**Part III**

**Estimating and modeling credit and market risks in banking**

**Bank credit risk modeling in emerging capital markets**

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**Abstract** Models for assessing the probability of default play an important role in the risk management systems of commercial banks, as they allow assessing the creditworthiness of various counterparties and transactions. At the moment, many Russian banks (from the top 10) are trying to switch to an advanced approach based on internal ratings (hereinafter IRB-approach) for evaluating regulatory capital. The main goals that Banks pursue when switching to an advanced approach are: stability of credit risk assessment for the ability to carry out strategic planning; the validity of the credit risk assessment to simplify interaction with the regulator (the Central Bank of the Russian Federation) and external and internal audit; potential reduction of regulatory capital due to the high quality of the forecast capabilities of the developed models, since the growth of the Gini coefficient of models in practice reduces risk-weighted assets (RWA), which leads to a reduction in the regulatory capital of banks. To use internal rating models in the calculation of regulatory capital banks have served the petition on them with the CBR, on basis of which Working Group of the Central Bank of the Russian Federation is carried out external validation of the models and a decision about the possibility of using Bank models for regulatory purposes. The main event of credit risk – the default event is determined by banks in the framework of credit policy, is consistent with the Central Bank of the Russian Federation, and is predicted using models for assessing the probability of default (PD – probability of default). Models for assessing the probability of default (PD-models) are the most popular in banking practice due to the fact that according to regulatory requirements, they are developed on the horizon of 1 year, and the minimum amount of statistical data for such models must be at least 5 years. Thus, many Russian banks have the appropriate data depth and are able to develop such models, while the LGD (Loss Given Default) and EAD (Exposure At Default) models require a much larger data availability horizon. The specific feature of developing such models is to predict default events based on internal and external statistics. Each PD-model should cover its own risk segment, i.e. a specific list of borrowers in the loan portfolio that are characterized by a common specificity of sources of repayment of obligations, reporting, risk metrics, the level of default of the loan portfolio, and so on. Thus, risk segments are identified using both economic and statistical evaluation criteria based on the Bank's available empirical data for each group of borrowers to build separate models. In particular, there are high-and low-default portfolios of Bank clients. The first group most often includes models for banking assets and subjects and municipalities of the Russian Federation, as well as the largest and largest Russian borrowers in certain industries, often being monopolists in them. The second group of clients (with a high level of risk) most often includes clients of small and medium-sized businesses, as well as project Finance clients. Depending on the available volume of default statistics, different approaches for modeling the probability of default are identified for clients. This Chapter will describe the specifics of developing models for low-default risk segments (Bank assets), both low-default and high-default risk segments (corporate borrowers) and high-default risk segments, including taking into account the availability of a small amount of static data (residential real estate lending and project Finance segments).

**Keywords** Credit risk, Logistic regression, Decision trees, Bayesian approaches

**JEL** G21, G24, G32

**1. Building models for low-default borrowers using banks as an example**

In current banking practice, the portfolios of Bank assets of the largest Russian banks are low-defaulted due to the fact that most often such lending is carried out with the best and most reliable borrowers in the market, and there are no default statistics for such banks, and the development of a model based on external license revocations or Bank failures will not be representative of existing Bank portfolios. In this case, the most common approach is based on approximating the frequency of default of external ratings (Shadow rating approach). The essence of this approach is to develop a linear regression model of one of the following 3 types:

, (1)

(2)

, (3)

where PD - average probability of default of the borrower's external ratings;

a - vector-row of regression coefficients for normalized risk factors;

b - intercept;

x - vector-column of normalized values of risk factors that affect the occurrence of a default event.

The weights of risk factors in models are defined as the ratio of modules of values of the corresponding regression coefficients to the sum of modules of regression coefficients, i.e., .

The correspondence between the ratings of S&P, Moody's, and Fitch and the annual probability of default is shown in Table 1, obtained from the annual reports of S&P, Moody's, and Fitch, which contain information on the default frequencies of external ratings (these are the probability of default for the economic cycle – TTC, which are used for regulatory purposes). The average probability of default of a borrower can be defined as the average probability of default for all external ratings available to it (S&P, Moody's, Fitch).

**Table 1** Correspondence between the ratings of S&P, Moody's, Fitch and annual probability of default

|  |  |  |  |
| --- | --- | --- | --- |
| **Rating S&P,Fitch** | **Rating Moody's** | **Scale\_num** | **PD (Migration matrix)** |
| AAA | Aaa | 1 | 0,00% |
| AA+ | Aa1 | 2 | 0,00% |
| AA | Aa2 | 3 | 0,02% |
| AA- | Aa3 | 4 | 0,03% |
| A+ | A1 | 5 | 0,05% |
| A | A2 | 6 | 0,06% |
| A- | A3 | 7 | 0,06% |
| BBB+ | Baa1 | 8 | 0,10% |
| BBB | Baa2 | 9 | 0,16% |
| BBB- | Baa3 | 10 | 0,24% |
| BB+ | Ba1 | 11 | 0,32% |
| BB | Ba2 | 12 | 0,53% |
| BB- | Ba3 | 13 | 0,95% |
| B+ | B1 | 14 | 2,01% |
| B | B2 | 15 | 3,41% |
| B- | B3 | 16 | 6,75% |
| CCC+ | Caa1 | 17 | 26,89% |
| CCC | Caa2 | 18 | 26,89% |
| CCC- | Caa3 | 19 | 26,89% |
| CC+ | Ca/C | 20 | 26,89% |
| CC | Ca/C | 21 | 26,89% |
| CC- | Ca/C | 22 | 26,89% |
| C+ | Ca/C | 23 | 26,89% |
| C | Ca/C | 24 | 26,89% |
| C- | Ca/C | 25 | 26,89% |
| RD | Ca/C | 26 | 100% |

Thus, the developed model in this case is a mapping of the probability of default of borrowers on the average assessment of the probability of default of external rating agencies Moody's, S&P, Fitch. In such an assessment, additional analysis should be carried out on the compliance of the internal bank definition of default with the definition of default of external rating agencies. In General, the main default criteria for both Moody's, S&P, Fitch, and most Russian banks are the facts of the borrower's insolvency (nonperforming loans for more than 90 days, forced restructuring, bankruptcy), so mapping to information from external rating agencies seems reasonable. The risk indicators (they can be either continuous or discrete) participate in the procedures of logistic transformation (continuous variables) and WOE-transformation (qualitative variables) before being used into the regression. The essence of logistics and WOE-transformations is to reduce the impact of outliers, the formulas for their implementation will be given below. It is also possible to potentially perform WOE- transformation for continuous risk factors, but this often leads to overfitting of the obtained intervals, i.e. the logistic transformation is generally more stable than the WOE transformation. Logistics transformation in the case when the growth of the factor reduces the level of credit risk of borrowers from an economic point of view, is carried out according to the formula (4):

(4)

where Ratiotr – transformed value of the risk factor;

Ratio – the value of the risk factor;

Slope – transformation coefficient for the risk factor;

Midpoint – (Ratio5% + Ratio95%)/2 risk factor, where Ratio5%&Ratio 95% - the risk factor percentiles are 5% and 95%.

If the growth of the factor increases the level of credit risk of borrowers from an economic point of view, the formula (5):

 (5)

The values of the Slope transformation coefficients are found from the following normalization condition (6):

 (6)

For qualitative (discrete) risk factors, the woe conversion is performed using the following formula for comparability of discrete values (groups of factors) by default level:

, (7)

where WOEi – value of the WOE indicator for the factor group with the sequence number i;

avgPDi – the average probability of default for the average PD of S&P, Moody's, and Fitch borrowers for the factor group with ordinal number i;

avgPDall – the average probability of default for the average PD of S&P, Moody's, and Fitch borrowers in the entire sample.

For the transformed coefficients, in order to bring the risk factors to a single scale in standard deviations, normalization was performed using the following formula:

 (8)

where RatioNorm – normalized value of the risk factor;

Ratiotr – transformed value of the risk factor;

Mean – average value of the transformed risk factor;

Std – standard deviation of the transformed risk factor.

Then the converted risk factors are substituted into formulas (1), (2) or (3) and the regression coefficients of various model variants are estimated using the least squares method. In other words, all possible models are sorted out and the best one is selected based on various statistical and expert criteria. As statistical criteria, the coefficient of determination *R2* or Adjusted *R2*or the Somers ' rank correlation coefficient can be used, calculated using the following formula:

 ,  (9)

where SD – value of indicator Somers’D;

NC – the number of matched pairs between the normalized risk factor values and the probability of default of the average PD of external ratings (1 - the probability of default of the average PD of external ratings);

ND – the number of inconsistent pairs between the normalized values of the risk factor and the probability of default of the average PD of external ratings;

NA – the total number of permutations in the sample (for a dimension selection N:);

NB – the total number of permutations of repeated values of the probability of default of the average PD of external ratings in the sample (, where ti – the number of duplicate i-th value of the probability of default is not given the S&P, and Q is the total number of duplicate i-th value of the probability of redefault average PD external ratings.

The predictive and discriminative ability of models is considered weak if the values of the coefficients R2 and Somers'D are less than 40% and strong if the values of these coefficients are more than 60%.To reduce the number of variables in the model iteration, one-factor analysis results are often used, excluding statistically insignificant variables. When selecting models, its stability is evaluated on a separate out-of-time sample and in the cross-validation procedure on average on out-of-time samples. The following 4 main groups of indicators can be used as groups of variables to iterate through Bank models:

1) Сapital adequacy Indicators;

2) Indicators that characterize the quality of banks ' assets;

3) Indicators that characterize the quality of management (business activity of banks);

4) Liquidity indicators of the banks.

Examples of group 1 ratios (capital adequacy):

• Sources of own funds/Total liabilities;

• Sources of own funds/Borrowed funds;

• Sources of own funds/ Assets generating direct income;

• Authorized capital/Sources of own funds;

• Sources of own funds/Deposits of individuals;

Examples of group 2 coefficients (Bank asset quality):

• Assets generating direct income/Total assets;

• Risk protection coefficient (retained earnings of previous years (uncovered losses of previous years) + Unused profit (loss) for the reporting period + Reserve Fund)/ Assets generating direct income;

• Level of assets with increased risk (Other loans + Loans and other placed funds with overdue payments + Investments in Finance leases and acquired rights of claim + Investments in securities + abs(Accounts Receivable - Accounts Payable))/Total assets;

• Overdue debt/Loans, deposits and other placed funds

• Accounts receivable/(total assets-Assets generating direct income).

Examples of group 3 coefficients (quality of management):

• Loans and other deposited /Total assets;

• Loans and other deposited /Borrowed funds;

Examples of group 4 coefficients (liquidity indicators):

• Liquidity ratio of the «first stage reserve» (Cash currency and payment documents + In the Bank of Russia)/(Interbank loans (deposits) received (borrowed) + Loans (deposits) received from the Bank of Russia + Funds of clients who are not credit institutions), where, In the Bank of Russia = On the organized securities market + Savings accounts of credit organizations in the issuance of shares + Funds of authorized banks deposited with the Bank of Russia + Funds on account with the Bank of Russia + Accounts for other operations with the Bank of Russia

• Liquidity ratio of the «second stage reserve» (Cash currency and payment documents + In the Bank of Russia + Debt obligations of the Russian Federation + Debt obligations of subjects of the Russian Federation and local governments + Debt obligations of foreign States + Debt obligations of the Bank of Russia)/(Interbank loans (deposits) received (borrowed) + Loans (deposits) received from the Bank of Russia + Funds of clients who are not credit institutions)

• Cash/Total assets

• Cash/Borrowed funds

• Balance ratio of the Bank's active and passive policies (Cash + Mandatory reserves + Interbank loans (deposits) provided (deposited) + Until demand + Demand loans and promissory notes at sight + Financial assets at fair value + Net investments in HTM-securities + Net investments in available-for-sale securities + Accounts Receivable)/(Funds on correspondent Bank accounts + Interbank loans (deposits) received (attracted) + Funds in legal entitie’s accounts of the individuals (non-credit organizations) + Deposits and other borrowed funds on demand + Accounts payable)

By iterating through models with functional dependencies (1), (2), and (3), you can develop a model that maps the probability of default on the probability of default of clients with external ratings that cover a particular Bank's portfolio. In addition, it should be noted that often the approach based on external ratings gives an excessively conservative PD forecast and does not take into account internal statistics of customer observations. For this purpose, many banks perform additional calibration of the models based on Bayesian methods, taking into account real Bank statistics of observations. This approach consists in obtaining a posteriori probability of default for borrowers with available default statistics using the closest possible loan portfolio (CPP), which has a priori probability of default on external ratings and is based on the Bayes formula of conditional probability density:

, (10)

where x – a random variable that characterizes the a priori probability of default;

t – a random variable that characterizes a posteriori number of defaulted borrowers with available statistics;

ƒ– a random variable that characterizes a posteriori number of dissatisfied borrowers with available statistics;

T,F – the number (historical number) of defaulted and non-defaulted borrowers, respectively, with available default statistics for the risk segment

Assuming that the a posteriori number of defaults in the loan portfolio is distributed by the binomial distribution *Bin(T, F)*, and the a posteriori probability of default is distributed by the beta distribution *Beta (a,b)*, we get:

, (11)

where - number of combinations without repetitions;

t - parameters of the beta distribution that characterizes the a priori probability of default x.

After making the transformations in formula (10), we get:

. (12)

Thus, the a posteriori distribution in the presence of T default borrowers and F non-default borrowers is approximated by the beta distribution *Beta(T+a, F+b)*. From the properties of the beta distribution, it follows that PDTTC (PD for the economic cycle, used for evaluating regulatory capital) is determined by the formula:

. (13)

The coefficients *a* and *b* are determined based on approximating the historical probability distribution of default clients with external ratings by beta distribution by maximizing the maximum likelihood function.

The transition from PD accounting for Bayesian adjustment to PD with this adjustment (a posteriori PD) can be performed using the following formula:

, (14)

|  |  |
| --- | --- |
| where – | a priori probability of default (obtained using a linear regression model); |
| – | a posteriori probability of default (obtained with Bayesian adjustment); |
| *N* – | probability function of the standard normal distribution; |
| *b*  – | intercept. |

The intercept of calibration is selected for the entire historical loan portfolio using the formula (14), taking into account the need to obtain the average PDTTC value determined by the formula (13).

**2. The construction of models for corporate borrowers**

At the moment, Russian banks are focusing considerable attention on lending to the largest borrowers. This is largely due to the fact that in Russia there is instability in the economy with regular recessionary and crisis phenomena (falling GDP, inflation). This is due to the dependence of the Russian economy on raw materials and energy prices, which are quite volatile. The most stable borrowers with minimal credit risk are the largest borrowers. In the largest Russian banks, borrowers with annual revenue or average annual assets of more than 20-30 billion rubles are considered as the largest russian borrowers. The number of defaults for such clients is insignificant and it is impossible to build standard statistical models for assessing the probability of default (logistic regression, classification trees, and other classical algorithms) in this case. At the same time, the limit of indebtedness of such clients in the largest banks reaches significant amounts. The largest Russian banks prefer to work now with the largest clients and only slightly try to develop the direction of lending to small and medium-sized businesses.

For this reason, to develop rating models for the largest borrowers, an approach for low-default portfolios is used, similar to the shadow rating approach for banks, only the are other borrower’s risk factors. At the same time, it is necessary to tell about the specifics of allocating the risk segment of the largest (low-default borrowers). There are 2 main approaches for identifying the largest borrowers segment:

• Based on the identification of the threshold for borrowers, above which no defaults were recorded in the Bank, and the development of the model based on external ratings or, more rarely, on expert ranking;

• Based on the identification of a threshold for borrowers that provides optimal coverage of the resulting portfolio of borrowers in terms of external ratings (at this threshold, a small number of clients with external ratings out of all possible clients with external ratings doesn’t fall into the segment, and at the same time, there should also be a minimum number of clients in the segment without external ratings, it is based on maximizing the F1 measure) and in this case, the development of the model is based on external ratings.

The expert ranking approach can also be applied to individual sub-segments of the corporate portfolio if there is insufficient volume of external ratings and default statistics. It consists in the fact that each client is ranked by business departments, receiving an expert rating from 1 to R (1 – the worst, R-the best) according to strictly defined criteria. It is better to conduct the ranking for the same client employees in the business department and the underwriting department. Then the model reproduces expert ratings and allows you to get a score for the client, which allows you to rank it in terms of the level of creditworthiness. Calibration of such portfolios is most often based on available external ratings, which are not enough to develop a separate model, but enough to map the resulting ranking score on the external ratings. The algorithm for developing an expert ranking model is based on the construction of ordinal logistic regression models (ordered choice models) and is shown below. It allows you to get cumulative probabilities of being in expert ratings with ordinal numbers 1; 1,2; 1,2,3; 1,2,3,...,R-1 provided the same values of regression coefficients for risk factors for each cumulative probability using a logistic functional relationship:

, (15)

where – cumulative probability of finding a borrower in expert ratings with ordinal numbers 1,2,..., j;

– ordinal number of the corresponding expert rating (j = 1,..., R-1);

– a column vector of the normalized values of risk factors on the expert rating of the borrower;

 – vector row of regression coefficients for normalized risk factors;

– the regression coefficient is an intercept when evaluating the cumulative probability of finding a borrower in expert ratings with ordinal numbers 1,2, … ,j, at the same time for any j и j+1: bj+1 > bj.

The vector coefficients and free regression terms are based on the maximization of the logarithmic likelihood function (16):

(16)

where – binary variable from the set {0;1} that records the fact that the I-th borrower is in the expert rating with the ordinal number j;

– cumulative probability of finding a borrower with an ordinal number in expert ratings with ordinal numbers 1,2, …, j, obtained using the logistics function (15), at the same time =1;

N – number of borrowers in the sample.

The overlap of the condition for identical values of regression coefficients for risk factors is due to the need to obtain the parameter , which allows you to rank borrowers in terms of creditworthiness. As the value of the Score parameter increases, the probability of being a borrower in expert ratings with a higher creditworthiness (with a larger sequential number) increases.

For corporate borrowers with sufficient default statistics, the most commonly used models are binary logistic regression, an interpreted classification tree (CART algorithm), or an ensemble of interpreted decision trees (usually 2-4 trees). The most popular approach is based on logistic regression, which is used to predict the event of default/non-default of the borrower {0;1}. The functional dependency PD for logistic regression looks like this:

, (1)

where – vector-column of normalized values of risk factors that affect the occurrence of a default event for the borrower;

 – vector-row of regression coefficients for normalized risk factors;

– intercept

The coefficients of the vector  and intercept  are based on the maximization of the logarithmic likelihood function (11):

(2)

where – a binary variable from the set {0;1} that records the fact that the borrower has not defaulted in 1 year horizon;

– probability of default for a borrower with an ordinal number obtained using the logistics function.

The transformations of risk factors for a binary variable that records the presence or absence of a default event are similar to those that were described in banks (logistics and WOE transformation and normalization of risk factors), but there is a difference in the implementation of WOE transformation:

, (19)

where WOEi – value of the WOE indicator for the factor group with the sequence number *i*;

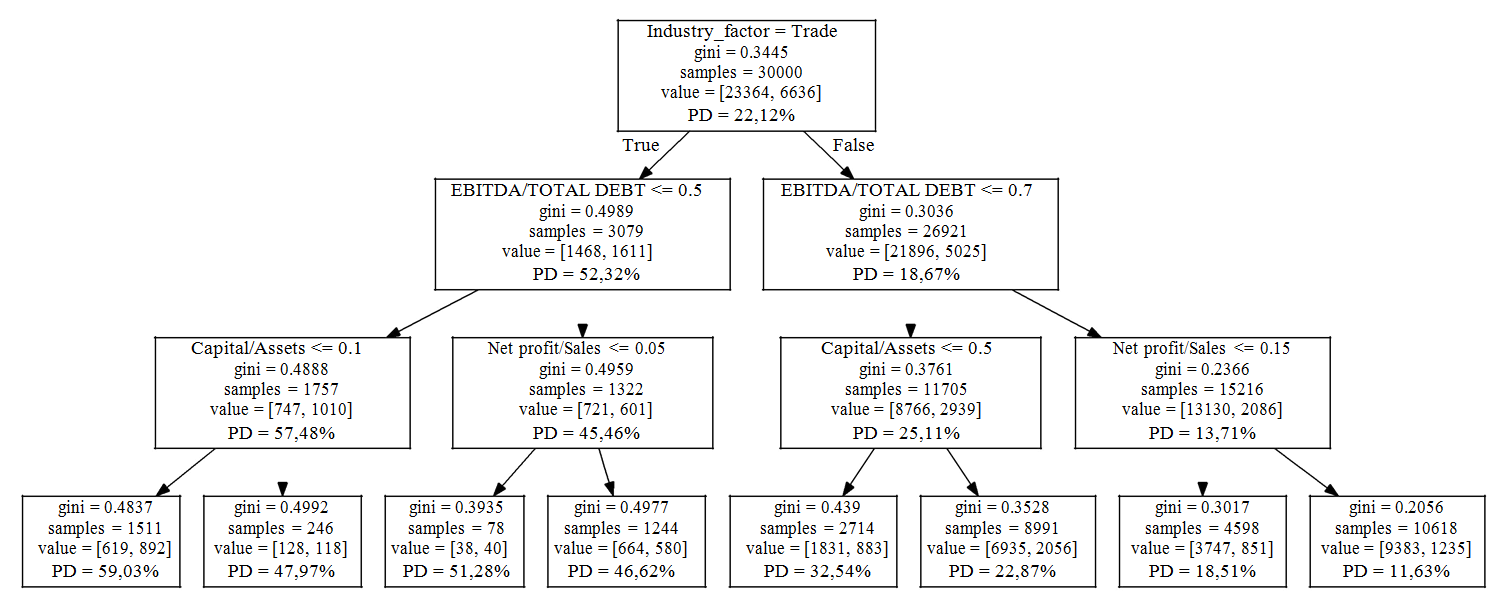
Ngoodi – the number of non-default borrowers in the factor group with the sequential number *i*;

Ngoodall – total number of non-defaulted borrowers;

Nbadi – the number of defaulted borrowers in the factor group with the sequence number i;

Nbadall – total number of defaulted borrowers.

The CART (Classification and Regression Tree) algorithm is designed for building a binary decision tree. At each step of building the tree, the rule generated in the node divides the specified set of examples into two parts – the part where the rule is executed (the right subtree) and the part where the rule is not executed (the left subtree). The CART method is used for continuous and discrete variables. This method iterates through all possible branching options for each node, and selects the variable for which the evaluation function gives the best indicator.

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**Fig 1** Example of using the CART classification tree

**Table 2** List of indicators for evaluation in corporate modeling

| Group of factors | Factor name |
| --- | --- |
| Liquidity | Cash/Current assets |
| (Cash + Short-term financial investments)/Current assets |
| (Cash + Short-term financial investments)/Short-term liabilities |
| Current assets/Current liabilities |
| (Cash + Short-term financial investments +Accounts receivable +Taxes)/Short-term liabilities |
| Non-current assets /Non-Current liabilities |
| Working capital /Assets |
| Debt load | EBITDA/Interest Expense |
| EBITDA/Total debt |
| Revenue/Total debt |
| Cost/Revenue |
| Income from operating activities/(Cost of sales + Commercial expenses + Management expenses) |
| Leverage | Capital/Assets |
| Equity/Current liabilities |
| Equity/Long-Term liabilities |
| Capital/Long-term borrowings + Short-term borrowings |
| Equity/Net debt |
| Capital/Long-Term borrowings |
| Capital/Short-term borrowings |
| Turnover | Mid-annual value of accounts receivable/Revenue |
| Mid-annual value of inventory/Revenues |
| Mid-annual value of accounts payable/Revenue |
| Accounts receivable turnover + Inventory turnover |
| Mid-annual value of assets/Revenue |
| Mid-annual value of non-current assets/Revenue |
| Profitability | Gross profit/Revenue |
| Gross profit/Assets |
| Operating income/Revenue |
| Income before taxes/Revenue |
| Net profit/Revenue |
| EBITDA/Revenue |
| Net profit/Mid-annual value of assets |
| Net profit/Mid-annual value of capital |
| (Commercial expenses + Management expenses)/ Revenue |
| Debt structure | Short-term debt / short-term debt + long-term debt |
| Size | Natural logarithm of assets |
| Natural logarithm of capital |
| Natural logarithm of revenue |

The estimation function used by the CART algorithm is based on the intuitive idea of reducing the uncertainty (heterogeneity) in the node and is based on the Gini impurity index:

G i n i ( T ) = 1 − ∑ i = 1 n p i 2 {\displaystyle Gini(T)=1-\sum \_{i=1}^{n}p\_{i}^{2}} (20)

where *pi* is the probability (relative frequency) of class *i* in *T*.

If the set T is split into two parts T1 and T2 with the number of examples in each N1 and N2, respectively, then the split quality indicator is equal to: G i n i split ( T ) = N 1 N ⋅ G i n i ( T 1 ) + N 2 N ⋅ G i n i ( T 2 ) {\displaystyle Gini\_{\text{split}}(T)={\frac {N\_{1}}{N}}\cdot Gini(T\_{1})+{\frac {N\_{2}}{N}}\cdot Gini(T\_{2})} . The best partition is the one for which Ginisplit(T) is minimal. The choice of the best tree is determined using the definition of such a level of its depth, after increasing which the predictive ability of the tree in cross-validation begins to decrease or slightly increases, not in proportion to the complication of the algorithm. When building a tree, its individual branches may not be interpreted. For such cases, the tree is manually pruned with minimal loss of accuracy and the absence of non-interpreted branches (most often due to a small number of observations). An example of developing a classification tree for assessing the probability of borrowers defaulting on financial statements is shown in the figure below.

An ensemble of decision trees constructed using the CART algorithm from random subsamples of the General population can also be developed as a model. This improves the stability of the developed models. To obtain an estimate of the probability of default on the forecast horizon of 1 year, models based on default statistics are calibrated for the economic cycle using the formula (21):

(21)

where & –the regression coefficients of the model;

& – coefficients determined when calibrating the rating model based on the Central tendency (TTC concept).

These modules are aggregated and allow you to get the resulting scoring score, which is converted to the probability of default for the model based on the calibration results. Also it should be noted that the specifics of corporate borrowers in different sectors varies, for this reason, in the framework of the development of a single model need to take into account the specifics of different groups, similar sort of activity and the level of turnover, adequately conducting their comparability when developing models.

The following table provides a list of financial risk factors and groups that can be used in developing corporate models. In practice, most often there are groups of liquidity, debt load, financial leverage, borrower turnover, profitability, debt structure and scale of operations.

**3. Specifics of developing models for clients of residential real estate lending segments**

Construction occupies a significant part of the Russian GDP structure. In recent years, the share of GDP has decreased from 5,9% in 2014 to 5,4% in 2018. If we look at absolute indicators (the amount of funds and the number of housing units entered), they are also declining. So, in record 2015, the figure of housing commissioning volume was 85,35 million square meters. Summary data for 2015-2019 is shown in table 3.

**Table 3** Volume of housing commissioning in Russia in 2015-2018

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Year** | **2015** | **2016** | **2017** | **2018** |
| Housing commissioning volume, million sq. m. | 85,35 | 80,2 | 78,6 | 75,66 |

Thus, currently, construction, and residential real estate to a greater extent, is stagnating. There are the following reasons for this:

• Construction is sensitive to the economic situation in the country. GDP grows faster during periods of growth and falls more strongly during the times of economic instability.

• If the infrastructure of the projects are mainly financed by the State, then the construction of residential real estate primarily depends on the dynamics of the population’s disposable income, which decreased by 9,4% over the same period.

• The third factor is changes in the legislation of the Russian Federation-the ban on shared-equity construction from 2018 and the mandatory transition to escrow accounts.

The conclusion from this is an increase in risks for construction companies, especially those engaged in housing construction, that reflected in an increase in the number of bankruptcies of companies.

**Table 4** Number of bankruptcies of housing construction companies (turnover from 50 million rubles to 3 billion rubles)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Year** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** |
| The number bankruptcies | 14 | 21 | 24 | 16 | 82 | 88 |

In this situation, banks that issue loans for housing construction need to have high-precision models for assessing borrowers.

**Table 5** Risk factors of project companies based on financial statements

|  |  |  |
| --- | --- | --- |
| № | Factor name | Description |
| 1 | Profitability of sales, % | Gross profit / Revenue |
| 2 | EBITDA margin, EBITDA, % | EBITDA/ Revenue |
| 3 | Current liquidity ratio, % | Current assets/Сurrent liabilities |
| 4 | Quick liquidity ratio, % | Describes the company's ability to repay short-term liabilities using the sale of liquid assets |
| 5 | Absolute liquidity ratio, % | Most liquid assets / short-term liabilities |
| 6 | Coefficient of the provision of own working capital, % | Own circulating assets/Current assets |
| 7 | Total debt to EBITDA ratio, % | Total debt / EBITDA |
| 8 | Repayment period of accounts receivable, days | - |
| 9 | The period of repayment of accounts payable, days | - |
| 10 | Gross margin, % | Gross profit/Revenue |
| 11 | Total debt to equity ratio, % | - |
| 12 | Revenue | - |
| 13 | Total assets | - |
| 14 | Return on assets ROA, % | Net profit/Assets |

The specifics of developing models for the construction of residential real estate is that many housing companies have separate projects, the success of which directly depends on their creditworthiness. It should also be noted that with a small number of projects, the company's financial statements may not allow us to predict exactly the risks of borrowers of residential real estate construction, especially before such borrowers enter the operational phase when making a decision on their lending. Thus, the role of using in models of risk indicators that characterize individual projects of such companies is increasing (for example, residual value-weighted indicators for 5 major projects of the project company) and the models include both the module based on reporting of the project companies and the module based on financial indicators of major projects (including qualitative, expert risk factors that characterize the construction risks of individual projects).

When building a module based on the financial statements of project companies you should pay attention to the following risk factors.

Thus, the role of accounting in models of risk indicators that characterize individual projects of such companies is increasing (for example, residual value-weighted indicators for 5 major projects) and the models include both a module based on reporting and modules based on financial indicators of major projects (including qualitative, expert risk factors that characterize the construction risks of individual projects).

When building a Finance module, you should pay attention to the following risk factors.

The following factors can be attributed to the risk factors of the module based on individual projects.

**Table 6** Risk factors of the project module

| **№** | **Factor name** | **Description** |
| --- | --- | --- |
| 1 | IRR | The interest discounted rate at which the net cash flow from operating activities, including income from participation in the capital of third parties, is equal to investment costs of the project |
| 2 | Weighted DSCR (Debt Service Coverage Ratio) | It characterizes the quality of debt service for the project, that is, the adequacy of funds to repay liabilities:  where CFADS (Cash Flow Available for Debt Service) - cash flow for servicing borrowed funds;  PR (Principal Repayment) – payments in part of the principal amount of loans and loans;  IP (Interests Payments) – interest payments on borrowed funds;  LP (Lease Payments) – lease payments;  t – number of the payment period (total H payments) relative to the start of the project |
| 4 | LLCR (Loan Life Coverage Ratio) | It characterizes the company’s ability to pay off project debts at the expense of future cash flows:  where CF - project cash flow from operating activities;  i – project interest rate (or WACC);  DR – provisions for repayment of project obligations;  Debt – outstanding balance as of the current date |
| 5 | LTV | The ratio of the loan amount to the market (or estimated) value of the collateral of the project |
| 6 | The ratio of the market and book value of the project | The market value of the project is determined at the current date based on the method of analogues, the book value is equal to the original cost less depreciation |
| 7 | Percentage of beneficiaries ' own participation | Share own participation of the beneficiaries in project financing |
| 8 | The payback period of the project | The period of time required for the income generated by the investment to cover the cost of the investment of the project |
| 9 | The term of the project | The term of project in years |
| 10 | Whether balloon-payment is available | Payment at the end of the project implementation period |
| 11 | The industry of the project. |  |

The risk factors of the project module are calculated for project companies, taking into account the residual value weighting for individual projects. The most significant in practice for housing construction are such risk factors as LTV, The ratio of the market and book value of the project, The fact of balloon-payment of the project, because the creditworthiness of project companies is directly affected by the liquidity and quality of collateral for its projects.

Approaches to implementing PD estimation models in this area are similar to the main interpreted approaches used in developing models based on default statistics: logistic regression, classification trees, interpreted ensembles of classification trees, and model calibration is performed using the formula (21) based on the resulting final score for the models. In this case, the target variable is used as the fact of default of the project company, the module variables based on the project company's financial statements are used only after the company enters the operational phase, and only the project module is used until the company enters the operational phase.

**4. The specificity of the development of models for investment projects**

The specifics of developing models for investment projects differ from the development of models for housing projects in that the financial reporting indicators of project companies don’t work for such transactions. Only weighted indicators of the project module are good for PD prediction, the most significant of which for investment projects are IRR, Weighted DSCR (Debt Service Coverage Ratio), The payback Period of the project, The project Term, and the share of own participation of the beneficiaries. Statistical approaches to the implementation of portfolio models are similar to those applied to residential real estate models. Additionally, if there is a small amount of statistical data of defaults, an expert ranking approach can be used.

Taking into account the specifics of investment projects, simulation (individual) PD models are often developed for SPV companies with a single project. The definition of default used in simulation models in practice is often taken to be different from the classic one and represents the implementation of at least one of the following events (for the most part – the event №2, due to the fact that investment projects in practice most often pay off the main part of the debt at the end of the term (the project has balloon payment):

Default of at least one of the project companies (borrowers) carrying out the project, that is, the presence of at least one company participating in the project, one of the following signs:

The project company was declared insolvent (bankrupt);

The project company is persistently insolvent, that is, it does not fulfill its obligations to creditors for more than 90 calendar days.

The fact of simultaneous implementation of the following two events:

Reducing the debt service coverage ratio (DSCR) below 1;

Reduction of the principal repayment and servicing ratio (LCR) below 1.

The above definition of default is used in many foreign and russian credit organizations and is related to the experience of work of the credit organizations with the investment projects.

The simulation model generates a scenario distribution of the project’s cash flow based on a number of risk factors. The complexity of the simulation model is determined by the method of selecting risk factors and the method of determining scenarios.

The selection of risk factors for the simulation model can be performed as follows:

Risk factors are selected by the user;

Risk factors are selected from a pre-defined set of factors;

Risk factors are selected from a pre-defined set of factors for each type of project.

You can define scenarios for a simulation model as follows:

Average values, spreads, and correlation coefficients are set by the model user;

The average values are set by the model user, and the variance and correlation coefficients are estimated based on empirical data;

Average values, spreads, and correlation coefficients are estimated using macroeconomic indicators (for example, the GDP index, consumer price index, and others).

Building a simulation model involves three main stages:

Input of source data;

Simulation covenant-based scenarios and compare them with the definition of default;

Getting output data and determining the final score.

The source data of the simulation model can be external (exogenous) and internal (endogenous). Internal data – the parameters contained in the model itself that don’t depend on a specific project: sector volatility, forward rates and exchange rate volatility. External data – the project parameters entered in the model and set by the model user.

For the covenant simulations, such as DSCR and LLCR, the following parameters are used:

• Cash flow and scenarios for its development;

• Forward and interest rates;

• The parameters of the deal.

When simulating data on the cash flow of an investment project, the Monte Carlo method is used, which allows you to get a set of iterations (scenarios for the development of the situation) based on a random number generator and mathematical expectations and standard deviations of the cash flow of the investment project. Scenarios for forward and interest rates are also stimulated by the Monte Carlo method based on a random number generator and stochastic process parameters – mathematical expectations and standard deviations of interest/forward rates and the exchange rate. Transaction parameters include incoming data for each tranche for each element that affects the amount and timing of debt coverage in the event of default. Based on the data obtained during scenario simulation, you can calculate the number of implementations of default events and, accordingly, the probability of default (PD).

**5. Conclusion**

The materials discussed in this Chapter show the difference in approaches to the development of separate rating models for different risk segments in certain areas of lending.

It should be noted that each Bank has a specific loan portfolio related to the volume of available statistics (including default statistics). That is why the approaches used to assess the probability of default for different risk segments in different banks may differ.

In addition to developing PD models, an important stage of working with models is the monitoring stage, i.e. their periodic validation to assess the possibility of using models on actual data using statistical tests. Periodic model validation should take place at least once a year and cover all the main stages of model development:

The impact of data quality on the model’s performance;

Evaluating the discriminatory and predictive ability of models (including the quality of model calibration);

Assessment of the discriminatory and predictive ability of models of individual risk factors of models.

In addition, it is necessary to conduct regular risk audits of the models used in banks, covering:

Assessment of the independence and adequacy of the rating process;

Quality of filling in information by business and underwriting departments of the bank;

Adequacy of the results of periodic validation;

Independent making of recommendations for updating or fully updating models, if necessary, based on the results of their own, alternative researches within the same risk segments.

Only the well-coordinated work of the development and validation teams when building models, as well as the independent opinion of the internal audit, allow the bank to develop an independent and best-quality concept when working with models and as part of the rating process. It is also necessary to fully engage in the process of working with models of business and underwriting departments in order to take into account in the models the risk factors that characterize the specifics of individual risk segments that are identified in the lending process of the customers in practice.

**References:**

Ayvazyan S. A. (1989) Applied statistics: Classification and reducing of dimension [Text]. – M.: Finance and statistics, 1989. – 607 p.

Allen, S. (2003) Financial risk management: A practioner’s guide to managing market and credit risk [Text] / S. Allen. – Hoboken, N.J.: John Wiley & Sons, Inc., 2003. – 288 p.

Breiman, L. (1984) Classification and regression trees. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software, 1984.

Breiman, L. (2001) «Random Forests». Machine Learning 45 (1), 2001. P. 5–32.

Benninga, S. (2008) Financial Modelling. [Text] / S. Benninga. – 3 ed. – The MIT Press, 2008. – 1168 p.

Coleshaw, J. (1989) Credit analysis [Text] / J. Coleshaw. – Woodhead-Faulkner, 1989. – 240 p.

Davis, H.A. (2003) Project finance: Practical Case Studies [Text] / H.A. Davis. – 2 ed. – Published by Euromoney Books, Nestor House, Playhouse Yard, London, United Kingdom, 2003. – 237 p.

Esty, B. (2003) Modern Project Finance: A Casebook [Text] / B. Esty . – Wiley, 2003. – 544 p.

Fight, A. (2006) Introduction to project finance [Text] / A. Fight. – Elsevier, 2006. – 205 p.

Finnerty, J. (2013) Project Financing: Asset-Based Financial Engineering [Text] / J. Finnerty. – 3 ed. – Wiley, 2013. – 560 p.

Jorion, P. (2007) Financial risk manager instruction manual [Text] / P. Jorion. – 4 ed.–N.Y.: John Wiley & Sons, Ltd., 2007. – 736 p.

Joseph, C. (2013) Advanced Credit Risk Analysis and Management [Text] / C. Joseph – Wiley, 2013. – 448 p.

Lynch, P. (2010) Financial Modelling for Project Finance [Text] / P. Lynch – 2 ed. – Euromoney Trading Ltd., 2010. – 212 p.

Karminsky, A.M. (2013) Modeling the probability of default of Russian banks: extended opportunities [Text] / A.M. Karminsky, A.V. Kostrov // Journal of the New economic Association. 2013. no. 1, vol. 17. P. 64-86.

Karminsky, A. M. (2015) Credit ratings and their modeling [Text] / A.M. Karminsky; National research University Higher school of Economics, Moscow, Publishing house of the Higher school of Economics, 2015, 304 p.

Karminsky, A. M. (2015) Evaluation of the probability of default of project Finance transactions [Text] / A. M. Karminsky, A. V. Morgunov, P. M. Bogdanov // Journal of New economic Association. – 2015. – No. 2. –Vol. 26. – P. 99-122.

Lobanov, A.V. (2009) Encyclopedia of financial risk management [Text] / under the editorship of Cand. Econ. Sciences A. A. Lobanov, A.V. Chugunov. - 4th ed., ISPR. and add. — M.: Alpina Business books, 2009. - 932 p.

McCullagh, P. (1990) Generalized Linear Models [Text] / P. McCullagh, J.A. Nelder. – New York: Chapman & Hall, 1990. – 511 p.

Mills, Terence C. (2003) Modelling Trends and Cycles in Economic Time Series [Text] / Terence C. Mills. – New York: Palgrave McMillan, 2003. – 180 p.

Pugachev, V. S. (2002) Probability theory and mathematical statistics [Text]: Textbook. Manual / V. S. Pugachev. - M.: FIZMATLIT, 2002. - 496 p.

Rogov, M. A. (2001) Risk management [Text] / M. A. Rogov. - Moscow: Finance and statistics, 2001. - 120 p.

Rees, M. (2008) Financial Modelling in Practice: A Concise Guide for Intermediate and Advanced Level [Text] / M. Rees. – Wiley, 2008. – 295 p.

Rud, O. (2001) Data Mining Cookbook [Text] / O. Rud. – Hoboken. NJ: John Wiley and Sons, 2001. – 429 p.

Siddiqi, N. (2006) Credit Risk Scorecards Developing and Implementing Intelligent Credit Scoring [Text] / Siddiqi N. – Published by John Wiley & Sons, Inc., Hoboken, New Jersey, 2006. – 196 p.

Zhevaga, A. A. (2015) Use of summary macroeconomic indicators for calibration of internal rating models in banks [Text] / A. A. Zhevaga, A.V. Morgunov // Money and Credit, 2015, No. 8, Pp. 39-46.

**Loss given default estimations in emerging capital markets**

**Mikhail Pomazanov [[2]](#footnote-2)\***

**Abstract** This chapter proposes an approach to decompose the RR / LGD model development process with two stages, specifically, for the RR / LGD rating model, and to calibrate the model using a linear form that minimizes residual risk. The residual risk in the recovery of defaulted debts is determined by the high uncertainty of the recovery level according to its average expected level. Such residual risk should be considered in the capital requirements for unexpected losses in the loan portfolio. This chapter considers a simple residual risk model defined by one parameter. By developing an optimal RR / LGD model, it is proposed to use a residual risk metric. This metric gives the final formula for calibrating the LGD model, which is proposed for the linear model. Residual risk parameters are calculated for RR / LGD models for several open data sources for developed and developing markets. An implied method for updating the RR / LGD model is constructed with a correction for incomplete recovery through the recovery curve, which is built on the training sets. Based on the recovery curve, a recovery indicator is proposed which is useful for monitoring and collecting payments. The given recommendations are important for validating the parameters of RR / LGD model.

**Keywords** credit risk, residual risk, IFRS 9 standards, unexpected losses, loss given default, recovery rate, recovery curve, capital requirements

**JEL** C58, G17, G28, G32

**1 Introduction**

LGD - Loss given default is one of the most important credit risk assessment parameters. Along with PD - Probability of default and EAD - Exposure at default, LGD contributes as a key parameter in calculating regulatory requirements, as well as economic capital requirements, as part of an approach based on internal IRB ratings (International convergence, 2006). The purpose of the LGD assessment is to accurately and efficiently quantify the level of recovery risk inherited as part of the default risk. The incentive to build LGD valuation models is the possibility of obtaining permission from the regulator to use the bank's approach based on internal ratings to calculate reserves and requirements for economic capital. The inverse of LGD is the RR (Recovery Rate), RR = 1 – LGD, so the RR simulation is identical to LGD. Recovery from default RR or its inverse value LGD = 1 – RR in practice demonstrates random dynamics and has a typical frequency profile, shown in Fig. 1.

Many empirical studies have noted bimodality with a higher concentration of observations at zero and close to one and a higher LGD during periods of economic recession. This is evidenced by the results of a number of empirical works on mortgage lending (Araten et al., 2004, Karminsky et al., 2016) and corporate lending, including corporate bond market (Qi, Zhao, 2011; Dermine, Carvalho de, 2006; Schuermann, 2004; Felsovalyi, Hurt, 1998). Therefore, to calculate unexpected losses, it is necessary to take into account the volatility of LGD in addition to its expected estimate. The dispersion of LGD, reinforced by bimodality of distribution, contributes to unexpected losses, which are the basic component of residual credit risk[[3]](#footnote-3).



**Fig**. **1** Typical frequency distribution of the level of losses after LGD model.

The typical model of LGD dispersion is not difficult to determine with the commonly used relation (Gordy, Lutkebohmert, 2013):

), (1)

where is the variance (squared standard deviation), is the mathematical expectation, is the index of a model-homogeneous population for LGD[[4]](#footnote-4), is a RR / LGD dispersion parameter theoretically belonging to the interval of [0,1], its mean value is proposed, for example, in the CreditMetrics approach (CreditMetrics, 1997). Assuming that, within the framework of the TAC, the LGD model corresponds to the average statistical observations of reconstructions, i.e. relatively medium, it does not overestimate or underestimate the calculations, we put . In practice, the parameter γ can be statistically refined at the stage of validation of the internal LGD model, for example, by the formula:

, (2)

where is the model estimate of the one default to the LGD before default, is the observed loss after the completion of the default debt recovery process.

The study (Antonova, 2012) presents the result of the LGD assessment of Russian default issuers according to the information-analytical agency Cbonds. During the observation period from December 31, 2002 to December 31, 2011, 124 Russian corporate issuers made a real default on ruble corporate bonds that were traded on the MICEX. A real default is understood as failure to fulfill an obligation by the issuer before the expiration of the grace period. Based on the calculation method chosen by the author, RR: RR = 1-LGD were calculated for defaults of corporate bonds issued by Russian issuers in 59 cases, which formed a statistical sample. The overall outcome of the assessment was the average rate RR = 48.8% (LGD = 51.2%) with a standard deviation of . For the case of an LGD-insensitive assessment model, formula (2) takes a simple form:

. (3)

The numerical estimate of is based on the result of the evaluation of LGD model as the average LGD, without constructing a refinement model. This estimate given by issuers can be considered a conservative estimation of uncertainty parameter of the LGD for the Russian bond market. It is useful to estimate the statistical error of the parameter , since, when developing the LGD model, statistics are often not enough. The estimate of is as follows:

, (4)

Formula (4) gives the standard deviation of the statistical error , provided that the model LGD is equal to the average. The statistical error (estimation of the standard deviation of the error) for the above sample of 59 issuers was = 0.06.

The study of (Antonova, 2012), indicators of average RR and standard deviations for several industry segments were also evaluated separately. The results of the evaluation of individual parameters are presented in Tab. 1.

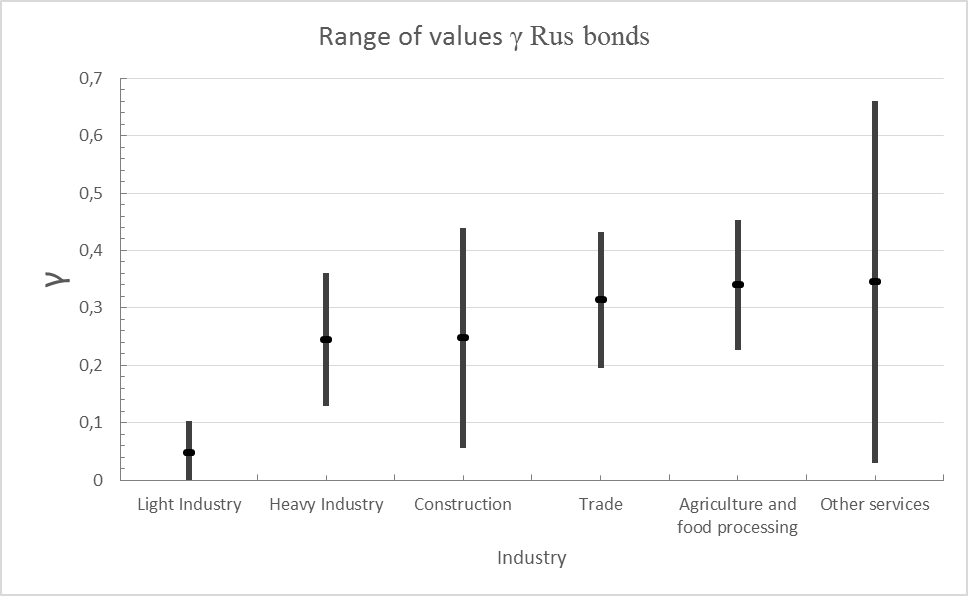
**Table** 1 Parameters for various industry segments of the default bonds of Russia

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Industy | Average,  in % | Standard deviation, in % | Number of observations | γ |
| Light Industry | 19,4 | 10 | 4 | 0,05 |
| Heavy Industry | 63,3 | 25 | 11 | 0,24 |
| Trade | 48,5 | 29 | 15 | 0,31 |
| Construction | 57,2 | 27 | 6 | 0,25 |
| Agriculture and food processing | 50,6 | 30 | 18 | 0,34 |
| Other services | 24,4 | 28,2 | 5 | 0,34 |
| Total | 48,8 | 29,2 | 59 | 0,34 |

The work of (Jankowitscha R., et al. 2014) presents the calculation of recovery levels for defaulted US bonds for the period July 2002 to October 2010, as well as standard deviations. A similar calculation of γ for non-financial sector companies is shown in Table 2 by industry and in general.

Fig. 2 shows the ranges of taking into account standard deviations due to statistical error. It can be seen from Fig. 2 that, taking into account the statistical error for different industry segments, the ranges of possible values of γ substantially intersect. An exception is only for the light industry. But in this segment there are very few measurements and, perhaps, this is just an extreme result, which is usually discarded in statistical measurements (see Fig. 2).

Comparing the results of recoveries of default bonds of the US and Russia obtained at the same observation periods, it is obvious that the average recovery level in the US was 10% lower than the Russian ones, however, the average volatility parameter γ practically coincided with the Russian one at the level γ = 0.34. However, a clear stratification of the values of γ by industry segments is revealed, in particular, the real estate differs in the minimum level of the volatility parameter, γ = 0.1, the sectors Retail and Media & Communications, γ = 0.5, have the maximum. The inclusion of statistical error, obviously, rejects the hypothesis of independence of γ, in particular, from the industry segment. Therefore, it makes sense when building the LGD model to a model for the volatility parameter γ, too. With a lack of observations, it is possible to assume that γ = const for all measurements within a model-homogeneous population, but this will fix the model error.

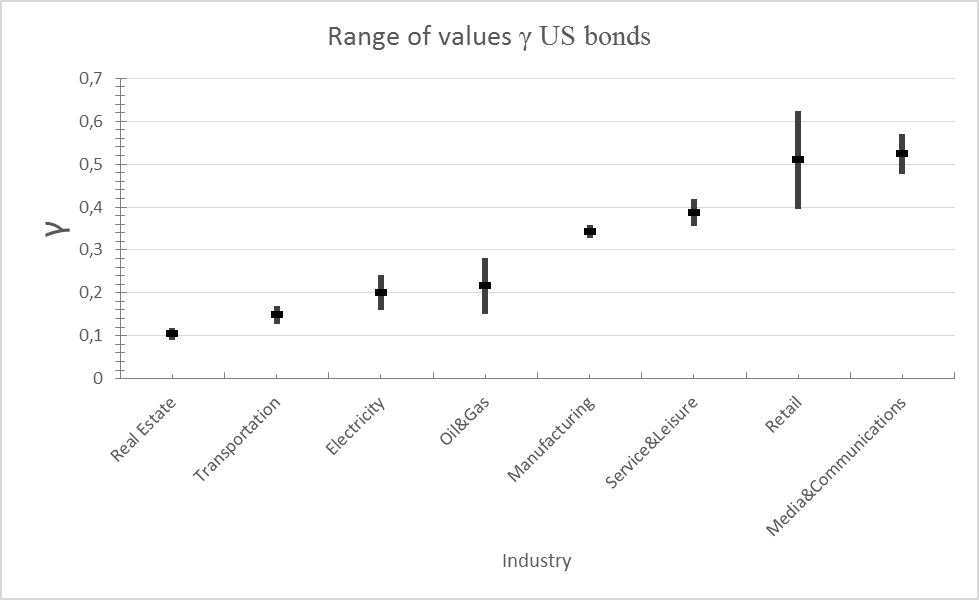


**Fig. 2** Ranges for different industry segments of Russia, taking into account standard deviations due to statistical error

**Table** **2** Parameters γ for various industry segments of US default bonds

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Industry | Average recovery, in % | Standard deviation, in % | Number of observations | γ |
| Real estate | 41,97 | 16,05 | 71 | 0,10 |
| Transportation | 38,17 | 18,85 | 70 | 0,15 |
| Electricity | 48,03 | 22,67 | 39 | 0,20 |
| Oil&Gas | 44,37 | 23,68 | 21 | 0,22 |
| Manufacturing | 38,93 | 28,55 | 573 | 0,34 |
| Service&Leisure | 38,65 | 30,37 | 190 | 0,39 |
| Retail | 33,4 | 34,19 | 33 | 0,51 |
| Media&Communications | 34,7 | 34,56 | 163 | 0,52 |
| Total | 38,68 | 28,22 | 1160 | 0,34 |

Figure 3 shows the ranges of γ according to the standard deviations due to statistical error.



**Fig.** 3 Ranges γ for different US industry segments, taking into account standard deviations due to statistical error

In the next part of the work, it is necessary to answer these questions: how to take into account the results of recoveries of default borrowers, if the provided the recovery process is incomplete? How to use statistically implemented recovery dynamics to build recovery indices for early defaults? What functionality should be optimized to build an LGD model while minimizing residual risk? How does residual risk affect economic capital requirements? What is the model? A simple, but optimal from the point of view of residual risk, LGD model will be proposed, based on a positively discriminatory rating of LGD.

**2 Recovery curve**

The start of identifying the types of RR (LGD) that can be considered as measures of LGD. In the extensive literature on LGD, for example (Vujnović M., et al., 2004), four are represented.

**Table 3** LGD assessment method

|  |  |  |
| --- | --- | --- |
|  | Default count averaging | Exposure weighted averaging |
| Default weighted averaging | LGD = (5) | LGD = (6) |
| Time weighted averaging | LGD = (7) | LGD = (8) |

where i is the observation of default, y is the year of default,

ny is the number of defaults in each year, m is the years of observation,

LR is the loss coefficient or LGD for each observation.

For practical purposes, it suffices to contrast on two approaches for calculating RR.

A. Simple recovery index (medium / median or frequency):

(9)

where is the amount of funds received to repay the debt of borrower i, discounted to the default date (both direct and indirect recovery are taken into account), is the exposure to default (EAD) of borrower i. EAD - the amount of the main debt, accrued interest, fines and other charges to the reporting period before default. After the moment of default, fines, interest and other accruals after default are not included in the EAD exposure, the off-balance part is not included, but the amounts issued after default are included.

The net credit exposure is the adjusted (reduced) credit exposure for the amount of the discounted financial collateral. The simple recovery index (RR) is not oriented to amounts; it shows the average share of recovery among defaulting borrowers.

B. Weighted Average Recovery Index

*.*  (10)

The weighted index is sensitive to the defaulted amounts (to losses). Thus, the indicators RRavg and RRw will differ if the share of recovery depends on the amount in default. If large loans recover heavier than small ones, then a simple recovery index exceeds a weighted one and vice versa. The recovery amount is calculated based on recovery payments discounted to the default date.

, (11)

where - recovery payments at time t from the date of default, - costs of bank recovery costs – - discount factor with the rate q, the sign "∞" means that theoretically wait for the a completed collection can indefinite (in practice, of course, the wait is limited and will be seen later). The repayment history for the sample of default loans (at least ) is presented in Tab. 4. The sample is taken for a sufficiently wide period of "observing" > 3-5 years. Those. on the interval of , where t is the current moment of observation of defaults (reporting date - 90 days).

**Table 4** Parameters of repayment history

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **ID** | **EAD** | Discount rate, **q in %** | **Default date** | **Recovery period after default (year)** | | | | | | |
| **1** | **2** | **3** | **…** | **S** | **…** | **P** |
| 1 | E1 | 10 | 01.05.2008 | R11 | R12 | R13 | … | R1S | … | R1P |
| 2 | E2 | 9 | 01.08.2008 | R21 | R22 | … | … | … | R2… |  |
| … |  |  |  | … | … | … | … | R…S |  |  |
| k | Ek | 11 | 01.08.2011 | RK1 | … | … | … |  |  |  |
| … |  |  |  | … | … | … |  |  |  |  |
| … |  |  |  | … | … | … |  |  |  |  |
| … |  |  |  | … | … |  |  |  |  |  |
| … |  |  |  | … | R..2 |  |  |  |  |  |
| N | EN | 6 | 01.01.2020 | RN1 |  |  |  |  |  |  |

The list of repayment history parameters:

1. ID (number) of the borrower;

2. Exposure in default (EAD, taking into account possible loans issued after default, discounted by default date);

3. Discount rate (q, in practice, the average rate for the lending period is often used in a model-uniform sample of all loans);

4. Date of default, (month of default);

5. Repayment payments discounted with the rate (q) on the maturity date, counted from the date of default (exposure period after default).

For ease of calculation, repayments are sorted in descending order of exposure after default. The applied formulas for calculating the recovery curve are selected from two possible formats:

*1. Simple format (medium / frequency)*

, (12)

where is the number of default loans that "survived" until the payment of in the period , i.e. only those loans i are taken into account for which there may be a payment V (obviously, if , n(0) = all default loans in the database). is discounted payments in the period s from the moment of default (discount), is amount in the default.

Moreover, the square of the standard deviation (the square of the error ) is substantially heterogeneous due to the different dimension for each period . is calculated by the formula:

. (13)

*2. Weighted average format (taking into account default amounts):*

. (14)

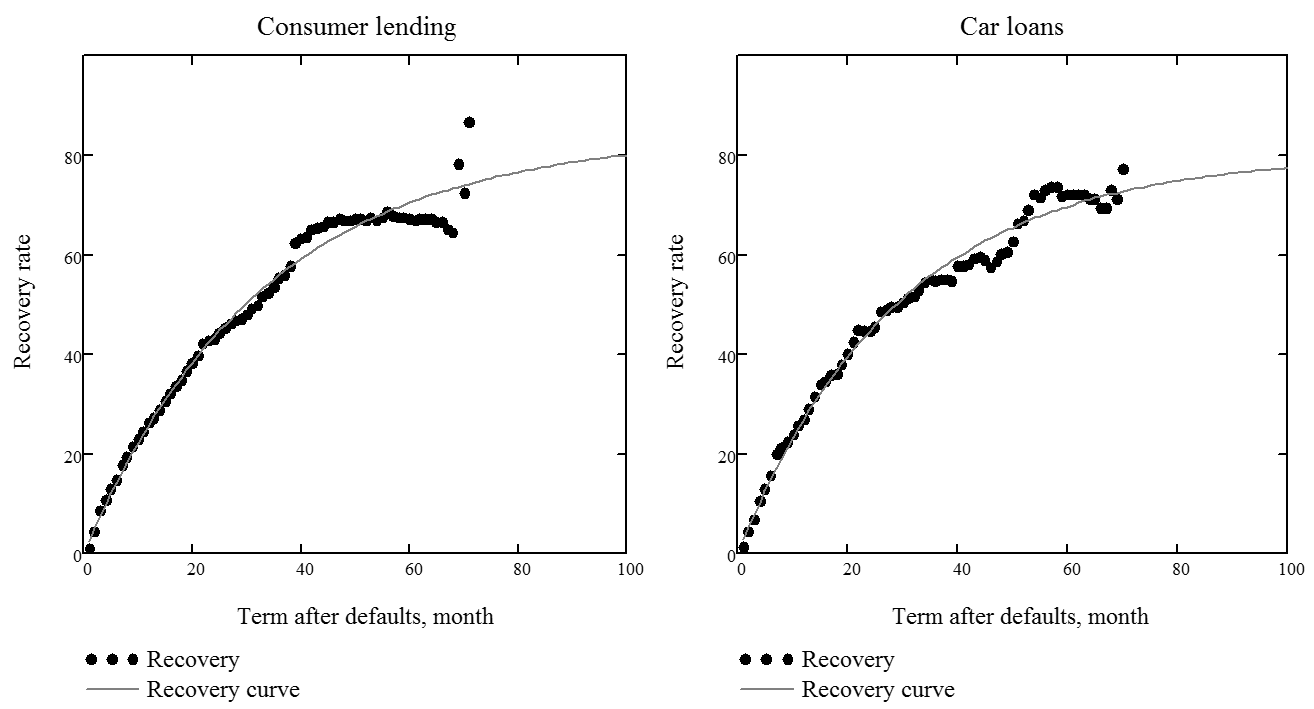
The square of the standard deviation can be estimated by the formula:

(15)

where is the Herfindahl-Hirschman index is calculated as:

(16)

An example of recovery curves is shown in Fig. 4.



**Fig. 4** Examples of constructing recovery curves

The practice implication shows that the curve can be approximated with high accuracy by a function of the form:

(17)

*,*

where T is the average recovery time.

The maturity curve limit is the recovery forecast for a non-default company, and , term T is the average recovery period. In the work of (Benjelloun M., 2019) proposed a method for modeling LGD / RR through a random process, averaging of which gives dynamics close to the behavior of Fig. 4.

To approximate of curve (17), the weighted least squares method is used (see, for example, (Strutz T., 2016), in which the residual is calculated in the Euclidean metric with weights and is minimized by the parameters **(**limit recovery**)** and ***T*** ((average recovery period):

(18)

In this case, the error of the estimate is estimated using linearized regression (18) at the optimal point . The detailed formula for estimating is given in Appendix 1.

The output is a calculation of the “slow” values of and in the current long-term “viewing window” for interval . . For example, for the data in Fig. 4 values of recovery parameters were calculated (see Table 5).

**Table 5** Statistical parameters of recovery curves

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Product** | **Recovery period** | **Total**  **size** |  | **T,**  **months** | **R-sq.** | **Error** |
| Consumer lending | 2011-2016 | 1309 | 83.8% | 32.8 | 97.6% | 17.6% |
| Car loans | 2011-2016 | 228 | 80.0% | 29.4 | 98.5% | 12.3% |

Numerous empirical calculations show a high level of fit of the recovery curve using the parametric formula (17), for example, for retail products and consumer lending R-sq. = 97-99%.

**3 Recovery indicators**

For a company that has an exposure in default with a period of τ and a certain negative account balance, the loss forecast will be estimated using the conditional LGD (τ):

(19)

or, using the parametric formula (17):

. (20)

Therefore, based on the current estimations, at the time τ> 0, the recovery value, we can construct an unbiased estimate of recovery “for infinity” as:

, i.e.

(21)

Obviously, for large waiting times τ after default, the correction to , estimated by the second term in (6), tends to zero and , which goes to the statistical base model LGD / RR.

Evaluation (21) should be used as a model estimate of the expected recovery of the debt of borrower in the case when the period after default has not passed, sufficient so that the issue of debt recovery is considered closed. Then it makes sense to determine the recovery indicator for the entire model-homogeneous segment of the population.

Recovery indicator determines the forecast of recovery on loans that defaulted on a given “short” indicative moving horizon . A simple (or a medium) recovery indicator is constructed as:

1. (22)

2. And, a weighted average indicator, taking into account the amounts of at the time default, , is constructed as:

, (23)

where ) is the number of borrowers defaulted on a given “short” indicative interval .

The recovery indicator is of a great practical importance for monitoring the process of collecting defaulted debts, the strategy for securing loans, segmenting credit policy, etc.

If the average recovery indicator exceeds the weighted average, then this means small loans (below average) are more easily repaid than large ones and vice versa.

**4 Residual risk at loss given default models.**

The question of residual risk LGD is associated with at least two risk drivers of unexpected losses, which can be underestimated when calculating the requirements for the own economic capital of the loan portfolio. The first driver is macroeconomic, this is a possible correlation of the default rate (i.e. PD) of the loan portfolio and the average LGD, associated with crisis phenomena in the economy, as well as the correlation of the average LGD with other macroeconomic factors. The second driver is local, it is associated with the LGD uncertainty (volatility), for which a “typical” model (1) with parameter γ has been selected.

Historical data on the correspondence between the level of default and the level of recovery after default on the corporate bond market in America and Europe (Moody’s data) gives the following dependence for the historical period 1982-2016. (Fig. 5).



**Fig. 5** Historical relationship between the default rate and the recovery rate for the period 1982-2016 according to US corporate bonds and EU (data Moody’s, 2017).

According to historical data, the credit risk assessment methodology recommends applying a stress correction to the unperturbed value of losses after default LGD in the form , where EDR is the expected default rate (central tendency), and is the unperturbed LGD value in the stable period. For Moodys data, the .

The correlation problem between PD and LGD (or RR) is one of the key issues in assessing credit risk. For example, a study of (Allen and Saunders, 2005) demonstrates calculations according to which the interaction of PD and LGD increases expected losses and capital requirements by up to 30%. However, portfolio credit risk assessment models are often based on the assumption that LGD is fixed and independent of PD. The authors Miu P. and Ozdemir B. note that if PD and LGD correlations are ignored in the model, the LGD should be increased on average by 6% (from 35% to 41%) to compensate for the correlation effect of PD and LGD.

At the same time, the results of study of (Ermolova and Penikas, 2017) do not allow us to state that there is a relationship between these components of credit risk for the Russian corporate bond market. A generalization of risk metrics that takes into account the dependence of LGD on PD within the framework of the proposed approach can be represented as the dependence of LGD on a random, normally distributed variable, implying that the parameter γ is a constant. In this case, it is recommended to use one of the LGD models (PD (Y)) presented in (Frye and Jacobs,2012) but it should be borne in mind that the basic requirements for the economic capital of an infinitely granular portfolio within the framework of the adjusted one-factor model will differ from the calculation formula recommended by the Basel Committee.

Within the framework of approach (1) simulating the dispersion of LGD, the simplest, continuous version of modeling the distribution of losses after default is possible — these are losses Loss = L × EAD with probability pL and losses (Loss = 0) with probability (1 – pL). The parameters L and pL can be determined from the following conditions:

; (24)

These conditions give a unique solution for L and pL:

. (25)

Then, the metrics in which the adjusted PD and EAD can be determined will be set in the form:

, (26)

.

The boundary values А: (the lack of LGD uncertainty) and B: (maximum LGD uncertainty) will mean, for case A:, ;for case B: .

Obviously, case B implies a greater exposure to default and the capital requirement should be higher for it, despite the fact that the probability of losses will decrease. This issue was investigated in (Witzany and Jiří, 2009). The authors used the one-factor approach to calculating capital recommended by the Basel Committee, taking into account the LGD parameter, first introduced in (Vasicek O., 1987). Based on the extreme scenarios presented above, it was possible to evaluate VAR (Value at Risk) LGD as the difference between the capital requirement in case B and A. The difference turned out to be positive and monotonous with respect to the model parameters, including expected level of LGD.

In the current approach, we will act similarly in the paradigm of the recommended Basel-2 approach to assessing the requirements for economic capital, created on the basis of the Vasicek formula, under these conditions:

, (27)

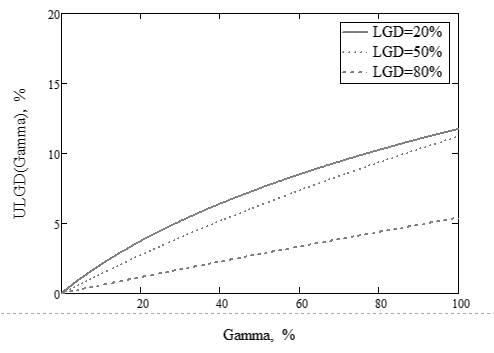
where UL is for the estimate of unexpected losses at the recommended reliability level of 0.999 (can be changed), are the standard normal and inverse distributions, respectively, R is the correlation parameter, from equation (7). The is the standard recommended form for evaluating the capital of the Basel-2 Advanced Approach. Define as a contribution to equity in relation to :

, (28)

which will be responsible for the influence of the dispersion parameter γ of LGD on capital requirements (i.e. unexpected losses).

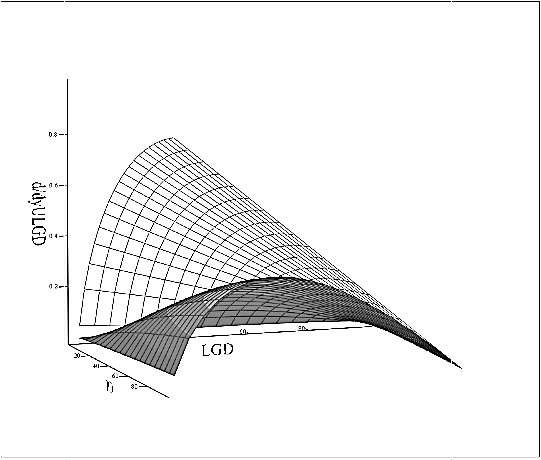
. (29)

Obviously, . Figure 6 shows graphs of behavior over the entire range of values .



**Fig. 6** A graph of the dependence of the additional ULGD requirement for capital on γ (in %) for PD = 10%, correlation R = 0.2, and significance level at 99.9%.

Fig. 6 shows that, the values of the correlation R, reliability 0.999 and PD, the capital requirements monotonously increase with increasing uncertainty coefficient γ. Fig.7 shows the surfaces at the extreme points γ = 0 (upper surface) and γ = 1 (lower surface). In the entire “working” range , the surfaces are located above the zero plane.



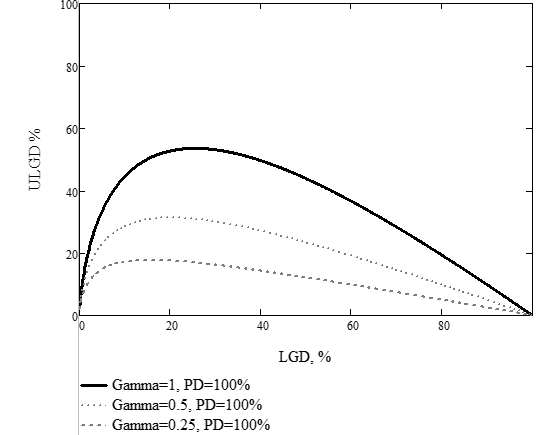
**Fig. 7** The surfaces of the derivatives for the correlation value K = 0.2 and the reliability 0.999. Lower for γ = 1, upper for γ = 0 over the area space of .

The study shows that the parameter γ is monotonic with respect to unexpected losses and its growth leads to an increase in the additional capital requirement due to the dispersion of LGD. Therefore, when developing the LGD model, it is reasonable to minimize the uncertainty parameter γ.

The largest contribution to capital will be at γ = 1 and the probability of default PD = 1:

. (30)

Fig. 8 shows a graph of .



**Fig. 8** The graph of the contribution to capital due to the dispersion of LGD for the values PD = 100%, maximum γ = 1 (black), γ = 0.5 (light grey), γ = 0.25 (dark grey) and the correlation R = 0.2.

The maximum function achieved when:

. (31)

For correlation parameters R = 0.2 and significance level (0.999) . Obviously, the shift of the shift down of unexpected losses is towards LGD <50%. This indicates increased responsibility for the model in the event of a model error in the direction of lowering LGD (increasing RR).

**5 Optimal loss given default model from the point of residual risk.**

Let introduce θ as the dimension LGD[[5]](#footnote-5) (or RR) rating of an indifferent internal structure. The linear model of the recovery level RR relative to the rating θ can be estimated as:

, (32)

where is the mean value of n realized recoveries of level R, in other words, is the standard deviation of R, measured by a biased estimation as .

Equally, is defined as the average value of θ over the entire set of reconstruction implementations on which the model is built, . The most important parameter sought for model (32) is μ – multiplicator, which should depend on the risk-determinism of the LGD rating and minimize the LGD dispersion coefficient indicated by the γ RR / LGD dispersion parameter. The observed recovery of R will be determined by the random variable ε and the model in the form , where the variance ε is modeled, according to (32), by the relation as:

(33)

In this case, the mathematical expectation Mε = 0 by the definition of the model. Further, at the input of the model, it is necessary to determine the correlation ρ between the implemented restorations R and the LGD rating indicated by θ, the estimate of which will be given by the equation:

. (34)

The more complex, non-linear LGD model in practice makes little sense. It will not provide a significant increase in the estimation accuracy due to the high volatility of LGD due to the two-mode distribution of Fig. 1. The proposed linear LGD model does not automatically guarantee natural restrictions on the simulated recovery level such as, the popular logistic representation of the type , but practice shows (see Section 6) that the LGD model cannot be created so powerful that the results of its forecast differ by multiples.

For example, if we turn to the recommendations on LGD of the Basel Committee [Basel II, 2005], then the recommendations of the minimum LGD vary in the range of 35-45%. Below these values, LGD can be formally evaluated only if there is financial security, which, in fact, should adjust the exposure to default EAD, and not LGD. If this is not done, then LGD uncertainty model is formally destroyed, since financial security is a 100% realizable recovery.

Below we will show the range of parameters for which the linear model does not go beyond the limits of natural restrictions. Passing to estimates of the observed quantities, it can be equated as[[6]](#footnote-7):

. (35)

Otherwise, it can be written as:

. (36)

Equating the expressions obtained above, the dependence γ (μ) is described as:

, (37)

where is denoted is the value of the parameter γ for the case that is not sensitive to the LGD estimation model considered in Section 2.

To find the solution for the optimal value of μ, the problem can be solved with:

, (38)

where, the optimal point for solution is .

Problem (38) is solved by the standard method of finding the minimum of a function using the first derivative optimum condition . Without bothering the reader with standard mathematical calculations, one can write out the solution to (38):

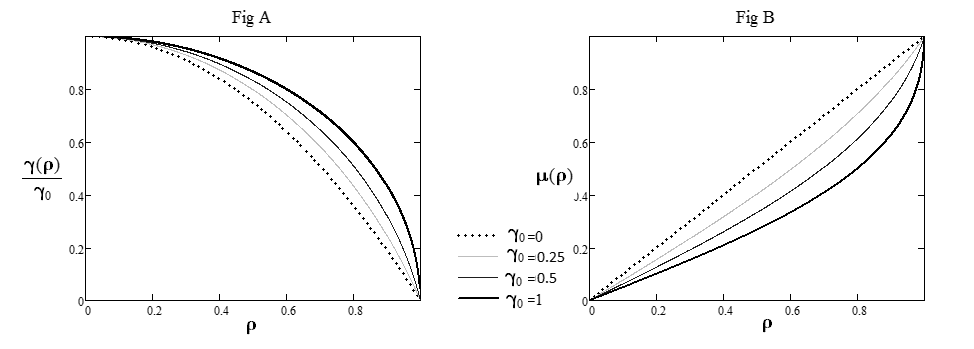
,

, (39)

.

For (in the case when the LGD rating does not work properly), an obvious solution is obtained , .

Fig. 9 shows the graphs of solutions (39) in the full range of non-negative correlation of the LGD rating with real measurements for different levels of LGD dispersion.



**Fig. 9** The dependences of LGD dispersion parameter (Fig. A) and – multiplicator of model (Fig. B) from correlation upon solution (33).

It can be seen from Fig. 9 that the effect of minimizing the dispersion of LGD becomes most significant as the risk-determinism of the LGD rating increases. However, for the optimal parameter μ of the LGD model, the effect appears immediately and μ becomes less than ρ as soon as the LGD volatility appears.

The boundary parameters for the proposed linear model (32) are calculated from the condition: . Assume, without loss of generality, that the rating θ is normally distributed over the interval [0; 1][[7]](#footnote-8), when , .

According to the model: , then the boundary values of recovery will be:

. (40)

It means that: .

Avoiding the analysis of the full variety of the three-dimensional parameter region , in which the restriction is satisfied, we will calculate for typical LGD parameters according to the recovery of US corporate bonds (see Section 2). For them, , , which corresponds to very high risk-determinism indices of the LGD model with a correlation , which is not achieved by any models.

In the practically significant range of possible models of LGD ratings and not “extreme” practical levels of average recovery (that is, not close to 0 and 1), the linear LGD model (32) will not give out a range of predictive recoveries beyond the limits of [0,1]. In practice, when constructing the LGD model, it is recommended to convert the LGD rating to a range of uniformly distributed values, evaluate (39) and check constraint (39).

In the next section, we will consider several public models for the LGD rating and their authors' assessments show the applicability of the approach described.

**6 Practical drivers of loss given default models.**

The level of recovery of the borrower after default is very specific and depends on many factors. In the literature (see, for example, (Grunert, J., Weber, M. 2009) four categories of factors for corporate borrowers are defined (see Fig. 10), which correspond to:

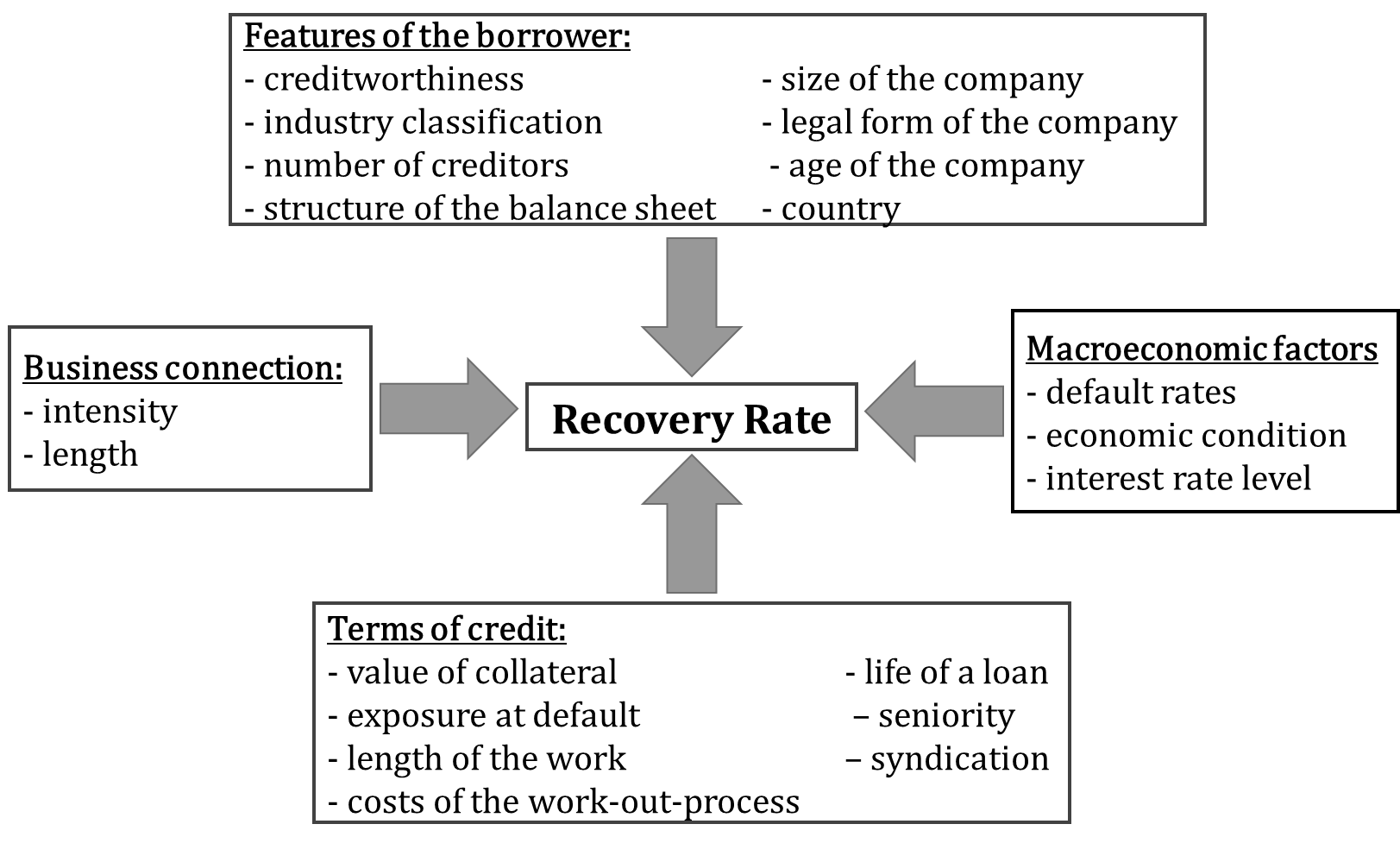
- for the borrower, the company of the borrower, incl. creditworthiness (rating) above all;

- for macroeconomics, incl. default rate;

- for the condition of the loan, incl. collateral in the first place;

- for business relations of the borrower, incl. their intensity.

Factors are divided into quantitative and qualitative groups, involving expert assessment. A set of factors forms a long-list from which factors are selected that correlate with the level of implemented LGD results.



**Fig. 10** Drivers for RR / LGD

To build models for various asset classes, data sources and measurement methods, which are classified in Table 6.

**Table 6** Classification of evaluation methods LGD

|  |  |  |  |
| --- | --- | --- | --- |
| **Source** | **Measure** | **Methods** | **Exposure** |
| Market values | Price differences | Market LGD | Large corporate,  sovereigns, banks |
| Credit spreads | Implied market LGD | Large corporate,  market LGD sovereigns, banks |
| Recovery and cost experience | Discounted cash flows | Workout LGD | Retail, SMEs, large corporate |
| Historical losses and estimated PD | Implied historical LGD | Retail |

Various linear and non-linear algorithms are used to train the LGD classification model. In the literature, (Loterman G., et al. 2012), a range of methods are analyzed:

- Ordinary Least Squares (OLS);  
- Ridge Regression (RiR);  
- Robust Regression (RoR);  
- Ordinary Least Squares with Beta transformation (B-OLS);  
- Beta Regression (BR);  
- Ordinary Least Squares with Box-Cox transformation (BC-OLS);  
- Regression trees (RT);  
- Multivariate Adaptive Regression Splines (MARS);  
- Least Squares Support Vector Machines (LSSVM);  
- Artificial Neural Networks (ANN);  
- Linear regression + non-linear regression (OLS+);  
- Logistic regression + (non)linear regression (LOG+).

Nevertheless, even on impressive empirical data (Table 7), with tens of thousands of measurements for corporate and consumer portfolios of banks, it was found that the obtained models have limited predictive characteristics regardless of which method is used, although non-linear methods give higher characteristics than traditional linear methods.

**Table 7** Source data

|  |  |  |
| --- | --- | --- |
| **Dataset** | **Type** | **Total size** |
| BANK1 | Personal loans | 47853 |
| BANK2 | Mortgage loans | 119211 |
| BANK3 | Mortgage loans | 3351 |
| BANK4 | Revolving credit | 7889 |
| BANK5 | Mortgage loans | 4097 |
| BANK6 | Corporate loans | 4276 |

Source: Loterman G., et al, 2012

The banks analyzed by the author have unique LGD distributions, which are shown in Fig. 11.

Table 8 shows the result of measuring the linear Pearson correlation predicted and implemented by LGD for different banks.

Table 8 shows that significant differences in the results obtained by different methods are observed only for Bank N 3, and for the data of this Bank, even the best models show a weak result. In general, one can notice that the linear OLS model gives an average level result, for corporate bank N6 even above the average.



**Fig. 11** Density of LGD distribution by Loterman G.

**Table 8** The result of measuring the linear Pearsons’ correlation predicted and implemented for different LGD methods for different banks.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Pearson’s R (Cohen, Cohen, West, & Aiken, 2002) measures the degree of linear relationship between predictions and observations. | | | | | | |
| Technique | BANK1 | BANK2 | BANK3 | BANK4 | BANK5 | BANK6 |
| OLS | 0,311 | 0,485 | 0,117 | 0,664 | 0,474 | 0,350 |
| B-OLS | 0,295 | 0,477 | 0,077 | 0,651 | 0,507 | 0,305 |
| BR | 0,260 | 0,464 | 0,157 | 0,653 | 0,456 | 0,321 |
| BC-OLS | 0,240 | 0,472 | 0,137 | 0,573 | 0,501 | 0,286 |
| RiR | 0,306 | 0,492 | 0,146 | 0,666 | 0,478 | 0,354 |
| RoR | 0,306 | 0,477 | 0,173 | 0,653 | 0,454 | 0,349 |
| RT | 0,300 | 0,582 | 0,387 | 0,692 | 0,506 | 0,339 |
| MARS | 0,321 | 0,558 | 0,502 | 0,692 | 0,567 | 0,362 |
| LSSVM | 0,347 | 0,569 | 0,453 | 0,702 | 0,579 | 0,396 |
| ANN | 0,360 | 0,603 | 0,378 | 0,705 | 0,596 | 0,362 |
| LOG+OLS | 0,326 | 0,484 | 0,076 | 0,668 | 0,498 | 0,348 |
| LOG+B-OLS | 0,317 | 0,529 | 0,121 | 0,665 | 0,512 | 0,323 |
| LOG+BR | 0,280 | 0,453 | 0,074 | 0,668 | 0,457 | 0,335 |
| LOG+BC-OLS | 0,213 | 0,463 | 0,167 | 0,666 | 0,510 | 0,310 |
| LOG+RiR | 0,329 | 0,539 | 0,132 | 0,676 | 0,492 | 0,341 |
| LOG+RoR | 0,326 | 0,535 | 0,151 | 0,673 | 0,474 | 0,339 |
| LOG+RT | 0,330 | 0,555 | 0,455 | 0,666 | 0,500 | 0,335 |
| LOG+MARS | 0,332 | 0,553 | 0,488 | 0,675 | 0,569 | 0,329 |
| LOG+LSSVM | 0,340 | 0,559 | 0,415 | 0,677 | 0,580 | 0,365 |
| LOG+ANN | 0,350 | 0,559 | 0,538 | 0,670 | 0,585 | 0,369 |
| OLS+RT | 0,338 | 0,579 | 0,258 | 0,678 | 0,536 | 0,362 |
| OLS+MARS | 0,339 | 0,562 | 0,502 | 0,692 | 0,577 | 0,363 |
| OLS+LSSVM | 0,371 | 0,567 | 0,465 | 0,700 | 0,576 | 0,349 |
| OLS+ANN | 0,372 | 0,601 | 0,261 | 0,705 | 0,557 | 0,350 |
| <r> | **0,32** | **0,53** | **0,28** | **0,67** | **0,52** | **0,34** |
| dr | **0,04** | **0,05** | **0,17** | **0,03** | **0,05** | **0,02** |

Source: Cohen, West, Aiken, 2002.

The study (Seidler, Jakub et all, 2017) presented the LGD model, trained in the Czech consumer lending market. The aim of the study was to show that lag macro variables involved in the delayed model are still strong risk factors. As a result, the authors agreed on a meaningful set of factors presented in Table 9.

**Table 9**Variables included in the LGD model.

|  |  |  |
| --- | --- | --- |
| **Explanatory variable logit LDG** | **Macroeconomic variables, current values** | **Macroeconomic variables, lagged and lead values** |
| Client- specific factors | Real GDP growth (y-o-y) | Real GDP growth (y-o-y) (t-1) |
| Exposure at default | Real GDP growth (y-o-y) | Real GDP growth (y-o-y) (t-2) |
| Relationship with bank | Real Consumption Growth (y-o-y) | Real investment growth (y-o-y) (t-2) |
| Age | Real Investment Growth (y-o-y) | Unemployment rate (t-8) |
| Children | Real Pribor3m | Real wage growth (y-o-y) (t-3) |
| Phone | Inflation rate (y-o-y) | Real wage growth (y-o-y) (t-4) |
| Employment | Property prices (y-o-y) | Real wage growth (y-o-y) (t-5) |
| Education | Default rate |
| Female | Retail loan growth (y-o-y) |

Source: Seidler, Jakub et al., 2017

The following informative LGD model is presented in (Košak, M., Poljšak, Ju., 2010). The model has been trained in the rapidly developing small and medium business borrowing market (SME) of Eastern Europe. Table 10 shows the risk-dominant variables that were identified by the authors as defining the LGD model.

**Table 10.** Variables included in the LGD model.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Collateral type** | **Industry** | **Period** | **Rating of the borrower before default** | **EAD** |
| Assignment of receivables  Financial collateral  Personal guarantee  Physical collateral  Real Estate collateral  Unsecured | Manufacturing  Real  Service  Trade | Long-term loan  Short-term loan | Last rating C  Last rating D  Last rating E . | Large  Medium  Small |

Source: Košak, M., Poljšak, Ju, 2010.

Table 12 also presents calculations of model parameters (32) for Košak, M., Poljšak, Ju, 2010. The authors used a limited number (124 observations), which gives rise to a tangible statistical error in determining the parameters characterizing the uncertainty. For the parameter and according to formula, the statistical error is at the level of 10%. A third example of the LGD model is proposed to consider a model prepared by linear regression based on 10 years of historical development of real data on corporate and retail loans from a group of European commercial banks under the control of the ECB [Bonini. S., Caivano, G., 2014, 2016]. 26,000 cases were processed, including 7,500 large and medium corporate defaults. The result is a recovery level model presented in Tab. 11.

**Table 11** Model RR (recovery rate)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | **Grouping** | **Coefficient** | **p-value** | **Variable weight** |
| Macro-geographical area | Intercept | 0,1001 | <,0001 |  |
| Center | 0,2145 | <,0001 | 13,87% |
| North East | 0,1113 |
| Sud & Island | 0,0788 |
| North West | 0 |
| Exposure at Default | EAD | 0,1567 | <,0001 | 10,13% |
| Portfolio segmentation | Medium – Large Corporate | 0,594 | 0,0033 | 38,40% |
| Small Business (Retail) | 0,377 | 0,0022 |
| Individuals (Retail) | 0 | <,0001 |
| Type of product | Mortgages | 0,1876 | <,0001 | 12,13% |
| Other products | 0 |
| Presence of personal guarantess | Absence | 0,1134 | <,0001 | 7,33% |
| Presence | 0 |
| Presence of mortgages | Absence | 0,1609 | <,0001 | 10,40% |
| Presence | 0 |
| Type of recovery process | Out of court | 0,1189 | <,0001 | 7,69% |
| In court | 0,0533 |
| No information | 0 |

Source: Bonini. S., Caivano, G.

The authors considered several times more risk-dominant factors, the set in Table 11.

Table12 shows the calculations of the parameter of the “LGD dispersion” without taking into account the LGD model, the optimal from the point of view of residual risk after applying model (8), the optimal sensitivity parameter , and also the range of possible values for the model RR as it applied in (8). The correlation ρ between the implemented LGD and the model was estimated by the formula . The calculations were carried out for three sources in which the parameters of the models are indicated.

**Table 12** Calculations of the parameter for LGD dispersion without taking into account the LGD model, optimal in terms of residual risk after solution of problem (33), which are presented (39), optimal value multiplicator, and also the boundary values of recovery , which are described in (40).

|  |  |  |  |
| --- | --- | --- | --- |
| **Source** | Seidler,  Jakub et all, 2017 | Košak, M.,  Poljšak, Ju., 2010 | Bonini. S.,  Caivano, G., 2016 |
| **LGD model** | GLM[[8]](#footnote-9) | GLM | OLS |
| **Type of asset** | Retail,  2003q1-2010q2,  18 698 obs. | SME,  2002 – 2005,  124 obs. | Individuals (Retail),  Small size  Corporate (Retail), Medium – Large size Corporate,  2002q4-2012q4,  26 000 obs. |
| **Mean value of**  **realized recoveries** | 0.42 | 0.73 | 0.51 |
| **Standard deviation of**  **recoveries** | 0.40 | 0.35 | 0.46 |
| **Pseudo R-squared** | 0.152 (Adjusted) | 0.363 (Nagelkerke) | 0.31 (Adjusted) |
| **Starting value**  **dispersion parameter** | 0.657 | 0.622 | 0.847 |
| **Optimal value**  **dispersion parameter** | 0.594 | 0.468 | 0.692 |
| **Optimal value**  **multiplicator of model (9)** | 0.245 | 0.421 | 0.329 |
| **Boundary values**  **of recovery** | 0.25-0.59 | 0.48-0.98 | 0.25-0.77 |

Table 12 shows that the model recovery level (8) does not go beyond the range range (0.1). Judging by the relation and Fig. 6, the models presented in Tab. 12 can provide a 10–25% reduction in the residual risk of LGD relative to how if LGD were assessed in the zero-approximation by the average LGD.

Summing up the results of a sample study of the results of RR / LGD modeling performed by different authors on different statistical recovery databases, we can draw the following conclusions:

1. It is impossible to unequivocally give preference to a particular method that is optimal in terms of modeling accuracy. In many cases, for example, see Tab. 7, an increase in the complexity and accuracy of the methods does not lead to a noticeable improvement in the results of the RR / LGD model and, on the other hand, often to a deterioration;
2. The set of risk-dominant parameters of the RR / LGD model can vary significantly when analyzing the statistical bases of different banks and different economies or different model-homogeneous populations;
3. The average recovery parameters and their dispersion can fluctuate significantly with a narrowing of model-homogeneous populations, including lending segments including in different banks. The maximum accuracy achieved on certain optimal models is also significantly heterogeneous.

The general results of the maximum achieved accuracy of LGD modeling, measured in various metrics, such as the correlation of the realized and model LGD, show a rather modest result. Very rarely a correlation greater than 0.6 is achieved, the average achieved on the best models is about 0.45.

All this convincingly argues the practical expediency of using simple methods, such as (9), for which the optimal sensitivity setting is possible to minimize residual risk. The construction of the model is based on the maximum Pearson correlation. The results of other models can be compared with the results of model (9) to identify their effectiveness.

**7 Recommendation for generation and validation of LGD models.**

In this study, it is proposed an approach to divide the RR / LGD model development process into two stages, namely: the RR / LGD rating model and calibrate the latter using a linear form that minimizes residual risk. The RR / LGD rating model is constructed in such a way as to ensure the maximum Pearson correlation with the implemented RR / LGD on the training statistical sample. In preparing the RR statistical base, correction (4) for the incomplete recovery process for part of the sample is taken into account. To do this, the recovery curve parameters (4) should be estimated using the method (5) on the historical recovery base (see Table 4). At the same time, recovery payments, net of costs, must be cleared of non-payments and discounted at the time of default. Financial support should be included in the EAD model. The RR / LGD rating model is based on risk-dominant factors, examples of which are presented in section 6. In the process of setting the optimum, from the point of view of correlation, RR / LGD rating model, it should be normalized so that the distribution of ratings is statistically (with an acceptable error) uniform.

At the next step, the optimal sensitivity parameter μ is calculated by formula (12) with allowance for the parameter of the LGD dispersion and the correlation parameter ρ. When calculating these parameters, the correction for the incomplete recovery process should be taken into account. Including for the recovery sample according to Table 4:

,

, (41)

where is the share of the implemented borrower recovery , is the recovery function (4) if recovery is not completed, or if it is completed by the time after default, is rating borrower's RR / LGD ID and average rating respectively.

The verification of the model is determined by formula (9). The validity of the model within the limits of the model RR restriction should be verified by formula (13). The value of the final adjustment and calibration of the LGD model can be estimated as a percentage of the EAD of economic capital savings on residual risk through the difference according to formula (8). For example, a capital saving of 1% EAD is tangible and comparable to the countercyclical capital premium (buffer) introduced by Basel – III (maximum 2.5% from Basel III, 2011). In addition, it is necessary to take into account the forecast / adjustment of the expected average RR (parameter in formula (9), taking into account the macroeconomic scenario and forecast. A reliable LGD driver, according to Moody’s (see Fig. 5), is the central trend of PD.

To check and validate the already built “M” of RR / LGD model, it is necessary to compare it with the reference model (9), built on the data of the “M” model being tested. To do this, calculate the correlation ρ of the implemented LGD- construction with , taking into account the possible incompleteness of recovery (all values for are recommended to be consistent to a normal distribution). The second step will be the direct calculation of by the formula (2) for “M”. Obviously, the average value of the realized LGD model should follow the rule, i.e. (4), where is the error of the estimate in problem (5), estimated (A2) in Appendix 1. One of the concepts of the recovery calculation format, or simple frequency, should be adhered to be weighted by means. It is generally accepted to adhere to the “simple” format, and balance on EAD should be taken into account in the LGD model, which depends on EAD. After calculating the optimal reference model (9) using formula (11), the obtained parameters of the LGD dispersion should be compared. If , where σγ is the statistical error (3), then the “M” model is not optimal and can be improved.

The next step is to check whether the values goes beyond the lower limit of constraints (13). The values of significantly (outside the statistical error) lower than the lower limit of the constraints (13) are not permissible, since the conservative principle should be violated. In this case, the power of the “M” model is not enough to assign significantly lower values to the LGD model level. This can lead to a significant model risk, transformed into credit risk with the significant volumes for individual loans.

**Appendix. The estimation procedure of the calculated standard error for the average marginal share of repayment**

The solution of problem (5) gives the optimal values of the recovery period T and the limiting recovery . The error of the values depends on the quality statistics of the approximation of the cumulative recovery of the recovery curve (4). The linear problem of the parameter estimation question for the nonlinear regression problem , near the optimal solution of problem (5) is given a linear regression relation for the error in the standardized form:

, (42)

where is composed by the partial derivatives matrix assumed to be normal uncorrelated random variable with unknown variance for each recovery period , of which there are n. Apparently, for an optimal solution in the sense of equation (5) for , the solution of problem (A1) for will be obvious . However, the error will be expressed through the covariance matrix according to the well-known formula (see, for example, Strutz, T., 2016):

, (43)

where for (A1):

.

Denoting the partial derivatives as:

;

; (44)

and according for the estimation error R, the only the upper diagonal element of the matrix , it is needed to obtain:

. (45)

To estimate the error as the measure for the standard deviation , it is necessary in formula (45) to substitute the solution of problem (5) as R – the limiting recovery , the time for recovery T, and or , these replacements depend on the calculation of the recovery curve.

**References**

Allen L. Saunders A. (2005). A Survey of Cyclical Effects in Credit Risk Measurement Models. — https://papers.ssrn.com/sol3/papers.cfm?abstract\_id=315561.

Antonova B.N. Ocenka stavki vosstanovleniya po rossijskim korporativnym obligaciyam // Journal of Corporate Finance Research, 2012. T. 6. № 4. PP. 130-143. [in Russian]

Araten M., Jacobs M., Varshney P. Measuring LGD on Commercial Loans: An 18-year Internal Study // RMA Journal. 2004. Vol. 86. Iss. 8. P. 96–103.

Basel II (2006) International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version. Part 2.pp. 295. https://www.bis.org/publ/bcbs128b.pdf

Basel III (2011) A global regulatory framework for more resilient banks and banking systems. Part 1, pp. 139. https://www.bis.org/publ/bcbs189.pdf

Benjelloun М., 2019, Stochastic modelling of the loss given default (LGD) for non-defaulted assets. This work was supported by the Global Research & Analytics Dept. of Chappuis Halder & Co. https://www.chappuishalder.com/wp-ontent/uploads/2019/03/GRA\_White\_Paper\_LGD\_stochastic.pdf

Bonini. S. , Caivano, G. , 2014, Development of a LGD Model Basel2 Compliant: A Case Study. DOI https://doi.org/10.1007/978-3-319-05014-0\_10, In book: Mathematical and Statistical Methods for Actuarial Sciences and Finance, 2014, pp 45-48, ISBN : 3319050141, Publisher by : Springer

Bonini. S. , Caivano, G. , 2016, Econometric approach for Basel II Loss Given Default Estimation : from discount rate to final multivariate model. White paper. https://www.semanticscholar.org/paper/Econometric-approach-for-Basel-II-Loss-Given-%3A-from/fc954a9ac25c2fd9f2de67b9f89b53aa36742e6c

CreditMetrics, 1997. Technical Document. JP Morgan.

Dermine J., Carvalho C.N. de (2006) Bank Loan Losses-given-default: A Case Study. Journal of Banking and Finance, 30, 4, pp. 1219–1243

Ermolova M. D., Penikas H. I. PD-LGD correlation study: Evidence from the Russian corporate bond market. Model Assisted Statistics and Applications. 2017. Vol. 12. No. 4. P. 335-358.

Felsovalyi A., Hurt L. Measuring Loss on Latin American Defaulted Bank Loans: A 27-year Study of 27 Countries // Journal of Lending and Credit Risk Management. 1998. Vol. 80. P. 41–46.

Frye J., Jacobs M. Jr. (2012). «Credit loss and systematic loss given default». The Journal of Credit Risk, Vol. 8(1), pp. 109–140.

G. Loterman, I. Brown, D. Martens, C. Mues, and B. Baesens. (2012) Benchmarking regression algorithms for loss given default modeling. International Journal of Forecasting, 28:p.161–170

Grunert, J. , Weber, M., (2009) "Recovery rates of commercial lending: Empirical evidence for German companies," Journal of Banking & Finance, Elsevier, vol. 33(3), pages 505-513, March. https://doi.org/10.1016/j.jbankfin.2008.09.002

Jankowitscha R., Naglerb F., Subrahmanyam M. G. The determinants of recovery rates in the US corporate bond market //Journal of Financial Economics. 2014, Vol. 114, No. 1, P. 155-177 https://doi.org/10.1016/j.jfineco.2014.06.001

Karminsky A.M, Lozinskaia A.M., Ozhegov E.M. Estimation methods of creditor’s loss in residential mortgage lending // HSE Economic Journal, 2016. Т. 20. № 1. PP. 9-51. [in Russian]

Košak, Marko ; Poljšak, Jure. (2010) Loss given default determinants in a commercial bank lending : an emerging market case study. Zbornik radova Ekonomskog Fakulteta u Rijeci : časopis za ekonomsku teoriju i praksu. - Rijeka, ISSN 0353-3689, ZDB-ID 12830379. - Vol. 28.2010, 1, p. 61-88

Miu P., Ozdemir B. Basel Requirement of Downturn LGD: Modeling and Estimating PD & LGD Correlations // Journal of Credit Risk. 2006. Vol. 2. Iss. 2. P. 43–68.

Moody’s Corporation, 2017, Annual Default Study: Corporate Default and Recovery Rates, 1920-2016 - Excel data

Qi M., Yang X. Loss Given Default of High Loan-to-value Residential Mortgages // Journal of Banking and Finance. 2009. Vol. 33. Iss. 5. P. 788–799.

Qi M., Zhao X. Comparison of Modeling Methods for Loss Given Default // Journal of Banking and Finance. 2011. Vol. 35. Iss. 11. P. 2842–2855.

Schuermann T. (2004) What Do We Know About Loss Given Default? (February 2004). Wharton Financial Institutions Center Working Paper No. 04-01. Available at SSRN: https://ssrn.com/abstract=525702 or http://dx.doi.org/10.2139/ssrn.525702

Seidler, Jakub & Konečný, Tomáš & Belyaeva, Aelita & Belyaev, Konstantin, 2017. "The time dimension of the links between loss given default and the macroeconomy," Working Paper Series 2037, European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp2037.en.pdf

Strutz, T. (2016). Data Fitting and Uncertainty (A practical introduction to weighted least squares and beyond). Springer Vieweg. ISBN 978-3-658-11455-8., chapter 3

Vasicek,O. (1987). Probability of Loss on a Loan Portfolio. [on-line], San Francisco, KMV, c1987, [cit. 27th March, 2009], <http://www.moodyskmv.com/research/files/wp/Probability\_of\_Loss

Vujnović M., Nikolić N., Vujnović A. Validation of loss given default for corporate//Journal of Applied Engineering Science, 2016, vol. 14, No. 4, P. 465-476. doi:10.5937/jaes14-11752

Witzany, Jiří (2009). Unexpected Recovery Risk and LGD Discount Rate Determination, European Financial and Accounting Journal, ISSN 1805-4846, University of Economics, Faculty of Finance and Accounting, Prague, Vol. 4, Iss. 1, pp. 61-84, http://dx.doi.org/10.18267/j.efaj.63

**Comparing bankruptcy prediction models in emerging markets**

**Roman Burekhin [[9]](#footnote-10)\***

**Abstract** This paper presents an overview of the main models for predicting bankruptcies of companies and considers the classification of existing approaches. Examples of using algorithms such as logistic models, classification trees, random forests, and artificial neural networks are highlighted. Particular attention is paid to comparing traditional and advanced (based on ML) algorithms. The main development trends of this class of models are considered in Russia, China, and in developed markets of the USA and Europe. This paper forms the basis for the practical use of such models in solving risk management problems.

**Keywords** bankruptcy; machine learning models; deep learning models; parametric models of prediction of bankruptcy; imbalance data.

**JEL** G01; G11; G17; G32; G33

**1 Introduction**

The ability of investors or potential lenders to correctly assess the credit risks of companies is a problem that has historically attracted the attention of financial experts. To achieve this goal, different methods of assessing credit risks are used, the purpose of which is to effectively predict the onset of an unfavorable situation at the enterprise. Typically, these methods represent traditional models (logistic models, multiple discriminant analysis models), characterized by a relatively simple mathematical apparatus and simple qualitative interpretation. Nevertheless, these methods are quite static and do not consider subtle economic or behavioral factors; the predictive ability of these models decreases with the non-linear nature of the relationships between the indicators.

To conduct an effective credit policy, new methods must be flexible and adaptable to the changing realities of market economies. Therefore, there is currently an interest in new, advanced models built on the basis of artificial intelligence: classification forests, random forests, gradient boosting, artificial neural networks, etc. Today even a minimal improvement in accuracy is a significant achievement, leading to the increased financial stability of the company. This paper provides an overview of the main approaches to the prediction of bankruptcies and discusses the advantages and disadvantages of these methods (Section 2). Section 3 provides examples of the use of these techniques in the Russian market. In Section 4, the main research trends in the prediction of bankruptcy are considered.

**2 An overview of default probability models**

Currently, many models have been developed and tested to assess the credit risk of borrowers. The classification of existing models is extremely important for the selection, implementation and adaptation of the most appropriate model for assessing credit risk. The choice of approach depends on the nature and quality of the data, the mathematical apparatus available, the planning horizon, the research objectives pursued, and the availability of IT infrastructure in the organization.

Totmyanina (2011) provides an overview of the fundamental models for assessing the probability of default. The author considers the advantages and disadvantages, prerequisites, and the classification of bankruptcy forecasting models (Figure 1). She distinguishes the following types of models for assessing default probabilities: market models (structural models, reduced form models); models based on fundamental indicators (models based on financial indicators, macroeconomic models, models based on data from rating agencies); advanced models (based on ML algorithms).

Models for assessing the probability of default

Market models

Structural models

Reduced models

Models based on fundamental indicators

Models based on financial indicators

Macroeconomic models

Models based on data from rating agencies

Advanced models

Based on ML

**Fig. 1** Classification of default probability models

**2.1 Market models**

Market models make up a large block of default forecasting models. They are based on market information, primarily on the value and various characteristics of the issuer's securities.

The founder of the structural approach is Merton (1974). This approach assumes that equity is a European call option on the assets of the company, and the default of the company occurs when the value of the assets, which are subject to the simplest diffusion process, falls to a level determined by the constant amount of debt. However, this approach has several limitations, the main one being the assumption that all the company's assets are traded on the market and their market value is uniquely determined. In reality, this does not happen. However, the Merton model, based on various assumptions, led to the emergence of a number of models which attempt to ease restrictions used. Black and Cox (1976) expanded Merton's model, allowing default to maturity. Taking into account that zero-coupon bonds are a special case of models used for coupon bonds, Longstaff and Schwartz (1995) include in the model the possibility of the default of the company before the maturity date. The empirical evidence for the use of structural models is mixed. Eom et al. (2004) conducted an empirical study to compare the effectiveness of various structural models. Their analysis is based on cross-sectional data of US corporate bonds. They conclude that none of the models considered confirmed the observed data.

Jarrow (2009) argues that a structural model is preferable to internal (corporate) risk management. A reduced model is preferable when assessing credit risks. Huang et al. (2009) uses a structural model to predict defaults of Taiwanese construction companies. The authors note the difficulty of collecting the necessary information and the dominant role of market factors in building insolvency forecasting.

Structural models are based on the premise that economic agents are well informed about the value of assets and liabilities of a company. In reality, this is not always the case. Structural models rely on information about changes in the value of the company and its modeling, while reduced models miss the problem of determining the value of a company and directly model the probability of default and the scale of default as a random process. Unlike structural models, reduced models consider default as an unexpected event and associate it primarily with prices, bond yields, and not with the value of the firm’s assets. It is assumed that this approach uses only available market information. One of the limitations of this approach is the assumption that the default processes within the same rating class are the same when it is empirically determined that bond credit spreads can vary significantly within the same rating group. Another key limitation of the reduced models is that they ignore the fundamental indicators of the company’s functioning, such as the value of assets, financial leverage, or level of profitability. In these models, it is problematic to link the probability of default and the recovery rate with the fundamental characteristics of the bond and its issuer, which makes the models more difficult to interpret from an economic point of view.

Trujillo-Ponce et al. (2014) determined which model, based on financial statements or market information, better assesses credit risk. As a proxy for credit risk, the authors use 2,186 CDS spreads on the European market from 2002 to 2009. Models based on accounting information are criticized because of the historical nature of the information used as input and because they do not consider the volatility of the value of the company during the analyzed period. However, the proponents of this approach argue that capital market inefficiencies can lead to more significant errors in predicting credit risks. The authors emphasize the inconsistency of the results of previous works. Trujillo-Ponce et al. (2014) consider various credit risk proxies: the default or non-default of a company, credit ratings, corporate bond spreads, and CDS spreads. They give preference to CDS spreads because these reflect information about credit risks continuously, reflect the market’s perception of a possible default, and not the opinion of a rating agency, reflect information about the risk of default, and not about the return of the principal amount; CDS spreads are less affected by taxes and liquidity, unlike bond spreads calculated using an “unknown” risk-free rate, CDS spreads themselves reflect credit risk.

The authors compare three models in which the dependent variable is represented by the natural logarithm of CDS spreads. The first model includes variables derived from financial statements. The second model includes factors based on market information (based on the structural approach). The third model includes both financial and market regressors. They did not find significant differences in the predictive ability of the approaches, concluding that the two types of data are complementary, and the complex model shows the best result. The predictive power of the models increases during periods of macroeconomic uncertainty (e.g. financial crisis).

Market models are often too complex or market dependent. Their application requires access to a large amount of data (knowledge of the market value of share capital, debt obligations, spreads of bond yields, etc.). Despite the widespread use of market models by Western companies, their use in the Russian market is difficult due to the small number of listed securities.

**2.2 Models based on fundamental indicators**

Totmyanina (2011) identifies three groups of models, based on fundamental indicators, depending on the nature of the indicators underlying them:

1. based on macroeconomic indicators;

2. based on indicators of financial and accounting statements;

3. based on indicators of external rating agencies.

A feature of models based on *macroeconomic indicators* is the idea that the probability of default is cyclical and increases during an economic recession. The macroeconomic indicators used in these include: GDP, inflation, national currency, and unemployment rate. That allows us to give a long-term estimate of the probability of default. A classic example of such models is the Wilson model (1997), which was the basis for the development of CreditPortfolio View, designed to assess credit risk and developed by the consulting group McKinsey & Co.

Financial ratios derived from *financial statements* are an important source for constructing default forecasting models. Beaver (1966) and Altman (1968) were the first to use financial ratios to analyze and predict the probability of default; their work was continued by Abidali and Harris (1995). These works focus on the application of multiple discriminant analysis in determining the probability of defaults in the corporate sector using financial ratios. Ohlson (1980) was one of the first to successfully use logistic analysis to predict company insolvency.

Illustrative is the work of Ping Tserng et al. (2014), which is devoted to assessing the probability of defaults of construction companies based on financial ratios using the logit model. The authors conduct multivariate and univariate analysis. The logistics model included 21 ratios, divided into five groups (liquidity, financial leverage, turnover, profitability, market factors). The final sample consisted of 87 US companies, 29 of which defaulted between 1970 and 2006. Forecasting horizons of 1, 2 and 3 years were considered. The results show that the addition of market variables (the ratio of the market value to the book value) increases the accuracy of default forecasting, especially when the forecast horizon is within one year. Of the models considered, the best was one that included the following factors: ROA, financial leverage, total assets turnover, current liquidity ratio, and the ratio of the market value to the book value. The AUC of this model is 0.7918 and 0.7951 when forecasting for one and two years, respectively. The greatest predictive ability was shown by ROA.

The class of models based on data from *rating agencies* is widespread. The rating contains important information with an average market efficiency if it provides the market with non-public confidential information. An important argument in favor of this thesis is that rating agencies have long-term relationships with various issuers and investors. Discussions with senior management, the telephone and personal contacts of analysts with issuers provide valuable and reliable information about the internal affairs of companies, which is not always available to external users. Rating agencies learn about planned issues, strategic plans, reserves, future dividend policies and anticipated corporate actions. They analyze financial statements, assess risks, and extract more accurate information about the company's profit and loss. It is also more preferable for a company to disclose information to rating agencies than to the public or the media, as rating agencies are required to maintain confidentiality under the terms of the rating assignment agreement.

To determine the probability of default, a *cohort approach* is used, based on which *transition matrices* are constructed, which estimate the frequency of credit ratings changing for a given sample of companies. In this case, the probability of default can be obtained on the basis of the analysis of historical data as the ratio of the number of firms that made the transition to the default rating to the total number of observations. This information is periodically published by the largest world rating agencies.

**2.3 Advanced models**

Discriminant, logistic analysis is a popular traditional tool for predicting bankruptcies, but it has a number of drawbacks associated with its low predictive power and the presence of restrictions on its use. Therefore, nonparametric methods have become widespread.

Frydman et al. (1985) were among the first to use *classification trees* to predict company bankruptcies. They found that their classification trees outperform discriminant analysis. It was also noted that with the complication of the model (including more factors), the accuracy of the model deteriorated due to overfitting. However, this success did not increase the frequency use of decision trees in this area.

Further development of the use of classification trees is the use of algorithms based on bootstrap approaches. *Random forest* is a ML algorithm that represents a combination of using classification trees.

Based on financial reporting data, Behr and Weinblat (2017) use random forest models to predict the defaults of companies from seven European countries (Finland, France, Germany, Italy, Portugal, Spain and the United Kingdom) and to identify specific signs of defaults of companies in various countries. The authors note that the source data cannot be used as input due to the low share of insolvent companies (the problem of imbalance). The most common method of dealing with data imbalance is undersampling or oversampling. Since undersampling in the work would lead to the loss of more than 96% of observations, the authors use the oversampling approach, paying attention to the fact that the calculation process is complicated, since such a model requires about two million objects. The authors note that the model is highly dependent on internal parameters (the number of trees; the number of parameters used to construct one tree; the maximum number of layers in a tree; the minimum number of objects in a descendant node or the parent node), and their determination is based on the cross-validation procedure.

Behr and Weinblat (2017) note the advantages of random forests such as high accuracy and resistance to emissions. In addition to high forecasting accuracy (AUC is in the range from 0.6903 to 0.8530), random forests made it possible to identify country-specific factors that have the greatest impact on a company's insolvency. It is determined that the use of a general model which does not take into account country specifics leads to a decrease in the effectiveness of the model. It was found that the greatest impact on a company's insolvency is provided by the ratios: Debt ratio, ROA, ROS, Net Debt to EBITDA Ratio.

The idea of *neural networks* is based on how the human brain analyzes data. Currently, this algorithm is used in various tasks, for example, pattern recognition, classification, and time series forecasting. Neural networks have a built-in ability to adapt their weights to changes in the environment.

Odom and Sharda (1990) were among the first to use a neural network to predict bankruptcy. They built a neural network with several hidden layers and used the financial ratios from the Altman model as input. The share of correctly classified companies was about 80%.

Tam and Kiang (1992) were among the first to compare the predictive power of the logit model, the k nearest neighbors method, classification trees, and neural networks. They conclude that the neural network is superior to all the other methods.

The main disadvantage of neural network modeling is the fact that a neural network acts as a “black box”, i.e. the result is not interpretable. Altman et al. (1994) conduct a comparative analysis of neural networks and linear discriminant analysis. They conclude that neural networks show high accuracy in determining the solvency category of a company. Nevertheless, this model is inferior to the predictive quality of the traditional logit model. The authors note the disadvantages of neural networks: the problem of overfitting, training time and the non-interpretability of the model parameters.

We can conclude that at present there are many works proving the possibility of using advanced methods for predicting the insolvency of companies. These algorithms often show higher efficiency, even though they are characterized by significant time and physical costs. The next section discusses examples of the successful application of various bankruptcy forecasting methods in Russian practice.

**3 Russian modelling experience**

Despite the importance of the task of predicting the bankruptcy of counterparties using more advanced methods, there are not so many Russian works in this area. Works devoted to comparing the accuracy of traditional and non-traditional models in predicting bank defaults are more likely the exception. In many Russian studies that use non-traditional methods, special attention is not paid to the training of the algorithm. In this case, default algorithm parameters are often used, which may not be the most optimal.

Karminsky et al. (2012) consider the features of modeling the probability of a bank default in the context of Russian reality using a logistic model. Based on Russian banking statistics, macroeconomic and institutional data for 1998–2011, a number of default probability models for the Russian banking sector were constructed. The logistic model, combined with the CAMELS approach in selecting the best explanatory variables, demonstrated high predictive power when testing outside the sample: more than 60% of defaults that occurred in 2010–2011 were correctly predicted. The authors conduct a comparative analysis of traditional models with neural networks. According to the results of testing on the test set of the neural network, 42% of defaults were predicted, which is a low indicator compared to logistic models.

Bogdanova et al. (2013), based on the data of financial indicators of public reporting, conducted an analysis of the solvency of Russian enterprises in the manufacturing industries. The authors compare neural network models with well-known traditional models. In this study, the best model had one inner layer consisting of four neurons, providing a forecast accuracy of 85.1%. Researchers conclude that neural network models are superior to logit models in accurately identifying potential defaults.

Demeshev and Tikhonova (2014) compare approaches to modeling the critical financial situation of Russian SME in various industries using financial and non-financial indicators from 2011 to 2012. The authors consider four industries: manufacturing, real estate, wholesale and retail, construction. A feature of the work is the amount of data (almost 1 million observations), the number of statistical methods: logit and probit models, linear discriminant analysis, quadratic discriminant analysis, discriminant distribution mixture analysis, the classification tree method and random forest algorithm. The greatest predictive power was shown by the random forest algorithm, regardless of industry and type of sample (balanced or unbalanced). They concluded that nonlinear algorithms show the best results. The most significant non-financial factors were industry, federal district and the age of the enterprise. The size of the enterprise and its organizational legal form had a weak impact on defaults.

Despite the advantages of non-linear models, works using traditional binary choice models to predict the probability of defaults prevail in Russian practice. Rybalka (2017) uses logistic regressions to test the hypothesis of the influence of corporate structure (such as characteristics of the general director, board of directors, ownership structure) on the predictive power of the models. He confirms his hypothesis and notes the convenience of using traditional models to solve similar tasks.

Kostrov (2016) compares statistical classification methods for predicting bankruptcies of Russian banks. The author notes that only a small number of Russian banks have an international rating, however, the relevance of the forecast for revoking a bank’s license at that time was especially high (60-80 financial institutions went bankrupt annually). The author described a linear discriminant analysis, a naive Bayesian classifier, logistic regression, decision trees, a neural network when forecasting the bankruptcy of Russian banks over a 6-month horizon. In this case, to combat imbalance, the author uses the oversample method with the duplication of observations of the bankruptcy type *m* times, where *m* takes the following values {1, 5, 10, 25, 50, 100}. As a measure of the quality of the models, the author used the arithmetic mean of the proportion of outcomes of the True Positive Rate (TPR) and the proportion of outcomes of the True Negative Rate (TNR). The author concludes that cases of bankruptcy of a bank with negative capital are predictable on the forecast horizon of six months. The naive Bayesian classifier was the best model; logistic regression was next. The use of neural network modeling and the decision tree method showed poor results. The author used the default neural network with one hidden layer and 10 neurons. In our view, the process of learning and the search for the optimal architecture of the neural network could improve the predictive accuracy of the models (which is also characteristic of decision trees).

Karminsky and Burekhin (2019) compare the ability of traditional and advanced models to predict the bankruptcy of Russian construction companies on a one-year horizon. They consider logistic models and their modifications using the WOE metric, classification trees, random forests, artificial neural networks. Particular attention is paid to the features of ML models, the problem of data imbalance, the analysis of the influence of non-financial factors on the predictive ability of models. The authors used financial and non-financial indicators from 2011 to 2017. AUC was used as a metric for the quality of the models. The authors focus on identifying companies which were in danger of bankruptcy, including companies for which the legal bankruptcy procedure had been launched and companies that have liquidated voluntarily.

It is concluded that the algorithms show acceptable quality for use in bankruptcy forecasting. Artificial neural networks were found to outperform other methods, while logistic regression models combined with WOE adjustments closely follow them. It was found that the effectiveness of the method of overcoming data imbalances depends on the type of models used. For logistic regressions, artificial neural networks, and classification trees, oversampling showed higher quality. However, using oversampling in the random forest method leads to overfitting. Therefore, for random forests undersampling is more efficient. A significant effect of the imbalance of the training set on the predictive ability of the model was not revealed. The significant effect of non-financial indicators on the likelihood of bankruptcy was also not confirmed.

**4 The main trends in forecasting bankruptcies**

In this chapter, we showed there are many models for assessing the probability of default, each of which has advantages and disadvantages. In the last decade, most studies have focused on improving and comparing existing models. A broad review was conducted by Kumar and Ravi (2007) who reviewed 128 scientific papers from 1968 to 2005. They note that most methods (discriminant analysis, logit analysis, classification trees, etc.) can be used to predict bankruptcies and give satisfactory results. However, the neural network algorithm has the greatest accuracy. At the time of writing, the authors noted that there is a tendency for algorithms based on one method to lose popularity, while ensemble or hybrid models are becoming more popular and show better performance. A striking example is provided by Xiao et al. (2012), where the prognostic ability of logistic regression, support vector machine (SVM) and neural networks are combined. The results of three separate models were combined into an “ensemble model” and weighted. They conclude that the combined method was superior to the predictions of the three methods individually. They also note that the lack of generally accepted procedures when building hybrid models are serious barriers to the use of these techniques.

Qu et al. (2019) review bankruptcy forecasting models using ML and DL models. They note the interest of researchers in the use of DL not only in problems related to pattern recognition, voice, NLP, but also in financial fields, including in solving problems of forecasting defaults. They consider the work of Hosaka (2019), as a successful application of a convolutional neural network in predicting the bankruptcy of Japanese companies. Mai et al. (2019) is an example of the use of NLP and neural networks in assessing the credit risk of US public companies. Mai et al. (2019) note the significant contribution of textual information (such as financial reports, expert opinions, and media reports) in improving the accuracy of the models. This textual information can become a new driver for the development of predictive models. The authors also note a tendency to obtain interpretable results from the black box while maintaining the high accuracy of these models.

In Russia, there is also a tendency towards more complicated predictive models using ML algorithms. However, there are few such studies, which may be due to the lack of similar models in business processes, insufficient management awareness of the possibilities of such algorithms, and the high cost of developing and implementing such models. There is also a clear interest in the development of more diversified models. Despite the clear superiority of non-linear algorithms in accuracy over traditional models, Russian researchers continue to use them because of their simple interpretation, the ease of construction, and the ability to answer questions of interest to the researcher.

**References**

Abidali, A.F., & Harris, F.C. (1995). A methodology for predicting company failure in the construction industry. Construction Management and Economics, 13(3), 189–196.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4), 589–609.

Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience), Journal of banking & finance, 18(3), 505-529.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Journal of Accounting Research, 4, 71–111.

Behr, A., & Weinblat, J. (2017). Default Patterns in Seven EU Countries: A Random Forest Approach. International Journal of the Economics of Business, 24(2), 181–222.

Black, F., & Cox, J. (1976). Valuing corporate securities: some effects of bond indenture provisions. Journal of Finance, 31, 351–367.

Bogdanova, T.K., Shevgunov, T.Y., & Uvarova, O.M. (2013) Using neural networks for predicting solvency of Russian companies on manufacturing industries. Business Informatics, 2, 40–48.

Demeshev, B. B., & Tikhonova, A. S. (2014). Bankruptcy Forecasting of Russian Companies: Cross-Industry Comparison [Electronic resource]. Working paper WP2 / 2014/04 (Series "Quantitative Analysis in Economics").

Eom, Y. H., Helwege, J., & Huang, J.Z. (2004). Structrual Models of Corporate Bond Pricing: An Empirical Analysis, Review of Financial Studies, 17(2), 499-544.

Frydman H., Altman, E. I, & Kao, D.L. (1985). Introduction recursive partitioning for financial classification: the case of financial distress. Journal of Finance, 40(1), 269–291.

Hosaka, T. (2019) Bankruptcy prediction using imaged financial ratios and convolutional neural networks. Expert Systems with Applications, 117, 287-299.

Huang, Y. (2009). Prediction of contractor default probability using structural models of credit risk: an empirical investigation. Construction Management and Economics, 27(6), 581-596.

Jarrow, R. A. (2009). Credit Risk Models. Annual Review of Financial Economics. Journal of Contemporary Accounting & Economics, 6(1), 34–45.

Karminsky, A.M., & Burekhin, R.N. (2019). Comparative analysis of methods for forecasting bankruptcies of Russian construction companies. Business Informatics, 13(3), 52–66.

Karminsky, A.M., Kostrov, A.V., & Murzenkov, T.N. (2012) Approaches to evaluating the default probabilities of Russian banks with econometric methods. Working paper WP7/2012/04 (Series “Mathematical methods of decision analysis in economics, business and policies”).

Kostrov, A.V. (2016). Comparison of statistical classification methods to predict Russian banks failures. Management of Financial Risks, 47(3), 162–180.

Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques: A review. European journal of operational research, 180(1), 1-28.

Longstaff, F., & Schwartz, E. (1995). A simple approach to valuing risky fixed and floating rate debt. Journal of Finance, 50(3), 789–819.

Mai F, Tian S, Lee C, et al. (2019) Deep learning models for bankruptcy prediction using textual disclosures. European Journal of Operational Research, 274(2), 743-758.

Merton, R.C. (1974). On the pricing of corporate debt: the risk structure of interest rаtes. Journal of Finance, 29(2), 449–470.

Odom, M. D., & Sharda, R. (1990). A neural network model for bankruptcy prediction. Neural Networks, 1990 IJCNN International Joint Conference, 2, 163- 168.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, 18, 109-131.

Ping Tserng, Po-Cheng Chen, Wen-Haw Huang, Man Cheng Lei, & Quang Hung Tran (2014) Prediction of default probability for construction firms using the logit model. Journal of Civil Engineering and Management, 20(2), 247-255.

Qu Y, Quan P, Lei M, et al. (2019). Review of bankruptcy prediction using machine learning and deep learning techniques. Procedia Computer Science, 162, 895-899.

Rybalka, A.I. (2017). Modeling the Probability of Default in the Construction Sector: Factors of Corporate Governance. Journal of Corporate Finance Research, 3(13), 79-99.

Tam, K. Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: the case of bank failure predictions, Management science, 38(7), 926-947.

Totmyanina, K.M (2011). A review of default probability models. *Financial Risk Management*, 01(25), 12-24.

Trujillo-Ponce, A., Samaniego-Medina, R., & Cardone-Riportella C. (2014). Examining what best explains corporate credit risk: accounting-based versus market-based models. Journal of Business Economics and Management, 15(2), 253-276.

Wilson, T. (1997). Portfolio Credit Risk: part I. Risk Magazine, September, 111–117.

Wilson, T. (1997). Portfolio Credit Risk: part II. Risk Magazine, October, 56–61.

Xiao, Z., Yang, X., Pang, Y., & Dang, X. (2012). The prediction for listed companies' financial distress by using multiple prediction methods with rough set and Dempster-Shafer evidence theory. Knowledge-Based Systems, 26, 196–206.

**Measures and assessment of ALM-risks in banks: case of Russia**

**Ekaterina Seryakova [[10]](#footnote-11)\***

**Abstract** This сhapter focuses on the assessment and management of ALM risks: liquidity risk and interest rate risk. The first part is devoted to liquidity risk: various types of liquidity risk, its sources, measures and the principles of liquidity risk management, as well as scenarios for stress testing of liquidity risk. The second part focuses on the concept and types of interest rate risk, the methods of evaluation (metrics) and approaches to its management. In the conclusion, current challenges in assessing and managing ALM risks are presented.

**Keywords** ALM risks, Stress testing, Interest rate risk, Liquidity risk, Management

**JEL** G21, G32

**1 Introduction**

*Liquidity risks* in banks are divided into two categories: *market liquidity risk* and *liquidity funding risk*. Market liquidity risk occurs due to a slump in the price of any financial instrument which a bank possesses (as an asset). Liquidity funding risk arises due to a mismatch in the terms of assets and liabilities. This paragraph will mainly concentrate on funding liquidity risk which can be divided into three types:

* physical liquidity risk;
* risk of regulatory liquidity;
* structural liquidity risk.

*Physical liquidity risk* occurs due to the incapability of a bank to fulfill its obligations in any currency due to a deficit of cash or non-cash money in this currency.

The risk of regulatory liquidity occurs when a bank violates the regulatory requirements for liquidity ratios. The risk of structural liquidity is explained with existing disbalances on both the asset and liabilities side of balance sheets. For instance, the concentration risk of non-stable deposits or imbalances of deposits in different currencies are examples of structural liquidity risk.

Sources of liquidity risk can be classified into *external* (shocks in market interest rates, client panic) or *internal* (the default of a client and the realization of credit risk).

Liquidity funding risk can be realized through several channels:

1. *Slump in liquidity buffer.* The price of high-liquidity assets portfolio slumps due to an increase in market interest rates. High-liquidity asset portfolios include cash, nostro-accounts with other banks, accounts with the Central Bank and high-liquidity bonds (with rating at least BBB- according to S&P rating scale). The liquidity buffer represents sources of funding available in a stressed period which consists of confirmed funding sources adjusted by a surplus or deficit of cash. Elements of liquidity buffers are repurchase agreement operations with Central Bank and funding collateralized by credit portfolios recognised with a discount.
2. *An increase in off-balance operations* which are driven by a higher part of loan drawing in stress periods when borrowers anticipate further growth in interest rates. For instance, during crises, the average loan drawing could increase from 50% up to 90%.
3. The r*ealization of a credit risk*of a heavy borrower.
4. *Client outflows*which occur due to a lack of confidence in the banking sector. Such behavior could provoke a chain of bankruptcies in the banking sector and lead to the realization of systemic liquidity risk.

There are two main methods of liquidity risk estimation:

1. *Cashflow forecasting.* Cashflow forecasting amid normal market conditions is based on behavior balance models (models of prepayment, models of renegotiation) and suggests measures in case of liquidity risk aggravation.
2. *Stress-testing.*Stress-testing is necessary for defining an adequate volume of the liquidity buffer and elaborating financial resilience restoration plan in case of crisis realization.

**2 Measures of liquidity risk and principles of liquidity management**

After the 2007-2009 financial crisis, liquidity risk became a key banking risk. The standards of Basel III, which appeared in 2010, implemented new requirements for liquidity risk measurement. In particular, such metrics as LCR (Liquidity coverage ratio) and NSFR (Net Stable Funding Ratio) were introduced to measure bank capabilities to resist stress for 1 month and for 1 year respectively.

LCR is a ratio of high-liquidity assets to net cash outflow for 1 month. Minimum requirements for LCR is set by Central banks. The minimum value of LCR starting from 01.01.2019 is 100%.

Managerial LCR (MLCR) is calculated as:

MLCR = , (1)

where *Available high-liquidity assets* = cash + nostro-accounts with other banks + account with Central Bank + high-liquidity bonds (with rating at least BBB- according to S&P rating scale);

*Net cash outflow* = (2)

where *О* is cash outflow (deposit outflow, utilization of credit lines);

*I is* cash inflow (e.g., credit redemption).

NSFR defines the volume of stable resources necessary for funding long term assets amid stress on a 1-year horizon. NSFR can be represented as the ratio of available stable funding to required stable funding. The minimum value of NSFR is 100% starting from 01.01.2018.

Banks regularly conduct *gap-analysis* which represents the difference between all cash inflows and outflows. There are three scenarios which define the breakdown of cashflows into time buckets:

1. Gap\_Plan CCYi defines the liquidity gap, calculated by currencies and time buckets according to the planned operations of a bank within a period of operational plan of a bank (usually 3 months).
2. Gap\_Stress CCYi defines the liquidity gap, calculated by currencies and time buckets considered in stress periods.
3. Gap contractual\_CCYi defines the liquidity gap, calculated by currencies and time buckets according to the contract maturity of instruments.

*The solvency horizon of a bank* which is usually called the survival horizon is a period within which the solvency of a bank is provided by a liquidity buffer in stress periods.

**3. Principles of liquidity management**

Important *principles of liquidity risk management* are the following:

1. The management of liquidity risk is conducted in accordance with risk-appetite which is constrained by liquidity risk measures: constraints on the liquidity contract gap and constraints on bank-calculated MLCR and NSFR.
2. The management of banking balance. In a normal market situation, liquid assets are planned first and then their funding is provided.
3. The diversification of resources by clients, sources, instruments and terms.
4. The costs of liquidity risk management are allocated by business-departments by means of transfer pricing.
5. The principle of “three lines of defence” (see Table 1).

**Table 1** Principle of “three lines of defence”

|  |  |  |
| --- | --- | --- |
| First line of defence | Treasury | Forward-looking approach to risk of liquidity management, setup of limits |
| Second line of defence | Risk-management | Control of limits on risk of liquidity measures |
| Third line of defence | Internal audit | Independent validation of models, procedures and processes of the risk of liquidity management in Treasury and Risk-management |

The elaboration of scenarios for stress-testing risk of liquidity is considered to be the most sophisticated in banking risk-practices as it requires assumptions for both assets and liabilities. *Assumptions for assets* can be:

* a rise in overdraft drawings;
* an increase in the probability of defaults for some borrowers;
* a reduction of cashflows from interbank operations due to the default of one of another bank;
* the default of one or several heavy borrowers (concentrated risk realization).

*Assumptions for liabilities* can be:

* the reduction of refinancing and the reduction of attracting long-term deposits;
* the early termination of the agreement on current accounts with minimum balances;
* the reduction of cash “on demand” below a stable level;
* the outflow of funds of the largest creditor within one quarter;
* the early demand of deposits;
* the increase in collateral for margin transactions;
* the inaccessibility of a bank to capital markets.

Scenario analysis by product when setting or reviewing limits and approving new types of operations may include a set of risk factors corresponding to certain types of risk of the instrument or product, operational risk factors, and other risk factors.

If modeling technologies allow a bank to take into account time factors in the results of stress-testing, dynamic stress testing is used. Dynamic stress testing is applied to take into account the severity of risk losses when forming or adjusting the strategy of a bank. Dynamic stress testing can include (individually or in combination) the following elements:

- the dynamic Stress scenario, with a certain duration, gradual deployment, reaching peak values, and then reducing the intensity etc.

- the deferred reaction of financial indicators, which is especially relevant when assessing the impact of changes in the macro parameters on the stress-tested indicators of a bank's performance.

**4. Interest-rate risk**

**4.1 Types of Interest-rate risk**

Interest-rate risk management is a set of actions and procedures that manage and control a bank’s interest-rate risk arising from its assets and liabilities, including their effect on the balance sheet and income statement. Interest‐rate risk is the risk of losses due to adverse movements of market interest rates. A bank manages its assets and liabilities regularly and measures, manages and monitors its interest-rate risk on a stand‐alone and consolidated basis. Interest-rate risk limits cover all interest-rate risk metrics and correspond to the risk-appetite of a bank in respect of interest-rate risk. A bank recognizes the importance of asset-liability management (ALM) as part of the effective management of its balance sheet and income statement. Before granting substantial new loans, purchasing bonds or making any other type of investment, the impact of the transaction on a bank’s interest-rate risk profile and liquidity situation is assessed. The main interest-rate sensitive assets are corporate loans, bonds, term deposits, nostro accounts with other banks and corresponding accounts of the Central Bank, client account overdrafts and financial derivatives. The main interest-rate sensitive liabilities are received term funds (deposits), client accounts, accounts from other banks and financial derivatives. Table 2 contains risk mitigation actions and risk remediation actions in respect of interest-rate risk.

**Table 2** Risk mitigation actions and risk remediation actions in respect of interest-rate risk

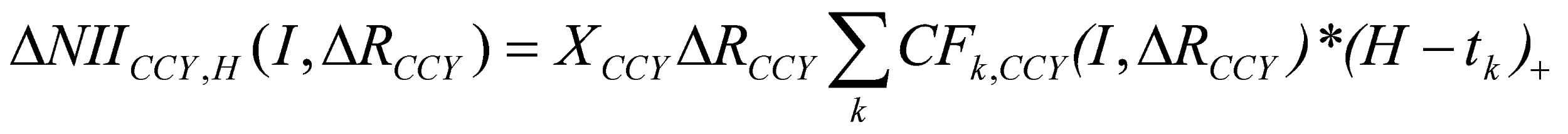
|  |  |
| --- | --- |
| **Risk mitigation actions** | **Risk remediation actions** |
| * Generally avoid, minimize or hedge open interest-rate risks * Manage the balance sheet in a term-congruent manner * Ensure that the approved limits are sufficient for the business plan or strategy * Pre-check the available limits before entering into new transactions * Establish netting (ISDA) and credit support (CSA) agreements and sufficient limits with hedge counterparties to be prepared for risk transfers * Show early warning indicators in the limit utilization report | * Hedge excessive interest-rate risk through risk transfer with hedge counterparties * Interest-rate risk-management through transfer pricing policy * Temporarily or permanently review limits via the authorized approval body |

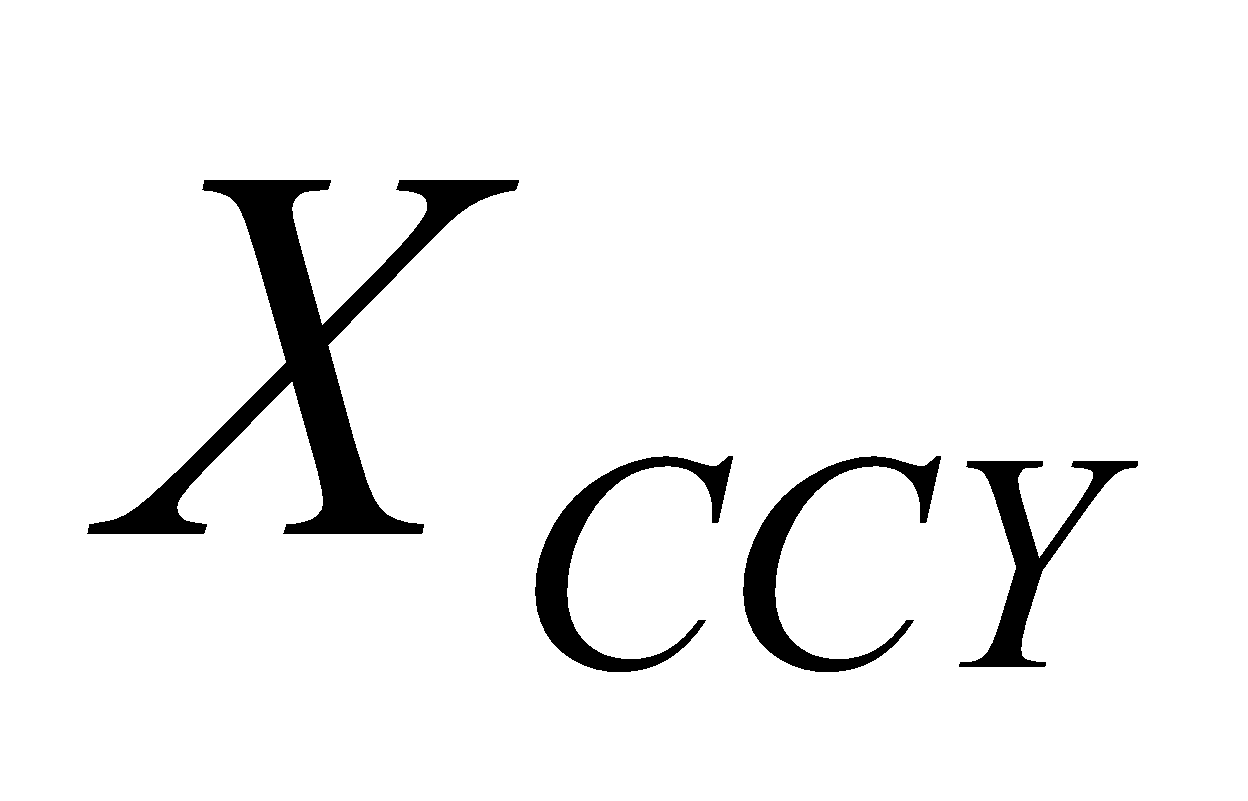
According to “Interest-rate risk in the banking book” (IRRBB) types of interest-rate risk:

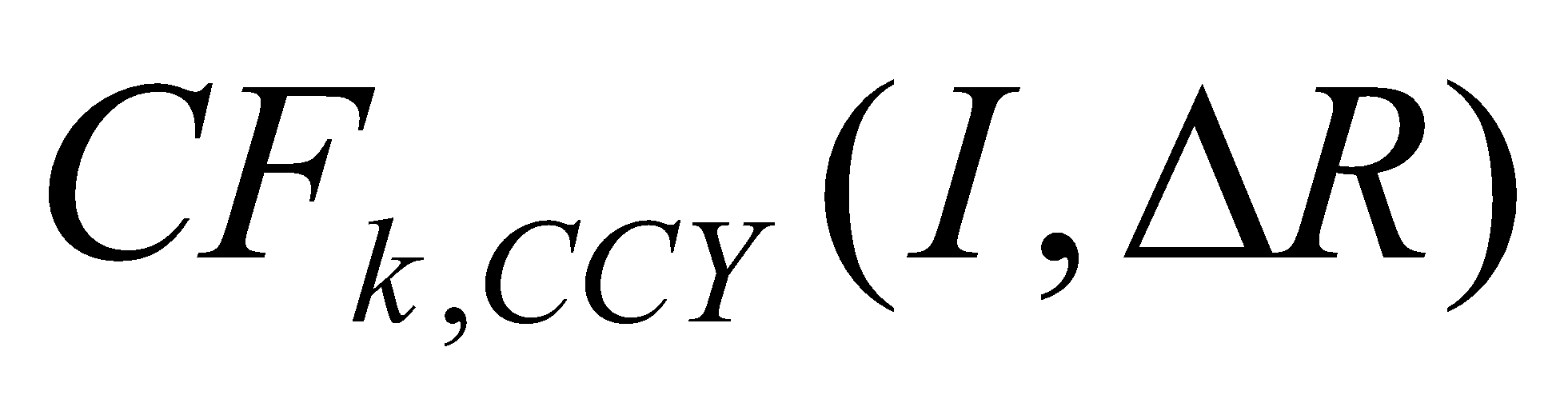
* *Repricing risk:*risk which occurs due to maturity term mismatches or repricing term mismatches. The examples illustrating this type of risk:
* 1-year assets are funded with 3-month deposits;
* a loan with floating rate (6-month LIBOR +0,2% spread) is funded with a 3-month deposit.
* *Yield curve shift risk:*unfavourableparallel or non-parallel shifts of the market yield curve, leading to a Net Interest Income (NII) slump and the aggravation of sensitivity of Net Present Value (NPV).
* *Basis risk:*
* risk which occurs to the different pace of loan and deposit rates changes in the condition that loans and deposits are of the same term and with fixed rates; this difference in pace is explained by the different sensitivity of loans and deposits to changes in market rates: for example, risk of losses due to adverse changes in the spreads between the rates of borrowing and placement for one term in one currency (Mosprime 3M and RUONIA) or for one term in different currencies (Mosprime 3M and EURIBOR 3M);
* risk which occurs to the different bases of interest floating rates (loan has a rate equal to RUONIA +2% spread and deposit has Mosprime Overnight +1% spread);
* *Optionality risk:*risk of losses due to behavioral models (prepayment and repricing) applied to financial instruments subject to interest-rate risk;
* *Risk of funding spread change:* risk of losses due to changes in the spread between the cost of borrowing resources by a bank in the financial market and the credit spread of this bank, which depends on the market interest curve. Banks in Russia are exposed to this type of risk on positions in foreign currencies.

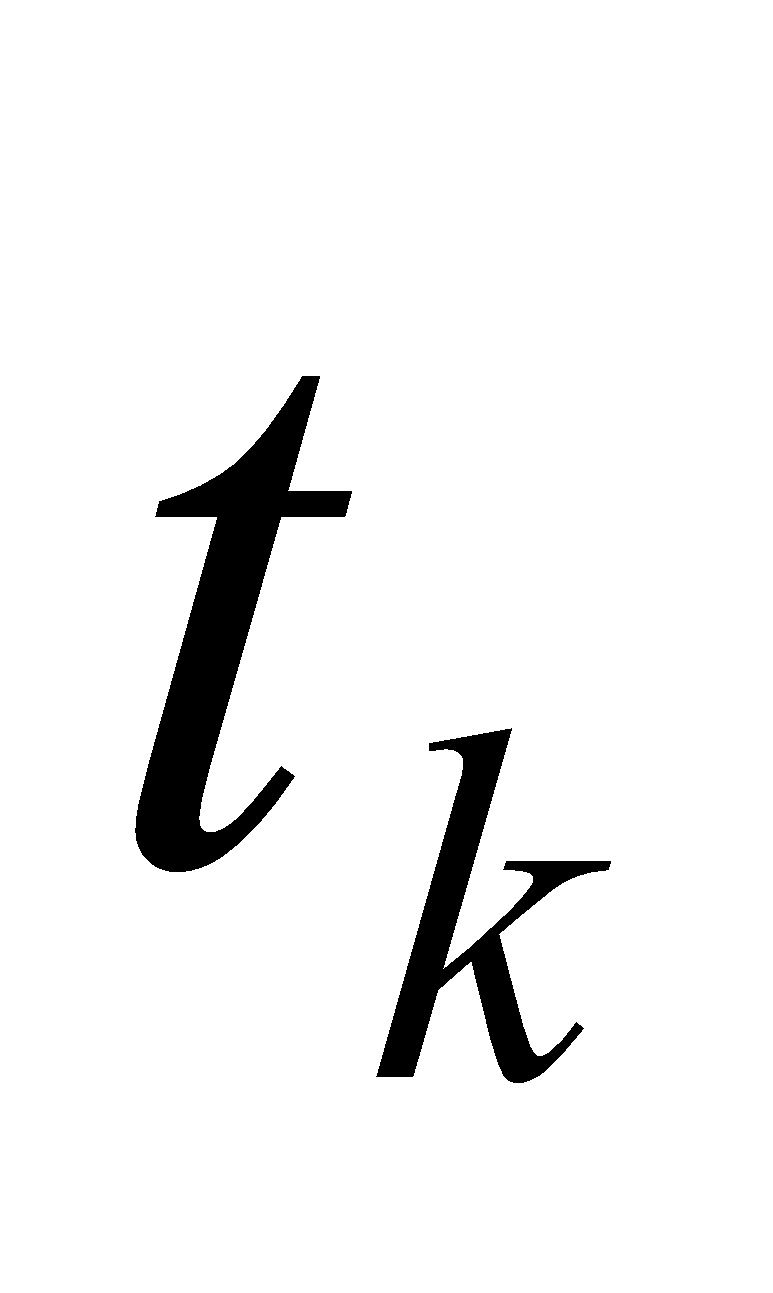
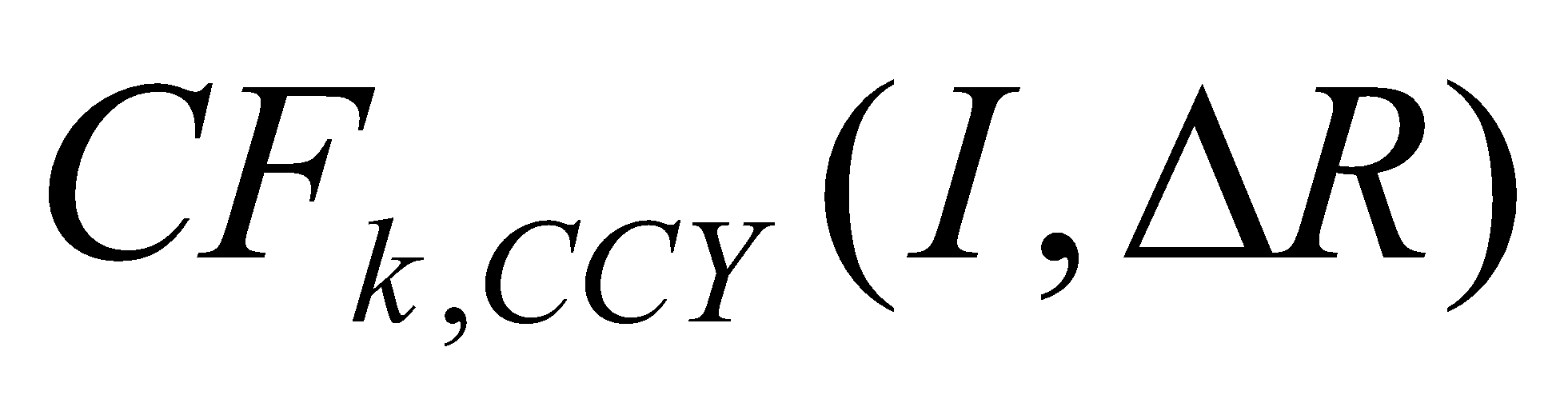
**4.2 Metrics of Interest rate Risk**

*Sensitivity of interest rate risk (∆NII):*

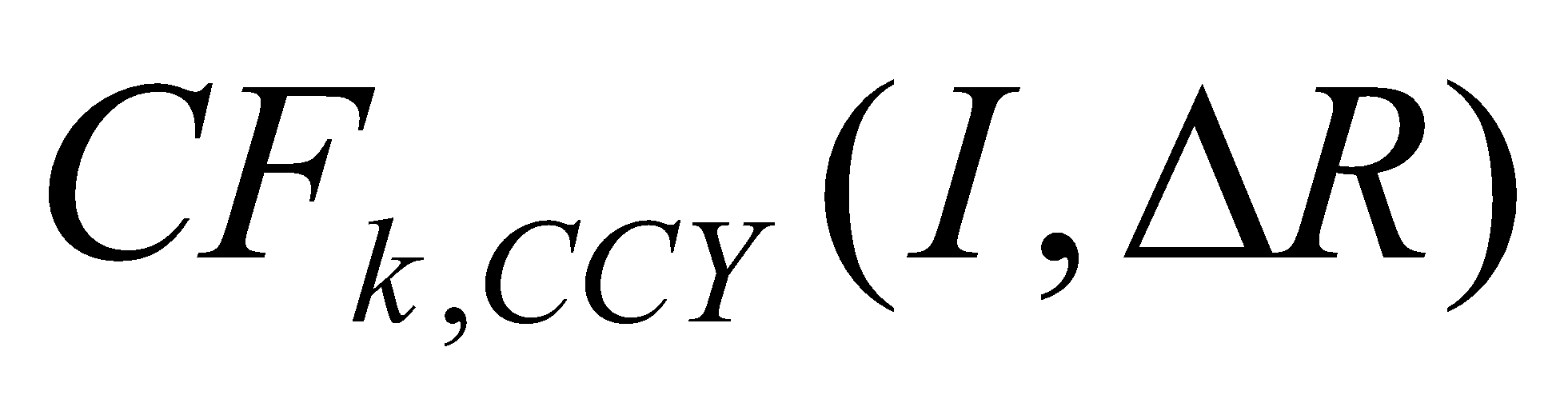
, (3)

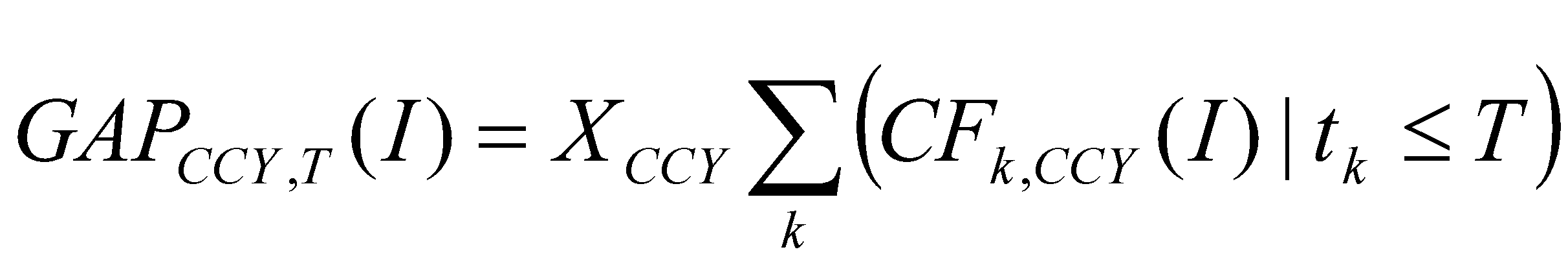
where  is the currency exchange rate for instruments in non-national currencies;

 are cash flows (positive for assets, negative for liabilities) for instrument *I* in currency *CCY*; cash flows do not include interest payments;

 is the term of maturity of  or the term of interest-rate repricing on financial instrument *I*;

∆R is the market interest-rate parallel shift.

*Interest rate risk gap* in CCY currency for financial instrument *I* for period *T* is computed with a breakdown into time buckets for . Such gaps calculated by term buckets are called marginal. The consequent summing of marginal gaps can give a cumulative gap for each bucket:

. (4)

*Sensitivity of Net Present Value (ΔNPV)* in CCY currency for financial instrument *I* is calculated as:

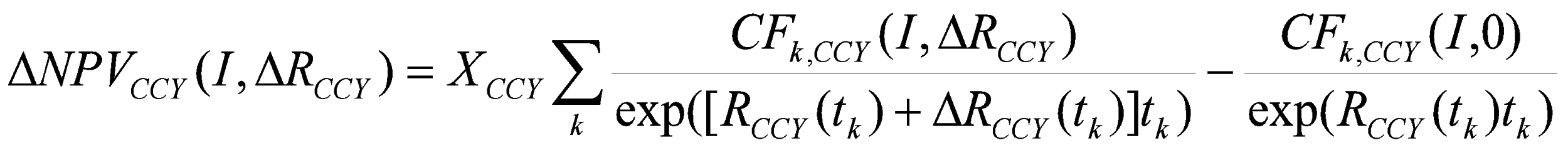
. (5)

Table 3 contains approaches to evaluating interest-rate risk according to Basel III recommendations.

**Table 3** Approaches to evaluating interest rate risk according to Basel III

|  |  |  |  |
| --- | --- | --- | --- |
| **Metrics** | **Scenarios** | **Calculations** | **Portfolios** |
| EV/EVE  Economic Value of Equity | 6 scenarios by currency for EVE (Δ𝑅):  (i) parallel shift of market curve up;  (ii) parallel shift of market curve down;  Δ𝑅𝑝arallel, 𝑐(𝑡𝑘) =± 𝑅𝑐(𝑡𝑘)∙𝛼𝑝arallel,  𝑅𝑐(𝑡𝑘) is the parallel shift  с is currency  𝑡𝑘 is the time bucket from o to k;  (iii) change of the short, middle or long end of the curve (shift up);  (iv) change of the short, middle or long end of the curve (shift down)  Δ𝑅𝑠hort,𝑐(𝑡𝑘) =± 𝑅𝑐(𝑡𝑘)∙𝛼𝑠ℎort∙ e(-tk/4)  Δ𝑅𝑚edium,𝑐(𝑡𝑘) =± 𝑅𝑐(𝑡𝑘)∙𝛼𝑚*ediu*𝑚∙𝑆𝑚*ediu*𝑚(𝑡𝑘)  Δ𝑅long,𝑐(𝑡𝑘) =± 𝑅𝑐(𝑡𝑘)∙𝛼𝑙ong∙(1- e-tk/4)  (v) anti-clockwise turn of market curve (steepening);  Δ𝑅𝑐,(𝑡𝑘) =-0,65\*Δ𝑅𝑠hort,𝑐(𝑡k) +0,9\*Δ𝑅𝑙ong,𝑐(𝑡𝑘)  (vi) clockwise turn of market curve  (flattening)  Δ𝑅𝑐,(𝑡𝑘) =0,8 \*Δ𝑅𝑠hort,𝑐(𝑡k) -0,6\*Δ𝑅𝑙ong,𝑐(𝑡𝑘) | EVE i,c = CFi,c (k) \* e (-Ri,c (tk) \*tk)  Risk-parameters:  for parallel shift 𝛼=60%;  for short end of the market curve 𝛼 =85%;  for middle part of the market curve 𝛼 =55%;  for long end of the market curve 𝛼 =40%. | Banking and trading books |
| EaR  (Earnings-at- Risk)  (ΔNII) | Scenarios by currencies:  (i) parallel shift up of the market curve;  (ii) parallel shift down of the market curve. | Δ𝑁II i,c = Δ𝑁II i,c g + Δ𝑁II cb  i is the scenario;  c is the currency;  g is the component 1: change of NII due to scenario i;  b is component 2: change of NII due to basis risk. | Banking and trading books |

* 1. **Managing interest-rate risk**

There are three main objectives for managing interest rate risk:

1. *Hedging the interest position of the bank*. This is carried out in order to reduce net interest income and to minimize the risk of a parallel shift in the market interest curve. The goal is mainly applied in countries with low interest rates and flat market interest curves.

2. *The transformation of balance term-structure* (placement of short-term liabilities into long-term assets). The goal is to maximize income within predetermined limits. The goal is applied in countries with an increasing market interest curve.

3. *The acceptance of interest-rate risk within the specified limits*. The goal is justified in countries with low market liquidity and insufficiently developed market of derivatives (IRS).

*The main factors* influencing *the choice of the interest-rate risk-management g*oals are:

1. The shape and slope of the market interest curve;

2. Market development of derivative financial instruments;

3. The share of bank assets in the banking sector;

4. A bank’s risk appetite for interest-rate risk (the level of limits on interest-rate risk metrics);

5. The ratio of interest and commission income in the total income of a bank.

Interest-rate risk management in a bank is conducted using the transfer pricing system and is concentrated in the internal audit service of the bank. The internal audit carries out centralized ALM risk management. The main functions of transfer pricing are the redistribution of risks and the determination of the internal cost of resources in a bank. A bank has a special unit - the internal treasury department - which manages interest-rate risk. The essence of management is to transform the current interest position (interest gap) into the target one, which corresponds to the risk appetite of a bank, namely, the existing limits on the interest gap. The following tools are used to manage interest-rate risk:

-limits on interest-rate risk metrics (interest gap, sensitivity of interest income, sensitivity of net present value);

-hedging an interest position using interest rate derivatives (IRS and CIRS);

-changing the transfer curve in different time-buckets to stimulate attracting or placing bank units to attract or place funds for necessary terms;

-performing operations:

-to purchase or sell securities in the available-for-sale portfolio of the bank;

  -in the money market;

  -in the capital market: issuing bonds, issuing subordinated loans;

  -in the market for derivative financial instruments: the conclusion of interest rate transactions (IRS) and currency interest rate swaps (CIRS).

Models used in calculating interest-rate risk:

- model of the prepayment of loans to individuals: for instance, for mortgage loans, 2 options are taken into account: prepayment and refinancing at a lower rate in case of decrease in market rates.

- model of the prepayment of corporate loans;

- model for revising interest rates for loans with a quasi-floating interest rate.

The purpose of using these models is to reduce the effective term of loans.

-model of the early termination of term deposits due to an increase in market interest rates.

**Conclusion**

In conclusion, it is worth mentioning current challenges in asset-liabilities (ALM) risk assessment and management, including:

1. The separation of interest-rate risk from other types of risk when elaborating scenarios for integrated stress tests
2. The elaboration of complex stress scenarios: it is difficult to separate the effects of changes in interest-rate risks, total credit spread (CSRBB) and individual credit spread when calculating interest-rate risk metrics.
3. The issue of attributing an instrument to the banking or the trading book is ambiguous: in international practice and in practice of leading Russian banks, derivatives and debt instruments of the trading portfolio (re-evaluated daily through profit or loss) are referred to the trading book, while the rest are referred to the banking book.
4. It is challenging to evaluate ∆NII metric for a non-parallel shift of a market curve, i.e. for different shifts of the curve in different time buckets.
5. The qualitative judgement of changes in the interest-rate risk gap is not obvious: changes in the shape of the interest-rate risk gap cannot be clearly interpreted as better or worse.
6. It is difficult to conduct dynamic modelling when stress testing both interest-rate risk and liquidity risk. Dynamic modeling involves: (1) changes in market rates on the evaluation horizon more than once; (2) and/or changes in the balance structure on the evaluation horizon. The main challenge is to develop assumptions for changing the balance sheet structure (scenarios and assumptions for reinvesting contracts), and scenarios for the evolution of market interest rates. For some metrics, a full dynamic analysis is not possible (changes in both market interest rates and balances): for example, the sensitivity of net present value (NPV) is a static measure and can be only used to evaluate sensitivity from a point in the future, taking into account changes only in the balance in this point.
7. The final challenging issue is to select the base indicator for products with a floating rate, for instance, the key rate of Central Banks which serves a base indicator for loans and causes both liquidity and interest-rate risks in the absence of deposits with the key rate as the base indicator.
8. The hedging of interest-rate risk, an underdeveloped IRS market.

**References**

Kulik V., Vedyakhin A. Fundamentals of risk management // Textbook for the programs of Sberbank Corporate University. - Moscow: ANO DPO “Sberbank Corporate University, 2017. - 384 p.

On the best practices for managing interest rate risk on the banking portfolio in credit institutions // Bank of Russia Report for public consultation. Moscow, 2020. URL: https://cbr.ru/Content/Document/File/98190/Consultation\_Paper\_200120.pdf

Risk management in a commercial bank: monograph / team of authors; under the editorship of I.V. Larionova. - M.: KNORUS, 2014 .-- 456 p.

ALM risk management and bank liquidity. Textbook / ed. A.V. Morozova, A.Yu. Lyakina, I.V. Malakhovoy, M.V. Vorobyov. - Moscow: ANO DPO “Sberbank Corporate University, 2017. - 336 p.

Interest rate risk in the banking book (IRRBB), BIS, BCBS, 2016. URL: https://www.bis.org/bcbs/publ/d368.pdf

Stress-testing principles, BIS, BCBS, 2018. URL: https://www.bis.org/bcbs/publ/d450.pdf

Principles for sound liquidity risk management and supervision, BIS, BCBS, 2000. URL: https://www.bis.org/publ/bcbs144.pdf

Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools, BIS, BCBS, 2013. URL: https://www.bis.org/publ/bcbs238.pdf

**Forecasting and back-testing of market risks in emerging markets**

**Dean** **Fantazzini [[11]](#footnote-12)\***

**Abstract** Emerging markets often go through periods of financial turbulence and the estimation of market risk measures may be problematic. Online search queries and implied volatility may (or may not) improve the model estimates. In these situations a step-by-step analysis with R and Russian market data is provided. Four classes of models are considered (GARCH, HAR, ARFIMA, and realized-GARCH), and a detailed forecasting and backtesting investigation is performed.

**Keywords** Forecasting, Value-at-Risk, Realized Volatility, Google Trends, Implied Volatility, GARCH, ARFIMA, HAR, Realized-GARCH.

**JEL** C22, C51, C53, G17, G32

**1 Introduction**

The Value-at-Risk (VaR) is the most well-known market risk measure and can be defined as the maximum portfolio loss over a determined time horizon at a given confidence level, see Jorion (2007) and the Basel Committee on Banking Supervision (2013, 2016) for more details. VaR is not sub-additive when the portfolio returns are not elliptically distributed, and for this reason, the risk of a portfolio can be larger than the sum of the separate risks of its components, see Artzner et al. (1997) and Artzner et al. (1999). An alternative risk measure which satisfies the property of sub-additivity is the Expected Shortfall (ES), which computes the average of the portfolio losses given a specific probability level, see Acerbi and Tasche (2002). Gneiting (2011) showed that ES does not satisfy a mathematical property called elicitability (while VaR does), and it cannot be directly backtested. In this regard, Emmer et al. (2015) and Kratz et al. (2018) showed that ES is elicitable conditionally on VaR and it can be backtested using a multinomial test of VaR violations at multiple confidence levels.

This chapter provides a step-by-step analysis with R and Russian market data to verify whether adding Google search queries and implied volatility (IV) from option prices to several volatility models can improve their estimated market risk measures. This analysis was recently performed by Fantazzini and Shangina (2020) and this paper is a practical complement to that paper, by showing step-by-step how to implement this backtesting exercise using R.

Google search data is a useful indicator of the behavior of the general public and small investors (Da, Engelberg and Gao (2011), Goddard et al. (2012), Vlastakis and Markellos (2012), and Vozlyublennaia (2014), Campos et al. (2017), while IV represents a forward-looking estimate of the volatility mainly driven by the expectations of institutional investors and market makers (Mayhew (1995), Martens and Zein (2004), Busch et al. (2011), Bazhenov and Fantazzini (2019).

These two variables are added to four volatility models to forecast VaR at multiple levels for the daily data of the Russian RTS index. The forecasted VaR of these models are then compared using the tests by Kupiec (1995) and Christoffersen (1998), the asymmetric quantile loss (QL) function proposed by Gonzalez-Rivera et al. (2004), the Model Confidence Set by Hansen et al. (2011) and the the multinomial test of VaR violations by Kratz et al. (2018). Moreover, a robustness check to measure the accuracy of VaR forecasts obtained with a multivariate model is also discussed.

The rest of this chapter is organized as follows. Section 2 reviews the literature dealing with Google Trends and IV, while the forecasting methods for VaR are briefly discussed in Section 3. The empirical exercise with R is reported in Section 4, while a robustness check is discussed in Section 5. Section 6 concludes.

**2 Literature review**

There is a large body of literature that shows that IV delivers better forecasts for volatility than GARCH models, see Christensen and Prabhala (1998), Corredor and Santamaría (2004), Martens and Zein (2004), Busch et al. (2011), Haugom et al. (2014a), and references therein. Nonetheless, there are a few cases when this was not true as shown by Agnolucci (2009) and Birkelund et al. (2015). Moreover, the best results are often achieved when both IV and other market variables are included in the forecasting model, see Taylor and Xu (1997), Pong et al. (2004), and Jeon and Taylor (2013). Instead, the results are not that favorable when IV is used to forecast the future quantiles of the returns’ distribution, see Chong (2004), Christoffersen and Mazzotta (2005), Giot (2005), Jeon and Taylor (2013), just to name a few.

Bams et al. (2017) represent the largest backtesting exercise dealing with VaR forecasts, using more than 20 years of daily data from US markets. Their analysis shows that IV based VaR tends to be outperformed by GARCH based VaR, due to the volatility risk premium embedded in IV. In general, Bams et al. (2017) showed that even though IV can be useful for forecasting future volatility, this is not the case for forecasting the returns' distribution quantiles, due to the complex dependence structure between the volatility risk premium and the extreme returns.

Google online queries can be a proxy for investor attention and information demand, see Ginsberg et al. (2009), Choi and Varian (2012), Da et al. (2011), Vlastakis and Markellos (2012), Vozlyublennaia (2014), Goddard et al. (2012), and Fantazzini and Toktamysova (2015). They can help to forecast future volatility, as discussed by Vozlyublennaia (2014), Dimpfl and Jank (2016), Campos and Cortazar (2017), Xu et al. (2017) and Seo et al. (2019). For market risk management, the literature working with Google Trends is almost nonexistent: there are very few with empirical studies limited in scope and time, see Hamid et al. (2015), Basistha et al. (2018) and Bazhenov and Fantazzini (2019). Fantazzini and Shangina (2020) was the first work analyzing almost two decades of daily data for an emerging market, using a large scale backtesting analysis similar to the work by Bams et al. (2017): they found that the predictive power of several models did not increase if IV and Google data variables were added, while other models augmented with these variables did not reach numerical convergence. Fantazzini and Shangina (2020) showed that, in the case of Russian future markets, T-GARCH models with IV and Student’s t errors are the best choice if robust market risk measures are of concern.

**3 Methodology**

This section shows how to implement and replicate with R most of the empirical analysis presented in Fantazzini and Shangina (2020), to ultimately verify whether adding IV and Google data to volatility models improves the quality of the forecasted VaR at multiple confidence levels for the Russian RTS index. I provide below a brief review of the theoretical aspects involved, while I refer the interested reader to Fantazzini and Shangina (2020) for more details.

**3.1 Measures of volatility**

I use two volatility measures: the realized variance (RV) and IV from options prices (IV). The RV is a nonparametric and consistent estimator of the daily integrated variance, see Meddahi (2002) and Andersen et al. (2001):

, (1)

where △=1/*M* is the time interval of the intraday prices, *M* is the number of intraday returns, while is the intraday return. The weekly RV *w* at time *t* is the given by:

, (2)

where we considered a weekly time interval of five working days. If the underlying stochastic process for the log-prices contains jumps, then it is possible to show that the RV converges to the sum of the integrated variance and the cumulative squared jumps, see Barndorff-Nielsen and Shephard (2004), Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007). The continuous sample path variation can be estimated non-parametrically using the standardized Realized Bipower Variation measure:

, (3)

while the jump component can be estimated by , where the non-negativity truncation on the actual empirical jump measurements was proposed by Barndorff-Nielsen and Shephard (2004b) because the difference between RV and BV can become negative with real data. More elaborate methods to compute the jump components were proposed by Huang and Tauchen (2005) and Andersen et al. (2007).

If the financial market under consideration is not open 24 hours (like for cryptocurrencies, see Fantazzini (2019), then the RV must be adjusted for the return in the overnight gap from the market close on day t to the market open on day t+1. I scaled up the market-open RV using the unconditional variance estimated with the daily squared returns,

, (4)

where are the daily squared returns computed using the close-to-close daily prices, while is the RV computed with intraday data when the RTS future market is open, see Hansen and Lunde (2005), Christoffersen (2012), and Ahoniemi and Lanne (2013).

An implied volatility (IV) index computes the market expectations for future volatility implied by options prices. Differently from Fantazzini and Shangina (2020), I will use only the Russian Volatility Index (RVI) which was introduced on 16 April 2014, and which measures the market expectations for volatility over a 30-day period using prices of the nearby and next RTS Index option series[[12]](#footnote-13). The RVI formula is reported below:

, (5)

where stands for 30 days expressed as a fraction of a calendar year, for 365 days expressed as a fraction of a calendar year, is the time to expiration of the near-series options expressed as a fraction of a calendar year, is the time to expiration of the next far-series options expressed as a fraction of a calendar year, is the variance of the near-series options and is the variance of the next-series of options[[13]](#footnote-14).

**3.2 Volatility Models**

I employ the four models considered by Fantazzini and Shangina (2020): the Threshold-GARCH(1,1) proposed by Glosten et al. (1993) and Zakoïan (1994), models the conditional variance as follows:

, (6)

where *I* = 1 if and the error term takes the leverage effect into account. A specification including the (implied) volatility index and Google Trends as additional regressors is considered,

*,* (7)

The second model will be the HAR model by Corsi (2009),

,

where *D*,*W* and *M* stand for daily, weekly and monthly values of the realized volatility, respectively. The HAR model augmented with the implied volatility and Google data will also be considered:

(8)

The third model is the *Auto-Regressive Fractional Integrated Moving Average -ARFIMA(p,d,q)-* model proposed by Andersen et al. (2003):

Φ(*L*)(1 *– L*)*d*(*RVt*+1 *− µ*) = Θ(*L*)εt+1, (9)

where *L* is the lag operator, Φ(*L*) = 1 *−* φ1*L − ... −* φ*pLp,* Θ(*L*) = 1 + θ1*L* + *...* + θ*qLq* and (1 *− L*)*d* is the fractional differencing operator defined by and Γ(*•*) is the gamma function. Similarly to the HAR and GARCH models, I will also consider IV and Google Trends as additional regressors:

Φ(*L*)(1 *− L*)*d*(*RVt*+1 *− µ*) = γ*GTt* + α*IVt* + Θ(*L*)*ε*t+1, (10)

Finally, I also estimate the realized GARCH with a log-linear specification proposed by Hansen et al. (2012), which jointly models the returns and the realized measures of volatility:

;

; (11)

.

Similarly to previous models, an augmented model with IV and Google Trends as additional regressors is considered.

**3.3 Market Risk Measures and Backtesting Methods**

VaR can be defined as the maximum market loss of a financial position over a time horizon h at a pre-defined confidence level (1-α), or alternatively, the minimum loss of the worst losses (α) over the time horizon (h). For GARCH and Realized-GARCH models with Student’s t errors, the 1-day ahead VaR is given by , where is the 1-day-ahead forecast of the conditional mean, is the 1-day-ahead forecast of the conditional variance, while is the inverse function of the Student’s t distribution with υ degrees of freedom at the probability level α. For HAR and ARFIMA, the 1-day ahead VaR is computed as follows, , where is the inverse function of a standard normal distribution function at the probability level α, while is the 1-day-ahead forecast for the realized volatility.

The Expected Shortfall (ES) measures the average of the worst losses, where α is a percentile of the returns’ distribution, and it is computed as follows, , where is the inverse function of the returns’ distribution, that is the VaR. Wimmerstedt (2015) and Emmer et al. (2015) showed that the ES2.5% proposed by the Basel Committee on Banking Supervision (2013, p. 18) can be approximated using the VaR computed at different probability levels as follows:

. (12)

The null hypothesis that the average number of VaR violations is equal to α% can be tested using the unconditional coverage test by Kupiec (1995), while the joint null hypothesis that the average number of VaR violations is correct and the violations are independent can be tested using the conditional coverage test by Christoffersen (1998).

The magnitude of the VaR violations can be evaluated by computing the asymmetric quantile loss (QL) function by Gonzalez-Rivera et al. (2004), , where if and zero otherwise. The losses of the competing models can be compared using the Model Confidence Set (MCS) by Hansen, Lunde, and Nason (2011) to select the best VaR forecasting models at a specified confidence level.

Finally, the estimated VaR at different confidence levels can be jointly tested using the multinomial VaR test by Kratz et al. (2018), which implicitly backtests ES using the previous idea by Emmer et al. (2015) to approximate the ES at several VaR levels. A discussion at the textbook level of these backtesting methods and market risk management in general, can be found in Fantazzini (2019).

**4 Empirical analysis**

As anticipated in the previous section, this analysis will use only free resources to be fully reproducible. I consider the following data:

* *RTS index future*: intraday data sampled every 5 minutes is downloaded from the website finam.ru. The sample ranges from January 2015 till August 2019. The 5-minutes squared log-returns are then used to calculate the daily, weekly and monthly realized variance measures. Daily returns are also computed.
* *RVI (Russian Volatility Index)*: this is the IV of the RTS index future computed from option prices.
* *Google Trends*: this is a standardized index ranging between 0 and 100 which shows the number of search queries for a topic or a keyword over a specific period and a specific region. Its computation requires dividing the number of searches by the total amount of searches for the same period and region, and the resulting time series is then divided by its highest value and multiplied by 100. The average of the Google Trends data for the query "RTS index", both in English and in Russian is used. It is now time to introduce R to download the data and to perform the VaR backtesting analysis with competing volatility models:

|  |
| --- |
| **# Load the Russian Volatility Index (RVI)**  library(rusquant)  getSymbols("SPFB.RVI", from='2015-05-05', to='2019-08-09', src="Finam", period="day")  RVI<-SPFB.RVI$SPFB.RVI.Close; colnames(RVI)<-"RVI"; rm(SPFB.RVI)  **# Load RTS intraday data (max 3 years of 5-min data per single download)**  getSymbols("SPFB.RTS", from="2015-01-01", to="2017-12-31", src="Finam", period="5min"); a1=SPFB.RTS  getSymbols("SPFB.RTS", from="2018-01-01", to='2019-08-09', src="Finam", period="5min"); a2=SPFB.RTS  dat<-rbind(a1,a2); rm(SPFB.RTS);rm(a1);rm(a2)  **# Compute the daily returns and the daily RV for the RTS index**  library(xts);library(highfrequency)  closep<-dat[,"SPFB.RTS.Close"]  intraday\_squared\_returns <- highfrequency::makeReturns(closep)^2  daily\_RV <- aggregatets(intraday\_squared\_returns, on = 'days', k = 1, dropna = T, FUN="sum")  daily\_returns <- highfrequency::makeReturns(aggregatets(closep, on = 'days', k = 1, dropna = T))  A<-cbind(daily\_returns, daily\_RV); colnames(A)<-c("daily\_returns","daily\_RV")  rm(intraday\_squared\_returns); rm(dat)  **# Merge the datasets**  A <- merge(A,RVI, all=F)  rm(daily\_returns); rm(daily\_RV); rm(RVI)  **# Download first Google monthly data, then daily data and finally concatenate them**  library(gtrendsR)  res\_en\_all <- gtrends(keyword = c("RTS index"), time = "2015-05-01 2019-07-30")  res\_en\_all<-xts::xts(x = res\_en\_all$interest\_over\_time$hits, order.by = res\_en\_all$interest\_over\_time$date)  res\_en\_all<-xts::as.xts(aggregate(res\_en\_all, as.yearmon, mean))  res\_ru\_all <- gtrends(keyword = c("Индекс РТС"), time ="2015-05-01 2019-07-30")  res\_ru\_all<-xts::xts(x = res\_ru\_all$interest\_over\_time$hits, order.by = res\_ru\_all$interest\_over\_time$date)  res\_ru\_all<-xts::as.xts(aggregate(res\_ru\_all, as.yearmon, mean))  len=length(res\_ru\_all)  startdate<- seq(as.Date("2015-05-01"),length=len+1,by="months")  enddate<- seq(as.Date("2015-05-01"),length=len+1,by="months")-1  GT<-NULL  for (i in 1:len){  daily\_date<-seq(startdate[i], enddate[i+1], by="days")  res\_en <- gtrends(keyword = c("RTS index"), time = paste(startdate[i],enddate[i+1],sep=" "))  if (is.null(res\_en$interest\_over\_time$hits)==FALSE){  res\_en<-res\_en$interest\_over\_time$hits\*(as.numeric(res\_en\_all[i])/100)  }else{  res\_en <-0  }  res\_ru <- gtrends(keyword = c("Индекс РТС"), time = paste(startdate[i],enddate[i+1],sep=" "))  if (is.null(res\_ru$interest\_over\_time$hits)==FALSE){  res\_ru<-res\_ru$interest\_over\_time$hits\*(as.numeric(res\_ru\_all[i])/100)  }else{  res\_ru <-0  }  res<-(res\_en+res\_ru)/2; rts<-xts::xts(x = res, order.by = daily\_date)  GT<-rbind(GT,rts)  }  **# Substitute zero values in GT with small positive number**  GT[GT==0] <- 0.1  **# Merge the datasets**  A <- merge(A,GT, all=F); rm(GT)  # **Adjust the daily Realized Variance for the night market closure**  A$daily.RV.adj<-(sum(A$daily\_returns^2)/sum(A$daily\_RV))\*A$daily\_RV |

Note that the quality of this downloaded dataset is worse than the dataset used by Fantazzini and Shangina (2020) because there are several missing values. Nevertheless, I continue working with these data to allow readers without access to commercial databases to fully reproduce this analysis. After the data download, we estimate the volatility models using a rolling window of 400 observations and then compute the VaR forecasts till the end of the available sample.

The R code below considers only the models which reached numerical convergence, whereas models which failed to converge are discarded. The R scripts *HARRV\_forecast\_functions.R* and *ARFIMA\_LOG\_forecast\_functions.R* which are loaded below contains functions to estimate and forecast with HAR models and with ARFIMA models using the logarithm of the RV as dependent variable, respectively. Their full contents are reported in the Appendix 1.

|  |
| --- |
| library(rugarch);library(doParallel); library(xts); library(highfrequency); ncores=detectCores()-1  A[A==0]<-0.0000001 ### Problems with too many zeroes in the data: substitute small pos. numbers  **# 1) =================== GARCH models =================================================**  **# Basic T-GARCH(1,1)**  v\_alpha <- c(0.005, 0.01, 0.015, 0.02, 0.025)  garch.spec = ugarchspec(variance.model = list(model = "gjrGARCH", garchOrder=c(1,1)),  mean.model = list(armaOrder=c(0,0), include.mean = TRUE),  distribution.model = "std")  ctrl = list(outer.iter = 100, inner.iter = 650, tol = 1e-5)  cl<-makeCluster(ncores)  registerDoParallel(cl)  tgarch11.roll = ugarchroll(spec=garch.spec, data = A$daily\_returns, n.ahead = 1,  n.start = 400, refit.every = 1, refit.window = "moving",  solver = "solnp", solver.control = ctrl, calculate.VaR = TRUE, VaR.alpha = v\_alpha,  keep.coef = FALSE, cluster=cl, window.size = 400)  stopCluster(cl)  **# 2) =================== HAR models ====================================================**  source('D:/Dean/Papers/Shangina/HARRV\_forecast\_functions.R')  results.HARRV.LOG <- HARRV.all.1step.forecast.night(dat=closep, roll.window = 400, type="HARRV",  transform="log")  results.HARRVIV.LOG <- HARRV.all.1step.forecast.night(dat=closep, roll.window = 400, type="HARRV", external =  lag(A$RVI), transform="log")  results.HARRVGT.LOG <- HARRV.all.1step.forecast.night(dat=closep, roll.window = 400, type="HARRV", external =  lag(A$GT), transform="log")  **# 3) =================== ARFIMA models =================================================**  **# Basic ARFIMA (1,1)**  arfima.spec<-arfimaspec(mean.model = list(armaOrder =c(1,1), include.mean=TRUE,arfima=TRUE ))  cl<-makeCluster(ncores); registerDoParallel(cl); n.start=400  arfima.roll = arfimaroll(arfima.spec, data = A$daily.RV.adj, n.ahead = 1,n.start = n.start,  window.size = 400, refit.every = 1, refit.window = "moving",  solver="hybrid",calculate.VaR=FALSE,keep.coef=FALSE, cluster=cl)  stopCluster(cl)  RV\_fore<-arfima.roll@forecast$density$Mu  RV\_fore<-ifelse(RV\_fore<0,min(RV\_fore[RV\_fore>0]),RV\_fore)  RV\_fore<-xts::xts(RV\_fore, order.by = arfima.roll@model$index[(n.start+1):nrow(A$daily\_returns)] )  # Compute VaR  v\_alpha <- c(0.005, 0.01, 0.015, 0.02, 0.025)  m <- matrix(sqrt(RV\_fore),nrow=length(sqrt(RV\_fore)),ncol=length(v\_alpha), byrow=FALSE)  m\_VaR <- xts::xts( t(t(m) \* qnorm(v\_alpha)), index(RV\_fore))  source('D:/Dean/Papers/Shangina/ARFIMA\_LOG\_forecast\_functions.R')  RV.VaR.fore.IV <-ARFIMA.RV.1step.log.fore(dat.daily.RV=log(A$daily.RV.adj), external=lag(log(A$RVI)),  windowsize = 400)  RV.VaR.fore.GT <-ARFIMA.RV.1step.log.fore(dat.daily.RV=log(A$daily.RV.adj), external=lag(log(A$GT)),  windowsize = 400)  **# 4) ====================== Realized-Garch =============================================**  **# Basic Realized-Garch(1,1)**  rgarch.spec <- ugarchspec(mean.model = list(armaOrder=c(0,0), include.mean=TRUE),  variance.model = list(model = 'realGARCH', garchOrder = c(1, 1)))  cl<-makeCluster(ncores)  registerDoParallel(cl)  rg.roll = ugarchroll(rgarch.spec, data = A$daily\_returns, n.ahead = 1,  n.start = 400, refit.every = 1, refit.window = "moving",  solver = "hybrid", calculate.VaR = TRUE, VaR.alpha = v\_alpha,  keep.coef = FALSE, cluster=cl, realizedVol = A$daily.RV.adj, window.size = 400)  stopCluster(cl) |

We now proceed to merge all VaR forecasts, to compute the previously discussed market risk back-tests:

|  |
| --- |
| # ========================== **LOAD and MERGE VaR forecasts** =========================  library(MCS);library(rugarch);library(highfrequency)  tgarch\_all05<-xts::xts(cbind(tgarch11.roll@forecast$VaR[,1]), order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR)) ); colnames(tgarch\_all05)=c("TGARCH")  tgarch\_all10<-xts::xts(cbind(tgarch11.roll@forecast$VaR[,2]), order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR)) ); colnames(tgarch\_all10)=c("TGARCH")  tgarch\_all15<-xts::xts(cbind(tgarch11.roll@forecast$VaR[,3]), order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR)) ); colnames(tgarch\_all15)=c("TGARCH")  tgarch\_all20<-xts::xts(cbind(tgarch11.roll@forecast$VaR[,4]), order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR)) ); colnames(tgarch\_all20)=c("TGARCH")  tgarch\_all25<-xts::xts(cbind(tgarch11.roll@forecast$VaR[,5]), order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR)) ); colnames(tgarch\_all25)=c("TGARCH")  tgarch\_realized<-xts::xts(tgarch11.roll@forecast$VaR[,6],order.by =  as.Date(rownames(tgarch11.roll@forecast$VaR))); colnames(tgarch\_realized)=c("realized")  HARRV.all05.LOG<- cbind(results.HARRV.LOG$m\_VaR[,1],results.HARRVIV.LOG$m\_VaR[,1],  results.HARRVGT.LOG$m\_VaR[,1]);  colnames(HARRV.all05.LOG)<-c("HARRV.LOG","HARRV\_IV.LOG","HARRV\_GT.LOG")  HARRV.all10.LOG<- cbind(results.HARRV.LOG$m\_VaR[,2],results.HARRVIV.LOG$m\_VaR[,2],  results.HARRVGT.LOG$m\_VaR[,2]);  colnames(HARRV.all10.LOG)<-c("HARRV.LOG","HARRV\_IV.LOG","HARRV\_GT.LOG")  HARRV.all15.LOG<- cbind(results.HARRV.LOG$m\_VaR[,3],results.HARRVIV.LOG$m\_VaR[,3],  results.HARRVGT.LOG$m\_VaR[,3]);  colnames(HARRV.all15.LOG)<-c("HARRV.LOG","HARRV\_IV.LOG","HARRV\_GT.LOG")  HARRV.all20.LOG<- cbind(results.HARRV.LOG$m\_VaR[,4],results.HARRVIV.LOG$m\_VaR[,4],  results.HARRVGT.LOG$m\_VaR[,4]);  colnames(HARRV.all20.LOG)<-c("HARRV.LOG","HARRV\_IV.LOG","HARRV\_GT.LOG")  HARRV.all25.LOG<- cbind(results.HARRV.LOG$m\_VaR[,5],results.HARRVIV.LOG$m\_VaR[,5],  results.HARRVGT.LOG$m\_VaR[,5]);  colnames(HARRV.all25.LOG)<-c("HARRV.LOG","HARRV\_IV.LOG","HARRV\_GT.LOG")  arfima.all05<- cbind(m\_VaR[,1], RV.VaR.fore.IV$m\_VaR[,1],RV.VaR.fore.GT$m\_VaR[,1]);  colnames(arfima.all05)=c("ARFIMA","ARFIMA\_IV","ARFIMA\_GT")  arfima.all10<- cbind(m\_VaR[,2], RV.VaR.fore.IV$m\_VaR[,2],RV.VaR.fore.GT$m\_VaR[,2]);  colnames(arfima.all10)=c("ARFIMA","ARFIMA\_IV","ARFIMA\_GT")  arfima.all15<- cbind(m\_VaR[,3], RV.VaR.fore.IV$m\_VaR[,3],RV.VaR.fore.GT$m\_VaR[,3]);  colnames(arfima.all15)=c("ARFIMA","ARFIMA\_IV","ARFIMA\_GT")  arfima.all20<- cbind(m\_VaR[,4], RV.VaR.fore.IV$m\_VaR[,4],RV.VaR.fore.GT$m\_VaR[,4]);  colnames(arfima.all20)=c("ARFIMA","ARFIMA\_IV","ARFIMA\_GT")  arfima.all25<- cbind(m\_VaR[,5], RV.VaR.fore.IV$m\_VaR[,5],RV.VaR.fore.GT$m\_VaR[,5]);  colnames(arfima.all25)=c("ARFIMA","ARFIMA\_IV","ARFIMA\_GT")  rg\_all05<-xts::xts(cbind(rg.roll@forecast$VaR[,1]), order.by = as.Date(rownames(rg.roll@forecast$VaR)) );  colnames(rg\_all05)=c("RG")  rg\_all10<-xts::xts(cbind(rg.roll@forecast$VaR[,2]), order.by = as.Date(rownames(rg.roll@forecast$VaR)) );  colnames(rg\_all10)=c("RG")  rg\_all15<-xts::xts(cbind(rg.roll@forecast$VaR[,3]), order.by = as.Date(rownames(rg.roll@forecast$VaR)) );  colnames(rg\_all15)=c("RG")  rg\_all20<-xts::xts(cbind(rg.roll@forecast$VaR[,4]), order.by = as.Date(rownames(rg.roll@forecast$VaR)) );  colnames(rg\_all20)=c("RG")  rg\_all25<-xts::xts(cbind(rg.roll@forecast$VaR[,5]), order.by = as.Date(rownames(rg.roll@forecast$VaR)) );  colnames(rg\_all25)=c("RG")  VaR.all.05 <- merge(tgarch\_all05, arfima.all05,rg\_all05, HARRV.all05.LOG, tgarch\_realized, all=F)  VaR.all.10 <- merge(tgarch\_all10, arfima.all10,rg\_all10, HARRV.all10.LOG, tgarch\_realized, all=F)  VaR.all.15 <- merge(tgarch\_all15, arfima.all15,rg\_all15, HARRV.all15.LOG, tgarch\_realized, all=F)  VaR.all.20 <- merge(tgarch\_all20, arfima.all20,rg\_all20, HARRV.all20.LOG, tgarch\_realized, all=F)  VaR.all.25 <- merge(tgarch\_all25, arfima.all25,rg\_all25, HARRV.all25.LOG, tgarch\_realized, all=F) |

The following R code compute Kupiec’s and Christoffersen’s tests for all competing models with *α*=0.5%. These two tests are computed using two alternative R functions: *VaRTest* from the rugarch package, and *BacktestVaR* from the GAS package. The latter has better numerical routines for zero violations or too many violations, as is visible below (see Table 1):

|  |
| --- |
| test\_VaR\_mat = NULL;test\_VaR\_mat2 = NULL  for (i in 1: 8){  test\_Var\_RG <- rugarch ::VaRTest(alpha=0.005,actual=VaR.all.05[,9], VaR.all.05[,i])  test\_VaR\_mat <- rbind(test\_VaR\_mat, cbind(test\_Var\_RG$uc.LRp,test\_Var\_RG$cc.LRp,  100\*test\_Var\_RG$actual.exceed/243))  test\_Var\_RG2 <- GAS::BacktestVaR(alpha=0.005,data=VaR.all.05[,9], VaR=VaR.all.05[,i])  test\_VaR\_mat2 <- rbind(test\_VaR\_mat2, cbind(test\_Var\_RG2$LRuc[2],test\_Var\_RG2$LRcc[2],  test\_Var\_RG2$AE\*0.5))  }  rownames(test\_VaR\_mat) = rownames(test\_VaR\_mat2) <-colnames(VaR.all.05[,1:8])  colnames(test\_VaR\_mat) = colnames(test\_VaR\_mat2) <- c("p-value UC","p-value CC", "% violations")  test\_VaR\_mat; test\_VaR\_mat2 |

**Table 1** Results of various models

|  |  |  |  |
| --- | --- | --- | --- |
| **Model type** | **p-value UC** | **p-value CC** | **% violations** |
| TGARCH | 0.51387733 | 0.7947332 | 0.8230453 |
| ARFIMA | 0.51387733 | 0.7947332 | 0.8230453 |
| ARFIMA\_IV | NA | NA | NA |
| ARFIMA\_GT | NA | NA | NA |
| RG | 0.51387733 | 0.7947332 | 0.8230453 |
| HARRV.LOG | 0.17188569 | 0.3787542 | 1.2345679 |
| HARRV\_IV.LOG | 0.04564615 | 0.1268776 | 1.6460905 |
| HARRV\_GT.LOG | 0.17188569 | 0.3787542 | 1.2345679 |
| TGARCH | 0.51387733 | 0.7947332 | 0.8230453 |
| ARFIMA | 0.51387733 | 0.7947332 | 0.8230453 |
| ARFIMA\_IV | 0.00000000 | 0.0000000 | 37.4485597 |
| ARFIMA\_GT | 0.17188569 | 0.3787542 | 1.2345679 |
| RG | 0.51387733 | 0.7947332 | 0.8230453 |
| HARRV.LOG | 0.17188569 | 0.3787542 | 1.2345679 |
| HARRV\_IV.LOG | 0.04564615 | 0.1268776 | 1.6460905 |
| HARRV\_GT.LOG | 0.17188569 | 0.3787542 | 1.2345679 |

The results of the Kupiec’s and Christoffersen’s tests are similar to those reported by Fantazzini and Shangina (2020): the TGARCH model and the models without additional regressors tend to perform better than the competitors and, importantly, they managed to reach numerical convergence in the very volatile Russian market. The computation of the Kupiec’s and Christoffersen’s tests for the remaining quantile levels α2=1%, α3=1.5%, α4=2% and α5=2.5% is left to the reader as a small exercise.

The next step is to compute the asymmetric MCS by Hansen et al. (2011) with the quantile loss by Gonzalez-Rivera et al. (2004) to select the best VaR forecasting models at a specified confidence level (see Table 2):

|  |
| --- |
| **# MCS**  loss.VaR05 = loss.VaR10 = loss.VaR15 = loss.VaR20 = loss.VaR25 = matrix(0,nrow = nrow(VaR.all.05)-1,ncol=8);  colnames(loss.VaR05)=colnames(loss.VaR10)=colnames(loss.VaR15)=colnames(loss.VaR20)=colnames(loss.VaR25)=colnames(VaR.all.05[,1:8])  for (i in 1:8){  loss.VaR05[,i] = LossVaR(VaR.all.05[-1,9], VaR.all.05[-1,i], which = 'asymmetricLoss', type = 'normal', tau=0.005)  loss.VaR10[,i] = LossVaR(VaR.all.10[-1,9], VaR.all.10[-1,i], which = 'asymmetricLoss', type = 'normal', tau=0.01)  loss.VaR15[,i] = LossVaR(VaR.all.15[-1,9], VaR.all.15[-1,i], which = 'asymmetricLoss', type = 'normal', tau=0.015)  loss.VaR20[,i] = LossVaR(VaR.all.20[-1,9], VaR.all.20[-1,i], which = 'asymmetricLoss', type = 'normal', tau=0.02)  loss.VaR25[,i] = LossVaR(VaR.all.25[-1,9], VaR.all.25[-1,i], which = 'asymmetricLoss', type = 'normal', tau=0.025)  }  cl <- makeCluster(4);clusterEvalQ(cl, library(MCS))  MCS05<-MCSprocedure(loss.VaR05,alpha=0.15,B=5000,cl=cl,ram.allocation=TRUE,statistic="Tmax",k=NULL)  MCS10<-MCSprocedure(loss.VaR10,alpha=0.15,B=5000,cl=cl,ram.allocation=TRUE,statistic="Tmax",k=NULL)  MCS15<-MCSprocedure(loss.VaR15,alpha=0.15,B=5000,cl=cl,ram.allocation=TRUE,statistic="Tmax",k=NULL)  MCS20<-MCSprocedure(loss.VaR20,alpha=0.15,B=5000,cl=cl,ram.allocation=TRUE,statistic="Tmax",k=NULL)  MCS25<-MCSprocedure(loss.VaR25,alpha=0.15,B=5000,cl=cl,ram.allocation=TRUE,statistic="Tmax",k=NULL)  stopCluster(cl)  MCS05 |

**Table 2** Superior set of models

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Rank\_M | v\_M | MCS\_M | Rank\_R | v\_R | MCS\_R | Loss |
| TGARCH | 3 | -0.7991426 | 1.0000 | 1 | -0.3496199 | 1.0000 | 0.0005746541 |
| ARFIMA | 2 | -0.8332644 | 1.0000 | 3 | 0.5539961 | 0.9704 | 0.0005882636 |
| ARFIMA\_GT | 4 | 0.4772198 | 0.9158 | 4 | 0.8969138 | 0.9394 | 0.0006036455 |
| RG | 1 | -0.9346006 | 1.0000 | 2 | 0.3496199 | 0.9834 | 0.0005856780 |
| HARRV\_LOG | 7 | 1.1778874 | 0.5276 | 7 | 1.5933009 | 0.4710 | 0.0006179435 |
| HARRV\_IV\_LOG | 6 | 0.9060525 | 0.7394 | 6 | 1.2918698 | 0.6946 | 0.0006117858 |
| HARRV\_GT\_LOG | 5 | 0.5958863 | 0.8894 | 5 | 0.9517833 | 0.9260 | 0.0006040453 |
| Number of eliminated models : 1  Statistic : Tmax  Elapsed Time : Time difference of 18.07589 secs | | | | | | | |

The TGARCH model showed the smallest quantile loss, while the ARFIMA model with IV was eliminated. The results for the remaining quantiles are left to the reader.

Finally, the last step of our (baseline) analysis is the computation of the multinomial VaR test by Kratz et al. (2018) to implicitly back-test the ES by approximating it with several VaR levels:

|  |
| --- |
| **# Multinomial test**  test\_VaR\_mat = NULL  for (i in 1: 8){  test\_Var\_05 <- VaRTest(alpha=0.005,actual=VaR.all.05[-1,9], VaR.all.05[-1,i])  test\_Var\_10 <- VaRTest(alpha=0.01,actual=VaR.all.10[-1,9], VaR.all.10[-1,i])  test\_Var\_15 <- VaRTest(alpha=0.015,actual=VaR.all.15[-1,9], VaR.all.15[-1,i])  test\_Var\_20 <- VaRTest(alpha=0.02,actual=VaR.all.20[-1,9], VaR.all.20[-1,i])  test\_Var\_25 <- VaRTest(alpha=0.025,actual=VaR.all.25[-1,9], VaR.all.25[-1,i])  tv<- c(test\_Var\_05$actual.exceed, test\_Var\_10$actual.exceed, test\_Var\_15$actual.exceed,  test\_Var\_20$actual.exceed,test\_Var\_25$actual.exceed)  test\_VaR\_mat <- rbind(test\_VaR\_mat, tv)  }  **#Number of VaR violations in each cell**  rownames(test\_VaR\_mat)<-colnames(VaR.all.05[,1:8]); test\_VaR\_mat  [,1] [,2] [,3] [,4] [,5]  TGARCH 2 3 4 7 9  ARFIMA 2 3 4 6 6  ARFIMA\_IV 91 93 96 96 97  ARFIMA\_GT 3 4 6 8 8  RG 2 4 6 6 7  HARRV.LOG 3 6 6 8 10  HARRV\_IV.LOG 4 6 6 9 10  HARRV\_GT.LOG 3 5 6 7 9  test\_VaR\_multi = NULL  for (i in 1: 8){  # Compute the number of violations in each cell  n\_cell<-c(test\_VaR\_mat[i,], 242) - c(0, test\_VaR\_mat[i,])  #and test all VaR jointly using the multinomial VaR backtest by Kratz et al.(2018)  theo\_cell <- c(v\_alpha, 1) - c(0, v\_alpha)  aa=XNomial::xmonte(n\_cell, theo\_cell, detail=2)  test\_VaR\_multi <- rbind(test\_VaR\_multi, aa$pLLR)  }  **#P-values of the multinomial test for each forecasting model**  rownames(test\_VaR\_multi)<-colnames(VaR.all.05[,1:8]); test\_VaR\_multi  TGARCH 0.88254  ARFIMA 0.79732  ARFIMA\_IV 0.00000  ARFIMA\_GT 0.57569  RG 0.73951  HARRV.LOG 0.32676  HARRV\_IV.LOG 0.15547  HARRV\_GT.LOG 0.88254 |

The results of the multinomial test confirm the previous empirical evidence, where the null hypothesis is strongly rejected only for the ARFIMA model with the IV index. This model showed very unstable numerical estimates which resulted in extremely poor VaR forecasts.

**5 A robustness check: forecasting the VaR using Hierarchical-VAR models**

Similar to Fantazzini and Shangina (2020), we now proceed to check how our results change with a multivariate model able to accommodate a large number of regressors and parameters.

More specifically, we employ the *Hierarchical Vector Autoregression* (HVAR) model estimated with the Least Absolute Shrinkage and Selection Operator (LASSO) proposed by Nicholson et al. (2018). The starting point is the following VAR model,

, (13)

where is a vector containing the daily returns, the daily realized volatility, the implied volatility and the Google data, ***ν*** is an intercept vector, while are the usual coefficient matrices.

This model is estimated using the following penalized least squares optimization:

, (14)

where denotes the Frobenius norm of matrix A (that is, the elementwise 2-norm), is a penalty parameter, while is the group penalty structure on the endogenous coefficient matrices. The *elementwise penalty function* which allows every variable in every equation to have its own maximum lag was used in the estimation process (see Nicholson et al. (2018) for more details):

. (15)

|  |
| --- |
| **# HVAR model VaR forecast ======================================================**  library(BigVAR); library(doParallel); library(xts)  A= as.xts(read.zoo("A.csv", sep="", header=T))  A.adj = A; A.adj$daily\_RV =NULL  num.data=nrow(A.adj)  window\_roll=400  n = nrow(A.adj$daily\_returns) - window\_roll - 1  **# Prepare function to create multivariate forecasts**  col\_for <- function(i) {  fcst\_on<-vector('numeric')  # Prepare the data  data<-A.adj[i:(i+window\_roll),]  #Elementwise HVAR for data in log-returns  try({  ModelHVAR<-cv.BigVAR( constructModel(as.matrix(data),p=22,  struct="HVARELEM",gran=c(25,10), verbose=FALSE,IC=TRUE) )  fcst\_on[1]<- max( predict(ModelHVAR, n.ahead=1)[4], 0 )  })  fcst\_on[2]<-i  return(fcst\_on)  }  # Parallel computation setup  no\_cores <- detectCores()-1  cl <- makeCluster(no\_cores)  clusterExport(cl, varlist <- c("A.adj","window\_roll","col\_for"))  clusterEvalQ(cl, library(BigVAR))  # Small trial with 3 out-of-sample data  seqa= 1:n #1:n /(n-1):n  sh <- parLapply(cl,seqa, col\_for)  stopCluster(cl)  **# Organise forecasts**  forecasts<-data.frame(matrix(unlist(sh),nrow=length(seqa), byrow=T)) #length(1:n)  colnames(forecasts)<-c("RV.HVAR", "row")  forecasts<-xts::xts(forecasts, order.by = zoo::index(A$daily\_returns)[seqa+window\_roll+1] )  **# Compute VaR**  RV\_fore<-forecasts$RV.HVAR  v\_alpha <- c(0.005, 0.01, 0.015, 0.02, 0.025)  m <- matrix(sqrt(RV\_fore),nrow=length(sqrt(RV\_fore)),ncol=length(v\_alpha), byrow=FALSE)  HVAR\_VaR <- xts::xts( t(t(m) \* qnorm(v\_alpha)), index(RV\_fore))  **# Test the VaR forecasts for each quantile using Kupiec (UC) and Chirstoffersen (CC) VaR tests**  test\_HVaR\_mat = NULL  for (i in 1: length(v\_alpha)){  test\_HVar<-VaRTest(alpha=v\_alpha[i],actual=as.numeric(tail(A$daily\_returns,242)),VaR=HVAR\_VaR[,i])  test\_HVaR\_mat <- rbind(test\_HVaR\_mat, cbind(test\_HVar$uc.LRp,test\_HVar$cc.LRp, 100\*test\_HVar$actual.exceed/242))  }  colnames(test\_HVaR\_mat)= c("UC pvalue", "CC pvalue", "Actual exceed.")  test\_HVaR\_mat  # UC pvalue CC pvalue Actual exceed.  [1,] 0.5106661 0.7920842 0.8264463  [2,] 0.7179413 0.9020792 1.2396694  [3,] 0.8473260 0.9175503 1.6528926  [4,] 0.6909964 0.8637100 1.6528926  [5,] 0.9835531 0.8577689 2.4793388  **# P-values of the Multinomial VaR test by Kratz et al.(2018) with α1=0.5%,α2=1%,α3=1.5%,α4=2%, α5=2.5%**  n\_cell<-c(test\_HVaR\_mat[,3], 242) - c(0, test\_HVaR\_mat[,3])  #and test all VaR jointly using the multinomial VaR backtest by Kratz et al.(2018)  theo\_cell <- c(v\_alpha, 1) - c(0, v\_alpha)  XNomial::xmonte(n\_cell, theo\_cell, detail=2)  P value (LLR) = 0.71366 +/- 0.00143  1e+05 random trials  Observed: 0.8264463 0.4132231 0.4132231 0 0.8264463 239.5207  Expected Ratio: 0.005 0.005 0.005 0.005 0.005 0.975 |

In contrast to empirical evidence reported by Fantazzini and Shangina (2020), the HVAR model passes all specification tests. This should not come as a surprise, given that the time sample used for this backtesting analysis is very small and it ranges from mid-2017 till mid-2019, which was much less volatile than the (larger) sample used by Fantazzini and Shangina (2020).

**6 Conclusions**

This work provided a step-by-step analysis with R and Russian market data to partially replicate the analysis performed by Fantazzini and Shangina (2020) to verify whether adding Google search queries and IV from option prices to several volatility models could improve their estimated market risk measures.

Despite the fact that the dataset used in this work was much smaller than the one employed by Fantazzini and Shangina (2020) due to the limitations of freely available resources, the results reported here did not greatly differ from those reported in the original publication: the TGARCH model without regressors was able to pass the Kupiec and Christoffersen's tests for almost all quantiles, and it also reported the lowest asymmetric quantile losses. Moreover, very few models augmented with IV and Google data managed to reach numerical convergence, thus highlighting the importance of choosing a model able to withstand volatile periods and sudden market crashes, which is the typical situation for an emerging market.

It is hoped that this work can be helpful to professionals and students in finance who want to see a detailed application of backtesting techniques for market risk measurement and management, particularly in view of the Basel III agreement that will come into force on January,1 2022.

**7** **Appendix**

I report below the two functions contained in the R scripts *HARRV\_forecast\_functions.R* and *ARFIMA\_LOG\_forecast\_functions.R*, respectively. Appendix 1:

|  |
| --- |
| **# ================ HAR-RV model with corrections for night returns ========================**  **HARRV.all.1step.forecast.night <- function(dat, roll.window = 2000, type="HARRV", external=NULL,**  **transform=NULL,v\_alpha=c(0.005,0.01,0.015,0.02,0.025)){**  dat\_ret <- highfrequency::makeReturns(dat)  daily\_returns <- highfrequency::makeReturns(aggregatets(dat, on = 'days', k = 1, dropna = T));colnames(daily\_returns)="daily\_returns"  #btc\_harrv <- highfrequency::harModel(data=dat\_ret,periods=c(1,5,22),type=type, h=1,transform=transform)  btc\_harrv <- highfrequency::harModel(data=dat\_ret,periods=c(1,5,22),type=type, h=1,transform=transform,inputType = "returns")  daily\_dat<-xts::as.xts(btc\_harrv$model, order.by =btc\_harrv$dates)  zoo::index(daily\_dat)<-as.Date(zoo::index(daily\_dat))  **# Merge daily returns and daily RV and adjust RV for night returns**  if (is.null(transform)==TRUE){  correction<-merge(daily\_returns, daily\_dat$y, all=F)  daily\_dat<-(sum(correction$daily\_returns^2)/sum(correction$y))\*daily\_dat  }  if (transform=="log"){  correction<-merge(daily\_returns, exp(daily\_dat$y), all=F)  correction<-sum(correction$daily\_returns^2)/sum(correction$y)  }  **# Merge possible external data and original daily RV data**  if (!is.null(external)==TRUE){ daily\_dat<- merge(daily\_dat,external, all=F) }  names\_for\_eq <- colnames(daily\_dat)  formula\_RV<-stats::as.formula( paste(names\_for\_eq[1], paste0(names\_for\_eq[2:length(names\_for\_eq)], collapse="+"), sep = '~') )  h=1  prediction\_recursive<-function(series){  mod <- stats::lm(formula = formula\_RV, data = series)  date\_last<-zoo::index(last(series))  nextOb<-nrow( window(daily\_dat, start=index(daily\_dat)[1], end=date\_last) ) + 1  # t+1  fore\_all<-matrix(NA, ncol = ncol(daily\_dat)+1, nrow=h)  if (is.null(transform)==TRUE){  predicted <- max( stats::predict( mod,newdata=data.frame(daily\_dat[nextOb,] )), 0)  realized<-zoo::coredata(daily\_dat[nextOb,"y"])  }  if (transform=="log"){  predicted <- correction\*exp( stats::predict( mod,newdata=data.frame(daily\_dat[nextOb,] )) )  realized<-correction\*exp( zoo::coredata(daily\_dat[nextOb,"y"]) )  }  dat\_pred<-c(realized, predicted)  names(dat\_pred)=c("realized", "predicted")  return(dat\_pred)  }  roll.fore<-zoo::rollapply( daily\_dat[1:(nrow(daily\_dat)-h),], width=roll.window, FUN=prediction\_recursive, by.column=F, align='right')  roll.fore<-xts::xts( roll.fore, zoo::index(daily\_dat)[(1+h):nrow(daily\_dat)] )  HARRV.fore=na.omit(roll.fore$predicted)  # Compute VaR  m <- matrix(sqrt(HARRV.fore),nrow=length(sqrt(HARRV.fore)),ncol=length(v\_alpha),  byrow=FALSE)  m\_VaR <- xts::xts( t(t(m) \* qnorm(v\_alpha)) , index(HARRV.fore))  results <-list(roll.fore=roll.fore, m\_VaR=m\_VaR)  return(results)  **}** |

Appendix 2:

|  |
| --- |
| **# ======================== ARFIMA model with log dependent variable ========================**  **ARFIMA.RV.1step.log.fore <- function(dat.daily.RV, windowsize = 500, external=NULL,**  **v\_alpha=c(0.005,0.01,0.015,0.02,0.025)){**  dat.arf<-dat.daily.RV[-1,]  n.fore= nrow(dat.arf)-windowsize  m\_VaR <- matrix(NA,nrow=length(dat.arf),ncol=length(v\_alpha),byrow=FALSE)  m\_RV <- matrix(NA,nrow=length(dat.arf),ncol=1,byrow=FALSE)  if (!is.null(external)==TRUE){  external<-external[-1,]  }  for (i in 1:n.fore){  if (!is.null(external)==TRUE){  arfima.spec<-rugarch::arfimaspec(mean.model=list(armaOrder=c(1,1), include.mean=TRUE, arfima=TRUE, external.regressors=as.matrix(external[i:(i+windowsize-1),]) ) )  } else {  arfima.spec<-rugarch::arfimaspec(mean.model=list(armaOrder=c(1,1), include.mean=TRUE, arfima=TRUE, external.regressors= NULL ) )  }  arfima.fit <- rugarch::arfimafit(arfima.spec, data = dat.arf[i:(i+windowsize-1),], out.sample = 1, solver="hybrid")  arfima.fcst <- rugarch::arfimaforecast(arfima.fit, n.ahead=1)  sigma.hat <- sqrt( exp(arfima.fcst@forecast$seriesFor) )  # Insert VaR and RV  m\_VaR[(i+windowsize),] = sigma.hat\*qnorm(v\_alpha)  m\_RV[(i+windowsize),] = sigma.hat^2  }  m\_VaR <- xts::xts( m\_VaR , order.by=index(dat.arf))  m\_RV <- xts::xts( m\_RV , order.by=index(dat.arf))  results <-list(m\_RV=m\_RV, m\_VaR=m\_VaR)  return(results)  **}** |

**References**

Acerbi, C., Tasche, D. (2002). On the coherence of expected shortfall. *Journal of Banking and Finance*, 26(7), 1487–1503.

Aganin, A. (2017). Forecast comparison of volatility models on Russian stock market. *Applied Econometrics*, 48, 63-84.

Aganin, A., Peresetsky, A. (2018). Volatility of ruble exchange rate: Oil and sanctions. *Applied Econometrics*, 52, 5-21.

Agnolucci, P. (2009). Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models. *Energy Economics*, 31(2), 316-321.

Ahoniemi, K., Lanne, M. (2013). Overnight stock returns and realized volatility. *International Journal of Forecasting*, 29(4), 592-604.

Andersen, T. G., Bollerslev, T., Diebold, F.X., Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), 43–76.

Andersen, T. G., Bollerslev, T., Diebold, F.X., Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71(2), 579-625.

Andersen, T. G., Bollerslev, T., Diebold, F.X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics*, 89(4), 701–720.

Artzner, P., Delbaen, F., Eber, J.M., Heath, D. (1997). Thinking coherently. *Risk*, 10(11), 68–71.

Artzner, P., Delbaen, F., Eber, J.-M., Heath, D. (1999). Coherent measures of risk. Mathematical finance, 9(3), 203–228

Bai, J. (1997). Estimating Multiple Breaks One at a Time. *Econometric Theory*, 13, 315–352.

Bai, J., Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, 66, 47–78.

Bai, J., Perron, P. (2003a). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics,* 18, 1–22.

Bai, J., Perron P. (2003b). Critical Values for Multiple Structural Change Tests. *Econometrics Journal*, 18, 1–22.

Bams, D., Blanchard, G., Lehnert, T. (2017). Volatility measures and Value-at-Risk. *International Journal of Forecasting*, 33(4), 848-863.

Barndorff-Nielsen, O.E., Shephard, N. (2004). Econometric analysis of realized covariation: High frequency based covariance, regression, and correlation in financial economics. *Econometrica*, 72(3), 885–925.

Barndorff-Nielsen, O.E., Shephard, N. (2004b). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, 2(1), 1–37.

Barndorff-Nielsen, O.E., Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, 4(1), 1–30.

Basel Committee on Banking Supervision (2009). *Findings on the Interaction of Market and Credit Risk*. Bank for International Settlements, Working paper n. 16, May.

Basel Committee on Banking Supervision (2013). *Fundamental review of the trading book: A revised market risk framework*. Consultative Document, October.

Basel Committee on Banking Supervision (2016). *Minimum capital requirements for market risk*. Consultative Document, January

Basistha, A., Kurov, A., Wolfe, M. (2018). Volatility Forecasting: The Role of Internet Search Activity and Implied Volatility, West Virginia University working paper.

Bazhenov, T., Fantazzini, D. (2019). Forecasting Realized Volatility of Russian stocks using Google Trends and Implied Volatility. *Russian Journal of Industrial Economics*, 12(1), 79-88.

Bianchi, C., De Giuli, M. E., Fantazzini, D., Maggi, M. (2011). Small sample properties of copula-GARCH modelling: a Monte Carlo study. *Applied Financial Economics*, 21(21), 1587-1597.

Birkelund, O. H., Haugom, E., Molnár, P., Opdal, M., Westgaard, S. (2015). A comparison of implied and realized volatility in the Nordic power forward market. *Energy Economics*, 48, 288-294.

Busch, T., Christensen, B. J., Nielsen, M. (2011). The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. *Journal of Econometrics*, 160(1), 48-57.

Cai, Y., Krishnamoorthy, K. (2006). Exact size and power properties of five tests for multinomial proportions. Communications in Statistics, Simulation and Computation, 35(1):149–160.

Campos, I., Cortazar, G., Reyes, T. (2017). Modeling and predicting oil VIX: Internet search volume versus traditional variables. *Energy Economics*, 66, 194-204.

Caporale, G.M., Luis A., Trilochan T. (2019). Volatility Persistence In The Russian Stock Market. *Finance Research Letters*, forthcoming.

Choi, H., Varian, H. (2012). Predicting the present with Google Trends. *Economic* *Record*, 88, 2-9.

Chong, J. (2004). Value at risk from econometric models and implied from currency options. *Journal of Forecasting*, 23(8), 603–620.

Christensen, B. J., Prabhala, N.R. (1998). The relation between implied and realized volatility. *Journal of Financial Economics*, 50(2), 125–150.

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International economic review*, 39, 841-862.

Christoffersen, P. (2012). *Elements of financial risk management*. Academic Press.

Christoffersen, P., Mazzotta, S. (2005). The accuracy of density forecasts from foreign exchange options. *Journal of Financial Econometrics*, 3(4), 578–605.

Corredor, P., Santamaría, R. (2004). Forecasting volatility in the Spanish option market. *Applied Financial Economics*, 14(1), 1-11.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7(2), 174-196.

Da, Z., Engelberg, J., Gao, P., (2011). In search of attention. *Journal of Finance,* 66(5), 1461–1499.

Dimpfl, T., Jank, S. (2016). Can internet search queries help to predict stock market volatility?. *European Financial Management*, 22(2), 171-192.

Emmer,S., Kratz, M., Tasche, D. (2015).What Is the Best Risk Measure in Practice? *Journal of Risk,* 18,31-60.

Fantazzini, D. (2019) *Quantitative Finance with R and Cryptocurrencies*. Amazon KDP, ISBN-13: 978-1090685315.

Fantazzini, D., Toktamysova, Z. (2015). Forecasting German car sales using Google data and multivariate models. *International Journal of Production Economics*, 170, 97-135.

Fantazzini D., Shangina T. (2020) The importance of being informed: forecasting market risk measures for the

Russian RTS index future using online data and implied volatility over two decades, *Applied Econometrics*, forthcoming.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, 457(7232), 1012.

Giot, P. (2005). Implied volatility indexes and daily value at risk models. *The Journal of Derivatives*, 12(4), 54–64.

Glosten, L., Jagannathan, R., Runke, D., (1993). Relationship between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance,* 48, 1779–1801

Gneiting, T. (2011). Making and evaluating point forecasts. *Journal of the American Statistical Association*, 106(494), 746-762.

Goddard, J., Kita, A., Wang, Q., (2015). Investor attention and FX market volatility. *Journal of International Financial Markets, Institutions and Money,* 38, 79-96

González-Rivera, G., Lee, T. H., Mishra, S. (2004). Forecasting volatility: A reality check based on option pricing, utility function, value-at-risk, and predictive likelihood. *International Journal of forecasting*, 20(4), 629-645.

Hamid, A., Heiden, M. (2015). Forecasting volatility with empirical similarity and Google Trends. *Journal of Economic Behavior and Organization*, 117, 62-81.

Hansen, P.R., Lunde, A. (2005). A realized variance for the whole day based on intermittent high-frequency data. *Journal of Financial Econometrics*, 3, 525–554

Hansen, P. R., Lunde, A. (2005b). A forecast comparison of volatility models: does anything beat a GARCH (1, 1)? *Journal of Applied Econometrics*, 20(7), 873-889.

Hansen, P. R., Lunde, A., Nason, J. M. (2011). The model confidence set. *Econometrica*, 79(2), 453-497.

Hansen, P.R., Huang, Z., Shek, H. H. (2012). Realized GARCH: a joint model for returns and realized measures of volatility. *Journal of Applied Econometrics*, 27(6), 877-906.

Haugom, E., Langeland, H., Molnár, P., Westgaard, S. (2014). Forecasting volatility of the US oil market. *Journal of Banking and Finance*, 47, 1-14.

Huang, X., Tauchen, G. (2005). The relative contribution of jumps to total price variance. *Journal of Financial Econometrics*, 3(4):456–499.

Hyndman, R.J., Khandakar, Y. (2008). Automatic Time Series Forecasting: the forecast Package for R. *Journal of Statistical Software*, 27(3).

Hwang, S., Valls Pereira, P.L. (2006). Small sample properties of GARCH estimates and persistence. *The European Journal of Finance*, 12(6-7), 473-494.

Jeon, J., Taylor, J.W. (2013). Using CAViaR Models with Implied Volatility for Value‐at‐Risk Estimation. *Journal of Forecasting*, 32(1), 62-74.

Jorion, P. (2007). *Financial Risk Manager Handbook*. Vol. 406. Wiley.

Kratz, M., Lok, Y.H., McNeil, A. J. (2018). Multinomial VaR Backtests: A simple implicit approach to backtesting expected shortfall. *Journal of Banking and Finance*, 88, 393-407.

Kupiec, P. H. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, 3(2), 73-84.

Liu, J., Wu, S., Zidek, J.V. (1997). On segmented multivariate regression. *Statistica Sinica,* 7, 497–525

Liu, L. Y., Patton, A. J., Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. *Journal of Econometrics*, 187(1), 293-311.

Malakhovskaya, O., Minabutdinov, A. (2014). Are commodity price shocks important? A Bayesian estimation of a DSGE model for Russia*. International Journal of Computational Economics and Econometrics*, 4(1/2), 148-180.

Martens, M., Zein, J. (2004). Predicting financial volatility: High‐frequency time‐series forecasts vis‐à‐vis implied volatility. *Journal of Futures Markets*, 24(11), 1005-1028.

Mayhew, S. (1995). Implied volatility. *Financial Analysts Journal*, 51(4), 8-20.

McNeil, A. J., Frey, R., Embrechts, P. (2015). *Quantitative Risk Management: Concepts, Techniques and Tools.* Revised edition. Princeton university press.

Meddahi, N. (2002). A theoretical comparison between integrated and realized volatility. *Journal of Applied Econometrics*, 17(5), 479–508

Newey, W.K., West, K.D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4), 631-653.

Nicholson, W. B., Wilms, I., Bien, J., Matteson, D. S. (2018). High dimensional forecasting via interpretable vector autoregression. arXiv preprint arXiv:1412.5250.

Perron, P. (2006). Dealing with structural breaks. *Palgrave handbook of econometrics*, 1(2), 278-352.

Pesaran, M.H., Timmermann, A. (2007). Selection of estimation window in the presence of breaks. *Journal of Econometrics*, 137(1), 134-161.

Pong, S., Shackleton, M. B., Taylor, S. J., Xu, X. (2004). Forecasting currency volatility: A comparison of implied volatilities and AR (FI) MA models. *Journal of Banking and Finance*, 28(10), 2541–2563.

Seo, M., Lee, S., Kim, G. (2019). Forecasting the Volatility of Stock Market Index Using the Hybrid Models with Google Domestic Trends. *Fluctuation and Noise Letters*, 18(01), 1950006.

Taylor, S. J., Xu, X. (1997). The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance*, 4(4), 317–340.

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

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking and Finance*, 41, 17-35.

Xu, Q., Bo, Z., Jiang, C., Liu, Y. (2019). Does Google search index really help predicting stock market volatility? Evidence from a modified mixed data sampling model on volatility. *Knowledge-Based Systems*, 166, 170-185.

Wimmerstedt, L. (2015). Backtesting expected shortfall: the design and implementation of different backtests. Technical report, Swedish Royal Institute of Technology.

Yao, Y. C. (1988). Estimating the number of change-points via Schwarz'criterion. *Statistics and Probability Letters*, 6(3), 181-189.

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

Zeileis, A., F. Leisch, K. Hornik, Kleiber, C. (2002). strucchange: An R package for testing for structural change in linear regression models. *Journal of Statistical Software*, 7(2), 1–38

Zeileis, A. (2005). A unified approach to structural change tests based on ML scores, F statistics, and OLS residuals. *Econometric Reviews*, 24(4), 445-466.

Zeileis (2006). Object-oriented computation of sandwich estimators. *Journal of Statistical Software*, 16(9), 1–16.

Zeileis, A., Shah, A., Patnaik, I. (2010). Testing, monitoring, and dating structural changes in exchange rate regimes. *Computational Statistics and Data Analysis*, 54(6), 1696-1706.

**Integrated risk measurement system in commercial bank**

**Alexander Zhevaga, Alexei Morgunov [[14]](#footnote-15)\***

**Abstract** Integrated risk management means the comprehensive and effective management all significant risks affecting the bank’s activities, taking into account the interdependence of risks, including building a corporate culture of risk management and integrating risk management into strategic planning. The risks are significant the consequences of the implementation of which have a significant, impact on the financial result of the bank, its capital, and liquidity, business reputation and the ability to comply with RM regulators. In the context of economic crises and sanctions, the role of effective risk management in banks is significantly increasing, as it allows the bank to adequately distribute its capital and reserves and contributes to its stable existence in the face of uncertainty. The most significant risks in banking are credit and liquidity risks. In the banking sector, a significant methodological base has now been accumulated for assessing and managing these types of risks. The purpose of this study is to systematize the approaches to the formation of a risk management system in Russian and world practice, to assess their advantages and disadvantages, and also to formulate a list of recommendations for improving the existing system. Decision making at management levels takes place in conditions of uncertainty in the external and internal environment, which causes partial or complete uncertainty in the final results of activities. In economics, uncertainty is understood as incompleteness or inaccuracy of information on the conditions of economic activity, including the costs and the results. The causes of uncertainty are three main factors: ignorance, randomness and competition. In particular, the uncertainty is explained by the fact that the problems are reduced to the tasks of choosing from a certain number of alternatives, while the banks do not have full knowledge of the situation to work out the optimal solution, and do not have the resources to adequately account for all the information available to them. A measure of uncertainty is risk, i.e. the probability of occurrence of events, as a result of which unexpected losses of income, property, cash and other assets are possible. In modern banking risk management systems, procedures for influencing individual risk events or types of risk are increasingly being replaced by the organization of continuous monitoring of the bank’s aggregate risk and the management of the value of various businesses of a credit institution adjusted for their inherent risk. This conceptual approach is called Integrated Risk Management (IRM). In the international banking regulation standards, the IRM logic is disclosed by the requirements of Component 2 of the Basel II and Basel III agreements (BKBN, 2004), (BKBN, 2010), in Russian practice - Bank of Russia Ordinance No. 3624-U “On requirements for the risk and capital management system credit organization and banking group ”(Bank of Russia, 2015).

**Keywords** IRM, credit risk, market risk, alm risk, liquidity risk, operational risk, risk culture

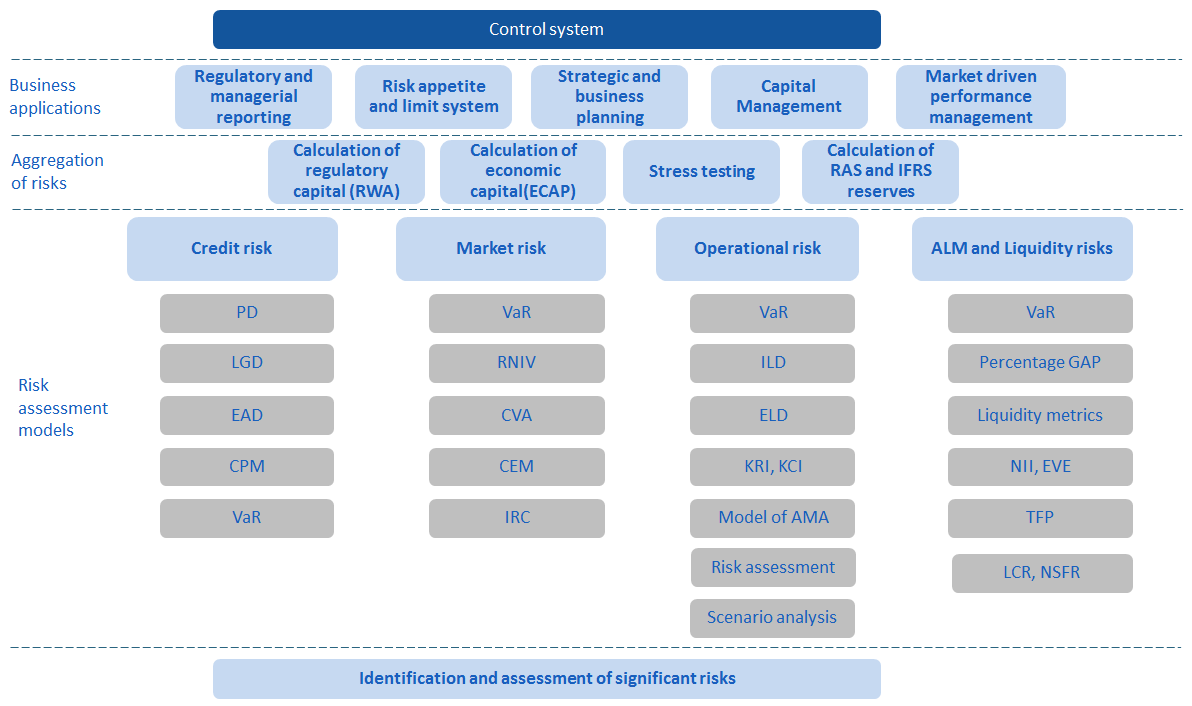
**JEL** G21, G24, G32

**1 Problems of IRM implementation in Russian banks**

The introduction of IRM in Russian commercial banks faces a number of challenges related to the imperfection of corporate and strategic management systems, the lack of processes and technologies for accumulating and verifying risk information, and the insufficient resources to implement large-scale tasks. On the one hand, IRM procedures make it possible to build bank management in the context of individual lines of business and products based on determining the target ratio of their profitability and risks (risk appetite), determined by the shareholders. On the other hand, these procedures are extremely complex require the involvement of highly qualified personnel and the use of sophisticated information tools. The costs associated with the implementation of the IRM system may turn out to be higher than the savings from reducing the risk level if this implementation is formal and does not lead to a change in the risk culture of the bank and the harmonization of the processes of strategic development and risk management. Therefore, the introduction of IRM in bank management practice requires a systematic approach that integrates risk management, strategic and financial planning, performance management, and liquidity management. This integration should be based on the use of unified tools for managing these processes: a unified financial structure, a unified methodology of financial estimates and forecasts and a unified information space. This section is devoted to the description of the standard of building an IRM bank system that meets these requirements. It reflects the ideas of standardizing the quality of banking, developed by the Russian banking community as part of the activities of the ARB Committee on Banking Quality Standards (ARB, 2014), (Mardanov, 2008), including IRM and ICAAP standards (Pomorina, 2015), as well as the best international practices of organizing IRM (ISO, 2018), (COSO, 2017), (FERMA, 2003).

**2 The main content and elements of the IRM system**

The integrated risk management system can be represented by the following scheme.



**Fig. 1** The integrated risk-management system»

IRM provides the aggregation various types of risks and communication with business processes. Risk management is based on large volumes of data and requires a modern, industrial IT infrastructure. Analysis of the accumulated data allows banks to identify risks and assess their materiality. Risk management processes should be launched for each significant risk and closely connected with business processes, while risk management is carried out by means of modeling and quantitative risk assessment. Estimates for certain types of risks are aggregated to assess the cumulative and adjusted impact both on the credit institution as a whole and on the group to which the organization is a member, while resistance to market disasters and specific crises is assessed through stress testing. The integration risks into the assessment of the effectiveness of a credit institution allows us to assess real profitability, risk appetite and the limits of various levels to link the achievement of business goals with the goals of ensuring stability and sufficient capital to cover losses. A separate role is given to risk reporting, which allows banks to see a slice of quantitative and qualitative information. IRM can be described by sequentially determining the content of its main elements:

• Targeted;

• Resultant;

• Methodological;

• Organizational;

• Informational;

• Technological;

• Resource.

Target elements determine the desired result of the functioning of the system and, therefore, the content of all other elements. In the modern interpretation, the goal of the IRM is to optimize the value of the bank in the long run taking into account risks. Often, the term “risk-return management” is used to denote it. The resulting elements of the system are its final product, transmitted to the external environment (in our case, the bank’s internal product, which is used by all its subjects). The functioning of the IRM system are its results such as:

• Bank’s risk and capital management strategy integrated into the bank’s development strategy;

• Results of the identification and assessment of bank risks;

• A system to limit the level of risk;

• Management decisions regarding measures aimed at maintaining consistency between the target and actual risk levels,

• Reporting, providing control over the level of risks.

Methodological elements determine the standards and methods of risk assessment, as well as approaches to risk management.

Organizational elements determine the subjects of the IRM system, among which the following bodies and subdivisions of the bank traditionally distinguish:

• Corporate governance bodies (Board of Directors and IAS),

• Executive bodies (the Board and its committees),

• Specialized departments responsible for risk management,

• Other divisions of a credit institution, from which risks arise.

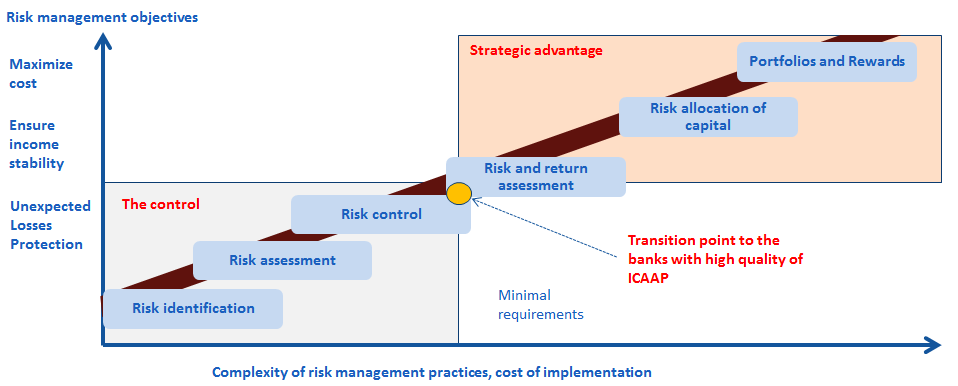
The most important element of the IRM system is its information component: data that allows banks to evaluate both realized and potential risks, as well as the technological component, which is a combination of tools for accumulating, analyzing, exchanging and using risk information.

Resource elements determine the infrastructure of the IIR: human and technological potential that can be used for risk management purposes.

The IRM system contains subsystems for managing certain types of banking risks: credit, market, operational, liquidity risks, etc. It does not simply combine of these subsystems, but defines general principles and approaches to constructing management systems for certain types of banking risks. Let us consider in more detail the content of each of the listed elements of the IRM system and their main subsystems.

**3 Target elements of the IRM system**

The goals of these systems have recently changed significantly. The focus is no longer on risks, but on their impact on the value of the bank.



**Fig. 2** Target elements of IRM system

**4 Methodological elements of the IRM system**

To ensure the effective functioning of the IRM system, it is necessary to form a continuously repeating risk management cycle based on a unified methodology.

The main stages of this cycle are the identification of risks, the determination of their quantitative and qualitative assessments and the actual risk management and control over management effectiveness based on the assessments made.

As part of the identification:

-risk information is collected;

-fundamentally measurable and unmeasured risks are identified;

-risks are identified that require special attention and risks that can be neglected.

At the stage of risk assessment, the relationship between the balance sheet structure and risk positions is clarified. The sources of information in this case are the balances of certain types of risks. These balances systematize the company's positions in accordance with the risks associated with them. Using risk balances, an analysis of the sensitivity of the result to specific risk factors is carried out.

At the risk management stage, the following occurs:

- The development of methods, regulations, procedures. Effective risk management involves the professional selection and application of special methods and tools: statistical analysis methods, expert forecasting methods, hierarchy analysis methods, simulation methods, etc.

-Information support for decision makers. Risk decision makers need comprehensive information. Along with information on possible risks, information is also needed on the positive or negative consequences of various risk management measures. The successful implementation of this task involves solving the problem of ensuring the completeness, reliability, efficiency and visibility of the provision of information.

-The creation of a risk reporting system. The risk reporting system serves to inform the management of the organization and the structural units of systematized data on the identification, analysis and assessment of risks. Reporting also serves to control and monitor risks and is an important component of bank documentation, which is provided to market regulators, exchange analysts and other market participants.

***4.1 Risk Identification Methods***

An integral component of Integrated Risk Management is the procedure for determining the significant risks of a credit institution. This procedure includes:

1. The list to identify risks:

1.1. Annual process initiation.

1.2. Formation of a long list, including identification of emerging risks and confirmation of existing ones.

1.3. Drawing up a work plan for the process as a whole. Here, the main focus is on default risk on loans, market and operational risks, concentration and liquidity risks, business risk, strategic and compliance risks, reputational risk, etc.

2. Materiality assessment:

2.1. Creation and identification of scripts.

2.2. Modeling the impact of scenarios.

2.3. Assessment of materiality of risks and documentation of conclusions.

3. Risk management decision:

3.1. Selection of significant risk management options.

3.2. Reporting findings.

3.3. Linking results to other processes.

Examples of risk identification, their assessment of significance and the development of control measures are given in the following table.

**Table 1** Risk identification methods

|  |  |  |
| --- | --- | --- |
| **Type of risk** | **Materiality** | **Proposed Management Approach** |
| Concentration risk | Significant | Capitalization |
| Reputational risk | Significant | Control |
| Insurance risk | Insignified | Monitoring |

***4.2 Risk Assessment Methods and Risk Metrics***

Risk analysis and assessment can be qualitative and quantitative. Qualitative analysis aims to identify factors, areas and types of risk. Quantitative analysis allows you to evaluate the value of individual risks and the value of the overall risk of the enterprise. To evaluate counterparties, the monitoring of data and publications about the counterparties (partner, client, competitor), assessing independent appraisers, analysing materials about them or the relevant industry, region, country, etc is carried out. A distinctive feature of these approaches is the relatively high cost and in relatively low efficiency.

In this regard, remote assessment tools that are based on current and historical data on the subject of assessment and do not imply face-to-face contacts with the analyzed subject seem to be quite important. These methods are significantly less costly, do not require expert opinion, but the cost for this is a potentially higher possibility of estimation and forecast errors. Indeed, the corresponding estimates may not take into account some factors and are probabilistic in nature. Among such tools are remote ratings, including these based on models.

Risk aggregation and the business application of integrated risk management are carried out taking into account the risk appetite of the bank. Risk appetite is the risk limit set by the governing body, within the framework of which the strategy is determined and the budget of the credit organization is formed.

The following are the goals of defining risk appetite:

1. Fulfillment of regulatory requirements for an internal assessment of capital adequacy taking into account risks.

2. Management of a holistic and structured picture of risks, consistent with the expectations of the shareholders of a credit institution.

3. Ensuring the transparency of an acceptable level of risk in business units.

4. Understanding the maximum accepted risks as part of the planning process, ensuring the implementation of a long-term strategy of a credit institution.

5. Involving stakeholders in the risk management process, such as senior management through their direct participation and external participants (shareholders, investors, analysts, etc.) through regular informing

6. The possibility of cascading risk appetite through mechanisms of communication with lower-level limits and risk control in business processes.

Risk appetite is also a tool for managing the risk profile of a credit institution. For indicators of risk appetite, it is desirable to establish signal limits. Signal levels are necessary for effective management and early response to worsening situations. Examples of such restrictions can be: at the level of the credit institution - the target rating, as well as capital adequacy levels; at the level of the risk types for credit - economic capital of the loan and retail portfolios; at the portfolio level - NPL and EL; at the market level - the VAR limit and stop loss at the operating level - the share of operating expenses in the expenses of the credit institution, at the level ALM - the economic capital of the interest and currency risks of the bank book.

Risk appetite metrics can be divided into three categories:

1. Metrics with covenants S & P / other credit rating agencies. Here, the limits are set depending on the covenant S&P.

2. Regulatory standards. Here, the limits are set depending on the covenants of the Bank of Russia and the results of scenario planning.

3. Additional internal metrics, excluding the external factor. Limits are set based on historical data, current and planned values ​​and expert judgment.

An important tool for integrated risk management is the risk analysis of profitability, which can be based on economic and regulatory capital. Depending on current needs, a credit institution can use both risk-based performance indicators based on the calculation of economic and regulatory capital.

In the case where a more stringent restriction for a credit institution sets economic capital, the Economic Profit and RAROC indicators should be maximized. The features of this approach are the following postulates:

1. The increase in profitability per unit of economic capital and ROE, in a situation where economic capital is very scarce.

2. Economic capital is more sensitive to risk (internal models of a credit organization are used, additional forms of risk manifestation, for example, concentration, are taken into account).

3. Capital is allocated to business lines, portfolios and transactions that create the highest added shareholder value.

4. Transparent rules that allow managing a credit organization on a portfolio basis.

If regulatory capital sets a stricter restriction on a credit institution, the RoRWA indicator should be maximized. The following postulates are important:

1. Increase in profitability per unit of RWA and ROE, in a situation when Regulatory capital is very scarce.

2. Automatic implementation of regulatory restrictions and standards.

3. RWAs are less risk sensitive, especially in the absence of TAC models in a credit institution (additional forms of risk manifestation, for example, concentration, are not taken into account).

4. RoRWA optimization can lead to the formation of ineffective portfolios based on the risk / return criterion.

**4.3 Planning and stress testing methods**

The process of business planning must be carried out taking into account risk metrics and indicators of risk return of a credit institution.

The main tasks of introducing risk metrics into the business and strategic planning process are improving the quality of planning and increasing the level of risk control. The main objectives of business planning are:

1. Determining the level of risk at the planning stage. As part of this task, it is necessary to assess the level of risks taken for the established goals and strategic objectives of the credit institution and plan measures to control and minimize risks.

2. Maximizing profitability. Maximize the achievable level of profitability by allocating resources to the most effective risk-taking business units.

3. Communication with risk appetite. The actualization of risk appetite is carried out as part of the business planning process, and the consistency of business indicators and risks is ensured.

4. Improving the quality of planning. The most qualitative forecast of the business plan of a credit institution are forecasts of reserves, arrears, losses using forecasts of macroeconomic factors.

An important tool for managing the risks and activities of a credit institution is stress testing.

Stress testing is a tool for assessing the impact of specific exceptional events, such as the financial crisis, the collapse of the securities market, etc., on the activities of a credit institution. The stress testing procedure can be carried out both from top to bottom and from bottom to top. In the first case, an upper-level analysis of the impact of stress scenarios on the performance of a credit institution is carried out. The main tool is a single model for all types of risk, which uses simplified sensitivities and correlations. As a forecasting horizon, a forecast of up to 3-5 years is used on the basis of the portfolio, which takes into account the dynamics over time and the dependence on macro factors.

In the case of applying the bottom-up stress testing procedure, a detailed analysis of the impact of stress scenarios on the performance of a credit institution is carried out. In this case, the main tools are bottom-up individual stress testing models that use regression analyzes, correlation matrices. The planning horizon is narrowed to 1 year based on a static portfolio (as of the date of stress testing).

**4.4 Risk management methods**

Risk management methods can be divided into groups:

-Obtaining additional information;

-Risk distribution;

- Risk insurance;

- Reservation of funds;

- Diversification;

- Measures of active influence (for example, incoming quality control).

Risk management is implemented as a complex process and involves a preliminary and final (post-event, posterior) analysis. This analysis is identifies risks, controls risk limits, improves the distribution of risks and their diversification.

The risk management philosophy is based on three main principles:

-Risk management along with the risks of individual transactions requires special attention to structural risks. As practice shows, managing specific risks is not enough to manage the risk of a credit institution, since the most important risks arise not at the level of specific operations, but at the level of the structure of the entire business system.

-Risk management focuses on the allowable loss potential of the entire bank. The potential loss is determined by all categories of risks associated with its activities.

- The level of the maximum allowable loss potential is determined by such factors as:

-The ability of the bank to take risks;

- The probability of losses;

- The need to ensure operations.

**5 Organizational elements of the IRM system.**

For the successful development of the IRM, it is mandatory to have a risk unit for resolving issues that are not related to a certain type of risk, providing a link between risk management and financial and strategic planning processes. The functional responsibilities of this unit include the calculation of aggregate risk indicators of the entire credit institution, including group relationships and the implementation of macroeconomic stress testing.

The fundamental factors in the formation of such a unit are the involvement of senior management and the clearly defined role of the risk function. In particular, it is mandatory that management participate in determining the risk appetite for the credit institution as a whole and for certain types of risks and business areas, including the existence of regular management risk reporting. A necessary condition for the qualitative formation of such a unit is the introduction of a model of three lines of defense, within which the functions of risk acceptance, risk management and audit are clearly separated. A clear understanding of the risks of its role as a service function aimed at creating benefits for the business, given the functional, organizational and staff separation from the business.

The greatest role is played by the understanding of the importance of risk management both at the leadership level and at the level of performers (risk culture). The desire to use quantitative indicators in risk analysis, including the practice of making decisions based on risk analysis, becomes undeniable.

Risk culture is the established standards of employee behavior in the organization aimed at identifying and managing risks.

In credit risk management organizations, either formal procedures or informal principles and beliefs often dominate. The most successful organizations develop a risk culture in all areas.

In an ideal credit institution, a risk culture pervades the organization and defines the actions of employees, including risk-prudent business behavior, strengthening the methodological and expert functions of risk management and impact through communication / risk-based compensation.

The following tools for developing a risk culture in the organization are distinguished.

• Work with job seekers when applying for a job. The level of risk culture of employees is assessed at the stage of an interview for vacancies in a credit institution. Recruitment criteria should include risk culture issues. Activities for new employees should include topics promoting the organization’s risk culture.

•Professional Development. Training all employees in risk culture and its principles. It is advisable to conduct separate, specialized training in risk culture, depending on the role, function and status of the employee in the organization.

•Current activity. Each employee should have access to materials-materials on risk culture. Within the framework of a credit institution, standards of risk culture in the style of "Do /Do not do" should be in place. It is mandatory to consider incidents in terms of risk culture.

• Rewards and promotions policy. Dependence of career progression incl. must steadily take into account compliance with the rules of risk culture.

• The role of leadership. Behavioral approaches that define elements of risk culture.

High-quality risk management gives a credit institution a competitive advantage, and therefore the identification and assessment of risks is the task of each employee. All employees of a credit organization strive to be professionals in risk management and for this works openly and together. Each employee of a credit institution complies with the rules, and if they are incomplete or imperfect, they openly speak about this and are guided by the interests of the credit institution.

**6 Information and technological elements of the IRM system**.

Financial risks, due to their global nature and high volatility, are becoming increasingly susceptible to crise. Tools for collecting, maintaining, maintaining integrity, analysing data and for forecasting, use databases on financial results, transaction results and macroeconomic indicators.

**7 Credit risk management system**

Credit risk presents the possibility of losses due to the counterparty's failure to fulfill its contractual obligations.

The most typical manifestation of credit risk is default - the counterparty's failure to fulfill the terms of the loan agreement. The category of credit risk primarily includes losses associated with the announcement by the counterparty of default. In addition, losses associated with lowering the borrower's credit rating can also be attributed to credit risk, since this usually leads to a decrease in the market value of its obligations and losses in the form of lost profits due to early repayment of the loan by the borrower.

Credit risk includes credit concentration risks, such as country risk, industry risk, and counterparty risk. Country risk arises when it becomes impossible for the counterparty to fulfill its obligations as a result of government actions (for example, when implementing currency control measures). Country risk is primarily determined by the specifics of the country, state control, macroeconomic regulation and management. Industry risk is associated with specific market situations and relations both within the country and internationally. Counterparty credit risk can be divided into two components: risk to settlements and risk calculations.

The risk before settlements is the possibility of losses due to the counterparty's refusal to fulfill its obligations during the term of the transaction (before settlements). This type of credit risk is typical for long time intervals: from the moment of the transaction to the settlement.

Settlement risk refers to the possibility of the non-receipt of funds at the time of settlement of the transaction due to default or lack of liquidity or operational failures. In other words, this is a risk that transactions will not be settled on time. This risk is characteristic for relatively short time intervals.

By source of manifestation, credit risk can be divided into two groups:

- External risk (counterparty risk);

- Internal risk (credit product risk).

External risk is due to the solvency or reliability of the counterparty, the likelihood of defaulting and potential losses in the event of default. The composition of the external risk includes:

-Counterparty risk - the risk of the counterparty not meeting its obligations;

-Country risk - the risk that all or most of the counterparties (including authorities) in a given country will not be able to fulfill their financial obligations for any internal reason;

- The risk of restricting the transfer of funds outside the country due to a shortage of foreign exchange reserves;

-Concentration risk - the risk of an unbalanced distribution of funds between various industries, regions or counterparties.

Internal risk is associated with the features of the loan product and the possibility of losses it due to the non-fulfillment by the counterparty of its obligations. The composition of internal risk includes:

- Risk of non-payment of principal and interest;

- Risk of completion of the operation - the risk of the counterparty failing to fulfill its obligations on time or late fulfillment;

-Loan security risk - of losses associated with a decrease in the market value of the loan security, the inability to enter into the right to own collateral, etc.

An important concept in assessing credit risk is a credit event. A credit event refers to a change in the borrower's creditworthiness or the credit quality of a financial instrument, the onset of which is characterized by clearly defined conditions. There are 6 main types of credit events:

1. Bankruptcy of a subject or instrument. This type of credit event may include:

- Liquidation of the company (with the exception of mergers);

- Insolvency (insolvency) of the company;

-Assignment of claims (cession);

- Initiating bankruptcy proceedings in court;

- Appointment of an external debtor's property manager;

-Seizure by a third party of the property of the debtor.

2. Early maturity of the obligation, which means a default (other than non-payment of the due amount) for any other similar obligation of the borrower and the entry into force of the reservation on the early maturity of this obligation.

3. Default on the obligation (cross-default), which means the declaration of default (other than non-payment of the due amount) for any other similar obligation of the borrower.

4. Insolvency, which implies non-payment by the borrower of a certain (exceeding the agreed limit) amount on time (after the expiration of the agreed grace period).

5. A moratorium in which the counterparty refuses to make a payment or disputes the legal force of the obligation.

6. Debt restructuring which entailed a unilateral refusal, deferral or change of the debt repayment schedule on less favorable terms for the lender.

The following facts can also be recognized as a credit event:

7. Downgrade or recall by the rating agency of the borrower's credit rating;

8. Currency inconvertibility caused by state restrictions;

9. Actions of state bodies jeopardizing the legal force of the obligation; war or hostilities that impede the government or the banking system.

The credit risk management system in the bank is formed on the following key principles of formation:

-Independence of decision making. Organizational independence of risk management departments and direct reporting of the head of these departments to the management of the company

- Representation in specialized committees. Representation of heads of risk management units on all relevant committees of the bank, which are competent to accept credit risk.

-Systematic credit risk management. Using a systematic approach to risk management of both the loan portfolio as a whole and individual transactions with specific borrowers (a group of related borrowers).

- Integration in the lending process. Mandatory availability of an independent risk assessment of all operations bearing credit risk.

- Adequacy of credit risk management methods. Application of an adequate methodology to the scale of operations to identify and quantify credit risk.

-Granting authority to limit risk. The head of the risk management departments has the authority to promptly suspend the limits on counterparties and credit organizations and limits on transactions with securities.

- Unity of approaches to credit risk management. The credit process in the head office, branches and subsidiaries is based on common approaches, principles and regulatory documents of the bank.

- Using a delegation of authority system. It includes a balanced combination of centralized and decentralized decision-making in transactions involving the adoption of credit risk.

- Reliability and independent evaluation. Independence and objectivity is ensured by its obligatory coordination with representatives of risk management divisions.

A significant role in the development of a credit institution and in the management of its risks is played by the credit policy, which is the program and direction in the provision of loans to legal entities and individuals. The credit policy is based on a risk-return ratio of operations acceptable for a credit institution.

The main objective of the credit policy is to maximize profits with minimal risk. Based on the possible correlation of these components, as well as available resources, the credit institution determines the current tasks: areas of lending, technology for carrying out credit operations and control in the lending process.

Credit policy should be reviewed depending on changing economic conditions. Credit risk management is carried out as part of an integrated risk analysis, management and control system, which includes a combination of qualitative (expert) and quantitative (statistical) assessment of credit risk. Credit risk assessment is carried out on the basis of individual (examination of individual transactions) and portfolio (assessment of risk concentrations) approaches. Credit risk management is carried out at all stages of the lending process from the moment the client's application for the provision of borrowed funds is examined until the full repayment of theobligations. The main elements of a credit risk management system at the level of individual transactions are:

- An independent comprehensive examination of credit risk;

- Analysis of the forecast cash flow of the borrower;

- Assessment of the business reputation of the counterparty;

-Monitoring the level of accepted credit risk;

- Assessment of the need to include borrowers in the register of counterparties subject to special supervision by the bank;

- System of limits for accepting credit risk.

The main elements of the credit risk management system at the level of the loan portfolio (certain areas of lending) are:

- Minimal level of internal rating, below which operations are not allowed;

-Loan portfolio quality indicators;

-Minimal discount rates used in assessing the effectiveness of projects;

-Minimal collateral discounts used in assessing the adequacy of collateral;

- Standard parameters of lending programs and limits for self-acceptance of credit risks;

- Arguments and restrictions in the field of lending to borrowers of certain sectors or areas of lending.

An important element of the credit risk management system is monitoring, which allows you to identify in advance an increased level of credit risk in the early stages of its occurrence and quickly implement measures to minimize and limit it. The main tools for monitoring:

-system of limits for accepting credit risk;

- Control conditions that must be met before the transaction and additional conditions that must be met within a specified period after the transaction.

Monitoring of the financial position of the counterparty is carried out by credit units with subsequent monitoring of the results. Monitoring includes assessing the financial position of the borrower based on official financial statements, cash flow forecasts and other information characterizing the current and future solvency of the borrower. Along with the expert opinion included in the file of the borrower, the monitoring results are recorded in the form of an internal rating of the borrower, the category of which characterizes the level of accepted risk. In turn, the internal rating affects the amount of reserves for the transaction and the need to take additional measures to monitor the transaction and minimize the risks taken. In order to limit the bank's operations with counterparties having a dubious business reputation, the counterparty’s business reputation is monitored. In addition, the bank may maintain a register of counterparties subject to special monitoring (the so-called Watch List). The criteria for inclusion of counterparties in this registry may be:

- The presence of any negative (financial and non-financial) information received from open or other sources of information that calls into question the ability of the counterparty to timely fulfill its obligations;

-The presence of overdue obligations;

-Restructuring of obligations;

- The occurrence of debt as a result of repayment of debt on a pre-existing asset;

-Loss of part of collateral.

-Default of the counterparty;

- Initiation of bankruptcy proceedings against the debtor;

-Adoption of measures by the third parties regarding the debtor to take over the business or reorganization actions;

- Repeated failure to submit reports and other documentation required by agreements, poor-quality preparation of necessary documents and similar violations of obligations;

- The seizure or adoption of other restrictive measures in respect of the property of the borrower in favor of third parties;

- Actions to withdraw the borrower's assets without prior approval from the bank;

- Identification of facts of obtaining false or incomplete information at the stage of issuing a loan.

The result of a qualitative assessment of credit risk is the preparation of expert opinions on the acceptability of the requested transaction parameters, the required measures to minimize the accepted credit risks and the compliance of the requested form and the purpose of the transaction to finance the cash flow model. A qualitative assessment of credit risk is usually carried out in the context of the following groups of transactions:

- Current and investment financing;

-Project financing;

- Transactions with financial institutions;

-Transactions with administrations;

-Transactions with individuals;

- Operations in financial markets.

A Qualitative assessment of credit risk allows you to:

-Structure the loan transaction in accordance with the individual characteristics of the borrower's business and the forecast of its cash flow;

-Evaluate the sufficiency and validity of the sources of repayments of obligations available to the borrower;

-Identify risks inherent in the activities of the borrower and develop measures to minimize them;

- Evaluate the appropriateness of the availability and sufficiency of the security accepted for the transaction;

-Establish pricing conditions adequate for the level of accepted credit risk.

The results of a qualitative assessment of credit risk are usually presented in the form of a report by an expert unit, which is mandatory to be included in the materials submitted to the authorized bodies of the bank when considering issues of accepting credit risk. A quantitative assessment of credit risk complements the qualitative one and allows you to get a quantitative expression of the credit risk accepted by the bank for individual transactions and the loan portfolio as a whole. A tool for quantitative assessment of credit risk is the mathematical apparatus, which includes various approaches to modeling risk events, in particular:

- Econometric models allow based on regression analysis (in particular, binary and multiple choice models. These models are used to predict the probability of default and ratings as a function of several independent variables). They allow you to get estimates of the probability of an event (for example, default, with the sufficiency of the available statistics of defaults) and ratings;

-Neural networks - computer algorithms that simulate the work of the human brain through interconnected neurons. The neural networks use the same input data as with the econometric approach, and the relationships between them are highlighted by repeated repetition by trial and error;

-Optimization models based on mathematical programming methods that allow you to minimize lender errors and maximize profits, taking into account various restrictions. Using mathematical programming methods, it is possible to determine, in particular, the optimal parameters of credit products;

-Expert models used to simulate the risk assessment process carried out by an experienced and qualified specialist (models reproducing the work of credit experts, including ratings of international rating agencies, used for low-default portfolio of borrowers);

-Hybrid models that use statistical estimation and simulation and can be based on cause-effect relationships (for example, if there is insufficient default statistics, new defaults can be modeled and used to build econometric models);

-Simulation models - allow you to determine the risk characteristics of borrowers for individual borrowers and transactions based on a scenario analysis of the borrower’s cash flows — generating a scenario distribution of the project’s cash flow based on risk factors relevant to the borrower.

An integral part of the quantitative assessment is the classification of the assets of the banking book. The banking book is the assets classified as “corporate”, “sovereign”, “banking”, “retail” or “participation” in accordance with the requirements of Section III of the Basel Agreement. The Bank Book does not include assets that meet the criteria of the trading book (according to the requirements of the Basel Agreement). Classification objective: to determine the classification algorithms for the assets necessary to highlight the individual components of credit risk used in the calculation of expected and unexpected losses. Five classes are distinguished in the Bank Book Assets: “Corporate Assets”, “Retail Assets”, “Banking Assets”, “Sovereign Assets”, “Participation”. Within these classes of assets, risk segmentation of borrowers is carried out: separate risk segments are distinguished, characterized by a single list of indicators that affect the level of credit risk of these counterparties. In particular, examples of risk segments in corporate assets include: “Largest and largest corporate assets”, “Medium and other corporate assets”, “Project finance”, Income-generating real estate”,“ Commodity financing ”,“ High-risk commercial real estate ” . As part of the credit risk management system, all models must undergo validation and internal audit procedures. The purpose of these events is to improve the quality, visibility and interpretability of the developed models and to reduce model risks arising during the development. To form common standards, banks formulate methods for the development and validation of models, covering the specifics of models developed by banks. Validation and internal audit of models should be carried out at least once a year in order to assess the quality of existing models on relevant data, as well as take into account the conformity of the models used to current business processes and business strategies of the bank. Validation of models and internal audit of business processes in the bank can be divided into “deep” (as part of the development of new models) and “periodic” (as part of the verification of existing models in the bank)

**8 Liquidity risk management system**

Specialists in the field of risk management do not have unity in approaches to determining the liquidity risk of a credit institution. Some believe that the liquidity risk is the risk of losses resulting from the bank's inability to meet its obligations at the expense of the funds at its disposal due to the unbalanced timing and volume of future incoming and outgoing cash flows.

Another group of specialists determines the liquidity risk as the risk of insufficient (or negative) liquidity:

- Lack of assets for timely fulfillment of obligations;

- The impossibility of a quick conversion of financial assets into means of payment without significant losses;

-Losses due to the need for a quick conversion of financial assets;

-Change in net income and market value of shares.

-There is a known classification of liquidity risks in terms of excess or shortage of cash or highly liquid assets:

- Excess liquidity risk - the risk of losses resulting from a decrease in bank profitability due to an imbalance in the timing and volume of future incoming and outgoing cash flows (Cash-flow);

- Insufficient liquidity risk - the risk of default due to lack of cash or other highly liquid assets (this risk seems to be significantly more dangerous for the financial stability of the bank).

For banks, compliance with liquidity at any given time is one of the primary goals, as they live off the trust of customers. Therefore, the exclusion or significant limitation of liquidity risks is the central task of banking risk management.

The tasks of managing short-term liquidity risks of a credit institution include:

- Determination of the net outflow of funds based on historically observable statistical data (statistical analysis and valuation), as well as by analyzing the status of all accounts with the Bank of Russia and cash positions at the beginning and end of the day

Liquidity Calculation at Risk (LAR) - the expected excess of payments (Net need for financing) for a certain period of time, which is with a given probability (95% - under normal financial load; 99% - with increased load; 99.9% - with maximum load) will not be implemented.

- Optimization of liquidity reserves, which consists in classifying the potential of the assets at the bank’s disposal in terms of their ability to turn into liquid assets and contrasting the potential with the risks arising from net cash outflows as a result of external factors.

The classification of liquidity risks typical of a credit institution can be carried out as follows:

-Refinancing risks arise as a result of the transformation of the terms, which is carried out in order to obtain profitability through the formation of a normal interest structure (interest on long-term investments should be greater than on short-term attraction). With repeated refinancing, there is a danger that funds cannot be raised at all to close long-term positions, or they will be very expensive.

- The risks of an unplanned extension of the capital binding period lead to the fact that the debt and interest on the debt return more slowly than planned.

- The risk of unexpected withdrawal of deposits from the accounts is the risk that the agreed loan is unexpected, that is, earlier than the scheduled term, is claimed, or deposits are withdrawn before the agreed term. This type of risk is typical for large banking transactions.

Professional liquidity management of a credit institution involves the structuring of measures to guarantee liquidity.

The above measures are aimed primarily at managing the balance sheet structure and are a long-term oriented structural liquidity management. But in order to ensure sustainable solvency, operational liquidity management is necessary, in which the movement of specific means of payment is analyzed.

In liquidity risk management, instrumental and organizational aspects should be distinguished. Naturally, without the systematization of the instrumental component, it is impossible to create an effective risk management process. However, an equally important aspect of the successful functioning of the process and the liquidity risk management system is its organizational and cultural component. The latter includes such essential components as: risk culture, decision-making culture in a conflict situation, that is, in the presence of opposing alternative solutions, as well as risk management methodology and approaches.

**9 Market risk management system**

Market risk is the risk of losses resulting from adverse changes in market risk factors. Market risks are associated with the uncertainty of market fluctuations - price and exchange rate (currency) risks, interest rate risks, liquidity - and sensitivity to these fluctuations of risk-bearing objects (for example, assets). Market risks are sometimes called technical risks in association with technical analysis used to study and forecast prices, rates, volumes and other indicators related to the market. Not only direct price factors are sources of market risks. For example, the correlation between the returns of various instruments is not a direct price factor, but indirectly affects the price characteristics of a portfolio containing these instruments.

Classification of market risks allows you to clearly structure the problems and affects the analysis of situations and the choice of effective management. The classification of market risks should correspond to the specific goals of each study and be carried out from the perspective of a systematic approach. Based on these principles, we can distinguish the most widely used classification of market risks by market segments:

• Interest rate risk (risk of losses on positions in debt securities and other instruments sensitive to changes in interest rates);

• Currency risk (risk of fluctuations in the value of positions in foreign currencies);

• Stock risk (risk of fluctuations in the value of positions in shares and their derivatives);

• Market risk of derivative financial instruments (risk of a decrease in the value of derivative financial instruments (options, futures contracts and others);

• Commodity risk (the risk of fluctuations in the value of positions under contracts for goods).

Each of the above types of risk is affected to one degree or another by the risk of market liquidity, which is associated with losses that a participant may suffer due to insufficient market liquidity. A measure of market liquidity risk is the realized spread - the difference between the weighted average prices of transactions for a certain period of time, committed at the bid price, and transactions, made at the bid price. Calculating this value is quite problematic.

As the problem is examined, the types of risks associated with a particular aspect of the problem or parameter are often introduced: for example, the risk associated with the possibility of a parallel shift in the interest rate curve; risk associated with changes in financial results due to currency fluctuations and others.

As methods of managing market risk, the approaches most often used are those associated.

The risk limitation system may be as follows:

-VAR - the value of the possible (with probability %) maximum depreciation of the trading portfolio on the horizon of T days;

- DV01 - the value of the possible depreciation of the trading portfolio when the rates change by 1 bp (sometimes 1 p.p. is used);

-CS01 - the value of possible impairment of the trading portfolio when the credit spread changes by 1 bp (sometimes 1 p.p. is used);

- Stop Loss - the amount of the maximum allowable loss for a financial instrument / portfolio. Upon reaching the specified limit, the position in the financial instrument is closed in whole or in part;

- Max Loss - the amount of the maximum allowable loss on the portfolio. After its achievement, trading in the portfolio is suspended and the question of further plans is reviewed by the management of the company together with the shareholders or the Board of Directors;

- The maximum allowable amount of open positions in financial instruments within the portfolio;

Limitations on the period of holding securities in a portfolio.

The structure of limits for transactions with derivative financial instruments (hereinafter - the derivatives) its own characteristics; the following types of limits are distinguished for such transactions:

- Maximum portfolio volume.

-Restriction on types of underlying assets.

- Limitation on types of derivatives.

- Limitation on the urgency of transactions.

-Restriction on the Greeks.

-Restriction on currency risk.

- Limit on interest rate risk.

- Limitation on the delta hedged position.

-The Stop-loss indicator shows at what negative difference between the position and the delta hedge the trader is obliged to take actions for additional hedging.

- Max-Loss - the maximum allowable loss on the portfolio.

- Limit on negative or positive Fair Value.

The main approaches to assessing the cost-based measure of market risk for the value of the possible maximum depreciation of the trading portfolio on the horizon of T days:

-Delta-normal approach (taking into account the log-normality of the distribution of return on assets);

-The method of historical modeling (based on a complete revaluation of the current portfolio at market prices modeled on the basis of historical scenarios, that is, the method is based on the assumption that the behavior of market prices is stationary in the near future);

-Monte Carlo method (based on modeling random processes with given characteristics).

Approaches to assessing market risk, as well as credit, should undergo annual procedures for periodic validation and internal audit.

**10 Operational risk management system**

Operational risk (as defined by the Basel Committee on Banking Supervision) is the risk of losses caused by inadequate or erroneous internal processes, employee actions, systems, or the influence of external events. Includes legal risk, but excludes reputational and strategic risks.

At the same time, according to the definition of the Bank of Russia, operational risk is the risk of losses resulting from unreliability and inadequacies in the internal management procedures of a credit institution, failure of information and other systems, or due to the impact of external events on the activities of a credit institution.

Sources of operational risk are people, systems, processes, external influences.

Operational risk management principles:

• Compliance with legislation

• Anti-corruption policy

•Protection of information

• Countering internal fraud

• Ban on concealing information on facts / threats of loss

• Risk analysis when creating new / changing existing products

• Separation of powers, prevention of conflicts of interest

• Prohibition of transactions on customer accounts in the absence of an appropriate order

• Acquisition of goods / works / services on a competitive basis

• Documentation of business processes and control procedures

• Availability of plans to ensure the continuity and restoration of the credit institution.

An integral part of operational risk is a risk event. A risk event is an event that has occurred due to operational risk, which has caused or is likely to lead to operational losses of the bank and has occurred due to erroneous or faulty banking processes, actions of people and systems, as well as due to external events - realization of risk (threat).

The consequences of risk events can carry both a financial and non-financial component. The former include both the past and possible (including expected / forecasted) financial consequences (except for the lost profit), and the latter - both past and possible (including expected / forecasted) negative consequences of a non-financial nature, including lost profits.

The difference between risk and risk event is presented in the table.

**Table 2** Risk vs Risk event

|  |  |
| --- | --- |
| **Risk** | **Risk event** |
| Risk (threat) - opportunity, uncertainty, perspective | Risk event - specific fact, past event |
| Risk (threat) may exist but not be realized  Risk (threat) can be realized by several risk events of various types | A risk event is the realization of risk (threat)  A risk event, in turn, can have consequences: realized, not realized - expected, possible, uncertain. |
| Risk (threat) may or may not be tied to a specific time and place | A risk event has a specific time and place  (even if they are unknown) |
| Risk minimization - these are measures related to preventing the implementation of relevant events / reducing their adverse effects in the future | Minimizing the consequences of a risky event are measures related to the settlement of the consequences of a specific adverse event |

The registration of data on events caused by operational risk that entailed or could result in losses in an amount exceeding the established cut-off level and their consequences is carried out by the unit that revealed the risk event or the unit-owner of the risk.

An important component of operational risk is a key indicator of operational risk. A key indicator of operational risk is a quantitative indicator that allows monitoring the level of risk and the effectiveness of control procedures aimed at minimizing risk. For key indicators of operational risk, threshold risk levels are established, which serve to determine the level of risk, the measured indicator.

The main advantages of monitoring the level of risk with the help of key indicators of operational risk:

• The ability to effectively localize problem areas (departments, systems, employees) for their further in-depth analysis and organize risk management depending on the dynamics of indicator values;

• The ability to take risk management measures in a proactive mode;

• Absence of discrepancies in assessments of the significance of risk.

Key indicators of operational risk are most effective for use:

• For monitoring and forecasting the level of risk, which is easily measured by quantitative indicators and has an “audit trail”;

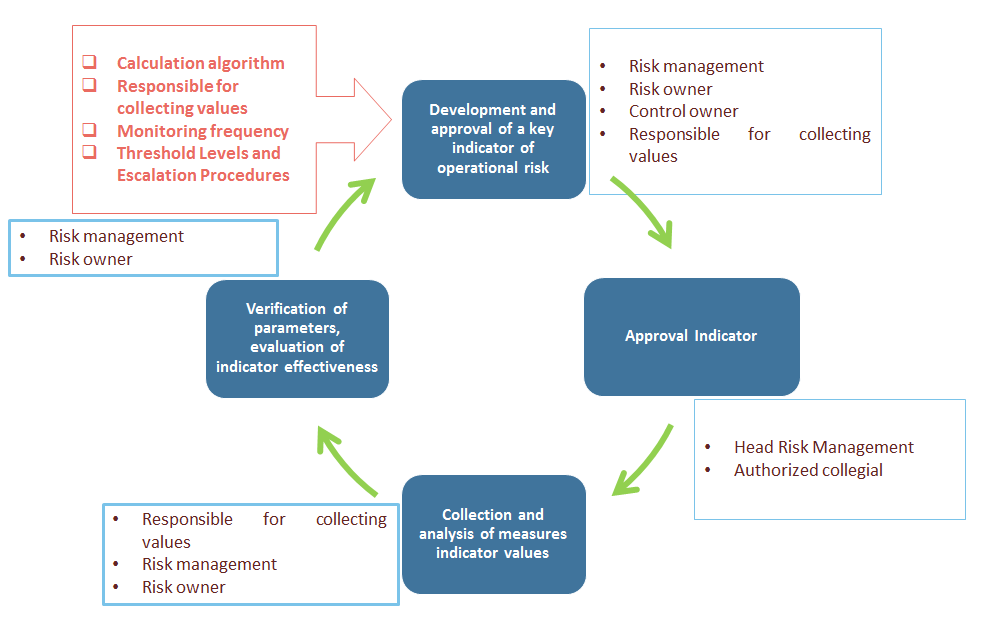
• To assess the effectiveness of control procedures (at the level of business processes);

• To identify areas of increased attention - “hotspots”;

• For use in establishing risk-based KPIs.

At the same time, key indicators of operational risk may not be effective enough, for example, to monitor rare events such as the Black Swan, to measure risks associated with the distribution of powers, including a conflict of interest and to measure specific risks associated with the provision of complex non-mass services.

The life cycle of a key indicator of operational risk is presented in the figure.



**Fig. 3** The life cycle of a key indicator of operational risk

One of the main tasks of the operational risk management system is to ensure the continuity of the credit organization. Ensuring continuity - a set of organizational, technical and programmatic measures aimed at minimizing bank losses in case of emergency, emergency and emergency situations. Its formal basis is action plans in case of emergency, emergency and emergency situations, including the following sections:

• General provisions;

• Necessary resources;

• Staff and external services;

• Reserves;

• Criteria for identifying a problem situation;

• Procedure for notification of a possible situation;

• Sequence of actions to restore activity;

• Test plan;

• The order of introduction and updating.

Important elements of a system for ensuring business continuity are:

• Identification of threats (risk factors) significant for the continuity of a credit institution.

• Formation of scenarios for the implementation of continuity threats.

• Analysis of the impact of downtime on the business of a credit institution, determination of recovery targets.

• Developing response strategies for the implementation of the scenario.

• Implementing activities to ensure the feasibility of strategies.

• Maintaining the strategy in readiness for execution.

• Monitoring the situation for signs of emergency situations.

**11 Conclusion**

A significant factor in the sustainable development of a credit institution is risk management as one of the key requirements of corporate governance. This is an integral management system in the face of uncertainty in production and economic situations. Integrated risk management is focused on reducing risks associated with the variability of the external environment and internal conditions of the credit institution. The main emphasis is on forecasting trends and using appropriate forecasts when making planning decisions that take into account the dynamics of markets, as well as on the use of monitoring results and forecasts.

Management of certain basic risks of a credit institution (credit, liquidity, market, operational) does not ensure the stability of its development and financial stability in the long term. Only the integrated risk management system described in this Chapter will allow a credit institution to form adaptive strategies that quickly respond to continuous technological changes, the impact of new crisis factors, and the tightening of global competition, as well as to ensure the stability of its development and financial stability in the long term It is the integrated risk management system that forms such approaches to Bank risk management that allow us to take into account the widest possible range of risks and their interaction, long-term aspects of their impacts and constantly changing forms of their manifestation.

**References:**

Allen S. Financial risk management: A practitioner’s guide to managingmarket and credit risk. — Hoboken, N.J.: John Wiley & Sons, Inc., 2003.

Altman, E.I., Saunders A. (1998) Credit risk measurements: Developments over the last 20 years // Journal of Banking and Finance.– № 21. - P. 1721–1742.

Aleskerov F., Ersel H., Yolalan R. (2004) Multicriterial Ranking Approach for Evaluating Bank Branch Performance // International Journal of Information Technology and Decision Making. – V.3. – No.2. – pp. 321–335.

Berger A., Mester L. (1997) Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? // Journal of Banking and Finance. – № 21. – P. 895 – 947.

BCBS (2004) Basel II: International convergence of capital measurement and capital standards: a Revised Framework// Basel Committee on Banking Supervision - www.bis.org, 10 Jun 2004, PP.1-251.

BCBS (2010) Basel III: A global regulatory framework for more resilient banks and banking systems// Basel Committee on Banking Supervision - www.bis.org, 16 Dec 2010, PP.1-77.

Bank of Russia (2015) On Requirements for the Risk and Capital Management System of a Credit Institution and a Banking Group// Bank of Russia Directive No. 3624 U - www.cbr.ru, 15.04.2015, PP.1-28.

Banking quality standards. Key Points and Requirements (Версия 2014)// Association of Russian Banks - https://arb.ru/arb/bureaux-and-committees/29634/documents/, 20.02.14, СС. 1-21.

Dowd K. Measuring market risk Hoboken, John Wiley & Sons Ltd, 2002

Enhancing Corporate Governance for banking organizations. Basel Committee on Banking Supervision. BIS Publication. February 2006. Basel. URL: http://www.bis.org/publ/bcbs122.pdf

International regulatory framework for banks (Basel III). URL:http://www.bis.org/bcbs/basel3.htm?m=3%7C14%7C572

Mardanov R. Kh. (2008) On the development of conceptual approaches to standardization of the quality of banking // Money and credit. № 2, С. 8–17.

Pomorina M.A. About the draft quality standard for the organization of IRM and ICAAP in banks // XI Scientific and Practical Conference “Banks and Financial Organizations: Processes. Standards Quality "http://npk.akforb.ru/upload/doc/2015/Поморина.pdf, 2015.

The international standard "Risk Management – Guide ISO 31000:2018 - https://pqm-online.com/assets/files/pubs/translations/std/iso-31000-2018-(rus).pdf

FERMA. Risk management standards// https://www.aoosk.ru/about/vnutrenniy-kontrol-upravlenie-riskami/standart%20ferma\_russia.pdf, 2003, PP.1-16.

COSO. Enterprise Risk Management// http://www.coso.org/, 2017.

Bondarenko D.V., Pomorina M.A. (2016) Quality standard for integrated risk management and organization of internal procedures for assessing capital adequacy in banks // Money and credit,№1, СС.61-68

Jorion P. (2007) Financial risk manager handbook. Wiley. 736 pages. 4th edition 4.8. Merton R. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance. 1974. V. 29. No. 2.

**Economic capital structure and banking financial risks aggregation**

**Marina Pomorina [[15]](#footnote-16)\***

**Abstract** Banks must maintain a balance between their own capital and the level of accepted aggregate risk to ensure financial stability. This paradigm is expressed in terms of capital adequacy requirements to both the minimum capital required to cover regulatory risks and the risk capital required to fully cover bank's total risk (economic capital). Therefore, the Basel Committee on Banking Supervision requires banks to implement ICAAP procedures to ensure regular risk assessment and maintain a sufficient level of capital. The Basel Committee on Banking Supervision regularly analyzes the implementation of ICAAP by global systemically important banks (G-SIB). Following the results of the analysis, the Committee has identified a number of relevant development areas: selection of approach to aggregate different material risks, detection and allocation of risk capital taking into consideration the effect of diversification, and setting limits as a function of capital allocation by activities and types of risks. This section offers a solution to the problem. It presents a conceptual approach to determining economic capital structure, which is based on material risk identification and on the determination among them of financial risks, assessed using quantitative methods. We propose a simulation model of the bank’s economic capital corresponding to this structure and including material risk factors and financial result positions, which one associated with these factors and determined the material risks distribution weight in the economic capital model. The economic capital model makes it possible to assess the distribution of the bank’s total risk at different management levels (products - departments - total bank), disaggregate the available capital by products, business lines and types of risks and, on this basis, establish limits based on the distribution of capital in accordance with the Pilar-2 requirements of Basel II.

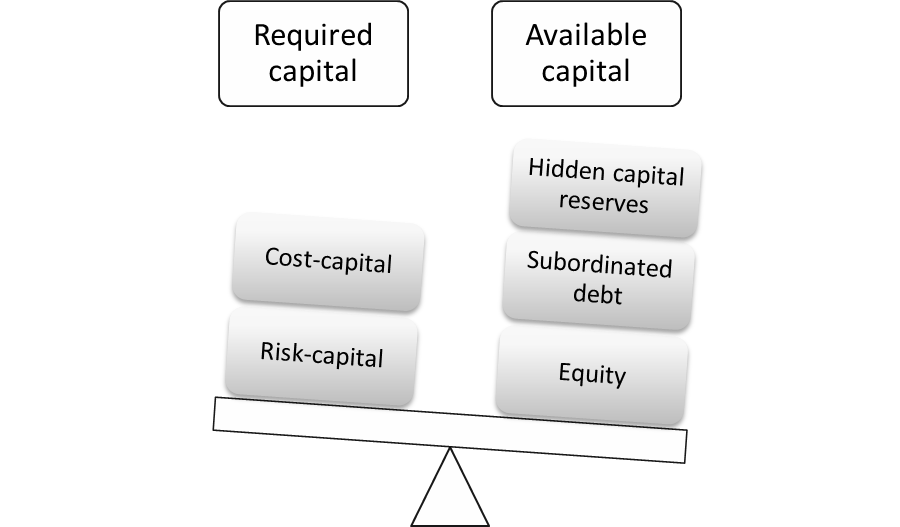
**Keywords** Internal capital adequacy, Pilar 2 Basel II and Basel III, material risks, total risk, IRM system, material risk identification, material risk measurement (quantification), material risk aggregation, risk covering principle, “going concern” and “gone concern” approaches, allocation of capital by material risk types, required capital, available capital, risk-capital, cost-capital, economic capital structure, economic capital model, internal capital adequacy assessment procedures (ICAAP), risks aggregation methods, capital allocation by business lines and types of material risks, limits based on the capital allocation, bank strategy based on the available capital distribution, identifying and setting limits on risk appetite, risk limits control, RORAC, ICAAP and corporate governance integration, simulation methods.

**JEL** C53, D81, G21, G32, G38

**1 Internal capital adequacy assessment processes in the IRM system.**

The IRM system is aimed at the comprehensive management of all banking risks. One of its most important functions is to determine the level of materiality of the impact of each bank risk on the activities of a bank, to assess the correlations of such impacts and to make decisions about the acceptable level of both individual risks and their totality.

Ultimately, in order to maintain the stability of the bank, it is necessary to ensure that all its risks are covered by its own capital since servicing the borrowed capital (attracted resources) requires regular interest payment for its use. The source of these payments is the interest and commissions that the bank receives for placing the attracted resources in income-generating assets. If the assets depreciate and / or show signs of default, the operating income flow becomes insufficient to meet the obligations on the borrowed capital, which ultimately leads to the bankruptcy of the bank.



**Fig. 1** Proper risk – capital balance

This fact has led to the emergence and constant development of regulatory requirements for capital adequacy. These requirements are aimed per se at controlling the maintenance of the required capital level, which provides coverage of all risks accepted by the bank (risk-capital), as well as capital expenditures (cost-capital). Maintaining this balance is the main goal of the bank's IRM system (Fig. 1).

To maintain capital adequacy in the IRM system, banks must establish procedures for assessing the required capital and risk management to ensure that the risks taken are limited within the bank's available capital (equity). In modern banking practice, they are called internal capital adequacy assessment procedures (ICAAP).

**2 Reasons for the introduction of the ICAAP concept in the Basel II and Basel III recommendations**

Since compliance with the principle of covering the risks of a credit institution with its own capital is one of the most important factors for its stability, this issue is the focus of banking regulation systems in all countries. Standards for such regulation for the affiliated countries are developed by the Basel Committee on Banking Supervision (BCBS, 1988).

The requirements for assessing the need for risk capital first appeared in 1988 in the Basel I agreement and only concerned capital to cover credit risk (CR). In 1996, a market risk amendment (MR) supplemented the capital adequacy requirements (BCBS, 1996). In 1999, the development of Basel II began, which significantly changed the approaches to assessing CR, and also introduced a capital requirement to cover operational risk (OR) (BCBS, 2004). Basel III continued these changes taking into account the factor of the crisis of 2008-2010 (BCBS, 2010).

However, current practice, including recent financial crises, has shown the weaknesses of the standardized approach to assessing capital adequacy, since many banks with officially adequate capital under Basel I, II, and III in times of crisis could not always meet their obligations to customers and investors.

Therefore, the most significant change in Basel II in terms of risk capital requirements was the introduction of Pilar 2, which formulated **the concept of economic capital** as a more accurate assessment of the overall banking risk compared to regulatory capital. Pilar 2 suggested that regulatory capital requirements (Pilar 1) should be treated as a minimum assessment of risk capital. The bank must now determine the real need for capital based on estimates of economic capital.

Economic capital in Basel II is considered as an assessment of the overall bank’s risk based on internal models (BCBS, 2004, P.158). The list of risks that bank must allocate capital to cover was significantly expanded. In addition to CR, MR, and OR capital should be allocated for all types of *material risks*. The functions of identifying material risks are assigned to credit institutions. The list of potential material risks includes the interest rate risk of the banking book (IRRBB), liquidity risk, concentration risks, as well as legal, reputational, and regulatory risks. The list of potential material risks is not closed: credit institutions can expand it during the identification process.

To assess material risks, banks must develop internal models that may differ from regulatory capital assessment models. If regulatory approaches do not provide a sufficiently accurate assessment of the level of the bank's risk under consideration, the regulator may require creating *an internal model* that adequately assesses this risk

To assess the total capital requirement to cover all material risks, the bank must also determine *the aggregation methods*, and establish *procedures for determining the available risk capital* and *its allocation by business lines and types of material risks.*

In the course of operations and risk monitoring, the bank should focus on this distribution of capital and set and control *the limits based on the capital allocation*.

The bank strategy should also be based on the available capital adequacy to cover the overall risk inherent in the strategy. In this sense Basel II requires the integration of risk management processes and strategic management processes.

Thus, Pilar 2 defines the following structure of ICAAP:

* material risk identification;
* material risk measurement (quantification);
* material risk aggregation;
* allocation of capital by material risk types;
* maintaining compliance with the strategy and the available capital allocation.

The global financial crisis of 2008-2009 revealed the weaknesses of the Basel II agreement, which led to its revision and the emergence of Basel III. However, the requirements of Pilar 1 and Pilar 2 were not canceled. An important addition to the concept of risk capital assessment appeared. In accordance with this, banks should switch to risk assessments based on “going concern”, as opposed to previous approaches based on “gone concern”. Accordingly, the risk assessment models developed by banks should be based not only on statistics of historical losses, but also include factors that change the level of risks in the future depending on external and internal fundamental factors: the macro situation, the loan portfolio structure, the client base composition, changes in the profile of banking products, etc.

**Pilar 2** defines the following basic principles for the organization of ICAAP:

* **Principle 1**: Banks should have procedures for assessing their overall capital adequacy in relation to the risk profile and a strategy for maintaining the capital level.
* **Principle 2**: Supervisors should review and evaluate banks’ internal capital adequacy assessments and strategies, as well as their ability to monitor and ensure their compliance with regulatory capital ratios. Supervisors should take appropriate supervisory actions if they are not satisfied with the result of this process.
* **Principle 3**: Supervisors can expect banks to operate above the minimum regulatory capital ratios and should be able to require banks to maintain capital in excess of the minimum.
* **Principle 4**: Supervisors must intervene proactively to prevent capital from falling below the minimum level required to support the risk characteristics of a particular bank and must take urgent corrective measures if capital is not maintained at a sufficient level or is not restored to a sufficient level

The issues of ICAAP methodology and organization received more detailed coverage in such BCBS documents as “Range of practices and issues in economic capital frameworks”(BCBS, 2009) and “Principles for effective risk data aggregation and risk reporting”(BCBS, 2012). The documents were prepared by the Risk Management and Modeling Group and the Standards Implementation Group. It was assumed that the Financial Stability Board (FSB), in cooperation with task managers, would develop methods for supervising risk aggregation tools, especially for G-SIB. The goal is for the supervisory authorities to be confident that the management reporting fully reflects the level of existing credit institution risk.

The Bank of Russia introduced Pilar 2 requirements in the regulation of Russian credit institutions by issuing Directive No. 3624 U ‘On Requirements for the Risk and Capital Management System of a Credit Institution and a Banking Group’[[16]](#footnote-17) (together with" Requirements for the organization of procedures for managing certain types of risks").

To meet the requirements of Directive No. 3624-U, banks must ensure the implementation of such ICAAP procedures as

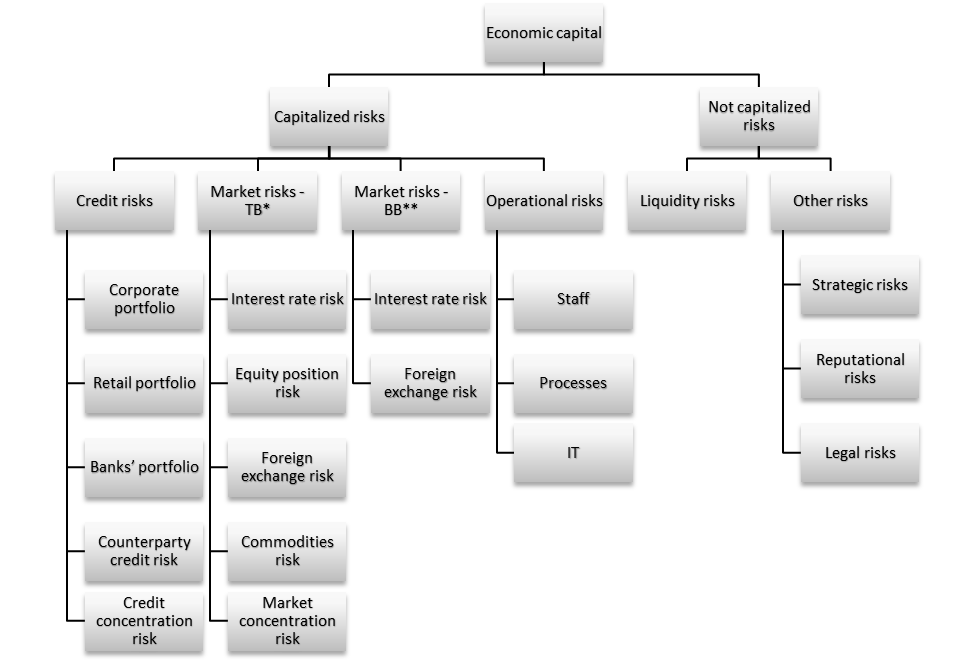
* material risk identification,
* material risk assessment,
* identifying and setting limits on risk appetite,
* risk limit control,
* ICAAP and corporate governance integration.

This chapte is devoted to developing the appropriate methodological approaches to the economic capital assessment that meet the requirements of BCBS and of the regulator for their further implementation ICAAP procedures.

**3 Concept and structure of the bank’s economic capital and available risk capital**

The bank's ***economic capital*** can be defined as the amount of potential losses of the Bank from all types of risks it accepts, which will not be exceeded with a high level of probability (usually 99.99%).

The structure of economic capital is determined by the types of *material risks accepted by the Bank* and is shown in Fig.2.



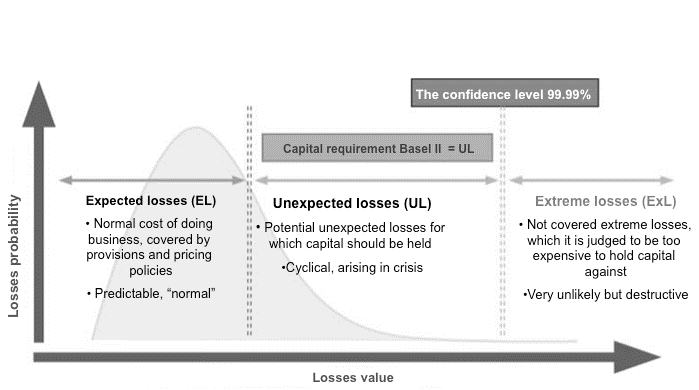
**Fig. 2** The Bank’s economic capital structure

\* TB - Trading Book

\*\* BB - Banking Book

BCBS determined the following economic capital covering principle, which determines the structure of the bank’s risk capital:

* the expected risk level (EL - Expected losses) should be covered by reserves for losses from the bank's profit;
* the remaining risk - unexpected losses (UL-Unexpected losses) must be covered by the bank's own capital;
* extreme losses are covered by the remaining capital, as well as hidden (quasi-capital) reserves.



**Fig. 3** The principles of banks’ economic capital covering as defined by the BCBS

**4 Financial and non-financial risks: specificity of assessment and capital requirements**

The basis for assessing risk capital is the value of each individual material banking risk. The BCBS and the Bank of Russia recommend determining an approach to capital allocation based on two alternative principles (Bank of Russia, 2015, P.10, paragraph 4.9.1):

* on quantitative methods based on empirical models for risk allocation assessment. This approach should be applied at least to CR, MR and OR;
* on capital buffer allocation methods. This approach is applied to risks for which not enough historical data has been accumulated or quantitative models development is impractical due to cost and benefit mismatchas.

The question of choosing a method for assessing capital requirements for material risks is closely related to the problem of dividing risks into financial and non-financial. The BCBS and the Russian regulator do not specify any definition for non-financial risks. In paragraph 3.3 of Directive No 3624-U, the Bank of Russia simply lists the non-financial risk types: legal risk, regulatory risk, strategic risk and the risk of loss of business reputation (Bank of Russia, 2015, P.P.6-7, paragraph 3.3). Some authors believe that CR and MR are financial, while others are non-financial (Bank Saint Petersburg, 2013). Others associate non-financial risks with the external environment or stakeholder impacts (Green, 2009), (Galushkin, Zagidulin, Flyar, 2007), (Dugin et al, 2019). They refer to non-financial risks such as reputational, regulatory (compliance risk), legal, business risk, strategic risk.

Another group of authors emphasize the peculiarity of implementing non-financial risks, saying that “non-financial risks differ from the main business risks since no one expects any benefits from them”(Orlova, 2012).

A fourth group allow for the occurrence of both damage and benefits from the effects of non-financial risks, but they speak about a broader impact of these risks on the companies’ activities, as opposed to financial risks: “In this case, the measure of damage or benefit is not only a direct impact on profit/costs and share price but also the impact on the reputation and human capital development as the main intangible companies’ assets, as well as on the general socio-political situation in the territories of its presence and the country as a whole.”(Galushkin, Zagidulin, Flyar, 2007).

We are closest to the latter point of view. In our opinion, non-financial risks can be defined as the external and internal impacts which directly or indirectly affect the company's value, profit, strategy, reputation, and other intangible assets. At the same time, a quantitative financial assessment of the results of such impacts is difficult due to the uncertainty of the model of the direct impact of these risks on the company's financial results and/or due to the lack of sufficient historical data on risk losses to build a statistical model. The each type of risks or their individual components can be both regular and observable[[17]](#footnote-18), and rare, and therefore not available for quantitative statistical forecasting. In the first case, for minimizing the damage of risk realization, the bank builds risk management procedures based on quantitative risk distribution assessments. In the second case, they capture and evaluate the risk impact, including potential risk and direct damage, using qualitative methods, but they do not use statistical models to forecast, because they do not have a sufficient base for their construction and validation. Thus, it is possible to associate bank’s financial risks with the risks that can be assessed based on applying quantitative assessment models of risk capital requirements, and non-financial risks with those ones for which it is advisable to apply qualitative assessments and capital buffer allocation methods. However, it should be emphasized that the inability to conduct quantitative statistical assessments does not mean that the risk is not managed and measured. Simply, the control and measurement methods will be different (Table 1).

**Table 1** Differences in methods for assessing financial and non-financial risks

|  |  |  |
| --- | --- | --- |
| **Assessment and management methods** | **Financial risks** | **Non-financial risks** |
| *Evaluation Methods* | | |
| Historical data | Regular and observable realization | There were no historical realizations or they were extremely rare. The sample size is not sufficient to build a risk distribution assessment |
| Risk factors | Sufficiently determined for quantitative models building | The risk factors list is not uniquely defined |
| Assessment Methods | Statistical Models | Expert Assessments |
| *Management methods* | | |
| Provisions for losses from current profits | There are underlying assets or other financial indicators to regularly determine the size of the reserve | A reserve is formed for specific events on the basis of expert judgment |
| Capital coverage | Based on quantitative models individually for each material risk position | Based on expert judgment in the form of a capital buffer |
| Capital Limits | Set | Not Set |

The choice of methods for quantitative assessments of capital requirements for financial risks, and determining the capital buffer size is left to the bank. For risks that are subject to quantitative capital requirement models, the task of aggregating the distributions of individual risks into the distribution of total risk arises at the aggregate risk assessment stage. One of the approaches to solving this problem is suggested in the next section.

**5 A structural model for the economic capital assessment**

Mathematically, the task of overall risk assessment is reduced to constructing the random value sum distribution of losses from risks exposed to aggregation, the so-called distribution convolution:

, (1)

where is the distribution of losses from the i-th type of risk.

Practices and techniques in risk aggregation are generally less developed than the methodologies that are used in measuring individual risk components. The BCBS highlights such problems in risk aggregation methodology as

* assuming diversification gains across all components;
* estimating the variance-covariance matrix which represents the co-movement between risks;
* lack of relevant data to assess risk interactions;
* lack of unification risk account units (risk measures), risk metrics, confidence levels and time horizons, used for different risk type assessments (BCBS, 2009).

From our point of view, the main problem of material risk aggregation is the lack of a universal approach to various kind risk assessment. Not only types of risk distributions are distinguished, but also *risk metrics and measures*.

***By risk metric*** we understand the approach to assessing the losses incurred from the risk implementation. In practice, there are various risk type metrics that do not match significantly:

* credit risk in the current approach, IFRS 9 is estimated on the basis of expected losses, measured as the difference in the present value of the contractual and risk-adjusted cash flow based on the actual state of affairs. Thus, the credit risk metric is the difference between the planned cash flow indicator and the expert assessment based on current facts (the so-called plan-fact analysis);
* market risk measurement is based on the dynamic analysis of the financial instruments prices volatility (FI volatility). In this case, the risk is perceived as a change in the FI fair value over time;
* operational risk is measured mainly as incurred losses, sometimes adjusted for other bank benchmark data;
* gap analysis or duration methods are used to assess interest rate risk, which is the net interest income sensitivity to changes in market interest rates, etc.

Obviously, it is pointless to sum up various risk metrics to determine the overall risk. The indicator will not have a clear economic interpretation.

The frequency of various risk metric assessment also varies in financial statements: credit and operational risks are assessed on a monthly basis, market risk on a daily basis, non-financial risks losses can be assessed once a year, etc.

***A risk measure*** refers to the characteristics of the random risk distribution used for risk assessment. They may vary in practice as well. Typically, the measure of risk is VaR, but the standard deviation is often used for market risks. Recently, risk measures such as Shortfall and spectral measures have become widespread.

In addition, different time horizons and levels of confidence are used for the statistical assessment of various risk type measures:

* time horizons for market risks, the intraday and monthly VaR are calculated, for credit risks, the annual VaR is calculated,
* levels of confidence can take values 97.5%, 99%, 99.9%, 99.99%.

At the stage of Pilar 2 Basel II implementation, the BCBS conducted an analysis and systematized the risk aggregation practice in banks (BCBS, 2009). It found gaps in the economic capital evaluation and managment practice of G-SIB. These gaps related to the application of various risk measures and metrics, the inability of management systems and information systems to implement ICAAP processes.

Following the results, in January 2013 the BCBS formulated the principles of effective data aggregation and risk reporting (BCBS, 2013), highlighting 4 main areas of activity:

1. *Comprehensive management and infrastructure*, requiring the bank management to form adequate and effective mechanisms for managing data aggregation processes and preparing risk reports and the practice of risk reporting integrated with other principles and guidelines of the Basel Accords (Principle 1), as well as the development, creation and support of appropriate data architectures and IT infrastructure that fully provide data aggregation and risk reporting capabilities beyond just normal times, but also during periods of stress or crisis (Principle 2).

2. *Risk Data Aggregation Capabilities* that provide

* the accuracy and integrity of risk data and conditions for automating their aggregation processes (Principle 3);
* the completeness of data on all material risks of the bank and its group by business lines, types of assets, industries, regions and other groups (Principle 4);
* the timely generation of summary and up-to-date risk data (Principle 5);
* the adaptability of risk data to meet a wide range of requests (Principle 6).

3. The practice of risk reporting, guaranteeing the accuracy, completeness, transparency and usefulness of reporting for its users (Principles 7-9), as well as the establishment by stakeholders of its frequency and confidentiality (Principles 10-11).

4. Regulatory supervision, tools and cooperation that imply compliance with the periodicity of supervisory audits of data aggregation and reporting processes, ensuring the implementation of measures to eliminate identified shortcomings, and international cooperation of supervisory authorities in this area. (Principles 12-14).

Since 2013, BCBS has been analyzing the progress G-SIB in implementing the principles of risk aggregation and the preparation of risk reporting (BCBS, 2013), (BCBS, 2015-Jan), (BCBS, 2015-Dec), (BCBS, 2017), (BCBS, 2018). However, in 2018, BCBS’s findings highlighted the difficulties of implementation and the need to continue working on improving risk aggregation and risk reporting systems, despite the fact that the project completion date was initially set as 2016. In this regard, the relevant area of scientific and applied research is the further development of aggregating risk methodology.

In international and domestic practice to assess economic capital various methods of simulation modelling and stress testing of bank portfolios are used. Most of them belong either to the class of one-factor models or to the class of models with the same type of risk factors. From our point of view, the best direction of this methodology development is ***multifactor model development for assessing total financial risk based on the full modeling method***.

We offer an example of building such a model based on the identifying elements of the bank’s profit formation that are exposed to certain material risks, as well as the determination of the factors of these risks, the change of which determines the volatility of the corresponding profit element. This approach, combined with the management accounting methodology, reveals the bank's financial result (profit) structure in terms of business lines, products, customers, and geographical regions, allows us to assess the total impact of material risks to the bank, and to implement risk aggregation / disaggregation procedures, to assess allocation capital to cover risks and, establish risk limits based on the capital allocation and risk strategies.

The proposed approach will allow the harmonization of the procedures for assessing individual components of economic capital based on the following principles:

1) ensuring consistent disaggregation of the total financial result to positions exposed to various risks types;

2) the unified risk measures used for all material risks based on deviations of the financial result from the planned indicators both at the overall bank and business line levels, as well as individual product lines and customer groups;

3) the use of a universal risk metric - VaR and a universal tool for its assessment - stochastic modelling;

4) integration of ICAAP procedures in the processes of strategic and financial planning by using indicators of the risk appetite /the disposable capital of the bank when selecting planned alternatives.

To solve this problem, we suggest choosing the following ***metric and risk measurs***:

* as a risk indicator - the absolute change in profit (or one of its components exposed to risk) compared with the target indicator with the opposite sign (SRisk)[[18]](#footnote-19);
* as a horizon for risk forecasting - 1 year:
* as a step of risk modelling - 1 day;
* as a risk measure - VaR.

To select the overall risk components we use differential function that reflects the influence of qualitative (intensive) and quantitative (extensive) revenue generation factors. The qualitative factor is ROAt, and the quantitative factor is asset volume –At. Profit is the product of these two factors:

. (2)

We use this function differential with the negative sign as the overall risk metric at all the analysis levels: total bank operations, business units, products, and clients:

, (3)

*the first component of the expression (3))* reflects the impact of risk factors determining assets’ profitability.

the second component (3)) reflecs the factors, determining assets volume change.

*The second component* of *expression (3)* can be interpreted as an indicator of strategic / business risk, as it reflects the banks ability to expand its business and attract the necessary capital for this purpose (both its own and borrowed). Therefore, we can use this indicator to model and assess business risk:

. (4)

*The first component of expression (3)* reflects the influence of all other risks. In order to highlight the individual aggregate risk components, we associate these components with various elements of a banks’ Profit and Loss Statement (P&L). In doing so, we try to find the appropriate type of financial material risk prescribed by ICAAP for each P&l element. Bank profit is a combination of the following elements:

(5)

where:

NIIt is net interest income, which is the sum of

* interest income of banking book (IIBBt) = average credit interest rate (ICRt)\*average credit portfolio volume (CPt),
* and interest income of trading book (IITBt) = average interest yield of trading book (CYt)\*average trade portfolio volume (BPt),
* minus interest expenses (IExpt ) = average deposits interest rate (IDRt)\*average deposits portfolio volume (DPt).

ALLLt is Allowance for Loan and Lease Losses (or provisions charge for loan impairment) = average provisions rate (PRt)\* CPt.

NTIt  is net trade income, which is the sum of

* net gain of equity portfolio (NGEPt) = average equity portfolio profitability (EPPt)\*average equity portfolio volume (EPt),
* and net gain of commodity portfolio (NGComPt) = average commodity portfolio profitability (СomPPt)\*average commodity portfolio volume (СomPt).

NFXEt is net foreing exchange earnings, which is equal to the difference of

* FX gain (FXGt)– FX loss (FXLt),

or product of

* average exchange rate change (FXCht )\*average open currency positions (OCPt),

NFCIt is net fee and commission income, which is equal to the difference of

* fee and commission income (FCIt)– fee and commission expenses (FCExpt)

or product of

* net average fee and commission profitability (NFCPt)\*At.

OOIt is other operations income, which is equal to product of

* net average other operations profitability (NOOPt)\*At,

OExpt is operations expenses, which is equal to product of

* average operations cost for assets unit (UOCt)\*At.

Taxt  is taxes paid, which is equal to product of

* average income tax rate for assets unit (ITaxRt)\*At .

Using expression (5) we can present the first component of expression (3) as:

. (6)

Now we correlate the components of expression (6) with individual material risk types:

* ***credit risk:***

; (7)

* ***market risk:***

, (8)

where

* + is interest rate risk of trading book,

; (9)

* + is equity risk of trading book,

; (10)

* + is  commodity risk of trading book,

; (11)

* + is foreign exchange risk,

; (12)

* ***operational risk***

; (13)

* ***interest rate risk of banking book***

(14)

* ***price risk on fees, commissions and other deals***

(15)

* ***tax risk***

. (16)

We presented the overall financial risk of the bank as the sum of the main material risks. Each material risk corresponds to a certain risk factor and an element of P&L which determines the weight for aggregating the risk factor into the overall risk model (Table 2).

The model created (3-16) **unambiguously** **links the components of the total risk with the elements of the banks’ profit formation**. Further within each component, it is possible to separate more granulated risk elements. For example, it is possible to divide credit risk into certain credit portfolios, FX risk for currencies, equity risk for security portfolios and other kinds of securities.

Thus, in general terms, the aggregate risk model (3-16) can be represented as a linear combination of various risk factors:

, (17)

where N is number of risk factors in the economic capital model;

is the i-th risk factor change at time t;

is risk position, corresponding with the i-th risk factor.

**Table 2** The overall financial risk model components

|  |  |  |
| --- | --- | --- |
| **Material risks** | **Risk factors** | **Risk weights** |
| Business risk (BusinessRisk) | Assets volume change (Ach) | Profit |
| Credit risk (CR) | Change of average provision rate – PR | Allowance for Loan and Lease Losses - ALLL |
| *Market risks (MR)* | | |
| Interest rate risks of trading book (IRRTB) | Change of average interestyield of trading book – CY | Interest income of trading book –IITB |
| Equity risk of trading book (ER) | Change of average equity portfolio profitability –EPP | Net gain of equity portfolio – NGEP |
| Commodity risk of trading book (ComR) | Change of average commodity portfolio profitability –ComPP | Net gain of commodity portfolio – NGComP |
| Foreign exchange risk (FXR) | Change of average exchange rate change – FXCh | Net foreign exchange earnings – NFXE |
| *Interest risks of banking book (IRRBB)* | | |
| Interest rate risks of credit portfolio (IRRBB - CP) | Change of average credit interest rate (ICR) | Interest income of banking book (IIBB) |
| Interest rate risks of deposit portfolio (IRRBB - DP) | Change of average deposit interest rate (IDR) | Interest expenses (IExp) |
| *Operational and other risks* | | |
| Operational risks (OR) | Change of average operational cost for assets unit – UOC | Operational expenses (OExp) |
| Price risk on fees, commissions and other deals (PriceRisk) | Change of net average fee and commission profitability - NFCP  Change of net average other operational profitability – NOOP | Net fee and commission income (INFCI)  Other operations income (OOI) |
| Tax risk (TaxRisk) | Average tax rate – TaxR | Tax paid (Tax) |

The result of expression (17) is a random variable[[19]](#footnote-20) of the total risk. To assess the aggregate risk metrics, it is necessary to evaluate its distribution based on the given distributions of individual material risks types.

If all the risk factors presented in expression (17) have a normal distribution, then the ratio can be used to calculate the total risk VaR:

, (18)

where is a vector-line whose coordinates are the VaR values for the i-th risk factor multiplied by the corresponding position: ,

is a vector-column with similar coordinates.

COR is a matrix of correlation coefficients between different risk factors 0.

However, if the risk factors have different types of distributions or these distributions are not normal, the task of assessing the total risk is complicated. Here you can use either a simple historical method, or parametric methods for calculating the convolution of random variables (for example, the copula method), or the stochastic modelling method.

Due to the complexity of the convolution parametric approximation, one of the most popular methods for assessing total risk is the stochastic modeling method (or Monte Carlo method). However, for its application it is necessary to evaluate not only the individual distributions of risk factors, but also their joint distribution, taking into account the correlation between individual factors.

If the individual risk factors distributions laws are different or cannot be approximated based on known parametric distributions, a discrete approximation can be used:

, (19)

where is the convolution distribution;

K is the interval number of risk distributions;

is the probability that the k-th risk value falls into the interval lk;

is the intersection area of the hyperplane

with cube }

is the interval lk center,

is the risk-weight of the k-th factor.

Note that expression (17) is valid both for a single transaction/a separate financial instrument profit calculation, and for profit in the context of products, projects, customers, business lines and the total financial result of the bank.

The overall risk model is integrated with the financial banking model. Due to this, it is possible to assess the total risk within the financial planning process using stochastic modelling and stress testing. Financial planning and aggregate risk models have the same parameters including interest rates on loans and deposits, reserve rates for the impairment of assets, exchange rates and rates of return on financial market instruments, unit costs for bank processes and products, tax rates, etc.

The proposed approach to economic capital assessment makes it easy to disaggregate it in the context of business areas, products, customer groups based on traditional methods of functional-value analysis (cost-effective value engineering) used in management accounting systems. The data accumulation for this model can also occur within the framework of traditional managerial accounting and budgeting systems (Teplova , 2019), (Pomorina, 2017), (Cedric Reed, Hans-Dieter Scheuerman, 2012), (Karpov, 2007). It should be noted that the model (3-16) also allows us to evaluate the diversification effect for covering economic capital at different levels of analysis. Note that in the model, such risk components as business risk, tax risk and price risk on bank fees, commissions and other deals have appeared. These risks are not traditionally considered in economic capital models, but, nevertheless, their impact on bank profits can be significant.

The operational risk measurement differs from that adopted in regulatory approaches as it shows its impact on the bank’s costs. This approach is more consistent, since its manifestations lead to an increase in bank costs, and the occurrence of fines and compensation for losses incurred.

Note that BCBS allows the possibility of using various risk assessment methods in individual models and economic capital models, as identical measures and metrics must be used when aggregating risks[[20]](#footnote-21).

The aggregated financial risk model advantages include:

1. quantitative accounting of a wide range of financial risks;
2. defining a unified approach to assessing certain material risks based on the bank's financial results;
3. the reflection of the effect of diversification;
4. using non-parametric methods for aggregate financial risk distribution assessment;
5. integration of the economic capital model with the financial planning processes.
6. universality: the applicability of the approach for any financial institution.

**6 Forming of ICAAP procedures based on the economic capital model and available risk capital. The bank’s risk limit system based on the distribution of available risk capital**

BCBS and the Bank of Russia put forward requirements for ICAAP both for individual material risks and for economic credit institution capital (total risk). These procedures must include:

* + methods for assessing and forecasting material risks and the economic capital of a bank;
  + capital management procedures based on determining the planned (target) level of available risk capital, current capital requirements, and the allocation of capital by types of material risks and activities;
  + a system for monitoring capital adequacy, and limits for material risks.

In order to control the accepted risks, the bank determines the planned (target) risk levels, the target risk structure and the risk limits system for each material risk based on the business cycle phase, tolerance for risks and strategic and business objectives.

In order to control its capital adequacy, the bank establishes procedures for the capital allocation through a limits system in business line and in material risks, taking into account reserves for non-financial risks and for the new business projects implementation. The limits system must have a multi-level structure. Control over the established limits is carried out by setting signal values. If these limits are exceeded, an anti-crisis measure system must be developed and implemented and, possibly, capital reallocation should be carried out (Bank of Russia, 2015, paragraph 4.11-4.14).

The proposed model of economic capital allows the creation of the above-described procedures for managing economic capital, based on the allocation and distribution of available capital by types of material risks and setting limits. We can suggest the following scheme for implementing the regulator's requirements based on the integrated assessment of the economic capital model.

At ***the first stage***, the bank’s need for risk capital is estimated, using the economic capital model proposed above. Required capital depends on the business structure, development plans, including bank projects, the external economic situation, client base features, business process efficiency, etc.

Consider an example in which the estimate of the bank’s economic capital amounted to 95 billion rubles (Table 3).

**Table 3** Diversification factors for the allocation of capital determining

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Bank Economic Capital / Diversification Ratio | | | | | | | | |
| Diversification Ratio for Aggregated level | DR1 = (85+65+40)/95 = 2 | | | | | | | | |
| EC - Aggregated level | EC = 95 billion rub. | | | | | | | | |
| Diversification Ratio for Business areas | DR21=  85/(55+40+32,5) =1,5 | | | DR22= 65/(55+40+35) =2 | | | DR23=  40/(25+30+5)  = 1,5 | | |
| EC for Business areas | Corporate block - 85 billion rub | | | Retail block - 65 billion rub | | | Development projects - 40 billion rub | | |
| Material risks | CR | MR | OR | CR | MR | OR | CR | MR | OR |
| EC for SR | 55 | 40 | 32,5 | 55 | 40 | 35 | 25 | 30 | 5 |

At ***the second stage***, the need for risk capital is settled, which is determined by the economic capital assessment regulated by the bank's financial model formed as part of its strategy development and development plans, and the available risk capital allocated by the Board of Directors.

The procedure must be organized *within the framework of the strategic and business planning process* and may require a number of iterations if the allocated risk capital is not sufficient to cover the risks of the bank's strategy and development. Shareholders can review their risk appetite, or require the bank to implement a more conservative strategy.

Suppose that according to the results of the coordination, the Board of Directors allocated 100 billion rubles capital to cover risks.

Risk capital can be allocated both in absolute terms and on the basis of various indicators of risk appetite, for example, on the basis of setting a target level of the RAROC indicator, the possibilities of using which are described in the next section.

At ***the third stage***, the allocated risk capital should be distributed between business areas, customer groups, products, and material risks. To do this, based on the model, diversification coefficients must be determined. The function is implemented based on the calculation of economic capital at the selected planning levels. In this case, a unified assessment model is used, which is applied to calculate the EC of all business areas, bank projects, and certain types of material risks (See Table 3).

Further, the obtained diversification coefficients can be used to allocate capital at different hierarchical levels of setting risk limits (See Table 3).

**Table 4** Allocation of risk capital taking into account diversification factors

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Risk Capital / Diversification Ratio | | | | | | | | |
| Aggregated level | RC = 100 billion rub. | | | | | | | | |
| Business areas | Corporate block | | | Retail block | | | Development projects | | |
| RC for 2 level = 2\*100=200 billion rub | 88 billion rub. | | | 68 billion rub. | | | 44 billion rub. | | |
| Material risks | CR | MR | OR | CR | MR | OR | CR | MR | OR |
| RC for 3 level | 88\*1,5=  132 billion rub. | | | 68\*2  =136 billion rub. | | | 44 \*1,5  = 66 billion rub | | |
|  | 57 | 42 | 33 | 58 | 42 | 36 | 27 | 32 | 7 |

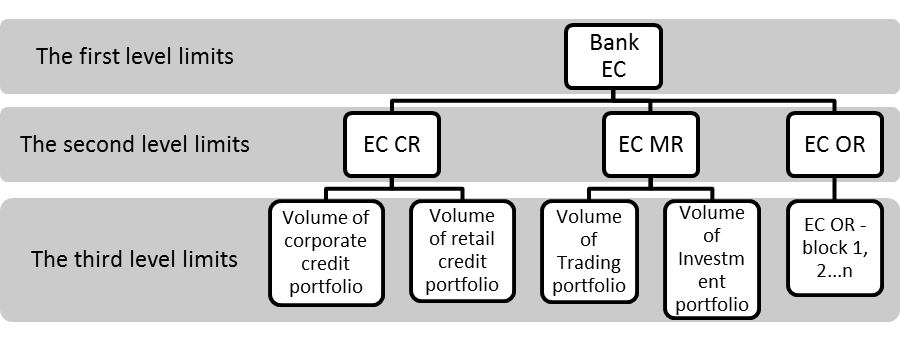
At ***the fourth stage***, limits must be set based on the allocated risk capital. This can be both direct restrictions on the volume of losses incurred from risks in the context of business areas and material risks, and limits that restrict the volume of operations.

When setting limits for losses incurred, the bank must determine the metrics of losses incurred on loans and financial assets, on operational and other risks. For example, the losses incurred on loans can be estimated as direct costs to write them off, and the difference between the amortized costs of actually received loan flow from its target value.

The latter is more consistent with the current concept of measuring the fair value of financial assets, as reflected in IFRS 9.

When setting limits on the volume of operations, the risk factor VaR estimates obtained in the model can be used. If based on the ratio , the limit on the volume of the loan portfolio can be set in the amount equal .

As a result, on the basis of the described principles, the bank can form a hierarchical system of limits, presented in Fig. 4. Further, if necessary, they are disaggregated by individual products or financial instruments.



**Fig. 4** An example of a system of limits based on the allocation of bank risk capital

**7 ICAAP integration in the processes of strategic and operational bank management using RORAC**

For business development, it is important to balance risks and benefits. In this sense, restrictions can be set not only on the maximum amount of risk accepted, and on the profitability / risk ratio. This approach compares the level of risks with the benefits received, which makes it easier for shareholders to determine their risk tolerance (risk appetite). Most often, RORAC is used as such a target.

. (20)

The economic meaning of RORAC can be interpreted as the ratio of the annual profit received by the bank under normal operating conditions to loss in a crisis situation. Accordingly, if the indicator is 100%, then unforeseen losses will be covered within one year, if 50% - within 2 years, 30% - within 3.3 years, etc.

This indicator can be calculated within the multifactor model of bank economic capital described here in the context of departments, products, groups of customers. The target level can be defined as one common value for the entire bank, and differentiated by levels of analysis.

An example of the RORAC application in the strategic management process is shown in Table 5.

**Table 5** An example of RORAC assessment and use for strategic management

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Business areas** | **Corporate block** | **Retail block** | **Development projects** | **Total** |
| 1.Position at risk (in billion rubles) | 81 600 | 34 000 | 20 400 | 136 000 |
| 2.Profitability (in%) (plan) | 3,25% | 4,60% | 6,00% | 4,00% |
| 3.Expected income (in billion rubles) | 652 | 1 564 | 1 224 | 5 440 |
| 4.VAR (in billion rubles) | 8 054 | 4 396 | 3 550 | 16 000 |
| 5.RORAC - plan | 32,93% | 35,58% | 34,48% | 34,00% |
| 6.The purpose of RORAC | 30,00% | 30,00% | 30,00% | 30,00% |
| 7.Profit (in billion rubles) | 660 | 1 618 | 890 | 5 168 |
| 8.Actual return | 3,26% | 4,76% | 4,36% | 3,80% |
| 9.RORAC - fact | 33,03% | 36,80% | 25,07% | 32,30% |
| 10.RORAC deviation from the target | 3,03% | 6,80% | -4,93% | 2,30% |

In the presented example, the target for the bank is set to 30% RORAC level. In developing the financial plan for both the main business units and projects, the RORAC goal was observed (line 5 of Table 2). However, in the process of implementing the plan, the profitability level of the Projects turned out to be lower than planned. The target RORAC level has been violated (row 9 of Table 2). In this situation, managerial impacts (system of measures) should be defined to eliminate excess risk. Since in our example the indicator for the bank is generally respected, one of the solutions may be the reallocation of risk capital if the Board of Directors is ready to accept a higher risk for projects that are significant for the future development of the bank.

Thus, the RORAC indicator can be used as one of the key indicators for strategy implementation, as it will allow the identification of high risk points at various management levels and the timely formulation of anti-crisis plans to reduce risks. Similar to other limits for RORAC, a warning and critical level can be defined, and anticipatory actions should be formed when moving to the warning zone.

**8 Conclusion**

The multifactor model for assessing economic capital proposed above can be implemented within the traditional bank model, as the parameters of the financial model are also risk factors in the proposed model for assessing economic capital. Thus, this model is naturally integrated into the strategic planning and management system, since, simultaneously with the selection of planned alternatives, their risks will be assessed and economic capital estimates will be calculated at all hierarchical levels of management: departments, products, customers.

The approach based on the use of Income Statement Analysis to identify positions exposed to various types of risk allows you to automatically determine weights for aggregating estimates of economic capital of certain material risks into an assessment of the total risk of a bank.

As shown above, the use of the proposed model fulfills all the requirements of Pilar 2 and Bank of Russia regulations regarding ICAAP procedures.

**References:**

BCBS (1988) International convergence of capital measurement and capital standards// Basel Committee on Banking Supervision - www.bis.org, 15 Jul 1988, PP.1-30.

BCBS (1996) Amendment to the capital accord to incorporate market risks. // Basel Committee on Banking Supervision - www.bis.org, 04 Jan 1996, PP.1-56.

BCBS (2004) Basel II: International convergence of capital measurement and capital standards: a Revised Framework// Basel Committee on Banking Supervision - www.bis.org, 10 Jun 2004, PP.1-251.

BCBS (2010) Basel III: A global regulatory framework for more resilient banks and banking systems// Basel Committee on Banking Supervision - www.bis.org, 16 Dec 2010, PP.1-77.

BCBS(2010) Basel III: International framework for liquidity risk measurement, standards and monitoring// Basel Committee on Banking Supervision - www.bis.org, 16 Dec 2010, PP.1-53.

BCBS (2009) Range of practices and issues in economic capital frameworks// Basel Committee on Banking Supervision - www.bis.org/publ/bcbs152.pdf, 27 Mar 2009, PP.1-73.

BCBS (2012) Principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document - www.bis.org/publ/bcbs222.pdf, 25 Jun 2012, PP.1-24.

BCBS (2013) Principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document - www.bis.org/publ/bcbs239.pdf, 8 Jan 2013, PP.1-28.

BCBS (2013) Progress in adopting the principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document www.bis.org/publ/bcbs268.pdf, 17 Dec 2013, PP.1-34.

BCBS(2015) Progress in adopting the principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document www.bis.org/publ/d308.htm, 23 Jan 2015, PP.1-25.

BCBS (2015) Progress in adopting the principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document www.bis.org/publ/d348.htm, 16 Dec 2015, PP.1-18.

BCBS (2017) Progress in adopting the principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document www.bis.org/publ/d399.htm, 27 Mar 2017, PP.1-23.

BCBS (2018) Progress in adopting the principles for effective risk data aggregation and risk reporting// Basel Committee on Banking Supervision Consultative Document www.bis.org/publ/d443.htm, 20 Jun 2018, PP.1-26.

Bank of Russia (2015) On Requirements for the Risk and Capital Management System of a Credit Institution and a Banking Group// Bank of Russia Directive No. 3624 U - www.cbr.ru, 15.04.2015, PP.1-28.

Bank Saint Petersburg (2013) Annual report 2013// http://www.bspb.ru/investors/annual-reports/2013. P.56.

Alexander Green (2009) Management of risks: Business strategy development// <https://subscribe.ru/archive/economics.school.riskmanagement/200906/25140618.html>, PP.1-3.

Galushkin S.V., Zagidullin J.K., Flyar M.G. (2007) Business and society: corporate integration// Corporation and development. Collection of works on the philosophy of corporate development, Vol. 2 (under the editorship of O.B. Alekseev and O.I. Genisaretsky) – M.: Europe. PP. 122-140

Dugin A.D. and Co (2019) Risk and capital management system development (ICAAP) (under the editorship of Dugin A.D. and Penicas G.I.) // - M.:Urait. PP.145-167

Orlova O.E. (2012) Non-financial risk management// Actual issues of accounting and taxation, 2012, N 10, PP.89-97.

Teplova, T. V. (2019) Effective financial director: textbook. allowance // –M.: ID Urait LLC.

Pomorina M.A.(2017) Financial management in a commercial bank// - M.: Knorus

Cedric Reed, Hans-Dieter Scheuerman (2012) Financial Director as an integrator of business // - M.: Alpina Publisher.

Karpov A.E. (2007) 100% of practical budgeting // Series of books (1-8) - M.: From “Result and Quality”.

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3. According to the definition given, for example, by the Bank of Russia (see Bank of Russia Ordinance No. 3624-U, dated April 15, 2015, “On Requirements for the Risk and Capital Management System of a Credit Organization and Banking Group”), residual risk is the risk remaining after the Bank’s actions to reduce inherent risk. Suppose a bank takes measures (that is, requires collateral) to recover debt after default, based on which it statistically fairly expects a recovery share of RR = 1-LGD. And, let's say, on a statistically significant portfolio, this share of recovery will take place. However, due to the dispersion of LGD and the granularity of the default part of the portfolio, deviations from the expected value will be observed, including towards losses. This gives unexpected losses related to residual risk. [↑](#footnote-ref-3)
4. A model-homogeneous population should be understood, for example, such industry segments of borrowers as “Banks”, “Individuals, consumer loans”, “Mass segment of small business”, “Large corporate business” including credited to a particular bank, etc. It is reasonable to classify LGD segments of credit assets by business model or financial instrument. For each segment, various parameters γ are possible. [↑](#footnote-ref-4)
5. LGD rating means any specially developed function that depends on the risk-dominant parameters of LGD / RR, which correlates with the implemented LGD / RR. [↑](#footnote-ref-5)
6. MSE - Mean Square Error [↑](#footnote-ref-7)
7. A normal distribution of the random parameter ξ can be described using the substitution for F (ξ), where F is the distribution function of ξ. [↑](#footnote-ref-8)
8. Generalized linear model / GLM [↑](#footnote-ref-9)
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12. Fantazzini and Shangina (2020) used a composite volatility index ranging from January 2006 till April 2019, containing both the new RVI index and the previous RTSVX (Russian Trading System Volatility Index) which was discontinued on 12 December 2016. At the time of writing this paper, the time series for the RTSVX was no more available for free, so that I stuck to the current RVI index to make the analysis fully reproducible also for readers who have no access to the commercial database. [↑](#footnote-ref-13)
13. The full description of the RVI methodology: http://fs.moex.com/files/6757 [↑](#footnote-ref-14)
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16. Bank of Russia Directive No. 3624 U ‘On Requirements for the Risk and Capital Management System of a Credit Institution and a Banking Group’ [↑](#footnote-ref-17)
17. i.e. the organization collects data on risk exposure factors and outcomes [↑](#footnote-ref-18)
18. The use of the opposite sign will lead to the fact that the reduction in profits will mean and reflect the effects of risk, and the increase - its opposite side - the receipt of economic benefits, which will be reflected in the left tail of the risk distribution, which completely coincides with the approaches used in VaR models for assessing market risk [↑](#footnote-ref-19)
19. more precisely, a random process [↑](#footnote-ref-20)
20. Basel Committee on Banking Supervision. Range of practices and issues in economic capital frameworks. Part IV.B – March 2009//www.bis.org [↑](#footnote-ref-21)