EVENT-DRIVEN DONATION BEHAVIOR IN WARTIME UKRAINE: AN EVENT STUDY OF THE 28 AUGUST MISSILE ATTACK

by

Borys Bobrovnik

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Thesis Supervisor: ____________________________ Professor Dariia Mykhailyshyna

Approved by ____

Head of the KSE Defense Committee, Professor [Type surname, name]

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The author desires to share a deep gratitude to all those who became a part of fundraising and thanks to which 167,843,35 UAH has been raised, and to the 253 participants who provided their responses for the survey

A specific note of thanks is owed to all individuals who assisted in this initiative by establishing supporting fundraising accounts, especially thanks to Anastasiia Sakvenko, who was able to cooperate throughout the entire fundraising process and helping to build a team.

Heartfelt appreciation is also extended to Yaroslav Petrynka, the main organizer of the campaign and the individual responsible for procurement, whose initiative was joined through the creation of my own mentorship account.

As a result of all these collective efforts, the acquisition of essential equipment for the Armed Forces of Ukraine has been successfully completed. This procurement includes anti-drone rifles, a vehicle, drones, electronic warfare systems, radios, and other vital materiel designated for the 5th Separate Assault Brigade and the 101st Separate Brigade of the General Staff of the Armed Forces of Ukraine.

My profound respect goes to all Ukrainian soldiers who continue to fight for peace. Without their sacrifice, I could not have completed this research

Finally, I would like to express my deepest appreciation to my thesis supervisor, Professor Dariia Mykhailyshyna, for her guidance and support at every stage of writing this thesis.

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LIST OF ABBREVIATIONS

BMI Business Monitors International agency

SSSU State Statistical Service of Ukraine

WHO World Health Organization

DEA Data Envelopment Analysis

NGO Non-Governmental Organization

DiD Difference-in-Differences

OLS Ordinary Least Squares

RMSPE Root Mean Squared Prediction Error

Chapter 1. RESEARCH QUESTION AND MOTIVATION

The full-scale war in Ukraine has reshaped not only the country's security landscape but also how citizens take part in public life. Millions of people now donate on a daily basis–to foundations, volunteer initiatives, and individual campaigns–to support the military and relief efforts. Giving has become more than a civic duty; it is a key mechanism for pooling resources at scale.

Yet we still know little about what prompts donors to act. In wartime, the news cycle is crowded: reports of missile strikes, shifts on the front line, international assistance, and civilian losses all compete for attention and may influence willingness to give. Prior research shows that salient events can move donations, but it mostly studies large charities or nationwide drives. This thesis shifts the focus to the ground level, tracing how war-related shocks translate into contributions to small, campaign-specific fundraisers–the point at which individuals actually decide to donate.

This thesis applies an event study approach. I initiated a personal fundraising campaign via Monobank ("jar," launched on August 11, 2025) to support units of the 5th Separate Mechanized Brigade and the 101st Separate Security Brigade of the General Staff of the Armed Forces of Ukraine. Alongside the fundraising, a donor survey was conducted. The survey does not focus on specific events but instead collects broader indicators such as demographic and socio-economic characteristics (age, gender, region of birth, settlement size, education, employment status), amount donated, self-reported news consumption (daily time spent following news) and perceived emotional impact of war-related news (scale 0–5).

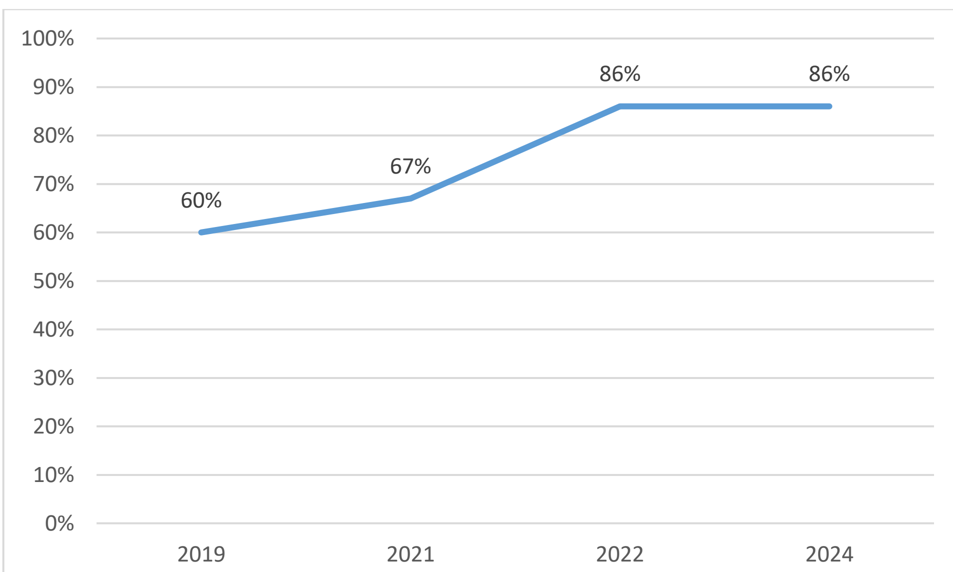
We combine the survey data with the timing of a single large-scale wartime event – the unexpected missile attack of August 28. This allows me to combine the survey with the timing of the 28 August missile attack to estimate its causal effect on donation behavior. We examine whether–and to what extent–attention to wartime news and the emotions it provokes shape Ukrainians' readiness to contribute to military fundraisers.

This thesis makes two main contributions. First, it shifts the lens to small, grassroots wartime fundraisers in Ukraine–a widespread practice that has received little systematic study. Second, it offers practical guidance for NGOs and campaign organizers by documenting how socio-demographic differences and information environments are linked to changes in donation behavior.

CHAPTER 2. BACKGROUND AND RELATED STUDIES

Public engagement in charitable activity in Ukraine has expanded dramatically since 2019 and consolidated into a new social norm during the full-scale war. According to the Zagoriy Foundation (2024), charitable engagement (the share of adults who report that in the last 12 months they personally donated money or goods, helped someone (financially or by actions), or volunteered) rose from roughly 60% in 2019 to 86% in 2022, remaining at 86% in 2024. The sustained high level suggests that many people continued to give even after the initial shock of 2022 faded. Because participation is already broad, the central issue for fundraisers and policymakers is what determines how much people donate–not merely whether they donate (Zagoriy Foundation, 2024).

Figure 1. Charitable Engagement of Ukrainians

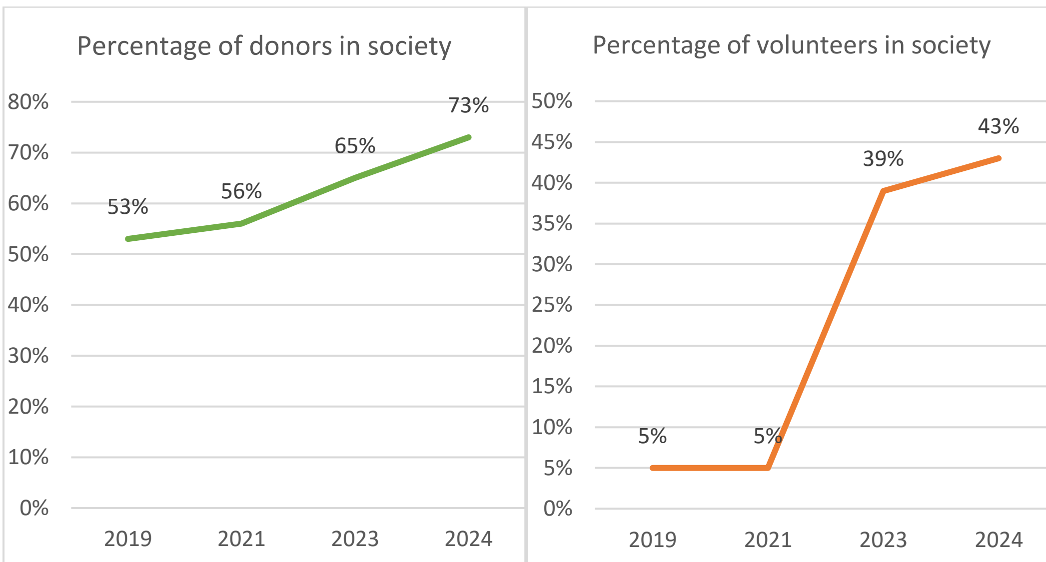


Source: Created by the author using data from the Zagoriy Foundation's 2024 study.

The donor pool has expanded. About 73% of Ukrainians said they donated in 2024, up from the mid-50% range in 2019. This matters for reading funding trends: overall inflows can change because more people join in (the extensive margin) or because donors give larger amounts on average (the intensive margin). In short, the same total can come from different mixes of participation and per-donor generosity.

Volunteering spiked right after the invasion and then leveled off. The 2022 surge reflects a rapid mobilization of time and skills, and the fact that high levels persist into 2024 suggests volunteering has become part of everyday routines. This trajectory is relevant for how time and money interact: in some periods more volunteering may go hand in hand with higher donations, while in others it may temporarily crowd them out as households manage limited budgets and attention.

Figure 2. Percentage of donors and volunteers in society



Source: Created by the author using data from the Zagoriy Foundation's 2024 study.

While in the first months of the invasion donations were largely spontaneous and uncoordinated, over time fundraising has become more structured and professionalized. Citizens increasingly contribute to established foundations such as Come Back Alive and the Serhiy Prytula Foundation, but also respond rapidly to event-driven campaigns – for instance, calls to raise funds after high-profile attacks, battlefield developments, or stories of individual heroism. These patterns suggest that the news cycle itself functions as a trigger for donation behavior.

Finally, the fundraising landscape has professionalized. Donations flow to large, reputable organizations as well as to event-driven campaigns that react to battlefield developments, major attacks or high-salience stories. This institutionalization coexists with strong event sensitivity, implying that the information environment–and the emotions it elicits–can shape not only whether people give but how much they give in a given moment (Zagoriy Foundation, 2024; Artem Fonariuk, 2024).

According to the Zagoriy Foundation's 2024 study, the main motivations for Ukrainians to engage in charity include: Compassion for those in need is 33%, Patriotism is 17%, Sense of duty to society is 16% and finally Desire to support the military to bring victory closer is 15%.

These figures point to a mixed motivational picture. Compassion still anchors giving, but it now sits alongside civic motives–patriotism and a sense of duty. The share of respondents who name support for the Armed Forces, although ranked fourth, shows how the war has reframed donations around national survival. Whereas pre-war philanthropy focused more on vulnerable groups, today many contributions are tied directly to the goal of victory (Zagoriy Foundation, 2021). In short, emotional solidarity remains the base, but wartime conditions have added a strong layer of collective responsibility.

In addition to general motives like compassion and civic responsibility, more recent findings suggest that emotional attitudes such as gratitude and guilt also play a role in motivating charitable behavior during wartime. Artem Fonariuk (2024) using survey data from Ukrainian citizens, found that 72.7% of respondents expressed the highest level of gratitude toward the Armed Forces, reflecting not just support but deep emotional alignment with defense efforts. In contrast, feelings of guilt – while present – were more moderate and diffuse.

These emotions show up clearly in people's priorities. When respondents ranked which areas most deserve support, almost two-thirds (62%) gave defense a full 10/10, while only

21% did so for healthcare. Gratitude toward medical staff was also very high–about 60.7% rated them 10/10–but that feeling did not convert into the same donation push. Overall, the pattern suggests that giving to the Armed Forces is driven not only by civic duty but by a strong moral pull, which helps explain why military aid has dominated charitable giving since 2022.

Research outside Ukraine points to a simple pattern: when an event dominates the news, donations jump. Spikes in media coverage tend to move in step with spikes in giving (Stoddard et al., 2015). After the 2010 Haiti earthquake, the spread of mobile and social platforms greatly widened the reach of appeals, and U.S. "text-to-donate" records show that many people gave by phone for the first time–evidence that the event, amplified by media, pulled in new donors (Pew Research Center, 2010). A similar rhythm appeared during COVID-19: philanthropic flows swelled around highly visible moments that were pushed hard by the media. As documented in Philanthropy and COVID-19 in the First Half of 2020 (Candid & Center for Disaster Philanthropy, 2020), large virtual events and online campaigns used broadcast and social channels to raise substantial sums within very short windows. The lesson is consistent across these cases: visibility concentrates attention, and attention concentrates donations. While these settings are not the same as Ukraine's wartime reality, the underlying mechanism–emotional salience coupled with intense media attention creating urgency–helps explain why donation activity rises around salient incidents.

At the same time, two basics still do the heavy lifting: trust and transparency. Baur and Schmitz (2012) note that clear, verifiable reporting builds trust, and trust, in turn, makes it easier to raise money. Meyer et al. (2013) add a simple checklist for nonprofit performance–efficiency, effectiveness, relevance, and sustainability. When those boxes are ticked, donors read the effort as credible and are more willing to give again, even in fast-moving, event-driven settings.

Much of the giving literature splits along two lines. One stream looks at how efficiently gifts are used or at total fundraising volumes. Classic work on altruism and donor behavior stresses "warm-glow" motives and signaling (Andreoni, 1989, 1990; Harbaugh, 1998). A second stream studies responses to shocks and humanitarian crises. Brown and Minty (2008) show that donations jump after sudden-onset disasters, while Eisensee and Strömberg (2007) document how media coverage powerfully steers the flow of international aid.

In Ukraine we still have only a small body of evidence. A recent study by Klymak et al. (2025) uses administrative records from large national campaigns and shows that sudden missile attacks with civilian casualties trigger short-run spikes in donations, with media coverage building the effect over time. That work, however, concentrates on flows to the major foundation Come Back Alive, leaving the behavior around small, grassroots fundraisers largely unexamined.

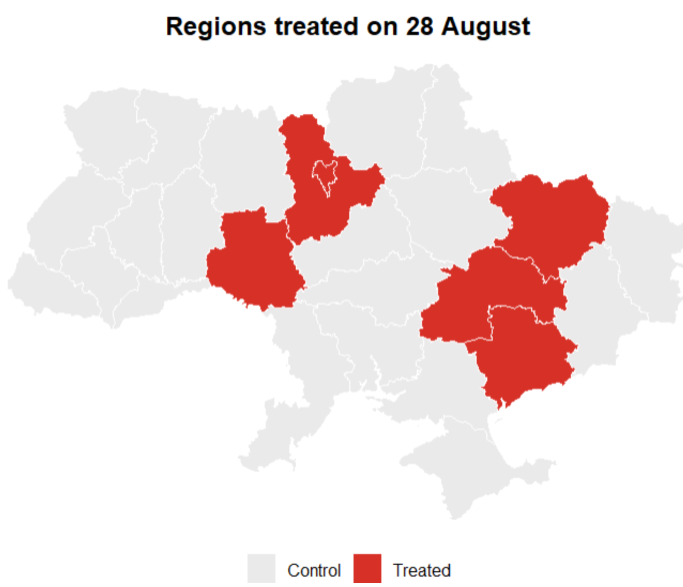
This thesis takes a different angle. I shift the lens to individual donors and decentralized giving. Using survey data with time-stamped small contributions, I provide evidence that complements the literature focused on big charities and institutional trust. The analysis links donations to news exposure, emotional reactions, and basic socio-demographic traits, showing how these factors jointly shape giving during an ongoing war.

CHAPTER 3. METHODOLOGY

To identify the effect of a major missile strike on donations, I use an event-study set within a difference-in-differences design. The focal event is the 28 August 2025 attack, when Russia carried out one of the month's most intense strikes on Ukrainian cities. The assault produced multiple explosions across several regions, caused civilian casualties, and received extensive coverage in national media. Its abrupt, exogenous timing provides a suitable setting to study short-run changes in charitable giving during wartime.

The treatment is defined using the respondent's region of origin as captured by the survey item "Which region are you from?". Respondents whose origin region was directly affected by the 28 August 2025 missile strike are classified as treated; those from unaffected regions form the control group. The treated regions are Kyiv, Dnipro, Kharkiv, Zaporizhzhia, and Vinnytsia (see Figure 3). Using region of birth emphasizes emotional attachment to place of origin, rather than current place of residence or temporary relocation, and thus captures a distinct mechanism from personal on-site exposure.

Figure 3. Regions treated on 28 August



In this specification, the outcome is the (log of) donated amount, so the coefficient on treated × after identifies an effect on the intensive margin–how much a donor gives, conditional on making a donation to this campaign. It does not capture the extensive margin (whether additional people start donating). At the respondent level, this is a natural limitation of the data because the sample consists of individuals who donated to the campaign at least once; hence, variation is primarily within-donor amounts rather than entry into donating. At the aggregate (oblast × day) level, using the log of total donations combines both margins, but it still does not separately identify changes in the number of donors. For completeness, I interpret the estimates as within-campaign adjustments in donation size; where feasible, I also examine auxiliary outcomes.

The baseline specification is:

$$Y_{irt} = \alpha + \beta(Treated_r \times After_t) + \gamma X_i + \mu_r + \delta_t + \varepsilon_{irt} \quad (1)$$

where

Y_{irt} – logarithm of the donation amount made by individual i from region r at time t;

$Treated_r$ – indicator equal to one if region of birth r was affected by the 28 August attack;

$After_t$ – indicator equal to one for donations made on or after 28 August;

X_i – vector of individual covariates (gender, settlement size, education, self-reported emotional impact of news, and daily time spent following war-related news);

μ_r – region fixed effects;

δ_t – date fixed effects;

ε_{irt} – error term.

To examine dynamic treatment effects and test the parallel trends assumption, I extend the model to an event-time specification:

$$Y_{irt} = \alpha + \textstyle\sum_{k \neq -1} \beta_k \left(Treated_r \times D_{t=k}\right) + \gamma X_i + \mu_r + \delta_t + \varepsilon_{irt} \quad (2)$$

where $D_{t=k}$ are event-time dummies indicating the number of days before (k<0) or after (k>0) the event relative to 28 August. The coefficient for k=−1 (the day before the attack) serves as the reference category. Plotting the β_k provides a visual diagnostic of pre-event parallel trends and post-event dynamics.

This specification follows recent guidance on event-study/difference-in-differences estimation with heterogeneous treatment effects (Sun, 2021). Estimation is implemented in R using the fixest package, which supports high-dimensional fixed effects and cluster-robust inference.

I also estimate a difference-in-differences model on an oblast–day panel. For oblast r and date t, let $Total_{rt}$ be the sum of donations reported by respondents born in r that were made on day t; if no such donation occurs, $Total_{rt}$=0. The dependent variable is y_{rt}=log(1+Totalrt).

Define $Treated_r$=1 for oblasts directly hit on 28 August and $After_t$=1 for dates on/after 28 August. The preferred specification is

$$y_{rt} = a_r + \delta_t + \beta(Treated_r \times After_t) + X'_{rt}\gamma + \varepsilon_{rt} \qquad (3)$$

where a_r and $\delta_t$are oblast and date fixed effects. X_{rt} contains oblast–day aggregates of individual covariates (share male, average settlement rank, average education rank, mean emotional impact, mean news-time). With fixed effects, the main effects of $Treated_r$ and $After_t$ are absorbed, so identification relies on the interaction coefficient β, which is our average DiD effect. Standard errors are heteroskedasticity-robust and clustered at the oblast (birth-region) level.

Also, I implemented robustness check and DID heterogeneity analysis.

Placebo Cut-off: Reassigning the treatment date to 25 August tests whether effects appear spuriously before the actual event;

Heterogeneity Analyses: I estimate interactions with gender only to explore whether responses differ by sex.

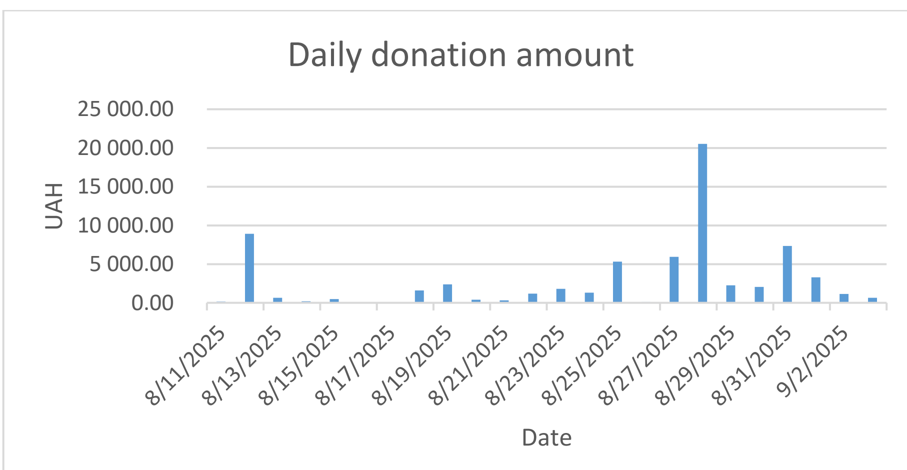
Identification relies on the parallel-trends assumption: in the absence of the 28 August shock, outcomes for treated and control origin regions would have evolved in parallel. I assess this using two complementary diagnostics. First, I estimate an event-study with day-level leads and plot the coefficients for pre-event days; the estimates fluctuate around zero without systematic drift. Second, as an additional pre-trend check, I construct a synthetic control for the aggregate treated series using only pre-event data (11–27 August). The treated unit is the sum of daily donations from the five treated origin oblasts; donor units are the remaining origin oblasts. Because the treated unit aggregates K oblasts, donor outcomes are scaled by K so a convex combination can match a treated total. Weights are chosen to minimize the pre-event RMSPE, using the average outcome over the full pre-period and separately for its early and late halves as predictors. The synthetic path closely tracks the treated series before 28 August, supporting the plausibility of parallel trends. The donor weights and the pre-period RMSPE. The synthetic control is used here purely as a additional robustness check, not for post-event causal estimation.

CHAPTER 4. DATA

The empirical analysis relies on an original dataset collected through a structured online survey of individuals who donated to my Monobank fundraising campaign between 11 August and 3 September 2025. In total, 253 valid responses were obtained. The survey recorded socio-demographic characteristics, labor-market status, patterns of news consumption, emotional responses to wartime information, and details of the donation. As a descriptive overview of fundraising dynamics in the sample, Figure 4. Daily donation amount plots the total amount contributed by respondents each day over the field period.

The dataset is cross-sectional: each observation represents one individual donor. It is merged with an event indicator that marks whether the donation occurred before or after the large-scale missile attack on 28 August 2025. The same date is highlighted in Figure 4, which shows a highly skewed distribution with a few pronounced spikes amid otherwise modest daily inflows. Importantly, the figure reflects respondent-reported donations only and does not represent totals.

Figure 4. Daily donation amount



The sample is dominated by young donors. As Figure 5 shows 88.1% of respondents are between 14 and 34 years old, 10.6% are aged 35–59, and less than 2% are either below 14 or above 60. Within our sample, younger respondents account for most donations. Because the survey is not designed to be representative of the donor population, we refrain from generalizing this age profile beyond the sample. Female donors constitute the majority, though the distribution is relatively balanced. Specifically, 56.4% of respondents are women, while 43.6% are men.

Figure 5. Sex and age data

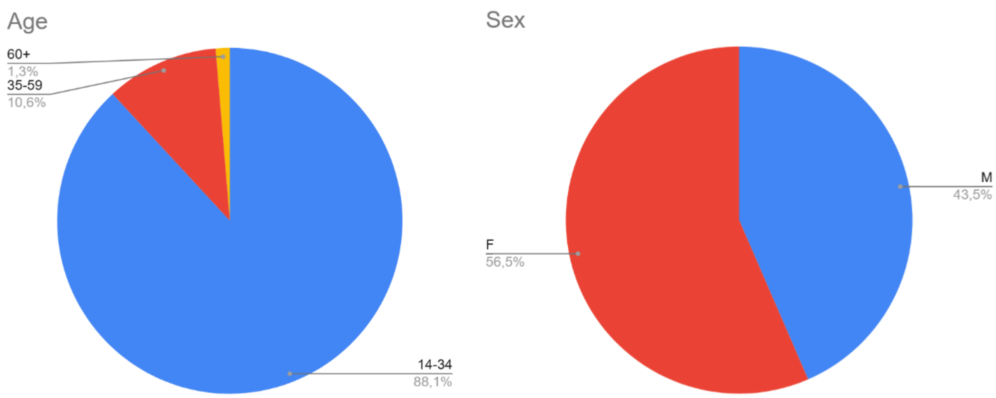
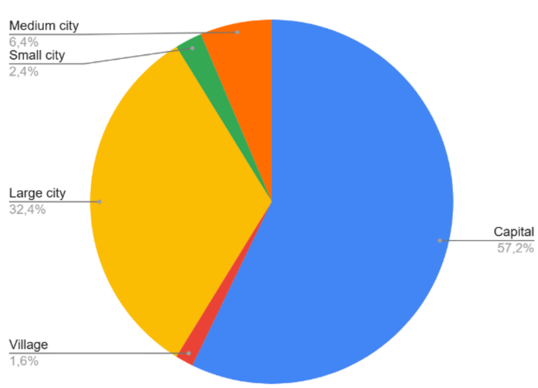


Figure 6 illustrates the distribution by place of residence. More than half of respondents (57.2%) live in the capital city, 32.4% in large cities, and the rest are spread across smaller towns and villages. This urban concentration suggests that fundraising campaigns are most effective in densely populated areas with high digital penetration.

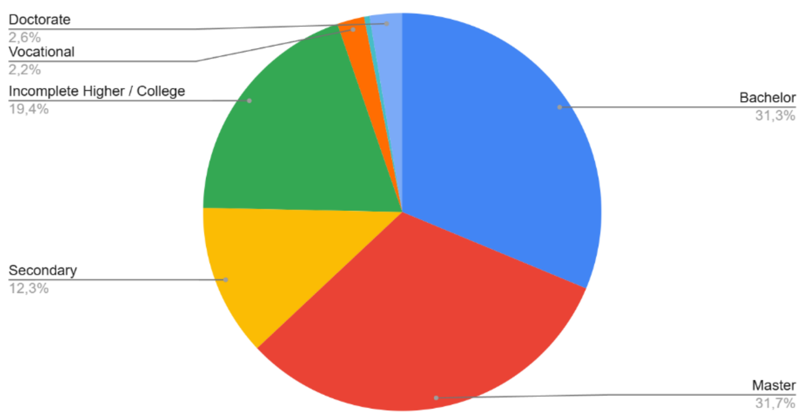
Figure 6. Place of residence



Educational attainment is high. As shown in Figure 7, about 32% hold a Master's degree, 31% a Bachelor's degree, and 19% vocational or incomplete higher education. Only 11% reported secondary education as their highest level, while very few hold a doctorate.

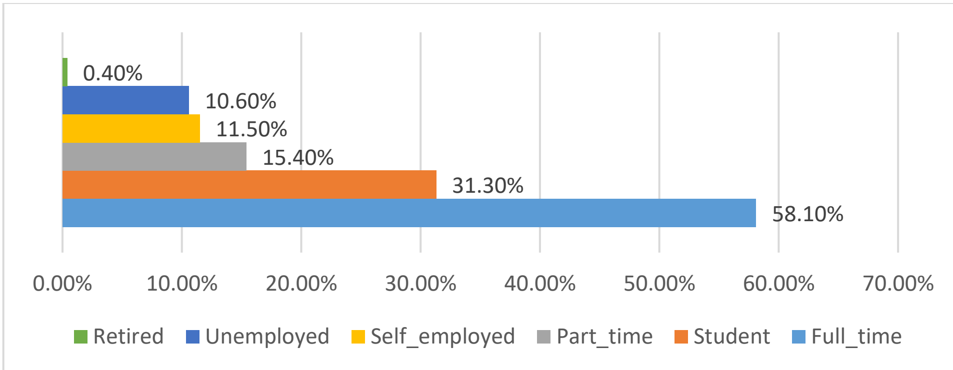
Because the treatment in our empirical design is assigned using donors' region of birth, I report the distribution of respondents by birth region. Kyiv accounts for 80 of 253 observations (31.6%), followed by Lviv (17; 6.7%), Luhansk (15; 5.9%), Ivano-Frankivsk (13; 5.1%), and Cherkasy (10; 4.0%); the remaining regions each contribute between 3 and 8 observations. The complete breakdown is provided in Appendix A

Figure 7. Education



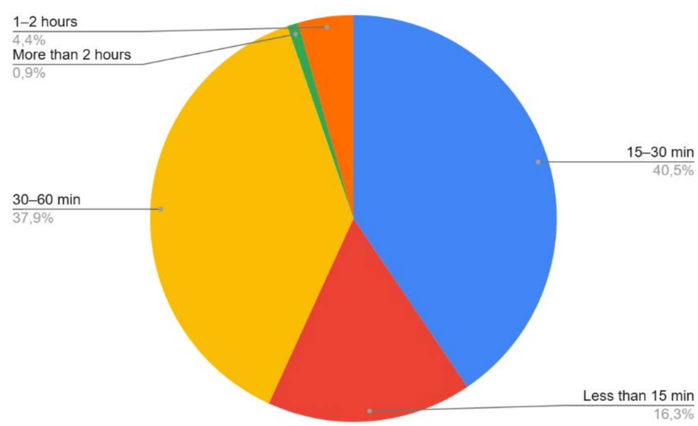
Employment status. Figure 8 shows that 58% of donors work full-time, 31% are students, and smaller shares are part-time (15.4%), self-employed (12.5%), or unemployed (11%); only one respondent reported being retired. Categories were not mutually exclusive: respondents could select multiple statuses at the same time (e.g., student and part-time). Therefore, percentages need not sum to 100% and should be read as the share of respondents who reported each status.

Figure 8. Employment



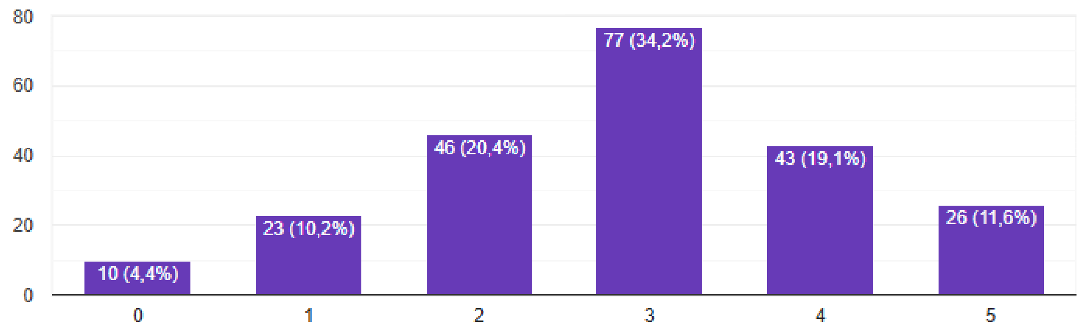
The survey asked respondents how much time they spend following the news daily. As Figure 9 shows, 40% reported 15–30 minutes per day, 38% between 30–60 minutes, and 16% less than 15 minutes. Only a small minority (around 5%) follow news more than 1 hour.

Figure 9. News consumption



Respondents also rated how strongly war-related news affects their emotional state on a 0–5 scale. The distribution is approximately bell-shaped, with the mode at 3 ("moderate impact"). About 34% of respondents selected 3, 19% selected 4, and 12% reported the maximum level of emotional influence (5). Only 4% indicated that news does not affect them at all.

Figure 10. Emotional impact



Beyond demographics and information exposure, the dataset contains self-reported donation amounts. The variable is highly skewed: most donors contributed relatively modest sums (100–500 UAH), while a few made substantially larger transfers. For the econometric analysis, this outcome was log-transformed.

Overall, the donor pool in our data is young, urban, and highly educated. This composition is consistent with the idea that donation activity may be more prevalent among groups with stronger digital access and civic engagement, although external evidence would be needed to confirm this at the population level.

CHAPTER 5. RESULTS

For each calendar day and each oblast of birth I construct one observation equal to the total amount donated by survey respondents born in that oblast on that day. If there were no donations from donors born in oblast r on day t, the oblast-day cell is set to 0. The dependent variable is log(1+total donations_{rt}), denoted log_total. The treatment indicator treated equals 1 for oblasts directly hit by the 28 August 2025 strike; after2 equals 1 for dates on or after 28 August. In the specification with controls, I include cell-level averages of donor characteristics (share male, mean education/settlement rank, mean emotional impact, and mean time spent following the news). Standard errors are clustered by oblast. These aggregates reflect donations reported by respondents rather than totals.

Table 1 reports the aggregated DiD estimation (475 oblast × day cells). In the no-controls specification, the interaction after2×treated is positive but statistically insignificant (0.926, s.e. 0.658). Adding the oblast–day averages as controls yields a very similar coefficient (0.977, s.e. 0.626), also imprecise. By contrast, the main post-period indicator after2 is large and precisely estimated in both columns (2.128, s.e. 0.418 without controls; 2.060, s.e. 0.393 with controls), indicating a common increase in reported donations across all oblasts after 28 August. The main-effect treated term is small and imprecise. Among controls, higher settlement size is associated with lower donations (–0.171, s.e. 0.078), while education is positively related (0.108, s.e. 0.056); other controls are not statistically significant. Model fit rises modestly with controls ($R^2 = 0.118 \rightarrow 0.132$).

Taken together, the aggregated DiD does not detect a statistically significant treatment–control divergence in daily totals after the strike. The positive point estimates on after2×treated (≈0.93–0.98 log points) hint at an upward response in treated oblasts, but the confidence intervals are wide. The precisely estimated after2 effect points to a broad, period-wide shift that the DiD comparison nets out.

Event-time plots show that any treatment response, if present, is short-lived. To focus on the immediate aftermath and avoid contamination by later dynamics, I also estimate two model variants that restrict the post-event window to 28–29 August (inclusive). Results are similar and reported in Appendix Table 1 and Table 2. Results are unchanged: the after × treated interaction remains statistically insignificant, reinforcing the conclusion that the strike did not generate a persistent, differential change in aggregated daily donations between treated and control oblasts among our respondents.

Table 1. Aggregated DiD Analysis at the oblast × day level

	Dependent variable:	
	log= log(1 + total	
	no controls	+ controls
	(1)	(2)
after2	2.128^{***}	2.060^{***}
	(0.418)	(0.393)
treated	0.296	0.165
	(0.447)	(0.450)
avg_gender		-0.025
		(0.186)
avg_settlement		-0.171^{**}
		(0.078)
avg_education		0.108^{*}
		(0.056)
avg_emotional		0.134
		(0.093)
avg_news		-0.174
		(0.147)
after2:treated	0.926	0.977
	(0.658)	(0.626)
Constant	0.796^{***}	0.770^{**}
	(0.110)	(0.361)
Observations	475	475
R^2	0.118	0.132
Adjusted R^2	0.113	0.117
Residual Std. Error	2.016 (df = 471)	2.011 (df = 466)
F Statistic	21.087^{***} (df = 3; 471)	8.850^{***} (df = 8; 466)
Note:		$^{*}p^{**}p^{***}p<0.01$

Table 2 reports respondent-level regressions where the dependent variable is log(1+amount) and the key regressor is an indicator after that equals one for donations made on/after 28 August 2025. The models progressively add controls (M1–M3) and, in the most demanding specification (M4), include region×date fixed effects and clustered standard errors.

Across specifications, the main after2 coefficient is not stable in sign or significance: −0.311 (0.189) in M2, −0.623 (0.207) in M3, and 0.760 (0.542) in M4. With region×date FE (M4) it becomes imprecise, so we do not interpret it as evidence of a systematic post-event shift. By contrast, the DiD term after2×treated is positive in all models–0.416 (0.330) in M1, 0.588 (0.280) in M2, 0.681 (0.322) in M3, and 0.636 (0.420) in M4–statistically significant in M2–M3 but imprecise once region×date FE are included (M4). Thus, any post-event increase for treated oblasts is not robust to the most demanding specification.

Higher education is strongly associated with larger donations (Master: 0.544, Doctorate: 0.838). Relative to the capital, living in a large city is associated with smaller donations (−0.405, −0.487, −0.590). Gender and self-reported emotional impact are small and statistically insignificant. News-consumption categories are generally negative but not statistically significant. Model fit rises from R^2=0.010 (M1) to R2=0.390 (M4); N=200 in M1–M2 and N=199 in M3–M4.

Overall, the individual-level results provide no robust evidence of a post-event change in average donation amounts once region×date fixed effects are absorbed, while socio-demographic characteristics–especially higher education and settlement size–are the more consistent correlates of giving in this sample.

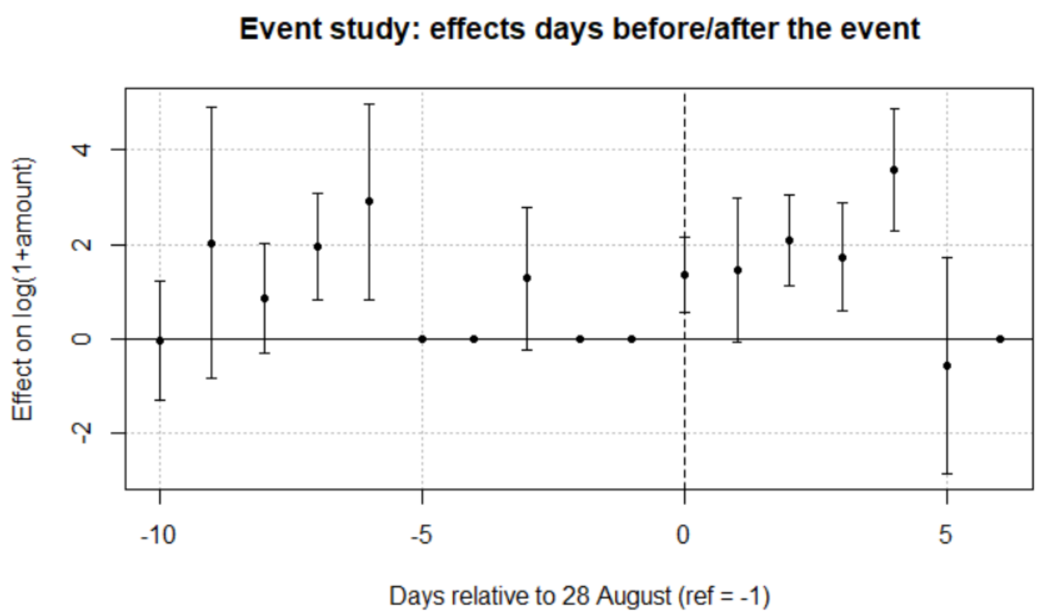
Table 2. Individual-level DiD analysis

	Dependent variable:			
	log(1 + amount)			
	no controls	+ controls	+ emotions/news	FE(region,date)
	(1)	(2)	(3)	(4)
after2	-0.311	-0.499***	-0.623***	0.760
	(0.227)	(0.189)	(0.207)	(0.542)
treated	-0.026	-0.270*	-0.369**	-0.524*
	(0.141)	(0.162)	(0.145)	(0.277)
genderMale		0.076	0.106	0.065
		(0.171)	(0.163)	(0.246)
settlementLarge city		-0.405**	-0.487***	-0.590**
		(0.157)	(0.169)	(0.299)
settlementMedium city		-0.178	-0.143	-0.046
		(0.298)	(0.264)	(0.315)
settlementSmall city		-0.409	-0.418	-0.313
		(0.355)	(0.364)	(0.488)
settlementVillage		-0.459	-0.512	-0.109
		(0.491)	(0.511)	(0.307)
educationDoctorate		0.838***	0.833***	0.668**
		(0.201)	(0.151)	(0.329)
educationIncomplete Higher / College		-0.533***	-0.549***	-0.757***
		(0.189)	(0.199)	(0.259)
educationMaster		0.544***	0.557***	0.443**
		(0.167)	(0.169)	(0.225)
educationSecondary		-0.744***	-0.787***	-1.222***
		(0.265)	(0.285)	(0.362)
educationVocational		0.557	0.540	0.826
		(0.455)	(0.488)	(0.586)
emotional_impact			-0.038	-0.026
			(0.045)	(0.078)
news_time15â€“30 min			-0.756	-1.039
			(0.647)	(0.805)
news_time30â€“60 min			-0.472	-0.587
			(0.487)	(0.702)
news_timeLess than 15 min			-0.652	-0.969
			(0.647)	(0.748)
news_timeMore than 2 hours			-2.544	-2.673
			(2.554)	(2.600)
after2:treated	0.416	0.588**	0.681**	0.636
	(0.330)	(0.280)	(0.322)	(0.420)
Controls	No	Yes	Yes	Yes
Region FE	No	No	No	Yes
Date FE	No	No	No	Yes
Clustered SE	region	region	region	region
Observations	200	200	199	199
R^2	0.010	0.188	0.231	0.390

To trace dynamics around the strike, I estimate event-study specifications with daily leads and lags relative to 28 August 2025, using day −1 as the reference category. Figures 11 (individual level) and 12 (aggregate oblast×day totals) plot the coefficients {βk} for each relative day k together with 95% confidence intervals.

On the individual level (Figure 11), several pre-event days around k∈[−9,−6]k display positive coefficients, while the remaining pre-period observations hover closer to zero with wide intervals. Immediately after the event, the first four post days (k=1 to k=4) show a clear positive response in log(1+amount); thereafter the estimates quickly attenuate, with a sizable but imprecise negative spike around k=5. Overall, the pattern is consistent with a short-lived increase in reported donations rather than a persistent post-event shift.

Figure 11. Individual-level event study: effects days before/after the event



The aggregate series (Figure 12) shows a similar shape. Pre-event coefficients are mixed and mostly close to zero. In the immediate post period (k=1 – k=4) the totals rise, followed by one distinctly negative day around k=5 where the confidence interval lies below zero. Effects dissipate afterwards, and there is no evidence of a lasting treatment–control divergence in total daily donations at the aggregate level.

Figure 12. Aggregated oblast × day event study: effects days before/after the event

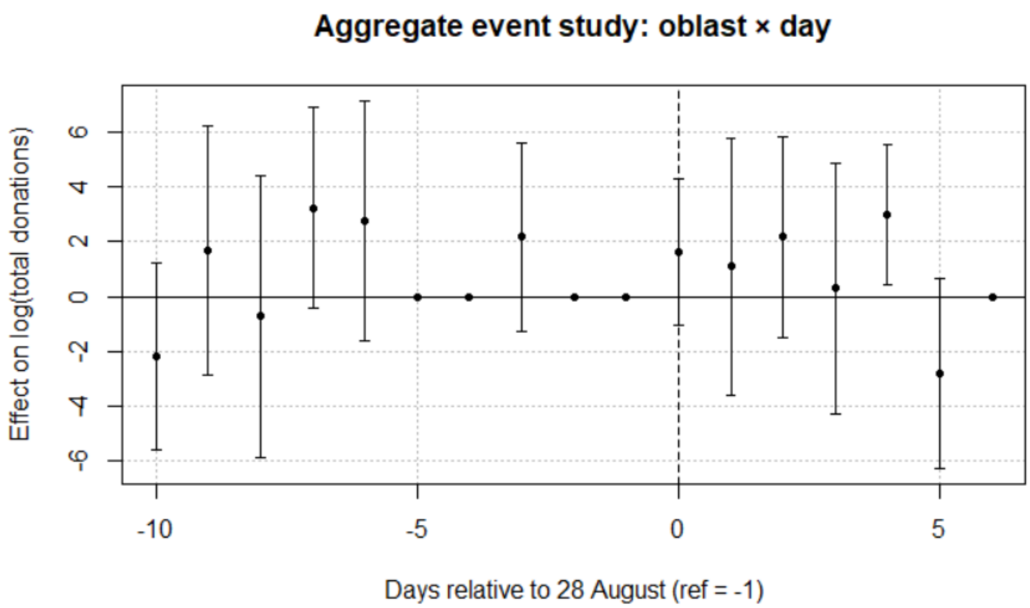
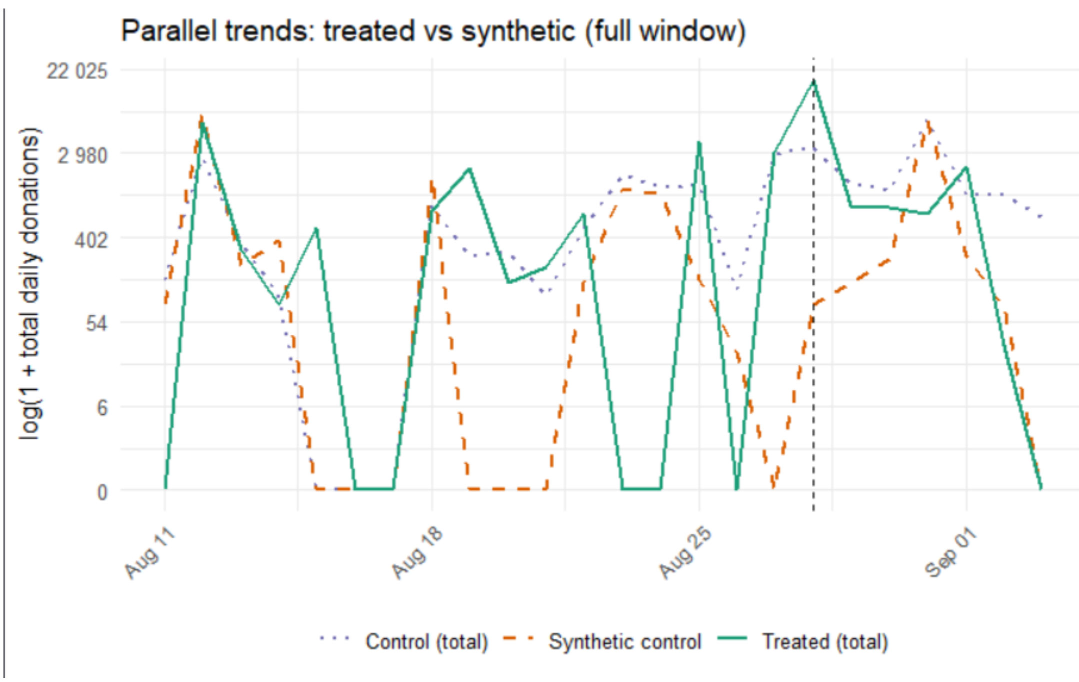


Figure 13 compares the evolution of donations in treated regions with a synthetic control and with the pooled control series over the full sample window (11 Aug–3 Sep 2025). The treated series is the sum of daily donations from the five directly hit oblasts (Kyiv, Dnipro, Kharkiv, Zaporizhzhia, Vinnytsia); the donor pool comprises all non-treated oblasts. I construct a balanced day-by-oblast panel and estimate a synthetic control as a convex combination of donor oblasts that minimizes the pre-event (11–27 Aug) mean squared prediction error of the outcome. Predictors are the average of daily totals over the entire pre-period and separately for its early and late halves. Because the treated unit is an aggregate of five oblasts, donor outcomes are scaled by the same factor so that levels are comparable. The synthetic is fitted on raw daily totals, whereas the figure plots values on the log(1 + total daily donations) scale; the vertical dashed line marks 28 Aug. Before the event, the treated and synthetic series co-move closely (with normal day-to-day noise). Immediately after the strike, the treated series shows a short-lived deviation and then re-converges toward the synthetic path, indicating no persistent gap. Consistent with the DiD estimates and the event-study plots, any post-event movement is short-lived–there is a small immediate increase and then a return toward the synthetic/pooled control–with no persistent treated–control divergence. The pooled control series is shown for reference. Table 3 reports the donor weights used to form the synthetic control and the pre-period RMSPE.

Figure 13. Parallel trends: treated vs control regions



Day-to-day gaps between treated and synthetic largely reflect the short training window and small, sparse donor pool (two positive weights; high pre-period RMSPE). The synthetic series is thus used as an additional robustness check of pre-trends, while inference follows from the DiD/event-study evidence.

Table 3 reports the donor weights used to construct the synthetic control in Figure 13; only two donor oblasts receive positive weights, and the fit is evaluated by the pre-period RMSPE (RMSPE = 1408.535).

Table 3. Synthetic-control donor weights (pre-period: 11–27 August 2025)

donor_oblast	weight	cum_weight
Luhansk	0.746	0.746
Ivano-Frankivsk	0.254	1.000

Pre-period RMSPE (11–27 Aug 2025): 1408.535

As a robustness check, I estimate a placebo DiD on the aggregated oblast×day panel, using 25 August 2025 (three days before the strike) as the cut-off. The outcome is log(1 + total donations) in an oblast on a given day, and standard errors are clustered by region. Table 3 reports estimation with and without controls. The interaction after_placebo × treated is positive but imprecise–1.111 (s.e. 0.570) without controls and 0.936 (s.e. 0.564) with controls, based on 600 observations–and is statistically indistinguishable from zero in both cases. Shifting the treatment date to the pre-event period therefore produces no discontinuity in donation behavior. The absence of a detectable placebo effect supports the identification strategy and suggests that the main results are not driven by spurious pre-trends or anticipatory responses.

Table 4. Placebo DiD (cut-off = 25 August 2025).

	Placebo DiD (aggregate): no controls	Placebo DiD (aggregate): + controls
after_placebo × treated	1.111	0.936
	(0.570)	(0.564)
Observations	600	600
R^2	0.020	0.033
Adj. R^2	0.018	0.024

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 reports separate DiD regressions on aggregated totals (oblast × day) estimated for men and women. The interaction after × treated is positive but imprecise for men (0.326, s.e. 0.320) and close to zero for women (0.077, s.e. 0.516); neither estimate is statistically different from zero. The number of observations is the same across sexes (600) because the oblast–day grid is balanced and days with no donations are coded as zeros. Overall, there is no robust evidence that the strike generated a differential post-event change in aggregated daily donations for men versus women in our sample.

Table 5. Aggregated DiD by gender

	DiD (aggregated): males only	DiD (aggregated): females only
after × treated	0.326	0.077
	(0.320)	(0.516)
Observations	600	600
R^2	0.210	0.202
* p < 0.1, ** p < 0.05, *** p < 0.01		

Subgroup analyses help reconcile the muted average effects. Offsetting responses across groups–a modest uptick among treated men–attenuate the overall DiD estimate. This indicates that the impact of the 28 August 2025 attack on charitable giving was not uniform. Socio-demographic context meaningfully shape donation behavior under wartime stress. Men show a small positive response while women show no discernible change; however, these gender differences are estimated imprecisely and should be viewed as suggestive.

Why average effects are short-lived. Two features plausibly account for the muted aggregate impact:

Campaign decay: fundraising naturally follows a saturation/decay path, so shocks generate only brief deviations before reversion to trend.

Attention saturation: Ukraine's information space is shock-dense; even large strikes face strong competition for attention, producing fatigue and reallocation across appeals rather than net increases.

Additional channels consistent with the data include precautionary saving and tighter liquidity constraints, temporary infrastructure/connectivity disruptions, substitution toward hyper-local urgent causes, and media crowd-out. These mechanisms align with the transient movements around the event.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

This thesis examined whether a large-scale missile strike alters charitable giving in wartime Ukraine. Using original microdata from a donor survey merged to time-stamped donations, I estimated an event-time specification alongside difference-in-differences models. Treatment was assigned by region of birth: respondents from oblasts directly hit on 28 August 2025 were classified as treated, while those from unaffected oblasts served as controls. Defining exposure via origin mitigates concerns related to current residence, post-invasion migration to large cities, and temporary relocations that could blur on-the-ground exposure. The analysis was carried out at two levels–aggregated donations by oblast–day and individual donations–with clustered standard errors, day and region fixed effects where appropriate, and a suite of diagnostic checks, including placebo cut-offs and visual pre-trend assessments. As an additional plausibility probe, I compared treated dynamics with a synthetic control constructed on the pre-event window only; the close pre-event co-movement reinforces the credibility of the DiD identification and suggests that parallel trends are a reasonable approximation over the short horizon considered.

Across specifications, there is no statistically robust average change in giving after the attack. Aggregated oblast-by-day regressions and individual-level models yield small and imprecisely estimated average effects across a variety of control sets and clustering choices. Event-time plots indicate that movements around the strike are brief: coefficients shift modestly in the first days after 28 August and then revert toward the pre-existing campaign trajectory, with pre-event coefficients fluctuating narrowly around zero. Re-defining the post window to focus on the first forty-eight hours, trimming the outcome's right tail, and shifting the cut-off to a placebo date all deliver substantively similar null results. Subgroup checks by gender point to a modest post-event uptick for men in simpler specifications, while women show no detectable change; however, these differences become imprecise in the most demanding model with saturated fixed effects, and thus should be interpreted as suggestive rather than conclusive given the available sample and power.

The short-lived and muted aggregate response is consistent with two complementary mechanisms. First, single-campaign fundraisers typically follow a natural saturation–decay path in which attention and marginal willingness to give diminish over time; salient shocks can bend that path temporarily but rarely deliver a durable level shift absent additional interventions. Second, Ukraine's information environment is dense with wartime incidents competing for finite attention, so even large shocks can yield fatigue and substitution across appeals rather than a net increase in total donations. Additional channels plausibly operate in the background: transient infrastructure or connectivity disruptions that raise transaction costs exactly when attention is highest, tighter short-run liquidity and precautionary saving by households amid heightened uncertainty, substitution toward hyper-local urgent causes that crowd out broader campaigns, and media crowd-out that diffuses focus across many simultaneous calls to give. The observed pattern–a brief post-event blip followed by rapid reversion–fits these mechanisms and aligns with evidence that emotionally salient events without operational reinforcement tend to produce short bursts rather than persistent shifts.

For practice, the evidence implies that high-salience shocks open a narrow mobilization window that should be used quickly and with minimal friction. Outreach is most effective when it begins within twenty-four to forty-eight hours and unfolds as a sequence of succinct touchpoints rather than a single blast, with copy that ties urgency to specific, verifiable needs and near-term delivery milestones. Donation flows improve when forms are short, payment details are pre-filled or saved, suggested amounts are calibrated to the audience, and multiple payment rails–including simple offline options such as QR or short codes–are available so that contributions can be completed even with weak connectivity. Credible, timely information remains central: transparent budgets, clear procurement timelines, and prompt post-event reporting sustain trust, while frequently refreshed creative helps limit fatigue as the news cycle shifts. Short, capped matching windows immediately after the incident can counter natural decay and amplify small gifts, especially when paired with social proof (progress bars, recent-donor tickers) and low-friction "topup" prompts for those who already gave. Operational readiness matters as much as messaging: diversifying payment processors, pre-approving emergency limits, caching lightweight landing pages, and preparing a minimal set of pre-cleared creatives reduce the risk of failure at peak load. Partnerships with trusted local implementers can shorten delivery times and provide credible updates that feed back into the communication loop, while rigorous measurement–UTM tagging, cohort tracking, and pre-registered rapid A/B tests–helps accumulate evidence across shocks without over-interpreting noisy day-to-day fluctuations.

These lessons scale to platforms and policy. Payment providers and fundraising platforms could temporarily waive fees or prioritize throughput for vetted humanitarian campaigns during the first forty-eight hours after major incidents, when giving is most sensitive to friction. Privacy-preserving transaction dashboards and standardized transparency templates would enable independent scrutiny, facilitate media coverage that focuses on verified progress rather than raw appeals, and build donor confidence. Limited-time coordination tools that allow verified campaigns to pool matching funds or share audience segments for a clearly defined window could reduce duplication and mitigate crowd-out across overlapping appeals. Over a longer horizon, investments in connectivity and backup power–in particular outside major urban centers–would strengthen the resilience of philanthropic infrastructure by easing operational bottlenecks during crises; parallel investments in basic fundraising literacy for small initiatives could increase the share of campaigns that are "operationally ready" when shocks occur.

Several limitations qualify the findings and point to future work. The study focuses on a single campaign, relies on self-reported amounts, and observes a short post-event window, which constrains statistical power, precision, and external validity. The sample tilts toward younger, digitally connected respondents, and while this is typical for grassroots online fundraising, it limits generalization to the broader donor population. Linking survey responses to platform transaction data (with consent) would reduce measurement error and allow sharper timing tests around the event. Extending the analysis to multiple shocks and campaigns over a longer horizon would support hierarchical pooling and tighter estimates of heterogeneous effects by audience and message. Richer covariates on psychology, risk perceptions, media diets, and prior giving histories could help separate attention from liquidity channels, while pre-registered field experiments around shock-responsive messaging, match ratios, and timing cadences would deliver actionable effect sizes for practitioners. Finally, documenting and sharing negative results–such as non-effects for certain message framings–would improve collective learning and temper unrealistic expectations about what single events can achieve without strong operational follow-through.

In sum, a high-salience security shock does not produce a large, persistent, population-wide shift in giving within this campaign. The data point to a brief, non-uniform blip that fades quickly; men may exhibit a small, imprecisely estimated uptick, but overall the donation path appears resilient and shaped more by the campaign's life-cycle and the allocation of attention than by any single incident. Practically, major incidents should be treated as narrow windows for mobilization: set realistic expectations, move fast, and rely on targeted, transparent, locally adapted outreach–supported by robust operations, credible reporting, and disciplined measurement – to cushion the return to baseline after the initial surge of attention.

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APPENDICES

Appendix A.

Distribution of Respondents by Region