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Identifying SIFI Determinants for Global Banks and Insurance Companies: Implications for D-SIFIs in Russia

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Abstract

The increased role of financial institutions in the economy leads to a need to determine those that are systemically important. The bankruptcy of such institutions creates negative effects for the economy on the global scale. The aim of this article is to identify important financial coefficients that can be used in the methodology of identification of G-SIB and G-SII.

Models of binary choice and models of ordered choice are used in this article, several models are highly predictive. Besides this paper has revealed several financial coefficients, that helped to find the probabilities of G-SIF for Russian banks and insurance companies.

Keywords: Systemic importance; Basel committee, probability of default, financial coefficients; models of ordered choice, models of binary choice, global systemically important banks (G-SIB), insurance company.

JEL Codes: C70, E58, G21.

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The financial institute is declared as a systemically important if its default causes significant consequences for an economy as a whole. That's why it becomes important to create methodologies of identification of such institutes.

In November 2011 the IAIS published a document «Insurance and financial stability». According to indicator-based assessment approach the IAIS emphasized 5 groups of indicators representing systemic importance of an insurer: size (assets and revenues); global activity (revenues earned abroad); interconnectedness (debts from other financial institutions, reinsurance), non-traditional and non-insurance activities (financial guaranties) and substitutability. The interconnectedness and non-traditional and non-insurance activities have the highest weight among these indicators – they have 40 and 45% correspondingly meanwhile other indicators' weights are equal 5%. Indicators are estimated as a ratio of the insurance company in the sample of insurers.

At the same time, in November 2011, the Basel Committee on Banking Supervision (BCBS) published a global methodology for systemically important banks. The financial crisis showed that problems of systemically important banks undermine the stability of the financial sector on a global scale. [26]

The proposed BCBS methodology consists of 12 indicators that are divided into the following categories: cross-border activities; bank size; interconnectedness; interchangeability and complexity. When calculating total points for a bank, each category with all its indicators has a total weight of 20%.

Comparing these two methodologies, it can be seen, that the indicators are the same, but the weights are different.

The aim of this paper is to detect financial indicators from public reports to reconstruct the BCBS and IAIS methodologies of identification of global systemically important insurance companies and banks. Financial indicators are taken from the literature devoted to the factors of default probabilities of financial institutes.

The research consists of the following sections. The second section presents literature analysis that focuses on the financial coefficients of the default probability of insurance companies and banks. The third section presents data, used in the research. The next section demonstrates an econometric analysis to identify important determinants for insurance companies and banks, including models of binary and ordered choice. The next section focuses on analysis of results, given by models. The conclusion demonstrates all results of the research.

Literature review

To the best of authors knowledge no one searched systemical importance determinants, many authors investigated the probability of default determinants. Thus this article is focused on the latter.

(Karminsky, 2013) emphasizes following reasons of default of a bank:

a) a decrease of capital adequacy to 2% and lower;
b) a decrease of equity lower than minimal value;
c) the bank does not fulfill the requirements of the central bank and the Federal law;
d) the bank does not satisfy the requirements of creditors or does not pay for necessary payments;
e) the sanitation of the bank.

The authors assume that the most important factor influencing bank's sustainability is a size of the bank. Usually this index is estimated as a logarithm of assets of the bank or equity to assets ratio. Overall, the authors select the relevant variables using the database, the gained experience and the statistical analysis of appropriate variables. Then these variables are combined according to CAMELS scheme: capital adequacy (capital to assets ratio); asset quality (logarithm of net assets; overdue loans to loans); management (logarithm of turns on correspondent accounts to net assets ratio); earnings (balance profit to net assets ratio); liquidity and sensitivity (volume of corporate securities to net assets ratio).

The probability of default of the bank is analyzed in the paper (Estrella A., 2000) by applying different techniques. One technique is the Fisher's linear discriminant analysis (LDA), which allows defining a linear function (scores) on some variables. Variables in this case are the coefficients taken from the financial statements (the ratio of working capital to total assets, etc.), taking into account these variables maximize the variance of the two groups of firms (good and bad - with low and high risk, respectively) and to minimize variance within each group.

Another technique for estimating the probability of default is logit-analysis. This method also uses financial ratios from the financial statements with the assumption that the desired probability takes the form of the logistic equation defined on the interval from 0 to 1. Linear logistic model suggests that the dependent variable is the logarithm of the financial coefficient. The main advantage of this approach is that there is no need to statistical limitations of variables. Moreover, the relative importance of components ratios can be determined by t-test.

The examples of empirical analysis of the probability of default and the accuracy of the research are presented in the Table 1. (in Appendices)

The most accurate model in all these research was the Taffler's model – a number of correctly predicted banks bankrupts equal 97%, that may indicate the significance of the selected variables. It should be noted that the sample is relatively small: less than 100 firms were analyzed when some research included several thousand firms. In the Taffler's model following financial ratios were used: profit before tax/current liabilities; current assets/total liabilities; current liabilities/total assets.

(Cole, Gunther, 1998) also studied the problem of assessing the probability of default of a financial institution. In the United States for the same purpose system CAMEL is used (capital adequacy, asset quality, management, earnings and liquidity) and Early Warning System (EWS), capable of reflecting more quickly the occuring changes in financial institutions. Both of these models use a logit-analysis. Based on these studies concluded that a direct relationship exists between the probability of default and distressed assets (overdue by 90 days or more loans etc.) - higher net income reduces the potential financial problems, what leads to a drop in the probability of default.

The study (Estrella A., Pakroma S., Peristiani S., 2000) used statistical methods for estimating the relationship between capital and default of banks. The main conclusion of the authors was that for an accurate prediction the one should use equity-to-revenue ratio and debt to equity coefficient. The risk of default increases as the size of the firm's assets becomes almost equal to the liabilities and default occurs when the market value of assets becomes unable to cover all payments for liabilities. Hence, in accordance with the Merton's model default probability of the firm may be determined by the market valuation of the firm's assets, the volatility of its assets and capital structure of the company (duration and the share of liabilities of the company).

The book (Sinkey D., 1977) consists of a few studies (Sinkey D., 1975), (Sinkey D., 1985) in which two groups of banks are compared. In (Sinkey D., 1985) the first group –is comprised of 37 banks went bankrupt in 1970-1975, and the second group is comprised of 37 banks that had no financial problems during this period. The author uses the profitability of the bank to determine the significant parameters of the first to fifth year before the bankruptcy of the bank.

The author highlights the following significant parameters:

1). "Total operating expenses / total operating income." The higher the index, the more the bank is prone to go bankrupt;

2). "Investment / total assets." The greater the contribution to long-term growth, the less the bank is susceptible to bankruptcy;

3). "Operating profit / total assets." The smaller the value, the more the bank is prone to bankruptcy;

4). "Loans /Deposits." The smaller the value, the bank is less prone to go bankrupt.

According to the OLS model (Sinkey D., 1975), there are significant indicators that include operating expenses and net income.

The author concludes following facts:

1). the value of capital adequacy is less than the capital adequacy in the control bank (control bank is the non-problem bank). The problem bank has fewer reserves to absorb the amount of loans;

2). the problem bank is less effective than control bank. The problem bank has more operating expenses in operating profit than control bank has;

3). less liquidity. It is measured by coefficient liquidity.

As a result of analysis of the research papers on the probability of default of the financial institution, all the used financial coefficients were ranked in descending order of times mentioned. The following table represents 15 most mentioned coefficients (Appendices, Table 2).

Rating agency Standard & Poor's evaluating the effectiveness of the insurance company uses the following indicators: the loss ratio (insurance payments, divided by premiums), expense ratio (the ratio of expenses to insurance premiums) and following ratios - profit to income, profit to assets (before and after-tax), profit to investment, profit to equity. In addition, the agency pays great attention to the dimensions of financial leverage, defined as the proportion of debt in the capital, the share of hybrid debt capital, interest coverage ratio, ratio of coverage of fixed debt payments and the ratio of hybrid capital to equity.

Description of data

The first step of work with data was the accounting of exchange rates of every currency in which data were performed initially.

Balance sheets consist of indicators that can be flow indicators and fixed. Accounting of exchange rates of balance sheet indicators that are fixed is made at the end of every period, so the exchange rates at the end of December 2010, 2011 and 2012 are used. Profit and loss statement, in contrast, consists of flow indicators, so there are used average exchange rates for each year.

The next step was the removal of outliers. They are observations with values that significantly deviated from the mean. After that relationships between financial coefficients and systemic importance were detected.

I. Financial coefficients for banks.

A data source is database Bankscope. To conduct the study data are taken from the annual reports of global banks (rated by the largest banks, depending on the total assets [42] in 2010, 2011 and 2012. Banks' indicators that were taken: total assets, total loans growth, the growth of total assets, total capital, equity, net income, net interest income, total operating expenses, operating income, net loans, current liabilities, liquid assets, allowance for doubtful accounts. There were 29 G-SIB and 29 non-GSIB banks in the initial sample. From the summary table one bank was deleted because of lack of data (Sumitomo Mitsu FG, 2012). Categories of systemic importance of banks determined annually for each bank in accordance with the document developed by the Financial Stability [29], [30].

Following relationships are identified without outliers:

1) "Total operating expenses / total assets" (code «toetta») - the quadratic relationship with the systemic importance.

2) "Net profit / total assets" (code «nitta») - a negative linear relationship with the systemic importance.

3) "Net income / Total operating income" (code «nittoe») - a negative linear relationship with the systemic importance.

4) "Operating expenses / operating income" (code «toettoi») - a positive linear relationship with the systemic importance.

5) "Ln of total assets" (code «lnta») - a positive linear relationship with the systemic importance.

6) "The growth of total assets" (code «gta») - a negative linear relationship with the systemic importance.

7) "The growth of total loans" (code «gtl») - a negative linear relationship with the systemic importance.

8) "Net loans / total assets" (code «nltta») - a negative linear relationship with the systemic importance.

9) "The amount of allowance for doubtful loans / net loans" (code «llrtnl») - a negative linear relationship with the systemic importance.

10) "The total capital / total assets" (code «tctta») - a positive linear relationship with the systemic importance.

11) "Net interest income / total assets" (code «nirevtta») - a negative linear relationship with the systemic importance.

12) "Net profit / equity" (code «nitce») - a negative linear relationship with the systemic importance.

(See Appendix, Table 3,4).

II. Financial coefficients for insurance companies.

The rating of world's largest companies Global 2000 was used for creating a sample of insurance companies. Fifty insurers were selected from this list including 9 systemically important. Using Thomson Reuters Fundamentals financial statements of each firm at the end of 2011 were extracted. In order to expand the sample, the financial statements of the same firms in 2012 were added. It has been suggested that systemically important insurance companies have not changed. The final sample included 90 firms, 18 of which are systemically important. The following financial information was needed: equity, insurance reserves, current liabilities, current assets, insurance payments, insurance premiums, expenses, net income, revenues, investment, assets.

After removing the outliers the dependence between the systemic importance and each factor was determined graphically.

The types of relationships:

1). «Equity/insurance reserves» (code «eqres»). Negative linear relationship was detected.

2). «Short-term liabilities/current assets» (code «srlica»). Positive linear relationship was detected.

3). «Insurance payments/insurance premiums» (code «papr»). Quadratic relationship was detected.

4). «Expenses/insurance premiums» (code «expr»). Quadratic relationship was detected.

5). «Net income/revenues» (code «inre»). Positive linear relationship was detected.

6). «Net income/assets» (code «inas») . Negative linear relationship was detected.

7). «Net income/investment» (code «ininv»). Negative linear relationship was detected.

8). «Net income/equity» (code «ineq»). Positive linear relationship was detected.

9). «Equity/assets» (code «eqas»). Negative linear relationship was detected.

(See Table 5 in Appendices).

After an analysis of the original sample it was found that the values of financial ratios non-systemically significant insurance companies have a much greater variation in the values (minimum and maximum) compared with systemically important (Appendices, Table 6).

Econometric analysis.

I. Methodology for banks.

We consider several models: model of the binary choice, ordered choice and model of ordered choice with data of 2010. The model of binary choice determines the factors that are significant in the separation of institutions into two categories: systemically important and not systemically important. The ordered model takes into account the probability of different categories of systemic importance. The third define financial indicators that influenced the selection of a systemically important bank group in the first year of existence of this category.

Model 1. Model of binary choice.

The new variable «y2» divides banks into two categories: systemically important and not important.

We use models «probit» and «logit». The findings comparable to those obtained by the method of least squares.

The probability of «logit» model: $p_i = F\left(X\right) = \frac{1}{1-e^{-y}}$ (1)

The probability of «probit» model: $p_i = F\left(X\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^2}$ (2)

Where $Y = bX$ in general terms.

In our case: $p_i\left(y2\right) = \begin{cases} 1, if\ G-SIB \\ 0, if\ non-G-SIB \end{cases}$ (3)

The table 1 shows the results obtained by the three models. Dummy variables were insignificant. Models "logit" and "probit" have explanatory power is higher than the OLS model. Quality of models of binary choice is high because the area under the ROC-curve more than 0.9. The same indicators are significant in all three models.

Table 1. Coefficients of significant indicators.

X	Mean	Cor(Var; Y)	OLS	Probit	Logit
lnta	13.98	0.38	0.09	0.49	0.88
gtl	0.05	-0.42	-0.74	-5.03	-8.92
toetta	0.02	0.21	81.74	405.16	738.65
nittoe	0.43	-0.24	0.53	3.81	6.93
latshf	0.41	0.2	0.59	3.63	6.64
nirevtta	0.02	-0.3	-12.81	-104.3	-172.93
nitce	0.1	-0.33	-1.9	-10.4	-18.62
toetta2	0	-0.14	-1113.17	-4610.08	-8740.63
_cons			-1.71	-11.36	-20.86
obs	153	153	153	153	153
R^2 adj			0.51	0.54	0.54
ROC				0.92	0.92

Signs of marginal effects are the same in all three models. *(Table 2)* The only difference observed in the net profit to total costs «nittoe». Despite the fact that the rate of Spearman correlation revealed a negative relationship, the model proves the opposite sign of relationship. This fact explains by the influence of other variables, which are ignored in the index of correlation.

Table 2. Marginal effects of significant indicators.

X	Mean	Cor(Var; Y)	OLS	Probit	Logit
lnta	13.98	0.38	0.09	0.19	0.21
gtl	0.05	-0.42	-0.74	-1.93	-2.10
toetta	0.02	0.21	81.74	155.45	173.82
nittoe	0.43	-0.24	0.53	1.46	1.63
latshf	0.41	0.20	0.59	1.39	1.56
nirevtta	0.02	-0.30	-12.81	-40.02	-40.69
nitce	0.10	-0.33	-1.90	-3.99	-4.38
toetta2	0.00	-0.14	-1113.17	-1768.73	-2056.83

Thus, the best model of binary choice is «probit», because it has the greatest explanatory power.

Model 2. Models of ordered choice.

Banks of the higher group of systemic importance should increase its capital absorbency by the amount which is presented in the table. The table is taked from the paper of BCBS «Global systemically important banks assessment methodology and the additional loss absorbency requirement»

Bucket (y)	Score range	Higher loss absorbency requirement (tctta)
5	D–E	3.50%
4	C–D	2.50%
3	B–C	2.00%
2	A–B	1.50%
1	Cutoff point–A	1.00%

As you know, the capital absorbency is the capital as percentage of the value of total assets, weighted by risk. We have no information about levels of risk of assets of each global bank, we assume that capital adequacy is measured as a proportion of the total capital to the bank's total assets.

Thus, the level of capital adequacy depends on the category of systemic importance, which belonged to the bank in the previous year, it speaks about the endogeneity of this variable. The final model is:

$$\begin{cases} y_t = f(x_{i,t-1}; d1; d2; d3; toetta^2) \\ \qquad tctta_t = f(y_{t-1}) \end{cases} \tag{4}$$

This system is time-series vector autoregression, which must be taken into account when comparing models. According to the table 3, the model of vector autoregression has the highest explanatory power ($R^2 = 0.58$), and it is the highest compared to other models.

Table 3. Coefficients of significant indicators.

X	Mean	Cor(Var; Y)	OLS	oProbit	oLogit	Var
lnta	13.98	0.30	0.15	0.26	0.45	0.17
gta	0.08	-0.33	-1.89	-3.28	-5.97	-2.13
gtl	0.05	-0.34	-	-2.34	-4.25	1.99
toetta	0.02	0.23	171.18	248.50	433.51	206.44
latshf	0.41	0.29	1.17	1.46	2.54	0.42
nltta	0.46	-0.50	-2.52	-4.00	-6.73	-4.00
tctta	0.06	0.06	16.03	23.14	42.98	14.45
toetta2	0.00	0.13	-3909.96	-5444.76	-9475.72	-4679.81
_cons			-2.62			-2.20
obs			153	153	153	102
R^2 adj			0.55	0.35	0.35	0.58

The table 4 presents marginal effects of significant determinants. Model «logit», «probit» and model of vector autoregression present the same significant indicates, in contrast to the OLS model, which demonstrate one additional significant indicate "growth of total loans." This indicator has a positive association with systemic importance in the model of vector autoregression. It explains by simultaneous evaluation of all parameters of regressions with a lag of one period.

Table 4. Marginal effects of significant figures.

X	Mean	Cor(Var; Y)	OLS	oProbit	oLogit	Var
lnta	13.98	0.30	0.15	1.10	1.11	0.17
gta	0.08	-0.33	-1.89	-0.29	-0.47	-2.13
gtl	0.05	-0.34	-	0.08	-0.05	1.99
toetta	0.02	0.23	171.18	98.88	107.79	206.44
latshf	0.41	0.29	1.17	1.58	1.63	0.42
nltta	0.46	-0.50	-2.52	-0.57	-0.66	-4.00
tctta	0.06	0.06	16.03	10.11	11.59	14.45
toetta2	0.00	0.13	-3909.96	-2143.64	-2333.25	-4679.81

The model of vector autoregression is the model with the greatest explanatory power.

Model 3. Models with data of 2010.

Several banks have received the status of systemic importance since 2010, when the first monitoring was hold. Some financial indicators played an important role in determining banks as systemically important. According to the table 5, OLS model has the highest explanatory power.

Table 5. Coefficients of significant indicators.

X	Mean	Cor(Var; Y)	OLS	oProbit	oLogit
lnta	13.84	0.30	0.14	0.30	0.50
toetta	0.02	0.24	278.62	533.35	924.46
toettoi	0.56	0.35	-2.24	-10.65	-18.66
nltta	0.47	-0.45	-3.75	-5.23	-53.19
nirevtta	-	-	-	-100.70	-169.34
nitce	0.11	-0.29	-5.04	-12.37	-21.98
toetta2	0.00	0.18	-5478.46	-7388.10	-12923.20
obs	51	51	51	51	51
R^2 adj			0.70	0.38	0.37

Marginal effects of variables have the same signs in all three models. *(Table 6)*

Table 6. Marginal effects of significant indicators

X	Mean	Cor(Var; Y)	OLS	oProbit	oLogit
lnta	13.84	0.30	0.14	1.12	1.12
toetta	0.02	0.24	278.62	212.00	229.90
toettoi	0.56	0.35	-2.24	-3.21	-3.62
nltta	0.47	-0.45	-3.75	-11.78	-12.17
nirevtta	-	-	-	-38.84	-40.93
nitce	0.11	-0.29	-5.04	-3.90	-4.44
toetta2	0.00	0.18	-5478.46	-2921.78	-3198.90

OLS model was chosen because it has greater explanatory power.

II. Methodology for insurance companies.

It is used probit model. Variables were added in accordance with the hypothesis of a quadratic dependence - squared financial ratios: code papr2 – squared papr (insurance payments/insurance premiums); expr2 - squared expr (expenses/insurance premiums).

Table 7. Estimated coefficients of the model (probit, logit, OLS)

Variable	probit		logit		OLS	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
expr	20.78	9.06	37.42	17.59	0.42	0.26
inre	9.3	4.65	15.59	8.14	1.78	0.85
eqas	-10.54	4.82	-17.13	8.56	-2.17	0.72
expr2	-6.46	3.07	-11.63	5.93	-0.12	0.06
const	-16.12	6.61	-29.08	13	0.04	0.27
R^2/Pseudo R^2	0.4		0.39		0.17	

Then marginal effects (relationship between change in the financial ratio and change in the probability of systemic importance) were analyzed (*Table 8*).

Table 8. Marginal effects of financial coefficients

Variable	probit		logit		OLS	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
expr	0.14	0.38	0.24	0.38	0.42	0.26
inre	0.06	0.2	0.1	0.2	1.78	0.85
eqas	-0.07	0.23	-0.11	0.23	-2.17	0.72
expr2	-0.04	0.12	-0.01	0.12	-0.12	0.06

The analysis of the impact of marginal effects on the probability function of systemic importance proves the direction of influence of the coefficients. Furthermore, the obtained effects are statistically significant at the 5% significance level that confirms this effect.

Results of models.

I. Results that are given from models for banks.

Thus, variables are significant in three cases:

1) The Bank goes from non-G-SIB in the G-SIB in the first year of existence of this category. (Table 8,9, «probit (y2)») In this case, the higher the probability of the bank to get in a category, the more bank's value of total assets (bank size), less operating costs as a percentage of operating profit, less the share of net loans in the bank's assets and less net income in shareholders' equity (ROE).

2) Bank moves from one G-SIB category to another. Banks of higher category of systemic importance have more total assets, banks unable to fulfill short-term liabilities, as evidenced by the positive relationship of the "liquid assets to short-term liabilities." In addition, banks should regulate the value of loans and raise capital adequacy (that meets the requirements of the Basel Committee). (Table 8,9, «var (y)»)

3) Indicators that are relevant when all categories of systemic importance consider as a group of systemic importance with the requirements of the Basel Committee for systemically important banks.

Table 9. Significant indicators by chosen models.

X (coef)	Probit (y2)	Var (y)	OLS (for 2010)
lnta	0.49	0.17	0.14
gta	-	-2.13	-
gtl	-5.03	1.99	-
toetta	405.16	206.44	278.62
toettoi	-	-	-2.24
nittoe	3.81	-	-
latshf	3.63	0.42	-
nltta	-	-4.00	-3.75
tctta	-	14.45	-
nirevtta	-104.30	-	-
nitce	-10.40	-	-5.04
toetta2	-4610.08	-4679.81	-5478.46
_cons	-11.36	-2.20	-
obs	153.00	102.00	51.00
R^2 adj	0.54	0.78	0.70

Table 10. Marginal effects of significant coefficients.

X (mfx)	Probit (y2)	Var (y)	OLS (for 2010)
lnta	0.19	0.17	0.14
gta	-	-2.13	-
gtl	-1.93	1.99	-
toetta	155.45	206.44	278.62
toettoi	-	-	-2.24
nittoe	1.46	-	-
latshf	1.39	0.42	-
nltta	-	-4.00	-3.75
tctta	-	14.45	-
nirevtta	-40.02	-	-
nitce	-3.99	-	-5.04
toetta2	-1768.73	-4679.81	-5478.46

Banks of category G-SIB have more total assets, give less loans, have a great share of the net profit in total operating costs, unable to meet its short-term liabilities. In addition, the share of profit in equity of systemically important banks compared with non-important banks. (Table 8,9, «OLS for 2010»)

Determinant «total operating expenses/total assets» has a quadratic relationship with systemically importance. Bank should increase total costs in total assets to increase the likelihood of becoming systemically important, or change the category of systemic importance, but after a certain point the further the increase in total costs would entail a risk of losing the status of G-SIB.

The next step was checking the quality of the selected models. (see Appendices, Table 7,8)

Histograms of model errors are very close to a normal distribution in three models, although the test Chapiteau - Wilk rejects the null hypothesis of normality of residuals in the first two cases. In the third case, the Shapiro-Wilk test showed that the residues satisfy the normal distribution at the 5% level of significance (Pv = 0.06586). Therefore, we can conclude that the model "probit" and vector autoregression have a problem of error autocorrelation. The reason of this problem is panel type of data. As it is known, the autocorrelation leads to inefficient estimates and forecasts, so type I errors and type II error can exist.

The table demonstrates the position of domestic banks in the ranking of systemic importance by the methodology of CB [24] and BCBS using selected models.

Table 11 Probabilities of systemic importance of Russian banks.

Bank	CB	probit (y2)	var (y)	OLS (2010)
Sberbank	1	23	12	2
VTB	2	6	3	4
GPB	3	10	28	18
VTB 24	4	22	25	26
Russian Agricultural Bank	5	13	15	41
Bank of Moscow	6	2	7	23
Alfa Bank	7	21	29	39
UniCredit Bank	8	5	6	3
Raiffeisenbank	9	3	4	25
Rosbank	10	29	41	40
PSB	11	20	43	27
NOMOS BANK	12	18	48	1
Uralsib	13	35	39	14
MDM Bank	14	4	19	10
Bank «Saint Petersburg»	15	9	9	20
Bank «Russia»	16	41	42	19
Bank of Khanty-Mansiysk	17	17	38	45
Citibank	18	27	27	42
Nordea Bank	19	8	10	22
Credit Bank of Moscow	20	15	42	24
Russian Standard Bank	21	43	30	49
"Ak Bars" Bank	22	44	47	17
HCF Bank	23	45	37	28

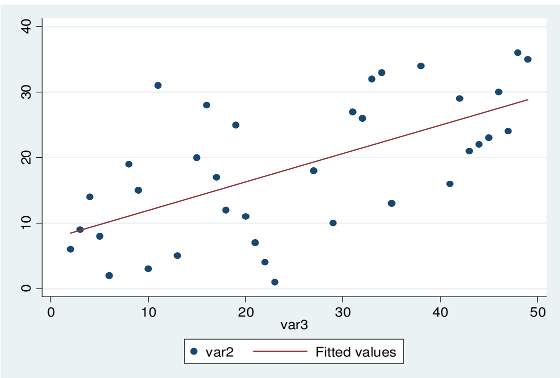
ING Bank Eurasia	24	47	5	7
Petrocommerce	25	19	8	15
Svyaz bank	26	32	50	30
Bank “Vozrozhdenie»	27	31	33	32
Bank «Zenit»	28	16	46	44
"Vostochnii" (Express Bank)	29	42	18	48
NB "Trust"	30	46	44	46
Globeksbank	31	11	35	38
Bank "Otkritie"	32	33	34	35
"BIN" bank	33	34	36	11
Industrial Bank	34	38	45	34
Deutsche Bank	35	49	16	47
OTP Bank	36	48	1	21

Examine the relationship of bank rating by the methodology of BSBC by three selected models with bank rating of the Central Bank.

Methodologies of CB and BCBS by "probit" model.

The figure 1 shows a positive relationship between ratings, although Spearman correlation test denies any connection (Pv = 0.0001), the null hypothesis of independence methodologies rejected at 10% significance level.

Figure 1. Relationship between methodologies of CB and BCBS by "probit" model.

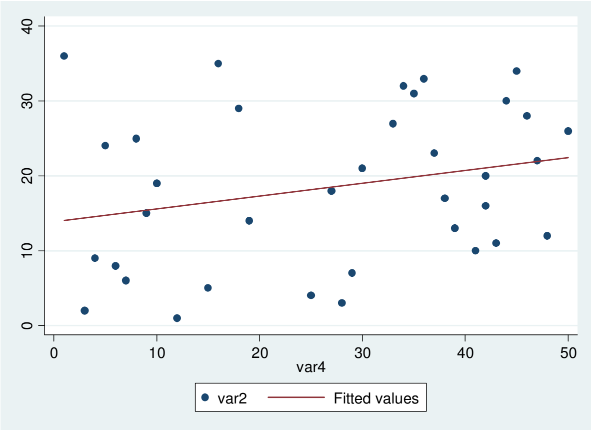


Note: on the vertical axis – rating of Russian banks by BCBS, on the horizontal axis – rating of Russian banks by CB.

Methodologies of CB and BCBS by vector autoregression model.

The figure 2 shows the weak relationship between two methodologies, test Spearman denies any connection. Null hypothesis of independence of the methodologies adopted by 10% significance level (Pv = 0.1272).

Figure 2. Relationship between methodologies of CB and BCBS by vector autoregression model.

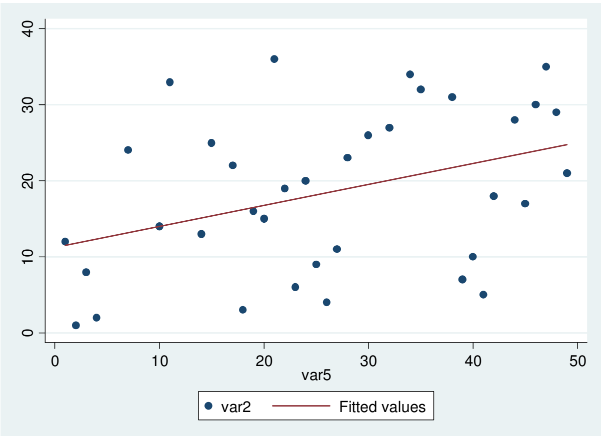


Note: on the vertical axis – rating of Russian banks by BCBS, on the horizontal axis – rating of Russian banks by CB.

Methodologies of CB and BCBS by OLS model.

The figure 3 shows a positive relationship between two methodologies. Spearman test confirms the connection by 10% significance level (Pv = 0.0275).

Figure 3. Relationship between methodologies of CB and BCBS by OLS model.



Note: on the vertical axis – rating of Russian banks by BCBS, on the horizontal axis – rating of Russian banks by CB.

Thus, the model "probit" demonstrates the relationship between methodologies of the Basel Committee and the Central Bank.

II. Results that are given from models for insurance companies.

To assess the quality of the resulting model ROC-curve was constructed (Appendices, *Fig.1*). The area under ROC-curve in case of probit-model equals 0.896 and in case of logit-model equals 0.9, which means that the model is highly accurate. Histogram analysis of the regression errors gave reason to believe that the errors have a normal distribution (Appendices, Fig. 2), but the Jarque-Bera test showed that the hypothesis of normality of residuals is rejected at the 5% significance level (p-value = 0.0394). Graphical analysis of regression errors (Appendices, Fig.3) represents that the errors of the resulting model has a heteroscedasticity. After plotting a scatter diagram of errors of observations (Appendices, Fig..4) the autocorrelation of the errors was detected.

Summarizing the obtained results of the regression analysis, the following relationship between the coefficients and significance of the system was found:

1) Insurance payments/Insurance premiums – quadratic relationship with the maximum probability of obtaining the status of systemic importance at expr = 1.61;

2) Net income/revenues – a linear positive relationship;

3) Equity/assets - linear negative relationship.

To analyze the probability of obtaining the status of systemic importance of Russian insurance companies the financial statements according to IFRS were used.

Table 12. Probabilities of systemic importance of Russian companies.

Company	Probability (%)	Position of a company according to the central bank methodology	Position of a company according to the IAIS methodology
Rosgosstrakh	0.003	1	8
Sogaz	7.88e-06	2	16
Ingosstrakh	0.001	3	10
RESO-garantiya	0.005	4	6
VSK	0.001	5	11
AlfaStrakhovanie	0.02	6	3
Soglasie	0.03	7	2
Al’yans	4.94e-4	8	13
MSK	1.76e-4	9	14
Renessans	1.68e-5	10	15
MAKS	0.003	11	7
URALSIB	7.25e-06	12	17
ZHASO	3.24e-08	13	19

Yugoria	0.18	14	1
VTB Strakhovanie	2.49e-09	15	20
Generali PPF	0.006	16	5
Transneft'	4.18e-07	17	18
Kapital Strakhovanie	0.012	18	4
Zurich	0.002	19	9
GUTA- Strakhovanie	9.2e-04	20	12

To conclude, the central bank should pay maximal attention to companies having the highest probability and reduce the degree of control of companies having the lowest probability – for example, "VTB Strakhovanie" (2.49e-09%).

Conclusion

In this paper the leading global insurance companies and banks were analyzed for a relationship between systemic importance and financial ratios. Three models were used for banks: the binary choice (logit model, probit and OLS); ordered choice model (logit, probit, OLS and vector autoregression) and ordered choice models with data for 2010. (logit, probit, OLS).

As a result, the following models identified as models with the highest explanatory power: a binary choice model "probit" in the case of the separation of banks to the category G-SIB and non-G-SIB; vector autoregression model in the case of an ordered selection that takes into account not only the existence of the category of systemic importance, but also several subgroups of systemic importance. The third case considers the indicators that were significant in the first year (2010) of the existence of systemic importance and OLS model was highlighted. The analysis of this model considers what factors contributed to the initial allocation of a group of banks as systemically important.

Following indicators were significant in all these three models:

1)."logarithm of total assets" with positive correlation with systemic importance. Increasing this coefficient by 0.1%, systemic importance increases by 1.9%, 1.7% and 1.4% according to «probit», «var» and OLS model respectively.

2) "total operating expenses / total assets" with a quadratic relationship.

Other significant parameters are different in the models. It should be noted that in the case of considering the systemic importance with several categories variable "total capital / total assets" becomes meaningful with positive correlation with systemic importance. Increasing by 0.1% coefficient "total capital / total assets" leads to an increase by 140% of systemic importance. This fact can be explained by BSBC's requirements of capital adequacy under the category of systemic importance, in which the bank is located.

It was also concluded that systemic importance is really related to the following coefficients: insurance payments/insurance premiums, net profit/revenues, equity/assets:

1) Insurance payments/insurance premiums –quadratic relationship with maximal probability of systemic importance when expr = 1.61.
2) Net income/revenues –the linear positive relationship was detected. Increasing by 0.1% coefficient "net income/revenues" leads to an increase by 0.65% of systemic importance.
3) Equity/assets –linear negative relationship. Increasing by 0.1% coefficient "equity/assets" leads to an decrease by 0.7% of systemic importance.

References

1) International Association of Insurance Supervisors. Global Systemically Important Insurers: Initial Assessment Methodology, 18 July 2013. http://www.iaisweb.org/view/element_href.cfm?src=1/19151.pdf
2) Financial Stability Board. Global systemically important insurers (G-SIIs) and the policy, measures that will apply to them, 18 July 2013. http://www.financialstabilityboard.org/publications/r_130718.pdf
3) Estrella A., 2000, Credit ratings and complementary sources of credit quality information, BCBS Working paper №3, August
4) Cole R.A, and Gunther J.W., Predicting Bank Failures: A comparison of on- and off-site monitoring systems, 1998 Journal of Financial Services Research, vol. 13 (2),
5) Estrella A., Park S. and Peristiani S. 2000. Capital ratios as predictors of bank failure, FRBNY Economic Policy Review, July.
6) Tabakis, E., Vinci, A., 2002. Analyzing and combining multiple credit assessments of financial institutions, ECB Working Paper No. 123,
7) Golovan S., Karminsky A., Kopylov A., Peresetsky A., 2003, Models of the probability of default of Russian banks I. Preprint WP#2003/039, New Economic School,.[in Russian]
8) Tam K.Y., 1991. Neural Network Models and the Prediction of Bank Bankruptcy, Omega, vol.19.
9) Yildiz B., Akkoc S.,. Bankruptcy Prediction Using Neuro Fuzzy: An Application in Turkish Banks, 2010 International Research Journal of Finance & Economics.60 114.
10) Olmeda I., Fernandez E., Hybrid Classifiers for Financial Multicriteria Decision Making: 1997 The Case of Bankruptcy Prediction, Computational economics 10
11) Canbas S., Caubak A., Kilic S.B., Prediction of commercial bank failure via multivariate statistical analysis of financial structures: The Turkish case, 2005 European Journal of operational research, 166, Issue 2,.
12) Beynon M.J., Peel M.J., 2001. Variable precision rough set theory and data discretization: an application to corporate failure prediction, Omega, vol.29.
13) Barr R.S., Siems T.F., Bank Failure Prediction Using DEA to Measure Management Quality, 1996 Interfaces in Computer Science and Operations Research, vol.7, June
14) Martin D., Early-warning of Bank Failure: A Logit Regression Approach, 1977 Journal of Banking and Finance, vol.1
15) Hanweck, G. A. 1977. Predicting Bank Failure, Research Papers in Banking and Financial Economics,

16) Pantalone, C. C., and Platt, M. B. 1987. Predicting Commercial Bank Failure Since Deregulation, New England Economic Review,
17) Alam, P., Booth, L.K., Thordason, T., The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: An experimental study, 2000 Expert Systems with Applications. 18 185–199.
18) Salchenberger, L. M., Cinar, E. M., & Nash, N. A., Neural networks: a new tool for predicting thrift failures, 1992 Decision Sciences, 23 899–916,.
19) Kolari, J., Glennon, D., Shin, H., Caputo, M., Predicting large us commercial bank failures. 2002 Journal of Economics & Business. 54 361–387
20) Karminsky A., Kostrov A., Modeling the probability of default of Russian banks: Advanced, vol.17, 2013 Journal of the New Economic Association 17 №1. [in Russsian].
21) Shikhov A., Insurance. 2000 YUNITY-DANA. 431 [in Russian]
22) Aivazyan S.A., Penikas G.I., Connolly R., Andrievskay I.K. Detection of systemically important financial institutions: a review of methodologies / / 2011 Money and loan. 8 13—19. [in Russian]
23) Bank rating by total assets for 1.01.2014.
URL: http://vid1.rian.ru/ig/ratings/banki_05_01_14.pdf (Режим доступа: открытый)
24) Bank of Russia on January 16, 2014 № 3174-U "Determination of the list of systemically important credit institutions." 3 February 2014. [in Russian]
URL:http://www.garant.ru/products/ipo/prime/doc/70475610/#review
25) A list of systemically important banks according to experts RIA Rating, 6 July 2013. [in Russian]
URL: http://riarating.ru/banks_study/20131206/610600343.html
26) BCBS. Global systemically important banks assessment methodology and the additional loss absorbency requirement. 1 November, 2011.
URL: http://www.bis.org/publ/bcbs201.pdf
27) Beaver W. Financial ratios as predictors of failure. 1966 Journal of Accounting Research. 4 71-111
28) Bech M., Chapman J., Garratt R. 2008 Which Bank is the «Central» Bank? An application of Markov Theory to the Canadian Large Value Transfer System. Federal Reserve Bank of New York Staff Reports 356.
29) FSB. Policy Measures to Address Systemically Important Financial Institutions, 3 November 2011.
URL: http://www.financialstabilityboard.org/publications/r_111104bb.pdf
30) FSB. 2013 update of group of global systemically important banks (G-SIBs), 4 November 2013.
URL: https://www.financialstabilityboard.org/publications/r_131111.pdf
31) Furfine C. 1999. Interbank Exposures: Quantifying the Risk of Contagion. BIS Working Papers 70,
32) Hanson S., Schuermann T. 2004. Estimating Probabilities of Default. Federal Reserve Bank of New York. Staff Reports 190.
33) Kaufman G. George. Too big to fail in banking: What remains?. 2002 The Quarterly Review of Economics and Finance, 42 423–436.
34) Kolari, J., Glennon, D., Shin, H., Caputo, M., Predicting large us commercial bank failures. 2002 Journal of Economics & Business. 54 361–387.
35) Meyer, Paul A. and Howard W. Pifer, Prediction of bank failures. 1970 Journal of Finance. 27 853-868.

36) Ohlson, J. Financial Ratios and the Probabilistic Prediction of Bankruptcy. 1980 Journal of Accounting Research, 19 109–131.
37) Santomero A., Vinso J. Estimating the Probability of Failure foe commercial banks and the banking system. 1977 Journal of Banking and Finance. 1 185-205
38) Sinkey F. Joseph. Problem and Failed Institutions in the Commercial Banking Industry, 1977.
39) Sinkey, Joseph F., A multivariate statistical analysis of the characteristics of problem banks. 1975 Journal of Finance, March. 21-36.
40) Sinkey, J. E., Jr., The Characteristics of Large Problem and Failed Banks, 1985 issues in Bank Regulation. 43-53.
41) Thomson, J. B. Predicting Bank Failures in the 1980s, 1991 Economic Review 27, Federal Reserve Bank of Cleveland, 9-20.
42) Top 150 Banks Worldwide Ranked By Asset Size, July 2013.
URL: http://www.cba.ca/contents/files/statistics/stat_bankranking_en.pdf

Appendices.

Table 1. The examples of empirical analysis of the probability of default and the accuracy of the research.

Research	Model	Sample		Accuracy
		Number of bankrupt firms	Number of non - bankrupt firms	
Altman, 1968	LDA	33	33	95%
Altman, Haldman, Narayan, 1977	LDA	53	58	93%
Taffler-Tishou, 1977	LDA	46	46	97%
Altman -Laval, 1981	LDA	27	27	83.3%
Izan, 1984	LDA	50	50	91.8%
CFSD of Italy	LDA	1885	1920	91.7%
CFSD of France	LDA	809	1381	70%
CFSD of Germany	LDA	677	677	89.3%
CFSD of Austria	LDA	103	103	78.5%
Gilbert and others, 1990	logit	76	304	88.5%
Kesey-McGuinn, 1990	logit	43	43	81.5%
Platte-Platte, 1990	logit	57	57	90%
Laviola-Trapaniz, 1997	logit	1274	2022	91%

Table 2. Financial coefficients connected with the probability of default of the financial institutions.

№	Financial coefficient	Quantity
1	net income/assets	15
2	equity/assets	9
3	total assets (ln)	7
4	net credits/assets	4
5	net income / total operating income	3
6	the sum of cash and bank treasury bonds / assets	3
7	commercial and industrial credits / net credits and leases	3
8	total operating expenses / total operating income	2
9	liabilities / total assets	2
10	earnings before interest and tax / total assets	2
11	operating expenses / total assets	2
5	gross written off debts / net operating profit	2
6	overdue credits/assets	2
7	equity/credits	2
8	net profit/credits	2
9	net working capital/total assets	2
10	interest payments/ average earning assets	2
11	deposits/assets	2
12	liquid assets/assets	2
13	provisions for possible losses from financial operations/assets	2
14	net income/equity	2
15	interest income/assets	2

Table 3. Financial coefficients for banks.

Code	**Variable**	**Measure**	**Relationship with SI**
«lnta»	Ln of total assets	units	positive linear relationship
«nittoe»	Net income / Total operating income	per cent	negative linear relationship
«nirevtta»	Net interest income / total assets	per cent	negative linear relationship
«nltta»	Net loans / total assets	per cent	negative linear relationship
«nitce»	Net profit / equity	per cent	negative linear relationship

«nitta»)	Net profit / total assets	per cent	negative linear relationship
«toettoi»	Operating expenses / operating income	per cent	positive linear relationship
«llrtnl»	The amount of allowance for doubtful loans / net loans	per cent	negative linear relationship
«gta»	The growth of total assets	per cent	negative linear relationship
«gtl»	The growth of total loans	per cent	negative linear relationship
«tctta»	The total capital / total assets	per cent	positive linear relationship
«toetta»	Total operating expenses / total assets	per cent	quadratic relationship

Table 4. Analysis of the values of financial ratios for systemically important (SI) and non-systemically important (NSI) banks.

	Mean		**Min**		**Max**	
Variable	**G-SIB**	**non-G-SIB**	**G-SIB**	**non-G-SIB**	**G-SIB**	**non-G-SIB**
lnta	14.95	12.81	11.99	9.14	22.04	20.79
gta	0.04	0.12	-0.14	-0.12	0.35	0.44
gtl	0.01	0.1	-0.23	-0.09	0.22	0.35
toetta	0.02	0.01	0.01	0	0.04	0.04
nitta	0	0.01	-0.01	-0.01	0.01	0.03
nittoe	0.26	0.69	-0.55	-0.77	1.49	1.49
toettoi	0.64	0.48	0.3	0.27	0.89	0.79
latshf	0.47	0.32	0.12	0.07	1.29	0.6
nltta	0.39	0.54	0.05	0.19	0.65	0.77
llrtnl	0.03	0.03	0	0.01	0.07	0.13
tctta	0.06	0.06	0.02	0.02	0.13	0.12
nirevtta	0.01	0.02	0	0	0.04	0.06
nitce	0.07	0.14	-0.17	-0.17	0.21	0.34

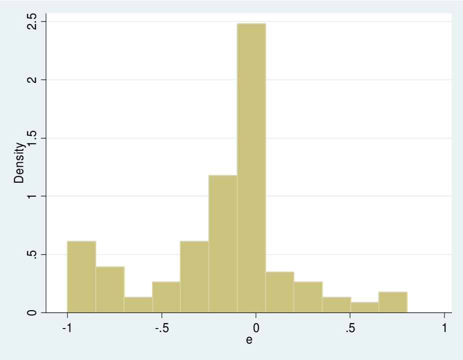
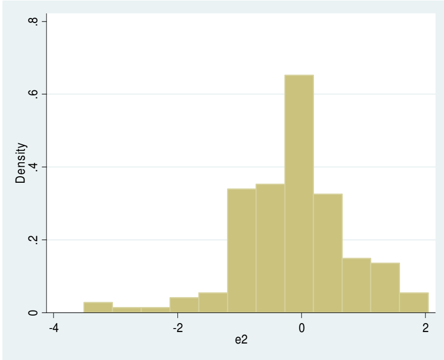
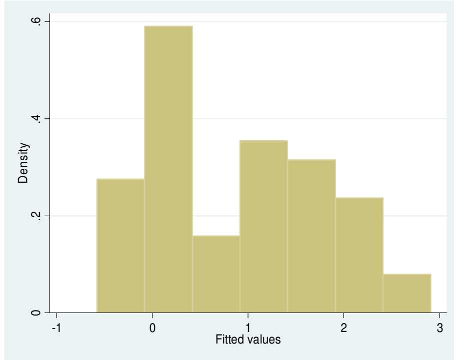
Table 5. Financial coefficients for insurance companies.

Code	Variable	Measure	Relationship with SI
«eqas»	Equity/assets	per cent	Negative linear relationship
«eqres»	Equity/insurance reserves	per cent	Negative linear relationship
«expr»	Expenses/insurance premiums	per cent	Quadratic relationship
«papr»	Insurance payments/insurance premiums	per cent	Quadratic relationship
«inas»	Net income/assets	per cent	Negative linear relationship
«ineq»	Net income/equity	per cent	Positive linear relationship
«ininv»	Net income/investment	per cent	Negative linear relationship
«inre»	Net income/revenues	per cent	Positive linear relationship
«srlica»	Short-term liabilities/current assets	per cent	Positive linear relationship

Table 6.Analysis of the values of financial ratios for systemically important (SI) and non-systemically important (NSI) insurance companies

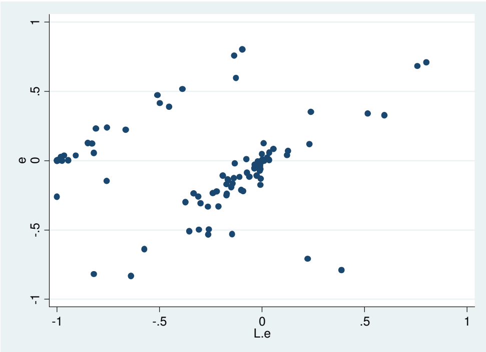
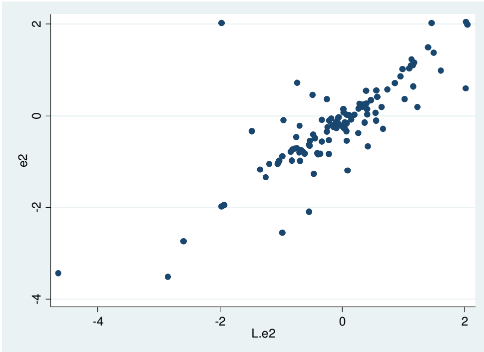
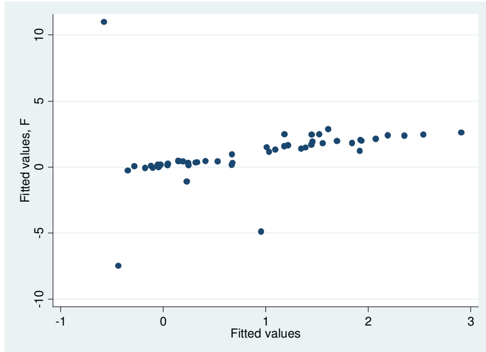
Variable	Mean value		Minimum		Maximum	
	SI	NSI	SI	NSI	SI	NSI
eqres	0.12	0.2	0.03	0.02	0.35	0.64
srlica	0.26	0.26	0	0	0.87	5.15
papr	0.32	0.31	0.19	0.03	0.6	0.97
expr	1.47	1.42	1.08	0.26	1.99	4.35
inre	0.05	0.06	-0.07	-0.08	0.34	0.54
inas	0.01	0.1	-0.01	0.01	0.04	0.05
ininv	0.008	0.014	-0.02	-0.015	0.06	0.06
ineq	0.07	0.08	-0.38	-0.17	0.24	0.21
eqas	0.06	0.11	0.03	0.02	0.18	0.29

Table 7. Histograms of errors.

Probit (y2)	**Var (y)**	**OLS (за 1-ый год)**
		

Note: Histograms represent model errors and their probability density. On the vertical axis –probability density; on the horizontal axis - the values of errors.

Table 8. Plots of relationship of errors.

Note: The graphs represent model errors and their lagged values based on the formula of autocorrelation:

$\varepsilon_t = \alpha*\varepsilon_{t-1} + \theta_t$. On the vertical axis - the values of errors; on the horizontal axis - the values of errors with a single lag.

Figure 1. ROC-curve for probit-model

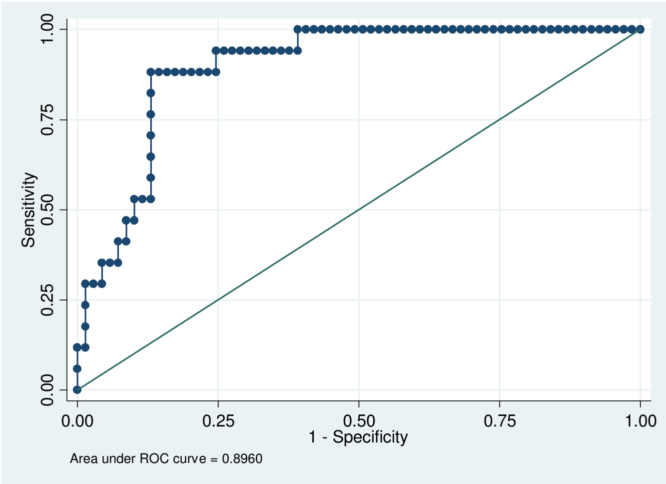
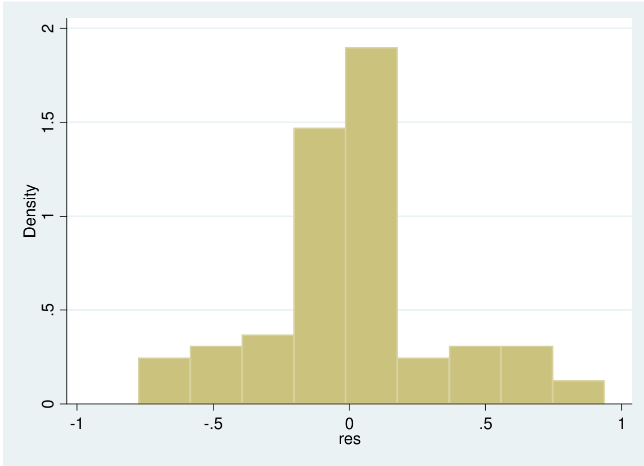
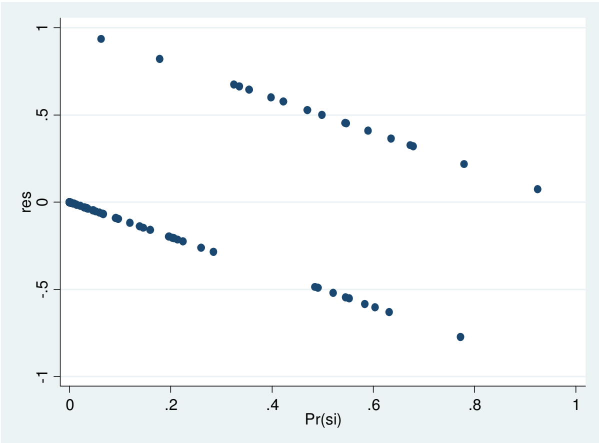


Figure 2. Histogram of errors of the regression



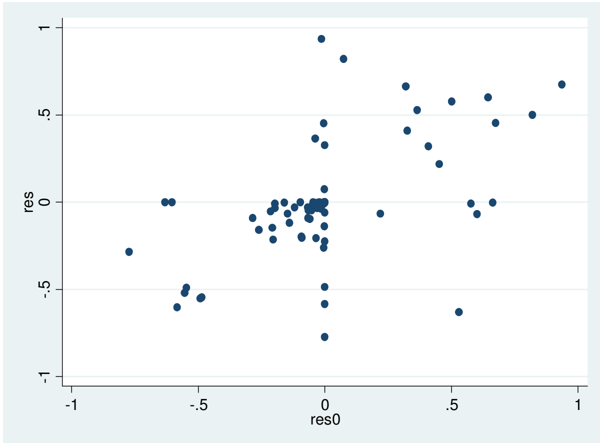
Note: On the vertical axis –probability density; on the horizontal axis - the values of errors.

Figure 3. Errors of the regression



Note: On the vertical axis - the values of errors; on the horizontal axis –the probability of systemic importance.

Figure 4. Relationship of the errors



Note: On the vertical axis - the values of errors; on the horizontal axis - the values of errors with a single lag.