0.00	-0.01	-0.02	-0.12	1	
purpose_cnsumer_credit	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	-0.05	-0.15	-0.57	-0.06	1

Appendix 2

Full regression model results

Model summary	
Multiple R	0.994077865
R-square	0.988190802
Adjusted R-square	0.988188587
Std. error	0.004563083
Observations	80 000

ANOVA

	df	*SS*	*MS*	*F*	*F sig*
Regression	15	139.36	9.29	446 203	0.00
Residual	79 984	1.67	0.00		
Total	79 999	141.03			

	Coefficients	Std. error	t-Statistic	Prob.	Lower 95%	Upper 95%
const	0.052151	0.000123	423.784894	0.000000	0.051910	0.052392
term	0.000572	0.000042	13.698514	0.000000	0.000490	0.000654
grade	0.006537	0.000003	2145.478352	0.000000	0.006531	0.006543
inq_last_6m	0.000160	0.000016	9.968949	0.000000	0.000129	0.000192
years_since_last_delinq	-0.000019	0.000009	-2.151359	0.031451	-0.000037	-0.000002
revol_util	0.000356	0.000074	4.818033	0.000001	0.000211	0.000500
debt_to_income	0.001212	0.000165	7.355325	0.000000	-0.001535	0.008891
home_own	0.000027	0.000058	0.469873	0.638447	-0.000086	0.000141
home_rent	0.000095	0.000035	2.669838	0.007590	0.000025	0.000164
credit_history_length	0.000002	0.000002	0.707263	0.479405	-0.000003	0.000006
employment	-0.000027	0.000024	-1.123822	0.261092	-0.000075	0.000020
purpose_car	-0.000270	0.000199	-1.356122	0.175064	-0.000660	0.000120
purpose_home	0.000118	0.000101	1.168020	0.242802	-0.000080	0.000316
purpose_debt_consolidation	-0.000154	0.000079	-1.935994	0.052872	-0.000309	0.000002
purpose_small_business	-0.000042	0.000186	-0.227046	0.820389	-0.000406	0.000322
purpose_cnsumer_credit	-0.000064	0.000083	-0.767950	0.442519	-0.000226	0.000099

Appendix 3

Abbreviated regression model results

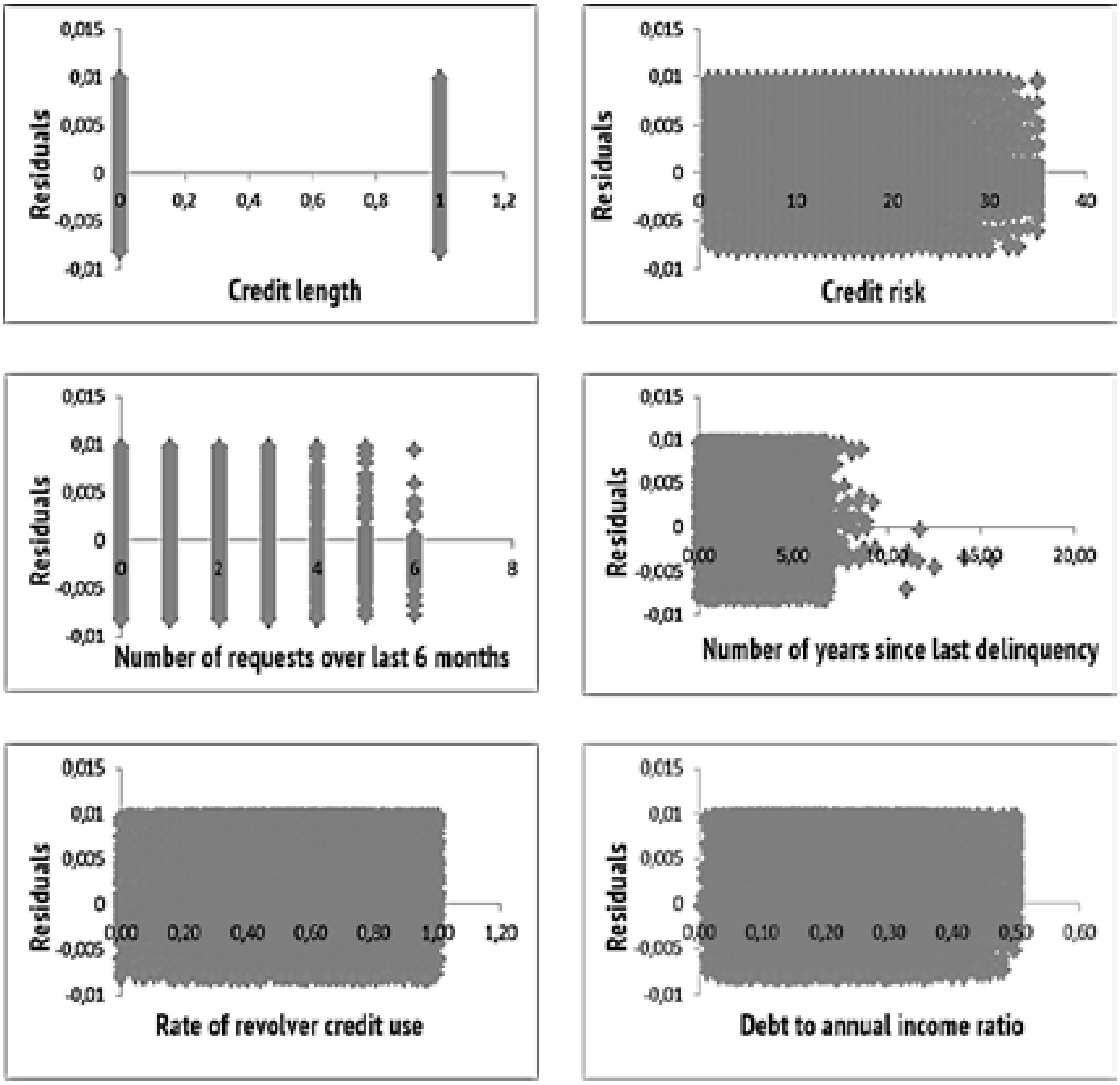
Model summary	
Multiple R	0.898540619
R-square	0.893217349
Adjusted R-square	0.89320934
Std. error	0.00
Observations	80 000

ANOVA

	Coefficients	Std. error	t-Statistic	Prob.	Lower 95%	Upper 95%
const	0.052042	0.000082	636.1935	0.000000	0.051881	0.052202
term	0.000585	0.000041	14.16905	0.000000	0.000504	0.000666
grade	0.006538	0.000003	2155.373	0.000000	0.006532	0.006544
inq_last_6m	0.000158	0.000016	9.839076	0.000000	0.000126	0.000189
years_since_last_delinq	-0.000018	0.000009	-1.994834	0.046064	-0.000035	0.000000
revol_util	0.000348	0.000074	4.730443	0.000002	0.000204	0.000492
debt_to_income	0.001204	0.000165	7.317657	0.000000	-0.001526	0.002408

Appendix 4

Residuals plots by regressor



CONFIRMATION OF THE RELATIONSHIP BETWEEN STOCK MARKET PARAMETERS AND INTERBANK CREDIT MARKET ON THE EXAMPLE OF THE KAZAKHSTAN STOCK EXCHANGE

Magomet Yandiev
Lomonosov Moscow State University, Faculty of Economics
Altana Andzhaeva
Lomonosov Moscow State University, Faculty of Economics

Abstract: The paper presents calculations confirming practical applicability of the earlier formulated theoretical model that explains the relationship between the rate of one-day loans in the interbank market, volume of speculative investments and total securities under which transactions have been closed. The paper is based on the Kazakhstan stock exchange data[1].
Keywords: interbank credit market, equity market, stock market, speculations, trading volumes, KASE .
JEL Classification G12, G14, G17, G21

1. Review of literature

This paper belongs to a series of studies that examine the relationship between the rates of one-day loans in the interbank market and a mumber of stock market parameters.

The original formula (Yandiev, 2011) describes the relationsship in the following way:

- u is the mean loss per a deal involving one stock;

$$u = I * R * \frac{1}{365} * \frac{1}{U}$$

- I is the volume of speculative investments (amount of money on accounts in the authorized bank to the stock exchange and intended for speculations);
- R is the rate of one-day loans on the interbank market, in fractions;
- U is the total amount of stocks involved in the deals;

The logic of the formula means that: the rate of one-day loans on the interbank market is inversely proportional to the number of securities traded on the stock exchange. The formula is purely theoretical as for its proof assumptions were used, but, because of its simplicity, it is quite suitable for implementation of practical calculations. According to the logic of the formula, it can be considered workable in practice if the parameter u remains constant during calculations.

Calculations in the paper of Pakhalov and Yandiev (2013) were carried out on the basis of data received from Moscow Stock Exchange. In another paper (Matveev, 2014) calculations were carried out based on the Bahrain Stock Exchange. In both cases, positive results were obtained, indicating that the formula correctly reflects the relationship of the parameters for the studied time intervals.

It should be noted that stock exchange management usually prefer not to disclose some parameters of the formula, such as the amounts of clients' money and number of securities deposited within the exchange system. This position is understandable as the disclosure of this information under certain circumstances

1 Authors express their gratitude to the management of the Kazakhstan stock exchange and personally to Ms. Zarina Konkasheva for assistance in receiving necessary input data.

may be a bad marketing move capable of undermining investor confidence in the validity of quotations received at the exchange. On the other hand, general lack of such information in free access only aggravates consequences of quite common situations when the quotation of particular issuer is formed at the exchange in the course of trading of absolutely scanty number of actions stocks.

In the present paper, we test the formula using the data of Kazakhstan stock exchange for the period 2010 – 2014.

2. Input data

In order to test the applicability of the formula, the following data provided by Kazakhstan Stock Exchange were used (on a daily basis, for the period 2010–2014.):

- total amount of money deposited within the exchange system in m. tenge (analogue of I parameter, refer to Appendix 1);
- number of stocks (blue chips) deposited in the clearing exchange system, in pcs (U parameter, refer to Appendix 2);
  We examined data on 10 most liquid stocks traded on KASE rather than on all of them, i.e. blue chips: Bank CenterCredit, Kazkommertsbank, KEGOC, Kazakhtelecom, KazMunaiGas Exploration Production, KazTransOil, KAZ Minerals, Kcell, Halyk Bank, Eurasian Natural Resources Corporation;
- fraction of blue chips in the total volume of stock trading, % (this information is needed to be sure that blue chips data are representative and reflect the situation on the stock market, refer to Appendix 3);
- rate of one-day loans on the interbank market, % a year (R parameter, refer to Appendix 4);
- number of securities involved in the stock exchange deals (as the analogue and substitute for the "number of all deposited stocks within the exchange system", refer to Appendix 5).

Verification of practical applicability of the formula is performed as follows. The parameter u is calculated for every day during the entire analyzed period (1232 trading days for 2010–2014). Next, we use two different approaches. The formula will be considered correct if the parameter u has the minimum volatility (the first approach). The formula will be considered correct if the constructed regression equation corresponds to the theoretical model (the second approach)

At the same time in both approaches, the parameter U is substituted in two ways; firstly and mainly as the quantity of all deposited stocks within the exchange system and, secondly, as the quantity of securities involved in the stock exchange deals (the second option).

It is noteworthy that substantially more securities are deposited in the exchange system, than it is necessary for daily trading, 5000 times approximately (refer to Appendix 6). This reserve provides the Kazakhstan Stock Exchange with an extremely high degree of stability in case of a surge in demand for the shares.

3. First approach. Formula verification based on standard deviation of the "u" parameter

The purpose of the first approach is to make sure that the standard deviation of parameter u is insignificant. We calculated mean and standard deviation for both options and plotted graphs for visual analysis of parameter u dispersion degree.

On the basis of performed calculations one can draw the following conclusions:

- If we compare the standard deviation of parameter u with the average value of parameter u for the entire period of our analysis, the range of values of the parameter u looks rather wide, but if we compare the standard deviation with the average quotation per share, the volatility of the parameter u seems to be of insignificant value (refer to Appendix 7).
- From a visual assessment of the u parameter dispersion, it is obvious that in general it is insignificant (refer to Appendices 8, 9, where parameter u is shown in historical sequence and to Appendices 10, 11, where parameter u is shown after sorting «from bigger to smaller»).

Thus, it can be argued that parameter u has low volatility and can be considered as a value close to a constant.

4. Second approach. Formula verification based on linear regression

This approach involves the use of regression analysis of time series in order to identify relationships between the model parameters and to check them for compliance with the theoretical model under consideration.

Input set of data consists of 1232 observations for each of six variables (refer to Appendix 12). Calculations were performed in the Gretl econometric package.

Since the regression analysis of time series requires that all variables be stationary, the first stage of econometric analysis involves an augmented Dickey-Fuller test (ADF) for each of the variables. Lag length in each case was set based on the Schwarz information criterion (SIC). All time series were examined for stationarity excluding trend. Results of tests are given in Appendix 13.

ADF test has shown that all variables except u_big_dep are stationary, therefore the variable has to be tested for cointegration. According to Verbeek M., the existence of cointegration between the variables allows to get super consistent estimates of the model parameters, and the received results will make sense. Residuals of both regressions based on the deposited quantity and trading volume are stationary at 1% level of significance (refer to Appendix 14). It allows us to draw some conclusions:

- The first regression equation is on the whole significant, as well as all its variables. The second equation is insignificant, and only one variable in it has the 10% level of significance, which implies that the option of U calculation as the number of securities involved in the stock exchange deals is unreliable, and the impact of the variables included in the equation on the dependent variable may not even exist.
- Despite this, in both regression equations the I and R variables have positive coefficients, and the variable U has negative coefficient that completely corresponds to the logic of theoretical model.

Thus, the regression analysis confirms the significance of the tested formula.

5. Summary

Results of calculations for both options prove that the tested formula accurately reflects the relationship between parameters of the interbank credit market and the stock market.

Calculation of parameter U as the number of all deposited stocks within the exchange system is more correct, than understanding under it the number of securities involved in the stock exchange deals.

The findings of this work are consistent with the conclusions obtained in the previous similar studies in Moscow (Pakhalov, Yandiev, 2013) and Bahrain stock exchanges (Matveev, 2014).

6. References

1. Yandiev M. The Damped Fluctuations as a Base of Market Quotations // Economics and Management. 2011. N 16. URL: http://ssrn.com/abstract=1919652

2. Yandiev, Magomet and Pakhalov, Alexander, The Relationship between Stock Market Parameters and Interbank Lending Market: An Empirical Evidence (September 23, 2013). Available at SSRN: http://ssrn.com/abstract=2329871

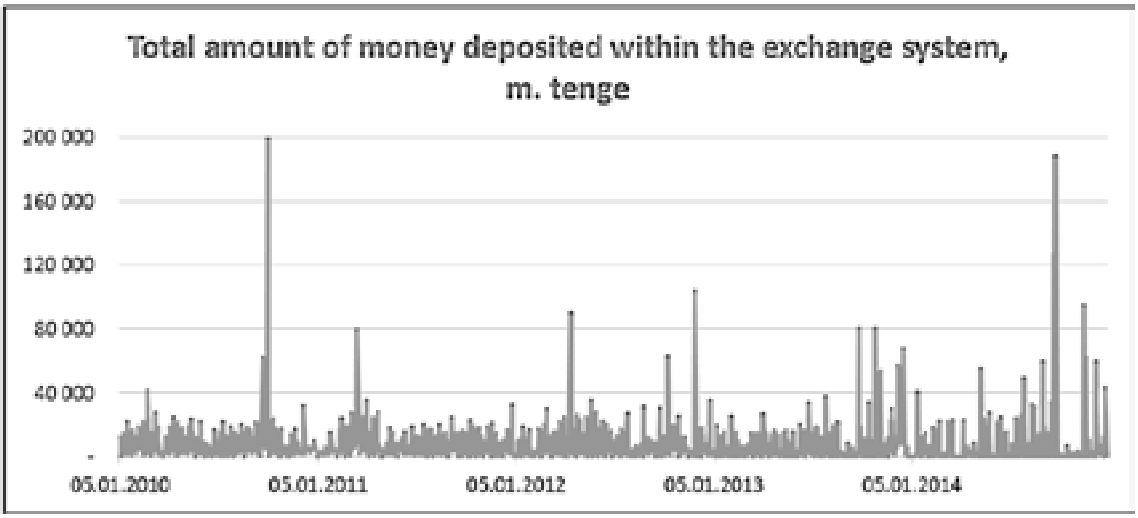
3. Matveev, Aleksandr (2014) «Proving The Association Between Stock Market And Interbank Lending Market Parameters: The Bahrain Stock Exchange». Journal of Russian Review (ISSN 2313-1578), VOL. (0), 21-32. Available at: http://rusreview.com/journal/vol-0-2014/14-proving-the-association-between-stock-market-and-interbank-lending-market-parameters-the-bahrain-stock-exchange-aleksandr-matveev.html

4. Verbeek M. A Guide to Modern Econometrics. 2nd ed. Chichester, 2004.

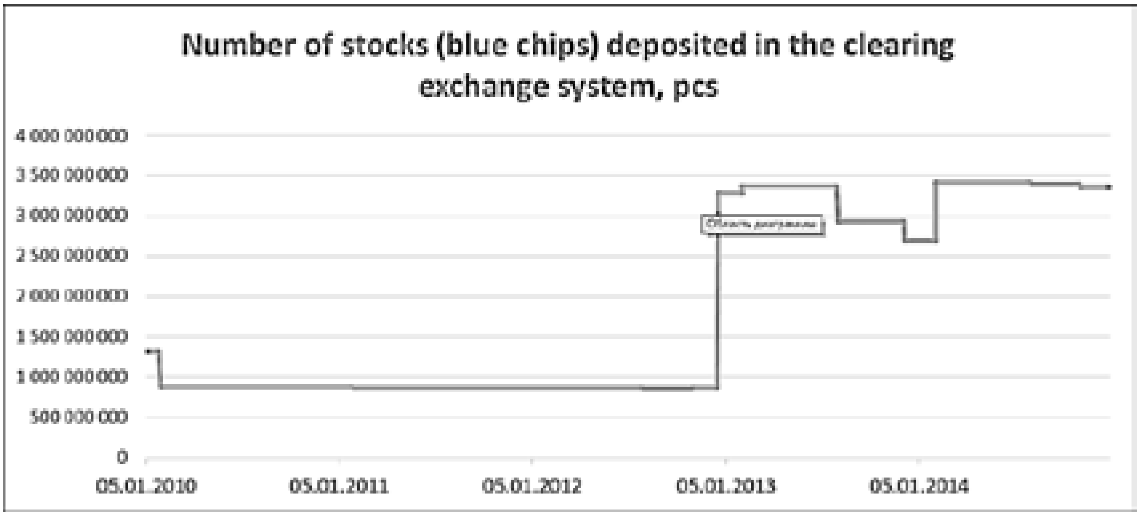
7. Appendices

Appendices 1–6. Input data

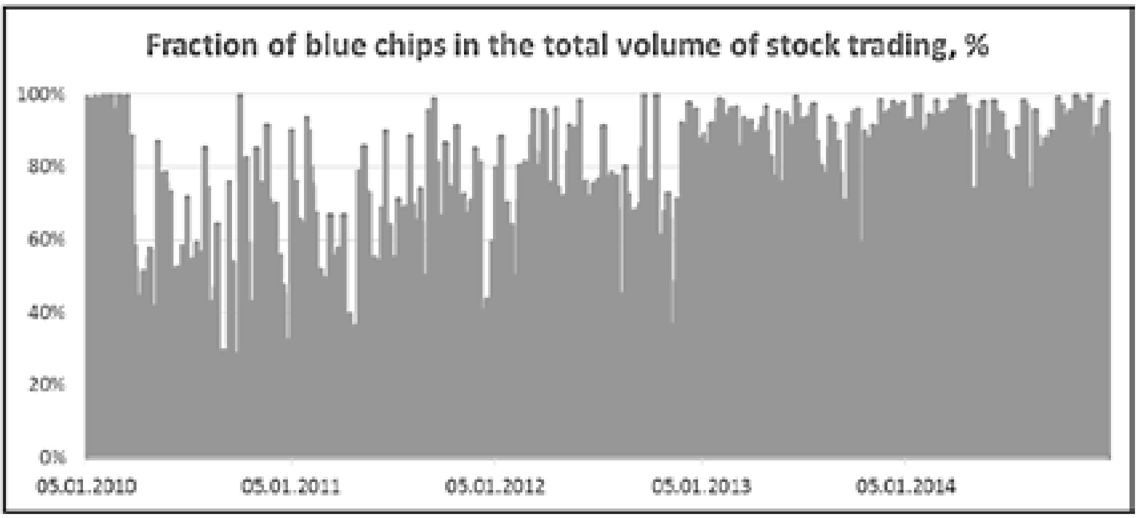
Appendix 1



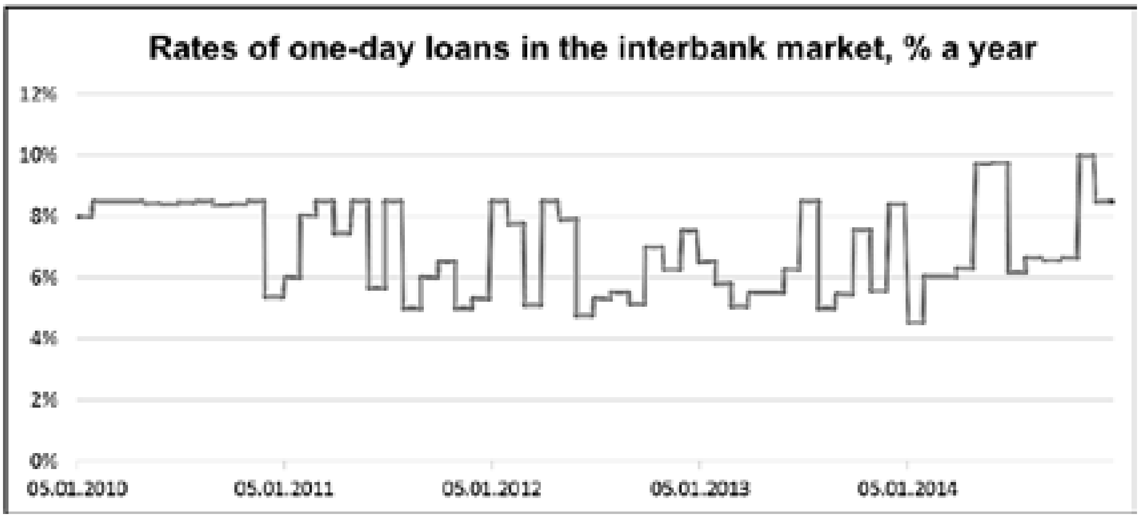
Appendix 2



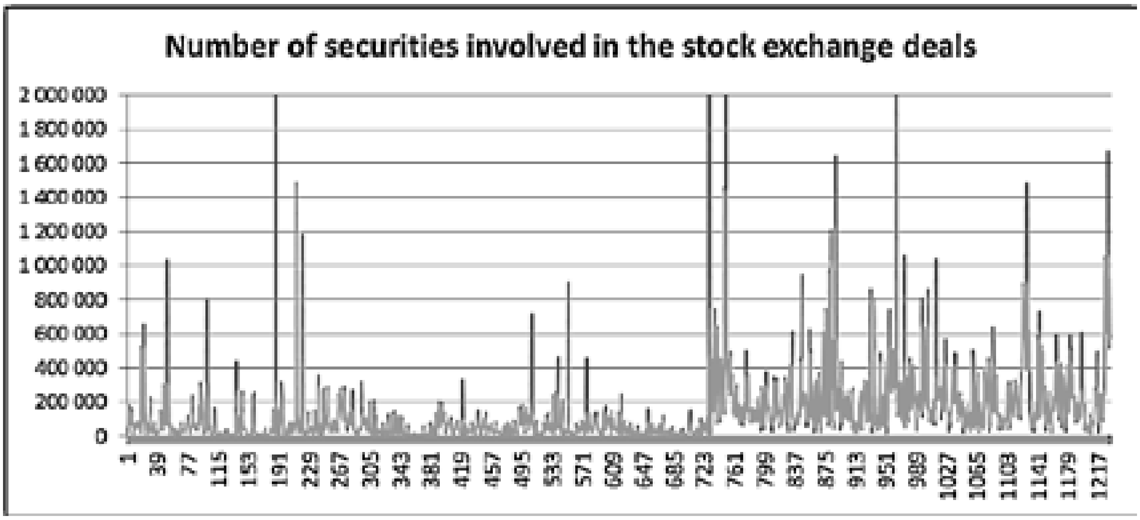
Appendix 3



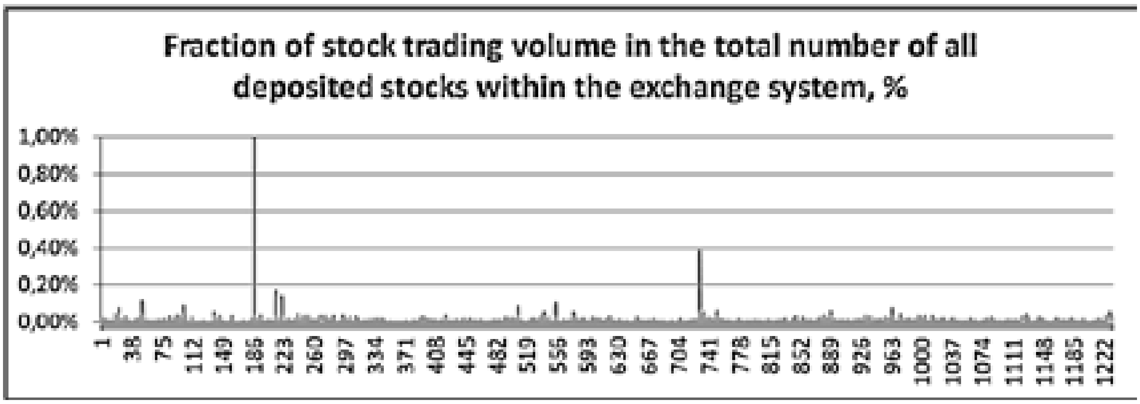
Appendix 4



Appendix 5



Appendix 6

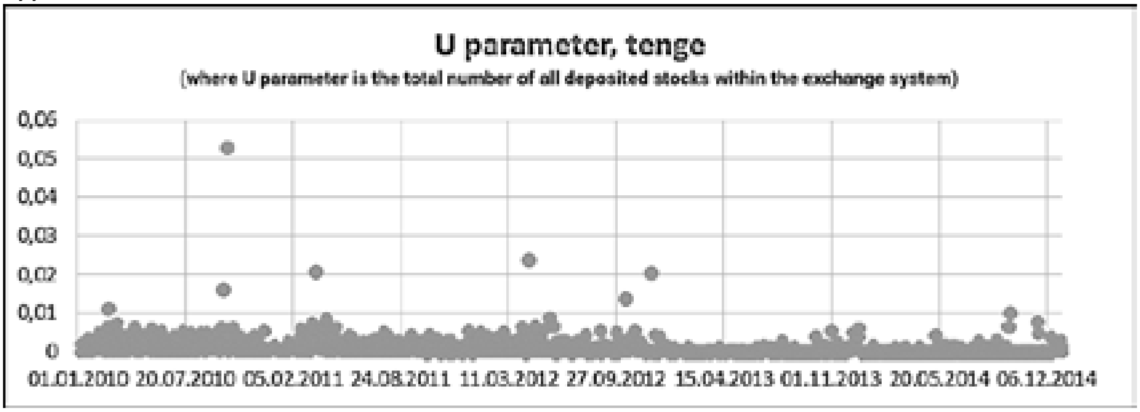


Appendices 7–11. Results of the first approach calculations

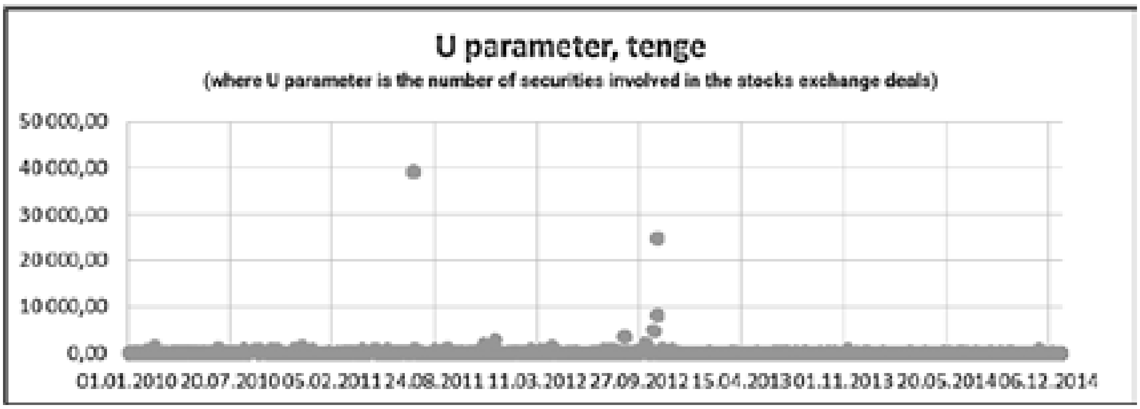
Appendix 7. U parameter calcualtions

	Calculation, where U parameter is the number of securities involved in the stock exchange deals	Calculation, where U parameter is the total number of all deposited stocks within the exchange system
Arithmetic mean, tenge	0,0011	124,90
Standard deviation, tenge	0,0024	1 357,60

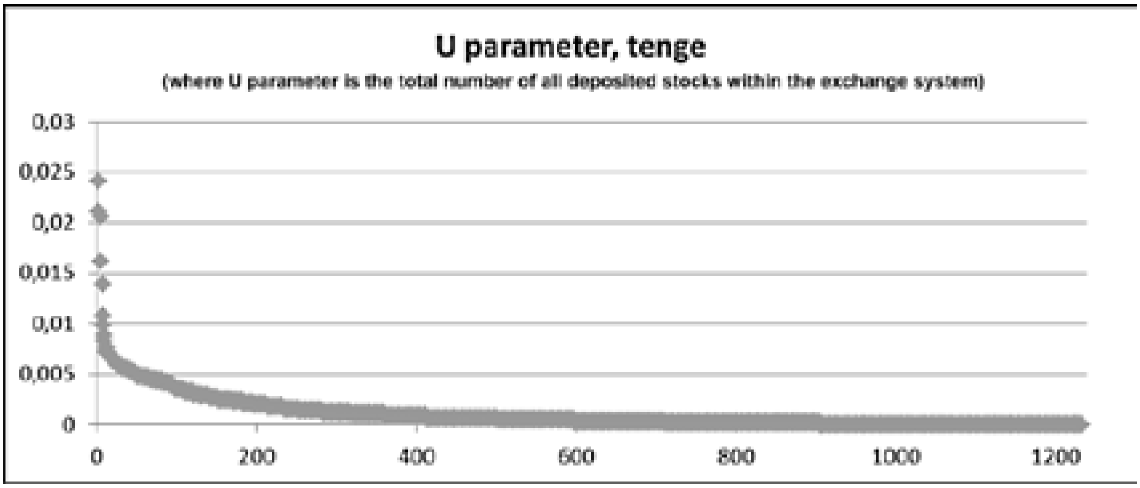
Appendix 8



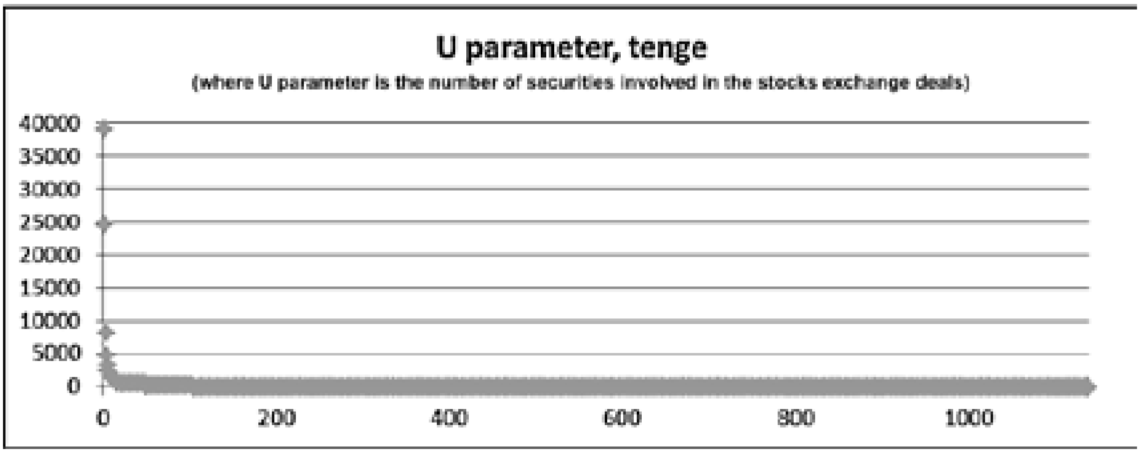
Appendix 9



Appendix 10



Appendix 11



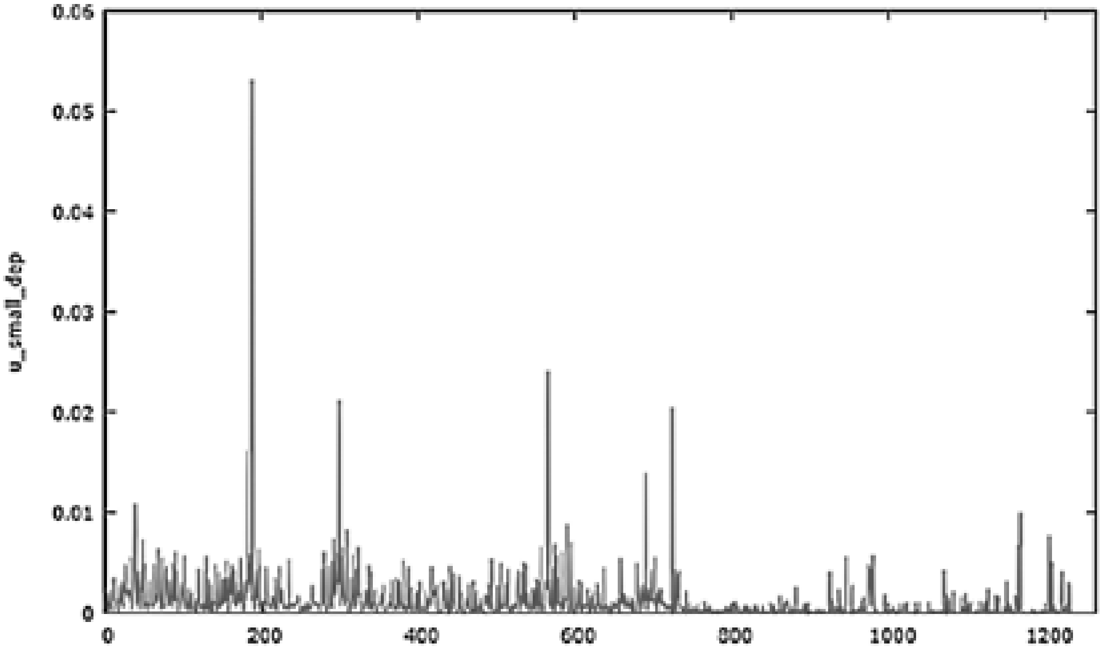
Appendices 12–14. Results of the second approach calculations

Appendix 12

Variable name in the theoretical model	Variable name in Gretl	Definition
u	u_small_dep	Mean loss per deal involving one stock (calculated using the amount of deposited stocks)
u	u_small_vol	Mean loss per deal involving one stock (calculated using the amount of stocks involved in deals)
I	I	Volume of speculative investment (amount of money in the exchange's authorized bank)
R	R	Rate of one-day loans in the interbank market
U	U_big_dep	Total amount of deposited stocks within the exchange system
U	U_big_vol	Total amount of stocks involved in the stock exchange deals

Appendix 13

13. 1 Unit root test for u_small_dep



Augmented Dickey-Fuller test for u_small_dep

including 18 lags of (1-L)u_small_dep (max was 22)

sample size 1213

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.001

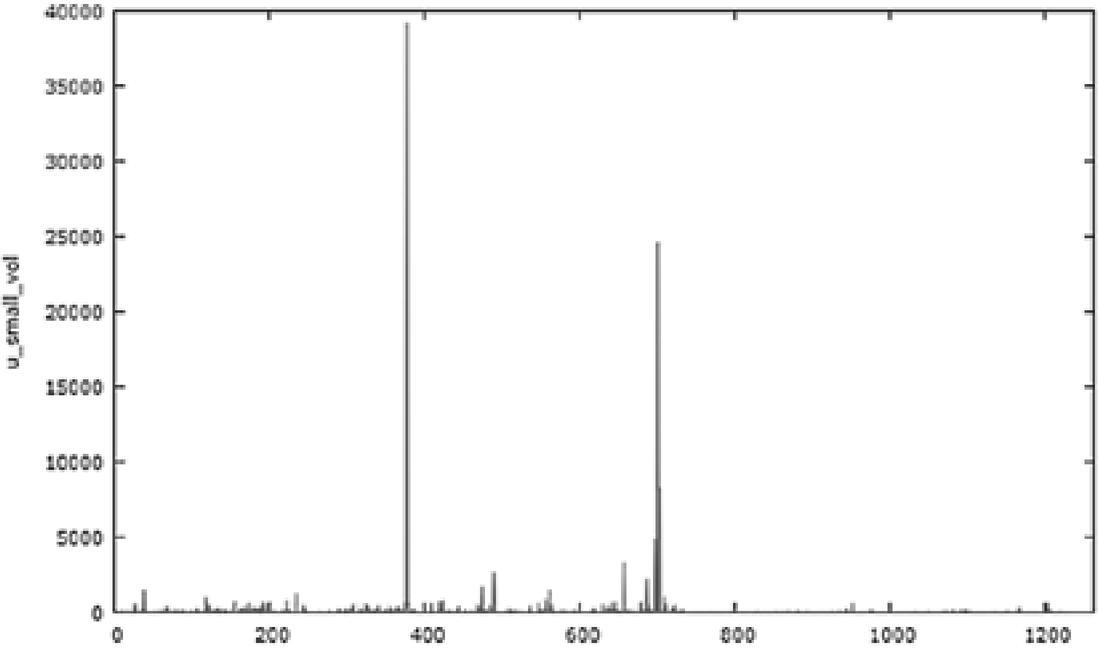
lagged differences: F(18, 1193) = 6.776 [0.0000]

estimated value of (a - 1): -0.363392

test statistic: tau_c(1) = -5.24083

asymptotic p-value 6.397e-006

13.2 Unit root test for u_small_vol



Augmented Dickey-Fuller test for u_small_vol

including one lag of (1-L)u_small_vol (max was 22)

sample size 1230

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

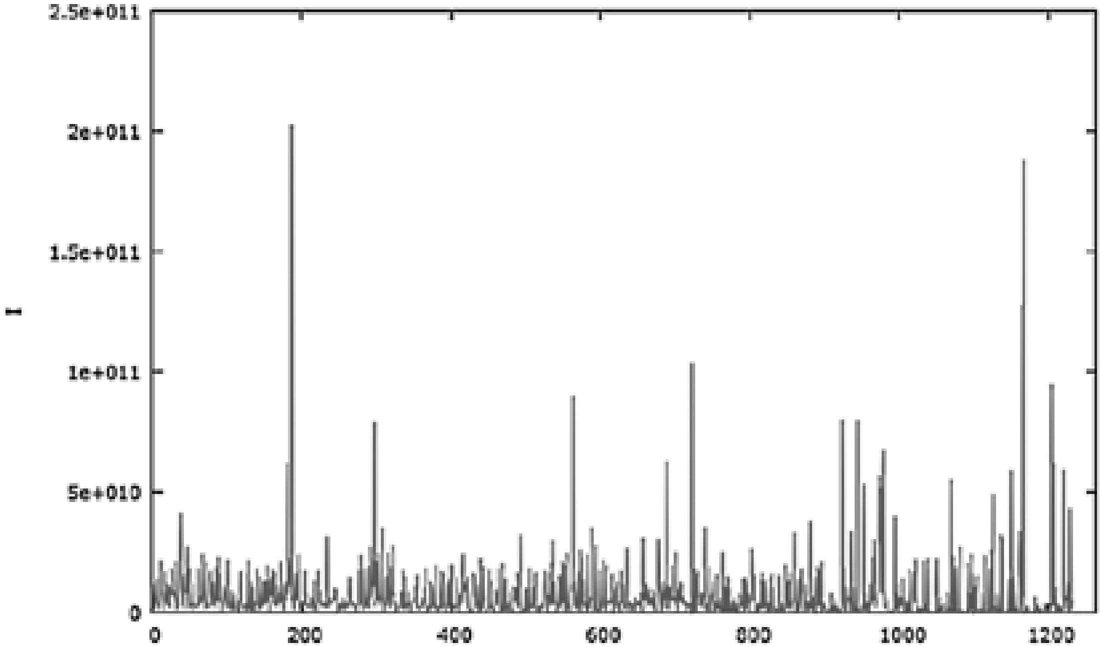
1st-order autocorrelation coeff. for e: 0.000

estimated value of (a - 1): -0.886475

test statistic: tau_c(1) = -22.1575

asymptotic p-value 1.601e-050

13.3 Unit root test for l



Augmented Dickey-Fuller test for l

including 17 lags of (1-L)l (max was 22)

sample size 1214

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.001

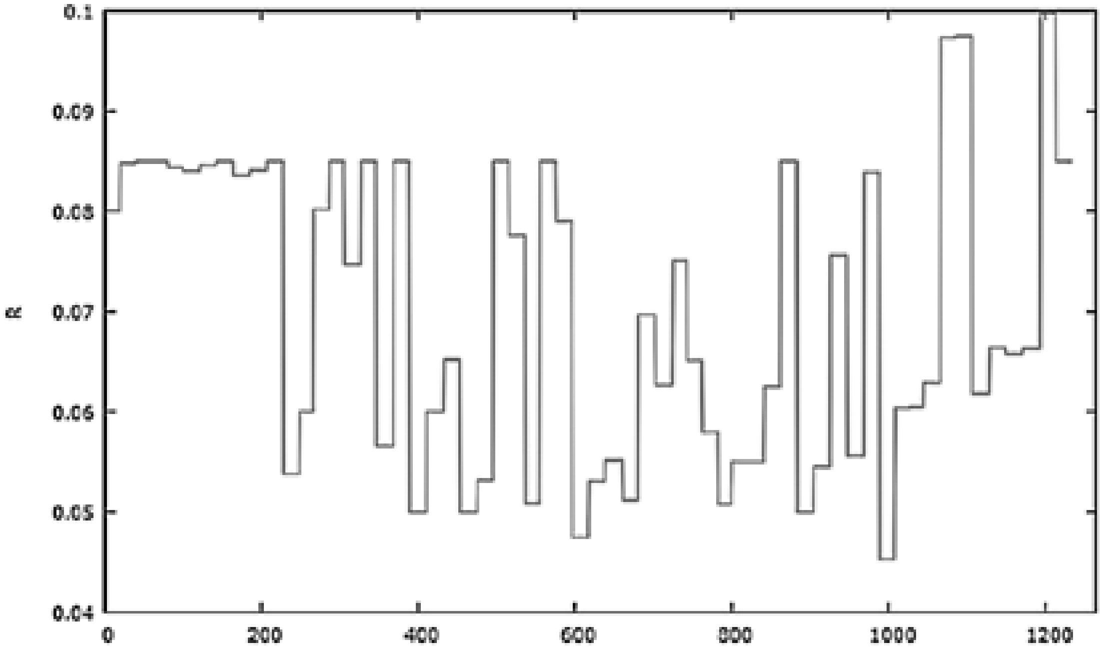
lagged differences: F(17, 1195) = 2.007 [0.0088]

estimated value of (a - 1): -0.793051

test statistic: tau_c(1) = -7.75998

asymptotic p-value 2.491e-012

13.4 Unit root test for R



Augmented Dickey-Fuller test for R

including 22 lags of (1-L)R (max was 22)

sample size 1209

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: 0.001

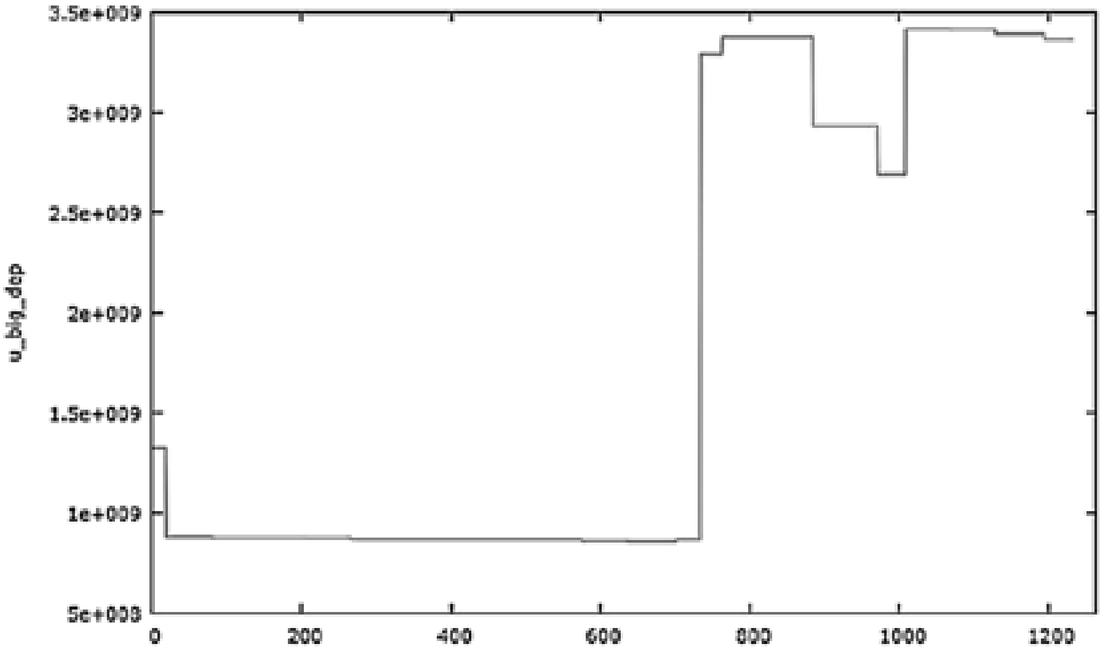
lagged differences: F(22, 1185) = 2.461 [0.0002]

estimated value of (a - 1): -0.0349829

test statistic: tau_c(1) = -3.67816

asymptotic p-value 0.004453

13.5 Unit root test for u_big_dep



Augmented Dickey-Fuller test for u_big_dep

sample size 1231

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + e

1st-order autocorrelation coeff. for e: 0.000

estimated value of (a - 1): -0.00140949

test statistic: tau_c(1) = -0.778644

p-value 0.8242

Augmented Dickey-Fuller test for d_u_big_dep

sample size 1230

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + e

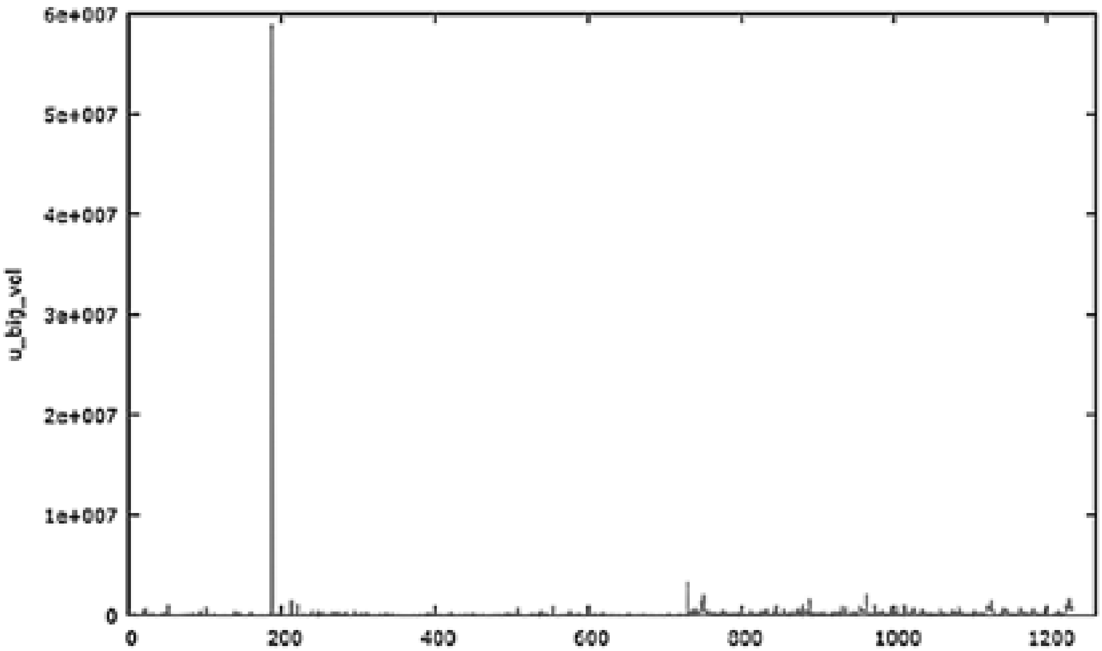
1st-order autocorrelation coeff. for e: -0.000

estimated value of (a - 1): -1.00049

test statistic: tau_c(1) = -35.0601

p-value 9.696e-025

13.6 Unit root test for u_big_vol



Dickey-Fuller test for u_big_vol

sample size 1231

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + e

1st-order autocorrelation coeff. for e: -0.000

estimated value of (a - 1): -1.00024

test statistic: tau_c(1) = -35.0651

p-value 9.836e-025

ADF test results summary:

Variable name in Gretl	ADF test result
u_small_dep	Variable is stationary at the 1% level of significance
u_small_vol	Variable is stationary at the 1% level of significance
I	Variable is stationary at the 1% level of significance
R	Variable is stationary at the 1% level of significance
U_big_dep	Variable is stationary in first differences at the 1% level of significance
U_big_vol	Variable is stationary at the 1% level of significance

Appendix 14

14.1 Calculation with amount of deposited stocks

Linear regression of u_small_dep using u_big_dep, I, R and constant

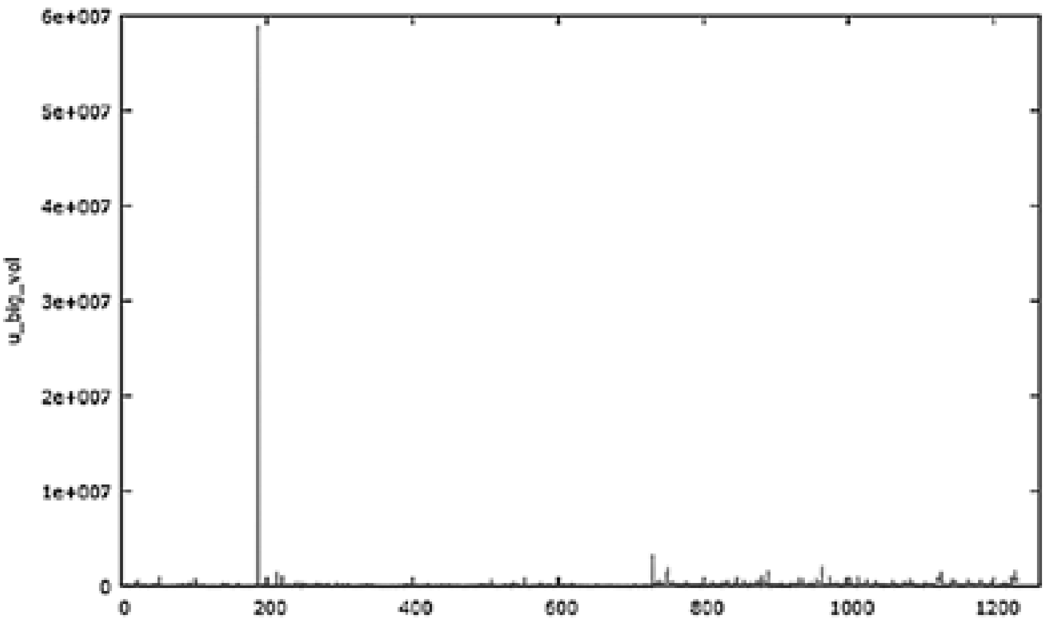
Model 1: OLS, using observations 1–1232

Dependent variable: u_small_dep

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−5.39328e−05	0.000191808	−0.2812	0.77862	
R	1.44129e−013	0	52.9767	<0.00001	***
u_big_dep	0.0148303	0.00249189	5.9514	<0.00001	***
u_big_dep	−4.66606e−013	0	−15.0063	<0.00001	***

Mean dependent var	0.001137		S.D. dependent var	0.002413
Sum squared resid	0.002000		S.E. of regression	0.001276
R-squared	0.721051		Adjusted R-squared	0.720369
F(3, 1228)	1058.078		P-value(F)	0.000000
Log-likelihood	6463.734		Akaike criterion	−12919.47
Schwarz criterion	−12899.00		Hannan-Quinn	−12911.77
rho	0.014530		Durbin-Watson	1.970819

ADF test results for residuals:



Augmented Dickey-Fuller test for u_small_dep_residual

including 5 lags of (1-L)u_small_dep_residual (max was 22)

sample size 1226

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: -0.002

lagged differences: F(5, 1219) = 9.465 [0.0000]

estimated value of (a - 1): -0.671148

test statistic: tau_c(1) = -11.0798

asymptotic p-value 1.053e-022

14.2 Calculation with volume of trade

Linear regression of u_small_vol using u_big_vol, I, R and constant

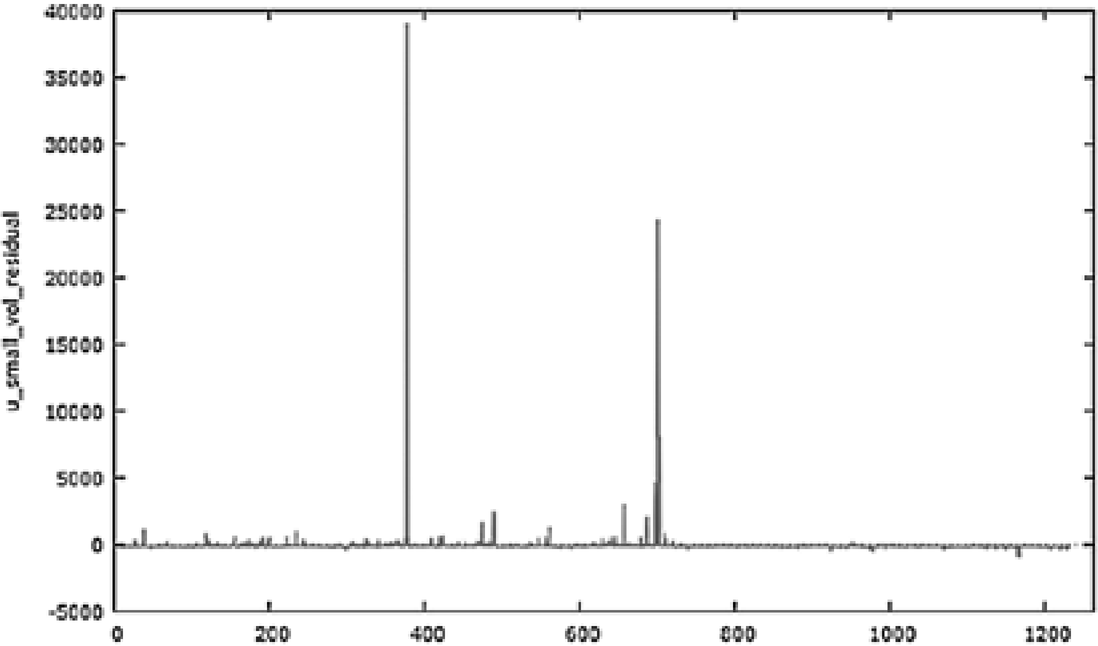
Model 2: OLS, using observations 1-1232

Dependent variable: u_small_vol

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	-48.3371	188.06	-0.2570	0.79720	
I	6.18352e-09	3.17654e-09	1.9466	0.05181	*
R	1934.66	2636.76	0.7337	0.46325	
u_big_vol	-2.8605e-05	2.51251e-05	-1.1385	0.25513	

Mean dependent var	124.9018		S.D. dependent var	1357.595
Sum squared resid	2.26e+09		S.E. of regression	1356.684
R-squared	0.003776		Adjusted R-squared	0.001342
F(3, 1228)	1.551350		P-value(F)	0.199535
Log-likelihood	-10632.30		Akaike criterion	21272.59
Schwarz criterion	21293.06		Hannan-Quinn	21280.29
rho	0.007715		Durbin-Watson	1.984558

ADF test results for residuals



Augmented Dickey-Fuller test for u_small_vol_residual

including one lag of (1-L)u_small_vol_residual (max was 22)

sample size 1230

unit-root null hypothesis: a = 1

test with constant

model: (1-L)y = b0 + (a-1)*y(-1) + ... + e

1st-order autocorrelation coeff. for e: 0.000

estimated value of (a - 1): -0.886062

test statistic: tau_c(1) = -22.1592

asymptotic p-value 1.594e-050

EARLY WARNING SYSTEM FOR BANKING LIQUIDITY CRISES

Alena Starkova
Lomonosov Moscow State University, Faculty of Economics

Abstract. The present paper is a review of two of the most widely used approaches to constructing an early warning system for banking crises: the econometric and the signals approach. Building upon the econometric approach, the paper goes on to construct its own early warning system for banking liquidity crises that, through analysing behaviour of chosen indicators, is able to predict a liquidity crisis one year ahead of its likely onset.
Keywords: banks, liquidity crisis, indicators, financial instability, early warning system
JEL Classification: G01, G21

1. Introduction

Instability in the banking sector, be it through loss of deposits, substantial slumps in lending, bank failures, or one of the many other factors, is a sight not infrequent in both developed and developing economies. The banking sector woes in their turn may soon result in a financial crisis. Therefore, prevention of banking crises plays a pivotal role in maintaining financial stability both domestically and internationally.

A crisis early warning system (EWS) that signals the likelihood of the economy going into a decline within a certain time horizon is one of the measures used to prevent such crises. The present paper aims to construct an econometric approach-based early warning system for liquidity crises that could warn of the event one year ahead of the crunch.

2. Literature review

1990s saw a number of studies that dealt with establishing systems of early warning indicators. These models can be divided into two major groups according to the approach used in their construction: the econometric and the signals models.

The econometric models of crisis early warning systems usually involve constructing a multivariate regression model that would evaluate the correlation between selected indicators (macroeconomic, financial, monetary, etc.) and the probability of a crisis event. This most usually employs bivariate or multivariate logit and probit models, with probit models most often used for predicting currency crises, and logit models for banking, balance of payment, and other types of crises.

Among the first researchers to advocate econometric EWSs were IMF economists Asli Demirgüç-Kunt and Enrica Detragiache. In their 1998 paper *The Determinants of Banking Crises in Developing and Developed Counties* they focused on the economic environment factors that led to banking instability and, therefore, caused banking crises, and used these factors to construct a multivariate logit model [3]. For many researchers this model became their point of reference, and the present paper, too, will be making use of many of its computations.

Demirgüç-Kunt and Detragiache were not the only researchers seeking to design early warning systems for banking crises. Also working on an econometric logit model for predicting banking crises were economists Davis and Karim. Utilising Demirgüç-Kunt and Detragiache's basic method, sources, and indicators, they used a much wider sample of 105 countries in the 1979-2003 period [2].

The economist Kasper Lund-Jensen presented his own fixed effect binary response dynamic model for conditional probability of a systemic banking crisis [5]. His paper identifies several important factors directly linked to risk of crisis in the banking sector: banking sector leverage, the credit-to-GDP gap, changes in the banks' lending premium, equity price growth, the degree of banks' interconnectedness, and real effective exchange rate appreciation. Lund-Jensen also developed a method of translating his systemic risk estimates into crisis probability signals, a method that provided accurate crisis signals in terms of type I and type II errors.

The basic premise of the signals approach is that the economy behaves differently on the eve of financial crises and that this aberrant behaviour has a recurrent systematic pattern manifested in a broad array of economic and financial indicators. Constructing the model, one must select a threshold or critical value that divides the probability distribution of that indicator into two regions. If the observed outcome for a particular variable falls into the rejection region, that variable is said to be sending a signal. If a variable is often seen sending 'good' signals (that is, proving highly efficient), one may expect that the probability of volatility if preceded by a signal (conditional probability) is higher than the unconditional probability.

The signals approach to crisis prognostication was pioneered by Graciela Kaminsky, Saul Lizondo, and Carmen M. Reinhart. It was their 1998 paper *Leading Indicators of Currency Crises* that brought about a widespread use of the signals model [4].

A more integrated approach to constructing a signals-based EWS was introduced by Claudio Borio and Mathias Drehmann. The underlying principles of their model, described in the 2009 paper *Assessing the Risk of Banking Crises*, bear strong resemblance to Kaminsky and Reinhart's, even their method of historical data analysis for the identification and timing of banking crises is identical to the latter [1].

Despite the plethora of different models for predicting future crises developed by various researchers, none of them is totally satisfactory. It is not even possible to determine which approach, the signals or the econometric one, is more efficient.

The present paper will be using the econometric approach to prognosticating crises. The matter is that, choosing the significant variables, authors of signals-based EWSs tend to select macroeconomic indices. It may mean that the signals approach is more sensitive to underlying factors of instability hidden behind systemic failures of economic performance, while its econometric rivals are more sensitive to failings in the financial sector. Since we are more interested in the latter (because errors in the financial sector are taken to be more representative of national peculiarities), the econometric model for predicting liquidity crises was considered to be more appropriate.

3. Method

As stated earlier, the present econometric model of liquidity crisis early warning system will be based on the Demirgüç-Kunt and Detragiache model, and the Davis and Karim model derived from it.

The econometric model of early warning system for liquidity crisis in the banking sector will be based on a multivariate logit model

where x will be the indices (outlined below) characteristic of the onset of a liquidity crisis. Finding the values of the coefficients β will require constructing a learning sample containing data from 40 developing countries

$$p = F(Z) = \frac{1}{1 + e^{-Z}}$$
$$Z = \beta_1 x_1 + \cdots + \beta_n x_n$$

over the period of 1998 to 2012.

Crisis indicators, which the current model will introduce as independent variables, will include

1. Macroeconomic indices:
    a. Real GDP growth
    b. Unemployment rate
    c. Inflation rate
2. Exchange-related indices:
    a. National currency to US dollar exchange rate

b. Foreign currency assets to total assets ratio

3. Internal banking sector indices:

    a. Loan interest and deposit rates spread

    b. Real interest rate

4. Balance sheet banking indices:

    a. Non-performing to total loans ratio (proportion of loans overdue by more than 90 days in total number of loans)

    b. Deposit growth

    c. Liquid assets to current liabilities ratio (liquidity rate)

    d. Volume of created reserves

    e. Liquid reserves to bank assets ratio

5. Real economy indices:

    a. Household consumption

    b. Household savings

Let us specify why each of these indices can be included in the list of indicators.

Indices such as real GDP, unemployment and inflation rates describe the of internal conditions and may indicate that an economy is experiencing systemic difficulties. GDP is representative of the population's standard of living. The larger the amount of finance at people's disposal, the more money will be deposited in bank accounts, and a steady growth means lower risk of premature withdrawals of bank deposits. By contrast, a rise in inflation or unemployment rate means higher risk of premature withdrawals. With prospects of currency depreciation or loss of wage, citizens tend to turn to their savings to complement their income. Real sector indices, like macroeconomic indicators, are representative of how stable an economy is overall.

As was already noted, depreciation of a country's currency makes investing in it significantly less attractive. Among other things, with subsequent currency appreciation the value of assets (loans) will go down and the banks will receive less funds than they expected.

Trends in various interest rates may also serve as an indicator of crises. An upward real interest rate trend indicates that the bank needs to raise substantial additional funds, which may result from its current underliquidity. The same may be said for a fall in interest rates to deposit rates ratio.

A rise in non-performing loans, along with a rise in provisions, means the banking sector is having trouble with its portfolio of assets, and may signify an increased risk of a bad debts crisis, which will inevitably lead to a run by depositors. A slowdown in deposit growth or a negative growth trend will indicate that a run on the banks is probably at hand. A fall in liquid assets to current liabilities ratio may speak of a mismatch in maturities of assets and liabilities on the balance sheet and a possible further increase in liquidity risk.

The second step in finding the values of the β coefficients is to determine the criteria for identifying crisis years to be used by the model.

The present paper's author believes that the most telling indicators of a liquidity crisis are deposit growth, non-performing loans ratio, and liquidity rate. It is these indicators that will be used to determine whether an economy is going through a crisis or not. Therefore, this paper treats an economy as going through crisis if any one of these variables has deviated from its long-term trend downwards (for deposit growth and liquidity rate) or upwards (for non-performing loans ratio) by more than 50%. To build a model for predicting a crisis one year ahead of its onset, it is necessary to ignore all time periods from one year after the onset till after the crisis is over.

Having chosen the criteria for identifying a banking liquidity crisis, we proceed to determining the values of coefficients used by the model. To this end, the log-likelihood function will be employed, as was the case with Demirgüç-Kunt and Detragiache, and Davis and Karim:

The quality of the model built with these coefficients will then be evaluated by testing its efficiency on the data used in its construction.

Since the model's output is the probability of a crisis for a given year, a threshold value must be determined

$$Log_e L = \sum_{i=1}^{n} \sum_{t=1}^{T} [(Y_{it} \, log_e F(\beta^{'X_{it}})) + (1 - Y_{it}) log_e (1 - F(\beta' X_{it}))]$$

beyond which one should start contemplating preventive measures. To do so, a threshold of probability must be selected starting from which an economy will be deemed set to experience a crisis in a year's time. Unlike the previous values, this one will not be calculated by minimizing a total loss function, since parameters like crisis prevention cost (that is, the cost of crisis prevention measures) and crisis recovery costs (that is, the amount of funds expended on compensating for the impact of the crisis) cannot be accurately estimated.

Potential threshold values will be set at 20%, 40%, 60%, and 80%. Each value will be substituted into the model to determine the probability of type I (false positive) and type II (false negative) errors. Since crisis prevention (in case the model returns a false positive) and crisis compensation (in case the model returns a false negative) expenses cannot be accurately evaluated, the threshold value will be decided by overall model accuracy.

As the final test of its operability, the model will be fed the same countries' data from 2013.

4. Intermediate results

When built around the above variables, the logit model, somewhat surprisingly, failed to prove the supposed significance of many of the original indicators (cf. Appendix 1). Only *volume of created provisions* and *non-performing loans ratio* variables were significant at the 5% level, and only *household consumption* and *household savings* variables were significant at the 10% level. Among the worst performing predictors of a future crisis were, surprisingly, the *liquidity rate* and *foreign assets to total assets* variables.

To improve its quality, adjustments were made to the model: instead of absolute values, first order differences of variables were used (see Appendix 2). This time *the interest rate* and *non-performing to total loans ratio* variables were significant at the 5% level, while the *inflation rate, loan interest and deposit rates spread, volume of created reserves*, and *liquid reserves ratio* variables were significant at the 10% level. In addition to that, there was a sharp increase in the significance of how the *foreign assets to total assets ratio* indicator was behaving.

Choosing between the two models, it was decided that Z values should be calculated with β coefficients generated by the second model. The calculations resulted in the following accuracy values:

	Threshold values			
	20%	40%	60%	80%
Events predicted	73.0%	74.3%	79.7%	78.4%
Crisis years predicted	83.3%	33.3%	22.2%	11.1%
Non-crisis years predicted	69.6%	87.5%	98.2%	100.0%

Going by the method of choosing the threshold discussed previously, the ideal threshold value should be set at 60%. In this way the model is able to predict nearly 80% of events. The choice is also deemed well-founded because it enables the model to predict over 98% of non-crisis years, that is, to minimize crisis prevention expenditure in case of a false positive result.

Tested on the 2013 data, the result was 71% accurate. That is, the present model was able to correctly predict 71% of events, while correctly predicting 85% of non-crisis years and 19% of crisis years.

5. Conclusions

1. According to the present model, the most significant indicators of a liquidity crisis are: interest rate, non-performing assets ratio, inflation rate, loan interest and deposit rates spread, reserve growth, and liquid reserves ratio.
2. The present model sends out a signal one year ahead of a crisis whenever its probability exceeds 60%. Depending on their aims, individual users may substitute various threshold values: to maximize the number of correctly forecasted crisis years one must choose a 20% threshold, to maximize the number of correctly forecasted non-crisis years – an 80% one.

6. References

1. Borio, C. and Drehmann, M. (2009) “Assessing the risk of banking crises revisited”, BIS Quarterly Review, March 2009
2. Davis, E.P. and D. Karim, (2008), “Comparing early warning systems for banking crises,” Journal of Financial Stability, 4 (2), 89–120.
3. Demirgüç-Kunt, A. and E. Detragiache, (1998), “The determinants of banking crises in developing and developed countries,” International Monetary Fund Staff Paper, 45 (1), 81–109
4. Eichengreen, B. and Rose, AK. (1998), “Staying afloat when the wind shifts: External factors and emerging-market banking crises”, NBER Working Paper Series 1998.
5. Lund-Jensen, K. (2012), “Monitoring Systemic Risk Based on Dynamic Thresholds”, IMF Working Paper WP/12/159.

7. Appendices

Appendix 1

Model 1: logit, observations 1 to 159

Dependent variable: Crisis

Standard errors – QML

	Coefficient	*Std. Error*	*z*	*Prob.*	
const	−22.8086	11.5277	−1.9786	0.04786	**
GDP	−0.0919857	0.135535	−0.6787	0.49734	
Inflation	−0.0244832	0.0516897	−0.4737	0.63574	
Unemployment	−0.0411338	0.0575689	−0.7145	0.47491	
Exchange_rate	−0.000150038	0.000290081	−0.5172	0.60500	
Interest_rate	0.0437718	0.0873304	0.5012	0.61622	
Spread_of_rates	−0.0844109	0.10353	−0.8153	0.41489	
NPL	−0.372395	0.184153	−2.0222	0.04316	**
Consumption	0.212121	0.113444	1.8698	0.06151	*
Savings	0.260769	0.145212	1.7958	0.07253	*
Deposits	4.12874	3.32037	1.2435	0.21370	

	Coefficient	*Std. Error*	*z*	*Prob.*	
Foreighn_assets	0.00136639	0.0112114	0.1219	0.90300	
Liquidity_rate	−0.00124636	0.0100808	−0.1236	0.90160	
Reserves	1.15026e−013	0	2.3042	0.02121	**
Liquid_reserves	0.0197005	0.0195555	1.0074	0.31373	

Mean dependent var	0.220183	S.D. dependent var	0.416284
McFadden's R-squared	0.237065	Adjusted R-squared	-0.023994
Log likelihood	-43.83692	Akaike info criterion	117.6738
Schwarz criterion	158.0441	Hannan-Quinn criter.	134.0454

f(beta'x) for mean independent var = 0.416

Likelihood ratio: chi–square(14) = 27.2427 [0.0179]

Appendix 2

Model 2: logit, observations 1 to 159

Dependent variable: Crisis

Standard errors – QML

	Coefficient	*Std. Error*	*z*	*Prob.*	
const	-1.77579	0.46919	-3.7848	0.00015	***
GDP	-0.0376588	0.205549	-0.1832	0.85463	
Inflation	0.159227	0.0882775	1.8037	0.07128	*
Unemployment	0.290385	0.186652	1.5558	0.11977	
Exchange_rate	0.0021913	0.00258899	0.8464	0.39733	
Interest_rate	0.259595	0.107047	2.4250	0.01531	**
Spread_of_rates	-0.460876	0.243956	-1.8892	0.05887	*
NPL	-0.223213	0.112613	-1.9821	0.04746	**
Consumption	0.439753	0.507295	0.8669	0.38602	
Savings	0.408848	0.519446	0.7871	0.43123	
Deposits	3.71625	5.7172	0.6500	0.51568	
Foreighn_assets	0.0760201	0.0470772	1.6148	0.10635	
Liquidity_rate	-0.00640899	0.0378503	-0.1693	0.86554	
Reserves	3.51435e-013	1.85219e-013	1.8974	0.05778	*
Liquid_reserves	-0.133402	0.0714644	-1.8667	0.06195	*

Mean dependent var	0.243243		S.D. dependent var	0.431969
McFadden's R-squared	0.208802		Adjusted R-squared	-0.156567
Log likelihood	-32.48219		Akaike info criterion	94.96438
Schwarz criterion	129.5254		Hannan-Quinn criter.	108.7512

f(beta'x) for mean independent var = 0.432

Likelihood ratio: chi-square(14) = 17.1445 [0.2486]

SUKUK VS CONVENTIONAL BONDS: A VALUE-AT-RISK BASED COMPARATIVE ANALYSIS

Bakhshi Kostandyan[1]
Lomonosov Moscow State University, Faculty of Economics

Abstract. The present paper looks into the question of whether including *sukuk* (Islamic bonds) in the bond portfolio provides the investor with diversification benefits and how they what might be quantified. We analysed the sovereign bonds of Bahrain, Pakistan, Qatar, Malaysia, and the UAE. The conclusion is that using sukuk to diversify a portfolio yields substantial benefits.
Keywords: Islamic finance, sukuk, bonds, value-at-risk
JEL Classification: G11, G15, G39

1. Introduction

Over the last decade, Islamic finance as an alternative to traditional finance has been growing at a significant pace. It has gained popularity not only in Islamic countries, but also in countries with a minority Muslim population like Great Britain or Japan. In theory, Islamic finances use the principles similar to those in traditional financing; however, the two differ in their application, structure, and content. In terms of issued volumes, one of the fastest growing instruments of Islamic finance is *sukuk*. Sukuk is a financial security based on Sharia principles that bears external resemblance to a bond. The peculiarities of sukuk's structure, which is different from that of a bond, leave the question of its reliability and diversification benefit for an investor's portfolio open. The present study, therefore, is undertaken to determine whether sukuk is a more reliable financial instrument than a conventional bond in terms of risk, and, specifically, whether it helps the investor to minimise portfolio losses.

2. Literature review

To present a review of literature on the subject separate searches for relevant studies in Russian and English were performed. Russian-language sources were searched for using the Russian Science Citation Index (RSCI) Electronic Library web site (elibrary.ru), English-language ones were searched for using the Social Science Research Network (SSRN) web site (ssrn.com), with the time horizon of 2005 to 2015.

The search at RSCI employed the following keywords (in Russian): *Islamic finance, sukuk, Eurobonds, VaR analysis of sukuk*. The web site's search engine came up with 49 articles, out of which 3 were chosen by their titles and abstracts for further reading. However, upon reading the articles in full all 3 had to be dismissed as not relevant to the subject or having nothing of input for the present study, therefore leaving the Russian-language part of the Literature review section empty.

The search at SSRN employed the following keywords: *sukuk, sukuk and Eurobonds, sukuk value-at-risk*. The web site's search engine came up with 102 articles, out of which 21 were chosen by their titles and abstracts for further reading. However, upon reading the articles in full 18 were dismissed as not relevant to the subject of or having nothing of input for the present study, producing 3 articles for the English-language part of the Literature review section.

The first of these, titled *Comparison between Sukuk and Conventional Bonds: Value at Risk Approach* (Khalid Abbasher Hassan, 2012) deals with various ways to combine sovereign Eurobonds with (international) sukuk of Malaysia and Dubai, as well as corporate Eurobonds and (international) sukuk of these countries. As data

1 Academic advisor: Magomet Yandiyev, Associate Professor, Department of Economics, Lomonosov Moscow State University.

for his analysis, the author uses the bonds' market price for the period of October 30, 2009 (or the earliest available data) to July 18, 2009 (or the latest available data).

The paper looks at three portfolios, one consisting of Eurobonds only (sovereign and corporate), one consisting of sukuk only (sovereign and corporate), and one combining all of the selected bonds (sovereign Eurobonds and sukuk, and corporate Eurobonds and sukuk). For each portfolio VaR calculations were performed, which allowed the author to claim that including sukuk in a portfolio yields diversification benefits. VaR was measured using the delta-normal method.

The study concludes that supplementing a portfolio of conventional bonds with sukuk yields diversification benefits, significantly lowering portfolio risks. At the same time sukuk are found to possess higher market and credit risks compared to conventional bonds owing to the limitations imposed by Sharia laws. Moreover, sukuk introduce additional risks due to a higher correlation between sukuk compared to internal bond correlation.

The paper *Sukuk vs. Eurobonds: Is There a Difference in Value-at-Risk?* (Selim Cakir and Faezeh Raei, 2007) also compares sukuk's reliability in terms of risk to that of the bond. It analyses sovereign sukuk and Eurobonds of Malaysia, Pakistan, Qatar, and Bahrain. The data consisted of sukuk and Eurobonds market values starting from their date of issue or the earliest data available to the end of June, 2007.

This second paper analyses four portfolios, each containing securities (sukuk and Eurobonds) of the corresponding country. The study first calculates VaR for each country portfolio's Eurobonds contents, and then adds the corresponding sukuk part to observe the change in VaR. Two methods are used: the delta-normal method, and the Monte-Carlo method (1% level of significance with a 5-day horizon).

The conclusion is that portfolios combining sukuk and Eurobonds definitely have a lower VaR than Eurobonds-only portfolios. Therefore, including sukuk in a portfolio of Eurobonds may provide diversification benefit. It is also said that the correlation between sukuk and Eurobonds yield is much lower than the correlation between Eurobonds. But the paper argues that sukuk yields are lower than bond yields, and that, owing to a small secondary market, sukuk is an instrument of lower liquidity.

The third paper, titled *Differences and Similarities in Islamic and Conventional Banking* (Muhammad Hanif, 2014), provides a theoretical angle on why, in terms of risk, sukuk is a more reliable financial instrument than the bond.

In points out that in Sharia-based Islamic finance usury is forbidden, therefore the use of bonds creating a creditor/debtor relationship (that is, pure indebtedness) is forbidden, too. Sukuk gives its holder the right to a part of the underlying asset, which the bond holder may lend to the issuer, receiving a rent for its use, and the right to coupon payments. When the bond expires, the sukuk issuer is obliged to buy back the corresponding part of the underlying asset, paying the sukuk off. Therefore, sukuk is creating an owner/renter relationship. The same principle, reminiscent of the lease agreement, lies behind *ijara*, a type of sukuk. Whereas the price of a bond is largely dependent on the quality (rating) of the borrower, the price of sukuk is also influenced by the value of the underlying asset itself, which is a more objective factor. Therefore the paper calls sukuk a more reliable financial instrument than the bond in terms of risks.

3. Data

Serving as data for the present study were market values of sovereign (international) sukuk and Eurobonds of the following countries: Bahrain, Pakistan, Qatar, Malaysia, and the UAE for the period starting from their issue or the earliest (first traded) date available to January 1, 2016. Quotations were taken from official Bloomberg financial databases and the website www.finanz.ru publishing trading summaries from German exchanges. For the list of all the securities used in this study see Appendix, Table 1.

The method for selecting the securities was as follows: first, choosing an issuer that has been issuing both Eurobonds (US dollar bonds listed on international exchanges) and sukuk listed in the US dollars on international exchanges. Therefore, all of the analysed securities share a common currency, the US dollar. The securities were picked on the secondary market, as it provides the data required for turther analysis. Each country had one sukuk and one Eurobond selected.

The present study is not without its limitations, owing to the fact that the number of emitters issuing both international sukuk and Eurobonds is limited, and most of them are sovereign nations. There are virtually no companies that issue both international sukuk and Eurobonds, so the analysis of corporate securities is restricted or impossible to carry out due to scarcity of data. Also noteworthy is the fact that, while the number of sukuk-issuing companies is greater than the number of sukuk-issuing countries, the former are traded either on the primary market (where quotations are unavailable), or on the domestic market (for which there is a limited secondary market, and time-series long enough to be analysed are unavailable). Owing to these restrictions, the scope of the present paper is limited to sovereign sukuk and Eurobonds listed on international exchanges.

4. Method

The present paper compares the reliability of sukuk in terms of risk against that of the bond by comparing VaR values of portfolios containing these securities in various combinations. Each portfolio consists of five securities, but with a different ratio of sukuk to Eurobonds. The description of the portfolios in question and the way they are built is as follows:

1) 5 Eurobonds and 0 sukuk. This combination can form only one portfolio of 5 Eurobonds and 0 sukuk.
2) 4 Eurobonds and 1 sukuk. This type of portfolio gets constructed by taking type 1 portfolio and substituting a single Eurobond for a sukuk of the same issuer. The total number of possible combinations is
3) 3 Eurobonds and 2 sukuk. This type of portfolio is constructed by taking type 1 portfolio and simultaneously substituting two Eurobonds for two sukuk of the same issuer. The total number of possible combinations

   $$\frac{5!}{1! \times 4!} = 5$$

   is
4) 2 Eurobonds and 3 sukuk. This type of portfolio is constructed by taking type 1 portfolio and simultaneously substituting three Eurobonds for three sukuk of the same issue R. The total number of possible

   $$\frac{5!}{3! \times 2!} = 10$$

   combinations is
5) 1 Eurobonds and 4 sukuk. This type of portfolio is constructed by taking type 1 portfolio and substituting

   $$\frac{5!}{2! \times 3!} = 10$$

   four Eurobonds for four sukuk of the same issuer. The total number of possible combinations is
6) Eurobonds and 5 sukuk. This combination can form only one portfolio of 0 Eurobonds and 5 sukuk.

   $$\frac{5!}{4! \times 1!} = 5$$

In total, this makes for 32 different portfolios that provide the corresponding VaR figures for further analysis.

Analysis of the possibility of gaining diversification benefit from including sukuk into a portfolio and comparing it to that of the bond was be carried out using the Value-at-Risk model. A portfolio's VaR value indicates its maximum possible loss of value over a given period with a certain probability. Therefore, by taking a portfolio and swapping one Eurobond for one sukuk of the same issuer while leaving other securities in place, it is possible to compare the two VaR values in order to determine which of the instruments, other things equal, is more reliable in terms of risk and yields greater diversification benefit. The lower a portfolio's VaR, the more reliable in terms of risk it is.

VaR values were measured using the delta-normal method at a 1% level of significance (the possibility of a portfolio having its value fall lower than its VaR figure is 1%) for a time horizon of 1 and 5 days. The delta-normal method is one of the more popular parametric methods of calculating portfolio VaR. This method assumes that asset returns are normally distributed, which, in a stable economy with few major shocks, is consistent with the theory of finance. The present paper likewise assumes that returns on all securities to be analysed are normally distributed. For the returns distribution curves of the selected securities see Appendix, Diagrams 1 to 10.

Portfolio VaR was calculated in three stages. First, each sukuk's and Eurobond's return was calculated using a lognormal formula

where

$$ln(\frac{P_2}{P_1})$$

P_2 is the instrument's new price

P_1 is the instrument's previous price

Then, within a portfolio, individual susuk and Eurobond's VaR values were calculated using the formula

where

$$VaR_i = \alpha \times \sigma_i \times Pos_i \times \sqrt{T}$$

α is the standard normal deviation (that is, 2.33 for a 1% level of significance, or a 99% confidence level);

σ_i is the standard deviation of the security no. i

Pos_i is the investment in security no. i

T is the time horizon (in this case, either 1 or 5 days)

It should be noted that, given the assumed normal distribution of returns for these securities, their theoretical mean distribution would be zero. The proportion of each security in a portfolio is equal. This stage produced for each portfolio a column vector consisting of five VaR values (given the 5 securities in each portfolio).

The final stage saw the calculation of portfolio VaR using the formula

where

$$VaR_p = \sqrt{(VaR)^T \times R \times (VaR)}$$

$(VaR)^T$ is the transposed column vector of individual VaR values;

R is the correlation matrix for all 5 securities in a portfolio;

(VaR) is the column vector of individual VaR values.

The study analysed all possible portfolio combinations, a total of 32 portfolios. See Appendix, Tables 2.1 and 2.2 for calculated portfolio VaR (by what percentage the value of a portfolio can fall within the selected time horizon, compared to its initial value at 99% probability).

5. Findings

1. For the 1-day and 5-day time horizons, the sukuk-only portfolio was found to have a lower VaR than the Eurobonds-only portfolio. For the 1-day time horizon, sukuk-only portfolio VaR (0.4730%) was 0.0777 percentage points lower than a Eurobonds-only portfolio VaR (0.5507%). For the 5-day time horizon, sukuk-only portfolio VaR (1.0576%) was 0.1739 percentage points lower than a Eurobonds-only portfolio VaR (1.2315%). These VaR figures show that for 1- and 5-day time horizons, maximum value loss for a sukuk-only portfolio would, with a 99% probability, be lower than that of a Eurobonds-only portfolio. This indicates that a sukuk-only portfolio is more reliable in terms of risk than a Eurobonds-only portfolio. This may be explained by the fact that the return on a sukuk is underpinned not only by its issuer's credit rating, but also by the underlying asset, a portion of which its holder is entitled to. This finding corroborates the theoretical conclusions of Hanif, 2014.

2. By comparing average portfolio VaR for different sukuk and Eurobond combinations, it is possible to say that, on average, substituting sukuk for a Eurobond of the same issuer lowers the portfolio's VaR (see Appendix, Tables 3.1 and 3.2). This indicates that, on average, substituting sukuk for a Eurobond of the same issuer makes a portfolio more reliable in terms of risk, that is, on average, it lowers the maximum possible loss in portfolio value. Nevertheless, it should be noted that this does not always apply to individual emitters, since in case of Bahrain, for example, substituting sukuk for one of its sovereign bonds leads to a rise in portfolio VaR. This is true for both the 1-day and 5-day time horizons. Also of note is that, analysing changes in average VaR, each subsequent same-issuer Eurobond to sukuk substitution seems to produce a greater drop in VaR, that is, the maximum loss in portfolio value. This means that the more sukuk-heavy a portfolio is, the more pronounced the drop in VaR from same-issuer Eurobond to sukuk substitution will be.
3. Analysing the resulting portfolio VaR, it is possible to conclude that the lowest value corresponds to a portfolio consisting of four sukuk and one Eurobond (a Pakistani Eurobond plus sukuk of other nations). This result is shown in Tables 3.1 and 3.2. A slightly higher VaR corresponds to a portfolio of three sukuk and two Eurobonds and two sukuk and three Eurobonds. This allows us to conclude that, in terms of risk, the most reliable portfolio composition is a mixed one, that is, a portfolio containing both sukuk and Eurobonds, since its VaR is lower than that of sukuk-only or Eurobonds-only portfolios. This finding corroborates the conclusions of Hassan, 2012, and Cakir and Raei, 2007.

6. References

1. Khalid Abbasher Hassan. Comparison between Sukuk and Conventional Bonds: Value at Risk Approach // University of Westminster, September 2012; available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2215194
2. Muhammad Hanif. Differences and Similarities in Islamic and Conventional Banking // National University of Computer & Emerging Sciences, April 2014; available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1712184
3. Selim Cakir and Faezeh Raei. Sukuk vs. Eurobonds: Is There a Difference in Value-at-Risk? // International Monetary Fund Working Paper, October 2007; available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1087156

7. Appendices

Appendix 1. Table 1. Sovereign sukuk and Eurobonds used in the study

Issuer	Type	ISIN	Date of issue	Expiry date	Warrant
Bahrain					
CBB International Sukuk	Sukuk Ijara	XS0708899272	20.11.2011	20.11.2018	6.273% fixed
Bahrain, 2010	Eurobond	XS0498952679	31.03.2010	31.03.2020	5.5% fixed
Pakistan					
Pakistan International Sukuk	Sukuk Ijara	XS1147732553	26.11.2014	26.11.2019	6.75% fixed
Pakistan, 2014	Eurobond	XS1056560763	15.04.2014	15.04.2019	7.25% fixed
Qatar					
State of Qatar Sukuk	Sukuk Ijara	XS0801656330	18.07.2012	18.01.2023	3.241% fixed

Issuer	Type	ISIN	Date of issue	Expiry date	Warrant
Qatar, 2009	Eurobond	XS0423038875	09.04.2009	09.04.2019	6.55% fixed
Malaysia					
Malaysia Sukuk	Sukuk Ijara	USY5749LAA99	15.04.2015	22.04.2025	3.043% fixed
Malaysia, 2015	Eurobond	MYBM01500010	15.09.2015	15.09.2025	3.955% fixed
UAE					
Dubai DOF Sukuk	Sukuk Ijara	XS0778097088	02.052012	02.05.2017	4.9% fixed
Government of Dubai	Eurobond	XS0546428144	04.10.2010	04.10.2020	7.75% fixed

Appendix 2.

Table 2.1. Portfolio VaR for a 1-day time horizon (in % of initial portfolio value)

Portfolio composition					16	eb:B,P,Q suk:M,UAE	26	eb:M,UAE suk:B,P,Q				
					15	eb:B,P,M suk:Q,UAE	25	eb:Q,UAE suk:B,P,M				
					14	eb:B,P,UAE suk:Q,M	24	eb:Q,M suk:B,P,UAE				
					13	eb:B,Q,M suk:P,UAE	23	eb:P,UAE suk:B,Q,M				
					12	eb:B,Q,UAE suk:P,M	22	eb:P,UAE suk:B,Q,M				
			6	eb:B,P,Q,M suk:UAE	11	eb:B,M,UAE suk:P,Q	21	eb:P,Q suk:B,M,UAE	31	eb:UAE suk:B,P,Q,M		
			5	eb:B,P,Q,UAE suk:M	10	eb:P,Q,M suk:B,UAE	20	eb:B,UAE suk:P,Q,M	30	eb:M suk:B,P,Q,UAE		
			4	eb:B,P,M,UAE suk:Q	9	eb:P,Q,UAE suk:B,M	19	eb:B,M suk:P,Q,UAE	29	eb:Q suk:B,P,M,UAE		
			3	eb:B,Q,M,UAE suk:P	8	eb:P,M,UAE suk:B,Q	18	eb:B,Q suk:P,M,UAE	28	eb:P suk:B,Q,M,UAE		
	1	B,P,Q,M,UAE	2	eb:P,Q,M,UAE suk:B	7	eb:Q,M,UAE suk:B,P	17	eb:B,P suk:Q,M,UAE	27	eb:B suk:P,Q,M,UAE	32	B,P,Q,M,UAE
Portfolio VaR	**suk (0) eb (5)**		**suk (1) eb (4)**		**suk (2) eb (3)**		**suk (3) eb (2)**		**suk (4) eb (1)**		**suk (5) eb (0)**	
	1	0.5507	2	0.5795	7	0.6096	17	0.4434	27	0.4811	32	0.4730
			3	0.5857	8	0.5702	18	0.4913	28	0.4391		
			4	0.5422	9	0.5462	19	0.5208	29	0.4849		
			5	0.5179	10	0.5000	20	0.5498	30	0.5157		
			6	0.5001	11	0.5810	21	0.4561	31	0.5719		
					12	0.5507	22	0.4800				
					13	0.5346	23	0.5405				
					14	0.5132	24	0.5308				
					15	0.4815	25	0.5740				
					16	0.4587	26	0.6039				

Key: eb – number of Eurobonds in a portfolio; suk – number of sukuk in a portfolio; B – Bahraini security; P – Pakistani security; Q – Qatari security; M – Malaysian security; UAE – UAE security.

Table 2.2. Portfolio VaR for a 5-day time horizon (in % of initial portfolio value)

Portfolio composition					16	eb:B,P,Q suk:M,UAE	26	eb:M,UAE suk:B,P,Q				
					15	eb:B,P,M suk:Q,UAE	25	eb:Q,UAE suk:B,P,M				
					14	eb:B,P,UAE suk:Q,M	24	eb:Q,M suk:B,P,UAE				
					13	eb:B,Q,M suk:P,UAE	23	eb:P,UAE suk:B,Q,M				
					12	eb:B,Q,UAE suk:P,M	22	eb:P,M suk:B,Q,UAE				
			6	eb:B,P,Q,M suk:UAE	11	eb:B,M,UAE suk:P,Q	21	eb:P,Q suk:B,M,UAE	31	eb:UAE suk:B,P,Q,M		
			5	eb:B,P,Q,UAE suk:M	10	eb:B,M,UAE suk:P,Q	20	eb:B,UAE suk:P,Q,M	30	eb:M suk:B,P,Q,UAE		
			4	eb:B,P,M,UAE suk:Q	9	eb:P,Q,UAE suk:B,M	19	eb:B,M suk:P,Q,UAE	29	eb:Q suk:B,P,M,UAE		
			3	eb:B,Q,M,UAE suk:P	8	eb:P,M,UAE suk:B,Q	18	eb:B,Q suk:P,M,UAE	28	eb:P suk:B,Q,M,UAE		
	1	B,P,Q,M,UAE	2	eb:P,Q,M,UAE suk:B	7	eb:Q,M,UAE suk:B,P	17	eb:B,P suk:Q,M,UAE	27	eb:B suk:P,Q,M,UAE	32	B,P,Q,M,UAE
	suk (0) eb (5)		**suk (1) eb (4)**		**suk (2) eb (3)**		**suk (3) eb (2)**		**suk (4) eb (1)**		**suk (5) eb (0)**	
Portfolio VaR	1	1.2315	2	1.2957	7	1.3631	17	0.9915	27	1.0757	32	1.0576
			3	1.3097	8	1.2749	18	1.0987	28	0.9819		
			4	1.2124	9	1.2213	19	1.1646	29	1.0842		
			5	1.1580	10	1.1181	20	1.2294	30	1.1531		
			6	1.1182	11	1.2991	21	1.0198	31	1.2789		
					12	1.2315	22	1.0732				
					13	1.1953	23	1.2086				
					14	1.1476	24	1.1870				
					15	1.0766	25	1.2836				
					16	1.0257	26	1.3504				

Key: eb – number of Eurobonds in a portfolio; suk – number of sukuk in a portfolio; B – Bahraini security; P – Pakistani security; Q – Qatari security; M – Malaysian security; UAE – UAE security.

Table 3.1. Portfolio VaR and average VaR for different sukuk–Eurobonds portfolio combinations for a 1-day

time horizon (in % of initial portfolio value)

Portfolio combination	suk (0) eb (5)	suk (1) eb (4)	suk (2) eb (3)	suk (3) eb (2)	suk (4) eb (1)	suk (5) eb (0)
Portfolio VaR	0.5507	0.5795	0.6096	0.4434	0.4811	0.4730
		0.5857	0.5702	0.4913	0.4391	
		0.5422	0.5462	0.5208	0.4849	
		0.5179	0.5000	0.5498	0.5157	
		0.5001	0.5810	0.4561	0.5719	
			0.5507	0.4800		
			0.5346	0.5405		
			0.5132	0.5308		
			0.4815	0.5740		
			0.4587	0.6039		
Average combination VaR	0.5507	0.5451	0.5346	0.5191	0.4985	0.4730
Average VaR change (in percentage points)	¬–	-0.0056	-0.0105	-0.0155	-0.0205	-0.0255
Min. VaR of the combination	0.5507	0.5001	0.4587	0.4434	0.4391	0.4730

Table 3.2. Portfolio VaR and average VaR for different sukuk–Eurobonds portfolio combinations for a 5–day time horizon (in % of initial portfolio value)

Portfolio combination	suk (0) eb (5)	suk (1) eb (4)	suk (2) eb (3)	suk (3) eb (2)	suk (4) eb (1)	suk (5) eb (0)
Portfolio VaR	1.2315	1.2957	1.3631	0.9915	1.0757	1.0576
		1.3097	1.2749	1.0987	0.9819	
		1.2124	1.2213	1.1646	1.0842	
		1.1580	1.1181	1.2294	1.1531	
		1.1182	1.2991	1.0198	1.2789	
			1.2315	1.0732		
			1.1953	1.2086		
			1.1476	1.1870		
			1.0766	1.2836		
			1.0257	1.3504		
Average combination VaR	1.2315	1.2188	1.1953	1.1607	1.1148	1.0576
Average VaR change (in percentage points)	–	-0.0127	-0.0235	-0.0346	-0.0459	-0.0572
Min. VaR of the combination	1.2315	1.1182	1.0257	0.9915	0.9819	1.0576

Diagram 1. Distribution of returns, CBB International Sukuk

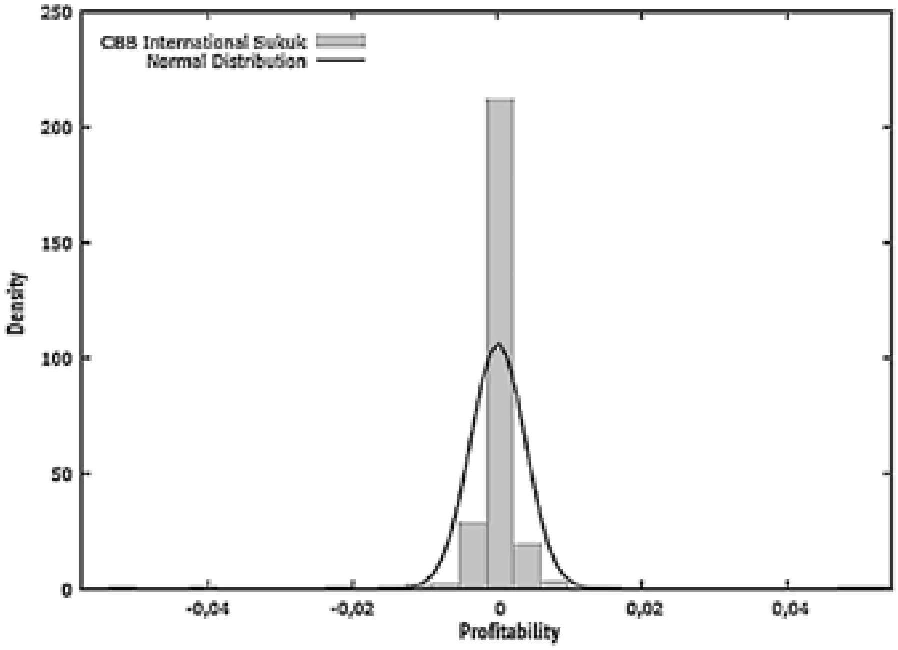


Diagram 2. Distribution of returns, Bahrain, 2010 bond

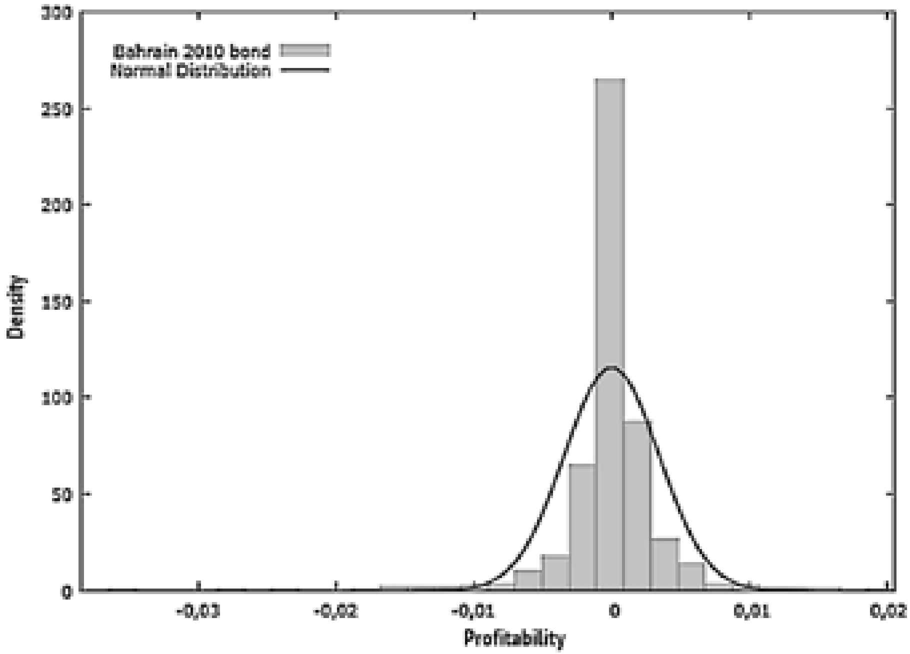


Diagram 3. Distribution of returns, Pakistan International Sukuk

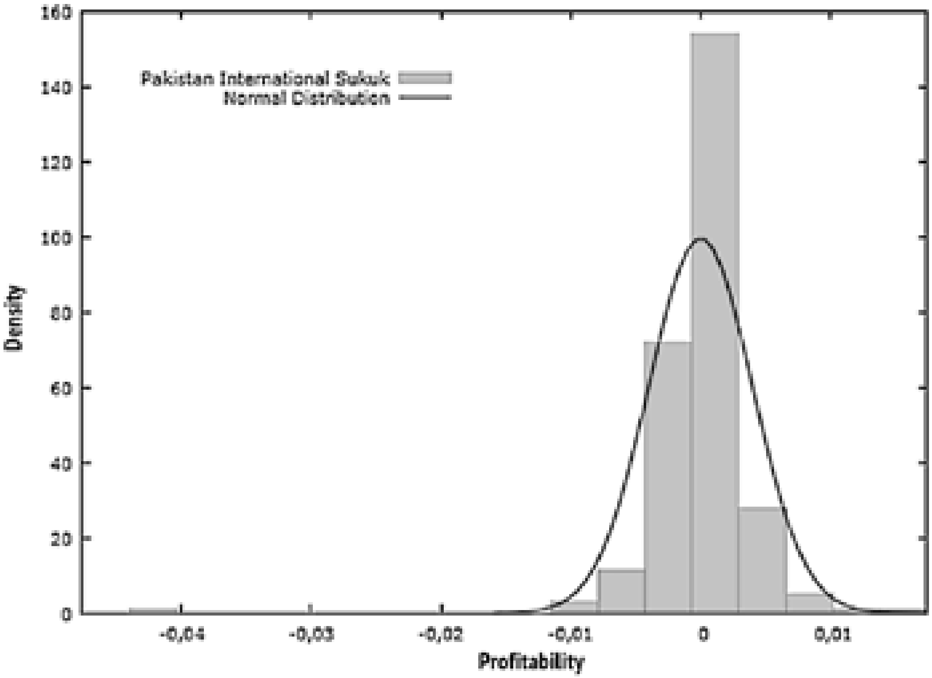


Diagram 4. Distribution of returns, Pakistan, 2014 bond

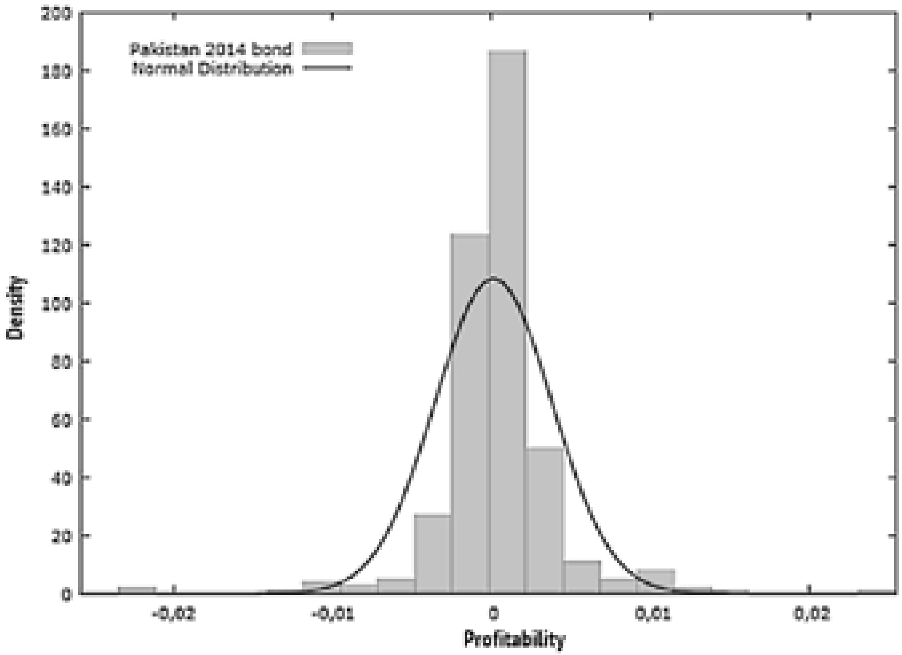


Diagram 5. Distribution of returns, State of Qatar Sukuk

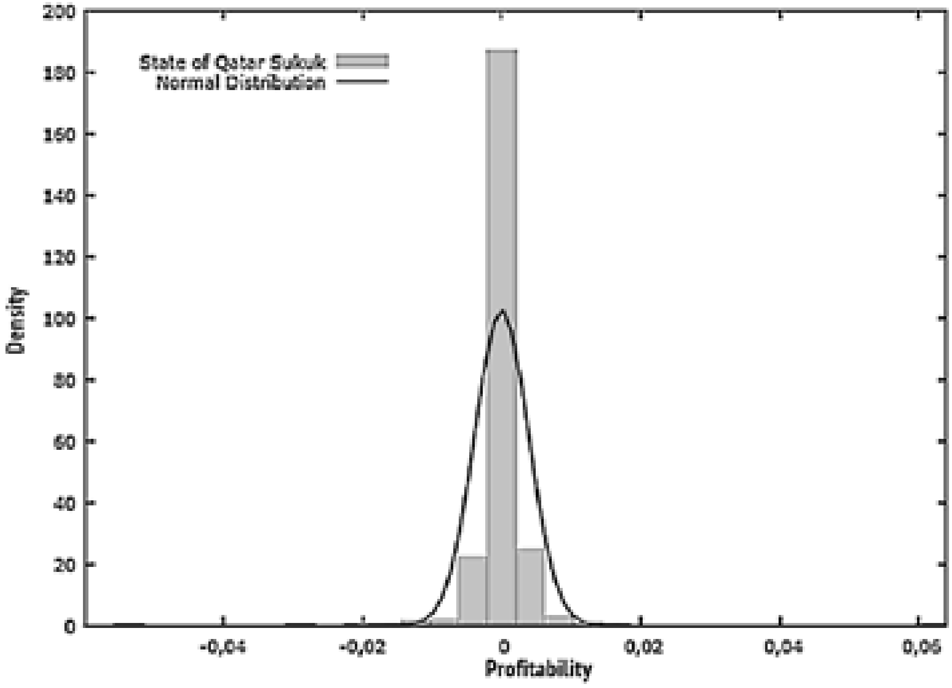


Diagram 6. Distribution of returns, Qatar, 2009 bond

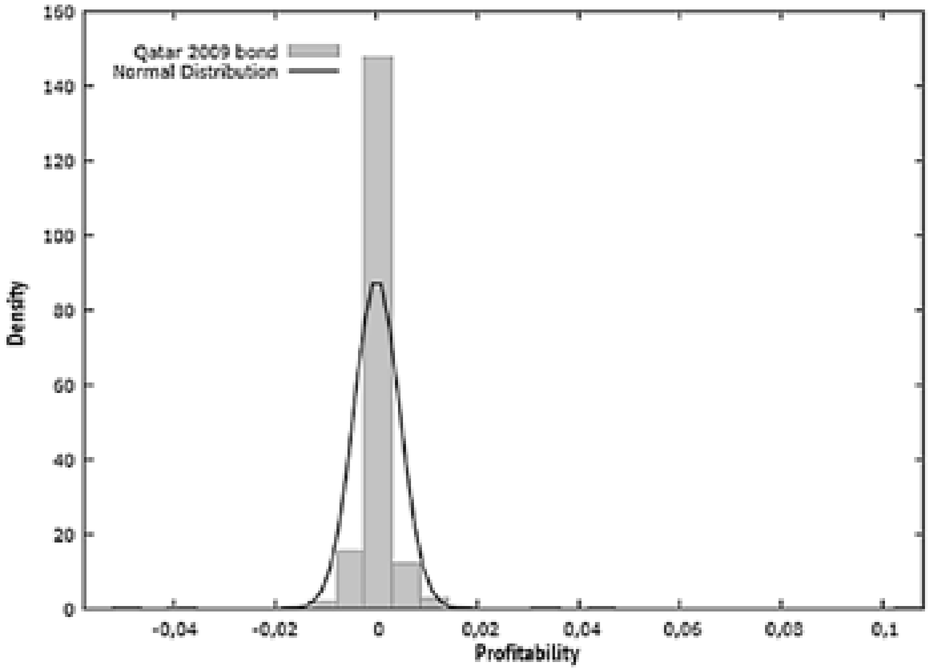


Diagram 7. Distribution of returns, Malaysia Sukuk

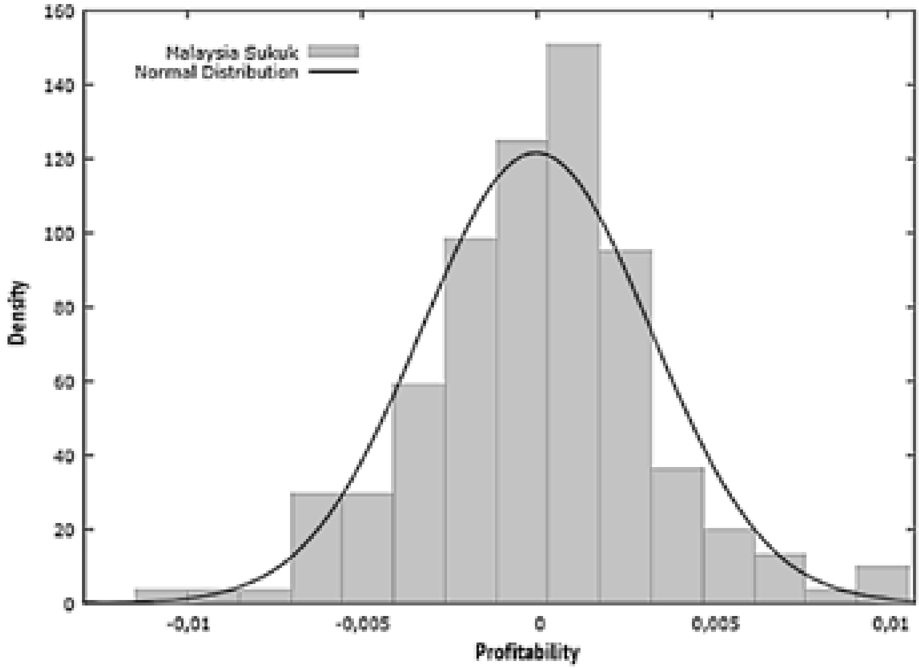


Diagram 8. Distribution of returns, Malaysia, 2015 bond

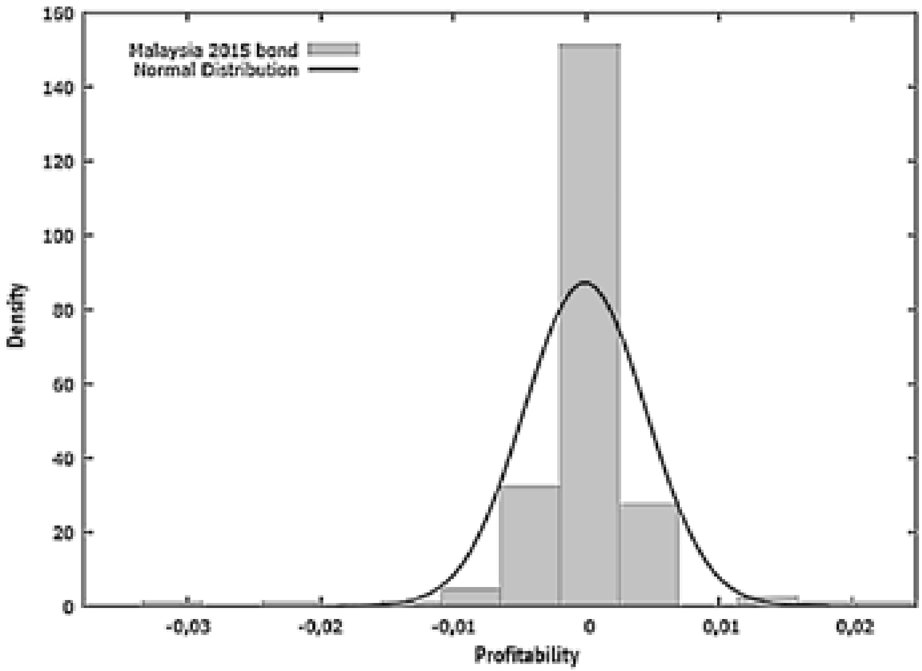


Diagram 9. Distribution of returns, Dubai DOF Sukuk

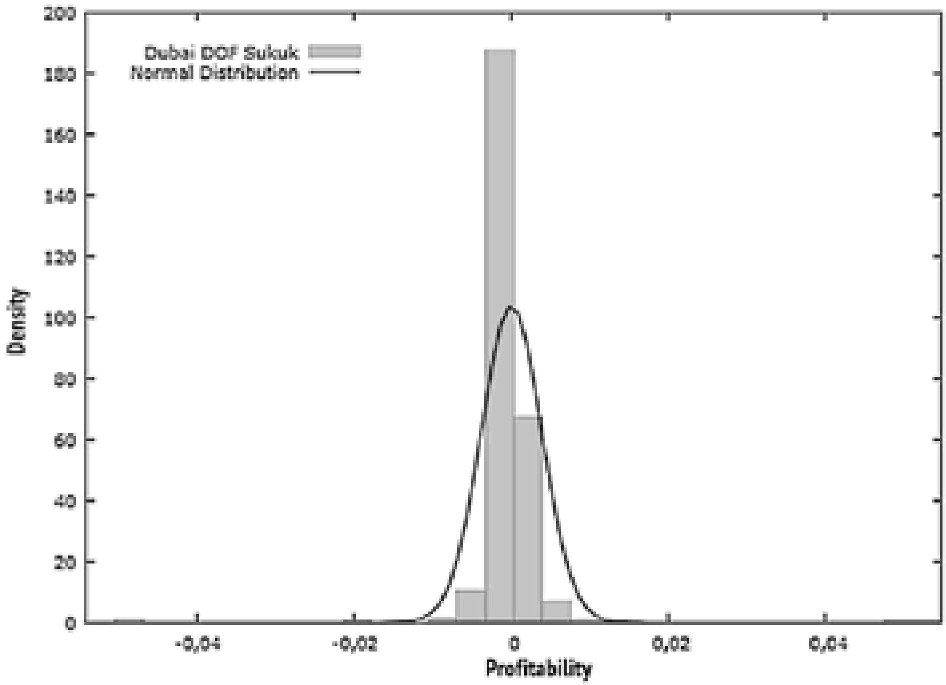
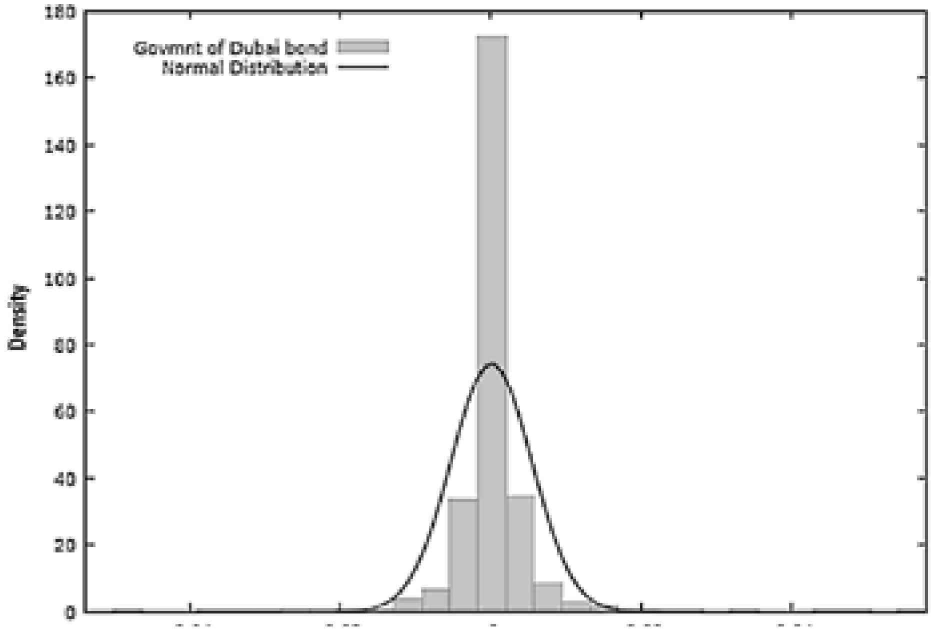


Diagram 10. Distribution of returns, Government of Dubai bond



COMPARISON OF ISLAMIC AND CONVENTIONAL BANK STOCKS BY VALUE-AT-RISK METHOD

Nursultan Abdrashev
Lomonosov Moscow State University, Faculty of Economics

Abstract. This article is focused on comparison of Islamic and conventional bank stock volatility by VaR (Value-At-Risk) risk assessment method. The performed analysis has shown that factors affecting stock values for different financial models are very similar, and that including stocks of both Islamic and conventional banks in an investor's portfolio gives no significant benefits in terms of diversification.
Keywords: Islamic finance, Islamic banking, market risk, portfolio risk, volatility
JEL Classification: F33, G21, C22, C53

1. Introduction

The major principle of conventional financing is 'the higher the investment risk, the higher the returns'. However, the relationship between risk and asset returns in Islamic financial institutions, which are an alternative type of stock market investors, still needs to be studied.

The purpose of the work is to find out if Islamic bank stocks are less susceptible to financial crises. For this purpose, a comparison of volatility for Islamic and conventional bank stocks is performed using VaR (Value-At-Risk) method of risk assessment.

Ideally, an Islamic financial institution's stock value should be less fluctuating and less susceptible to influence of microeconomic factors. Therefore, these stocks are to be less risky and more immune to financial crises. Accordingly, they can bring some benefits if used for investment portfolio diversification purposes.

That said, it remains unclear if all financial instruments of companies that position themselves as Islamic really comply with Sharia principles. Here the assumption is that they do comply with these principles.

In the course of the study, the following **hypotheses** were to be verified.

- A portfolio consisting only of Islamic bank stocks will have much lower volatility (lower VaR values);
- Including stocks of both Islamic and conventional banks in a portfolio will give significant benefits for the investor in terms of diversification;
- Correlation between returns on Islamic and conventional bank stocks would be negative in most cases due to differences in the factors affecting stock prices for the two dissimilar financial models

The study covers a broad time frame including both pre-crisis and post-crisis periods – 2007 to 2014.

2. Literature review

In economic literature, there are few works discussing stocks of Islamic financial institutions. Derigs and Marzban (2009) made a comparison of portfolios consisting of Islamic and conventional assets (stocks) from an asset structure perspective. They concluded that, by developing a portfolio strategy based on market capitalization, a portfolio consisting of Sharia-compliant assets can be as profitable as a portfolio consisting of conventional assets.

Guyot (2012), based on his analysis of The Dow Jones Islamic Market Index (DJIMI)[1], says that in comparison the DJIMI is more susceptible with the regular Dow-Jones index, to such macroeconomic factors as mortgage crisis. Also, the author maintains that the Islamic index has no co-integration (relationship) with other indices and is therefore reliable from long-term portfolio diversification perspective. Additionally, Derbel, Bouraoui and Dammak concluded in their study (2011) that the Islamic financial model can reduce crisis influence, and that this influence is less evident in countries which use Islamic financing methods.

Herwany and Febrian (2013) conducted a portfolio analysis of Islamic and conventional stocks on Indonesian stock exchange. They reported high volatility of a portfolio consisting of Islamic stocks and its strong dependence on changes of macroeconomic indicators. In another study (Yusop, 2008), the author used the Kuala Lumpur Syariah Index (KLSI) and concluded that beta of Islamic company stocks is positive and below 1, which means that investment risk for Islamic stocks on Kuala Lumpur stock exchange is lower than the market risk. Selim (2008) made a similar conclusion.

From this review of empirical studies, we can see that the studies were based mainly on the Islamic index rather than on individual stock prices. Along with that, the analysis of prices for Islamic financial institutions within a portfolio structure makes it possible to obtain more information and allow for volatility. Also, Cakir and Raei (2007) used portfolio analysis to compare sukuk and conventional bonds. To conduct an analysis by VaR assessment method, hypothetical portfolios were built, which consisted of sukuk and conventional bonds from different countries. The results were in sukuk's favour; when included in a portfolio of conventional bonds, sukuk gave the investor diversification benefits due to significant decrease in the portfolio's VaR value. We shall apply a similar methodology in this work.

3. Methodology

The VaR method will be used to analyze a portfolio consisting of Islamic and conventional bank stocks, in order to find out if this kind of diversification provides any benefits.

For the analysis, we shall take six hypothetical portfolios of Islamic and conventional bank stocks. The banks of the following countries were selected: Bahrain, UAE, Jordan, Kuwait and Qatar. The country selection was partly determined by restricted amount of available data. Countries where numerous Islamic financial institutions operate without any obvious restrictions that is, Islamic countries, were selected intentionally. Islamic and conventional banks were selected based on comparability of their market capitalization. In the frame of the study, data on stock prices for these banks for the period of 2007-2014 were used. All the data were taken from the finanz.ru service.

The first portfolio will contain only Islamic bank stocks. In the second portfolio, one Islamic bank will be replaced with a conventional one. In the next portfolio, two banks will be replaced, and so on. As a result, the fifth portfolio will contain stocks of one Islamic and four conventional banks. The sixth portfolio will consist of conventional bank stocks only. VaR of each portfolio will be calculated. Based on the results, conclusions will be made. The table below represents banks selected for the study:

Table 1. List of banks selected for the study

№	Islamic bank	Conventional Bank	Country
1	Al Baraka Banking Group	Al Salam Bank - Bahrain	Bahrain
2	Dubai Islamic Bank	Commercial bank of Dubai	UAE
3	Jordan Islamic Bank	Jordan Ahli Bank	Jordan
4	Kuwait Finance House	Gulf Bank	Kuwait
5	Qatar Islamic Bank	Commercial Bank of Qatar	Qatar

1 The Dow Jones Islamic Market Index (DJIMI) is a basic index of Islamic companies' capitalization. It makes part of the group of global Dow-Jones indices, which are calculated based on company stocks from 34 countries of the world. The purpose of DJIMI is to establish a clear standard of measuring global stock market indicators according to the existing methodology of calculating DJ indices and to Islamic investment guidelines established by Sharia supervisory board (Musaev, Magomedova - - Special regulations of Islamic financial institutions, 2015. http://rifc.su/?p=840)

There are different methods to calculate a portfolio's VaR value. In this work, we shall use the one where individual VaR values for portfolio assets are calculated first, then the total portfolio VaR is determined (Nikiforova, 2010). The method uses the formula:

$$V_{ar_p} = \sqrt{V'pV}$$

where

V – a column matrix of VaR values for each share,

V'– transpose of a column matrix of VaR values for each share, i.e. a row matrix,

p– n x n correlation matrix (n – the number of assets in a portfolio).

To calculate the VaR risk measure for each asset, a method of simulation on history ('delta normal method') will be applied. Among all methods of VaR calculation, this is the most popular one. The simulation will be made in Excel.

Let's consider an example of VaR calculation for one of the selected Islamic bank stocks – Qatar Islamic Bank. First of all, prices for the period under discussion are to be loaded. According to Bank of International Settlements' guidelines, minimum 250 price data are to be used for VaR calculation[2]. We have daily stock prices for 8 years (in average, 2000 prices per bank).

The next step is to calculate daily returns for the company's shares. They can be derived as the natural logarithm of the previous day close to the current day close ratio.

Then, we have to calculate the mathematical expectation and standard deviation values. These are the major parameters of the returns distribution. The mathematical expectation is calculated as an average of all daily returns on shares. For Qatar Islamic Bank shares, the average annualized return for the period under discussion was 3.31%. The standard deviation of return on stock for the bank was 1.95%.

The next step is to determine the normal distribution quantile. In statistics, quantile is the value of the Gaussian distribution function with the defined parameters (mathematical expectation and standard deviation). That is, at these parameters, the function must not exceed the derived value with the defined probability. In our analysis, a 99% probability level will be used. For the bank under discussion, the quantile was 4.56%.

Then, the future stock value at the defined returns distribution parameters is forecasted. To this end, the following formula is applied:

$$P_{t+1} = (q+1) \cdot P_t$$

where

q – quantile of the stock return distribution,

Pt – stock price at the moment t,

P_{t+1} – minimum stock value in the next time period t at the defined quantile level.

To determine forecasted values of the future stock price some periods in advance, the modification of the above formula is used:

$$P_{t+1} = \left(q\sqrt{n} + 1\right) \cdot P_t$$

where

q – quantile of the stock return distribution,

2 Supervisory framework for the use of «backtesting» in conjunction with the internal models approach to market risk capital requirements. Basle Committee on Banking Supervision, 1996. -http://www.bis.org/publ/bcbs22.pdf

P_t – stock price at the moment t,

P_{t+1} – minimum stock value in the next time period t at the defined quantile level.

n – forecast depth, for which a probable minimum stock value is determined.

For Qatar Islamic Bank, Pt+1 value was 97.54 Qatar reals. This means that, with a probability of 99%, the stock value on the next forecasted day will be 97.54 Qatar reals minimum. The stock value on the last day (Dec. 31, 2014) was 103.1 Qatar reals.

Then, the VaR value itself for the bank is calculated a certain number of days in advance. To calculate a relative VaR value (for the analysis in this work, relative VaR values will be used, because the downloaded data on stock prices are in different currencies), we have to calculate the natural logarithm of the stock price forecasted some days in advance to the stock price on the last day ratio (Dec. 31, 2014). That said, VaR_{t+1} for the bank under examination was 4.76%; this means, with a probability of 99%, the stock price on the next forecasted day will be lower by 4.67% maximum than the previous day price. However, for the purposes of the analysis, as the available data cover a large time frame, we shall use a 5-day period (i.e. we'll analyze in what lower limits a stock price will be in 5 days with a probability of 99%). This time frame is also more representative (the selected countries have different working days, which results in different trade operations; so one day would be insufficient for correct forecasting) and more often used in studies. For Qatar Islamic Bank, the VaR_{t+5} value was 10.77%. Using this methodology, VaR_{t+5} values for all banks under consideration were determined.

Table 2. VaR values for Islamic banks

	Banks	VaR_{t+5}
1	Al Baraka Banking Group	0.1717
2	Dubai Islamic Bank	0.1448
3	Jordan Islamic Bank	0.0889
4	Kuwait Finance House	0.1285
5	Qatar Islamic Bank	0.1076

Table 3. VaR values for conventional banks

	Banks	VaR_{t+5}
1	Al Salam Bank - Bahrain	0.2167
2	Commercial bank of Dubai	0.1211
3	Jordan Ahli Bank	0.1821
4	Gulf Bank	0.2880
5	Commercial Bank of Qatar	0.0834

We can see that individual Islamic banks do not outgo their conventional 'rivals' on this criterion very much, with the exception of Kuwait banks – the Islamic bank's VaRt+5 is 12.85%, while that of the conventional one is 28.8%.

4. Calculation

We make calculations according to the analysis methodology.

Portfolio 1:

Table 4. Correlation matrix of daily returns for portfolio 1 stocks:

	Al Baraka Banking Group	Dubai Islamic Bank	Jordan Islamic Bank	Kuwait Finance House	Qatar Islamic Bank
Al Baraka Banking Group	1	0.91	0.87	0.49	0.37
Dubai Islamic Bank	0.91	1	0.82	0.54	0.42
Jordan Islamic Bank	0.87	0.82	1	0.76	0.60
Kuwait Finance House	0.49	0.54	0.76	1	0.69
Qatar Islamic Bank	0.37	0.42	0.60	0.69	1

For this portfolio consisting of Islamic banks only, VaRt+5 is 8.31%. This means that, with the probability of 99%, an investor holding a portfolio that consists of these bank stocks in equal proportion can lose in 5 days maximum 8.31% of the current portfolio value.

Then, to verify the suggested hypotheses, we replace one Islamic bank after another with conventional ones. The order is determined by the level of correlation between an Islamic and conventional bank of the country (from lower to higher correlation levels).

The correlation of daily returns for Islamic and conventional bank stock prices is presented below by country.

Table 5. The correlation of returns for Islamic and conventional bank stocks

Country	Correlation of returns
UAE	0.96
Qatar	0.76
Jordan	0.64
Bahrain	0.62
Kuwait	0.54

Portfolio 2:

Table 6. Correlation matrix of daily returns for portfolio 2 stocks:

	Al Baraka Banking Group	Dubai Islamic Bank	Jordan Islamic Bank	Gulf Bank	Qatar Islamic Bank
Al Baraka Banking Group	1	0,91	0,87	0,25	0,37
Dubai Islamic Bank	0,91	1	0,82	0,25	0,42
Jordan Islamic Bank	0,87	0,82	1	0,20	0,60
Gulf Bank	0,25	0,25	0,20	1	0,41
Qatar Islamic Bank	0,37	0,42	0,60	0,41	1

VaR_{t+5} = 8.45%. We can see that this portfolio's VaR is 0.14% higher as compared to the previous one, ie, the replacement of an Islamic bank by a conventional one so far has caused losses.

Portfolio 3:

Table 7. Correlation matrix of daily returns for portfolio 3 stocks:

	Al Salam Bank - Bahrain	Dubai Islamic Bank	Jordan Islamic Bank	Gulf Bank	Qatar Islamic Bank
A lSalamBank - Bahrain	1	0,66	0,33	0,12	-0,07
Dubai Islamic Bank	0,66	1	0,82	0,25	0,42
Jordan Islamic Bank	0,33	0,82	1	0,20	0,60
Gulf Bank	0,12	0,25	0,20	1	0,41
Qatar Islamic Bank	-0,07	0,42	0,60	0,41	1

VaR_{t+5} = 8.00%. In this case, after replacement of two Islamic banks by conventional ones, VaR is slightly lower; it declined by 0.31%.

Portfolio 4:

Table 8. Correlation matrix of daily returns for portfolio 4 stocks:

	A lSalam Bank - Bahrain	Dubai Islamic Bank	Jordan Ahli Bank	Gulf Bank	Qatar Islamic Bank
Al Salam Bank - Bahrain	1	0,66	0,53	0,12	-0,07
Dubai Islamic Bank	0,66	1	0,82	0,25	0,42
Jordan Ahli Bank	0,53	0,82	1	0,63	0,68
Gulf Bank	0,12	0,25	0,63	1	0,41

VaR_{t+5} = 8.32%, which is practically identical to the original portfolio which consisted of Islamic banks only.

Portfolio 5:

Table 9. Correlation matrix of daily returns for portfolio 5 stocks:

	Al Salam Bank - Bahrain	Dubai Islamic Bank	Jordan Ahli Bank	Gulf Bank	Commercial Bank of Qatar
Al Salam Bank - Bahrain	1	0,66	0,53	0,12	-0,20
Dubai Islamic Bank	0,66	1	0,82	0,25	0,45
Jordan Ahli Bank	0,53	0,82	1	0,63	0,63
Gulf Bank	0,12	0,25	0,63	1	0,66
Commercial Bank of Qatar	-0,20	0,45	0,63	0,66	1

VaRt+5 = 7.95%. The risk decreased.

Portfolio 6.

Table 10. Correlation matrix of daily returns for portfolio 6 stocks:

	Al Salam Bank - Bahrain	Commercial bank of Dubai	Jordan Ahli Bank	Gulf Bank	Commercial Bank of Qatar
Al Salam Bank - Bahrain	1	0,60	0,53	0,12	-0,20
Commercial bank of Dubai	0,60	1	0,84	0,29	0,56
Jordan Ahli Bank	0,53	0,84	1	0,63	0,63
Gulf Bank	0,12	0,29	0,63	1	0,66
Commercial Bank of Qatar	-0,20	0,56	0,63	0,66	1

VaR_{t+5} = 8.23%. The risk increased.

5. Conclusion

It was found that VaR values for both the portfolio consisting of only Islamic bank stocks and the portfolio consisting of only conventional bank stocks are practically equal (for conventional banks, the value was even slightly better – by 0.08%). This means that the first hypothesis has to be rejected: the statement, 'A portfolio consisting of only Islamic bank stocks will have much lower volatility' was not corroborated.

We assumed that the investment diversification could bring significant benefits; however, from the portfolio analysis we can conclude that no significant benefits were achieved. For all portfolios consisting of both Islamic and conventional bank stocks, the VaR value did not deviate more than by 0.5% from VaR of the original portfolio, which consisted of Islamic bank stocks only, and from VaR of the portfolio, which consisted of conventional bank stocks only. Thus, the second hypothesis also has to be rejected: the statement, 'Including stocks of both Islamic and conventional banks in a portfolio will give significant benefits for the investor in terms of diversification' was not corroborated.

In practice, all signs of correlation matrices of the portfolios under examination, which included both Islamic and conventional banks, are positive. This means that factors, which affected stock prices of both Islamic and conventional banks of the selected countries, were much alike. That said, the third hypothesis also has to be rejected: the statement, 'Correlation between returns of Islamic and conventional bank stocks will be negative in most cases due to differences in factors affecting stock prices for the two dissimilar financial models' was not corroborated.

The objective of the research – to find out if Islamic bank stocks are less susceptible to financial crises – is achieved. The major conclusion of the study can be formulated as follows: the popular opinion that Islamic financial institutions are less susceptible to financial crises than conventional ones can not be corroborated.

The final results were certainly affected by the selection of countries, whose banks were included in the portfolios. While these countries are formally Islamic, they are far from leading positions in the rating of compliance with Islamic economic principles: Kuwait holds position No, 42, Bahrain – 61, UAE – 64, Jordan – 74 and Qatar – 112[3] . It is worth noting that our study was limited by ten banks only, due to data availability. However, probably the major factor was infrastructural imperfection of Islamic stock exchanges as well as the fact that they allow speculations with financial assets, which is confirmed by Bekkin and Yandiev (2010). This fact apparently levels the originally high immunity of Islamic financial assets to financial crises.

3 Scheherazade S. Rehman, Hossein Askari (2010) An Economic Islamicity Index(EI2) (Global Economy Journal)

6. References

1. Bekkin, Renat & Yandiev, Magomet. Credit in the Structure of the Market Quotation of Financial Assets in Relation to the Islamic Financial Law. Problemy Sovremennoy Economiki, № 1, 2010.http://ssrn.com/abstract=1929384
2. Cakir Selim & Raei Faezeh; Sukuk vs. Eurobonds: Is There a Difference in Value-at-Risk? IMF Working Paper 07/237; October 1, 2007.
3. Derbel, Hatem, Bouraoui, Taoufik, & Dammak, Neila. (2011). Can islamic finance constitute a solution to crisis. International Journal of Economics and Finance, 3(3), 9.
4. Derigs, Ulrich, & Marzban, Shehab. (2009). New strategies and a new paradigm for Shariah-compliant portfolio optimization Journal of Banking & Finance, 33, 11.
5. Guyot, Alexis. (2012). Efficiency and dynamics of islamic investment: Evidence of geopolitical effects on Dow Jones islamic market indexes. Emerging Market Finance & Trade, 47(6), 22.
6. Herwany, Aldrin, & Febrian, Erie. (2008). Co-integration and causality analysis on developed asian market for risk management & portfolio selection. Gadjah Mada International Journal of Business, 10(3), 28.
7. Musaev, Rasul & Magomedova, Yulduz. Special regulations of Islamic financial institutions, 2015.URL: http://rifc.su/?p=840
8. Nikiforova V. Security market. Teaching aid. SPBU - Faculty of Economics, 2010.
9. Scheherazade S. Rehman, Hossein Askari : An Economic Islamicity Index (EI2) // Global Economy Journal, 2010.
10. Selim, Tarek H. (2008). An Islamic capital asset pricing model. Humanomics, 24(2), 8.
11. Supervisory framework for the use of «backtesting» in conjunction with the internal models approach to market risk capital requirements Basle Committee on Banking Supervision, 1996. URL: http://www.bis.org/publ/bcbs22.pdf
12. Yusop, Mohd Mahyudi Bin Mohd. (2008). The Malaysian islamic stock market: a study on performance and the conditional capital asset pricing model (Doctoral), International Islamic University Malaysia, Malaysia.

The Safe Internet League is the largest and most reputable Russian organization fighting dangerous Web content. Our aim is to eradicate dangerous content through community action by IT professionals, industry players, and regular Internet users.

Our mission consists in complete eradication of dangerous online content by inviting members of professional community and industry players to adopt self-regulation in order to avoid censorship.

To accomplish this, members of the League undertake the following tasks:

- Fighting the dissemination of dangerous Web content using every means available;
- Uniting the professional community and industry players to work out self-regulation mechanisms in order to avoid top-down regulation and Internet censorship;
- Providing genuine help to children and teenagers victimized by the spread of dangerous Internet content;
- Assisting the authorities in tackling web site owners who are creating and distributing dangerous content – child pornography, materials encouraging violence and illegal drug use;
- Participating in drawing up legislation aimed at eradicating dangerous Internet content.

www.ligainternet.ru/en/

ISSN 2313-1578 IN
15002
9 772313 157009

NATIONAL RATING AGENCY

One of Russia's leading credit rating agencies, established in 2002. NRA specializes in assigning individual credit, financial reliability and financial stability ratings to entities from both financial and non-financial sectors. NRA plays an active role in a number of social impact projects and provides research and analytical data on a range of subjects such as macroeconomics, banking, insurance, MFIs, collective investments, stock market, oil and gas sector, Russian regions' investment potential and others

As one of Russia's leading independent credit rating agencies, we maintain ratings on more than 400 legal entities. Over 1000 companies are involved in our other projects, whose products are regularly covered by the media and appear on NRA's website and social networks. NRA is in the register of rating agencies accredited by the Ministry of Finance of the Russian Federation. Our ratings are officially recognized by the Central Bank of the Russian Federation, Moscow Exchange, Ministry of Economic Development, Russian National Association of Securities Market Participants (NAUFOR), National Securities Market Association (NSMA), Association of Russian Banks (ARB) etc.

In 2008, NRA adopted the Code of Professional Conduct for Russian Rating Agencies, approved by the National Securities Association. NRA has been a member of the European Association of Credit Rating Agencies (EACRA) since 2011. In 2014 NRA has established a subsidiary company in Austria – NRA International GmbH.

www.ra-national.ru

RUSSIAN REVIEW
РУССКОЕ ОБОЗРЕНИЕ
FOUNDED AND PUBLISHED WITH THE SUPPORT OF Safe Internet League
VOL. 2 (3) 2015