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Synthesis of Socio-Economic Maps and Visualization of Deviant Activity Measures of Financial Monitoring of Entities

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ABSTRACT
The task analysis of the Federal Financial Monitoring Service has revealed that the money laundering risk assessment process is greatly limited by insufficient resources. The **aim** of the study is to increase the efficiency of decision-making processes by using visualization of financial monitoring data. The **methodological basis** of the study suggests to rank objects in order to map financial monitoring data. However, the objects of financial monitoring, such as business entities, professional securities market participants, have sets of characteristics, i.e. are of vector nature. As known, there is no mathematical definition of ordinal relations for vectors. The author used the **method** of principal component to estimate a scalar value of financial monitoring. The article provides a subject area modeling of financial monitoring, and the author used mathematical and methodological tools to map deviant objects of financial monitoring. The **result** of the study presents the geographical infographics of the money laundering process. The author refers to socio-economic regional maps obtained from various official **sources** (arbitration case files, the Unified State Register of Legal Entities, the crime rate in Russia from the Ministry of Internal Affairs). The maps include information about the business activity of the federal districts, regions with a propensity for illegal and legal financial activities, crime rate. The author **concludes** that the results of the study may serve as a powerful tool to support the strategic decision-making process and microanalysis of financial monitoring.
Keywords: decision making support; mapping; integrated assessments; deviant activity measures; financial monitoring; scientific visualization

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Синтез социально-экономических карт и визуализация девиантной деятельности объектов финансового мониторинга

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АННОТАЦИЯ
Анализ задач Росфинмониторинга по противодействию отмыванию доходов показал, что фактическая потребность в количестве объектов, подлежащих анализу, многократно превышает возможности аналитиков. **Цель исследования** состоит в повышении оперативности оценки обстановки лицами, принимающими решения, за счет визуализации данных финансового мониторинга. **Методологическую основу** исследования определил тот факт, что для картирования информации об объектах финансового мониторинга необходимо провести их ранжирование. Однако объекты финансового мониторинга — хозяйствующие субъекты, профессиональные участники рынка ценных бумаг — описывают наборами характеристик, т.е., по сути, являются объектами векторной природы. В математике же порядковые отношения для векторов, как известно, не определены. Для отыскания скалярных оценок объектов финансового мониторинга перспективным является **метод** главных компонент. Произведено моделирование предметной области

финансового мониторинга и подобран математический и методологический инструментарий для решения задачи картирования девиантных объектов финансового мониторинга. **Результатом** моделирования является инфографика географической составляющей отмывания преступных доходов. На основе государственных данных из различных **источников** — картотеки арбитражных дел, единого государственного реестра юридических лиц, сведений о состоянии преступности МВД России — получены социально-экономические карты: бизнес-активности федеральных округов, федеральных округов по склонности предоставления теневых финансовых услуг, регионов по склонности к легализации денежных средств, состояния преступности. Автор делает **вывод** о том, что приведенные результаты исследования могут служить мощным инструментом поддержки принятия стратегических решений и макроанализа ситуации в сфере финансового мониторинга.

Ключевые слова: поддержка принятия решений; картирование; интегральные оценки; меры девиантной деятельности; финансовый мониторинг; научная визуализация

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INTRODUCTION

Management efficiency in various sectors, in the field of public administration in particular, is largely based on objective assessment of the situation and quick response to changes.

The author considers the problem of assessing the situation on the example of the Federal Financial Monitoring Service (hereinafter referred to as "Rosfinmonitoring").

The Rosfinmonitoring is a main component of the state financial monitoring system in Russia — federal executive body responsible for combating money laundering and terrorism financing, public policy development, implementation of legal regulations and coordination of the activities of other federal executive bodies in this area[1].

According to the Federal Law No. 115-FZ "On Counteracting the Legalization (Laundering) of Criminally Obtained Incomes and the Financing of Terrorism"[2] Rosfinmonitoring receives messages from credit organizations about financial transactions of their customers, analyzes these messages, and then transfers the data to the law enforcement authorities of the Russian Federation, as well as in cases provided for by international agreements — to foreign financial intelligence units in order to combat money laundering[3].

An effective system to combat money laundering largely depends on its ability to timely identify trends and patterns in the activities of entities. To do this it is important to promptly receive objective assessments of the activities of business entities.

Traditionally, public authorities use an approach when experts consistently inspect one object after another. The results of such inspections are based on experts' subjective judgment [1, 2]. Besides, this approach is time-consuming and resource-intensive.

The increasing volume of incoming information (approximately 20% annually) leads to decreased efficiency when processing it. Decision-makers have to deal with missed deadlines and data based on subjective judgment.

The task analysis of Rosfinmonitoring has revealed that the money laundering risk assessment process is greatly limited by insufficient resources. This problem has to be addressed and considered as a priority.

A large amount of information and a variety of sources makes it impossible to evaluate and process data manually.

It is necessary to move from successive expert assessment of individual objects to automated collective evaluation process, considering modern methodological and instrumental approaches amid the digital transformation of public administration.

An important task of the decision-makers at Rosfinmonitoring is not only to reduce the response time to emerging threats but also to detect and suppress them on time. This area of analysis is of strategic importance for both financial monitoring and the national security system.

One of the ways to make inspections more effective is to visualize financial monitoring data.

Data visualization and visual analysis find their application in various sectors –industry and production, development and design, scientific research, public administration, and economics. Visual analytics provides a visualization of the phenomenon under consideration, helps to quickly catch the essence of the studied

[1] Decree of the President of the Russian Federation of November 1, 2001 No. 1263 "On the authorized body to combat the legalization (laundering) of proceeds of crime".

[2] Federal Law of 07.08.2001 No. 115-FZ "On Combating the Legalization (Laundering) of Criminally Received Incomes and the Financing of Terrorism".

[3] World Bank, Financial Markets Integrity Division. Financial Intelligence Bodies. International Monetary Fund. 2004. No. 2.

phenomena, and graphic images represent a natural and convenient means of interpreting the results [3–5].

The effective decision-making process in the field of financial monitoring consists of at least two components: the effective assessment of the situation at the tactical level, and the effective assessment at the strategic level.

The tactical component ensures the classification of individual objects of financial monitoring and assessment of the activities of groups of entities united by some common signs of financial activity. And strategic component ensures assessment of the situation at the level of territorial units of Russia.

Thus, the author proposes two approaches to visualization: assessment of the situation at a tactical level, based on the financial monitoring of individual objects; and assessment of the situation at a strategic level, based on the socio-economic mapping.

PROBLEMATIC SITUATION ANALYSIS

In the field of financial monitoring, analysts have to deal with a considerable amount of information. Statistics provides more details on these volumes.

According to the provisions of the Federal Law No. 115-FZ, the Federal Financial Monitoring Service receives information of about 100,000 financial transactions daily. It contains details of payers and recipients of funds, their accounts, and credit organizations.

As of January 2020, 3.7 million legal entities were registered in the Unified State Register of Legal Entities[4]. 286 organizations have a license to carry out brokerage activities, 314 have dealer licenses[5].

According to official information of the Central Bank of Russia, as of 01.01.2020, 442 credit organizations and their 618 branches carry out activities in the Russian Federation[6]. Bank statements contain hundreds of data fields.

In addition, the federal database of Rosfinmonitoring maintains its own accounting information for each credit institution with up to 50 data fields.

Also, the Federal Financial Monitoring Service compiles statistics for each type of object, and additional identification information, such as addresses, data of identity documents, etc.

The departmental information of Rosfinmonitoring is enriched with data from various state registers, data on the foreign economic activity of entities, and tax information [6].

The visualization of assessments of identified entities solves the problem of primary identification of financial transactions.

Currently, methods of socio-economic mapping are widely used to visualize and analyze data in various fields.

The definition of mapping is given in GOST R 52438–2005[7] as a method of modeling, graphic, digital display of geoinformation, geospatial information "with an indication of its identifier, coordinate and attribute data". Another, broader interpretation of the term "mapping" is found in spatial studies. Mapping is defined as a method of modeling, visualization, graphic representation of any spatially localized information in accordance with the specified parameters in order to cognize the depicted phenomena [7–10].

Mapping is widely used in sociology, economics, philosophy, history, psychology to study pressing problems of territorial development and systematization, the visual presentation of information about the objects of study.

Socio-economic mapping as a scientific method dates back to the 1889 study of Charles Booth, who charted London's poverty[8]. This was followed by the work of researchers of the Chicago school E. Burgess and R. Park [11] on the territorial zoning of cities in relation to migration, urbanization, inequality, crime. The compilation of social maps was based on factual information collected through interviews, statistical observation, document analysis, which was then generalized and systematized.

The works of U. Teichler, I. Ferencz, B. Wächter serve as an example of socio-economic mapping put into practice. The works present a map of international academic mobility in Europe [12]. E.S. Kuzmina [13] provides maps of the exports and imports of the education services with quantitative indicators of the social process under study.

Another example of the social mapping method put into practice is found in the analysis of urban space and presented in the works of O.I. Vendina, N.N. Veselkova, K.P. Glazkova, N.D. Vavilina, I.A. Scalaban, K. Lynch, S. Milgram [14].

The study [15] focuses on the socio-territorial structure of Moscow with statistical data put on the city map, and the authors used a socio-statistical approach.

[4] The Unified State Register of Legal Entities. URL: https://www.nalog.ru/rn77/related_activities/statistics_and_analytics/forms/8376083 (accessed on 24.01.2020).

[5] The register of brokers. Electronic resource. URL: https://www.cbr.ru/registries/ (accessed on 24.01.2020).

[6] Directory of credit organizations. URL: https://www.cbr.ru/banking_sector/credit (accessed on 24.01.2020).

[7] GOST R 52438–2005 National standard of the Russian Federation. Geographic information systems. Terms and Definitions. Moscow: Standartinform, 2006. 26 p.

[8] Charles Booth online archive. Poverty maps of London. 2002. URL: http://booth. lse.ac.uk/static/a/4.html#v (accessed on 24.01.2020).

Thus, an analysis of the sources showed that socio-economic maps generally have one or two characteristics, quantitative one-dimensional data expressed in physical units — quantity, amount, etc. For example, the number of foreign students, or data expressed in a ratio — the ratio of resident to non-resident students.

At the same time, various industries, financial monitoring in particular, have tasks that require to display objects defined by a large number of characteristics. In other words, vector objects, which have no defined order relations.

In practice, there are situations in financial monitoring when ordinal relations between regions and constituent entities are important, and specific values of rating estimates are not.

To establish ordinal relations between regions, it is necessary to rank them. However, the objects of research are of vector nature and have sets of characteristics. As known, there is no mathematical definition of ordinal relations for vectors.

Thus, it is necessary to find a scalar function of the vector argument to solve the problem of data mapping in the field of financial monitoring.

Usually, the problem of finding a scalar function of a vector argument in various fields of human activity (politics, economics, sociology, sport, etc.) is solved by experts assigning weighting factors to vector elements. In other words, a weight vector in which the scalar product is the initial vector of the object's characteristics is selected, and the desired scalar estimate is generated. However, a subjective or politically driven judgment may impact this approach.

METHOD OF PRINCIPAL COMPONENTS

A comparative analysis of methods for reducing the dimension, convolution, and scalarization of vector indicators makes it possible to classify the method of principal components as promising [16–20].

The principal components method enabled us to synthesize integral estimates of objects of financial monitoring, regions, and federal districts. The obtained scalar values made it possible to rank them and served as a basis for visualization and mapping.

The most interesting indicators demonstrate maximum variability in passing from one object to another when dealing with practical and data processing issues.

At the same time, it is not obligatory to use characteristics directly measured for a particular object. Two artificial parameters can serve as an example — size and height when choosing clothes, instead of a tailor taking specific body measurements of a person. Although some of the information gets lost and coarsened, daily practice shows that such an approach gives quite acceptable results.

These prerequisites are fundamental in finding a linear transformation of the original set of indicators, which allows us to obtain principal components.

The method of principal components analysis is based on a linear model. Taking the number of analyzed objects for *N*, the number of parameters of objects for *n*, the mathematical model will be written as:

$$y'_j = \sum_{r=1}^{n} a_{jr} f_r,$$

where $r = 1, 2,\ldots, n$; $j = 1, 2,\ldots, n$; f — r-th main component; a_{jr} — weight of the r-th component in the j-th variable; y'_j — normalized value of the j-th attribute, known from observations or obtained as a result of the experiment.

FINDING AN INTEGRAL INDICATOR OF THE DEVIANT ACTIVITY OF BUSINESS ENTITIES FOR VISUALIZATION AND MAPPING

The Supreme Arbitration Court of the Russian Federation analyzes the financial and economic activities of a liquidated legal entity during bankruptcy procedure, with an absent debtor. The results of such analyses are given in court decisions.

Shell companies are usually established for certain operations. When a shell company fulfills its assigned role, it is simply "abandoned" without any liquidation procedures to the extent required by the applicable law. Thus, shell companies often fall into the category of absent debtors, and court decisions on their forced liquidation have indicators of shell companies.

The selection, analysis, and systematization of the decisions of the Arbitration Court of the Russian Federation made it possible to form a sample of legal entities that have features of shell companies.

The value of this sample is that it includes organizations classified as shell companies, based not on intuitive guesses of experts, but on confirmed evidence supported by court decisions.

According to the obtained sample, the variances of the main components and the correlation coefficients of the characteristics of economic entities with internal factors (principal components) are calculated on the basis of this matrix.

The interpretation of the projections of the source variables on the principal components (*Table 1*) proves that the second principal component is adequate from the point of view of assessing the situation in the industry.

Ten principal components (*Fig. 1*) describe the overall data variation.

Consider the second principal component. Part of the indicators correlates positively with it, another part — negatively. Wherein, features have a negative connotation.

Table 1 and *Fig. 2* show that the most important indicators that positively correlate with the second principal component are "lack of staff", "organization activity period" and "absence of non-current assets".

These are inherent characteristics of shell companies established to conduct suspicious financial transactions and cover illegal activities.

The second internal factor is negatively related to the indicators such as "lack of movement of funds in accounts", "absence of settlement accounts" and "absence at address". These are typical signs of organizations being on the verge of bankruptcy, facing financial difficulties under adverse circumstances.

The higher the value of the second principal component, the higher the money laundering risks of the business entity.

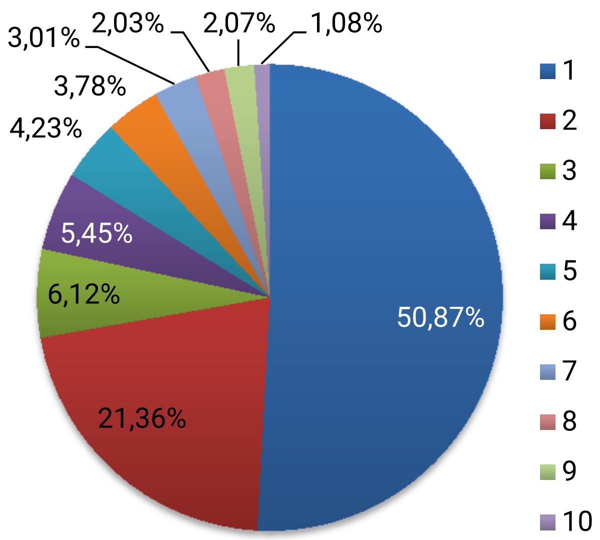

Fig. 1. **The total contribution of principal components to the total variance**

Source: compiled by the author.

INTEGRAL INDICATOR OF THE DEVIANT ACTIVITY OF PROFESSIONAL SECURITIES MARKET PARTICIPANTS USED FOR VISUALIZATION

The securities market plays an important role in a state's financial system and has its specifics. It is an attractive platform for money laundering, due to favorable trading conditions (for example, electronic bidding) and simplified process of international transactions. The securities market is a place to generate legitimate profit from money laundering.

Based on the federal financial monitoring database for professional securities market participants, the principal components variances and the characteristics' correlation coefficients of business entities with internal factors (main components) have been calculated.

The projections of the source variables on the principal components *(Table 2)* describe that the tenth principal component is adequate for the assessment process in the industry.

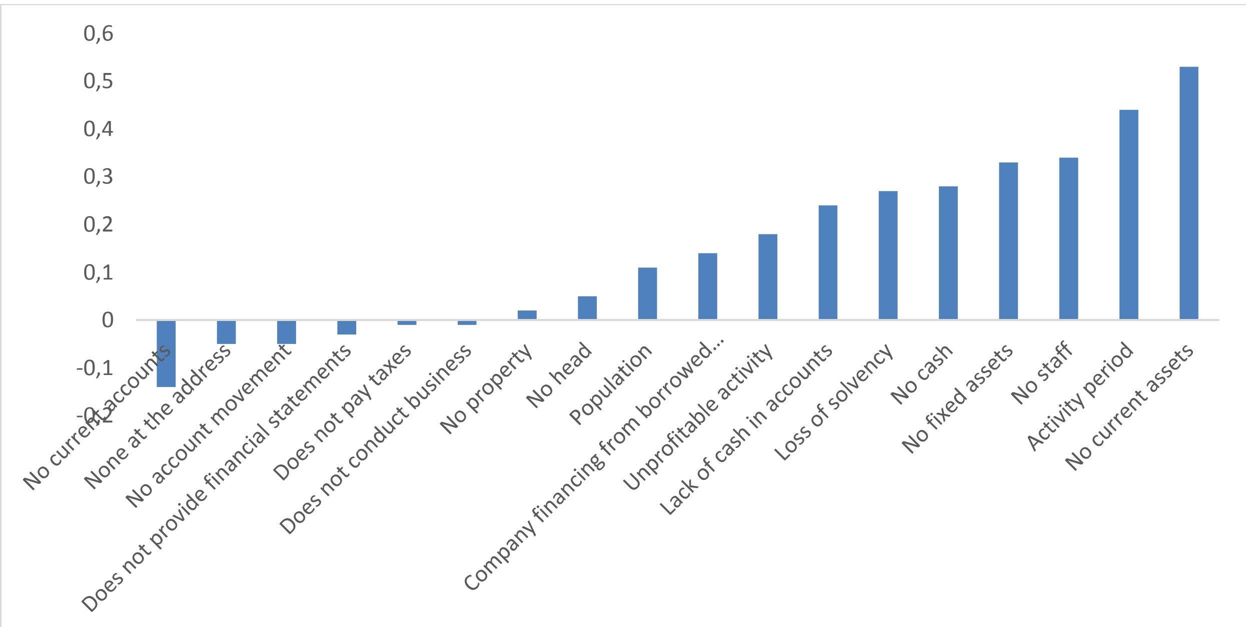

Fig. 2. **Correlation coefficients of the initial features and the second principal component**

Source: compiled by the author.

Table 1

Projections of the source variables on the new subspace

	Population	Does not pay taxes	None at the address	Does not conduct business	No property	Does not provide financial statements	No cash	No fixed assets	No current assets	No staff	Unprofitable activity	Company financing from borrowed funds	Lack of cash in accounts	Loss of solvency	No account movement	No current accounts	No head	Activity period	Contribution to the total variance in %
PC 1	0.02	−0.36	−0.36	−0.36	−0.35	−0.36	−0.03	0.03	0.04	−0.06	−0.12	−0.12	−0.16	0	−0.36	−0.34	−0.23	0	50.77
PC 2	0.11	−0.01	−0.05	−0.01	0.02	−0.03	0.28	0.33	0.53	0.34	0.18	0.14	0.24	0.27	−0.05	−0.14	0.05	0.44	21.32
PC 3	0.53	0.03	−0.03	0.02	0.07	−0.03	0.45	−0.24	−0.23	−0.28	−0.25	0.02	0.47	−0.08	−0.01	−0.12	−0.1	0.1	6.11
PC 4	−0.03	0.03	−0.05	0.08	0.1	0.07	−0.11	0.33	0.21	−0.46	−0.14	0.36	−0.15	−0.33	0.05	0.14	−0.48	0.26	5.44

Source: compiled by the author.

Table 2

Projections of source variables on a new subspace

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
Feature 1	0.37	−0.29	−0.38	−0.03	0.34	0.13	−0.06	0.59	0.39	−0.08
Feature 2	0.27	0.43	0.12	0.04	−0.11	0.57	−0.06	0.38	−0.46	0.18
Feature 3	−0.33	0.38	0.08	0.05	0.32	0.51	−0.17	−0.21	0.47	−0.30
Feature 4	0.44	0.07	0.16	−0.06	−0.56	−0.07	−0.54	−0.11	0.31	−0.23
Feature 5	−0.03	−0.09	0.67	0.55	0.26	−0.23	−0.19	0.28	0.06	0.07
Feature 6	0.40	−0.17	0.42	−0.11	0.01	0.19	0.62	−0.15	0.05	−0.41
Feature 7	−0.27	0.42	−0.09	0.14	−0.39	−0.28	0.38	0.48	0.21	−0.28
Feature 8	0.3	0.34	−0.18	0.05	0.43	−0.34	−0.15	−0.12	−0.34	−0.46
Feature 9	0.35	0.45	0.05	−0.09	0.16	−0.22	0.24	−0.17	0.39	0.59
Feature 10	−0.19	0.06	0.38	−0.81	0.16	−0.17	−0.15	0.29	−0.03	−0.03

Source: compiled by the author.

Ten principal components describe the overall data variation (*Fig. 3*). *Table 2* presents calculations of factor loads — projections of the initial variables on each of the principal components.

The tenth internal factor is the most interesting. This factor corresponds to the deviant component, i.e. the securities market is vulnerable to the activities of money laundering.

The obtained results reflected the subject area under consideration, and the securities market experts confirmed it.

VISUALIZATION OF THE INTEGRATED ASSESSMENTS OF ENTITIES' FINANCIAL MONITORING

The scientific visualization was based on the deviant activity measures of business entities, credit organizations, and the securities market participants.

Figure 4 shows a diagram of financial transactions.

The "house" icon indicates business entities, red circles indicate high-ranked subjects, and green circle — low-ranked subjects.

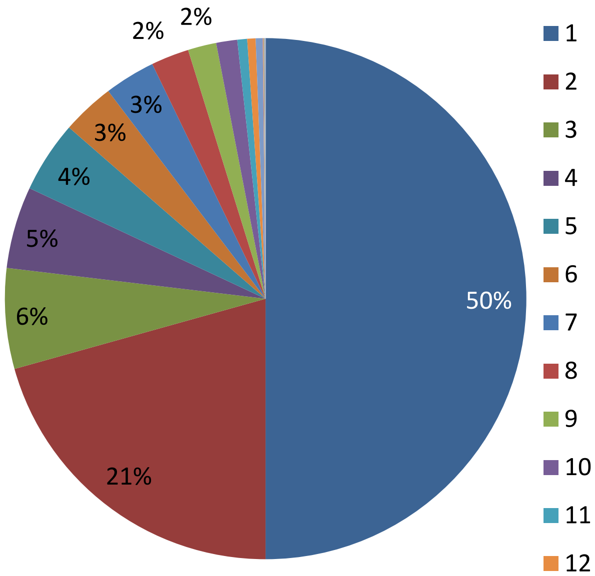

Fig. 3. **The total contribution of principal components to the total variance**

Source: compiled by the author.

Thus, it is the first scientific solution to the problem of visualization of the measure of the deviant activity of entities: business entities, credit organizations, and professional securities market participants. The article explores and solves the problem of synthesizing measures of the deviant activity of entities' financial monitoring.

A socio-economic map, based on the deviant activity measures of business entities, has been created. It reflects the money laundering situation in Russian regions (*Fig. 5*).

These are important results for strategic decision-making, with the main focus on problematic regions.

We study if this approach applies to other official data analysis.

RUSSIAN LEGAL ENTITIES DATA. BUSINESS ACTIVITY MAPPING

The Unified State Register of Legal Entities (hereinafter referred to as USRLE) provides information about Russian legal entities. The USRLE is a part of the Fed-

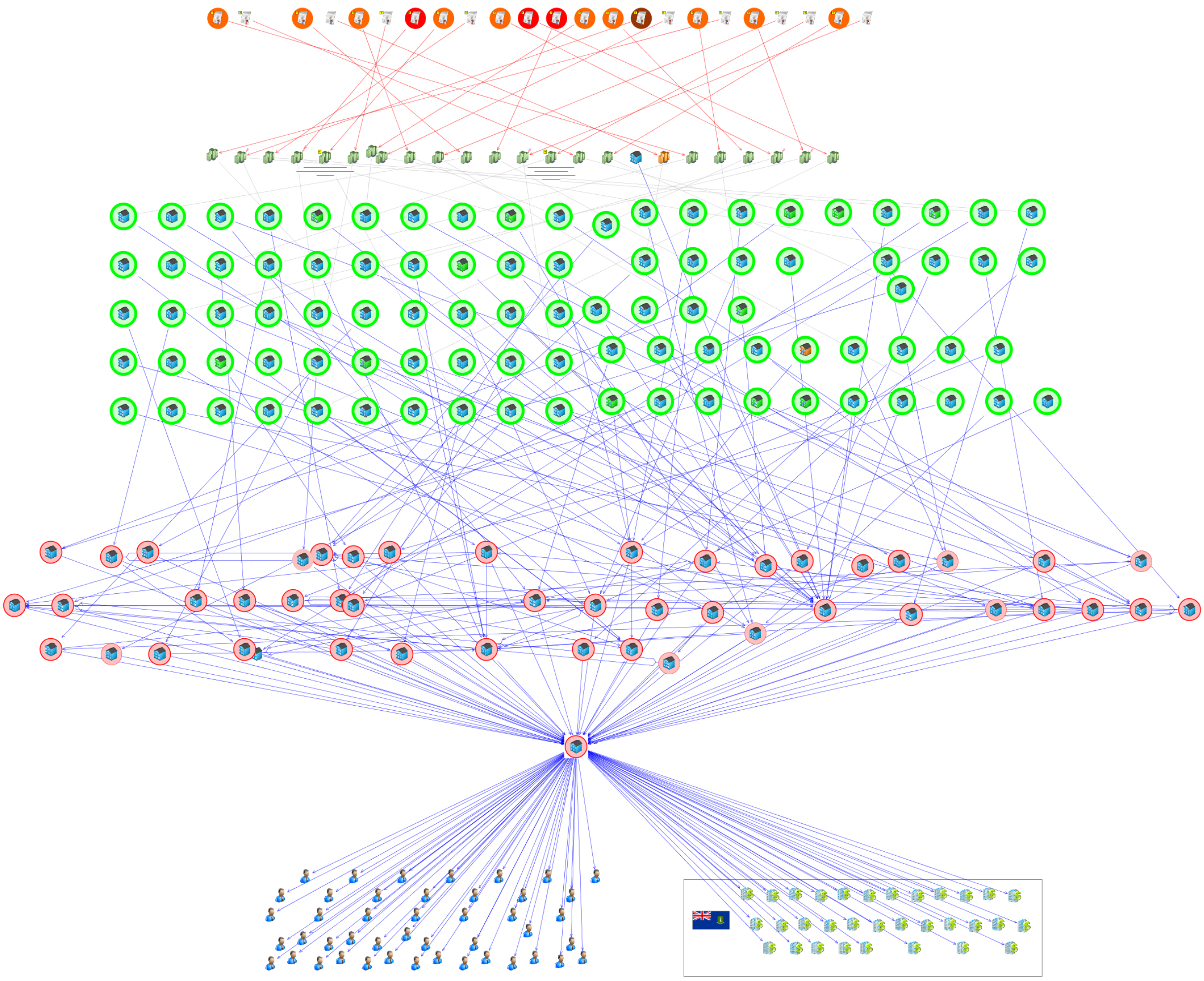

Fig. 4. **Financial transactions diagram**

Source: compiled by the author.

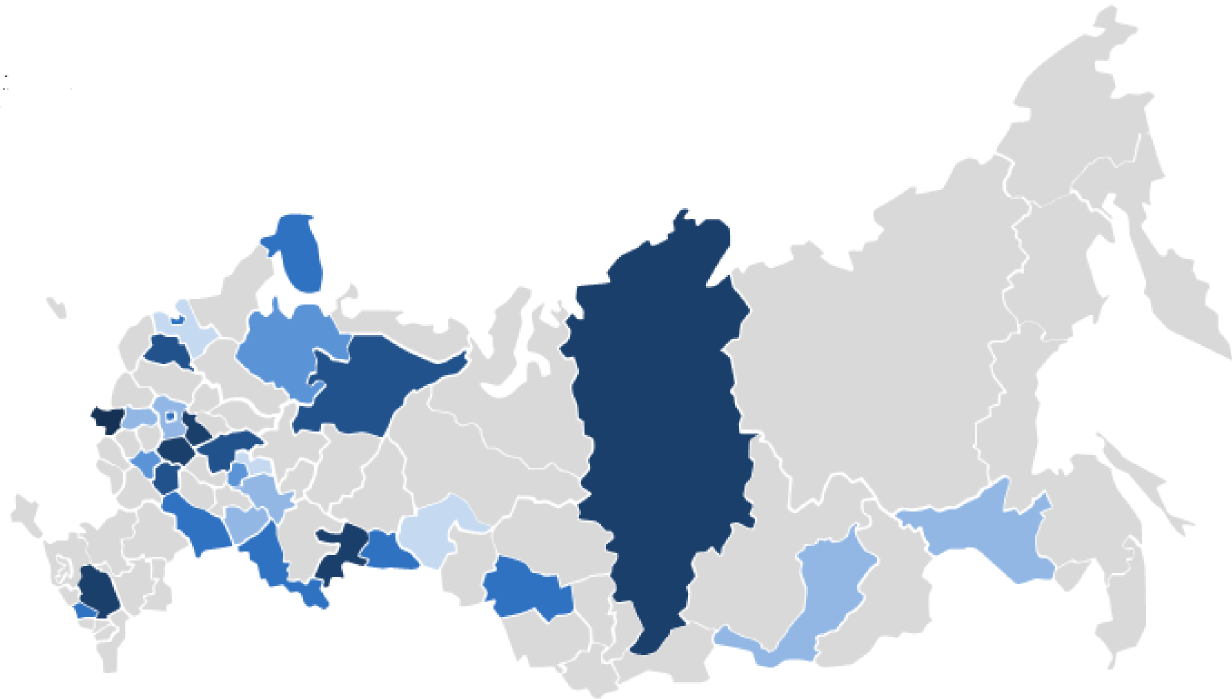

Fig. 5. **Mapping the propensity to legalize cash**

Source: compiled by the author.

eral Tax Service of Russia, which contains information about registration, reorganization, and liquidation of Russian companies.

We study the geographical component of this information by considering the legal entities' registration statistics.

We apply the method of principal components to the initial data.

We calculate the variances of the main components and the correlation coefficients of the indicators with internal factors (main components) based on this matrix. Six main components describe the overall variation of the data. The first two main components contribute 75% of the total variance. *Figure 6* presents a graphical illustration of the contribution of the internal factors to the total variance.

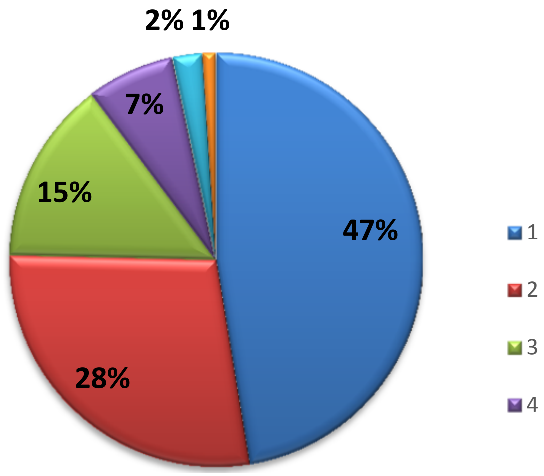

Fig. 6. **Total contribution of the main components to the total dispersion**

Source: compiled by the author.

Consider the first major component. There is a negative correlation between the signs of "legal entities that have ceased their activity due to bankruptcy", "legal entities that have ceased their activities, total", "legal entities that ceased their activities by the registration authority decision" and "legal entities that ceased their activities as a result of liquidation".

In addition, a positive correlation is evident with the signs of "legal entities under reorganization", "legal entities that ceased their activities as a result of reorganization", "total operating legal entities" and "total legal entities created". On this basis, we can talk about the bipolarity of the first principal component. The tendency to register new legal entities and reorganize previously registered ones is a positive sign of the factor. The tendency to liquidate organizations for various reasons is negative. The first major component reflects the business activity of the region. *Figure 7* shows the mapping of business activity in federal districts. A more intense colour represents higher values of the first principal component.

The inverse factor solution allowed to rank the federal districts according to the situation assessment and use the results for visualization purposes.

Table 3

Correlation coefficients of indicators and principal components

Name of indicator, pcs.	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Total operating legal entities	0.4005	0.0383	−0.207	0.0622	0.0102	−0.21
Total legal entities created	0.3883	−0.001	−0.265	0.081	−0.09	−0.321
Existing legal entities formed by creation	0.3865	0.0003	−0.275	0.0716	−0.093	−0.317
Existing legal entities created through reorganization	0.1417	−0.086	0.5672	0.5852	0.1991	−0.301
Existing legal entities registered before 07/01/2002	0.3702	0.2021	0.093	−0.033	0.4433	0.3206
Legal entities under liquidation	0.2351	−0.361	−0.012	0.4817	−0.367	0.3827
Legal entities under reorganization	0.1218	−0.43	−0.303	−0.034	0.6885	0.1861
Legal entities that ceased operations, total	−0.212	−0.443	−0.215	0.0245	−0.072	−0.123
Legal entities that ceased operations as a result of reorganization	0.3897	−0.022	−0.025	−0.337	−0.338	0.2523
Legal entities that ceased operations as a result of liquidation	−0.176	0.296	−0.412	0.5083	−0.045	0.426
Legal entities that ceased their activities due to bankruptcy	−0.186	0.391	−0.378	0.1874	0.1221	−0.297
Legal entities that ceased their activities by the registration authority decision	−0.223	−0.444	−0.172	0.0136	−0.037	−0.171

Source: compiled by the author.

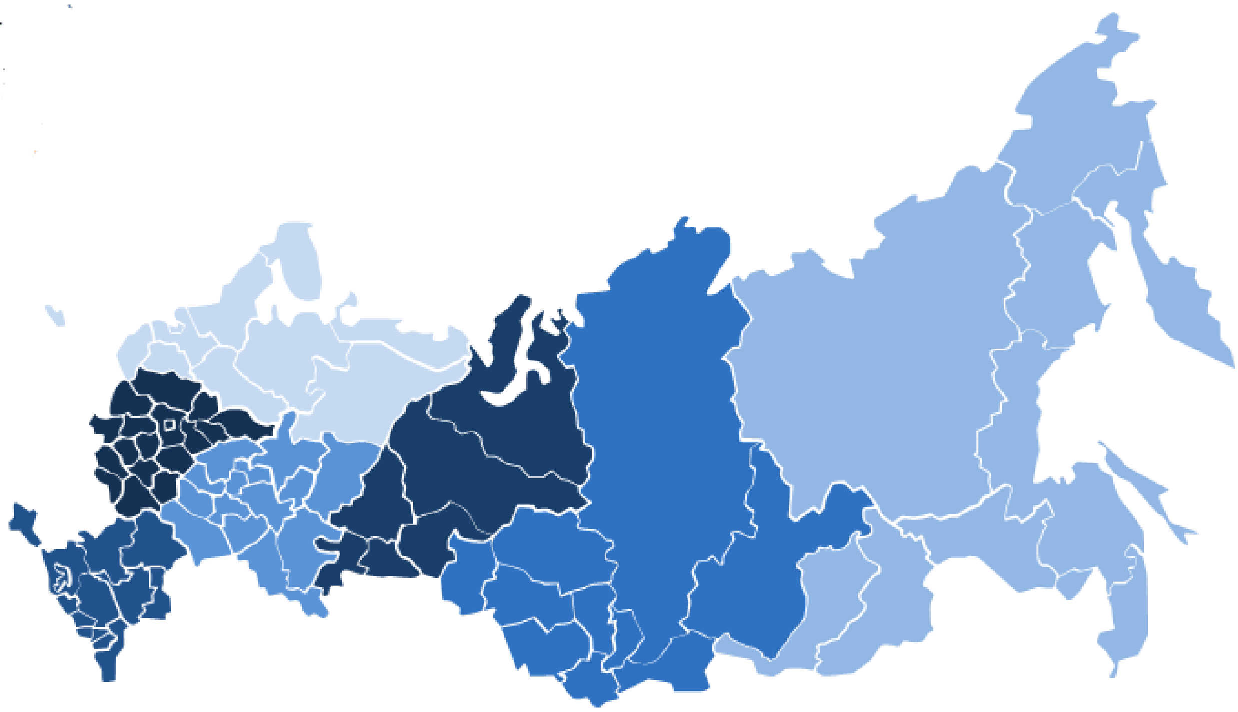

Fig. 7. **Mapping business activity of federal districts**
Source: compiled by the author.

Table 4

The value of the principal components for the federal districts

Federal District	PC 1	PC 2	PC 3	PC 4	PC 5
Central	2.262	−0.307	1.256	0.420	0.149
Northwestern	−0.065	−0.296	0.138	−2.083	1.292
Southern	0.103	−0.506	−0.558	−0.342	−1.278
Volga	0.793	1.066	−1.855	0.297	−0.314
Ural	−0.547	0.332	0.040	1.558	1.233
Siberian	−0.614	1.968	1.019	−0.589	−0.826
Far Eastern	−0.891	−0.060	0.247	0.527	0.858
North Caucasian	−0.184	−0.986	−1.011	−0.215	0.156

Source: compiled by the author.

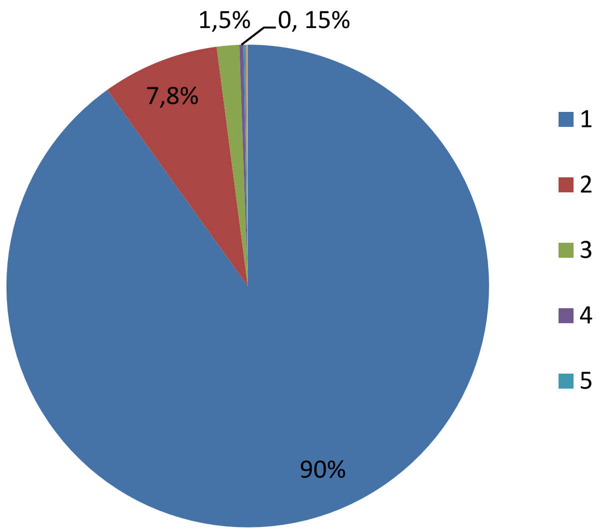

Fig. 8. **Total contribution of the principal component to the total variance**

Source: compiled by the author.

CRIME DATA MAPPING

The crime rate in the country is an indicator of the well-being of society and the quality of life of the population. At the same time, the state audit plays an important role in planning and conducting comprehensive control and supervisory measures.

In terms of national security mapping, scientific evidence requires an in-depth study of factors. The main component method was used to analyze official crime data of the federal districts (information taken from the official website of the Ministry of Internal Affairs of Russia). *Table 4* presents the values of the main components for the federal districts.

The pie chart (*Fig. 8*) represents the contribution of each component to the total variance. The first major component makes the biggest contribution of 90% and is an integral characteristic of the crime rate in the federal district.

Figure 9 shows the ranking of federal districts by the first main component — the more intense the color, the higher the value of the main component. The highest values are in the Central, Volga and Southern federal districts, and the lowest are in the Far East, Crimean, Siberian and Ural.

CONCLUSIONS

Two options are proposed to visualize financial monitoring information in order to assess the situation at the tactical and strategic levels. The problem of sci-

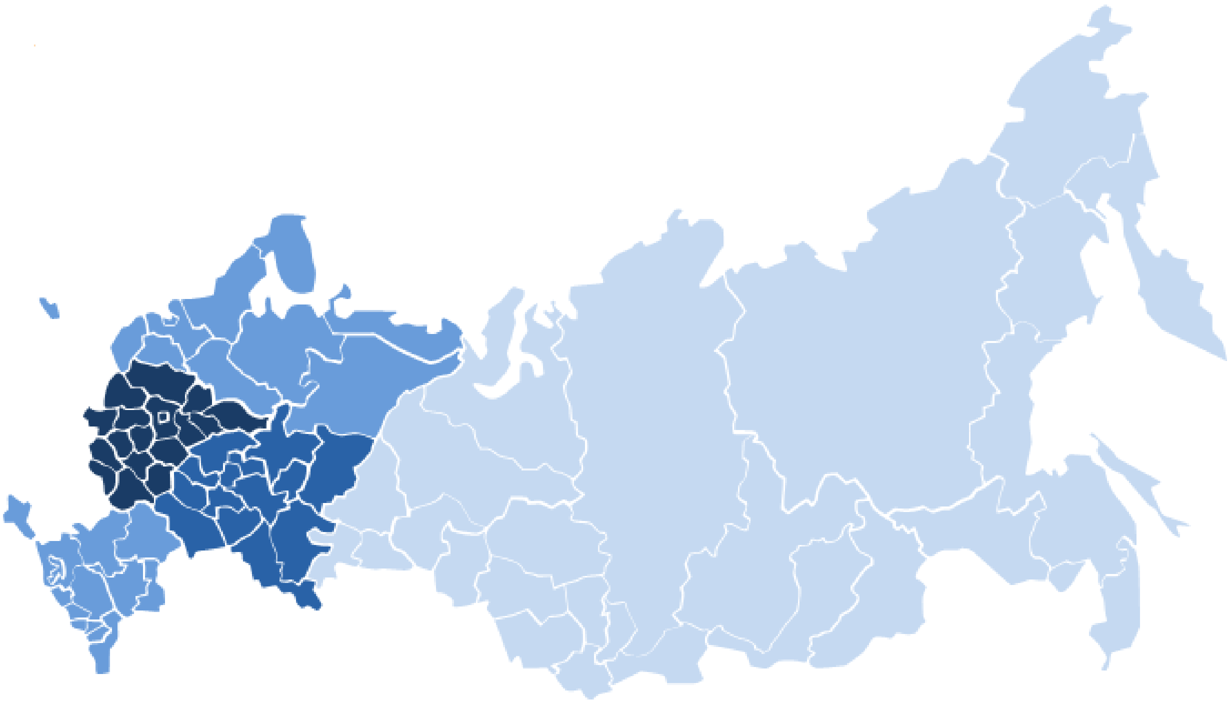

Fig. 9. **Crime mapping**

Source: compiled by the author.

entific visualization of the deviant activity measures for business entities has been solved.

The mapping process was based on the integrated assessments of the situation in the field of financial monitoring, the economic activity of regions, and the crime rate.

The visualization of the deviant activity measures provided the necessary information for decision-makers.

Thus, decisions about high-ranked entities should be made relying on financial investigations and information received from the law enforcement authorities.

In the case of low-ranked entities, decision-makers should take preventive measures aimed at suppressing negative trends and further situation development.

The proposed solution has significantly improved efficiency in identifying business entities' involvement in illegal activities.

As a result, the method of principal components applied to analyze data allowed to successfully rank regions, establish ordinal relations of the constituent entities of Russia in the field of financial monitoring, and create socio-economic maps.

The proposed method of presenting information in the field of financial monitoring should be used to solve related problems in other sectors of the economy.

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