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An approach to measuring credit risk in a banking institution from Romania

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Abstract. *Studying the behavior of banking systems both at the macroeconomic level and with the external environment, as well as at the level of financial institutions associated with their dynamic character, in the current context is in the attention of all specialists. Risk quantification is an important aspect in making strategic decisions regarding maintaining financial stability and maintaining a high level of performance of any banking institution. The complexity of current financial systems around the world makes it difficult to create indicators that accurately assess the systemic risk of any institution. This paper has shown that an incorrect credit risk assessment can lead to a decrease in the performance of banking units and can generate a systemic shock that can affect both financial networks and the national or global economy.*

Keywords: credit risk, banking, financial stability, expected credit loss.

JEL Classification: G17, G21, G28, G32.

1. Introduction

In recent years, banking accidents have led to a significant disruption of the financial system around the world. Even the economic crisis of 2008 has shown that we need to better understand financial networks and systemic risk.

The complexity of current financial systems around the world makes it difficult to create indicators that accurately assess the systemic risk of any institution. One of the most important issues that has been highlighted in recent years has been the interconnection of banks in the financial network. This has led to an increase in the likelihood of contagion, a scenario in which small shocks, which initially impact only a part of the institutions in the system, spread throughout the network. Another very important aspect in choosing the decision-making strategies at bank level is the correct quantification of the credit risk. (Nica et al., 2018)

Taking into account recent events in the financial system such as the appreciation of the Swiss franc against the euro and the dollar which has caused great difficulties to the economy, national and international companies, including people, or the phenomenon of "Brexit", studying methods to identify early effects affects an entire system, by diminishing negative events, is very important.

The complexity of current financial systems around the world makes it difficult to create indicators that accurately assess the systemic risk of any institution. One of the most important issues that has been highlighted in recent years has been the interconnection of banks in the financial network. This has led to an increase in the likelihood of contagion, a scenario in which small shocks, which initially impact only a part of the institutions in the system, spread throughout the network. (Nica and Chiriță, 2020)

2. Literature review

The Swedish Central Bank, the first central bank in the world to set up a financial stability department and published its first financial stability report in 1998, defined financial stability as "the safe and efficient operation of the entire payment system" and considered that the most important pillars that ensure balance are:

- A regulatory framework composed of regulations and decrees, complemented by concrete risk assessment actions and inspections on irregularities of individual institutions.
- Another important pillar is the timely monitoring of the central bank on systemic risk.
- Crisis management measures is another important part. All pillars require the division and cooperation of central banks and supervisory departments.

Dexu He, professor from the University of Finance and Economics in China, argues that in the process of developing economic theory, the stability of the financial system has been the focus of economists around the world. Studies on this topic can be divided into two categories: the analysis of the instability of the monetary economy from the Marxist[(1)] perspective, on the one hand, and the various studies on the financial stability of economists, on the other.

Duisenberg (2001), the first president of the European Central Bank (ECB), believed that although there is no coherent definition of financial stability, there is some common consensus: that under the condition of financial stability, every component of the financial system can its economic function freely.

Padoa-Schioppa (2003), a former member of the executive board of the European Central Bank, considered that financial stability means that the financial system is able to withstand economic shocks, avoid the accumulation of contradictions, continue to mobilize economies to invest in sectors with high efficiency and to achieve payment and settlements.

The financial system in that statement includes financial intermediaries, formal and informal financial markets, payment and settlement systems, technical support platforms, financial laws and regulations and financial regulators. Thus, the systematic study of the stability of the financial system could be carried out through studies on the configuration of savings, disclosure and treatment of information, risk transfer behaviors of brokers, as well as payment and settlement methods.

3. Conceptual dimensions of banking risk

Since the onset of the credit crunch in the United States and Europe in 2006, risk managers have learned valuable lessons about quantifying, assessing, and the importance of properly measuring bank risk. The field of risk management has undergone an enormous change in the last 50 years, and the pace of change is accelerating, largely due to the latest crises and speculative bubbles that have occurred so far. The events of the last decade have also changed the way of thinking, good practices and definitions of risk management. Below I will mention some of the most significant definitions of risk management.

Risk management is a discipline that clearly indicates the risk management and returns of each major strategic decision at both institutional and transactional level. Risk management discipline shows how to change the strategy to align the compensation of long-term and short-term risk profitability in an enterprise. This discipline includes several subdomains that are inseparable and can overlap. We mention some of the most important: credit risk, market risk, asset and liability management, liquidity risk, methodology for calculating and allocating capital, operational risk and performance measurement. (Arianminpathy et al., 2012)

In general, banking risks fall into three main categories: financial, operational and environmental risks. Financial risks are classified into 2 categories: traditional banking risks and treasury risks. Traditional banking risks include balance sheet structure, income statement, credit and solvency risks. These can lead to huge losses for a bank if not managed properly. Treasury risks include currency risks, interest rate risk, market risk and liquidity risk. Financial risks are subject to complex interdependencies, which can significantly increase the bank's overall risk profile. For example, banks that trade foreign currencies against the national currency are subject to currency risk, but also to liquidity and interest rate risk if the bank does not manage open foreign exchange positions well.

Operational risks are related to the bank's general business processes and their potential impact, in compliance with banking policies and procedures, internal systems and technologies, information security, mismanagement measures, fraud identification and interest in business continuity concerns. Another aspect of the description of operational risk includes governance, strategic management planning, and the organizational structure of the bank, internal resource management, product development, and the approach to acquiring new customers.

Environmental risks are analyzed and described in the context of the bank's business environment, including macroeconomic and policy concerns, legal and regulatory factors, and the overall infrastructure of the financial sector and the payment systems of the jurisdictions in which it operates. Environmental risks encompass all classes of exogenous risks that could jeopardize the bank's operations or undermine its ability to continue to operate if they materialized.

The economic literature has used the term systemic risk in the context of financial systems for many years. However, Kaufman, Scott and Taylor argue that there is still no generally accepted definition of the concept of systemic risk. Thus, we will list some proposed definitions for systemic risk.

Kaufman describes systemic risk as the probability that accumulated losses result from an event that triggers a series of successive losses along a network of institutions or markets comprising a system, i.e. systemic risk is the risk of a reaction in such as the domino effect in interconnected domains.

4. Credit risk assessment in a banking institution

The Commercial Bank has been viewed in the past from the perspective of two major functions it held: setting up deposits and granting loans. Meanwhile, the bank has developed quite a lot and offers much more complex services and important roles in an economic system.

In a bank, loans for the individual segment are classified into:

- Unnamed, treasury loans, no mortgage, unsecured: personal needs credit, credit card and overdraft (overdraft).
- Mortgages, guaranteed: mortgages, real estate, mortgage.

The loan is an asset and represents an amount of money that the bank grants to an individual, called a customer. Loans without a mortgage are granted as a loan for a period of time, at least a few months, maximum 5 years.

From the beginning, the bank sets an annual interest rate level, called the APR (annual effective interest rate).

The interest can be fixed for the whole period of the credit agreement or variable. It consists of a fixed bank margin and the reference index for the RON currency, at 3 months, called ROBOR 3M. When the interest rate is fixed, the bank no longer takes into account the evolution of ROBOR and assumes the risk that ROBOR will increase a lot. This risk is mitigated from the outset by setting a higher than variable fixed interest margin. During the contractual development of the credit line, the bank monitors the monthly payments made by customers.

The most significant risk in this process is the credit risk which means that a customer who has accessed a loan no longer pays the monthly installments. Depending on the default period of the loan, it can be marked as default (in a state of default). Delays in payment are reported to the Credit Bureau.

Probability of default is a key risk parameter used in the context of credit risk management. It is a measure that assigns a numerical value between 0 and 1 to the probability of a properly defined credit event (such as default, bankruptcy), within a specified time horizon. In the internal valuation approach, the probability of default of a counterparty is estimated over a period of one year.

Loss given default (LGD) is the share of an asset that is lost if a debtor defaults. Estimating banks with LGD records is difficult because, fortunately, bank failures are very rare. Moreover, analyzing the actual losses of a bank can be very complicated, because they depend on the chosen time horizon. In fact, the first effect of the counterparty is the immediate imbalance of financial flows that induce the need to rebalance by reducing the issuance of new loans or by selling assets.

In a longer horizon, the default value will be recovered almost partially with the fraction of the residual assets of the unpaid company, and a certain value returns to the bank balance sheet. Because this process takes time, it is not easy to measure the actual effect of the default values, as recovery is usually recognized a few years later than the default, so the effect cannot be directly related to the cause.

Banks determine credit losses by analyzing the loan not repaid definitively. Quantifying losses can be complex and requires an analysis of several variables. As I said, LGD captures the uncertainty about the real loss that will be realized following a credit event. It is calculated as the ratio of the loss to an exposure due to non-payment of a counterparty and the outstanding amount of non-payment.

An organization may use risk-taking, risk avoidance, risk retention, risk transfer, or any other strategy or combination of strategies in order to have proper management of future events. The main objective of risk management is to maximize profitability while maintaining acceptable levels of risk without minimizing losses.

The bank needs to define an acceptable level of risk and must work to maintain it. The concept of reducing risk to zero is like not starting a certain business. Instead, taking unnecessary risks will diminish long-term profitability.

In order to build the framework for the exercise proposed by this case study, I need to present the following general information.

When a customer goes to a bank to make a credit application he is registered in a system and receives several questions to be given a credit simulation. After the simulation, the client receives a score. When accessing the loan, the client is associated with a client rating, in my case study will be marked with AAA + best rating and C the rating associated with a client in default.

In the table below, I assumed the following information about a credit product, which I called Product A, and simulated a number of customers, probability of default, default loss, gross exposure, and default exposure for each rating in part. The table below contains only the ratings from AAA+ to B-, considered a database with customers who have not yet gone into default, but have a certain associated probability, established based on late payment.

Table 1. *General information on the main risk models*

Product	Rating	LGD	PD	Number of customers	Exposure	EAD
A	BBB+	0.6	0.15%	40,000	1,100,000,000	1,100,000,000
A	BBB	0.6	0.29%	70,000	1,500,000,000	1,500,000,000
A	BBB-	0.6	0.56%	50,000	1,200,000,000	1,200,000,000
A	BB+	0.6	1.08%	20,000	600,000,000	600,000,000
A	BB	0.6	2.04%	18,000	500,000,000	500,000,000
A	BB-	0.6	4.16%	15,000	400,000,000	400,000,000
A	B+	0.6	6.10%	9,000	200,000,000	200,000,000
A	B	0.6	12.10%	4,000	80,000,000	80,000,000
A	B-	0.6	30.49%	6,000	150,000,000	150,000,000

Source: Authors' own research results.

According to the Regulation issued by the European Parliament on 26 June 2013, number 575, the calculation formula for risk-weighted exposure (RW)[(2)] is as follows:

$$RW = \left[LGD * N * \left(\frac{1}{\sqrt{1-R}} * G(PD) + \sqrt{\frac{R}{1-R}} * G(0{,}999)\right) - LGD * PD\right] * \\ * \frac{1+(M-2.5)*b}{1-1.5*b} * 12.5 * 1.06$$

R[(3)] represents the correlation coefficient and is calculated according to the same regulation 575/2013.

$$R = 0{,}12 * \frac{1-e^{-50*PD}}{1-e^{-50}} + 0{,}24 * (1 - \frac{1-e^{-50*PD}}{1-e^{-50}});$$

b – represents an adjustment coefficient calculated on the basis of the maturity of the credit product according to the following formula:

$b = (0{,}11852 - 0{,}05478 * \ln(\mathrm{PD}))^2$ and M represents the maturity of the asset.

Thus, we obtained the following values for the correlation coefficient corresponding to each rating:

$$R_{BBB+} = 0{,}03 * \frac{1-\exp(-30*0{,}15\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*0{,}15\%)}{1-\exp(-30)}\right) = 0{,}154;$$

$$R_{BBB} = 0{,}03 * \frac{1-\exp(-30*0{,}29\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*0{,}29\%)}{1-\exp(-30)}\right) = 0{,}149;$$

$$R_{BBB-} = 0{,}03 * \frac{1-\exp(-30*0{,}56\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*0{,}56\%)}{1-\exp(-30)}\right) = 0{,}139;$$

$$R_{BB+} = 0{,}03 * \frac{1-\exp(-30*1{,}08\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*1{,}08\%)}{1-\exp(-30)}\right) = 0{,}124;$$

$$R_{BB} = 0{,}03 * \frac{1-\exp(-30*2{,}04\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*2{,}04\%)}{1-\exp(-30)}\right) = 0{,}100;$$

$$R_{BB-} = 0{,}03 * \frac{1-\exp(-30*4{,}16\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*4{,}16\%)}{1-\exp(-30)}\right) = 0{,}067;$$

$$R_{B+} = 0{,}03 * \frac{1-\exp(-30*6{,}10\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*6{,}10\%)}{1-\exp(-30)}\right) = 0{,}050;$$

$$R_{B} = 0{,}03 * \frac{1-\exp(-30*12{,}10\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*12{,}10\%)}{1-\exp(-30)}\right) = 0{,}033;$$

$$R_{B-} = 0{,}03 * \frac{1-\exp(-30*30{,}49\%)}{1-\exp(-30)} + 0{,}16 * \left(1 - \frac{1-\exp(-30*30{,}49\%)}{1-\exp(-30)}\right) = 0{,}030.$$

Risk-weighted assets (RWA) are used by a banking institution to determine the minimum amount of capital that the institution must hold so as to reduce the risk of insolvency. Based on the assessment of the risk associated with each banking asset, the minimum capital requirement is determined.

The risk-weighted value of a banking institution is calculated according to the following formula:

$RWA = RW * EAD$, where EAD represent exposure at default.

Table 2. *RWA calculations*

Rating	EAD	RW	RWA (expressed in RON)
BBB+	1,100,000,000	4.483369	4,931,706,099
BBB	1,500,000,000	5.653243	8,479,863,834
BBB-	1,200,000,000	6.794119	8,152,942,899
BB+	600,000,000	7.595417	4,557,249,989
BB	500,000,000	7.684116	3,842,058,086
BB-	400,000,000	6.812735	2,725,094,104
B+	200,000,000	6.124765	1,224,952,936
B	80,000,000	5.333471	426,677,713
B-	150,000,000	5.048754	757,313,033

Source: Authors' own research results.

According to the calculation in the table above, for asset A, I value a total risk-weighted amount of RON 35,097,858,696. This value was calculated following a simulation based on own knowledge gained from banking work experience and may represent the risk-weighted value for a portfolio of a large bank on the Romanian market, from the top 6 banks ranked in terms of asset view.

Below I will calculate the expected value of the loss following asset A, in English Expected Credit Loss (ECL). It is calculated according to the following formula:

$ECL = PD * LGD * EAD$, formula that we rewrite according to a stochastic dynamic system as: $ECL(t) = PD_{t-1,t} * LGD_t * EAD_t$

$ECL_A = ECL_{BBB+} + ECL_{BBB} + \cdots + ECL_{B-} = 68{,}193{,}000\ RON.$

The expected loss over the life of the credit product is calculated according to IFRS9 standards, being a financial calculation tool that replaces the IAS39 standard, emphasizing the depreciation requirements, in addition to those of recognition and measurement. The expected credit loss model applies to debt instruments recorded at amortized cost or fair value through other comprehensive income such as loans, debt securities or financial collateral agreements. Depending on the occurrence of a significant increase in credit risk, banking institutions must forecast and calculate a provision for expected credit losses over 12 months or over the life of the loan.

The IFRS9 financial standard is based on 3 scenarios in the calculation of the ECL value: positive scenario, with an associated weight of 25%, average scenario with a weight of 50% and negative scenario with a weight of 25%.

From a statistical point of view, for the credit risk assessment, risk assessment models are built from the point of view of PD, LGD. In the construction of these models, certain aspects are taken into account, such as the stability of the population, the power of discrimination, the accuracy of the data, etc. Population stability assesses whether there are recent changes in the distribution of asset accounts by rating classes, by comparison with the development sample of the model.

The power of discrimination assesses the model's ability to differentiate exposures in terms of their risk characteristics. Accuracy assesses risk estimates by comparing them with historical observations and analyzes whether the differences between them can be explained by the data scattering property or whether they indicate a systemic underestimation.

Each statistical test performed is verified by the traffic light technique and each color is assigned a value or a range of values in which the test results can be found.

In the case of analyzing an evaluation model such as the Probability of Default model, its statistical testing is performed. The performance of the model (stability and concentration of the population), the power of discrimination and the accuracy of the model are tested. Next, I will present each test area and show how it is applied in a banking model and what statistical tests are used for each assessment tool.

Population stability index is a very important concept in model management. It is crucial to monitor whether the current population has changed from the original population used during the development of a model. For example, the distribution of credit scores may change and the model may still be valid or there may be changes in the population such as changes in the economic environment, political changes, strategic changes in business or even changes in the banking regulatory framework.

Pruitt (2010) affirmed that the Population Stability Index (PSI) is one of the widely used model monitoring values, which measures the difference between the model development sample and the current sample for which the model is used and therefore is implemented in several statistical packages.

PSI can be calculated according to the following formula:

$$PSI_{t,t-a} = \sum_{i=1}^{n} (p_i - q_i) * \ln\left(\frac{p_i}{q_i}\right)$$

Table 3. *PSI Calculations*

1	2	3	4	5	6
Credit score	**Development base**	**Current base**	**(2) - (3)**	**ln ((2) / (3))**	**PSI**
A	0.11	0.09	0.02	0.20	0.0040
B	0.34	0.29	0.05	0.16	0.0080
C	1.21	1.19	0.02	0.02	0.0003
D	3.23	2.96	0.27	0.09	0.0236
E	5.71	5.02	0.69	0.13	0.0889
F	7.15	7.13	0.02	0.003	0.0001
G	9.27	9.19	0.08	0.01	0.0007
H	12.81	12.69	0.12	0.01	0.0011
I	4.72	4.7	0.02	0.004	0.0001

Source: Authors' calculation.

The above values were simulated for each grade and is based on over 30,000 observations/ grade.

$$PSI = 0.02 * 0.2 + 0.05 * 0.16 + 0.02 * 0.02 + 0.27 * 0.09 + 0.69 * 0.13 + 0.02 * 0.003 + 0.08 * 0.01 + 0.12 * 0.01 + 0.02 * 0.004 = 0.1266$$

So $PSI = 12.66\%$

According to the literature (Yurdakul, 2018), the traffic light technique for the population stability index is as follows:

PSI	< 10%	(10% - 25%]	>25%

Evaluating the PSI value obtained above, it can be seen that it falls under the scenario related to the color yellow. Certain conditions may be imposed on the existing model and its redevelopment may be required.

The PSI horse method used is the one proposed by Kullback-Liebler. The two distributions p_i and q_i are considered the distributions of a random variable in discrete time, which we can call X. The literature for explaining and analyzing the stability index is not extremely rich, and the calculation formula is called the Kullback-Liebler divergence being noted in the research conducted by Wu and Olson (2010), Yousefi et al. (2016) or Lin (2017).

Another test that can be used to assess population stability is the Herfindahl index. It is defined by the following formula:

$$Herfindahl = \frac{n * \sum_{i=1}^{n} z_i^2 - 1}{n - 1}$$

where n represents the number of bands that include the non-default accounts and z_i - the distribution of the accounts of the model for the investigated year. The specialized literature proposes the following evaluations according to the traffic light technique:

Herfindahl	< 10%	(10% - 20%]	>20%

As you can see, for the model that validates according to the statistical results on green it has the same value as the one in the PSI table. The rigor is a bit higher for the next 2 evaluations, everything that is over 20% being framed as a model that needs to be redeveloped urgently. We will calculate the Herfindahl index for the following example:

Table 4. *Herfindahl calculation*

1	2			
Credit score	**Number of account (nr_cont)**	z_i	z_i^2	**Herfindahl**
A	11	0.02%	0.000004%	
B	682	1.24%	0.015376%	
C	5730	10.42%	1.085385%	
D	9279	16.87%	2.846276%	
E	10630	19.33%	3.735435%	
F	10571	19.22%	3.694084%	
G	9830	17.87%	3.194344%	
H	6164	11.21%	1.256030%	
I	2103	3.82%	0.146202%	
Total	55000		15,97%	

Source: Authors' calculation.

$$z_i = nr_{cont_i}/sum(nr\_cont)$$

$$z_A = \frac{11}{55000} = 0{,}02\%$$

$$Herfindahl = \frac{9 * 15{,}97\% - 1}{8} = 5{,}47\%.$$

The value of the Herfindahl index is <10% which means that the model is still valid for the distribution of accounts above. This means that these accounts are well distributed on the scoring bands from A to I.

Another statistically important tool in evaluating a model is the power of discrimination. In the context of credit risk analysis, the power of discrimination is the ability to discriminate ex-ante between default and non-default accounts. The following statistical tests can be used to evaluate this tool:

- Gini index.
- Kendall's Tau.
- Somers'D.

From the point of view of the Basel II agreement, the statistical instruments for measuring the discriminatory power of a credit rating system represent a major quantitative test, as well as the calibration assessment test, which is also necessary to assess the adequacy of capital requirements.

The Gini Index, developed in 1912 by the Italian statistician, ideologue, demographer Gini Corrado, is a statistical measure of distribution, conceived as a gap of economic inequality, measuring the distribution of income among a population. It can take values between 0% and 100%, the extremes expressing either a perfect equality or a perfect inequality for the upper limit. In the case of credit risk assessment, the Gini index measures how good-paying and bad-paying customers are clustered. Thus, I will propose the following portfolio of accounts:

Table 5. *Distribution of the portfolio of accounts*

Credit Score	Good Customers	Bad Customers	Increased cumulative frequency of good customers	Increased cumulative frequency of bad customers	Frequency cumulative share. Good customers	Frequency cumulative share. Bad customers
A	210	128	210	128	1.53%	3.35%
B	304	38	514	166	3.75%	4.35%
C	316	173	830	339	6.06%	8.88%
D	332	90	1162	429	8.48%	11.24%
E	287	48	1449	477	10.58%	12.50%
F	381	43	1830	520	13.36%	13.62%
G	338	38	2168	558	15.83%	14.62%
H	455	31	2623	589	19.15%	15.43%
I	288	22	2911	611	21.25%	16.01%
Total	2911	611	13697	3817	100%	100%

Source: Authors' calculation.

We will name the class of customers who pay their loan installments on time, so there are no delays, in good customers and in bad customers those who are part of the cluster of individuals who have registered various delays in paying debts. I will calculate the Gini index to measure the power of discrimination for each score band according to the following formula:

$$I_{Gini} = 1 - \sum_{i=1}^{n} (CB_i + CB_{i-1}) * (CR_i - CR_{i-1})$$

The above formula is generalized according to the following formula proposed by Yitzhaki (1983) where:

I_{Gini} – represents the Gini index.

CB_i – represents the values of the share of the increasing cumulated frequency of the good customers related to a score band i and CB_{i-1} is related to the previous band.

CR_i – represents the values of the weight of the increasing cumulated frequency of bad customers related to a score band i.

Then:

$$I_{Gini} = 1 - (1{,}53\% * 3{,}35\% + 5{,}29\% * 1\% + 9{,}81\% * 4{,}53\% + 14{,}54\% * 2{,}36\% + 19{,}06\% * 1{,}26\% + 29{,}94\% * 1{,}13\% + 29{,}19\% * 1\% + 34{,}98\% * 0{,}81\% + 40{,}40\% * 0{,}58\%) = 97{,}69\%$$

The value of the Gini index is 97.69%, which expresses the fact that the distribution of accounts tends towards a perfect inequality between good customers and bad customers, which means in terms of credit risk that there is a great power of discrimination for the distribution of accounts on the score bands formed.

5. Conclusions

The expected loss over the life of the credit product is calculated according to IFRS9 standards, being a financial calculation tool that replaces the IAS39 standard, emphasizing the depreciation requirements, in addition to those of recognition and measurement. The expected credit loss model applies to debt instruments recorded at amortized cost or fair value through other comprehensive income such as loans, debt securities or financial collateral agreements. Depending on the occurrence of a significant increase in credit risk, banking institutions must forecast and calculate a provision for expected credit losses over 12 months or over the life of the loan.

From a statistical point of view, for the credit risk assessment, risk assessment models are built from the point of view of PD, LGD. In the construction of these models, certain aspects are taken into account, such as the stability of the population, the power of discrimination, the accuracy of the data, etc. Population stability assesses whether there are recent changes in the distribution of asset accounts by rating classes, by comparison with the development sample of the model. The power of discrimination assesses the model's ability to differentiate exposures in terms of their risk characteristics. Accuracy assesses risk estimates by comparing them with historical observations and analyzes whether the differences between them can be explained by the data scattering property or whether they indicate a systemic underestimation.

In our opinion, credit risk assessment is one of the most sensitive and important issues at the level of a financial institution. An underestimation of the probability of default, the instability of the analyzed population or in general an incorrect assessment of a credit risk model can lead to a significant increase of the portfolio of clients with default status. Therefore, it can become a systemic effect within the bank, but with an impact on other institutions or other banks as well.

Notes

(1) The Marxist perspective represents the fact that certain notions and concepts can be described at a theoretical level, which can be influenced by certain political-economic or legislative practices, having perhaps even totally different meanings. The main founder of Marxism was Karl Max, a German philosopher and economist. The perspective was strengthened by the collaboration of the German economist with Friedrich Engels, together developing the communist theory.

(2) According to Regulation 575/2013, p. 97, available online at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:176:0001:0337:RO:PDF

(3) According to Regulation 575/2013, p. 97, available online at: https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:176:0001:0337:RO:PDF

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