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Promoting Public Integrity and Combating Financial Crime: Challenges on the Pathway to Sustainable Development

Serhiy LYEONOV
Victoria BOZHENKO
Serhiy MYNENKO

Centre of Sociological Research

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Reviewers:

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Prof. Dr. Bhola Khan

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INTRODUCTION

The Sustainable Development Goals envisage the implementation of systemic reforms by 2030, which will contribute to the qualitative transformation of the economic, social, and environmental spheres of society. However, corruption schemes and unscrupulous behaviour of public administration representatives can undermine the successful implementation of all 17 Sustainable Development Goals. Therefore, the effective anti-corruption system and anti-money laundering at the global level, which will be based on the principles of transparency, accountability, and integrity, is one of the key tasks of international organizations and national regulators.

Due to economic fraud and corruption, the world's health care system loses an average of about $455 billion annually out of $7.35 trillion, or 6.2% of the total. Corruption and economic fraud in these areas deprives a citizen of his fundamental rights to receive fundamental right to get education, personal health safety status and so on. Corruption contributes to the irrational use of public funds, the residual principle of financing the medical industry, uneven access to medical services, a decrease in the quality of medical care, etc.

Digital technologies and artificial intelligence algorithms can serve as tools to combat corruption and business misconduct by expanding access to public information, monitoring the activities of public administration and local government, digitizing administrative services, and providing opportunities to report corruption. The United Nations estimates that about $ 1 trillion is paid annually as bribes, and $ 2.6 trillion is stolen because of worldwide corruption.

The purpose of this monograph is to investigate threats and obstacles arising from corruption and economic crime to sustainable development. It is necessary to solve such tasks to achieve the goal:

- to analyse the impact of corruption and crime on the achievement of certain sustainable development goals;
- to investigate transformational changes in the implementation of illegal activities caused by the rapid development of civil and information technologies;
- to examine the impact of the development of cryptocurrencies on the spread of cyber fraud
- to study the manifestations of corruption in climate finance.

The monograph was performed within the framework of the research themes «Data Mining for Countering Cyber Fraud and Money Laundering in the Context of Digitalization of the Financial Sector of the Ukrainian Economy» (0121U100467), «Modeling mechanisms for de-shadowing and de-corumping the economy to ensure national security: the impact of the financial behavioral patterns transformation» (0122U000783), "National security through the convergence of financial monitoring systems and cyber security: intelligent modelling of financial market regulation mechanisms" (0121U109559) which are financed by the State budget of Ukraine.

CHAPTER 1. CORRUPTION AND FINANCIAL CRIME: THREATS FOR SUSTAINABLE DEVELOPMENT

1.1. Financial Crime and Corruption: barriers to achieving Sustainable Development Goals

Corruption is not a problem of any individual countries or regions, it has become a global challenge for the international community. The World Bank (2000) describes corruption as the "use of public office for private gain". This definition concentrates on some illegal activity that involves public officials, civil servants, or politicians. However, corruption in health care is unique because it includes not only abuses by public officials, but also unscrupulous behaviour by other actors (drug manufacturers, medical professionals, patients, etc.). Corruption in healthcare can range from petty corruption to corruption at the national or international level (Transparency International, 2006).

Aidt (2010) empirically proved the existence of a negative correlation between corruption and sustainable development. In addition, the author substantiated that corruption increases economic instability in the country due to the eroded capital base. Therefore, the destructive consequences of corruption permeate various spheres of human life:

– Politics and Government - lobbying the private interests and making favourable regulatory environment to the business activity; the imperfection of judicial control in the country.

– Economy - tax avoidance, money laundering, illegal trade, inefficient and inappropriate use of public funds, reducing the country's investment attractiveness, restraining the pace of innovative development.

– Society – increasing income inequality, poverty growth, limited access to essential basic needs (electricity, water, food, education, healthcare), rising violence and crime etc.

– Ecology – irrational mining and subsoil use, depletion of forest resources due to their uncontrolled deforestation, non-compliance with the special regime of use of natural resources within the relevant territories.

The health care system is characterized by a high level of decentralized relations with limited supervision, which makes it relatively attractive for violators (WHO, 2011). This means that financial relations in the medical field arise between a wide range of persons who can act as initiators of corruption decisions and/or their executors (Hussmann, 2020):

– state regulatory bodies (parliament, Ministry of Health, specialized institutions).

– manufacturers and suppliers of medical drugs and equipment.

– providers of medical services (state and private hospitals, doctors, pharmacists).

– payers of medical services (enterprises, private individuals).

– consumers of medical services.

– International organizations in the field of health care.

Corruption in the healthcare and education system can take the form of bribery, extortion, theft, embezzlement, and undue influence. The main types of corruption offenses in the healthcare sector are:

– non-transparent procedure for applying positions in health facilities.

– providers of medical services can be fictitious companies that are created for money laundering and other illegal purposes.

– receipt of illegal benefits by specialists of the health care system to popularize the products of pharmaceutical companies (GRECO, 2020).

– avoiding or speeding up the procedure of registration of medicinal products due to bribery of executive branch officials (UN Human Rights).

– bribery of employees of regulatory bodies and medical professionals to provide false data about the results of clinical trials of medicinal products (UN Human Rights);

– non-targeted and ineffective use of state funding for the health care system.

– non-transparent public procurement procedure etc.

The main manifestations of corruption in the education system are:

– illegal collection of funds from parents for admission to an educational institution.

– a non-transparent admission procedure for students of higher education.

– unequal conditions in the recruitment process.

Thus, corruption is accompanied by a violation of ethical standards and principles of integrity, which leads to irrational or untargeted use of public funds in the field of health care and education.

To test the relationship between sustainability indicators and the Corruption Perceptions Index (CPI), a model was built based on balanced panel data. Panel data combines the advantages of spatial data and time series, which allows to analyse and isolate changes at the individual level of each object. Panel data provide more informative data, greater variability, less collinearity between variables, more degrees of freedom, and greater efficiency. Within this study, it was decided to analyse the impact of corruption on government spending on essential services: domestic general government health expenditure, % of GDP (HLT), government expenditure on education, % of GDP (EDC). Data from The World Bank Group website and Transparency International served as the source of primary data.

To obtain more reliable results of assessing the impact of corruption on the financing of basic public needs, it was decided to generate panel data based on homogeneous countries according to the level of corruption in them. Thus, the average value of the index of perception of corruption during 2012-2020 was determined for each country, the minimum and maximum values of the index were calculated, and three groups of countries were distinguished based on them:

– countries with low-level corruption (65,1 <CPI ≤ 89,4): Australia, Austria, Belgium, Canada, Chile, Denmark, Germany and others (26 countries).

– countries with middle-level corruption (40.8 < CPI ≤ 65.1): Czech Republic, Hungary, Italy, Latvia, Lithuania, Poland, Portugal and others (36 countries).

– countries with high-level corruption (16.4 ≤ CPI ≤ 40.8): Albania, Armenia, Egypt, Vietnam, Belarus, Bolivia, Bangladesh, Nepal, Kenya, Ukraine and others (78 countries).

The main hypotheses of this study are:

H1. Corruption affects the government spending on essential services.

H2. The level of corruption (low, medium, high) unevenly affects government spending on essential services.

Based on this, three arrays of statistical data were formed for countries with high, medium and low levels of corruption for the period 2012-2019. All indicators have been prologarithmized, which made it possible to reduce the residuals of the model and increase their compliance with the normal distribution law.

Assessing the impact of corruption on individual indicators of sustainable development involves the following steps: testing data for stationarity; determining the presence of cointegration between the variables; estimation of parameters according to the econometric model; checking the adequacy of the models.

The initial condition for a panel regression model is to test variables for stationarity. For panel data it can be used the following criteria to check for unit roots: Levin-Lin-Chu, Khadri, Pesaran and Chin, Dickey-Fuller tests. All mathematical calculations were performed in the Eviews program. Testing for the presence of a unit root in panel data involves testing the null hypothesis that the series is stationary at $p<0.05$. The results of testing the variables for stationarity are presented in Table 1.1.

Table 1.1. Results of panel data testing for unit root

Group of countries	Indicator			Levin, Lin & Chu Test		IM, Pesaran and Shin Test	
				statistic	prob.	statistic	prob.
Low-level corruption (26 countries)	Domestic general government health expenditure (% of GDP)	CPI_1	level	-3,965	0,000	0,665	0,747
			1st difference	-11,735	0,000	-3,812	0,000
		HLT_1	level	-12,632	0,000	-0,759	0,224
			1st difference	-5,517	0,000	-3,170	0,022
Middle-level corruption (36 countries)		CPI_2	level	-25,093	0,000	-5,672	0,000
			1st difference	X	X	X	X
		HLT_2	level	-19,907	0,000	-3,481	0,002
			1st difference	X	X	X	X
High-level corruption (75 countries)		CPI_3	level	-8,876	0,000	1,312	0,905
			1st difference	-23,419	0,000	-3,627	0,000
		HLT_3	level	-18,513	0,000	3,232	0,001
			1st difference	X	X	X	X
Low-level corruption (22 countries)	Government expenditure on education(% of GDP)	CPI_4	level	-7,498	0,000	-0,882	0,189
			1st difference	-10,407	0,000	-3,298	0,001
		EDC_1	level	-5,500	0,000	-1,3378	0,084
			1st difference	-16,117	0,000	-5,531	0,000
Middle-level corruption (29 countries)		CPI_5	level	-24,178	0,000	-5,988	0,000
			1st difference	X	X	X	X
		EDC_2	level	-15,384	0,000	-3,325	0,000
			1st difference	X	X	X	X
High-level corruption (59 countries)		CPI_6	level	-8,239	0,000	-0,054	0,478
			1st difference	-21,164	0,000	-7,343	0,000
		EDC_3	level	-8,910	0,000	-0,824	0,205
			1st difference	-36,563	0,000	-10,012	0,000

The results of estimation the statistical criteria for checking the presence of unit roots allow us to state that most of the indicators at the actual levels are non-stationary time series. To convert them into stationary variables, their first differences are determined. Among the analyzed indicators, the following variables were immediately stationary: HLT2, HLT3, CPI5, EDC2.

Since there is integration for some indicators, it is necessary to carry out tests for cointegration between the variables – to test the assumption of long-term relationship between them. The Kao statistical test was used for verification, which involves testing the null hypothesis of the absence of cointegration relationships between variables. Since the p-value < 0.05 we can assert the presence of cointegration and a long-term relationship between the variables (table 1.2).

Table 1.2. Results of testing variables for cointegration

Indicator	Group of countries	t-Statistic	Prob.	Result
Domestic general government health expenditure (% of GDP)	low-level corruption	-2,5095	0,0060	cointegration
	middle-level corruption	-2,0742	0,0190	cointegration
	high-level corruption	0,1102	0,4561	no cointegration
Government expenditure on education (% of GDP)	low-level corruption	-0,7562	0,2248	no cointegration
	middle-level corruption	-2,8780	0,0020	cointegration
	high-level corruption	-0,7803	0,2176	no cointegration

Table 1.2 indicates the existence of a long-term relationship between corruption and domestic general government health expenditure for countries with low-level and middle-level corruption. In addition, there is a co-integration relationship between corruption and government expenditure on education for countries with middle-level corruption.

Considering the results of the previous stage on checking the cointegration relationship between variables, panel regression models were built. The following methods were used to determine the regression coefficients: there is cointegration – fully modified least squares; no cointegration – least squares.

The results of the calculation of the regression parameters for three groups of countries are shown in tables 1.3, 1.4.

Table 1.3. Results of assessing the impact of corruption on domestic general government health expenditure.

Group of countries	CPI			Coefficient of determination
	coefficient	t-Statistic	Prob.	
low-level corruption	-0,0439*	-2,4597	0,0146	0,9867
middle-level corruption	-0,0355*	-179,4797	0,0000	0,9946
high-level corruption	0,0436*	54,9932	0,0000	0,9882

* statistically significant

Table 1.3 indicates that the level of corruption (low, middle, high) affects the financing of the health care system in different ways. In countries with a low and medium level of corruption, an increase in the CPI by 1 point in the long term leads to a decrease in the share of domestic general government health expenditure in GDP by 0.0439% and 0.0355%, respectively. This shows that the improvement of the anti-corruption system in countries with low and medium levels leads to the optimization of public spending on the medical system and the involvement of private institutions in the co-financing of medical services.

For countries with a high level of corruption, an inverse relationship has been proved: an increase in the CPI by 1 point is accompanied by an increase in the share of public spending on the health care system in relation to GDP by 0.0436%. The obtained results of panel regressions are adequate, as evidenced by the high level of the coefficient of determination and statistically significant regression coefficients (prob <0.05).

Table 1.4. Results of assessing the impact of corruption on government expenditure on education

Group of countries	CPI			Coefficient of determination
	coefficient	t-Statistic	Prob.	
low-level corruption	-0,0114*	-2,0604	0,0411	0,9941
middle-level corruption	-0,0218*	-15,3380	0,0000	0,9904
high-level corruption	-0,0031	-0,2659	0,7904	0,8716

* statistically significant

An increase in the corruption perception index (in fact, a decrease in the risk of corruption in the country) causes a decrease in government expenditure on education on GDP. Only for countries with high-level corruption this pattern is not legitimate since there is no statistically significant relationship between the analysed variables. In confirmation of the validity of the above conclusions, we note that the constructed regression models based on panel data are adequate. The coefficient of determination for countries with low-level and middle-level corruption is 0.9941 and 0.9904, respectively, that is, the independent variables that are included in the econometric models describe the change in the performance indicator by 99.41% and 99.04%.

Today, corruption is key threats to achieving the Sustainable Development Goals. Corruption creates destructive mechanisms for stable economic development, weakens democratic institutions and the principle of the rule of law, exacerbates the problem of uneven distribution of income and access to medical, educational, and other services. In addition, corruption destroys public trust in representatives of public administration, as well as the formation of an established opinion in society about the possibility of solving any issue through bribery or bribery. This is a worldwide concern, as corruption acts as a trigger for growing social discontent that leads to violent extremism, conflict, crime, terrorism, etc.

1.2. Digital Technologies and Artificial Intelligence: ways of preventing and solving financial crimes, promoting public governance.

The last decade has seen the rapid development of digital information technology, the intellectualization of control systems, the increase in the number and capacity of mobile and computer devices, the accumulation of large data sets and their processing by machine learning algorithms. Digitalization has led to improved performance in various areas. For example, the level of transparency of public administration increased, public control strengthened, the bureaucratization was reduced. Therefore, digital technologies and artificial intelligence algorithms can serve as tools to combat corruption and business misconduct by expanding access to public information, monitoring the activities of public administration and local government, digitizing administrative services, and providing opportunities to report corruption.

Artificial intelligence technologies, machine learning, and big data analysis are increasingly used to improve anti-corruption systems globally. Establishing international standards and cooperation at the international level allows forming a basis for reducing the manifestations of business misconduct in the global dimension. Innovative methods and algorithms for processing big data allow identifying anomalies, establishing patterns of informal relationships, as well as minimizing the role of human in the system of decision support for corruption.

The latest technologies allow decisions to be made based on big data analysis, which reduces the risk of corruption by eliminating the human factor. According to the Open Government Partnership (OGP, 2020), digital governance is the second-fastest-growing policy area in the current OGP action plans. More members focus on accountability using government machine learning and artificial intelligence (AI) algorithms. In recent years, open data has become one of the most important methods in the fight against corruption, so the priority steps are the introduction of open data and accountability of public procurement, the activities of government officials.

Thus, the Netherlands, in its action plan for 2020-2022, noted the improvement of algorithms for monitoring the transparency of procurement, the commitment to promote digital platforms for citizen participation, and promote their use by local authorities (United Nations, 2018). Spain's Action Plan for 2020-2024 includes a commitment to introduce legislative measures and instruments that strengthen integrity and prevent corruption in government. An important step is the creation of manuals on the use of artificial intelligence in the public sector. In addition, the plan includes a commitment to establish a Data and Ethics Centre for Innovation, which will provide guidance and advice to civil servants on the ethical use of new technologies in public practice.

In Ukraine, the active process of digitalization began in 2019. The mobile application Dia (derived from the web portal), which serves as an online public service, has 11 million users in two years. In 2020, 17 types of administrative services were available online. According to research, the potential economic effect of digitalization of only 17 administrative services in seven areas is almost UAH 495 million per year. The expecting anti-corruption performance is UAH 841 million per year. As of 2021, 74 services have been ported to digital format. The strategic plan of the Ministry of Digital Transformation of Ukraine includes the transfer of all offline services to the digital format by 2024. Ukrainian public procurement system Prozorro has been operating since 2015, and, as of 2019, has saved UAH 63 billion of the government budget (Ukrinform, 2019).

By using systems Prozorro and Dozorro it is possible to monitor tenders and public procurement. Furthermore, Ukraine has such tools as the Repair Map (a tool that allows you to find how much money from the budget of any level spent on a particular repair), Road Geocalculator. In addition, there is portal "Hidden interests" (on the portal, artificial intelligence technology allows you to find connections between the person and the companies participating in the tender). Ukraine has also created a single state web portal of open data, where you can quickly find statistical information on sectors of the national economy, government revenue and expenditure, enterprises, infrastructure, and more.

An example of the successful implementation of digital technologies in the public sector is Estonia - the country with the most developed digital society in the world. In 1996, Estonia had introduced the National Program for the Development of IT Infrastructure. Thanks to the implementation of the program, in 2021, Estonia has such achieving: high-quality e-banking; digital identification based on a mandatory ID card, which has 98% of the population; electronic medical cards for each patient, 99% of medical prescriptions are processed online; paying taxes takes about 3 minutes online; 98% of people declare their income electronically; administrative services provided online; 95% of parking fees are paid by mobile phone (Estonian m-parking system is accepted in countries around the world). The digitalization of the public sector is the main reason for minimizing bureaucracy in Estonia and saving money. For example, digital signatures save 2% of GDP annually, and thanks to the electronic portal of the Estonian Road Administration, services are provided six times faster and 20% cheaper (E-Estonia, 2022). In 2020 Estonia launched the National Open Data Portal, which provides free access to data (U4, 2020).

Brazil has developed a software product based on machine learning, which allows assessing the risk of corrupt behaviour among civil servants based on data on criminal records, education, political affiliation, business relationships.

IBM specialists with the Government of Kenya cooperated to optimize the administrative procedures required to start a business (from 11 to 3 steps). The usage of artificial intelligence has allowed Kenya to rise from 92 to 61 place in the ranking of "Ease of doing business" (CMI. Chr. Michelsen Institute, 2019).

In Britain, the tax authorities have used computer technology for digital transformation and data collection to reduce the tax gap. As a result, the Connect system analyses taxpayers' data to identify potential tax evaders. The algorithm identifies people who are most likely to commit tax fraud and helps to develop precautionary measures. From 2008 to 2014, thanks to the system, an additional 3 billion pounds of tax revenue were received (OECD, 2021).

Transparency as a property of public administration provides an opportunity to openly implement public policy through transparent tools and clear procedures. The higher the level of openness, transparency, and publicity of public authorities, the less opportunity for unscrupulous public officials to implement corruption schemes and make ineffective or criminal decisions. With the development of transparency of public authorities, the welfare of society increases.

In turn, society’s scientific and technological progress does not stand still. The development of digital technologies opens vast opportunities for ensuring the transparency of public authorities. Using the latest tools, it is possible to implement e-government directly by the region's residents, simplify the receipt of public services, monitor the use of the budget, and the voting results of MPs at any level of government.

A deeper understanding of digitalization's impact on public administration's transparency is possible through canonical analysis. The general form of the dependence in the canonical analysis is as follows (formula 1.1):

$$a_1 * x_1 + a_2 * x_2 + \ldots + a_n * x_n = b_1 * y_1 + b_2 * y_2 + \ldots + b_m * y \qquad (1.1)$$

where $x_1 .. x_n$ – variables, definingdigitalization (left side);
$y_1 .. y_m$ – variables, defining public administration (right side);
$a_1 .. a_n$ – coefficients of the canonical variable for the left side;
$b_1 .. b_m$ – coefficients of the canonical variable for the right side.

31 European countries were selected for the study. The input

data are 11 indicators divided into two groups: indicators of the level of digitalization and characteristics of public authorities. The first group includes the following indicators. Digital Development Level from E-Governance Academy Foundation. The selected indicator summarizes the level of development of information and communication technologies (ICT Development Index) and the network readiness indicator (Network Readiness Index). IMD World Digital Competitiveness Ranking is built on 51 criteria and characterizes the level of competitiveness of the country's digital sector. ICT goods exports (% of total goods exports) describe the demand for information technology in the international market and the share of the ICT market in the country. ICT goods imports (% total goods imports), which characterizes the country's digitalization level. ICT service exports (% of service exports, BoP) reflect how much the country's digital services are in demand in the international market.

Indicators that characterize public authorities include six indicators of The Worldwide Governance Indicators (WGI): Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. These indicators characterize all aspects of public authorities in the country, freedom of elections, transparency, tolerance for corruption and the overall quality of governance. The statistical package Statistica 12 was used to implement the canonical analysis (figure 1.1).

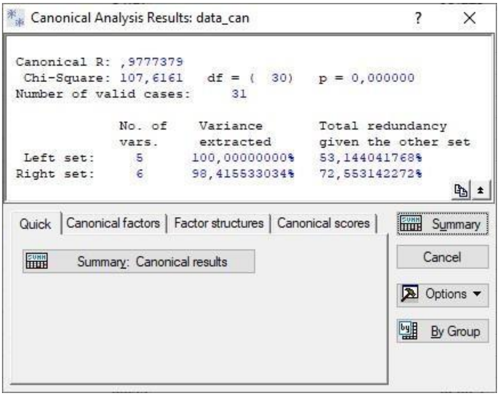
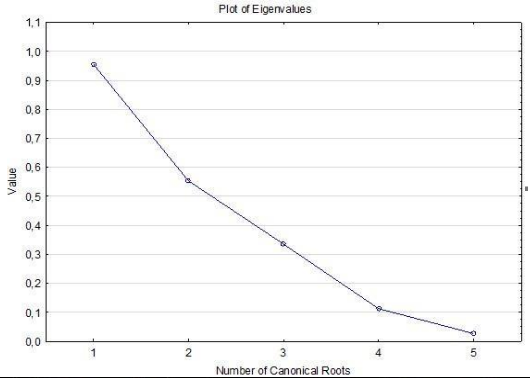


Figure 1.1. The Results of Canonical Analysis

According to Figure 1.1, the canonical correlation (R) between the two groups of variables is 0.978, indicating a strong relationship between them. Chi-Square 107,616 with a significance level of $p<0.05$ confirms the statistical significance of the correlation coefficient R.

Considering the contributions of each set of variables to the variance (Figure 1.1), we see that the variation of digitalization indicators (Left Set) is taken into account by 100%, and the variation of public authorities (Right Set) by 98.42%. At the same time, Total redundancy reflects that 72.55% of the public administration variation is due to the Left Set variation.

According to Figure 1.2, the result of the canonical analysis is five canonical roots. According to the value of p of the Chi-Square criterion, the statistically significant roots 0 and 1. However, the canonical root 0 explains 95.597% of the variance, and the canonical root 1 − only 55.351%. Therefore, only the canonical root 0 needs to be considered further.



Root Removed	Chi-Square Tests with Successive Roots Removed					
	Canonicl R	Canonicl R-sqr.	Chi-sqr.	df	p	Lambda Prime
0	0,977738	0,955971	107,6161	30	0,000000	0,011288
1	0,743980	0,553506	32,6662	20	0,036766	0,256381
2	0,579034	0,335281	13,3143	12	0,346665	0,574209
3	0,335638	0,112653	3,5129	6	0,742246	0,863837
4	0,162775	0,026496	0,6445	2	0,724530	0,973504

Figure 1.2. Graph and Table of Eigenvalues of Canonical Roots

Figure 1.3 shows the correlations between groups of variables. The strongest link between Digital Development Level and Government Effectiveness, Digital Development Level and Rule of Law, IMD World Digital Competitive Ranking and Government Effectiveness.

Root Removed	Correlations, left set with right set					
	Voice and Accountabi lity	Political Stability and Absence of Violence/Terrorism	Government Effectivenes:	Regulatory Quality	Rule of Law	Control of Corruption
ICT goods exports	0,114	0,235	0,037	0,224	0,082	-0,031
ICT service exports	0,138	0,049	0,048	0,151	0,083	0,345
ICT goods imports	-0,010	0,150	0,034	0,124	0,030	-0,013
Digital Development Level	0,809	0,638	0,952	0,902	0,922	0,321
IMD World Digital Competitiveness Ranking	0,748	0,574	0,939	0,858	0,890	0,261

Figure 1.3. Correlation Between Groups

According to factor structures (figure 1.4), Digital

Development Level and IMD World Digital Competitive Ranking have the highest correlation with the canonical root, with correlation coefficients of -0.973 and -0.945, respectively. And from the indicators of public administration Government Effectiveness, Regulatory Quality, and Rule of Law with coefficients -0.976, -0.974 and -0.963.

Root Variable	Factor Structure, left set Root 1	 Root 2	 Root 3	 Root 4	 Root 5
ICT goods exports	-0,144	-0,487	0,806	0,304	0,018
ICT service exports	-0,128	-0,529	-0,185	0,419	-0,703
ICT goods imports	-0,097	-0,218	0,688	0,683	0,048
Digital Development Level	-0,973	0,122	-0,120	0,087	0,126
IMD World Digital Competitiveness Ranking	-0,945	0,266	-0,087	0,098	-0,141

Root Variable	Factor Structure, right set (data_can) Root 1	 Root 2	 Root 3	 Root 4	 Root 5
Voice and Accountability	-0,870	-0,229	-0,119	-0,366	0,197
Political Stability and Absence of Violence/Terrorism	-0,688	-0,176	0,170	-0,075	0,675
Government Effectiveness	-0,976	0,182	-0,075	-0,002	0,090
Regulatory Quality	-0,974	-0,156	0,092	-0,134	0,033
Rule of Law	-0,963	0,025	-0,068	-0,136	0,135
Control of Corruption	-0,315	-0,403	-0,599	0,570	-0,026

Figure 1.4. Factor Structures

By plotting the canonical variables derived from the canonical root, we see a direct relationship between Left Set and Right Set, i.e., between digitalization and the quality of public administration (figure 1.5).

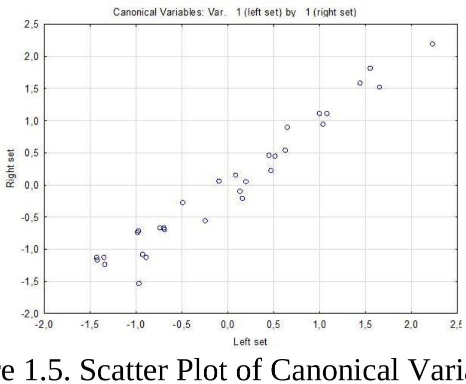


Figure 1.5. Scatter Plot of Canonical Variables

Examining the canonical scores for the first canonical root (Root 1), we see that the contribution to the canonical variable is greatest at the Digiral Development Level (-0.682), so this indicator has the greatest impact on the quality of public administration. And in terms of the quality of public power, the indicators Regulatory Quality (-0.699) and Government Effectiveness (-0.544) have the greatest impact (figure 1.6).

Variable	Canonical Weights, left set (data_can) Root 1	Root 2	Root 3	Root 4	Root 5
ICT goods exports	-0,457	-0,913	1,190	-1,523	-0,451
ICT service exports	-0,046	-0,747	-0,596	0,389	-0,464
ICT goods imports	0,363	0,801	-0,185	1,919	0,525
Digital Development Level	-0,682	-1,933	-1,630	0,757	2,460
IMD World Digital Competitiveness Ranking	-0,317	2,149	1,597	-0,797	-2,457

Variable	Canonical Weights, right set (data_can) Root 1	Root 2	Root 3	Root 4	Root 5
Voice and Accountability	0,122	-0,505	-1,859	-1,593	0,465
Political Stability and Absence of Violence/Terrorism	0,050	-0,198	0,574	0,598	1,415
Government Effectiveness	-0,544	1,704	-0,796	1,292	0,579
Regulatory Quality	-0,699	-1,853	2,618	1,131	-1,686
Rule of Law	0,093	0,927	-0,376	-1,666	-0,317
Control of Corruption	-0,060	-0,559	-0,593	0,686	0,014

Figure 1.6. Canonical Contributions of Variables to the Canonical Root

Accordingly, general formula 1.1 takes the form:

−0,457 ∗ ICT goods exports − 0,046 ∗ ICT service exports + 0,363 ∗ ICT goods imports − 0,682 ∗ Digital Development Level − 0,317 ∗ IMD World Digital Competitiveness Ranking + 0,122 ∗ Voice and Accountability + 0,05 ∗ Political Stability and Absence of Violence(Terrorism) − 0,544 ∗ Government Effectiveness − 0,699 ∗ Regulatory Quality + 0,093 ∗ Rule of Law − 0,06 ∗ Control of Corruption

Accordingly, digitalization has an impact on the quality and efficiency of public administration.

Risk cannot be neglected by assessing the positive impact of digitalization on public authorities' transparency. The main risks in introducing digitalization to ensure public authorities' transparency are digital security, maintaining a balance between liberalization and oversight, and lack of system flexibility. When implementing digital services and placing information in the public environment, it is worth paying attention to cybersecurity and the need for reliable data protection. Attackers can access a person's electronic documents by hacking servers and social engineering methods: pretexting, phishing, telephone phishing, “road apple” etc. In this case, public authorities should not shift the blame on the citizen but build a security system for their services so that criminals do not have access to information.

Maintaining a balance between liberalization and oversight is a hotly debated issue. Increasing bureaucratization and supervision will slow down and increase the cost of the entire public administration but, at the same time, will not leave opportunities for corruption. On the other hand − by simplifying all procedures and algorithms to a minimum, information flows will be accelerated, and information will become more accessible. Still, it will increase the possibility of the implementation of corruption schemes. The main tool for ensuring this balance is a risk-oriented cost approach: with decreasing transaction costs, liberalization increases. This approach is far from ideal. It is necessary to introduce automation of decision-making processes in public administration, which will simultaneously reduce opportunities for corruption and increase the time of the operation. In this case, digitalization will show itself to the best extent. The existence of transparent, accessible to all procedures and rules that ensure the transparency of public authorities cannot always be adapted to the need to ensure the interests of the population during force majeure.

CHAPTER 2. FINANCIAL CRIME IN THE DIGITAL AGE

2.1. Determination of impulses for activating financial crimes caused by the digitalization of the economy

In the modern conditions of the 4.0 economy, innovations are closely connected with financial and, especially, cyber crimes. Since there is a problem of protecting innovative investigations and their results from the fraudsters' encroachments, it is necessary to use appropriate advanced methods and models that effectively reveal the relationship and mutual influence of innovations and related crimes to prevent and counter modern financial and cyber threats.

One of these methods is spline modelling. It is one of the most effective modern ways of building multi-component mathematical functions and equations, three-dimensional 3D models, where splines are component mathematical functions. Spline lines are defined by a three-dimensional set of control positions of points in space that determine the shape and flexibility of the curve. The basic tools of spline modelling are algebraic polynomials, mathematical variables, the simplest functions, and spline primitives (the simplest objects from which a spline model is formed), such as Arc, Circle, Donut, Ellipse, Helix, Line, NGon, Rectangle, Section, Star, Text and other more complex spline elements. Spline modelling has many advantages, particularly universality, wide application, possible use in various computing software complexes, computer modelling, high computing capabilities, approximate properties, high accuracy, flexible setting, and ease of implementation of computational functions. Besides, in case of scaling within any limits, the quality of spline modelling does not deteriorate, and it is possible to change the forms of spline objects at any stage.

At the first stage of the scientific-methodical approach to the application of multivariate adaptive regression MAR-splines to determine the influence of factors (the development of financial technologies, the state of financial monitoring of banks and insurance companies, trading volumes on the stock exchange) on financial crimes, cyber crimes and money laundering, the input information base of the research is formed. It contains

five regressors:

X1 – fintech development indicator, represented by the specific weight of the number of Internet users in the population of Ukraine,

X2 – the number of reports of suspicious transactions considered by the State Financial Monitoring Service,

X3 – the total volume of trading on the stock exchange during the period,

X4 – an indicator of the insurance companies' activity (the ratio of the insurance payments and insurance indemnities to the amount of insurance payments),

X5 – an indicator of the banks' activity (the ratio of cash and deposits to the total assets);

three regressands:

Y1 – the number of criminal crimes under Articles 222 (Fraud with financial resources) and 222-1 (Manipulation of the stock market of Ukraine) of the Criminal Code of Ukraine, in which a pre-trial investigation was conducted in the reporting period,

Y2 – the number of criminal offenses under Articles 361 (Unauthorized interference with the operation of electronic computing machines (computers), automated systems, computer networks or telecommunication networks), 361-1 (Creation of malicious software or technical means for the purpose of use, distribution or sale), 361-2 (Unauthorized sale or distribution of information with limited access, which is stored in electronic computing machines (computers), automated systems, computer networks or on media of such information), 362 (Unauthorized actions with information processed in electronic computing machines (computers), automated systems, computer networks or stored on the media of such information, committed by a person with the right to access it), 363 (violation of operation of electronic computing machines (computers), automated systems, computer networks or telecommunication networks or the procedure or rules for the protection of information processed in them), 363-1 (Interference with the operation of electronic computing machines (computers), automated systems, computer or telecommunication networks by means of mass distribution of electronic communications) of the Criminal Code of Ukraine, in which a pre-trial investigation was conducted in the reporting period,

Y3 – Number of criminal offenses under Article 209 (Legalization of proceeds obtained through criminal means (money laundering)) of the Criminal Code of Ukraine, in which the pre-trial investigation was conducted in the reporting period.

It is proposed to build a separate spline model in each specified regressand section, taking the same set of indicators as regressors. Quarterly data from the first quarter of 2013 to the fourth quarter of 2020 are suggested to be taken in the study.

In the second stage of the scientific and methodological approach, the behaviour dynamics of the regressor and factors are studied.

The third stage involves spline modelling. When constructing regression MAR-splines, the following parameters are obtained (table 2.1): number of independent variables – 5, number of dependent variables – 1, number of terms – 5, number of basic functions – 5, order of interaction (number of components of the basic functions product) – 2, and the number of references to regressor factors: the largest - 2 to X1, X2, then 1 - X3; in addition, factors X2 and X5 are insignificant.

Table 2.1. Model specification parameters and the number of references to relevant regressor factors in the analysis of financial crimes

Model specifications	Value
Independents	5
Dependents	1
Number of terms	5
Number of basic functions	5
Order of interactions	2
Penalty	2.00000
Threshold	0.00050
GCV error	3153.12

Dependents	Number of references References (to Basic Functions)
X1	2
X2	0
X3	1
X4	2
X5	0

The results of estimating the parameters of regression MAR-splines are presented in Figure 2.1.

	Model coefficients (Spreadsheet9.sta) NOTE: Highlighted cells indicate basis functions of type max(0, independent-knot), otherwise max(0, knot-independent)					
Coefficients, knots and basis functions	Coefficients Y1	Knots X1	Knots X2	Knots X3	Knots X4	Knots X5
Intercept	-15,34					
Term.1	-2200,14				0,239473	
Term.2	0,23			7464,630	0,239473	
Term.3	330,14	0,557544				
Term.4	250,80	0,371405				

Figure 2.1. Coefficients and terms of the model

Thus, considering the above coefficients, terms and parameters, the model of the influence of fintech, financial monitoring of banks and insurance companies, trading volumes for financial and cyber crimes, and money laundering in the form of multivariate adaptive regressive MAR-splines takes the form:

$$Y1 = -1{,}53418216810049e{+}001 - 2{,}20013777098280e{+}003*\max(0;\ 2{,}39473128974892e{-}001 - X4) + 2{,}28135475716692e{-}001*\max(0;\ X3 - 7{,}46462968235000e{+}003)*\max(0;\ 2{,}39473128974892e{-} \qquad (2.1)$$

001-X4) + 3,30135483180817e+002*max(0; 5,57544361572743e-001-X1) + 2,50799012955197e+002*max(0; X1-3,71405276737145e-001)

Analyzing equation 2.1, the authors conclude that the activity of insurance companies decreases the rate of financial crimes, provided that the insurance companies’ activity indicator is less than 0.2395; otherwise, the activity of insurance companies alone will not have any impact. The total volume of trading on the exchange with the insurance companies’ activity, if the volume of trading exceeds 7464.63, and the insurance companies’ activity indicator is less than 0.2395, will have a multiplicative positive effect on financial crimes. The fintech development will have a positive impact on the number of financial crimes, while if the indicator is from 0.3714 to 0.5575, the effect will be as the sum of two terms, and if it exceeds 0.5575 units - only one.

In general, only the insurance companies’ activity affects the number of financial crimes for which proceedings were conducted. One should note that the number of reports sent to the State Financial Monitoring Service and the performance of banks have no influence at all.

The sufficiency of the model in the form of multivariate adaptive regression MAR-splines is confirmed by the minimum value of the general model quality criterion - the generalized cross validation error (GCV error), which takes the value of 3153.12 (Figure 2.2); the determination coefficient acquires a value of 0.803, indicating the high quality of the model; insignificant deviation of the actual and predicted values of the number of financial crimes for which there were proceedings in the reporting period.

Regression statistics	Regression statistics (Spreads Y1
Mean (observed)	100,8125
Standard deviation (observed)	92,3770
Mean (predicted)	100,8125
Standard deviation (predicted)	82,7772
Mean (residual)	0,0000
Standard deviation (residual)	41,0055
R-square	0,8030
R-square adjusted	0,7651

Figure 2.2. Regressive statistics of the financial crime dependence on factors in the form of multivariate adaptive regression MAR-splines

Turning to the practical implementation of the model in terms of the cyber crimes' dependence on five factors in the form of multivariate adaptive regression MAR-splines, the following parameters were obtained (table 2.2): number of independent variables - 5, number of dependent variables - 1, number of terms - 8, number of basic functions - 14, the order of interaction (the number of components of the basic functions product) - 3, as well as the number of references to regressor factors: the largest is 5 to X1, 4 to X3, 3 to X2, 2 to X5; in addition, factor X4 was found to be insignificant.

Table 2.2. Model specification parameters and the number of references to relevant regressor factors in the cyber crimes analysis

Model specifications	Value
Independents	5
Dependents	1
Number of terms	8
Number of basic functions	14
Order of interactions	3
Penalty	2,00000
Threshold	0,00050
GCV error	218725

Dependents	Number of references References (to Basic Functions)
X1	5
X2	3
X3	4
X4	0
X5	2

The results of estimating the regression MAR-splines parameters are presented in Figure 2.3

Coefficients, knots and basis functions	Model coefficients (Spreadsheet9.sta) NOTE: Highlighted cells indicate basis functions of type max(0, independent-knot), otherwise max(0, knot-independent)					
	Coefficients Y2	Knots X1	Knots X2	Knots X3	Knots X4	Knots X5
Intercept	397,1					
Term.1	33871,6	0,371405				
Term.2	110777,2					0,183132
Term.3	-0,0	0,371405	1836938			
Term.4	0,0	0,371405	1836938	7464,63		
Term.5	-0,0		209449	7464,63		0,183132
Term.6	-1,8	0,371405		7464,63		
Term.7	-1,4	0,371405		26173,17		

Figure 2.3. Coefficients of the model and terms of the model of factors influence on cyber crimes

Y2 = 3,97130455471352e+002 + 3,38716423357658e+004*max(0; X1-3,71405276737145e-001) + 1,10777191998577e+005*max(0; X5-1,83132301034698e-001) - 3,44120331174238e-002*max(0; X1-3,71405276737145e-001)*max(0; X2-1,83693800000000e+006) + 2,11976578551327e-006*max(0; X1-3,71405276737145e-001)*max(0; X2-1,83693800000000e+006)*max(0; X3-7,46462968235000e+003) - 2,15529085157748e-006*max(0; X2-2,09449000000000e+005)*max(0; X3-7,46462968235000e+003)*max(0; X5-1,83132301034698e-001) - 1,78240383752107e+000*max(0; X1-3,71405276737145e-001)*max(0; X3-7,46462968235000e+003) - 1,37560299832438e+000*max(0; X1-3,71405276737145e-001)*max(0; 2,61731749103700e+004-X3) (2.2)

Analyzing the cyber crime determinants, the fintech development indicator will positively impact if it acquires a value greater than 0.3714. At the same time, the fintech development indicators and the number of reports of suspicious transactions will affect the reduction of the resulting feature if the first is more than 0.3714 and the second is more than 1836938. If the number of trades on the exchange exceeds 7464.6297 before the previous condition, the multiplicative effect of three indicators will influence the growth of the resulting feature. The indicator of banks' activity will affect the increase in cybercrimes if it exceeds the value of 0.1813. The multiplicative effect of indicators X2, X3 and X5 at the same time under certain conditions will affect the reduction of the number of cyber crimes.

Sufficiency of the built model in the form of multivariate adaptive regression MAR-splines is confirmed by the minimum value of the general criterion of the model quality – the generalized cross validation error (GCV error), which takes the value of 218725 (Figure 2.4); the determination coefficient acquires a value of 0.886, indicating the high quality of the model; insignificant deviation of the actual and predicted values of cybercrimes.

	Regression statistics (Spreads
Regression statistics	Y2
Mean (observed)	935,0938
Standard deviation (observed)	746,4649
Mean (predicted)	935,0937
Standard deviation (predicted)	702,4872
Mean (residual)	0,0000
Standard deviation (residual)	252,4312
R-square	0,8856
R-square adjusted	0,8459

Figure 2.4. Regressive statistics of the financial crime dependence on factors in the form of multivariate adaptive regression MAR-splines

Moving on to the practical implementation of the model in terms of the laundered money dependence on five factors in the form of multivariate adaptive regression MAR-splines, the following parameters are obtained (table 2.3): the number of independent variables - 5, the number of dependent variables - 1, the number of terms - 3, the number of basic functions – 3, the order of interaction (the number of components of the product of basic functions) – 2, as well as the number of references to regressor factors: the largest and the same – 1 to X1, X2, X3, factors X4 and X5 were found to be insignificant.

Table 2.3. Model specification parameters and the number of references to relevant regressor factors in analyzing money laundered

Model specifications	Value
Independents	5
Dependents	1
Number of terms	3
Number of basic functions	3
Order of interactions	2
Penalty	2,00000
Threshold	0,00050
GCV error	767,732

Dependents	Number of references References (to Basic Functions)
X1	1
X2	1
X3	1
X4	0
X5	,

The results of estimating the regression MAR-splines parameters are presented in Figure 2.5.

	Model coefficients (Spreadsheet9.sta) NOTE: Highlighted cells indicate basis functions of type max(0, independent-knot), otherwise max(0, knot-independent)					
Coefficients, knots and basis functions	Coefficients Y3	Knots X1	Knots X2	Knots X3	Knots X4	Knots X5
Intercept	32,92918					
Term.1	-0,00002		1836938			
Term.2	15,03185	0,557544		22330,43		

Figure 2.5. The model coefficients and model terms of influence on the money laundering

Thus, considering the coefficients, terms and parameters presented above, the model of the influence of fintech, financial monitoring of banks and insurance companies, trading volumes for financial crimes, cyber crimes, money laundering in the form of multivariate adaptive regressive MAR-splines takes the form:

$$Y3 = 3{,}29291807569567e{+}001 - 1{,}77427285069972e{-}005 \cdot \max(0;\ 1{,}83693800000000e{+}006 - X2) + 1{,}50318465753288e{+}001 \cdot \max(0;\ X1 - 5{,}57544361572743e{-}001) \cdot \max(0;\ 2{,}23304254185900e{+}004 - X3) \quad (2.3)$$

The number of money laundering crimes has a negative impact on the number of suspicious transaction reports if they are less than 1836938 units. On the other hand, the multiplicative effect of fintech and trading volumes on the stock exchange will have a positive impact, provided that the first indicator is greater than 0.5575 and the second is less than 22330.4254. The influence of other indicators has not been proven.

The adequacy of the formed model in the form of multivariate adaptive regression MAR-splines is confirmed by the minimum value of the general model quality criterion - the generalized cross validation error (GCV error), which takes the value 767 (Figure 2.6).

	Regression statistics (Spreads
Regression statistics	Y3
Mean (observed)	23,95273
Standard deviation (observed)	30,78833
Mean (predicted)	23,95273
Standard deviation (predicted)	19,58905
Mean (residual)	-0,00000
Standard deviation (residual)	23,75269
R-square	0,40481
R-square adjusted	0,34104

Figure 2.6. Regressive statistics of the dependence of the money laundered on factors

The determination coefficient acquires a value of 0.405, indicating the high quality of the model; insignificant deviation of the actual and predicted values of the number of money laundering crimes.

The conducted modelling singles out the trends of interrelationships of cyber crimes, financial crimes and money laundering with the generalized features of fintech development, the number of reports on suspicious transactions submitted to the State Financial Monitoring Service and the development of key financial activity areas: banks, insurance companies and stock exchanges.

It was determined that financial crimes are not influenced by the number of reports about suspicious operations and activities of banking institutions submitted to the state financial monitoring. Instead, the multiplicative effect of trading on stock exchanges and the insurance companies' activities was defined.

The insurance companies' activity does not influence cybercrimes. Instead, the fintech indicator of all other indicators provides a multiplicative effect, including a triple one. It indicates that digitisation and fintech development stimulate other areas of financial activity and provide new opportunities for cybercriminals.

The number of money laundering crimes is explained by the number of suspicious transactions submitted to the State Financial Monitoring Service and the multiplicative effect of trading on the stock exchange and the level of fintech, indicating a significant number of money laundering schemes using securities.

Therefore, on the one hand, the modern world has great hopes for innovations, relating them to improving society's welfare, strengthening competitiveness, and accelerating economic growth. On the other hand, it suffers from the intensification of illegal actions of cybercriminals. It is necessary to constantly use a specific set of adequate regulatory measures to prevent and counteract financial and cyber crimes and their negative consequences. Among them, analytical processes based on modelling of financial and economic processes and trends take a significant place.

The spline models of such interdependence of FinTech innovations and financial and cyber crimes are flexible. They act as a worthy alternative to standard mathematical models that financial intermediaries can use to prevent negative consequences for the economic system. Spline models provide sound, accurate results, and predictions on the studied data demonstrate some of the best correlations of the studied functions. The practical application of the spline model for the interdependence of FinTech innovations and financial and cybercrimes through the mediation of financial institutions will benefit financial intermediaries, financial system users, and state regulatory and supervisory bodies. This model can be useful and interesting to international organizations, investors, developers of regulatory standards, banking institutions, and other scientists conducting research in this area.

2.2. How does the cryptocurrency circulation affect the national cyber security?

Due to the increase in cyberattacks, hacker activity and society digitalization, the governments in most countries, in cooperation with private sector organizations, academic circles and cyber security specialists, are forced to resort to deliberate measures to increase cyber security for protecting national security and developing the information sector. It is worth noting that implementing the government policies and strategies aimed at improving the country's cyber security requires thorough research and understanding of the factors that affect the spread and activity of digital threats.

One of the factors that can affect cyber security is the digitalization of society. Dissemination of such new technologies as artificial intelligence, the Internet of Things, cloud computing or cryptocurrencies can create new attack vectors for cybercriminals, potential risks for information security, the need to develop new standardized practices for checking and countering identified crime methods, etc. For example, cybercriminals can use cryptocurrencies to launder money, pay ransomware, and finance criminal activities due to the decentralization, weak regulation, and privacy of blockchain technology. In addition, the confidentiality of payments can prevent the tracking and investigation of cybercrimes by law enforcement agencies. A better understanding of the impact of cryptocurrencies on cybersecurity can help governments develop effective programs to improve cybersecurity and combat digital attacks.

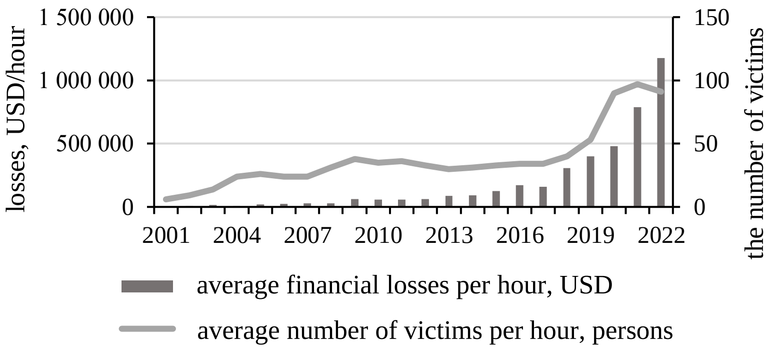


Figure 2.7. Dynamics of losses from cybercrime in the world during 2001-2022

Source: European Union Agency for Network and Information Security (2020)

The increasing relevance of cyber security for the reasons given earlier and cryptocurrency dissemination contributes to increasing the scientists' attention to studying the mutual influence of these phenomena. This trend can be observed via a significant increase in the number of scientific works containing phrases close to “impact of cryptocurrencies on cyber security” published in the Science Direct scientific publications database during 2016-2022, shown in Figure 2.8.

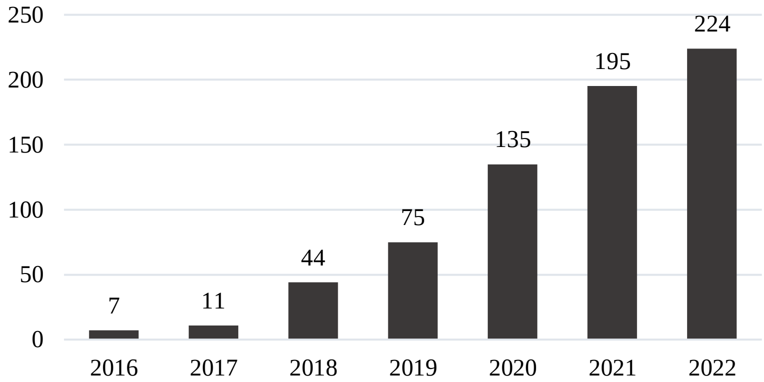


Figure 2.8. Number of articles containing phrases similar to "impact of cryptocurrencies on cyber security" published in Science Direct during 2016-2022

Source: compiled by the authors based on information from the Science Direct database of published scientific studies

We collected a data set with 10-factor variables that characterize aspects of cryptocurrency use and one outcome variable demonstrating the country’s cyber security level to conduct the modelling. The data set was collected for 24 countries of the European Union in 2020.

We chose the country's overall cyber security rating according to SEON Global Cybercrime Report (SEON, 2023) as the dependent feature since it assesses the country's overall cyber security level on a 100-point scale based on such aspects as the National Cyber Security Index (an index assessed by the NCSI Project Team, which is focused on assessing the countries’ readiness to prevent cyber threats based on the implementation of relevant regulatory and legal acts), the Global Cyber Security

Index (an indicator created by ITU-D, a division of the International Telecommunication Union, in addition to legal measures it evaluates technical, organizational, cooperative measures, as well as capacity development countries in cyber security) and the Cyber Security Risk Index (an index evaluated by PasswordsManagers.co, based on country rankings by the number of detected cases of various digital threats). Thus, the overall assessment of the country's cyber security considers the largest number of aspects of the country's cyber security, starting from the legal field assessment and ending with the number of detected cyber crimes. It is a representative indicator of the country's overall protection against digital threats. As of 2020, countries of the European Union such as Belgium, Finland, and Spain have the highest cyber security ratings for this indicator (Fig. 2.9).

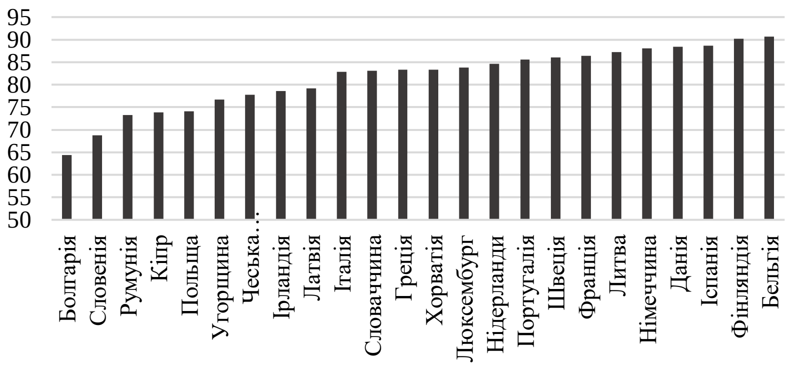


Figure 2.9. Assessment of cyber security (y_2) of the European Union countries as of 2020
Source: based on SEON's Global Cybercrime Report (SEON, 2023)

The list of factor variables (given in Table 2.4) characterizes five aspects of the cryptocurrencies used by the country's population, in particular:

– the prevalence of ownership and use of cryptocurrencies among the country's population (variables x1, x3, x4, x8): the cryptocurrency market can attract additional attention of cybercriminals to possible fraud and theft of users' funds, cryptojacking, use of cryptocurrencies for money laundering or sponsoring criminal activities, etc.

– state legal regulation the cryptocurrencies use (variable x6): effective regulation of cryptocurrency activities by governments and regulatory authorities can contribute to the identification of users on cryptocurrency exchanges, ensuring security measures, and preventing money laundering and terrorist financing; all this should have a positive impact on the country's cyber security;

– digital literacy of citizens (variables x2 and x7): digital literacy of citizens can reduce the risks of cybercrime using cryptocurrencies because it helps users to be aware of standard methods of cybercrime (in particular, phishing, fraud, hacking, etc.), to create more reliable keys for protection of cryptocurrencies wallets, detect suspicious actions of other users, use more secure exchanges and other platforms with cryptocurrency transactions, etc.

– investment literacy of the population (variables x8 and x9): investment literacy of the population can have a positive effect on the level of country's cyber security as it indicates the awareness of the population about investment fraud, understanding of market instability and the need to protect investment platforms, the ability to assess investment risks, etc.

– the prevalence of the criminal use of cryptocurrencies in the country (x5 and x10): variables of this category characterize the volume of the country's darknet market and its shadow economy. A high level of both variables can negatively affect the level of the country's cyber security since payment for criminal goods and services using cryptocurrency in the darknet or outside state accounting and control (shadow economy) may indicate the unregulated cryptocurrency market and criminal cryptocurrency transactions

Table 2.4. Factor variables characterizing aspects of the cryptocurrency use in the country

Index		Source of the data
x_1	a share of the population that owns cryptocurrencies	Triple-A
x_2	a share of individuals with basic or above general digital skills	Eurostat
x_3	a share of respondents who have or had cryptocurrencies (other source)	Flash Eurobarometer FL509
x_4	a share of respondents who use a mobile application for investing in cryptoassets once a week or more often; total income of the darknet market (in EUR per capita) assessment of legal measures in regulating digital assets (on a 20-point scale)	
x_5	total income of the darknet market (in EUR per capita)	Grauer & Jardine, 2022
x_6	assessment of legal measures in regulating digital assets (on a 20-point scale)	International Telecommunication Union
x_7	a share of people who used the Internet during the last 3 months	Eurostat
x_8	a share of the population that invests in cryptocurrency	Flash Eurobarometer FL509
x_9	a share of the population that invests in traditional assets	
x_{10}	the size of the shadow economy in 2020 (in % of official GDP)	Schneider& Asllani, 2022

Source: compiled by the authors

In this way, a data set was formed for further constructing a regression model to assess the influence of the cryptocurrency use on the cyber security evaluation in the countries of the European Union (Table 2.5).

Table 2.5. A set of data for regression model

Country	y	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
Belgium	90,7	1,4	54,2	6,5	4,3	260,9	20,0	81,1	6,0	32,0	16,2
Bulgaria	64,4	2,2	31,2	13,1	10,8	328,9	17,3	19,8	13,0	13,0	32,9
Greece	83,4	1,5	52,5	10,0	8,0	110,8	19,4	54,0	10,0	11,0	20,9
Denmark	88,4	1,2	68,7	7,6	6,4	244,0	19,3	95,7	8,0	36,0	9,8
Ireland	78,6	1,1	70,5	10,9	6,7	310,4	20,0	77,7	11,0	21,0	9,9
Spain	88,6	3,0	64,2	7,8	7,7	154,6	20,0	69,4	8,0	27,0	17,4
Italy	82,8	2,4	45,6	5,7	7,7	79,1	19,7	55,3	6,0	31,0	20,4
Cyprus	73,9	1,2	50,2	13,1	9,9	386,0	20,0	71,3	13,0	10,0	24,3
Latvia	79,1	1,3	50,8	8,1	5,8	830,3	20,0	87,9	8,0	11,0	20,9
Lithuania	87,3	1,2	48,8	11,1	5,9	441,5	20,0	83,3	11,0	14,0	23,1
Luxembourg	83,8	1,0	63,8	13,9	8,0	778,0	20,0	72,7	14,0	36,0	8,6
Netherlands	84,7	2,7	78,9	11,6	8,5	454,7	20,0	96,0	12,0	19,0	8,1
Germany	88,1	4,2	48,9	6,4	9,4	174,4	20,0	55,1	6,0	33,0	10,4
Poland	74,1	2,8	42,9	8,1	9,2	171,6	19,4	61,2	8,0	14,0	22,5
Portugal	85,5	2,6	55,3	12,1	9,7	201,3	20,0	64,2	12,0	23,0	17
Romania	73,2	1,6	27,8	8,2	9,4	127,0	18,6	18,5	8,0	12,0	29,3
Slovakia	83,1	1,4	55,2	12,2	8,3	347,4	20,0	65,1	12,0	25,0	14
Slovenia	68,8	1,1	49,7	17,5	12,3	633,5	20,0	64,2	18,0	22,0	23,1
Hungary	76,7	1,3	49,1	8,3	3,7	137,5	18,2	63,2	8,0	19,0	26
Finland	90,2	1,4	79,2	9,1	7,5	494,3	20,0	96,4	9,0	42,0	11,4
France	86,4	5,9	62,0	4,7	5,7	156,1	20,0	78,2	5,0	22,0	13,6
Croatia	83,4	1,2	63,4	16,1	10,7	206,5	20,0	68,4	16,0	17,0	29,6
Czech Republic	77,7	1,9	59,7	12,0	8,6	367,3	18,9	81,9	12,0	24,0	14,2
Sweden	86,0	1,6	66,5	9,9	5,0	516,0	20,0	86,3	10,0	60,0	11,7

Source: compiled by the authors

The authors used general scientific methods such as analysis, synthesis, abstraction, analogy and generalization during the research. The main modelling method is to use multivariate regression. This method was chosen because of its simple and flexible nature to study the influence of multiple factors on the outcome variable, and it enables the assessment of the relative importance of different independent variables in explaining the variation of the dependent variable and conducting an economic interpretation of the identified relationships.

For the first time, the concept of cryptocurrency appeared in the scientific environment in an article by Nakamoto (2008) devoted to Bitcoin as a peer-to-peer electronic cash system. The identity of the author (or authors) remains unknown to this day. However, cryptocurrencies continue gaining popularity and opening new opportunities for financial transactions and digital assets to society. Cryptocurrencies are currently understood primarily as digital assets in a system that are sent cryptographically from one user of the blockchain network to another using digital signatures with asymmetric key pairs (Yaga et al., 2018).

Despite the benefits and opportunities that cryptocurrencies open up for investors and other users, their dissemination also raises concerns, including the potential impact of cryptocurrencies on cybercrime. First, due to decentralization, low government regulation, difficulty in identifying the participants of transactions, availability, irrevocability and low cost of transfers, cryptocurrencies are an attractive tool for cybercriminals. Second, the short historical experience of these systems and the relative novelty of the mechanisms ensuring their operation can also raise questions about the risks and reliability of these financial assets. Therefore, the amount of cryptocurrency involved in criminal activity continues to grow. For example, according to Chainalysis Inc. research (2023), in 2022, the value of cryptocurrency, the acquisition of which was related to crime, reached a record value of 20.6 billion US dollars (Figure 2.7). Cryptocurrencies often become a tool in digital crimes such as illicit digital commerce (mainly on the

Darknet), money laundering, hacking, cryptojacking and fraud, etc. At the same time, the adoption of cryptocurrencies continues to grow, so understanding the complex relationship between their use and cyber threats becomes a top priority for providing robust digital security measures.

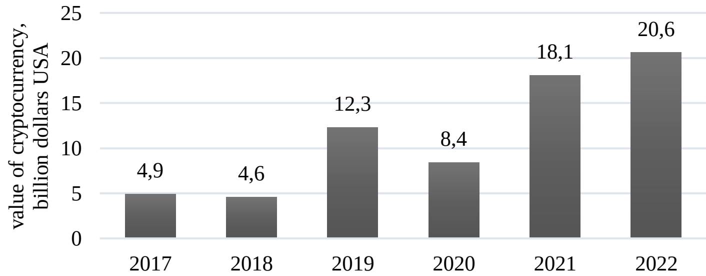


Figure 2.7. The value of cryptocurrency received by illegal accounts in 2017-2022

Source: Chainalysis (2023)

The countries of the European Union are known for their commitment to innovation, digital transformation and data protection. So, they were chosen as an environment to study the impact of the cryptocurrency use on the state cyber security. Therefore, the authors built a multiple linear regression model with stepwise exclusion of variables. The results of the stepwise exclusion of variables are shown in Fig. 2.8.

	Results of stepwise regression						
variable	step	R	R-square	R-square. corrected	F - incl/excl	p-value	number of
X10	-1	0,88	0,78	-0,00	0,01	0,94	7
X1	-2	0,88	0,78	-0,00	0,05	0,83	6
X3	-3	0,88	0,77	-0,01	0,64	0,43	5
X2	-4	0,86	0,75	-0,03	2,10	0,16	4
X9	-5	0,82	0,68	-0,07	5,28	0,03	3
X5	-6	0,77	0,60	-0,08	4,70	0,04	2

Figure 2.8. The results of creating a regression model with stepwise exclusion of variables

Figure 2.8 demonstrates that the model becomes statistically significant after the fourth step and after excluding variables x10, x1, x3 and x2. As a result, there is a model with four-factor variables x4 (a share of the population using a mobile application for investing in cryptoassets once a week or more often), x5 (total revenue of the darknet market), x6 (estimation of legal measures in regulating digital assets) and x9 (investment of the population in traditional assets). This model includes variables that describe four different aspects of using cryptocurrencies by the country's population and is statistically significant according to Fisher's F-test. In more detail, the results of the obtained model with four-factor features are shown in Fig. 2.9.

	Regression Outcomes R= ,86380253 R2= ,74615481 Correct. R2= ,69271372 F(4,19)=13,962 p<,00002 Standard estimation error: 3,8483					
N=24	BETA	St. r. BETA	B	St. r. B	t(19)	p-value
intercept			-24,08	23,75	-1,01	0,32
X4	-0,37	0,12	-1,18	0,40	-2,98	0,01
X5	-0,32	0,12	-0,01	0,00	-2,61	0,02
X6	0,59	0,13	5,83	1,23	4,73	0,00
X9	0,30	0,13	0,17	0,08	2,30	0,03

Figure 2.9. A regression model with four-factor variables

The multiple correlation coefficient (R) of the regression model is equal to 0.86, which exceeds the critical value of 0.7. It indicates a strong relationship between the outcome and factor features. The multiple determination coefficient proves that 74.62% of the cyber security assessment distribution among the countries of the European Union in 2020 is explained by the variation of the factor variables.

For the created model, Fisher's F-criterion is equal to 13.96, with a significance level of $p < 0.05$, confirming the statistical significance of the regression equation. It means that with a probability of 95%, the obtained result can be extended to the general population. It is possible to make the same conclusion regarding the statistical significance of independent variables since their actual values of the Student's t-test also have a significance level of $p < 0.05$, i.e., all variables included in the model are statistically significant according to the Student's t-test.

It is also necessary to check the array of explanatory variables for multicollinearity since it can cause a decrease in the accuracy and interpretability of further modelling results. The variance inflation factor (VIF) was used as a criterion for the collinearity between the factor variables since it allows us to quantitatively assess the overestimation of the variance of the regression parameter estimates due to multicollinearity. According to the test results (Table 2.6), the VIF value for none of the variables exceeds five (generally accepted critical value). Thus, it can be concluded that there is no multicollinearity among the set of factor variables.

Table 2.6. Testing for multicollinearity using the variance inflation factor (VIF)

Variable	VIF
x_4	1,13
x_5	1,10
x_6	1,17
x_9	1,24

In fig. 2.9 one can see estimates of the equation parameters of the obtained model. Based on their value, the regression equation is as follows (2.4):

$$y_2 = -24{,}08 - 1{,}18x_4 - 0{,}01x_5 + 5{,}83x_6 + 0{,}17x_9 \quad (2.4)$$

where y_2– the overall assessment of the country's cyber security, a scale from 0 to 100 points (where 0 is the minimum estimate, and 100 is the maximum);

x_4– a share of the population using a mobile application for investing in cryptoassets once a week or more often;

x_5– total revenue of the darknet market, EUR per capita;
x_6– assessment of legal measures in regulating digital assets, on a 20-point scale (where 0 is the minimum assessment, and 20 is the maximum);
x_9– a share of the population investing in traditional assets.

This equation (2.4) determines the values of the outcome features predicted by the regression model and compares them with the determined overall cyber security assessments in the countries. According to Fig. 2.10, there is a positive correlation between these values because the points on the graph are grouped around a diagonal line from the lower left corner to the upper right corner. It indicates that the regression model works well and captures the relationship between the predictors and the outcome. The proximity of the points to the diagonal line also indicates that the model predictions are close to the actual values of the countries' cyber security assessments.

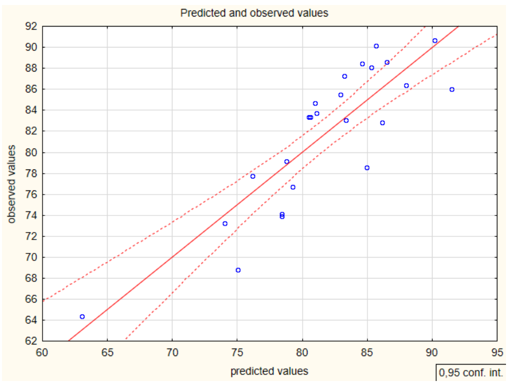


Figure 2.10. Graph of the relationship between the actual and the predictions of the regression model

Based on the regression parameter estimates, the authors can hypothesize that an increase in the percentage of the population actively using cryptocurrencies (x4 - the share of people using mobile application for investing in cryptoassets once a week or more often) by 1% on average can lead to a decrease in the assessment of cyber security by 1.18. It can be explained by the fact that the decentralized nature and anonymity of cryptocurrencies make them attractive tools for cybercriminals. It is difficult for law enforcement agencies to track cryptocurrency transactions, making it easier for criminals to carry out illegal transactions. At the same time, the reliable security measures and the growing awareness of the population regarding the safe use of digital assets may not keep up with the rapid growth of cryptocurrency users. Such processes can attract hackers' attention and encourage them to use cryptocurrencies in several directions, in particular, as a tool for:

– ransomware attacks (criminals encrypt victims' data and demand a ransom in cryptocurrency for providing a decryption key, etc.);

– cryptojacking (cybercriminals use victims' computer resources to mine cryptocurrencies without their knowledge or consent, while generating new digital assets at the expense of the victim's system performance and electricity consumption);

– fraud, including phishing (cybercriminals impersonate legitimate cryptocurrency exchanges, wallets or initial coin offerings (ICOs) to trick users into revealing their private keys, passwords or sending funds to fraudulent addresses);

– illegal trade in the darknet (cryptocurrencies are a common method of payment in the trade of stolen data, hacking tools and other illegal goods in the darknet);

– money laundering (criminals can convert their ill-gotten gains into cryptocurrencies and then back into traditional currencies in various ways, making it difficult to trace the origin of the funds).

On the other hand, although cryptocurrencies have provided new opportunities for cybercriminals in the short term, they are not inherently linked to cybercrime. Many legitimate companies and individuals use cryptocurrencies for legitimate purposes, and the technology can potentially improve security and privacy in various areas. Thus, the impact of cryptocurrency dissemination on the cyber security assessment in the long term is less clear-cut.

To a lesser extent, the level of cyber security assessment is negatively affected by the increase in the popularity of the darknet (x_5 - the total revenue of the darknet market). According to the regression parameter estimation, an increase in the income of the darknet market by 1 EUR per capita can, on average, cause a decrease in the cyber security estimate by 0.01. This impact can be caused by the fact that the darknet market is one of the sources of funding for cyber criminals and is used to sell stolen data since cryptocurrencies allow buyers and sellers to transact without revealing their identity or location. That is why cryptocurrencies are the primary form of payment for electronic transactions on the Dark Web (Naik & Serumula, (2015). Thus, although cryptocurrencies can benefit various industries, their anonymity and decentralization make them attractive to cybercriminals seeking to carry out illegal activities while maintaining a certain anonymity degree.

Measures that mitigate the negative impact of cryptocurrency dissemination on cyber security can be the development of digital and investment literacy of users, increased awareness of the risks related to cryptocurrencies and cybercrime, the development of specific legislation and control over the reliability of security protocols of cryptocurrency exchanges, the introduction of rules and standards to ensure the protection of users' funds and personal information, international cooperation, development and improvement of blockchain analysis tools, etc.

An increase in the assessment of legal measures in the regulation of digital assets has a significant positive effect on assessing the country's cyber security (x_6). According to the estimate of the relevant regression parameter, an increase in the assessment of legal measures in regulating digital assets by one on average can lead to an increase in cyber security assessment by 5.83. It is easy to explain because the legal regulation of cryptocurrencies can promote transparency, compliance with user identification and anti-money laundering standards, international cooperation and information exchange, etc.

However, although legal regulation of cryptocurrencies positively impacts cybersecurity, a balance between regulation and innovation should be maintained since excessive and burdensome regulations can hold back technological progress and hinder the legitimate use of cryptocurrencies. This balance can be partially determined by relying on government practices using the example of European Union countries with high ratings of legal measures in regulating digital assets (x6). The leading policy for regulating digital assets in the European Union is carried out following the Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on a digital finance strategy for the EU. According to this document, the main goals of regulating digital assets are:

– ensuring legal certainty;

– supporting innovation and removing regulatory obstacles that may hold back the development of financial technologies, reducing risks arisen;

– protecting European users, investors and businesses by creating trust and confidence in the integrity of the market;

– supporting financial stability at the European level.

Thus, the effective legal regulation of digital assets aimed at the listed goals can contribute to a significant increase in the country's cyber security rating.

The increase in investment literacy of the population, represented by the variable x_9 (a share of the population investing in traditional assets), also positively impacts the cyber security assessment. A 1% increase in this metric can, on average, increase the cybersecurity estimate by 0.17. The reason for that may be that the increased investment literacy gives people the knowledge and skills to make informed financial decisions, recognize potential cyber threats, and take preventative measures to protect their investments and personal information.

Implementing the mentioned measures to prevent and counter the criminal use of cryptocurrencies requires active actions from many stakeholders, including cryptocurrency stock exchanges, governments, regulatory authorities and individuals, to jointly solve problems and mitigate the negative impact of cryptocurrencies on cyber security. The development and implementation of security measures related to the use of cryptocurrencies may require considerable effort. However, they can significantly reduce the negative impact of cryptocurrencies on cybersecurity.

Therefore, the obtained model confirmed the influence of cryptocurrency use on the country's digital security. According to Fisher's F-test, it was statistically significant and contained only statistically significant variables. The absence of multicollinearity between independent traits was also confirmed using the variance inflation factor (VIF). The economic interpretation of the estimates of the regression equation parameters allows us to state that the number of active cryptocurrency users and state regulation of digital assets have the greatest influence on the country's cyber security.

According to the modelling results, the increase in the number of mobile application users for investing in cryptoassets once a week or more often is a significant factor in increasing the cyber security risks. Given the growing popularity and use of cryptocurrencies, this fact requires the attention of government and organizations to develop effective strategies and rules for regulating digital assets. Another factor in the decline in cybersecurity is the rise in darknet market revenue, which is a popular platform for selling stolen data and other illegal goods and services, often using cryptocurrency as a means of payment.

Modelling also identifies a significant positive impact of improving legal measures in regulating digital assets on assessing the country's cyber security. Clear and effective regulations significantly prevent cyber threats related to cryptocurrencies and their rapid detection. It creates prospects for the future study of the regulatory and legal field of the countries of the European Union with the highest evaluations of legal measures in regulating digital assets and prospects for the adaptation of similar legal practices in Ukraine. Another factor that positively affects the level of state cyber security is the investment literacy of the population. A possible explanation for this is that citizens who invest in traditional assets increase their investment literacy, which helps them recognize the risks of investing in digital assets as well.

The study provides reasons for increasing public attention to implementing effective state regulation of cryptocurrency activities and promoting investment literacy of the population, creating measures designed to increase cyber security and ensure the country's stable and safe development of the digital environment. Such actions require further research of the specific practices in regulating digital assets in the countries of the European Union, analysis of their suitability for the Ukrainian context, and the development of a political system to minimize the negative impact of cryptocurrencies on cyber security.

2.3. Determination of interrelationships in the chain "digitalization - financial market regulation - law enforcement and judicial bodies"

The active digitalization in the work of all subjects of the anti-money laundering system is an integral component of its effective work and further strategic development. However, the reform of each subject in the anti-money laundering system should be based on an individual approach, according to the level of digitalization impact and the existing involvement in this process. Developing an appropriate economic-mathematical model, which in our case is structural equation modelling, becomes relevant for the most efficient solution to this task. According to this method, various software such as lavaan (R Package), Python, STATISTICA are used for calculations.

The influence of digitalization on the controlling authorities' effectiveness in anti-money laundering was studied based on indicators of regulating the financial services market, law enforcement activities and judicial activities. Processing of gaps in the input database of statistical data was carried out using the method of the moving average growth rate. For each group of input indicators of the financial services market, law enforcement activities, judicial activities and digitalization, relevant factors were selected based on the principal component method. Structural equation modelling of the 1%-change impact of the latent variable of digitalization development on the latent integral features of the controlling bodies' activity in anti-money laundering is proposed to carry out using the Statistica program.

Considering the scientific-methodical approach to evaluating the effectiveness of the anti-money laundering system through digitalization implemented using structural equation modelling, we note that it consists of six stages. So, it is necessary to consider each of them in more detail.

In the first stage, the input information base of statistical data regarding the digitalization impact on the controlling authorities' effectiveness in anti-money laundering is formed. Its implementation is proposed to be carried out based on indicators of regulating the financial services market, law enforcement activities, and judicial activities in the dynamics from 2000 to 2021.

It is proposed to consider the following indicators, grouped by clusters:

1) Regulation of the financial services market: RMFS1 – The number of suspicious transactions taken into account for one formed material (units/units); RMFS2 – The number of recorded suspicious transactions per one UAH of the funds involved (units/million UAH); RMFS3 – Amount of property seized and transferred to state income (million UAH);

2) Law enforcement activity: LS1 – Number of criminal proceedings that were opened or developed using new materials (units); LS2 – Number of indictments referred to the court (units); LS3 – Amount of property seized and transferred to state income (million UAH);

3) Judicial activity: CS1 – Number of guilty verdict cases (units); CS2 – Amount of property seized and income transferred to state (million UAH);

4) Digitalization: DG1 – Gross domestic product of the information and telecommunications sector, in actual prices (million UAH); DG2 – Export of information and telecommunication goods (% of all exports of goods); DG3 – Import of information and telecommunication goods (% of all imported goods); DG4 – Export of information and telecommunication services (% of all exported services); DG5 – Number of mobile phone users (units); DG6 – Number of Internet users (%).

Based on the fact that the current information base is characterized by the absence of data for certain years, at the second stage, it is proposed to determine them using the moving average growth rate method:

– predicted values of the i-indicator of digitalization indicator for 2021 based on available data from 2003 to 2020:

$$DG_{it+1} = DG_{it} \cdot \sqrt[t-4]{\frac{DG_{it}}{DG_{i4}}} \tag{2.5}$$

where DG_{it+1} – forecast value of the i-indicator of digitalization for the (t+1)-year;
DG_{it} – the actual value of the i-indicator of digitization for the (t)-year;

– forecast values of regulating financial services market, law enforcement activity, judicial activity in the middle of the row level:

$$RMFS_{it} = \frac{RMFS_{it-1} + RMFS_{it+1}}{2} \tag{2.6}$$
$$LS_{it} = \frac{LS_{it-1} + LS_{it+1}}{2}$$
$$CS_{it} = \frac{CS_{it-1} + CS_{it+1}}{2}$$

$$DG_{it-1} = DG_{it} / \sqrt[t-j]{\frac{DG_{it}}{DG_{ij}}}$$
$$RMFS_{it-1} = RMFS_{it} / \sqrt[t-j]{\frac{RMFS_{it}}{RMFS_{ij}}}$$
$$LS_{it-1} = LS_{it} / \sqrt[t-j]{\frac{LS_{it}}{LS_{ij}}} \tag{2.7}$$
$$CS_{it-1} = CS_{it} / \sqrt[t-j]{\frac{CS_{it}}{CS_{ij}}}$$

where DG_{ij} –i-indicator of digitalization for the first j-year; $RMFS_{ij}$ –i-indicator of regulating the financial services market for the first available j-year;
LS_{ij} – i-indicator of the legal system for the first j- year;
CS_{ij} –i-indicator of the judicial system for the first j-year.

Within the framework of any process modelling, the key stage is to define relevant variables. This task is significant considering the need to achieve maximum simplicity of calculations at the fourth stage of implementing the methodology for evaluating the digitalization impact on the controlling authorities' effectiveness in the anti-money laundering field. Therefore, the selection of relevant factors for each group of input indicators in regulating the financial services market, law enforcement activity, judicial activity and digitalization is proposed to be carried out based on the principle component method. For this stage, the Statistica program, in particular, Statistics/Multivariate Exploratory Techniques/Principal Components and Classification Analysis are used (table 2.7).

Table 2.7. Eigenvalues of correlation matrix, and related statistics for regulating the financial services market

Value number	Eigenvalue	Total variance, %	Cumulative Eigenvalue	Cumulative, %
1	1,9656	65,5197	1,9656	65,5197
2	0,7561	25,2048	2,7217	90,7244
3	0,2783	9,2756	3,0000	100,0000

Source: compiled by the authors

Thus, the obtained eigenvalues of the correlation matrix (table 2.7 and figure 2.11), in particular the accumulated total variance (the last column of table 2.7), assert the reasonability to consider the first two factors for further substantiation of the relevant indicators of input data for regulating the financial services market.

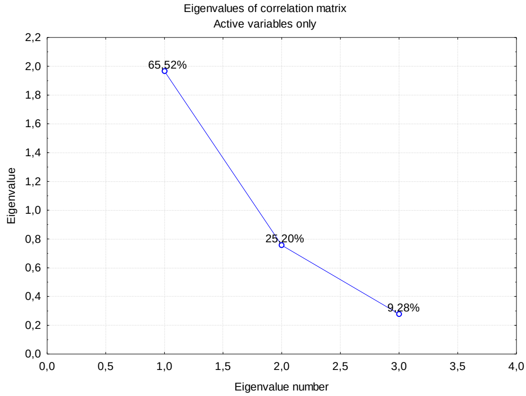


Figure 2.11. A scree plot of % total variation in factors regulating the financial service market

Source: compiled by the authors

Having considered the contribution of correlation-based variables to regulating the financial service market in terms of the first two factors ("Factor 1" and "Factor 2" columns of Table 2.9) and taking into account the variation percentages due to these two factors, RMFS1 and RMFS2 should be recognized as relevant.

As a result of a similar to the above analysis of the relevance of the law enforcement activity indicators based on Tables 2.10 and 2.11 and Figure 2.12, it is appropriate to assert the need to recognize the relevant indicators LS1 and LS2.

Table 2.9. Contributions of correlation-based variables to financial service market regulation

Indicator	Factor 1	Factor 2	Factor 3
RMFS1	0,2227	0,7241	0,0533
RMFS2	0,4207	0,0249	0,5544
RMFS3	0,3566	0,2511	0,3923

Source: compiled by the author

Table 2.10. Eigenvalues of correlation matrix, and related statistics for the direction of law enforcement activities

Value number	Eigenvalue	% Total variance	Cumulative Eigenvalue	Cumulative %
1	1,6569	55,2286	1,6569	55,2286
2	1,0031	33,4351	2,6599	88,6637
3	0,3401	11,3363	3,0000	100,0000

Source: compiled by the author

Table 2.11. Variable contributions, based on correlations for the direction of law enforcement activities

Indicator	Factor 1	Factor 2	Factor 3
LS1	0,5011	0,0001	0,4988
LS2	0,4750	0,0520	0,4730
LS3	0,0239	0,9479	0,0282

Source: compiled by the author

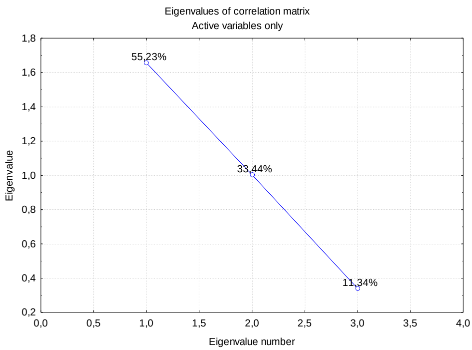


Figure 2.12. Scree plot of % of the total variation factors in law enforcement activity

Source: compiled by the author

Considering that the input array of statistical information consists of different indicators, at the fourth stage of the proposed study, it is advisable to standardize the value of assessing the digitalization impact on the controlling authorities' effectiveness in the anti-money laundering field. It is suggested to use the Statistica program toolkit, in particular the Data/Standardize command, which involves the application of the formula:

$$\widetilde{DG_{it}} = \frac{DG_{it} - \overline{DG_{it}}}{\sigma_{DG_i}} \qquad (2.8)$$

$$R\widetilde{MFS}_{it} = \frac{RMFS_{it} - \overline{RMFS_{it}}}{\sigma_{RMFS_i}}$$

$$\widetilde{LS}_{it} = \frac{LS_{it} - \overline{LS_{it}}}{\sigma_{LS_i}}$$

$$\widetilde{CS}_{it} = \frac{CS_{it} - \overline{CS_{it}}}{\sigma_{CS_i}}$$

where $\widetilde{DG_{it}}$ – standardized value of the i-digitization indicator for the t-year;

$\overline{DG_{it}}$ – the average value of the i-digitization indicator for the t-year;

σ_{DG_i} – mean square deviation of the i-digitization indicator for the studied period.

The results of calculations carried out according to formula (2.8) are presented in table 2.12.

The fifth stage of the proposed scientific and methodological approach involves structural equation modelling of a 1%-change impact in the latent variable of digitalization development on the latent integral features in the controlling bodies' work in the anti-money laundering field using the Statistaca program, particularly Statistics/Advanced linear/nonlinear Models/Structural Equation Modelling.

Table 2.12 – Standardized values of the input indicators for assessing the impact of digitalization on the controlling authorities' effectiveness in anti-money laundering

Year	Indicators								
	RMFS1	RMFS2	LS1	LS2	CS1	CS2	DG1	DG5	DG6
2000	1,51	-0,59	-1,32	-0,98	-1,02	-0,51	-0,92	-1,91	-1,07
2001	1,51	-0,55	-1,32	-1,02	-1,03	-0,49	-0,90	-1,85	-1,05
2002	1,36	-0,51	-1,31	-0,97	-1,01	-0,47	-0,88	-1,79	-1,03
2003	1,08	-0,49	-1,30	-1,02	-1,03	-0,46	-0,86	-1,66	-0,99
2004	-0,32	-0,44	-1,23	-0,97	-1,01	-0,44	-0,81	-1,34	-0,97
2005	-0,68	-0,40	-0,71	-0,87	-1,01	-0,42	-0,76	-0,62	-0,96
2006	-0,80	-0,41	-0,55	-0,89	-1,01	-0,41	-0,71	0,23	-0,94
2007	-0,79	-0,39	-0,03	-0,35	-0,51	-0,41	-0,62	0,50	-0,87
2008	-0,84	-0,44	0,37	0,95	0,57	-0,55	-0,51	0,52	-0,71
2009	-1,02	-0,48	1,10	1,51	1,45	0,63	-0,48	0,49	-0,47
2010	-0,93	-0,42	0,33	0,76	0,32	-0,52	-0,42	0,44	-0,28
2011	-0,80	-0,36	-0,36	1,37	-0,26	-0,49	-0,33	0,52	-0,10
2012	-0,91	-0,60	-0,14	1,93	1,03	-0,46	-0,25	0,68	0,13
2013	-0,94	-0,67	2,60	1,96	1,36	-0,44	-0,17	0,82	0,33
2014	-0,84	-0,74	1,27	0,31	2,22	0,09	-0,11	0,76	0,52
2015	0,11	0,35	0,38	-0,04	0,43	0,61	0,20	0,74	0,61
2016	0,98	2,44	-0,04	-0,31	-0,05	4,08	0,55	0,57	0,75
2017	1,10	2,37	0,14	0,04	1,36	0,15	0,91	0,52	0,96
2018	0,96	-0,15	0,47	-0,48	-0,59	0,37	1,43	0,44	1,08
2019	1,41	2,11	0,37	0,23	0,59	0,59	2,17	0,48	1,35
2020	-0,26	0,82	0,18	-0,38	-0,45	0,01	2,39	0,44	1,52
2021	-0,89	-0,45	1,12	-0,77	-0,36	-0,46	1,08	1,00	2,20

Source: compiled by the authors

A prerequisite for structural equation modelling is a clear definition and justification of the relationships between groups of indicators. Further, the authors define the system of linear paired and multiple regression equations, introducing the following assumptions:

– regulation of the financial services market has an impact on the law enforcement system;

– the state of the law enforcement system determines the judicial system;

– digitization determines the development of regulating the financial services market and the state of the law enforcement and judicial systems;

– it is proposed to choose an implicit latent variable of the digitalization level as an endogenous variable, determined by three explicit indicators of the digitalization feature, while all other variables are exogenous.

Taking into account the given assumptions, the authors build a model of structural equations, the parameters and statistical features of which are listed in Table 2.12.

Table 2.12. Estimates of the digitalization impact model on the controlling authorities' effectiveness in the anti-money laundering field

	Parameter Estimate	Standard Error	T Statistic	Prob. Level
(DG)-1->[DG1]	0,905	0,170	5,317	0,000
(DG)-2->[DG5]	0,675	0,194	3,489	0,000
(DG)-3->[DG6]	0,993	0,159	6,257	0,000
(DELTA1)-->[DG1]				
(DELTA2)-->[DG5]				
(DELTA3)-->[DG6]				
(DELTA1)-4-(DELTA1)	0,181	0,077	2,334	0,020
(DELTA2)-5-(DELTA2)	0,544	0,172	3,171	0,002
(DELTA3)-6-(DELTA3)	0,014	0,064	0,217	0,828
(RMFS)-->[RMFS1]				
(RMFS)-7->[RMFS2]	1,461	0,705	2,074	0,038
(LS)-->[LS1]				
(LS)-8->[LS2]	0,641	0,167	3,827	0,000
(CS)-->[CS1]				
(CS)-9->[CS2]	0,176	0,215	0,821	0,412
(EPSILON1)-->[RMFS1]				
(EPSILON2)-->[RMFS2]				
(EPSILON3)-->[LS1]				

(EPSILON4)-->[LS2]				
(EPSILON5)-->[CS1]				
(EPSILON6)-->[CS2]				
(EPSILON1)-10-(EPSILON1)	0,691	0,246	2,810	0,005
(EPSILON2)-11-(EPSILON2)	0,339	0,281	1,205	0,228
(EPSILON3)-12-(EPSILON3)	0,000	0,000		
(EPSILON4)-13-(EPSILON4)	0,589	0,182	3,240	0,001
(EPSILON5)-14-(EPSILON5)	0,000	0,000		
(EPSILON6)-15-(EPSILON6)	0,969	0,299	3,240	0,001
(ZETA1)-->(RMFS)				
(ZETA2)-->(LS)				
(ZETA3)-->(CS)				
(ZETA1)-16-(ZETA1)	0,219	0,186	1,178	0,239
(ZETA2)-17-(ZETA2)	0,384	0,201	1,908	0,056
(ZETA3)-18-(ZETA3)	0,420	0,130	3,240	0,001
(DG)-19->(RMFS)	0,301	0,182	1,659	0,097
(DG)-20->(LS)	0,926	0,290	3,189	0,001
(DG)-21->(CS)	-0,088	0,179	-0,490	0,624
(LS)-22->(CS)	0,811	0,178	4,563	0,000
(RMFS)-23->(LS)	-1,076	0,635	-1,694	0,090

Source: compiled by the author

Thus, based on the data presented in Table 2.12, the authors form an economic-mathematical model of the structural equations of digitalization impact on the controlling authorities' effectiveness in the anti-money laundering field:

$$\begin{cases} DG1 = 0.905 \cdot DG + 0.181 \\ DG5 = 0.675 \cdot DG + 0.544 \\ DG6 = 0.993 \cdot DG + 0.014 \\ RMFS1 = RMFS + 0.691 \\ RMFS2 = 1.461 \cdot RMFS + 0.339 \\ LS1 = LS \\ LS2 = 0.641 \cdot LS + 0.589 \\ CS1 = CS \\ CS2 = 0.176 \cdot CS + 0.969 \\ RMFS = 0.301 \cdot DG + 0.219 \\ LS = 0.926 \cdot DG - 1.076 \cdot RMFS + 0.384 \\ CS = -0.088 \cdot DG + 0.811 \cdot LS + 0.420 \end{cases} \quad (2.9)$$

where DG – latent implicitly specified (defined by the system of structural equations) variable characterizing the generalizing digitization;
$RMFS$ – latent variable of developing financial service market regulation;
LS – latent variable of developing the law enforcement system;
CS – latent variable of developing the judicial system.

Therefore, the analysis of the system (2.9) allows us to draw the following conclusions regarding the digitalization impact on the controlling authorities' effectiveness in the anti-money laundering field:

– with an increase in the level of digitalization by 1%, development of financial services market regulation will increase by 0.30%;

– a 1%-increase in the level of digitization positively affects law enforcement system development, which will increase accordingly by 0.93%;

– there is a negative impact of digitization on the judicial system, the level of which will decrease by 0.09% with a 1%-increase in digitization;

– a directly proportional influence was found in terms of the dependence of the law enforcement and judicial systems, i.e. with an increase in the level of law enforcement system development by 1%, the level of the judicial system development will increase by 0.81%;

The last and one of the most important stages in the proposed methodology is the sixth stage, which assesses the adequacy of all the above calculations. It is necessary to analyze the adequacy criteria to confirm the adequacy of the detected dependencies (table 2.13). Thus, the minimum value of the disagreement function is 4.09, while the values of the Maximum Residual Cosine, Maximum Absolute Gradient, ICSF Criterion and ICS Criterion indicators are heading towards zero levels, indicating the adequacy of the constructed model. In addition, the Chi-Square criterion is relatively high and takes a value of 85.88, significantly higher than the critical permissible level. The p-level value, which goes towards the zero level, confirms adequacy of the constructed model of structural equations.

Table 2.13. Summary statistics of the model

	Value
Discrepancy Function	4,089566
Maximum Residual Cosine	0,003074
Maximum Absolute Gradient	0,012139
ICSF Criterion	0,000313
ICS Criterion	0,007515
ML Chi-Square	85,880895
Degrees of Freedom	22,000000
p-level	0,000000
RMS Standardized Residual	0,254755

Source: compiled by the authors

In addition, an important criterion for the model adequacy is the statistical significance of the parameters of the linear paired and multiple equations of the system (2.9), confirmed by the Student's test ("T Statistic" column of Table 2.12) and the value of Prob. Level about the probability of rejection of the statistical insignificance hypothesis for the corresponding parameter. Thus, the values of p-levels for most of the parameters do not exceed the level of 0.05, and the value of the Student's criterion takes a level not lower than the critically permissible level.

Analysing the following essential criterion of the adequacy and accuracy regarding the model of the structural equations of the digitalisation impact on the effectiveness of the controlling authorities’ work in the anti-money laundering field, i.e., to the conformity with the normal distribution law of the normalised residuals of the model (Figure 2.13), the authors note the proximity of the actual points to the line that defines the normal distribution law.

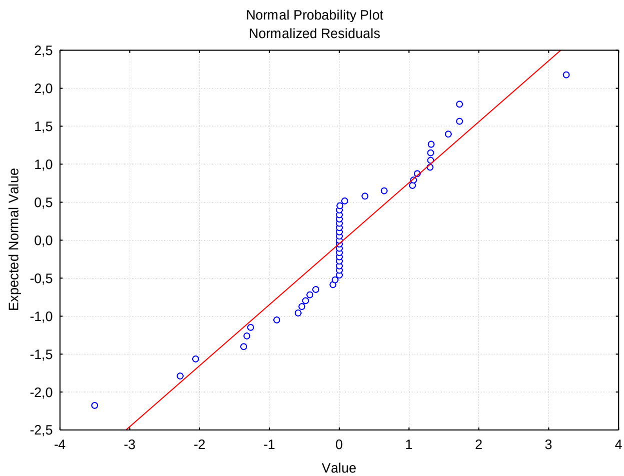


Figure 2.13 – A fragment of compliance with the normal distribution law of the normalized residuals

Source: compiled by the authors

One of the sensitivity criteria of the structural equations model regarding the digitalization impact on the controlling authorities’ effectiveness in the anti-money laundering field is the reflector matrix presented in Table 2.14. Based on the analysis of the data in Table 2.14, it can be asserted that the model is insensitive to changes in the scale of the input data, as the matrix values approach zero levels.

Table 2.14. Reflector matrix

	RMFS1	RMFS2	LS1	LS2	CS1	CS2	DG1	DG5	DG6
RMFS1	0,002	-0,001	0,646	0,570	0,480	0,022	0,281	0,908	0,444
RMFS2	0,005	-0,002	-0,428	-0,409	-0,612	-0,803	-0,374	-0,602	-0,282
LS1	0,300	0,106	0,008	0,283	0,141	-0,262	-0,180	-0,407	-0,225
LS2	0,357	0,177	0,000	0,000	-0,459	0,175	0,372	-0,157	0,357
CS1	-0,082	-0,312	0,003	-0,627	0,000	-0,029	0,122	-0,115	0,058
CS2	-0,344	-0,680	-0,017	0,145	0,000	0,000	-0,319	-0,166	-0,296
DG1	-0,955	-0,895	0,740	0,657	0,752	-0,110	-0,000	0,475	-0,007
DG5	1,048	0,158	-0,744	-0,903	-0,715	-0,058	0,158	-0,000	-0,002
DG6	0,205	0,653	-0,179	0,301	0,020	0,296	-0,088	-0,075	-0,006

Source: compiled by the authors

Thus, it is fair to conclude that the proposed methodology for assessing the digitalization impact on the controlling authorities' effectiveness in anti-money laundering and the calculations obtained due to its practical implementation are adequate and can act as an information base for effective management decisions. Executive authorities and public oversight bodies may use the available results for the annual review of the implemented reforms and the transformation of the digitalization impact trajectory on the controlling authorities' work effectiveness in the financial sphere, law enforcement agencies and courts.

Digitalization has a significant impact on the functioning of law enforcement and financial system controlling authorities in Ukraine. The conducted research confirmed that it is possible to increase the effectiveness of the anti-money laundering system by developing information technologies. Digitalization has the strongest impact on the law enforcement system. Collection of evidence and formation of documents on the case is naturally more effective using information technologies. The effectiveness of authorities controlling the development of the financial service market is also gradually increasing. Thus, the maximum transfer of all payments into non-cash form allows state controlling authorities to form an effective financial monitoring system.

However, the research revealed the problem of the current digitalization impact on the judicial system. Thus, with a 1%-increase in digitalization, the effectiveness of the judicial system will decrease by 0.09%, explained by the modern legislation incompatibility with the latest technologies, since the development of the law enforcement system by 1% increases the development of the judicial system by 0.81%. In addition, the existing staff of the judicial branch of government in Ukraine is not so slow to adapt to the latest technologies as they are against their implementation. Therefore, the judicial system of Ukraine needs to be reformed, considering the modern possibilities of digital technologies.

CHAPTER 3. COMBATING CORRUPTION AND PROMOTING GOOD GOVERNANCE IN CLIMATE ACTION

3.1. Climate finance and corruption: trends, threats, and typologies

The UNFCCC defines climate change finance as "local, national or transnational financing, derived from public, private and alternative sources of finance, to support mitigation and adaptation actions to address climate change". In other words, climate finance includes support for policies and technologies that reduce greenhouse gas emissions and/or help society adapt to the effects of climate change.

The IMF (2022) estimates that government spending on climate change adaptation over the coming decades will average 0.25 percent of the global gross domestic product annually. At the same time, the annual needs of low-income countries over the next ten years will exceed 1 percent of GDP. As of 2020, developed countries have invested over $600 billion in zero and low-carbon infrastructure projects in underdeveloped countries (figure 3.1.) (Climate Policy Initiative, 2021). Almost 90% of the current climate capital is used to finance measures and actions aimed at mitigating the effects of climate change (transition to renewable energy sources, reduction of fossil fuel consumption, stopping illegal deforestation, etc.) The main area of climate change mitigation financing is investments in renewable energy sources, which account for almost 70% of total climate capital. However, the fastest growing area is investment in low-carbon transport. At the same time, to achieve the internationally agreed climate goals, annual climate funding must increase by at least 590% by 2030. It indicates that developed countries will increase their investment in the future to counteract climate change following the Paris Agreement.

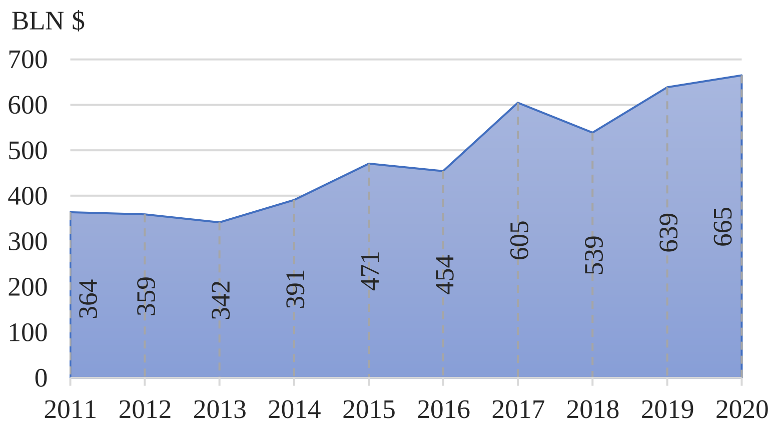
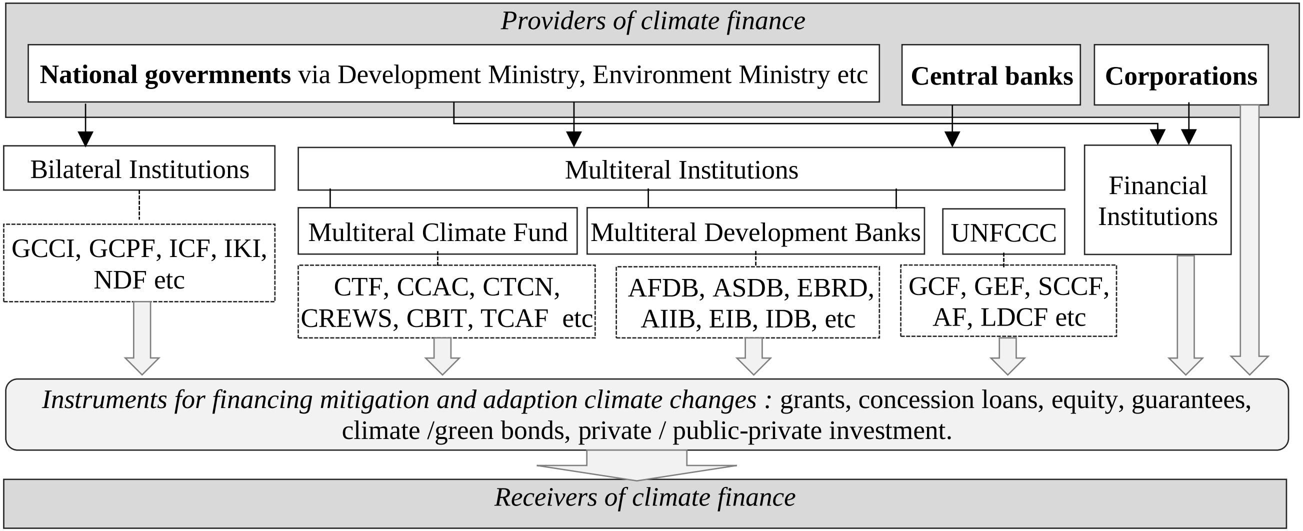


Figure 3.1. Global climate finance flows, bln us dollar
Source: Climate Policy Initiative (2022)

The urgent need to increase the scale of climate finance commitments has become one of the reasons for the search for additional financial instruments to raise capital and stimulate the transition of businesses to a sustainable development model. In 2020, the European Union Taxonomy Regulation was adopted, which defines a "green" list of sustainable activities and establishes obligations for companies to disclose information on sustainable finance. In addition, the International Financial Reporting Standards Foundation announced the creation of the International Sustainability Standards Board, the successful development of which will require financial institutions to systematically assess the impact of their assets on climate change. Central banks are active participants in transformational changes in the field of climate investment. For example, financial regulators from 31 countries have used the climate scenario to assess the sustainability of the financial system and the macroeconomic situation in their countries (United Nations, 2023). Figure 3.2 shows the institutional infrastructure of global climate finance.



Bilateral Institutions: GCCI - Global Climate Change Initiative, GCPF - Global Climate Partnership Fund, ICF - International Climate Finance, IKI - International Climate Initiative, NDF - Nordic Development Fund.

Multiteral Institutions: *Multiteral Climate Fund:* CTF - Clean Technology Fund, CCAC - Climate and Clean Air Coalition Trust Fund, CTCN - Climate Technology Centre and Network, CREWS -Climate Risk Early Warning System Initiative, CBIT - Capacity Building Initiative for Transparency, TCAF - Transformative Carbon Asset Facility; *Multilateral Development Banks:* AFDB - African Development Bank, ASDB - Asian Development Bank, EBRD - European Bank for Reconstruction and Development, AIIB - Asian Infrastructure Investment Bank, EIB - European Investment Bank, IDB - Inter-American Development Bank; *UNFCCC:* GCF - Green Climate Fund, GEF - Global Environment Facility, SCCF - Special Climate Change Fund, AF - Adaptation Fund, LDCF - Least Developed Country Fund.

Figure 3.2. Institutional infrastructure of global climate finance

Source: Climate Funds Update (2023), OECD (2022) & Atteridge et al (2009)

The main source of climate financing is the funds of national governments. International agreements have approved national targets for reducing greenhouse gas emissions and established contributions for developed countries to finance climate change mitigation. In 2021, 58.7% of global climate finance came from just 3 countries - Japan (USD 9.7 billion or 20.7% of the total), Germany (USD 9.4 billion or 20.0% of the total) and France (USD 8.5 billion or 18.1% of the total). A country may decide to finance a project, company, or country directly or indirectly through specialised institutions.

Central banks, by implementing monetary, investment, micro- and macroprudential policies, determine the vectors of development of the country's financial sector in terms of supporting sustainable financing and considering environmental and carbon risks by financial institutions. Established environmental risk management standards serve as the basis for bank lending, and therefore banks and other financial institutions prioritize financing environmentally and socially responsible projects. McKibbin et al (2017) have analyzed the impact of changes in carbon policy instruments (carbon tax, emissions trading system, etc.) on monetary policy indicators. In particular, the introduction of a carbon tax causes a decline in aggregate output and a sharp rise in inflation. Under a strict inflation targeting regime, the central bank would be able to slow down inflation, thereby further restraining the pace of economic development.

Central banks participate in global climate finance by contributing to multilateral development banks. In line with the Paris Agreement, the multilateral development banks have set ambitious targets for the rapid and further expansion of climate finance activities. Thus, the multilateral development banks have committed to increase climate investment by coordinating and scaling up activities to strengthen policies, build institutional capacity, provide access to finance, and provide technical support to client countries and their private sectors. By 2025, multilateral development banks plan to invest at least USD 65 billion in climate action projects, with USD 50 billion of that to be directed to low- and middle-income countries (European Bank for Reconstruction and Development, 2020). Despite declaring their intention to prioritize investments in underdeveloped countries, in 2015-2020, multilateral development banks mainly invested in projects in developed countries. As of 2020, 37% of the climate funds of multilateral development banks (or USD 24 billion out of USD 66 billion) were allocated to finance climate change measures in low- and lower-middle-income countries. The table 3.1 shows climate project financing by bilateral development banks and the level of transparency of these institutions.

Table 3.1 – The volume of climate finance from multilateral development banks and their level of transparency as of 2021

Multilateral development banks	Climate Finance		DFI Transparency Index
	mln $	% of the total volume	
African Development Bank (AfDB)	2429	4,79	73
Asian Development Bank (AsDB)	4764	9,40	75,9
Asian Infrastructure Investment Bank (AIIB)	2746	5,42	47,1
European Bank for Reconstruction and Development (EBRD)	4777	9,43	48,4
European Investment Bank (EIB)	3371	6,65	37
Inter-American Development Bank (IDB)	4819	9,51	69,9
Islamic Development Bank (IsDB)	684	1,35	7
World Bank Group (WBG)	27989	55,24	65,4

Source: European Bank for reconstruction and Development (2020), Publish What You Fund (2023)

Analyzing the level of transparency of multilateral development banks, the DFI Transparency Index was selected, which includes data on 47 indicators from the following categories: basic information, impact management, ESG and community accountability, financial information, and financial intermediation sub-investments (Publish What You Fund, 2023).

The World Bank Group provide the largest share of climate finance, but their transparency score is 65.4. Although the World Bank has demonstrated relatively good results in disclosing information at the project level, there are still shortcomings in the policy of early disclosure and explanation of project environmental and social risk categorization. The Asian Development Bank has the highest level of transparency among multilateral development banks.

In summary, international climate finance can flow through various bilateral, multilateral and other channels, involving a number of different public and private institutions. Therefore, a degree of coordination between different institutions is required to monitor financial flows from different sources that are channelled to or through different end-users. Some funds may be directed to the state treasury and distributed through state or extra-budgetary funds, while others may be directed to other actors. Given the wide range of actors involved in climate finance projects and the growing volume of climate finance, transparency and efficiency in the allocation and use of climate finance is a key issue for building trust between developed and developing countries.

The issue of increasing the level of transparency of climate finance in underdeveloped countries requires a comprehensive approach to address - on the one hand, improving the level of justice, judiciary, local regulatory authorities, and legislation in recipient countries of international financial assistance.

The basic provisions on transparency of countries' policies in the field of climate risk management are set out in Article 13 of the Paris Agreement. The level of reporting detail depends on the type of national contributions to the global climate fund, data availability, etc. The countries participating in the Paris Agreement are required to submit transparency reports at least every two years. In terms of greenhouse gas emissions, developed country parties report annually in separate national reports. However, the existing reporting forms on climate finance for developing countries do not contain detailed information to monitor the effectiveness of the funds used and the achievement of the green targets set. In particular, the issue of accounting and reporting on non-financial support (technology transfer, capacity building) remains unresolved.

Governments are trying to develop robust national monitoring systems based on domestic policy priorities and specific institutional arrangements. If information on climate finance is integrated into targets related to climate change plans and priorities, it can potentially allow governments to understand the impact or outcomes of these funds (e.g. whether they contribute to climate goals). Countries also take different approaches to tracking the impact of climate finance according to their specific priorities, such as economic efficiency, human well-being or transformative change. The monitoring of financial resources received takes place in the context of tracking government budgets and expenditures related to climate action, as well as monitoring and evaluation systems in place for climate action itself.

While significant financial flows are channeled to such multilateral institutions, access to this funding requires successful accreditation. As a result, the majority of climate finance is allocated to international organizations that have the capacity to conduct accreditation. National societies cannot directly apply for climate finance from these funds, but they can be implementing partners for an accredited organization.

However, there is not always strict adherence to the rules and requirements for reporting on funds received under climate finance programs. Climate experts of the United Nations Framework Convention on Climate Change (UNFCCC) point to problems in the methodological assessment of mobilized climate capital (Caruso and Ellis, 2013), namely, determining the optimal proportion between the amount of public funding and mobilized private climate finance.

The key challenges that hinder the formation of an effective monitoring system for climate funds include (OECD, 2016):

– data collection and reporting system (climate finance can take different forms (off-budget financing, grant financing, technical and in-kind assistance, guarantees and mobilized private finance) and it is therefore advisable to use harmonized indicators and make them publicly available);

– accounting and reporting system (most countries have systems for budgeting, monitoring and reporting on financial flows and expenditures, but they are generally not designed for climate finance);

– coordination system (the distribution of responsibilities for managing climate finance is often spread across different ministries, organisations and agencies, and international institutions, leading to duplication of functions and increased operational and administrative costs).

The least developed countries and tiny island states are the most vulnerable to the negative consequences of climate change. Cantelmo, Giovanni and Papageorgiou (2019) find that more frequent and severe weather events in these countries cause an average welfare loss equivalent to a permanent reduction in consumption of 1.6%. At the same time, countries that are most vulnerable to the consequences of climate change have a high level of corruption, which determines the relevance of this study and the increased attention of the international community to the effectiveness of the financial aid aimed at climate goals. In particular, the correlation level between the Global Adaptation Index of Notre Dame (ND-GAIN) and the corruption perception index (CPI) is 0.83, asserting a reasonably close relationship between these indicators. The Global Adaptation Index of Notre Dame in low-income countries averages 34.4, while the corruption level is relatively high (CPI is 33.1). In addition, countries with a low, below/above average level of income are characterized by a high corruption risk.

Having analysed the recipients of international climate aid, it is worth noting that the countries that receive the most funding have a high level of corruption in the public sector. In particular, the corruption perception index of the first ten countries that receive the largest amount of climate finance is 33.36% on average (table 3.2). The ten countries in the table account for 44.77% of the total volume of climate finance.

Table 3.2. Top recipients of climate-related development finance and their corruption during 2005-2021

	Climate-related development finance		Corruption Perceptions Index, median score
	bln US dol	% of total volume	
India	31,380	11,167	36,188
Indonesia	16,133	5,741	31,519
China	12,946	4,607	37,400
Bangladesh	12,429	4,423	24,225
Brazil	11,963	4,257	37,669
Vietnam	9,969	3,548	36,936
Turkey	8,243	2,934	42,319
Egypt	7,954	2,831	32,350
Kenya	7,625	2,714	24,650
Marocco	7,158	2,547	36,588
Ukraine	4,267	1,518	27,063
% of all climate-related development finance	125,799	44,769	-

Therefore, investing significant sums of money in infrastructure projects of underdeveloped and sufficiently corrupted countries requires increasing transparency in the use of international aid funds and accountability level. Corruption can level up the international community's efforts to ensure carbon-neutral economies, namely reducing greenhouse gas emissions and neutralizing the negative consequences of climate change in the world. Therefore, local authorities must not only fulfil the climate obligations specified in international agreements and national strategies but also implement measures to combat corruption.

Case studies testify to the numerous cases of corrupt interventions in the use of international aid funds in combating climate change. Examples of corruption crimes in international climate financing are:

– about 7–15% (1–2 billion USD) of multilateral climate funds allocated to the water sector is lost due to corruption each year;

– about 35 % of the budget for climate projects in Bangladesh was rubbed or misappropriated (Transparency International Bangladesh, 2006);

– more than one quarter of solar energy projects in India have to pay bribes during the contracting or construction phase (Sovacool, 2021);

– bribery infrastructure facility projecting in Indonesia in the amount of USD 148,000, due to which the project was stopped in 2016 due to environmental, social and corruption problems. The director of the enterprise was imprisoned for three years, and the city council deputy - for ten years.

The authors note that the main corruption risks in the financing of programs aimed at combating climate change are financing for significant sums of money, low level of effectiveness of project implementation monitoring, low level of transparency based on the results of the works received, systemic corruption in the countries-recipients of international aid in such sectors of the economy as construction, energy and forestry; the urgency of financing measures to combat climate change in the world, etc.

Thus, by actively and explicitly embedding integrity, transparency, accountability, inclusiveness and zero tolerance for corruption in climate finance and activities, multilateral funds can maximise the effectiveness of climate change mitigation and adaptation programmes. The highest standards in these areas reinforce anti-corruption measures such as policy dialogue and participatory learning, improved lobbying practices, better laws and policies, open data, monitoring and reporting mechanisms, and whistleblower protection. Only by increasing transparency in the use of climate finance can climate professionals and stakeholders ensure that global climate finance and adaptation programmes are as effective as possible. Countries that receive climate finance desperately need and deserve it. Our recommendations will help build confidence in climate finance opportunities, which will ultimately reduce greenhouse gas emissions.

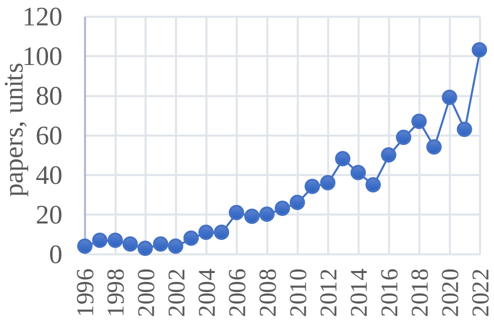
The dynamic development of modern science, to a large extent, is determined by the strengthening of collaboration between research centres of different countries, the dissemination and exchange of scientific knowledge thanks to the use of modern digital and information technologies, the provision of open access to the scientific research results, etc. These changes open up new opportunities for qualitative analysis of scientific work on specific issues and expansion of scientific research. A modern means of analyzing the scientists' publishing activity is bibliographic analysis using scientometric databases and the latest methods and tools for analyzing textual data.

Bibliographic analysis enables to consolidate information about the subject area in a single information resource, analyze trends within subject-oriented topics, determine the most cited scientific publications, establish research centers on specific issues; to ensure an adequate reflection of the subject field of research; conduct an analysis of research areas in SciVal to determine the compliance of publications with the Sustainable Development Goals; build clusters of scientific publications using the VOSViewerv.1.6.10 toolkit.

The main goal of this study is to transfer from the traditional review of scientific publications to the latest approach, involving the establishment of cross-topics, interdisciplinary and international connections in the study of a certain scientific issue, as well as the construction of scientific publications clusters on a certain issue.

One of the tools for monitoring scientific publications included in the Scopus scientometric database is SciVal. It accumulates the studies of thousands of research institutions and their associated researchers from 231 countries, allows the analysis of research by more than 30 different metrics, and evaluates the level of prominence of the chosen scientific direction.

Within the framework of this study, scientific publications containing the keywords "corruption" and "climate" were analyzed. When considering a larger number of scientific publications with different endings of the above keywords, the search query was carried out in the following form: "corrupt* AND climat*". Based on the search query results, 847 publications on this issue were published in the Scopus scientometric database during 1991-2022. The data in Figure 3.3 visually testify to the chosen research direction's relevance and the permanent growth of scientific publications with slight reductions in certain periods (2019 and 2021). In 2022, scientists from different countries published 103 works devoted to studying corruption in terms of climate change, which is two times more than in 2019.



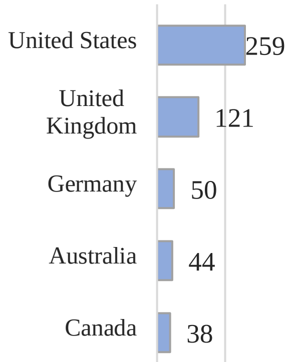


Figure 3.3 – Dynamics of the scientific papers in the scientometric database Scopus on “corruption & climate” during 1996-2022

As for the geographical distribution, 60% of scientific publications on this issue during 1991-2022 were published by scientists from the USA, Great Britain, Australia, Germany and Canada. At the same time, scientists from the USA published 259 publications or 30.6% of the total volume on this topic.

The interdisciplinary structure of the articles included in the sample is given to confirm the relevance of the chosen scientific direction. During 2012-2021, most publications on this issue (27.93% of the total volume) belongs to "social sciences", while 15.36% - to "environmental protection", 11.33% - to "business, management and accounting", 7.84% - to "economy, econometrics, finance" (Fig. 3.4). At the same time, about a third of the publications refer to other fields, indicating the interdisciplinary nature of research with the predominance of research in humanitarian sciences.

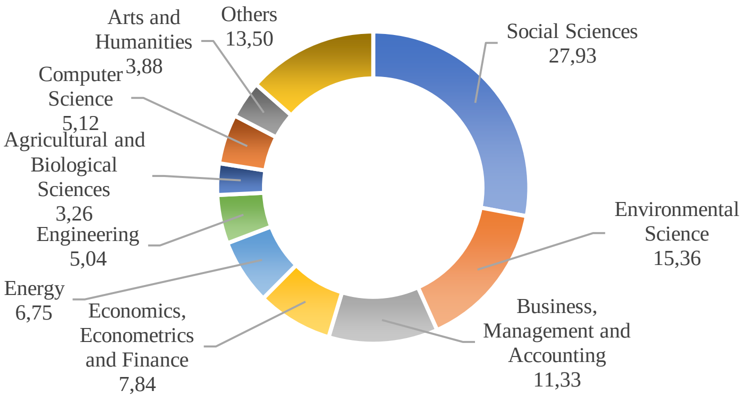


Figure 3.4. Structure of topics in the articles devoted to corruption and climate change

While analysing the scientific community's interest in published studies dealing with the study of corruption and climate challenges, it is possible to note that scientific works on the subject under study, which are among the 10% of the most cited publications in the world, make an average of 13.3% in 2021. 35.8% of published scientific works are in the TOP 25 cited publications in the world, which is a third higher than in the previous year (in 2020 - 27.1% in the TOP 25). During 2012-2021, only 1.6% of the works on the studied issues were in the TOP 1 of the most cited publications.

During 2012-2021, 68% of publications on the studied issues were published in high-rated scientific journals, particularly, 48.6% of works in journals with a Q1 rating and 19.4% - in Q2.

The SciVal service allows you to analyze the dynamics of publications on this issue and assess the importance of the chosen scientific direction based on the topic prominence indicator (Topics Prominence). In the SciVal service, the prominence analysis can be carried out across 96,000 thematic areas and 1,500 clusters. "Prominence" in SciVal is an algorithm that analyses an array of publications from the Scopus database, combines them into thematic clusters/topics and assigns a numerical index to each topic (the maximum value is 100). The prominence level of the thematic area is calculated based on three indicators: the number of citations of the article, the number of views of this article, and the average CiteScore. The higher the value of the prominence index, the more weight this direction has in the world scientific community and is promising for funding. Table 3.3 shows the main thematic areas in which works dealing with corruption and climate issues are published.

Table 3.3. The top five areas in SciVal in which the most articles on the studied issues were published for the period 2012-2021.

Topic area		Prominence percentile	Publications		
Identi-ficator	Topic		number, units	share in the sample, %	Field-Weighted Citation Impact
T.2603	Firm; Bribes; Anti-corruption Measures	98,700	33	6,03	1,20
T.3883	Environmental Kuznets Curve; China; Trade Openness	99,945	17	3,11	3,17
T.1567	Climate Change Adaptation; Urban Climate; Resilience	99,878	13	2,38	1,00
T.4690	Intergovernmental Panel on Climate Change; Climate Change; Skepticism	99,711	10	1,83	0,63
T.2790	Community Forestry; Forest Governance; Environmental Protection	98,310	10	1,83	0,57
T.2491	Foreign Direct Investment; Bilateral Investment Treaties; Inflow	95,177	10	1,83	0,34

The data in Table 3.3 indicate that most publications devoted to corruption and climate belong to the thematic area "Companies; bribes; Anti-corruption measures". The prominence level of this thematic area is 98,700, indicating the public importance and priority to fund scientific research on this topic. The average weighted level of citations of the thematic area "Companies; bribes; Anti-corruption measures" is 1.20. It means that this area is cited by scientists 20% more than the average rate of citations for all other publications.

Among the top five thematic areas in SciVal, the highest level of citation (3.17) is "Kuznets ecological curve; China; Openness of trade", i.e., the citation of this area is three times higher compared to the statistical average.

For a more in-depth analysis of relationships at the theoretical and empirical levels in the selected scientific publications, a bibliographic analysis was carried out using the VOSviewer toolkit. It is a keyword collaborative network mapping software tool developed by N.J. van Eck and Waltman L. at the Center for Science and Technology Research, Leiden University. These network maps make it possible to distinguish clusters of scientific publications by the strength degree of links between a keyword and other keywords. According to the VOSviewer guide, the closer keywords in a cluster are to each other, the stronger their relationship and the more posts that combine those keywords.

Graphical interpretation of bibliometric analysis results using the VOSviewer toolkit is presented in Figure 3.5. The threshold value was a minimum of six keyword repetitions to visualize a common keyword. As a result, out of 4,853 keywords, 161 keywords meet this restriction.

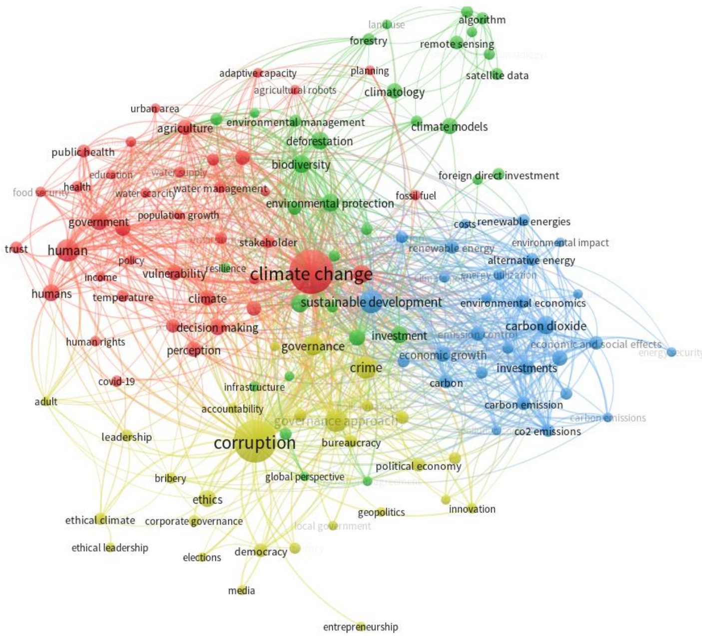


Figure 3.5. Network visualization of citations of scientific publications on climate change and corruption

Source: compiled by the author using VOSviewer toolkit

Based on the co-occurrence analysis results (reflecting the close relationship between the key categories of the formed sample), four scientific patterns were identified in the study:

Scientific cluster No. 1 (red colour) studies the forms of climate change and their consequences on the socio-economic development of countries (39 keywords). This cluster includes scientific publications, the keywords of which are adaptive management, agriculture, climate change, environment, fossil fuel, food security, global warming, vulnerability, water management, temperature etc.

Crate and Nuttall (2016) determined that high levels of resource concentration, social inequality, lack of political voice and representation, social exclusion of women from public life, and systemic corruption cause destructive climate change in the country. Based on data on pollution levels in 94 countries from 1987 to 2000, it was found that corruption led to an increase in emissions from sulfur oxide and carbon dioxide per capita (Cole, 2007). Welsch (2004) proved that corruption could delay the turning point of the environmental Kuznets curve (EKC). The environmental Kuznets curve is a hypothetical correlation between different indicators of environmental degradation and income levels per capita (Saraç & Yağlikara, 2017).

Haseeb & Azam (2021) estimated the relationship between tourism, corruption, democracy, and carbon dioxide emissions by constructing a regression model based on panel data from 1995-2015 in the context of countries with different income levels. First, the results of using the Granger causality test proved that there is a two-way relationship between the level of corruption and carbon dioxide emissions. Second, the long-term link assessment found that a 1% increase in corruption would lead to a 0.09% increase in CO2 emissions. Third, corruption significantly impacts increased CO2 emissions in all countries, regardless of their income per capita. Leitão (2021), based on panel data for European countries (Portugal, Spain, Italy, Ireland, and Greece)in 1995-2015, proved the existence of a unidirectional causal relationship between carbon dioxide emissions and corruption, i.e., the corruption index has a statistically significant positive impact on carbon dioxide emissions. Analyzing the work of Haseeb & Azam (2021) and Leitão (2021), we note that the relationship between corruption and carbon dioxide emissions can be diverse depending on the selected sample of countries for the study.

The paper of Ahmad et al. (2021) analyzed data from 72 middle-income countries for the period from 2010 to 2017 using a dynamic panel assessment by the generalized method of moments. It was found that combating corruption in environmental management could minimize the harmful effects of PM 2.5 microparticles on the population's life expectancy in these countries.

Scientific cluster No. 2 (blue colour) studies investment in infrastructure facilities for developing renewable energy, and reducing emissions into the environment (28 keywords). The main keywords of this cluster are alternative energy, carbon dioxide, carbon emissions, CO2 emissions, emission control, energy efficiency, energy security, pollution, investments, renewable energy etc.

Case studies confirm the existence of numerous cases of corrupt interference in the use of international assistance to combat climate change. Examples of corruption offences in the field of international climate finance are: about 7-15% ($1-2 billion) of multilateral climate funds allocated to the water sector are lost annually due to corruption (GIZ, 2019); about 35 percent of the budget for climate projects in Bangladesh has been stolen or misappropriated; more than a quarter of solar energy projects in India are forced to pay bribes during the contract or construction phase; bribery in the design of an infrastructure facility in Indonesia for $148,000, which caused the project to be shut down in 2016 due to environmental, social and corruption issues (Sovacool, 2021). The director of the enterprise was jailed for three years and the city council deputy – for ten years.

Analyzing the activities of climate funds in Bangladesh, the authors of the article (Kabir et al., 2021) focus on the following main issues: limited access to information, political considerations when approving the fund, lack of transparent accountability, unknown applicants' basic criteria for selecting projects, as well as political influence and conflicts of interest in the distribution of climate resources.

The paper of Devine et al. (2022) justified the expediency of using green building certification to combat corruption and attract climate investment to achieve carbon neutrality goals.

Scientific cluster No. 3 (green colour) focuses on identifying the mechanisms of combating climate change in the world, preserving biodiversity and the environment in general (32 keywords). The keywords of scientific cluster No. 3 are biodiversity, climate effect, climatology, deforestation, environmental protection, foreign direct investment, forest management, forestry, international agreement, investment, law, sustainability etc.

Citizens' involvement in monitoring climate funds' use makes it possible to improve the quality of project implementation and national farms' resilience to climate change's effects. . In particular, the experience of non-governmental organizations in Tunisia that receive funds for implementing climate action programs shows that they are focused exclusively on this task. Hence, the efficiency of using climate funds is relatively high. In addition, representatives of public organizations are actively involved in discussing climate issues at international forums, symposia, and the development of regulations in this area, etc. (Youssef et al., 2021).

The paper substantiates the expediency of involving the public to control the targeted use of climate project funds by the example of Bangladesh (Khan et al., 2022). Dual-use investments bring immediate benefits to local community residents and minimize the adverse effects of climate change. However, ensuring that the local community is involved in climate change management is quite a complex process. However, it can bring greater benefits to local communities and create stronger barriers to corruption or misappropriation of financial or natural resources (Oviedo, 2022). Ratmono & Darsono (2022) empirically substantiate that fiscal decentralization allows to reduce levels of corruption at country level. In addition to fiscal decentralization, it is advisable to implement a reliable system of internal control to fight corruption (Ratmono et al., 2021; Chand et al., 2022).

Abidin et al. (2015) note that countries with a high level of governance have a higher potential for effective environmental management compared to states with a low level of public administration and a low quality of democratic institutions. The fundamental mechanisms for ensuring transparency and minimizing corruption is the process simplification and transactions reduction through automation (Kharabsheh & Gharaibeh, 2022; Popescu et al., 2022), blockchain (Kuzior et al., 2022; Pisár et al., 2022; Mynenko & Lyulyov, 2022) and supervisory artificial intelligence (Gladden et al., 2022).

Mačiulytė-Šniukienė & Sekhniashvili (2021) and Szczepańczyk (2022) prove that innovation in public and ecological spheres influences not only economic growth but also has a positive effect on environmental performance.

Scientific cluster No. 4 (yellow) studies corruption and other unscrupulous behaviour in managing climate resources (28 keywords). The keywords of scientific cluster No. 3 are accountability, bribery, corruption, bureaucracy, crime, corruption, democracy, ethical climate, ethics, governance, institutional framework, law enforcement, laws and legislation, media, policy-making, transparency etc.

Saha & Gounder (2013) proved that civil servants might use illegal tools to influence the environment and access natural resources for their financial benefit. The Rahman (2018) survey showed that 77 out of 108 respondents (71.3%) are forced to pay bribes to run their businesses. The victims of these acts of corruption are beekeepers, forestry workers, fishermen, and palm leaf collectors. Corruption in the forestry sector can occur starting with access to raw materials and ending with the transportation of timber to places of sale. Specific types of corruption in forestry may include changing product information, falsifying sales and transportation certificates, replacing tree identification codes, and intentionally updating trees by foresters with stems in operational diameters (Hatibovic et al., 2022).

Thus, the problem of corruption is closely connected with the climate change in the world, namely the non-transparent procedure of infrastructure objects for investment, misuse of climate funds, illegal deforestation or mining, etc.

The VOSviewer toolkit tracks the relevance of case studies in retrospect and the current period. The network map (Fig. 3.6) shows that during the last three years, the most researched topic is the study of the mechanisms for reducing emissions into the environment and the study of the impact of investments in low-emission infrastructure, transport and production.

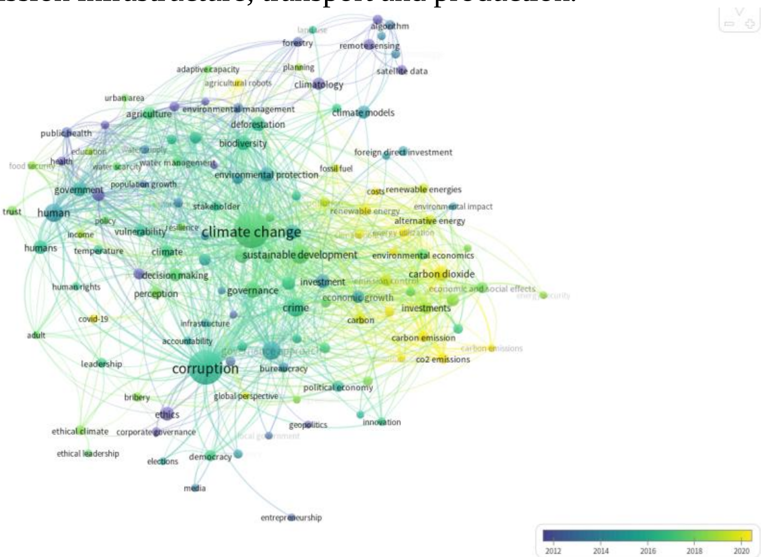


Figure 3.6. Network of scientific publications' citations on climate change and corruption depending on the date of publication of the works

Thus, corruption in climate changes is the focus of many scientific studies. However, the assessment of the impact made by climate financing and corruption on the reduction of greenhouse gas emissions has been still understudied.

3.2. The survival analysis approach for modelling the effects of corruption on efforts to address climate change

For more than a decade, developed countries have been obliged to mobilize significant sums of money to support developing countries in adapting to the effects of climate change and reducing emissions. This study proposes a scientific and methodological approach for assessing the impact of corruption in climate financing on climate change dynamics based on the use of survival analysis methods.

Unlike the above methods, survival analysis allows applying a probabilistic approach to assess the relationship between climate finance, considering corruption and greenhouse gas emissions. The first use of survival analysis and life expectancy models was carried out in medical studies. However, over time, the scope of the practical application of survival analysis techniques has significantly expanded, and now scientists call this type of analysis "time to event analysis." This statistical analysis method allows estimating the cumulative probability of occurrence of a certain event and simulating the influence of individual factors on this probability. We use two survival models in this study:

1. The Kaplan-Meier method (KM) is a nonparametric method used to estimate the probability of survival ($S(t_i)$) from the observed survival time

$$S(t_i) = S(t_{i-1})(1 - {}^{d_i}/_{n_i}) \tag{3.1}$$

$S(t_{i-1})$ – probability of reducing emissions by 5 % in the period t_i compared to t_{i-1}

n_i – the number of countries that achieved a 5% reduction in emissions immediately before t_i

d_i - number of events as of t_{i-1}

The Kaplan-Meier survival function is used to study general patterns of climate finance efficiency. The survival function estimates the probability of climate finance efficiency in a given time t.

2. The Cox proportional hazards regression model is a nonparametric method used to estimate the hazard function h(t)– the risk of an event occurring at time t

$$h(t) = h_0(t)e^{b_1x_1+b_2x_2+\cdots+b_px_p} \qquad (3.2)$$

t – survival time
$h(t)$ – risk function defined by the set of p covariates (x_1, x_2, ….x_p)
b_1, b_2, ….b_p –coefficients that measure the effect of covariates
h_0 – basic danger.

The Cox proportional hazards regression model is based on two assumptions: first, the survival function is exponential ; second, the risk ratio for the two groups compared is constant throughout the study period. Within the framework of this study, the Cox proportional hazards regression model is used to assess the degree of impact of independent variables (amount of climate funding, level of corruption) on greenhouse gas emissions.

Empirical verification of the proposed scientific and methodological approach for assessing the impact of corruption in the field of climate finance on the dynamics of climate change will allow testing of the following main working hypotheses of this study:

Hypothesis 1: the probability of reducing carbon emissions increases due to climate finance.

Hypothesis 2: corruption plays a vital role in the relationship between climate finance and carbon reduction.

The scientific and methodological approach to assessing the impact of corruption in the field of climate finance on the dynamics of climate change involves the implementation of the following steps: 1) collection and processing of statistical information on the volume of climate finance in the context of developing countries; 2) determination of trigger dates as criteria for the effectiveness of climate finance programs in the context of the studied countries; 3) censorship of countries that failed to achieve a reduction in greenhouse emissions; 4) determination of the specification of the form of distribution of the survival function; 5) construction of survival tables that reflect the allocation of time before the occurrence of a particular analyzed event – reduction of greenhouse emissions; 6) calculation of the probability of occurrence of an event (carbon dioxide emissions reduction) for a certain period of time by plotting a Kaplan-Meier curve; 7) defining the determinants of the impact on the period of greenhouse gas emissions reduction based on the construction of the Cox proportional hazards model; 8) interpreting findings and model adequacy checking.

The scientific and methodological approach to assessing the impact of corruption in climate finance on the dynamics of climate change provides for the implementation of the following steps:

1. Collection and processing of statistical information on the amount of climate finance in developing countries. 114 countries received international climate assistance were selected for the study. The countries mentioned above received international climate assistance for $281 billion in the context of 48,703 projects (table 3.4) during 2005-2021. Regionally, Sub-Saharan Africa received 17,112 projects worth $62.4 billion, or 22.2% of global funding from 2005 to 2021. East and South Asian countries have accumulated $113.8 billion, or 40.5% of total financing.

The leading intermediaries in providing this assistance to underdeveloped countries are Green Climate Fund, Clean Technology Fund, IKI, Adaptation Fund, Global Environment

Facility, Asian Development Bank, BMZ, EBRD, European Commission French Development Agency, Japanese International Co-operation Agency, Japan Bank for International Co-operation, European Development Fund, European Investment Bank, Export-Import Bank of Korea, etc.

Table 3.4. Distribution of international climate assistance by region during 2005-2021

Region	**Amount of climate funding**		**Number of climate finance projects**	
	bln US dol	**% of the total volume**	**units**	**% of the total volume**
East Asia and the Pacific	57.2	20.4	11,483	23.6
Europe and Central Asia	36.2	12.9	3,422	7.0
Latin America and the Caribbean	40.4	14.4	9,124	18.7
Middle East and North Africa	28.2	10.0	2,499	5.1
South Asia	56.6	20.1	5,063	10.4
Sub-Saharan Africa	62.4	22.2	17,112	35.1
TOTAL	281.0	100.0	48,703	100.00

Source: compiled by the authors

2. The trigger dates determination as criteria for the effectiveness of climate finance programs in countries under consideration.

Survival analysis involves analyzing the length of time before a particular event occurs. As part of this study, a specific event is the reduction of greenhouse gas emissions.

The first date is the year of entry into force of the Kyoto Protocol (February 16, 2005). It is the first addition to the UN Framework Convention on climate change

The second date is the year when a particular country achieved an average 5 percent reduction in emissions compared to the previous year.

3. Censoring countries that have failed to achieve a reduction in greenhouse emissions.

An important advantage of the Kaplan-Meier curve is that the method can consider "censored" observations, i.e., identify countries that could reduce emissions during the study period. This censorship is called right-hand censorship because there have been no changes in environmental improvement over a fixed period. A fragment of the definition of "censored" data is shown in Figure 3.7.

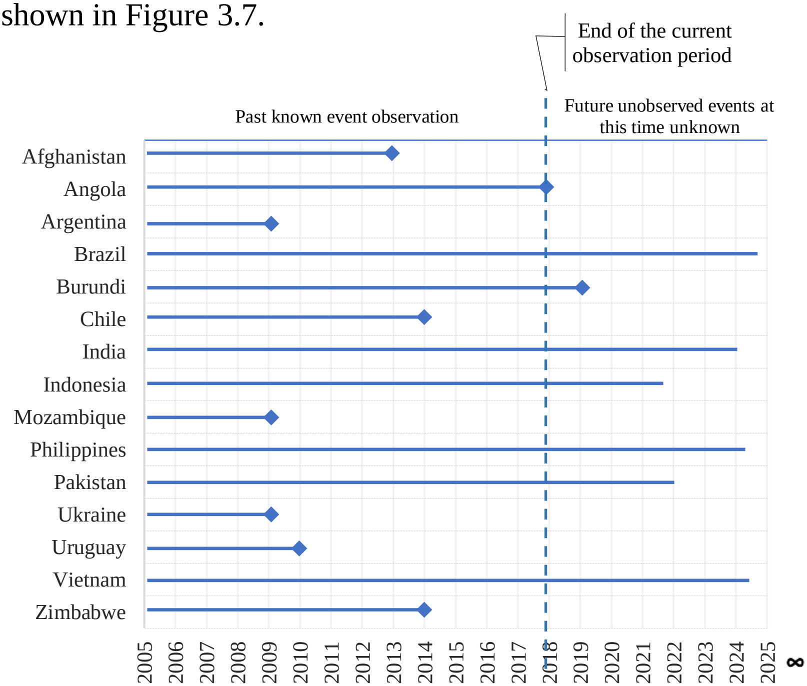


Figure 3.7. Survival analysis graph (fragment)
Source: compiled by the authors

According to the analysis of greenhouse gas emissions, it was found 57.89% (66 out of 114 countries) of the analyzed countries failed to reduce emissions by at least 5% during 2005-2020. After analyzing the countries that could not achieve a reduction in greenhouse gas emissions, we note that during 2005-2020, these countries attracted $218.193 billion or 80.18% of the total amount of climate funding. Based on this, due to the failure to achieve a 5% reduction in greenhouse gas emissions by the end of 2020, 66 countries fell under right-wing censorship, i.e., they were not used for further analysis.

4. Definition of the distribution form of the survival function.

The parametric model $S(t)$ is constructed by selecting the theoretical distribution of a random variable T. We used specialized STATISTICA software, which provides for the calculation of four types of distribution: exponential, linear, Weibull, and log-normal, to perform the survival analysis. Estimates of distribution parameters are calculated using the maximum likelihood estimation (Weight 1), the method of moments (Weight 2), or the least squares method (Weight 3). The adequacy of the model is evaluated based on the values of the significance level of the p criterion. If the criterion is significant ($p<0.05$), the chosen form of distribution significantly differs from the analyzed data. The results of determining parameters for various forms of distribution are presented in Table 3.5.

As a result of the calculations, the Gompertz distribution and exponential distribution are not adequately applied in modelling the effects of climate finance. The best level of adequacy is inherent in the Weibull distribution and the linear distribution is the closest to the actual distribution of the studied parameters among all distributions. At the same time, the Weibull distribution shows the adequacy of the model simultaneously in the context of three methods for calculating parameters (Weight 1-3) since the p-value is greater than 0.05. The smaller the obtained chi-square value, the more accurate the parameter estimate is.

Table 3.5. Results of parameter estimation for various distribution forms

Estimation method	Parameter Estimates, Model: Linear Hazard (Spreadsheet1) Note: Weights: 1=1., 2=1./V, 3=N(I)*H(I)									
	Lambda	Variance Lambda	Std.Err. Lambda	Gamma	Variance Gamma	Std.Err. Gamma	Log-Likelhd.	Chi-Sqr.	df	p
Linear Hazard										
Weight 1	0.063440	0.002569	0.050687	0.020676	0.000128	0.011300	-67.1967	9.264659	2	0.009739
Weight 2	-0.013144	0.000600	0.024485	0.035755	0.000051	0.007163	-63.8233	2.517780	2	0.283983
Weight 3	0.007794	0.000879	0.029640	0.033080	0.000059	0.007651	-64.1794	3.230052	2	0.198902
Gompertz										
Weight 1	-2.90282	0.143994	0.379465	0.158588	0.003113	0.055793	-67.9587	10.78855	2	0.004547
Weight 2	-2.75280	0.118248	0.343872	0.180178	0.002340	0.048374	-66.7289	8.32904	2	0.015546
Weight 3	-3.29938	0.167914	0.409774	0.250459	0.003294	0.057395	-67.2267	9.32449	2	0.009452
Weibull										
Weight 1	0.015624	0.000094	0.009710	1.977525	0.078290	0.279803	-64.7687	4.408488	2	0.110351
Weight 2	0.014443	0.000069	0.008325	2.092044	0.062487	0.249973	-63.7703	2.411708	2	0.299450
Weight 3	0.010953	0.000047	0.006846	2.209008	0.076586	0.276741	-63.7999	2.471042	2	0.290697
Exponential										
Weight 1	0.208175	0.001473	0.038381	x	x	x	-79.1263	33.12370	3	0.000000
Weight 2	0.082603	0.000232	0.015218	x	x	x	-82.9435	40.75819	3	0.000000
Weight 3	0.161997	0.000459	0.021427	x	x	x	-76.5156	27.90236	3	0.000004

Source: compiled by the authors

5. Construction of survival tables that reflect the time distribution before a particular analyzed event – reduction of greenhouse emissions. Considering the subject of this study – climate financing, it is advisable to rename the "survival" tables to "performance" tables instead of "survival".

The performance table summarizes the length of the period required to reduce greenhouse emissions for a particular set of observations. The construction of performance tables involves dividing the observation period of the sample into smaller time intervals. As part of this study, it is proposed to divide the follow-up period of 14 years into eight periods with a break of 2 years. The results of constructing performance tables that reflect the probability of reducing greenhouse emissions are presented in Table 3.6.

Table 3.6. Climate finance performance chart for 2005-2020

Interval	**Interval Start**	**Interval Width**	**Number Entering**	**Number Exposed**	**Number Dying**	**Proportn Dead**	**Proportn Survivng**
Intno.1	0.00	2.000	48	48.00	1	0.021	0.979
Intno.2	2.00	2.000	47	47.00	6	0.128	0.872
Intno.3	4.00	2.000	41	41.00	20	0.488	0.512
Intno.4	6.00	2.000	21	21.00	7	0.333	0.667
Intno.5	8.00	2.000	14	14.00	8	0.571	0.429
Intno.6	10.00	2.000	6	6.00	1	0.167	0.833
Intno.7	12.00	2.000	5	5.00	3	0.600	0.400
Intno.8	14.00		2	2.00	2	0.750	0.250
Intno.1	1.000	0.011	0.000	0.010	0.011	5.700	0.346
Intno.2	0.979	0.068	0.021	0.024	0.028	3.750	0.343
Intno.3	0.854	0.323	0.051	0.036	0.068	2.143	0.915
Intno.4	0.438	0.200	0.072	0.025	0.074	2.875	0.573
Intno.5	0.292	0.400	0.066	0.027	0.130	1.750	0.468
Intno.6	0.125	0.091	0.048	0.010	0.091	3.333	0.816
Intno.7	0.104	0.429	0.044	0.017	0.224	1.667	0.745
Intno.8	0.042		0.029				

Source: compiled by the authors

Table 3.6 shows that among 48 developing countries (column "Number Entering") only one country (column "Number Dying") was able to reduce greenhouse gas emissions through the climate finance programs implementation from the beginning of the observation (2005) to 2007. Significant changes in the effectiveness of climate finance programs are recorded from 2009 to 2010 (interval 3). In particular, the share of countries that recorded a reduction in greenhouse gas emissions during this period by at least 5% for the first time was 0.488. Accordingly, the probability of reducing carbon dioxide emissions into the atmosphere within 4-5 years from the beginning of the transition of the world community to a carbon-neutral economy was 0.323 (Hazard rate). Only 0,146 developing countries have been able to reduce their carbon dioxide emissions in the first five years since the entry into force of the Kyoto Protocol.

6. Determining the probability of an event occurring over a certain period – reducing carbon dioxide emissions.

The nonparametric Kaplan–Meier method was used to visualize the survival function (or effectiveness of climate finance), which reflects the probability of reducing carbon emissions over the appropriate time interval (figure 3.8). The horizontal axis (x) represents time in years. In contrast, the vertical axis (y) shows the probability of climate finance effectiveness or the share of countries that have reduced greenhouse gas emissions by at least 5%. The vertical step in the Figure indicates the event.

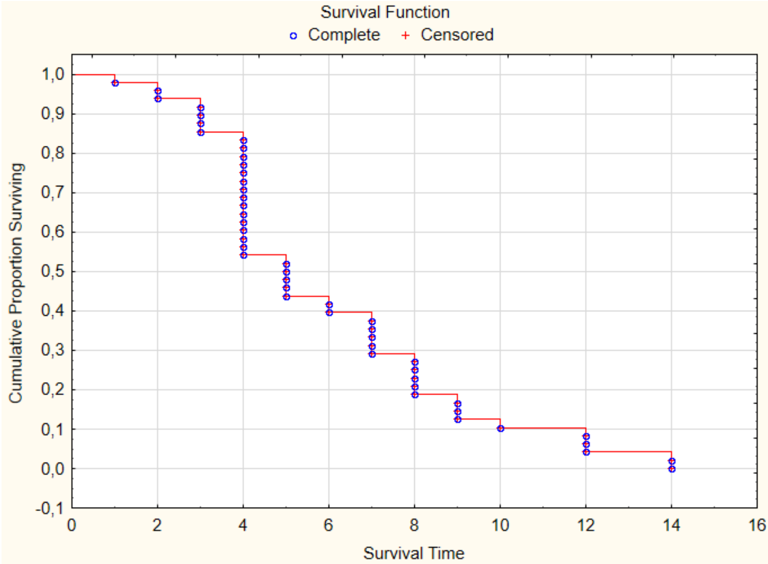


Figure 3.8. Visualization of the dependence of climate finance performance based on the Kaplan-Mayer curve
Source: compiled by the authors

The probability of climate finance being effective is 1.0 (or 100% of countries have not reduced their carbon emissions) at zero point in time. Figure 3.8 shows that the average time to reduction is 5 years, indicating that 50% of countries have achieved emission reductions in the 5th year after adopting the Kyoto Protocol. The probability of non-reduction of carbon emissions in the fourth year was 0.86; starting from the fifth year (2009), the probability of obtaining an impact from climate finance projects increased.

Since numerous scientific papers and reports of international organizations have proved the existence of corruption schemes in the implementation of climate finance programs, therefore, it was decided to group countries according to a homogeneous level of corruption in them and review the effectiveness of climate finance in the context of selected groups. The Corruption

Perception Index (Cor) was selected to characterize the level of corruption and the following levels of corruption were identified:

$0 < COR \leq 25$ – very high level of corruption (extreme);

$25 < COR \leq 50$ – high level of corruption (high);

$50 < COR \leq 75$ – average level of corruption (medium);

$75 < COR \leq 100$ – low level of corruption (low).

The average value was determined for 114 countries based on data on the Corruption Perception Index for 2005-2020. 76 countries were included in the group with a high level of corruption (or 66.6% of the total). In comparison, a quarter of the analyzed countries (29 countries) had a very high level of corruption. Visualization of the effectiveness of climate finance by countries with different levels of corruption is shown in Figure 3.9.

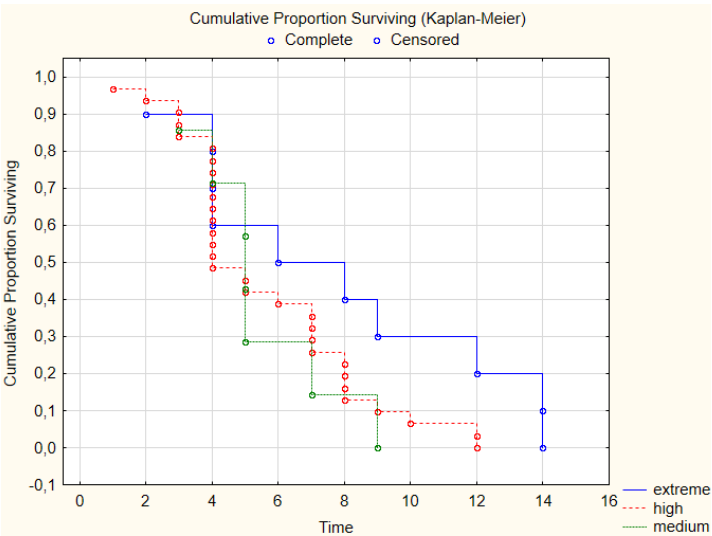


Figure 3.9. Visualization of the dependency of climate finance effectiveness in countries with different levels of corruption based on the Kaplan-Meier curve construction

Source: compiled by the authors

Figure 3.9 shows that the response of climate finance to reducing greenhouse emissions in countries with medium levels of corruption is faster compared to countries with high and very high levels of corruption. In particular, countries with moderate levels of corruption could reduce their greenhouse gas emissions by receiving climate funding from the developed world during the first nine years, while countries with high levels of corruption during 12 years, and countries with very high levels of corruption during 14 years.

7. Determinants of the impact on the period of greenhouse gas emissions reduction based on the construction of the Cox proportional hazards model.

The Cox proportional hazards model was used to define the relationship between the period of obtaining the effect of climate finance and individual impact factors. This econometric model allows including all countries initially selected for the study (114 countries), despite censorship,because the basic assumption of the Cox proportional hazards model is that the reduction in carbon dioxide emissions occurs randomly. The basic assumptions of Cox regression are: all explanatory variables are independent and linearly affect the probability of occurrence of an event. The results of calculating the Cox regression parameters are presented in Table 3.7.

Table 3.7. Results of estimation of the Cox regression model parameters

	Status Chi = 9,47963 df = 2 p = ,00875							
N=114	Beta	Standard Error	t-value	Wald Statist.	p	Risk ratio	Risk ratio 95% lower	Risk ratio 95% upper
Funding	-0.000	0.000	-1.59	2.520	0.112	1.000	1.000	1.000
Corruption	0.024	0.011	2.30	5.287	0.021	1.025	1.004	1.046

Source: compiled by the authors

We note that the constructed model is statistically significant, confirmed by the chi-square test value (p-value 0.00875 < 0.05), based on the data in Table 3.7. In addition, the Wald test shows that all covariates are significant. If the Corruption Perception Index increases by 1 point, the probability of reducing emissions increases by 2.4581% (1.024581*100-100). Thus the annual probability of reducing emissions is possible from 0.3591% to 4.6011% if the Corruption Perception Index increases by 1 point. This variable is statistically significant when constructing the Cox regression model since the significance of the Wald test (0.0215) is less than 0.05.

The second covariant – the amount of climate funding – not statistically significant for the constructed model. Given the current level of climate funding (according to experts, current funding is insufficient to minimize the negative impact) from the consequences of climate change, natural results were obtained. Funding of climate programs in the actual amount does not affect the period of the beginning of reducing greenhouse emissions in the world.

The Cox proportional hazards model confirms the hypothesis of the importance of overcoming corruption in reducing carbon emissions and increasing transparency in climate finance. At the same time, another hypothesis about the probability of reducing carbon emissions increases due to climate finance should be rejected, explaining that there is no effect between the existing investment in climate projects in developing countries and the reduction of greenhouse gases in the environment of these countries.

So, the main corruption risks in financing programs aimed at countering climate change are financing with significant amounts of money; low level of efficiency in monitoring the implementation of the project; low level of transparency on the results of the work received; systemic corruption in the recipient countries of international assistance in such sectors of the economy as building, energy, and forestry; the urgency of financing measures to combat climate change in the world, etc. have a problem of corruption. The highest standards in these areas strengthen anti-corruption contributions such as policy dialogue and participatory training, improved lobbying practices, better laws and policies, open data, monitoring and reporting mechanisms, and whistleblower protection.

3.3. Fuzzy cognitive mapping approach for decision making in tackling corruption in climate action

At the Conference of the Parties (COP) to the UNFCCC, important decisions were made regarding implementing global initiatives to combat climate change, including reducing greenhouse gas emissions, developing clean technologies, preserving the biosphere, greening industrial production, and agriculture, etc. During 2011-2020, projects for climate goals in the amount of 4.8 trillion US dollars were accumulated and financed (Climate Police Initiative, 2022).

However, significant revenues for financing climate projects may only partially reach the final user or be used for other purposes due to the risk of corruption (Jakob et al., 2015). It occurs since there is cooperation with various high-level actors, such as political elites, state administrations or departments (responsible for land use planning, infrastructure, health care and natural resource management), officials and employees of legal entities (responsible for project development, provision of construction and other related services), at all stages of the investment climate project. Corruption can divert resources from efforts to address, mitigate, and adapt to climate change. According to a study conducted by Transparency International Bangladesh, 2010-2020, about 35% of project funds were embezzled, while almost 80% of projects were implemented ineffectively due to the detection of corruption offences (Khan et al., 2020).

The implementation of climate finance programs goes beyond the boundaries of several jurisdictions. Therefore, the fairness of the fund distribution, monitoring fund use and controlling their use effectiveness form a complex problem that requires a systematic approach to establishing a complex of cause-and-effect relationships between sustainable development indicators, transparency and openness of public administration and other indicators of the socio-economic development. This problem is solved using fuzzy cognitive modelling, which combines elements of artificial neural network construction and principles of fuzzy logic. Kosko (1986) first proposed fuzzy cognitive modelling, improving Axelrod's approach (1976). This toolkit is widely used for studying the interaction of man and nature in complex systems, making management decisions, modelling the covid pandemic impact on the functioning of various elements of the ecosystem.

Fuzzy cognitive modelling involves the construction of an oriented sign (weighted) graph, which has a system of factors (concepts/nodes) representing important elements of the studied system, and arcs representing causal relationships between factors.

When constructing a directed weighted graph, the factors will be denoted as Ci ($i = 1, 2, \ldots n$). The connections between them (arcs) will be wi (directed edges in the graph). Arcs on the graph are denoted by fuzzy values in the interval $[-1, +1]$, demonstrating the strength of influence between factors (Papageorgiou & Salmeron, 2014). A positive value of the weights wij indicates that an increase (decrease) in the concept Ci leads to an increase (decrease) in the concept Cj. Each concept Ci on the graph has a value Ai, which reflects the degree of influence made by one concept on another (rules of derivation, inference rules).

Three indicators are used to quantitatively characterize the graph vertices: input centrality (indegree) is the cumulative volume of the number of connections directed from other vertices to the defined concept; output centrality (outdegree) is the cumulative volume of the number of links directed from the defined concept to other vertices; general centrality (centrality) is the sum of indegree and outdegree, or reflects the importance of a component when constructing a cognitive map.

There are 3 main approaches to building a cognitive map as a fuzzy directed graph (Kokkinos et al., 2018):

– Kosko's inference:

$$A_i(k+1) = f\left(\sum_{J=1, j\neq i}^{N} w_{ji} \times A_j(k)\right) \quad (3.3)$$

– Modified Kosko's inference:

$$A_i(k+1) = f\left(A_j(k) + \sum_{J=1, j\neq i}^{N} w_{ji} \times A_j(k)\right) \quad (3.4)$$

– Rescale inference:

$$A_i(k+1) = f\left((2 \times A_j(k) - 1) + \sum_{J=1, j\neq i}^{N} w_{ji} \times (2 \times A_j(k) - 1)\right) \quad (3.5)$$

$A_j(k), A_i(k+1)$ – value of i- concept in a moment of time t+1 and t;

w_{ji}– degree of influence between concepts;

f – activation function

The activation function can take different forms:

– bivalent $$f(x) = \begin{cases} 1, x > 0 \\ 0, x \leq 0 \end{cases} \quad (3.6)$$

– trivalent $$f(x) = \begin{cases} 1, x > 0 \\ 0, x = 0 \\ -1, x < 0 \end{cases} \quad (3.7)$$

– sigmoid $$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (3.8)$$

– hyperbolic $$f(x) = \tanh(\lambda \times x) \quad (3.9)$$

where λ – a real positive number (λ > 0), indicating the slope of the continuous function f
$x - A_i(k)$ at the equilibrium point.

Fuzzy cognitive modelling is widely used to solve problems in situations where it is believed that there are numerous interdependencies between important components or system variables. However, quantitative, empirically verified information about the forms of these interdependencies is not available. This approach allows for forming scenarios for developing events under the condition of changing one of the concepts. Fuzzy cognitive modelling is a widely used approach to solving real practical problems by modelling the system of relationships between factors (Dickerson & Kosko, 1994).

A scientific and methodological approach is proposed to model the relationships in the "corruption - climate financing - combating climate change" chain of relations". It involves the stepwise implementation of the following tasks:

– determination of significant influencing factors in the "corruption - climate financing - climate change prevention" chain of relations;

– determination of causal relationships between variables based on the empirical studies;

– defuzzification or transition from linguistic to quantitative values of influence of one factor on another;

– establishing causal relationships between factors and forces of influence between them to build an initial cognitive map;

– modelling of the action development scenarios.

The Mental Modeler web application is used to construct fuzzy cognitive maps.

The authors did not use the experts' survey but the results of empirical research in this scientific direction to determine the degree and nature of the causal relationships between factors.

Scientific articles indexed by the Scopus scientometric database and published over the past ten years (2014-2023) were selected for analysis (Appendix A). Since the underdeveloped countries of the world with a low transparency of public administration and tolerance of corrupt practices when making management decisions are the main recipients of international climate aid, the main emphasis was placed on the analysis of scientific empirical studies, where the research object included countries with low and average level of income per capita or the world.

Based on the bibliographic analysis of scientific articles devoted to corruption and climate change, it is proposed to single out 13 key factors that will potentially have an impact on the management decision-making system.

C1 corruption
C2 effectiveness of climate financing
C3 emissions of greenhouse gases
C4 environmental protection costs
C5 income from environmental taxes
C6 criminogenic situation
C7 poverty among the population
C8 unemployment
C9 consumption of renewable energy sources
C10 deforestation
C11 carbon neutrality
C12 economic growth
C13 transparent public administration

An important stage for building a fuzzy cognitive map is the transition from linguistic data describing the relationship between concepts to a qualitative and quantitative scale of their assessment (Table 3.8).

Table 3.8 – The scale of the transition from linguistic features to a qualitative and quantitative assessment

Linguistic terms extracted from literature	Assessment			
	qualitative		quantitative	
insignificant, low correlation, week, no link, maybe	→	extremely low	→	0,1
obvious, partly respond, likely to, may experience, may trigger, might be, not significant	→	low	→	0,3
correlated, associated, significant, increase, decrease, more likely, most common, relatively, usually, widely used to, associated with, medium	→	medium	→	0,5
crucial, highly predictive, important, key factor, much higher/lower, play important role, significant, strong, great, high	→	high	→	0,7
extensive, extremely, most effective, more prominently, tremendous, very high, vital, fundamental	→	extremely high	→	0,9

Source: Liu et al., 2018; Mago et al, 2013

The main causal relationships between the identified factors are presented in Appendix B. A visual representation of these relationships in the form of a fuzzy cognitive map is presented in Figure 3.10.

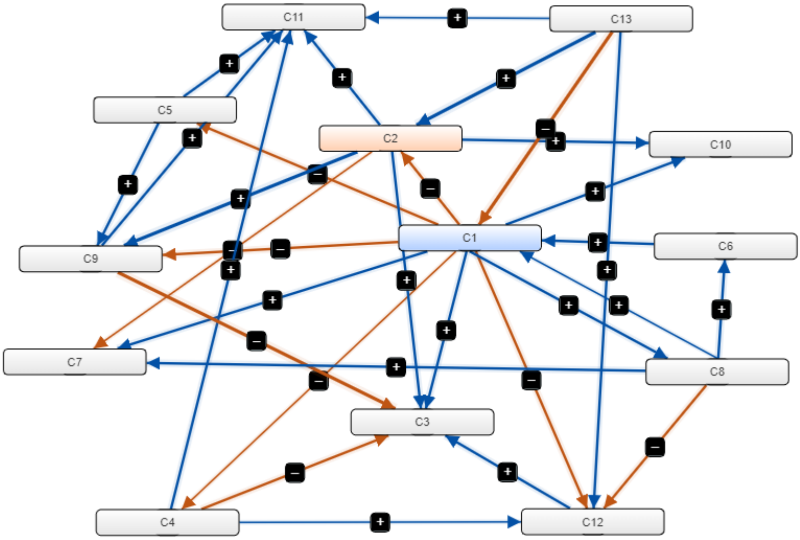


Figure 3.10. Cognitive map for modelling connections between concepts

The cognitive map is built based on 31 empirically confirmed connections between concepts. The density degree of the constructed cognitive map is 0.20, representing a sufficiently large number of connections between concepts. Quantitative features of the concepts based on which the cognitive map was built, are presented in Table 3.9.

Table 3.9 – Quantitative features of cognitive map concepts

Concept	Input centrality	Output centrality	General centrality
C1	1,8	5,1	6,9
C2	1,6	3,3	4,9
C3	3,5	0,0	3,5
C9	1,9	1,6	3,5
C12	2,4	0,7	3,1
C13	0,0	2,8	2,8
C8	0,5	2,2	2,7
C11	2,7	0,0	2,7
C4	0,3	1,3	1,6
C7	1,51	0,0	1,5
C5	0,5	1,0	1,5
C10	1,4	0,0	1,4
C6	0,5	0,6	1,1

The data from the table show that the C1 indicator (corruption), used as a "cause" in 75% of cases (the original centrality is 5.1 units), had the greatest influence on the construction of the cognitive map. The concept C2 (effectiveness of climate finance) takes the second position among other concepts regarding the importance of impact on causal relationships. C6 (criminogenic situation) and C10 (deforestation) indicators have the least influence among the established connections.

The final stage of the developed scientific and methodological approach is scenario modelling. It involves changing several input data to model changes' reactions in other concepts. Scenario modelling allows the analysis of systems' complexity and new aspects, facilitating the identification of essential points of influence and the trade-off evaluation (Gray et al., 2019). The hyperbolic tangent function is used as the basis for activating the scenario modelling. Within the framework of the study, it is proposed to consider several scenarios (Table

3.10) aimed at reducing carbon dioxide emissions and achieving carbon neutrality:

Scenario 1. Reducing the corruption level by 20%.

Scenario 2. Reducing the corruption level by 20%, improving the public administration openness by 20%.

Scenario 3. Increasing the effectiveness of climate finance by 20%.

Scenario 4. Reducing the corruption level by 20%, increasing the climate financing effectiveness by 20%.

Table 3.10 – Results of scenario modelling

Concept		Scenario 1	Scenario 2	Scenario 3	Scenario 4
C1	Corruption	– 0,20	– 0,20	-	– 0,20
C2	effectiveness of climate financing	+0,12	+0,06	+ 0,20	+ 0,20
C3	emissions of greenhouse gases	-0,11	-0,13	-0,04	-0,17
C4	environmental protection costs	+0,06	+0,06	-	+0,06
C5	income from environmental taxes	+0,09	+0,09	-	+0,09
C6	criminogenic situation	-0,01	-0,01	-	-0,01
C7	poverty among the population	-0,11	-0,11	+0,02	-0,08
C8	unemployment	-0,09	-0,09	-	-0,09
C9	consumption of renewable energy sources	+0,11	+0,10	-0,07	+0,03
C10	deforestation	-0,10	-0,11	-0,05	-0,17
C11	carbon neutrality	+0,04	+0,02	-0,04	-0,02
C12	economic growth	+0,17	+0,09	-	0,14
C13	transparent public administration	-	+ 0,20	-	-

The implementation of scenario 1 reduces corruption by 20% (or 0.20 c.u.). It will have the following chain reactions in the change of other concepts: an increase in the effectiveness of climate financing by 0.12 c.u., a reduction in poverty by 0.11 c.u., the growth rate of economic development by 0.17 c.u. and a reduction of greenhouse gas emissions by 0.11 c.u.

Scenario 2, focusing on reducing corruption by 20% and improving the openness and transparency of public administration, contributes to an increase in the climate financing effectiveness by 0.06 c.u., an increase in the consumption of renewable energy sources by 0.10 c.u., a reduction in carbon emissions by 0.13 c.u.

Scenario 3 is based on improving the climate financing mechanism that will have the following effects: reduction of deforestation by 0.05 c.u., reduction of energy consumption from renewable sources by 0.07 c.u. and reduction of greenhouse emissions by -0.04 c.u.

The impetus for scenario 4 was a reduction of corruption and an increase of climate financing effectiveness, which led to a reduction in deforestation by 0.17 c.u., stimulating economic growth by 0.14 c.u.

A comparative analysis of the proposed scenarios allows us to state that the greatest effect for reducing greenhouse gases is possible not only by increasing the effectiveness of climate financing but also by reducing the corruption level.

In conclusion, the authors note that the proposed methodological approach for modelling the system of relations in the "corruption-climate financing-carbon neutrality" chain by building a fuzzy cognitive map allows analyzing chain reactions to changes in key concepts.

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APPENDIX A

Table A.1 - Systematisation of empirical studies on corruption and climate change

Authors	Period	Countries	Main findings
d'Agostino et al., 2016	1996–2010	106 countries	Corruption has a strong negative effect on economic growth in countries
Lisciandra Migliardo, 2017	2002–2012	153 countries	Corruption leads to increased carbon dioxide emissions and a deterioration in overall environmental quality
Zhang et al., 2016	1992–2012	19 APEC countries	Corruption reduces emissions in low-emitting countries, but not in high-emitting countries.
Yao et al., 2021	1995-2014	BRICS and the next 11 countries	A transparent public administration system will improve environmental quality by reducing the ecological footprint. Natural resource rents and technological innovations will contribute to energy efficiency
Povitkina, 2018	1970-2011	144 countries	Countries with high levels of democracy and low levels of corruption are characterised by low carbon dioxide emissions.
Danish & Ulucak, 2020	1992-2015	18 APEC countries	Renewable energy reduces carbon emissions; a unidirectional causal link starting from the quality of the institutional environment to carbon dioxide emissions.
Habibullah et al., 2022	n/a	115 countries	Good governance reduces biodiversity loss and contributes to the effectiveness of climate change policy
Afrifa et al., 2020		29 developing countries	Investing in climate change helps reduce emissions
Hargrove et al., 2019	1996-2011	162 countries	Governmental accountability, transparency and legitimacy affect the effectiveness of multilateral environmental treaties in reducing emissions

Ganda, 2020	2010-2017	16 countries of the southern region of Africa	a 1% reduction in corruption leads to a significant 0.127% reduction in environmental sustainability; a bi-directional relationship between ease of doing business and environmental sustainability
Sahli et al., 2015	1996-2013	21 Middle East and North Africa countries	The impact of corruption on gross domestic product per capita is negative, leading to a decline in living standards; corruption contributes to an increase in carbon emissions.
Akhbari & Nejati, 2019	2003-2016	23 developing countries	Corruption has a destructive impact on environmental degradation and the increase of pollutants
Kwakwa, 2023	2002-2021	32 Africa countries	enewable energy reduces carbon emissions; Institutional quality variables (anti-corruption, rule of law, quality of regulation, political stability and absence of violence, voice and accountability, government effectiveness and institutional index) reduce emissions
Stef et al., 2023	1996-2016	136 countries	High values of institutional characteristics contribute to economic development by increasing the use of renewable energy and significantly reducing fossil fuel consumption.
Doku, 2022	2006-2017	44 Sub-Saharan Africa countries	Climate finance helps fight poverty
Rajkoomar et al., 2022	2018-2022	Africa countries	the existence of both positive and negative correlations between economic growth and carbon emissions
Supriyanto et al., 2022	2011-2020	10 Asia countries	збільшення державних витрат на one per cent increase in economic growth of 0.01775 per cent; a 1 per cent increase in CO2 emissions leads to an increase in economic growth of 0.005423 per cent
Forson et al., 2017	1996-2013	22 Sub-Saharan Africa countries	Corruption is a long-term threat to sustainable development development

Jungo et al., 2023	2011, 2014, 2017	46 Africa countries	financial inclusion and education significantly reduce corruption.
Wang et al., 2023	1991-2018	111 countries	better control of corruption enhances the positive impact of democracy on forest protection, while the use of renewable energy, trade globalisation and business freedom weaken it.
Sinha et al., 2021	1990-2017	BRICS and the next 11 countries	Corruption contributes to environmental degradation by reducing the positive impact of renewable energy consumption on environmental quality and increasing the negative impact of fossil fuel consumption
Uddin & Rahman, 2023	2002-2018	79 countries	In the long run, corruption, unemployment and political stability have a negative impact on GDP per capita, while inflation, government efficiency and the rule of law have a positive impact on GDP per capita
Ngono, 2022		54 Africa countries	Corruption affects unemployment primarily through its impact on public sector jobs
Oueghlissi & Derbali, 2023	1990-2018	80 developing countries	Democracy reduces corruption; high unemployment fuels corruption
Ata et al., 2019	1995-2015	50 developing countries	Unemployment contributes to an increase in the uneven distribution of income
Han & Jun, 2023	1990-2015	141 countries	Renewable energy consumption is an effective means of reducing CO2 emissions; the effectiveness of climate policy is influenced not only by the amount of funds raised, but also by technical assistance, transparent and accountable governance or research and development expenditures

APPENDIX B

Table B.1 – The links between indicators based on the results of empirical studies

Edge of the FCM		Type of influence	Level	
			quali-tative	quanti-tative
Corruption → Effectiveness of Climate Funding	C1-C2	indirect	high	0,7
Corruption →Government Expenditure on Environmental Protection	C1-C4	indirect	low	0,3
Corruption →Environmental tax revenue	C1-C5	indirect	medium	0,5
Corruption → Poverty	C1-C7	direct	medium	0,5
Corruption →Economic growth	C1-C12	indirect	high	0,7
Unemployment → Economic growth	C8-C12	indirect	high	0,7
Corruption →Greenhouse Gas Emission	C1- C3	direct	high	0,7
Criminality → Corruption	C6-C1	direct	high	0,7
Corruption→Unemployment	C1-C8	direct	medium	0,5
Unemployment → Corruption	C8 -C1	direct	low	0,3
Unemployment → Poverty	C8-C7	direct	high	0,7
Effectiveness of Climate Funding → Poverty	C2-C7	indirect	low	0,3

Unemployment →Criminality	C8-C6	direct	medium	0,5
Effectiveness of Climate Funding → Renewable Energy Consumption	C2- C9	direct	extremely high	0,9
Effectiveness of Climate Funding → Greenhouse Gas Emission	C2- C3	direct	high	0,7
Effectiveness of Climate Funding → Deforestation	C2- C10	direct	high	0,7
Corruption → Renewable Energy Consumption	C1- C9	indirect	medium	0,5
Economic Growth → Government Expenditure on Environmental Protection	C12-C4	direct	low	0,3
Corruption → Deforestation	C1- C10	direct	high	0,7
Expenditure on Environmental Protection → Greenhouse Gas Emission	C4- C3	indirect	medium	0,5
Environmental Taxes Revenue → Renewable Energy Consumption	C5- C9	direct	medium	0,5
Economic growth → Greenhouse Gas Emission	C12-C3	direct	high	0,7
Renewable Energy Consumption → Greenhouse Gas Emissions	C9-C3	indirect	extremely high	0,9
Transparent Governance - Effectiveness of Climate Funding	C13-C2	direct	extremely high	0,9
Transparent Governance → Economic growth	C13-C12	direct	high	0,7
Transparent Governance →	C13- C11	direct	low	0,3

Carbon Neutrality				
Effectiveness of Climate Funding→Carbon Neutrality	C2-C11	direct	high	0,7
Government Expenditure on Environmental Protection → Carbon Neutrality	C4-C11	direct	medium	0,5
Environmental Tax Revenue Protection → Carbon Neutrality	C5-C11	direct	medium	0,5
Renewable Energy Consumption → Carbon Neutrality	C9-C11	direct	high	0,7
Transparent Governance → Corruption	C13 -C1	indirect	extremely high	0,9

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Authors

© Prof. Dr. Serhiy Lyeonov
Sumy State University, Ukraine

PhD Victoria Bozhenko
Sumy State University, Ukraine

PhD Serhii Mynenko
Sumy State University, Ukraine

Reviewers

Prof. Dr. Maxim Korneyev Malyarets
University of Customs and Finance, Ukraine

Prof. Dr. Bhola Khan
MJP Rohilkhand University, India

Prof. Dr. Anton Boyko
Sumy State University, Ukraine

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