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FUELLING HOPE: HOW PUBLIC EMOTION SHAPES DONATIONS TO UKRAINE

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Abstract

The 2022 Russian invasion of Ukraine has prompted a powerful global support action, with an unprecedented amount of bilateral aid committed to Ukraine and numerous initiatives attracting private contributions to military and humanitarian needs. This major crisis event setting is ideal for investigating a driver of private donations largely overlooked in the charitable giving literature—the emotional factor. Our paper proposes to disaggregate this factor into three components: emotional intensity, degree of exposure to an emotion, and type of emotion. A unique transaction-level donation dataset allows us to separate the effects on Ukrainian, Foreign, and Cryptocurrency donors. We find that military donation flows are highly responsive to peaks in emotional intensity. Donations are at least 2.4 times more sensitive to negative intensity compared to positive intensity, in particular such emotions as fear and sadness. A broader extent of exposure to emotions via social media (but not via traditional media) also increases donation flows. We find evidence that, on average, Ukrainian flows are more responsive to emotional intensity than Foreign flows, while Crypto flows are mostly determined by exposure. Finally, we test whether public funding crowds out private donations in a heightened emotional intensity setting. We find evidence for crowding out in the case of EU donors after announcements of all types of aid, whilst US and EU donors do not appear to be affected by military government transfers to Ukraine.

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Contents

1 Introduction

The 2022 Russian invasion of Ukraine horrified those observing it from near and far, while the resilience of Ukrainians in response to it gave hope to many. As much as these events caused powerful emotions, they also prompted a global support response, ranging from encouraging posts on social media to volunteering efforts and monetary donations. As of 19 March 2023, just a single organisation—the official fundraising platform of the Ukrainian government, UNITED24—has raised around $300m in private donations (UNITED24, 2023). Between January 2022 and January 2023, the military, financial, and humanitarian bilateral aid pledged to Ukraine totalled around $145bn (Bushnell et al., 2023).

Literature on donations has explored ‘charitable giving’ as an economic decision, a strategic market interaction, a social phenomenon, and as a response to inner ‘conscious and unconscious urges’ (Andreoni & Payne, 2013). Few papers place emphasis on the fourth approach, which, we believe, is key to understanding the drivers behind crisis donations, such as in the case of the Russo-Ukrainian war. Empirically, donation flows during crisis events are found to be driven by crisis severity and media attention to the crisis (Eisensee & Strömberg, 2007; Scharf, Smith, & Wilhelm, 2017): variables that characterise how individuals experience and react to shocking events. Donation flows are likewise found to decay as time passes after the crisis outbreak, linked to an experiential overload by Eckel, Grossman, and Milano (2007). There is an evident emotional dimension to the donation response. We therefore propose to investigate a driver that we believe the literature has avoided to tackle directly—the aggregate emotions experienced by observers and participants of a crisis.

Compared to previous studies on psychological drivers of donation flows, our setting is unique in several aspects. First, we have a crisis event that unfolds over a long period of time (more than several days, unlike in the case of a natural disaster), and with differing intensity over time. Second, due to the nature of our unique dataset, we are able to observe different types of donors (UAH/USD/EUR/BTC) who may have different emotional reactions, given overseas donors are more removed from the situation on the ground and are less emotionally engaged compared to donors located in Ukraine and/or those originally from Ukraine.

We propose a framework for how the emotional factor leads to charitable action, consisting of three components: the severity of the cause (emotional intensity), the degree of exposure to emotion-inducing events, and the type of emotion felt. To test the relation between emotions and donations, we use variables that proxy for these three dimensions. First, the number of battles and attacks on the civilian population across Ukraine is one of the proxies for the intensity of negative emotions felt by observers of the unfolding conflict. Further, we gauge the extent of the global emotional response by analysing the number and content of more than five million tweets, which provide a more effective way of amplifying the emotions on the ground than, for example, traditional media articles. We hypothesise that as individuals become more exposed to developments in the war, particularly to events that induce strong negative emotions like fear and disgust, their propensity to donate increases, leading to a higher number and value of donations. We extend our analysis by investigating the causal relation of emotional intensity to donations by comparing the differences in behaviour between Ukrainian and Foreign donors, using emotionally intense war events as treatments. Finally, we test the crowding out hypothesis in a setting of high emotional intensity to understand if emotions can counteract the predicted stifling of private donations by bilateral aid packages.

Due to the nature of our dataset, we focus our research on the drivers of military-targeted donations, as contrasted with donations for humanitarian, financial, or reconstruction purposes.

To guide our approach, we formulate the following general research question:

RQ1: What is the role of public sentiment (emotions) in motivating military donations to Ukraine during the 2022 Russian invasion of Ukraine?

We further decompose our general research question as follows:

RQ1.1: Does emotional *intensity* explain donation flows across donor types (e.g., UAH donors vs. other fiat currency donors vs. BTC donors)?

RQ1.2: What is the effect of broader *exposure* to emotions via media on donation flows?

RQ1.3: Does the *type of emotion* matter for donation flows?

RQ1.4: In a setting of high emotional intensity, does bilateral aid *crowd out* private donations?

Our findings show that military donation flow spikes correspond to emotional intensity peaks, with negative emotions having at least a 2.4 times greater impact than positive ones. Exposure to emotions through social media also increases donations, but traditional media does not have the same effect. Fear is found to increase donations, while sadness is found to negatively affect donation frequency. We observe that Ukrainian donations are more sensitive to emotional intensity than foreign donations, while Crypto donations are more influenced by exposure. Additionally, our findings suggest that private EU donors may be crowded out by all types of EU government transfers to Ukraine, while US and EU donors are not affected by military government transfers.

Our paper contributes to the interdisciplinary field of neuroeconomics, which brings insights from neuroscience and psychology to analyse economic choices. We believe that our findings could further the understanding of the drivers of donor behaviour. We also believe that our findings could be used by charities to create a fundraising strategy for disaster or war relief efforts.

The paper is organised as follows. Section 2 sets the research context by describing the events in Ukraine. Section 3 synthesises existing research on charitable giving, discusses crypto philanthropy, and reviews the theoretical and empirical considerations for studying emotions. Section 4 describes the data. Section 5 describes the method. Section 6 discusses the results of the empirical analysis. Section 7 concludes.

2 Research Context

24 February 2022 marked a steep escalation of the ongoing Russo-Ukrainian war, resulting in an event of unprecedented magnitude and emotional charge. Between February and April 2022, the areas of active fighting stretched from southern and eastern Ukraine to as far as Kyiv and the Northeast; at the same time, Russian missile strikes were launched throughout most of the Ukrainian territory. Since April, the war has focused on the Southeastern front, where, from September, the Ukrainian counteroffensive began to gain ground. In November 2022, the second stalemate began, with a new wave of strikes to infrastructure (Institute for the Study of War, 2023). As of March 2023, active fighting continues.

Major news organisations dedicate extensive media space to the events in Ukraine. More than 4.5 million news articles covering Russo-Ukrainian tensions were published between 1 January and 31 October 2022. One could compare this to the same 4.5 million news articles covering the topic ‘Ukraine’ published during the previous 11 years, between 2010 and 2021 (Factiva, 2022). Politicians, journalists, and civilians make use of social media like Twitter, Telegram, and TikTok to transmit and discuss real-time updates on war events. The war has produced an unprecedented amount of sensitive material in the media, especially in reference to civilian casualties and civilian infrastructure destruction in locations like Bucha or Mariupol.

The media space is where influence operations or ‘the information war’ takes place. Ukrainian media outlets boost morale by focusing on military victories and Russian casualties and under-score Russian violations of the Geneva Conventions—the treaties on the restriction of violence during conflict (Pavlik, 2022). The Ukrainian media avoids reporting the damage sustained by the Ukrainian Armed Forces (foreign journalists also report difficulty accessing this information). The strategic communication by the Ukrainian media has the ultimate aim of rallying support (Theron, personal communication, November 8, 2022). In the opposite camp, Russian media outlets paint the war as a 'special operation' of 'denazification' (Pavlik, 2022). On social media, propaganda bots spread contentious information to instigate conflict, damage the reputation of the enemy in the eyes of supporters, and disrupt international aid (Pavlik, 2022). 'The information war' further adds to making the media space where the invasion is discussed a highly charged emotional environment.

To finance the Ukrainian defence efforts, active fundraising has been in progress, gathering donations for the Ukrainian army and civilian population, as well as reconstruction funds. The convention is to distinguish three types of aid by purpose: military, financial, and humanitarian (Bushnell et al., 2023). The biggest organisation by the number of donations and amount raised from private donors is UNITED24, a fundraising platform launched in May 2022 by the Ukrainian government. The initiative rallies donors through its extensive media communication. Big Ukrainian media personalities also make use of their media exposure to attract donations (Prytula Foundation). Some charities that existed before the invasion reshaped their focus after the situation escalated (Razom for Ukraine, Come Back Alive, Prytula Foundation). There are also countless small private fundraisers initiated by individuals in Ukraine and abroad.

A noteworthy part of Ukrainian fundraising efforts is the cryptocurrency donation campaign. It is the largest cryptocurrency project of its kind, with participation of grassroots initiatives all the way to the official government fundraising platform. Prompted by the risk of a Russian attack on the national banking system (Gailey, 2022), on 26 February 2022, the Ukrainian government publicised their Bitcoin and Ethereum wallets. As of 31 October 2022, donations in cryptocurrency accounted for around 20% of the total donations amount attracted by the Come Back Alive charity and totalled $28 million (Come Back Alive, 2022). Since the start of the invasion, Ukrainian charities tapped into various cryptocurrencies and tokens as the denomination of aid with varied success: Bitcoin, Ethereum, Tether, Polkadot, Dogecoin, TRON, Solana, and NFTs.

3 Review of Literature and Analytical Framework

3.1 Charitable giving: motives and contributing factors

In his seminal work, Andreoni (1989) derives the utility function of charitable giving. The model incorporates three main categories of motives behind individual donors' choice to donate in an economy that has one public good (representing donations) and one private good. The first category, the *egoistic self-regarding* motive, refers to donors reaping benefits from donations to personal welfare and to the welfare of people closest to them (also referred to as pure egoism). The second category, the *altruistic other-regarding* motive, refers to donors deriving utility from tangibly improving the welfare of strangers and not their own (pure altruism). The model also accounts for a third category of motives known as the warm glow mechanism: it allows for personal utility to be derived from the welfare of strangers (the *egoistic other-regarding* motive or impure altruism).

Andreoni and Payne (2013) provide a comprehensive overview of the four complementary theories of charitable giving, which, taken together, attempt to conceptually reconcile the egoistic and altruistic motives. These theories also address the role of contributing factors that determine the timing of and the amount that an individual donates due to either motive. The four theories are as follows:

1. charitable giving as an economic decision (i.e., the quantity of a gift should maximise individual utility subject to a budget constraint),

2. giving as a strategic interaction between parties involved in the 'charity market' (e.g., governments, foundations, donors),

3. giving as a social exchange (related to the sociality of giving, interactions that prompt the 'giving' response),

4. giving in response to conscious or unconscious, empathic, moral, or cultural urges (including emotional promptings).

Andreoni and Payne (2013) note that the fourth approach has been explored the least. It is plausible, however, that the empathetic, moral, and cultural urges must play a significant role as a factor contributing to the motives for crisis giving. Evidence for this, for instance, comes from how the warm glow mechanism leads to donations.

The definition of warm-glow giving is twofold. On the one hand, warm-glow giving (or impure altruism giving) is contrasted with pure altruism giving as the two separate mechanisms that form the *other-regarding* donor behaviour component (Andreoni, 1989). On the other hand, warm-glow giving accounts for the deviation of the component of *egoistic* donor behaviour predicted in models of rational decision-making from the observed one. In other words, warm-glow giving is both *other-regarding* and *egoistic*: a type of selfish 'joy' caused by the act of giving. Empirical studies find that the perception of the victim's actual need or deservingness and other features of context can influence the amount of warm glow a donor gets (Konow, 2010). In other words, if a greater amount of suffering is associated with the donation recipient, and this suffering is made salient to the donor, it would enhance the donor's propensity to give through the warm glow mechanism. We may then conclude that various emotions, caused by perceiving the recipient's suffering, could be responsible for the effect transmission.

Given the theories above, we argue for the following concrete donor motives in the case of donating to Ukrainian charities. The egoistic component of donor behaviour consists of two parts. First, donating to Ukraine raises hopes that donors' and donor families' safety will be enhanced as a result of the Ukrainian army combating the dangerous aggressor—which can be considered a purely *egoistic self-regarding* motive. We can suppose that this motive is relevant for military-targeted donations. Second, donating to Ukraine gives donors joy via the warm glow mechanism, caused both by the Ukrainians expressing thankfulness and by the approval of fellow donors and other observers—this is the *egoistic other-regarding* motive. This motive should be applicable to donations of all types by purpose. Finally, the *altruistic other-regarding* motive would refer to donating towards the goal of alleviating as much human suffering as possible (unconditionally contributing to the public good (Andreoni, 1989)). This motive could be more applicable to humanitarian and other non-military donations. We argue that emotional factors can influence all three of these motives.

An alternative decomposition of donor utility is possible from the perspective of moral ethics. This function is constructed based on Hart, Thesmar, and Zingales's (2022) approach to deriving the individual utility from the moral choice of boycotting companies supporting Russia:

$$U_i = U_i\left(-c_i, D_i, C_i\right), \quad i = 1, \ldots, n \tag{1}$$

where i refers to each individual donor up to the n-th donor, U_i is the total individual utility obtained from the act of donating, $-c_i$ is the material cost from giving money away as a donation, D_i is the non-consequentialist (deontological)[1] benefit from donating that is roughly equivalent to the benefit derived via the warm glow mechanism in the previous model, C_i is the consequentialist benefit that comes from the perceived positive impact of a donation on social welfare, both own and of strangers.

Whether an individual is currently donating predominantly to gain the deontological or the consequentialist benefit, we argue that the emotional factor, once again, may influence both. Emotions may regulate the elasticities of D_i and C_i, in other words, how much donors care about the consequences of their donation making a tangible difference to welfare or about the personal satisfaction from acting virtuously.

3.1.1 Crowding out hypothesis

So far in this paper we discuss private giving, which refers to charitable contributions made by individual donors and the private sector. However, public giving in the form of government transfers has been frequent and prominent during the Russian invasion of Ukraine, evidenced by the sheer amount of bilateral aid pledged by the US, the EU, and other friendly governments. This warrants a deeper discussion of the strategic dimension of giving alongside the emotional one. We do so by addressing the crowding out hypothesis, a prominent issue in the theoretical literature, which states that public giving crowds out private donations in conditions of fiscal transparency (Andreoni, 1989; Eckel, Grossman, & Johnston, 2005).

In theory, crowding out is predicted to happen through the tax channel. Put simply, tax payers to a government reduce their contributions to a cause that has received initial endowment by their government, as they perceive that they have already ‘contributed’ to the cause through tax. In this setting, fiscal transparency implies that private donors know that the source of government transfers is their tax money.

The crowding out hypothesis has been tested empirically, but the evidence is inconclusive. Crowding out is often incomplete; among possible reasons, Andreoni (1989) mentions warm glow that can incite donors to double-spend by the added value of personal contribution. Another explanation for the lack of crowding out is the ‘endorsement effect’ (Vesterlund, 2003), whereby an institutional donor sends a positive signal about the quality of the donation recipient and the worthiness of the cause, sometimes even inducing crowding in.

[1] Similar to Hart et al. (2022), we define ‘deontological’ as a motive that arises from the moral quality of the action itself, regardless of consequences—the moral imperative. In turn, we define ‘consequentialist’ as a motive that hinges on the welfare impact of the action.

Previous studies indicated that the amount of warm glow that donors get is regulated by the emotional factor. By extension, this may have an effect on the dynamics of crowding out. In a situation when emotional intensity is high, crowding out may be completely eliminated—we believe that this hypothesis is worth testing.

3.2 Crisis fundraising and its empirical determinants

War is characterised by typical features of a disaster event. As defined by McFarlane and Norris (2006, p. 4), disaster is ‘a potentially traumatic event that is collectively experienced, has an acute onset, and is time-delimited’, either natural (hurricane, tornado, pandemic), technological (oil spill), or human-caused (war, civil unrest), locally or globally. Research on fundraising around disaster events, or crisis fundraising, is a distinct branch within the literature on donations. While donating towards combating world famine or cancer research is an ongoing, steady concern for insofar as the ultimate goal is not reached, crisis fundraising is prompted by a sudden large-scale event.

A distinction between war and other types of disasters is that a war setting allows to distinguish between donations for military and non-military purposes. This distinction is not well-researched—therefore, we do not include the discussion of differences in donation drivers by purpose in this review.

3.2.1 Disaster severity

Studies find evidence that coming into contact with disasters boosts prosocial (i.e., other-regarding) behaviour in individuals: sympathy, a desire for community belonging, and generosity in donating. Tedeschi and Calhoun (1995) refer to the changes in the patterns of behaviour and attitude following a disaster as ‘post-traumatic growth’. A recent paper by Fridman, Gershon, and Gneezy (2022) investigates the effect of the threat of COVID-19 and finds a pattern of what the authors call ‘catastrophe compassion’, whereby the pandemic seems to have led to an increase in charitable giving. Conceptually, these dynamics are explained by several mechanisms: first, experiencing a disaster raises the salience of one’s mortality, which in turn increases the marginal utility of donating to the detriment of the marginal utility of consumption (Scharf et al., 2017). Second, prosociality itself has a network effect, where people who see others acting pro-socially will adopt these behaviours too or will even be overtly pressured to adopt them—this dimension was investigated by, Exley (2018) and Nook, Ong, Morelli, Mitchell, and Zaki

(2016).

Fridman et al. (2022) additionally find evidence for increased generosity associated with more severe episodes of the pandemic. Thus, the empirical literature seems to suggest that the more severe the disaster is, the more intense a prosocial behavioural response it elicits. One common measure for disaster severity (also referred to as disaster scale or intensity) is the death and destruction toll of the event—the number of casualties, the count of destroyed property, inter alia. For example, Smith, Wilhelm, and Scharf (2017) evaluate two proxies for the scale of natural disasters like tsunamis, earthquakes, and similar and find a strong positive relation between the number of killed and injured to the magnitude of the aid response. A dimension to this, however, is that natural disasters are events that usually unfold quickly over the course of a day. There is often little dynamism to the severity that is meaningful for analysis—the overall toll of the event is marked, and the correlation with total donations is determined from a sample of many disaster events, like in Smith et al. (2017). On the other hand, disasters like wars and pandemics have a more dynamic quality, where the events unfold over several months or years, and the toll can be calculated for each time interval and compared against incoming donations.

Regarding war, the number of battlefield deaths comes across as the most prominent proxy for conflict severity in the peace and conflict studies literature (Lacina & Gleditsch, 2005). Another salient proxy for conflict intensity is the number of conflict events that occurred during a time interval in, e.g., a civil war (Miranda, Perondi, & Gleditsch, 2016). Other possible proxies include the movement and concentration of military forces, the type/volume of ammunition used, the topographical scale of war activity or occupation (the number of kilometres of territory seized), the type of physical violence imposed, and others (Theron, personal communication, November 8, 2022).

3.2.2 Media coverage

The prosocial drivers of disaster donating get activated and enhanced by media attention to the event (Méon & Verwimp, 2022). Media reduces the donor-recipient distance and enhances mortality salience by allowing people all over the world to follow the dramatic event closely and in real time (Smith et al., 2017). Media exposes users to sensitive materials that are circulated by affected users; thus, reinforcing the 'identifiable victim' effect, where the media transforms the victims of the event from purely 'statistical' to real in the eyes of donors—this effect is identified to increase donations (Schelling, 1984). The positive relationship between natural disasters and media coverage is documented by Eisensee and Strömberg (2007) who reverse-engineered the effect of media coverage on donations by studying the crowding out effect of other newsworthy events.

An important consideration in terms of media attention is the type of platform that publishes information about the disaster. An operational, albeit uneven, distinction is between the traditional media (legacy news outlets) and online social networks—a number of studies test the effects of these two types separately (Sylvester, Healey, Wang, & Rand, 2014). Social media has an advantage over traditional media in disaster communication 'in terms of information flow, information control, adaptability, relevance for local residents, intelligence, empowerment, dependency on the power grid, cost, accessibility, and timeliness of information' (Keim & Noji, 2011, p. 2). While making significant contributions to the information flow on its own, social media propagates the news reported by traditional media via emergent network effects and overall richer content possibilities (Houston et al., 2015; Ren, Dong, Popovic, Sabnis, & Nickerson, 2022). Although it is challenging to speak of objectivity in the contemporary media landscape, social media content is a less mediated mix of opinion and news, while the credibility of traditional media generally rests on better verification and stricter filtering of published content (Fenton, 2009). Given the arguments above, social media has the additional power to enhance the emotionality and salience of disaster events.

While one dimension of media attention is the pure scope of coverage (often proxied by the number of articles published / TV news stories shown), another dimension is the type of coverage. One way to separate the types of coverage is by the sentiment the news story expresses about the disaster event. This is especially interesting in the case of a conflict event, where different sides of the conflict have different sentiments. Sentiment analysis of media reports on the conflict is perhaps the closest to extracting emotions that are involved in the perception of conflict. A number of studies attempted to extract conflict perceptions and sentiment for the Syrian war, Israeli-Palestinian war, and the Russo-Ukrainian war (Caprolu, Sadighian, & Di Pietro, 2022; Öztürk & Ayvaz, 2018; Siapera, Hunt, & Lynn, 2015).

3.2.3 Donor fatigue

The phenomenon of donor fatigue is well-documented empirically. The bulk of existing research notes that after the initial shock of a disaster event is over, donations will tend downwards (Brown & Wong, 2009; Smith et al., 2017). To control for the effect of donor fatigue, Brown and Wong (2009) include a proxy for 'days elapsed since the event' when investigating the relationship between donations to the Myanmar hurricane relief and news coverage. Eckel et al. (2007), studying the relationship between Hurricane Katrina and donations to charity, identify the effect that they call 'Katrina overload', which occurs when the demand for support lasts too long. The overly lengthy appeal causes burnout and, subsequently, donation flows become less responsive to support pleas. Following this, we expect to see a downward trend in giving after the initial spike at the beginning of the invasion.

3.3 Considerations for crypto philanthropy

One of our research questions addresses the heterogeneous effects of public sentiment between different types of donors, including crypto vs. fiat currency donors. Indeed, all theories of donor behaviour have been tested on donations in traditional currencies.

The bulk of research on cryptocurrencies points to the fact that sentiment-related drivers are among the most significant drivers of the adoption and value of cryptocurrencies. Liu and Tsyvinski (2021) find that the amount of investor attention on social media plays an important role in explaining cryptocurrency returns. Karalevicius, Degrande, and De Weerdt (2018) perform a lexicon-based analysis of positive/negative media attention to cryptocurrencies, finding it to be a decent short-term predictor of price movements. This leads us to suppose that public sentiment might be more relevant when it comes to crypto fundraising than traditional fundraising.

An alternative way to approach this discussion is from the perspective of the psychology of cryptocurrency users. Dylan-Ennis (2021) makes the case for a separate 'cryptoculture' to describe the crypto community that is 'strong and vibrant', shares common goals and is built around social media platforms like Reddit, Twitter, Telegram, and Discord. Delfabbro, King, and Williams (2021) also point out that social media is an essential element of the cryptocurrency community. Crypto influencers and advisers make widespread use of social media; as a result, a wider range of promotional materials with higher interactivity is available about crypto than about other asset classes. This, in turn, strengthens network effects and draws in more crypto adopters. At the same time, social media reinforces such psychological effects as the fear of missing out [2] and preoccupation [3], which makes crypto community members susceptible to social media momentum and herding. It is plausible that donors among the crypto community could be susceptible to the same effects.

3.4 Classification of emotions and public sentiment

In previous sections, we refer to the media discourse on the Russian invasion of Ukraine as 'highly emotionally charged'. While it may appear intuitive what emotions are, the exact meaning and typology of emotions is the domain of neuroscience and psychology. Public sentiment studies often lack grounding in these.

In the domain of emotion studies, the two most influential theories have been basic emotion theory and dimensional theory. Basic emotion theory states that there is a limited number of 'base' emotions, each of which has universal behavioural manifestations (Ekman, 1992; Wilson-Mendenhall, Barrett, & Barsalou, 2013). On the other hand, dimensional theory states that emotions should be considered on a spectrum with two dimensions: hedonic (pleasant-unpleasant spectrum) and arousal (rest-activated spectrum) (Russell, 1980). Essentially, both theories seem to accommodate that there exists at least four emotions that are more fundamental than others: anger, fear, sadness, and joy. They are located on the four axes of the dimensional circumplex, and manifest distinctive enough behavioural phenotypes (Gu, Wang, Patel, Bourgeois, & Huang, 2019; Shpigler et al., 2017). Other researchers also single out disgust and surprise as emotions that are specific enough and come close to being classified as fundamental (Gu et al., 2019). Drawing on Ekman (1992), we use the six widely-accepted types of emotions (fear, anger, surprise, disgust, joy, and sadness) to classify public sentiment in response to war. A more detailed description of these emotion types is provided in Table A.1.

Empirically, analysing public emotion often means conducting sentiment analysis of textual data collected from social media [4]. The simplest analysis involves dictionary-based approaches that can classify a sentence as expressing a positive/negative/neutral sentiment or a more specific emotion based on matching words against a predefined dictionary. There are also more precise tools that can analyse sentences as a whole, determine irony and other nuances of tone.

[2] Fear of missing out (FOMO) refers to feeling irrationally compelled to participate in an activity for fear that the opportunity would be missed (Delfabbro et al., 2021).

[3] Preoccupation refers to the difficulty of disengaging from an addictive activity and prioritising it over other responsibilities (Delfabbro et al., 2021).

[4] We refer to 'emotions' and 'public sentiment' interchangeably throughout the paper, unless otherwise specified.

For instance, Twitter sentiment has been used for such purposes as evaluating financial market sentiment or conflict event perception. Relevant for us, several niche studies have tried to single out specific emotions and test them against donor behaviour. For example, van Doorn, Zeelenberg, and Breugelmans (2017) look at whether angry appeals to donate correlate with higher donations and find a positive relationship, given that individuals perceive their donation as a compensation for the victim's misfortune.

Overall, it appears that the literature lacks a good understanding of how various emotions and emotional intensities affect charitable giving, which is also indicated by Andreoni and Payne (2013). Albeit emotions seem to underpin variables that are found to correlate with donations, there is no framework for systematically investigating the relation between emotions and giving. We believe that our setting is ideal to address this gap.

3.5 Summarising the analytical framework

Our determinant of interest for donation flows is the aggregate emotions felt by individuals when exposed to news about the war in Ukraine. We propose that it is possible to decompose the emotional factor into three drivers:

1. *Emotional intensity*—how deeply affected these people are by what they learn (i.e., how severe an event is, how many casualties it has inflicted).

2. *Degree of exposure*—how many people learn about an event (i.e., by reading news or social media articles, or by witnessing an event live), the distance between an event and the people who learn about it.

3. *Emotion of response*—the type of emotion people respond with, once exposed (i.e., what type of sentiment their reactions contain).

4 Data and Descriptive Statistics

4.1 Data collection

Unless specified otherwise, we obtain data for all variables between 1 February 2022 and 28 February 2023.

For donations in traditional currencies (UAH, USD, EUR, PLN, etc.), we extract transaction-level data from the financial report of the Come Back Alive foundation (CBA), a Ukraine-based charity that gathers donations for predominantly military purposes (1,981,941 transactions). For donations in cryptocurrency, we extract the incoming transactions to CBA Bitcoin and Ethereum wallets (9,188 and 1,176 transactions respectively) and to the Ukrainian government's official Bitcoin and Ethereum wallets (19,276 and 74,050 transactions respectively)[5] from the public blockchain. Bitcoin transactions are collected using the Blockchain.info API, Ethereum transactions are collected using the Covalent API.

To gauge heightened emotional intensity, we construct a timeline featuring 31 significant positive (13) and negative (18) war events partly based on Bigg (2022) and the 2023 New Year greetings by President Zelenskyy (Zelenskyy, 2023). We treat attacks by Russian forces and losses to Ukraine as negative events, and Ukrainian gains, victories, and celebrations as positive events. For the hourly dataset, we manually time-stamp the events according to the hour of its intensity peak using reporting times from the archive of Ukrainska Pravda, a leading Ukrainian online newspaper (with reporting in both English and Ukrainian). All times are converted to UTC. The full list of events is available in Table B.1.

We also obtain war severity variables: 1) data on individual conflict events (battles, missile strikes, attacks on civilians) from ACLED (2022), 2) the daily number of Russian casualties as reported by the Armed Forces of Ukraine (MinfinMedia, 2022), 3) the weekly number of civilian casualties from OCHA (2022). All war severity variables are from 24 February 2022, except data on civilian casualties, which is available from 26 February 2022.

As a social media exposure variable, we obtain 5,858,089 public English-language tweets (excluding replies and retweets) queried by keywords 'Ukraine' and 'war' from the Academic Research Twitter API. These keywords were judged as the most contextually relevant terms for our purposes. Besides tweet content, other relevant Twitter data include the time when the tweet was posted and the author handle. We separate social media exposure for Ukrainian donors by selecting tweets by 30 influential Ukrainian accounts; we define 'influential Ukrainian accounts' as users who are either Ukrainian by nationality or are currently located in Ukraine and have at least 60 thousand subscribers. We include only accounts by individuals or communities and not news organisations. The list of accounts is available in Table C.1. We obtain 63,333 such tweets. We then gauge Foreign exposure using the full tweet dataset after filtering out the

[5]The number of Ethereum transactions includes all transactions on the Ethereum blockchain, including token-specific transactions.

tweets by the selected Ukrainian accounts.

We also obtain the number of news articles published daily from the news aggregator Europresse, queried by keywords ‘Ukraine’ and ‘war’ (103,766 articles in total).

To test the crowding out hypothesis, we retrieve the Kiel Institute database of bilateral aid to Ukraine committed by foreign governments (Bushnell et al., 2023). We select the top 20 bilateral military aid packages by value committed separately for the US and for EU countries. We additionally take the top 20 bilateral aid packages of any type (financial, humanitarian, and military) by value pledged by the EU, as the largest EU aid packages are financial or humanitarian in kind, while the largest US aid packages are military ones. The choice of aid sources is determined by the fact that USD and EUR are the two biggest currencies among the CBA donation flows. For the hourly dataset, we manually time-stamp the bilateral aid events by the time of the first announcement of a package. All times are converted to UTC. The full list of events is available in Table B.2.

Some aid announcement days can potentially be classified as significant positive events: e.g., the visit of President Zelenskyy to Washington on 22 December 2022 coincides with the announcement of a $1bn US military aid package. We consistently classify the days with announcements as aid events to avoid having the estimates of the effect of pure emotional intensity be biased by possible crowding out.

4.2 Data filtering and transformations

We convert all donation data to USD: at the minute-by-minute exchange rate for BTC and the day-by-day exchange rate for the traditional currencies. ETH was converted automatically during the extraction process. To appraise the impact of fluctuations in exchange rates, we repeat our analysis using constant exchange rates from the first date of the collection period (01/02/2022) and the average exchange rates over the analysis period. We observe only slight changes in coefficient point estimates.

For analysis at a daily frequency, we convert all individual transaction time-stamps to UTC to match the transactions to the correct days on which they happened.

We exclude as outliers the individual donations that exceed the 99th percentile of observations when converted to USD value, separately for donations in UAH, donations in other fiat currencies, and donations in cryptocurrencies, to eliminate the effect of large one-off donations.

We exclude all data before the outbreak of the war and two weeks after (until 16/03/2022) from our regression analysis, as the outbreak period and the accompanying spike in donation counts would significantly bias our results.

To remove day-of-week seasonality effects, we regress donation flow variables (donation counts and total USD values) on day-of-week dummies, as in the regression below. We do the same for the traditional media counts.

$$Y_t = \alpha + Tuesday_t + Wednesday_t + Thursday_t + Friday_t + Saturday_t + Sunday_t + \varepsilon_t \quad (2)$$

where Y is the variable to be deseasonalised; day-of-week dummies = 1 if date t is the corresponding day-of-week, 0 otherwise. We explicitly state which plots use deseasonalised data.

4.3 Dataset structuring

The main unit measures for our dependent variable of interest are count-type-day and total value-type-day. For descriptive purposes, we also construct a mean value-type-day variable. These measures represent the count, total and mean value of donations contributed by a specific type of donor on a specific day of the war. We classify donors into three types according to the currency denomination of contributions: Ukrainian donors (UAH), Foreign donors (other traditional currencies), Crypto donors (BTC and ETH). We also create a more granular dataset at a count-type-hour and total value-type-hour resolution. To test the crowding out hypothesis separately for the US and the EU, we augment the hourly dataset with USD and EUR donors as separate types.

4.4 Sentiment analysis of tweet content

We perform sentiment analysis of tweet content and assign an emotional score to each tweet that represents the dominating emotional colouring of a tweet. We describe the technical details of the analysis, give examples of classified tweets, and address the limitations of a machine learning-based method in Appendix A. As a result, we obtain the count of tweets with each emotion on each given day of the war.

We use a machine-learning model trained by Hartmann (2022) on multiple datasets containing tweets, Reddit posts, and other texts. The model matches English text to six emotions (anger, disgust, fear, joy, sadness, surprise) and an additional 'neutral' emotion. The classification that the model developers use is based on the theory of emotions by Ekman (1992).

4.5 Descriptive statistics

The definitions for all variables used in our empirical analysis are provided in Table D.1.

In Figure 1, we plot the time series for log-transformed donation counts, total and mean USD values for each of the three donor types between 1 February 2022 and 28 February 2023.

As expected, both donation count and mean value experience a huge spike at the start of the war. Daily count and total daily value of donations follow similar trends: with the Ukrainian donation flows being consistently the highest among the three types.

Figure 1 also offers an insight into the trends of donation fatigue throughout the war. After the outbreak spike (55,000 donations in UAH on 24 February), the number of Ukrainian contributions dropped to 700 per day (by 7,860%) until the end of April, but rebounded to a daily average of 4,500 between May 2022 and February 2023 (a decrease of 1,137% from the outbreak). Some later spikes, e.g., 29,886 donations on 16/11/2022, approach the initial spike. Daily total value has decreased more significantly: from \$2.7M on 24 February to around \$30,000 by the end of April—by 8,900%; however, the trend also levelled off around May 2022, with the average of \$100,000 per day subsequently (down by 2,000% from the outbreak). From the mean value plot, we observe that UAH donors generally have the highest number of donations but the lowest mean value per contribution. The mean value has decreased over time, reflecting more stable counts.

Despite the less pronounced and lagged initial spike (3,837 donations with a total value of around \$1M on 28 February 2022), Foreign donations trailed the Ukrainian trend at first. The two diverged post-May 2022, where Foreign donations continued to fall, indicating higher fatigue in counts and total value. By the end of July 2022, Foreign counts fell by 1,889% and the total daily value by 3,661%—both subsequently levelled off. An average daily contribution, however, has been stable, reflecting that daily counts and values changed dynamically.

Crypto donations, having experienced an even larger spike than UAH donations in terms of counts and total value initially, dropped to a level below other types. We observe a downward trend from February to September 2022, with a 398,566% decrease in counts (from 35,880 donations on 3 March 2022 to a mean of 9 between September 2022 and February 2023) and a 221,995% decrease in total daily values (from \$4.2M to \$1,884). As a result, donation fatigue for the Crypto type appears to be the highest, with other negative crypto-related events (crypto winter; FTX crash) likely contributing to it. An average daily contribution for Crypto has been the largest among all types, which indicates the presence of a few large donations. It is also

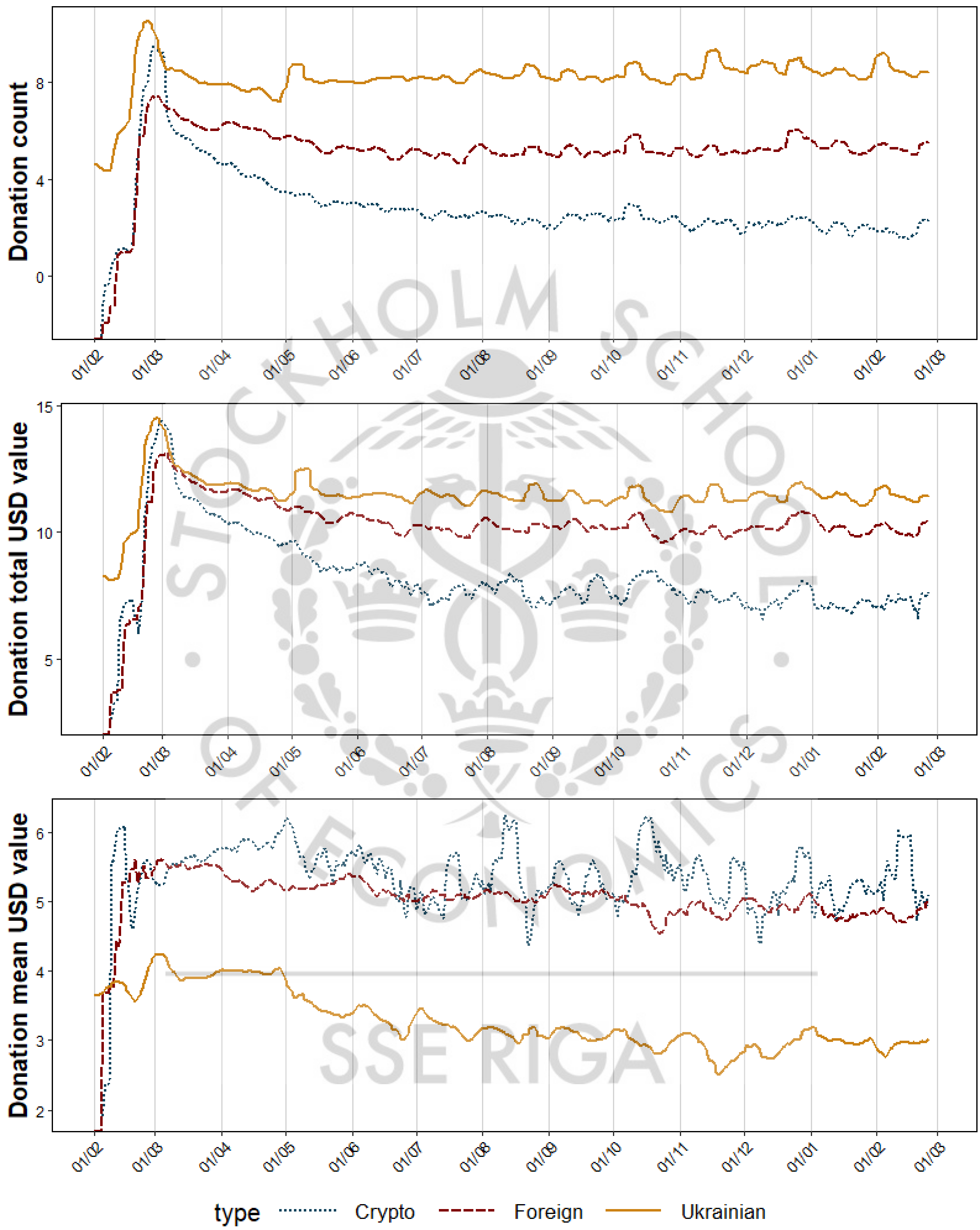

Figure 1: Log of the seven-day moving average of daily donation count, total and mean USD donation value by type (Y-axis) vs. time (X-axis). The period is between 1 February 2022 and 28 February 2023.

rather volatile, exhibiting no trend.

4.5.1 War outbreak period: 21 February–15 March 2022

Table E.1 shows the descriptive statistics for donations received only during the war outbreak period (between 21 February and 15 March 2022). 21 February 2022 corresponds to V. Putin's announcement about the recognition of the independence of the Donetsk and Luhansk regions of Ukraine, which we consider as the beginning of the outbreak period. The outbreak period values are not used in further empirical analysis, because these values are significantly inflated compared to the rest of the war time and may skew the analysis. We choose 16 March 2022 as the cut-off point for the end of the outbreak period and begin our main analysis there. Nevertheless, it is useful to show the outbreak period, especially as 23.6% of all-time number of donations and 43.7% of total donation value come from just these first 23 days of the war. Compared to the analysis period, the average donation count per day for the outbreak is 4.7 times larger. The daily total value is \$4.9M on an average day, compared to around \$150,000 later.

The outbreak period constitutes an extreme case of emotional intensity, illustrating how donation flows of different types react to a shock. Figure 2 illustrates that donation counts start to gain momentum around 21 February, although flows in UAH react earlier. As for total value, Foreign and Crypto donors supply the most donation value in these days.

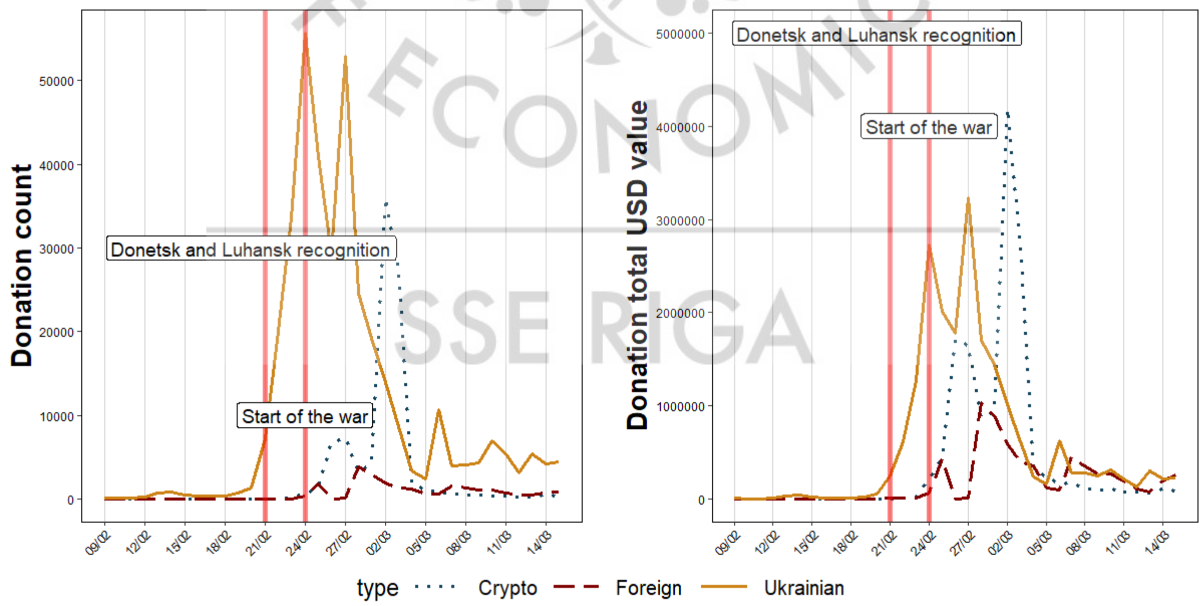

Figure 2: Daily donation count (left) and donation total USD value (right) by type (Y-axis) vs. time (X-axis) with start of the war events overlayed. Timeline is between 1 February and 15 March 2022.

4.5.2 Main analysis period: 16 March 2022–28 February 2023

Table 1 shows the summary statistics of our dependent variables (donation count and total USD value for the three types, and, additionally, mean USD value) and independent variables (proxies for emotional intensity, exposure, and type of emotion) for the main analysis period.

Table 1: Descriptive statistics for the main analysis period (16 March 2022–28 February 2023).

The table reports descriptive statistics for the non-deseasonalised variables used in the regression analysis. The sample period is between 16 March 2022 and 28 February 2023, yielding 350 observation days for each variable. Donation characteristics are reported at a daily frequency by type (Crypto, Foreign, Ukrainian). Variable definitions are provided in Table D.1.

Variable	**Type**	**Min**	**q25**	**Median**	**Mean**	**q75**	**Max**	**St dev**
$DonCount$	All Types	792	3,304	3,820	4,499	4,756	30,162	2,892
	Crypto	1	8	12	24	19	274	40
	Foreign	71	144	186	226	253	905	136
	Ukrainian	509	3,064	3,632	4,249	4,467	29,886	2,863
$DonTotalUSD$	All Types	36,892	98,401	125,779	147,442	164,388	1,054,825	91,219
	Crypto	14	958	2,109	6,615	5,062	88,860	12,373
	Foreign	6,571	19,668	28,813	38,396	44,592	187,841	32,049
	Ukrainian	23,262	70,431	91,131	102,431	118,764	984,107	66,788
$DonMeanUSD$	All Types	116	272	370	423	522	1,876	222
	Crypto	3	102	186	237	306	1,716	208
	Foreign	62	127	149	160	188	303	48
	Ukrainian	9	19	23	27	30	64	12
Emotional intensity variables								
$CivCasualtiesCount$		46	125	199	282	316	2,298	381
$RusMilCasualtiesCount$		70	200	320	387	550	1,140	235
$ConflEvsCount$		38	90	113	114	135	215	33
Degree of exposure variables								
$TweetCount$		4,295	7,623	9,349	12,308	13,697	50,299	7,967
$NewsCount$		41	140	232	251	320	859	151
Emotion type variables								
$TweetJoyCount$		97	184	243	330	375	2,064	244
$TweetAngerCount$		403	791	1,039	1,389	1,567	6,931	986
$TweetSurpriseCount$		70	125	166	224	274	1,711	164
$TweetFearCount$		2,153	3,635	4,632	6,003	6,683	23,869	3,874
$TweetSadnessCount$		217	421	563	752	872	3,726	547
$TweetDisgustCount$		56	105	145	205	235	1,454	173
$TweetNeutralCount$		810	1,256	1,592	2,013	2,315	8,439	1,210

On an average post-outbreak day of the war, donors in UAH contribute the most in terms of pure counts—4,249 times. At the same time, with a mean value of the contributions of around $27, they have the lowest daily average donation. Regarding the Foreign donors, they contribute 226 times on average with the daily mean value of $160. Crypto donors are the least numerous, contributing on average 24 times per day, but with the highest average daily mean value of $237.

An average day of the war produces 12.7 thousand English-language tweets and 251 English-language news articles on the topic. The correlation matrix (Figure E.1) reports correlations between all dependent and independent variables. Traditional media reporting and social media publicity are only moderately positively correlated, with Pearson's r of 0.59 (Figure E.1).

As classified by the sentiment analysis, the most prominent negative emotion expressed on English-speaking social media is fear—48.9% on an average day. Joy, the positive emotion, constitutes just 2.5% of all social media interactions. Figure 3 shows the weekly development of emotion-laden tweets. Overall, the proportions of the six emotions stay stable relative to one another, exhibiting short-lived spikes.

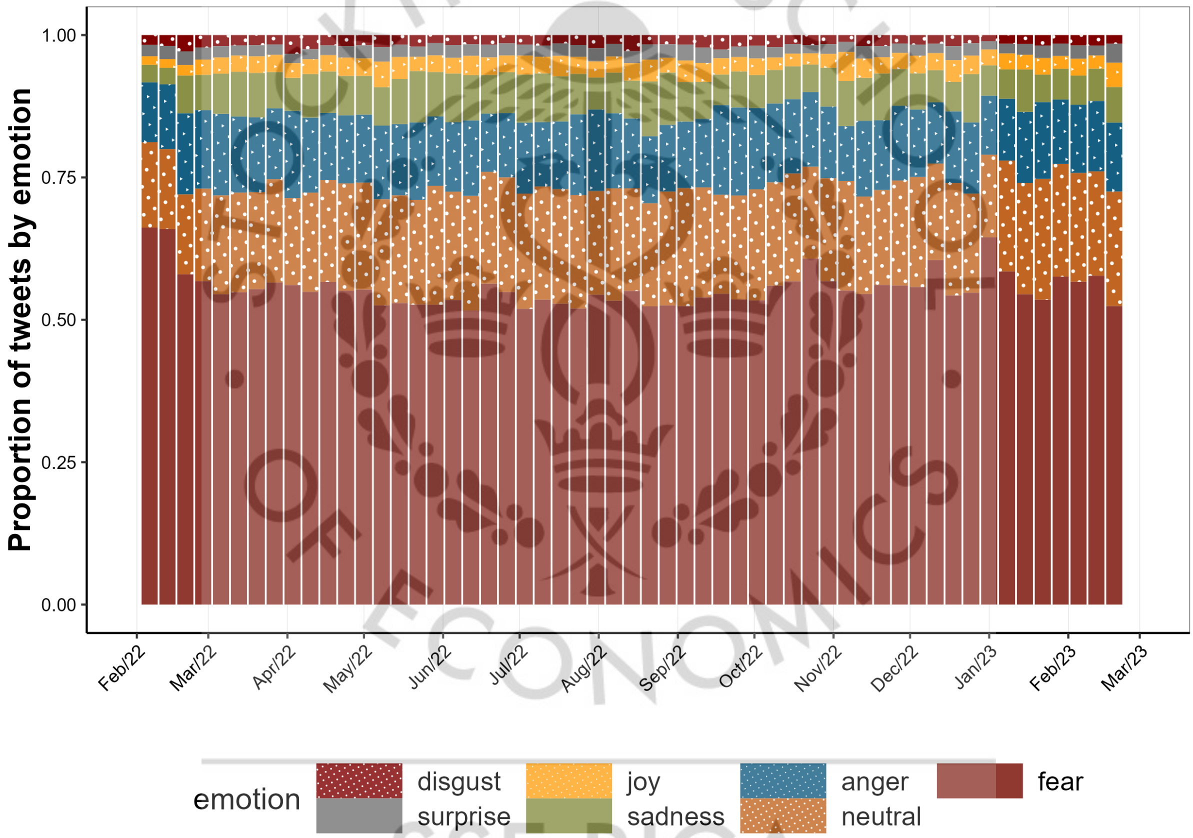

Figure 3: Composition of week-on-week English-language tweet count by emotion, between 1 February 2022 and 28 February 2023.

Perhaps surprisingly, the proportion of anger is rather low—this may be due to the fact that our sample contains only English-language tweets. While angry sentiment could be more characteristic of interactions between Ukrainians, the engagement with and interactions among the foreign audience may be less heated.

Figure 4 shows the direction of the expected relation between deseasonalised donations flows and tweet counts. We observe that for the Foreign and Crypto types the number of donations and the total donation value appear to increase as the number of tweets increases. The relation between UAH values and tweet counts appears to be uncertain. This may be related to the fact that we are using English-language tweets in our analysis. Total daily donation value exhibits a somewhat positive relation with tweet counts.

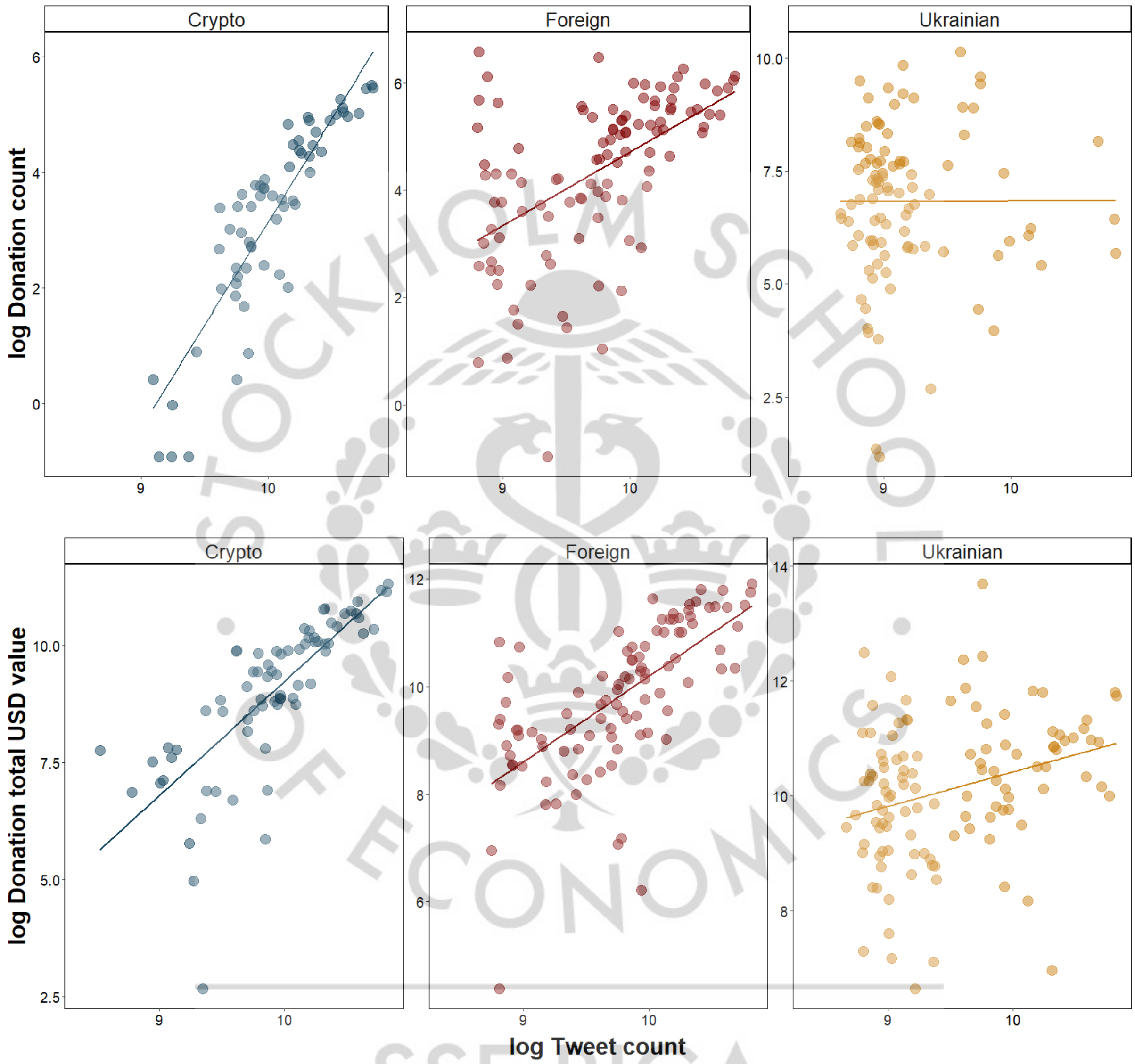

Figure 4: Deseasonalised daily log donation count (top) and total value (bottom) by type (Y-axis) vs. daily log tweet count (X-axis). The period is between 16 March 2022 and 28 February 2023.

Figure 5 confirms the intuition that spikes in the number of donations and in the total USD value of donations mostly correspond to significant and emotional war events.

To better illustrate the relationship between donations and events, we zoom in on the specific period of the war that begins one week before the Kerch bridge explosion (01/10/2022) and ends one week after the nationwide Russian missile strikes in response to it (17/10/2022) (Figure 6).

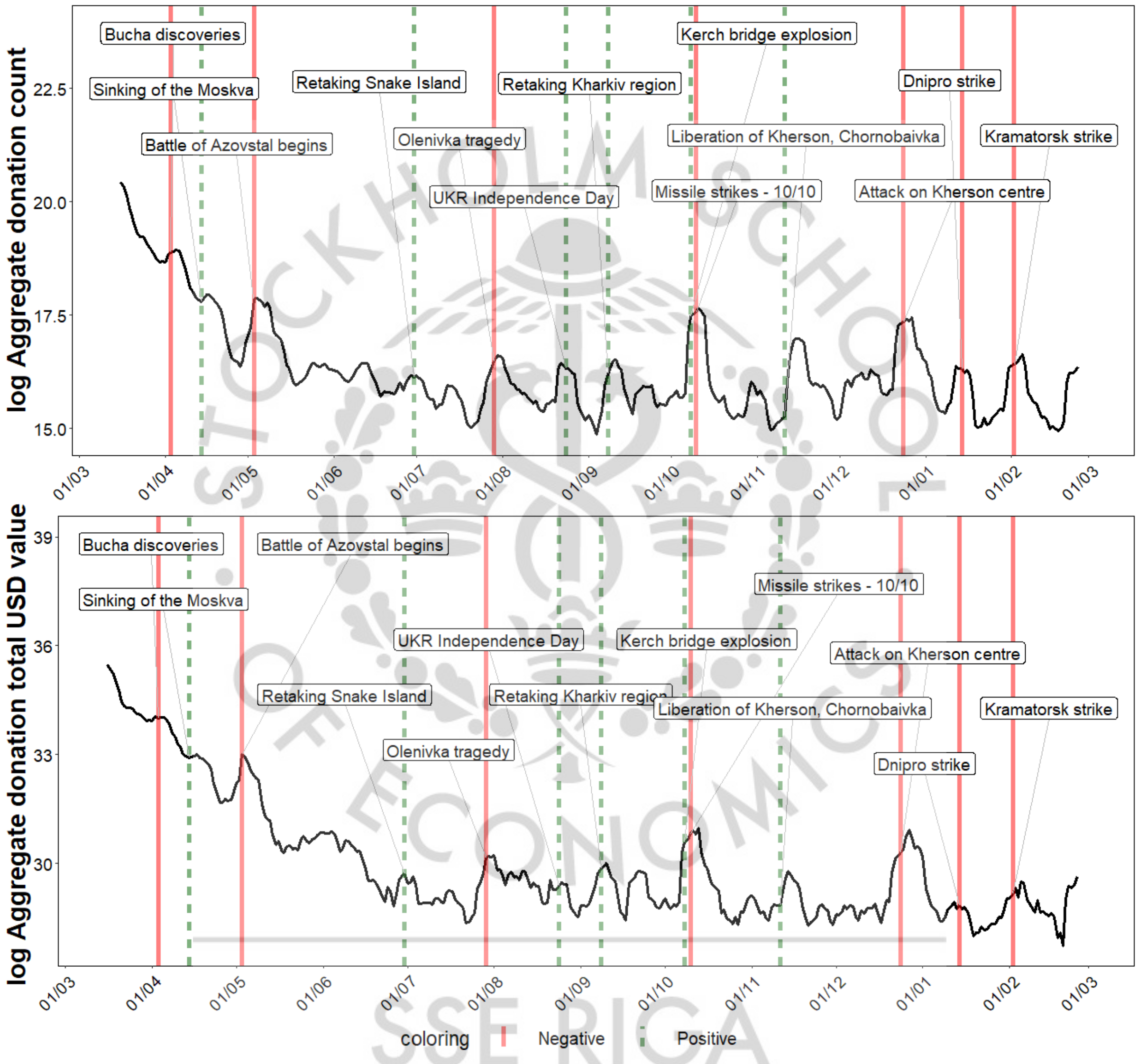

Figure 5: Log of the seven-day moving average of donation flows (Y-axis) vs. time (X-axis), with select significant war events overlayed. The period is between 16 March 2022 and 28 February 2023.

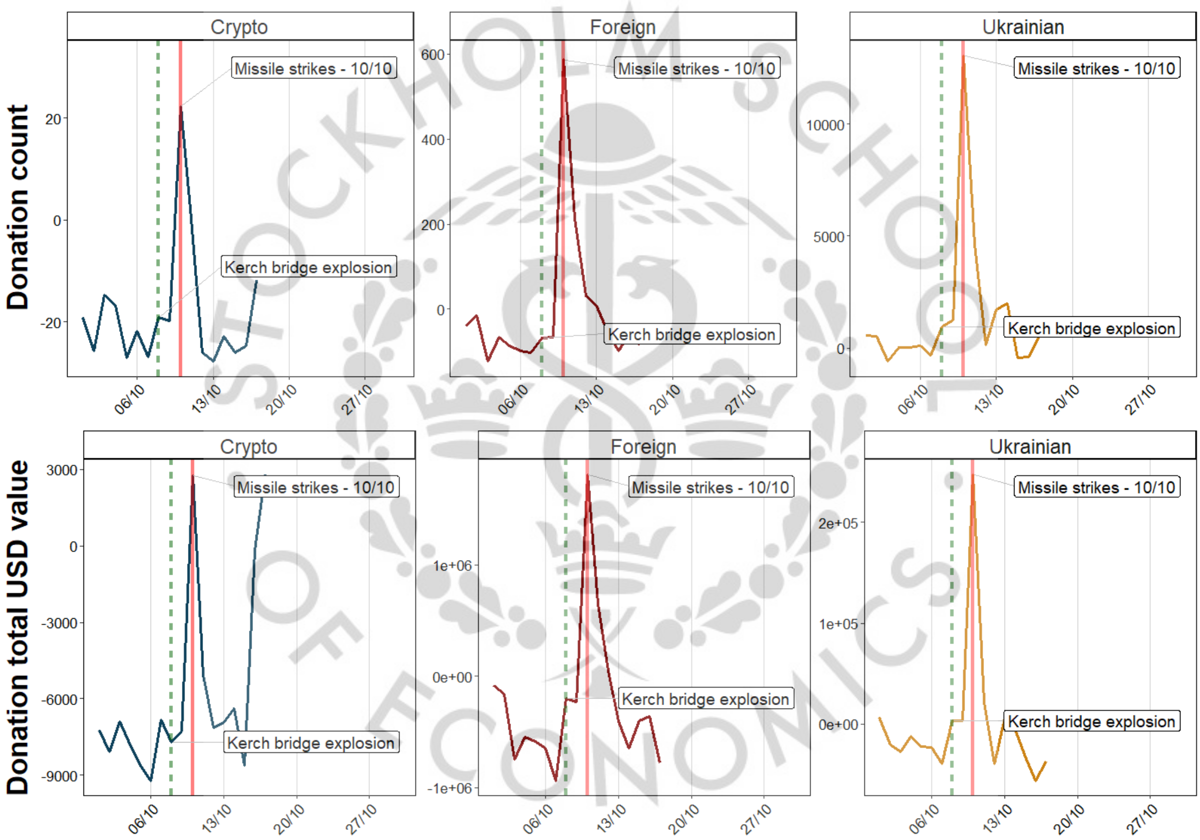

Figure 6: Deseasonalised donation flows by type (Y-axis) vs. time (X-axis), with 'Kerch bridge explosion' and 'Missile strikes - 10/10' events overlayed. Timeline is between 1 and 17 October 2022.

We observe that the positive event produced a smaller spike in the donation count and total value than the negative one, but both are correlated with a positive change.

5 Method

5.1 Testing how emotions drive donation flows

5.1.1 Significant war events as highest emotional intensity days

Following our proposed framework, we first test the relation between donations and emotional intensity. Significant war events represent days with heightened emotional intensity over the course of the war (the list of all significant events is reported in Table B.1). As shown in Figure 5, spikes in donations tend to coincide with significant events; further, we wish to understand the magnitude of this relation and compare the effects between different types of sentiment. To do so, we regress log-changes in donation count and donation total USD value on dummies representing significant war events: $EventPositive$ (= 1 if there is a positive war event on date t, 0 otherwise) and $EventNegative$ (= 1 if there is a negative war event on date t, 0 otherwise). Thus, we are able to separate the impact of different types of sentiment.

To capture the effects of donor fatigue, we follow Brown and Wong (2009) and include a term for the number of days since the outbreak of the war, $DaysSince$.

Finally, we include weekday dummies (**Weekdays**) for Tuesday to Sunday (= 1 on a particular day of the week) to account for day-of-week seasonality. We include donor fatigue and seasonality-related variables in all regressions, but suppress the coefficients on these variables in the main text.

We apply a seemingly unrelated regressions model (SUR), simultaneously estimating a set of three equations corresponding to the types of donations (Ukrainian, Foreign, Crypto) for each donation characteristic separately. A benefit of SUR is that error terms are allowed to correlate between equations, making it possible to compare effect estimates across them. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are used.

Variable definitions can be found in Table D.1.

The resulting equations are:

$$
\begin{aligned}
DonCount_{it} &= \alpha_{1i} + \beta_{1i1}\, EventPositive_t + \beta_{1i2}\, EventNegative_t \\
&\quad + \mathbf{Weekdays}_t'\, \boldsymbol{\zeta_{1i}} + \eta_{1i}\, DaysSince_t + \varepsilon_{1it} \\
DonTotalUSD_{it} &= \alpha_{2i} + \beta_{2i1}\, EventPositive_t + \beta_{2i2}\, EventNegative_t \\
&\quad + \mathbf{Weekdays}_t'\, \boldsymbol{\zeta_{2i}} + \eta_{2i}\, DaysSince_t + \varepsilon_{2it}
\end{aligned} \tag{3}
$$

where $i \in \{Ukraine, Foreign, Crypto\}$, $DonCount_{it}$ is the daily log-change in donation count, $DonTotalUSD_{it}$ is the daily log-change in donation total USD value.

5.1.2 War severity measures as a proxy for negative intensity

Based on the established literature, we extend our initial SUR model with general measures of war severity to capture the average impact of varying emotional intensity: $CivCasualtiesCount$ (daily log-change in the number of civilian casualties), $RusMilCasualtiesCount$ (daily log-change in the number of Russian military personnel casualties), $ConflEvsCount$ (daily log-change in the total number of conflict events).

$$
\begin{aligned}
DonCount_{it} &= \alpha_{1i} + \mathbf{Events}_t'\, \boldsymbol{\beta_{1i}} + \gamma_{1i1}\, CivCasualtiesCount_t \\
&\quad + \gamma_{1i2}\, RusMilCasualtiesCount_t + \gamma_{1i3}\, ConflEvsCount_t \\
&\quad + \mathbf{Weekdays}_t'\, \boldsymbol{\zeta_{1i}} + \eta_{1i}\, DaysSince_t + \varepsilon_{1it} \\
DonTotalUSD_{it} &= \alpha_{2i} + \mathbf{Events}_t'\, \boldsymbol{\beta_{2i}} + \gamma_{2i1}\, CivCasualtiesCount_t \\
&\quad + \gamma_{2i2}\, RusMilCasualtiesCount_t + \gamma_{2i3}\, ConflEvsCount_t \\
&\quad + \mathbf{Weekdays}_t'\, \boldsymbol{\zeta_{2i}} + \eta_{2i}\, DaysSince_t + \varepsilon_{2it}
\end{aligned} \tag{4}
$$

where $i \in \{Ukraine, Foreign, Crypto\}$, $DonCount_{it}$ is the daily log-change in donation count, $DonTotalUSD_{it}$ is the daily log-change in donation total USD value; $\mathbf{Events}_t$ is the set of event dummies from the previous specification.

5.1.3 Media variables as measures of the extent of exposure

As the next step in decomposing the emotional response to the war, we extend our model by including measures of the salience of emotional events (i.e., exposure). Thus, we introduce $TweetCount$ (daily log-change in the number of English-language tweets with keywords 'Ukraine' and 'war') to represent emotional reactions on social media. As a control for the release of actual information, we additionally include $NewsCount$ (deseasonalised daily log-change in the number of traditional media articles with keywords 'Ukraine' and 'war').

$$
\begin{aligned}
DonCount_{it} &= \alpha_{1i} + \mathbf{Events}_t' \boldsymbol{\beta_{1i}} + \mathbf{Severity}_t' \boldsymbol{\gamma_{1i}} + \lambda_{1i1}\, TweetCount_t + \lambda_{1i2}\, NewsCount_t \\
&\quad + \mathbf{Weekdays}_t' \boldsymbol{\zeta_{1i}} + \eta_{1i}\, DaysSince_t + \varepsilon_{1it} \\
DonTotalUSD_{it} &= \alpha_{2i} + \mathbf{Events}_t' \boldsymbol{\beta_{2i}} + \mathbf{Severity}_t' \boldsymbol{\gamma_{2i}} + \lambda_{2i1}\, TweetCount_t + \lambda_{2i2}\, NewsCount_t \\
&\quad + \mathbf{Weekdays}_t' \boldsymbol{\zeta_{2i}} + \eta_{2i}\, DaysSince_t + \varepsilon_{2it}
\end{aligned} \tag{5}
$$

where $i \in \{Ukraine, Foreign, Crypto\}$, $DonCount_{it}$ is the daily log-change in donation count, $DonTotalUSD_{it}$ is the daily log-change in donation total USD value; $\mathbf{Events}_t$ is the set of event dummies, $\mathbf{Severity}_t$ is the set of severity-related variables from the previous specifications.

5.1.4 Six types of emotion

Finally, to understand how donors respond to various emotions caused by the events on the ground, we disaggregate the daily count of English-language tweets into individual log-changes of counts for all of the types of emotions expressed on social media (**TweetEmotionCount** for anger, disgust, fear, joy, sadness, and surprise). The log-change of neutral-emotion tweet counts is excluded.

$$
\begin{aligned}
DonCount_{it} &= \alpha_{1i} + \mathbf{Events}_t' \boldsymbol{\beta_{1i}} + \mathbf{Severity}_t' \boldsymbol{\gamma_{1i}} + \mathbf{Exposure}_t' \boldsymbol{\lambda_{1i}} \\
&\quad + \mathbf{TweetEmotionCount}_t' \boldsymbol{\theta_{1i}} + \mathbf{Weekdays}_t' \boldsymbol{\zeta_{1i}} + \eta_{1i}\, DaysSince_t + \varepsilon_{1it} \\
DonTotalUSD_{it} &= \alpha_{2i} + \mathbf{Events}_t' \boldsymbol{\beta_{2i}} + \mathbf{Severity}_t' \boldsymbol{\gamma_{2i}} + \mathbf{Exposure}_t' \boldsymbol{\lambda_{2i}} \\
&\quad + \mathbf{TweetEmotionCount}_t' \boldsymbol{\theta_{2i}} + \mathbf{Weekdays}_t' \boldsymbol{\zeta_{2i}} + \eta_{2i}\, DaysSince_t + \varepsilon_{2it}
\end{aligned} \tag{6}
$$

where $i \in \{Ukraine, Foreign, Crypto\}$, $DonCount_{it}$ is the daily log-change in donation count, $DonTotalUSD_{it}$ is the daily log-change in donation total USD value; $\mathbf{Events}_t$ is the set of event dummies, $\mathbf{Severity}_t$ is the set of severity-related variables, and $\mathbf{Exposure}_t$ is the set of media-related variables from the previous specifications.

As this specification represents our complete model, we report the Variance inflation factor (VIF) statistic of each independent variable in Table F.1. The low values (<5) indicate that multicollinearity between the independent variables is not an issue.

5.2 Testing causality between emotional intensity and donation flows

While we have argued that emotional intensity has an effect on donation flows, we must note that the exact causal relation may be muddled. Thus, to more closely examine the potential for a causal relation between public emotional sentiment and donations, we apply the Difference-in-Differences method. The unique dataset of donations from Come Back Alive, which is time-stamped and split by currency (UAH, USD, EUR, and others), allows us to draw a direct link from an emotional event to donation activity with hour-by-hour precision. This also allows us to, in turn, quantify precisely how much emotional intensity contributes to donation spikes and provide causal not just correlational evidence. The treatment effect we are testing is an average emotional shock arising from all positive and negative war events in our sample.

We estimate the average treatment effect as the difference between how donations of a treatment group exposed to the event and a control group differ 48 daytime hours before a war event and 48 daytime hours after. In our event window, we skip nighttime hours (00:00–05:59), as the majority of donors may be asleep and thus not able to react to events. Here, 'donations around the event' refer to the aggregate averaged donations around 31 sample events. If an event happens during the night, we move it to the next morning at 06:00.

Leveraging the data on what currency fiat donations are made in, we construct a treatment group of donations from Ukraine and a control group of donations from other countries. We hypothesise that the treatment group of Ukrainian donors is more emotionally charged and more susceptible to emotional shocks than foreign donors, as war events are more salient to the Ukrainian population.

Given the evidence in Figure 7, we assume that in absence of emotional shocks, donation flows should develop the same way for both groups, maintaining parallel trends. We observe that donation flows follow a random walk before the event and there is a clear uptick in donation counts and values following the event for both donor types.

We construct the following regressions:

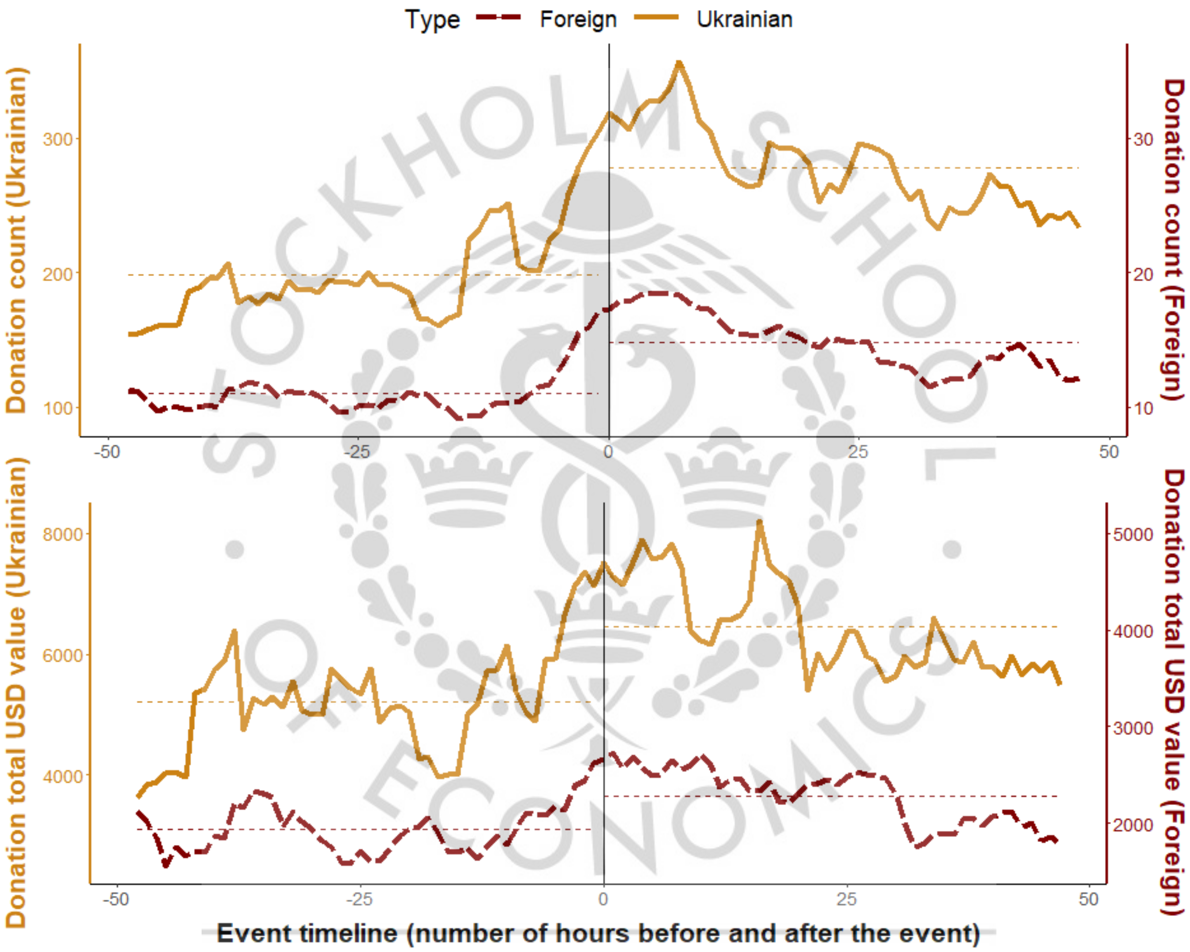

Figure 7: Difference-in-Differences parallel trends plot for Ukrainian vs. Foreign donation flows. The Y-axis displays five-hour moving average donation flows, averaged across 31 events. The mean flows before and after the event are shown by the dashed line. The X-axis shows the event timeline in relative terms for 48 daytime hours before and after the event.

$$DonCount_{it} = \alpha + \beta_{11}\, Ukrainian_i + \beta_{12}\, After_t + \delta\, Ukrainian_i \times After_t + \varepsilon_{1it}$$
$$DonTotalUSD_{it} = \alpha + \beta_{21}\, Ukrainian_i + \beta_{22}\, After_t + \delta\, Ukrainian_i \times After_t + \varepsilon_{2it} \tag{7}$$

where $i \in \{Ukrainian, Foreign\}$; $Ukrainian_i = 1$ if $i = Ukrainian$, 0 otherwise; $After_t = 1$ if time t is up to 48 hours after an event, 0 otherwise; $Ukrainian_i \times After_t$ is an interaction term (= 1 if $i = Ukrainian$ and time t is up to 48 hours after an event, 0 otherwise).

The average treatment effect of war events is given by the coefficient δ on $Ukrainian_i \times After_t$.

We do acknowledge that, while there could be an emotional intensity differential between the Ukrainian and the foreign donors, these two groups also differ in the extent of their informational exposure to the war events (Ukrainians are more likely to both be emotionally charged and know more about the events). To somewhat ameliorate this concern, we construct a Twitter exposure proxy, $TweetCount$, that is equal to the daily log-count of foreign-made tweets as a control for Foreign donations and the daily log-count of Ukrainian-made tweets as a control for Ukrainian donations. Our D-i-D analysis, therefore, provides a test for whether more emotionally charged Ukrainian donors (who are also likely more exposed to war-related information) donate more in the immediate aftermath of war events, compared to Foreign donors.

5.3 Testing the crowding out hypothesis

Whether the crowding out phenomenon holds in the event of heightened emotional intensity is an empirical question. Leveraging the ability to separate donation counts and total values by currency, we construct a Difference-in-Difference set-up whereby we assume that donors in USD and EUR have been 'treated' by the announcement of bilateral aid from their respective government institution. The list of bilateral aid announcements is reported in Table B.2.

We treat UAH donors as a control group, given that the Ukrainian government cannot make transfers to itself. We hypothesise that there will be no crowding out for the treated donors, because the heightened emotional intensity of the war setting will boost the amount of warm glow received by donors and neutralise the potential crowding out.

Since government transfers can also be subdivided into types by purpose, we further test whether private military donations are crowded out by specifically military-targeted bilateral aid or by bilateral aid in general.

We estimate the average treatment effect around the aid events in the same way as for significant war events. The regression set-up closely resembles Equation 7, where the dummy $Ukrainian_i$ is replaced with USD_i (= 1 if $i = USD$, 0 otherwise) for USD donors and EUR_i (= 1 if $i = EUR$, 0 otherwise) for EUR donors.

6 Analysis and Discussion

We report our findings in three parts. We begin by discussing the emotional framework: first, we consider the intensity component of emotion, then analyse the degree of exposure component, and finalise by discussing the effects of various types of emotions. Next, we report the results of the Difference-in-Differences test for the causal relation between emotional intensity and donations for Ukrainian and non-Ukrainian donors. Finally, we report the results of the empirical test of the crowding out hypothesis in a heightened emotional setting.

6.1 The three-part emotional framework

6.1.1 The role of emotional intensity

Table 2 reports the results from regressing military donation flows on the dummies for the days of the war with the highest emotional intensity, either positive or negative. Broadly, we test the magnitude of the effect of events of significant severity on military donation flows and distinguish between positive and negative sentiment.

For donation count, we observe that *negative* intensity is highly statistically significant for Ukrainian and Foreign donors (at the 1% level), and for Crypto donors (at the 5% level). *Positive* intensity is significant only for the Ukrainian and Foreign types (at the 5% and 1% level respectively).

We conduct F-tests (see Table G.1 for details) to understand if the intensity shocks statistically differ between the Ukrainian and Foreign flows and, furthermore, if the effects of *negative* and *positive* intensity statistically differ. We find that the effects are not statistically different across donor types. On the other hand, the magnitude of effects of *negative* and *positive* events appears statistically different.

Negative sentiment intensity has a larger magnitude of impact in both cases: for UAH donors, the change in donations is by 45pp larger on high *negative* intensity days compared

Table 2: The relation between event type (positive vs negative) and donation flows.

The table displays the results from regressing donation flows on dummies that equal 1 on the days of the war with the highest emotional intensity, either positive (*EventPositive*) or negative (*EventNegative*). The results are compared across three donor types: Ukrainian, Foreign, and Crypto. The sample period is between 16 March 2022 and 28 February 2023, resulting in 350 $\times$ 3 day-type observations. Donation flows are log-differenced donation count (*DonCount*) and donation total USD value (*DonTotalUSD*). Variable definitions are provided in Table D.1. We control for day-of-week seasonality and days since the start of the war. Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$			$DonTotalUSD$		
	Ukrainian	Foreign	Crypto	Ukrainian	Foreign	Crypto
Intercept	-0.03	0.41^{***}	0.00	-0.02	0.80^{***}	0.08
	(0.06)	(0.05)	(0.08)	(0.06)	(0.06)	(0.18)
Event types						
$EventPositive$	0.20^{**}	0.26^{***}	0.24	0.19^{**}	0.09	0.51
	(0.08)	(0.09)	(0.15)	(0.08)	(0.09)	(0.37)
$EventNegative$	0.45^{***}	0.55^{***}	0.38^{**}	0.43^{***}	0.39^{***}	0.74^{**}
	(0.13)	(0.14)	(0.17)	(0.13)	(0.13)	(0.34)
Day-of-week fixed effects	YES	YES	YES	YES	YES	YES
DaysSince	YES	YES	YES	YES	YES	YES
R^2	0.27	0.47	0.04	0.47	0.63	0.04
Adj. R^2	0.25	0.46	0.01	0.46	0.62	0.02

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

to a 20pp larger change on *positive* intensity days; for Foreign donors, the difference in the effect is similar (donation counts increase by 55pp and by 26pp for the respective event type).

For donation total USD values, *negative* intensity is highly significant for both Ukrainian and Foreign donations (at the 1% level). *Negative* intensity is likewise significant at the 5% level for the Crypto type. The changes in total value on *negative* intensity days are by 43pp, 39pp, and 74pp larger for Ukrainian, Foreign, and Crypto donors respectively.

Nevertheless, Foreign and Crypto donors do not seem to donate more in monetary terms on *positive* intensity days, while Ukrainian ones do (by 19pp, significant at the 5% level).

Negative intensity seems to account for a larger response in military donation flows for both counts and values. Suffering and destruction that prompts *negative* emotions seem to be a robust strong catalyst for the giving response across all donor types. This ties in with both the impure and the pure altruism motives for donating. The donors might aim to alleviate suffering, but the high intensity of the alleviated suffering also increases the amount of received warm glow. This finding is also related to negative events enhancing mortality salience more effectively; thus, increasing donor propensity to behave prosocially.

At the same time, *positive* events signal the prowess of the Ukrainian people and convincingly show that the rallied support will not be wasted, which could explain their potential to catalyse donations. This ties in with the egoistic motive of donating, whereby, via strengthening the Ukrainian army, the donors can contribute to their own safety. This must matter more for the Ukrainian type, which is reflected in the results.

All Crypto donations regressions have significantly lower adjusted R^2s than other types (e.g., close to 0 for Crypto, given 0.25 (0.46) for UAH and 0.46 (0.62) for Foreign for counts (total values)). This could indicate that emotional intensity is a rather weak determinant of Crypto donations. Still, the coefficients on *negative* intensity are significant, which adds weight to the claim that *negative* intensity is a stronger driver of donations overall.

To further explore emotional intensity, we regress military donation flows on other intensity proxies. The additional variables represent daily changes in the level of emotional intensity as opposed to concrete spikes. Table 3 reports the results.

For the Foreign type, a 1pp increase in the number of conflict events on a given day brings a 0.11pp larger change in the donation count (significant at the 10% level). However, there is no impact on the total value, which makes us conjecture that the attracted donors contribute only small sums.

Table 3: The relation between donation flows and emotional intensity.

The table displays the results from regressing donation characteristics on a range of emotional **intensity** proxies: 1) dummies that equal 1 on the days of the war with the highest emotional intensity, either positive (*EventPositive*) or negative (*EventNegative*), 2) proxies for war severity (log-differenced count of Ukrainian civilian casualties (*CivCasualtiesCount*), log-differenced count of Russian military casualties (*RusMilCasualtiesCount*), log-differenced count of all conflict events (*ConflEvsCount*). The results are compared across three donor types: Ukrainian, Foreign, and Crypto. The sample period is between 16 March 2022 and 28 February 2023, resulting in 350 $\times$ 3 day-type observations. Donation characteristics are log-differenced donation count (*DonCount*) and donation total USD value (*DonTotalUSD*). Variable definitions are provided in Table D.1. We control for day-of-week seasonality and days since the start of the war. Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$			$DonTotalUSD$		
	Ukrainian	Foreign	Crypto	Ukrainian	Foreign	Crypto
Intercept	-0.03	0.41^{***}	0.01	-0.02	0.80^{***}	0.08
	(0.06)	(0.05)	(0.08)	(0.06)	(0.06)	(0.19)
Event types						
$EventPositive$	0.19^{**}	0.25^{***}	0.24	0.18^{**}	0.09	0.51
	(0.08)	(0.09)	(0.16)	(0.08)	(0.09)	(0.37)
$EventNegative$	0.47^{***}	0.56^{***}	0.36^{**}	0.44^{***}	0.39^{***}	0.74^{**}
	(0.13)	(0.14)	(0.18)	(0.14)	(0.13)	(0.35)
War severity						
$CivCasualtiesCount$	-0.01	0.00	0.07	0.03	0.02	-0.01
	(0.06)	(0.03)	(0.07)	(0.06)	(0.05)	(0.18)
$RusMilCasualtiesCount$	0.04	0.04	-0.05	0.03	0.02	-0.05
	(0.05)	(0.04)	(0.07)	(0.04)	(0.05)	(0.17)
$ConflEvsCount$	0.10	0.11^{*}	-0.04	0.12	-0.02	0.03
	(0.09)	(0.07)	(0.13)	(0.08)	(0.08)	(0.28)
Day-of-week fixed effects	YES	YES	YES	YES	YES	YES
DaysSince	YES	YES	YES	YES	YES	YES
R^2	0.27	0.48	0.04	0.48	0.63	0.04
Adj. R^2	0.25	0.46	0.01	0.46	0.61	0.01

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Overall, non-categorical war severity variables appear to be relatively poor predictors of military donation flows in our setting. We observe that while the most intense war events have an effect on donations, the baseline fluctuations in intensity are, for the most part, not significant enough to matter. This should be especially the case for Ukrainian donors, who might be more used to the general heightened intensity of the war setting. Additionally, days with the most conflict events or the most casualties may not necessarily correspond to the most emotionally intense days in our setting—other factors like the location of the event (e.g., events happening in large cities may be perceived as more significant) or people involved (whether the key actors are affected) may determine the emotional significance of a day.

Another complication determining the impact of intensity is information release and spread patterns: the potential lags between the time of the event, the time of its first discovery by witnesses, and, further, the time of its availability to the wider public. Most battles and attacks are not immediately or never salient to the donors, resulting in no effect. The fact that civilian casualties are insignificant in our specifications could be attributed to information release patterns. The UN reports daily casualties on a weekly basis, in essence, dating them back in time; therefore, the day-to-day patterns of emotional response do not appear to be captured.

6.1.2 The role of the extent of exposure

In addition to the intensity variables, Table 4 reports the results from regressing military donation flows on a range of proxies for the degree of exposure to emotional events: 1) the log-differenced count of tweets on a given day that represents the degree of event publicity on social media, 2) the log-differenced count of news articles that represents the degree of event publicity in traditional media.

The count of traditional media news does not seem to be correlated with military donation flows. Traditional media represents a more unbiased view on the events, without emotional amplification; therefore, it does not add to the already captured intensity dimension.

On the other hand, we observe that social media publicity is highly significant for all donor types for both counts and total values. For Ukrainian donors, a 1pp larger change in the tweet count drives up the change in donation counts by 0.34pp and in donation daily total value by 0.37pp. For Foreign donors, the effects are of a larger magnitude: 0.57pp and 0.55pp respectively. There is also a positive relation between Crypto donation flows and social media publicity (significant at the 5% level for counts and at 10% for values). The change in the number

Table 4: The relation between donation flows and emotional intensity, exposure.

The table displays the results from regressing donation characteristics on a range of emotional **intensity** and **exposure** proxies. In addition to the intensity variables (see Table 3), we include exposure proxies: 1) log-differenced count of tweets on a given day that represents the degree of event publicity on social media (*TweetCount*) and 2) log-differenced count of news articles that represents the degree of event publicity in traditional media (*NewsCount*). The results are compared across three donor types: Ukrainian, Foreign, and Crypto. The sample period is between 16 March 2022 and 28 February 2023, resulting in 350 × 3 day-type observations. Donation characteristics are log-differenced donation count (*DonCount*) and total USD value (*DonTotalUSD*). Variable definitions are provided in Table D.1. We control for day-of-week seasonality and days since the start of the war. Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$			$DonTotalUSD$		
	Ukrainian	Foreign	Crypto	Ukrainian	Foreign	Crypto
Intercept	-0.09	0.31^{***}	-0.09	-0.08	0.71^{***}	-0.08
	(0.06)	(0.05)	(0.08)	(0.05)	(0.06)	(0.21)
Event types						
$EventPositive$	0.16^{*}	0.20^{**}	0.18	0.15^{*}	0.03	0.42
	(0.08)	(0.09)	(0.16)	(0.08)	(0.09)	(0.38)
$EventNegative$	0.42^{***}	0.50^{***}	0.31^{*}	0.39^{***}	0.33^{**}	0.64^{*}
	(0.14)	(0.14)	(0.19)	(0.14)	(0.13)	(0.36)
War severity						
$CivCasualtiesCount$	-0.03	-0.02	0.06	0.01	0.01	-0.03
	(0.06)	(0.03)	(0.06)	(0.06)	(0.04)	(0.18)
$RusMilCasualtiesCount$	0.02	0.00	-0.08	0.01	-0.01	-0.10
	(0.04)	(0.03)	(0.08)	(0.04)	(0.04)	(0.18)
$ConflEvsCount$	0.11	0.13^{**}	-0.02	0.14	-0.00	0.05
	(0.09)	(0.06)	(0.14)	(0.08)	(0.07)	(0.28)
Media						
$TweetCount$	0.34^{**}	0.57^{***}	0.57^{**}	0.37^{***}	0.55^{***}	0.92^{*}
	(0.16)	(0.17)	(0.28)	(0.14)	(0.16)	(0.56)
$NewsCount$	0.09	0.01	-0.07	0.07	-0.05	-0.04
	(0.09)	(0.07)	(0.11)	(0.07)	(0.08)	(0.22)
Day-of-week fixed effects	YES	YES	YES	YES	YES	YES
DaysSince	YES	YES	YES	YES	YES	YES
R^2	0.30	0.53	0.06	0.50	0.65	0.05
Adj. R^2	0.27	0.51	0.02	0.48	0.63	0.01

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

of Crypto contributions increases by 0.57pp and total daily value by 0.92pp with a 1pp larger change in tweets on a given day. It is plausible that this finding is related to the less mediated, more immediately accessible, and overall richer content of social media networks as compared to traditional media, which leads to greater potential to amplify emotional effects.

We conduct another F-test (see Table G.2 for details) to understand if the coefficients are significantly different among donor types. We find that the differences are insignificant in our estimation. However, from the conceptual point of view, there is a potential for the differing effects. The events were already more salient for Ukrainian donors, while more Foreign donors are getting reached because of the amplifying effect. The fact that the magnitude of amplification could be the largest for Crypto donors is not surprising. As previous literature on cryptoculture suggests, the Crypto community consists of active and opinionated Twitter, Reddit, and other social media users, so the potential for network effects in the spreading of information is significant.

6.1.3 The role of the type of emotion

Finally, we take a closer look at the impact of different types of emotion that characterise each day of the war. Adding to intensity and exposure, Table 5 reports the results of regressing military donation flows on the counts of tweets expressing one out of six types of emotions according to Ekman (1992). Emotions that appear as significant drivers of either donation counts or values are fear and sadness.

In Ekman (1992), fear is defined as a reaction to a threatening stimulus that can harm us psychologically or physically. Fear is traditionally considered a negative emotion; however, as opposed to anger, which may translate into destructive behaviour, fear translates into constructive, protective behaviour aimed to reduce harm. This may potentially include taking such steps as donating in an attempt to meaningfully protect the Ukrainians. Thus, fear has the potential to enhance both the egoistic and the altruistic drivers of donations, related to protecting oneself and others from danger. The 'fear' coefficient is positive and statistically significant at 5% for donation count for the Foreign and Crypto types and at 10% for total value for Crypto.

Sadness is associated with loss and misery. It may have a demoralising effect on donors: negative war events that refer to military losses (e.g., the Azovstal surrender) may call into question the capabilities of the army or the sensibility of the use of donated funds. As a result, the propensity to donate through the egoistic and altruistic drivers can diminish. This can explain

Table 5: The relation between donation flows and emotional intensity, exposure and emotion type.

The table displays the results from regressing donation characteristics on emotional **intensity** and **exposure** proxies, and on the predominant **type of emotion** on a given day. In addition to the intensity and exposure (see Table 4), we replace the total count of tweets with log-differenced counts of tweets representing particular emotions (joy, anger, surprise, fear, sadness, disgust) on a given day, classified using sentiment analysis. The count of tweets with neutral emotion is omitted. The results are compared across three donor types: Ukrainian, Foreign, and Crypto. The sample period is between 16 March 2022 and 28 February 2023, resulting in 350 $\times$ 3 day-type observations. Donation characteristics are log-differenced donation count ($DonCount$) and donation total USD value ($DonTotalUSD$). Variable definitions are provided in Table D.1. We control for day-of-week seasonality and days since the start of the war. Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$			$DonTotalUSD$		
	Ukrainian	Foreign	Crypto	Ukrainian	Foreign	Crypto
Intercept	-0.09	0.31^{***}	-0.10	-0.08	0.71^{***}	-0.11
	(0.06)	(0.05)	(0.08)	(0.05)	(0.06)	(0.21)
Event types						
$EventPositive$	0.17^{**}	0.21^{**}	0.19	0.16^{*}	0.03	0.43
	(0.08)	(0.08)	(0.15)	(0.08)	(0.10)	(0.38)
$EventNegative$	0.43^{***}	0.50^{***}	0.31	0.40^{***}	0.34^{**}	0.64^{*}
	(0.14)	(0.14)	(0.19)	(0.15)	(0.13)	(0.37)
War severity						
$CivCasualtiesCount$	-0.02	-0.02	0.05	0.02	0.01	-0.04
	(0.06)	(0.03)	(0.07)	(0.06)	(0.04)	(0.18)
$RusMilCasualtiesCount$	0.02	0.00	-0.09	0.01	-0.01	-0.11
	(0.04)	(0.03)	(0.08)	(0.04)	(0.05)	(0.19)
$ConflEvsCount$	0.13	0.13^{**}	-0.02	0.15^{*}	0.01	0.04
	(0.09)	(0.07)	(0.14)	(0.09)	(0.08)	(0.29)
Media						
$NewsCount$	0.09	0.00	-0.07	0.07	-0.06	-0.05
	(0.08)	(0.07)	(0.11)	(0.07)	(0.08)	(0.22)
Emotion type						
$TweetJoyCount$	0.02	0.01	0.01	0.01	0.07	0.02
	(0.08)	(0.06)	(0.12)	(0.07)	(0.06)	(0.39)
$TweetAngerCount$	0.11	0.00	-0.06	0.13	0.04	-0.15
	(0.11)	(0.09)	(0.18)	(0.10)	(0.11)	(0.42)
$TweetDisgustCount$	0.05	0.07	0.03	0.04	0.11	-0.05
	(0.05)	(0.05)	(0.11)	(0.04)	(0.07)	(0.29)
$TweetSurpriseCount$	0.05	0.08	0.08	0.03	0.03	0.22
	(0.07)	(0.06)	(0.12)	(0.06)	(0.08)	(0.29)
$TweetSadnessCount$	-0.18^{**}	-0.01	0.00	-0.08	0.02	-0.01
	(0.08)	(0.07)	(0.12)	(0.08)	(0.07)	(0.25)
$TweetFearCount$	0.23	0.37^{**}	0.49^{**}	0.18	0.26	0.90^{*}
	(0.14)	(0.16)	(0.24)	(0.14)	(0.19)	(0.47)
Day-of-week fixed effects	YES	YES	YES	YES	YES	YES
DaysSince	YES	YES	YES	YES	YES	YES
R^2	0.31	0.53	0.07	0.50	0.65	0.06
Adj. R^2	0.27	0.50	0.02	0.47	0.63	0.00

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

the negative 'sadness' coefficient for Ukrainian donation counts (significant at 5%).

Anger, especially when it reaches its highest intensity, has the potential to become a dangerous emotion and can be linked to violence. Subsequently, anger is a destructive, rather than a constructive impulse, which may not necessarily motivate charitable action—as observed in the regression.

Disgust denotes the feeling of loathing or revulsion towards something that is perceived as offensive or repulsive. The fundamental purpose of disgust is to prompt individuals to distance themselves and block or eliminate anything harmful. Similar to anger, disgust may not result in constructive action; thus, not being a driver of donations.

Surprise is an emotion that has a very short duration. If one concludes that a surprising event has no relevance to them, no subsequent emotion may follow. As it lasts only briefly, there could be little potency for surprise to prompt a constructive charitable action, regardless of what caused the emotion.

Joy refers to experiencing pleasurable states of being. There are few occasions for experiencing joy in our setting, apart from a few strongly positive events. The presence of joyful emotion could be too scarce for it to be a meaningful driver of donations.

6.2 Difference-in-Differences test for emotional intensity

Even though the magnitudes of the impact of high emotional intensity on Ukrainian and Foreign donors appear to differ in the SUR regressions (Table 2), we, in fact, cannot reject the null hypothesis that they are the same (see Table G.1). Additionally, it is possible that the relationship portrayed in the SUR analysis is muddled by a third variable; thus, we cannot claim that the impact is causal. Therefore, we are looking at an exogenous shock to the emotional intensity with the Difference-in-Differences specification, which allows us to measure the difference from the treatment between two populations, assuming that other unobserved differences between them are the same.

Table 6 reports the results.

The D-i-D estimator $Ukrainian \times After$ is significant at the 1% level for donation count and at the 5% level for donation total value, which indicates that for both there is a statistically significant difference in the impact of emotional intensity between the groups. Donation count for Ukrainian donors increases by 72.42 more on average if treated by an intense emotional event, as compared to Foreign donors. In terms of total USD value, Ukrainian donors donate

Table 6: Difference-in-difference analysis of Ukrainian vs foreign donations around significant war events.

This table reports D-i-D results for the difference in donation flows between the treatment group (Ukrainian donors, assumed to be more intensely affected by significant war events) and the control group (Foreign donors). Donation flows are hourly counts (*DonCount*) and total USD values (*DonTotalUSD*) 48 before and after 31 sample events. *Ukrainian* $= 1$ if the donor type is Ukrainian, 0 otherwise; *After* $= 1$ if time t is up to 48 hours after an event, 0 otherwise; *Ukrainian* $\times$ *After* is the interaction term $= 1$ if the donor type is Ukrainian and time t is up to 48 hours after an event, 0 otherwise. *TweetCount* is a control for social media exposure for the treatment group (tweets by influential Ukrainian accounts in the form $log(x+1)$), and social media exposure for the control group (all English-language tweets except tweets by influential Ukrainian accounts in the form $log(x+1)$). Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$	$DonCount$	$DonTotalUSD$	$DonTotalUSD$
$Ukrainian$	189.24***	262.57***	3285.85***	7710.64***
	(7.73)	(27.24)	(273.18)	(835.60)
$After$	3.66***	2.43***	322.80**	248.58*
	(0.46)	(0.71)	(125.30)	(127.08)
$Ukrainian \times After$	72.42***	73.34***	853.80**	909.32**
	(11.06)	(12.77)	(376.85)	(386.63)
$TweetCount$		17.94***		1082.53***
		(6.33)		(216.35)
R^2	0.26	0.26	0.07	0.08
Adj. R^2	0.25	0.26	0.07	0.08

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

$853.80 more on average if treated by an intense emotional event, as compared to Foreign donors.

The results do not change significantly when we control for exposure. After adding $TweetCount$, the interaction coefficients for donation count and total value increase slightly (to 73.34 and $909.32 respectively) and maintain significance.

From the descriptive statistics, we observe that Ukrainians donate the most in value terms on an average day of the war and are generally the more numerous donors; Foreign donors contribute less in USD terms and in pure counts. The D-i-D confirms the intuition that intense events drive up the count and total daily value of Ukrainian donations more than Foreign donations.

Given the D-i-D result, we suppose that the fact that Ukrainian donors are more impacted by intense events is likely causally related to the higher increase in donation counts and total value donated for this donor type. This finding may imply that emotional intensity is a more prominent donation driver for Ukrainian donors than for Foreign donors. This may be a consequence of the stronger egoistic donor motives, whereby the need to strengthen the army for own protection increases military-targeted donations for Ukrainians.

6.3 Difference-in-Differences test for crowding out

We test the crowding out hypothesis using the largest EU and US bilateral aid announcements. Table 7 reports results for US military aid announcements. The coefficient $USD \times After$ for donation counts is not statistically significant in our specification with and without controlling for exposure. The interaction coefficient for total USD value is statistically insignificant. This implies that there is no statistically significant difference in the dynamics of USD and UAH donation counts after a large US military bilateral aid package announcement.

Table 8 reports the results for EU military aid announcements.

We reach a similar conclusion for large EU military bilateral aid announcements. The coefficient $EUR \times After$ is not statistically significant for neither donation counts nor total values.

Table 9 reports the results for EU announcements for all types of aid.

Unlike in the previous specifications, the coefficient $EUR \times After$ for donation counts is significant at the 1% level with and without controlling for exposure, implying a statistically significant difference between donations in EUR and control group donations after a large EU bilateral aid package announcement. In terms of magnitude, the count of donations in EUR

Table 7: Difference-in-Differences test for the crowding out hypothesis: USD (military; treatment) vs. UAH (control) donations.

This table reports D-i-D results for the difference in donation flows between the treatment group (private USD donors, potentially crowded out by US military bilateral aid) and the control group (UAH donors). Donation flows are hourly counts (*DonCount*) and total USD values (*DonTotalUSD*) 48 hours before and after the top 20 US military bilateral aid announcements. *USD* $= 1$ if the donation is in USD, 0 otherwise; *After* $= 1$ if time t is up to 48 hours after an event, 0 otherwise; *USD* $\times$ *After* is the interaction term $= 1$ if the donation is in USD and time t is up to 48 hours after an event, 0 otherwise. *TweetCount* is a control for social media exposure for the treatment group (all English-language tweets except tweets by influential Ukrainian accounts in the form $log(x+1)$) and the control group (tweets by influential Ukrainian accounts in the form $log(x+1)$). Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$	$DonCount$	$DonTotalUSD$	$DonTotalUSD$
USD	-232.31^{***}	-258.95^{***}	-4797.94^{***}	-7732.10^{***}
	(9.44)	(24.31)	(297.75)	(737.56)
$After$	-17.24	-16.71	-771.58^{*}	-712.92^{*}
	(12.61)	(12.16)	(400.11)	(404.68)
$USD \times After$	16.90	16.85	615.86	610.58
	(12.61)	(12.18)	(404.89)	(408.01)
$TweetCount$		6.31		695.05^{***}
		(5.57)		(182.54)
R^2	0.26	0.26	0.12	0.13
Adj. R^2	0.26	0.26	0.12	0.12

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 8: Difference-in-Differences test for the crowding out hypothesis: EUR (military; treatment) vs. UAH (control) donations.

This table reports D-i-D results for the difference in donation flows between the treatment group (private EUR donors, potentially crowded out by EU military bilateral aid) and the control group (UAH donors). Donation flows are hourly counts (*DonCount*) and total USD values (*DonTotalUSD*) 48 hours before and after the top 20 EU military bilateral aid announcements. *EUR* $= 1$ if the donation is in EUR, 0 otherwise; *After* $= 1$ if time t is up to 48 hours after an event, 0 otherwise; *EUR* $\times$ *After* is the interaction term $= 1$ if the donation is in USD and time t is up to 48 hours after an event, 0 otherwise. *TweetCount* is a control for social media exposure for the treatment group (all English-language tweets except tweets by influential Ukrainian accounts in the form $log(x+1)$) and the control group (tweets by influential Ukrainian accounts in the form $log(x+1)$). Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$	$DonCount$	$DonTotalUSD$	$DonTotalUSD$
EUR	-210.47^{***}	-278.17^{***}	-5903.45^{***}	-7994.28^{***}
	(7.64)	(29.55)	(368.91)	(936.56)
$After$	13.56	13.34	155.90	149.02
	(12.27)	(14.71)	(563.90)	(557.08)
$EUR \times After$	-13.87	-12.77	-358.96	-325.05
	(12.24)	(14.56)	(567.91)	(559.34)
$TweetCount$		16.07^{**}		496.44^{**}
		(6.93)		(243.31)
R^2	0.24	0.24	0.11	0.11
Adj. R^2	0.24	0.24	0.11	0.11

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 9: Difference-in-Differences test for the crowding out hypothesis: EUR (all types; treatment) vs. UAH (control) donations.

This table reports D-i-D results for the difference in donation flows between the treatment group (private EUR donors, potentially crowded out by EU bilateral aid) and the control group (UAH donors). Donation flows are hourly counts (*DonCount*) and total USD values (*DonTotalUSD*) 48 hours before and after the top 20 EU bilateral aid announcements. $EUR = 1$ if the donation is in EUR, 0 otherwise; $After = 1$ if time t is 48 hours after an event, 0 otherwise; $EUR \times After$ is the interaction term $= 1$ if the donation is in USD and time t is 48 hours after an event, 0 otherwise. *TweetCount* is a control for social media exposure for the treatment group (all English-language tweets except tweets by influential Ukrainian accounts in the form $log(x+1)$) and the control group (tweets by influential Ukrainian accounts in the form $log(x+1)$). Standard errors are heteroskedasticity and autocorrelation consistent (in parentheses).

	$DonCount$	$DonCount$	$DonTotalUSD$	$DonTotalUSD$
EUR	-177.04^{***}	-182.70^{***}	-5063.50^{***}	-5451.94^{***}
	(7.63)	(20.86)	(387.47)	(900.69)
$After$	42.32^{***}	42.30^{***}	129.25	128.10
	(13.04)	(12.65)	(553.32)	(544.46)
$EUR \times After$	-42.85^{***}	-42.74^{***}	-377.77	-370.28
	(13.04)	(12.57)	(558.08)	(547.56)
$TweetCount$		1.32		90.85
		(5.29)		(232.28)
R^2	0.23	0.23	0.10	0.10
Adj. R^2	0.23	0.22	0.10	0.10

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

after an EU bilateral aid announcement decreased by 42.85 more on average, compared to UAH counts. The interaction coefficient for total value is statistically insignificant.

Given that the Foreign donation count on an average day of the war is 226, while the Ukrainian count is much larger—4,249, the difference between changes in the EUR and UAH counts in the post period is sizeable. Our findings may be interpreted as evidence for the crowding out of private EU donor contributions on days when their government promises to deliver aid of any type. We infer that the warm glow effect could not completely neutralise the crowding out of EU donors during periods of heightened emotional intensity. The lack of a warm glow effect could be related to the findings in Section 6.2, where emotional intensity was found to be a weaker determinant of Foreign donation flows than of Ukrainian donation flows. Additionally, the endorsement effect may not have occurred because intergovernmental transfers are not carried out through a specific charity, which could have crowded in contributions to that particular charity.

On the other hand, we do not find a statistically significant crowding out effect for US and EU military donation counts. There is no evidence that US and EU donor contributions are lower on days when the respective government commits military bilateral aid to Ukraine. This may be related to the fact that donors' emotional committed to their contributions is less displaced by military-targeted bilateral aid; alternatively, fiscal transparency could be lower for military aid.

We must note, however, that the effect of bilateral aid announcement days on total value donated is unclear both for the US and the EU. For EU donors, this implies that most of the crowded out donors are making very small contributions in the first place, while donors who commit large amounts still contributed. By extension, if a donor is committing a larger sum, they are more likely to be more emotionally involved and experience a stronger warm glow than those committing a smaller sum; therefore, less likely to be crowded out.

6.4 Limitations

After reviewing the findings, we must acknowledge the limitations of our study.

First, one must be careful with extending our conclusions to drivers of donations for primarily humanitarian, financial, and reconstruction purposes, since our dataset is limited to mostly military-targeted donations. It is possible that the asymmetric effects of negative events might be milder for non-military-targeted donations. Although hypotheses like the one above can be made, we are unable to extend our analysis to robustly compare the structure and dynamics of private donations by purpose.

A related concern is that we analyse donations to only one charity—Come Back Alive. This creates a concern about the applicability of our study across charities, with the findings potentially biased by charity-specific determinants.

Second, our Twitter sample contains only English-language tweets, which may not allow us to perfectly capture the sentiment of Ukrainian donors. Likewise, there is a lack of emotional classification tools that are compatible with the Ukrainian language. We have already seen that the proportion of anger in social media sentiment is rather small. Ukrainians are perhaps more likely to feel more animosity towards the aggressor than foreigners.

Third, the choice of high emotional intensity events was ultimately based on a subjective decision by the authors, despite being, for the major part, verified against reputable sources. In addition, when time-stamping events, it was possible to misjudge the peak intensity points. There must also be a careful balance between not including too many events to not dilute the emotional intensity, but also not too few in order to provide significance. It is difficult to completely remove the above biases, and they must be considered when reviewing our findings.

Fourth, even though we have taken steps to eliminate these, potential biases may arise from imperfectly matched timezone differences and currency conversions (from crypto and fiat currencies to USD) in our dataset.

Fifth, we do not possess data on donor characteristics beyond the currency of donation. It would be illuminating to distinguish between different demographic groups in analysing the impact of emotion.

Sixth, as we observe only outcomes, it is difficult to claim that we can probe directly into the neural processes that lead to the giving decision. We must therefore be careful in interpreting our results from the psychological point of view.

7 Conclusions

Following the literature on charitable giving (Andreoni, 1989; Andreoni & Payne, 2013; Eckel et al., 2005; Eckel et al., 2007; Fridman et al., 2022), our paper explores the role of emotions as a factor that regulates motives for donating in a crisis event setting. The subject of our study is military donations to Ukraine during the first year of the full-scale Russian invasion. We test the emotional factor through the lens of a three-part framework, where it is decomposed into emotional intensity, degree of exposure to emotion, and emotion type.

To test the intensity component, we study military donation flows around 31 major war events using time-stamped currency-specific donation data from the Come Back Alive foundation, a major Ukrainian charity. In a seemingly unrelated regressions (SUR) model, we show that Ukrainian and foreign donation counts spike by, respectively, 43pp and 50pp more after negative events (e.g., Russian missile strikes on Kyiv on October 10, 2022), and by, respectively, 17pp and 21pp more following positive events (e.g., the sinking of the Russian warship 'Moskva'). Answering RQ 1.1, we conclude that heightened intensity matters. Additionally, there is an assymetric response to positive and negative intensity for Ukrainian (in UAH), Foreign (in USD, EUR, PLN etc.), and Crypto (BTC, ETH) donors. We observe that donations are at least 2.4 times more sensitive to negative events, as compared to positive events. Thus, we find evidence for 'catastrophe compassion', whereby the most severe events of the war significantly increase donation flows, signifying an increase in prosocial behaviour in response to high mortality salience.

Compared to a selection of significant events, we find that day-to-day fluctuations in intensity throughout the war are a weak predictor of military donation flows. We observe some impact of war severity variables on Foreign but not on Ukrainian flows—Ukrainian donors may be more accustomed to daily fluctuations in intensity and do not adjust their donation response. Further research is needed to determine whether this finding should be attributed to information release patterns instead.

Regarding the exposure component, the SUR analysis reveals that the impact of traditional media publicity on military donation flows is limited. However, social media exposure, proxied by the frequency of Twitter posts mentioning 'Ukraine' and 'war', is significantly and positively related to donation counts and dollar values. We find that a 1pp increase in the day-to-day percentage change in the count of Ukraine-focused tweets is associated with a 0.34pp higher change in the count of Ukrainian donations, a 0.57pp higher change in the count of Foreign donations, and a 0.73pp higher change in the count of Crypto donations. The effects on the dollar value of donations are of similar magnitude. The significance of social media exposure may be attributed to emergent network effects and richer content possibilities than on traditional media. Answering RQ 1.2, we observe that the degree of exposure is a strong driver of military donations for all donor types; it appears that Crypto donations are driven more by exposure rather than by the intensity component.

To understand the impact of different types of emotion, we analyse the content of 5.8 million tweets with keywords ‘Ukraine’ and ‘war’ using a machine learning model. We classify these tweets into six types of emotional sentiment: anger, fear, disgust, sadness, joy, and surprise. In response to RQ 1.3, we show that sadness-related tweets are negatively related to how frequently Ukrainians donate, and fear-related tweets are positively related to Foreign and Crypto donation flows.

We revisit the intensity component in a Difference-in-Differences set-up. We show that between two groups of donors (Ukrainian vs. Foreign), Ukrainian military donation counts exceed foreign ones by 72 on average every hour in the immediate 48 hours after major war events (e.g., Russian missile strikes on Kyiv on 10 October 2022). Even though Ukrainian donations are smaller in size than Foreign ones ($27 vs. $162 on average during the sample period of 16 March 2022-–28 February 2023), Ukrainians donate $853 more on average every hour (compared to foreigners) in the immediate 48 hours after major war events.

The final part of our analysis looks at whether bilateral aid from European and US governments crowd out private military donations in EUR and USD, respectively, in a setting of prolonged heightened emotional intensity such as war. Comparing EUR donations to UAH donations in the 48 hours after European announcements for all types of bilateral aid, we find that EUR donation counts are lower than UAH ones by 42 on average every hour, which is in line with the presence of crowding out. Responding to RQ 1.4, it appears that crowding out can persist in a high emotional intensity setting. We observe that European tax payers decrease their donation frequency when their governments announce major aid to Ukraine, but the crowded out donors represent only a small fraction of total value donated. Interestingly, announcements of military bilateral aid to Ukraine are not associated with a similar crowding out effect. Further research is needed to understand why the response differs for military bilateral aid.

Overall, we find that the emotional factor has the potential to both enhance and decrease individuals’ propensity to donate, depending on the type of emotion. We also find evidence that emotions may regulate the amount of crowding out of private donations by public donations. Our findings speak to the literature on charitable giving as a response to empathic and moral urges, and more broadly—to theories of moral action such as consequentialism and deontology.

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9 Appendices

A Description of sentiment analysis

A.1 Classification of emotions

Table A.1: Classification of basic (universal) emotions from Ekman (1992) used for social media sentiment analysis.

Emotion	Definition	Response
Anger	Response to being blocked or treated unfairly.	Undermine, suppress, use physical force, brood, scream
Fear	Response to the threat of harm.	Worry, ruminate, scream, avoid
Disgust	Response to something offensive, repulsive or toxic.	Dehumanise, avoid, withdraw, vomit
Sadness	Response to loss.	Withdraw, ruminate, seek comfort, protest, mourn
Joy/Enjoyment	Response to sensory pleasure.	Engage, gloat, indulge, maintain
Surprise	Response to sudden, unanticipated stimuli.	Focus

A.2 Procedure

We follow the following procedure for preparing English-language tweet text for classification:

1. The text of each tweet is split into a list of tokens.

2. Each tokenised tweet is run through Hartmann's (2022) *Emotion English DistilRoBERTa-base* model, assigning the probability of a tweet conveying each of Ekman's (1992) emotions and the neutral class.

3. Each tweet is classified according to the emotion with the highest probability.

A.3 Examples

- Anger: 'Asshole signed a law that criminalizes public opposition to the war against Ukraine. CAN THEY GO LOWER????'

- Disgust: 'It's completely outrageous how many celebrities who were so eager to educate ppl about other, much more questionable things, are now silent about horrible war crimes russians commit in Ukraine. Shame on them'

- Fear: ‘War is nothing but pain, death, injury, sexual violence, destruction, inflation, increased taxes, debt, stock market crash and a possible recession. None of us need that.. God please help Ukraine and innocent people there..’
- Joy: ‘The War on Ukraine has shown that most human beings art kind, warm, helpful, giving, loving people who want to enjoy a peaceful world which has no room for destructive terrorists who delight in bombing countries and citizens of all ages.’
- Sadness: ‘I cried last night because of the disturbingly sad, heartbreaking development of Putin’s War... It’s so sad, unfair and wrong. The people of Ukraine we will rebuild and we will become better together.’
- Surprise: ‘Global media is oddly not as loud on the war tension brewing in Ukraine, as one would ordinarily expect. That’s wild!’

A.4 Limitations

We acknowledge that using an automated classification tool does not perfectly capture the range of real human emotions. The model achieves a 66% evaluation accuracy (Hartmann, 2022). Our interpretations are based on the assumption that an aggregate pool of textual data, when classified, would be representative of the general sentiment with some, even if not perfect, accuracy.

B Events

Table B.1: Significant war events proxying days with the highest emotional intensity.

This table lists significant war events that represent days with highest emotional intensity during the analysis period. A total of 31 events were selected between 16 March 2022 and 28 February 2023, with 13 positive and 18 negative events. Dummy *Colouring* equals 0 if the event is positive and 1 if the event is negative. We manually timestamp each event according to the hour of its intensity peak using reporting times from the Ukrainska Pravda, a leading Ukrainian online newspaper (with reporting in both English and Ukrainian). We do not consider positive events that represent armament announcements and state visits, as these coincide with bilateral aid events.

Datetime	Name	Colouring
2022-03-16 18:26:00	Mariupol Theatre bombing	1
2022-03-30 10:19:00	Chernihiv attacks	1
2022-04-03 00:27:00	Bucha discoveries	1
2022-04-14 22:54:00	Sinking of the Moskva	0
2022-05-03 14:11:00	Battle of Azovstal begins	0
2022-05-15 00:19:00	Eurovision statement	0
2022-05-17 01:15:00	Azovstal surrender	1
2022-06-30 11:47:00	Retaking Snake Island	0
2022-07-03 19:28:00	Lysychansk falls	1
2022-07-14 10:55:00	Vinnytsia strikes	1
2022-07-27 02:54:00	Antonivsky bridge	0
2022-07-29 11:50:00	Olenivka tragedy	1
2022-08-24 00:00:00	UKR Independence Day	0
2022-09-08 15:16:00	Retaking Kharkiv region	0
2022-09-10 15:16:00	Retaking Izyum	0
2022-09-30 16:55:00	Ukraine NATO application	0
2022-10-08 06:55:00	Kerch bridge explosion	0
2022-10-10 08:26:00	Missile strikes - 10/10	1
2022-10-31 10:06:00	Missile strikes - 31/10	1
2022-11-11 14:51:00	Liberation of Kherson, Chornobaivka	0
2022-11-15 17:03:00	Missile strikes - 15/11	1
2022-12-05 16:55:00	Missile strikes - 05/12	1
2022-12-09 20:04:00	Bakhmut difficulties	1
2022-12-11 00:35:00	Attacks on occupied Melitopol	0
2022-12-18 23:49:00	Russian drones attack	1
2022-12-24 13:11:00	Attack on Kherson centre	1
2023-01-02 18:43:00	Makyivka strike	0
2023-01-14 22:14:00	Dnipro strike	1
2023-01-26 09:38:00	Missile strikes - 26/01	1
2023-02-02 01:55:00	Kramatorsk strike	1
2023-02-24 04:55:00	One year anniversary	1

Table B.2: Bilateral aid announcement days.

This table lists days with the top 20 largest military bilateral aid announcements from the US and the EU, and the top 20 largest bilateral aid announcements of any kind from the EU (53 in total) between 16 March 2022 and 28 February 2023. We manually timestamp the announcements according to the time of publication using reporting times from the Ukrainska Pravda archive and official government sources.

Datetime	Name	Currency	Amount in bn
2022-12-23 12:39:00	United States	USD	45.000
2022-05-19 14:41:00	United States	USD	40.000
2022-12-10 15:20:00	EU (Commission and Council)	EUR	18.000
2022-11-09 14:37:00	EU (Commission and Council)	EUR	18.000
2022-05-18 11:21:00	EU (Commission and Council)	EUR	9.000
2022-08-24 20:41:00	United States	USD	2.980
2023-01-06 22:03:00	United States	USD	2.850
2023-01-20 02:05:00	United States	USD	2.500
2023-02-03 17:19:00	United States	USD	2.175
2023-02-24 14:42:00	United States	USD	2.000
2022-04-29 12:05:00	Poland	EUR	1.800
2022-04-25 05:18:00	United States	USD	1.547
2022-06-15 19:12:00	United States	USD	1.225
2022-09-28 02:08:00	United States	USD	1.100
2022-05-19 14:02:00	Germany	EUR	1.000
2022-11-11 13:41:00	Germany	EUR	1.000
2022-12-13 04:12:00	EU countries	EUR	1.000
2022-08-08 20:08:00	United States	USD	1.000
2022-12-22 10:29:00	United States	USD	1.000
2022-03-16 20:46:00	United States	USD	0.800
2022-04-13 04:09:00	United States	USD	0.800
2022-04-21 04:26:00	United States	USD	0.800
2022-08-19 16:39:00	United States	USD	0.775
2022-07-01 20:48:00	United States	USD	0.770
2022-10-15 00:24:00	United States	USD	0.725
2022-06-01 23:31:00	United States	USD	0.700
2022-09-08 16:00:00	United States	USD	0.675
2022-04-09 14:56:00	EU (Commission and Council)	EUR	0.600
2022-10-17 11:02:00	European Peace Facility	EUR	0.600
2023-02-02 12:10:00	European Peace Facility	EUR	0.545
2022-03-23 16:20:00	European Peace Facility	EUR	0.500
2022-04-08 20:17:00	European Peace Facility	EUR	0.500
2022-05-13 08:23:00	European Peace Facility	EUR	0.500
2022-09-04 14:19:00	Austria	EUR	0.500
2022-07-22 12:30:00	European Peace Facility	EUR	0.500
2023-01-23 17:04:00	EU (Commission and Council)	EUR	0.500
2022-05-05 15:42:00	France	EUR	0.300
2022-05-21 13:08:00	Portugal	EUR	0.250

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2022-06-09 11:21:00	EU (Commission and Council)	EUR	0.205
2022-05-05 11:07:00	EU (Commission and Council)	EUR	0.200
2022-07-05 13:01:00	Netherlands	EUR	0.200
2022-08-16 09:38:00	Italy	EUR	0.200
2022-12-29 10:46:00	France	EUR	0.200
2022-10-07 17:38:00	France	EUR	0.100
2023-02-03 08:43:00	Germany	EUR	0.100
2023-01-27 13:16:00	Belgium	EUR	0.092
2022-11-17 10:27:00	Finland	EUR	0.056
2022-06-10 09:36:00	Finland	EUR	0.055
2022-07-20 16:23:00	Lithuania	EUR	0.036
2022-09-07 10:35:00	Lithuania	EUR	0.036
2022-10-02 14:08:00	Norway	EUR	0.031
2022-12-20 13:11:00	Finland	EUR	0.029
2022-05-25 10:35:00	Lithuania	EUR	0.016

C Media

Table C.1: Influential Ukrainian accounts.

This table lists influential Ukrainian accounts that gauge social media exposure for Ukrainian donors. We define 'influential Ukrainian accounts' as users who are either Ukrainian by nationality or are currently located in Ukraine and have at least 60 thousand subscribers. We include only accounts by individuals or communities and not news organisations.

Name	Username	Subscribers
Olga Tokariuk	olgatokariuk	420K
The Ukrainian Toronto Television	tvtoront	60K
Serhiy Prytula	serhiyprytula	675K
Volodymir Zelensky	zelenskyyua	7.1M
Dmytro Kuleba	DmytroKuleba	1.1M
Illa Ponomarenko	IAPonomarenko	1.2M
Defense of Ukraine	DefenceU	1.8M
Christopher Miller	ChristopherJM	419K
Oleksii Reznikov	oleksiireznikov	626K
Mikhailo Podolyak	Podolyak_M	775K
Ukraine	Ukraine	2.3M
Nika Melkozerova	NikaMelkozerova	207.2K
Anton Geraschenko	Gerashchenko_en	277K
Olexander Scherba	olex_scherba	266K
Olga Lautman	OlgaNYC1211	257K
Olena Halushka	OlenaHalushka	119K
Saint Javelin	saintjavelin	113K
Maria Avdeeva	maria_avdv	138K
Euan McDonald	Euan_MacDonald	76K
BackAlive Twitter	BackAndAlive	262K
Inna Sovsun	InnaSovsun	109K
Lesya Vasylenko	lesiavasylenko	338K
Kira Rudik	kiraincongress	190K
Maksym Eristavi	maksymeristavi	99K
Iuliia Mendel	IuliiaMendel	145K
Oliver Carroll	olliecarroll	141K
Mykhailo Fedorov	FedorovMykhailo	305.9K
Olena Zelenska	ZelenskaUA	186.5K
Oleksandra Matviichuk	avalaina	204.2K
Commander-in-Chief of the AFU	CinC_AFU	320.7K

D Variable definitions

Table D.1: Variable definitions.

This table defines variables used in the empirical analysis, detailing the source and the unit of measurement. Siren and air strikes variables, $RusMilCasualtiesCount$ and $ConflEvsCount$ variables are available 24/02/2022–28/02/2023. $CivCasualtiesCount$ is from 26/02/2022 to 28/02/2023. All other variables are available 01/02/2022–28/02/2023. All variables are available at a **daily** frequency; data on donation characteristics ($DonCount$, $DonTotalUSD$, $DonMeanUSD$) and $TweetCount$ are also available at an **hourly** frequency.

Variable	Definition	Source
Donation characteristics		
$DonCount$	The count of donations to Ukrainian charities Come Back Alive and UNITED24 by type (Ukrainian, Foreign, Crypto), classified by currency of donation.	Come Back Alive public financial data, Blockchain.info API, Covalent API.
$DonTotalUSD$	The total USD value of donations to Ukrainian charities Come Back Alive and UNITED24 by type (Ukrainian, Foreign, Crypto), classified by currency of donation.	Come Back Alive public financial data, Blockchain.info API, Covalent API.
$DonMeanUSD$	The mean USD value of donations to Ukrainian charities Come Back Alive and UNITED24 by type (Ukrainian, Foreign, Crypto), classified by currency of donation.	Come Back Alive public financial data, Blockchain.info API, Covalent API.
Event types		
$EventPositive$	A dummy that equals one if there has been a positive war event on a given day, zero otherwise. We treat the Ukrainian gains, victories and celebrations as positive events.	Partly based on Bigg (2022) and New Year greetings of President of Ukraine Volodymir Zelenskyy (Zelenskyy, 2023).

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$EventNegative$	A dummy that equals one if there has been a negative war event on a given day, zero otherwise. We treat attacks by the Russian forces and losses to Ukraine as negative events.	Partly based on Bigg (2022), New Year greetings of President of Ukraine Volodymir Zelenskyy (Zelenskyy, 2023).
Emotional intensity variables		
$CivCasualtiesCount$	The count of Ukrainian civilian casualties.	The Office of the UN High Commissioner for Human Rights (OHCHR) (OCHA, 2022).
$RusMilCasualtiesCount$	The count of Russian military casualties.	The Armed Forces of Ukraine (MinfinMedia, 2022).
$ConflEvsCount$	The count of individual conflict events (battles, missile strikes, attacks on civilians) happening in Ukraine.	The Armed Conflict Location & Event Data Project (ACLED) (ACLED, 2022).
Degree of exposure variables		
$TweetCount$	The count of English-language tweets with keywords 'Ukraine' and 'war'.	Twitter Academic API.
$NewsCount$	The count of traditional media articles with keywords 'Ukraine' and 'war'.	Europresse (2023).
Emotion type variables		
$TweetJoyCount$	The count of tweets classified as having *Joy* as a predominant emotion by sentiment analysis.	Twitter Academic API.
$TweetAngerCount$	The count of tweets classified as having *Anger* as a predominant emotion by sentiment analysis.	Twitter Academic API.
$TweetSurpriseCount$	The count of tweets classified as having *Surprise* as a predominant emotion by sentiment analysis.	Twitter Academic API.

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$TweetFearCount$	The count of tweets classified as having *Fear* as a predominant emotion by sentiment analysis.	Twitter Academic API.
$TweetSadnessCount$	The count of tweets classified as having *Sadness* as a predominant emotion by sentiment analysis.	Twitter Academic API.
$TweetDisgustCount$	The count of tweets classified as having *Disgust* as a predominant emotion by sentiment analysis.	Twitter Academic API.
$TweetNeutralCount$	The count of tweets classified as having *Neutral* as a predominant emotion by sentiment analysis.	Twitter Academic API.

E Additional descriptive statistics

E.1 Outbreak period descriptive statistics

Table E.1: Descriptive statistics for the war outbreak period (21 February–15 March 2022).

The table reports descriptive statistics for donation characteristics in the war outbreak period between 21 February and 15 March 2022. 99th percentile of donations is included. These values are omitted from regression analysis, as they represent significant deviations from the mean severity of war and may skew the results. Donation characteristics are reported at a daily frequency by type (Crypto, Foreign, Ukrainian). Variable definitions are provided in Table D.1. Donation count in the outbreak period represents 23.6% of all-time donations, while total value represents 43.7% of all-time donation value (until 28 February 2023).

Variable	**Type**	**Min**	**q25**	**Median**	**Mean**	**q75**	**Max**	**St dev**
Donation characteristics								
$DonCount$	All Types	3,907	6,128	8,555	21,268	35,429	61616	19,255
	Crypto	4	345	632	4,128	2,557	36,069	9,055
	Foreign	8	413	826	1,054	1,330	3,927	968
	Ukrainian	2,412	4,364	7,239	16,131	22,778	56,350	16,524
$DonTotalUSD$	All Types	440,522	1,513,320	2,668,444	4,979,133	7,290,665	20,201,304	5,479,445
	Crypto	731	212,382	688,019	1,767,094	3,271,951	7,528,687	2,177,444
	Foreign	4,572	10,6824	451,392	545,181	718,076	1,866,201	532,025
	Ukrainian	159,908	640,638	1,202,151	2,690,561	2,798,919	14,774,982	3,772,643
$DonMeanUSD$	All Types	315	7,318	8,856	8,642	10,022	18,223	3,288
	Crypto	101	221	236	236	268	343	55
	Foreign	169	403	505	604	664	2,086	457
	Ukrainian	32	47	61	59	71	76	14

E.2 Variable correlations

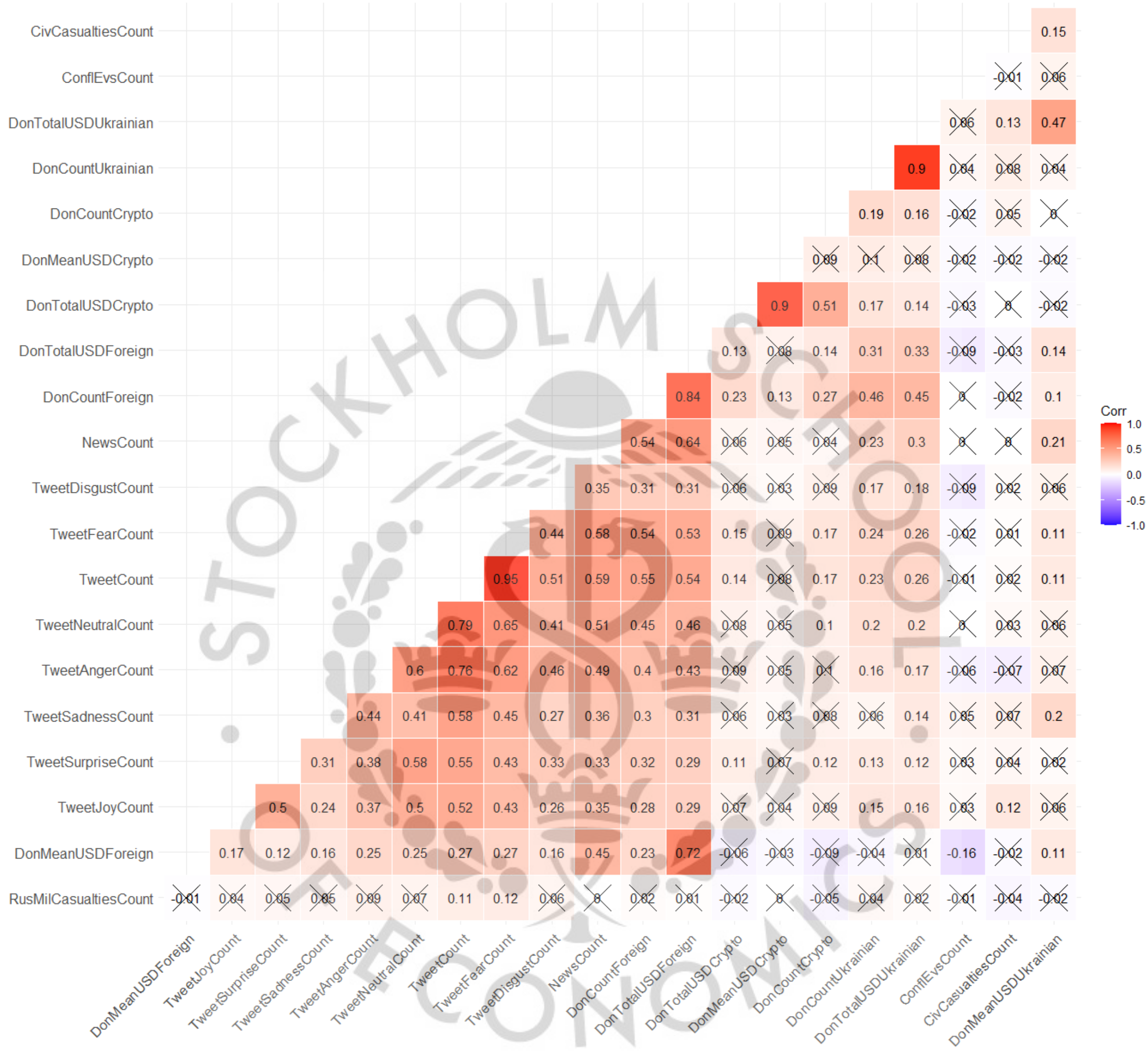

Figure E.1: Pearson correlation coefficients for all dependent and independent variables in SUR. The crossed-out values represent the correlation coefficients that are not statistically significant. Correlations are computed between 16 March 2022 and 28 February 2023. Variable definitions are provided in Table D.1.

F VIF statistics for SUR variables

Table F.1: Variance inflation factor values for SUR regression variables.

This table reports VIF statistics for independent variables in the SUR regression. If VIF < 10, including variables in the same regression specification does not lead to multicollinearity.

	VIF	Df
$EventPositive$	1.06	1.00
$EventNegative$	1.09	1.00
$CivCasualtiesCount$	1.11	1.00
$RusMilCasualtiesCount$	1.04	1.00
$ConflEvsCount$	1.34	1.00
$NewsCount$	1.13	1.00
$TweetJoyCount$	1.53	1.00
$TweetAngerCount$	2.03	1.00
$TweetSurpriseCount$	1.55	1.00
$TweetFearCount$	2.31	1.00
$TweetSadnessCount$	1.39	1.00
$TweetDisgustCount$	1.41	1.00
$Weekdays$	2.43	6.00
$DaysSince$	1.01	1.00

Note: VIF for $Weekdays$ is a combined VIF for the 6 weekday dummies.

G Coefficient comparisons

Table G.1: F-test statistics for the difference between Ukrainian vs. Foreign coefficients on *EventPositive* and *EventNegative* and the difference between *EventPositive* vs. *EventNegative* coefficients for Ukrainian and Foreign in Table 2. If an F-statistic is significant, the coefficients are statistically different.

	$DonCount$	$DonTotalUSD$
UkrainianEventPositive = ForeignEventPositive	0.292	0.738
UkrainianEventNegative = ForeignEventNegative	0.225	0.037
UkrainianEventPositive = UkrainianEventNegative	3.042^{*}	2.313
ForeignEventPositive = ForeignEventNegative	2.940^{*}	3.955^{**}

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Degrees of freedom between groups = 1
Degrees of freedom within groups = 1020

Table G.2: F-test statistics for the difference between Ukrainian vs. Foreign vs. Crypto coefficients for *TweetCount* in Table 4. If an F-statistic is significant, the coefficients are statistically different.

	DonCount	*DonTotalUSD*
UkrainianTweetCount = ForeignTweetCount	0.958	0.762
UkrainianTweetCount = CryptoTweetCount	0.496	0.933
ForeignTweetCount = CryptoTweetCount	0.000	0.407

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Degrees of freedom between groups = 1
Degrees of freedom within groups = 1005

Acknowledgement of AI use

No text in this Thesis has been generated using AI-based tools.