Gravitational and intellectual data analysis to assess the money laundering risk of financial institutions

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Abstract. The wide variety of schemes to use companies for money laundering, such as oil smuggling, illegal gas sales, misappropriation of the Central Bank refinancing, misappropriation of bank funds and state-owned enterprises, form the research issues. The sample under study includes 102 countries around the world, which are closely monitored by the Financial Action Task Force (FATF) and have different levels of sociopolitical and economic development. The scientific and methodological approach to assess the financial monitoring risk in terms of the use of financial institutions for money laundering is based on the methods of multidimensional static analysis, descriptive, cluster and dispersive data analysis, gravity theory, nonlinear econometric modeling, differential and bifurcation analysis of dynamic nonlinear systems. The result of the study is a developed model of comprehensive risk assessment for the countries' financial institutions for money laundering, which considers grouping of countries by the

level of money laundering risk, identification of the cluster belonging to the state; formation of an integrated index as a money laundering risk rating assessment, and risk assessment based on the gravitational model; construction of a phase portrait for a dynamic system of the risk to use the countries' financial institutions based on a nonlinear econometric model.

Keywords: financial risk, money laundering, gravitational modeling, dynamic risk stability, bifurcation analysis, Ukraine

JEL Classification: C54, F38, G15

1. INTRODUCTION

Current trends in digital development, big-data implementation, blockchain technologies, introduction of innovative technologies in the business processes of almost all businesses require improvement of existing methods to assess the money laundering risk of financial institutions and to develop fundamentally new approaches to the assessment of such risks. The states of the European Union have stronger legal framework for criminal liability and specifications for financial operations and transactions. For example, the Fifth EU Anti-Money Laundering Directive (AMLD 5) has expanded the scope of virtual currency platforms and providers of tax-related wallets, services and art traders. Also, by this directive, the capabilities of the Financial Intelligence Units of the EU countries have been strengthened in requesting, receiving, and using information from "obligated entities" to prevent, detect and effectively combat money laundering and terrorist financing. Clarified the criteria for classifying third countries (non-EU members) as High-Risk Third Countries; transactions with these countries' residents should be subject to special scrutiny. The European Commission approves the list of such countries.

However, the results of monitoring and sanctions for detecting criminal offenses are also subject to different risks.

The primary information is usually processed in the form of messages received from banking and non-banking institutions (insurance institutions, other business entities providing financial services, professional stock market participants, business entities conducting lotteries, notaries) and distributed in the repository database SCFM with a certain degree of risk (Zakutniaia et al., 2017). Monitoring and control begin when the application is received from the entity (Horvathova et al., 2020; Kovacova et al., 2019).

The aim of the article is to conduct a comprehensive analysis of the money laundering risk of financial institutions. The authors propose to implement mathematical tools using the methods of data mining (Alimuddin et al., 2020), gravitational modeling (Stavytskyy et al., 2019), multidimensional statistical analysis (Faria et al., 2020; Malyarets et al., 2019), bifurcation models of nonlinear dynamic systems (Dvorsky et al., 2020; Lyeonov et al., 2019).

2. LITERATURE REVIEW

Money laundering, terrorist financing, the risk of financial institutions, the information security effectiveness

Over the last two decades, scholars from different countries have actively studied the transparency of public finances, the quality of financial monitoring by government services and international agencies. The team of authors from the For the Study of Democracy center (Pashev et al., 2007) justifies that the modern

impact assessment techniques should be applied to the regulations, considering the specific national circumstances. It allows assessing the social damage through the additional corruption risk, which also depends on the administrative and judicial anti-corruption barriers, and the benefits obtained from greater freedom for customers to negotiate the best terms and rules (Kaya et al., 2020).

The cybersecurity field has shown itself as a component of national security and the financial and economic security paradigm. Scientists (Legenzova et al., 2019; Constantinescu, 2018) emphasize that states must adapt their approaches to national security, including challenges related to technical and financial innovations of cryptocurrencies, blockchain technologies. In the study (Sebestova et al., 2018; Shtiller et al., 2017), the authors proposed a methodology based on distance metrics to define an integrated assessment for the financial control system effectiveness over public funds, which can evaluate the effectiveness in the entire financial control system.

3. DATA AND METHODOLOGY

The spatial analysis of data for 102 countries in 2018-2019, studied by the Financial Action Task Force on Money Laundering (FATF, 2018), forms the basis to review money laundering risk of financial institutions. The statistical input base of the study is formed using the data from the World Bank (The World bank: Data, 2018), the Financial Action Task Force on Money Laundering (FATF), the Institute of Economics and Peace. Economics & Peace, 2018), ratings representing the effectiveness degree of measures taken by countries to combat money laundering and terrorist financing and reflecting the state compliance degree with technical requirements (4th-Round-Rating, 2018).

The research indices include:

- Effectiveness (K1), technical compliance (K2), GDP per capita (current US$) (K3).
- Ease of doing business score (0 = lowest performance to 100 = best performance) (K4).
- Internally displaced persons, new displacement associated with conflict and violence (number of cases) (K5).
- Corruption perceptions index (K6).
- Global terrorism index (K7).
- Business freedom (K8).
- Monetary freedom (K9).
- Financial freedom (K10).

The index "effectiveness, K1" characterizes the effectiveness degree of countries' measures to combat money laundering and terrorist financing; the index "technical compliance, K2" – the degree of state compliance with technical requirements. According to the FATF methodology (4th-Round-Rating), these indices are measured qualitatively. Thus, for the effectiveness index, it is proposed to use a quantitative scale from 0.25 to 1: HE = 1 – high level of effectiveness, the immediate outcome is achieved to a very large extent (minor improvements required), SE = 0,75 – substantial level of effectiveness, the immediate outcome is achieved to a large extent (moderate improvements required), ME = 0,5 – moderate level of effectiveness, the immediate outcome is achieved to some extent (major improvements needed), LE = 0,25 – low level of effectiveness, the immediate outcome is not achieved or achieved to a negligible extent (fundamental improvements required). The technical compliance indicator uses the following scale: C = 1 – compliant, LC = 0,8 – largely compliant (there are only minor shortcomings), PC = 0,6 – partially compliant (there are moderate shortcomings), NC = 0,4 – non-compliant (there are major shortcomings), NA = 0,2 – not applicable (a requirement does not apply, due to the country's structural, legal or institutional features).

The authors in the study (Lyeonov et al., 2019) substantiate in detail the significance of all other indices, content, and relevance of use.

3.1. Cluster analysis, analysis of variance. Correlation analysis

Authors propose to cluster 102 countries using the k-means method by application software Statistica.10, procedure Analysis/Multidimensional exploration analysis/Cluster analysis. Euclidean distances from the grouping center and the arithmetic mean are used to quantify the distinctive features and differences between clusters. The results of variance analysis and the union protocol analysis, namely the agglomeration coefficients, confirm the number and composition of clusters. The calculation is as follows: n - number of objects (countries); N is the number of steps (n-1); k is the number of the step on which the jump occurred (a sharp change in the values of the agglomeration coefficient); N - k = number of clusters. Thus, the optimal number of clusters is 10 (Popov et al., 2019; Fomina et al., 2017). Besides, the requirements for the fullness and stability of clusters are used to define the optimal number of clusters. At least 10% of the total number of objects must be in each cluster. One should consider it to avoid the empty groups or groups with very few objects. The objects inside the cluster must be similar. Checking the stability of clusters, i.e., the division of countries into 10, 11, or 12 clusters, does not reveal any fundamentally new structures. Therefore, the model is optimally stable when it forms 10 clusters (Buriak et al., 2019; Vasilyeva et al., 2017).

As a result of the clustering, the following content of clusters is received. The first and ninth clusters include five countries – Bhutan, Guatemala, Iceland, Latvia, Peru and Denmark, Ireland, Singapore, Switzerland, United States. The second cluster includes Australia, Austria, Belgium, Canada, Finland, Hong Kong, China, Israel, Sweden, Chinese Taipei, United Arab Emirates, United Kingdom. The third cluster is formed by Bahamas, Cyprus, Italy, Korea, Malta, Slovenia, Spain. The fourth cluster comprises Bahrain, Barbados, Czech Republic, Greece, Hungary, Lithuania, Palau, Panama, Portugal, Saudi Arabia, Seychelles, Trinidad and Tobago, Uruguay. The sixth cluster includes nine countries: Belarus, Botswana, Colombia, Cuba, Dominican Republic, Fiji, Serbia, Thailand, Turks&Caicos. Ukraine is in the seventh cluster together with: Albania, Armenia, Cabo Verde, Indonesia, Jamaica, Jordan, Moldova, Mongolia, Morocco, Philippines, Sri Lanka, Tunisia, Ukraine, Vanuatu. The eighth cluster is the largest. There are 28 countries, namely: Andorra, Bangladesh, Bermuda, Burkina Faso, Cambodia, Cayman Islands, Cook Islands, Ethiopia, Ghana, Gibraltar, Haiti, Honduras, Isle of Man, Kyrgyzstan, Macao, China, Madagascar, Malawi, Mali, Mauritania, Myanmar, Nicaragua, Pakistan, Samoa, Senegal, Solomon Islands, Tajikistan, Uganda, Zambia. Norway is in the tenth cluster.

Thus, the cluster analysis results allow forming of ten groups on the money laundering risk by countries. This is necessary for more detailed tracking of financial transactions by a particular country within a particular cluster, a thorough analysis of economic and political relations between countries within a single cluster (Nguedie, 2018). The more countries in the same cluster, the higher the money laundering risk for these countries to use their financial institutions. And vice versa, the risk is lower for clusters with a small number of sites (five to nine countries). Thus, the interpretation is based on formal and logical conclusions about the complexity of the relation analysis (economic, social) and monitoring of financial and cash flows of countries, considering the national policy peculiarities, the level of economic development in each country. Besides, this hypothesis regarding the values of risks, i.e., which countries have low, medium and high level risk, will be tested using the investigated values of integrated indices.

The clustering corresponds to the general level of money laundering in countries from one cluster (the smaller the Euclidean distance from the grouping center for each cluster, the greater the countries in this cluster are more similar in money laundering methods and level) (Dudchenko, 2020; Pernica, 2017). It is

confirmed by the results of variance analysis based on a comparison of the corresponding values of intergroup (Between SS) and intragroup variances (Within SS), and the F-criteria and p-value.

The correlation matrix analysis shows the positive highly correlated relationships between indices in the following cases (direct proportional relationship): between GDP per capita (current US $) and corruption perceptions index at 79%, between ease of doing business and business Freedom at 86%, between ease of doing business and financial freedom – 77%, between corruption perceptions index and business freedom at 81%, between corruption perceptions index and financial freedom – 74%, between business freedom and monetary freedom – 82%, and between business freedom and financial freedom at the level of 80%. There is a relatively high proportional density of communication between indices of GDP per capita (current US $) and financial freedom (at the level of 0.604484 shares), between ease of doing business and monetary freedom (at the level of 0.702281 shares), between ease of doing business and monetary freedom (at the level of 0.704265 shares), between corruption perceptions index and monetary freedom (at the level of 0.679891 shares), and between monetary freedom and financial freedom – at the level of 71%. The effectiveness indices and GDP per capita (current US $) (at 52%), GDP per capita (current US $) and ease of doing business (at 53%) correlate positively at the average level.

3.2. Risk assessment by gravity modeling method

The assessment of the money laundering risk of financial institutions around the world implemented by gravity modeling based on the indices K1 - K10 in 2019, and the values of indices P1 - direct investment (equity) from around the world in the economy of the country; P2 - direct investment (equity) from the study country in the economies of the world; P3 - exports (million USD); P4 - imports (million USD) (Kliestik et al., 2020; Bilan et al., 2019).

The evaluation methodology will be presented in four stages (Zarutska et al., 2020; Kuzmenko et al, 2018).

Stage 1. Nonlinear normalization of input indices to compare them and calculate the integrated indicator (1)

$$\widetilde{K_{ij}} = \left(1 + e^{\frac{K_j - K_{ij}}{\sigma_K}}\right)^{-1}, \tag{1}$$

where $\widetilde{K_{ij}}$ – normalized value of the i-country of j-index K; $\underline{K_j}$– the average value of j-index K; K_{ij} – the value of i-country of j-index K; σ_{Π_j} – standard deviation of the j-index of P indicator.

Stage 2. Determination of weighting coefficients for factors. At this stage, the analysis of the principal components is used to calculate the weighting coefficients for integrated assessment of money laundering risk of financial institutions (Arambašić et al., 2020; Yakymova et al., 2019). The practical implementation is carried out using the tools of the statistical package Statistica 10, the procedure Multivariate Exploratory Techniques/Principal Components & Classification Analysis.

The calculation of weighting coefficients consists of the following actions: to construct a table of eigenvalues of factors, factor loads, scree plot; to determine the optimal number of relevant factors (the cumulative amount of selected factors variance should be more than 70%) based on the analysis of the table of eigenvalues and the scree plot; to calculate weighting coefficients for each index based on variances regarding the influence of factors and factor loads using the weighted average (2, 3)

$$\underline{x} = \frac{\sum_{i=1}^{n} x_i * f_i}{\sum_{i=1}^{n} f_i}, \tag{2}$$

where $\underline{x}$ – the average value of index x; x_i– i-value of the index x, i = 1..n; f_i – i-value of the frequency index x, i = 1..n.

$$w_j = \frac{\sum_{i=1}^{n} F_{ji} * \sigma_i^2}{\sum_{i=1}^{n} \sigma_i^2}, \tag{3}$$

where w_j – the weighting coefficient of the j-index; F_{ji} – the j-value of the factor load of the i-factor, i = 1..n; σ_i^2 – the value of the i-factor variance, i = 1..n.

Stage 3. Calculation of a rating assessment for the level of money laundering risk of financial institutions based on the integrated index (Malyarets et al., 2019, Palienko, 2018).

The integral index is formed using the Minkowski metric, which calculates the distance between points in Euclidean space and is a proper generalization of Euclidean space. In general, the Minkowski metric is as follows (4)

$$F(x_i) = 1 - \sqrt{\sum_{j=1}^{k} \omega_j \left|1 - \frac{x_{ij}}{x}\right|^2 + \sum_{j=k+1}^{n} \omega_j \left|1 - \frac{x}{x_{ij}}\right|^2}, \tag{4}$$

where $F(x_i)$ – integral index; x_{ij} – i-value of j-index, j = 1..k; ω_j – weighting factor of j-index.

The integrated index, calculated according to formula 4, considers indicators-stimulants (weighing the maximum index) and indicators-disincentives (the minimum index value ratio to the value of the index). Since in our case, all indices are disincentives, and the values have already been normalized. The integrated index formula of the money laundering risk of financial institutions is as follows (5)

$$I_i = 1 - \sqrt{\sum_{j=1}^{k} w_j \left|1 - \widetilde{K}_J\right|} \tag{5}$$

where I_i – value of the integrated index; $\widetilde{K}_J$– i-value of j-index, normalized by formula 2, j = 1..k; w_j – weighting coefficient of j-index, calculated by formula 3.

Stage 4. Construction of an integrated money laundering risk of financial institutions based on the gravitational model.

Gravitational modeling is based on the law of gravitational force and gravitational attraction in social phenomena (Drelich-Skulska et al, 2019; Mishchuk et al, 2019) (6)

$$V_{ij} = k \frac{p_i \cdot p_j}{d_{ij}^2} \tag{6}$$

where V_{ij} – assessment of the interaction between two objects i and j; the value of the integrated index; k - the coefficient of conformity; p - estimated importance of the object (weight); d_{ij}^2 - the distance between objects.

The money laundering risk of financial institutions is assessed by formula:

$$L_j = \frac{I_i \cdot I_j}{d_{ij}^2}, \tag{7}$$

where L_j – assessment of the strength in the interaction between the financial institutions of the observed country and the j-country in terms of money laundering; I_i and I_j – integrated rating evaluations of the financial institution risk in the studied country and the j-country for money laundering; d_{ij}^2 – the distance between countries, characterizing the estimated difference between the observed state and the j-country. Distance d_j^2 between the studied country and j-country is calculated as a sum of four constituents P1 – direct investment (share capital) from the countries all over the world in the economy of the studied state; P2 – direct investment (share capital) from the studied country in the world countries' economies; P3 – exports (mln. US dollars); P4 – imports, (mln.US dollars).

The values of the money laundering risk of financial institutions calculated by formula 7 should be normalized by bringing the value to the interval [0; 1] (Morscher et al., 2017). A value close to zero has the lowest level of money laundering risk of financial institutions. The value close to one, on the contrary – the highest level of risk. The normalized value of the risk assessment is calculated by formula 8

$$\widetilde{L_J} = \frac{L_j}{L + \sigma(L_j)} \tag{8}$$

where $\widetilde{L_J}$ – assessment of the risk to involve the studied country by j-state in the money laundering scheme [0;1]; L_j – assessment of the risk to involve the studied country by the j-country into money laundering; L – maximum value of the risk to involve the observed country by j-state in money laundering; $\sigma(L_j)$ – standard deviation to assess the risk in the surveyed country by the j-th country in the money laundering.

3.3. Bifurcation analysis of the study regarding the nature of the dynamic stability in a group of countries

The method of analysis will be presented in three stages.

Stage 1. Specification of the functional dependence of the money laundering risk of financial institutions, on nonlinear factor characteristics identified as the most influential in the previous stage of modeling (Table 1), based on the highest values of the Student's t test (t-Stat).

Table 1

T-statistics regarding the significance of functional dependence specification of money laundering risk of financial institutions, on nonlinear factor characteristics

t-Stat	Ease of doing business (K4)	Corruption perceptions index (K6)	Monetary Freedom (K9)	Financial Freedom (K10)
Intercept	10,9110	-3,1137	-1,6865	-2,4246
x	-0,1164	-2,9062	-1,6752	-2,6373
x^2	0,1075	2,6779	1,6603	2,5434
x^3	0,0263	**-3,4588**	-1,6376	-2,3222
sin x	**0,6827**	-0,9699	1,6818	-0,8187
sqrt x	0,1445	3,0784	**-1,7947**	**2,7927**

Source: Authors' calculations

Stage 2. Investigation of an econometric model for nonlinear multifactor regression dependence of the money laundering risk of financial institutions on the relevant factors of its formation.

Stage 3. Construction of a phase portrait for a dynamic system of money laundering risk of financial institutions in the studied country. Implementation of this step involves preliminary calculations in terms of differential calculus, namely identifying partial derivatives of the risk function via financial institutions for money laundering in the studied country on its constituent factors. They form the basis for further study of dynamic stability (Vasylyeva et al., 2016; Kuzmenko et al., 2014, Karaaslanlı, 2012).

4. EMPIRICAL RESULTS AND DISCUSSION

Following the calculation of the integrated index of the money laundering risk of financial institutions in the studied countries based on the methodology proposed in part 3.2, table 2 is formed.

Table 2

Integrated rating index (I) of the money laundering risk of financial institutions, and risk assessment based on the gravity model ($\widetilde{L}_j$)

Country	I/ $\widetilde{L}_j$	Country	I/ $\widetilde{L}_j$	Country	I/ $\widetilde{L}_j$	Country	I/ $\widetilde{L}_j$
Albania	0,4968/ 0,6010	Lithuania	0,6053/ 0,3461	Cyprus	0,5725/ 0,6925	Senegal	0,4096/ 0,4463
Andorra	0,2570/ 0,3109	Macao, China	0,2080/ 0,2517	Czech Republic	0,6094/ 0,2747	Serbia	0,4497/ 0,4095
Antigua & Barbuda	0,3977/ 0,4811	Madagascar	0,3753/ 0,4540	Denmark	0,6593/ 0,5345	Seychelles	0,4473/ 0,4963
Armenia	0,5180/ 0,6267	Malawi	0,3860/ 0,4670	Dominican Republic	0,4322/ 0,5229	Singapore	0,6364/ 0,5974
Australia	0,7278/ 0,4872	Malaysia	0,5400/ 0,5234	Ethiopia	0,3507/ 0,4243	Slovenia	0,4889/ 0,5064
Austria	0,6365/ 0,7363	Mali	0,4148/ 0,5018	Fiji	0,2783/ 0,3366	Solomon Islands	0,4236/ 0,5124
Bahamas	0,4976/ 0,3138	Malta	0,4450/ 0,4788	Finland	0,6960/ 0,6541	Spain	0,6434/ 0,2812
Bahrain	0,5820/ 0,7040	Mauritania	0,3833/ 0,4376	Ghana	0,4074/ 0,4265	Sri Lanka	0,4500/ 0,5444
Bangladesh	0,3667/ 0,367	Mauritius	0,4786/ 0,5789	Gibraltar	0,2445/ 0,2952	Sweden	0,7054/ 0,5072
Barbados	0,5031/ 0,6086	Mexico	0,5134/ 0,5075	Greece	0,5643/ 0,4916	Switzerland	0,6511/ 0,1996
Belarus	0,4199/ 0,4340	Moldova	0,4663/ 0,3295	Guatemala	0,3890/ 0,4520	Chinese Taipei	0,6290/ 0,7457
Belgium	0,7050/ 0,4340	Mongolia	0,3827/ 0,4629	Haiti	0,3159/ 0,3821	Tajikistan	0,3837/ 0,4641
Bermuda	0,4546/ 0,5500	Morocco	0,4651/ 0,4471	Honduras	0,4651/ 0,5627	Thailand	0,5671/ 0,5102
Bhutan	0,3750/ 0,4537	Myanmar	0,3402/ 0,4116	Hong Kong, China	0,6402/ 0,7746	Trinidad and Tobago	0,4444/ 0,5376
Botswana	0,4628/ 0,5599	Nicaragua	0,4234/ 0,5122	Hungary	0,5322/ 0,1783	Tunisia	0,4516/ 0,4272
Burkina Faso	0,4178/ 0,5054	Norway	0,5316/ 0,5463	Iceland	0,5742/ 0,6481	Turkey	0,5237/ 0,1335
Cabo Verde	0,4095/ 0,4953	Pakistan	0,3768/ 0,4017	Indonesia	0,5550/ 0,4082	Turks&Caicos	0,2482/ 0,3002
Cambodia	0,3630/ 0,4391	Palau	0,3027/ 0,3662	Ireland	0,7150/ 0,7325	Uganda	0,3972/ 0,4805
Canada	0,6551/ 0,6211	Panama	0,5132/ 0,5036	Isle of Man	0,2458/ 0,2974	Ukraine	0,4283/ 0,5182
Cayman Islands	0,2032/ 0,2459	Peru	0,5304/ 0,6412	Israel	0,7000/ 0,8468	United Arab Emirates	0,5844/ 0,4912
China	0,4294/ 0,0858	Philippines	0,50589/ 0,4688	Italy	0,5591/ 0,1343	United Kingdom	0,7065/ 0,2109
Colombia	0,5380/ 0,6508	Portugal	0,5908/ 0,5856	Jamaica	0,4369/ 0,5285	United States	0,7297/ 0,1805
Cook Islands	0,2583/ 0,3125	Russian Federation	0,4226/ 0,0833	Jordan	0,5404/ 0,5847	Uruguay	0,4825/ 0,5837
Costa Rica	0,5240/ 0,5779	Samoa	0,3967/ 0,4800	Korea	0,6105/ 0,4695	Vanuatu	0,3858/ 0,4667
Cuba	0,3310/ 0,4005	Saudi Arabia	0,4871/ 0,3447	Kyrgyzstan	0,4609/ 0,5576	Zambia	0,4338/ 0,5247
				Latvia	0,5685/ 0,4920	Zimbabwe	0,2742/ 0,3317

Source: Authors' results

Analyzing Table 2, we can conclude that countries of the first, third and fourth clusters have the average money laundering risk of the countries' financial institutions. The average values of the risk factors

calculated by the gravitational modeling method are 0.537, 0.545 and 0.513, respectively. The highest value of the risk factor was found in the countries from the second cluster. All other countries are at risk of using their financial institutions for below-average money laundering.

The proposed technique is implemented on the example of the Ukrainian financial institutions. The reduced initial information space without losing representativeness based on the analysis of the principal components consists of four features, namely: ease of doing business (K4), corruption perceptions index (K6), monetary freedom (K9), financial independence (K10).

The econometric model of nonlinear multifactor regression dependence of the money laundering risk of financial institutions, on relevant factors of its formation is investigated by means of MS Excel toolkit, Data Analysis/Regression package (Levchenko et al., 2019; Zheng et al., 2019) (Table 3).

Table 3

The statistical analysis results regarding the dependence of the money laundering risk of financial institutions, on nonlinear factors

	Coef-ficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0,0324	0,0883	-0,3671	0,7143	-0,2077	0,1429
sin K4	-0,0054	0,0077	-0,7048	0,4826	-0,0207	0,0098
$(K6)^3$	0,0000	0,0000	0,0688	0,9453	0,0000	0,0000
sqrt K9	0,0317	0,0118	2,6738	0,0088	0,0082	0,0552
sqrt K10	0,0234	0,0059	3,9721	0,0001	0,0117	0,0350
K4 K6 K9 K10	0,0000	0,0000	3,5595	0,0006	0,0000	0,0000

The results of Table 3 indicate the insignificance of the sinusoid K4 and paraboloid K6 because the p-value for these indicators is greater or equal to 0.5. For sin K4, the p-value is 5%, and for $(K6)^3$, the p-value is 9%. Besides, the actual value of the Student's t-test is less than the theoretical for these indicators, which characterizes their statistical insignificance (critical values of the Student's t-test is 1,984). So for the next stage of modeling, we will form Table 4.

Table 4

The basic statistical analysis results regarding the dependence of the risk to use financial institutions for money laundering, on nonlinear factors

	Coef-ficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0,0398	0,0858	-0,4638	0,6438	-0,2102	0,1305
sqrt K9	0,0330	0,0116	2,8458	0,0054	0,0100	0,0561
sqrt K10	0,0229	0,0051	4,4618	0,0000	0,0127	0,0331
K4 K6 K9 K10	0,0000	0,0000	8,3178	0,0000	0,0000	0,0000

As we can see, all indicators from Table 4 are significant (p-value is less than 0.05, and the actual value of the Student's t-test is greater than the theoretical one).

The econometric model of nonlinear multifactor regression dependence of the money laundering risk of financial institutions on the relevant factors of its formation is represented by formula 9

$$f(ed, c, mf, ff) := -0.0398 + 0.0330 \cdot mf^{\frac{1}{2}} + 0.0229 \cdot ff^{\frac{1}{2}} + 4.62 \cdot 10^{-9} \cdot ed \cdot c \cdot mf \cdot ff \qquad (9)$$

where ed – ease of doing business; c – corruption perceptions index; mf – monetary freedom; ff – financial freedom.

A phase picture of the dynamic system regarding the risk of the money laundering risk of the Ukrainian financial institutions is constructed using differential calculations. Namely, they include identifying partial derivatives of the function regarding the dependence of money laundering risk of the Ukrainian financial institutions on its shaping factors, which form the basis for further study of the dynamic stability of the considered system (formula 10) (Yarovenko, 2020; Dean et al., 2017; Kuzmenko et al., 2014). They describe the behavior of the dynamic system of the money laundering risk indicator of the Ukrainian financial institutions

$$\frac{d}{ded} f(ed, c, mf, ff) \rightarrow 4.62\text{e-}9 \cdot c \cdot ff \cdot mf$$

$$\frac{d}{dc} f(ed, c, mf, ff) \rightarrow 4.62\text{e-}9 \cdot ed \cdot ff \cdot mf$$

$$\frac{d}{dmf} f(ed, c, mf, ff) \rightarrow \frac{0.0165}{\sqrt{mf}} + 4.62\text{e-}9 \cdot c \cdot ed \cdot ff$$

$$\frac{d}{dff} f(ed, c, mf, ff) \rightarrow \frac{0.01145}{\sqrt{ff}} + 4.62\text{e-}9 \cdot c \cdot ed \cdot mf$$

$$(10)$$

Thus, a nonlinear approach based on the bifurcation theory allows building a "phase picture" of the money laundering risk of the Ukrainian financial institutions, i.e., to reflect the trajectories on the selected phase space (Vasilyeva et al., 2019; Shkolnyk et al., 2018).

Authors build the phase picture based on differential equations using mathematical software MathCad:

$$
\text{Faza}(ed0, c0, mf0, ff0, dt, N) := \left|
\begin{array}{l}
\left(ed_0 \leftarrow ed0 \quad c_0 \leftarrow c0 \quad mf_0 \leftarrow mf0 \quad ff_0 \leftarrow ff0 \right) \\
\text{for } k \in 0..N \\
\left|
\begin{array}{l}
fff \leftarrow f\left(ed_k, c_k, mf_k, ff_k\right) \\
ed_{k+1} \leftarrow \left[ed_k + dt \cdot \left(4.62\text{e-}9 \cdot c_k \cdot ff_k \cdot mf_k\right)\right] \\
c_{k+1} \leftarrow \left[c_k + dt \cdot \left(4.62\text{e-}9 \cdot ed_k \cdot ff_k \cdot mf_k\right)\right] \\
mf_{k+1} \leftarrow \left[mf_k + dt \cdot \left(\frac{0.0165}{\sqrt{mf_k}} + 4.62\text{e-}9 \cdot c_k \cdot ed_k \cdot ff_k\right)\right] \\
ff_{k+1} \leftarrow \left[ff_k + dt \cdot \left(\frac{0.01145}{\sqrt{ff_k}} + 4.62\text{e-}9 \cdot c_k \cdot ed_k \cdot mf_k\right)\right]
\end{array}
\right. \\
(ed \quad c \quad mf \quad ff)
\end{array}
\right.
\qquad (11)
$$

According to the bifurcation theory and the variety of phase picture of two-dimensional space, we describe the money laundering risk of the Ukrainian financial institutions (Kuzmenko et al., 2020)

$$
\begin{array}{l}
(ed1 \quad c1 \quad mf1 \quad ff1) := \text{Faza}(66, 36, 82, 70, 0.001, 1000000) \\
(ed10 \quad c10 \quad mf10 \quad ff10) := \text{Faza}(73, 35, 75, 70, 0.01, 1000000) \\
(ed13 \quad c13 \quad mf13 \quad ff13) := \text{Faza}(54, 57, 83, 60, 0.01, 1000000) \\
(ed58 \quad c58 \quad mf58 \quad ff58) := \text{Faza}(68, 38, 81, 60, 0.01, 1000000) \\
(ed98 \quad c98 \quad mf98 \quad ff98) := \text{Faza}(68, 44, 82, 50, 0.01, 1000000)
\end{array}
\qquad (12)
$$

The obtained trajectories of phase picture have the type of bifurcation "unstable focus" (Fig. 1) and "unstable node" (Fig. 2). This behavior is inherent in nonlinear systems that are in an unstable equilibrium (Biegun et al., 2020; Leonov et al., 2019, Karaaslanlı, 2012).

Phase portrait, which characterizes the projections of monetary freedom, financial freedom also has a type of bifurcation "unstable node".
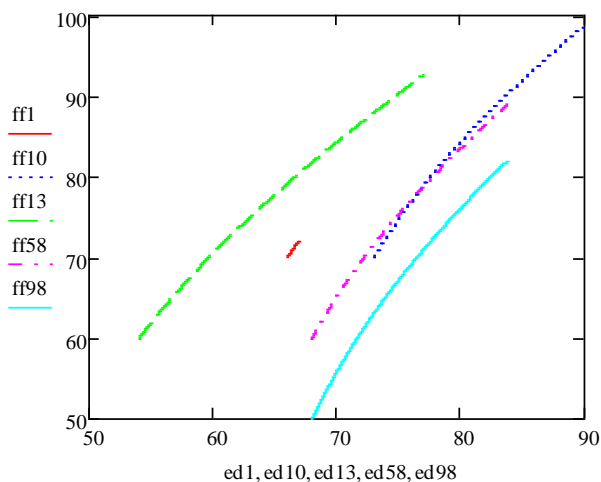

Figure 1. Fragment of the phase picture "unstable focus" in a dynamic system that is in an unbalanced state, in terms of the risk to use Ukraine's financial institutions for money laundering

(abscissa axis – ease of doing business, ordinate axis – financial freedom)
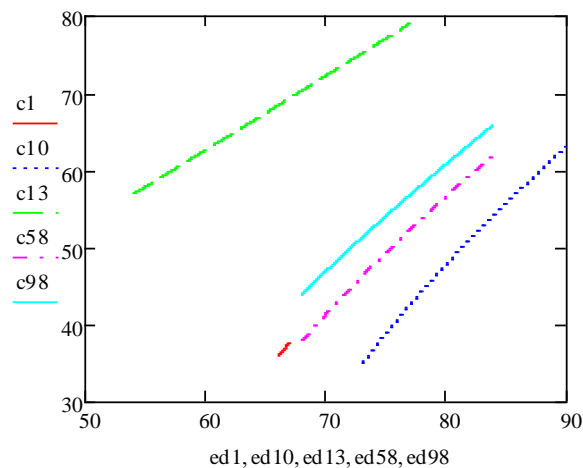
Figure 2. Fragment of the phase picture "unstable node" in a dynamic system that is in an unbalanced state, in terms of the risk to use Ukraine's financial institutions for money laundering

(abscissa axis – ease of doing business, ordinate axis – corruption perceptions index)

Both types of bifurcation, both unstable focus, and unstable node characterize the state of unstable equilibrium. Thus, when the value varies towards any indicator of the econometric model (9) (ease of doing business; corruption perceptions index; monetary freedom; financial freedom), the value of the risk of using financial institutions to legalize money laundering can both increase and decrease (a two-dimensional unstable equilibrium is repelling in two directions). Today's realities fully confirm this behavior of the

simulated complex system of risk assessment for using the financial institutions for money laundering of the studied country in terms of fluctuations in political and economic direction processes. As a result, the obtained types of bifurcation confirm the tendency to use financial institutions of Ukraine to legalize criminal proceeds.

5. CONCLUSION

Scientific and methodological approach to assess the risk in financial monitoring regarding the money laundering risk of financial institutions through the gravitational and data mining methods is based on complex stages of implementation. In the first stage, the cluster-variance and correlation analysis tools are used to divide countries into 10 groups and analyze the density of relationships between the observed money laundering risk of financial institutions. The variance analysis tools confirm the optimal number of clusters. The second stage of modeling allows identifying relevant features of the dynamic money laundering risk of financial institutions via key components analysis and rating assessment, that is an integrated money laundering risk index of financial institutions and to evaluate the risk based on the gravitational model. It is necessary to use four factors to determine the level of risk: ease of doing business; corruption perceptions index; monetary freedom; financial freedom. In the third stage, a bifurcation analysis of nonlinear dynamics models for different countries is performed. It defines the state of the system in terms of the probability of the money laundering risk of financial institutions. The practical calculations for the Ukraine establish that the non-linear dynamic system is in unstable equilibrium and the phase portraits are of a "unstable node" type and "unstable focus."

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