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THE TRANSFORMATION OF THE RELATIONSHIP BETWEEN ECONOMIC WELFARE AND CRIME UNDER THE IMPACT OF WAR: A LEGAL AND ECONOMETRIC ANALYSIS OF PANEL DATA FROM UKRAINIAN REGIONS BEFORE AND DURING THE FULL-SCALE INVASION

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Abstract. The full-scale Russian invasion of Ukraine has fundamentally altered the region's socioeconomic conditions, demographic structures and crime patterns, creating new challenges in authors' understanding of the relationship between economic welfare and crime. While traditional economic theory assumes that improved economic conditions reduce criminal activity by increasing the opportunity cost of offending, wartime conditions can substantially modify these relationships through forced displacement, regional heterogeneity, and institutional disruption. This study examines how the relationship between economic welfare and crime rates in Ukrainian regions changed during the full-scale war, and whether this relationship varies according to regional exposure to military conflict. The study uses a balanced panel dataset covering 25 Ukrainian regions (24 oblasts and the city of Kyiv) from 2018 to 2025. Economic welfare is operationalised using average monthly wages, while crime rates are measured as the number of registered criminal offences per 100,000 people in a given region. The analysis incorporates the proportion of internally displaced persons (IDPs) and distance from the active front line as indicators of the demographic and spatial effects of war. The empirical strategy is based on two-way fixed-effects panel regression models with Driscoll–Kraay standard errors. These were selected following diagnostic testing for cross-sectional dependence, autocorrelation, multicollinearity and model specification. Robustness analyses include alternative functional forms, subsample estimation, sensitivity tests and Granger causality analysis. The results show that the relationship between economic welfare and crime changed significantly following the full-scale invasion. There is no statistically significant direct association between average wages and regional crime rates. However, the interaction between wages and the wartime period is significant, suggesting that war has altered the underlying relationship. The strongest finding is the positive correlation between the proportion of internally displaced people and crime rates, which remains consistent across different models and robustness checks. Furthermore, the impact of economic welfare varies according to regional exposure to war, confirming pronounced spatial heterogeneity. Further analyses indicate that the observed relationships are nonlinear and that registered crime does not provide statistically significant predictive information for macroeconomic forecasting. The present study makes a significant contribution to the extant literature by providing one of the first panel-data assessments of the interaction between economic welfare, forced displacement, wartime spatial heterogeneity, and regional crime in Ukraine. From a methodological perspective, the study highlights the importance of diagnostic-based model selection, demographic controls and spatial measures of war exposure. The findings support the development of evidence-based regional public safety policies and post-war recovery plans.

Keywords: economics of crime, regional crime, panel data analysis, economic well-being, welfare, internally displaced persons, armed conflict, Ukraine.

JEL Classification: C23, D74, I31, K42, O15

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1. Introduction

The full-scale invasion of Ukraine by the Russian Federation[1] has triggered an unprecedented transformation of the country's socio-economic environment. The destruction of infrastructure, large-scale internal population displacement, changes to the way the law enforcement system functions, and regional disparities in the security situation have created a new context in which the traditional relationship between economic conditions and crime must be examined again. This study is relevant because it addresses the need to reassess the relationship between economic welfare and crime in wartime. Classical economic theories of crime emerged in stable institutional environments. However, full-scale war has fundamentally altered the way the economy, law enforcement system and labour markets function. These changes necessitate a re-examination of the robustness of established empirical relationships, as well as an evaluation of whether they have been altered by war-related factors. They also necessitate analytical approaches that can account for temporal dynamics and spatial heterogeneity in the war's impact, as well as the demographic consequences of internal population displacement. This study's scientific novelty lies in providing one of the first empirical justifications of how the wartime context reshapes the relationship between economic welfare and crime, and in demonstrating that this relationship varies according to the intensity of war in a given area. The study introduces the War-Related Regional Exposure Index (WRREI): a composite measure combining geospatial distance from regional administrative centres and the city of Kyiv to the active frontline, and official statistics on internally displaced persons (IDPs). This approach jointly captures the spatial and demographic dimensions of wartime exposure. Furthermore, the study proposes a diagnostic-driven approach to model specification, whereby the choice of estimation procedure is determined by diagnostic test results rather than a priori assumptions. At the same time, this study does not seek to establish causal relationships, and its findings should be interpreted as statistically supported empirical associations rather than as evidence of causality. Additionally, the study proposes a sequential model specification strategy, whereby the choice of estimation procedure is determined by diagnostic testing rather than a priori assumptions. The study does not seek to establish causal relationships; rather, its findings are interpreted as statistically robust empirical associations. This study aims to provide a legal and econometric assessment of the relationship between economic welfare and crime rates in Ukraine's regions during the pre-war period and Russia's full-scale invasion, by identifying statistically significant patterns and examining how the wartime context affects this relationship. To achieve the stated aim, the study pursues the following objectives:

1. To assess whether the full-scale invasion by the Russian Federation has altered the crime situation across the regions of Ukraine compared with the pre-war period.
2. To identify the relationship between economic welfare and crime rates and to examine whether this relationship remained stable before and during the full-scale war.
3. To determine whether the effects of economic factors exhibit spatial heterogeneity and whether they are moderated by the level of regional war exposure, measured by proximity to the active frontline and the scale of internal population displacement.
4. To examine the relationship between crime dynamics and macroeconomic indicators in the pre-war and wartime periods.
5. To establish the methodological framework for analysing the relationship between economic welfare and crime across the regions of Ukraine before and during Russia's full-scale invasion.

2. Literature Review

According to the rational choice model, the theoretical foundation of the economic analysis of crime is the idea that the decision to engage in criminal activity results from weighing the expected benefits of unlawful behaviour against the risk of punishment and the opportunities to earn income through legitimate means (Becker, 1968). The subsequent development of this framework (Ehrlich, 1973) and its application to panel data studies (Cornwell & Trumbull, 1994) formed the basis of modern econometric crime analysis, in which economic welfare is considered a key factor in criminal activity. Despite the existence of a well-established theoretical framework, the available empirical evidence remains inconclusive. While some studies demonstrate that increases in legitimate income primarily reduce property crime (Machin & Marie, 2011), others suggest that the strength and direction of this relationship depend on spatial and institutional context (Glaeser & Sacerdote, 1999). Similar inconsistencies are observed regarding the role of income inequality. Findings range from a positive association with violent crime (Fajnzylber et al., 2002), to limited evidence of a robust relationship (Neumayer, 2005). More recent regional studies have emphasised the significance of spatial effects and the diversity of economic factors influencing crime (Suess, 2019; Temidayo J. A. et al., 2024). Overall, the impact of economic factors on crime varies depending on the broader contextual environment. Concurrently, a growing body of research has examined the consequences of armed conflicts. War profoundly affects economic activity, employment and regional

1 For the purposes of this study, the terms full-scale armed aggression, full-scale invasion, and war are used interchangeably.

development (Almazán-Gómez et al., 2024), while also reshaping criminal activity patterns by increasing the risks associated with migration, the illicit arms trade and human trafficking (UNODC, 2025). Furthermore, exposure to war has heterogeneous effects on the socioeconomic conditions of the population (Frizell et al., 2025). Despite advances in both areas of research, the two fields have largely evolved in isolation from each other. While research on the economic determinants of crime has focused on stable institutional settings, studies of war have predominantly examined its macroeconomic and humanitarian consequences. The extent to which the wartime context moderates the relationship between economic welfare and crime, and whether this relationship varies with the spatial intensity of war exposure, remains largely unexplored. Addressing this gap constitutes the central objective of the present study.

3. Methodology

In order to achieve the research objectives, the study employed an integrated methodological framework combining interdisciplinary approaches from economics, criminology and legal scholarship. The methodological design is founded on complementary theoretical and empirical perspectives, thus facilitating a comprehensive analysis of the relationship between economic welfare and crime under wartime conditions. The research incorporates statistical, hypothetical, cybernetic, comparative and synergetic approaches, as well as econometric modelling and forecasting methods. The study uses a balanced panel design integrating both spatial and temporal dimensions. This enables the analysis to consider cross-regional heterogeneity, temporal dynamics and unobserved, time-invariant regional characteristics simultaneously (Hsiao, 2014). The analysis covers the period from 2018 to 2025, enabling comparison between the pre-war period (2018–2021) and the wartime period (2022–2025). Methodologically, the full-scale invasion is treated as an exogenous structural shock. As the decision to launch the invasion originated outside of Ukraine's economic and legal systems, and was not related to regional socio-economic processes, any changes in the estimated model parameters between the two periods can be interpreted as reflecting the effects of this shock. At the same time, however, the proposed research design does not allow for full causal identification, given that the war affected numerous socioeconomic and law enforcement factors simultaneously. Accordingly, the findings should be interpreted as evidence of statistical associations rather than definitive causal effects. The study's empirical basis consists of analytical reports published by national and international organisations, reference and statistical publications, administrative records, official statistical data, and other relevant empirical sources. The empirical analysis is based on a balanced panel dataset covering Ukraine's 24 oblasts and the city of Kyiv. There are 25 cross-sectional units, with 200 region-year observations over eight years. Data on recorded crimes were obtained from the official statistics of the Office of the Prosecutor General of Ukraine, including a formal data request (March 17, 2026, No. 25/4-39vykh-26, Office of the Prosecutor General of Ukraine, June 30, 2026). Population data for the period 2018–2021 was sourced from the State Statistics Service of Ukraine (June 30, 2026), while figures for the period 2022–2025 were obtained from the International Monetary Fund (June 30, 2026). Data on the average monthly wage for the period 2018–2022 and 2025 was compiled from Minfin Media LLC (June 30, 2026). Data on internally displaced persons (IDPs) were compiled from Bulhakova (2023) for 2018–2021, the Ukrainian Parliament Commissioner for Human Rights (2022) for 2022, and reports of the International Organization for Migration (2023, 2025, 2026) for 2023–2025. Geospatial data on the active frontline were obtained from the DeepState platform (June 30, 2026), using the frontline position as of April 3 in each year. Applying a common reference date ensures temporal comparability, as the platform has systematically published frontline data since April 3, 2022. This analysis combines reliable statistical data with publicly accessible geospatial information. The outcome variable is the regional recorded crime rate, which is measured as the number of recorded crimes per 100,000 people in a given region. All regression models use the natural logarithm of the crime rate to reduce distributional skewness and enable the estimated coefficients to be interpreted as elasticities. The main explanatory variable is the natural logarithm of the average monthly wage. The wage variable is expressed in logarithmic form to improve its distributional properties and enable the estimated coefficients to be expressed as percentages. WRREI is measured using two complementary indicators. The first captures the spatial dimension of war exposure by measuring the distance (in kilometres) from the administrative centre of each region to the nearest segment of the active frontline. In the case of the Donetsk and Luhansk regions, where the administrative centres are temporarily occupied, the distance was measured from the largest city under the control of the Ukrainian government. The second indicator is the proportion of internally displaced persons (IDPs) within the regional population, which reflects the demographic impact of the war. Additionally, the regression models incorporate a wartime dummy variable (War = 1 from 2022 to 2025) and interaction terms between the logarithm of the average monthly wage and the two war exposure indicators. Ukraine's nominal gross domestic product (GDP) is only included to provide

a description of the national macroeconomic context. It is excluded from the panel regression models because it does not vary across regions, meaning it is perfectly collinear with the time fixed effects. Consequently, the macro-level analysis is presented separately from the regional panel analysis.

Data imputation procedures were documented to ensure reproducibility. Missing observations for the average monthly wage variable (46 out of 184, primarily from 2023–2024) were imputed using linear interpolation within each region. The choice of linear interpolation rather than more complex methods (e.g., ARIMA models, splines or the Kalman filter) was determined by the short time dimension of the panel (T = 8). Such methods would provide limited advantages for this panel, while increasing the risk of model overfitting. In a similar fashion, 15 missing observations for population size and three observations for the number of internally displaced persons (IDPs) were imputed. Each imputed value was assigned an indicator variable, and the robustness of the results was assessed by comparing them with observed (non-imputed) data, as presented below. The empirical strategy is structured as a sequence of diagnostic procedures in which the result of each test determines the subsequent model specification. Because the Granger causality test is valid only for stationary series, the first step tests for unit roots using the Levin–Lin–Chu test (2002), the Im–Pesaran–Shin (IPS) test (2003), and the Fisher-type augmented Dickey–Fuller (ADF) test. These procedures allow for heterogeneity in the autoregressive parameters across panel units. The IPS test statistic is defined as follows:

$$W_{tbar} = \sqrt{N} * \frac{t' - E[t]}{\sqrt{Var(t)}}, \mathrm{t}' = \frac{1}{N}\sum t_i$$

where t_i – denotes the individual ADF test statistic for region i. The Fisher-type ADF test aggregates individual p-values as follows:

$$P = -2 * \sum \ln(p_i) \sim \chi^2(2N). \quad (2)$$

Ukrainian regions operate within a shared institutional and security environment, which can create interdependencies between different regions. The presence of such dependencies violates the assumption of cross-sectional independence on which conventional standard errors are based. To test for cross-sectional dependence, the Pesaran (2004) test is applied:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right), \rho_{ij} \sim N(0,1) \quad (3)$$

where ρ_{ij} denotes the sample correlation coefficient of residuals between regions (i) and (j).

As the Durbin–Watson statistic is not fully suitable for panel data, the Wooldridge test (2010) has been applied instead. The test is based on a regression of first-differenced residuals on their lagged values under the null hypothesis of no first-order serial correlation:

$$H^0 : corr(\Delta\varepsilon it, \Delta\varepsilon i, t-1) = -0.5 \;\; 4 \quad (4)$$

The choice between pooled OLS, random-effects (RE) and fixed-effects (FE) specifications is determined using the Mundlak approach (1978). This approach extends the standard random-effects model by permitting correlation between unobserved regional effects and explanatory variables, which is achieved by incorporating regional means of time-varying covariates. The RE model is therefore augmented with regional averages of the explanatory variables.

$$ln(Crime)_{it} = \beta_0 + \beta_1 X_{it} + \gamma \bar{X}_i + u_i + \varepsilon_{it} \quad (5)$$

The joint significance of the γ coefficients, as determined by the Wald test, rejects the null hypothesis

Table 1

Variables, Measurement, and Data Sources

Notation	Variable	Measurement and Data Source
ln(Crime)	Crime rate	ln(regional recorded crime rate, measured as the number of recorded crimes per 100,000 resident population in regions). Data sources: Office of the Prosecutor General of Ukraine, including a formal data request (March 17, 2026, No. 25/4-39-26; Office of the Prosecutor General of Ukraine, June 30, 2026)
ln(Wage)	Average monthly wage	ln(average monthly wage in each region (oblast) and the city of Kyiv (UAH). Data sources: Minfin Media Limited Liability Company (LLC).
Distance	Distance to the active frontline	Distance (km) from the administrative centre of each region to the nearest segment of the active frontline. Data source: DeepState.
IDP share	Share of internally displaced persons (IDPs)	IDPs as a percentage of the regional population. Data sources: Bulhakova (2018-2021), Ukrainian Parliament Commissioner for Human Rights (2022), International Organization (2023-2025).
War	Full-scale invasion (wartime dummy)	Dummy variable equal to 1 for 2022–2025 and 0 for 2018–2021.
WRREI (war exposure)	War-Related Regional Exposure Index	Calculated as the number of IDPs per 1,000 population in region and distance (km) of region to the active frontline for the wartime period (2022–2025). Equal to 0 for the pre-war period (2018–2021).

Source: Compiled by the authors based on the cited data sources

that the unobserved regional effects are uncorrelated with the explanatory variables. This supports the fixed-effects specification. Two-way fixed effects are selected for two main reasons. Regional fixed effects capture time-invariant characteristics of regions, including geographic location and the long-term features of regional socioeconomic and law enforcement systems. Time fixed effects capture nationwide shocks such as full-scale invasions, legislative changes, inflationary pressures and macroeconomic fluctuations. Without controlling for these effects, the influence of such shocks could be incorrectly attributed to regional-level explanatory variables. The baseline specification is defined as follows: $\alpha_i \lambda_t$

$$ln(Crime)_{it} = \alpha_i + \lambda_t + \beta_1 ln(Wage)_{it} + \beta_2 IDP_{it} + \beta_3 WarExp_{it} + \varepsilon_{it} \quad (6)$$

Estimation is performed using the within transformation with two-way demeaning:

$$\tilde{y}_{it} = y_{it} - y'_{it} - y'_{it} + y' \quad (7)$$

The Pesaran test indicates strong cross-sectional dependence. This implies that the conventional heteroskedasticity-consistent standard errors (White, 1980) derived under the assumption of cross-sectional independence would underestimate the true uncertainty of the estimates. Statistical inference is therefore conducted using two alternative procedures. The main specifications are estimated using robust standard errors clustered by region (Arellano), which account for heteroskedasticity and serial correlation within regions. As an additional robustness check, Driscoll–Kraay standard errors (1998) are reported, since they are also robust to cross-sectional dependence:

$$V_{DK}(\beta) = (X'X)^{-1}\left[\sum_{l=0}^{m} \omega(l,m)(\Omega_l + \Omega_l')\right](X'X)^{-1} \quad (8)$$

where Ω_l – denotes the autocovariance matrix of time-aggregated moment conditions, $w(\ell, m) = 1 - \ell/(m+1)$ represents – the Bartlett kernel, and the bandwidth parameter (m) is selected according to the rule $m = 4\left(\frac{T}{100}\right)^{\frac{2}{9}}$. Reporting both types of standard error enables the sensitivity of the empirical results to alternative assumptions about the dependence structure to be evaluated.

The optimal lag order for the causality analysis was selected using the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC) and the Hannan–Quinn Information Criterion (HQIC) within a panel autoregressive specification, with lag lengths ranging from one to three periods. Interaction terms are introduced to test the third research objective. The interaction between the wartime dummy variable (War) and the logarithm of average monthly wages (\ln(Wage)) reveals how the relationship between wages and crime changed after 2022. The interaction between the logarithms of wages and distance to the front line examines whether the relationship between wages and crime varies across regions with different distances to the front line. In the second specification, the marginal effect of the logarithm of wages is a function of the logarithm of the distance to the front line:

$$ln(Wage) \times Warln(Wage) \times ln(Distance) \quad (9)$$

$$\frac{\partial ln(Crime)}{\partial ln(Wage)} = \beta_1 + \beta_3 * \ln(Distance) \quad (10)$$

The logarithmic specification of wages is justified for three reasons. First, the distribution of wages in levels exhibits substantial right skewness (skewness coefficient = 1.024; the Jarque–Bera test rejects the null hypothesis of normality at ($p < 0.001$)), whereas the logarithmic transformation reduces skewness to 0.096, and the null hypothesis of normality is not rejected after transformation (($p = 0.121$)). Second, the logarithmic form allows the estimated coefficients to be interpreted as elasticities. Third, when combined with the logarithmic specification of the dependent variable, the model takes the form of a constant elasticity specification, which is consistent with economic models of criminal behavior based on rational choice assumptions. Since the functional form may influence the empirical results, alternative transformations are compared systematically below. The logarithm of relative average wages is not considered as a separate specification because, when time fixed effects are present, it does not provide any additional identifying variation and is linearly dependent on the logarithm of absolute average wages:

$$\ln\left(\frac{w_{it}}{\overline{w}_t}\right) = \ln(w_{it}) - \ln(\overline{w_t}) \quad (11)$$

The second component is fully absorbed by the time fixed effects λ_t.

Multicollinearity was assessed using variance inflation factors (VIF), with a threshold value of 5. All calculations were performed in Python 3.11 using the NumPy, SciPy and matplotlib libraries. The within transformation, region-clustered robust standard errors and Driscoll–Kraay standard errors were implemented by the authors according to Equations (7)–(8), thereby ensuring the estimation procedure is fully reproducible.

4. Results and Discussion

A comparison of the two periods (see Table 2) shows that there have been significant changes in the key indicators. The average crime rate increased from 974 to 1,168 offences recorded per 100,000 inhabitants, while the standard deviation nearly doubled, indicating greater interregional heterogeneity. Furthermore, the highest crime rates were observed in the Donetsk, Zaporizhzhia, Luhansk and Kherson oblasts following the full-scale invasion. Notably, these are the very

Table 2

Regional Crime Rate Summary by Period: Evidence for research objective 1

Region	Group	Pre-war avg (2018–2021)	2022 (onset)	Wartime avg (2022–2025)	Change (%)
Cherkasy	Rear	998.8	707.0	971.9	-2.7%
Chernihiv	Front line	1211.1	1114.8	1217.3	+0.5%
Chernivtsi	Rear	768.0	669.2	797.3	+3.8%
Dnipro	Rear	1143.9	660.3	1224.6	+7.1%
Donetsk	Critical	525.9	1007.8	22103.3	+4103.0%
Ivano-Frankivsk	Rear	529.1	427.3	547.5	+3.5%
Kharkiv	Front line	1124.3	1289.5	1772.5	+57.7%
Kherson	Critical	1329.0	1803.4	7313.3	+450.3%
Khmelnytskyi	Rear	659.7	441.9	686.4	+4.1%
Kirovohrad	Rear	1301.8	935.5	1027.4	-21.1%
Kyiv City	Rear	1618.1	1170.0	1357.3	-16.1%
Kyiv Region	Rear	976.9	1460.5	1146.3	+17.3%
Luhansk	Front line	395.2	979.2	905.7	+129.2%
Lviv	Rear	892.0	617.4	1059.1	+18.7%
Mykolaiv	Front line	1395.7	1075.5	1222.6	-12.4%
Odesa	Rear	1047.2	718.5	997.0	-4.8%
Poltava	Rear	1249.7	921.4	1140.8	-8.7%
Rivne	Rear	845.1	647.4	1135.4	+34.4%
Sumy	Front line	972.8	841.3	1969.2	+102.4%
Ternopil	Rear	631.6	508.1	646.4	+2.3%
Vinnytsia	Rear	725.1	597.1	917.2	+26.5%
Volyn	Rear	936.8	725.8	1014.8	+8.3%
Zakarpattia	Rear	802.8	760.8	862.9	+7.5%
Zaporizhzhia	Front line	1219.0	952.9	2970.4	+143.7%
Zhytomyr	Rear	962.1	723.6	1267.3	+31.7%

Note: Critical regions (Donetsk, Kherson) shaded red. Frontline regions – amber (Chernihiv and Sumy oblasts are also classified as frontline regions because they have repeatedly experienced cross-border military incursions by Russian forces during the full-scale invasion.). Rear regions – grey.

Source: Authors' calculations.

regions through which the active frontline passes. Prior to the large-scale invasion, the highest crime rates were recorded in the Dnipropetrovsk, Kirovohrad, Mykolaiv, Poltava and Chernihiv oblasts, as well as in the city of Kyiv (Prosecutor General of Ukraine, 2026). The following figure and table show that the full-scale invasion significantly altered the level of crime rates and their variation between regions. Table 2 shows the annual crime rate in each of the 25 main regions from 2018 to 2025, with 2022 highlighted.

The average monthly wage increased from 8,984 UAH to 16,710 UAH. Meanwhile, the proportion of internally displaced persons (IDPs) in the regional population rose from 1.9% to 11.5%, reaching 39.7% in certain regions.

The unit root tests fail to reject the null hypothesis of a unit root for either variable at its level (see Table 4). However, given the short time dimension ($T = 8$), the power of these tests is limited. Therefore, the results should be interpreted as indicative rather than conclusive. Accordingly, the baseline specification is estimated using log levels with two-way fixed effects to absorb common stochastic trends. The first-difference specification is then presented as a robustness check. Pesaran's CD test provides clear evidence of strong cross-sectional dependence (CD = 22.94 for the crime rate and 44.83 for the average monthly wage, $p < 0.001$). The average interregional correlation in average monthly wages equals 0.997, reflecting common nationwide wage dynamics. This finding challenges the assumption of independently and identically distributed errors, thereby justifying the use of Driscoll–Kraay standard errors. Wooldridge's test further confirms the presence of first-order serial correlation ($F = 66.20$, $p < 0.001$), which is addressed by clustering standard errors at the regional level.

According to the information criteria, the Granger causality test indicates that the first lag is optimal (AIC = −12.38, compared with −9.91 and 8.61 for the alternative lag specifications). The bivariate test reveals a significant causal relationship running from the average monthly wage to the crime rate ($F = 29.99$, $p < 0.001$), whereas no evidence is found for reverse causality ($F = 1.52$, $p = 0.220$). However, this relationship is not robust to the inclusion of a control variable. When the share of internally displaced persons (IDPs) is included

Table 3
Comparison of the Pre-War and Wartime Periods and Descriptive Statistics for the Study Variables

Variable	Period	Mean	Standard deviation	Minimum	Maximum
Crime rate (per 100,000 population)	Pre-War	974.2	335.0	328.2	2034.6
	Wartime	1167.7	648.8	427.3	3854.6
Average monthly wage (UAH)	Pre-War	8983.7	2151.7	5865	17533
	Wartime	16709.6	4106.3	11326	34978
IDP share (%)	Pre-War	1.9	2.9	0.2	13.6
	Wartime	11.5	7.6	2.3	39.7
Distance to the front line (km)	Wartime	384.7	304.4	2.0	1125.0

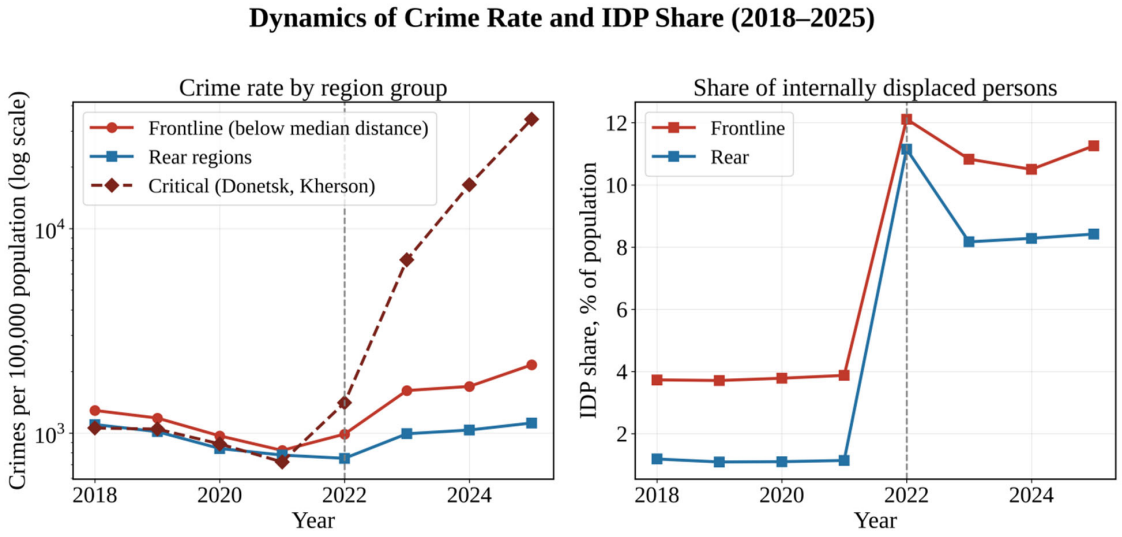


Figure 1. Trends in Crime Rates and IDP Shares by Regional Group, 2018–2025

Source: Authors' calculations based on publicly available data from sources [3; 13-15; 18; 22-23; 25; 28]

Table 4
Results of the Diagnostic Tests Described in Methodology

Test	Variable	Test Statistic	Conclusion
IPS unit root test	ln(Crime)	W = –0.762 (p = 0.223)	Not rejected
	ln(Wage)	W = 1.699 (p = 0.955)	Not rejected
ADF-Fisher	ln(Crime)	χ^2 = 56.74 (p = 0.133)	Not rejected
Pesaran CD	ln(Crime)	CD = 22.94 (p < 0.001)	Strong cross-sectional dependence
	ln(Wage)	CD = 44.83 (p < 0.001)	Strong cross-sectional dependence
Wooldridge AR(1)	Residuals	F = 66.20 (p < 0.001)	First-order serial correlation
Mundlak (Wald)	Cross-sectional average correlation (γ^-)	$\chi^2(3)$ = 44.28 (p < 0.001)	Fixed effects justified
Maximum VIF	war	3.31	Acceptable (< 5)

Source: Authors' calculations

in the model, both directions of causality become statistically insignificant (F = 2.59, p = 0.110 and F = 0.28, p = 0.597, respectively). These findings suggest that the observed relationship between average monthly wages and the crime rate is largely mediated by forced population displacement. Therefore, it would be misleading to interpret the bivariate result as evidence of a direct causal effect of wages on crime.

The results of the four sequentially expanded specifications are presented in Table 5. The most significant finding remains consistent across all models: the proportion of internally displaced persons (IDPs) exhibits a statistically significant positive correlation with the crime rate (β ≈ 0.029–0.031, p < 0.001 for both types of standard error). An increase in the IDP share by one percentage point is associated with a rise

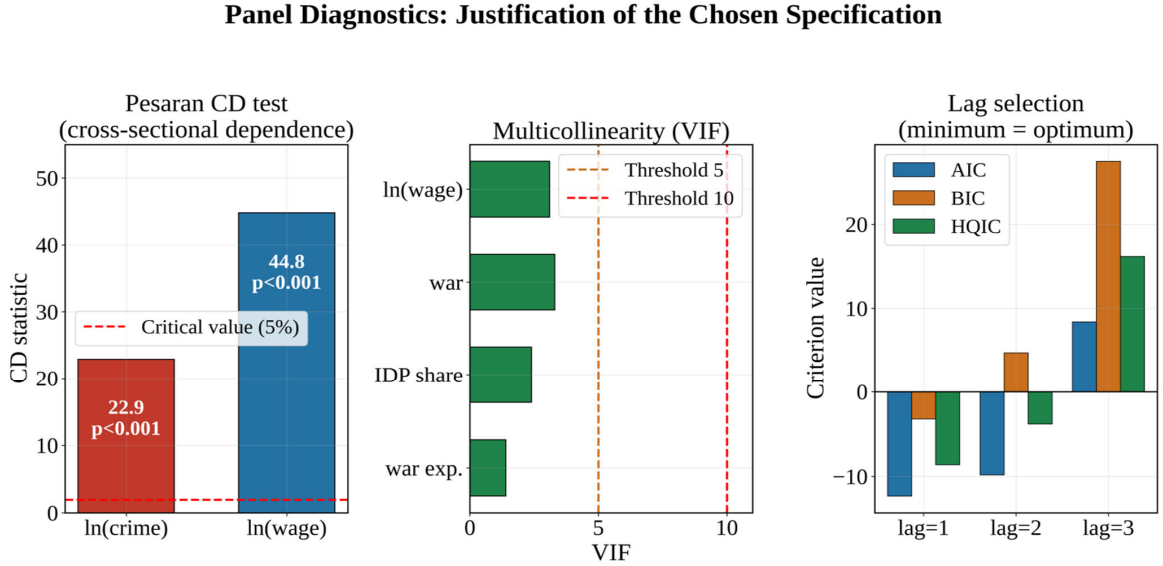


Figure 2. Panel Data Diagnostics: Cross-Sectional Dependence, Multicollinearity, and Lag Selection

Source: Prepared by the authors

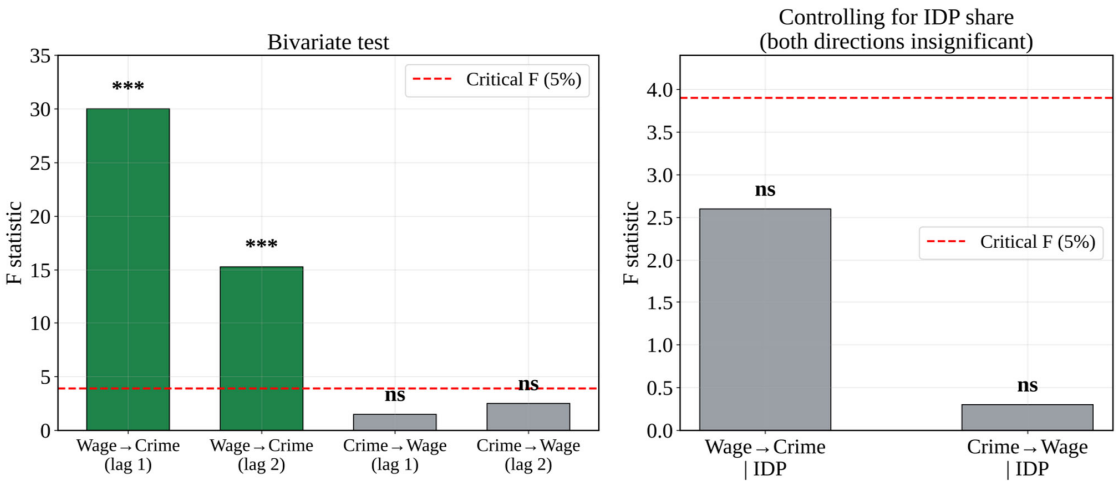


Figure 3. Granger Causality Test: Bivariate and Multivariate Specifications

Source: Prepared by the authors

in the crime rate of around 3%. However, the coefficient of the average monthly wage is statistically insignificant in all specifications, contradicting a straightforward interpretation of Becker's economic model of crime. Nevertheless, the interaction term ln(Wage) × War is statistically significant ($\beta = -0.448$, $p = 0.020$ with clustered standard errors; $p = 0.014$ with Driscoll–Kraay standard errors). This suggests that the relationship between average monthly wages and the crime rate changed significantly with the onset of full-scale war. During wartime, higher wages are associated with lower crime rates, which supports the second research objective.

The overall significance of the models is confirmed by the robust Wald test. M2–M4 specifications are all highly statistically significant ($p = 0.0004$, 0.0004 and 0.00002 respectively), whereas the M1 specification, which only includes the average monthly wage, is not ($F = 2.61$, $p = 0.120$). This finding has two key implications. Firstly, the economic indicator alone does not adequately explain variations in crime rates. Secondly, the inclusion of demographic controls produces a statistically significant model. The test of fixed effects significance rejects the null hypothesis of their absence in all specifications ($F(29,150–153) = 5.69–6.74$, $p < 0.001$), confirming the appropriateness

Table 5
Results of the Panel Data Models

Variable	M1	M2	M3	M4
ln(Wage)	0.556	−0.026	0.502	0.873
	(0.344)	(0.614)	(0.859)	(0.794)
IDP share	—	0.029***	0.030***	0.031***
		(0.006)	(0.006)	(0.006)
War exposure	—	—	−0.0008	−0.0008
ln(Wage) × War	—	—	—	−0.448*
				(0.191)
R^2 (within)	0.011	0.217	0.224	0.246
R^2 (overall)	0.552	0.606	0.608	0.614
Wald F (robust)	2.61	11.42***	9.29***	12.05***
p (Wald F)	0.120	0.0004	0.0004	0.00002
F: FE vs. OLS	5.69***	6.74***	5.96***	5.74***
AIC	−500.8	−540.4	−538.9	−541.0
N	184	184	184	184

Note: *Authors' calculations. Standard errors in parentheses are clustered-robust standard errors at the regional level. Wald F denotes the robust test of joint significance of the regressors; F: FE vs. OLS denotes the test for the significance of fixed effects. All models include regional and time fixed effects. Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05*

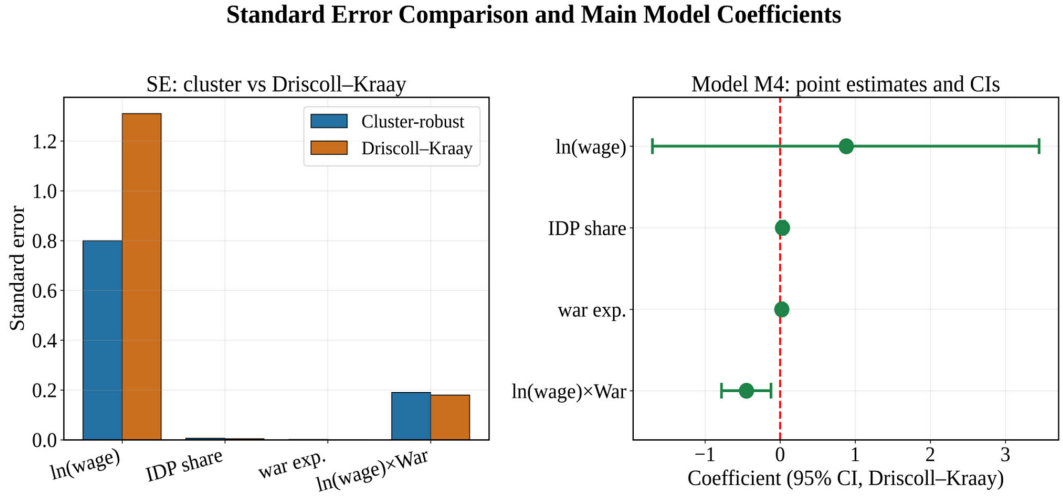


Figure 4. Comparison of Standard Errors and Estimated Coefficients of Model M4 with 95% Confidence Intervals

Source: Prepared by the authors

of the panel data approach. Overall R^2 ranges from 0.55 to 0.61, which is acceptable given the short time dimension.

The third research objective is tested using a specification that includes the interaction between the average monthly wage and the distance to the front line for the wartime subsample (see Table 6). All three coefficients are statistically significant under both types of standard error. The interaction term is positive (β = 0.246, p < 0.001 with Driscoll–Kraay standard errors), indicating that the marginal effect of average monthly wages increases with greater distance from the front line. Near the line of contact, the wage effect is strongly negative, whereas in more distant rear regions it approaches zero or becomes positive.

The robustness of the results is assessed across four dimensions (see Table 7). Firstly, including outlier regions (all 25 regions) does not change the sign or statistical significance of the IDP coefficient; rather, its magnitude increases. Secondly, a split-sample analysis based on median distance from the front line shows that the IDP coefficient remains statistically significant in both subgroups, whereas the wage coefficient is only significant in rear regions. Thirdly, estimations over subperiods confirm the absence of a direct association between wages and crime rates. Fourthly, replacing clustered standard errors with Driscoll–Kraay standard errors does not alter the substantive conclusions.

To investigate whether the results are influenced by the logarithmic specification, five alternative wage

Table 6

Results of the Test of the Third research objective

Variable	Coefficient	Clustered SE	SE (D–K)	p (D–K)
ln(Wage)	–2.721	0.828	0.137	< 0.001
ln(Distance)	–2.363	1.032	0.111	< 0.001
ln(Wage) × ln(Distance)	0.246	0.109	0.012	< 0.001
IDP share	0.038	0.005	0.006	< 0.001
R^2 (within) = 0.375			N = 92	

Note: Authors' calculations. All models include two-way fixed effects. D–K denotes Driscoll–Kraay standard error

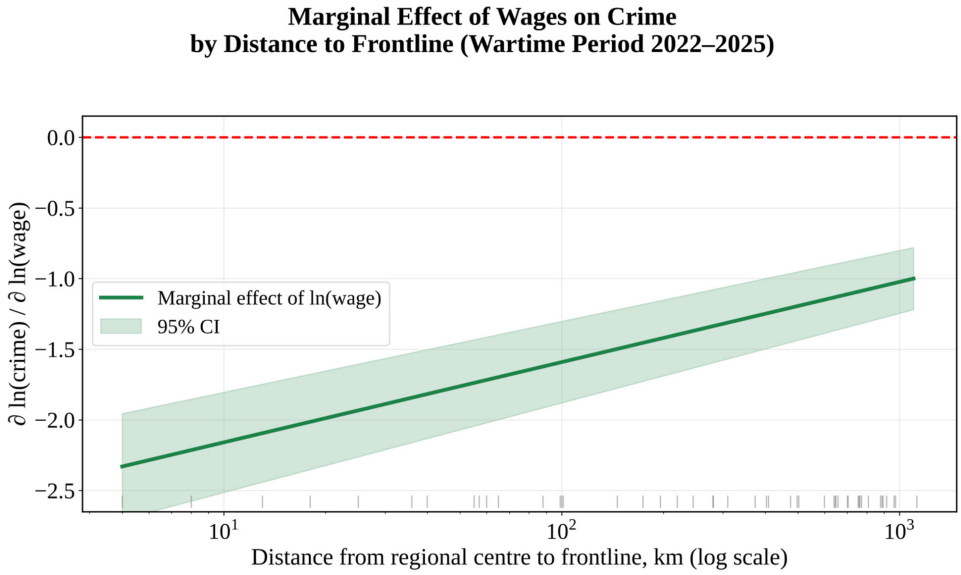


Figure 5. Marginal Effect of Average Monthly Wages on Crime Rates Conditional on Distance from the Front line

Source: Prepared by the authors

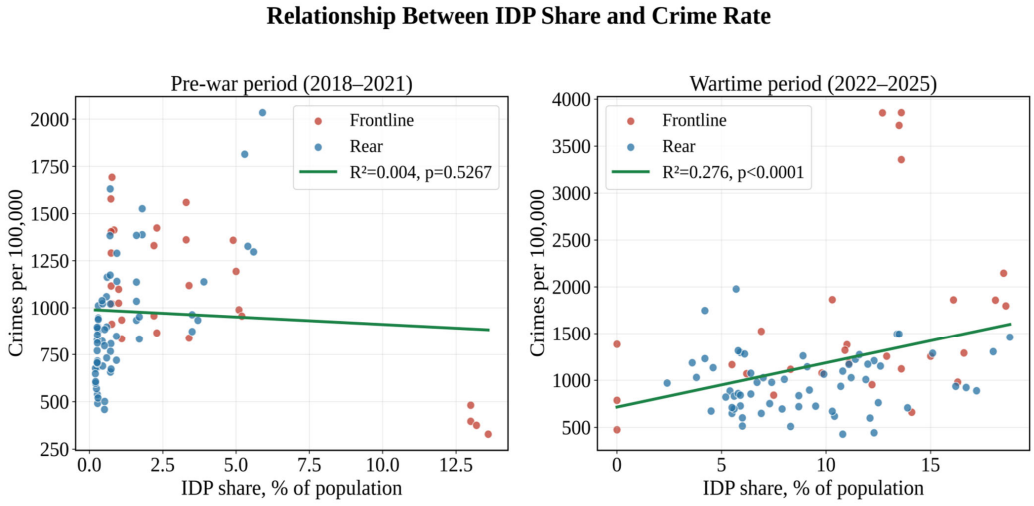


Figure 6. Association Between the Share of Internally Displaced Persons and Crime Rates Across Two Periods

Source: Prepared by the authors

Table 7
Robustness Checks of the Estimation Results

Specification	β ln(Wage)	β IDP	Conclusion
Baseline (23 regions)	0.502 n.s.	0.030***	Reference specification
All 25 regions	−2.843***	0.055***	IDP effect remains robust; sensitive to outliers
Frontline regions (< median distance)	−0.154 n.s.	0.031***	IDP effect remains robust
Non-frontline regions (≥ median distance)	1.764***	0.054*	Evidence of spatial heterogeneity
Pre-war period	−0.286 n.s.	—	No statistically significant association
Wartime period	−1.635 n.s.	—	Coefficient sign changes

*Note: Authors' calculations. *** p < 0.001, ** p < 0.01, * p < 0.05; n.s. – not statistically significant*

transformations were estimated within specification M2 (see Table 8). All of the alternative specifications produced highly statistically significant models ($p < 0.002$), and the IDP coefficient remained robust, which provides the main evidence for the reliability of this finding. At the same time, the wage coefficient is sensitive to the functional form. It is statistically significant under the inverse transformation (1000/Wage; $\beta = -7.035$, $p = 0.032$) and approaches significance at the level ($p = 0.064$), but remains insignificant in logarithmic form. Despite its lower AIC, the authors deliberately retain the logarithmic specification as the baseline model rather than adopting the inverse transformation for three reasons. Firstly, the inverse transformation lacks a well-established theoretical basis in the field of criminology. Secondly, its marginal effect is highly non-linear and concentrated within the lower wage range, which makes interpretation difficult. Thirdly, residual diagnostics suggest that the data are less normal (Jarque–Bera statistic of 614.3 compared with 417.0). Selecting a specification based solely on statistical significance would constitute specification searching and contradict the principles of reproducible research. Therefore, it appears that the relationship between wage levels and crime rates under wartime conditions is nonlinear. This pattern is primarily observed in regions with lower wages and weakens as income levels increase. This pattern is consistent with specification M5 and supports the third research objective concerning the spatial and economic heterogeneity of the relationship.

The fourth objective of this study is examined below. Ukraine's nominal GDP increased from 3,558.7 billion UAH in 2018 to 8,931.2 billion UAH in 2025 (a 2.5-fold increase). At the same time, the average monthly wage increased by a factor of 2.9, indicating that the observed growth was largely driven by inflationary processes. This requires caution when interpreting macroeconomic dynamics during wartime. The correlation between the regional crime rate and changes in nominal GDP is negative: −0.891 in the pre-war period; +0.966 during the wartime period; and +0.633 over the entire sample period. This sign reversal provides evidence consistent with a structural break. Under stable conditions, economic growth was associated with declining crime rates. However, after 2022, both indicators increased simultaneously due to common shocks, such as inflation, fiscal expansion and changes in crime registration practices, rather than reflecting a causal relationship. The inclusion of crime indicators in macroeconomic forecasting models requires careful consideration. The reviewed literature on this topic conceptualises crime as a factor that affects economic development by increasing transaction costs, raising security expenditure, reducing investment inflows, deteriorating the institutional environment and eroding trust in the legal system. Theoretically, these mechanisms justify crime as a potential leading indicator of regional investment attractiveness and economic resilience. To test this research objective, lead–lag correlations were estimated between the growth rates of crime and nominal GDP.

Table 8
Comparison of Wage Transformations and Functional Specifications

Transformation	β	p	R^2 within	Wald F (p)	AIC
Level (Wage/1000)	−0.032	0.064	0.243	17.06 (<0.001)	**−546.7**
ln(Wage) – baseline specification	−0.026	0.966	0.217	11.42 (<0.001)	−540.4
$\sqrt{(Wage)}$	−0.008	0.256	0.230	16.55 (<0.001)	−543.5
Inverse transformation (1000/Wage)	**−7.035**	**0.032***	0.242	8.42 (0.002)	−546.4
Relative wage	−0.159	0.767	0.218	12.80 (<0.001)	−540.7

Note: Authors' calculations. All specifications include the IDP share as a control variable and two-way fixed effects. The IDP coefficient is statistically significant at the 0.001 level (p < 0.001) in all specifications. p < 0.05

The correlation between crime growth and subsequent GDP growth is 0.123 (p = 0.817), while the correlation between GDP growth and subsequent crime growth is −0.343 (p = 0.506). Neither of these relationships is statistically significant, which is consistent with the results of the multivariate Granger causality test. Therefore, it is currently not methodologically justified to incorporate registered crime as an independent predictor into macroeconomic forecasting models. Recorded crime is not a direct measure of criminal activity, but rather reflects the interaction between the incidence of crime and the capacity of law enforcement, both of which underwent substantial changes during the war. In particular, underreporting of crime may have increased due to restricted access to affected areas and limited institutional capacity near the line of contact. Both indicators are influenced by the same factors, including military invasion, the intensity of hostilities and demographic changes. This creates a potential problem of omitted variables. Furthermore, nominal GDP lacks regional variation and is absorbed by time fixed effects. However, excluding these effects would confuse regional heterogeneity with macro-level shocks. The empirical analysis does not identify a statistically significant leading relationship in either direction. This finding does not imply that crime is irrelevant to macroeconomic analysis. Instead, it outlines the circumstances in which its inclusion is justified, such as using indicators that are less dependent on registration practices, regionally disaggregated macroeconomic measures (e.g., gross regional product), longer time series for dynamic estimators and instrumental variable approaches to address endogeneity. Identifying these conditions constitutes an independent methodological contribution and outlines directions for future research. The practical implication of the final conclusion is that crime indicators should not be treated as predictors of economic growth when constructing forecasting models for post-war recovery. Instead, they can be used to indicate institutional quality and the conditions under which economic policies are implemented, thus avoiding unsupported causal assumptions.

5. Reverse Causality Concerns

The issue of reverse causality requires separate consideration. While high crime rates may negatively impact economic activity, this reverse effect cannot be completely ruled out. However, three factors reduce the likelihood of this occurring. Firstly, during wartime, wages were largely determined by nationwide factors, such as indexation, public sector financing and inflation. These factors are accounted for by time-fixed effects. Secondly, the Granger causality test did not identify a statistically significant relationship between crime and wages (F = 1.52, p = 0.220). Thirdly, the main empirical finding relates to the proportion of IDPs, with population displacement being primarily driven by security-related factors rather than criminological ones. Complete resolution of endogeneity would require instrumental variable approaches or dynamic panel estimators. This is an area for future research.

6. Limitations

The findings should be interpreted in light of the following limitations. Firstly, the short time dimension (T = 8) reduces the statistical power of unit root tests and prevents the application of dynamic estimators. Secondly, registered crime rates may be influenced by reporting and registration practices in wartime. Thirdly, some of the wage and population data were reconstructed using linear interpolation, making the dataset partially synthetic. Although sensitivity analysis did not reveal a significant impact of these reconstructed values, some uncertainty remains. Fourthly, the demographic indicators for 2022–2025 are based on official estimates rather than census data. Fifthly, as the analysis relies on aggregated regional data, the identified patterns should not be interpreted as being applicable at the individual level. Finally, the research design does not allow for full causal identification. Therefore, the results should be interpreted as statistical associations observed under conditions of a structural shock.

7. Conclusions

The study's findings demonstrate that full-scale war resulted in increased regional crime rates in Ukraine and fundamentally altered the relationship between economic welfare and crime. Before the war, the relationship was primarily examined through the lens of economic determinants. However, under conditions of a large-scale invasion, demographic processes and the spatial heterogeneity of war exposure have become substantial mediators of this relationship. This highlights the need to adapt traditional economic models of crime analysis to conditions in armed conflicts and in the event of large-scale structural shocks. Descriptive statistics support the first research objective and the significance of interaction with the wartime period: crime rates and their interregional variation changed substantially after 2022. Following the onset of the full-scale invasion, regional crime rates have increased. Since 2022, the highest rates have consistently been observed in areas affected by active hostilities and located closer to the front line. The most robust finding across all model specifications is the positive correlation between the regional proportion of internally displaced persons (IDPs) and crime rates ($\beta \approx 0.029–0.031$, $p < 0.001$), as determined using cluster-robust and Driscoll–Kraay standard errors. An increase of one percentage point in the

proportion of IDPs in a region is associated with a rise of around 3% in the recorded crime rate. However, this relationship should not be interpreted as evidence of a higher criminal propensity among IDPs. Instead, it most likely reflects the broader demographic and institutional changes that accompany large-scale internal displacement. These changes include increased pressure on regional infrastructure, changes in population composition and alterations to the denominator used to calculate crime rates. Consistent with social disorganisation theory, these processes may weaken regional-level mechanisms of informal social control. Furthermore, after the regional share of IDPs is included in the model, the bivariate association between wages and crime rates loses statistical significance. This suggests that studies failing to account for internal population displacement may incorrectly attribute demographic effects to economic factors. The obtained results are consistent with the onclusions of UNODC (2025) regarding the transformation of the criminal landscape under wartime conditions and with the findings of Almazán-Gómez et al. (2024), who demonstrated the spatial unevenness of the economic consequences of the full-scale invasion. The scientific contribution of this study lies in transforming these qualitative observations into quantitatively verified results obtained through panel data analysis, as well as in clearly distinguishing between the economic and demographic components of the war's impact on regional crime. The second research objective is only marginally supported. The direct relationship between wages and crime rates is statistically insignificant across all model specifications (i.e., the hypothesis is not supported in its direct formulation). However, the interaction term ln(Wage) × War is statistically significant ($\beta = -0.448$, $p = 0.020$), indicating a structural change in the nature of this relationship after 2022. Specifically, higher wage levels are associated with lower crime rates during wartime compared to the pre-war period, supporting the hypothesis that the nature of the relationship changes under the influence of war. The third research objective, which states that the impact of economic factors is characterised by spatial heterogeneity determined by war exposure, is supported. The interaction between wages and the logarithm of the distance to the front line ($\beta = 0.246$, $p < 0.001$; Driscoll–Kraay standard errors) suggests that the effect of wages on crime rates is strongly negative in regions closer to the active front line. In more distant rear regions, however, this effect gradually approaches zero or becomes positive. This conclusion is further substantiated by the results of the analysis based on separate subsamples. The fourth research objective. The empirical analysis conducted did not identify a statistically significant leading relationship between crime dynamics and macroeconomic indicators. The correlation between crime rates and changes in nominal gross domestic product (GDP) varies across different periods, indicating the influence of a common structural shock rather than the existence of a causal relationship. Specifically, the correlation was −0.891 in the pre-war period and +0.966 during the war period. Based on the available data, recorded crime cannot be considered an independent predictor in macroeconomic forecasting models. Instead, it should be used as an indicator of the quality of the institutional environment, rather than as a leading macroeconomic indicator.

The fifth research objective. The methodological contribution of the study is threefold. Firstly, the proposed war exposure index combines spatial distance to the active frontline and population displacement to create a composite measure of the intensity of the war's impact. Secondly, the model specification selection strategy is based on the results of diagnostic tests rather than a priori assumptions about the most suitable estimator. Thirdly, the study provides a separate evaluation of the potential application of crime indicators as predictors in macroeconomic forecasting, identifying the circumstances in which such an approach could be justified in future research.

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