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

Margaryta Klymak* Andrew Kosenko Oleg Korenok Dariia Mykhailyshyna
Kathryn Vasilaky

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Abstract

We analyze how military events, casualties, and media coverage influence same-day donations to a major Ukrainian nonprofit supporting the military 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 $4,860 and $6,992 in same-day donations, and leads to at least $15,550 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 $2,584 increase in same day donations and an $8,121 increase in cumulative donations.

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*Klymak: King's College London, margaryta.klymak@kcl.ac.uk. Kosenko: Marist College, andrew.kosenko@marist.edu. Korenok: Virginia Commonwealth University, okorenok@vcu.edu. Mykhailyshyna: University of Bologna, dariia.mykhailyshyn2@unibo.it. Vasilaky: Cal Poly, kvasilak@calpoly.edu. We thank Come Back Alive for allowing the use of their data; Tetyana Deryugina, Nate Neligh, Luke Fesko, David Zuchowski, Harald Puhr, Guglielmo Barone, Eduardo Zambrano and Tim Vlandas for helpful conversations and comments; and the audiences at the CSAE Conference 2025, the 2024 European Winter Meeting of the Econometric Society, the 94th Southern Economic Association Annual Meeting, the 99th Western Economic Association International Annual Conference, and seminar participants at Marist University, Columbia University, the University of Bologna, and the National Bank of Ukraine.

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. Rather than aiming to rebuild physical and community conditions to their previous state, wartime giving to a defense effort represents a long-term investment to achieve victory in a conflict, often without a clear or certain route to success. This type of giving operates within the uncertainty of war, where timelines are undefined, outcomes are unpredictable, and the strategy for achieving objectives may be changing from day to day. 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 examines this unique form of grassroots giving in the context of Russia's full-scale invasion of Ukraine on February 24, 2022, addressing a significant gap in the existing research on wartime charitable giving. Our purpose is to document and explain the unprecedented surge in individual donations to national defense during a full-scale invasion by a neighboring country.

The full-scale 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 forced into internal displacement. 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).

Unprecedented levels of foreign aid and charitable donations to Ukrainian causes from abroad and from its own citizens were part of the response. Ukraine also 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 *lethal* aid - Come Back Alive (CBA) - and examining direct individual donations to the Ukrainian military, channelled through CBA.[1] For CBA, charitable giving between the start of the full-scale invasion and December 2023 has totalled 10 billion Ukrainian hryvnia (UAH) (Come Back Alive, 2025), 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

[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.

air attacks versus hospital strikes, the number of civilian casualties they cause, and the media coverage that they receive. This comprehensive dataset allows us to trace how different war-related events and media coverage influence donations.

We use a unique, 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, as that captures the total contribution to the public good, while we report results for other measures in the appendix. 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: an 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, over time, 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, we find that civilian casualties increase donations. A 1% increase in civilian casualties increases daily donations by 0.25-0.36% daily, and cumulatively by 0.8%. Air strikes and attacks on hospitals are the classes of events that have the largest impact on giving. The effect of all military mentions appear to be larger than the effect of civilian casualties, with a 1% increase in military mentions lead to the 0.46% 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 and mentions linger for several days, peaking on the day following the event.

Studies examining charitable contributions during wars are notably absent, making it important to understand this kind of charitable giving. Furthermore, the Ukrainian response to the war has generated remarkable levels of such giving. Few, if any, examples exist of ordinary citizens so extensively supporting military efforts in their country (Wood, 2019), making this a particularly important and interesting instance. This grassroots giving has been important both for sustaining defenses as well as for self-reinforcement of citizen morale and resilience.

Our paper is structured as follow. Section 2 discusses the related literature. Section 3 provides the historical background, details on CBA, and highlights factors that make this setting unique. Section 4 describes the data sources and the variables we construct. Section 5 lays out the empirical estimation. Section 6 reports the results: in Subsection 6.1 we focus on *events* and document that casualties are positively associated with the 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 and Subsection 6.4 describes additional results. We present additional results and robustness checks in Supplemental Appendices.

2 Related Literature

Charitable giving to specific causes is a central focus of the economics of philanthropy and public goods, which explains donations as arising from preferences for others' well-being, personal satisfaction, or both. Altruism, the desire to improve the welfare of others, is often a primary motivation for giving (Andreoni, 1989, 1990). Other factors include social norms, peer pressure, and the psychological rewards of giving, such as the "warm glow" effect (Harbaugh, 1998). Emotional appeals also play a powerful role; for example; 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 be driven by empathy and altruism (Adena and Harke, 2022; Black et al., 2021) but can also include self-interested 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). Donations can also yield tangible returns, such as rebuilding infrastructure and improving economic activity beyond pre-disaster levels (Deryugina and Marx, 2021; Jayaraman, Kaiser and

Teirlinck, 2023). Media coverage significantly amplifies giving (Adena and Harke, 2022; Eisensee and Strömberg, 2007; Jayaraman, Kaiser and Teirlinck, 2023), with both the frequency and specificity of reporting influencing donation levels. For instance, Brown and Minty (2008) showed that additional nightly news coverage following the 2004 tsunami boosted donations by 13.2%, while coverage in major newspapers increased contributions by 18.2%. Adena and Harke (2022) showed that media coverage of local Covid-19 severity significantly increased charitable giving, with each additional 10 related news articles associated with an increase of approximately 5 to 11 pence in donations per participant.

Charitable giving during wartime differs fundamentally from disaster-related giving. 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. Both the afflicted and the donors may benefit from this support, albeit for different reasons. Donations are not tied to a discrete recovery period but require a sustained flow over an indeterminate timeline, as the end of the conflict and its resolution remain uncertain. This presents a unique scenario that extends beyond traditional models of charitable giving, necessitating further exploration.

While there is limited literature on charitable giving during wars, some parallels can be drawn from responses to crises like the September 11 terrorist attacks. In that context, 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 in their ongoing nature and their collective investment in a public good, making Ukraine's case particularly compelling and underexplored.[2]

There is also a large literature documenting the inefficiency of private provision of public goods, as well as work on overcoming this issue (Bagnoli and Lipman (1989), Alberti and Mantilla (2024), Van Essen and Walker (2017), to give but a few examples). This literature focuses on mechanisms that overcome the various problems (participation, free-riding, incomplete information, inefficiency, balancing the budget) that may arise in this setting. 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 what is essentially a voluntary contributions mechanism; we review additional unusual features of this situation in subsection 3.3.

When government provision of public goods is insufficient to meet individual preferences, vol-

[2]Our findings are consistent with research 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.

untary organizations may emerge to address the gap (Weisbrod, 1975). These organizations are sustained by private donations, suggesting that those who donate are motivated for reasons that extend beyond pure economic rationality (Andreoni and Payne, 2013; Echazu and Nocetti, 2015). However, when public provision relies only on voluntary contributions, the free-rider problem still remains a persistent challenge, and underfunding is common (Bagnoli and Lipman, 1989; Palfrey and Rosenthal, 1984). This raises the questions about what drives private giving and how voluntary provision can be sustained.

3 Background

3.1 Historical Context and Origins of the Volunteer Movement

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. The Ukrainian military successfully resisted. Russian plans for a quick victory were foiled by stiff resistance by the Ukrainian military and civilians. 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. There is also a robust system of small fundraisers initiated by individuals and operated via Monobank, a Ukrainian bank. Between February 2022 and March 2024 users donated almost 50 billion UAH (approx. $1.25 billion) using this mechanism (Gorokhovskiy, 2024). Thus, donors can donate to a variety of organizations - governmental and nongovernmental, those based in Ukraine or those based abroad, and there is significant heterogeneity in the kinds of aid (lethal military, non-lethal military, tactical medicine, civilian medicine, civilian support, rehabilitation, support for refugees and internally displaced persons, and others) the organizations provide.

3.2 Come Back Alive Foundation

We focus on Come Back Alive for several reasons. It is one of the largest, most important, and best-known organizations of its kind. Furthermore, its transparency - the organization lists all of its donations and expenditures on its website - allows for unprecedented access into the inner workings of a unique non-profit organization. Its self-stated aim is:

> *Our primary objective is to enhance the effectiveness of the Ukrainian Defense Forces, save the lives of our servicemen, and systematically counteract the enemy. To achieve this, the Foundation procures equipment, including thermal optics, drones, vehicles, and surveillance and reconnaissance systems. Come Back Alive is also the first charity organization in Ukraine authorized to purchase and import military and dual-purpose goods.*

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 is the largest NGO providing lethal aid to the military. In some ways, it is emblematic of the surge of support for the Ukrainian military.

3.3 Donation Behavior and Setting: Crowdfunding the State

Our primary interest is in documenting patterns of charitable giving. The literature on natural disasters has already established clear behavioral patterns in response to sudden crises, providing a useful point of comparison. However, the setting we analyze is quite different: donations are directed toward a pure public good—national defense. This form of giving is both interesting and unusual because it is:

1. Decentralized: while there are periodic fundraising campaigns by CBA, donations are "bottom-up" - large numbers of individuals making relatively small contributions;
2. Non-governmental: not coordinated or mandated by the state, and bypassing the usual governmental channels in both raising funds and spending them;
3. Unlike other wartime fundraising campaigns (such as war bonds campaigns in the World Wars), these donations have no return on investment and there is no single national fundraising campaign;
4. Numerous, repeated, and large-scale (approximately 3,900,000 donations totaling to approximately $385 million, from 2014 onward, as of October 2024), at a relatively constant frequency over the course of at least two and a half years;
5. Not targeted: individuals generally cannot direct their donations to any specific initiative or use. While there are some specific campaigns advertised by the CBA (examples include a

campaign to procure 300 mortar artillery pieces, and a campaign to procure thermal imaging for aerial reconnaissance), donors generally have no control over the specific use of funds (where the procurement takes place or at what price);

6. Largely anonymous: while some individual donors choose to self-identify (for instance, in the "comment" section to a donation), most remain anonymous;

7. Voluntary: there are no direct or indirect adverse consequences for not donating to this charity (because donations are anonymous, no punishment is possible).

These factors come together to create a unique economic situation; large numbers of individuals repeatedly donate significant amounts to a pure public good over time. Among our contributions is to document the mere existence of this phenomenon and to describe it.

These considerations raise the question: Why do individuals and organizations donate large amounts for public goods for sustained periods of time during a crisis? Identifying potential answers to this question is beyond the scope of our work here (in no small part due to data limitations). We note simply that this is, indeed, a very puzzling — yet very real — phenomenon. Donating to a public good on such a scale begs the question: why do individuals not simply pay taxes?[3] Anonymity of small online donations rules out a potential reputation motive as well as the social pressure motive. The inability to direct donations rules out donating because the donor believes the donation will directly help a relative or an acquaintance. Given the features described in the list above, a "tragedy of the commons" and free-riding might be expected, yet we document quite the opposite.

We can, however, answer a related question: *When* do people donate? As we describe further below, it is civilian casualties and mentions of military events that drive donations, and most people donate immediately after an event.

4 Data Sources

We use three primary data sources: donation records from CBA, media coverage data from the Global Database of Events (GDELT), and conflict incident data from the Violent Incident Information from News Articles (VIINA). Summary statistics for these datasets are provided in Supplementary Appendix B.

[3] A part of the story may be the relative inefficiency and potential corruption in state mechanisms of procurement and use of war-related matériel, echoed by one of CBAs slogans "The fund for *competent* aid to the military" (emphasis added) but this is unlikely to be the only explanation. In addition, some people may contribute on the top of paying their taxes, as they realize that the existing taxes are not enough to sustain the military in the wartime.

4.1 Donations: Come Back Alive Foundation

All of CBA's donations, procurements, and disbursements are available on its website. We use all individual-level donations spanning from February 24, 2022, and December 31, 2023. 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 observe information about the amount donated, the original currency, the timestamp of the donation, and the bank that processed the donation as well as all large fundraiser launches or other important events.[4] 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 facilitate comparisons with GDP figures.

4.2 Military Events: Violent Incident Information from News Articles

Our second source, the Violent Incident Information from News Articles 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 news channel), and Russian-language sites located outside of Russia (such as *Meduza*, an opposition news site located in 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." VIINA is also our source for the data on Ukrainian civilian fatalities.

4.3 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 recorded in the GDELT dataset in the world, which is used as a control variable in our specification.

[4] We excluded all transactions under 1 UAH, as these were mostly transaction fees rather than actual donations. 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.

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. [5] 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 the Ukraine-related mentions by a type of media. In particular, we create a variable *all Ukrainian mentions*, which includes only mentions by the Ukrainian media sources (those that have a ".ua" domain name or one of the manually selected Ukrainian websites that do not have a ".ua" domain name, but 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 media mentions of different types of events from Ukrainian sources and all variables based on the mentions only include mentions by Ukrainian media, unless explicitly specified otherwise.

Furthermore, the GDELT data contains 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).

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 happened.

[5] 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.

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 in Supplemental Appendix E). The emphasis on the intensive margin is driven by the fact that the total amount donated is what is crucial in 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 in Ukraine; although all public holidays were canceled because of the invasion, research shows that altruism may increase during the holidays (Ekström, 2018), and as such we take into account regular holidays (even if they are not technically holidays during wartime). 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. While substantial evidence indicates that Russian forces deliberately target civilian areas, there is also clear evidence of indiscriminate attacks. Even in targeted strikes, randomness plays a decisive role in determining the actual number of casualties. 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.

Russian forces appear to engage in both indiscriminate, random attacks, as well as targeted attacks, against civilians. First, there is extensive evidence[6] suggesting that the Russian military has repeatedly targeted civilians and civilian targets in Ukraine. These attacks are separate from Russian attacks on critical civilian infrastructure in Ukraine. Second, the pattern of civilian casualties appears to have a time trend, which would not be present if the attacks were randomized across time.

On the other hand, however, there is also extensive evidence of truly random, indiscriminate attacks on civilians.[7] 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, even if the intent to attack is not random in itself. Second, and perhaps more importantly, conditional on a strike at a particular location, the *number* of civilian fatalities is random - it is not known (even by the attacking side, with few exceptions), nor is it predetermined in advance. Conditional on being present at the site of an attack (and because we focus on *civilian* casualties, who can be killed in their own homes or in public spaces), the number

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

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

and severity of injuries (and whether an injury will lead to death) is determined by chance - and certainly this is true from the point of view of potential future donors.

Third, the location of an attack resulting in civilian casualties may itself be random. One is the imprecision of Russian artillery, bombs, drones, and missiles. Even Russia's guided missiles have notable targeting limitations; for example, the Kh-55 cruise missile, frequently used against Ukrainian infrastructure, has a circular error probable of up to 100 meters - meaning half of the missiles will miss their intended target by at least that margin. As a result, even 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. Ukrainian air defense units have become adept at intercepting certain kinds of munitions; and while they are a lot less able to intercept more sophisticated ballistic and cruise missile attacks, they have achieved considerable success against even the most advanced Russian weapons. The location, as well as the effectiveness of many of these air defense units, is itself random, as some are composed of mobile truck-mounted weapons systems; if such a unit damages a Russian drone or a missile in flight, the projectile might deviate from its course and crash 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:

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

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 identifying standard restriction through a Cholesky decomposition and the order of endogenous variables. We order donations first, casualties second, and media mentions 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 where spikes in the data do not appear to be associated with large rocket or drone attacks or events associated with particularly large Ukrainian civilian casualties. 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 (≈ 0.2881 casualties) leads to 0.25% - 0.36% increase in the same day donation amount (or ≈ \$1,400 – \$2,015 in February 2025 terms),[8] depending on the specification. Thus, one additional civilian fatality translates into between \$4,860 and \$6,992 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 roughly 0.8% (\$4,480 in 2025 terms) increase in the *cumulative* donation amount; in more readily interpretable terms, this implies that one more civilian fatality translates into cumulative donations of over \$15,550 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 what CBA reports it purchases, the cost of one drone (a disposable one-way weapon used heavily - by the millions - by both sides) at the beginning of 2025 varied between \$1,800 and \$4,000. Thus, same-day donations in response to one more civilian casualty are enough to purchase roughly two to four drones, and cumulative donations are enough to purchase as many as eight or nine.

We also find that other military-related events are positively associated with the donation amount, though the magnitude of their effects is smaller than the effect of civilian casualties. As different types of military events are correlated with each other, they are included in the regressions one 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 0.06%, 0.13% and 0.11% respectively. In addition, an additional media report mentioning sanctions against Russia leads to

[8] The average total daily donation is 3,034,405 UAH (we convert donation amounts to 2010 UAH levels); the estimated effect translates into 7,586 – 10,923 2010 UAH.

Table 1: Estimated OLS results for daily donations on mentions and events

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	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
	Panel B: Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	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 logarithm of the daily total donated amount, with robust standard errors in parentheses. *** denotes $p<0.01$, ** denotes $p<0.05$, and * denotes $p<0.1$. Controls include world event counts, a binary variable for Come Back Alive donation events, day of the week, month, and year fixed effects, and trend, and holiday indicators. In Panel (A), "Log civilian casualties" refers to the logarithm of reported Ukrainian civilian casualties. "Sanctions" capture the number of media reports mentioning economic sanctions imposed on Russia on that 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 military mentions" captures the log of military mentions in Ukrainian media on the same date. "Log missile mentions" capture the logarithm of missile-related mentions in Ukrainian media. "Log deescalation mentions" refers to the logarithm of media reports of deescalation, while "Log frontline mentions" reflects the logarithm 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	1.447***	1.523***	1.455***	1.433***
	(0.329)	(0.322)	(0.324)	(0.321)
Log civilian casualties	0.803***			
	(0.219)			
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	0.846***	0.852***	0.833***	0.803***
	(0.220)	(0.220)	(0.213)	(0.218)
Log civilian violence mentions	0.341***			
	(0.099)			
Log missile mentions		0.332***		
		(0.098)		
Log deescalation mentions			0.338**	
			(0.147)	
Log frontline mentions				1.339***
				(0.297)

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.

0.03% increase in the same-day donations. Table 2 shows that cumulative effect of these events are 0.16%, 0.38% and 0.32% increase in the amount donated respectively.

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.

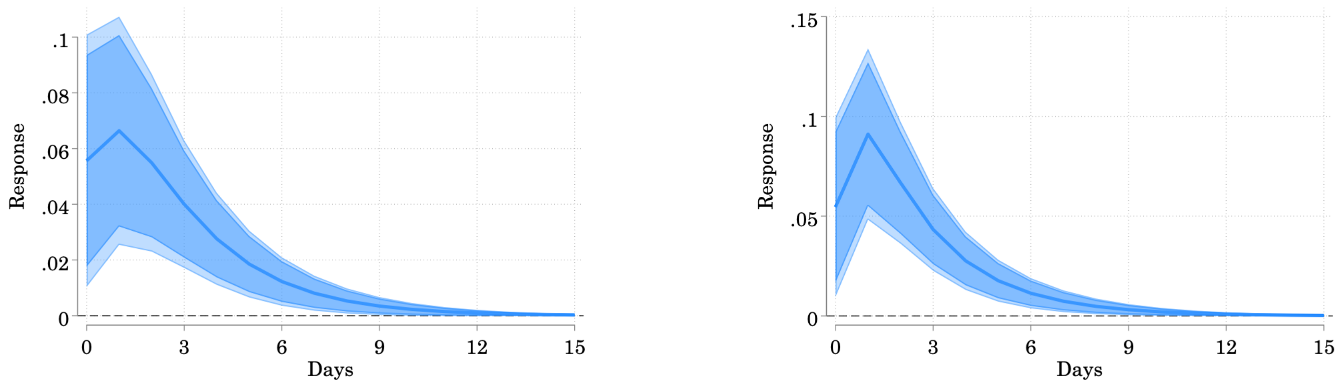
Table 3: Double machine learning for high-dimensional controls of donated amount

	(1)	(2)	(3)	(4)
	lasso-lasso	lasso-ridge	ridge-lasso	ridge- ridge
Log civilian casualties	0.14	0.14	0.13	0.11
	(0.04)	(0.04)	(0.04)	(0.03)
	[0]	[0]	[0]	[0]
Log military mentions	0.26	0.18	0.24	0.14
	(0.05)	(0.06)	(0.05)	(0.02)
	[0.0]	[0.0]	[0.0]	[0.02]

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 279 variables of 3rd order polynomial terms and their interactions of time covariates and other controls, as well as fixed effects for day, day of the week, week, month, year, holidays, CBA events, and total world events.

In Table 3 we report the results from applying DML after controlling for 279 controls that include fixed effects, and third order interactions and polynomial terms of time covariates and additional controls including holidays, CBA events and world events. The effects of Ukrainian civilian casualties remain statistically significant for log total amount donated. A 1% increase in Ukrainian civilian fatalities per day, or 2.9 more casualties, increases total amount donated by 0.11% - 0.14%. These effect sizes are on par with the original effect sizes we observed with the OLS estimation in Table 1. 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 0.14%- 0.26% 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

As for media reports affecting donations, our findings show that increased media coverage increases donations. From Table 1 we can see that all types of military-related mentions have positive and statistically significant effect on the same-day amount donated.[9] 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 0.45% and 0.46% increase ($2521) in same-day donations. A 1% increase in mentions of violence against civilians, missile attacks and deescalations leads to around 0.11-0.12% increase in the amount donated. This difference may be

[9]Unless mentioned otherwise, we only look at the mentions by Ukrainian media, as (according to the CBA Foundation statistics), 85% of CBA's donors are Ukrainians based in Ukraine, 10% are Ukrainians who live abroad and another 5% are foreigners.(Karpenko, 2024).

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. From Panel (A) we can observe that the effect of military mentions has a high and statistically significant event even when different events are controlled for. Overall, the cumulative effect of a 1% increase in military mentions is a 1.4%-1.5% increase ($\approx$ \$8122) in the amount donated. Looking at Panel (B), we conclude 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 1.34% cumulative increase in the amount donated. A 1% increase in mentions of violence against civilians, missile attacks and deescalation each leads to 0.33% - 0.34% cumulative increase in the amount donated.

6.4 Additional Results

We also present additional results in Supplemental Appendix. In Section C, we report further analyses using OLS estimates. Section D expands on our main findings by presenting additional VAR-based results. In Section E, we focus specifically on the number of donations as the outcome variable and replicate all main findings.

7 Conclusion

This work is, to the best of our knowledge, the first to leverage a quasi-natural experiment, and high-frequency, granular donation data to study the pattern of donations to a non-governmental organization providing lethal aid during a high-intensity and long-running conflict. The number of donations, and donation amounts (we focus on donors located in Ukraine) are large, both relative to the GDP of the country, as well as in terms of their impact on the battlefield;[10] furthermore, the effects of civilian casualties on donations are also large, on the order of thousands of dollars for each fatality, with a cumulative effect of over \$15,000. Furthermore, using plausible exclusion restrictions, we are able to disentangle the effects of factual events from media coverage. Donations peak the day following an event, and cumulative donations are roughly 2.5 times greater than the same-day donated amount. Mentions of military activity in the media also lead to large increases in donation amounts.

[10] A common refrain is that "The front is held by drones" - an item provided heavily by NGOs, and CBA in particular; our calculations show that an additional civilian casualty leads to donations sufficient to fund as many as nine drones.

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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.

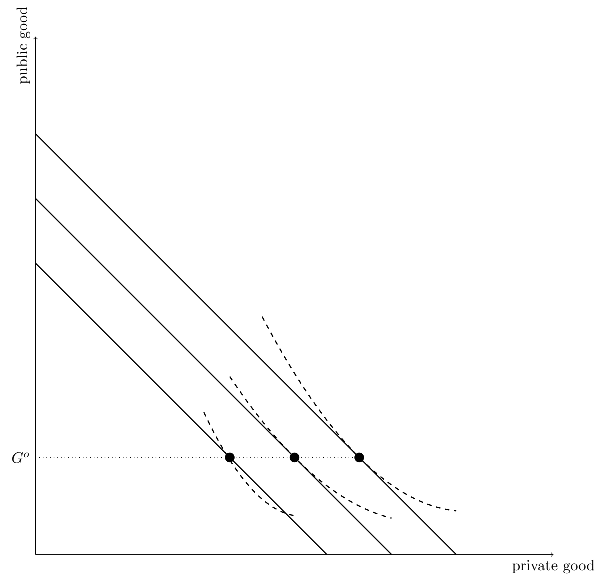


Figure A.2: An equilibrium with three individuals and two donors post-full-scale war

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.[11]

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.[12] 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 B.3 depicts a situation where, in equilibrium, if not globally, the marginal rates of substitution change. If we allow for the utility depend on the *type*

[11]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.

[12]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.

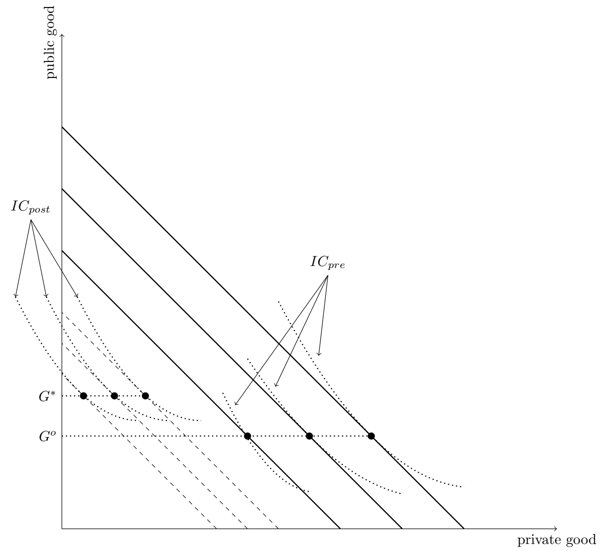


Figure A.3: An equilibrium with three donors

$\theta \in \{\theta_{pre}, \theta_{post}\}$, 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 a way 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 that, therefore, enables other consumption - for example, that one's household is not destroyed or occupied. 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, 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:

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

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

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

and

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

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

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

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 that 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 Summary Statistics

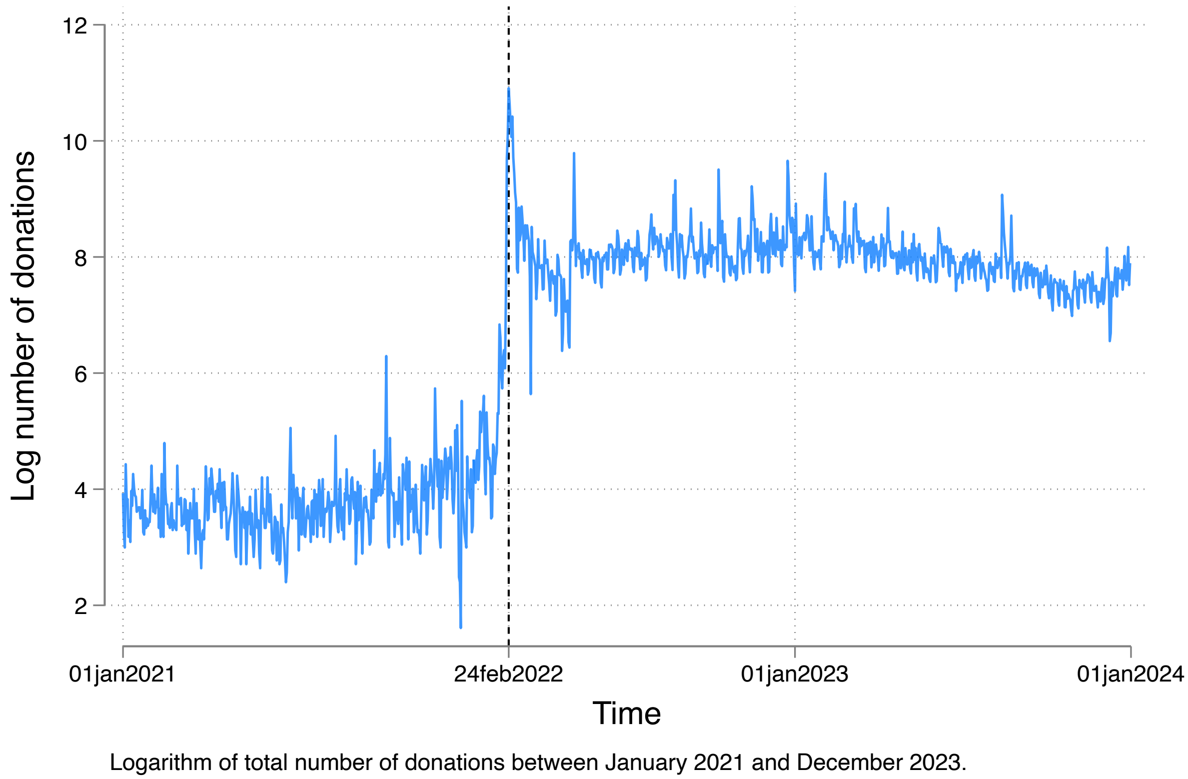
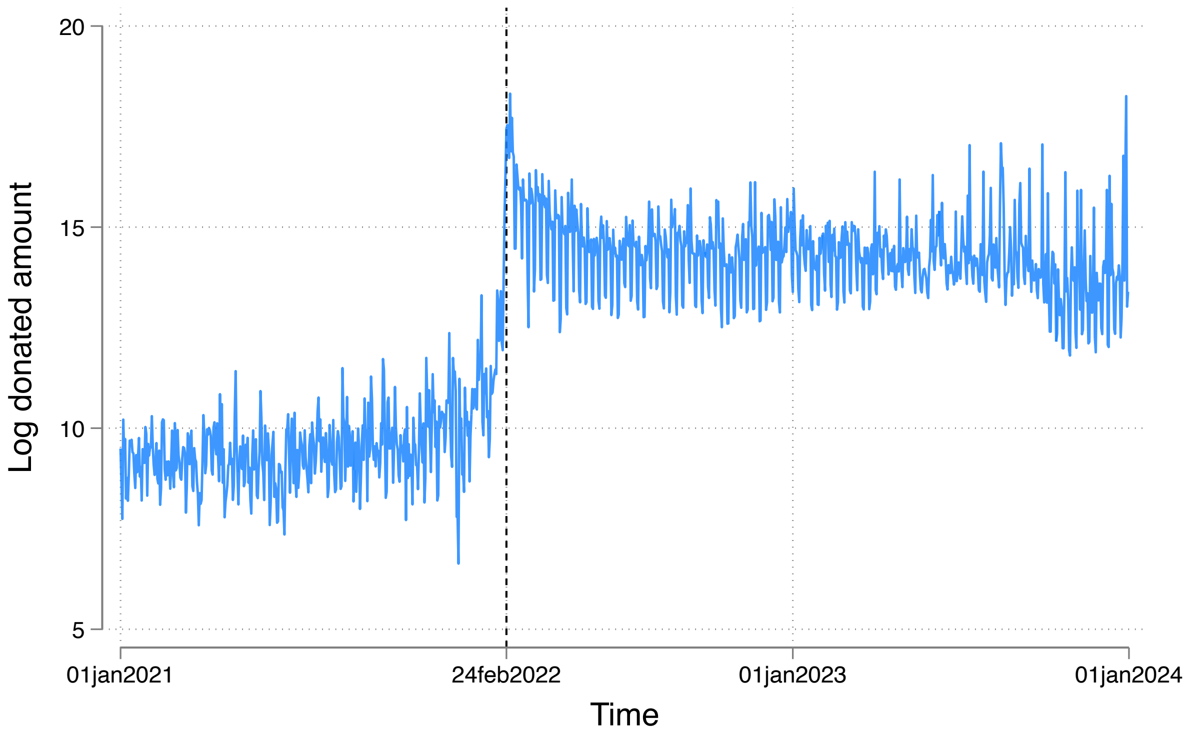


Figure B.1: Logarithm of number of donations over time

Note: This figure presents the daily log-transformed count of individual donations made to the Come Back Alive Foundation from January 1, 2021, to December 31, 2023. Peaks in donation counts often coincide with notable civilian casualties or media coverage of significant military events.



Logarithm of donated amount between January 2021 and December 2023.

Figure B.2: Logarithm of the amount donated over time

Note: This figure shows the daily log-transformed total amount donated to the Come Back Alive Foundation from January 1, 2021, to December 31, 2023. The fluctuations reflect donation spikes following major war-related events, such as large-scale missile attacks and key military developments.

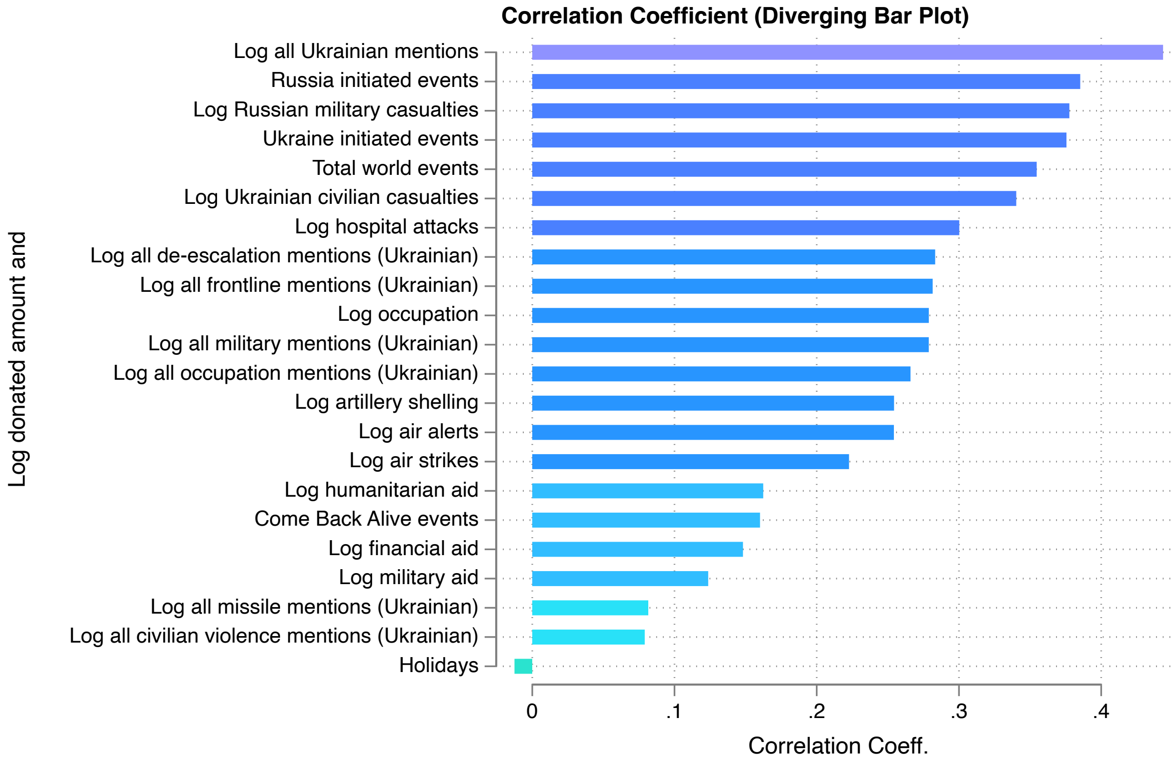


Figure B.3: Correlations between the total daily donated amounts and key variables

Note: The figure presents the correlations between the logarithm of the total daily donated amounts and key variables used for the analysis. Negative values on the bar indicate a negative correlation, while positive values signify a positive correlation between the variables.

Table B.1: Summary statistics

	Mean	Standard deviation	Min	Max
Number of donations	3441	3489	281	54601
Log number of donations	7.98	0.49	5.64	10.91
Donated amount (UAH)	3,034,405	6,314,561	134,164	90,335,312
Log donated amount (UAH)	14.30	1.02	11.81	18.32
Total world events	116,089	34,831	40,518	212,164
Holidays	0.03	0.17	0.00	1.00
Come Back Alive events	0.07	0.25	0.00	1.00
Log Russian military casualties	2.22	0.88	-0.69	4.96
Log civilian casualties	3.12	0.65	0.69	5.38
Log air alert	2.54	1.44	-0.69	4.96
Log air strike	2.73	0.77	-0.69	5.17
Log art. shelling	4.36	0.62	2.56	6.04
Log hospital attack	0.20	0.91	-0.69	3.30
Log tank battles	0.73	1.22	-0.69	3.85
Log territory control claim	2.18	0.85	-0.69	4.55
Russia initiated event	109	75	18	526
Ukraine initiated event	43	41	6	260
Occupation	4	6	1	50
Log Ukrainian mentions	7.81	0.31	5.86	8.66
Log Ukrainian military mentions	6.20	0.33	3.87	7.21
Log civilian violence mentions	2.62	0.92	-0.69	5.43
Log missile mentions	2.61	0.93	-0.69	5.43
Log deescalation mentions	3.30	0.54	1.10	5.20
Log occupation mentions	2.17	0.70	-0.69	4.80
Log frontline mentions	5.93	0.35	3.50	7.00
Log sanctions	1.56	1.28	-0.69	4.06
Log total mentions	9.45	0.51	7.14	11.48
Log financial aid	15.58	2.06	14.90	27.53
Log humanitarian aid	13.44	3.08	11.81	24.17
Log military aid	13.56	3.02	12.37	26.15
Observations				

Note: The table presents summary statistics for the key variables in the dataset for the post full-scale invasion period from the 24th of February 2022 until the 31st of December 2023. The donated amount is given in UAH in 2010 prices. 'Number of donations' and 'Log number of donations' denote the total number of daily donations and its logarithm, respectively. 'Donated amount' and 'Log donated amount' represent the total amount donated daily and its logarithm. 'Total world events' counts the total number of events in the world recorded on a given date, while 'Holidays' and 'Come Back Alive events' specify the occurrences of national holidays in Ukraine and Come Back Alive fundraising events. 'Log Russian military casualties' and 'Log Ukrainian civilian casualties' signify the logarithm of Russian military and Ukrainian civilian casualties. 'Log air alert', 'Log air strike', 'Log art. shelling', and 'Log hospital attack' depict logarithmic measures of different types of attacks. 'Log Russia initiated event' and 'Log Ukraine initiated event' denote logarithmic counts of events initiated by Russia and Ukraine, respectively. Lastly, 'Occupation' represents the occurrence of occupation events. 'Log UA mentions', 'Log UA mil mentions', 'Log UA civilian violence mentions', 'Log UA missile mentions', 'Log UA deescalation mentions', 'Log UA occupation mentions', and 'Log UA frontline mentions' describe logarithmic counts of various mentions recorded by Ukrainian media.

Table B.2: T-test of comparisons of means

	Before war		After war		Difference	
Variables	Mean	SD	Mean	SD	Diff.	p-value
Number of donations	75	612	3441	3489	-3366	< 0.001
Log number of donations	3.89	0.55	7.98	0.49	-4.10	< 0.001
Donated amount	31,621	273,534	3,034,405	6,314,561	-3,002,784	< 0.001
Log donated amount	9.66	0.89	14.30	1.02	-4.64	< 0.001
Total world events	154,224	50,725	116,089	34,831	38,135	< 0.001
Holidays	0.05	0.21	0.03	0.17	0.02	0.044
Come Back Alive events	0.01	0.11	0.07	0.25	-0.06	< 0.001
Log Ukrainian mentions	7.65	0.93	7.81	0.31	-0.16	< 0.001
Log Ukrainian military mentions	5.47	0.90	6.20	0.33	-0.74	< 0.001
Log civilian violence mentions	-0.01	0.87	2.62	0.92	-2.63	< 0.001
Log missile mentions	-0.11	0.82	2.61	0.93	-2.72	< 0.001
Log deescalation mentions	2.69	0.98	3.30	0.54	-0.61	< 0.001
Log occupation mentions	1.37	1.00	2.17	0.70	-0.80	< 0.001
Log frontline mentions	5.20	0.90	5.93	0.35	-0.73	< 0.001
Observations	2246		676		2922	

Note: The table provides a summary and t-test results of various variables for the sample before and after the full-scale invasion. We denote the period before the invasion as January 1, 2016 - February 23, 2022, while the period after is February 24, 2022 - December 31, 2023. ‘Number of donations’ and ‘Log number of donations’ denote the total number of daily donations and its logarithm, respectively. ‘Donated amount’ and ‘Log donated amount’ represent the total amount donated daily and its logarithm. The donated amount is given in UAH in 2010 prices. ‘Total world events’ counts the total number of events in the world recorded on a given date, while ‘Holidays’ and ‘Come Back Alive events’ specify the occurrences of national holidays in Ukraine and Come Back Alive fundraising events. The remaining variables: ‘Log UA mentions’, ‘Log UA military mentions’, ‘Log UA civilian violence mentions’, ‘Log UA missile mentions’, ‘Log UA deescalation mentions’, ‘Log UA occupation mentions’, and ‘Log UA frontline mentions’, denote logarithmic counts of various mentions as recorded by Ukrainian media.

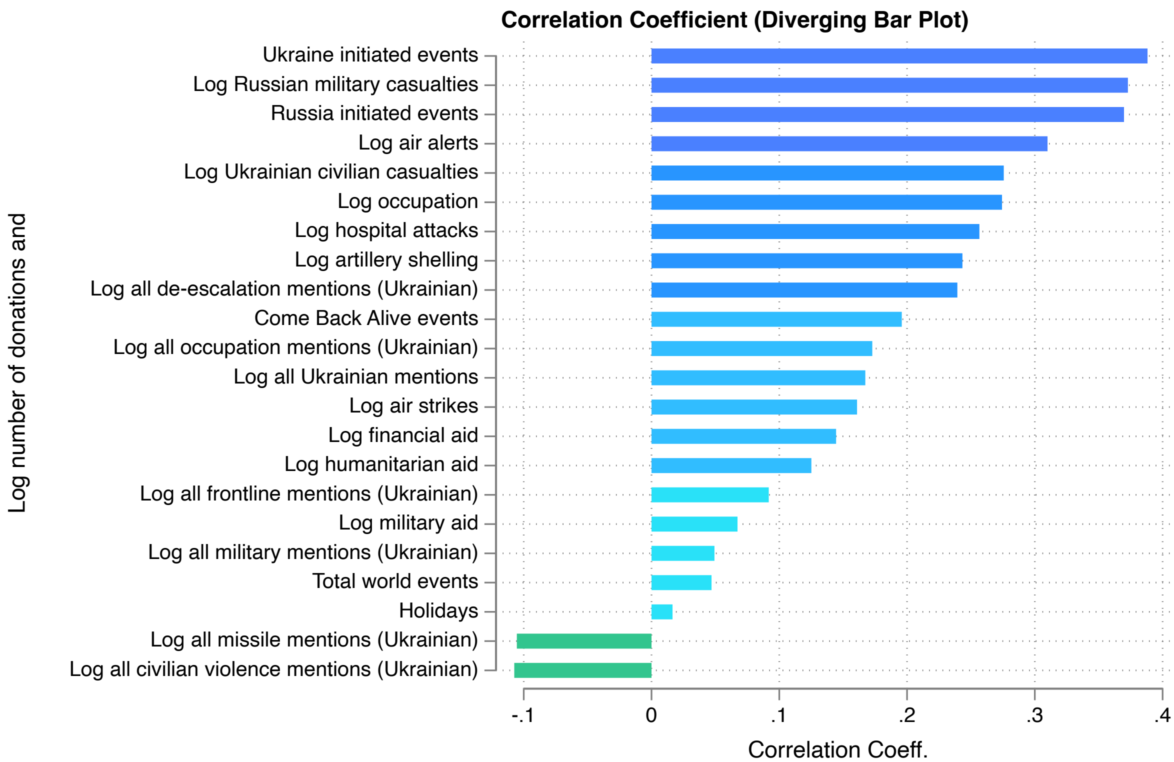
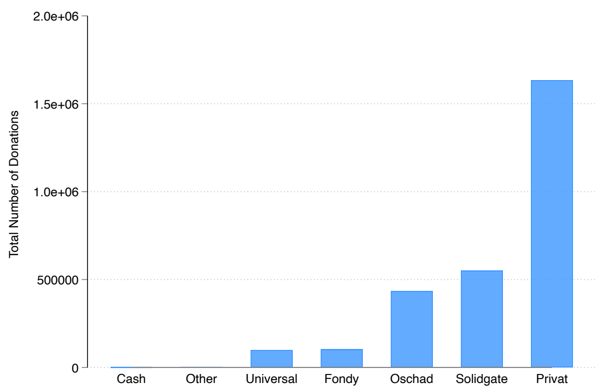
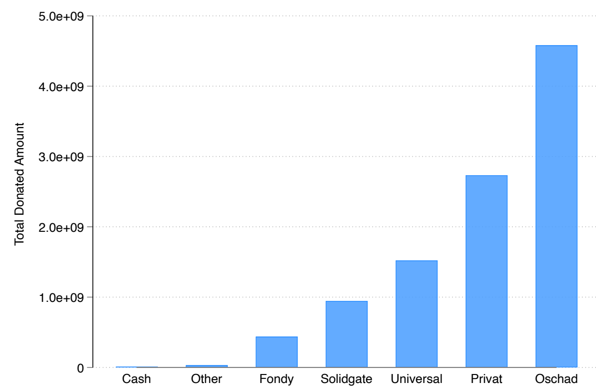


Figure B.4: Correlations between the total daily number of donations and key variables

Note: The figure presents the correlations between the logarithm of the total daily number of donations and key variables used for the analysis. Negative values on the bar indicate a negative correlation, while positive values signify a positive correlation between the variables.



(a) Number of donations



(b) Donated amounts

Figure B.5: Donations by the source

Note: This figure displays two histograms: (a) represents the total number of donations, while (b) depicts the amounts donated, both categorized by the bank through which the transactions took place. The sample comprises all donations made between the 24th of February 2022 and the 31st of December 2023.

C Further Analysis: OLS Estimates

Table C.1: Other events: OLS estimation of daily total donations

	Log donated amount			
	(1)	(2)	(3)	(4)
Log art. shelling	0.002			
	(0.077)			
Log occupation		0.040		
		(0.030)		
Log tank battles			0.054*	
			(0.028)	
Log territory control claim				-0.007
				(0.041)
R2	0.595	0.596	0.597	0.595
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. S Log territory control changes measure recorded shifts in territorial control.

Table C.2: The effect of military events. Joint effects

	(1)
	Log donated amount
Log civilian casualties	0.219**
	(0.085)
Log Ukrainian military mentions	0.386***
	(0.108)
Log air alert in Ukraine	-0.012
	(0.040)
Log air strike in Ukraine by Russia	0.087**
	(0.044)
Log art. shelling	-0.160*
	(0.084)
Log hospital attack in Ukraine by Russia	0.058*
	(0.034)
Log occupation	0.013
	(0.032)
Sanctions	0.022***
	(0.004)
Log tank battles	0.066**
	(0.027)
Log territory control claim	-0.048
	(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.3: 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.4: 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

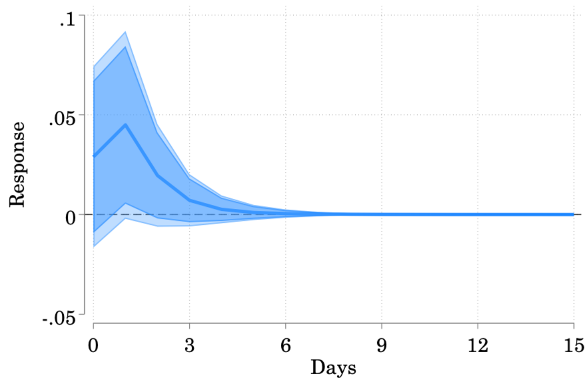
Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and dummies for holidays. The variable Log military aid represents the logarithm of military aid received from international sources. The variable Log financial aid captures the logarithm of financial assistance allocated to Ukraine. The variable Log humanitarian aid refers to the logarithm of humanitarian aid provided. We use aid-level data from the Ukraine Support Tracker, as documented in Kiel Working Paper No. 2218.

Table C.5: The effect of conscription announcements.

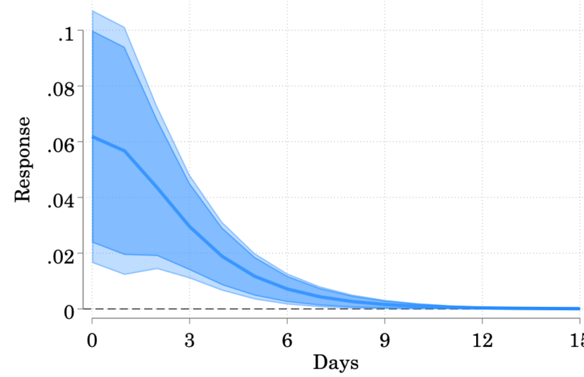
	Log donated amount			
	(1)	(2)	(3)	(4)
Conscription	-0.078	-0.049	-0.030	-0.121
	(0.265)	(0.272)	(0.234)	(0.265)
Log Ukrainian military mentions		0.564***		
		(0.122)		
Log civilian casualties			0.362***	
			(0.082)	
Log Russian military casualties				0.203***
				(0.051)
R2	0.570	0.594	0.595	0.584
N	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.

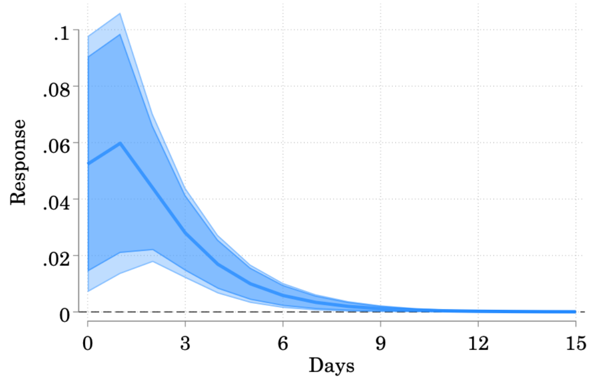
D Further Analysis: VAR



(a) Log air alert in Ukraine



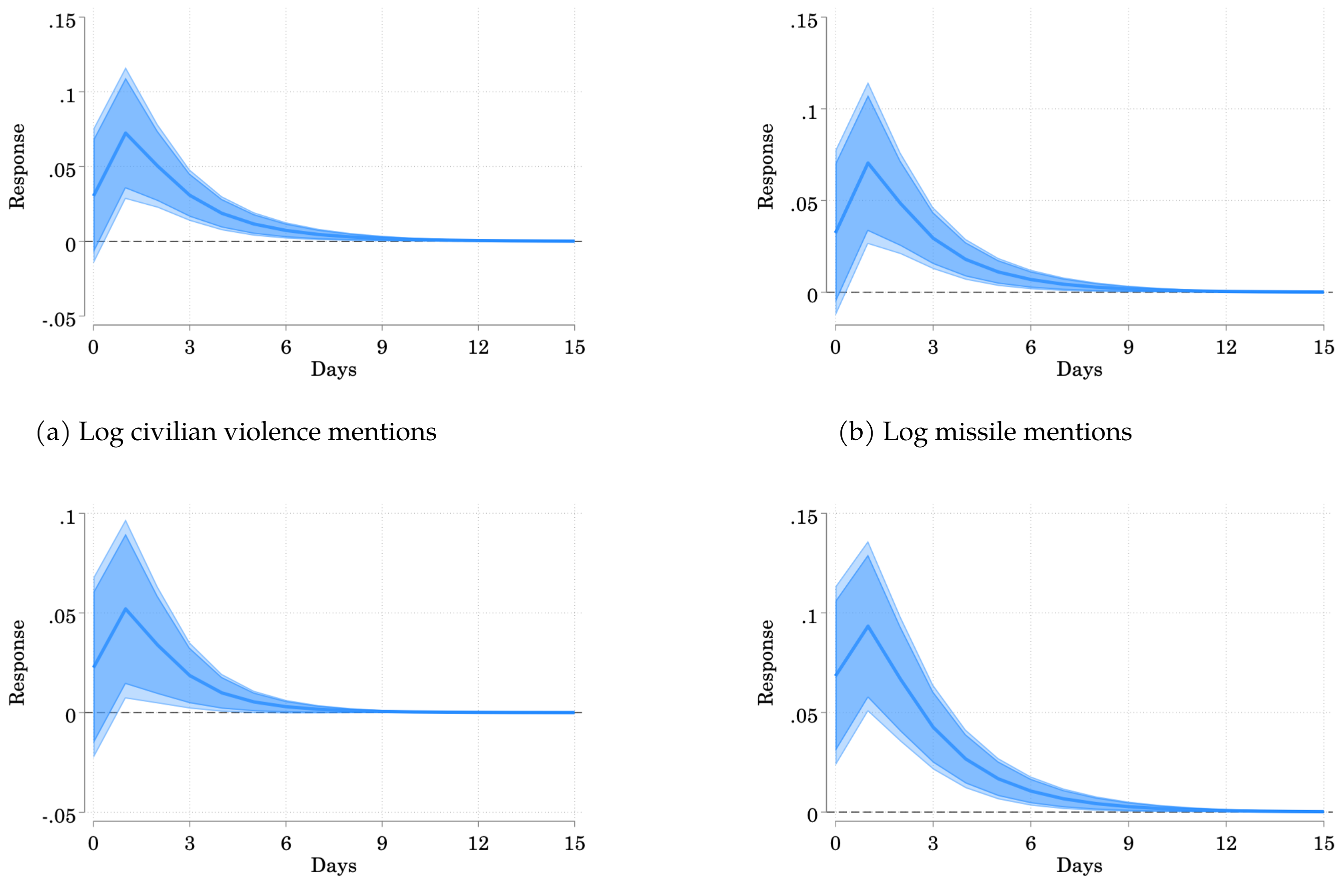
(b) Log air strike in Ukraine by Russia



(c) Log hospital attack in Ukraine by Russia

Figure D.1: Orthogonalized IRF of logarithm donated amount for other various events

Note: The dependent variable is the logarithm of the daily total donated amount. The figure presents orthogonalized impulse response functions (IRFs) estimating the impact of various conflict-related events on donations. Subfigure (a) shows the IRF for the logarithm of air alerts in Ukraine, Subfigure (b) for the logarithm of Russian air strikes in Ukraine, and Subfigure (c) for the logarithm of Russian hospital attacks in Ukraine. Blue shaded areas represent 90% and 95% confidence intervals. Controls include 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 air alert in Ukraine represents the logarithm of nationwide air alerts issued on a given date. Log air strike in Ukraine by Russia captures the logarithm of media reports of Russian airstrikes targeting Ukraine. Log hospital attack in Ukraine by Russia reflects the logarithm of reports of Russian attacks on medical facilities in Ukraine.



(a) Log civilian violence mentions

(b) Log missile mentions

(c) Log deescalation mentions

(d) Log frontline mentions

Figure D.2: Orthogonalized IRF of logarithm donated amount for mentions

Note: The dependent variable is the logarithm of the daily total donated amount. The figure presents orthogonalized impulse response functions (IRFs) estimating the impact of different media mentions on donations. Subfigure (a) shows the IRF for the logarithm of civilian violence mentions, Subfigure (b) for the logarithm of missile mentions, Subfigure (c) for the logarithm of deescalation mentions, and Subfigure (d) for the logarithm of frontline mentions. Blue shaded areas represent 90% and 95% confidence intervals. Controls include 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 civilian violence mentions represents the logarithm of media mentions of violence against civilians in Ukraine. Log missile mentions refers to the logarithm of missile-related coverage in Ukrainian media. Log deescalation mentions captures the logarithm of media reports of military deescalation (both from Ukrainian and Russian side). Log frontline mentions reflects the logarithm of media coverage of frontline military activity, excluding violence against civilians or missile strikes.

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	0.12	0.05	0.12	0.05
	(0.02)	(0.02)	(0.02)	(0.03)
	[0.0]	[0.02]	[0.0]	[0.07]
Log military mentions	0.15	0.03	0.13	0.0
	(0.02)	(0.03)	(0.02)	(0.04)
	[0]	[0.47]	[0]	[0.95]

Note: Robust standard errors in parentheses. 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 transactions. Column labels denote the method used to estimate the nuisance functions. Controls include 279 variables of 3rd order polynomial terms and their interactions of time covariates and other controls, as well as fixed effects for day, day of the week, week, month, year, holidays, CBA events, and total world events.

Table E.2: Estimated OLS results for the logarithm of daily number of donations on mentions and events

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	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 civilian casualties	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.3: Estimated cumulative impulse responses of number of donations to events and mentions

	Panel A: Events			
	(1)	(2)	(3)	(4)
Log military mentions	-0.217	-0.212	-0.215	-0.204
	(0.252)	(0.253)	(0.252)	(0.251)
Log civilian casualties	0.030			
	(0.167)			
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	0.019	0.019	0.019	0.031
	(0.168)	(0.168)	(0.164)	(0.165)
Log civilian violence mentions	-0.051			
	(0.077)			
Log missile mentions		-0.058		
		(0.076)		
Log deescalation mentions			0.275**	
			(0.116)	
Log frontline mentions				-0.130
				(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.