THE IMPACT OF WAR ON PHILANTHROPY: ANALYZING DONATION PATTERNS IN UKRAINE DURING WARTIME

by

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Kyiv School of Economics

Abstract

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Philanthropy in times of war has become an integral part of social resistance. Numerous fund-raising initiatives provide timely support and cover the immediate needs of not only the defense forces, but also the civilian victims. However, there remains a gap in understanding the dynamics of long-term social giving behavior in response to such crises.

In this work, we examine whether the intensity of air attacks during the Russian full-scale invasion reflected in the number of weapons and civilian casualties drive short-run changes in donations dynamics in Ukraine. Using the different specifications of time-series models, the goal is to provide a measurable effect of the air attacks on the aggregated daily donations amount controlling for other war-contextual factors.

The results could help policymakers and fundraisers in finding the most effective triggers and narratives to mobilize charitable behavior.

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Chapter 1

INTRODUCTION

In times of war, financial donations from people and businesses became a very important factor supporting Ukrainian resilience. Public fund-raising has helped provide both humanitarian and military aid in a much timelier manner than governmental programs, covering a substantial part of the immediate needs of defense forces and civilian victims of Russian aggression. For many Ukrainians, regular financial donations became an integral part of support, as the easiest and simplest way to contribute to Ukraine's defense and recovery efforts. But the dynamics of donations have been quite volatile over time, based on the statistics published by major Ukrainian public foundations such as Come Back Alive, UNITED24, Serhiy Prytula Charity Foundation. What are the factors impacting people's willingness to donate? In this research, we decided to estimate the effect of the destructive wartime events such as missile and drone strikes in Ukraine on philanthropic activity, controlling for other factors such as frontline major events, blackouts, political milestones, etc. using data published by the biggest Ukrainian fund-raising platforms.

The existing studies reveal that there is a dependency between the emotional response to crises and especially war conflicts, and the scale of individuals' prosocial behavior. Researchers indicate the feeling of personal responsibility, moral obligation, understanding the need and consequences of giving as the key drivers of philanthropy (Schwartz, 1977). Other studies reveal the positive impact of strong emotions, evoked by the images of suffering and pain, on the activity of donors (Bagozzi & Moore, 1994; Small & Verrochi, 2009).

Economic theories related to this topic are based on the utility concept. For example, research done by De Alessi (1967) and Dacy and Kunreuther (1969) states that marginal utility of giving increases during the disastrous events, leading to the increase of donation amount. Gary Becker (1974) applied a "family" concept to the society, where the individual utility functions are interdependent, therefore charity is perceived as a form of "self-insurance", as the utility of donors is highly dependent on the well-being of the recipients (Becker, 1974).

Most of the previous works investigating the effect of crisis events on philanthropy are based on the single case studies. The first research analyzing charitable activity dynamics over time was the one conducted by Claude Berrebi and Hanan Yonah in 2016, which examined the connection between terrorist attacks on Israel and philanthropic activity. To the best of our knowledge, none of the existing studies was referring to the wartime conditions. Therefore, there remains a gap in understanding the long-term dynamics of charitable activity of society in the times of war. This research aims to contribute to this emerging research area and provide specific quantitative evidence based on the analysis of the Ukrainian case.

As a first attempt to provide the measurable evidence of the war dynamics impact on philanthropy in Ukraine, this study can be useful for the optimization of the fundraising strategies to reach maximum social engagement. Understanding the patterns in giving behavior could also help to build a proper communication driving the philanthropic activity.

The main hypothesis suggests that war-related events like missile and drone strikes elicit strong negative emotions that positively impact the amount donated. On the other hand, the psychological aspect of war is very complex, as the responses to different war-related events are very individual. While for some people these events might be mobilizing, enhancing their willingness to contribute, for others the feelings of anxiety and helplessness in front of such devastating news may lead to apathy and demotivation, exhausting their abilities to cope and support (Dweck, 2006).

To test the hypothesis, we took the data from the United24 published reports. They contain data on daily received charitable amount on each of the five aims: defense, humanitarian demining, medical aid, rebuild Ukraine, education and science. Independent variables include air alarms data obtained from alarms.com.ua, US Google Trends for the "Ukraine" category, missile attacks data obtained from Wikipedia.

We proceed with different specifications of time series models, and finally settled on a two-step ARMA(1,0)×(0,0,1)/[7] mean model followed by a Student-t GARCH(1,1) on the residuals to jointly address the volatility clustering and heavy-tailed shocks.

The rest of this paper is structured as follows: Chapter 2 provides the literature review, in Chapter 3 describes the data and Chapter 4 offers a methodology description. Chapter 5 presents the estimation results and Chapter 6 draws conclusions.

C h a p t e r   2

LITERATURE REVIEW

Since 1980s, philanthropic studies have evolved into a new multidisciplinary field, as "a response to both practical and intellectual needs"(Katz, 1999). However, the progress of the field has been challenged by the diversity of perspectives from the scientists in distinct disciplines and a lack of sustainable, theoretical-based research of a charitable behavior, leading to a gap between research and practice (Lindahl and Conley, 2002).

The existing literature can be divided into two major groups: psychological and economic. First one is analyzing charitable behavior as a response to emotional stimuli, and factors evoking those stimuli. The second one is considering giving in the context of utility maximization. Studies described below were specifically chosen for this review as those that would be the most applicable to the wartime context.

Psychological aspect of giving was the first and one of the key areas of researchers focus. Schwartz in his Norm Activation Theory (1977) states that the cognitive structure of individuals' norms and values activates the feeling of personal responsibility in particular situations, leading to helping behavior. He also indicates the following key drivers of prosocial behavior: awareness of need, awareness of consequences and moral obligation. People are more willing to help when they believe that their actions can directly alleviate negative consequences for those in need, as well as when they feel morally obliged to act based on their values (Schwartz, 1977).

Another important research in this area was conducted by Cialdini in 1984. In his book "Influence. Psychology of Persuasion" the author argues that one's willingness to give is highly influenced by perceived societal norms and expectations. The experiments show that individuals are more likely to act charitably when they see others' engagement, feeling the psychological weight of conformity (Cialdini, 1984). Some researchers decided to examine charitable activity even on a physiological level. Harbaugh, Mayr, and Burghart (2007) demonstrated that a philanthropic behavior activates brain areas associated with the experience of pleasure and reward.

Economic perspectives on giving shed a new light on understanding prosocial behavior. For example, Gary Becker in his article „A Theory of Social Interactions" (1974) applied an economic concept of utility to social interactions. Perceiving givers and recipients as a "family" in which the utility functions of each party are interdependent, he argues that the utility of a giver depends not only on his own consumption, but on the well-being of the recipient (Becker, 1974). The concept of "warm-glow giving" introduced by James Andreoni also undermines the traditional pure altruistic explanation of giving donations, arguing that individuals might be motivated by personal satisfaction from the act of contributing ("warm glow"), social pressure and guilt, rather than by benefits their actions provide to others (Andreoni, 1989).

Both psychological and economic factors found their reflection in the context of crisis and wartime research. Research shows that the perception of higher personal threat increases the likelihood of engagement into charitable activity (Fowler & Kam, 2007).

Researchers De Alessi (1967) and Dacy and Kunreuther (1969) developed an economic theory based on the marginal utility of giving. The hypothesis states that individuals derive utility from the welfare of others, therefore, when the cost of acquiring this utility decreases compared to other sources (after the disastrous events), the scope of donations increase.

Two more theories suggest that the destructive wartime events translate into higher philanthropic activity. The first one, Terror management theory, developed by Becker (1971) and Greenberg et al. (1986), states that the awareness of mortality increases people's engagement into pro-social activities. The second, the identifiable victim effect, suggests that people tend to donate more to the victims that are recognizable, than to the same number of statistical victims (Jenni and Loewenstein 1997).

Based on the theories mentioned above, researchers Claude Berrebi and Hanan Yonah in 2016 investigated the connection between terrorist attacks on Israel and philanthropic activity. This study was the first one analyzing the impact of terrorist attacks on charitable giving over a long period of time.

The authors used an OLS model with the amount of individual donation as a dependent variable, and terrorist attacks, sociodemographic conditions and time fixed effect as independent variables. Findings show that there is a significant effect of the terror attacks on charitable activity among all income and age groups (Berrebi and Yonah, 2016).

Feelings of compassion and helplessness, common emotional responses to crises, are also well-documented drivers of charitable actions (Stonsy, 2022). Many previous studies on philanthropy agree on the existing positive relationship between the intensity of feelings such as sadness, empathy and compassion, and charitable activity. Images of suffering and pain elicit strong emotions, which in turn is reflected in the amount of donations (Bagozzi & Moore, 1994; Small & Verrochi, 2009). The study of Pamela Miles Homer (2021) shows also that mixed emotion appeals, such as hope and sadness eliciting, generated the highest level of donations. This could be relatable to the Ukrainian case: people may respond to the missile strikes with high number of casualties in increased philanthropic activity, feeling higher threat, but also compassion and hope that they can be helpful and contribute to the country's resilience.

The reviewed literature indicates the main drivers of charitable activity, considering both psychological and economic aspects of giving. The existing research provides an explanation of pro-social behavior based on emotional stimuli, such as moral obligation, guilt, conformity, stress, vulnerability; as well as economic stimuli, such as utility acquired from giving. Studies related to the charity during the long period of terrorist attacks highlight the significance of disastrous events in enhancing people's willingness to give. Negative feelings such as sadness, helplessness and personal threat, together with the short-run changes in the individual's utility function and a higher marginal utility of giving, translate into higher scope of donations. However, there remains a gap in understanding the effect of war over charity, particularly in a long-term perspective. This research aims to bridge the gap by investigating philanthropic behavior dynamics using the data from the full-scale invasion period in Ukraine.

Chapter 3

DATA

3.1 Data Preparation

To analyze the effect of air strikes on donations activity, we created a dataset containing the daily charitable transactions data merged with variables describing the current war-related events in the country, such as daily data on missiles and drones' attacks for the same period, dummies for positive and negative events from news articles, as well as Google trends for "blackouts" and "war in Ukraine" topics.

Data on the daily transactions amount was collected from UNITED24 platform reports. It includes five categories of donations according to their aim: "Defense", "Rebuild Ukraine", "Humanitarian demining", "Medical aid" and "Education and science". The overall size of the sample is restricted to 1003 observations - since the day when the first donations on the platform were reported - 5.05.2022 till 31.01.2025. Due to the absence of reporting on weekends, donations data from Mondays was divided into 3 equal parts and imputed to weekends.

The data is highly right-skewed for each of the donation categories due to the existence of a few large values. Since the outliers might be very important in terms of revealing the pattern in donation activity, we have firstly analyzed the nature of very extreme values. Some of the outliers are most probably coming from one big individual donation from business and are followed by the large drop in the following days reported amounts. To neutralize the dynamic distortion provided by such cases, we applied the linear interpolation of the preceding and following values for such cases.

The dataset on missile attacks contains daily information on Russian terror attacks, including the type of weapon (missile/Iranian-made Shahed-136 drone), number of launched weapons and number of the ones neutralized by Ukrainian air defense forces, as well as the number of casualties (wounded and killed). The data was taken from Wikipedia's articles, which are by now the most comprehensive source of this kind of data, gathered from hundreds of news reports generated by different media.

Variables based on Google Trends include weekly trends for "War in Ukraine" searches globally and "blackouts" searches among Ukrainian users only. The data was interpolated into each day of the week.

The set of positive and negative events was taken from the news articles, including various sources (Appendix A). It consists of the war-related events that are not directly connected to the air strikes. The events were divided into positive and negative categories based on their expected impact on the country's resilience and anticipated individual emotional response.

3.2 Descriptive Statistics

Table 1 presents the main statistical properties of the variables in the dataset. UAVs are the most frequently launched weapon type, with 17.2 daily launches on average, and maximum number of 187 launched units daily. An average number of killed people daily during the period studied is 1.2, and wounded – 4.8.

Table 1. Descriptive statistics of independent variables.

Variable	mean	min	50%	max	Std
Launched rockets	6.3	0	2	132	14.3
Destroyed rockets	2.9	0	0	102	10.2
Launched UAV	17.2	0	2	187	28.6
Destroyed UAV	15.8	0	2	185	27.7
Killed	1.2	0	0	131	6
Wounded	4.8	0	0	328	17
Negative events	0	0	0	1	0.2
Positive events	0	0	0	1	0.2
Blackouts GT	16.4	0	1	100	28
War in Ukraine GT	8.1	4	8	18	3
Defense (UAH thds)	45522.8	826.4	6910.8	8417274.9	346125.1
Rebuild (UAH thds)	776.1	0	35.6	372746.3	11943.1
Education (UAH thds)	1026.5	0	0.017	219355	9981.9
Demining (UAH thds)	287.2	0	0.1	72905.5	3061.1
Health (UAH thds)	2792	0	13	314051.6	15182.2
Total (UAH thds)	49926.1	829.2	8482.7	8494593	348745.9

3.2.1 Attacks data

Table 2 presents summary statistics on the attacks. Overall, an average of 190 missiles and 522 drones were launched each month during the data period, causing 37 fatalities and 150 injury cases on average. The most frequent method of attack was by drones (527 attacks, 17 216 launched drones in total) (not presented in the table), however missile attacks (700 attacks, 6 272 launched missiles in total) caused the largest number of fatalities (n = 1061).

During the period of study, the fatalities per missile attack (0.168 on average) were 16.8 times larger than fatalities per drone attack (0.01 on average).

Neutralized to launched ratio is gradually rising during the study period, reaching its maximum of 94% in December 2024.

The overall trend of the launched weapons is increasing, influenced mainly by a rapid increase in drones (UAVs) attacks activity during the last few months of the period studied (Figures 1, 2).

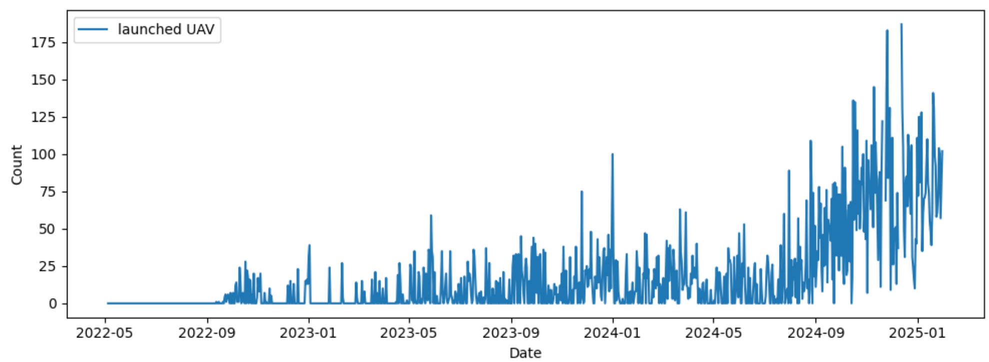

Figure 1. UAVs launches over time

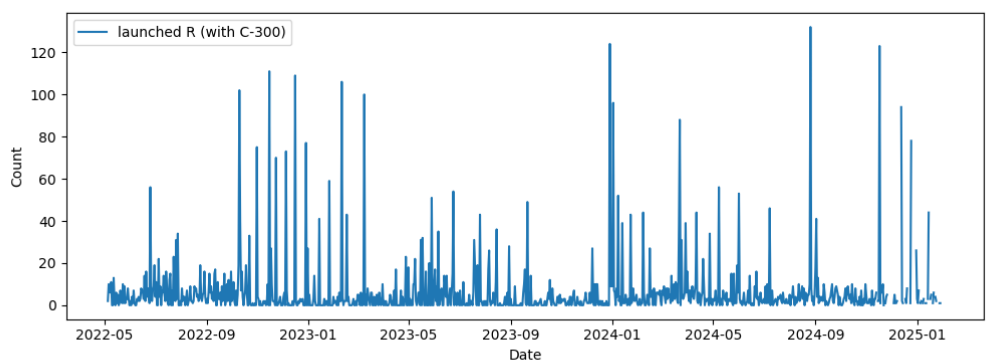

Figure 2. Missiles launches over time

Table 2. Descriptive statistics of attacks data

Month	Missiles	Drones	Neutralized / launched ratio	Wounded	Killed
2022-05-01	112	0	0.21	147	99
2022-06-01	204	0	0.19	48	163
2022-07-01	246	0	0.15	28	81
2022-08-01	145	0	0.19	48	81
2022-09-01	188	35	0.30	23	66
2022-10-01	366	213	0.57	32	135
2022-11-01	256	76	0.63	18	111
2022-12-01	323	120	0.68	9	16
2023-01-01	135	95	0.76	53	92
2023-02-01	190	49	0.53	10	45
2023-03-01	181	94	0.45	23	43
2023-04-01	78	89	0.57	26	32
2023-05-01	236	406	0.82	8	66
2023-06-01	240	201	0.73	29	135
2023-07-01	161	254	0.72	26	270
2024-08-01	149	186	0.73	34	270
2023-09-01	114	504	0.78	5	155
2023-10-01	63	285	0.71	64	69
2023-11-01	57	369	0.77	22	26
2023-12-01	226	625	0.76	25	130
2024-01-01	311	375	0.66	23	215
2024-02-01	149	377	0.69	18	160
2024-03-01	346	603	0.70	76	284
2024-04-01	205	295	0.67	58	269
2024-05-01	170	349	0.79	18	73
2024-06-01	144	328	0.84	25	154
2024-07-01	129	427	0.81	67	286
2024-08-01	261	789	0.84	27	147
2024-09-01	176	1327	0.89	88	567
2024-10-01	102	1917	0.91	29	154
2024-11-01	279	2406	0.94	44	244
2024-12-01	237	1833	0.94	20	105
2025-01-01	93	2589	0.88	25	100

3.2.2 Donations data

Table 3 presents descriptive statistics of different donations categories over time. Among the five donations categories, “Defense” has shown the highest monthly average donated amount - 828028.1k UAH , comparing to “Health” - 70672.5k UAH, demining - 3118.7k UAH, rebuild - 10273.6k UAH, and “Education” - 5082.9k UAH.

Table 3. Descriptive statistics of donations data (in thds UAH)

Month	Defense	Rebuild	Education	Health	Demining
2022-05-01	1,382,889	0	8,254	32,043	0
2022-06-01	568,324	0	11,031	56,007	0
2022-07-01	547,099	0	11,044	54,849	0
2022-08-01	408,291	0	4,490	96,050	0
2022-09-01	413,373	0	7,123	18,310	0
2022-10-01	604,090	0	14,122	69,728	0
2022-11-01	670,128	0	28,923	90,947	0
2022-12-01	728,153	0	15,416	280,055	0
2023-01-01	427,960	0	3,132	19,263	0
2023-02-01	306,478	0	19,900	168,857	0
2023-03-01	733,580	0	9,751	62,789	0
2023-04-01	284,159	0	3,358	100,852	0
2023-05-01	763,155	3,733	14,032	55,449	30
2023-06-01	1,374,779	3,566	8,636	46,261	5,863
2023-07-01	220,003	8,324	12,305	21,644	5,442
2024-08-01	209,190	8,105	15,319	48,388	1,149
2023-09-01	756,286	7,618	15,251	35,145	5,686
2023-10-01	204,726	3,845	3,812	4,227	5,455
2023-11-01	253,891	7,313	7,582	70,447	9,839
2023-12-01	1,074,673	10,861	4,856	124,705	774
2024-01-01	258,684	6,892	1,470	2,413	598
2024-02-01	674,680	16,681	4,790	73,579	1,009
2024-03-01	185,505	10,414	1,045	1,027	84
2024-04-01	300,958	5,539	489	28,633	1,168
2024-05-01	663,628	7,479	749	1,206	30
2024-06-01	111,115	9,938	519	41,016	65
2024-07-01	180,415	8,058	1,619	111,614	3,270

Table 3 – continued

2024-08-01	162,103	3,307	380	1,422	1,848
2024-09-01	597,213	3,003	522	2,018	1,872
2024-10-01	176,668	6,143	7,014	20,741	5,738
2024-11-01	233,536	2,003	4,063	75,400	3,581
2024-12-01	160,906	15,366	18,489	32,060	8,196
2025-01-01	1,298,948	19,545	374	396	569

Rebuild and Deming categories were created in May 2023, one year later than the other three, therefore there are zero values in the beginning of the studied period.

The dynamics of daily donations is quite volatile, with a few extreme spikes (Figure 3).

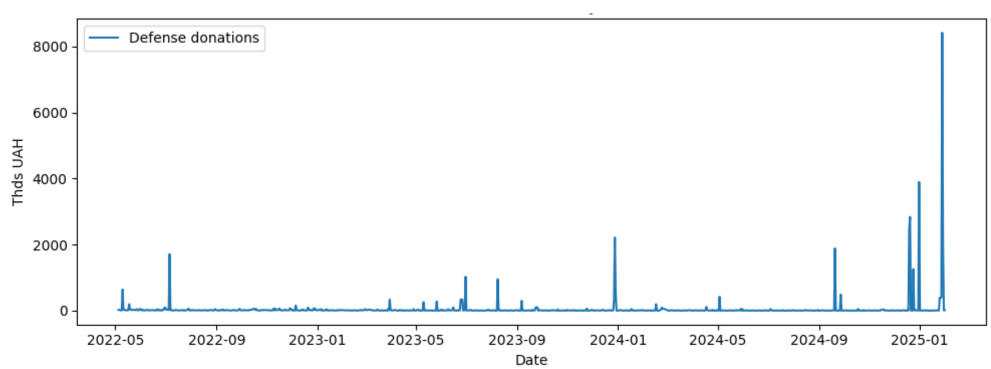

Figure 3. Daily sum of donations for "Defense" category (thds UAH)

We assume that a full social response on the attacks or other war-related events unfolds in a form of charity over several days, after the media coverage. Also, the activity could be dependent on the working schedule, therefore we decided to take a 7-day moving average to reduce noise but yet capture the short-time effect (Figure 4).

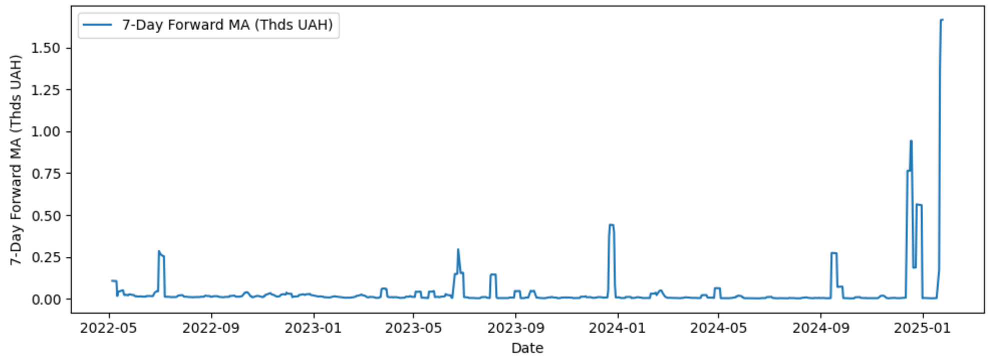

Figure 4. 7-day forward-looking moving average of the defense donations (thds UAH)

To further reduce noise, we decided to log-transform the 7-day moving average series (Figure 5). The overall trend seems to be declining, although a few extreme donations in the end revert this dynamic. However, the extreme spikes are single one-day outliers, followed by an instant fall, reverting the number to a previous level. Therefore, we assume that these are not increases in the amount of individual donations, but rather the one-time substantial donations from businesses or organizations. To address these outliers' issue, we later linearly interpolated these values with an average of a preceding and a previous value in each of the cases.

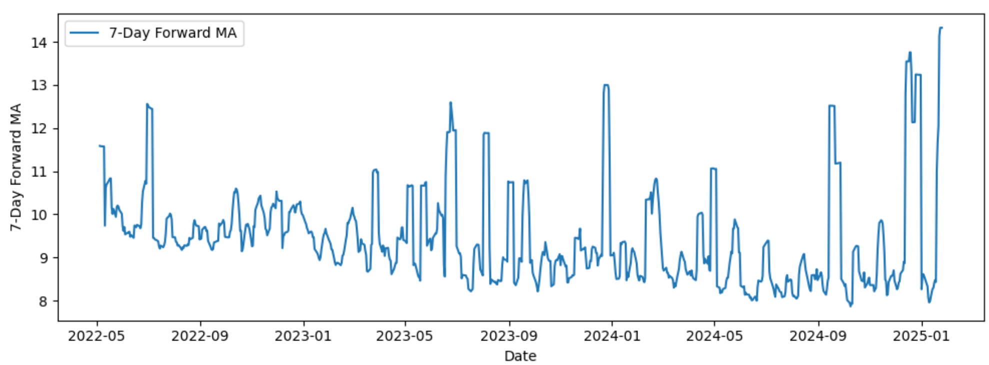

Figure 5. Log-transformed 7-day moving average of defense donations series

Chapter 4

METHODOLOGY

We have chosen an autoregressive model with exogenous regressors (ARX) due to several reasons. Firstly, it allows to control the time-series peculiarities, such as autocorrelation and seasonality, while isolating the direct effect of independent variables. Compared to the models with MA component, ARX makes the coefficients fully interpretable, as part of their impact would be absorbed in the moving average term. The model's simplicity and interpretability are crucial for further policymaking or decision-making processes. It allows us to quantify the effect of various analyzed factors on the dependent variable - willingness to donate expressed in daily donated amount.

$$\log(y_t) = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-7} + \beta_3 pos + \beta_4 neg + \sum_{k=0}^{5} \delta X_{k,t} + u_t \tag{1}$$

$\log(y_t)$ is a logged 7-day forward looking moving average donation amount. We assume that social response unfolds over several days after the attack and the media coverage. Also, the activity could be dependent on the working schedule, therefore we decided to take a 7-day moving average to reduce noise but yet capture the short-time effect.

We decided to use a 'Defense' donation category as a dependent variable in our model, since it is the biggest one and contains almost 90% of the total monthly donated amount on average, therefore it captures most of the fluctuations in charitable giving. All other categories include a much bigger number of extreme short-time outliers and substantial volatility over time, which could not be explained by a prolonged mass social response.

y_{t-1}, y_{t-7} are the 1-day and 7-day lags of the dependent variable, that were added due to the data's autocorrelation patterns, revealed by ACF and PCF functions (Figures 6-9). We inspected both 7- and 3-day moving average series of donated amount. Lag 1 spike indicates the connection of the consecutive days' charitable behavior, whereas lag 7 indicates the weekly pattern.

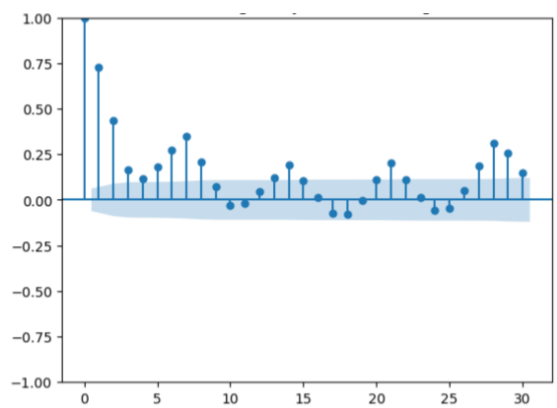

Figure 6. ACF function of 3-day MA donation amount

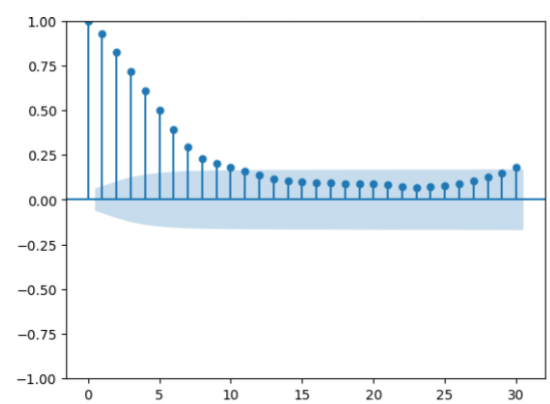

Figure 7. ACF function of 7-day MA donation amount.

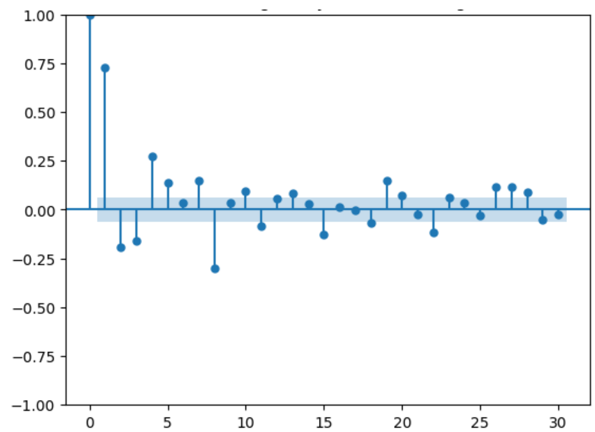

Figure 8. PACF of 3-day MA of donation series

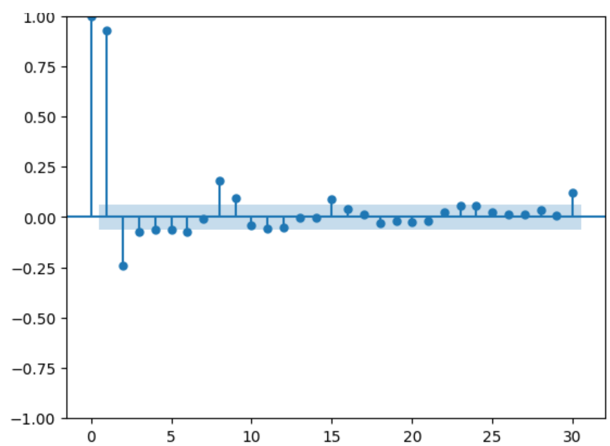

Figure 9. PACF of 7-day MA of donation series

$X_{k,t}$ represents a vector of independent variables expected to have an influence on the variable of interest: daily number of launched missiles and drones, number of casualties (wounded/killed), global weekly Google Trends values for the term "War in Ukraine" and weekly Google Trends values "Blackouts" search in Ukraine). These variables are supposed to reveal the effect of an international interest in the events in Ukraine, which could have correlated with a high number of international donations, and the frequency of blackouts, that are expected to affect charitable activity among Ukrainians by eliciting negative emotions of desperation, sadness and fear. To address the potential multicollinearity issue, we have combined the related variables into broader groups: total number of wounded, total number of killed, total weapons launched and total weapons destroyed, neutralized to launched ratio. The correlation matrix didn't show any significant correlation between the independent variables (Appendix B). Table 5 present a VIF table for independent variables. Since all of the regressors have VIFs<2, there are no multicollinearity concerns related to our model.

Table 4. VIF-table for independent variables

variable	VIF
const	127.67
Lag 1	1.15
Lag 7	1.10
Extreme values dummy	1.06
Total nr of killed	1.44
Total nr of wounded	1.44
Launched/Neutralized ratio	1.03
Negative events	1.06
Positive events	1.01
Blackouts GT	1.05
War in Ukraine GT	1.14

Firstly, we estimated the ARX model using OLS to derive baseline coefficients and examine the behavior of residuals. As Figures 10 and 11 show, the residuals exhibit heavy tails and skew.

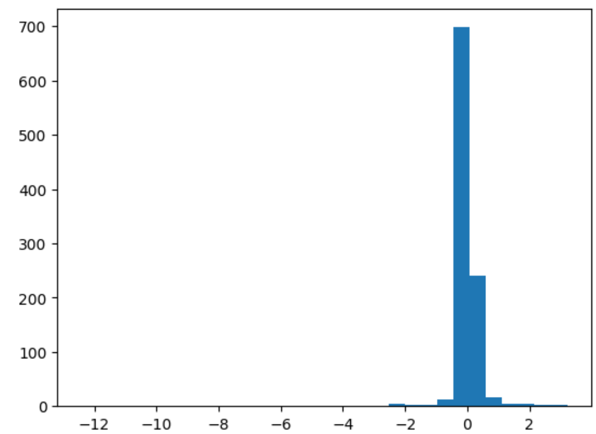

Figure 10. OLS residuals distribution

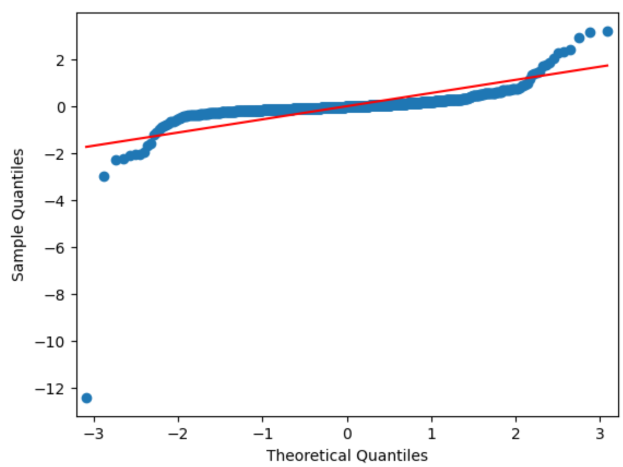

Figure 11. QQ-plot of the residuals

To ensure valid inference under such non-Gaussian errors, we re-estimated the model using Huber's robust M-estimator. using Huber's M-estimator (RLM). Unlike OLS, RLM does not require Gaussian errors for valid inference: it automatically down-weights outliers, yielding coefficient estimates and standard errors that are robust to heavy tails.

As Figure 12 shows, both OLS and RLM residuals have a clear, significant negative spike at lag 7, which confirms that our autoregressive lags cannot capture a moving-average seasonal error.

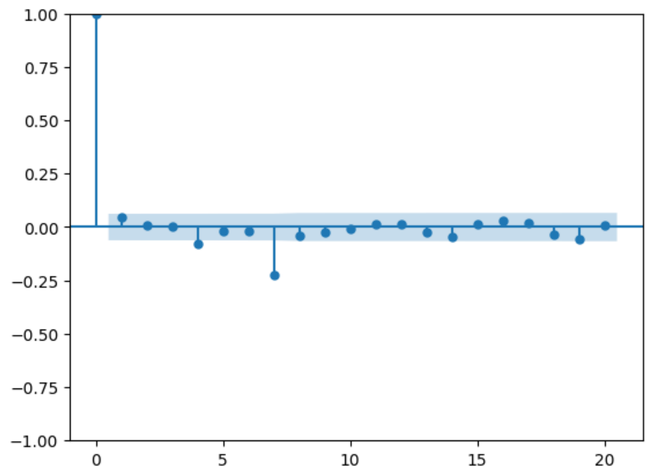

Figure 12. ACF of RLM model residuals

Therefore, to eliminate that lag-7 residual autocorrelation, we decided to switch to a SARIMAX(1,0,1)x(0,0,1,7). In this case we keep our AR components and add a seasonal MA(1) at period 7, which removes the weekly-cycle error, producing white residuals (Figure 13). Since AR7-lag turned to be insignificant, we re-run the model excluding it, therefore switching to a SARIMAX(1,0,0)x(0,0,1,7) specification.

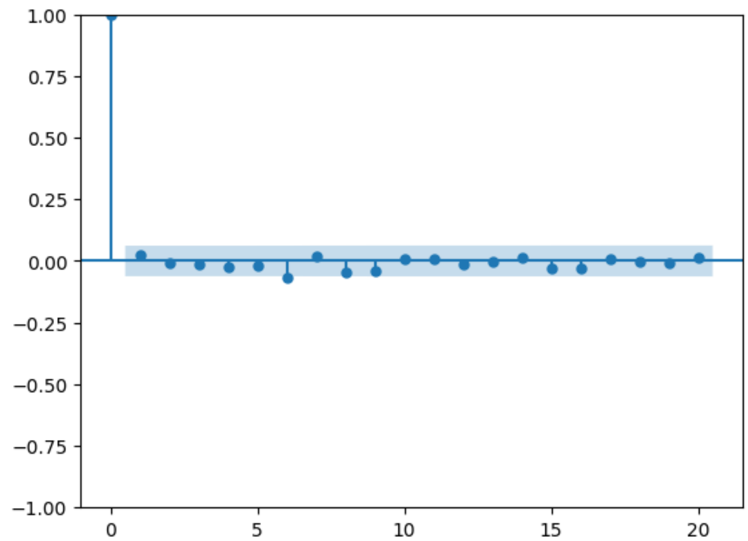

Figure 13. ACF of SARIMAX model results

Since SARIMAX MLE assumes Gaussian residuals, we should check if residuals are still heavy-tailed, which would make the model's standard errors and p-values unreliable. A Jarque–Bera normality test yields p-value of 0.006045, which indicates that the residuals distribution is very far from normal.

To solve this issue, we switch to a two-step ARMA–GARCH model with Student-t errors, will jointly model: AR lags in the mean, Student-t innovations for heavy tailed errors and GARCH(1,1) for dynamic variance. The GARCH term captures heteroscedasticity (so residual clustering vanishes). The Student-t innovation law captures fat tails in every period.

Our final two-step model—ARMA(1,0)×(0,0,1)[7] in the mean and GARCH(1,1) with student-t innovations in the variance — satisfies all key assumptions: no autocorrelation (Figure 14), correct heavy-tail distribution (Figure 15), and properly modeled volatility.

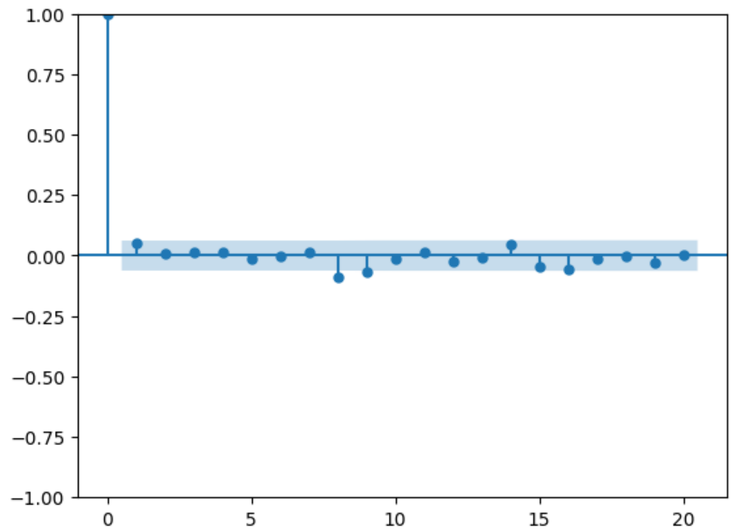

Figure 14. ACF of GARCH standardized residuals

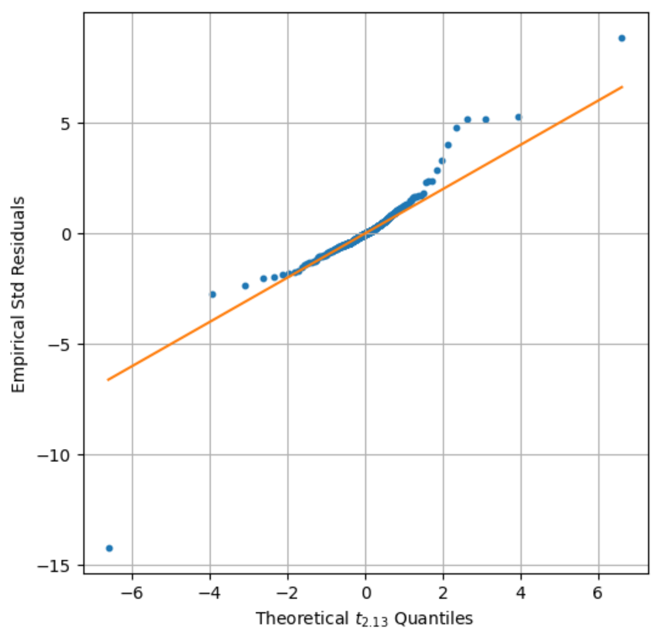

Figure 15. QQ-plot for empirical standardized residuals of ARMA-GARCH model

There is a high possibility of an endogeneity in our model. The higher donated amounts may be caused by the possible implications of media coverage on people's willingness to donate, which may cause endogeneity issues in the model. Emotional response could be affected by the way the event is covered in media - e. g. overall reporting of the casualties' number or highly sentimental personal stories. Those effects cannot be directly measured in our model due to the data limitations, however it would be important to include such variables in the future research.

Chapter 5

ESTIMATION RESULTS

Table 5 represents the results of the three different specifications of the model: OLS, Huber-RLM, and ARMA-GARCH.

Independent variables related to the attacks were combined into broader categories based on the result of the VIF. In case of each specification, the total number of launched weapons was the only attacks-related variable that remained statistically significant.

Global Google trends for "War in Ukraine" appear to be significant in some specifications. This could be explained by the peak of both global interest in the situation in Ukraine and strong emotions of the internal population in the beginning of the war, leading to higher activity in supporting the country's resilience.

Number of killed and wounded didn't show a statistically significant impact on philanthropic activity, which may be explained by the presence of endogeneity that cannot be addressed in the model - social media coverage may play a very important role in social perception of the attacks. Highlighting personal tragedies may evoke much stronger emotions and more compassion, as well as higher willingness to contribute, than general numbers of victims, even if they are higher.

Table 5. Summary of point estimates and p-values

dependent variable	(1) Baseline ARX	(2) Robust ARX	(3) ARMA-GARCH-t
lag_1	0.9896 (0.003)***	0.9896 (0.003)***	0.9731 (0.018)***

Table 5 - Continued

lag_7	-0.1398 (0.019)***	–0.0362 (0.004)***	
Killed total	0.009 (0.003)	6.651e-05 (0.001)	0.0002 (0.003)
Wounded total	-0.0006 (0.001)	7.052e-05 (0.000)	-1.892e-05 (0.002)
Launched total	0.0015*** (0.001)	0.0002** (0.000)	0.0011*** (0.000)
Negative events	-0.0411 (0.094)	-0.0220 (0.019)	0.0261 (0.123)
Positive events	0.0193 (0.091)	0.0164 (0.018)	0.0738 (0.093)
Blackouts GT	0.0002 (0.001)	-2.033e-05 (0.000)	0.0018 (0.004)
War Ukaine GT	0.0368 (0.007)***	0.0074 (0.001)***	0.0806 (0.041)
MA S lag7			-0.5977 (0.024)

As Table 6 shows, Ljung–Box results for residual autocorrelation in the ARMA–GARCH standardized residuals indicates no serial autocorrelation.

The Jarque–Bera Normality test on the standardized residuals implies that the distribution of the residuals is far from normal, as expected under a *t* specification).

Variance inflation factors for all regressors are < 2, indicating no multicollinearity present in the model.

Table 6. Diagnostic Tests and Multicollinearity (VIFs)

Test / Variable	Statistic	p-value
Ljung–Box Q(12)	8.45	0.78
Jarque–Bera (Std Res.)	25 720.7	<0.0001
Variance Inflation Factors (VIF)		
lag1	1.2	—
lag7	1.21	—
Total killed	1.86	—
Total wounded	1.88	—
Launched/destroyed ratio	1.04	—
Negative events	1.1	—
Positive events	1.08	—
Blackouts GT	1.02	—
War in Ukraine GT	1.03	—

To test the significance of the launched variable in different specifications, we run the following models: ARMA-GARCH with the number of launched missiles, and the same model with the number of UAVs launched instead. The result revealed that UAVs launched are the reason of the "total" variable significance.

We suppose that this dependency might be significant only due to the last months of the period studied, where the activity of drone attacks highly increased, and there were few significant spikes in donations. To check this assumption, we ran two separate models using the data cut to the end of November 2024. We tested two specifications for each case – with the dependent variables "launched UAVs" and "launched missiles".

Table 7 provides a summary of the key assumptions' validation for the final ARMA-GARCH model. The coefficients of interest were not significant in each case. Hence, the results are not robust and we fail to reject the null hypothesis.

Table 7. Robustness check

dependent variable	(1) Data < 30/11/2025	(3) Data < 30/11/2025	(4) Full series	(5) Full series
AR lag_1	0.9791*** (0.008)	0.9817*** (0.007)	0.966*** (0.017)	0.966*** (0.018)
MA S lag7	–0.2790*** (0.020)	-0.3184*** (0.019)	-0.5806*** (0.023)	-0.5687*** (0.023)
Killed total	54.2e-05 (0.002)	-9.066e-05 (0.002)	-0.0008 (0.007)	-0.0001 (0.008)
Wounded total	0.0001 (0.001)	9.847e-05 (0.001)	0.0002 (0.002)	0.001 (0.001)
Launched UAV	-1.119e-05 (0.000)		0.0009*** (0.002)	
Launched R		0.0001 (0.000)		0.001 (0.001)
Negative events	0.0387 (0.036)	0.0270 (0.38)	0.0680 (0.132)	0.0399 (0.134)
Positive events	-0.0102 (0.038)	-0.0051 (0.36)	-0.0005 (0.105)	-0.0180 (0.107)
Blackouts GT	–0.0004 (0.005)	–0.0002 (0.004)	–0.0002 (0.001)	0.0013 (0.005)
War Ukaine GT	0.0246 (0.007)	0.0175 (0.019)	0. 0836* (0.045)	0.0907** (0.042)

Chapter 6

CONCLUSIONS

This paper has empirically assessed the impact of air strikes and their human consequences on the short-term charitable behavior in Ukraine. To examine whether the factors mentioned have a measurable effect, we complied the data from UNITED24 platform daily reports since May 5, 2022 together with casualties' numbers - statistics for killed and wounded, taken from media sources, as well as launched to neutralized weapon data and Google Trends for 'war in Ukraine' and 'blackouts' categories. Then, we formulated a stepwise empirical approach, that allowed to ensure valid inference while accounting for serial dependence, outliers, volatility clustering, and heavy-tailed errors.

The baseline ARX(1,7) model estimated through OLS indicated significant day-to-day and weekly persistence, alongside heavy-tailed, autocorrelated residuals. The Huber-RLM ARX method effectively down-weighted outliers, maintaining the point estimates and confirming that extreme fundraising days did not influence the results. The SARIMAX(1,0,0)×(0,0,1)[7] model included seasonal MA(1) component that completely whitened the residuals. A two-step ARMA–GARCH(1,1) Student-t model, addressed issues of heteroskedasticity and fat tails, resulting in robust standard errors and valid p-values.

Across multiple specifications (OLS, robust M-estimation, SARIMAX and GARCH-t) the coefficients for all air strikes related variables remained statistically insignificant, with $p>0.5$ in every model. Therefore, contrary to the initial expectations, no short-run response in donation amount to the attacks' intensity was detected. The results are robust among different model specifications, with or without seasonal lags and log-transformed 7-day and 3-day donation series moving averages.

The research has a few possible limitations that could be addressed in the future studies. First of all, media-coverage metrics would capture the effect of psychological response on different ways of the delivery of information about attacks intensity and casualties. Also, including the individual transactions amount in the model instead of daily aggregated sum of donations would allow to examine the total number of transactions as a response for attacks activity, together with controlling for substantial donations from businesses. Including the donor demographics variables would allow to inspect the local response in charitable giving behavior in the areas where the attacks occurred. Finally, the choice of donation channels may change with time among givers – individual fundraising activities may have become more popular.

The findings suggest that policymakers should focus on the long-term broader narratives and alternative triggers to mobilize donor support, rather than appeal to the single war-related events.

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APPENDIX A

THE LIST OF KEY WAR-RELATED EVENTS OCCURRED DURING THE STUDIED PERIOD

3/16/2022 – Mariupol drama theater bombing.

3/24/2022 – Destruction of a Russian landing ship "Saratov".

4/1/2022 – Withdrawal of Russian troops from the Kyiv region.

4/2/2022 – Identification of civilians tortured by Russian soldiers in the liberated territories in the Buchansky district of the Kyiv region.

4/8/2022 – Missile strike on Kramatorsk railway station.

4/14/2022 – Destruction of the Russian missile cruiser "Moscow".

5/9/2022 – US President signed the Lend-Lease law for Ukraine.

5/20/2022 – The territory of "Azovstal" was occupied by the troops of the Russian Federation.

6/22/2022 – Ukrainian units left the city of Severodonetsk.

6/23/2022 – Ukraine was granted the status of a candidate for EU membership.

6/27/2022 – Russia had a default on its sovereign debt in foreign currency.

6/30/2022 – Liberation of Zmiinyi Island.

7/3/2022 – Ukrainian units left the city of Lysychansk.

7/29/2022 – Mass murder of prisoners in Olenovka.

8/9/2022 – The Armed Forces of Ukraine launched a missile strike on the Saki airbase in the occupied Crimea.

8/29/2022 – The Armed Forces of Ukraine have initiated a counteroffensive operation in Kherson.

9/5/2022 – The Armed Forces of Ukraine of Ukraine have initiated a counteroffensive operation in Kharkiv.

9/30/2022 – Humanitarian convoy in Zaporizhzhia was attacked by Russian soldiers.

10/1/2022 – Liberation of the city of Lyman in Donetsk region.

10/4/2022 – Russian government declared the illegal annexation of four regions of Ukraine.

10/8/2022 – Explosion on the Kerch bridge.

10/10/2022 – Russian troops launched the first massive missile strike on the energy infrastructure of Ukraine.

11/2/2022 – Zaporizhzhia Nuclear Power Station shut down due to Russian shelling.

11/11/2022 – Liberation of the city of Kherson.

12/5/2022 – Drone attack of the Russian Federation's strategic aviation base in Engels and Diaghilevo.

2/11/2023 – The end of massive blackouts in Ukraine.

2/20/2023 – US President Joe Biden visited Kyiv.

3/20/2023 – Series of drone strikes in temporarily occupied Dzhankoy.

5/3/2023 – Drone strike of Kremlin in Moscow.

5/21/2023 – Ukrainian troops have left Bakhmut.

6/6/2023 – Russian soldiers blew up the dam of the Kakhovka hydroelectric station.

6/23/2023 – "Wagner" rebellion in Russia.

7/11/2023 – The Armed Forces of Ukraine attacked an ammunition depot in occupied Novoalekseevka.

7/17/2023 – Explosion on the Kerch bridge.

8/4/2023 – Russian landing ship "Olenegorsky Gornyak" was damaged.

8/24/2023 – The Armed Forces of Ukraine liberated the village of Robotino, breaking through the first line of defense of the Russian occupation forces.

9/22/2023 – The Armed Forces of Ukraine significantly damaged the headquarters of the Russian black sea fleet in Sevastopol.

10/20/2023 – Russian soldiers suffered the greatest daily losses since the beginning of the full-scale invasion.

12/14/2023 – European Council started the negotiations on Ukraine's and Moldova's membership in the EU.

1/14/2024 – The Armed Forces of Ukraine destroyed Russian long-range radar detection aircraft A-50U.

2/14/2024 – The Armed Forces of Ukraine sank the Russian large landing ship "Caesar Kunikov".

2/16/2024 – Ukraine has signed agreements on security guarantees with Germany and France.

2/17/2024 – Withdrawal of Ukrainian troops from Avdiivka.

3/22/2024 – The Kharkiv CHP plant (TEC-5) destroyed.

4/11/2024 – A couple Ukrainian thermal power stations were attacked.

4/24/2024 – The tank farm in Voronezh was damaged.

5/10/2024 – Russian troops first attempted to break through the Ukrainian state border in Vovchansk.

5/18/2024 – Russia occupied Bugruvatka of Vovchansk area.

6/25/2024 – Ukrainian troops have reclaimed positions in Vovchansk.

8/4/2024 – The first F-16 aircrafts brought into service in Ukraine.

8/6/2024 – Ukrainian offensive operation in the Kursk region of Russia began.

10/1/2024 – Russian Armed Forces occupied Vugledar in Donetsk region.

11/2/2024 – Russian Armed Forces occupied the village of Yasnaya Polyana in Donetsk region.

11/4/2024 – The authorities of Udmurtia reported an explosion on the drone factory "Kupol".

20/1/2024 – US President Donald Trump ordered a 90-day pause on all U.S. foreign development assistance programs.

APPENDIX B

CORRELATION MATRIX OF THE INDEPENDENT VARIABLES

Table 8. Correlation matrix of the independent variables

	Defense	Education	Demining	Health	Rebuild	Total killed	Total wounded
Defence	1.00	0.11	0.10	0.00	0.00	0.00	0.00
Education	0.11	1.00	0.11	0.00	0.00	-0.01	-0.01
Demining	0.10	0.11	1.00	0.16	0.04	0.09	0.15
Health	0.00	0.00	0.16	1.00	0.02	0.01	0.00
Rebuild	0.00	0.00	0.04	0.02	1.00	-0.01	-0.01
Total killed	0.00	-0.01	0.09	0.01	-0.01	1.00	0.54
Total wounded	0.00	-0.01	0.15	0.00	-0.01	0.54	1.00
Total launched	0.07	0.06	0.13	0.04	-0.02	0.07	0.14
Total destroyed	0.08	0.06	0.10	0.04	-0.02	0.04	0.10
Blackouts GT	-0.01	-0.02	0.01	-0.02	-0.03	0.02	0.04
War in Ukraine GT	0.00	0.03	-0.02	0.11	-0.02	0.02	0.06
Negative events	-0.03	-0.10	-0.05	0.06	0.03	0.05	-0.05
Positive events	-0.02	-0.02	-0.01	-0.02	0.00	0.20	0.18

Table 8 - continued

	Total launched	Total destroyed	Blackouts GT	War in Ukraine GT	Negative events	Positive events
Defence	0.07	0.08	-0.01	0.00	-0.03	-0.02
Education	0.06	0.06	-0.02	0.03	-0.10	-0.02
Demining	0.13	0.10	0.01	-0.02	-0.05	-0.01
Health	0.04	0.04	-0.02	0.11	0.06	-0.02
Rebuild	-0.02	-0.02	-0.03	-0.02	0.03	0.00
Total killed	0.07	0.04	0.02	0.02	0.05	0.20

Table 8 - continued

Total wounded	0.14	0.10	0.04	0.06	-0.05	0.18
Total launched	1.00	0.97	0.12	0.05	-0.27	0.06
Total destroyed	0.97	1.00	0.05	0.07	-0.29	0.03
Blackouts GT	0.12	0.05	1.00	-0.16	0.05	0.03
War in Ukraine GT	0.05	0.07	-0.16	1.00	-0.11	-0.01
Negative events	-0.27	-0.29	0.05	-0.11	1.00	0.02
Positive events	0.06	0.03	0.03	-0.01	0.02	1.00