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A MECHANISM FOR CYCLIC-DYNAMIC SCREENING OF PRIMARY FINANCIAL MONITORING ENTITIES UNDER WARTIME CONDITIONS

ABSTRACT

This study aims to develop a mechanism for cyclic-dynamic screening of the activities of primary financial monitoring entities (PFMEs) under wartime conditions. The proposed mechanism identifies atypical behavioural patterns, enhances responsiveness to rapidly evolving risks, and improves the quality of financial offence detection. The study constructed additive time series models for two distinct periods: pre-war (2011–2019) and wartime (2021–2024). Smoothing techniques, time series decomposition, seasonal component estimation, and analytical trend modelling were applied. In the first period, the model demonstrated high accuracy (coefficient of determination R^2 = 90,87%), while in the second period, the accuracy remained acceptable (R^2 = 65,80%), reflecting increased volatility in the financial environment. The results highlight the importance of analyzing fluctuations and trends to detect suspicious financial transactions on time and to improve the effectiveness of primary financial monitoring procedures during wartime. The proposed mechanism enhances the accuracy of identifying anomalous operations, enables adaptive risk response, and strengthens the monitoring and control of financial flows. The practical implementation of this methodology contributes to ensuring national financial stability and security, which is critically important for maintaining the integrity of the state's financial system under wartime conditions.

Keywords: financial monitoring, wartime economy, primary financial monitoring entities (PFMEs), suspicious transactions, cyclic-dynamic screening, time series analysis, financial security

JEL Classification: G28, G18, C22, H56

INTRODUCTION

The intensification of economic crime, the expansion of illicit financial flows, attempts to launder proceeds of crime, and the escalation of cyber threats in the context of modern economic turbulence have contributed to the emergence of a new problematic environment for primary financial monitoring (PFMEs) entities (Sigetová et al., 2022). The uneven development of cybersecurity and information and communication technologies in different countries exacerbates the imbalance in financial control processes at different levels, creating new challenges for the PFMEs (Dobrovolska & Rozhkova, 2024; Vyas-Doorgapersad, 2024). In Ukraine, such challenges are exacerbated by a full-scale war (Zozulinskyy, 2024; Lavreniuk et al., 2023), and the lack of significant positive trends in reducing corruption risks (Kovbasyuk et al., 2024), which leads to the need to find new tools for implementing such monitoring.

Most of the analytical tools for primary financial monitoring today are inert and do not consider the cyclical variability of indicators and the impact of crisis events on the behaviour of economic agents. This highlights a complex scientific problem - the development of a mechanism that allows for a more flexible, cyclical assessment of the activities of enterprises engaged in financial transactions to improve the quality of risk identification and strengthen national financial security. In the scientific discourse, increasing attention is paid to the search for adaptive mechanisms and conceptual approaches capable of detecting suspicious financial transactions in real-time, responding to nonstandard patterns (Tertychnyi et al., 2022; Yarovenko et al., 2023), and taking into account various factors of the occurrence of such illegal actions (Pulungan et al., 2024; Morin & Burrell, 2024). Thus, the relevance of this study lies in the urgent need to increase the efficiency of the activities of SPFM by responding to atypical customer behaviour, as well as taking into account the unstable and dynamic conditions that characterize the financial system during armed conflict.

LITERATURE REVIEW

Periodic crises and wartime conditions have historically coincided with surges in illicit financial activity. Armed conflicts, in particular, create economic turmoil often exploited by criminals through fraud, corruption, money laundering, and sanctions evasion—activities pose serious threats to national security and financial stability (Hock & Quenivet, 2024; Zámek & Zakharkina, 2024; Tu et al., 2023). For example, the ongoing Russo-Ukrainian war has not only spurred traditional war profiteering but also introduced unprecedented flows of military and humanitarian aid, which carry major risks of diversion, embezzlement, and other internal economic crimes (Hock & Quenivet, 2024; Kupenko et al., 2023; Filatova et al., 2022; Vasylyeva et al., 2013; Vasylyeva et al.,2014).

The academic community increasingly emphasizes the need for enhanced financial monitoring mechanisms in response to these risks (Hock & Quenivet, 2024; Tertychnyi et al., 2022). Effective oversight becomes especially critical when geopolitical and economic disruptions enable atypical financial behaviour. However, systemic crises also weaken the institutional capacity of banks and regulators to perform timely detection of illicit transactions. For example, during the COVID-19 pandemic, the reallocation of resources toward core operations led to lapses in AML/CFT enforcement (Financial Action Task Force, 2020). As a result, recent studies (Yarovenko et al., 2023; Dobrovolska & Rozhkova, 2024; Dobrovolska et al., 2024; Sidii, 2024; Wright, 2023) advocate for developing mechanisms that combine proactive identification of financial risks with the ability to function effectively under crisis conditions.

Studies on post-2022 sanctions evasion have further highlighted the complexity of modern financial crimes. According to the U.S. Financial Crimes Enforcement Network (2023), financial institutions reported billions in suspicious transactions tied to export-control violations and illicit cross-border flows. These incidents often involved shell companies and complex transaction layering, reinforcing the need for robust real-time monitoring. In this context, timely and accurate Suspicious Activity Reports (SARs) serve as regulatory requirements and a foundation for enforcement actions, indicating the pivotal role of primary financial monitoring entities (PFMEs).

Despite their importance, traditional AML systems are criticized for their limited effectiveness. Scholars (Morris, 2020; Denman et al., 2023) point to structural inefficiencies, including over-reliance on rule-based scenarios and high false-positive rates, which dilute the quality of AML alerts. Recent reporting trends illustrate the urgency of reform. SAR filings surged to record levels in the United States after pandemic-era fraud waves (Thomson Reuters, 2023). One special review attributed a spike in fraud-related SARs to the extensive abuse of COVID-19 relief programs, which generated suspicious transactions linked to stimulus funds (Denman et al., 2023). While this increase in reporting reflects real growth in illicit activity, experts caution that it contains many redundant or low-value alerts. Indeed, regulators observed that a significant share of the pandemic-related SAR uptick was due to multiple institutions flagging the same well-publicized frauds or simply erring on the side of over-reporting. Such patterns reaffirm that quantity does not equal quality in AML reporting. The core challenge is improving the precision and proactivity of financial monitoring – especially in crisis scenarios – so that truly suspicious activities are detected early without overwhelming analysts with noise. This has driven researchers and practitioners to explore more dynamic and data-driven screening mechanisms that can adapt to emerging risks while filtering out normal fluctuations.

In response to traditional approaches' inefficiencies in detecting suspicious financial transactions, recent studies increasingly focus on applying advanced analytics, machine learning (ML), and adaptive systems. These approaches aim to shift from static, rule-based monitoring to systems capable of learning from behavioural patterns, adapting to emerging threats, and highlighting the most high-risk anomalies. Notably, the ML-based monitoring system proposed by Tertychnyi et al. (2022) enhances the accuracy and relevance of alerts by training classification models on rolling snapshots of customer transaction histories and implementing flexible alert thresholds. A key advantage of this model is its explainability. Each alert is accompanied by risk estimates and interpretability features based on probability calibration and Shapley value techniques, strengthening trust among compliance officers and regulators. Initial testing on real financial data demonstrated the system's effectiveness—particularly its improved detection accuracy enabled by an iterative feedback loop from industry experts.

Another promising direction in contemporary research is the application of network and graph analytics to identify complex money laundering schemes that are not detectable through traditional isolated transaction monitoring. Unlike one-off fraudulent acts, money laundering typically involves interconnected accounts and transactional flows that reveal suspicious patterns only when analyzed in aggregate. Leveraging the topological structure of financial networks, recent studies by Lu and Wang (2024) demonstrate the effectiveness of graph modelling and graph neural networks (GNNs) in enhancing the detection of such schemes. Their research shows that GNN-based approaches can more accurately classify transactions or entities as high-risk by incorporating link analysis and examining relationships among customers, intermediaries, and counterparties—alongside individual transaction behaviour. This methodology enables the identification of hidden structures, such as circular flows or layered transfers, that may escape detection under conventional, rule-based models. Thus, graph-driven systems offer a more dynamic and context-sensitive approach to financial monitoring, aligning with modern expectations of adaptive and continuous surveillance mechanisms.

A qualitative study of AML compliance professionals in 2024 reinforces this direction, noting that experts see entity resolution, machine learning, and network analytics as vital tools to overcome current monitoring inefficiencies (Oztas et al., 2024).

In practice, incorporating these tools means that primary monitoring entities continuously update their detection models as new typologies emerge, creating a cycle of screening, feedback, and model refinement – a concept at the heart of the cyclic-dynamic mechanism pursued in this research.

Importantly, real-world pressures have significantly accelerated the urgency to adopt advanced analytics in anti-money laundering (AML), particularly in regions affected by geopolitical conflicts. For instance, in response to war-related risks and sanctions regimes, financial institutions in Ukraine, Poland, and Estonia rapidly integrated AI/ML-based monitoring tools into their operations, often bypassing intermediate stages of technological development (Turksen et al., 2024). While this leap toward innovation has enhanced their capacity to detect complex laundering schemes, it has also exposed critical challenges—namely, regulatory scepticism toward opaque models, high implementation costs, and the burden of meeting evolving compliance requirements. Thus, as Turksen et al. (2024) argue, the effectiveness of cutting-edge technologies depends not only on their technical sophistication but also on their transparency, explainability, and alignment with legal frameworks. These findings underscore the broader consensus in the literature: any dynamic screening mechanism must strike a careful balance between agility and accountability, ensuring that financial institutions can adapt rapidly without compromising trust, compliance, or operational resilience.

Beyond technological innovations, recent studies highlight the need for systemic coordination and integrated governance, especially under socioeconomic stress. Effective financial monitoring depends on analytical tools and strong institutional frameworks that reduce information asymmetry and enhance cooperation (Ivashchenko et al., 2017). Strengthening governance and counteracting the shadow economy is essential for building financial resilience during wartime (Bilan et al., 2019; Ntshangase et al., 2024).

The reviewed literature reveals a growing recognition of the limitations of traditional AML systems, particularly during periods of systemic shock such as armed conflict. The convergence of rising financial crime risks and the reduced capacity of institutions to monitor them effectively calls for fundamentally new approaches. Against this backdrop, a cyclic-dynamic screening mechanism emerges as a timely and necessary innovation, especially for PFMEs operating under wartime conditions. By incorporating elements of time series analysis, behavioural adaptation, and real-time responsiveness, such a mechanism holds promise for enhancing the precision, agility, and transparency of suspicious transaction detection. Amid the war-driven challenges facing Ukraine's financial system and the pressing demand for resilient monitoring infrastructure, this research bridges the gap between theoretical advancements and practical tools needed to protect financial security in times of crisis.

AIMS AND OBJECTIVES

The objectives of the study are to critically analyze and synthesize current scientific approaches to the detection of suspicious financial transactions under crisis and wartime conditions, to compile and preprocess a comprehensive time series dataset reflecting the activities of primary financial monitoring entities for the periods of 2011–2019 and 2021–2024, and to develop additive time series models that capture the seasonal, trend, and random components of financial monitoring dynamics. The study further seeks to perform a comparative assessment of changes in financial monitoring activities before and during wartime, to evaluate the predictive performance and robustness of the constructed models, and to substantiate a cyclic-dynamic screening mechanism aimed at enhancing the adaptability, precision, and effectiveness of primary financial monitoring entities in conditions of heightened financial volatility and systemic risk.

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METHODS

The mechanism of cyclic-dynamic screening of the activities of PFMEs under wartime conditions involves the analysis of time series statistical data and sequential observations of PFMEs activities to identify key trends in their dynamics during both the pre-war and wartime periods, as well as to project these trends into the future. The purpose is to assess potential trajectories, forecast performance characteristics, and develop alternative strategic pathways. The input data for the analysis consists of a time series derived from the statistical reports of the State Financial Monitoring Service of Ukraine (State Financial Monitoring Service of Ukraine, 2024a, 2024b, 2024c), which include quarterly indicators of PFMEs activity spanning from the first quarter of 2011 through the third quarter of 2024. This dataset encompasses both peacetime and wartime periods, enabling the analysis of dynamic changes over time. The research methodology is based on a sequence of analytical procedures carried out using MS Excel tools.

The first step entails the construction of the input database using a time series of indicators—denoted as M_t—representing the number of financial transaction reports officially registered by the State Financial Monitoring Service. Visual preliminary analysis is conducted to detect anomalies and reduce Type II errors, followed by dividing the time series into pre-war and wartime periods.

The second step involves the decomposition of the time series. Each series component is modeled and forecasted individually, and the final prediction is obtained through additive recombination of the individual components. This decomposition into trend, seasonal, and irregular elements allows for a deeper understanding of institutional activity patterns, detect behavioural anomalies, and identify key influencing factors. This approach provides critical insights for improving the responsiveness of financial monitoring systems, optimizing resource allocation, and enhancing the timely detection of suspicious transactions.

To achieve high model accuracy, the time series is decomposed using standard additive methods (Formula 1) (Kozmenko & Kuzmenko, 2014):

$$M_t = T_t + S_t + E_t \tag{1}$$

where M_t – the level of the time series representing the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine at a given point in time t; T_t – the trend component of the time series at time t; S_t – the seasonal component of the time series at time t; E_t – the random (or irregular) component of the time series at time t.

The decomposition of the time series into seasonal and trend components with the construction of an additive model includes the following stages:

Step 1 – Smoothing the input data on the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine using the moving average method (Formula 2) and aligning them with actual time points through the application of the centred moving average method (Formula 3).

$$M'_t = (\sum M_t)/m' \tag{2}$$

where M'_t – the moving average, i.e., the smoothed values of the time series with the seasonal component removed; M_t – the level of the time series (the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine) at time t; $\sum M_t$ – the conditional annual number of reports, calculated as the sum of time series levels for each quarter with a one-period shift; m' – the length of the moving window (for quarterly data m' =4).

$$M''_t = (\sum(M'_{t-1} + M'_t)/2 \tag{3}$$

where M''_t – the centred moving average, calculated as the average of two consecutive moving averages; M'_{t-1}, M'_t – consecutive moving averages; $\sum(M'_{t-1} + M'_t)/2$ – the sum of the averaged values of two consecutive moving averages.

Step 2 – Calculation of the seasonal factor, i.e., the estimates of the seasonal component of the time series (Formula 4), and the adjusted estimates of the seasonal component (Formula 5).

$$S_t = M_t - M''_t \tag{4}$$

where S_t - estimates of the seasonal component of the time series of the analyzed data on PFMEs; M_t – the observed values of the time series representing financial transaction reports submitted to and recorded by the State Financial Monitoring Service of Ukraine at time t;

M_t'' – centered moving averages.

$$\hat{S}_q = \bar{S}_q - k, \sum \hat{S}_q = 0$$

$$\bar{S}_q = (\sum S_t)/q$$

$$k = \bar{S}/q$$

$$\bar{S} = \sum \bar{S}_q \qquad (5)$$

where $\hat{S}_q$ – adjusted estimates of the seasonal component of the time series represent the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine; k – adjustment coefficient for the seasonal component of the time series; $\bar{S}_q$ – average estimated value of the seasonal component for each quarter; $\bar{S}$ – overall average seasonal value of the time series; S_t - estimates of the seasonal component of the time series of the studied data related to PFMEs; $\sum S_t$ – the sum of average seasonal component estimates for each quarter; q – quarters (1,2,3,4).

Step 3 – Construction of the deseasonalized time series of PFMEs activity indicators by removing the identified seasonal component from the original time series. As a result, the resulting series will contain the trend and random components, which can be derived mathematically from Formula 1 and expressed in Formula 6.

$$M_t - \hat{S}_t = T_t + E_t \qquad (6)$$

Step 4 – Identification of the trend component of the time series representing the activity characteristics of PFMEs, based on analytical smoothing of the deseasonalized time series using both a linear trend and a second-degree polynomial trend.

Step 5 – Calculation of the non-random component of the time series using the additive model. This involves summing the trend component and the corresponding quarterly seasonal components of the time series, i.e., computing the values $(\hat{S}_t + T_t)$. This enables the construction of the forecast (theoretical) additive model of PFMEs activity.

The next step involves visualizing the actual and theoretical values of the time series levels for financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine, followed by an analysis of discrepancies, fluctuations, and trends.

The final step assesses the quality of the additive model of PFMEs activity based on the coefficient of determination, which is calculated using Formula 7.

$$R^2 = (1 - (\sum E^2 / \sum (M_t - M_{av})^2)) * 100\%, \qquad (7)$$

$$E = M_t - (\hat{S}_t + T_t)$$

where R^2 – coefficient of determination; $\sum E^2$ – the sum of squared residuals (random) components of the time series; M_t – actual levels of the time series (i.e., the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine) at time t; M_{av} – mean value of the actual levels of the time series.

RESULTS

In Step 1, a table of input data was compiled containing the activity indicators of PFMEs in terms of the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine (Table 1).

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Table 1. Input data for the analysis of PFMEs activities. Notes: M_t - number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine. *(Source: compiled by the authors based on State Financial Monitoring Service of Ukraine (2024a, 2024b, 2024c)*

year	quarter	t	Mt	year	quarter	t	Mt
2011	1	1	172538	2018	1	29	2144711
	2	2	274797		2	30	2266532
	3	3	331572		3	31	2688583
	4	4	300544		4	32	2870036
2012	1	5	226475	2019	1	33	2556759
	2	6	242325		2	34	2653997
	3	7	248021		3	35	3032677
	4	8	251000		4	36	3193941
2013	1	9	217322	2020	1	37	2913101
	2	10	221249		2	38	1033787
	3	11	258319		3	39	379338
	4	12	285251		4	40	399311
2014	1	13	235308	2021	1	41	346609
	2	14	269730		2	42	398513
	3	15	339413		3	43	445353
	4	16	443045		4	44	469460
2015	1	17	673817	2022	1	45	318524
	2	18	956463		2	46	226757
	3	19	1219269		3	47	308193
	4	20	1507568		4	48	325927
2016	1	21	1261927	2023	1	49	311141
	2	22	1468197		2	50	348400
	3	23	1680106		3	51	366216
	4	24	1909647		4	52	403837
2017	1	25	1740844	2024	1	53	377503
	2	26	1852430		2	54	436480
	3	27	2093939		3	55	488070
	4	28	2326287				

According to the preliminary visual analysis of the input time series (Figure 1), an anomalous decline in the sample data is observed from Q1 2020 to Q1 2021. In 2020, a "break point of the first kind" was detected when the continuity conditions of the function with a finite break were violated. An in-depth analysis of 2020 indicates that this period reflects the objective development of the economic process. However, it significantly deviates from the general trend. It can be considered a "second-order error," which is explained by the adoption of the Law of Ukraine No. 361-IX of 06.12.2019 "On Prevention and Counteraction to the Legalization (Laundering) of Proceeds of Crime, Financing of Terrorism and Financing of the Proliferation of Weapons of Mass Destruction" (Verkhovna Rada of Ukraine, 2019), which introduces changes to the financial monitoring methodology, therefore, the data for 2020 - the period of adaptation to the changes, are anomalous levels. As a result, according to the methodology proposed by the authors, the input time series was divided into 2-time series for further analysis: the first quarter of 2011 - the fourth quarter of 2019 (period 1, pre-war period) and the first quarter of 2021 - the third quarter of 2024 (period 2, includes the pre-war and war periods).

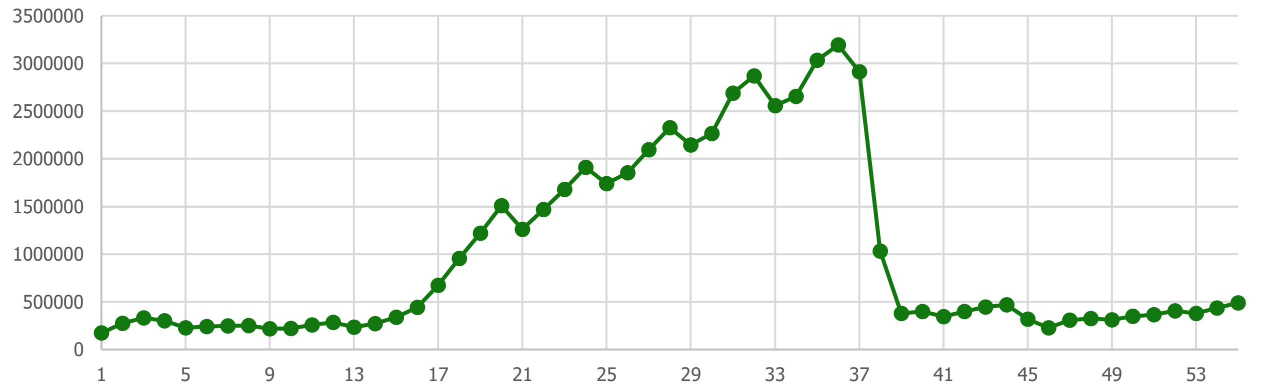

Figure 1. Scatter plot of the input time series data on PFMEs activity.

The results of Step 2 of the study present the time series decomposition into seasonal and trend components, with the construction of an additive model.

The intermediate results of the calculations include the smoothed input indicators of the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine, as well as the estimated seasonal components of the time series for the two time periods. These results are presented in Table 2 and Table 3.

Table 2. Results of calculations for smoothed input indicators and estimated seasonal components for period 1 (Q1 2011 – Q4 2019).
Notes: M_t - number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine; M_t' – moving average; M_t'' – centred moving average; S_t - estimated values of the seasonal component.

t	Mt	Amount for four quarters	M_t'	M_t''	S_t
1	172538				
2	274797	1079451	269862.75		
3	331572	1133388	283347.00	276604.88	54967.13
4	300544	1100916	275229.00	279288.00	21256.00
5	226475	1017365	254341.25	264785.13	-38310.13
6	242325	967821	241955.25	248148.25	-5823.25
7	248021	958668	239667.00	240811.13	7209.88
8	251000	937592	234398.00	237032.50	13967.50
9	217322	947890	236972.50	235685.25	-18363.25
10	221249	982141	245535.25	241253.88	-20004.88
11	258319	1000127	250031.75	247783.50	10535.50
12	285251	1048608	262152.00	256091.88	29159.13
13	235308	1129702	282425.50	272288.75	-36980.75
14	269730	1287496	321874.00	302149.75	-32419.75
15	339413	1726005	431501.25	376687.63	-37274.63
16	443045	2412738	603184.50	517342.88	-74297.88
17	673817	3292594	823148.50	713166.50	-39349.50
18	956463	4357117	1089279.25	956213.88	249.13
19	1219269	4945227	1236306.75	1162793.00	56476.00
20	1507568	5456961	1364240.25	1300273.50	207294.50
21	1261927	5917798	1479449.50	1421844.88	-159917.88
22	1468197	6319877	1579969.25	1529709.38	-61512.38
23	1680106	6798794	1699698.50	1639833.88	40272.13
24	1909647	7183027	1795756.75	1747727.63	161919.38
25	1740844	7596860	1899215.00	1847485.88	-106641.88
26	1852430	8013500	2003375.00	1951295.00	-98865.00
27	2093939	8417367	2104341.75	2053858.38	40080.63
28	2326287	8831469	2207867.25	2156104.50	170182.50
29	2144711	9426113	2356528.25	2282197.75	-137486.75
30	2266532	9969862	2492465.50	2424496.88	-157964.88
31	2688583	10381910	2595477.50	2543971.50	144611.50
32	2870036	10769375	2692343.75	2643910.63	226125.38
33	2556759	11113469	2778367.25	2735355.50	-178596.50
34	2653997	11437374	2859343.50	2818855.38	-164858.38
35	3032677				
36	3193941				

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Table 3. Results of calculations for smoothed input indicators and estimated seasonal components for period 2 (Q1 2021 – Q3 2024).

t	Mt	Amount for four quarters	M'_t	M''_t	S_t
1	346609				
2	398513	1659935	414983.75		
3	445353	1631850	407962.50	411473.13	33879.88
4	469460	1460094	365023.50	386493.00	82967.00
5	318524	1322934	330733.50	347878.50	-29354.50
6	226757	1179401	294850.25	312791.88	-86034.88
7	308193	1172018	293004.50	293927.38	14265.63
8	325927	1293661	323415.25	308209.88	17717.13
9	311141	1351684	337921.00	330668.13	-19527.13
10	348400	1429594	357398.50	347659.75	740.25
11	366216	1495956	373989.00	365693.75	522.25
12	403837	1584036	396009.00	384999.00	18838.00
13	377503	1705890	426472.50	411240.75	-33737.75
14	436480				
15	488070				

The intermediate results of the calculation of the adjusted estimates of the seasonal component of the time series related to PFMEs activity are presented in Table 4 and Table 5.

Table 4. Results of calculations for adjusted estimates of the seasonal component for period 1 (Q1 2011 – Q4 2019). Notes: S_t - estimated values of the seasonal component of the time series based on the analyzed PFMEs data; $\sum S_t$ – sum of the average seasonal component estimates for each quarter; q – quarters (1,2,3,4); $\bar{S}_q$ – average estimated value of the seasonal component for each quarter; $\bar{S}$ – overall average seasonal value of the time series; k – adjustment coefficient for the seasonal component of the time series; $\hat{S}_q$ – adjusted estimates of the seasonal component of the time series.

	Year	Quarter			
		1	2	3	4
S_t	2011			54967.13	21256.00
	2012	-38310.13	-5823.25	7209.88	13967.50
	2013	-18363.25	-20004.88	10535.50	29159.13
	2014	-36980.75	-32419.75	-37274.63	-74297.88
	2015	-39349.50	249.13	56476.00	207294.50
	2016	-159917.88	-61512.38	40272.13	161919.38
	2017	-106641.88	-98865.00	40080.63	170182.50
	2018	-137486.75	-157964.88	144611.50	226125.38
	2019	-178596.50	-164858.38		
$\sum S_t$		-715646.63	-541199.38	316878.13	755606.50
$\bar{S}_q$		-89455.83	-67649.92	39609.77	94450.81
$\bar{S}$	-23045.17				
k	-5761.29				
$\hat{S}_q$		**-83694.54**	**-61888.63**	**45371.06**	**100212.11**
$\sum \hat{S}_q$	0.00				

The seasonal components for the first, pre-war, study period related to PFMEs activity show a quarterly upward trend and are as follows: –83694,54 units for the first quarter, –61888,63 units for the second quarter, 45371,06 units for the third quarter, and 100212,11 units for the fourth quarter.

Table 5. Results of calculations for adjusted estimates of the seasonal component for period 2 (Q1 2021 – Q3 2024). Notes: S_t - estimated values of the seasonal component of the time series based on the analyzed PFMEs data; $\sum S_t$ – sum of the average seasonal component estimates for each quarter; q – quarters (1,2,3,4); $\bar{S}_q$ – average estimated value of the seasonal component for each quarter; $\bar{S}$ – overall average seasonal value of the time series; k – adjustment coefficient for the seasonal component of the time series; $\hat{S}_q$ – adjusted estimates of the seasonal component of the time series.

	Year	Quarter			
		1	2	3	4
S_t	2021			33879.88	82967.00
	2022	-29354.50	-86034.88	14265.63	17717.13
	2023	-19527.13	740.25	522.25	18838.00
	2024	-33737.75			
$\sum S_t$		-82619.38	-85294.63	48667.75	119522.13
$\bar{S}_q$		-27539.79	-42647.31	16222.58	39840.71
$\bar{S}$	-14123.81				
k	-3530.95				
$\hat{S}_q$		**-24008.84**	**-39116.36**	**19753.54**	**43371.66**
$\sum \hat{S}_q$	0.00				

The seasonal components for the second period, which also reflects wartime statistical data, differ from those of the first period in relation to the time series of PFMEs activity. The values are as follows: –24008,84 units for the first quarter, decreasing further to –39116,36 units in the second quarter, followed by an increase to 19753,54 and 43371,66 units in the third and fourth quarters, respectively.

The deseasonalized time series of the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine—under both pre-war and wartime conditions—along with the linear regression equation (for Period 1), the second-degree polynomial equation (for Period 2, reflecting wartime dynamics), and the computed trend component of PFMEs activity are presented in Tables 6 and 7, and in Figures 2 and 3.

Table 6. Results of deseasonalized time series construction and trend analysis of PFMEs for period 1. Notes: $\hat{S}_t$ – adjusted estimates of the seasonal component of the time series; Mt-Ŝt=Tt+Et – deseasonalized time series; T_t – trend component of the time series.

t	Mt	Ŝt	Mt-Ŝt=Tt+Et	Tt
1	172538	-83694.54	**256232.54**	-359935.00
2	274797	-61888.63	**336685.63**	-268868.00
3	331572	45371.06	**286200.94**	-177801.00
4	300544	100212.11	**200331.89**	-86734.00
5	226475	-83694.54	**310169.54**	4333.00
6	242325	-61888.63	**304213.63**	95400.00
7	248021	45371.06	**202649.94**	186467.00
8	251000	100212.11	**150787.89**	277534.00
9	217322	-83694.54	**301016.54**	368601.00
10	221249	-61888.63	**283137.63**	459668.00
11	258319	45371.06	**212947.94**	550735.00
12	285251	100212.11	**185038.89**	641802.00
13	235308	-83694.54	**319002.54**	732869.00
14	269730	-61888.63	**331618.63**	823936.00
15	339413	45371.06	**294041.94**	915003.00
16	443045	100212.11	**342832.89**	1006070.00
17	673817	-83694.54	**757511.54**	1097137.00
18	956463	-61888.63	**1018351.63**	1188204.00
19	1219269	45371.06	**1173897.94**	1279271.00
20	1507568	100212.11	**1407355.89**	1370338.00
21	1261927	-83694.54	**1345621.54**	1461405.00

(continued on next page)

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Table 6. Continued.

t	Mt	Ŝt	Mt-Ŝt=Tt+Et	Tt
22	1468197	-61888.63	**1530085.63**	1552472.00
23	1680106	45371.06	**1634734.94**	1643539.00
24	1909647	100212.11	**1809434.89**	1734606.00
25	1740844	-83694.54	**1824538.54**	1825673.00
26	1852430	-61888.63	**1914318.63**	1916740.00
27	2093939	45371.06	**2048567.94**	2007807.00
28	2326287	100212.11	**2226074.89**	2098874.00
29	2144711	-83694.54	**2228405.54**	2189941.00
30	2266532	-61888.63	**2328420.63**	2281008.00
31	2688583	45371.06	**2643211.94**	2372075.00
32	2870036	100212.11	**2769823.89**	2463142.00
33	2556759	-83694.54	**2640453.54**	2554209.00
34	2653997	-61888.63	**2715885.63**	2645276.00
35	3032677	45371.06	**2987305.94**	2736343.00
36	3193941	100212.11	**3093728.89**	2827410.00

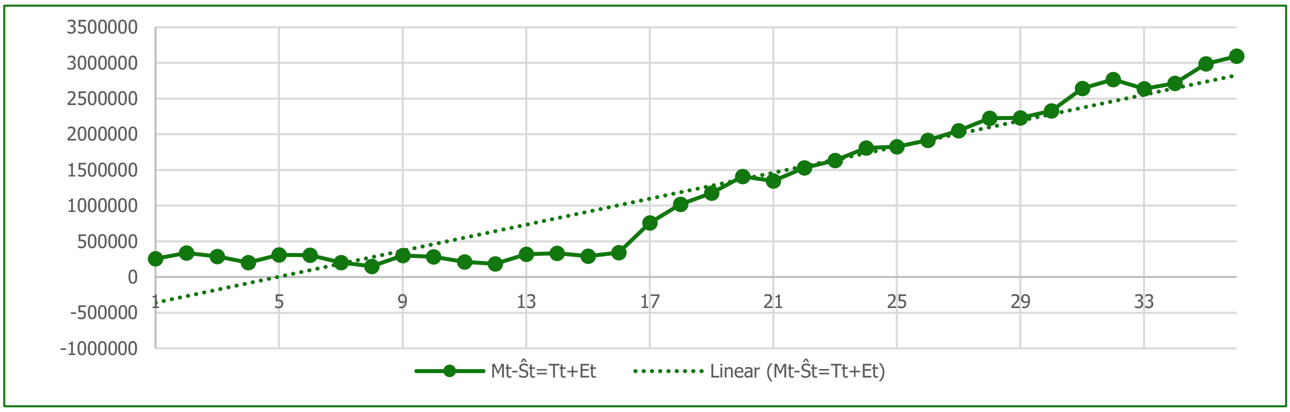

Figure 2. Linear regression construction (period 1) for the formation of the trend component of PFMEs activity.

The linear regression equation for the trend component of the time series of PFMEs activity during the period from Q1 2011 to Q4 2019 is presented in Formula 7. The coefficient of determination R^2=0,9069 indicates a high level of model quality.

$$y = -451002 + 91067 * x \tag{7}$$

Table 7. Results of deseasonalized time series construction and trend analysis of PFMEs for period 2. Notes: $\hat{S}_t$ – adjusted estimates of the seasonal component of the time series; Mt-Ŝt=Tt+Et – deseasonalized time series; T_t – trend component of the time series.

t	Mt	Ŝt	Mt-Ŝt=Tt+Et	Tt
1	346609	-24008.84	**370617.84**	440904.60
2	398513	-39116.36	**437629.36**	406423.40
3	445353	19753.54	**425599.46**	377703.40
4	469460	43371.66	**426088.34**	354744.60
5	318524	-24008.84	**342532.84**	337547.00
6	226757	-39116.36	**265873.36**	326110.60
7	308193	19753.54	**288439.46**	320435.40
8	325927	43371.66	**282555.34**	320521.40
9	311141	-24008.84	**335149.84**	326368.60
10	348400	-39116.36	**387516.36**	337977.00
11	366216	19753.54	**346462.46**	355346.60
12	403837	43371.66	**360465.34**	378477.40
13	377503	-24008.84	**401511.84**	407369.40
14	436480	-39116.36	**475596.36**	442022.60
15	488070	19753.54	**468316.46**	482437.00

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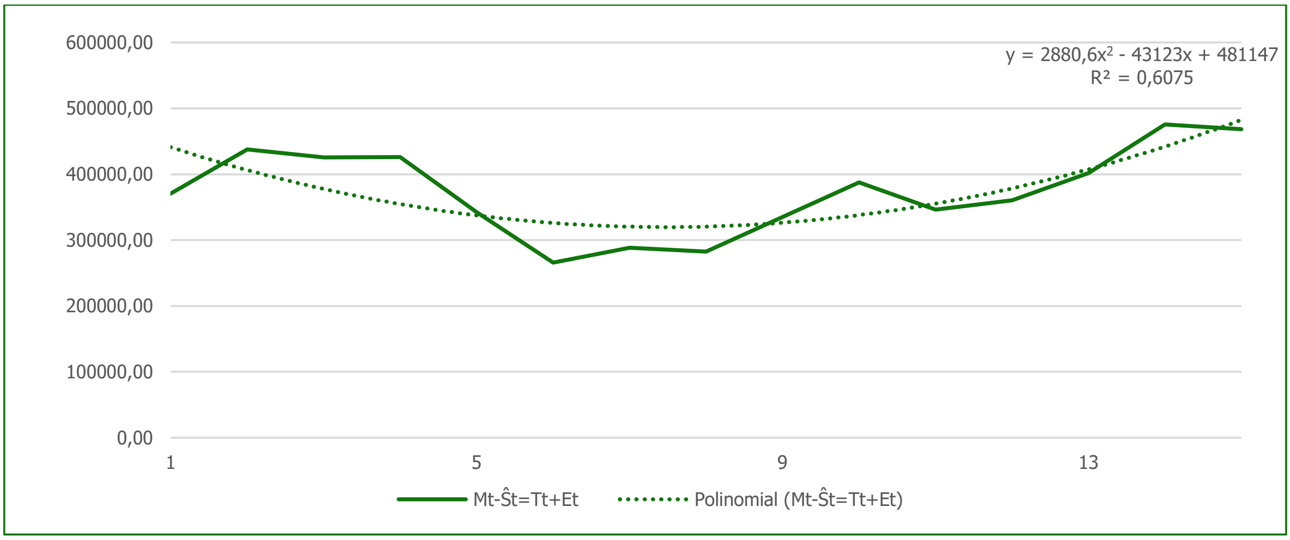

Figure 3. Construction of a second-degree polynomial equation (period 2, reflecting wartime conditions) for the formation of the trend component of PFMEs activity.

The second-degree polynomial equation for the trend component of the time series of PFMEs activity during the period from Q1 2021 to Q3 2024 is presented in Formula 8. The coefficient of determination R^2=0,6075 indicates an acceptable level of model quality.

$$y = 481147 - 43123 * x + 2880{,}6 * x^2 \quad (8)$$

The forecast (theoretical) time series of the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine, constructed using the additive model for two time periods of PFMEs activity, is presented in Tables 8 and 9.

Table 8. Forecast (theoretical) time series of PFMEs activity based on the additive model for period 1 (Q1 2011 – Q4 2019). Notes: $\hat{S}_t + T_t$ – non-random component of the time series of PFMEs activity based on the additive model.

t	Ŝt	Tt	Ŝt+Tt	t	Ŝt	Tt	Ŝt+Tt
1	-83695	-359935	**-443629.54**	19	45371.1	1279271	**1324642**
2	-61889	-268868	**-330756.63**	20	100212	1370338	**1470550**
3	45371.1	-177801	**-132429.94**	21	-83695	1461405	**1377710**
4	100212	-86734	**13478.1055**	22	-61889	1552472	**1490583**
5	-83695	4333	**-79361.535**	23	45371.1	1643539	**1688910**
6	-61889	95400	**33511.3711**	24	100212	1734606	**1834818**
7	45371.1	186467	**231838.059**	25	-83695	1825673	**1741978**
8	100212	277534	**377746.105**	26	-61889	1916740	**1854851**
9	-83695	368601	**284906.465**	27	45371.1	2007807	**2053178**
10	-61889	459668	**397779.371**	28	100212	2098874	**2199086**
11	45371.1	550735	**596106.059**	29	-83695	2189941	**2106246**
12	100212	641802	**742014.105**	30	-61889	2281008	**2219119**
13	-83695	732869	**649174.465**	31	45371.1	2372075	**2417446**
14	-61889	823936	**762047.371**	32	100212	2463142	**2563354**
15	45371.1	915003	**960374.059**	33	-83695	2554209	**2470514**
16	100212	1006070	**1106282.11**	34	-61889	2645276	**2583387**
17	-83695	1097137	**1013442.46**	35	45371.1	2736343	**2781714**
18	-61889	1188204	**1126315.37**	36	100212	2827410	**2927622**

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Thus, for the first study period, which covers the pre-war conditions, the model can be expressed as follows (Formula 9):

$$y = -451002 + 91067 * x + S \quad (9)$$

where $-451002 + 91067 * x$ *– is the trend component,* S *– is the seasonal component.*

Table 9. Forecast (theoretical) time series of PFMEs activity based on the additive model for period 2 (Q1 2021 – Q3 2024). Notes: $\hat{S}_t + T_t$ – non-random component of the time series of PFMEs activity based on the additive model.

t	Ŝt	Tt	Ŝt+Tt	t	Ŝt	Tt	Ŝt+Tt
1	-24009	440905	**416896**	9	-24009	326369	**302360**
2	-39116	406423	**367307**	10	-39116	337977	**298861**
3	19753.5	377703	**397457**	11	19753.5	355347	**375100**
4	43371.7	354745	**398116**	12	43371.7	378477	**421849**
5	-24009	337547	**313538**	13	-24009	407369	**383361**
6	-39116	326111	**286994**	14	-39116	442023	**402906**
7	19753.5	320435	**340189**	15	19753.5	482437	**502191**
8	43371.7	320521	**363893**				

Accordingly, for the second study period, which includes both pre-war and wartime conditions, the model can be expressed as follows (Formula 10):

$$y = 481147 - 43123 * x + 2880{,}6 * x^2 + S \quad (10)$$

where $481147 - 43123 * x + 2880{,}6 * x^2$ *– is the trend component,* and S – is the seasonal component.

The next step involves the graphical visualization of the actual and theoretical time series levels, obtained using the additive model, for financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine. These visualizations cover pre-war and wartime periods (Figures 4, 5).

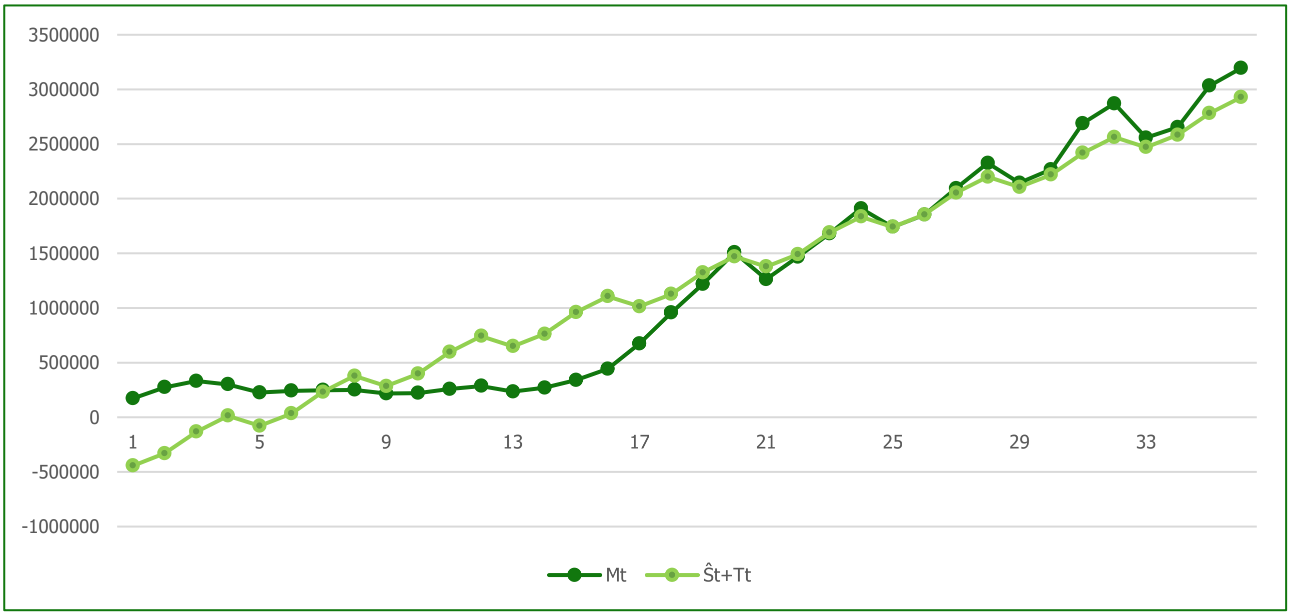

Figure 4. Graphs of actual and theoretical time series levels obtained using the additive model for PFMEs activity in the first (pre-war) period. Notes: M_t – actual number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine; $\hat{S}_t + T_t$ – theoretical (forecasted) number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine, based on the additive model.

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In the first, pre-war period, the actual number of financial transaction reports increased over time (from 172538 reports in Q1 2011 to 3193941 reports in Q4 2019), indicating a rise in PFMEs activity, as well as improvements in the registration and monitoring of such transactions. Theoretical (forecasted) values exhibit fluctuations: in the early periods, they are negative, but they increase over time, reflecting a projected growth in PFMEs activity. Notable discrepancies are also observed: for most periods, the actual number of reports is lower than the theoretical estimate; however, beginning in Q4 2016, the actual values exceed the forecasted ones (e.g., 1909647 actual reports vs. 1834818 forecasted). The theoretical and actual time series analysis reveals a sustained upward trend with a widening gap between the two. Both series reflect increasing activity, which indicates the improving effectiveness of financial monitoring processes and the growing volume of financial flows. In the most recent periods, the difference between actual and forecasted values has narrowed, confirming the improved accuracy of the predictive model and suggesting that financial transactions are becoming more transparent and predictable.

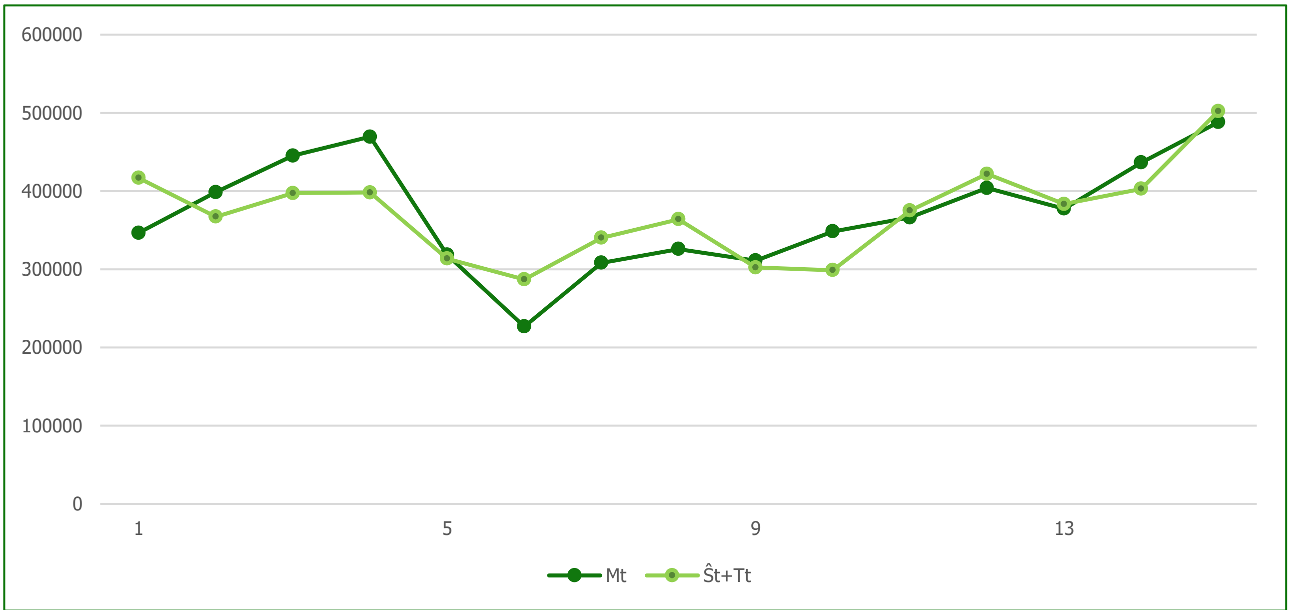

Figure 5. Graphs of actual and theoretical time series levels obtained using the additive model for PFMEs activity during the second (pre-war and wartime) periods. Notes: M_t – actual number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine; $\hat{S}_t + T_t$ – theoretical (forecasted) number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine, based on the additive model.

In the second period, which includes both pre-war and wartime conditions, the actual number of financial transaction reports fluctuated over time—ranging from a minimum of 226757 reports in Q2 2022 to a maximum of 488070 reports in Q3 2024—indicating increased PFMEs activity. The theoretical (forecasted) number of reports also exhibited similar fluctuations, with a minimum of 286994 reports in Q2 2022 and a maximum of 502191 reports in Q3 2024. Several key patterns can be observed: during the initial phase (Q2 2021 to Q1 2022), the actual values most exceeded the theoretical ones, reflecting positive momentum. In the middle of the period (Q2 2022 to Q2 2023), actual values were generally lower than the forecasts. Starting from Q2 2023, actual levels more frequently began to surpass the theoretical ones again. The analysis of the actual and forecasted time series revealed a pattern of positive dynamics with a temporary fluctuation in the middle of the period. The growth in actual figures indicates heightened financial activity, while the mid-period gap—where actual values occasionally fall below projections—may reflect the influence of economic and regulatory changes.

The final step presents the evaluation of the quality of the additive model of PFMEs activity based on the coefficient of determination (Tables 10, 11).

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Table 10. Evaluation of the quality of the additive model of PFMEs Activity for period 1. Notes: R^2 – coefficient of determination; E^2 – squared values of the random components of the time series; M_t – actual levels of the time series (i.e., the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine) at time t; M_{av} – average value of the actual time series levels.

t	Mt	(Mt-Mav)²	Et=Mt-(Ŝt+Tt)	(Et)²
1	172538	1.13E+12	616168	3.8E+11
2	274797	9.2E+11	605554	3.67E+11
3	331572	8.14E+11	464002	2.15E+11
4	300544	8.71E+11	287066	8.24E+10
5	226475	1.01E+12	305837	9.35E+10
6	242325	9.83E+11	208814	4.36E+10
7	248021	9.72E+11	16182.9	2.62E+08
8	251000	9.66E+11	-126746	1.61E+10
9	217322	1.03E+12	-67584	4.57E+09
10	221249	1.03E+12	-176530	3.12E+10
11	258319	9.51E+11	-337787	1.14E+11
12	285251	9E+11	-456763	2.09E+11
13	235308	9.97E+11	-413866	1.71E+11
14	269730	9.29E+11	-492317	2.42E+11
15	339413	8E+11	-620961	3.86E+11
16	443045	6.25E+11	-663237	4.4E+11
17	673817	3.14E+11	-339625	1.15E+11
18	956463	7.69E+10	-169852	2.88E+10
19	1219269	2.09E+08	-105373	1.11E+10
20	1507568	7.5E+10	37017.9	1.37E+09
21	1261927	7.95E+08	-115783	1.34E+10
22	1468197	5.5E+10	-22386	5.01E+08
23	1680106	1.99E+11	-8804.1	77511448
24	1909647	4.57E+11	74828.9	5.6E+09
25	1740844	2.57E+11	-1134.5	1287010
26	1852430	3.83E+11	-2421.4	5863038
27	2093939	7.4E+11	40760.9	1.66E+09
28	2326287	1.19E+12	127201	1.62E+10
29	2144711	8.3E+11	38464.5	1.48E+09
30	2266532	1.07E+12	47412.6	2.25E+09
31	2688583	2.12E+12	271137	7.35E+10
32	2870036	2.68E+12	306682	9.41E+10
33	2556759	1.75E+12	86244.5	7.44E+09
34	2653997	2.02E+12	70609.6	4.99E+09
35	3032677	3.24E+12	250963	6.3E+10
36	3193941	3.84E+12	266319	7.09E+10
	Sum	**3.62E+13**	**Sum**	**3.31E+12**
Mav	**1233740**		**R²**	**90.86844**

In the first period, the coefficient of determination is 90.87%, indicating a high-quality model. The additive model explains 90.87% of the total variation in the input time series levels of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine.

Table 11. Evaluation of the quality of the additive model of PFMEs activity for period 2. Notes: R^2 – coefficient of determination; E^2 – squared values of the random components of the time series; M_t – actual levels of the time series (i.e., the number of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine) at time t; M_{av} – average value of the actual time series levels.

t	Mt	(Mt-Mav)²	Et=Mt-Ŝt-Tt	(Et)²
1	346609	614537489.4	-70287	4940228836
2	398513	735176226.4	31206	973811900.5
3	445353	5469213837	47896.1	2294032903
4	469460	9615985871	71343.7	5089929029
5	318524	2795751525	4985.84	24858585.96
6	226757	20921269593	-60237	3628525158
7	308193	3994981581	-31996	1023739950
8	325927	2067690658	-37966	1441421823
9	311141	3631010495	8781.24	77110150.33
10	348400	528947868	49539.4	2454148127
11	366216	26862106.88	-8884.1	78927880.61
12	403837	1052232494	-18012	324434358
13	377503	37260443.75	-5857.6	34311026.24
14	436480	4235553916	33573.8	1127197319
15	488070	13612153353	-14121	199389549.9
	Sum	**69338627458**	**Sum**	**23712066596**
Mav	**371399**		**R²**	**65.80251518**

In the second period, the coefficient of determination is 65.80%, indicating an acceptable level of model quality. The additive model explains 65.80% of the total variation in the input time series levels of financial transaction reports subject to financial monitoring and registered by the State Financial Monitoring Service of Ukraine.

DISCUSSION

The study's results confirm the relevance of using an additive model with time series decomposition to assess the activity of PFMEs under instability caused by war. The division of the analysis into pre-war and wartime periods made it possible to better account for structural shifts in Ukraine's financial environment. Similar methodological approaches have been used in international research, particularly in studies examining changes in financial behaviour during pandemics or political crises (Denman et al., 2023; Tertychnyi et al., 2022).

The high coefficient of determination obtained for the first period (R^2 = 90.87%) demonstrates the constructed model's quality and ability to adequately reflect trends in PFMEs activity in a stable regulatory environment. This level of accuracy confirms the reliability of traditional trend analysis models in forecasting under conditions of relative macroeconomic stability. These findings are consistent with the conclusions of Morris (2020) and Kozmenko & Kuzmenko (2014), who emphasize the effectiveness of linear models in identifying fundamental trends in controlled environments.

In contrast, during the second period (covering both pre-war and wartime conditions), the coefficient of determination decreased to 65.80%, indicating an acceptable but lower level of model precision under high volatility. This decline can be attributed to external shocks, such as the imposition of new sanctions, adaptation of financial institutions to updated regulatory frameworks, shifts in client behaviour, and the rise of cyber threats. Notably, Financial Crimes Enforcement Network (2023) and Hock & Quenivet (2024) highlight that sanction-evasion schemes become more prevalent during armed conflicts, complicating the identification of typical transaction patterns.

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The shift in seasonal fluctuations observed in the second period compared to the first indicates a transformation in financial dynamics. The reduction in negative seasonal effects in the first two quarters and the increase in the third and fourth quarters may result from PFMEs adjusting to reporting regime changes, an expansion in the scope of reporting entities, or seasonal intensification of fraudulent activities during martial law. This hypothesis aligns with the position of Turksen et al. (2024), who stress the need for dynamic adaptation of control tools to real-time changes.

The visual interpretation of discrepancies between actual and theoretical levels also supports the assumption of cyclical and adaptive behaviour among PFMEs. The observed increase in model accuracy toward the end of each period suggests potential for further model refinement. This could involve integrating classical additive models with advanced machine learning and network analysis tools, as proposed by Lu & Wang (2024) and Oztas et al. (2024).

Therefore, the findings of this study contribute to the broader scientific discussion on the effectiveness of financial monitoring during crisis periods. The proposed cyclic-dynamic screening mechanism is a relevant practical tool for detecting irregularities and risk signals. However, the limitations of the applied methodology—such as the limited number of variables and the focus solely on quantitative indicators without accounting for the quality or content of the reports—require further scholarly consideration.

Future research should focus on integrating qualitative characteristics of suspicious transaction reports and developing hybrid models utilizing ML/AI for real-time risk analysis.

CONCLUSIONS

The study results confirm the effectiveness of the developed cyclic-dynamic screening mechanism for the activities of primary financial monitoring entities under wartime conditions. The constructed additive models of time series decomposition for two distinct periods – pre-war and wartime – demonstrated that cyclic behavioural patterns and structural shifts in financial monitoring dynamics can be effectively captured and forecasted despite increased environmental volatility. A high level of predictive accuracy during the pre-war period (R^2 = 90.87%) and an acceptable accuracy during the wartime period (R^2 = 65.80%) validate the relevance of this approach for enhancing risk detection capabilities under crisis conditions.

The time series decomposition into trend and seasonal components allowed for identifying critical points of fluctuation and adaptation in financial monitoring activities, reflecting changes in client behaviour and institutional responsiveness to regulatory reforms and external shocks. The results showed a substantial shift in seasonal dynamics during wartime, with a reduced negative impact in the year's first half. They intensified financial activity in the second half, indicating adaptive responses of primary financial monitoring entities to emerging risks.

The theoretical models revealed consistent upward trends in the volume of suspicious financial transaction reports. They highlighted periods of underperformance and overperformance relative to the projected levels, providing a basis for targeted analytical interventions. The findings suggest that dynamic screening mechanisms, based on statistical and cyclic sensitivity, significantly enhance the responsiveness and precision of financial monitoring systems in detecting atypical transaction behaviours under conditions of systemic instability.

Future research should focus on expanding the methodological framework by integrating qualitative indicators of suspicious activity reports, applying machine learning and graph-based network analytics, and developing hybrid screening models that combine statistical rigour with adaptive learning capabilities. Additionally, special attention should be given to ensuring the regulatory explainability and trustworthiness of advanced analytical models to support their practical implementation within national financial monitoring systems during and after periods of conflict.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All Authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

REFERENCES

1. Bilan, Y., Vasylieva, T., Lyeonov, S., & Tiutiunyk, I. (2019). Shadow Economy and its Impact on Demand at the Investment Market of the Country. *Entrepreneurial Business and Economics Review, 7*(2). https://doi.org/10.15678/EBER.2019.070202
2. Denman, J., Wolf, B., & Ehret, T. (2023). *Suspicious activity reports: Key trends 2023*. Thomson Reuters. Suspicious-Activity-Reports-2023.pdf
3. Dobrovolska, O., & Rozhkova, M. (2024). The Impact of Digital Transformation on the Anti-Corruption and Cyber-Fraud System. *Business Ethics and Leadership, 8*(3), 231–252. https://doi.org/10.61093/bel.8(3).231-252.2024
4. Dobrovolska, O., Ortmanns, W., Dotsenko, T., Lustenko, V., & Savchenko, D. (2024). Health Security and Cybersecurity: Analysis of Interdependencies. *Health Economics and Management Review, 5*(2), 84–103. https://doi.org/10.61093/hem.2024.2-06
5. Filatova, H., Voytov, S., Polishchuk, Y., & Dudchyk, O. (2022). The public debt of Ukraine in the economic development policy in the war and post-war periods: Bibliometric analysis. *Public and Municipal Finance, 11*(1), 142–154. https://doi.org/10.21511/pmf.11(1).2022.12
6. Financial Action Task Force. (2020). *COVID-19-related money laundering and terrorist financing Risks and policy responses*. FATF. https://www.fatf-gafi.org/en/publications/Fatfgeneral/Covid-19-ml-tf.html
7. Financial Crimes Enforcement Network. (2023, September). *Trends in Bank Secrecy Act data: Suspected evasion of Russian export controls*. U.S. Department of the Treasury. https://www.fincen.gov/sites/default/files/shared/FTA_Russian_Export_Controls_FINAL_508.pdf
8. Hock, B., & Quenivet, N. (2024). Economic crime in war. In Crime and its counteraction in wartime and in the post-war period: An interdisciplinary panorama. Abstracts of the International scientific and practical conference (Vinnytsia, April 19, 2024) (P. 221 – 223). https://doi.org/10.5281/zenodo.10997257
9. Ivashchenko, A., Sybirianska, Y., & Polischuk, Y. (2017). Information and communication platform as a complex approach for solving information asymmetry problems. *CEUR Workshop Proceedings, 1844*, 111–126. http://ceur-ws.org/
10. Kovbasyuk, L., Vakulenko, Y., Ivanets, I., Bozhenko, V., & Kharchenko, D. (2024). Forecast of Corruption: From Ethical to Pragmatic Considerations. *Business Ethics and Leadership, 8*(2), 184–199. https://doi.org/10.61093/bel.8(2).184-199.2024
11. Kozmenko, O. V., & Kuzmenko, O. V. (2014). *Economic and mathematical methods and models (econometrics): A textbook*. Universytetska Knyha. http://essuir.sumdu.edu.ua/handle/123456789/53231
12. Kupenko, O., Kostenko, A., Kalchenko, L., Pehota, O., & Kubatko, O. (2023). Resilience and vulnerability of a person in a community in the context of military events. *Problems and Perspectives in Management, 21*(1), 154–168. https://doi.org/10.21511/ppm.21(1).2023.14
13. Lavreniuk, V., Polishchuk, Y., Kornyliuk, A., Horbov, V., & Ivashchenko, A. (2023). Government response on russian war in Ukraine: Relocating business. *Problems and Perspectives in Management, 21*(4), 556–576. https://doi.org/10.21511/ppm.21(4).2023.42
14. Lu, H., & Wang, H. (2024). Graph contrastive pre-training for anti-money laundering. *International Journal of Computational Intelligence Systems, 17*, 307. https://doi.org/10.1007/s44196-024-00720-4
15. Morin, S. L., & Burrell, D. N. (2024). Diversity Dishonesty: Smoke and Mirrors in the Organization. *SocioEconomic Challenges, 8*(2), 109–125. https://doi.org/10.61093/sec.8(2).109-125.2024
16. Morris, N. (2020, September 25). *Anti money laundering has less than 1% impact on crime. At what cost?* Ledger Insights. https://www.ledgerinsights.com/anti-money-laundering-has-less-than-1-impact-on-crime-at-what-cost/
17. Ntshangase, B. A., Makole, K. R., & Msosa S. K. (2024). Overcoming the Socio-Economic Challenges to Good Governance: Streamlining Cooperative Governance Model. *SocioEconomic Challenges, 8*(4), 19–30. https://doi.org/10.61093/sec.8(4).19-30.2024
18. Oztas, B., Cetinkaya, D., Adedoyin, F., Budka, M., Aksu, G., & Dogan, H. (2024). Transaction monitoring in anti-money laundering: A qualitative analysis and points of view from industry. *Future Generation Computer Systems, 159*, 161–171. https://doi.org/10.1016/j.future.2024.05.027
19. Pulungan, A. H., Setiawan, S., & Windiarti, F. (2024). The Risk of Corruption and Money Laundering: An Analysis of Personal Predespositions and Socio-Economic Challenges. *SocioEconomic Challenges, 8*(4), 121–136. https://doi.org/10.61093/sec.8(4).121-136.2024
20. Sidii, F. S. (2024). Navigating the Intersection of Digital Security, Resilience and Sustainability in Healthcare: A Theoretical Framework and Case Study of Ghana. *Health Economics and Management Review, 5*(4), 130–146. https://doi.org/10.61093/hem.2024.4-09

21. Sigetová, K., Užíková, L., Dotsenko, T., & Boyko, A. (2022). Recent Trends in the Financial Crime of the World. *Financial and Credit Activity Problems of Theory and Practice*, *5*(46), 258–270. https://doi.org/10.55643/fcaptp.5.46.2022.3897

22. State Financial Monitoring Service of Ukraine. (2024a). Statistical information on the registered reports of financial transactions with signs of financial monitoring by regions in 2013. https://fiu.gov.ua/pages/dijalnist/funkcional/statistika-ta-infografika/statistika/2013-rik/statistichna-informacziya-shhodo-vzyatix-derzhfinmonitoringom-ukrajini-na-oblik-povidomlen-pro-finansovi-operacziji-z-oznakami-finansovogo-monitoringu-protyagom-2013-roku-v-rozrizi-regioniv.html

23. State Financial Monitoring Service of Ukraine. (2024b). *Statistical data on financial transaction reports received by the State Financial Monitoring Service of Ukraine in 2014-2024*. https://fiu.gov.ua/pages/dijalnist/funkcional/statistika-ta-infografika/statistika

24. State Financial Monitoring Service of Ukraine. (2024c). *Statistical information on financial transaction reports received in 2024*. https://fiu.gov.ua/pages/dijalnist/funkcional/statistika-ta-infografika/statistika/Informacziya-za-2024-rik/Info-za-2024-rik11.html

25. Tertychnyi, P., Godgildieva, M., Dumas, M., & Ollikainen, M. (2022). Time-aware and interpretable predictive monitoring system for anti-money laundering. *Machine Learning with Applications, 8*, 100306. https://doi.org/10.1016/j.mlwa.2022.100306

26. Thomson Reuters. (2023, June 9). *Special report: Suspicious activity reports surge; 2023 filings on pace for another record*. https://www.thomsonreuters.com/en-us/posts/investigation-fraud-and-risk/special-report-suspicious-activity-reports/

27. Tu, Y.-X., Kubatko, O., Piven, V., Kovalov, B., & Kharchenko, M. (2023). Promotion of Sustainable Development in the EU: Social and Economic Drivers. *Sustainability, 15*(9), 7503. https://doi.org/10.3390/su15097503

28. Turksen, U., Benson, V., & Adamyk, B. (2024). Legal implications of automated suspicious transaction monitoring: Enhancing integrity of AI. *Journal of Banking Regulation, 25*(3), 359–377. https://doi.org/10.1057/s41261-024-00233-2

29. Vasilyeva, T. A., Leonov, S. V., & Lunyakov, O. V. (2013). Analysis of internal and external imbalances in the financial sector of ukraine's economy. *Actual Problems of Economics, 150*(12), 176–184. https://www.scopus.com/record/display.uri?eid=2-s2.0-84922478082&origin=resultslist

30. Vasylyeva, T. A., Leonov, S. V., & Lunyakov, O. V. (2014). Countercyclical capital buffer as a macroprudential tool for regulation of the financial sector. *Actual Problems of Economics, 158*(8), 278–283. https://www.scopus.com/record/display.uri?eid=2-s2.0-84921979786&origin=resultslist

31. Verkhovna Rada of Ukraine. (2019, December 6). On prevention and counteraction to legalization (laundering) of proceeds from crime, terrorist financing and financing of proliferation of weapons of mass destruction: Law of Ukraine No. 361-IX, as of September 23, 2024. https://zakon.rada.gov.ua/laws/show/361-20#Text

32. Vyas-Doorgapersad, S. (2024). Assessment of the Shortcomings on Fight Against Corruption. *Business Ethics and Leadership, 8*(3), 219–230. https://doi.org/10.61093/bel.8(3).219-230.2024

33. Wright, J. (2023). Healthcare cybersecurity and cybercrime supply chain risk management. *Health Economics and Management Review, 4*(4), 17–27. https://doi.org/10.61093/hem.2023.4-02

34. Yarovenko, H., Kuzior, A., & Raputa, A. (2023). The Modeling of the Probable Behaviour of Insider Cyber Fraudsters in Banks. *Financial Markets, Institutions and Risks, 7*(4), 155–167. https://doi.org/10.61093/fmir.7(4).155-167.2023

35. Zámek, D., & Zakharkina, L. (2024). Research Trends in the Impact of Digitization and Transparency on National Security: Bibliometric Analysis. *Financial Markets, Institutions and Risks, 8*(1), 173–188. https://doi.org/10.61093/fmir.8(1).173-188.2024

36. Zozulinskyy, A. (2024). The Financial, Economic and Social Consequences of the Russo-Ukrainian War: Bibliometric Analysis. *Financial Markets, Institutions and Risks, 8*(3), 134–162. https://doi.org/10.61093/fmir.8(3).134-162.2024

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МЕХАНІЗМ ЦИКЛІЧНО-ДИНАМІЧНОГО СКРИНІНГУ ДІЯЛЬНОСТІ СУБ’ЄКТІВ ПЕРВИННОГО ФІНАНСОВОГО МОНІТОРИНГУ В УМОВАХ ВІЙНИ

Метою дослідження є розроблення механізму циклічно-динамічного скринінгу діяльності суб’єктів первинного фінансового моніторингу (СПФМ) в умовах війни, застосування якого дозволяє виявляти нетипові поведінкові патерни, підвищити адаптивність до швидкозмінних ризиків і сприяти підвищенню якості виявлення фінансових правопорушень. Основні результати. У дослідженні побудовано адитивні моделі часових рядів для двох окремих періодів: довоєнного (2011–2019) та періоду, що включає воєнні умови (2021–2024). Застосовано методи згладжування, декомпозиції часових рядів, розрахунку сезонних складових та аналітичного вирівнювання трендів. У першому періоді модель забезпечила високу точність (коефіцієнт детермінації 90,87%), водночас у другому періоді — прийнятний рівень точності (65,80%), що обумовлено підвищеною волатильністю у фінансовому середовищі.

Основні висновки. Результати дослідження підкреслюють важливість аналізу коливань і трендів для своєчасного виявлення підозрілих фінансових транзакцій, а також підвищення ефективності процедур первинного фінансового моніторингу в умовах війни. Запропонований механізм дозволяє не лише підвищити точність виявлення аномальних операцій і адаптивно реагувати на ризики, а й підсилити моніторинг обігу коштів і контроль за ним. Практичне впровадження цієї методики сприятиме забезпеченню національної фінансової стабільності та безпеки, що є критично важливим для підтримання цілісності фінансової системи держави в умовах воєнного часу.

Ключові слова: фінансовий моніторинг, воєнна економіка, суб'єкти первинного фінансового моніторингу (СПФМ), підозрілі транзакції, циклічно-динамічний скринінг, аналіз часових рядів, фінансова безпека

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