“GRU-based forecasting of conflict-related socio-economic vulnerabilities under illicit practices”


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| **ARTICLE INFO** | Hanna Yarovenko, Olena Pakhnenko, Liudmyla Riabushka, Iryna Tarasenko and Viktoriia Khmurova (2026). GRU-based forecasting of conflict-related socio-economic vulnerabilities under illicit practices. *Problems and Perspectives in Management*, *24*(3), 15-36. doi:10.21511/ppm.24(3).2026.02 |
| **DOI** | http://dx.doi.org/10.21511/ppm.24(3).2026.02 |
| **RELEASED ON** | Friday, 10 July 2026 |
| **RECEIVED ON** | Monday, 25 May 2026 |
| **ACCEPTED ON** | Friday, 03 July 2026 |
| **LICENSE** | This work is licensed under a Creative Commons Attribution 4.0 International License |
| **JOURNAL** | "Problems and Perspectives in Management" |
| **ISSN PRINT** | 1727-7051 |
| **ISSN ONLINE** | 1810-5467 |
| **PUBLISHER** | LLC “Consulting Publishing Company “Business Perspectives” |
| **FOUNDER** | LLC “Consulting Publishing Company “Business Perspectives” |

| NUMBER OF REFERENCES | NUMBER OF FIGURES | NUMBER OF TABLES |
|---|---|---|
| 47 | 9 | 3 |

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

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# GRU-BASED FORECASTING OF CONFLICT-RELATED SOCIO-ECONOMIC VULNERABILITIES UNDER ILLICIT PRACTICES

## Abstract

The study develops a framework for forecasting conflict-related socio-economic vulnerabilities in a cross-country sample using indicators of armed conflict risk, forced displacement, and illicit practices. The analysis uses panel data covering 135 countries over 2012–2024. The Conflict Risk Index, Refugee Load Index, and Cyber Vulnerability Index were constructed using standardized indicators and Principal Component Analysis. The Cyber Vulnerability Index is a proxy for digital exposure to cyber-related disruptions. First-difference panel regressions identified associations between conflict- and migration-related risks and socio-economic indicators. Separately, GRU neural networks were applied to forecast these indicators, while comparative quartile-based ablation and scenario-based perturbation analyses assessed the contribution and sensitivity of corruption, AML-related risk, and cyber vulnerability across country groups. Regression analysis showed that the Conflict Risk Index was statistically associated with deterioration in GDP, GDP per capita, GDP per capita growth, political stability, life expectancy, labor force dynamics, and migration balance. The Refugee Load Index was associated with positive net migration alongside weaker economic growth and lower political stability in host countries. Forecasting results were heterogeneous: adding corruption, AML-related risk, and cyber vulnerability indicators improved accuracy for several targets, but deteriorated performance for some variables and showed evidence of overfitting for GDP per capita in the conflict-risk specification. In high-conflict-risk countries, the largest forecast improvements were for life expectancy (61.02%), GDP per capita (43.96%), and net migration (10.75%); in high-refugee-load countries, they were observed for life expectancy (60.30%), political stability (38.41%), and net migration (16.20%). The framework can support early warning, resilience assessment, and crisis response.

**Keywords** vulnerability, conflict, corruption, migration, displacement, cybersecurity, forecasting, neural networks, panel data, resilience

**JEL Classification** F51, O11, K42, C45

**Type of the article:** Research Article

**Received on:** 25th of May, 2026
**Accepted on:** 3rd of July, 2026
**Published on:** 10th of July, 2026



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**Conflict of interest statement:**
Author(s) reported no conflict of interest

## INTRODUCTION

Armed conflicts have become one of the most destructive drivers of socio-economic instability in the contemporary world. Their consequences extend far beyond direct human losses and physical destruction, affecting labor markets, migration, macroeconomic stability, institutional performance, and the long-term capacity of countries to recover. These effects are often intensified by forced displacement, deterioration of governance quality, and the growing pressure on social and economic systems. As a result, vulnerability in such environments is formed not as an isolated reaction to military events, but as a cumulative outcome of interconnected economic, social, institutional, and technological disruptions.

At the same time, conflict conditions create favorable environments for illicit practices. In this study, illicit practices are understood as an umbrella concept covering corruption, money laundering and AML-related risks, shadow economic activities, and cyber-related vulnerabilities that may weaken institutional capacity, distort resource allocation, and intensify socio-economic vulnerability. These processes deepen institutional fragility, weaken state capacity, and reduce the effectiveness of recovery mechanisms. Under such conditions, socio-economic trajectories become increasingly nonlinear, volatile, and difficult to assess through conventional analytical perspectives.

This raises a broader scientific question related to understanding how conflict-related socio-economic vulnerabilities emerge and evolve under the simultaneous influence of military shocks and illicit practices. The complexity of this problem lies in the multidimensional and mutually reinforcing nature of these factors, which affect both immediate socio-economic conditions and long-term development prospects. The present study does not seek to isolate or estimate the independent causal effects of armed conflict or forced displacement on individual socio-economic variables. Rather, it focuses on incorporating conflict-related, institutional, financial, technological, and migration pressures into an empirical forecasting setting for assessing vulnerability under conditions of structural instability, institutional weakness, and rising uncertainty.

## 1. LITERATURE REVIEW

Understanding socio-economic vulnerability in conflict-affected environments provides a foundation for analyzing the broader implications of instability for economic systems and societal well-being. Contemporary research conceptualizes vulnerability as a multidimensional and dynamic phenomenon shaped by structural, institutional, and behavioral factors, reflecting both exposure to adverse shocks and the limited capacity to absorb and recover from them.

Vulnerability is closely linked to resilience, understood as the ability of systems to withstand and adapt to disruptions. At the micro- and meso-levels, it manifests through labor market instability, declining job security, and limited access to social protection, particularly under conditions of institutional and economic volatility (Novikova & Shamileva, 2020). At the community level, resilience depends on institutional preparedness, cross-sectoral coordination, effective communication, and the capacity for collective action, which become especially important during wartime and under hybrid threats (Danylenko & Zagorodsky, 2025).

At the macro level, socio-economic vulnerability is strongly associated with development trajectories and institutional quality. Conflict-affected countries often experience disruptions in human capital formation, governance systems, and economic performance, which hinder sustainable development. Evidence suggests that regulatory interventions in education and science can partially mitigate these effects by supporting long-term development pathways (Krawczyk et al., 2025). The literature also emphasizes that vulnerability extends beyond immediate economic effects to include broader social outcomes such as poverty, exclusion, and social isolation, which reinforce long-term development constraints in conflict environments (Lake et al., 2023).

Overall, socio-economic vulnerability in conflict-affected countries emerges as a complex, multidimensional construct shaped by the interaction of economic instability, institutional fragility, and social dynamics. However, existing studies tend to examine these dimensions in isolation, without fully capturing their interdependencies.

Given this limitation, further analysis requires a structured examination of the key transmission mechanisms through which conflicts influence vulnerability. In particular, the literature can be systematized around several interrelated dimensions:

(i) macroeconomic consequences of conflicts;

(ii) socio-economic effects associated with migration and forced displacement;

(iii) the expansion of illicit practices and shadow economic activities;



http://dx.doi.org/10.21511/ppm.24(3).2026.02

(iv) broader impacts on environmental systems, healthcare, and education; and

(v) emerging technological risks, particularly cybersecurity.

Armed conflicts generate profound macroeconomic disruptions that extend beyond immediate output losses and reshape the structural dynamics of national economies. Their effects are transmitted through interconnected channels, including energy markets, production and labor systems, demographic processes, and financial and asset markets. More broadly, intensifying geopolitical fractures contribute to a more volatile and fragmented global economic environment, reshaping cross-border business relations and the institutional context in which national economies operate (Luo, 2024).

One of the most important channels of macroeconomic transmission is the energy sector. Russia's invasion of Ukraine exposed Europe's dependence on Russian fossil fuels and transformed energy from a predominantly economic and environmental issue into a central security concern. The resulting policy responses included the diversification of energy supplies, an accelerated search for alternative energy sources, and a stronger role of the state in energy governance (Kuzemko et al., 2022). At the same time, rising energy prices spread across national economies through international and intersectoral production linkages. The magnitude of these effects varied across countries and industries depending on their energy intensity, production structure, and position within global value chains (Yagi & Managi, 2023).

At the national level, energy-related disruptions affect both production systems and labor markets. Evidence from energy-intensive manufacturing industries indicates that the energy crisis associated with the Russia–Ukraine war reduced production and real turnover while also weakening labor demand (Hutter & Weber, 2023). Geopolitical risks are also rapidly transmitted to asset markets. Event-study evidence demonstrates that listed real estate companies experienced a significant negative market reaction to the Russian invasion of Ukraine, with the magnitude of the response varying across market classifications, regions, and countries' geopolitical exposure (Yudaruddin & Lesmana, 2024). At the same time, demographic disruptions, particularly population decline and changes in age structure, undermine long-term growth potential by reducing labor supply and increasing dependency burdens (Posheliuzhnyi, 2024).

From a macro-financial perspective, conflicts exert significant pressure on fiscal systems and financial stability. Increased public expenditures, rising debt levels, and the need for countercyclical fiscal measures characterize wartime and postwar economic policies (Okwoche & Nikolaidou, 2024). These pressures are further reflected in financial markets, where conflicts contribute to exchange rate volatility and external imbalances, particularly in developing economies (Michail, 2021; Bukhtiarova et al., 2022).

In addition to domestic effects, conflicts generate substantial cross-border spillovers through disruptions of production networks and international trade. Supply chain interruptions in conflict-affected or neighboring regions reduce efficiency, increase transaction costs, and lead to the reconfiguration of global value chains (Ding et al., 2025).

Population displacement represents one of the most significant transmission channels through which conflicts affect socio-economic systems. Large-scale refugee inflows and forced migration reshape labor markets, public finance, and social structures in both origin and host countries, generating complex and often mixed economic effects. Empirical evidence suggests that migration flows can simultaneously create short-term pressures on public resources and long-term opportunities for economic adjustment, depending on institutional capacity and integration policies (Ridwan et al., 2026; Emmanouilidis & Bellos, 2026).

At the macroeconomic level, refugee inflows influence economic growth, investment dynamics, and external balances. While some studies highlight potential negative effects related to fiscal burden and labor market competition, others demonstrate positive contributions through increased labor supply, consumption, and foreign direct investment, particularly in resource-dependent or structurally constrained economies (Mansouri et al., 2025; Manthei, 2021). These findings indicate that the economic impact of migration is highly context-specific and mediated by structural and policy factors.

At the micro- and meso-levels, the socio-economic effects of displacement are closely linked to labor market integration, working conditions, and organizational dynamics. Evidence from host-country labor markets shows that refugees and asylum seekers frequently enter informal and precarious employment characterized by low wages, limited social benefits, weakened employment security, and restricted opportunities for long-term integration (Dimitriadis, 2023). At the same time, targeted policies that jointly promote financial inclusion, employment, access to information, digital connectivity, and social integration can strengthen refugees' self-reliance and facilitate their participation in the economic and social life of host communities (Okello, 2025).

In addition to labor market effects, migration also influences financial flows and economic resilience through mechanisms such as remittances. Digital remittance systems, for example, have become an important tool for supporting economies affected by crises, facilitating cross-border financial transfers, and strengthening household-level resilience (Polishchuk et al., 2023). More broadly, the development effects of migration are shaped by the interaction between remittance inflows and domestic financial systems, which can strengthen investment in education, healthcare, and other components of human capital, thereby influencing long-term development outcomes (Ali Bare et al., 2022).

Overall, the literature demonstrates that migration and forced displacement constitute a multidimensional factor of socio-economic transformation in conflict contexts, affecting both macroeconomic performance and micro-level social dynamics. These effects are mediated by institutional capacity, integration mechanisms, and economic structure, which determine whether migration acts as a source of vulnerability or a driver of resilience.

Illicit practices constitute a critical yet often underexplored channel through which conflicts amplify socio-economic vulnerabilities. Armed conflicts weaken institutional capacity, reduce regulatory effectiveness, and create conditions conducive to the expansion of shadow economic activities, including corruption, money laundering, and informal markets. These processes distort economic incentives and undermine fiscal stability and long-term development prospects.

At the macro level, empirical studies demonstrate a strong association between conflict dynamics and the growth of shadow economies. Internal conflicts and political instability tend to increase the scale of informal economic activity, as weakened governance and enforcement mechanisms reduce the effectiveness of formal institutions (Peksen & Early, 2020; Yoo & Kim, 2024). Similarly, peacekeeping operations, while stabilizing security conditions, may unintentionally contribute to the expansion of shadow economic activities in host countries due to increased external financial flows and institutional asymmetries (Blanton & Peksen, 2025). Evidence from country-specific analyses further confirms that conflict episodes significantly intensify shadow economy dynamics, particularly in developing economies with limited institutional resilience (Hu & Wang, 2025).

A key dimension of illicit practices in conflict environments relates to financial crime and anti-money laundering (AML) systems. The effectiveness of these frameworks depends substantially on institutional quality, regulatory capacity, and the ability of public authorities to ensure compliance and enforcement, all of which may be weakened during periods of conflict. Empirical evidence indicates that legislative deficiencies, inadequate national risk assessments, limited compliance, and weak enforcement reduce the effectiveness of national AML/CFT regimes (Tuhirirwe & Alexander, 2025). In extreme cases, such as conflict-affected economies, central banking systems and regulatory institutions face severe constraints in combating money laundering and terrorism financing, further exacerbating systemic risks (Lababidi, 2020).

Beyond financial systems, conflicts also facilitate the emergence of illicit markets and alternative economic structures. War economies often give rise to informal or illegal trade networks that exploit disrupted supply chains and weakened state control. For example, the development of illegal commodity markets, including agricul-


http://dx.doi.org/10.21511/ppm.24(3).2026.02

tural products, reflects the opportunistic adaptation of economic agents to conflict conditions and institutional gaps (Melnychuk, 2025). Similarly, the persistence of functional markets within war economies illustrates how informal mechanisms can substitute for formal institutions in maintaining economic activity under extreme conditions (Huddleston & Wood, 2020).

Recent research also highlights the interconnections between illicit practices, state vulnerability, and institutional transformation. Multidimensional analyses suggest that AML-related risks are not isolated phenomena but are embedded in broader systems of institutional fragility and governance weaknesses, generating cumulative and mutually reinforcing security threats (Kovalchuk et al., 2026).

Beyond economic disruptions, conflicts generate wide-ranging humanitarian and socio-ecological consequences that further intensify vulnerability. One of the most critical dimensions concerns the degradation of healthcare systems and the deterioration of population health. Empirical evidence shows that higher conflict intensity is associated with worsening health outcomes, largely due to the reduced functionality and accessibility of healthcare services (David & Eriksson, 2025). In fragile settings, weakened surveillance and response capacities also increase the risk of infectious disease outbreaks, as illustrated by the spread of measles in conflict-affected regions (Mehtar et al., 2021). More broadly, the interaction between armed conflicts and global health crises, such as pandemics, creates compounded risks that exceed the capacity of national and international response mechanisms (Saikia & Ghosh, 2026).

Conflicts also limit the effectiveness of disaster risk reduction and environmental management systems. In high-intensity conflict environments, institutional fragmentation and insecurity constrain the implementation of preventive and adaptive measures, increasing exposure to environmental hazards (Mena & Hilhorst, 2021). At the same time, post-war recovery processes reveal the long-term ecological consequences of conflicts, particularly in socio-ecological systems such as forests, where restoration requires coordinated institutional and policy interventions (Melnykovych et al., 2026).

In addition to health and environmental impacts, conflicts affect human capital formation through disruptions in education systems. Wartime instability also reshapes students' educational choices and mobility rationales, as academic, economic, and geopolitical considerations become increasingly intertwined under conditions of prolonged uncertainty (Oleksiyenko & Shchepetylnykova, 2024).

In addition to traditional economic and institutional factors, recent literature increasingly highlights the role of technological risks, particularly cybersecurity, as an emerging dimension of vulnerability in conflict-affected environments. Armed conflicts accelerate digital transformation while simultaneously exposing critical infrastructure to cyber threats, thereby expanding the spectrum of risks faced by national economies. Empirical studies demonstrate that the severity of cyberattacks on critical infrastructure is influenced by a combination of technological, organizational, and systemic factors, emphasizing the growing importance of cybersecurity within national risk frameworks (Roumani & Alraee, 2025). At the same time, the evolution of national cybersecurity strategies reflects the strategic role of digital resilience in modern conflicts, where cyber capabilities become an integral component of broader security architectures (Johansmeyer et al., 2024).

From a systemic perspective, cyber resilience is closely linked to institutional, technological, and financial capacities. In conflict and post-conflict settings, the ability of countries to withstand and recover from cyber threats depends on the interaction between these dimensions, highlighting the need to integrate cybersecurity into broader assessments of national resilience and vulnerability (Shkolnyk et al., 2025).

Taken together, these strands of literature confirm that socio-economic vulnerability in conflict-affected countries is shaped by multiple, mutually reinforcing economic, social, institutional, humanitarian, and technological factors.

Despite the extensive body of literature on socio-economic vulnerability in conflict-affected environments, several important limitations remain. First, existing studies predominantly focus on isolated dimensions of vulnerability, such as macroeconomic instability, migration dynamics, or the expansion of illicit practices, without adequately capturing their interdependencies. As a result, the cumulative and reinforcing effects of these factors on socio-economic systems remain insufficiently explored. Second, although recent research has begun to incorporate technological risks, particularly cybersecurity, these aspects are rarely integrated into broader frameworks of socio-economic vulnerability. This creates a gap in understanding how traditional and emerging risks jointly shape the resilience and fragility of conflict-affected economies. Third, methodological approaches in the existing literature are largely based on conventional econometric techniques or descriptive analyses, which may not fully capture the nonlinear relationships and complex interactions inherent in conflict-driven socio-economic processes. In this context, the application of advanced machine learning methods, particularly deep learning models, offers significant potential for improving analytical accuracy and predictive capabilities. Neural network-based approaches have demonstrated strong performance in modeling and forecasting macroeconomic dynamics by accounting for multidimensional and nonlinear dependencies among variables (Chen et al., 2025).

Therefore, there is a clear need for a comprehensive analytical framework that combines multiple dimensions of socio-economic vulnerability with advanced forecasting techniques. Addressing this gap is particularly important for conflict-affected countries, where the interaction between economic, institutional, and technological factors creates highly complex and dynamic risk environments.

Thus, the aim of this study is to model and forecast conflict-related socio-economic vulnerabilities across countries by accounting for illicit practices within an integrated GRU-based deep learning framework.

## 2. METHOD

The methodology for forecasting conflict-related socio-economic vulnerabilities included the following stages.

At the first stage, data preprocessing was carried out: gaps were addressed through extrapolation, interpolation, and averaging where necessary; time panels were harmonized by country and year; incorrect or incomplete observations were excluded. For individual variables (GDP, GDP per capita, official exchange rate, labor force), a logarithmic transformation was applied to normalize scales and reduce cross-country disparities.

The second stage involved composite indices: Conflict Risk Index, Refugee Load Index, as proxy indicators, and Cyber Vulnerability Index. Individual indicators were inverted, data were standardized, and Principal Component Analysis (PCA) was applied, which eliminated multicollinearity and produced normalized indices in the range from 0 to 1, where "1" corresponds to countries with high conflict risk, refugee load, and cyber vulnerability, and "0" indicates the opposite.

At the third stage, panel regressions were estimated in first differences (Wooldridge, 2010) for each target variable to identify socio-economic factors sensitive to conflict risks and refugee load.

The fourth stage involved the implementation of Gated Recurrent Unit (GRU) networks to forecast economic and social indicators (Cho et al., 2014). Baseline models were constructed using risk indices (Conflict Risk Index and Refugee Load Index) and extended models with corruption, AML-related risk, and cyber vulnerability. Model performance was evaluated using RMSE, MAE, and sMAPE metrics (Hyndman & Koehler, 2006), while consistency between training and test samples was used as an indicator of stability and absence of overfitting.

At the fifth stage, proxy feature importance analysis (Guyon & Elisseeff, 2003) was conducted, defined as correlations between risk indices, illicit-practice indicators, and predicted values, to identify key factors influencing target variables. Comparative quartile-based ablation analysis (Sheikholeslami et al., 2021) was implemented to evaluate the contribution of illicit practices to forecast accuracy depending on the type of target variable. For this analysis, countries were selected based on the 25th and 75th percentiles of the Conflict Risk Index and Refugee Load Index distributions.



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At the final stage, a scenario-based perturbation analysis was conducted using the trained GRU models to assess the sensitivity of socio-economic outcomes to illicit-practice indicators. The analysis focused on three explanatory variables: anti-money laundering risk, corruption risk, and the cyber vulnerability index. Perturbation scenarios corresponding to proportional increases of 1%, 5%, and 10% relative to the observed values of each indicator were applied individually, one variable at a time, while all other input variables remained unchanged. The perturbed input sequences were then used to generate counterfactual predictions, which were compared with baseline forecasts. The response was calculated as the percentage deviation between perturbed and baseline predictions, and the reported values represent the mean response across all observations in the test sample.

Three groups of indicators were selected to implement the methodology and predict socio-economic vulnerabilities associated with conflict, displacement, illicit practices, and cyber risks across the country panel (Table 1).

The first group of indicators identifies countries by their level of conflict risk and pressure. The main indicators are refugees and internally displaced persons, the growth of which signals an increase in conflict vulnerability. They were used to calculate conflict risk metrics and refugee burden, making it possible to classify countries by risk level more accurately and improve the efficiency of predictive neural network models.

The second group includes indicators of the impact of corruption, AML-related risk, and cyber threats on the socio-economic stability of countries. Accordingly, corruption, AML-related risk, and cyber vulnerability are treated as operational dimensions of illicit practices in the extended GRU models. Control of Corruption and Basel AML Index reflect the degradation of the institutional environment, the shadow economy, and the reduced efficiency of public administration. The Cyber Vulnerability Index was constructed to capture the technological dimension of socio-economic vulnerability. In this study, cyber vulnerability is understood not as the absence of cyberse-

**Table 1.** List of indicators

Source: The collected and pre-processed data are available at Yarovenko (2026).

| Indicator | Identifier |
|---|---|
| **Group 1. Conflict impact** | |
| Forcibly displaced people | FDP |
| Internally displaced persons, new displacement associated with conflict and violence (number of cases) | IDP |
| Refugees under the mandate of the UNHCR by country or territory of origin | R1 |
| Refugees under the mandate of the UNHCR by country or territory of asylum | R3 |
| Refugees under the mandate of the UNRWA by country or territory of asylum | R4 |
| **Group 2. Illicit practices** | |
| Control of Corruption: Estimate | CC |
| Basel AML Index | AML |
| Secure Internet servers (per 1 million people) | SISper |
| Fixed broadband subscriptions (per 100 people) | FBS |
| Individuals using the Internet (% of population) | IUI |
| ICT service exports (% of service exports, BoP) | ICTse |
| **Group 3. Indicators of socio-economic development** | |
| Political Stability and Absence of Violence/Terrorism: Estimate | PS |
| Official exchange rate (LCU per US$, period average) | OER |
| GDP (current US$) | GDP |
| GDP per capita (current US$) | GDPpc |
| GDP per capita growth (annual %) | GDPPCG |
| Life expectancy at birth, total (years) | LE |
| Unemployment, total (% of total labor force) (modeled ILO estimate) | UN |
| Net migration | NM |
| Inflation, consumer prices (annual %) | INF |
| Labor force, total | LF |
| Foreign direct investment, net inflows (BoP, current US$) | FDI |

curity protection mechanisms, but as the degree of exposure of a country's socio-economic system to potential cyber-related disruptions. Therefore, the index includes indicators characterizing the scale of digital infrastructure, connectivity, and integration into the digital economy, namely secure Internet servers, fixed broadband subscriptions, Internet use, and ICT service exports.

The rationale for this approach is that greater digital penetration expands the number of actors, transactions, services, and critical functions dependent on information and communication technologies. While these characteristics may reflect higher levels of digital development, they simultaneously increase the potential attack surface and the range of socio-economic processes that can be affected by cyber incidents. Consequently, countries with more intensive digitalization may face higher exposure to cyber-related risks, especially under conditions of institutional fragility, conflict, and illicit practices. Accordingly, the Cyber Vulnerability Index should be interpreted as a proxy measure of cyber exposure and technological susceptibility rather than a direct measure of cybersecurity capacity. Thus, within this study, cyber vulnerability is conceptualized primarily as systemic exposure and dependence on digital infrastructure rather than as insufficient cybersecurity capacity.

The third group characterizes socio-economic conditions and development dynamics that may be sensitive to conflict-related risks and illicit practices. It covers population well-being, the labor market, demographic processes, macroeconomic stability, and investment attractiveness. These indicators are sensitive to political instability, shadow economy, wars, and disruption in the institutional environment, and allow for the assessment of both short-term and long-term consequences of conflicts for socio-economic development. Indicators from this group were used as dependent variables to assess the scale and trajectories of socio-economic changes and identify patterns in the influence of conflict and illicit-practice factors.

The sample used for modeling comprised 135 countries observed over the period 2012–2024 and was constructed using indicators obtained from the World Bank databases and the Basel Institute on Governance. The final country coverage was determined by data availability and consistency after screening for missing and invalid observations. The complete list of countries, variable definitions, and data sources is available in the README file accompanying the publicly accessible dataset in the Zenodo repository (Yarovenko, 2026). All data processing and modeling procedures were implemented in Python.

## 3. RESULTS

The Conflict Risk Index and Refugee Load Index were obtained, acting as proxy risk markers for countries. Figure 1 demonstrates the spatial dynamics of the Conflict Risk Index during periods of major conflict escalation.

In 2012 (Figure 1a), most countries showed low index values, while elevated levels appeared in Colombia, Afghanistan, Pakistan, and India due to prolonged internal conflicts. In 2014 (Figure 1b), a sharp increase was observed in Ukraine due to the start of the Russian–Ukrainian war, as well as in Afghanistan, Nigeria, Colombia, Turkey, and Myanmar. In 2015 (Figure 1c), amid the migration crisis, high index values were observed in Afghanistan, Syria, Nigeria, Jordan, Ukraine, and Turkey, with Yemen also appearing. In 2020 (Figure 1d), the COVID-19 pandemic reduced overall population mobility, yet high risks remained in Afghanistan, as well as local escalations in several countries. In 2022 (Figure 1e), a sharp increase in the index for Ukraine followed the full-scale invasion, triggering the largest migration crisis in Europe. In 2023 (Figure 1f), high conflict values persisted in Ukraine, Afghanistan, Myanmar, Yemen, Colombia, and Nigeria, with new flows recorded in Sudan.

Figure 2 shows spatial differentiation across countries in the Refugee Load Index, with strong asymmetry driven by the concentration of migration pressure in first-reception countries.

In 2012 (Figure 2a), refugee load increased in Pakistan, Jordan, and Turkey due to wars in Afghanistan, Iraq, and Syria, forming them as


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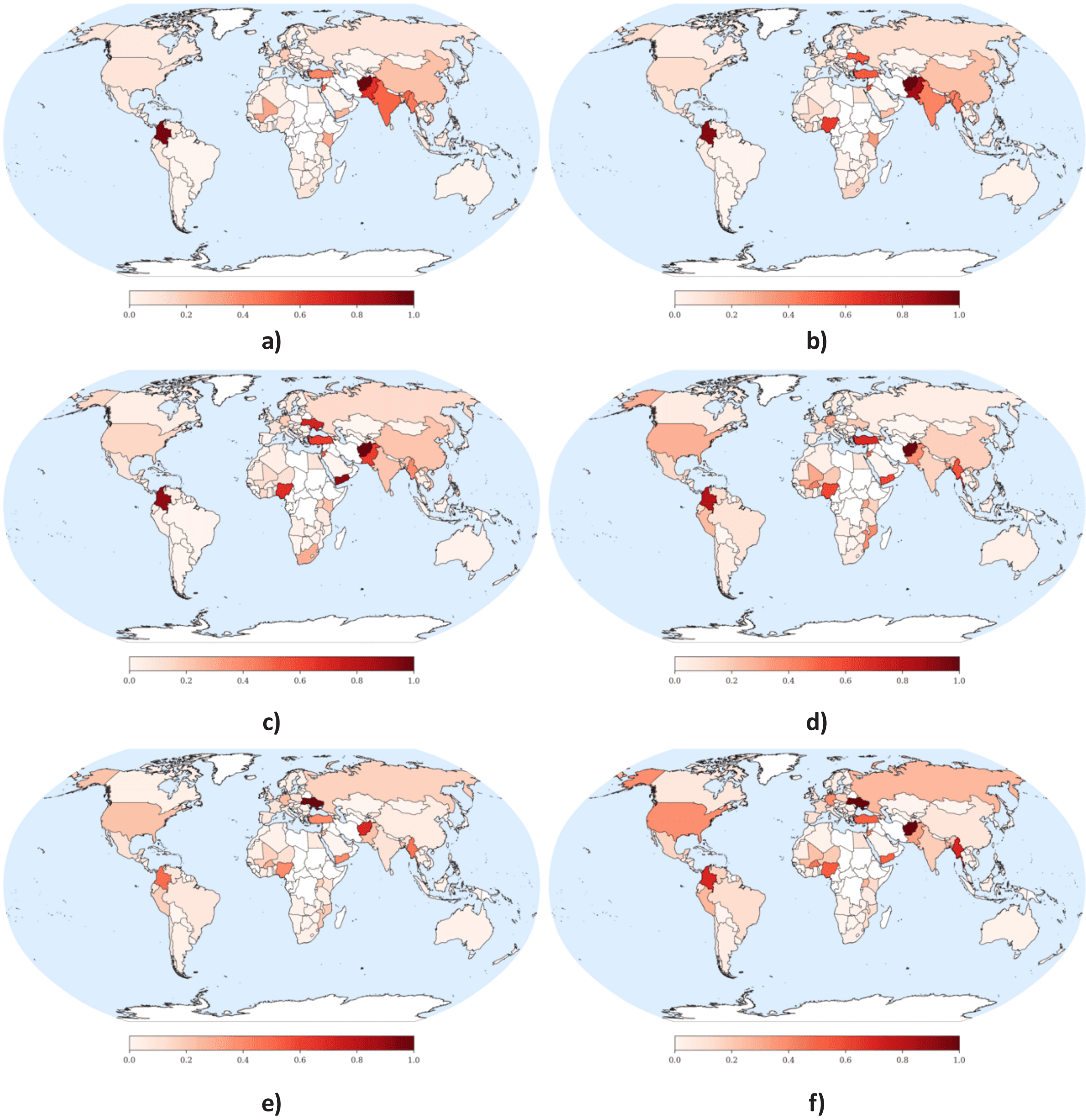


**Figure 1.** Spatial differentiation of countries worldwide by the Conflict Risk Index in: a) 2012; b) 2014; c) 2015; d) 2020; e) 2022; f) 2023

key regional refugee hubs. In 2014–2015 (Figure 2b-c), the index rose significantly in Turkey, as well as in Russia due to population displacement from eastern Ukraine. In 2020 (Figure 2d), high values persisted in Turkey, Uganda, Kenya, and Bangladesh, linked to prolonged crises and refugee inflows from Myanmar. In 2022–2023 (Figure 2e-f), a sharp increase in the Refugee Load Index was observed in Germany, Poland, the Czech Republic, France, Spain, and the United Kingdom due to the mass reception of Ukrainian refugees. Additionally, the burden increased in the USA and Canada, while migratory pressure also rose from countries in Asia, Africa, and Venezuela.

Panel regressions in first differences allowed identification of statistically significant variables most sensitive to conflict risk and refugee burden (Table 2). This approach removed fixed country effects and focused on dynamic socio-economic changes. No statistically significant relationships were found for official exchange rate, inflation, and foreign direct investment, so corresponding results are not reported.

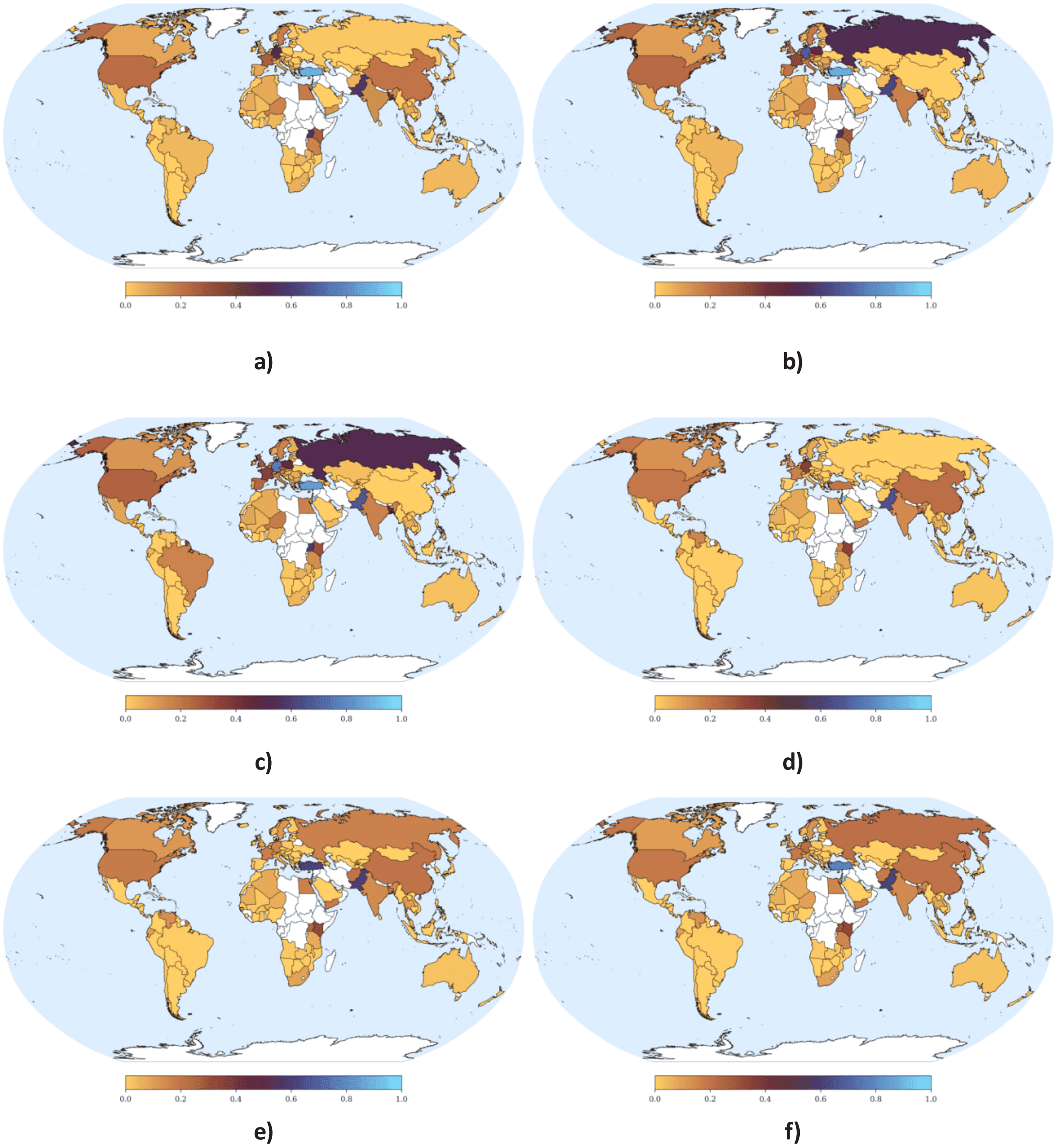


**Figure 2.** Spatial differentiation of countries worldwide by the Refugee Load Index in: a) 2012; b) 2014; c) 2015; d) 2020; e) 2022; f) 2023

The Conflict Risk Index results show population outflow from high-conflict-risk countries. The negative association between the Conflict Risk Index and GDP per capita growth is consistent with adverse economic dynamics in higher-risk countries. At the same time, rising unemployment (UN), declining life expectancy (LE), and political stability (PS) indicate worsening social conditions and institutional quality. Negative coefficients for GDP levels, GDP per capita, and labor force point to long-term structural losses driven by conflicts.

For the Refugee Load Index, a different pattern emerges: increases associate with positive net migration (NM) in recipient countries, but also with slower economic growth (GDPPCG) due to adaptation to rapid population inflows, mostly requiring additional social and economic support. Declining political stability (PS) reflects in-


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**Table 2.** Panel regression results for socio-economic indicators

| Model | Beta coefficient | Absolute beta coefficient | P-value |
|---|---|---|---|
| **Conflict Risk Index (CRI)** | | | |
| $\Delta NM_{i,t} = \alpha_1 + \beta_1 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –727,891.3416 | 727,891.3416 | 1.451626e-11 |
| $\Delta GDPPCG_{i,t} = \alpha_2 + \beta_2 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –13.7927 | 13.7927 | 1.040152e-07 |
| $\Delta UN_{i,t} = \alpha_3 + \beta_3 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | 3.5340 | 3.5340 | 2.591195e-13 |
| $\Delta LE_{i,t} = \alpha_4 + \beta_4 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –1.4182 | 1.4182 | 4.535285e-04 |
| $\Delta PS_{i,t} = \alpha_5 + \beta_5 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –0.4836 | 0.4836 | 2.641293e-11 |
| $\Delta ln(GDP)_{i,t} = \alpha_6 + \beta_6 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –0.1238 | 0.1238 | 1.603771e-02 |
| $\Delta ln(GDPpc)_{i,t} = \alpha_7 + \beta_7 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –0.1104 | 0.1104 | 2.128831e-02 |
| $\Delta ln(LF)_{i,t} = \alpha_8 + \beta_8 \Delta CRI_{i,t} + \varepsilon_{i,t}$ | –0.0332 | 0.0332 | 4.731785e-03 |
| **Refugee Load Index (RLI)** | | | |
| $\Delta NM_{i,t} = \alpha_9 + \beta_9 \Delta RLI_{i,t} + \varepsilon_{i,t}$ | 783,905.6391 | 783,905.6391 | 0.000046 |
| $\Delta GDPPCG_{i,t} = \alpha_{10} + \beta_{10} \Delta RLI_{i,t} + \varepsilon_{i,t}$ | –11.4257 | 11.4257 | 0.013465 |
| $\Delta LE_{i,t} = \alpha_{11} + \beta_{11} \Delta RLI_{i,t} + \varepsilon_{i,t}$ | 2.4605 | 2.4605 | 0.000618 |
| $\Delta PS_{i,t} = \alpha_{12} + \beta_{12} \Delta RLI_{i,t} + \varepsilon_{i,t}$ | –0.4648 | 0.4648 | 0.000334 |

stitutional pressures in recipient countries, while effects on life expectancy (LE) likely reflect the concentration of refugees in relatively more developed health and social protection systems. Overall, results confirm asymmetric effects of conflict and migration: the Conflict Risk Index captures destructive impacts in source countries, while the Refugee Load Index reflects institutional and socio-economic challenges for recipient countries. The obtained variables are used to build predictive GRU models.

The study involved 24 baseline GRU models incorporating the Conflict Risk Index or the Refugee Load Index, as well as extended models including corruption, AML-related risk, and cyber vulnerability. Model training results are presented in Table 3.

Baseline GRU models with the Conflict Risk Index demonstrate good consistency between training and test samples, confirmed by close RMSE, MAE, and sMAPE values (Table 3). This indicates their ability to capture stable patterns in the dynamics of net migration, unemployment, life expectancy, political stability, and economic development. Adding illicit-practice indicators improves forecast accuracy for several target variables; however, the magnitude and direction of the effect differed across indicators, and some extended models demonstrated limited gains or signs of overfitting. For GDP per capita, signs of overfitting appear in the extended model, confirming its structural instability over time.

For the Refugee Load Index specification, the extended models improved forecasting performance for net migration, life expectancy, and political stability. However, the results were not uniform across all targets: the GDP per capita growth model showed deterioration in test-sample accuracy after the inclusion of illicit-practice indicators. Overall, the results demonstrate that GRU models can capture heterogeneous patterns of socio-economic vulnerability, while the contribution of illicit-practice indicators depends on the specific target variable and country context.

As a result, associative relationships between the Conflict Risk Index and socio-economic indicators were assessed through proxy feature importance (Figure 3). The strongest relationship is observed for political stability (PS), indicating high

**Table 3.** Machine learning results of baseline and extended GRU models

| Target | RMSE | | MAE | | sMAPE | | Fit status |
|---|---|---|---|---|---|---|---|
| | train | test | train | Test | train | test | |
| **Baseline GRU models with the Conflict Risk Index** | | | | | | | |
| NM | 0.9831 | 0.9934 | 0.4123 | 0.3799 | 148.4519 | 149.5280 | Good fit |
| GDPPCG | 5.0694 | 5.6458 | 3.4857 | 3.2207 | 151.7217 | 147.9051 | Good fit |
| UN | 5.4136 | 4.9692 | 4.0180 | 3.7938 | 54.9173 | 57.3311 | Good fit |
| LE | 9.3649 | 9.9754 | 7.2598 | 7.4600 | 10.4311 | 10.5230 | Good fit |
| PS | 0.6814 | 0.6530 | 0.5763 | 0.5542 | 127.6069 | 127.0206 | Good fit |
| Ln(GDP) | 2.0037 | 1.9367 | 1.6196 | 1.5645 | 6.4585 | 6.1750 | Good fit |
| Ln(GDPpc) | 1.3401 | 1.3836 | 1.1167 | 1.1584 | 12.6423 | 12.8851 | Good fit |
| Ln(LF) | 1.4932 | 1.4871 | 1.1928 | 1.1976 | 7.8588 | 7.8459 | Good fit |
| **Extended GRU models with the Conflict Risk Index and Illicit Practices** | | | | | | | |
| NM | 0.7854 | 0.8865 | 0.3849 | 0.3804 | 128.0694 | 129.7755 | Good fit |
| GDPPCG | 5.0921 | 5.7099 | 3.5406 | 3.3046 | 163.4701 | 159.0420 | Good fit |
| UN | 4.7568 | 4.4901 | 3.4225 | 3.2670 | 47.7162 | 50.4736 | Good fit |
| LE | 4.7758 | 4.3665 | 3.9390 | 3.4915 | 5.5202 | 4.7757 | Good fit |
| PS | 0.4289 | 0.4408 | 0.3240 | 0.3270 | 74.8255 | 75.5609 | Good fit |
| Ln(GDP) | 1.7897 | 1.7764 | 1.4554 | 1.4587 | 5.8072 | 5.7486 | Good fit |
| Ln(GDPpc) | 0.6825 | 0.8625 | 0.5396 | 0.6819 | 6.1510 | 7.4174 | Overfitting |
| Ln(LF) | 1.7279 | 1.9354 | 1.3779 | 1.5464 | 9.0737 | 10.2084 | Good fit |
| **Baseline GRU models with the Refugee Load Index** | | | | | | | |
| NM | 0.9796 | 0.9833 | 0.4004 | 0.3693 | 163.1987 | 156.7998 | Good fit |
| GDPPCG | 5.0428 | 5.6042 | 3.4436 | 3.1703 | 145.7624 | 142.3256 | Good fit |
| LE | 7.9978 | 8.6995 | 6.6462 | 6.9194 | 9.2028 | 9.5705 | Good fit |
| PS | 0.8267 | 0.8542 | 0.6752 | 0.6884 | 165.0844 | 165.3184 | Good fit |
| **Extended GRU models with the Refugee Load Index and Illicit Practices** | | | | | | | |
| NM | 0.7375 | 0.8814 | 0.3537 | 0.3798 | 123.1138 | 122.9755 | Good fit |
| GDPPCG | 5.0923 | 5.7078 | 3.5410 | 3.2991 | 163.2762 | 158.4889 | Good fit |
| LE | 4.7062 | 4.0881 | 3.8488 | 3.4152 | 5.3940 | 4.6483 | Good fit |
| PS | 0.5699 | 0.5876 | 0.4417 | 0.4289 | 88.1243 | 88.0121 | Good fit |

dependence of the institutional environment on conflict intensity. High correlation values also appear for GDP per capita and its growth, pointing to a close relationship between conflict risk and population economic well-being. Moderate associations were found for net migration (NM) and labor force (LF_log), reflecting the impact of conflicts on demographic processes. However, relationships for life expectancy (LE), GDP, and unemployment (UN) are much weaker.

Extended models (Figure 4) demonstrate strong associations of corruption, AML-related risk, and cyber vulnerability with GDPPCG, LE, PS, and GDPpc_log (|corr| > 0.7), indicating a significant impact of illicit practices on socio-economic dynamics. For NM and LF_log, the association remains moderate, while for UN and GDP_log they are weak. Overall, the extended models produce a more heterogeneous correlation landscape depending on the type of illicit activity.

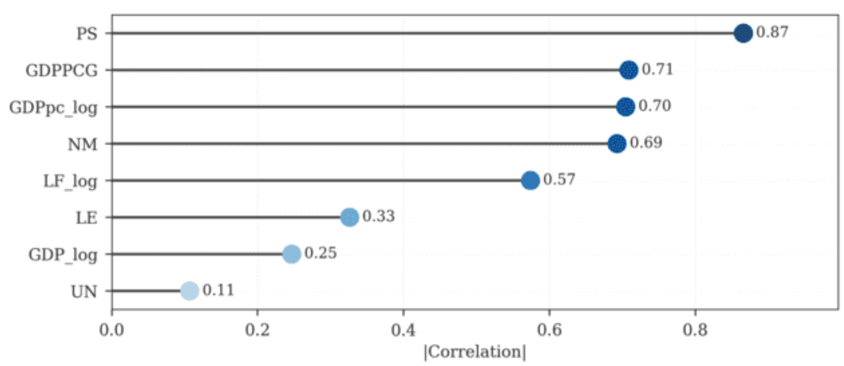


**Figure 3.** Proxy feature importance in baseline GRU models with the Conflict Risk Index


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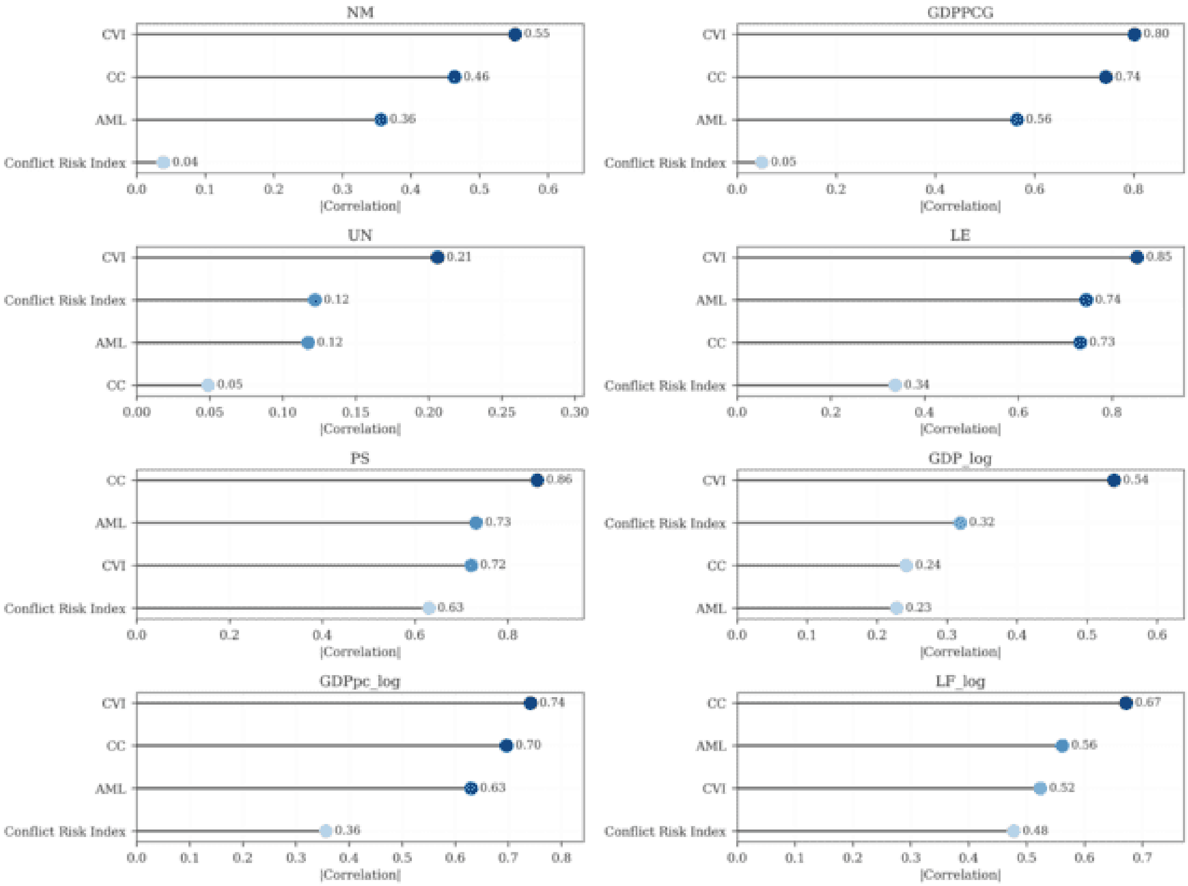



**Figure 4.** Proxy feature importance in extended GRU models with the Conflict Risk Index

Figure 5 shows proxy feature importance in baseline models for the Refugee Load Index and four targets. The strongest association appears for political stability (PS = 0.86), confirming high sensitivity of the institutional environment to migration load. Net migration (NM) shows a moderate association, while life expectancy (LE) shows a weak one. The lowest association is observed for GDP per capita growth, indicating minimal impact of migration load on economic growth in the baseline model.

Figure 6 presents extended GRU models including illicit-practice indicators. The strongest associations are observed between corruption control (CC), cyber vulnerability (CVI), AML-related risk (AML), life expectancy (LE), and political stability (PS), indicating a significant role of institutional and cyber risks in shaping social outcomes. For GDPPCG and net migration (NM), associations remain moderate. At the same time, the Refugee Load Index itself demonstrates weaker correlations compared to

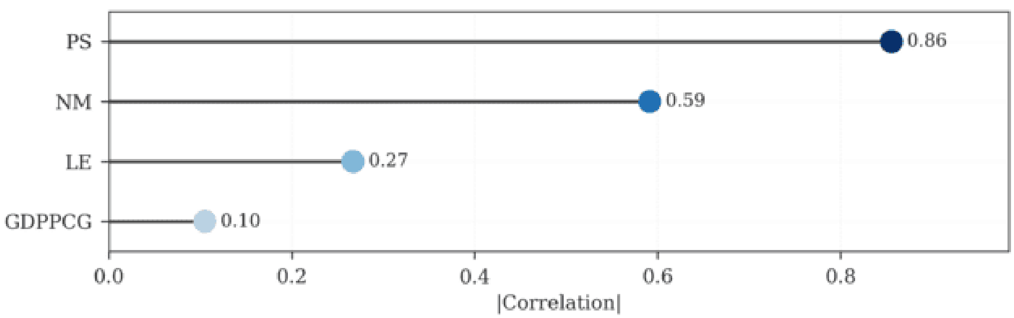



**Figure 5.** Proxy feature importance in baseline GRU models with the Refugee Load Index

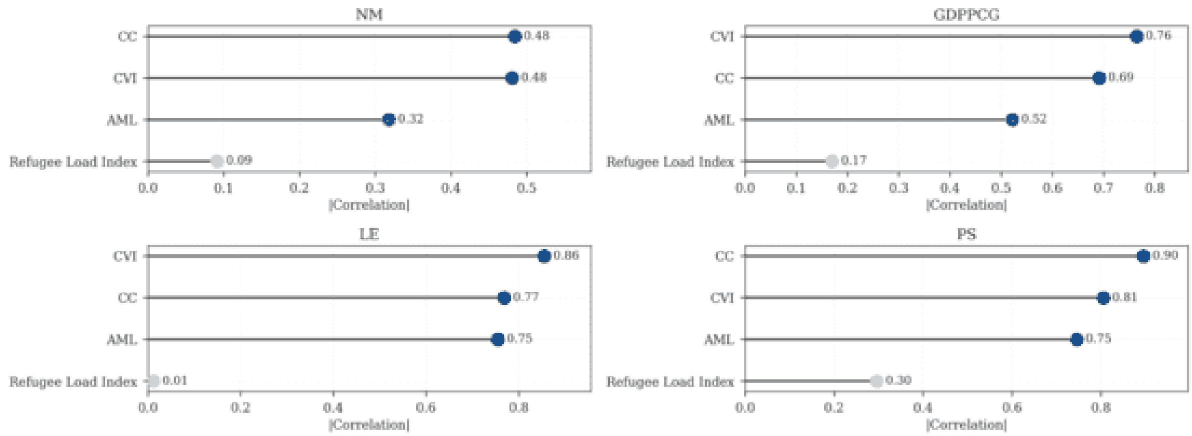


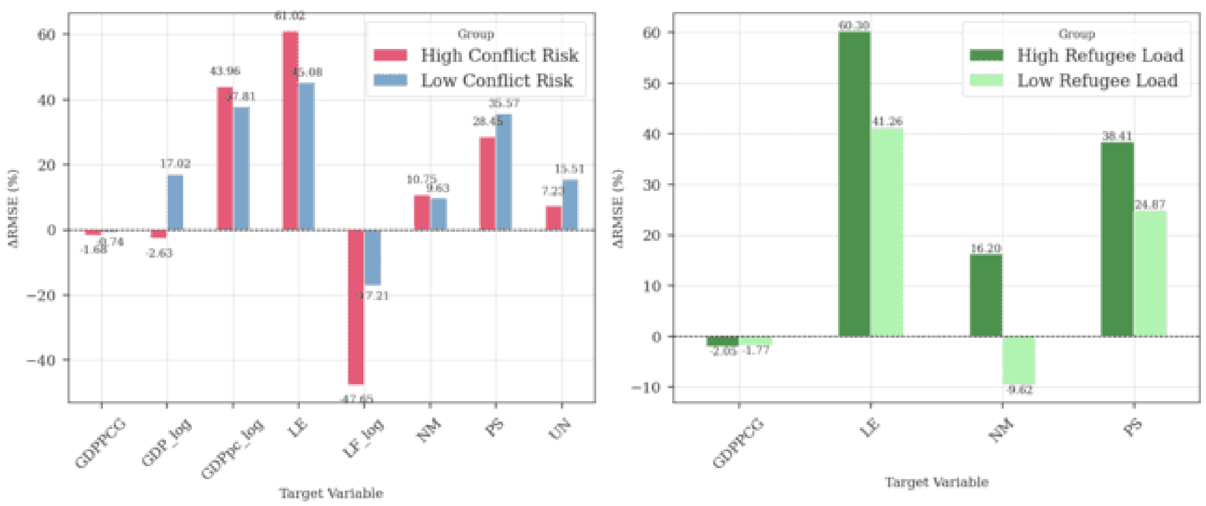

**Figure 6.** Proxy feature importance in extended GRU models with the Refugee Load Index

the baseline model, in some cases becoming almost negligible.

The results indicate that illicit practices may act as additional factors associated with variation in socio-economic targets alongside migration load.

The results of the comparative quartile-based ablation analysis (Figure 7) reveal a heterogeneous contribution of illicit-practice variables to predictive accuracy across different target variables. The primary performance indicator is the relative change in RMSE (ΔRMSE, %), which reflects the reduction or increase in prediction error following the inclusion of additional features in the extended model specification. Positive values of ΔRMSE indicate improved model performance (i.e., lower prediction error), whereas negative values indicate performance deterioration.

For high-conflict-risk countries (Figure 7a), adding illicit practices improves the prediction of most socio-economic indicators, indicating their sensitivity to expanded model specification. The largest effects are recorded for life expectancy (+61.02%), GDP per capita (+43.96%), and net migration (+10.75%). This suggests corruption, cyber vulnerability, and AML-related risk act as co-factors strengthening links between conflict and socio-economic dynamics. In low-conflict-risk countries, effects are selective: improvements appear for unemployment (+15.51%), political stability (+35.57%), and GDP (+17.02%), reflecting main-




**a)** **b)**

**Figure 7.** Comparative quartile-based ablation analysis for countries with high and low (a) conflict risk and (b) refugee load



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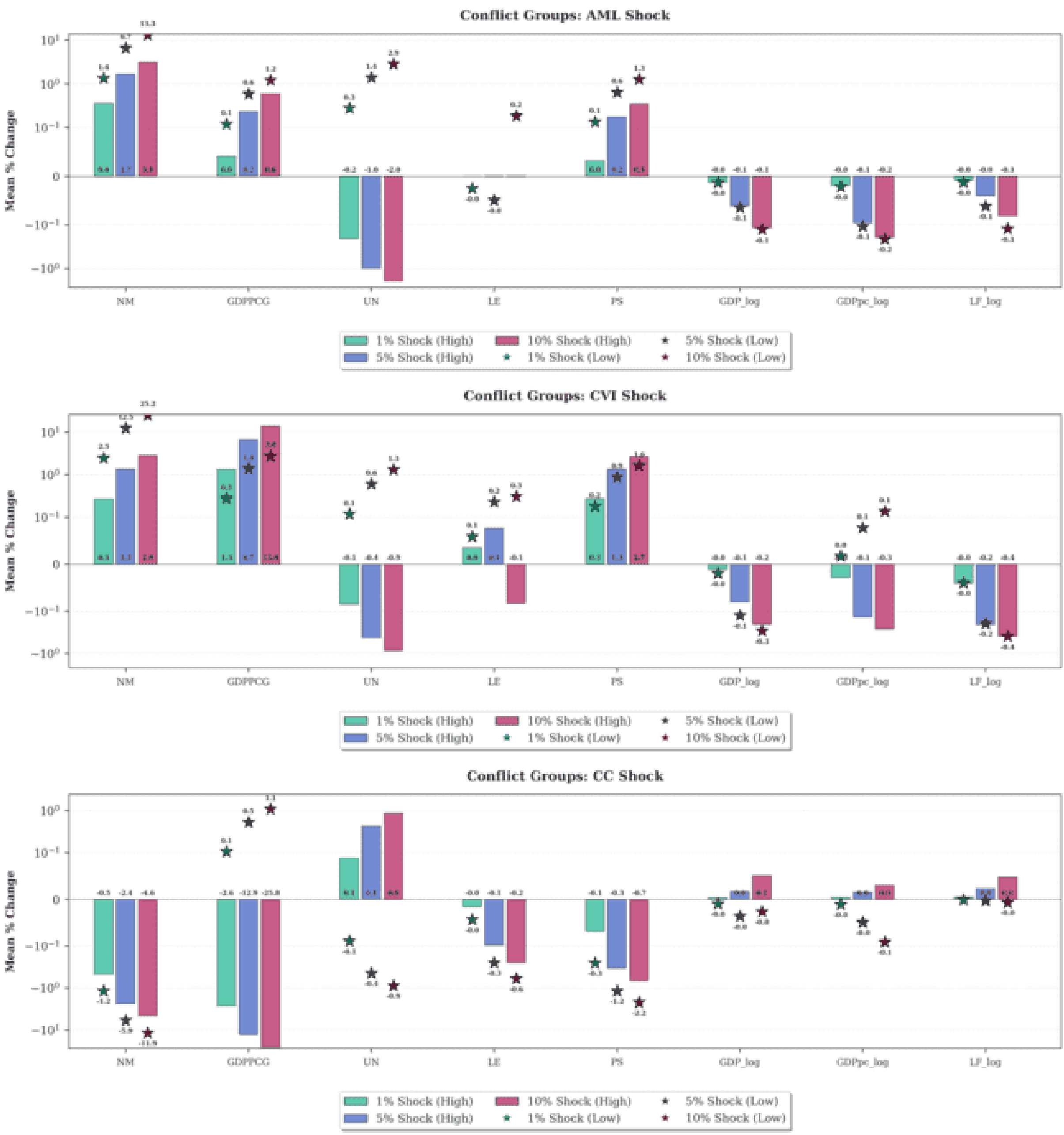
ly institutional and economic channels through which illicit practices affect labor markets, macroeconomic dynamics, and public administration efficiency. At the same time, for some variables (labor force, GDP growth), deterioration is observed, possibly indicating redundancy or limited relevance of the added feature.

Countries with a high refugee burden (Figure 7b) show greater sensitivity to inclusion of illicit practices than low-burden countries, especially for life expectancy (+60.30%), political stability (+38.41%), and net migration (+16.20%). This suggests that under high migration pressure, corruption, cyber threats, and AML-related risk relate more strongly to demographic dynamics, migration flows, and institutional stability. In low-burden countries, effects are weaker, particularly for net migration (–9.62%), indicating the limited usefulness of additional variables under stable conditions. For




*Note:* Asterisks indicate countries with low conflict risk, bars indicate countries with high conflict risk.

**Figure 8.** Scenario-based perturbation analysis under 1%, 5%, and 10% increases in AML, corruption risks, and cyber vulnerability for countries with high and low conflict risk

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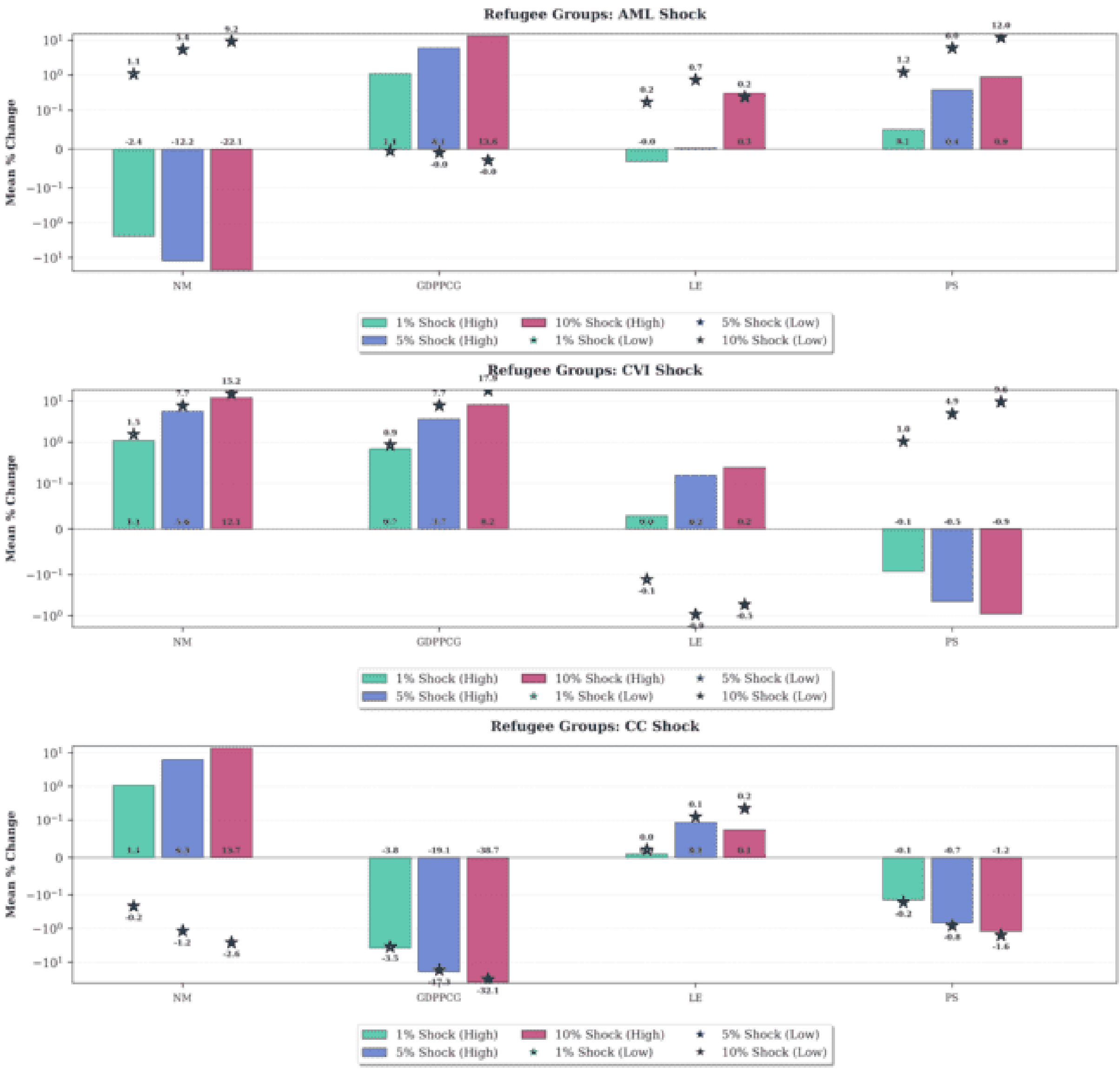
GDP per capita, changes in both groups remain insignificant (≈ −2%), indicating a weak linkage between this indicator and illicit practices within the model.

The results of the scenario-based perturbation analysis (Figures 8–9) show asymmetric responses of predicted socio-economic indicators to controlled increases in AML, corruption risks, and cyber vulnerability. The reported responses reflect percentage changes in model predictions under the 1%, 5%, and 10% perturbation scenarios relative to the baseline forecasts.

For AML-related risk (AML), low-conflict-risk countries (Figure 8) demonstrate stronger positive (NM, GDPPCG, UN, LE, and PS) and negative responses to shocks (LF_log, GDP_log, and GDPpc_log), while in high-conflict-risk countries, the effects are significantly weaker. This suggests higher elasticity to AML-related risk perturbations in more stable economies, while in high-conflict settings, the system reacts less to additional shocks. The most sensitive variable is net migration, confirming its close relationship with financial flows and migration mobility.




*Note:* Asterisks indicate countries with low refugee load, bars indicate countries with high refugee load.

**Figure 9.** Scenario-based perturbation analysis under 1%, 5%, and 10% increases in AML, corruption risks, and cyber vulnerability for countries with high and low refugee load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For cyber vulnerability (CVI), in low-conflict-risk countries, responses are stronger for net migration (NM = 25.23% at a 10% shock), unemployment (UN = 1.3%), and life expectancy (LE = 0.3%). In high-conflict-risk countries, the effect is weaker, explained by already elevated baseline risk levels. At the same time, political stability and GDP per capita growth show stronger shocks in high-conflict-risk countries, indicating higher institutional vulnerability under overlapping cyber and security risks. For logarithmic GDP, GDP per capita, and labor force, effects remain insignificant in both groups, indicating inertia of macroeconomic variables to short-term cyber shocks.

For corruption risks (CC), responses are mainly negative, most pronounced for net migration and political stability in low-risk countries, and for GDP per capita growth in high-risk countries. For unemployment, reactions remain weak and multidirectional. For other targets, shocks are absent or near zero, indicating the localized nature of corruption and dependence on initial institutional quality.

In the context of the Refugee Load Index for AML (Figure 9), contrasting dynamics are observed: in countries with a high refugee load, shocks negatively affect net migration (NM = –22.1% for a 10% shock) and positively affect GDP per capita growth (GDPPCG = +13.6%). In low-burden countries, the most noticeable effects are observed for political stability (PS = +12.0%) and net migration (NM = +9.2%). This indicates a different structural nature of responses: in countries with high migration pressure, reactions are more diverse, while in less burdened countries, they concentrate on individual indicators.

Cyber shocks demonstrate positive effects on net migration and GDP per capita growth, but the effect intensity is higher in low-burden countries. For life expectancy, shocks remain insignificant, while political stability is more sensitive in less loaded countries. This suggests cyber vulnerability is more dynamic in relatively stable systems, while marginal sensitivity is lower under high migration pressure.

Corruption shocks cause the largest decline in GDPpc in countries with high refugee burdens (–38.74% vs. –32.11%). Net migration is also the most sensitive in this group (+13.7%). This suggests corruption risks are especially sensitive to shocks under high migration pressure, where additional shocks significantly increase institutional instability. In both country groups, shocks to political stability are significant and negative, indicating declining trust in the political regime under corruption risks, regardless of migration conditions.

## 4. DISCUSSION

The results of this study confirm that socio-economic vulnerability is formed through the interaction of direct conflict shocks, forced displacement, institutional fragility, corruption, AML-related risks, and cyber vulnerability. The spatial dynamics of the Conflict Risk Index and Refugee Load Index demonstrate an asymmetric pattern of vulnerability: countries directly affected by armed conflicts experience population outflow, deterioration of political stability, weakening of labor market conditions, and economic losses, while host countries face additional institutional and socio-economic pressure caused by large refugee inflows.

These findings are consistent with Ridwan et al. (2026), who showed that refugee inflows have heterogeneous macroeconomic effects depending on the structural and institutional characteristics of receiving economies. They also correspond to Emmanouilidis and Bellos (2026), who emphasized the relationship between refugee flows, economic performance, security pressures, and political stability in Europe. The present study extends these findings by showing that forced migration changes the vulnerability profile not only of countries of origin but also of host countries, where migration pressure may create both demographic opportunities and additional adaptation costs.

The regression results indicate adverse associations between conflict risk and selected socio-economic outcomes. The Conflict Risk Index is associated with negative changes in GDP, GDP per capita, GDP per capita growth, life expectancy, political stability, and labor force, while also reflecting population outflow. These results can be explained by the destruction of productive capacity, human capital losses, deterioration of public

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services, and weakening of institutional control in conflict-affected countries. At the same time, the Refugee Load Index demonstrates a more mixed effect: it is associated with positive net migration but also with weaker economic growth and lower political stability in recipient countries. This confirms that the socio-economic consequences of conflicts extend beyond the countries where violence occurs and are transmitted through migration flows to recipient economies.

An important result of the study is that the inclusion of illicit-practice indicators improved forecasting performance for several socio-economic indicators, particularly political stability, life expectancy, and net migration. However, these improvements were not universal: some target variables showed limited gains or deterioration, indicating that the predictive value of additional indicators depends on the characteristics of the forecasted outcome. This finding is consistent with Peksen and Early (2020), who demonstrated that internal conflicts contribute to the expansion of shadow economic activity, and with Yoo and Kim (2024), who showed that terrorism and regime characteristics affect the scale of the shadow economy. The present study complements these works by demonstrating that corruption, AML-related risk, and cyber vulnerability are not only consequences of institutional weakness but also additional factors associated with the formation of socio-economic vulnerability.

The strong role of AML-related risks and corruption can be explained by the fact that conflict environments weaken regulatory institutions and create conditions for informal and illicit economic activity. Under such conditions, illicit financial flows distort resource allocation, reduce the effectiveness of public policy, and undermine trust in institutions. This interpretation is close to Kovalchuk et al. (2026), who argued that AML-related risks are embedded in broader systems of state vulnerability and institutional transformation. The results of this study support this argument, as AML and corruption indicators were strongly associated with political stability, life expectancy, migration dynamics, and GDP per capita in the extended models.

The findings also highlight the importance of cyber vulnerability as a component of socio-economic risk. Cyber-related variables demonstrated strong associations with several target indicators, especially political stability and life expectancy. This supports the conclusions of Shkolnyk et al. (2025), who emphasized the role of institutional, technological, and financial drivers of national cyber resilience under armed conflict and post-conflict recovery. In the present study, cyber vulnerability appears as an additional channel through which institutional and social vulnerability may intensify in conflict-affected environments.

The comparative quartile-based ablation and scenario-based perturbation analyses additionally confirm that the effects of corruption, AML-related risk, and cyber vulnerability differ across country groups. In high-conflict-risk countries, illicit practices were especially important for forecasting life expectancy, net migration, and GDP per capita, while in countries with lower conflict risk, they were more relevant for unemployment, political stability, and GDP. A similar asymmetry was observed for countries with different refugee loads. This suggests that the same risk factors may operate through different transmission channels depending on the initial level of conflict pressure and migration burden. In highly unstable countries, additional shocks may be partly absorbed by already elevated baseline vulnerability, while in more stable countries, marginal changes in institutional or cyber risks may generate more visible socio-economic responses.

Several limitations should be acknowledged. First, the use of composite indices allows multidimensional vulnerability to be captured, but it may also simplify country-specific institutional and conflict contexts. Second, the quality and availability of data on illicit practices, cyber risks, and conflict-related displacement remain uneven across countries. Third, the identified relationships should be interpreted mainly as associative and predictive rather than strictly causal, since the study focuses on forecasting socio-economic vulnerability rather than estimating direct causal effects. Fourth, the Cyber Vulnerability Index should be interpreted as a proxy measure of cyber exposure rather than cybersecurity effectiveness. The index captures the degree to which socio-economic systems depend on digital infrastructure, connectivity, and ICT-intensive activities. Consequently, higher index values reflect greater potential exposure to cyber-related disruptions and a broader attack surface, rather than weaker cyber-


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security capabilities or deficiencies in cyber defense mechanisms.

Overall, the results confirm that socio-economic vulnerability in conflict-affected countries cannot be fully explained by direct conflict indicators alone. Illicit practices act as additional factors that reveal hidden institutional and technological weaknesses. Therefore, the main contribution of this study lies in showing that the integration of conflict, migration, corruption, AML, and cyber-risk indicators provides a more comprehensive basis for forecasting socio-economic vulnerability and supporting early warning, resilience assessment, and crisis-response policy design.

## CONCLUSION

This study addressed the issue of identifying and forecasting conflict-related socio-economic vulnerability under forced displacement, illicit practices, and cyber risks. The proposed approach made it possible to consider vulnerability not as a consequence of a single destabilizing factor, but as the result of interacting conflict-related, institutional, financial, technological, and migration pressures.

First, the regression results identified statistically significant associations between the Conflict Risk Index, the Refugee Load Index, and changes in selected socio-economic indicators. Conflict risk was associated with weaker GDP and GDP per capita dynamics, lower political stability and life expectancy, labor force decline, and migration outflows. Refugee load was associated with positive net migration in host countries, alongside weaker economic growth and lower political stability. These findings describe distinct vulnerability profiles and should be interpreted as associative rather than causal.

Second, the forecasting results showed that corruption, AML-related risk, and cyber vulnerability provided additional predictive information for several targets. The largest improvements in high-conflict-risk countries were observed for life expectancy, GDP per capita, and net migration, while in high-refugee-load countries they concerned life expectancy, political stability, and net migration. However, these results were heterogeneous: some variables showed limited gains or deterioration, and the extended GDP per capita model in the conflict-risk specification showed evidence of overfitting.

Third, the perturbation analysis demonstrated that model responses to changes in AML-related risk, corruption, and cyber vulnerability varied across conflict-risk and refugee-load groups. Net migration and political stability were among the most sensitive outcomes in several scenarios. These results reflect model-based sensitivity patterns rather than causal effects of individual risk factors. The Cyber Vulnerability Index should likewise be interpreted as a proxy for digital exposure to cyber-related disruptions rather than a direct measure of cybersecurity capacity.

Finally, the scientific contribution of the study lies in combining conflict, migration, illicit-practice, and cyber-risk indicators within a unified forecasting framework for assessing socio-economic vulnerability. The obtained results may be useful for governments, international organizations, and analytical institutions in developing differentiated early warning systems, assessing national resilience, and designing crisis-response policies. Further research may expand the set of institutional, humanitarian, climate, and event-based variables and apply more interpretable artificial intelligence methods to improve the transparency and practical applicability of vulnerability forecasting.

## AUTHOR CONTRIBUTIONS

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Visualization: Hanna Yarovenko, Liudmyla Riabushka.
Writing – original draft: Hanna Yarovenko, Olena Pakhnenko, Viktoriia Khmurova.
Writing – review & editing: Hanna Yarovenko, Liudmyla Riabushka, Iryna Tarasenko.

## ACKNOWLEDGMENT

We acknowledge with gratitude the financial support provided by the Ministry of Education and Science of Ukraine for the research project "Cybersecurity and digital transformations of the country's wartime economy: the fight against cybercrime, corruption and the shadow sector," state registration number 0124U000544.

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