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Uneven Resilience and Recovery During War: Municipality-Level Evidence from Ukraine[§]

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Abstract

The Russian invasion of Ukraine in 2022 caused an unprecedented economic shock, yet reliable measures of economic activity during wartime are scarce, particularly at the subnational level. Official GDP statistics are available only at the national level and with substantial delays, while no systematic estimates exist on how the war affected economic activity across regions. This paper provides the first subnational assessment of the economic impact of the war in Ukraine by exploiting satellite-based nighttime light data as a proxy for local economic activity.
Using annual VIIRS Day/Night Band data for the period 2014–2024, we analyze changes in nighttime light intensity across Ukrainian urban areas and relate them to geographic exposure to armed conflict events recorded by ACLED. We estimate two-way fixed effects models that exploit within-urban area variation over time and spatial variation in distance to conflict locations following the escalation of the war in 2022. At the national level, we document a strong correlation between official GDP and nighttime lights, supporting the validity of the proxy in the Ukrainian context.
Our results reveal a pronounced spatial gradient in wartime economic disruption. Urban areas located closer to conflict events experienced significantly larger declines in nighttime light intensity after 2022, while economic losses attenuate sharply with distance and largely dissipate beyond approximately 50 kilometers. These findings highlight the highly localized nature of wartime economic damage and underscore the value of satellite data for measuring economic activity in settings characterized by data gaps, conflict, and institutional disruption.

Key Words: Nighttime lights; Armed conflict; Economic activity; Ukraine; War

JEL Codes: O47; R11; F51; C23

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1. Introduction

The Russian invasion of Ukraine in 2022 has generated a severe economic shock, with profound consequences for economic activity within the country. Recent evidence also points to substantial macroeconomic spillovers, with the war imposing large costs on the global economy and particularly severe contractions across Europe (e.g., Tank and Ospanova, 2022). While the aggregate effects of the war have been widely discussed, much less is known about how its economic impact varies within the country. The conflict has been highly uneven in its geographic intensity, with some regions experiencing direct military activity, infrastructure destruction, and population displacement, while others have remained relatively distant from active combat. Understanding this spatial heterogeneity is crucial for identifying which areas have been most affected in terms of economic contraction and which have shown greater resilience, providing key insights for both economic analysis and post-conflict reconstruction (Abadie and Gardeazabal, 2003). The impact of war on economic performance is not straightforward. While conflict often leads to substantial economic losses, its effects can be heterogeneous across regions and may even be locally positive in certain contexts, as shown by Sevastyanova (2009).

Answering this question is challenging due to severe data limitations; empirical evidence on the spatial economic effects of the war remains extremely limited. Existing assessments rely almost exclusively on national-level GDP estimates produced by international organizations such as the International Monetary Fund. While these figures provide a useful aggregate benchmark, they conceal substantial within-country variation and offer no information on how economic activity has evolved across regions and cities. The lack of subnational data is particularly problematic in a context of active conflict, where statistical systems are disrupted and timely regional accounts are unavailable. As a result, there is currently no systematic evidence on which areas of Ukraine have experienced the largest economic declines and how these effects relate to local exposure to conflict.

This paper addresses this gap by providing the first subnational assessment of the economic impact of the war in Ukraine. In the absence of reliable regional GDP statistics, we exploit satellite-observed nighttime light intensity as a proxy for local economic activity. A growing literature shows that nighttime lights closely track economic output, particularly in environments characterized by weak institutions, conflict, or data scarcity (Henderson et al., 2012; Pinkovskiy and Sala-i-Martin, 2016). In the Ukrainian context, satellite data offer a unique advantage: they provide consistent, spatially detailed, and timely information that is unaffected by wartime disruptions to administrative reporting.

We combine annual nighttime light data from the VIIRS Day/Night Band with georeferenced information on armed conflict events from the Armed Conflict Location & Event Data Project (ACLED). The analysis covers the period 2014–2024, allowing us to account for the earlier phase of conflict in Eastern Ukraine and to isolate the economic effects associated with the large-scale invasion that began in 2022. Nighttime light intensity is aggregated at the urban level, while conflict exposure is measured using geographic distance to recorded violent events, capturing differential local exposure to warfare.

Our empirical strategy exploits within-city variation over time using two-way fixed effects models with city and year fixed effects. Identification relies on differential changes in nighttime light intensity after 2022 across urban areas located at varying distances from conflict locations. We implement both continuous distance-decay specifications and flexible distance-bin models to allow for non-linear spatial effects and to avoid imposing restrictive functional form assumptions. Before turning to subnational analysis, we validate the use of nighttime lights in the Ukrainian context by documenting a strong correlation between national GDP and aggregate nighttime light intensity in the post-2013 period.

The results reveal a highly localized pattern of economic disruption. Urban areas located closer to conflict events experienced substantially larger declines in nighttime light intensity following the 2022 invasion, while economic losses attenuate rapidly with distance and become economically and statistically small beyond approximately 50 kilometers. This spatial pattern suggests that wartime economic damage is concentrated near active conflict zones, with limited spillovers to more distant urban areas.

This paper makes three main contributions. First, it provides the first subnational assessment of economic activity in Ukraine during the ongoing war, filling a critical gap in a context where official regional GDP data are unavailable and national aggregates conceal substantial spatial heterogeneity. Second, by combining satellite-based nighttime lights with georeferenced conflict data, it contributes to the growing literature that uses non-traditional data sources to measure economic activity during global crises, armed conflict, and institutional disruption (Henderson et al., 2012; Donaldson and Storeygard, 2016; Michalopoulos and Papaioannou, 2013). Third, the paper sheds light on the spatial economic footprint of war, documenting a sharp and localized decay of economic losses with distance to conflict, thereby informing debates on economic fragmentation, resilience, and post-conflict reconstruction in a globalized economy (Collier, 2007; Rohner et al., 2013). More broadly, the findings illustrate how global geopolitical shocks translate into highly uneven local economic outcomes, with important implications for regional policy and international recovery efforts.

The remainder of the paper is organized as follows. Section 2 provides an overview of Ukraine’s war economy, with a focus on how the conflict has affected economic activity across regions and over time. Section 3 describes the data sources and the construction of the main variables, including nighttime light intensity and measures of conflict exposure. Section 4 outlines the empirical strategy used to identify the relationship between conflict and local economic dynamics. Section 5 presents the main results, with particular attention to spatial variation in resilience and recovery across urban areas. The final section concludes.

2. Regional Ukraine's War Economy

Ukraine has long been characterized by substantial regional disparities in economic activity, reflecting differences in industrial structure, geographic location, and integration into domestic and international markets. Prior to the 2022 invasion, economic output in Ukraine was highly concentrated in a limited number of regions. The capital city of Kyiv alone accounted for approximately 24 percent of national gross regional product, highlighting a strong degree of economic centralization. In addition, a small group of industrial and metropolitan regions, including Dnipropetrovsk, Kharkiv, Kyiv oblast, and Odesa, collectively contributed more than half of total economic output (Huk and Zeynalov, 2022). In contrast, several western and peripheral regions exhibited significantly lower levels of income and productivity, reflecting a more limited industrial base and weaker economic integration. For example, regions such as Ternopil, Zakarpattia, and Chernivtsi each accounted for only around 1–2 percent of national output, while Luhansk contributed close to 1 percent prior to the full-scale invasion. These pre-existing disparities provide an important baseline for understanding how the war has reshaped the economic geography of the country (World Bank, 2020).

The large-scale invasion in February 2022 triggered a dramatic contraction in aggregate economic activity, with real GDP declining by approximately 29 percent in 2022 (IMF, 2023; World Bank, 2023). However, aggregate indicators mask substantial spatial heterogeneity in the economic impact of the war. The intensity of military operations, destruction of infrastructure, and population displacement has varied widely across regions, leading to sharply differentiated local economic outcomes. Eastern and southern regions, including Donetsk, Luhansk, Kharkiv, Zaporizhzhia, and Kherson, have suffered extensive destruction of physical capital and infrastructure, resulting in large declines in industrial output and overall economic activity (World Bank, 2023; IMF, 2023). By contrast, central and western regions have been relatively less exposed to direct conflict and, in some instances, have experienced stable or even increasing levels of economic activity. This relative resilience is partly driven by the relocation of firms and workers from conflict-affected areas, as well as by the reorganization of domestic supply chains (Darvas, 2023).

These dynamics have contributed to a reconfiguration of Ukraine’s economic geography. The war has accelerated a westward shift in economic activity, with regions such as Lviv, Ternopil, and Zakarpattia emerging as important destinations for internally displaced firms and populations. At the same time, Kyiv has maintained—and in some respects strengthened—its central role in the national economy, supported by its administrative functions, service sector concentration, and relatively lower exposure to sustained military operations (World Bank, 2024). This combination of severe contraction in frontline regions and relative resilience elsewhere implies a substantial widening of regional disparities.

Despite the growing recognition of these patterns, systematic evidence on subnational economic dynamics remains limited. Official statistics are primarily available at the national level, while regional accounts are either missing, delayed, or unreliable due to disruptions in data collection systems during the war. Existing evidence on regional disparities is therefore largely descriptive and based on partial indicators, such as sectoral output, infrastructure damage assessments, or firm relocation data. This lack of consistent and comparable subnational measures represents a major obstacle to understanding the magnitude and spatial distribution of economic losses.

In this context, satellite-based nighttime light data provide a valuable tool for measuring economic activity at a fine geographic scale. Nighttime lights offer a consistent proxy for local economic intensity that is not affected by wartime disruptions to statistical systems and can be used to track changes in economic activity across regions and cities over time (Henderson et al., 2012; Donaldson and Storeygard, 2016). By exploiting spatial variation in exposure to conflict, these data make it possible to quantify how economic losses are distributed across space and how they decay with distance from conflict zones. This approach is particularly well suited to the Ukrainian context, where understanding the spatial heterogeneity of wartime economic impacts is central to both academic analysis and policy design.

3. Data and Variables

This section describes the data sources used to measure economic activity and conflict exposure, as well as the construction of the main variables used in the empirical analysis.

3.1 Nighttime Lights

We use satellite-based nighttime light intensity as a proxy for local economic activity. Specifically, we rely on annual data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), which provides global observations of light emissions at high spatial resolution.

To ensure comparability over time and reduce measurement noise, we use yearly median-masked composites. This procedure removes ephemeral light sources such as fires, gas flaring, and background noise, yielding a stable measure of persistent human activity and economic intensity. Nighttime light data have been widely used in the literature as a proxy for economic activity, particularly in settings with data limitations or institutional disruption (Chen and Nordhaus, 2011).

Raster data are aggregated at the city level (administrative level 2) using area-weighted averages. The analysis covers the period 2014-2024, with robustness checks restricting the sample to the post-2018 period. The starting year, 2014, coincides with the onset of armed conflict in Eastern Ukraine and represents the earliest period in which nighttime lights plausibly reflect conflict-adjusted economic conditions.

The dependent variable is defined as:

$$y_{it} = \log\,(\text{Mean Nighttime Lights}_{it} + 1)$$

where i indexes cities and t indexes years. The logarithmic transformation reduces skewness and allows for an interpretation of coefficients in percentage terms. Summary statistics of the variables used in the analysis are shown in Table 1 below.

Table 1 Summary Statistics

Variable	**Mean**	**SD**	**Min**	**Max**	**N**
Log Nighttime Lights	0.245	0.398	0.000	3.633	1529
Log Distance to Conflict	2.659	0.818	0.221	4.469	1529
Conflict Events	1146.63	2923.35	1	18579	1529

An important caveat when using nighttime lights in a conflict setting concerns the interpretation of light intensity in areas exposed to active military operations. In such contexts, observed luminosity may reflect not only civilian economic activity but also conflict-related sources of light, including fires, explosions, and military infrastructure. This issue is particularly relevant in locations experiencing high-intensity violence, where these additional light emissions may attenuate or partially mask underlying declines in economic activity. At the same time, a large body of evidence shows that nighttime lights remain a reliable proxy for broad economic dynamics, especially when analysis focuses on relative changes across locations and over time. In this study, the use of spatial and temporal variation in luminosity, together with measures of conflict exposure, allows us to extract meaningful information on local economic activity while acknowledging these measurement limitations. This issue is explored in greater detail in Appendix, where we examine the relationship between conflict intensity and observed nighttime light emissions.

3.2 Armed Conflict Events

Information on armed conflict is obtained from the Armed Conflict Location & Event Data Project (ACLED), which provides georeferenced records of conflict events, including shelling, missile attacks, and other forms of remote violence.

We use the geographic location of these events to construct a measure of conflict exposure for each city. Specifically, for each city we compute the minimum geodesic distance to any recorded conflict event using spatial point-to-polygon distance measures. This approach captures the proximity of each city to areas affected by violence.

3.3 Measures of Conflict Exposure

Our empirical strategy relies on variation in geographic exposure to conflict across cities. To this end, we construct a time-invariant measure of distance to conflict, defined as the minimum distance between each city and the set of conflict events observed over the study period. This measure captures persistent spatial exposure to conflict intensity, abstracting from short-term fluctuations in conflict lines.

We consider two alternative specifications.

First, we define a continuous measure of distance:

$$\text{lndist}_i = \log(\text{Distance to nearest conflict event}_i + 1)$$

This specification allows us to estimate a continuous spatial decay in the economic impact of conflict.

Second, we construct discrete distance categories to allow for a flexible, non-parametric assessment of spatial effects. Municipalities are grouped into the following bins:

- 0-10 km (reference category)
- 10-25 km
- 25-50 km
- 50-100 km

This approach avoids imposing a specific functional form on the relationship between distance and economic outcomes and allows for potential non-linearities in the spatial decay of conflict effects.

4. Empirical Strategy

The empirical analysis exploits variation in geographic exposure to conflict across cities to identify how the escalation of war in 2022 affected local economic activity. The baseline approach compares changes in nighttime light intensity before and after the onset of the full-scale invasion across locations with different proximity to conflict events. Similar to Abadie and Gardeazabal (2003) and Besley and Mueller (2012) to estimate how conflict proximity affects economic activity after the escalation of war, we estimate:

$$y_{it} = \beta(\text{Post}_t \times \log(\text{Distance}_i + 1)) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Post_t equals 1 for years 2022 onward; α_i are city fixed effects controlling for time-invariant local characteristics, such as geography, pre-war economic structure, and infrastructure; λ_t are year fixed effects capturing aggregate shocks common to all cities, including nationwide macroeconomic trends.

The coefficient β identifies whether the post-2022 change in economic activity varies systematically with distance from conflict. A positive coefficient indicates that cities located farther from conflict areas experienced relatively smaller declines, or stronger recoveries, in nighttime lights.

To allow for a more flexible characterization of spatial effects, the analysis also considers a specification based on discrete distance categories:

$$y_{it} = \sum_k \beta_k (\mathbb{1}[\text{Distance}_i \in k] \times \text{Post}_t) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where k indexes distance bins and cities located within 0–10 km from conflict events serve as the reference category.

This specification does not impose a functional form on the relationship between distance and economic outcomes and allows for the identification of non-linearities in the spatial decay of conflict effects.

While the baseline specifications capture the average effect of conflict exposure on economic activity, urban areas may differ substantially in their ability to absorb and adapt to wartime shocks. Some urban areas experience persistent economic collapse, whereas others exhibit stabilization or partial recovery despite continued exposure to conflict.

To capture these heterogeneous responses, a municipality-level measure of economic resilience is constructed based on the regional resilience framework proposed by Martin (2012). In this framework, resilience is defined relative to the national trajectory and reflects how strongly a region responds to an adverse shock compared with the aggregate economy.

The key idea is to evaluate local economic performance in relative rather than absolute terms. Regions that experience larger declines than the national average are considered more sensitive to the shock, while those with smaller declines exhibit greater resistance.

In the original formulation, resilience is measured using employment data. Let E_r denote employment in region $r$and E_N national employment. The sensitivity index is defined as: $\beta_r = \frac{\Delta E_r/E_r}{\Delta E_N/E_N}$, where $\Delta E/E$denotes the percentage change during the shock period.

Given the lack of reliable subnational employment or GDP data during the war, this framework is adapted using nighttime light intensity as a proxy for economic activity, following a large literature validating its use in data-constrained environments (Henderson et al., 2012; Donaldson and Storeygard, 2016).

Let $NTL_{i,t}$denote average nighttime light intensity in municipality i at time t.

Resistance captures the immediate response of each municipality to the escalation of the war in 2022. The municipality-level change in nighttime lights between 2021 and 2022 is defined as:

$$\Delta NTL_i = \frac{NTL_{i,2022} - NTL_{i,2021}}{NTL_{i,2021}}$$

The corresponding national change is:

$$\Delta NTL_N = \frac{NTL_{N,2022} - NTL_{N,2021}}{NTL_{N,2021}}$$

where NTL_N denotes national average nighttime light intensity.

The index is then computed as $\beta_i = \frac{\Delta NTL_i}{\Delta NTL_N}$. Values greater than one indicate that a municipality experienced a larger decline than the national average, implying lower resistance, while values below one indicate higher resistance to the shock.

To facilitate interpretation, the resistance index, denoted by β_i^R, is defined as the complement of β_i :

$$\beta_i^R = 1 - \beta_i \quad (3)$$

Under this transformation, higher values correspond to greater resistance to the wartime shock. Because the war is ongoing, subsequent dynamics are interpreted as adaptive responses rather than post-conflict recovery. Adaptive recovery is defined as the relative change in nighttime lights following the initial shock.

The municipality-level change between 2022 and the most recent year $T$is:

$$\Delta NTL_i^{Rec} = \frac{NTL_{i,T} - NTL_{i,2022}}{NTL_{i,2022}}$$

The corresponding national change is:

$$\Delta NTL_N^{Rec} = \frac{NTL_{N,T} - NTL_{N,2022}}{NTL_{N,2022}}$$

The adaptive recovery index is therefore:

$$\beta_i^{Rec} = \frac{\Delta NTL_i^{Rec}}{\Delta NTL_N^{Rec}} \quad (4)$$

Values greater than one indicate stronger stabilization or improvement in economic activity relative to the national trend, while values below one indicate weaker adaptive performance.

To summarize overall urban economic resilience, a composite index is constructed by combining resistance and adaptive recovery. Both components are first standardized and then averaged:

$$\text{Resilience}_i = \frac{z(\beta_i^R) + z(\beta_i^{Rec})}{2} \quad (5)$$

where $z(\cdot)$ denotes standardization.

5. Results

The empirical analysis proceeds in a sequence of steps. The first part evaluates the relationship between official GDP statistics and nighttime lights to validate the use of luminosity as a proxy for economic activity. The core results then examine how wartime economic disruption varies with distance from conflict locations. The section then turns to heterogeneity in municipality-level responses using a resistance-recovery framework.

5.1 Nighttime Lights and GDP

The first analysis examines the relationship between national GDP and nighttime light intensity in Ukraine after 2013. Table 2 reports both Pearson and Spearman correlations between the two variables.

Table 2. Correlation between GDP and nighttime lights in Ukraine (post-2013)

Correlation measure	Coefficient
Pearson correlation	0.904
Spearman correlation	0.891

Both correlation measures indicate a strong association between official economic output and satellite-observed nighttime lights. The strength of this relationship is notable given the substantial institutional disruptions and economic shocks experienced during the study period.

Nighttime lights continue to closely track macroeconomic dynamics even under wartime conditions. This evidence supports the use of nighttime luminosity as a proxy for economic activity in Ukraine. The remainder of the analysis therefore relies on nighttime light data to investigate spatial economic dynamics at the municipality level. Satellite observations provide annual measurements at fine spatial resolution, allowing the analysis to capture localized war impacts that are not observable in official statistics.

5.2 Distance to Conflict and Spatial Gradients of Economic Disruption

The core analysis examines how changes in nighttime lights vary with distance from conflict locations. Two complementary specifications are used: a continuous distance model (eq. 1) and a distance-bin model (eq. 2). The empirical strategy identifies differential exposure to conflict based on geographic proximity to recorded events. Distance to conflict is interpreted as a measure of local exposure rather than an exogenous source of variation. While municipality fixed effects control for time-invariant differences across locations and year fixed effects absorb common shocks, the estimates should be interpreted as capturing spatial patterns of economic disruption associated with conflict exposure rather than causal effects of conflict placement.

Continuous distance models

The continuous specifications estimate the interaction between the post-war period (from 2022 onward) and the logarithm of distance to conflict events. Table 3 reports the results for two time windows: the full sample period (2014–2024) and a narrower period (2018–2024), the latter used as a robustness check.

Table 3. Continuous distance models

Time period	Coefficient (log distance × post) Std. error
2014–2024	0.051*** (0.007)
2018–2024	0.050*** (0.008)

The coefficients are positive and statistically significant in both specifications, indicating that municipalities located farther from conflict events experienced smaller declines in nighttime light intensity after 2022. Given the logarithmic specification, the estimates can be interpreted as semi-elasticities. A one-unit increase in log distance to the nearest conflict event is associated with an approximately 5.1 percent smaller decline in nighttime lights in the 2014–2024 specification and a 5.0 percent smaller decline in the 2018–2024 specification. To provide a more intuitive interpretation, consider a doubling of distance to conflict. Since a doubling corresponds to an increase of approximately 0.693 in log distance, the estimates imply that doubling the distance to the nearest conflict event is associated with about a 3.5 percent smaller decline in nighttime lights. These magnitudes are comparable to those reported by Abadie and Gardeazabal (2003), who document that per capita GDP in the Basque Country declined by approximately 10 percentage points relative to a synthetic control region following the onset of terrorism.

Distance-bin models

As mentioned in Section 4, the distance-bin specification allows for a flexible, non-linear assessment of spatial decay. Urban areas located within 0–10 km of conflict events serve as the reference group. Table 4 reports results for two-time windows: 2014–2024 and 2018–2024.

Table 4. Distance from conflict 2014–2024, 2018–2024

Variable	2014–2024	2018–2024
0–10 km × post (reference)		
10–25 km × post	0.051***	0.045**
	(0.012	(0.015)
25–50 km × post	0.090***	0.092***
	(0.015)	(0.018)
50–100 km × post	0.084**	0.085**
	(0.026)	(0.030)

The estimates show that municipalities located beyond the immediate conflict zone experience systematically smaller declines in nighttime lights. The difference increases between 10–25 km and 25–50 km, and stabilizes beyond 50 km.

These results identify a sharply localized pattern of economic disruption. The largest declines in nighttime lights are concentrated within close proximity to conflict events, while the magnitude of the shock decreases rapidly with distance.

Figure 1 illustrates the spatial gradient in the impact of conflict on economic activity. The estimated coefficients increase with distance from conflict locations, indicating that municipalities farther from conflict zones experience significantly smaller declines in nighttime lights. The effect rises sharply between 10–25 km and 25–50 km and stabilizes beyond 50 km, suggesting a highly localized pattern of economic disruption. This pattern is consistent with evidence that the economic impact of war might be localized (Dell and Querubin, 2018).

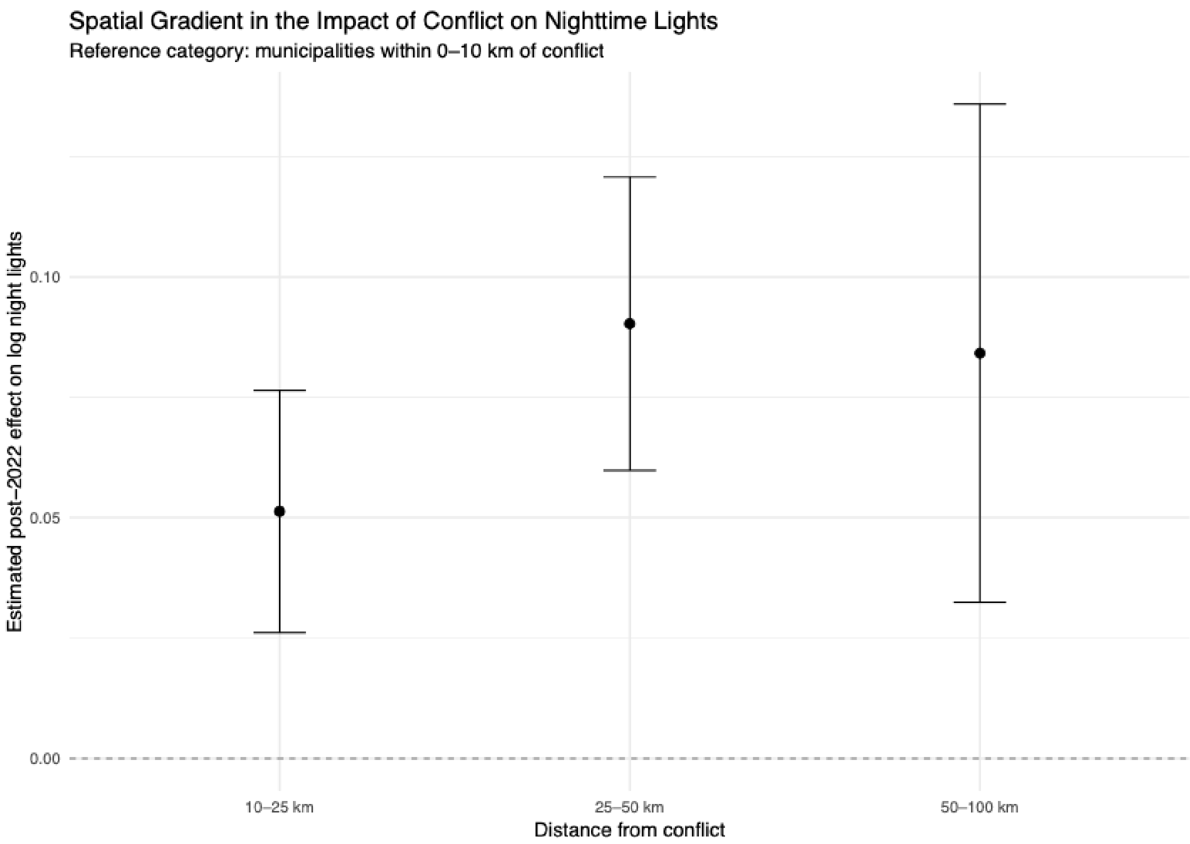

Figure 1: Spatial gradient in the impact of conflict on nighttime lights.

5.3 Urban Economic Resilience

To examine variation in local responses to the wartime shock, the Martin resistance–recovery framework is applied to nighttime light data. The findings presented below relate to the broader literature on regional economic resilience (Martin and Sunley, 2015). The resistance index (eq. 3) measures the initial change in nighttime lights between 2021 and 2022 relative to the national trend. Adaptive recovery index (eq. 4) measures the subsequent change relative to the national trajectory.

Table 5 reports municipalities with the Lowest Composite Resilience Scores. They are concentrated in areas exposed to sustained military activity. Beryslavskyi, Kupianskyi, and Khersonskyi show large negative resistance and recovery values. These municipalities experienced both strong initial declines and limited stabilization in nighttime lights.

Kramatorskyi, Pokrovskyi, and Bakhmutskyi display particularly large negative resistance values. Nighttime light intensity declines sharply in the first year of the invasion in these locations. Recovery remains limited, which results in persistently low composite scores. Other municipalities such as Okhtyrskyi, Bashtanskyi, and Chuhuivskyi exhibit large initial declines followed by partial stabilization. Their recovery scores are higher relative to their resistance values, which indicates some adjustment after the initial shock.

Table 5. Cities with the Lowest Composite Resilience Scores

Municipality	Resistance Index	Recovery Index	Composite Index
Beryslavskyi	-6.54	-37.8	-2.06
Kupianskyi	-4.32	-36.7	-1.72
Khersonskyi	-2.25	-36.6	-1.45
Kramatorskyi	-13.0	0.49	-1.35
Pokrovskyi	-9.42	-3.11	-1.03
Nikopolskyi	-5.43	-15.9	-1.03
Bakhmutskyi	-10.5	0.67	-1.02
Siverskodonetskyi	-8.83	0.27	-0.81
Sumskyi	-8.88	5.18	-0.61
Okhtyrskyi	-12.65	17.702	-0.60

Municipalities with the highest composite resilience scores are reported in Table 6 and display relatively stable nighttime light patterns or increases after the initial shock. Bilohirskyi, Dzhankoiskyi, Kurmanskyi, and Feodosiiskyi belong to this group. These municipalities show positive resistance values and moderate increases in nighttime luminosity.

Several high-ranking municipalities are located in Crimea, including Simferopolskyi, Kerchenskyi, Yevpatoriiskyi, and Yaltynskyi. These regions did not experience direct large-scale combat during the study period. Their position in the ranking reflects relative stability in nighttime light emissions rather than post-war economic recovery.

Some municipalities combine negative resistance with large recovery values. Mariupolskyi and Umanskyi fall into this category. These municipalities experienced substantial initial declines, followed by strong increases in the nighttime lights observed. The composite index therefore reflects a rebound relative to the initial shock. These patterns highlight strong spatial heterogeneity in observed nighttime activity. Municipalities located near active conflict zones show persistent reductions, while municipalities located farther away or outside direct combat areas display more stable trajectories.

Table 6. Municipalities with the Highest Composite Resilience Scores

Municipality	**Resistance Index**	**Recovery Index**	**Composite Index**
Bilohirskyi	1.03	2.44	0.569
Dzhankoiskyi	0.341	4.65	0.568
Kurmanskyi	0.326	3.36	0.514
Feodosiiskyi	0.197	3.67	0.510
Perekopskyi	0.176	3.28	0.491
Luhanskyi	0.226	2.82	0.479
Mariupolskyi	-5.22	20.0	0.463
Simferopolskyi	0.259	1.62	0.435
Kerchenskyi	0.237	1.44	0.425

The results are also reported in the maps in Figure 2, 3 and 4 below. Darker colors indicate lower performance, while lighter colors indicate higher performance. The maps reveal a clear and consistent spatial pattern in the economic response to the 2022 shock. Initial resistance exhibits strong heterogeneity, with the lowest values concentrated in eastern and southern regions closer to conflict zones, while western regions display relatively higher resistance. Estimated resilience appears more spatially uniform, yet clusters of lower resilience persist in heavily affected areas, indicating that initial vulnerabilities are not fully absorbed over time. Adaptive recovery remains uneven, with limited rebound in high-exposure regions and comparatively stronger recovery in more distant areas.

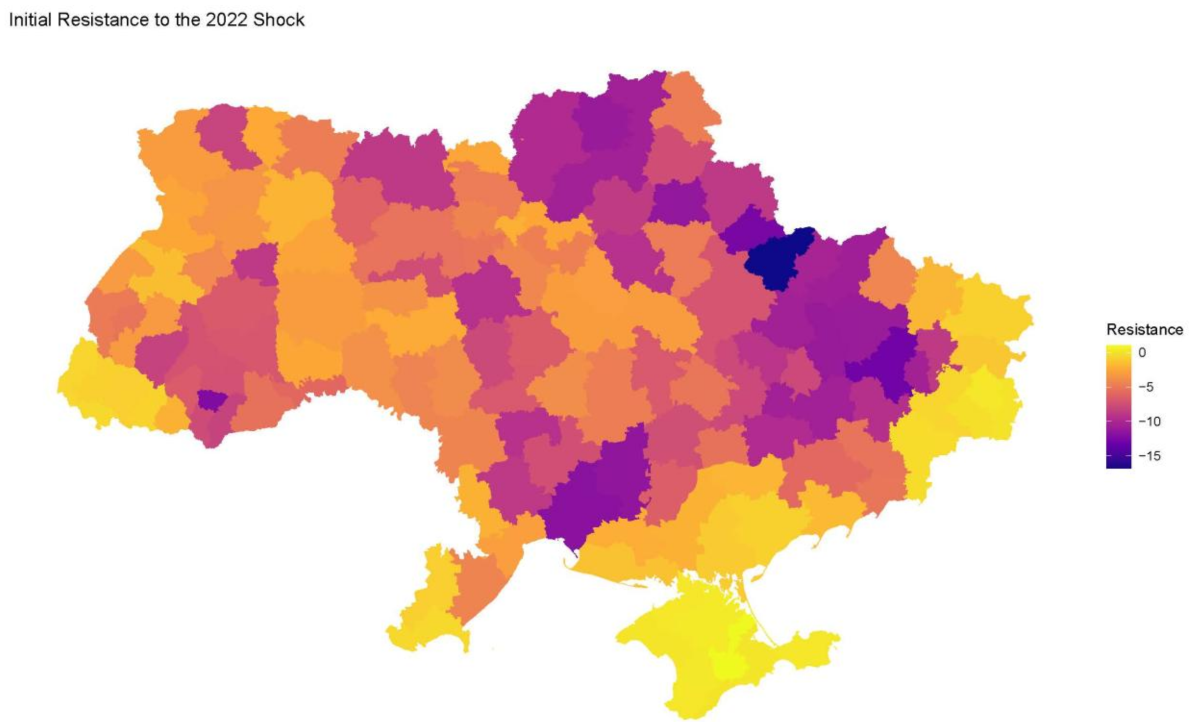

Figure 2: Spatial Distribution of Initial Resistance to the 2022 Shock in Ukraine

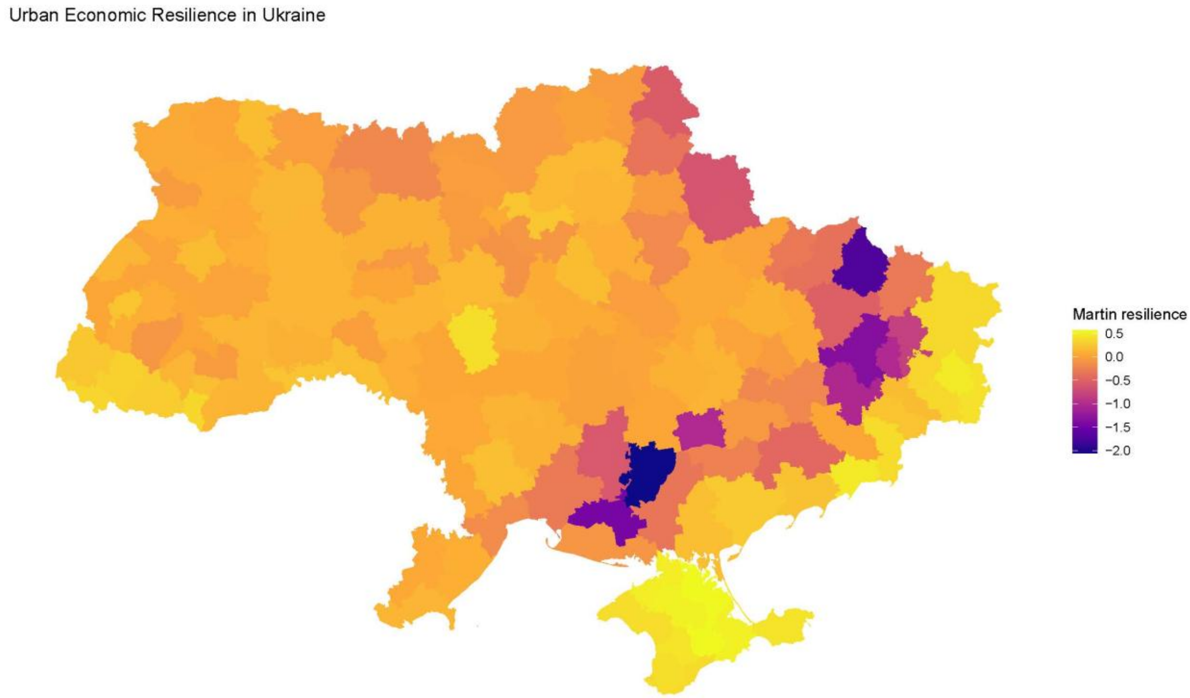

Figure 3. Spatial Patterns of Urban Economic Resilience in Ukraine

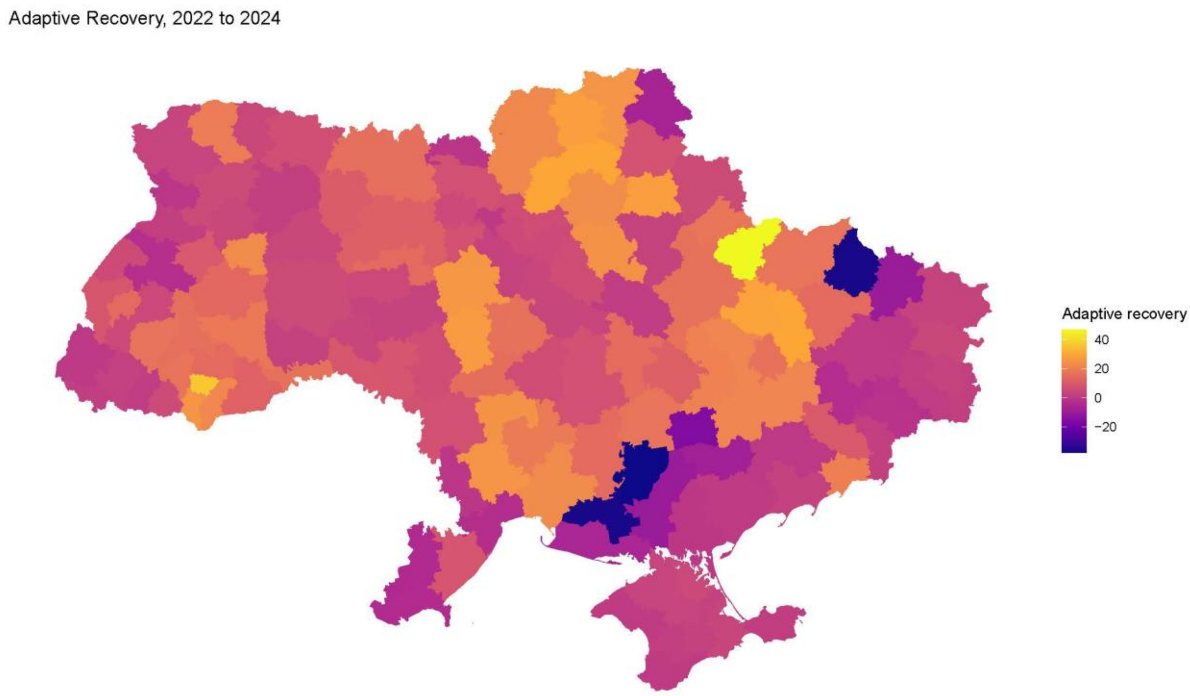

Figure 4. Spatial Variation in Adaptive Recovery, 2022–2024

To examine whether conflict intensity is systematically related to regional resilience, regression models were estimated using the logarithm of recorded conflict events as main explanatory variable. The results are shown in Table 7. They reveal a strong negative relationship between conflict intensity and the composite resilience index. The estimated coefficient indicates that municipalities experiencing higher numbers of violent events tend to display substantially lower resilience scores. Conflict intensity alone explains roughly 34% of the variation in the composite resilience indicator, highlighting the central role of local conflict exposure in shaping economic outcomes during the war.

When the two components are examined separately, conflict intensity is negatively associated with both resistance and recovery. Municipalities experiencing more violent events tend to experience larger initial declines in nighttime lights as indicated by the negative coefficient for the resistance score. In addition, these cities also display weaker recovery dynamics, suggesting that conflict not only generates immediate economic shocks but also slows subsequent recovery.

Table 7. Conflict Intensity and Regional Resilience

Dependent variable	**Coefficient (log events)**	**Std. error**	**p-value**	**R^2**
Composite resilience	-0.113	0.0079	<0.001	0.342
Resistance score	-0.423	0.081	<0.001	0.064
Recovery score	-1.421	0.272	<0.001	0.064

These results suggest that conflict exposure plays a central role in shaping spatial patterns of economic disruption across Ukrainian cities. Locations such as Kramatorskyi, Bakhmutskyi, and Pokrovskyi represent areas of severe economic collapse associated with intense military activity. At the same time, the variation in recovery scores indicates that some cities have been able to stabilize or partially restore nighttime lights levels despite large initial shocks.

However, nighttime light emissions during active conflict must be interpreted cautiously. In some cases, stable or increasing luminosity may reflect war-related activity, such as fires, military operations, or emergency infrastructure deployment, rather than genuine economic recovery. Consequently, while nighttime lights provide valuable information on spatial economic dynamics during conflict, they should be interpreted alongside conflict data and other contextual indicators.

The relationship between conflict exposure and regional resilience is consistent with the patterns observed in the nighttime light change analysis. Figure X illustrated that cities experiencing higher levels of conflict generally display larger declines in nighttime luminosity between 2021 and 2022. Municipalities such as Kramatorskyi, Bakhmutskyi, Pokrovskyi, and Kharkivskyi appear among the observations with both high numbers of violent events and some of the largest reductions in light emissions. These locations occupy the lower-right portion of the figure, indicating substantial contraction in observable nighttime activity following the escalation of hostilities.

The Martin resilience index results reinforce this pattern. Many of the municipalities with the lowest composite resilience scores correspond to areas that experienced intense military activity. For example, Kramatorskyi, Bakhmutskyi, Pokrovskyi, and Kupianskyi all appear among the lowest-ranked cities in the composite resilience measure. These locations exhibit strongly negative resistance scores, reflecting severe initial declines in nighttime lights, combined with weak or limited recovery dynamics.

A second group of municipalities, including Okhtyrskyi, Bashtanskyi, and Chuhuivskyi, experienced large initial shocks but display somewhat stronger recovery scores. In these cases, nighttime light levels appear to have partially stabilized following the initial disruption. This suggests that while the immediate impact of conflict was substantial, local economic activity or infrastructure may have recovered to some extent after the initial shock period.

The results from both the nighttime light change analysis and the Martin resilience framework point to a consistent pattern: municipalities exposed to more intense conflict tend to experience stronger economic disruption and weaker recovery trajectories. At the same time, the considerable variation across municipalities highlights the spatial heterogeneity of wartime economic dynamics. Importantly, the presence of a small number of high-conflict cities with relatively stable nighttime luminosity suggests that satellite-observed light emissions during active conflict may also reflect war-related activities, including military operations, fires, or emergency infrastructure deployment. Consequently, nighttime lights should be interpreted as an indicator of observed nighttime activity rather than a direct measure of economic performance during ongoing conflict.

6. Conclusions

The results provide several implications for the future spatial organization of economic activity in Ukraine. First, the strongly localized nature of nighttime light declines suggests that economic disruption is concentrated in close proximity to areas of intense conflict. This pattern indicates that the economic footprint of war is highly uneven across space and that post-war recovery is unlikely to follow a uniform trajectory. Instead, heavily affected cities are likely to face more persistent challenges, including damaged infrastructure, reduced productive capacity, and population losses, while locations farther from conflict zones may recover more rapidly and potentially attract economic activity.

Second, the substantial variation in resistance and adaptive recovery across cities points to the emergence of diverging local economic trajectories. Municipalities that experienced severe initial declines and limited stabilization, such as Kramatorskyi, Bakhmutskyi, and Kupianskyi, are likely to require extensive and sustained reconstruction efforts before economic activity can return to pre-war levels. In contrast, cities that maintained relatively stable nighttime light patterns or exhibited increases following the initial shock may act as short-term anchors of economic stability. These areas could play a key role in supporting national recovery, particularly if they continue to attract displaced firms, labor, and investment.

Third, the observed increase in inequality in nighttime light intensity suggests that the war has significantly reshaped the spatial distribution of economic activity. The concentration of economic activity in less exposed areas reflects both the collapse of production in conflict-affected regions and the reallocation of resources toward safer locations. If these dynamics persist, they may lead to a more polarized economic geography, with long-term implications for regional inequality, labor mobility, and infrastructure development. Without targeted policy interventions, such disparities risk becoming entrenched over time.

More broadly, these findings highlight the importance of spatially differentiated policy responses in the context of post-conflict reconstruction. Policies aimed at rebuilding economic activity should account for the highly localized nature of wartime damage and the heterogeneity in local resilience. In particular, heavily affected areas may require not only physical reconstruction but also targeted support to restore economic networks, attract population inflows, and rebuild local institutions. At the same time, relatively resilient areas may benefit from policies that support sustainable growth and prevent excessive congestion or over-concentration of economic activity.

Overall, the evidence suggests that the war is likely to leave a lasting imprint on Ukraine’s economic geography. Understanding these spatial dynamics is therefore essential for designing effective reconstruction strategies and for promoting a more balanced and inclusive recovery process.

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Appendix

Conflict Intensity and Nighttime Light Decline

This appendix complements the analysis by examining whether the intensity of conflict events is directly associated with changes in nighttime light emissions, and by discussing the implications for interpreting luminosity as a proxy for economic activity in a war context.

Figure A1 plots the change in nighttime light intensity between 2021 and 2022 against the logarithm of the number of recorded conflict events at the municipality level. A negative relationship emerges on average: municipalities experiencing a higher number of conflict events tend to exhibit larger reductions in nighttime lights. This pattern is consistent with the interpretation that intense military activity disrupts local economic systems, leading to declines in observable economic activity. Municipalities such as Kramatorskyi, Bakhmutskyi, Pokrovskyi, and Kharkivskyi illustrate this pattern, combining high conflict intensity with substantial decreases in luminosity during the initial phase of the invasion. However, the relationship is not uniform across locations. Several municipalities with high conflict intensity—such as Sumskyi, Beryslavskyi, Volnovaskyi, and Polohivskyi—display more limited reductions in nighttime lights. A further group, including Donetskyi, Khersonskyi, and Kupianskyi, shows relatively stable luminosity despite intense exposure to conflict.

These patterns highlight an important measurement issue. During active conflict, nighttime light emissions may reflect multiple sources of illumination beyond civilian economic activity. In particular, fires, explosions, military operations, and emergency infrastructure can generate light that is detected by satellite sensors. As a result, observed nighttime luminosity in high-intensity conflict areas may partially capture conflict-related light emissions, thereby attenuating or masking declines in underlying economic activity.

This evidence suggests that the relationship between conflict intensity and nighttime lights should be interpreted with caution. While nighttime lights remain informative about broad spatial patterns of disruption, they may overstate economic activity in areas experiencing intense violence. The main analysis therefore focuses on distance-based measures of exposure, which are less directly affected by contemporaneous light emissions generated by conflict events themselves.

Figure A1. Change in nighttime light intensity between 2021 and 2022 against the logarithm of the number of recorded conflict events at the municipality level.