Appendix

For Online Publication

A1 Training Set Intercoder Reliability

The current section reports intercoder reliability statistics for the subset of training set documents that were held constant across all coders. Two research assistants (coders 1 and 2) read 650 documents each, 300 of which overlapped. The author (coder 3) read all training set documents. Table A1.1 summarizes the intercoder reliability statistics, averaged across all variables. Table A1.2 reports full intercoder reliability statistics for each variable.

Coders	N Coders	Agreement	Holsti's CR	Krippendorff's α	Brennan Prediger's κ	Lotus
1,2,3 (N=300)	3	0.98	0.99	0.62	0.97	0.99
1,2 (N=300)	2	0.99	0.99	0.67	0.97	0.99
1,3 (N=650)	2	0.98	0.98	0.66	0.97	0.99
2,3 (N=650)	2	0.99	0.99	0.66	0.97	0.99

Table A1.1: **Intercoder Reliability Statistics, Averaged Over All Variables**

A2 Validation of Event Classifications

Table A2.3 reports validation accuracy statistics for LSTM models trained on the pooled, multilingual (Ukrainian and Russian) training set, compared to models trained on each monolingual training set alone. As the table reports, the pooled training set yields predictions with higher mean accuracy (i.e. averaged across variables) and lower variance (of accuracy statistics across variables) than either monolingual training set.

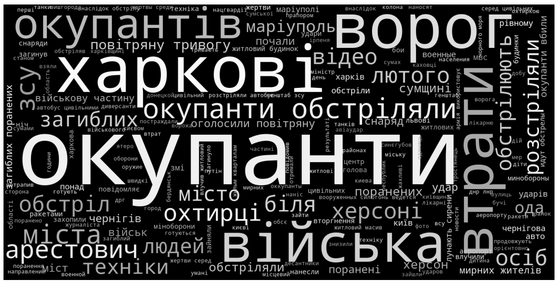
Figure A2.1 illustrates six of the event categories as wordclouds. These images represent the subset of reports in the test set, whose predicted probabilities of belonging to each category were in the 99th percentile. Font sizes are proportional to each word's frequency in the text. The wordclouds indicate that predicted labels generally align with the conceptual definitions in Table 1. For example, the `t_armor` category includes many documents mentioning tank battles, while `t_civcas` frequently mentions civilians in the accusative case, indicating that they are the direct object of an action. Figure A2.1 also reveals some idiosyncratic uses of language, which off-the-shelf dictionary classifiers — scanning the text for standard terms like "Russian forces" — might miss. For example, Ukrainian sources routinely refer to Russian troops as "occupiers" without mentioning their country of origin.

A3 Comparison of VIINA to Other Data Projects

Table A3.4 reports mean nearest neighbor distances between reported events in VIINA, GDELT, ICEWS and ACLED. The table shows that the average VIINA event is closest, on average, to events in ACLED (3.62 km), followed by GDELT (4.03 km) and ICEWS (5.68). Meanwhile, the average ACLED event is closest to events in VIINA (1.45 km), followed by GDELT (4.03 km) and ICEWS (6.37 km).

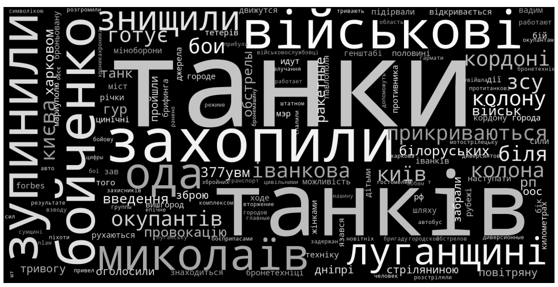
Table A3.5 reports Spearman's correlation coefficients for the time series of each dataset, both (a) in raw form, and decomposed into their (b) trend components, (c) seasonal components, and (d) residual components. The table shows that ACLED's time series is negatively correlated with the other three, both in raw form, and as a trend. The pairwise correlation coefficients are also substantially smaller for ACLED's seasonal and residual components than they are for any of the other datasets.

Figure A2.1: **Wordclouds of LSTM-Classified Events**.



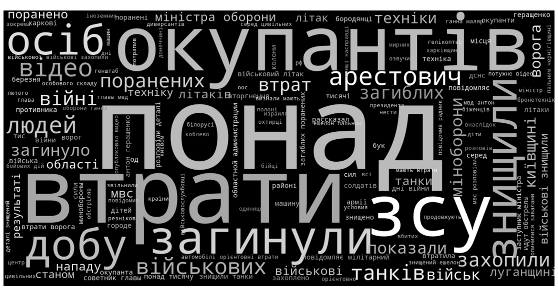
(a) **Russian-initiated events** [a_rus]
"окупанти" (okupanty) means "occupiers" (U)
"ворог" (voroh) means "enemy" (U)

(b) **Ukrainian-initiated events** [a_ukr]
"зсу" (zsu) is "Armed Forces of Ukraine" (U)
"всу" (vsu) is "Armed Forces of Ukraine" (R)

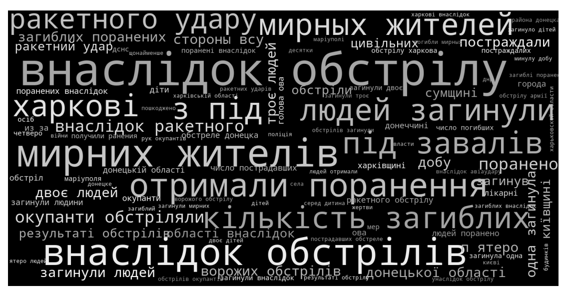


(c) **Armor / tank battles** [t_armor]
"танки" (tanki) means "tanks" (R)
"танків" (tankiv) means "tanks" (U, acc)

(d) **Arrests / detentions** [t_arrest]
"полон" (polon) means "captivity / POW camp" (U)
"захопили" (zahopyly) means "captured" (U)



(e) **Military casualties** [t_milcas]
"понад" (ponad) means "more than" (U)
"втрати" (vtraty) means "losses" (U)
"загинули" (zahynuly) means "died" (U)
"окупантів" (okupantiv) means "occupiers" (U, acc)



(d) **Civilian casualties** [t_civcas]
"внаслідок обстрілів" (vnasklidok obstriliv)
means "due to shelling" (U)
"мирних жителів" (myrnykh zhyteliv)
means "civilians" (U, acc)

Note: R: Russian language. U: Ukrainian language. acc: accusative case ending.

Variable	Agreement	Holsti's CR	Krippendorff's α	Brennan Prediger's κ	Lotus
t_mil	0.85	0.90	0.72	0.80	0.95
t_loc	0.89	0.93	0.78	0.85	0.96
t_san	0.97	0.98	0.67	0.96	0.99
a_rus	0.89	0.92	0.62	0.85	0.96
a_ukr	0.94	0.96	0.56	0.92	0.98
a_civ	0.97	0.98	0.10	0.96	0.99
a_other	0.95	0.96	0.51	0.93	0.98
t_aad	0.99	0.99	0.69	0.98	1.00
t_airstrike	0.98	0.99	0.73	0.97	0.99
t_armor	1.00	1.00	0.75	1.00	1.00
t_arrest	0.98	0.99	0.54	0.98	0.99
t_artillery	0.97	0.98	0.82	0.96	0.99
t_control	0.99	0.99	0.50	0.98	1.00
t_firefight	0.99	0.99	0.20	0.98	1.00
t_ied	0.98	0.98	0.62	0.97	0.99
t_raid	0.99	0.99	0.25	0.99	1.00
t_occupy	0.97	0.98	0.33	0.96	0.99
t_retreat	0.99	0.99	0.40	0.99	1.00
t_property	0.95	0.97	0.63	0.93	0.98
t_cyber	1.00	1.00	1.00	1.00	1.00
t_hospital	1.00	1.00	0.00	1.00	1.00
t_sexual	1.00	1.00	1.00		1.00
t_milcas	0.97	0.98	0.54	0.96	0.99
t_civcas	0.99	0.99	0.90	0.98	1.00

Table A1.2: **Intercoder Reliability Statistics, by Variable** (all three coders, N=300)

	Training Set		
Variable	Pooled	Russian	Ukrainian
t_mil	0.81	0.87	0.77
t_loc	0.85	0.86	0.83
t_san	0.93	0.89	0.91
a_rus	0.85	0.93	0.88
a_ukr	0.94	0.95	0.94
a_civ	1.00	0.99	1.00
a_other	0.96	0.95	0.95
t_aad	0.99	0.99	0.98
t_airstrike	0.98	0.99	0.98
t_airalert	1.00	1.00	0.99
t_armor	0.99	0.99	0.99
t_arrest	0.96	0.99	0.97
t_artillery	0.95	0.93	0.94
t_control	0.98	0.98	0.99
t_firefight	0.99	0.93	0.98
t_killing	0.99	0.99	0.98
t_ied	0.98	0.99	0.99
t_raid	0.99	1.00	0.99
t_occupy	0.99	1.00	0.96
t_property	0.95	0.97	0.92
t_cyber	0.96	0.99	0.97
t_hospital	0.99	1.00	0.98
t_milcas	0.98	0.99	0.94
t_civcas	0.95	0.97	0.97
Mean	0.96	0.96	0.95
Std.Dev.	0.05	0.04	0.06

Table A2.3: **Out-of-Sample Accuracy, Multilingual vs. Monolingual Training Sets**

	VIINA	GDELT	ICEWS	ACLED
VIINA	0.00	4.02	5.68	3.60
GDELT	8.74	0.00	1.87	8.98
ICEWS	1.48	2.23	0.00	2.01
ACLED	1.45	4.03	6.37	0.00

Table A3.4: **Mean Nearest Neighbor Distances Between Events in Each Dataset**. Each cell value d_{ij} represents the average distance, in kilometers, between each event in dataset i (in rows) and its geographically closest event in dataset j (in columns). Smaller values indicate greater similarity across point patterns.

	GDELT	ICEWS	ACLED
VIINA	0.61	0.63	-0.41
GDELT		0.75	-0.47
ICEWS			-0.50

(a) Raw Time Series

	GDELT	ICEWS	ACLED
VIINA	0.60	0.66	-0.48
GDELT		0.85	-0.72
ICEWS			-0.77

(b) Trend Component

	GDELT	ICEWS	ACLED
VIINA	0.84	0.96	-0.11
GDELT		0.88	0.25
ICEWS			0.11

(c) Seasonal Component

	GDELT	ICEWS	ACLED
VIINA	0.30	0.32	0.06
GDELT		0.37	0.13
ICEWS			0.07

(d) Residual Component

Table A3.5: **Pairwise Spearman's Correlation for Time Series of Event Data**

A4 Luminosity Validation Check

Luminosity is a valid proxy for economic activity only if it correlates in a predictable fashion with other sub-national measures of production and consumption. To establish this, we assessed the empirical relationship between gross regional product (GRP) and average annual luminosity in Ukraine prior to the war. Ukraine's State Statistics Service releases GRP estimates annually at the oblast level, from 2004 to 2021. We linked the GRP data to data on annual global VIIRS nighttime lights (Annual VNL v2.1, Elvidge et al. 2021), which are available at a resolution of 15 arc seconds from 2012 to 2021.[1] The combined dataset contains 254 oblast-year observations, including 27 oblasts from 2012 to 2013, and 25 oblasts from 2014 to 2021.[2]

We estimate the following regression model:

$$\log(\text{GRP}_{it}) = \gamma \log(\text{Luminosity}_{it}) + \alpha_i + \omega_t + \epsilon_{it} \tag{A4.1}$$

where i indexes oblasts and t indexes years. α_i and ω_t are oblast and yearly fixed effects. Our quantity of interest is the coefficient γ, which can be interpreted as the elasticity of GRP with respect to Luminosity, i.e., $\frac{\delta \text{ GRP}}{\delta \text{ Luminosity}}\left(\frac{\text{Luminosity}}{\text{GRP}}\right)$. We estimated the same model with GRP per capita as the dependent variable.

Table A4.6 reports coefficient estimates from these models. For both outcomes, the estimate is $\hat{\gamma} = 0.47$, meaning that a one percentage point increase in luminosity is associated with, on average, a 0.47 percentage point increase in an oblast's GRP (per capita).

Because oblasts differ in the composition of their economic bases, we may expect the elasticity of economic activity to luminosity to vary across space. To explore this possibility, Figure A4.2 reports estimates from an expanded specification of the model in equation (A4.1), replacing the parameter γ with oblast-specific coefficients γ_i. The black dots and

[1] We aggregated the VIIRS data in two steps. First, we calculated average annual luminosity in the same spatial units that we used in the main analysis (880 urban populated places). Second, we summed these average luminosity estimates across the urban populated places in each oblast. Formally, $\text{Luminosity}_{it} = \sum_k^{N_i} \text{Luminosity}_{kt}$, where $k \in \{1, \ldots, N_i\}$ indexes populated places inside oblast i, and Luminosity_{kt} is the average annual luminosity of populated place k in year t.

[2] After 2014, national accounts exclude Russian-occupied territories of Ukraine (i.e. Crimea and parts of Donets'k and Luhans'k oblasts). We exclude these areas from our aggregate oblast-level luminosity estimates, to ensure that both sets of data have common geographic support.

horizontal lines represent $\hat{\gamma}_i$ point estimates and 95 percent confidence intervals for each of Ukraine's 27 oblasts. The vertical lines and grey bars in the background represent the general $\hat{\gamma}$ point estimate and 95% confidence interval, as reported in Table A4.6. The $\hat{\gamma}_i$ estimates are positive in almost all cases, but vary in magnitude. Notably, the three largest regional elasticity estimates are in territories that are either fully (Sevastopol') or partially occupied by Russia (Luhans'k and Donets'k) — the latter of which have also been at the epicenter of ground combat operations in the war.

Table A4.7 further expands the model to explore variation in the GRP-luminosity relationship over time. Because GRP data are not yet available for 2022, we are unable to directly examine the extent to which Russia's full-scale invasion has disrupted the positive association between luminosity and GRP observed in 2012-2021. However, we are able to compare estimates taken before and after Russia's more limited intervention in 2014 — which began with the annexation of Crimea and Sevastopol' and evolved into a protracted war of attrition in the Donbas. To this end, Table A4.7 reports $\hat{\gamma}$ estimates, along with coefficient estimates for a "post-2014" interaction term. These estimates suggest that the positive link between GRP and luminosity has strengthened slightly over time. Taking the most conservative set of estimates, with oblast and annual fixed effects (Models 1 and 2), the estimated elasticity before 2014 is 0.45 for GRP and 0.46 for GRP per capita. After 2014, these estimates rise to $0.45 + 0.03 = 0.48$ and $0.46 + 0.03 = 0.49$.

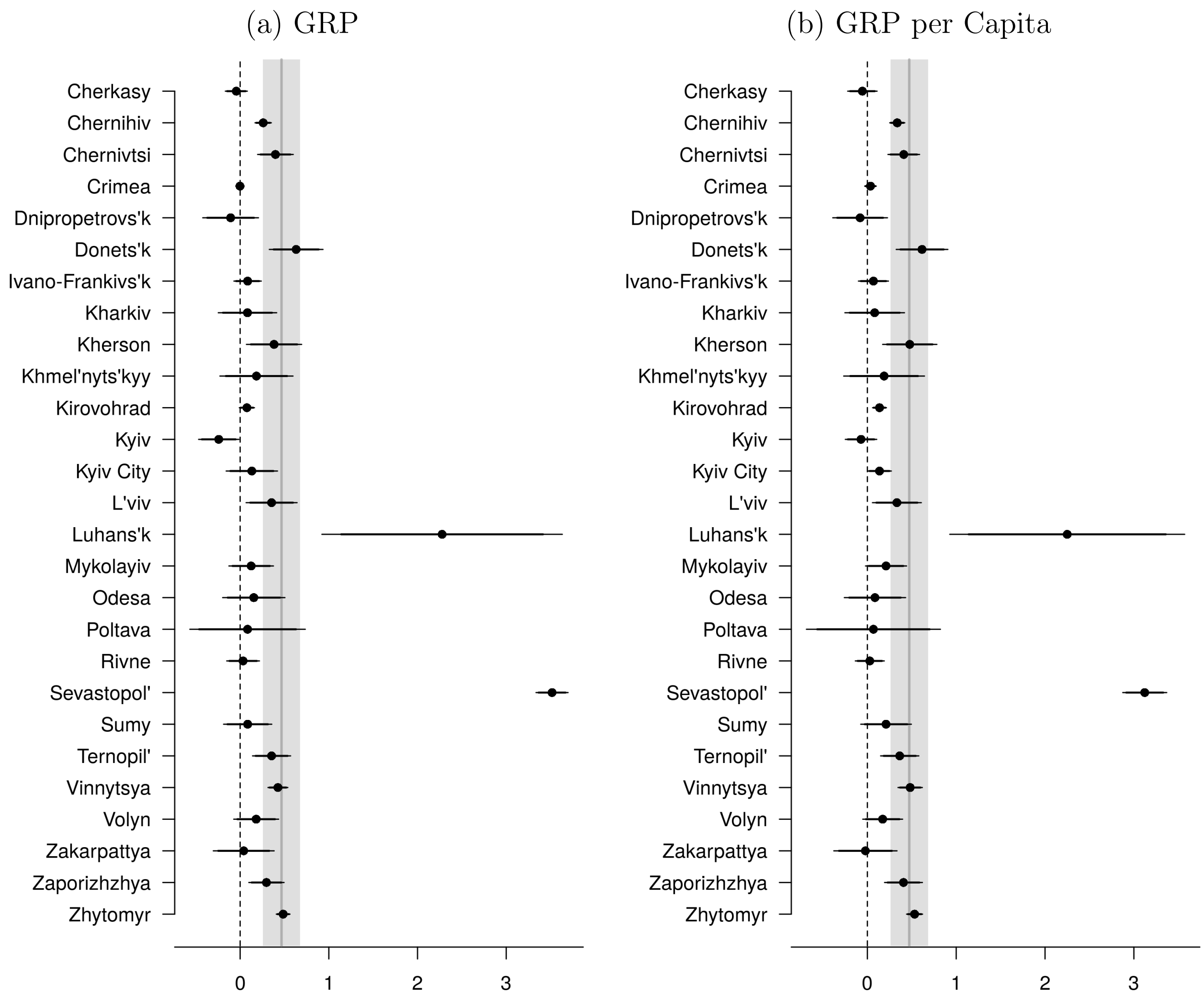
Table A4.7 also reports estimates from restricted versions of the same model, after omitting both sets of fixed effects (Models 3 and 4), oblast-level fixed effects α_i (Models 5 and 6), and yearly fixed effects ω_t (Models 7 and 8). These alternative specifications allow us to take stock of how unobserved sources of variation over time and space might affect the estimation of γ. For example, pooling the data across all oblasts and time periods may lead us to over-estimate the relationship between luminosity and GRP ($0.58 > 0.45$) and under-estimate the coefficient for GRP per capita ($0.28 < 0.46$). Estimates for models with time fixed effects (5 and 6) are numerically close to those in the pooled models (3 and 4), suggesting that correcting for time-specific shocks alone does not bring these estimates closer to values from the fully specified models (1 and 2), which include both types of fixed effects. In contrast, estimates for Models 7 and 8 — which account for unobserved factors specific to each oblast, but not time-specific shocks common to all oblasts — are substantially larger than for either the pooled or two-way models. These estimates suggest that omitted variable bias from unobserved variables that evolve over time may result in an over-estimation of the GRP-luminosity relationship. Unsurprisingly, model fit statistics are strongest for the two-way fixed effects models — with lower RMSE and AIC, and higher R^2. The inclusion of both sets of fixed effects enables us to explain substantially more variation in economic activity.

Table A4.6: Gross Regional Procuct (GRP) and Luminosity.

	GRP (1)	GRP per capita (2)
log(Average annual luminosity)	0.47^{**}	0.47^{**}
	(0.11)	(0.11)
Number of observations	254	254
RMSE	0.118	0.116
AIC	−291	−300
Adjusted R^2	0.982	0.97
FE: oblasts (α_i)	✓	✓
FE: years (ω_t)	✓	✓
Number of oblasts × years	27 × 10	27 × 10

Outcomes are (1) logged gross regional product and (2) logged per capita gross regional product in oblast i and year t. Fixed effect OLS coefficient estimates, heteroskedasticity and serial autocorrelation consistent standard errors in parentheses. Sample restricted to built-up areas. Russian-occupied Crimea and parts of Donets'k and Luhans'k oblasts omitted post-2014. Significance levels: $^{\prime}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Figure A4.2: Luminosity Validation Check with Oblast-Specific Coefficient Estimates



Points and horizontal lines are oblast-specific point estimates and 95% confidence intervals. Grey vertical line and region is the coefficient estimate and 95% CI from Table A4.6.

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Table A4.7: Temporal and Cross-Sectional Variation in the GRP-Luminosity Relationship.

	GRP (1)	GRP pc (2)	GRP (3)	GRP pc (4)	GRP (5)	GRP pc (6)	GRP (7)	GRP pc (8)
log(Average annual luminosity)	0.45^{**}	0.46^{**}	0.58^{**}	0.28^{**}	0.58^{**}	0.28^{**}	1.05^{**}	1.08^{**}
	(0.11)	(0.11)	(0.01)	(0.002)	(0.01)	(0.002)	(0.22)	(0.24)
× post-2014	0.03^{*}	0.03^{*}	0.04	0.07^{**}	0.02	0.05^{**}	0.07^{*}	$0.07^{'}$
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
Number of observations	254	254	254	254	254	254	254	254
RMSE	0.117	0.115	0.5	0.459	0.396	0.316	0.315	0.324
AIC	−293	−300	376	333	274	159	194	208
Adjusted R^2	0.982	0.97	0.679	0.527	0.799	0.776	0.872	0.764
FE: oblasts (α_i)	✓	✓					✓	✓
FE: years (ω_t)	✓	✓			✓	✓		
Number of oblasts × years	27 × 10	27 × 10	27 × 10	27 × 10	27 × 10	27 × 10	27 × 10	27 × 10

Outcomes are (1,3,5,7) logged gross regional product and (2,4,6,8) logged per capita gross regional product in oblast i and year t. Fixed effect OLS coefficient estimates, heteroskedasticity and serial autocorrelation consistent standard errors in parentheses. Sample restricted to built-up areas. Russian-occupied Crimea and parts of Donets'k and Luhans'k oblasts omitted post-2014. Significance levels: $^{'}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

A5 Robustness Checks

The current section considers the sensitivity of the results in Table 3 to several sources of uncertainty and bias, including:

- **Temporal autocorrelation**. The robust standard error estimates in Table 3 are clustered by populated place, which accounts for potential non-independence of observations taken within each geographic unit. As an additional check, Table A5.8 implements the Newey-West correction of standard errors for heteroscedasticity and serial autocorrelation, up to a first-order lag. The resulting standard error estimates are numerically close to those in Table 3.

- **Spatial autocorrelation**. While our clustered standard errors correct for non-independence within units and over time, they do not account for uncertainty due to spatial autocorrelation across nearby units. To this end, Table A5.9 reports Conley (1999) standard error estimates, which allow for both serial correlation over time periods, and spatial correlation among locations that fall within a set distance of each other. By way of a cutoff, we used the distance from the median populated place to the farthest of its $k = 5$ nearest neighbors (5.5 km for the night lights data, 4.8 km for the vegetation data). Our coefficient estimates in the night lights model remain significant at the $p < .05$ level or better, as does the estimate for Russian control in the NDVI model. The estimate for exposure to shelling in the NDVI model, however, becomes more uncertain after we account for spatial autocorrelation.

- **Alternative baseline for luminosity**. Our main model specification compares urban luminosity after February 24, 2022 (Y_{it}^{wartime}) to "peacetime" levels of luminosity in the same month during the previous year ($Y_{it}^{\text{peacetime}}$). A potential concern with this approach is that luminosity in 2021 may reflect, in part, light masking and other sources of variation related to Russia's military buildup on the border (which began as early as April 2021). To address this concern, Table A5.10 reports coefficient estimates for the luminosity model, using three different baseline periods: (a) 2/24/2021-2/23/2022, same as in Table 3, (b) 2/24/2020-2/23/2021, and (c) 2/24/2019-2/23/2020.[3] Our results are robust to these alternative baselines: coefficient estimates are numerically close across the board, and all three sets of estimates remain statistically significant at the $p < .05$ level or better. However, model fit statistics (R^2, AIC, RMSE) are strongest under the most recent baseline period.

- **War-related fires**. An important variable missing from our main specification is fire damage from shelling, airstrikes and other war-related events. These fires may explain variation in both luminosity (through destruction of physical structures, or by creating transient sources of nighttime light) and vegetation (by burning crops and farm equipment), in ways that VIINA data may not fully capture. Table A5.11 extends our main model specifications to include the (logged) number of war-related fires that occurred in the populated place during the previous month, as estimated by the Economist's war fire model (The Economist and Solstad, 2023). As one might expect, locations with greater exposure to war-related fires experienced a decline in vegetation during the following month: doubling the number of fires is associated with

[3] An important consideration is that using earlier baseline years risks introducing new sources of variation in luminosity that could be mis-attributed to war-related violence (e.g. light differences due to economic migration, urban growth, infrastructure development, Covid-19 restrictions).

a $(2^{-0.12} - 1) \times 100 = -8$ percentage point decrease in vegetation. The coefficient estimate on fires is also negative in the luminosity model, although the latter result is statistically insignificant. Our core results — for territorial control and shelling — remain significant and numerically close to those in Table 3.

- **Time-invariant covariates**. Our main specification includes fixed effects at the level of populated places. This estimation strategy helps account for unobserved local confounders and mitigates against omitted variable bias. It also precludes inferences about associations between observed time-invariant covariates and our outcome measures. Table A5.12 adjusts the specification to replace populated place-level fixed effects α_i with oblast-level fixed effects $\alpha_{j[i]}$, where $j[i]$ is the oblast that contains populated place i. This adjustment allows us to estimate coefficients for several covariates that vary across populated places, but not within them, including:

  - *Topographic features*, like elevation (NOAA National Geophysical Data Center, 2009) and distance to the nearest river, lake or other inland body of water (Defense Mapping Agency, 1992).
  - *Distance to strategically-important sites and infrastructure*, like administrative centers (geonames.org) and railroads (Defense Mapping Agency, 1992).
  - *Local demographics*, like population size (Schiavina, Freire and MacManus, 2019) and share of Russian speakers (State Committee on Statistics of Ukraine, 2001).
  - *Pre-2022 military geography*, like distance to the line of contact as it existed at the time of the Minsk II agreement in February 2015 (Zhukov, 2016).

  As Table A5.12 reports, our core results are robust to the inclusion of these time-invariant covariates. Our estimates for the luminosity model are of the same sign as in Table 3, and are statistically significant at the $p < .01$ level. The same is partly true for our vegetation model: the positive estimate for Russian control loses significance, but the negative estimate for contested control gains significance. Model fit statistics, however, are inferior to those from our main fixed effects specifications in Table 3.

- **Alternative measures of violence**. While shelling from field artillery and rocket systems represents the most frequent type of violent event in this war, it is important

Table A5.8: Estimates with Newey-West Standard Errors.

	Luminosity (1)	NDVI (2)
Contested control	-0.56^{**}	-0.01
	(0.11)	(0.01)
Russian control	0.26^{*}	0.07^{**}
	(0.1)	(0.01)
log(Distance from shelling)	0.09^{**}	0.01^{*}
	(0.02)	(0.004)
Number of observations	9,676	207,241
RMSE	0.659	0.352
AIC	21,176	190,996
Adjusted R^2	0.76	0.626
FE: populated places (α_i)	✓	✓
FE: months (ω_t)	✓	✓
Number of pop. places × months	880 × 11	17,513 × 12

Outcomes are (1) logged average nightly luminosity and (2) logged normalized difference vegetation index in populated place i and month t. Fixed effect OLS coefficient estimates, Newey-West heteroskedasticity and serial autocorrelation consistent standard errors in parentheses. All models adjust for (1) logged luminosity and (2) logged NDVI in the same month of past year. Sample restricted to (1) built-up areas and (2) irrigated cropland and pasture. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$

to consider how exposure to other types of violence might impact luminosity and vegetation. To this end, Tables A5.13 and A5.14 re-estimate our main models with several of the most common alternative measures of violence in VIINA, including air raid alerts, anti-air defenses, raids, troop withdrawals, events resulting in military casualties, and events resulting in civilian casualties. In almost all cases, the estimated coefficients are significant and of the same sign as that for exposure to artillery shelling. The sole exception is civilian casualties, the estimate for which fails to meet conventional levels of statistical significance in the luminosity model.

Table A5.9: Estimates with Conley Standard Errors.

	Luminosity (1)	NDVI (2)
Contested control	-0.56^{**}	-0.01
	(0.16)	(0.02)
Russian control	0.26^{*}	0.07^{**}
	(0.13)	(0.01)
log(Distance from shelling)	0.09^{*}	0.01
	(0.07)	(0.01)
Number of observations	9,676	207,241
RMSE	0.659	0.352
AIC	21,176	190,996
Adjusted R^2	0.76	0.626
FE: populated places (α_i)	✓	✓
FE: months (ω_t)	✓	✓
Number of pop. places × months	880 × 11	17,513 × 12

Outcomes are (1) logged average nightly luminosity and (2) logged normalized difference vegetation index in populated place i and month t. Fixed effect OLS coefficient estimates, Conley heteroskedasticity and spatial autocorrelation consistent standard errors in parentheses. All models adjust for (1) logged luminosity and (2) logged NDVI in the same month of past year. Sample restricted to (1) built-up areas and (2) irrigated cropland and pasture. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$

Table A5.10: Luminosity Estimates with Alternative Baseline Years.

	Luminosity (1)	Luminosity (2)	Luminosity (3)
Contested control	-0.56^{**}	-0.51^{**}	-0.59^{**}
	(0.12)	(0.13)	(0.14)
Russian control	0.26^{*}	0.27^{*}	0.27^{*}
	(0.11)	(0.13)	(0.13)
log(Distance from shelling)	0.09^{**}	0.09^{**}	0.07^{*}
	(0.03)	(0.03)	(0.03)
Number of observations	9,676	9,676	9,676
RMSE	0.659	0.715	0.71
AIC	21,176	22,756	22,612
Adjusted R^2	0.76	0.718	0.722
FE: populated places (α_i)	✓	✓	✓
FE: months (ω_t)	✓	✓	✓
Number of pop. places × months	880 × 11	880 × 11	880 × 11

Models adjust for logged luminosity in the same month of the time period (1) 3/2021-2/2022, (2) 3/2020-2/2021, (3) 3/2019-2/2020. Outcome is logged average nightly luminosity in populated place i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. Sample restricted to built-up areas. Significance levels: ' $p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Table A5.11: Estimates Adjusting for War-Related Fires.

	Luminosity (1)	NDVI (2)
Contested control	-0.56^{**}	-0.01
	(0.12)	(0.01)
Russian control	0.25^{*}	0.08^{**}
	(0.11)	(0.01)
log(Distance from shelling)	0.08^{*}	0.01^{*}
	(0.03)	(0.005)
log(Number of fires)	-0.04	-0.12^{**}
	(0.04)	(0.004)
Number of observations	9,676	207,241
RMSE	0.659	0.352
AIC	21,177	190,615
Adjusted R^2	0.76	0.626
FE: populated places (α_i)	✓	✓
FE: months (ω_t)	✓	✓
Number of pop. places × months	880 × 11	17,513 × 12

Outcomes are (1) logged average nightly luminosity and (2) logged normalized difference vegetation index in populated place i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. All models adjust for (1) logged luminosity and (2) logged NDVI in the same month of past year. Sample restricted to (1) built-up areas and (2) irrigated cropland and pasture. Significance levels: $^{'}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Table A5.12: Estimates Adjusting for Time-Invariant Covariates.

	Luminosity (1)	NDVI (2)
Contested control	-0.32^{**}	-0.02^{*}
	(0.11)	(0.01)
Russian control	0.46^{**}	0.004
	(0.09)	(0.003)
log(Distance from shelling)	0.13^{**}	0.01^{**}
	(0.03)	(0.003)
log(Elevation)	0.09^{**}	-0.003
	(0.02)	(0.002)
log(Distance to water)	$0.04^{'}$	-0.01^{**}
	(0.02)	(0.001)
log(Distance to admin center)	-0.01	0.005^{**}
	(0.02)	(0.002)
log(Distance to railroad)	0.002	-0.01^{**}
	(0.02)	(0.001)
log(Population size)	-0.07^{**}	-0.002^{**}
	(0.01)	(0.001)
Percent Russian	0.01^{**}	4e-04**
	(0.003)	(2e-04)
log(Distance to pre-2022 line)	$-0.1^{'}$	-0.01^{**}
	(0.06)	(0.002)
Number of observations	9,676	207,193
RMSE	0.765	0.368
AIC	22,378	174,234
Adjusted R^2	0.676	0.591
FE: oblasts ($\alpha_{j[i]}$)	✓	✓
FE: months (ω_t)	✓	✓
Number of oblasts × months	27 × 11	27 × 12

Outcomes are (1) logged average nightly luminosity and (2) logged normalized difference vegetation index in populated place i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. All models adjust for (1) logged luminosity and (2) logged NDVI in the same month of past year. Sample restricted to (1) built-up areas and (2) irrigated cropland and pasture. Significance levels: $^{'}$ $p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Table A5.13: Luminosity Estimates Adjusting for Other Violent Events.

	Luminosity (1)	Luminosity (2)	Luminosity (3)	Luminosity (4)	Luminosity (5)	Luminosity (6)	Luminosity (7)
Contested control	-0.56^{**}	-0.53^{**}	-0.59^{**}	-0.56^{**}	-0.5^{**}	-0.54^{**}	-0.63^{**}
	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Russian control	0.26^{*}	0.38^{**}	0.34^{**}	0.37^{**}	0.31^{**}	0.32^{**}	0.33^{**}
	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
log(Distance from shelling)	0.09^{**}						
	(0.03)						
log(Distance from air raid alerts)		0.22^{**}					
		(0.03)					
log(Distance from anti-air defense)			$0.05^{'}$				
			(0.02)				
log(Distance from raids)				0.3^{**}			
				(0.04)			
log(Distance from troop withdrawals)					0.12^{**}		
					(0.03)		
log(Distance from military casualties)						0.17^{**}	
						(0.04)	
log(Distance from civilian casualties)							-0.03
							(0.02)
Number of observations	9,676	8,796	9,676	9,676	9,676	9,676	9,676
RMSE	0.659	0.649	0.659	0.658	0.658	0.659	0.659
AIC	21,176	19,154	21,186	21,141	21,154	21,163	21,186
Adjusted R^2	0.76	0.779	0.76	0.761	0.761	0.76	0.76
FE: populated places (α_i)	✓	✓	✓	✓	✓	✓	✓
FE: months (ω_t)	✓	✓	✓	✓	✓	✓	✓
Number of pop. places × months	880 × 11	880 × 10	880 × 11	880 × 11	880 × 11	880 × 11	880 × 11

Outcome is logged average nightly luminosity in location i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. All models adjust for logged luminosity in the same month of past year. Sample restricted to built-up areas. Significance levels: $^{'}$ $p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

Table A5.14: Vegetation Estimates Adjusting for Other Violent Events.

	NDVI (1)	NDVI (2)	NDVI (3)	NDVI (4)	NDVI (5)	NDVI (6)	NDVI (7)
Contested control	-0.06^{**}	-0.02^{*}	-0.05^{**}	-0.01	-0.01	$-0.02^{'}$	-0.04^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Russian control	0.03^{**}	0.04^{**}	0.04^{**}	0.08^{**}	0.07^{**}	0.06^{**}	0.05^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(Distance from shelling)	-0.1^{**}						
	(0.003)						
log(Distance from air raid alerts)		0.17^{**}					
		(0.002)					
log(Distance from anti-air defense)			0.04^{**}				
			(0.003)				
log(Distance from raids)				0.29^{**}			
				(0.01)			
log(Distance from troop withdrawals)					0.21^{**}		
					(0.004)		
log(Distance from military casualties)						0.2^{**}	
						(0.004)	
log(Distance from civilian casualties)							0.05^{**}
							(0.003)
Number of observations	190,264	175,004	190,264	190,264	190,264	190,264	190,264
RMSE	0.246	0.212	0.247	0.244	0.244	0.245	0.247
AIC	41,497	−10,643	42,380	38,239	38,539	39,751	42,251
Adjusted R^2	0.629	0.694	0.627	0.635	0.635	0.632	0.627
FE: populated places (α_i)	✓	✓	✓	✓	✓	✓	✓
FE: months (ω_t)	✓	✓	✓	✓	✓	✓	✓
Number of pop. places × months	17,513 × 11	17,513 × 10	17,513 × 11	17,513 × 11	17,513 × 11	17,513 × 11	17,513 × 11

Outcome is logged normalized difference vegetation index in location i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. All models adjust for logged NDVI in the same month of past year. Sample restricted to irrigated cropland and pasture. Significance levels: $^{'}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$

References

Conley, Timothy G. 1999. "GMM estimation with cross sectional dependence.".

Defense Mapping Agency. 1992. "Development of the Digital Chart of the World." U.S. Government Printing Office.

Elvidge, Christopher D., Mikhail Zhizhin, Tilottama Ghosh, Feng-Chi Hsu and Jay Taneja. 2021. "Annual Time Series of Global VIIRS Nighttime Lights Derived from Monthly Averages: 2012 to 2019." *Remote Sensing* 13(5).
URL: *https://www.mdpi.com/2072-4292/13/5/922*

NOAA National Geophysical Data Center. 2009. "ETOPO1 1 Arc-Minute Global Relief Model." NOAA National Centers for Environmental Information.

Schiavina, Marcello, Sergio Freire and Kytt MacManus. 2019. "GHS population grid multitemporal (1975, 1990, 2000, 2015) R2019A." *European Commission, Joint Research Centre (JRC)* .

State Committee on Statistics of Ukraine. 2001. *Ukrainian census 2001*. State Committee on Statistics of Ukraine.

The Economist and Sondre Solstad. 2023. "The Economist war-fire model." First published in the article "A hail of destruction," The Economist, February 25th issue.
URL: *https://github.com/TheEconomist/the-economist-war-fire-model*

Zhukov, Yuri M. 2016. "Trading hard hats for combat helmets: The economics of rebellion is east Ukraine." *Journal of Comparative Economics* 44(1):1–15.