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CHARITABLE GIVING IN WARTIME: EVIDENCE FROM UKRAINE'S WAR FUNDRAISING

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ABSTRACT

Charitable Giving in Wartime: Evidence from Ukraine's War Fundraising

We analyze how military events, civilian fatalities, and media coverage influence same-day donations to a major Ukrainian nonprofit providing lethal aid during Russia's invasion of Ukraine. In a unique setting, we exploit random variation in attacks on civilians across time to estimate that one additional civilian fatality causes between $4,354 and $6,015 in same-day donations, and leads to at least $8,169 in cumulative donations. Disentangling the effects of events and media coverage, we estimate that a 1% increase in media mentions of military activity leads to a $2,906 increase in same-day donations and an $8,083 increase in cumulative donations.

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1 Introduction

Most studies of charitable giving focus either on responses to singular crises, such as natural disasters, or on long-term support for specific causes. Far less is known about giving in wartime, when donations fund a pure public good - national defense - on a large scale. The unique nature of this setting raises fundamental questions about conditions under which individuals continue to donate in the face of ongoing conflict and uncertainty.

Our study, the first of its kind to our knowledge, examines a unique form of grassroots giving within the context of Russia's full-scale invasion of Ukraine on February 24, 2022. By leveraging a quasi-natural experiment and high-frequency, granular donation data, we address a significant gap in the research on wartime charitable giving by studying patterns of donations to a non-governmental organization that provides lethal aid during a high-intensity and long-running conflict. Our purpose is to document and explain the unprecedented surge in individual donations to a pure public good - national defense during an invasion.

The Russian invasion has inflicted severe economic and humanitarian devastation on Ukraine. As of late 2024, over six million Ukrainians fled the country, becoming refugees abroad, and roughly five million were internally displaced. Over 41 thousand civilian casualties and injuries (OHCHR, 2025) have been confirmed (likely a serious underestimate, since most mass casualty events took place in regions currently under Russian control, where data is unavailable). Ukrainian GDP contracted by over 30% in 2022 (European Parliament, 2024), and 25% of the population was plunged into poverty (United Nations, 2023).

This widespread devastation galvanized an extraordinary global and domestic response, including unprecedented levels of charitable donations to Ukrainian causes. Ukraine rose sharply on the Charities Aid Foundation's World Giving Index, moving from 102nd in 2013 to 2nd in 2023 (Charities Aid Foundation, 2013, 2023).

We study this groundswell of support by focusing on giving to the largest Ukrainian non-profit organization providing both nonlethal and *lethal* aid - Come Back Alive (CBA) - and examining direct individual donations to the Ukrainian military, channelled through CBA.[1] Between the onset of the full-scale invasion in February 2022 and December 2023, CBA received a total of 10 billion Ukrainian hryvnia (UAH) in donations, on the order of 0.24% of Ukraine's annual GDP. We analyze these donations in conjunction with detailed information on the timing and type of Russian attacks, such as air attacks and hospital strikes, the number of civilian fatalities they cause, and the media

[1] Some other examples of institutions of charitable giving to military efforts across the globe include the United Service Organization (USO) and Wounded Warriors in the US, and the Friends of the Israel Defense Forces (FIDF) in Israel. At the same time, these organizations focus on humanitarian support for soldiers, while CBA provides lethal military aid, making it distinct.

coverage that they receive. This comprehensive dataset allows us to trace how different war-related events and media coverage influence donations.

We use a custom-collected dataset of almost 2.9 million unique donations combined with a database of war and media events, all aggregated at the daily level. Our sample runs from February 24, 2022 until December 31, 2023, and we focus on the total amount donated each day to capture the total contribution to the public good. The high frequency of our data is key to our identification strategy and assumes that daily casualties in Ukraine can be treated as good as random. We employ two main approaches: ordinary least squares (OLS) and a structural vector autoregression (SVAR).

In the OLS framework, we argue that civilian casualties are exogenous within a given day. There is considerable evidence of random, indiscriminate attacks; furthermore, even when Russian forces deliberately target civilians, there is clear uncertainty in whether, when, and who suffers from these targeted attacks. Further, the exact location is variable as weaponry can often miss their intended military targets. Finally, once a site is attacked the *number* of fatalities remains uncertain. This "assignment" of fatalities - random from the point of view of the victims and donors - gives a causal interpretation to our estimates of the relationship between fatalities and same-day donations across time. We supplement the OLS model with a double/debiased machine learning (DML) approach to account for a large number of controls, which supports our findings.

In our SVAR model, we impose the restriction that casualties influence media coverage within the same day, but media coverage does not, in turn, influence the number of casualties, *within the same day*. Our access to daily data are crucial for identification, in that donations could plausibly affect media mentions over time, but this is not likely within a day. We also assume that both casualties and media reports impact donations contemporaneously, whereas donations do not directly alter the number of casualties or the extent of media coverage on the same day. These restrictions allow us to identify the disparate effects of casualties and media mentions on donation amounts.

We uncover several key findings. First, civilian casualties cause a large increase in donations, on the order of thousands of dollars for each fatality. A 1% increase in civilian casualties increases daily donations by 0.097%-0.134% daily, and cumulatively by 0.182%. Air strikes and attacks on hospitals are the types of events that have the largest impact on giving. The effect of all military mentions appears to be larger than the effect of civilian casualties, with a 1% increase in military mentions lead to the 0.515% same-day increase in the amount donated and to 1.5% cumulatively. Second, mentions of frontline attacks, violence against civilians and missile attacks all increase daily donations. Finally, our impulse response functions show that the effects of casualties fall following an initial shock, while the effect of media mentions lingers for several days, peaking on the day following the event.

Our findings contribute significantly to an understudied area, as studies examining charitable contributions during wars are notably absent, particularly regarding instances where ordinary citizens extensively support military efforts. Furthermore, the Ukrainian response to the war has generated remarkable levels of such giving. Few, if any, examples of ordinary citizens extensively supporting military efforts exist (Wood, 2019), making this a particularly important and interesting instance.

The rest of the paper is structured as follows. Section 2 discusses the related literature, while Section 3 provides the historical background and details on CBA, and highlights the unique features of this setting. Section 4 describes the data sources and the variables we construct, and Section 5 presents our empirical strategy. Section 6 reports the main findings: in Subsection 6.1 we focus on *events* and document that casualties are positively associated with donation amounts; Subsection 6.2 documents that giving follows a repeated pattern of spikes after an event, followed by an immediate decline; Subsection 6.3 focuses on the *media* coverage of various military events. Section 7 discusses and concludes.

2 Related Literature

In the economics of philanthropy and public goods, charitable giving is primarily explained by preferences for others' well-being, personal satisfaction, or a combination of both. Altruism (Andreoni, 1989, 1990) is a primary motive, as are social norms, peer pressure, and the psychological ("warm glow") rewards (Harbaugh, 1998). Individuals are more likely to donate when they feel empathy or a personal connection to identifiable beneficiaries rather than abstract causes (Andreoni, 2014; Echazu and Nocetti, 2015).

Beyond specific causes, charitable giving also focuses on giving in the aftermath of singular events, such as natural disasters. Donations may still be driven by empathy and altruism (Adena and Harke, 2022; Black et al., 2021) but can also include motivations such as restoring stability in affected regions. Disaster-related giving helps mitigate short-term economic losses, enabling victims to recover and contribute to broader economic stability (Deryugina and Marx, 2021). Media coverage significantly amplifies giving (Adena and Harke, 2022; Brown and Minty, 2008; Eisensee and Strömberg, 2007; Jayaraman, Kaiser and Teirlinck, 2023), with both the frequency and specificity of reporting influencing donation levels.

Charitable giving during wartime is fundamentally different. Unlike disaster relief, which typically involves a one-time surge of donations aimed at restoring a community to its pre-crisis state, wartime giving supports an ongoing public good: the military. The donations mostly come from the people who are themselves affected by the war rather than from foreign donors. Donations are not tied to a discrete recovery period but require a sustained flow over an indeterminate timeline.

Literature on charitable giving during wars is limited; some parallels can be drawn from responses to crises like the September 11 terrorist attacks, where giving was motivated by a mix of altruism, patriotism, and self-interest, as donors perceived the event as a direct threat to themselves (Schuster et al., 2001). Berrebi and Yonah (2016) also find that the giving of Israelis increases following a terrorist attack. However, wartime donations are distinct from this strand of literature too in their ongoing nature and their collective investment in a public good, making Ukraine's case particularly compelling and underexplored.[2]

There is a large literature documenting the inefficiency of private provision of public goods, as well as work on overcoming this issue (Alberti and Mantilla (2024); Bagnoli and Lipman (1989); Palfrey and Rosenthal (1984); Van Essen and Walker (2017), to give but a few examples). The setting we study, however, is somewhat different: instead of the typical underprovision, we observe a situation where (a continuous) public good *is* provided privately through a voluntary contributions mechanism.

3 Background

3.1 Historical and Institutional Context

The full-scale Russian invasion of Ukraine on February 24, 2022 is the latest event in a long-running conflict. The Russian forces invaded Ukraine along the entire border shared by the two countries on February 24, 2022. Roughly 200,000 Russian and Russian-aligned troops attacked Ukraine in a combined arms attack on many fronts, in what quickly became the largest war on the European continent since World War II. Ukrainians at home and abroad rallied in a spirit of defiance in the face of catastrophe and a rush to help. *It is this groundswell of support that we consider in this paper.*

Several classes of organizations that coordinate aid to Ukraine have appeared. Some are run by the Ukrainian government (such as United24), some are non-governmental and based in Ukraine (such as Come Back Alive, Prytula Foundation, and Syla Hromad), and some non-governmental organizations (such as Razom and Nova Ukraine) are based outside of Ukraine.

Donating money to the armed forces is widespread in Ukraine; a 2024 survey found that 76% of respondents have donated to the military in the preceding three months. This figure is also

[2]Our research also complements the literature from post-conflict settings showing that exposure to war can strengthen prosocial behavior (Bauer et al., 2016). For example, lab-in-the-field experiments in Nepal (Gilligan, Pasquale and Samii, 2014) and Burundi (Voors et al., 2012) found that individuals who experienced violence were more likely to contribute to public goods and display increased altruism.

uniform across the country, varying from 69% in the eastern part to 80% in the western part, with numbers for central and southern regions falling between these figures (International Republican Institute, 2024).

3.2 Come Back Alive Foundation

We focus on Come Back Alive for several reasons. It is one of the largest and best-known organizations of its kind. Furthermore, its website provides an exceptionally comprehensive list of donations and expenditures, allowing unprecedented access to the inner-workings of a non-profit organization.

CBA is well-known in Ukraine because of its initiatives; it is active on social media and often mentioned in legacy media. Between its inception in early 2014 and early 2025, it collected almost $440 million in donations. As of 2024, CBA is the largest charitable foundation in Ukraine (Forbes, 2024) and the largest NGO providing lethal aid to the military.

3.3 Uniqueness of Donation Behavior: Crowdfunding the State

Our primary interest is in documenting patterns of charitable giving in wartime. This form of giving is both interesting and unusual because it is:

1. Decentralized: large numbers of individuals making relatively small contributions;
2. Non-governmental: not coordinated or mandated by the state, bypassing governmental channels in raising and spending funds;
3. Not interest-bearing, unlike war bonds campaigns in the World Wars;
4. Numerous, repeated, and large-scale: millions of donations totaling hundreds of millions of dollars, sustained over the course of three years;
5. Not targeted: individuals generally cannot direct their donations and have no control over where the procurement takes place or at what price;
6. Largely anonymous;
7. Voluntary.

This presents a unique economic situation: large numbers of individuals repeatedly donate significant amounts to a pure public good over time, effectively crowdfunding the state's defense. Among our contributions is to document and describe the mere existence of this phenomenon. In this setting, we show that civilian casualties and mentions of military events significantly drive these donations, with most people contributing immediately after an event. In this setting, we show that civilian casualties and mentions of military events drive donations, and most people donate immediately after an event.

4 Data Sources

We use four primary data sources: donation records from CBA, media coverage data from the Global Database of Events, Language and Tone (GDELT), data on civilian fatalities from the Armed Conflict Location and Event Data (ACLED), and conflict incident data from the Violent Incident Information from News Articles (VIINA).

4.1 Donations: Come Back Alive Foundation

All of CBA's donations, procurements, and disbursements are available on its website; the full record of donations on the CBA website includes over 3 million unique donations as of the end of 2023, but 95% of all donations were made after the full-scale invasion, highlighting the significant surge in public support during the war. We use all individual-level donations spanning from February 24, 2022, and December 31, 2023. We observe information about the amount donated, the currency, the timestamp of the donation, and the bank that processed the donation, as well as all large fundraiser launches or other important events.[3] We convert the contemporaneous donation amounts to 2010 Ukrainian hryvnia (the base year used by the State Statistics Service of Ukraine) to filter out exchange rate fluctuations and adjust for inflation.

4.2 Military Events: Violent Incident Information from News Articles

Our second source, the Violent Incident Information from News Articles (VIINA) database (Zhukov and Ayers, 2023) is an event-based dataset that classifies media reports from Ukrainian and Russian media into standard conflict categories using machine learning. The data come mostly from Ukrainian news sources (such as *Espreso*, a privately owned TV channel, *Ukrainska Pravda*, an influential news site, and others), Ukrainian news wire services (such as *Unian*), Russian pro-Kremlin news sources (such as *Komsomols'kaya Pravda*, a newspaper, *RIA Novosti*, a news site, and *NTV*, a

[3] We excluded all transactions under 1 UAH, as these were mostly transaction fees. We also removed donations from non-Ukrainian donors. The vast majority of donations - 85% come from Ukrainians in Ukraine, with another 10% from Ukrainians abroad and just 5% from foreign donors (Karpenko, 2024). Since the share of foreign donors is too small for a separate analysis, and we can't reliably distinguish between Ukrainians abroad and foreign donors, we focus our analysis on Ukrainian donors within Ukraine.

news channel), and Russian-language sites located outside of Russia (such as *Meduza*, an opposition news site operated from Latvia). The VIINA dataset disaggregates the events into a number of categories - missile attacks, artillery shelling, attacks on hospitals, and others. We use this dataset as our source for information on military "events."

4.3 Casualties: Armed Conflict Location and Event Data

For data on civilian casualties, we rely on a well-established database of conflict data, the Armed Conflict Location and Event Data. The source for ACLED data is contemporary news reports from social media, Ukrainian- and Russian-language media, and the Ukrainian and Russian ministries of defense.

We emphasize that ACLED provides *conservative* estimates of civilian fatalities. As a matter of policy, ACLED reports the lowest credible number of fatalities.[4] In addition, ACLED data does not distinguish between military and civilian casualties in the main data, and only provides information on how many of the casualties were civilian or military in the accompanying notes.[5]

4.4 Media Coverage: Global Database of Events, Language and Tone

Our third data source, the Global Database of Events, Language and Tone, monitors world news media in more than 100 languages in print, broadcast and web formats, and contains information on different types of media mentions of events. We use this dataset to construct several variables. First, we extract the total daily number of unique events, happening worldwide, recorded in the GDELT dataset, which is used as a control variable in our specification.

Next, we extract the events that are related to Ukraine (i.e., in which at least one of the actors involved in the event is from Ukraine). We use the Google BigQuery platform to extract data from the GDELT Event Database and Mentions Table. First, we extract all events from January 1, 2016, to December 31, 2023, where at least one of the actors involved is from Ukraine. Second, we extract all mentions of these events.[6] We then aggregate the data on the daily level and create a variable (*all mentions*) that represents the total number of Ukraine-related media mentions on a given day, which we then use in constructing other variables.

GDELT data enables us to categorize mentions by mention source. This allows us to separate

[4] *"ACLED defers to the most conservative number of fatalities reported and treats uncertainty around unspecified numbers of fatalities conservatively as well* [...]. *But ACLED aims to provide the best, if lower, estimate of fatalities, rather than entirely arbitrary ranges built on assumptions."* (Armed Conflict Location & Event Data Project, 2023), (Raleigh, Kishi and Linke, 2023)

[5] We used a large language model (ChatGPT 4 API) to extract the number of civilian casualties from the free-text notes in each cell of the ACLED data.

[6] We filter out mentions with a "Confidence" score below 50%, as these are less likely to reliably reference relevant events based on the manual observation of the data with the low confidence score.

the Ukraine-related mentions by type of media. In particular, we create a variable *all Ukrainian mentions*, which includes only mentions by the Ukrainian media sources (having a ".ua" domain name or one of the manually selected Ukrainian websites that are in the top-100 sources in our dataset). Given that the majority of donations in our dataset are made by Ukrainian donors,our analysis primarily focuses on the Ukrainian media, and all variables based on the mentions only include mentions by Ukrainian media, unless explicitly specified otherwise.

Furthermore, the GDELT data contain detailed information about the characteristics of each event and mention. Using the Conflict and Mediation Event Observations (CAMEO) event classification system, we create several specific variables: *all military mentions*, which includes mentions of only military-related events; *all missile mentions*, which only includes mentions of missile attacks: *all civilian violence mentions*, which only includes mentions of events that involve violence against civilians; *all deescalation mentions*, which includes all mentions of military deescalation; *all occupation mentions*, which includes all mentions of occupation of territories and *all frontline mentions*, which includes only military mentions that take place on the frontline (so, excluding the violence against civilians and missile attacks). We provide details on the exact definitions of mentions variables from the GDELT in the Appendix B.

While both VIINA and GDELT datasets extract information from media reports, they differ in what information exactly is extracted. VIINA dataset focuses on the specific *facts* about war, such as the number of casualties and other war-related events. The variables we use from the GDELT dataset, on the other hand, pertain to the number of *media mentions* of the events, which do not always reflect the number of events that actually occurred.[7]

5 Empirical Strategy

We estimate how events following Russia's full-scale invasion of Ukraine on February 24, 2022, along with their media coverage, impact daily donations to the Ukrainian military. Our primary specification models the logarithm of donations and is specified as follows:

$$\log(\text{Donations}_t) = \beta_0 + \beta_1 \log(\text{Civilian casualties}_t) + \beta_2' X_t + \Omega' Z_t + \varepsilon_t \tag{1}$$

For $\log(\text{Donations})_t$ we focus on the total amount donated rather than the total number of donations (results for the number of individual donations are available in Appendix E). The emphasis on the intensive margin is driven by the fact that the total amount donated is what is crucial in

[7]While we lack direct data on donor geolocation, this is unlikely to bias our estimates. Most attacks occur at the frontlines, and most donors are not likely to be located in those areas.

terms of supporting CBA's efforts in funding the war. And, from a charity's perspective, securing donors who can adjust their contributions based on day-to-day needs is more efficient than constantly seeking new donors. $\log(\text{Civilian Casualties}_t)$ represents the logarithm of civilian casualties reported on day t, and X_t is a column vector that captures war-related events or media mentions.

The term Z_t is a vector of controls. As CBA sometimes carries out targeted fundraising campaigns, we control for whether there was a fundraiser launch or other important event on a given day by constructing *Come Back Alive events*, an indicator variable. We include information on all national holidays (even though they have been officially suspended) in Ukraine. Finally, we control for the daily count of globally reported events as recorded by GDELT, a linear time trend in donation behavior, as well as fixed effects for year, month, and day of the week, which control for broader temporal patterns. The error term ε_t captures idiosyncratic shocks.

To estimate the effect of civilian casualties on donations, we employ both ordinary least squares and a structural vector autoregressive model. OLS serves as a useful benchmark that offers an estimate of the immediate impact of war-related events and media coverage on donations, while SVAR explicitly captures the dynamic interplay between donations, civilian casualties, and media coverage.

A causal interpretation of the effect of daily casualties (and other military events) on donations relies on the assumption that civilian casualties on a specific day are exogenous to donation behavior, conditional on past donations (in the SVAR model) and other control variables. That is, the effect of a casualty today is not contemporaneously confounded by other factors that can occur on the same day and also drive casualties *and* donations, including media mentions or political campaigns. Over longer time horizons, however, this assumption may weaken, as sustained media narratives could shape donor behavior. Our high-frequency data facilitates a quasi-experimental approach to measuring the causal effect of war-related shocks on donations. It is unlikely that a media mention on a given day causes a casualty within the same day. In essence, our OLS identification strategy assumes that the occurrence of civilian casualties on a given day is not systematically correlated with unobserved confounders that jointly drive both casualties and donations within that same day.

5.1 Variation Sources: Attack Randomness and Munition Imprecision

The patterns of Russian attacks on Ukrainian civilians are partially random. The extent of this randomness is crucial for our identification strategy: even if civilian casualties are, in part, the outcome of deliberate targeting, the *number* of casualties on any given day has a significant random component. We discuss both the random and the nonrandom component in turn.

First, there is extensive evidence[8] suggesting that the Russian military has repeatedly targeted civilian targets in Ukraine. Second, the pattern of civilian casualties appears to have a time trend, which would not be present if the attacks were completely random.

On the other hand, there is also extensive evidence of truly random, indiscriminate attacks on civilians.[9] Beyond this evidence, there are additional channels that drive the randomness of attacks. First, even if the Russian forces were planning a (non-random) attack on civilians, and if such attacks were predictable by Ukrainian civilians, needless to say, individuals would take every possible measure to avoid being in the target area. There is, therefore, a motive to randomize the time and place of an attack. Second, and perhaps more importantly, conditional on a strike at a particular location, the *number* of civilian fatalities is random - it is not known. Conditional on being present at the site of an attack, the number and severity of injuries is determined by chance.

Third, the location of an attack resulting in civilian casualties may itself be random. One reason is the imprecision of Russian weapons systems; as a result, when aimed at military or nonresidential targets, these projectiles frequently miss, leading to civilian casualties.

Fourth, the precision and location of Russian strikes are modulated by the effectiveness of Ukrainian air-defense and counter-battery fire. The effectiveness of many of these air defense units, is itself random; if such a unit damages a Russian drone or a missile in flight, the projectile might deviate from its course and impact at a random location.

Overall, the randomness in the daily number of casualties arising from targeting imprecision, variation in Ukrainian air defense effectiveness, and unpredictable civilian presence provide exogenous variation. This exogeneity enables us to estimate the causal effect of civilian deaths on donations. Crucially, it does not require assuming that Russian attacks are unplanned or arbitrary. Rather, we exploit the fact that even within a deliberate campaign, the within-day fluctuation in casualties is plausibly as good as random.

5.2 Vector Autoregressive Model

While battlefield events influence donation behavior, their effects are mediated by media coverage. Civilian casualties and events such as air strikes and attacks on hospitals can directly impact donations, but they also generate media attention, which can further amplify donor responses. To formally account for these dynamics, we use the SVAR framework to jointly model donations, casualties, and media mentions as follows:

[8] Amnesty International (2024), BBC News (2025), Reuters (2023), United Nations News (2022), Euronews (2023)

[9] Amnesty International (2022), U.S. Mission to the OSCE (2024), The New York Times (2024), Applebaum (2022)

$$\begin{bmatrix} log(\text{Casualties}_t) \\ log(\text{Media Mentions}_t) \\ log(\text{Donations}_t) \end{bmatrix} = A_0 + \sum_{j=1}^{p} A_j \begin{bmatrix} log(\text{Casualties}_{t-j}) \\ log(\text{Media Mentions}_{t-j}) \\ log(\text{Donations}_{t-j}) \end{bmatrix} + CZ_t + \varepsilon_t \tag{2}$$

where Z_t is a vector of exogenous controls to account for other factors that may impact donations independently of wartime events or media coverage as described in the previous section, A_0 is an 3×1 vector of parameters, A_j is an 3×3 matrix of parameters for $1 \leq j \leq p$, ε_t is a vector of structural error terms, assumed to be serially and contemporaneously uncorrelated. The lag order p is selected using the Bayesian Information Criterion (BIC).

The SVAR framework introduces structural identification restrictions to isolate structural shocks. We use the standard identifying restriction through a Cholesky decomposition and the order of endogenous variables. We order casualties first, media mentions second, and donations third.

The restriction assumes that casualties affect media coverage within the same day, but media coverage does not directly alter the number of casualties. It also assumes that casualties and media mentions impact donations contemporaneously, while donations do not directly affect casualties or media coverage within the same day. This creates two distinct pathways through which casualties can affect donations: a direct effect, where donors react immediately to an attack, and an indirect, amplified effect, where an attack triggers media attention, which in turn drives donations. This specification allows us to identify how an unexpected increase in casualties today influences media attention tomorrow, and how that, in turn, affects donations. By treating donations, casualties, and media mentions as endogenous variables, the model captures the feedback loop between battlefield events, media coverage, and donor behavior.

One of the key advantages of a SVAR model is its ability to track how shocks propagate over time. A single high-casualty event might trigger an immediate surge in donations, but it is not clear whether the effect would last. To quantify the persistence and magnitude of donation responses to conflict events, we compute orthogonalized impulse response functions (IRFs), which trace how a one-day increase in civilian casualties affects donations in the days that follow.

6 Results

We estimate how events during Russia's invasion of Ukraine, and the coverage of those events in the media, affect total donations to the Ukrainian military in our sample. Our primary specification uses the natural logarithm of the daily sum of donations. The log of sums is a stationary process. Beyond the overall effects of events and media mentions we ask more specific questions regarding the nature of the events (e.g. air alerts versus missile strikes) and what type of coverage (e.g. mentions of the events on the frontline vs mentions of violence against civilians) affects donations.

6.1 Finding One: Casualties Drive Donations

We first present the results of OLS models as a useful benchmark of the contemporaneous effect of events and media mentions on the total amount donated. We then use SVAR models and present the results of the cumulated impulse responses of donations to events, including total civilian casualties, military activities (such as air alerts, air strikes, and hospital attacks), sanctions, and media coverage of missile activity, de-escalation, frontline developments, and civilian violence. In all of the specifications we control for the donation campaign days by CBA, major holidays in Ukraine, as well as year, month and day of the week fixed effects. In the OLS regressions we also control for the total number of world events.

Tables 1 and 2 present our first finding: casualties drive donations. From Table 1 we observe that a 1% increase in the civilian casualties (≈ 0.1257 casualties) leads to 0.097% - 0.134% increase in the same day donation amount (or $\approx$ \$547 – \$756 in May 2025 terms),[10] depending on the specification. Thus, one additional civilian fatality translates into between \$4,354 and \$6,015 in *same-day* donations.

This result is supported by the findings of the SVAR models in Table 2 in which we observe that a 1% increase in civilian casualties leads to 0.182% (\$1,026 in 2025 terms) increase in the *cumulative* donation amount, controlling for military mentions; in more readily interpretable terms, this implies that one more civilian fatality translates into cumulative donations of at least \$8,169 in 2025 terms. This effect holds throughout all specifications in which casualties are included. The rise in donations in response to civilian casualties may be driven by empathy and solidarity with the victims, a drive to help, as well as a drive to prevent further casualties by donating to a military cause.

Relating these amounts to items that CBA buys, same-day donations in response to one more civilian casualty are enough to purchase roughly two to three drones (a disposable one-way weapon used by both sides by the millions), and cumulative donations are enough to purchase as many as four.

We also find that other military-related events are positively associated with the donation amount, where the magnitude of their effects is smaller than the effect of civilian casualties.[11] As different types of military events are correlated with each other, they are included in the regressions one

[10]The average total daily donation is 3,034,405 UAH; we convert donation amounts to 2010 UAH levels, then to 2010 USD levels at the 2010 average exchange rate, and then adjust for inflation.

[11]We expect that civilian casualties are the result of many different types of military-related events.

Table 1: Estimated OLS Results for Log Daily Total Amount Donated for Mentions and Events

	Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.134***	0.097***	0.133***	0.112***	0.117***
	(0.036)	(0.035)	(0.036)	(0.035)	(0.035)
Sanctions		0.028***			
		(0.004)			
Log air alert in Ukraine			0.088**		
			(0.039)		
Log air strike in Ukraine by Russia				0.181***	
				(0.041)	
Log hospital attack in Ukraine by Russia					0.134***
					(0.035)
R2	0.586	0.611	0.589	0.600	0.595
N	676	676	676	676	676

	Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.115***	0.125***	0.125***	0.132***	0.114***
	(0.033)	(0.034)	(0.034)	(0.036)	(0.032)
Log Ukrainian military mentions	0.515***				
	(0.108)				
Log civilian violence mentions		0.131***			
		(0.034)			
Log missile mentions			0.132***		
			(0.033)		
Log deescalation mentions				0.116**	
				(0.046)	
Log frontline mentions					0.496***
					(0.096)
R2	0.605	0.595	0.595	0.588	0.608
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is the log of the daily total donated amount, with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include world event counts, a binary variable for Come Back Alive donation events, day of the week, month and year fixed effects, trend, and holiday indicators. In Panel (A), Log civilian casualties refers to the log of reported Ukrainian civilian casualties. Sanctions capture the number of economic sanctions imposed on Russia on that date. Log air alert in Ukraine represents the log of air alerts issued nationwide, while Log air strike in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the log of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), Log civilian violence mentions represents the log of media mentions of civilian violence in Ukraine. Log military mentions captures the log of military mentions in Ukrainian media on the same date. Log missile mentions captures missile-related mentions in Ukrainian media. Log deescalation mentions refers to media reports of deescalation, while Log frontline mentions reflects the log of media mentions related to the frontline, all on the same date.

Table 2: Estimated cumulative impulse responses of donations to events and mentions

	Panel A: Events			
	(1)	(2)	(3)	(4)
Log military mentions	1.505***	1.523***	1.455***	1.433***
	(0.323)	(0.322)	(0.324)	(0.321)
Log civilian casualties	0.182***			
	(0.063)			
Log air alert in Ukraine		0.164*		
		(0.094)		
Log air strike in Ukraine by Russia			0.378***	
			(0.111)	
Log hospital attack in Ukraine by Russia				0.315**
				(0.091)

	Panel B: Mentions			
	(1)	(2)	(3)	(4)
Log civilian casualties	0.187***	0.189***	0.189***	0.186***
	(0.062)	(0.062)	(0.062)	(0.062)
Log civilian violence mentions	0.358***			
	(0.096)			
Log missile mentions		0.350***		
		(0.095)		
Log deescalation mentions			0.338**	
			(0.143)	
Log frontline mentions				1.392***
				(0.292)

Note: The dependent variable is the logarithm of the daily total donated amount. Standard errors in parentheses *** denotes p<0.01, ** denotes p<0.05, * denotes p<0.1. Controls include a binary variable for Come Back Alive donation events, day, week, daily trend, month and year fixed effects, and dummies for holidays. In Panel (A), "Log civilian casualties" refers to the logarithm of reported Ukrainian civilian casualties. "Log military events" capture the logarithm of military events on the same date. "Log air alert" in Ukraine represents the logarithm of air alerts issued nationwide, while "Log air strike" in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the logarithm of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), "Log civilian violence mentions" represents the logarithm of media mentions of civilian violence in Ukraine. "Log missile mentions" capture missile-related mentions in Ukrainian media. "Log deescalation mentions" refers to media reports of deescalation, while "Log frontline mentions" reflect the logarithm of media mentions related to the frontline, all on the same date.

at a time. For instance, a 1% increase in the number of air alerts, Russian air strikes in Ukraine or Russian attacks on Ukrainian hospitals increase *same-day* donations by 0.088%, 0.181% and 0.134% respectively. In addition, an additional media report mentioning sanctions against Russia leads to 0.028% increase in the same-day donations. Table 2 shows that cumulative effect of air alerts, air strikes, and hospital attacks, respectively, are 0.164%, 0.378% and 0.315% increase in the amount donated. We also examine potential crowd-out from international aid in Table C.5 and find small, negative, but statistically insignificant effects on domestic donations.

6.1.1 Robustness with High-Dimensional Controls

In this section, we consider a fuller set of controls in the form of time trends, interactions between time trends and other controls and higher order polynomials of the latter using double/debiased machine learning (DML) (Chernozhukov et al., 2017, 2018). This approach allows us to account for a large number of, potentially correlated, trends that might otherwise be overlooked, while still estimating treatment effect.

Table 3: Double machine learning for high-dimensional controls of donated amount

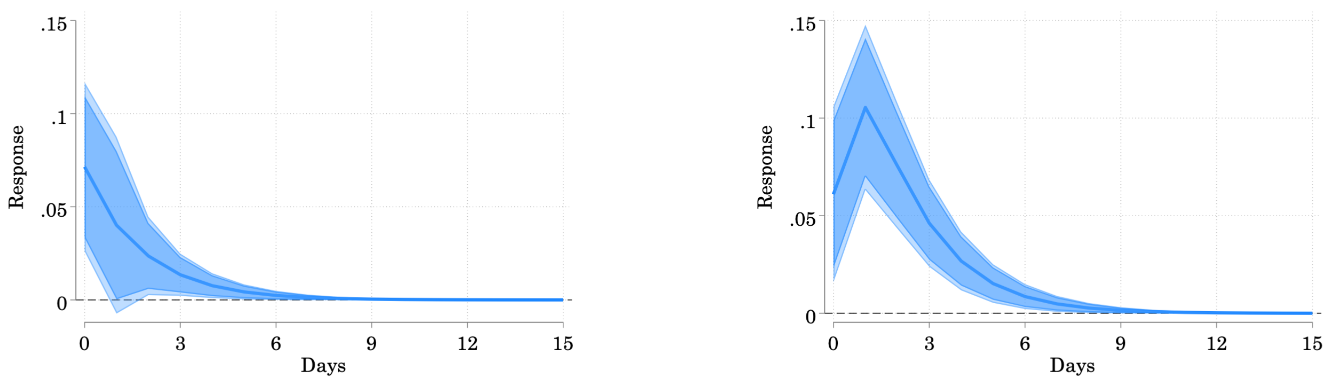
	(1)	(2)	(3)	(4)
	lasso-lasso	lasso-ridge	ridge-lasso	ridge- ridge
Log civilian casualties	0.09	0.07	0.08	0.06
	(0.03)	(0.02)	(0.03)	(0.03)
	[0]	[0]	[0.02]	[0.02]
Log military mentions	0.4	0.3	0.38	0.33
	(0.12)	(0.09)	(0.13)	(0.1)
	[0]	[0]	[0]	[0]

Note: The dependent variable is the logarithm of the daily total donated amount. Robust standard errors in parentheses, and p-values in brackets. Each panel estimates the ATE and standard errors of the effect of log civilian causalities, or log military mentions, on log donated amount. Column labels denote the method used to estimate the nuisance functions. Controls include 1st and 2nd order polynomial terms and their interactions of time dummies (year, month, day, dow, week) and holidays, CBA events, and total world events for a total of 6669 controls. A second-order polynomial was selected for the control variables based on 5-fold cross-validation, as it yielded lower mean squared errors for the nuisance functions compared to higher-order polynomials.

In Table 3 we report the results from applying DML after controlling for over six thousand controls that include the levels, interactions and second order polynomials of time dummies, CBA events and world events.

A 1% increase in Ukrainian civilian fatalities per day, or 0.1257 more fatalities, increases total amount donated by 0.06% - 0.09% (or \$340 - \$507 USD in 2025). These effect sizes are on par with the original effect sizes we observed with the OLS estimation in Table 1 (cf. our lowest point estimate from Table 1 was \$547 in 2025 USD). Thus, our results are robust to a rather large set of controls. In addition, a 1% increase in the number of media mentions of military results is associated with 0.3%- 0.4% increase in the amount donated.

6.2 Finding Two: Donations Rise Significantly in the Immediate Wake of an Event and Fall Immediately After



(a) Log civilian casualties

(b) Log military mentions

Figure 1: Orthogonalized IRF of donated amount

Note: This figure presents orthogonalized impulse response functions of the logarithm of donated amount in response to the logarithm of civilian casualties and military mentions. Blue shaded areas represent 90% and 95% confidence intervals.

Our second finding is presented in Figure 1, which shows orthogonalized impulse response function of donated amount for logarithm of civilian casualties and logarithm of media mentions, estimated using the SVAR approach. The donation responses to both civilian casualties and military mentions follow a similar pattern: the response peaks in the first 3 days following the civilian casualties or media mentions, followed by a steep decrease in the response, so that by day 10 the additional response is not statistically significantly different from 0.

6.3 Finding Three: Amount and Intensity of Media Coverage Affect Donations

Increased media coverage increases donations. Table 1 shows that all types of military-related mentions have positive and statistically significant effect on the same-day amount donated. Frontline mentions and all military mentions combined seem to have the highest impact, with a 1% increase in the mentions of military events that take place on the frontline leading to 0.515% (≈ \$2,906 in

2025 USD) and 0.496% (≈ $2,800 in 2025 USD) increase in same-day donations, respectively. A 1% increase in mentions of violence against civilians, missile attacks and deescalations leads to around 0.12%-0.13% increase in the amount donated. This difference may be attributed to the fact that most of the CBA funds are allocated to military units on the frontline, with only a small portion directed towards air defense units countering missile attacks.

Table 2 shows the cumulative response to the military mentions from the SVAR models. Panel (A) shows that the effect of military mentions has a high and statistically significant event even when different events are controlled for. The cumulative effect of a 1% increase in military mentions is a 1.433%-1.5% increase (greater than ≈ $8,083 USD in 2025) in the amount donated. Panel (B) shows that the cumulative effect of the frontline mentions remains higher than that of other types of mentions: a 1% increase in frontline mentions leads to a 1.33% cumulative increase in the amount donated. A 1% increase in mentions of violence against civilians, missile attacks and deescalation each leads to 0.33% - 0.36% cumulative increase in the amount donated.

7 Discussion

Our study documents an unprecedented pattern of sustained grassroots charitable giving during wartime, lasting over at least two years. This duration contrasts sharply with traditional models of giving that often focus on singular crisis responses. The sheer volume of donations, both in terms of frequency and cumulative amount, is substantial—significant relative to Ukraine's GDP and impact for the war effort. Donations peak the day following an event, and the same-day effects of civilian casualties on donations are also large: thousands of dollars for each fatality, with a cumulative effect of around $8,170.

Leveraging a quasi-natural experimental design and structural vector autoregression (SVAR) models, we disentangle the distinct effects of factual war events from their media coverage on donation behavior. A critical finding is that civilian casualties, representing the direct human cost of the conflict, exert a greater impact on donations than general military events. And while all military-related media mentions increase giving, it is specifically broad media coverage of overall war-related or frontline events that has the strongest cumulative impact.

From a policy and practical fundraising perspective, our finding that the immediate donation effects of shocks largely dissipate by day three is crucial. This suggests that NGOs like Come Back Alive could strategically time new fundraising campaigns to help sustain the flow of donations and ensure continuous support for the war effort even after an initial surge subsides. This research significantly contributes to the nascent literature on charitable giving in wartime, demonstrating how private citizens can effectively "crowdfund the state" for critical public goods like national defense. It highlights the critical role of transparent and agile NGOs in channeling citizen support during prolonged conflict.

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Supplemental Appendices

A Theoretical Discussion

There is, by now, a fairly large literature on various forms of altruism, a large literature on public goods, and a literature, specifically, on charitable giving. We begin by noting the following three stylized elements about our setting:

1. The wealth of most households fell as a result of the invasion, yet;
2. Both the number of donors and the individual contribution levels rose, and, furthermore;
3. Individuals appear to give for both instrumental/pecuniary and noninstrumental/non-pecuniary reasons.

To be sure, the charitable giving we study is giving above and beyond the level of the public good that is provided by the government through mandatory taxation; there is still a great deal of national defense provided without CBA. Thus, while there is a certain level of the government-provided public good, to simplify our discussion, we suppose that this baseline level of the government-provided public good is zero.

Consider a simple stylized model of public goods provision from Bergstrom, Blume and Varian (1986):

$$\max_{x_i, G} u_i(x_i, G) \tag{3}$$

$$\text{s.t. } x_i + g_i \leq w_i \tag{4}$$

$$G = \sum_i g_i \tag{5}$$

The solution yields $\frac{\partial G u_i(x_i^*, G^*)}{\partial x_i u_i(x_i^*, G^*)} = 1$, with a demand function for the public good $g_i^D(w_i, G_{-i}) = \max\{f_i(w_i + G_{-i)}, 0\}$. Introducing heterogeneity into the preference specification, positing that some individuals have a higher preference for the public good, yields the intuitive solution that higher-preference types contribute more. To this end, consider two types of consumers, $u_i^A(x_i, G)$ and $u_i^B(x_i, \kappa G)$, with $\kappa \geq 1$; the analogous optimization problem yields $\frac{\partial G u_i^B(x_i^*, G^*)}{\partial x_i u_i^B(x_i^*, G^*)} = \frac{1}{\kappa} \leq 1$ for $\kappa \geq 1$, implying that, $\forall w_i, G_{-i}$, and denoting by $g_i^{D,A}(w_i, G_{-i})$ and $g_i^{D,B}(w_i, G_{-i}, \kappa)$ the demand functions of the two types, we have $g_i^{D,A}(w_i, G_{-i}) \geq g_i^{D,B}(w_i, G_{-i}, \kappa)$; those who value the public good more contribute weakly more.

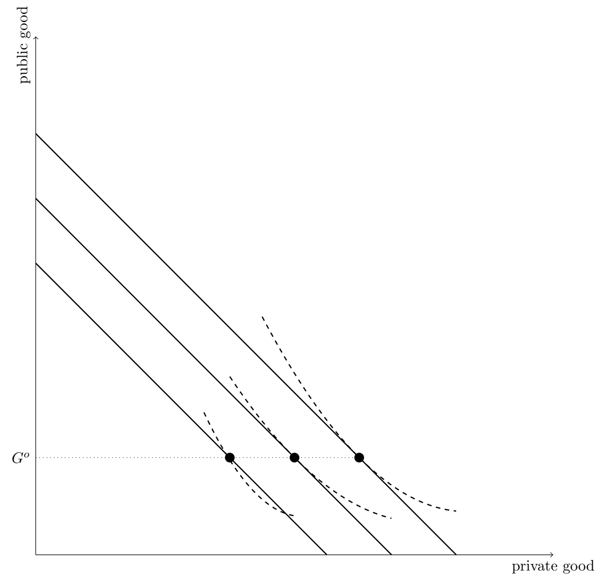

Figure A.2: An equilibrium with three individuals and two donors post-full-scale war

A typical Nash equilibrium reproduced from Bergstrom, Blume and Varian (1986), with three individuals, two of whom donate, and who have identical preferences but different wealth levels is depicted in Figure A.2:

However, after the onset of the full-scale invasion, we instead observe a point like G^* as depicted in A.3, where *i*) $G^* > G^o$, *ii*) the number of donors rises to three, and *iii*) more individuals donate. Figure A.3 suggests that preferences - if they are to be stable - are not homothetic. Furthermore, with unchanging preferences, this figure, reflecting the first two points above, implies that national defense is an inferior, and possibly even Giffen, good, which is at odds with the standard interpretation, and does not seem to be the case in our setting.[12]

We posit that the explanation, within the context of a standard model of choice with a private and a public good, is a sharp change in preferences.[13] While such an explanation may often be vacuous, this appears to be the only explanation that accounts for all of the features of the situation we discuss; indeed, perhaps war is one of the few instances where preferences do, in fact, change dramatically; indeed, if any situation is likely to lead to a change in preferences it is wartime, and learning about civilian casualties. Figure A.3 depicts a situation where, in equilibrium, if not globally, the marginal rates of substitution change. If we allow for the utility to depend on the *type*

[12] While there is some literature showing that less wealthy individuals give a higher share of their income to charity, in our case not only the share but the absolute level of giving, as well as the number of donors, rose after the full-scale invasion.

[13] In fact, from Figure A.3 it is apparent that the change in preferences resembles a typical figure from the economics of information, with a "high" and a "low" type, whose marginal rates of substitution differ.

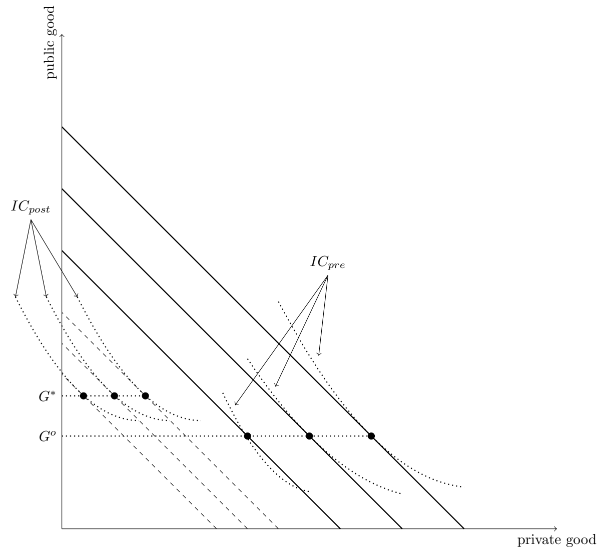

Figure A.3: An equilibrium with three donors

$\theta \in \{\theta_{pre}, \theta_{post}\}$, then the revealed slopes of the indifference curves satisfy

$$\frac{\partial^2 u_i(x_i, G, \theta_{post})}{\partial x_i \partial G}|_{G^o} < \frac{\partial^2 u_i(x_i, G, \theta_{pre})}{\partial x_i \partial G}|_{G^o} \tag{6}$$

$$\frac{\partial^2 u_i(x_i, G, \theta_{post})}{\partial x_i \partial G}|_{G^*} = \frac{\partial^2 u_i(x_i, G, \theta_{pre})}{\partial x_i \partial G}|_{G^o} \tag{7}$$

Equation (6) says that at the old equilibrium, the new indifference curve is steeper than the old indifference curve, while equation (7) says that because prices did not change, the slopes of the indifference curves at the new equilibrium (with new preferences) and the old equilibrium (with old preferences) did not change.

Furthermore, one might suppose that preferences changed in away so as to require a minimum level of consumption of the public good, with the reasoning that there needs to be a minimum level of defense provided by society to enable other forms of consumption. For example, little to no consumption would occur in a destroyed or occupied household. At least for a classic example of such preference specification (Stone-Geary preferences: non-homothetic preferences with a minimum consumption level), this does not appear to be the case, because this class of preferences also implies a linear expenditure function, which, again, appears to be violated in our setting.

Finally, why do individuals donate to a charity? In our setting it appears that giving directly to the government may be less salient because individuals may feel that they have "already done their duty" vis-a-vis the government by paying taxes, the government may take longer to procure the good due to bureaucracy, the government may be corrupt, or the government is not transparent. To this end, let us suppose again that there are two types of consumers (as above), and that individuals can donate to both a government-provided public good g_i^g, and a non-profit-provided good g_i^n. Referring back to CBA's description of itself as a "fund of competent [sic] aid to the military", let us also suppose that the government-provided good is less effective than the equivalent amount of the non-profit good. This can be because of corruption, perception of corruption, or simply a longer delay between a donation to the government and the delivery of the procured items. Thus, assuming both kinds of public goods contribute equally to the overall final public good, each type of consumer solves the following optimization problems:

$$\max_{x_i, G} u_i(x_i, G) \tag{8}$$

$$\text{s.t. } x_i + (1+\beta) g_i^g + g_i^n \le w_i \tag{9}$$

$$G = \sum_i (g_i^g + g_i^n) \tag{10}$$

and

$$\max_{x_i, G} u_i(x_i, \kappa G) \tag{11}$$

$$\text{s.t. } x_i + (1+\beta) g_i^g + g_i^n \le w_i \tag{12}$$

$$G = \sum_i (g_i^g + g_i^n) \tag{13}$$

The parameter $\beta > 0$ measures the extent of *bureaucracy* - the degree to which a donation to the government-provided good is less effective than a donation to a non-profit-provided good, which we model as a simple increase in the relative price.

Assuming that both kinds of donations are perfect substitutes (an assumption which can be relaxed without changing any of the the main conclusions) implies that at the optimum both types of individuals will make all of their contributions to the non-profit-provided good, and assuming that some individuals have a higher preference for the public good than others implies (as above) that those individuals will contribute more. This is precisely the insight of Weisbrod (1975). Finally, to the extent that information about civilian casualties affects individual demand for the public good, say, by increasing the κ parameter, this simple model predicts that individuals will donate more to the public good if they observe more civilian casualties.

It remains to consider why the specific kind of events that we focus on - namely, civilian casualties - among all of the possible events and media conversations that we observe in our data, cause an increase in the amount donated. A completely theoretical answer is impossible; instead, it is very likely a combination of psychological reasons, such as a sense of kinship with the victims, a sense of "it could have been me," and a drive to prevent future casualties. Relatedly, civilian casualties may be an indicator that the current level of spending on national defense (the public good) is evidently insufficient; military protection is one of the fundamental features of the state, and if there are persistently high civilian casualties, it is a signal that the funds allocated to national defense are lacking. Donating to the public good thus provides an outlet to the impossibly difficult situation many Ukrainians found themselves in, an outlet for the desire to help, and a sense of agency.

B GDELT dataset

Our mention variables are constructed from the GDELT dataset, which classifies events using the Conflict and Mediation Event Observations (CAMEO) coding system. We extract all Ukrainian media mentions of events where at least one actor is from Ukraine and which fall under specific CAMEO codes. Below, we list the codes used for each category and their definitions as specified in the GDELT CAMEO Event and Actor Codebook.

B.1 All military mentions

Includes CAMEO codes:

- 18: Assault, includes the following subcategories:
  - 180: Use unconventional violence, not specified below
  - 181: Abduct, hijack, or take hostage
  - 182: Physically assault, not specified below
  - 1821: Sexually assault
  - 1822: Torture
  - 1823: Kill by physical assault
  - 183: Conduct suicide, car, or other non-military bombing, not specified below
  - 1831: Carry out suicide bombing
  - 1832: Carry out car bombing
  - 1833: Carry out roadside bombing

  - 184: Use as human shield
  - 185: Attempt to assassinate
  - 186: Assassinate

- 19: Fight includes the following subcategories:
  - 190: Use conventional military force, not specified below
  - 191: Impose blockade, restrict movement
  - 192: Occupy territory
  - 193: Fight with small arms and light weapons
  - 194: Fight with artillery and tanks
  - 195: Employ aerial weapons
  - 196: Violate ceasefire

- 20: Unconventional Mass Violence, includes the following subcategories:
  - 200: Use unconventional mass violence, not specified below
  - 201: Engage in mass expulsion
  - 202: Engage in mass killings
  - 203: Engage in ethnic cleansing
  - 204: Use weapons of mass destruction, not specified below
  - 2041: Use chemical, biological, or radiological weapons
  - 2042: Detonate nuclear weapons

- 087: De-escalate military engagement, includes the following subcategories:
  - 0871: Declare truce, ceasefire
  - 0872: Ease military blockade
  - 0873: Demobilize armed forces
  - 0874: Retreat or surrender militarily

- 174: Expel or deport individuals

- 175: Use tactics of violent repression

B.2 Civilian violence mentions

CAMEO codes included:

- 20: Use unconventional mass violence, that includes the following subcategories:
  - 200: Use unconventional mass violence, not specified below
  - 201: Engage in mass expulsion
  - 202: Engage in mass killings
  - 203: Engage in ethnic cleansing
  - 204: Use weapons of mass destruction, not specified below
  - 2041: Use chemical, biological, or radiological weapons
  - 2042: Detonate nuclear weapons
- 195: Employ aerial weapons

B.3 Missile attack mentions

CAMEO code included:
195: Employ aerial weapons

B.4 Deescalation mentions

CAMEO codes included: 087: De-escalate military engagement, includes the following subcategories:

- 0871: Declare truce, ceasefire
- 0872: Ease military blockade
- 0873: Demobilize armed forces
- 0874: Retreat or surrender militarily

B.5 Frontline mentions

CAMEO codes included:

- 190: Use conventional military force, not specified below
- 193: Fight with small arms and light weapons

- 194: Fight with artillery and tanks

It is important to note that the military mentions, frontline mentions, missile attack mentions or violence against civilians mentions include mentions of these events in the press and do not include statements by politicians about these events, or announcement of military aid, as these categories are defined separately in the CAMEO classification.

C Further Analysis: OLS Estimates

Table C.1: Casualties and Other Events. OLS. Log Daily Total Amount Donated

	(1)	(2)	(3)	(4)
Log art. shelling	0.130*			
	(0.070)			
Log occupation		0.066**		
		(0.030)		
Log tank battles			0.063**	
			(0.028)	
Log territory control claim				0.041
				(0.042)
R2	0.589	0.589	0.589	0.586
N	676	676	676	676
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. Log artillery shelling represents the log of recorded artillery shelling incidents. Log occupation events denote reported territorial occupations. Log territory control changes measure recorded shifts in territorial control.

Table C.2: Robustness check. Estimated OLS Results for Log Daily Amount Donated by Mentions and Casualty Events

	Events				
	(1)	(2)	(3)	(4)	(5)
Log civ. casualty events	0.363***	0.254***	0.351***	0.274***	0.313***
	(0.082)	(0.079)	(0.082)	(0.088)	(0.082)
Sanctions		0.025***			
		(0.004)			
Log air alert in Ukraine			0.064*		
			(0.038)		
Log air strike in Ukraine by Russia				0.134***	
				(0.043)	
Log hospital attack in Ukraine by Russia					0.110***
					(0.035)
R2	0.595	0.615	0.596	0.602	0.601
N	676	676	676	676	676

	Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civ. casualty events	0.298***	0.327***	0.326***	0.358***	0.294***
	(0.075)	(0.079)	(0.079)	(0.081)	(0.075)
Log Ukrainian military mentions	0.461***				
	(0.102)				
Log civilian violence mentions		0.110***			
		(0.033)			
Log missile mentions			0.110***		
			(0.032)		
Log deescalation mentions				0.116***	
				(0.044)	
Log frontline mentions					0.449***
					(0.091)
R2	0.610	0.601	0.601	0.598	0.613
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is the log of the daily total donated amount, with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include world event counts, a binary variable for Come Back Alive donation events, day of the week, month and year fixed effects, trend, and holiday indicators. In Panel (A), Log civilian casualties refers to the log of reported Ukrainian civilian casualties. Sanctions capture the number of economic sanctions imposed on Russia on that date. Log air alert in Ukraine represents the log of air alerts issued nationwide, while Log air strike in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the log of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), Log civilian violence mentions represents the log of media mentions of civilian violence in Ukraine. Log military mentions captures the log of military mentions in Ukrainian media on the same date. Log missile mentions captures missile-related mentions in Ukrainian media. Log deescalation mentions refers to media reports of deescalation, while Log frontline mentions reflects the log of media mentions related to the frontline, all on the same date.

Table C.3: Robustness check. The effect of military events. Joint effects

	(1)
	Log donated amount
Log civilian casualties	0.079**
	(0.033)
Log Ukrainian military mentions	0.395***
	(0.107)
Log air alert in Ukraine	-0.008
	(0.040)
Log air strike in Ukraine by Russia	0.101**
	(0.042)
Log art. shelling	-0.094
	(0.080)
Log hospital attack in Ukraine by Russia	0.064*
	(0.033)
Log occupation	0.012
	(0.032)
Sanctions	0.023***
	(0.004)
Log tank battles	0.053**
	(0.027)
Log territory control claim	-0.041
	(0.046)
R2	0.631
N	675
Month FE	Yes
Year FE	Yes
Controls	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. Log civilian casualties represents the log of reported Ukrainian civilian casualties. Log all military mentions refers to the log of Ukrainian media mentions of military-related events. Log air alert captures the log of nationwide air alerts issued on a given date. Log air strike records the log of Russian air strikes on Ukraine. Log artillery shelling captures reported Russian artillery shelling incidents. Log hospital attack refers to Russian-initiated attacks on medical facilities. Log occupation events denote reports of Russian-occupied territories. Sanctions reflects the economic sanctions imposed on Russia. Log tank battles measures recorded tank engagements. Log territory control refers to shifts in territorial control reported in media sources.

Table C.4: Robustness check. The effect of bad and good events

	Log donated amount		
	(1)	(2)	(3)
Russia initiated event	0.004^{***}		0.004^{***}
	(0.001)		(0.001)
Ukraine initiated event		0.005^{***}	-0.001
		(0.001)	(0.002)
R2	0.610	0.595	0.609
N	676	676	676
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. The variable Russia initiated event represents major war-related events initiated by Russia, including large-scale attacks, missile strikes, and other forms of aggression. The variable Ukraine initiated event represents significant events initiated by Ukraine, such as successful military counteroffensives, territorial gains, or strategic advances.

Table C.5: Robustness check. The crowding out effect of international aid

	Log donated amount		
	(1)	(2)	(3)
Log military aid	-0.007		-0.007
	(0.008)		(0.009)
Log financial aid		-0.005	-0.003
		(0.012)	(0.012)
Log humanitarian aid		-0.001	-0.001
		(0.009)	(0.009)
R2	0.571	0.570	0.569
N	676	676	676
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. The variable Log military aid represents the log of military aid received from international sources. The variable Log financial aid captures the log of financial assistance allocated to Ukraine. The variable Log humanitarian aid refers to the log of humanitarian aid provided.

Table C.6: Robustness check. The effect of conscription announcements.

	Log donated amount			
	(1)	(2)	(3)	(4)
Conscription	-0.078	-0.049	-0.034	-0.121
	(0.265)	(0.272)	(0.266)	(0.265)
Log Ukrainian military mentions		0.564***		
		(0.122)		
Log civilian casualties			0.134***	
			(0.036)	
Log Russian military casualties				0.203***
				(0.051)
R2	0.570	0.594	0.585	0.584
N	676	675	676	676
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. The variable conscription is a binary indicator for official conscription announcements. The variable Log Ukrainian military mentions represents the log of all Ukrainian media mentions of military-related events. The variable Log civilian casualties refers to the log of reported Ukrainian civilian casualties, while Log Russian military casualties represents the log of reported Russian military casualties.

Table C.7: Disaggregated location-specific effects of civilian casualties.

	Log donated amount					
	(1)	(2)	(3)	(4)	(5)	(6)
Log civilian casualties in Kyiv	0.505***					0.324***
	(0.125)					(0.122)
Log civilian casualties in		0.119***				0.069**
major cities on the frontline		(0.037)				(0.029)
Log civilian casualties in			0.153			0.019
major cities away from the frontline			(0.096)			(0.059)
Log civilian casualties in				0.069**		0.054**
small cities on the frontline				(0.027)		(0.027)
Log civilian casualties in					0.249***	0.142**
small cities away from the frontline					(0.067)	(0.057)
R2	0.600	0.581	0.576	0.575	0.598	0.613
N	676	676	676	676	676	676
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All models control for a count of world events, a binary indicator for 'Come Back Alive' donation campaigns, day-of-week fixed effects, as well as month and year fixed effects, and dummies for holidays. Kyiv casualties measure daily civilian casualties in Kyiv city. Casualties in major cities on the frontline refer to regional (oblast) centers that were actively involved in frontline combat. Casualties in major cities away from the frontline refer to regional centers not directly exposed to fighting. Small cities on the frontline include casualties in towns and small urban settlements exposed to active fighting. Small cities away from the frontline include casualties in small urban areas distant from direct hostilities.

D Further Analysis: VAR

Table D.1: Estimated cumulative impulse responses of donations to events and mentions for other events

	(1)	(2)	(3)	(4)
Log military mentions	1.514***	2.210***	1.501***	2.243***
	(0.323)	(0.517)	(0.321)	(0.522)
Log tank battles	-0.001			
	(0.057)			
Russia initiated event		0.825**		
		(0.415)		
Ukraine initiated event			0.240**	
			(0.115)	
Log territory control claim				0.196
				(0.172)

Note: The dependent variable is the logarithm of the daily total donated amount. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, daily trends, month and year fixed effects, and dummies for holidays. Log military mentions represents the logarithm of media mentions of military events in Ukraine. Log tank battles refers to reported tank engagements. Russia-initiated event is a binary indicator of a significant military action initiated by Russia. Ukraine-initiated event is a binary indicator of a significant military action initiated by Ukraine. Log territory control claim refers to the logarithm of reported claims of changes in territorial control.

E Analysis for Number of Donations

Table E.1: Double machine learning for high-dimensional controls for number of donations

	Log donated transactions			
	(1)	(2)	(3)	(4)
	lasso-lasso	lasso-ridge	ridge-lasso	ridge- ridge
Log civilian casualties	0.04	0.04	0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.01)
	[0.02]	[0.02]	[0.03]	[0.1]
Log military mentions	0.03	0.11	0.06	0.1
	(0.05)	(0.05)	(0.06)	(0.05)
	[0.58]	[0.03]	[0.33]	[0.04]

Note: The dependent variable is the logarithm of the daily total donated amount. Robust standard errors in parentheses, and p-values in brackets. Each panel estimates the ATE and standard errors of the effect of log civilian causalities, or log military mentions, on log donated amount. Column labels denote the method used to estimate the nuisance functions. Controls include 1st and 2nd order polynomial terms and their interactions of time dummies ('year', 'month', 'day', 'dow', 'week') and holidays, CBA events, and total world events for a total of 6669 controls. A second-order polynomial was selected for the control variables based on 5-fold cross-validation, as it yielded lower mean squared errors for the nuisance functions compared to higher-order polynomials.

Table E.2: Estimated OLS Results for Log Daily Total Donations for Mentions and Events

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.028*	0.006	0.027*	0.024	0.025*
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Sanctions		0.017***			
		(0.003)			
Log air alert in Ukraine			0.047**		
			(0.021)		
Log air strike in Ukraine by Russia				0.035	
				(0.023)	
Log hospital attack in Ukraine by Russia					0.023
					(0.023)
R2	0.432	0.470	0.435	0.433	0.432
N	676	676	676	676	676

	Panel B: Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.028*	0.029**	0.029**	0.026*	0.025*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log Ukrainian military mentions	0.013				
	(0.058)				
Log civilian violence mentions		-0.015			
		(0.019)			
Log missile mentions			-0.015		
			(0.019)		
Log deescalation mentions				0.070**	
				(0.028)	
Log frontline mentions					0.069
					(0.054)
R2	0.431	0.432	0.432	0.436	0.433
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is the log of the daily total donations, with robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include world event counts, a binary variable for Come Back Alive donation events, day of the week, month and year fixed effects, trend, and holiday indicators. In Panel (A), Log civilian casualties refers to the log of reported Ukrainian civilian casualties. Sanctions capture the number of economic sanctions imposed on Russia on that date. Log air alert in Ukraine represents the log of air alerts issued nationwide, while Log air strike in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the log of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), Log civilian violence mentions represents the log of media mentions of civilian violence in Ukraine. Log military mentions captures the log of military mentions in Ukrainian media on the same date. Log missile mentions captures missile-related mentions in Ukrainian media. Log deescalation mentions refers to media reports of deescalation, while Log frontline mentions reflects the log of media mentions related to the frontline, all on the same date.

Table E.3: Robustness check. Estimated OLS Results for Log Daily Donations by Mentions and Casualty Events

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civ. casualty events	0.091**	0.021	0.084**	0.078**	0.085**
	(0.039)	(0.034)	(0.039)	(0.038)	(0.039)
Sanctions		0.016***			
		(0.003)			
Log air alert in Ukraine			0.041**		
			(0.021)		
Log air strike in Ukraine by Russia				0.020	
				(0.021)	
Log hospital attack in Ukraine by Russia					0.015
					(0.021)
R2	0.436	0.471	0.438	0.436	0.435
N	676	676	676	676	676

	Panel B: Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civ. casualty events	0.093**	0.099**	0.099**	0.089**	0.084**
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Log Ukrainian military mentions	-0.007				
	(0.056)				
Log civilian violence mentions		-0.022			
		(0.019)			
Log missile mentions			-0.023		
			(0.019)		
Log deescalation mentions				0.070**	
				(0.028)	
Log frontline mentions					0.053
					(0.053)
R2	0.435	0.436	0.436	0.440	0.436
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is the log of the daily total donations, with robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include world event counts, a binary variable for Come Back Alive donation events, day of the week, month and year fixed effects, trend, and holiday indicators. In Panel (A), Log civilian casualties refers to the log of reported Ukrainian civilian casualties. Sanctions capture the number of economic sanctions imposed on Russia on that date. Log air alert in Ukraine represents the log of air alerts issued nationwide, while Log air strike in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the log of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), Log civilian violence mentions represents the log of media mentions of civilian violence in Ukraine. Log military mentions captures the log of military mentions in Ukrainian media on the same date. Log missile mentions captures missile-related mentions in Ukrainian media. Log deescalation mentions refers to media reports of deescalation, while Log frontline mentions reflects the log of media mentions related to the frontline, all on the same date.

Table E.4: Estimated cumulative impulse responses of number of donations to events and mentions

	Panel A: Events			
	(1)	(2)	(3)	(4)
Log military mentions	-0.220	-0.212	-0.215	-0.204
	(0.253)	(0.253)	(0.252)	(0.251)
Log civilian casualties	0.042			
	(0.049)			
Log air alert in Ukraine		0.086		
		(0.073)		
Log air strike in Ukraine by Russia			0.008	
			(0.086)	
Log hospital attack in Ukraine by Russia				-0.008
				(0.071)

	Panel B: Mentions			
	(1)	(2)	(3)	(4)
Log civilian casualties	0.040	0.040	0.035	0.041
	(0.049)	(0.049)	(0.048)	(0.048)
Log civilian violence mentions	-0.052			
	(0.076)			
Log missile mentions		-0.059		
		(0.076)		
Log deescalation mentions			0.271**	
			(0.116)	
Log frontline mentions				-0.135
				(0.227)

Note: The dependent variable is the logarithm of the daily number of donations. Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a binary variable for Come Back Alive donation events, day, week, daily trend, month and year fixed effects, and dummies for holidays. In Panel (A), Log civilian casualties refers to the log of reported Ukrainian civilian casualties. Log military events captures the logarithm of military events on the same date. Log air alert in Ukraine represents the logarithm of air alerts issued nationwide, while Log air strike in Ukraine by Russia and Log hospital attack in Ukraine by Russia denote the logarithm of Russian air strikes and hospital attacks, respectively, on the given date. In Panel (B), Log civilian violence mentions represents the logarithm of media mentions of civilian violence in Ukraine. Log missile mentions captures missile-related mentions in Ukrainian media. Log deescalation mentions refers to media reports of deescalation, while Log frontline mentions reflects the log of media mentions related to the frontline, all on the same date.