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EXTERNAL SHOCKS AND SOCIETAL RESPONSES: AN ANALYSIS OF MIGRATION, WAR, AND THEIR EFFECTS ON SOCIETY

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External Shocks and Societal Responses: An Analysis of Migration, War, and Their Effects on Society

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Abstract

Societies are continually influenced by external shocks such as migration flows, armed conflicts, and natural disasters. These events can significantly alter political dynamics, economic behaviors, and social outcomes. Understanding how these shocks impact societies is crucial for policymakers, economists, and social scientists who seek to mitigate negative effects and enhance societal resilience. Against this backdrop, this thesis explores the socio-economic impacts of external shocks through three distinct yet interconnected essays.

The first essay, titled "How does temporary labor migration affect voting behavior and political polarization? Evidence from the USA", investigates the effects of temporary labor migration on political outcomes in the United States. Although extensive research has examined the impact of permanent migration, the influence of temporary migrants remains less understood. Exploiting granular microdata on employers' applications for H2A and H2B temporary work visas and employing a Bartik-type instrument for the number of temporary labor migrants in each county, this study examines how an influx of temporary workers affects voting behavior and political polarization. The findings suggest that temporary labor migration decreases the vote share of anti-immigration parties and reduces far-right political polarization while increasing far-left polarization.

The second essay, titled "Charitable Giving in Wartime: Evidence from Donations during Russia's Invasion of Ukraine", examines behavioral responses to conflict-induced shocks by analyzing charitable giving patterns during Russia's invasion of Ukraine. Utilizing unique, same-day donation data to a large Ukrainian charity aiding the military, the study assesses how military events, casualties, and media coverage influence philanthropic behavior. The results indicate that wartime donation patterns resemble those seen after natural disasters, with casualties driving increased giving. However, the study identifies a novel pattern wherein wartime donations stabilize at an elevated baseline due to ongoing events, contrasting with the decay typically observed in disaster-related philanthropy. Media mentions of war-related events also play a significant role in sustaining donation levels, highlighting the interplay between information dissemination and public generosity during conflicts.

The third essay, titled "The effect of war on academic achievement: Evidence from Ukraine", focuses on the impact of war exposure on academic achievement, using the case of Ukrainian students following the 2022 Russian full-scale invasion. Leveraging the data from the Programme for International Student Assessment (PISA) and a difference-in-differences approach, the analysis reveals a substantial deterioration in Ukrainian students' academic performance compared to peers in other countries following the invasion. These findings underscore the importance of addressing educational disruptions in war-affected regions.

These essays contribute to a deeper understanding of how external shocks like migration and war influence political behavior, economic actions, and social outcomes. By employing rigorous empirical methodologies and leveraging unique datasets, the studies offer valuable insights into the ramifications of external shocks on societies. The findings have important implications for policymakers seeking to design interventions that mitigate adverse effects and enhance societal resilience.

The remainder of the thesis is structured as follows: Chapter 1 presents the study on temporary labor migration and political outcomes in the United States. Chapter 2 examines charitable giving during Russia's invasion of Ukraine. Chapter 3 analyzes the impact of war exposure on academic achievement among Ukrainian students.

Contents

Chapter 1: How does temporary labor migration affect voting behavior and political polarization? Evidence from the USA

How does temporary labor migration affect voting behavior and political polarization? Evidence from the USA

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Abstract

In this paper, I examine how temporary labor migration affects political outcomes using microdata on employers' applications for H2A and H2B temporary work visas. I construct a Bartik-type instrument for the number of temporary labor migrants in each county and merge this data with election results and measures of political polarization. My results suggest that, unlike permanent migration, temporary labor migration decreases the vote share of anti-immigration parties and far-right political polarization while increasing far-left polarization. By focusing on temporary migration, this study contributes to the literature by demonstrating that it affects political outcomes differently from previously studied migration types. My findings remain robust across various checks, including constructing a simulated instrument, analyzing different election years, and using different model specifications.

JEL Classification: F22, D72, J61

Keywords: migration; voting; polarization; political economy

1 Introduction

Migration has been a highly debated topic in the field of economics and politics for many years (Halla et al., 2017; Cools et al., 2021; Dustmann et al., 2019; Mayda et al., 2022). Migrants have a large effect on labor market outcomes by competing for jobs with the locals and contributing to economic growth.

While much research has been conducted on how migration affects political outcomes, the focus has primarily been on permanent migration or refugee migration (e.g. Halla et al. (2017), Lonsky (2021), Barone et al. (2016), Dustmann et al. (2019)). However, little attention has been paid to the impact of temporary labor migration [1] on political outcomes.

This is quite surprising, as temporary labor migration has become an increasingly common phenomenon both in the US and globally (Klobucista and Roy, 2023). Although the annual inflow of temporary migrants is smaller than the annual number of new permanent migrants to the US (approximately 1 million people), it substantially exceeds the annual intake of refugees, which was only about 30,000 in 2019. At the same time, the effect of the temporary labor migration on political outcomes is a priori uncertain. On the one hand, temporary labor migrants may be perceived as an economic threat by the locals by competing for the same job,s thus making it more likely for them to vote for anti-immigration parties. On the other hand, as suggested by the contact hypothesis (Allport et al., 1954), when locals have greater contact with migrants, their attitudes toward migrants improve, making them less likely to support anti-immigration parties. Moreover, the spatial correlation between permanent migration and temporary labor migration in the US is low. When the change in temporary labor migration is regressed on the change in permanent migration and all other relevant control variables used in this paper, the resulting R-squared is only between 2 and 6 %. This means that temporary labor migration changes are not strongly correlated with changes in permanent labor migration and should be explored separately. The impact of temporary migration on political outcomes is thus a crucial question that deserves greater attention, especially given the growing political polarization and anti-immigrant sentiment in many countries.

This paper aims to fill this gap by exploring how temporary migration affects political outcomes, specifically the vote share for the Republican party and political polarization in the United States.

To investigate this issue, I use administrative data published by the US Department of Labor on the number of temporary migrants employed in the United States from 2016 to 2020. Specifically, I use data on H2A migrants, who are primarily employed in low-skilled agricultural occupations, and H2B migrants who are mainly employed in low-skilled non-agricultural occupations. This dataset contains information on the employers' applications to hire foreign workers, including whether the application was

[1] I would like to thank Guglielmo Barone, Enrico Cantoni, Tomasso Sonno, David Zuchowski, and the participants of the seminar at the University of Bologna for their feedback that helped me to improve this paper. All errors are my own.

[1] In this paper, I primarily consider temporary low-skilled migration and will, for the sake of brevity, refer to it as temporary migration or temporary labor migration interchangeably. While there exist other types of temporary labor migration, most notably high-skilled migration on H1B visas, this migration is often not truly temporary, as many workers who initially work on H1B visas proceed to become permanent residents. Thus, in this paper, I only focus on H2A and H2B visa holders, who are purely temporary labor migrants.

approved or denied, the number of workers approved for employment and how many of them actually arrived in the US, the address of the employer, the address of the work-site, the wage rate, occupation, dates of employment, education, experience, number of hours worked, and the primary crop (for H2A workers).

I aggregate the total number of foreign workers that were approved by county, visa type, and year. As the locations of the temporary migrant workers may be endogenous, for instance, by employers in regions with attitudes more sympathetic towards migration being more likely to employ migrant workers, I use a shift-share instrument based on the occupation of the migrants.[2] Using the shift-share instrument I run the first difference regressions (between years of 2016 and 2018) on the county-district level, controlling for population, population density, higher education, age, gender, race and permanent migration.

I find no evidence that increased temporary migration increases the Republican vote share, and that an increased number of temporary labor migrants who work in non-agricultural occupations actually decreases the Republican vote share. This could suggest that the opposite effects that arise after the arrival of new migrants nearly cancel each other out: for instance, while the perceived economic damage that the migrants cause may move more people to vote for the Republican party, which is generally seen as more anti-immigration, the contact with migrants may improve the locals' attitudes to them, causing them to be less likely to vote for the Republican party. In addition, the presence of both agricultural and non-agricultural temporary labor migrants decreases political polarization, especially when it comes to the far-right polarization, suggesting that the extreme far-right politicians, who are the most likely to be opposed to migrants, lose the most support. These results contrast with the findings of Mayda et al. (2022), who show that while high-skilled migrants decrease the vote share of the Republican party, while low-skilled migrants increase it.

The findings of this study have important implications for policymakers, particularly those concerned with immigration policy and its impact on political outcomes. By shedding light on the impact of temporary migration on political outcomes, this research adds to the ongoing debates surrounding migration and its role in shaping political attitudes and behaviors in the United States.

The literature has shown that permanent migration and refugee migration have a significant impact on political outcomes, although the direction of this effect is still debated.

The closest strand of literature to this paper is the literature on temporary refugee migration. Hangartner et al. (2019), for instance, show that exposure to refugees traveling through small Greek islands increased anti-immigration sentiments and support for anti-immigration policies among the residents of these islands. Dinas et al. (2019) in the same context show that the vote share of far-right parties also increased. These findings replicate in a different context as well: for instance, Gessler et al. (2021) show that in Hungary, the settlements through which refugees passed witnessed an increase in anti-immigrant sentiments and the vote share of the far-right.

[2] I use SOC classification of the occupations, used by the Bureau of Labor Statistics.

At the same time, a lot of the literature has looked at the effects of permanent migration on political outcomes, but came to different conclusions. Some studies find that immigration leads to more votes for center-right and far-right parties that oppose it (Halla et al., 2017; Barone et al., 2016; Brunner and Kuhn, 2018). On the other hand, different studies come to the opposite conclusion (Lonsky, 2021; Cools et al., 2021).

It is important to point out that all of the studies discussed above look at how migration affects political outcomes in European countries. While most research does focus on the effect of migration on political outcomes in Europe, some studies provide evidence for the US. For instance, Mayda et al. (2022), looking at the overall levels of migration, show that an increase in high-skilled immigrants decreases the share of Republican votes, while an inflow of low-skilled immigrants increases it. Baerg et al. (2018) look at the undocumented migrants in the US state of Georgia and show that the presence of undocumented workers in a county is associated with a higher share of Republican votes. Similarly, Camarena and Tiburcio (2024) find that unauthorized Mexican migration to the US increases vote share for the Republican party. On the other hand, Hill et al. (2019) show that the increased immigration did not benefit Donald Trump in the 2016 US presidential elections.

A lot of research has also focused on how refugees affect the voting behavior of the natives, but the findings of these studies also vary. For instance, Dustmann et al. (2019) find that in Denmark, the presence of refugees leads to the increased vote share of the right-wing anti-immigration parties. Steinmayr (2021) comes to a more nuanced conclusion, showing that in Austria, while the exposure to refugees may increase the vote share of far-right parties, contact and sustained interactions with refugees actually decrease the far-right support. Vertier et al. (2023) show that in France, the presence of an asylum center has led to the reduction of the far-right vote share, however, the effect depends on whether the migration inflow is large or small. Dreher et al. (2020) find that immigration, specifically an increase in the number of refugees in the US, contributed to an increase in political polarization.

With this paper, I contribute to this literature by looking at labor migrants who are present in a country for several months or even years. Such prolonged presence in the country (as compared to the temporary refugee migration) can potentially have a greater effect on voting behavior. In addition, as I focus on labor migration, it may affect voting behavior via different channels as compared to refugee or permanent migration. For instance, while the economic channel is very important for labor migration, it is less so for refugee migration. At the same time, the temporary labor migrants cannot, in the long run, become citizens, like permanent migrants, and vote against anti-immigration parties. Thus, I contribute to the literature by studying the effects of temporary labor migration, which has not been studied before and which is different both by the duration of time the migrants are present in the country as well as the type of migration (temporary vs refugee vs permanent).[3]

[3] It may be argued that from the perspective of natives, it is impossible to distinguish between permanent and temporary migration, as when meeting migrants they are not able to immediately tell what legal status they have. Yet, even if this is the case, temporary labor migrants still may have a different effect compared to the other types of migrants. First of all, they may encounter locals in different settings: while permanent migrants often bring their families with them, and thus encounter locals in school settings, etc.,

The rest of this paper is structured as follows: in section 2, I discuss the conceptual framework on the potential channels via which migration can affect political outcomes and provide some background information on H2A and H2B visa programs. In Section 3, I discuss my empirical framework and identification strategy. In Section 4, I outline the data sources and provide some descriptive statistics. In Section 5, I discuss my main results, in Section 6, I discuss the robustness checks, in Section 7, I look at whether there is heterogeneity in my results, and in Section 8, I conclude.

2 Conceptual Framework and Background Review

2.1 How can migration affect political outcomes?

Migration may affect political outcomes via several channels. Firstly, the contact hypothesis, proposed by Allport et al. (1954), suggests that when people encounter the representatives of the 'other' groups, interpersonal contact may help to reduce prejudice towards these groups. Thus, according to this hypothesis, increased immigration should decrease the support of anti-immigration political parties as when the locals are more exposed to immigration, they should reduce their negative stereotypes about immigrants. This hypothesis also finds support in the empirical work (Vertier et al., 2023; Steinmayr, 2021).

Another channel through which immigration could reduce the vote share of anti-immigration parties is the citizenship channel. In the long run, immigrants who settle in the country may get citizenship and thus the right to vote. It is likely that they would not vote for anti-immigration parties, thus reducing their vote share (Mayda et al., 2016).

On the other hand, there are also plausible ways in which the increase in immigration may increase the support of anti-immigration political parties. Firstly, the effect could come through the economic channel: immigrants may hurt the economy by increasing competition in the labor market, thus making it harder for locals to find a job and driving wages down. Another economic concern is that migrants receive disproportionately high levels of public funds. It is important to note that even when such negative economic effects do not actually exist, locals may still think that they do and oppose immigration, voting for anti-immigration parties for that reason. For instance, Becker et al. (2016) show that in the UK, the wave of migration, following the ascension of Eastern European countries to the EU, did lead to an increase in support of the anti-immigration UKIP party, due to the increased labor market competition with low-skilled locals and increased pressure on public finance.

Another channel through which the increased immigration may increase the anti-immigrant sentiment and voting for anti-immigration parties is the cultural channel. Some locals may be worried that increased immigration, especially from culturally distant countries, may hurt their local, traditional culture, and vote for anti-immigration parties for that reason. For instance, Mendez and Cutillas (2014) show that in Spain, immigrants from Latin American countries drive up the support of left-wing parties, while migrants from North Africa, on the contrary, lead to an increased share

the temporary migrants usually arrive alone, and thus mainly interact with locals in the course of their work duties, which, in case of H2B migrants often involves a lot of contact with the natives.

of votes for right-wing parties. As Latin American immigrants are more similar to Spanish natives both culturally and linguistically than North African immigrants, it is consistent with the cultural channel that they would drive up the anti-immigrant sentiments.

Thus, it is clear that immigration can have both positive and negative effects on the vote share of anti-immigrant parties through different channels. Which effect would dominate depends on the specific circumstances of the situation, including the type of migration.

For temporary labor migrants, who are considered in this paper, not all channels may be relevant and even those that are relevant may matter to a different degree than with permanent migrants. For instance, for temporary labor migrants, the citizenship channel is irrelevant, as due to the temporary nature of their stay, these migrants are unable to gain citizenship. Likewise, the cultural channel is likely to be less important than for the permanent migrants, as even if these migrants are from culturally distant countries, they are not going to stay in the receiving country permanently, thus even if there is some cultural change, it is only temporary. On the other hand, both the economic and contact effects could be present. Since temporary workers migrate for the purpose of employment, they, similarly to permanent migrants, could be perceived to be an economic threat in terms of creating additional pressure on the labor market (even if it is not so in reality). As for the contact effect, it is likely also to be present. While temporary migrants do not usually bring their families to the US, and thus do not interact with locals via schools and other similar activities, many of them work in the service and retail occupations, which entail a lot of contact with the locals. Overall, it is expected that the net effect of the temporary migration would be close to zero, as these effects would cancel each other.

2.2 Background

Temporary nonimmigrant worker visas are granted to foreign nationals who seek employment in the United States for a limited period of time. Of particular interest for this research are H2A and H2B nonimmigrant worker visas, which are designed for workers in agricultural and non-agricultural industries, respectively.

Both H2A and H2B visas have strict requirements on how long the workers can stay in the country. For H2B, the maximum duration depends on the reason for employment: if the reason for the need for foreign workers is seasonal, peakload, or intermittent, the maximum length for which the H2B visa will be granted is 9 months, while for the one-time need, the visa can be granted for longer. For both H2A and H2B visa holders, the maximum non-interrupted period of stay in the country is 3 years in total, however, the employer must submit a separate request, if they want to extend the stay of their workers and each request can be up to 1 year if the initial permit on stay is less than 3 years. After 3 years, both H2A and H2B workers must depart from the US and stay abroad for at least 3 months before they are allowed to reapply for another visa.

For those who overstay their visas, strict penalties apply, such as barring them from re-applying for another visa for at least 5 years. While it is unknown how many migrant workers overstay their visas, the available data suggests that this number is negligible: only 0.27% of H2A workers have been barred from participating in the program due to visa overstay. Moreover, out of all illegal immigrants who overstayed their visas, less than 1 % were on H2A visas (Bier, 2020). Similarly, illegal visa overstay is equally uncommon among H2B workers: between 2008 and 2019, the US government deported only 972 immigrants who overstayed the H2B visa, which represents only 0.1% of visas issued and just 0.05% of all immigrants deported from the US (Bier, 2021). Thus, all this evidence suggests that the overwhelming majority of workers on H2A and H2B visas do follow the rules and leave the US within the time that is specified by their visa. Thus, these people can truly be considered to be temporary migrants, as there is no evidence that they stay permanently.

Employers must advertise the position domestically before being allowed to employ foreign workers on H2B and H2A visas, and historically only 7% of vacancies advertised for H2B visas were filled by domestic workers, and 6% for H2A visas (Bier, 2020, 2021). Additionally, employers must pay their workers the prevailing wage, which should not be lower than the average wage paid to domestic workers. Therefore, foreign workers on H2A and H2B visas do not have a negative impact on the employment of domestic workers but are only employed when there is no interest in the position from domestic workers.

As of 2021, citizens of 82 countries were eligible to apply for H2A visas, and citizens of 83 countries were eligible to apply for H2B visas. Nevertheless, in practice, the vast majority of migrants on both of these visa types come from Mexico (OHSS, 2016).

A vast strand of academic literature focuses on Mexican migration into the US, including reasons for it (Garip and Asad, 2013; Naugler and Conroy, 2020), locations choices of migrants (McKenzie and Rapoport, 2010) and its impact on the economy of the United States (Albert, 2021; Borjas et al., 1997) and the political outcomes (Camarena and Tiburcio, 2024). Nevertheless, as H2A and H2B migrants only constitute around 4% of all Mexican migrants, these studies do not represent the migrants who come to the US on H2A and H2B visas. In addition, these migrants do not have a meaningful choice on which part of the US to settle in, as they have to go only to the places where they would be employed by a firm that can provide the documents for H2A or H2B visa application. Therefore, the subset of migration analyzed in this paper is distinct from the overall Mexican migration.

3 Empirical Framework

3.1 Specification

In this paper, I will estimate the following first-difference regression equation at the county-district level.

$$\Delta y_i = \beta_1 \Delta z_i + \theta \Delta X_i + \epsilon_i \tag{1}$$

Here y_i is the dependent variable (either the vote share for the Republican party in the House of Representatives in county-district i or the difference between donations to extreme candidates and donations to moderate candidates in thousand US dollars per capita) (following Dreher et al. (2020)).

z_i is the number of temporary migrants per thousand residents. Depending on the specification, it can either be the total number of H2A and H2B migrants combined or two separate variables for H2A and H2B migrants.

X_i is the vector of control variables, which includes:

- population
- population density
- percentage of the population with higher education
- age distribution
- percentage of males in the population
- percentage of African American residents
- percentage of Hispanic residents
- percentage of immigrant residents

These control variables are included to ensure that omitted variable bias does not influence the results, as they could be correlated both with the political outcomes in a county and the number of temporary labor migrants. For instance, counties with higher and denser populations could be more likely to vote Democrat, while at the same time having fewer agricultural facilities, and thus attracting fewer H2A migrants. Similarly, shares of residents with higher education, racial, age, and gender compositions are correlated both with the counties' voting patterns and demand for foreign workers.

3.2 Empirical strategy

Locations of the migrants may be endogenous. For instance, migrants may be more likely to go to regions in which the attitudes towards migrants are more positive and thus the regions that are more likely to vote for pro-immigration candidates. Similarly, companies from the regions with more migrant-friendly attitudes may be more likely to employ foreign workers.

In order to deal with the potential endogeneity problem, I use shift-share or Bartik instrumental variables based on the occupations in which migrants work. Shift-share or Bartik instrument is named after the Bartik (1991) paper that popularized it, and since then has been widely used in trade (Autor et al., 2013) and migration (Jaeger et al., 2018) literature. The instrument is constructed by multiplying the national level *shifts* in the certain phenomenon of interest (for instance, industry-level growth in the US imports from China (Autor et al., 2013)) by the local exposure to that shift, measured as a *share* (in the case of Autor et al. (2013) as a share of local employment across industries).

The identifying assumption behind this type of instrument is that either the *shift* or the *share* component is exogenous (Borusyak et al., 2025).

My instrument takes the following form:

$$\hat{z_i} = \sum_{k=1}^{K} s_{ik} * g_k \tag{2}$$

where $\hat{z_i}$ is the predicted number of temporary migrants in a given county i (per 1000 inhabitants), g_k is the national growth rate of employment of migrants in occupation k (the *shift* component of the instrument), and s_{ik} is the *share* component, defined as

$$s_{ik} = \frac{e_{ki}}{\sum_{k=1}^{K} e_{ki}} \tag{3}$$

where e_{ki} is the number of temporary labor migrants employed in occupation k in county i in 2016.

I argue that in my case, the *shift* component is exogenous. As discussed in section 2.2, the rules regarding the recruitment of new H2A and H2B workers are strict. Due to the cap on the overall number of workers and competition between employers of different industries for a limited number of places under the H2A and H2B workers visas, which industry would be successful in getting, and thus for which industry g_k will increase, is as good as random.

4 Data and Descriptive Statistics

4.1 Data

In this paper, I will use several data sources.

4.1.1 Temporary migration

The primary data source for this study is administrative data on temporary migrant inflows published by the US Department of Labor (DoL). Employers seeking to hire foreign workers on H2A or H2B visas must submit an official application to the Department of Labor, which either approves or denies each application. The Department of Labor publishes all submitted applications online, making this data available for researchers.

The data that is publicly available from the DoL website only covers the period from 2016 to the present, and in this research, I focus mainly on the 2016-2018 period, however, 2020 data is used for the robustness check. Applications for the employment of workers on H2B and H2A visas are published separately.

Each employer's application to hire foreign workers contains information on whether the application was approved or denied, the number of workers approved for employment, as well as the number of workers that actually arrived, the employer and worksite addresses, wage rate, occupation, dates of employment, education, experience, the number of hours worked, and primary crop (for H2A workers).

For the analysis, the total number of foreign workers approved is aggregated by county and visa type. Additionally, the occupation of the workers is utilized to create an instrumental variable, while other variables from the list above are used for robustness checks and heterogeneity analysis.

4.1.2 Data on voting

One of the key political outcomes of interest is the voting behavior in the US House of Representatives elections. Specifically, the analysis operationalizes voting as the vote share of the Republican party in each county-district cell[4] in the 2016 and 2018 elections. To ensure robustness, the vote share of the Democratic party is also examined as an alternative outcome variable (the results are very similar, not reported here, but available at the request). It is worth noting that almost all votes are received either by the Republican or Democratic parties. In addition, the elections to the US House of Representatives are chosen as they take place biennially (unlike the presidential elections) and are held simultaneously in all states (unlike the elections to the US Senate).

The data on voting behavior is collected from the MIT Election Data Science Lab (MIT, 2020). The data is then cleaned and aggregated at the county-district level.

4.1.3 Data on polarization

To measure political polarization in this study, I follow the approach of Dreher et al. (2020) and draw on the Database on Ideology, Money in Politics, and Elections (DIME) dataset collected by Bonica (2019). This dataset includes detailed information on political donations made to candidates running for Congress in each election cycle, from 1980 to 2018. For this study, I focus specifically on the DIME scores for congressional candidates in the 2016 and 2018 election cycles, as data on temporary migration is not available prior to 2016.

The DIME dataset provides me with information on the political ideology of each candidate running in the election for Congress, as well as the amount of donations they received. Based on the data on political ideology, I am able to separate candidates into 'moderate' and 'extreme', as well as into 'moderate left', 'moderate right', 'extreme left', and 'extreme right'. Following Dreher et al. (2020), I construct my measure of political polarization as the difference in donations received by all extreme candidates and all moderate candidates. Here, I define 'extreme' candidates as both far-left and far-right candidates, while 'moderate' candidates include moderate Republicans and Democrats, as well as Independents and candidates from other parties. In my further analysis, I also examine the impact of temporary migration on the support for far-left and far-right candidates separately.

4.1.4 Control variables

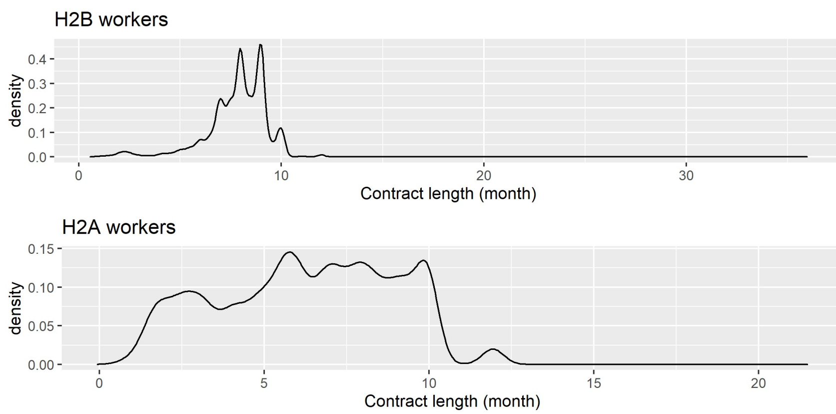
To control for other factors that may affect political outcomes, I use data from the American Community Survey conducted by the US Census Bureau. This dataset provides information on important economic and demographic variables at the county level. Specifically, I control for population, population density, the percentage of the population with higher education, age distribution, the percentage of males in the population, and the percentage of African American, Hispanic, and immigrant residents in each county.

[4] Congressional districts in the US do not always follow the county lines. Usually, congressional districts include several counties (or part of counties).

4.2 Descriptive statistics

Figure 1 shows the distribution of contract length of the temporary labor migrants by visa type. As discussed in Section 2.2, for the vast majority of workers, both on H2A and H2B visas, the contract length is below 10 months. For H2B worker,s the majority of contracts are around 8-9 months, while for H2A, there is more variation in contract length.

Fig. 1 Distribution of contract length of H2A and H2B migrants

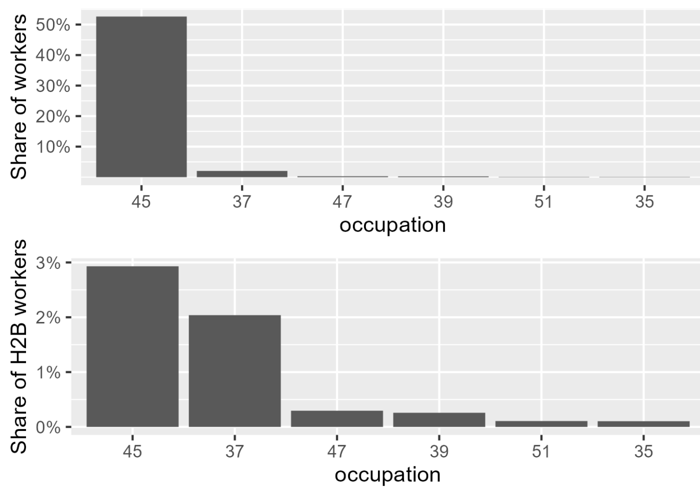


Another interesting phenomenon is how widespread the temporary labor migrants are. Figure 2 displays what share of workers in a given industry are migrants on H2A or H2B visas [5]. The top panel shows both H2A and H2B workers combined, while the bottom panel shows only H2B workers. H2A workers are not shown separately as all of them work in the same occupation (Farming, Fishing, and Forestry Occupations or 45 on the figure 2). As can be inferred from the diagram, the H2A and H2B workers combined constitute about half of all workers employed in Farming, Fishing, and Forestry Occupations. This is primarily driven by workers on H2A visas, as the workers on H2B visas account only for about 3% of the workers in these occupations. The occupation with the second highest share of workers on H2A and H2B visas is Building and Grounds Cleaning and Maintenance Occupations (occupation 37 on figure 2); however, here migrant workers only constitute around 2% of total workers. In all other occupations, temporary labor migrants on H2A and H2B visas constitute less than 1% of total workers. Thus, we can conclude that while in most occupations the presence of temporary labor migrants is negligible, Farming, Fishing, and Forestry Occupations rely on temporary labor migrants heavily.

In Figure 3, I plot the distribution of the number of temporary migrants per 1000 people across the US, both H2A and H2B migrants combined, as well as separately.

[5] The H2B and H2A workers are only employed in the six general occupations plotted here.

Fig. 2 Share of workers in a given occupation who are on H2A or H2B visas



Note: The occupations are as follows: 45 - Farming, Fishing, and Forestry Occupations, 37 - Building and Grounds Cleaning and Maintenance Occupations, 47 - Construction and Extraction Occupations, 39 - Personal Care and Service Occupations, 51 - Production Occupations, 35 - Food Preparation and Serving Related Occupations

The figures show that the distribution of migrants across the country does not follow any particular pattern.

Figure 4 shows how the number of temporary labor migrants changed in each county between 2016 and 2018. Overall, the number of temporary labor migrants remained relatively consistent throughout this time period.

In addition, tables 1 and 2 show the summary statistics of all the main variables of interest in levels (both for 2016 and 2018 combined) and the change between 2016 and 2018, respectively.

Table 1 Summary statistics in levels, 2016 and 2018

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
H2A migrants	7,163	79.621	342.326	0.000	0.000	7.000	40.000	12,161.000
H2B migrants	7,163	89.538	286.604	0.000	0.000	0.000	50.000	3,133.000
H2A migrants per 1000	7,163	2.796	10.948	0.000	0.000	0.098	1.199	270.656
H2B migrants per 1000	7,163	0.986	4.757	0.000	0.000	0.000	0.549	141.649
Total migrants per 1000	7,163	3.783	12.159	0.000	0.044	0.590	2.456	270.656
Share of immigrants	7,163	0.058	0.071	0.000	0.014	0.030	0.071	0.533
Hispanic share	7,163	0.103	0.143	0.000	0.022	0.044	0.112	0.990
Male share	7,163	0.499	0.022	0.414	0.488	0.495	0.504	0.790
African American share	7,163	0.093	0.139	0.000	0.007	0.028	0.115	0.862
Unemployed share	7,162	0.064	0.029	0.000	0.045	0.061	0.079	0.299
Income per capita	7,162	26,724.790	6,781.701	9,286.000	22,210.250	25,784.500	29,808.000	72,832.000
Population density	7,163	514.392	3,000.167	0.114	20.747	56.713	204.594	71,597.000
Republican vote share	7,165	0.630	0.196	0.000	0.514	0.656	0.759	1.486
Polarization	6,735	0.109	1.269	−4.055	−0.006	0.016	0.089	94.697

Fig. 3 Distribution of temporary labor migrants per 1000 people across US counties in 2016

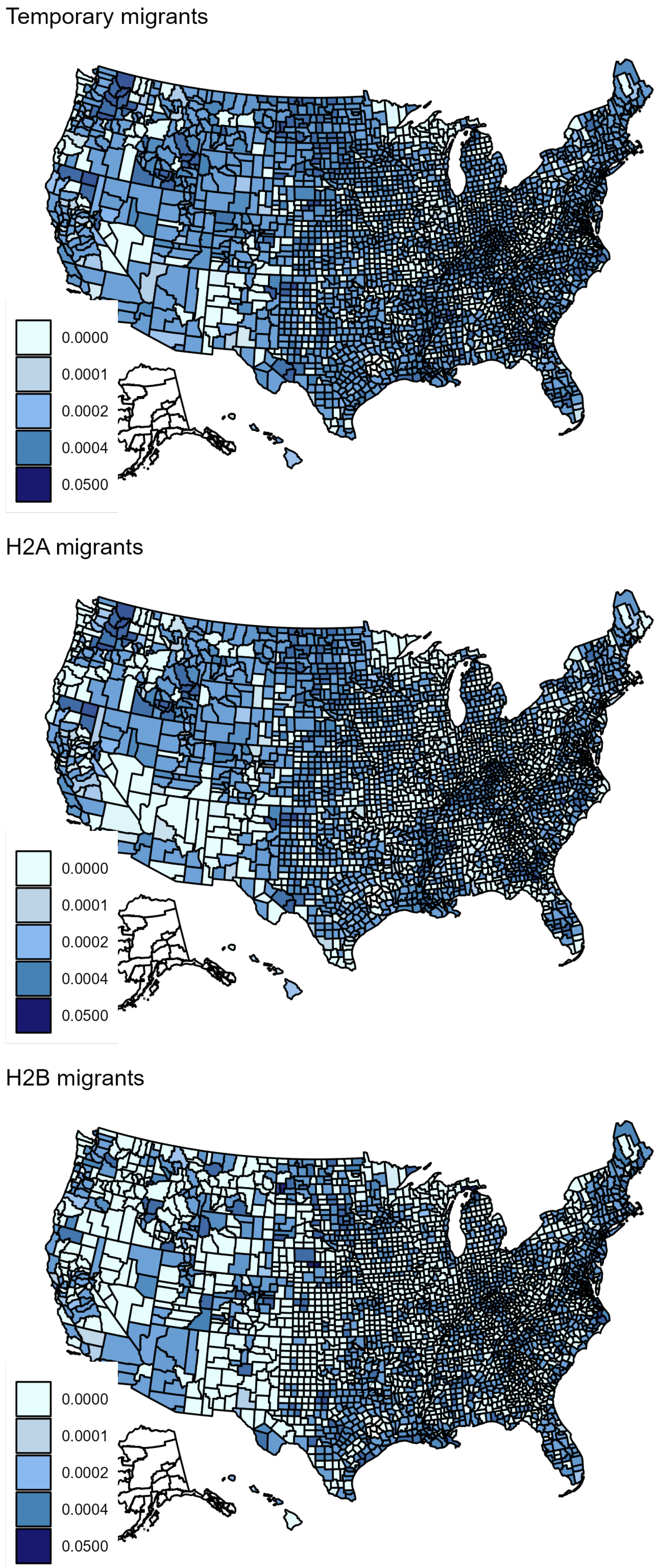


Fig. 4 Change in the distribution of temporary migrants per capita across US counties between 2016 and 2018

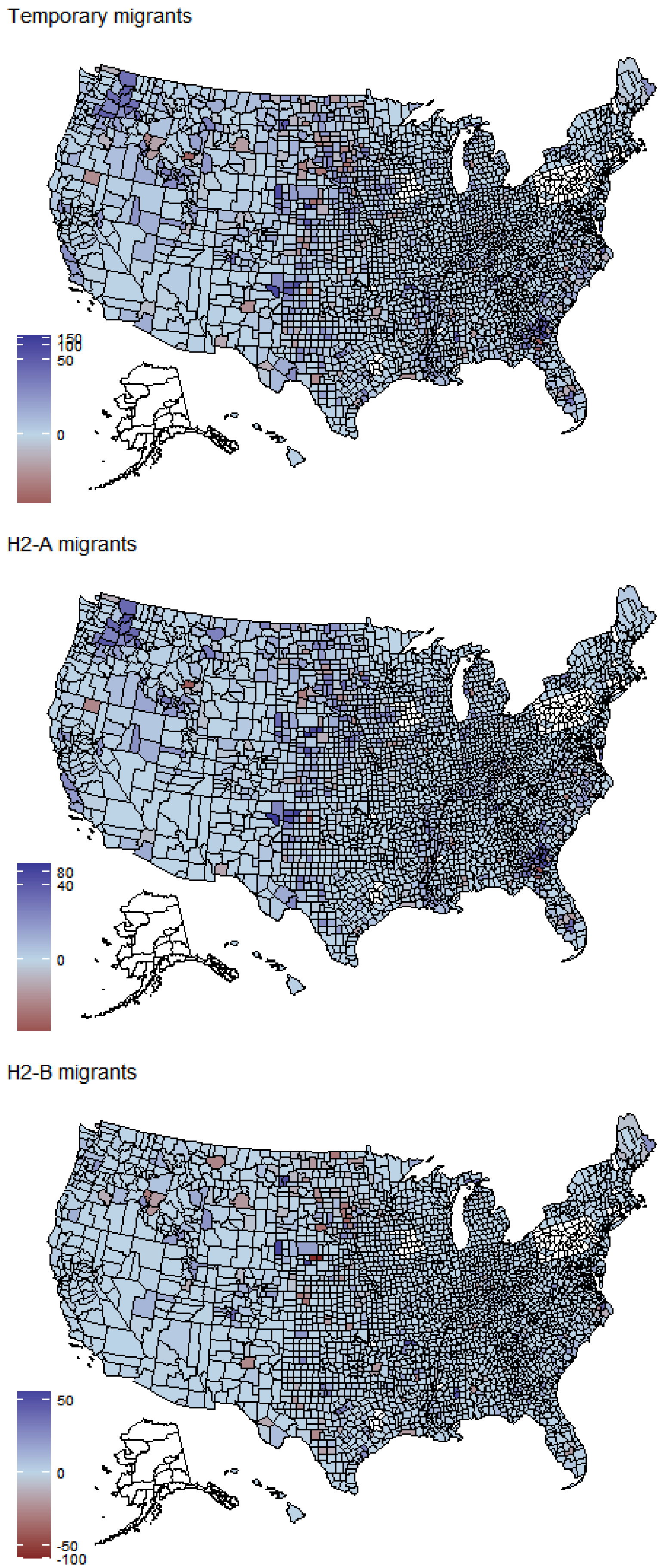


Table 2 Summary statistics in first difference between 2016 and 2018

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
H2A migrants	3,364	30.174	156.913	−541	0	0	14	2,825
H2B migrants	3,364	21.657	92.327	−536	0	0	14	950
H2A migrants per 1000	3,364	1.123	6.497	−35	0	0.002	0.4	116
H2B migrants per 1000	3,364	0.214	3.862	−103	0	0	0.1	74
Total migrants per 1000	3,364	1.337	7.324	−35	0	0.1	0.8	169
Share of immigrants	3,364	0.001	0.008	−0	−0.002	0.001	0.004	0
Hispanic share	3,364	0.003	0.009	−0	0.001	0.002	0.005	0
Male share	3,364	0.0003	0.008	−0	−0.001	0.0002	0.002	0
African American share	3,364	0.0005	0.007	−0	−0.001	0.0003	0.002	0
Unemployed share	3,363	−0.013	0.015	−0.101	−0.020	−0.013	−0.006	0.073
Income per capita	3,363	2,083.747	1,430.143	−9,161.000	1,377.500	2,135.000	2,851.000	13,160.000
Population density	3,364	3.442	17.858	−110	−0.3	0.002	1.1	422
Instrument (total)	3,364	0.267	0.211	−0.417	0.000	0.383	0.454	0.502
Instrument (H2A)	3,364	0.258	0.230	0.000	0.000	0.462	0.462	1.405
Instrument (H2B)	3,364	0.118	0.193	−0.417	0.000	0.000	0.284	0.501
Republican vote share	3,364	−0.041	0.109	−0.734	−0.075	−0.032	0.004	0.717
Polarization	3,159	0.067	1.286	−7.980	−0.004	0.007	0.056	68.328

5 Results

5.1 Main results

Table 3 presents the main estimates. In columns (1) and (2), the vote share of the Republican party in the election to the US House of Representatives is regressed on the instrumented number of temporary labor migrants (H2A and H2B combined in model 1 or H2A and H2B separately in model 2). In columns (3) and (4) the dependent variable is polarization. In Panel A, no controls are included. In Panel B all controls except for the number of permanent immigrants are included and in Panel C all control variables that are discussed in section 4.1.4 are included in the model.

The results show that temporary labor migration does not increase the vote share of the Republican party. If anything, the effect is negative, especially when it comes to H2B workers (non-agricultural migrants). We can also see a negative effect of the presence of temporary labor migrants on polarization. Here, this effect is negative and significant both for H2A and H2B migrants, however, the magnitude of the effect is still larger for the H2B migrants.

While these results may be different from the findings of the studies that focused on permanent migration, this is likely due to the fact that temporary migrants that are considered here differ from permanent migrants in several ways concerning the channels through which migration affects political outcomes.

As discussed previously, different channels influence voting behavior and polarization in different directions, thus resulting in overall zero or near-zero effects. Firstly, the cultural channel suggests that native populations may fear that immigrants will alter the existing culture of their society and, as a result, vote for right-wing parties that typically oppose immigration. In addition, they would also be more likely to vote for far-right candidates, as opposed to central right candidates, as far-right candidates are more likely to oppose migration, thus increasing both the vote share of the Republicans and polarization. However, the effect of this channel may be weaker for temporary labor migrants because natives recognize that these individuals will only

Table 3 Main results

	Dependent variable:			
	Voting		*Polarization*	
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.003 (0.003)		−0.049 (0.033)	
H2A migrants per 1000		−0.007 (0.005)		−0.066 (0.052)
H2B migrants per 1000		−0.017 (0.011)		−0.205 (0.147)
1st stage F	30.75	26.03, 15.40	27.83	25.13, 11.00
Observations	3,364	3,364	3,346	3,346
Panel B: No immigration controls				
Total migrants per 1000	−0.002 (0.002)		−0.031 (0.024)	
H2A migrants per 1000		−0.002 (0.003)		−0.039 (0.141)
H2B migrants per 1000		−0.014** (0.006)		−0.081 (0.078)
1st stage F	41.71	23.74, 13.52	40.70	26.61, 11.11
Observations	3,364	3,364	3,346	3,345
Panel C: With controls				
Total migrants per 1000	−0.002 (0.002)		−0.033 (0.025)	
H2A migrants per 1000		−0.001 (0.003)		−0.138*** (0.038)
H2B migrants per 1000		−0.013** (0.006)		−0.342*** (0.101)
1st stage F	42.17	24.36, 13.36	41.44	24.38, 11.04
Observations	3,364	3,363	3,346	3,345

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

be present in the country for a limited period and thus are unlikely to have a significant impact on the existing culture. Additionally, the economic channel may also have a weaker effect on political outcomes for temporary labor migrants. As I discuss in Section 2.2, temporary labor migrants are subject to strict employment laws that dictate that they can only be employed if local workers are unavailable. In contrast, permanent migrants may compete directly with locals for jobs. Thus, temporary labor migrants may not pose as much of an economic threat to the native workers as permanent migrants. Consequently, the effect of the economic channel, which can lead natives to vote for anti-immigration parties due to concerns about increased labor market competition, may be weaker for temporary labor migrants. Once again, this would both increase the vote share of central right candidates (as compared to central left candidates) and far-right candidates (as compared to central right candidates), thus increasing both the vote share of the Republican party and polarization.

However, the impact predicted by the contact hypothesis on political outcomes is more complex and varies depending on the type of migration. H2A migrants tend to work and live in rural areas, where they have little contact with natives. In contrast, H2B migrants often work in urban areas in jobs such as landscaping, building, and catering, which allow them to interact more frequently with native populations. Thus, the differences in results for H2B and H2A migrants may be due to the greater level of contact H2B migrants have with locals. According to the contact hypothesis, increased contact between immigrants and natives should reduce hostility towards immigrants and lead to less support for right-wing parties that seek to restrict immigration. This could explain why H2B migration has a more negative effect on the vote share of the Republican party and polarization than H2A migration.

What is also curious is that these results also stand in contrast to the studies specifically analyzing the differential effect of low and high-skilled migrants on political outcomes, as these studies, both in the US (Mayda et al., 2022) and in the European (Halla et al., 2017) contexts, find that while high-skilled migrants do decrease the vote share of anti-immigration parties, the low-skilled migrants actually increase it. There are several reasons why my results could be different from the previous research. Firstly, in the US, a large share of low-skilled migrants come to the country illegally and thus may face greater resistance from the locals than those who come to the country legally. As the migrants on H2A and H2B visas remain in the US legally, it is possible that they attract less resistance than an average low-skilled migrant. Moreover, as discussed above, the negative effect on the Republican vote share primarily comes from H2B migrants, who are more in contact with the locals than an average low-skilled migrant due to the fact that many of them work in high-contact occupations, leading to lower anti-immigrant sentiments as predicted by the contact hypothesis. Finally, the discussion above regarding the differences between temporary and permanent migrants applies also to the difference in results between my and other studies with regard to permanent and temporary low-skill migrants.

6 Robustness checks

6.1 Recentered instrument and simulated instrument

One potential concern that often arises when shift-share instruments are used is that the exposure to exogenous shocks is non-random, even if the shocks are exogenous. In this case, different regions may have different economic and political conditions, meaning that for some regions it is easier to integrate migrants than for others. To deal with this issue, I follow Borusyak and Hull (2023) and recenter my instruments. Using mean growth rate and standard deviation across the industries, I simulate 1000 growth rates for each industry and calculate 1000 instruments based on these growth rates. After that, I calculate the mean simulated instrument. Using the calculated mean simulated instrument, I perform two separate robustness checks. Firstly, I calculate the recentered instrument, which is equal to the difference between the real instrument and the simulated instrument, and use the recentered instrument as an instrument. Secondly, I use the mean simulated instrument as a control variable in the regression. The results are reported in Tables 4 and 5. The results remain similar to the main results, with vote share for the Republican parties being negatively influenced by the presence of H2B migrants and polarization being negatively influenced by the presence of both H2A and H2B migrants.

Table 4 Recentered instrument

	Dependent variable:			
	Voting		*Polarization*	
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.004 (0.003)		−0.033 (0.030)	
H2A migrants per 1000		−0.004 (0.006)		−0.078 (0.065)
H2B migrants per 1000		−0.012 (0.008)		−0.141 (0.116)
1st stage F	36.26	15.21, 22.01	32.74	14.42, 15.26
Observations	3,364	3,364	3,346	3,346
Panel B: No immigration controls				
Total migrants per 1000	−0.003 (0.002)		−0.024 (0.023)	
H2A migrants per 1000		−0.002 (0.004)		-0.182^{***} (0.045)
H2B migrants per 1000		-0.012^{***} (0.005)		-0.234^{***} (0.081)
1st stage F	45.68	12.61, 20.07	43.76	12.80, 15.30
Observations	3,364	3,364	3,346	3,345
Panel C: With controls				
Total migrants per 1000	−0.003 (0.002)		−0.025 (0.024)	
H2A migrants per 1000		0.001 (0.003)		-0.187^{***} (0.046)
H2B migrants per 1000		-0.011^{**} (0.005)		-0.241^{***} (0.083)
1st stage F	46.2	13.03, 20.01	44.48	13.30, 15.18
Observations	3,364	3,363	3,345	3,346

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

6.2 Only large scale migration

In Table 6, I examine the hypothesis that only large-scale migration may have a significant effect on the political preferences of the natives. The inflow of temporary migrants is unevenly redistributed in the country: while some counties witness large inflows of temporary migrants, in other counties, only a few migrants arrive and are barely noticeable to the natives. Thus, it could be argued that the effect of migration on political outcomes could be stronger in the counties where migration inflow is large

Table 5 Controlling for simulated instrument

	Dependent variable:			
	Voting		*Polarization*	
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.005** (0.003)		0.005 (0.031)	
Sim. instrument total	0.035 (0.037)		−0.836** (0.398)	
H2A migrants per 1000		−0.009* (0.005)		−0.003 (0.047)
H2B migrants per 1000		−0.012** (0.005)		−0.007 (0.063)
Sim. instrument H2A		0.003 (0.004)		−0.021 (0.037)
Sim. instrument H2B		−0.080 (0.052)		−0.654 (0.520)
1st stage F	33.03	10.86, 25.88	29.49	9.86, 17.10
Observations	3,364	3,364	3,346	3,346
Panel B: No immigration controls				
Total migrants per 1000	−0.004* (0.002)		−0.002 (0.027)	
H2A migrants per 1000		−0.003 (0.004)		−0.160*** (0.043)
H2B migrants per 1000		−0.011*** (0.004)		−0.125* (0.067)
Sim. instrument H2B		−0.030 (0.035)		−0.718 (0.496)
Sim. instrument H2A		0.001 (0.004)		0.078* (0.045)
Sim.instrument total	0.048 (0.037)		−0.585 (0.410)	
1st stage F	34.90	9.88, 23.87	31.53	9.47, 16.39
Observations	3,364	3,364	3,346	3,345
Panel C: With controls				
Total migrants per 1000	−0.004* (0.002)		−0.002 (0.027)	
H2A migrants per 1000		0.001 (0.003)		−0.157***(0.043)
H2B migrants per 1000		−0.011*** (0.004)		−0.124* (0.067)
Sim. instrument total	0.048 (0.037)		−0.621 (0.407)	
Sim. instrument H2B		−0.026 (0.034)		−0.765 (0.493)
Sim. instrument H2A		−0.001 (0.003)		0.074 (0.045)
1st stage F	35.37	9.98, 23.81	31.93	9.52, 16.28
Observations	3,364	3,363	3,346	3,345

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

enough to be noticeable by the local residents. To investigate this issue further, I recoded 'large migration inflow' as a binary variable which takes the value of 1 if the migration inflow in a particular county is above the 80th percentile nationwide and 0 if it is below the 50th percentile nationwide (observations that fall in between the 50th and the 80th percentile are dropped). The results of the estimation with this recoded variable are reported in Table 6. Overall, the results are similar to the main results reported in Table 3 and if anything, the results on the polarization become insignificant. Thus, it can be concluded that migration on a large scale does not impact the political outcomes more than the migration on a small scale, and if anything, the opposite is true: small-scale migration may be more important, rather than additional migrants in the counties with already high levels of migration.

Table 6 Only large-scale migration

	Dependent variable:			
	Voting		*Polarization*	
	(1)	(2)	(3)	(4)
Panel A: No controls				
Large migration total	−0.019 (0.016)		−0.273 (0.223)	
Large migration H2A		−0.016 (0.012)		−0.115 (0.178)
Large migration H2B		−0.007 (0.013)		−0.183 (0.191)
1st stage F	249.83	256.81, 264.85	247.81	254.21, 255.02
Observations	2,346	2,030	2,331	1,970
Panel B: No immigration controls				
Large migration total	−0.008 (0.015)		−0.308 (0.222)	
Large migration H2A		0.007 (0.012)		−0.128 (0.176)
Large migration H2B		−0.020 (0.013)		−0.122 (0.190)
1st stage F	211.04	192.09, 213.27	215.53	141.26, 137.17
Observations	2,346	2,030	2,331	1,969
Panel C: With controls				
Large migration total	−0.008 (0.015)		−0.317 (0.222)	
Large migration H2A		0.007 (0.012)		−0.136 (0.176)
Large migration H2B		−0.020 (0.013)		−0.122 (0.190)
1st stage F	211.067	127.84, 142.56	215.54	141.21, 137.13
Observations	2,346	2,029	2,331	1,969

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

6.3 2020 elections

I also look at the change in migration and the political preferences between 2016 and 2020, rather than between 2016 and 2018 as in the main model. Both the 2016 and 2020 elections had presidential elections and elections to the Congress on the same day. Presidential elections usually attract higher turnout and may attract different compositions of voters as compared to just congressional elections. Thus, the difference in voting outcomes between the 2016 and 2018 elections could be affected by the fact that 2016 was a presidential election year, while in 2018, only elections to Congress were held. Although it is unlikely that this difference in turnout is correlated with the change in temporary migration in a way that would affect the results, nevertheless, for a robustness check, I perform an estimation for the years 2016 and 2020. It is important to point out several things, however. Firstly, since the measure of polarization I am using is not available for 2020, I am only using voting as an outcome variable. Secondly, due to the restrictions implemented due to the COVID-19 pandemic in 2020, it became more difficult to enter the US for migrants. In addition, many jobs, especially those that require a lot of contact with the locals, especially in the hospitality and services industries, disappeared. Thus, due to the unusual conditions faced in 2020, most of my estimation focuses on the 2016-18 period. Nevertheless, Table 7 reports the results, where the dependent variable is the change in the vote share in the elections to the House of Representatives between 2016 and 2020. Overall, the results are very similar to the main results.

7 Heterogeneity

7.1 Far-left vs far-right polarization

Table 8 presents the results of the temporary labor migration separately on far-left and far-right polarization. Columns (1) and (3) show how temporary labor migration affects far-right polarization (which is defined, as discussed in Section 4.1.3, as the difference between donations to far-right candidates and the donations to center-right candidates) and columns (2) and (4) show the effect at the far-left polarization (defined as the difference in donations to far-left candidates and center-left candidates). As we can see from Table 8, while far-right polarization decreases, far-left polarization actually increases when the temporary labor migration increases.

7.2 Other heterogeneity results

I have also checked whether there is a differential effect of temporary migration on political outcomes along any other dimensions. The results show that while there are no significant differences in how temporary labor migration affects voting behavior, there are some interesting differences in how it affects political polarization. I find that the polarization is reduced more due to the presence of temporary migrants in rural counties, non-swing counties, counties that witness a net inflow of migrants, and counties that are not dependent on migrant-intensive industries. Moreover, in all of these cases, as in the main results, the effect is only present or is stronger for H2B (non-agricultural) migration. The Tables with these results are reported in the Appendix.

These results are interesting. The effect may be stronger in rural areas because people there could have been less exposed to immigrants (or people from different

Table 7 2016-2020 elections

	Dependent variable:	
	Voting	
	(1)	(2)
Panel A: No controls		
Total migrants per 1000	0.001 (0.001)	
H2A migrants per 1000		−0.004 (0.003)
H2B migrants per 1000		-0.021^{*} (0.012)
1st stage F	50.19	18.55, 16.52
Observations	3,343	3,343
Panel B: No immigration controls		
Total migrants per 1000	0.002^{*} (0.001)	
H2A migrants per 1000	0.00003 (0.002)	
H2B migrants per 1000		-0.014^{*} (0.008)
1st stage F	47.37	16.98, 14.95
Observations	3,343	3,343
Panel C: With controls		
Total migrants per 1000	0.002^{*} (0.001)	
H2A migrants per 1000		0.00003 (0.002)
H2B migrants per 1000		-0.014^{*} (0.008)
1st stage F	49.03	17.42, 14.90
Observations	3,343	3,343

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

Table 8 Heterogeneity by far-left vs far-right

	Dependent variable:			
	Far-right	Far-left	Far-right	Far-left
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.001 (0.007)	0.037* (0.020)		
H2A migrants per 1000			0.003 (0.010)	0.029 (0.026)
H2B migrants per 1000			0.030 (0.026)	0.148 (0.091)
1st stage F	27.53	20.10	24.97 ,10.92	21.04, 5.69
Observations	3,188	2,930	3,139	2,743
Panel B: No immigration controls				
Total migrants per 1000	−0.003 (0.005)	0.027* (0.014)		
H2A migrants per 1000			−0.006 (0.007)	0.043* (0.023)
H2B migrants per 1000			−0.012 (0.016)	0.168** (0.081)
1st stage F	40.51	30.93	24.55, 11.55	19.32, 4.87
Observations	3,188	2,930	3,138	2,742
Panel C: With controls				
Total migrants per 1000	−0.003 (0.005)	0.027* (0.014)		
H2A migrants per 1000			−0.007 (0.007)	0.041* (0.023)
H2B migrants per 1000			−0.014 (0.017)	0.174** (0.085)
1st stage F	41.25	31.54	23.57, 10.87	20.03, 4.54
Observations	3,188	2,930	3,138	2,742

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

cultures in general) before, as compared to people who live in urban areas. Thus, contact with migrants may have a stronger effect on them. The effect in the counties that are not dependent on migrant-intensive industries may be stronger due to the presence of economic effects that outweigh the contact effect in these regions. For instance, there local residents may be more likely to perceive migrants as 'stealing their jobs' (even if it is not the case in reality, as discussed previously), and thus be more resistant towards them. The fact that the results are stronger in non-swing counties could be driven by the fact that political parties usually invest more attention and money in the swing counties and thus there could be many more factors that could be driving the political preferences in the swing conunties, while in the non-swing counties, the effect of temporary migration could be isolated more precisely. Finally, the result could be stronger in the counties with the net inflow as compared to a net outflow of migrants as the effect of the contact with migrants could be long-lasting: if a county witnessed a higher number of migrants, even if their quantity has decreased over time, the locals still remember the contact and still have formed their political opinions based on it. At the same time, in the case of the net inflow of migrants, more locals, who have previously not encountered migrants, now do encounter them, thus increasing the overall exposure of locals to migrants.

8 Conclusion

In this paper, I have examined how the presence of temporary labor migrants affects political outcomes, namely voting and political polarization in the US. My results show that the presence of temporary migrants decreases the vote share of the Republican party and political polarization. The decrease in polarization, however, is driven by the decrease in the support of far-right politicians, while the support of far-left politicians actually increases. In addition, this decrease is mainly driven by the labor migrants on H2B visas, who work in non-agricultural occupations. These findings are consistent with the notion that interpersonal contact can mitigate negative stereotypes and reduce hostility toward migrants, dampening the appeal of anti-immigrant rhetoric.

These results carry important implications for policymakers and practitioners. First, they highlight the need to distinguish between different types of migration programs when crafting immigration policy. Policies directed at temporary labor migration cannot be approached in the same manner as those for permanent or refugee migration, given the unique channels - both economic and social - through which temporary migrants influence local communities. In particular, policymakers could consider programs and regulations that encourage regular, positive interaction between temporary migrants and local residents, which may help ameliorate anti-immigrant attitudes. Second, labor market regulations governing H2A and H2B visas, such as requirements to pay prevailing wages or demonstrate unfilled labor demand, appear to moderate the concerns about job competition and wage suppression that sometimes fuel anti-immigrant positions. Strengthening these provisions and enhancing their transparency could help sustain public support for such programs.

Furthermore, the evidence that temporary labor migration can decrease far-right polarization suggests that targeted community-building initiatives, such as local intercultural events, job fairs, and support networks that bring migrants and residents together, might reduce the conditions in which anti-immigrant political platforms gain traction. Finally, taking a more granular approach to labor needs and the distribution of temporary workers could ensure that these programs simultaneously address workforce shortages and foster beneficial contact between migrants and host communities. By carefully designing policies that reinforce the economic benefits of temporary migration while promoting positive social interactions, policymakers can lessen political polarization and foster greater community cohesion.

As argued previously, migration may affect political outcomes differently in different contexts. While this paper has focused on the little previously examined effect of temporary labor migration on the political outcomes in the US, there are also other types of migration, the effect of which on the political outcomes has not been studied before, and would be interesting to examine in future research. For instance, there is little evidence on how any type of migration affects political outcomes outside Europe and North America. Moreover, the effect of other types of migration on political outcomes (such as student migration, seasonal migration, return migration, etc.) is also understudied and could be explored in future research.

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9 Appendix

9.1 Heterogeneity tables

Table 9 Heterogeneity by urban vs rural areas

	Dependent variable:			
	Polarization			
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.038 (0.035)	0.001 (0.007)		
H2A migrants per 1000			−0.044 (0.039)	−0.0004 (0.009)
H2B migrants per 1000			−0.042 (0.079)	−0.015 (0.016)
1st stage F	28.97	18.02	10.93, 8.53	10.48, 37.11
Observations	1,612	1,723	1,612	1,723
Panel B: No immigration controls				
Total migrants per 1000	−0.041 (0.033)	−0.010 (0.006)		
H2A migrants per 1000			−0.143*** (0.045)	−0.002 (0.006)
H2B migrants per 1000			−0.215** (0.091)	−0.023 (0.014)
1st stage F	24.79	30.14	14.94, 10.28	12.27, 31.00
Observations	1,612	1,723	1,611	1,723
Panel C: With controls				
Total migrants per 1000	−0.042 (0.034)	−0.009 (0.006)		
H2A migrants per 1000			−0.145*** (0.045)	−0.003 (0.006)
H2B migrants per 1000			−0.212** (0.091)	−0.023 (0.015)
1st stage F	25.09	29.65	15.21, 10.32	12.52, 29.70
Observations	1,612	1,723	1,611	1,723

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

Table 10 Heterogeneity by swing vs non-swing counties

	Dependent variable: *Polarization*			
	Swing	Non-swing	Swing	Non-swing
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	−0.030 (0.031)	−0.049 (0.037)		
H2A migrants per 1000			−0.028 (0.035)	−0.075 (0.062)
H2B migrants per 1000			−0.029 (0.064)	−0.223 (0.176)
1st stage F	6.14	0.012	23.02, 8.39	0.24, 1.07
Observations	571	2,775	571	2,775
Panel B: No immigration controls				
Total migrants per 1000	−0.0003 (0.041)	−0.016 (0.027)		
H2A migrants per 1000			0.035 (0.073)	-0.133^{***} (0.040)
H2B migrants per 1000			−0.054 (0.081)	-0.379^{***} (0.113)
1st stage F	13.91	0.37	15.82, 15.83	0.66, 0.19
Observations	571	2,775	571	2,774
Panel C: With controls				
Total migrants per 1000	0.001 (0.042)	−0.019 (0.027)		
H2A migrants per 1000			0.030 (0.069)	-0.138^{***} (0.041)
H2B migrants per 1000			−0.050 (0.078)	-0.389^{***} (0.116)
1st stage F	14.18	0.38	16.04, 15.76	0.58, 0.14
Observations	571	2,775	571	2,774

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

Table 11 Heterogeneity by net inflow vs outflow of migrants

	Dependent variable:			
	Polarization			
	Net inflow	Net outflow	Net inflow	Net outflow
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	0.023 (0.020)	1.291 (11.849)		
H2A migrants per 1000			0.392 (21.032)	−0.321 (2.009)
H2B migrants per 1000			1.426 (78.962)	0.114 (1.020)
1st stage F	6.14	0.012	23.02, 8.39	0.24, 1.07
Observations	2,072	706	2,072	706
Panel B: No immigration controls				
Total migrants per 1000	0.012 (0.013)	−0.412 (0.831)		
H2A migrants per 1000			−0.010 (0.008)	0.018 (0.196)
H2B migrants per 1000			-0.051^{***} (0.019)	−0.162 (0.173)
1st stage F	13.91	0.37	15.82, 15.83	0.66, 0.19
Observations	2,072	706	2,072	706
Panel C: With controls				
Total migrants per 1000	0.015 (0.013)	−0.454 (1.056)		
H2A migrants per 1000			−0.011 (0.008)	0.006 (0.141)
H2B migrants per 1000			-0.052^{***} (0.019)	−0.157 (0.123)
1st stage F	14.18	0.38	16.04, 15.76	0.58, 0.14
Observations	2,072	706	2,072	706

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls is included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

Table 12 Heterogeneity by dependence on migrant-intensive industries

	Dependent variable:			
	Polarization			
	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)
Panel A: No controls				
Total migrants per 1000	0.003 (0.018)	−0.086 (0.062)		
H2A migrants per 1000			0.009 (0.273)	−0.096 (0.081)
H2B migrants per 1000			0.019 (1.167)	−0.198 (0.153)
1st stage F	7.32	24.43	9.23, 2.28	12.86, 15.33
Observations	1,361	1,581	1,361	1,581
Panel B: No immigration controls				
Total migrants per 1000	−0.001 (0.013)	−0.023 (0.042)		
H2A migrants per 1000			−0.005 (0.014)	−0.092 (0.065)
H2B migrants per 1000			−0.054 (0.045)	−0.349*** (0.108)
1st stage F	13.63	31.21, 5.85	33.64	20.1, 9.50
Observations	1,361	1,581	1,361	1,581
Panel C: With controls				
Total migrants per 1000	0.002 (0.014)	−0.028 (0.042)		
H2A migrants per 1000			−0.007 (0.013)	−0.099 (0.067)
H2B migrants per 1000			−0.057 (0.043)	−0.367*** (0.110)
1st stage F	13.47	31.80	8.97, 2.09	13.89, 18.05
Observations	1,361	1,581	1,361	1,581

Note: The table presents the results from the instrumental variable regressions with the shift-share instrument. Standard errors are reported in parentheses. The first panel presents the results from the regressions in which the full set of controls are included, and the second panel presents the results in which all controls other than immigration controls are included, and in the bottom panel, the full set of controls is included. Significance levels:*p<0.1; **p<0.05; ***p<0.01

Chapter 2: Charitable Giving in Wartime: Evidence from Donations during Russia's Invasion of Ukraine

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

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Abstract

We analyze how military events, casualties, and media coverage influence same-day donations to a major Ukrainian nonprofit supporting the military during Russia's invasion of Ukraine. In a unique setting, we exploit random variation in attacks on civilians across time to estimate that one additional civilian fatality causes between \$4,860 and \$6,992 in same-day donations, and leads to at least \$15,550 in cumulative donations. Disentangling the effects of events and media coverage, we estimate that a 1% increase in media mentions of military activity leads to a \$2,584 increase in same day donations and an \$8,121 increase in cumulative donations.

JEL: D64; D74; H41

Keywords: Charitable giving; conflict; public goods

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1 Introduction

Most studies of charitable giving focus either on responses to singular crises, such as natural disasters, or on long-term support for specific causes. Far less is known about giving in wartime, when donations fund a pure public good - national defense - on a large scale. Rather than aiming to rebuild physical and community conditions to their previous state, wartime giving to a defense effort represents a long-term investment to achieve victory in a conflict, often without a clear or certain route to success. This type of giving operates within the uncertainty of war, where timelines are undefined, outcomes are unpredictable, and the strategy for achieving objectives may be changing from day to day. The unique nature of this setting raises fundamental questions about conditions under which individuals continue to donate in the face of ongoing conflict and uncertainty.

Our study examines this unique form of grassroots giving in the context of Russia's full-scale invasion of Ukraine on February 24, 2022, addressing a significant gap in the existing research on wartime charitable giving. Our purpose is to document and explain the unprecedented surge in individual donations to national defense during a full-scale invasion by a neighboring country.

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

Unprecedented levels of foreign aid and charitable donations to Ukrainian causes from abroad and from its own citizens were part of the response. Ukraine also rose sharply on the Charities Aid Foundation's World Giving Index, moving from 102nd in 2013 to 2nd in 2023 (Charities Aid Foundation, 2013, 2023).

We study this groundswell of support by focusing on giving to the largest Ukrainian non-profit organization providing *lethal* aid - Come Back Alive (CBA) - and examining direct individual donations to the Ukrainian military, channelled through CBA.[1] For CBA, charitable giving between the start of the full-scale invasion and December 2023 has totalled 10 billion Ukrainian hryvnia (UAH) (Come Back Alive, 2025), on the order of 0.24% of Ukraine's annual GDP. We analyze these donations in conjunction with detailed information on the timing and type of Russian attacks,such as

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

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

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

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

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

We uncover several key findings. First, we find that civilian casualties increase donations. A 1% increase in civilian casualties increases daily donations by 0.25-0.36% daily, and cumulatively by 0.8%. Air strikes and attacks on hospitals are the classes of events that have the largest impact on giving. The effect of all military mentions appear to be larger than the effect of civilian casualties, with a 1% increase in military mentions lead to the 0.46% same-day increase in the amount donated and to 1.5% cumulatively. Second, mentions of frontline attacks, violence against civilians and missile attacks all increase daily donations. Finally, our impulse response functions show that the effects of casualties and mentions linger for several days, peaking on the day following the event.

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

Our paper is structured as follow. Section 2 discusses the related literature. Section 3 provides the historical background, details on CBA, and highlights factors that make this setting unique. Section 4 describes the data sources and the variables we construct. Section 5 lays out the empirical estimation. Section 6 reports the results: in Subsection 6.1 we focus on *events* and document that casualties are positively associated with the donation amounts. Subsection 6.2 documents that giving follows a repeated pattern of spikes after an event, followed by an immediate decline. Subsection 6.3 focuses on the *media* coverage of various military events and Subsection 6.4 describes additional results. We present additional results and robustness checks in Supplemental Appendices.

2 Related Literature

Charitable giving to specific causes is a central focus of the economics of philanthropy and public goods, which explains donations as arising from preferences for others' well-being, personal satisfaction, or both. Altruism, the desire to improve the welfare of others, is often a primary motivation for giving (Andreoni, 1989, 1990). Other factors include social norms, peer pressure, and the psychological rewards of giving, such as the "warm glow" effect (Harbaugh, 1998). Emotional appeals also play a powerful role; for example; individuals are more likely to donate when they feel empathy or a personal connection to identifiable beneficiaries rather than abstract causes (Andreoni, 2014; Echazu and Nocetti, 2015).

Beyond specific causes, charitable giving also focuses on giving in the aftermath of singular events, such as natural disasters. Donations may be driven by empathy and altruism (Adena and Harke, 2022; Black et al., 2021) but can also include self-interested motivations, such as restoring stability in affected regions. Disaster-related giving helps mitigate short-term economic losses, enabling victims to recover and contribute to broader economic stability (Deryugina and Marx, 2021). Donations can also yield tangible returns, such as rebuilding infrastructure and improving economic activity beyond pre-disaster levels (Deryugina and Marx, 2021; Jayaraman, Kaiser and

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

Charitable giving during wartime differs fundamentally from disaster-related giving. Unlike disaster relief, which typically involves a one-time surge of donations aimed at restoring a community to its pre-crisis state, wartime giving supports an ongoing public good: the military. Both the afflicted and the donors may benefit from this support, albeit for different reasons. Donations are not tied to a discrete recovery period but require a sustained flow over an indeterminate timeline, as the end of the conflict and its resolution remain uncertain. This presents a unique scenario that extends beyond traditional models of charitable giving, necessitating further exploration.

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

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

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

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

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

3 Background

3.1 Historical Context and Origins of the Volunteer Movement

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

Several classes of organizations that coordinate aid to Ukraine have appeared. Some are run by the Ukrainian government (such as United24), some are non-governmental and based in Ukraine (such as Come Back Alive, Prytula Foundation and Syla Hromad), and some non-governmental organizations (such as Razom and Nova Ukraine) are based outside of Ukraine. There is also a robust system of small fundraisers initiated by individuals and operated via Monobank, a Ukrainian bank. Between February 2022 and March 2024 users donated almost 50 billion UAH (approx. $1.25 billion) using this mechanism (Gorokhovskiy, 2024). Thus, donors can donate to a variety of organizations - governmental and nongovernmental, those based in Ukraine or those based abroad, and there is significant heterogeneity in the kinds of aid (lethal military, non-lethal military, tactical medicine, civilian medicine, civilian support, rehabilitation, support for refugees and internally displaced persons, and others) the organizations provide.

3.2 Come Back Alive Foundation

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

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

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

3.3 Donation Behavior and Setting: Crowdfunding the State

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

1. Decentralized: while there are periodic fundraising campaigns by CBA, donations are "bottom-up" - large numbers of individuals making relatively small contributions;

2. Non-governmental: not coordinated or mandated by the state, and bypassing the usual governmental channels in both raising funds and spending them;

3. Unlike other wartime fundraising campaigns (such as war bonds campaigns in the World Wars), these donations have no return on investment and there is no single national fundraising campaign;

4. Numerous, repeated, and large-scale (approximately 3,900,000 donations totaling to approximately $385 million, from 2014 onward, as of October 2024), at a relatively constant frequency over the course of at least two and a half years;

5. Not targeted: individuals generally cannot direct their donations to any specific initiative or use. While there are some specific campaigns advertised by the CBA (examples include a

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

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

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

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

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

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

4 Data Sources

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

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

4.1 Donations: Come Back Alive Foundation

All of CBA's donations, procurements, and disbursements are available on its website. We use all individual-level donations spanning from February 24, 2022, and December 31, 2023. The full record of donations on the CBA website includes over 3 million unique donations as of the end of 2023, but 95% of all donations were made after the full-scale invasion, highlighting the significant surge in public support during the war. We observe information about the amount donated, the original currency, the timestamp of the donation, and the bank that processed the donation as well as all large fundraiser launches or other important events.[4] We convert the contemporaneous donation amounts to 2010 Ukrainian hryvnia (the base year used by the State Statistics Service of Ukraine) to filter out exchange rate fluctuations and facilitate comparisons with GDP figures.

4.2 Military Events: Violent Incident Information from News Articles

Our second source, the Violent Incident Information from News Articles database (Zhukov and Ayers, 2023) is an event-based dataset that classifies media reports from Ukrainian and Russian media into standard conflict categories using machine learning. The data come mostly from Ukrainian news sources (such as *Espreso*, a privately owned TV channel, *Ukrainska Pravda*, an influential news site, and others), Ukrainian news wire services (such as *Unian*), Russian pro-Kremlin news sources (such as *Komsomols'kaya Pravda*, a newspaper, *RIA Novosti*, a news site, and *NTV*, a news channel), and Russian-language sites located outside of Russia (such as *Meduza*, an opposition news site located in Latvia). The VIINA dataset disaggregates the events into a number of categories - missile attacks, artillery shelling, attacks on hospitals, and others. We use this dataset as our source for information on military "events." VIINA is also our source for the data on Ukrainian civilian fatalities.

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

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

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

Next, we extract the events that are related to Ukraine (i.e., in which at least one of the actors involved in the event is from Ukraine). We use the Google BigQuery platform to extract data from the GDELT Event Database and Mentions Table. First, we extract all events from January 1, 2016, to December 31, 2023, where at least one of the actors involved is from Ukraine. Second, we extract all mentions of these events. [5] We then aggregate the data on the daily level and create a variable (*all mentions*) that represents the total number of Ukraine-related media mentions on a given day, which we then use in constructing other variables.

GDELT data enables us to categorize mentions by mention source. This allows us to separate the Ukraine-related mentions by a type of media. In particular, we create a variable *all Ukrainian mentions*, which includes only mentions by the Ukrainian media sources (those that have a ".ua" domain name or one of the manually selected Ukrainian websites that do not have a ".ua" domain name, but are in the top-100 sources in our dataset). Given that the majority of donations in our dataset are made by Ukrainian donors, our analysis primarily focuses on the media mentions of different types of events from Ukrainian sources and all variables based on the mentions only include mentions by Ukrainian media, unless explicitly specified otherwise.

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

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

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

5 Empirical Strategy

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

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

For $\log(\text{Donations})_t$ we focus on the total amount donated rather than the total number of donations (results for the number of individual donations are in Supplemental Appendix E). The emphasis on the intensive margin is driven by the fact that the total amount donated is what is crucial in terms of supporting CBA's efforts in funding the war. And, from a charity's perspective, securing donors who can adjust their contributions based on day-to-day needs is more efficient than constantly seeking new donors. $\log(\text{Civilian Casualties}_t)$ represents the logarithm of civilian casualties reported on day t, and X_t is a column vector that captures war-related events or media mentions.

The term Z_t is a vector of controls. As CBA sometimes carries out targeted fundraising campaigns, we control for whether there was a fundraiser launch or other important event on a given day by constructing *Come Back Alive events*, an indicator variable. We include information on all national holidays in Ukraine; although all public holidays were canceled because of the invasion, research shows that altruism may increase during the holidays (Ekström, 2018), and as such we take into account regular holidays (even if they are not technically holidays during wartime). Finally, we control for the daily count of globally reported events as recorded by GDELT, a linear time trend in donation behavior, as well as fixed effects for year, month, and day of the week, which control for broader temporal patterns. The error term ε_t captures idiosyncratic shocks.

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

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

5.1 Variation Sources: Attack Randomness and Munition Imprecision

The patterns of Russian attacks on Ukrainian civilians are *partially* random. While substantial evidence indicates that Russian forces deliberately target civilian areas, there is also clear evidence of indiscriminate attacks. Even in targeted strikes, randomness plays a decisive role in determining the actual number of casualties. The extent of this randomness is crucial for our identification strategy: even if civilian casualties are, in part, the outcome of deliberate targeting, the *number* of casualties on any given day has a significant random component. We discuss both the random and the nonrandom component in turn.

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

On the other hand, however, there is also extensive evidence of truly random, indiscriminate attacks on civilians.[7] Beyond this evidence, there are additional channels that drive the randomness of attacks. First, even if the Russian forces were planning a (non-random) attack on civilians, and if such attacks were predictable by Ukrainian civilians, needless to say, individuals would take every possible measure to avoid being in the target area. There is, therefore, a motive to randomize the time and place of an attack, even if the intent to attack is not random in itself. Second, and perhaps more importantly, conditional on a strike at a particular location, the *number* of civilian fatalities is random - it is not known (even by the attacking side, with few exceptions), nor is it predetermined in advance. Conditional on being present at the site of an attack (and because we focus on *civilian* casualties, who can be killed in their own homes or in public spaces), the number

[6] Amnesty International (2024), BBC News (2025), Reuters (2023), United Nations News (2022), Euronews (2023)
[7] Amnesty International (2022), U.S. Mission to the OSCE (2024), The New York Times (2024), Applebaum (2022)

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

Third, the location of an attack resulting in civilian casualties may itself be random. One is the imprecision of Russian artillery, bombs, drones, and missiles. Even Russia's guided missiles have notable targeting limitations; for example, the Kh-55 cruise missile, frequently used against Ukrainian infrastructure, has a circular error probable of up to 100 meters - meaning half of the missiles will miss their intended target by at least that margin. As a result, even when aimed at military or nonresidential targets, these projectiles frequently miss, leading to civilian casualties.

Fourth, the precision and location of Russian strikes are modulated by the effectiveness of Ukrainian air-defense and counter-battery fire. Ukrainian air defense units have become adept at intercepting certain kinds of munitions; and while they are a lot less able to intercept more sophisticated ballistic and cruise missile attacks, they have achieved considerable success against even the most advanced Russian weapons. The location, as well as the effectiveness of many of these air defense units, is itself random, as some are composed of mobile truck-mounted weapons systems; if such a unit damages a Russian drone or a missile in flight, the projectile might deviate from its course and crash at a random location.

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

5.2 Vector Autoregressive Model

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

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

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

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

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

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

6 Results

We estimate how events during Russia's invasion of Ukraine, and the coverage of those events in the media, affect total donations to the Ukrainian military in our sample. Our primary specification uses the natural logarithm of the daily sum of donations. The log of sums is a stationary process where spikes in the data do not appear to be associated with large rocket or drone attacks or events associated with particularly large Ukrainian civilian casualties. Beyond the overall effects of events and media mentions we ask more specific questions regarding, the nature of the events (e.g. air alerts versus missile strikes) and what type of coverage (e.g. mentions of the events on the frontline vs mentions of violence against civilians) affects donations.

6.1 Finding One: Casualties Drive Donations

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

Tables 1 and 2 present our first finding: casualties drive donations. From Table 1 we observe that a 1% increase in the civilian casualties (≈ 0.2881 casualties) leads to 0.25% - 0.36% increase in the same day donation amount (or $\approx$ \$1,400 – \$2,015 in February 2025 terms),[8] depending on the specification. Thus, one additional civilian fatality translates into between \$4,860 and \$6,992 in *same-day* donations.

This result is supported by the findings of the SVAR models in Table 2 in which we observe that a 1% increase in civilian casualties leads to roughly 0.8% (\$4,480 in 2025 terms) increase in the *cumulative* donation amount; in more readily interpretable terms, this implies that one more civilian fatality translates into cumulative donations of over \$15,550 in 2025 terms. This effect holds throughout all specifications in which casualties are included. The rise in donations in response to civilian casualties may be driven by empathy and solidarity with the victims, a drive to help, as well as a drive to prevent further casualties by donating to a military cause.

Relating these amounts to what CBA reports it purchases, the cost of one drone (a disposable one-way weapon used heavily - by the millions - by both sides) at the beginning of 2025 varied between \$1,800 and \$4,000. Thus, same-day donations in response to one more civilian casualty are enough to purchase roughly two to four drones, and cumulative donations are enough to purchase as many as eight or nine.

We also find that other military-related events are positively associated with the donation amount, though the magnitude of their effects is smaller than the effect of civilian casualties. As different types of military events are correlated with each other, they are included in the regressions one at a time. For instance, a 1% increase in the number of air alerts, Russian air strikes in Ukraine or Russian attacks on Ukrainian hospitals increase same-day donations by 0.06%, 0.13% and 0.11% respectively. In addition, an additional media report mentioning sanctions against Russia leads to

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

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

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.363***	0.254***	0.351***	0.274***	0.313***
	(0.082)	(0.079)	(0.082)	(0.088)	(0.082)
Sanctions		0.025***			
		(0.004)			
Log air alert in Ukraine			0.064*		
			(0.038)		
Log air strike in Ukraine by Russia				0.134***	
				(0.043)	
Log hospital attack in Ukraine by Russia					0.110***
					(0.035)
R2	0.595	0.615	0.596	0.602	0.601
N	676	676	676	676	676
	Panel B: Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.298***	0.327***	0.326***	0.358***	0.294***
	(0.075)	(0.079)	(0.079)	(0.081)	(0.075)
Log Ukrainian military mentions	0.461***				
	(0.102)				
Log civilian violence mentions		0.110***			
		(0.033)			
Log missile mentions			0.110***		
			(0.032)		
Log deescalation mentions				0.116***	
				(0.044)	
Log frontline mentions					0.449***
					(0.091)
R2	0.610	0.601	0.601	0.598	0.613
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

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

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

	Panel A: Events			
	(1)	(2)	(3)	(4)
Log military mentions	1.447***	1.523***	1.455***	1.433***
	(0.329)	(0.322)	(0.324)	(0.321)
Log civilian casualties	0.803***			
	(0.219)			
Log air alert in Ukraine		0.164*		
		(0.094)		
Log air strike in Ukraine by Russia			0.378***	
			(0.111)	
Log hospital attack in Ukraine by Russia				0.315**
				(0.091)

	Panel B: Mentions			
	(1)	(2)	(3)	(4)
Log civilian casualties	0.846***	0.852***	0.833***	0.803***
	(0.220)	(0.220)	(0.213)	(0.218)
Log civilian violence mentions	0.341***			
	(0.099)			
Log missile mentions		0.332***		
		(0.098)		
Log deescalation mentions			0.338**	
			(0.147)	
Log frontline mentions				1.339***
				(0.297)

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

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

6.1.1 Robustness with High-Dimensional Controls

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

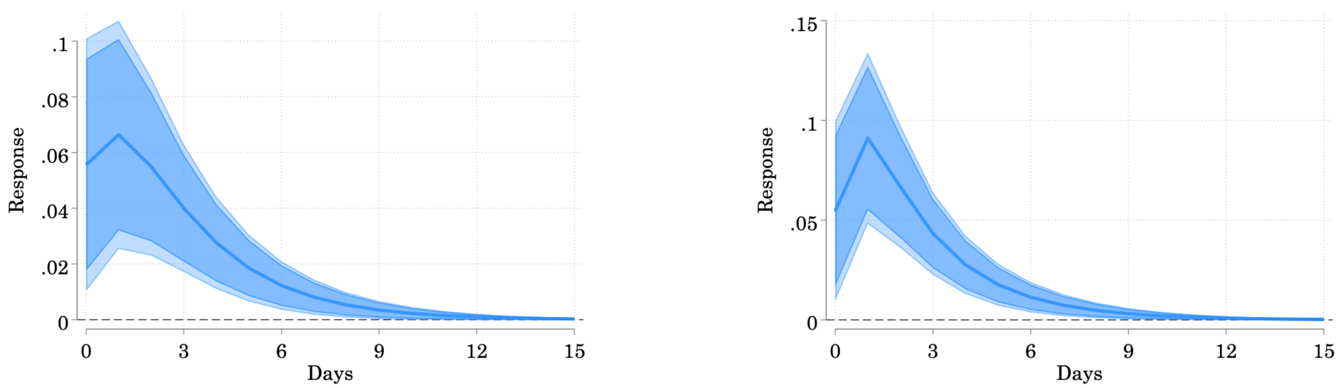
Table 3: Double machine learning for high-dimensional controls of donated amount

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

Note: The dependent variable is the logarithm of the daily total donated amount. Robust standard errors in parentheses, and p-values in brackets. Each panel estimates the ATE and standard errors of the effect of log civilian causalities, or log military mentions, on log donated amount. Column labels denote the method used to estimate the nuisance functions. Controls include 279 variables of 3rd order polynomial terms and their interactions of time covariates and other controls, as well as fixed effects for day, day of the week, week, month, year, holidays, CBA events, and total world events.

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

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



(a) Log civilian casualties

(b) Log military mentions

Figure 1: Orthogonalized IRF of donated amount

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

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

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

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

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

attributed to the fact that most of the CBA funds are allocated to military units on the frontline, with only a small portion directed towards air defense units countering missile attacks.

Table 2 shows the cumulative response to the military mentions from the SVAR models. From Panel (A) we can observe that the effect of military mentions has a high and statistically significant event even when different events are controlled for. Overall, the cumulative effect of a 1% increase in military mentions is a 1.4%-1.5% increase ($\approx$ \$8122) in the amount donated. Looking at Panel (B), we conclude that the cumulative effect of the frontline mentions remains higher than that of other types of mentions: a 1% increase in frontline mentions leads to a 1.34% cumulative increase in the amount donated. A 1% increase in mentions of violence against civilians, missile attacks and deescalation each leads to 0.33% - 0.34% cumulative increase in the amount donated.

6.4 Additional Results

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

7 Conclusion

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

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

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Supplemental Appendices

A Theoretical Discussion

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

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

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

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

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

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

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

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

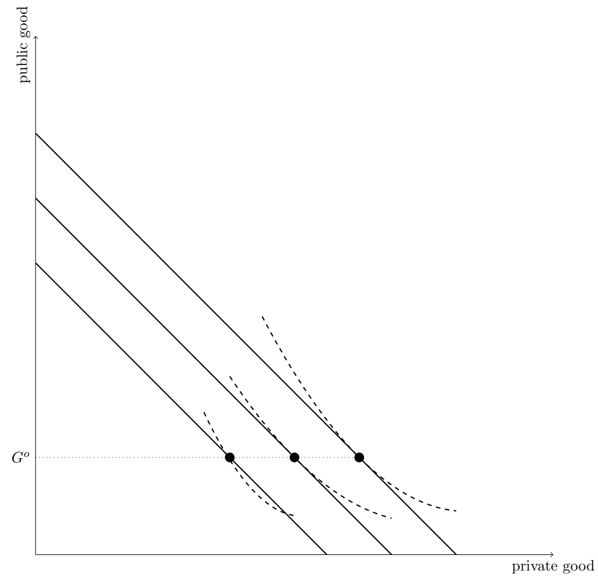


Figure A.2: An equilibrium with three individuals and two donors post-full-scale war

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

However, after the onset of the full-scale invasion, we instead observe a point like G^* as depicted in A.3, where $i) G^* > G^o, ii)$ the number of donors rises to three, and $iii)$ more individuals donate. Figure A.3 suggests that preferences - if they are to be stable - are not homothetic. Furthermore, with unchanging preferences, this figure, reflecting the first two points above, implies that national defense is an inferior, and possibly even Giffen, good, which is at odds with the standard interpretation, and does not seem to be the case in our setting.[11]

We posit that the explanation, within the context of a standard model of choice with a private and a public good, is a sharp change in preferences.[12] While such an explanation may often be vacuous, this appears to be the only explanation that accounts for all of the features of the situation we discuss; indeed, perhaps war is one of the few instances where preferences do, in fact, change dramatically; indeed, if any situation is likely to lead to a change in preferences it is wartime, and learning about civilian casualties. Figure B.3 depicts a situation where, in equilibrium, if not globally, the marginal rates of substitution change. If we allow for the utility depend on the *type*

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

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

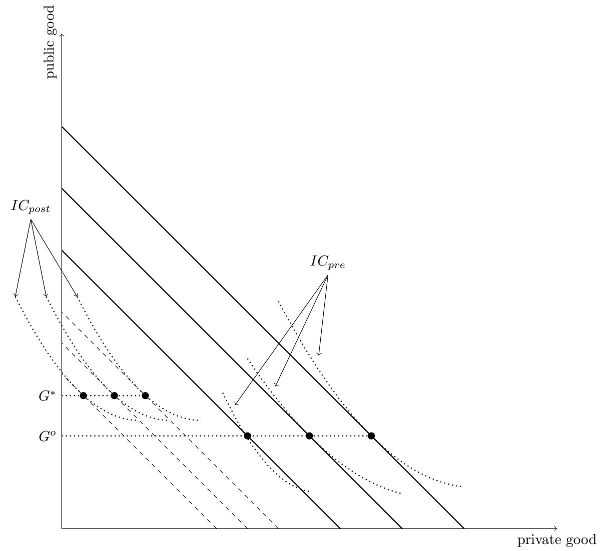


Figure A.3: An equilibrium with three donors

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

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

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

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

Furthermore, one might suppose that preferences changed in a way so as to require a minimum level of consumption of the public good, with the reasoning that there needs to be a minimum level of defense provided by society that, therefore, enables other consumption - for example, that one's household is not destroyed or occupied. At least for a classic example of such preference specification (Stone-Geary preferences: non-homothetic preferences with a minimum consumption level), this does not appear to be the case, because this class of preferences also implies a linear expenditure function, which, again, appears to be violated in our setting.

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

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

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

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

and

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

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

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

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

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

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

B Summary Statistics

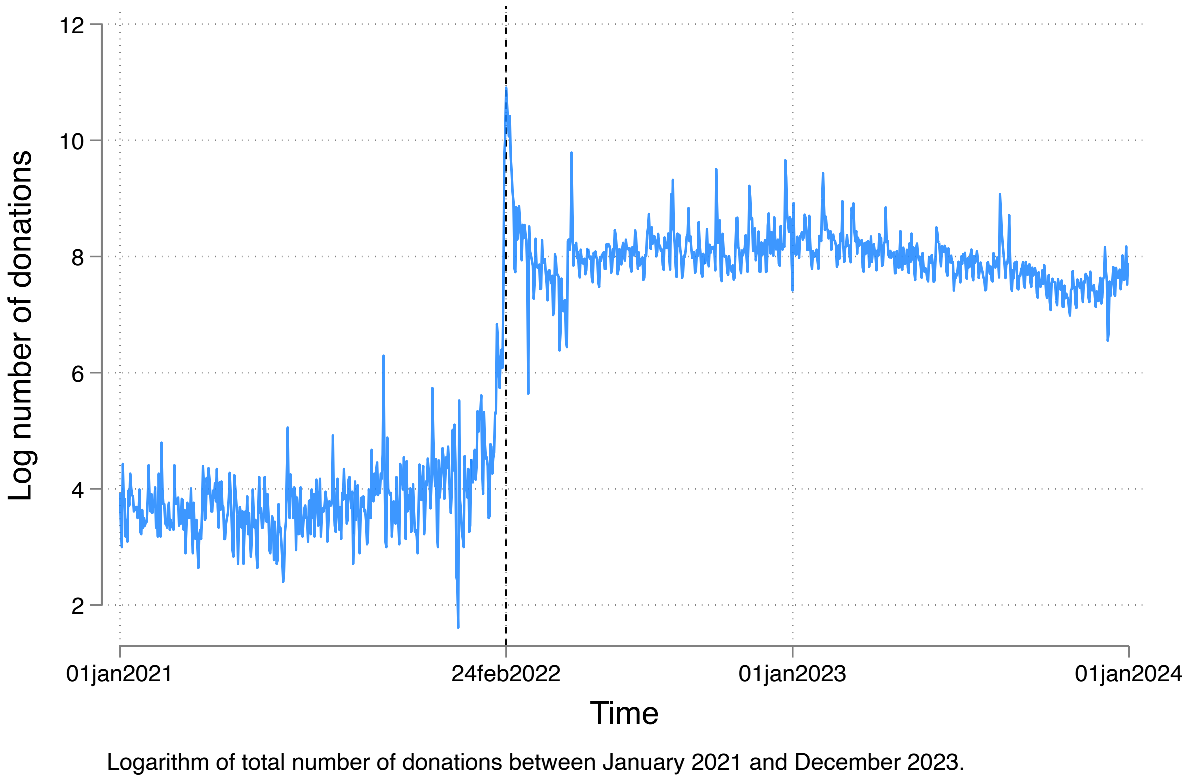


Figure B.1: Logarithm of number of donations over time

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

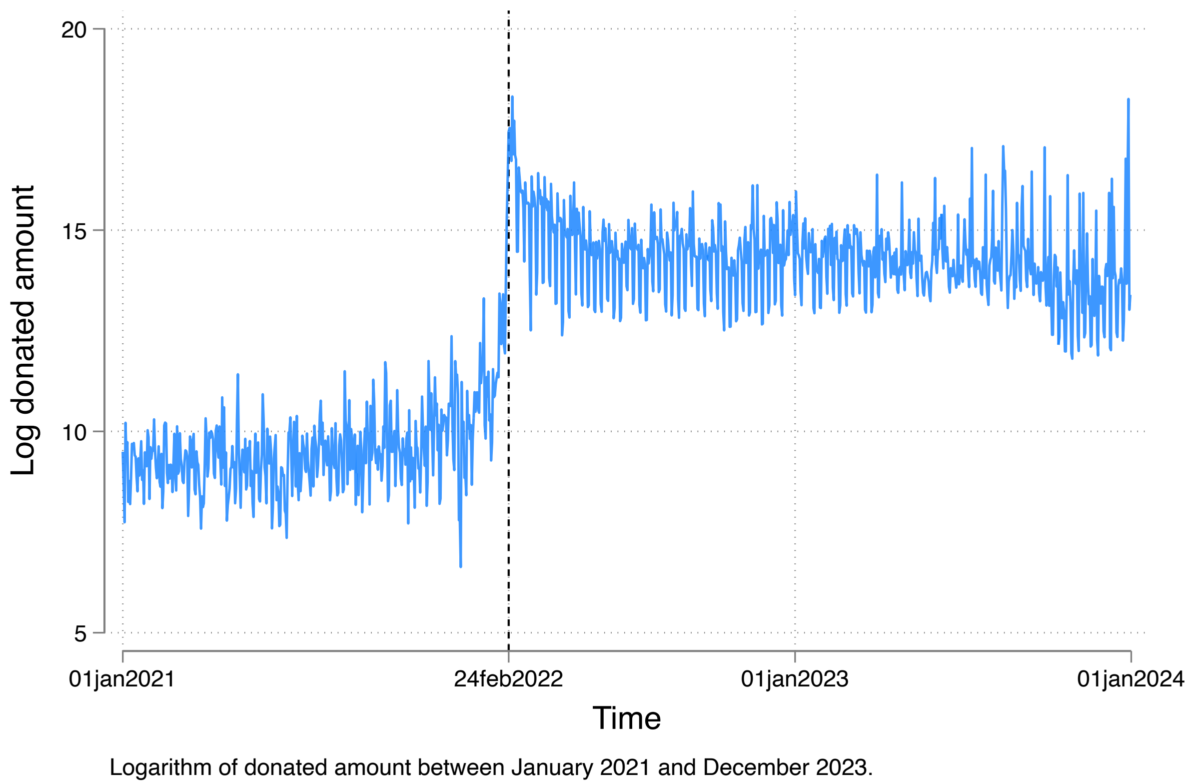


Figure B.2: Logarithm of the amount donated over time

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

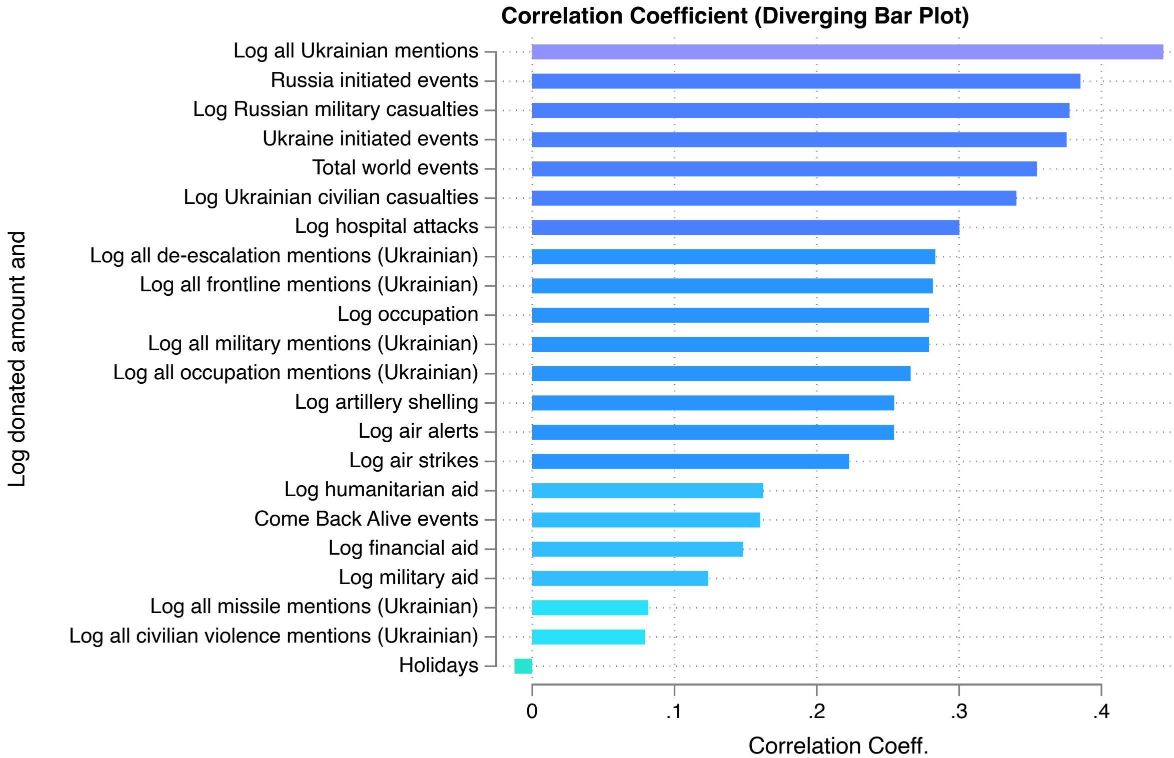


Figure B.3: Correlations between the total daily donated amounts and key variables

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

Table B.1: Summary statistics

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

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

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

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

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

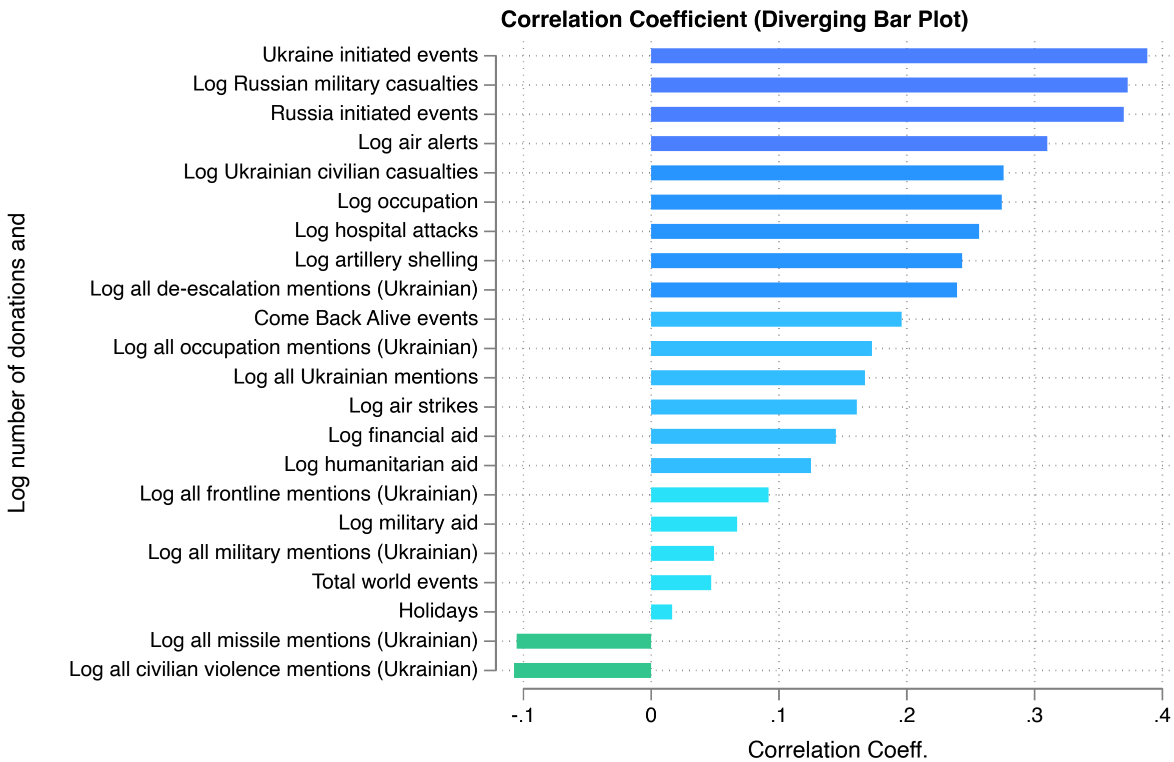
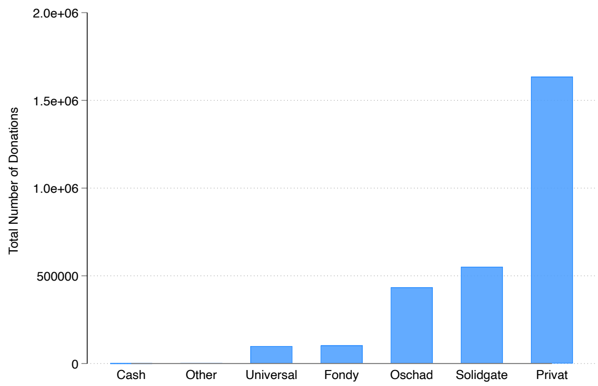
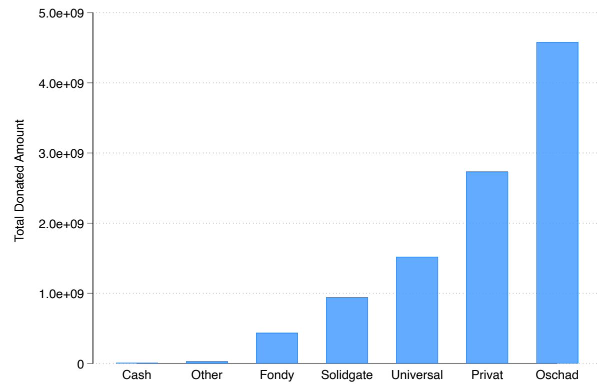


Figure B.4: Correlations between the total daily number of donations and key variables

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



(a) Number of donations



(b) Donated amounts

Figure B.5: Donations by the source

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

C Further Analysis: OLS Estimates

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

	Log donated amount			
	(1)	(2)	(3)	(4)
Log art. shelling	0.002			
	(0.077)			
Log occupation		0.040		
		(0.030)		
Log tank battles			0.054*	
			(0.028)	
Log territory control claim				-0.007
				(0.041)
R2	0.595	0.596	0.597	0.595
N	676	676	676	676
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

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

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

	(1) *Log donated amount*
Log civilian casualties	0.219**
	(0.085)
Log Ukrainian military mentions	0.386***
	(0.108)
Log air alert in Ukraine	-0.012
	(0.040)
Log air strike in Ukraine by Russia	0.087**
	(0.044)
Log art. shelling	-0.160*
	(0.084)
Log hospital attack in Ukraine by Russia	0.058*
	(0.034)
Log occupation	0.013
	(0.032)
Sanctions	0.022***
	(0.004)
Log tank battles	0.066**
	(0.027)
Log territory control claim	-0.048
	(0.046)
R2	0.631
N	675
Month FE	Yes
Year FE	Yes
Controls	Yes

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

Table C.3: The effect of bad and good events

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

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

Table C.4: The crowding out effect of international aid

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

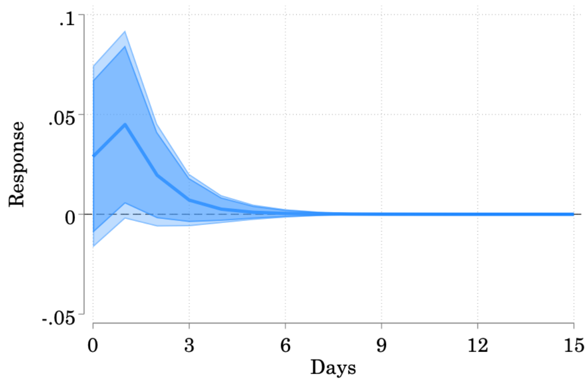
Note: The dependent variable is the logarithm of the total daily donated amount. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include a count for world events, a binary variable for Come Back Alive donation events, day-of-week fixed effects, month and year fixed effects, and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

Table C.5: The effect of conscription announcements.

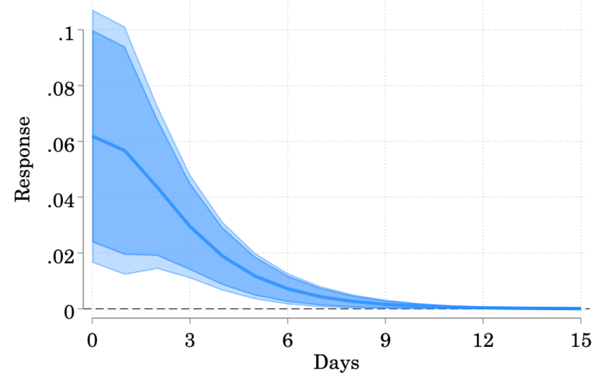
	Log donated amount			
	(1)	(2)	(3)	(4)
Conscription	-0.078	-0.049	-0.030	-0.121
	(0.265)	(0.272)	(0.234)	(0.265)
Log Ukrainian military mentions		0.564***		
		(0.122)		
Log civilian casualties			0.362***	
			(0.082)	
Log Russian military casualties				0.203***
				(0.051)
R2	0.570	0.594	0.595	0.584
N	676	675	676	676
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

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

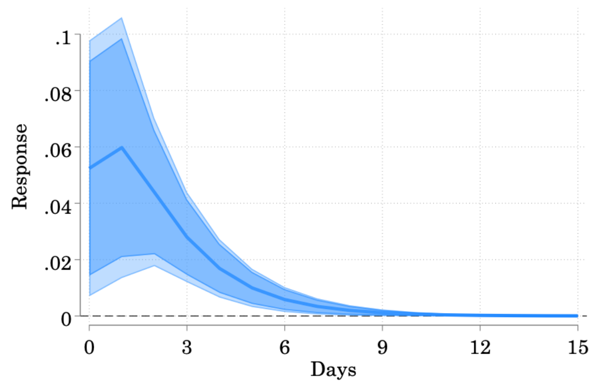
D Further Analysis: VAR



(a) Log air alert in Ukraine



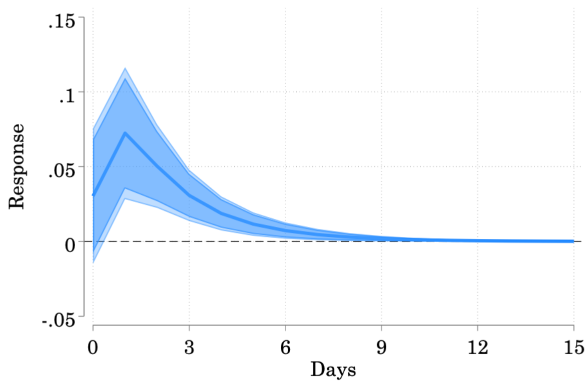
(b) Log air strike in Ukraine by Russia



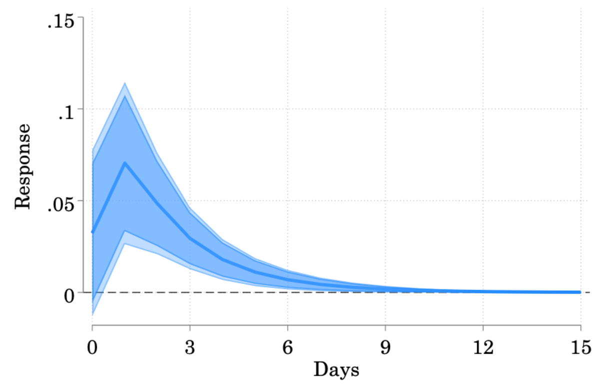
(c) Log hospital attack in Ukraine by Russia

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

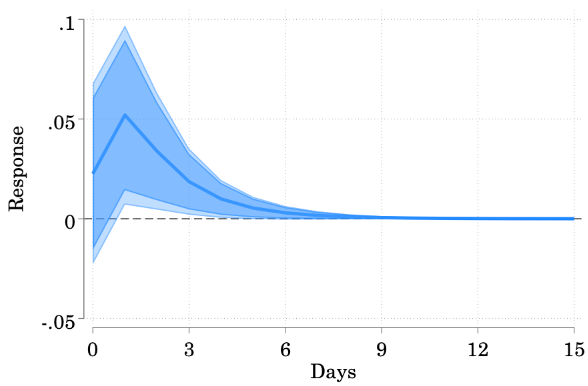
Note: The dependent variable is the logarithm of the daily total donated amount. The figure presents orthogonalized impulse response functions (IRFs) estimating the impact of various conflict-related events on donations. Subfigure (a) shows the IRF for the logarithm of air alerts in Ukraine, Subfigure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



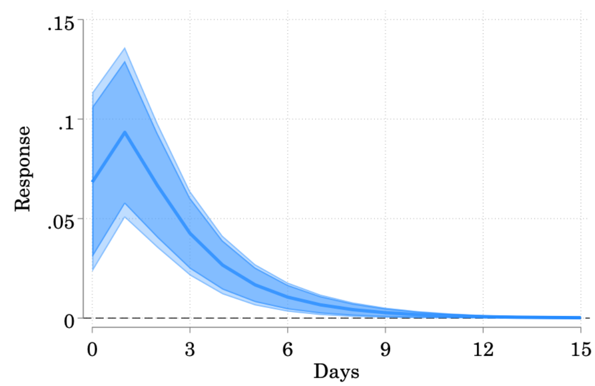
(a) Log civilian violence mentions



(b) Log missile mentions



(c) Log deescalation mentions



(d) Log frontline mentions

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

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

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

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

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

E Analysis for Number of Donations

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

	Log donated transactions			
	(1)	(2)	(3)	(4)
	lasso-lasso	lasso-ridge	ridge-lasso	ridge- ridge
Log civilian casualties	0.12	0.05	0.12	0.05
	(0.02)	(0.02)	(0.02)	(0.03)
	[0.0]	[0.02]	[0.0]	[0.07]
Log military mentions	0.15	0.03	0.13	0.0
	(0.02)	(0.03)	(0.02)	(0.04)
	[0]	[0.47]	[0]	[0.95]

Note: Robust standard errors in parentheses. P-values in brackets. Each panel estimates the ATE and standard errors of the effect of log civilian causalities, or log military mentions on log donated transactions. Column labels denote the method used to estimate the nuisance functions. Controls include 279 variables of 3rd order polynomial terms and their interactions of time covariates and other controls, as well as fixed effects for day, day of the week, week, month, year, holidays, CBA events, and total world events.

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

	Panel A: Events				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.091**	0.021	0.084**	0.078**	0.085**
	(0.039)	(0.034)	(0.039)	(0.038)	(0.039)
Sanctions		0.016***			
		(0.003)			
Log air alert in Ukraine			0.041**		
			(0.021)		
Log air strike in Ukraine by Russia				0.020	
				(0.021)	
Log hospital attack in Ukraine by Russia					0.015
					(0.021)
R2	0.436	0.471	0.438	0.436	0.435
N	676	676	676	676	676
	Panel B: Mentions				
	(1)	(2)	(3)	(4)	(5)
Log civilian casualties	0.093**	0.099**	0.099**	0.089**	0.084**
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Log Ukrainian military mentions	-0.007				
	(0.056)				
Log civilian violence mentions		-0.022			
		(0.019)			
Log missile mentions			-0.023		
			(0.019)		
Log deescalation mentions				0.070**	
				(0.028)	
Log frontline mentions					0.053
					(0.053)
R2	0.435	0.436	0.436	0.440	0.436
N	675	675	675	675	675
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

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

Table E.3: Estimated cumulative impulse responses of number of donations to events and mentions

	Panel A: Events			
	(1)	(2)	(3)	(4)
Log military mentions	-0.217	-0.212	-0.215	-0.204
	(0.252)	(0.253)	(0.252)	(0.251)
Log civilian casualties	0.030			
	(0.167)			
Log air alert in Ukraine		0.086		
		(0.073)		
Log air strike in Ukraine by Russia			0.008	
			(0.086)	
Log hospital attack in Ukraine by Russia				-0.008
				(0.071)
	Panel B: Mentions			
	(1)	(2)	(3)	(4)
Log civilian casualties	0.019	0.019	0.019	0.031
	(0.168)	(0.168)	(0.164)	(0.165)
Log civilian violence mentions	-0.051			
	(0.077)			
Log missile mentions		-0.058		
		(0.076)		
Log deescalation mentions			0.275**	
			(0.116)	
Log frontline mentions				-0.130
				(0.227)

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

Chapter 3: The effect of war on academic achievement: Evidence from Ukraine

The short-run effect of war on academic achievement: Evidence from Ukraine*

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Abstract

In this paper, I test whether exposure to war can affect the short-run academic performance of secondary school students, using the case study of Ukrainian students in the aftermath of the 2022 Russian full-scale invasion of Ukraine. Employing the data from the international PISA assessment, I apply the difference-in-difference approach. I show that the performance of Ukrainian students has deteriorated compared to that of students in the peer countries due to the Russian invasion, while cheating is unaffected.

1 Introduction

Educational attainment is a fundamental driver of economic development, human capital formation, and the overall prosperity of nations. Even short-term disruptions in education can profoundly affect children's future outcomes (Di Pietro, 2018; Lu et al., 2023; Özek, 2023).

In wartime, education faces unique and severe challenges: children are often unable to attend school in person, and even when they do, their learning is frequently hindered by factors such as sleep deprivation from night-time missile attacks, interruptions from air raid alerts during the school day, and mental health challenges stemming from war exposure. The Russian full-scale invasion of Ukraine in 2022 has introduced all of these challenges. In many regions, in-person schooling has been suspended due to security risks, while in relatively safer areas, air raid alerts regularly disrupt lessons, forcing students to seek shelter and pause learning. Furthermore, the mental health impact of the war creates additional barriers, affecting students' ability to concentrate and engage fully in their studies.

*I want to thank Guglielmo Barone, Annalisa Loviglio, and seminar participants at the University of Bologna for their comments that helped to improve this work. This project was partially funded by *La Fondazione Konrad Adenauer Italia*. The funding provider did not influence the study's design, data collection, analysis, interpretation, or presentation of the results.

In this paper, I examine the short-run impact of the war on academic achievement in Ukraine by analyzing changes in Ukraine's PISA results in Reading and Science [1] relative to peer countries, employing a difference-in-differences approach. I apply propensity score weighting to improve comparability between treated and control students. Additionally, I conduct a further robustness check to confirm that the results are not influenced by variations in levels of academic cheating.

I find that Ukrainian students' performance in Reading and Science has substantially worsened due to the war compared to the peer countries. Specifically, I find that the performance in Reading of Ukrainian students has decreased by 22.8 points (0.22 SD) more than that of the peer countries between 2018 and 2022, and the performance in Science by 8.8 points (0.08 SD). I argue that the main reasons for these declines are the school closures due to the war and the mental health toll on students, whereas the direct war-related events, such as missile attacks and air raid alerts play a smaller role, possibly due to adaptation.

This paper contributes to the literature in several ways. Firstly, while many other papers focus on the effects of natural disasters on academic performance, very few papers examine the effects of war, which has a lot more dimensions through which it could affect academic performance. Secondly, the studies that do examine the effects of war (Ichino and Winter-Ebmer, 2004; Swee, 2015) do so in a historical context, whereas my research examines a modern setting, where access to technology and remote learning could have mitigated the negative effects. Finally, while the existing studies focus on the long-run effects of the war, I analyze the immediate short-run effects on academic performance during the war. This study is also relevant from a policy perspective. It allows policymakers to quantify the immediate negative effects of war on academic achievement and provides suggestive evidence of which factors could be the most important in contributing to the decline in academic performance during war.

The rest of this paper is structured as follows: section 2 explores the relevant literature, section 3 provides background information on the educational system in Ukraine and how it was affected by the war and COVID-19, section 4 outlines the empirical strategy, section 5 discusses data sources, section 6 provides some descriptive statistics, section 7 presents the results, section 8 provides robustness checks while section 9 concludes.

2 Literature review

Several strands of literature are relevant to my research. The closest line of research is the one that looks at the long-run effects of war on educational attainment. While there are not that many papers in this area, two prominent examples include Ichino and Winter-Ebmer (2004) and Swee (2015). Ichino and Winter-Ebmer (2004) look at the long-run effect of World War II on the cohorts of Austrian and German children who were 10 years old during the war.

[1] The Maths section of the PISA is excluded from the analysis due to the potential confounders, see more information in section 4.

They find that these children have received less education than the comparable cohorts of children who have not been exposed to war, and their lifetime earnings were also decreased. Swee (2015) looks at the effect of the war in Bosnia and Herzegovina on educational attainment and finds that exposure to the higher war intensity led to lower educational attainment in the long run.

More recently, the literature has focused on the impact of the COVID-19 pandemic and the lockdowns that were enacted due to the pandemic. This strand of literature is less directly relevant to this paper, as the pandemic is different from war in many aspects. Nevertheless, it is worth briefly summarizing its main findings. Living through a pandemic may be stressful for students, affecting their academic performance, while the lockdowns limit their access to education.

For instance, both meta-analyses by König and Frey (2022) and Betthäuser et al. (2023) agree that COVID-19 school closures have negatively affected the students' education with younger students, students from low-income backgrounds and students from middle-income countries (as compared to students from high-income countries) being affected the most. At the same time, some studies find no negative effect of COVID-19 lockdowns on educational outcomes (Förster et al., 2023), especially when it comes to younger students who have not experienced a long lockdown (Birkelund and Karlson, 2023).

Finally, several papers explore the effect of large-scale stressful events, such as natural disasters. For instance, Di Pietro (2018) shows that the L'Aquila earthquake in Italy has negatively impacted students' performance in a local university. Similarly, Lu et al. (2023) finds that students who have experienced the Wenchuan earthquake in China performed worse on the exams, with students who were exposed to the earthquake for longer having the worst results. Özek (2023) looks at the indirect effect of natural disasters on academic performance. Hurricane Maria has resulted in a large inflow of migrants, many of whom enrolled in schools in Florida, resulting in overcrowding and a decrease in the performance of the existing students. At the same time, allocating additional resources to education mitigated a large part of such negative effects.

As most of the research focuses on how COVID-19 or natural disasters affect academic achievement, it is important to address why that research differs from this paper. Firstly, war may influence educational outcomes through many more channels as compared to COVID-19 or natural disasters: there could be a direct disruption of learning from the inability to attend school in person, difficulty in concentrating due to the psychological effect, a disruption to the education and sleep due to the missile attacks and air alerts, physical destruction of schools, and in some cases even direct physical trauma of students, that could prevent them from studying.

Secondly, the research on COVID-19 and natural disasters shows the effects of relatively short-term or medium-term negative events: natural disasters such as earthquakes or hurricanes last only a few days. While the lockdown lasted longer: depending on the country from weeks to months, it was nowhere as long as the wars could last. The extended length of exposure to the negative effects may compound them, but on the other hand, may also give the students time to adapt to the new circumstances, leading to a decrease in the negative impact on academic achievement.

The previous literature that does look into the effect of war on academic achievement (e.g. Ichino and Winter-Ebmer (2004), Swee (2015)) mostly focuses on the long-run impact of war on education - how the war exposure in the past has affected the long-run learning and career trajectories of people who have been children during the war. However, less research is dedicated to the immediate impact of the war on educational attainment while the war is still ongoing. Studying such short-run effects is important, however. Even the short-run exposure to war and short-run negative effects may result in long-run negative consequences: even if only one cohort of students is exposed to war and thus performs worse at school, making it more difficult for them to get admitted to the university and affecting the whole career trajectory of tens of thousands people.

3 Background

3.1 Educational system in Ukraine

Compulsory education in Ukraine begins at six when children start attending primary school. The students must attend primary school for four years and secondary school for another five years. After that, the students (normally aged 15 at the time) face a choice between continuing to high school, which lasts for another 2 years, applying to attend a professional education institution, or quitting the educational system altogether. The students who graduate from either high school (normally at the age of 17) or professional school can then apply to university.

3.2 COVID-19

After the start of the COVID-19 pandemic in March 2020, Ukraine, like many other countries around the world has declared a lockdown, which, in addition to other measures, closed down the schools and introduced remote learning. The remote learning continued until the end of the 2019-20 academic year. Later the government introduced the so-called 'adaptive lockdown' where the measures differed in different regions depending on the spread of the COVID-19 infection. The region's color changed if certain indicators of the spread of COVID-19 were above a certain threshold. In the "green" zone the educational institutions continued to work as normal, with students attending the schools in person. Educational institutions could operate normally in the "yellow" or "orange" zones; however, local authorities could implement additional measures to curb the spread of infection. These measures included reducing students' time on campus by moving certain subjects, such as Art or Physical Education, to remote learning. The "red" zone meant that all educational institutions had to close and learning continued remotely (Sirbu et al., 2020). The "adaptive lockdown" continued during the 2020-21 and 2021-22 academic years until the Russian full-scale invasion on February 24th, 2022.

At the beginning of the COVID-19 lockdown, most Ukrainian schools had no experience in remote teaching. The quality of remote education also varied depending on the school: while some schools introduced online lessons via video conferencing platforms, others assigned students homework to study independently. The lack of access to the internet and electronic devices also contributed to difficulties in learning. For instance, a survey of parents, whose children went to school during the lockdown revealed that 53% of parents from rural areas said that their children lacked devices necessary to attend online lessons, while 47% of all parents said that lack of reliable internet connection posed an issue (DIF, 2021).

3.3 Russian invasion

After the Russian invasion of Ukraine on February 24th, 2022 all schools switched to remote learning - in some regions it was simply impossible to attend schools due to the fighting or occupation, while in others many schools served as shelters for refugees. The experience of remote education acquired during the COVID-19 pandemic made the shift to remote learning smoother. Yet, by the start of the 2022-23 academic year, many schools have reopened for in-person learning: as of the end of August 2022 43% of schools worked remotely, 25% offered in-person learning, while 32% worked in a mixed format. The share of schools offering in-person learning has somewhat increased by the end of the 2022-23 academic year and as of May 2023 29% of schools were fully remote, 35% worked in a mixed format and 37% offered in-person learning (MESU, 2023). Several factors determine whether the school works remotely or in person during war. Firstly, schools in the regions that are occupied or too close to the frontline cannot provide in-person learning as it is too dangerous. As of May 2023, according to the Ukrainian Ministry of Education and Science, 894 schools were located on the occupied territories (MESU, 2023). Secondly, some schools, even in the regions that are located relatively far from the frontline, have been ruined due to the Russian missile attacks or shelling. As of the end of July 2023, 190 schools were destroyed completely and 1619 were damaged. In addition, during a state of war, schools are only allowed to operate in person if there is a bomb shelter located in or near a school, which would enable students to stay safe during the missile attack. As of September 2022, only 64% of schools had a bomb shelter (Trach, 2022), but by November 2023 this figure increased to 87% (Informator.UA, 2023).

In addition to forcing many students to switch to remote learning, the war introduced numerous other challenges to the educational process. Firstly, due to the frequent air alerts, children miss many hours of learning. When the air alert starts during the schooldays, the education is stopped and all children and teachers must proceed to the bomb shelter, losing hours of education. In addition, air alerts often happen at night, meaning that the students' sleep is interrupted and they may be less capable of studying the next day. Overall, between February 24th, 2022, and July 2024 there have been between 505 and 4698 air alerts depending on region, which lasted between 23 days and 11 hours and 823 days and 10 hours in total (alerts.in.ua, 2025). Secondly, for many children, the war affected their mental health, which in turn made it harder for them to learn. A survey of mothers of minor children, conducted in January-February 2023 showed that 13% of mothers said their children required psychological help (Rating, 2023). At the same time, the real number of children who require psychological help may be much higher, as the mental health stigma is widespread in Ukraine, meaning that mothers may be reluctant to admit that their children need help. Many children were also forced to move from their native region due to the war. They either had to study remotely or adapt to a new school, in addition to the stress of adapting to a new environment, which could also hurt their education. In the 2022-23 academic year 164.7 thousand internally displaced children were receiving education (MESU, 2023).

4 Empirical strategy

I analyze how the performance of Ukrainian students in the PISA exam has changed between 2018 and 2022 compared to the students in the peer countries. To do so, I use the following difference-in-difference specification 1.

$$pisa\_score_{ijt} = \alpha_1 + \beta_1 Ukraine\_22 + \beta_2 X_{it} + \vartheta_t + \gamma_j + \epsilon_{it} \tag{1}$$

The dependent variable is a plausible score in Reading or Science for student i in country j at time t. I only focus on the results in Reading and Science. This is due to the fact that the year 2020 was announced as a year of Maths in Ukraine and mathematical education was heavily emphasized. Since this happened between the two waves of PISA and this confounder occurs at the same level as treatment (country-level), it may significantly affect the results. I follow Zamarro et al. (2019) and OECD (2024) to run the regressions with each plausible value as a dependent variable separately and then aggregate the results using Rubin's rule for multiple imputation (Rubin, 1987). The main variable of interest is $Ukraine\_2022$, which is an interaction variable between Ukraine and the year 2022. This variable represents how much more the PISA results in Ukraine changed in between 2018 and 2022, as compared to peer countries. Variable ϑ_t is a year-fixed effect. γ_j is a country fixed effect.

The control variables (vector X_{it}) include gender, region, an indicator of whether the student lives in an urban area, type of school, parents' education, COVID-19 school closures, economic and social status of student's family, index of home possessions, and the number of teachers per students. The standard errors are clustered by country.

Other countries considered here are Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania.

4.1 Ukraine vs peer countries comparison

Table 1 compares the PISA scores and other educational and economic characteristics in Ukraine and the peer countries selected for the cross-country analysis as of 2018 (the year of the first PISA wave in Ukraine). The peer countries include Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania. [2] The indicators of interest here are average scores in PISA Reading and Science assessments, GDP growth in 2018, GDP per capita (in international dollars, adjusted for PPP) in 2018, Gini coefficient in 2018, government expenditures on education in 2018 (as % of GDP), the level of unemployment in 2018 and the average number of days the students who took PISA exam in 2022 experienced due to the COVID-19 pandemic.

In 2018, Ukraine's average PISA scores in Reading and Science were nearly identical to those of peer countries, with differences of less than 3 points (where the global average in each subject is 500, with a standard deviation of 100). The difference in scores between Ukraine and peer countries is insignificant in Science, while in Reading it is statistically significant at a 10% significance level, yet still very small.

In 2018, educational expenditure in Ukraine was slightly higher (and statistically significant) as a percentage of GDP compared to peer countries (5.3% vs. 4.3% on average). However, this difference may be attributed to Ukraine's significantly lower GDP than peer countries (12,708 vs. 28,803 international USD PPP). Other economic variables also indicate that the economic situation in Ukraine was worse than in peer countries, with unemployment being 1.5 percentage points higher than the average of the peer countries and GDP growth being 0.9 percentage points lower. Students who took PISA in 2022 in Ukraine on average were exposed to 104 days of school closures due to COVID-19, while the peer countries had an average of 115 days of school closures due to COVID-19 - a difference of 11 school days.

[2] These countries were selected due to being located in the same geographic region, having a similar institutional background and similar PISA scores to Ukraine in 2018. These countries share a broadly comparable institutional background due to their historical development trajectories and education governance structures. Most of them, like Ukraine, underwent significant transformations from centrally planned to market-oriented systems in the early 1990s, influencing how their respective governments fund and regulate education. They tend to exhibit similar approaches to curriculum design, teacher training, and school administration—often shaped by the Bologna Process and European Union–aligned reforms. Additionally, their economic contexts are relatively alike, with lower-to-mid income levels compared to Western Europe and persistent regional disparities in school resources. This parallel evolution of educational institutions and policy frameworks thus makes them an appropriate comparison group for Ukraine.

Table 1: PISA scores and other key indicators in Ukraine and peer countries

indicator	Ukraine	Peer countries	p-value
PISA Reading score (avg.)	467.201	464.532	0.062
PISA Science score (avg.)	468.819	467.563	0.359
GDP growth 2018	3.488	4.365	0
GDP per capita 2018	12,708.800	28,803.060	0
Gini 2018	26.100	32.087	0
Educational expenditure (as % of GDP)	5.320	4.277	0
Unemployment rate 2018	8.799	6.359	0
COVID-19 school closures	104.028	115.081	0

Note: The table compares PISA scores and other key indicators. Peer countries include Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania. For peer countries, the average value across all countries is given. The third column shows the p-value that represents whether the difference in value of the indicators is statistically significant between Ukraine and peer countries.

5 Data

My main data source is the Programme for International Student Assessment (PISA). PISA is an international test administered to 15-year-old students around the world to compare the educational attainments between countries and study the correlates of educational attainment within the countries (OECD, 2022). The test includes sections on Math, Science, and Reading comprehension (in a student's native language). In addition to the test itself, both students, who take the test, and their school representatives fill out a comprehensive questionnaire about their school and home life. The PISA assessments are organized by the OECD, and the data is freely available on the OECD website.

Each section of the PISA (Science, Math, and Reading) is graded separately. In addition, not all students receive the same questions, so it is impossible to compare their performance directly. Thus, to account for measurement error instead of assigning a single value that indicates a student's performance, each student's performance in each subject is given by a set of ten plausible values, that are generated via multiple imputation. Plausible values are used to improve population-level accuracy by creating multiple imputed ability scores per student, accounting for measurement error and the fact that students answer different subsets of questions, thus representing a range of potential outcomes for a given student.

PISA exams took place in Ukraine twice: in 2018 and 2022. The exam in 2022 had to be postponed to October, as due to the war it was impossible to conduct it earlier in the year, as planned originally. In addition, due to security concerns, the 2022 PISA only took place in 18 (out of 27) regions of Ukraine.[3]

[3]For comparability of the samples, I only use the PISA scores from the same 18 regions

To compare the performance of Ukrainian students to those in other peer countries, I also use the data on the PISA exams in Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, Lithuania. In all these countries, PISA was also conducted in 2018 and 2022. These countries were selected due to their average combination most closely resembling the Ukrainian PISA scores (more on this in Section 4.1).

The variables from PISA data that are of interest include plausible values in Science and Reading, student age, gender, type of school, region, economic and social status, whether their parents received higher education, number of days the school was closed due to COVID-19, number of teachers per student at school, and index of home possessions.

6 Descriptive statistics

Table 2 shows the summary statistics of all of the variables of interest from PISA data. These variables include PISA plausible values in Reading and Science, as well as the control variables that are used in the regressions. Both observations from 2018 and 2022 are included in the sample. The sample consists of Ukraine and peer countries (Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania).

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for 2018 as well.

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Reading PV 1	155,794	460.493	101.887	47.645	870.888
Reading PV 2	155,794	460.505	102.072	72.909	849.947
Reading PV 3	155,794	460.499	101.968	85.798	850.737
Reading PV 4	155,794	460.757	101.679	56.420	873.065
Reading PV 5	155,794	460.628	101.894	81.415	844.829
Reading PV 6	155,794	460.468	101.656	49.525	873.895
Reading PV 7	155,794	460.703	102.027	5.817	875.924
Reading PV 8	155,794	460.331	101.753	52.941	857.479
Reading PV 9	155,794	460.639	101.827	69.560	819.120
Reading PV 10	155,794	460.621	101.813	82.590	839.653
Science PV 1	155,794	467.405	98.943	58.736	870.721
Science PV 2	155,794	467.395	98.807	81.152	823.956
Science PV 3	155,794	467.409	98.814	101.282	868.504
Science PV 4	155,794	467.488	98.733	80.158	871.092
Science PV 5	155,794	467.731	98.889	121.988	868.597
Science PV 6	155,794	467.358	98.677	79.109	909.091
Science PV 7	155,794	467.611	98.609	101.932	880.216
Science PV 8	155,794	467.481	98.874	87.867	891.394
Science PV 9	155,794	467.716	99.111	64.461	840.847
Science PV 10	155,794	467.258	98.838	84.243	859.259
COVID-19 school closures	152,080	58.431	90.524	0	1,000
Econo-Social status	152,839	−0.148	0.910	−7.752	5.374
Female, share	155,794	0.495	0.500	0	1
Home possession index	153,930	−0.227	0.913	−9.100	10.405
Mother higher education, share	151,709	0.520	0.500	0	1
Father higher education, share	148,682	0.476	0.499	0	1
Student-teacher ratio	147,912	12.251	4.798	1.000	100.000
Urban, share	155,794	0.040	0.196	0	1
Private school, share	153,315	0.010	0.101	0	1

Figures 1 and 2 show the average PISA scores in Reading and Science respectively by country and year. The highest scores in both Reading and Science(in both years) are observed in Estonia, Poland, and Czechia, while Moldova, Bulgaria, and Montenegro have the lowest scores. Ukraine had the 8th highest average PISA result in Reading (out of 13 countries considered here) and the 8th highest average PISA score in Science in 2022.

Figure 1: Average PISA scores in Reading, by country and year

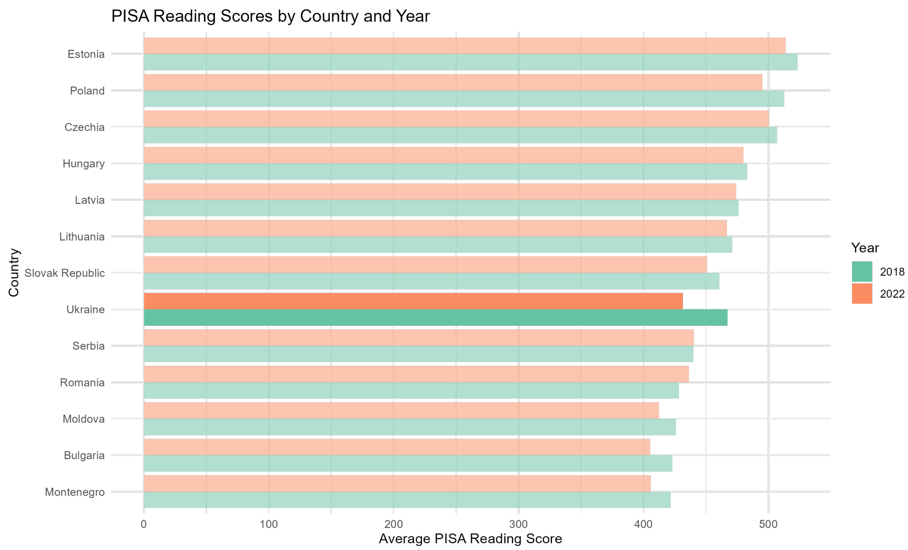
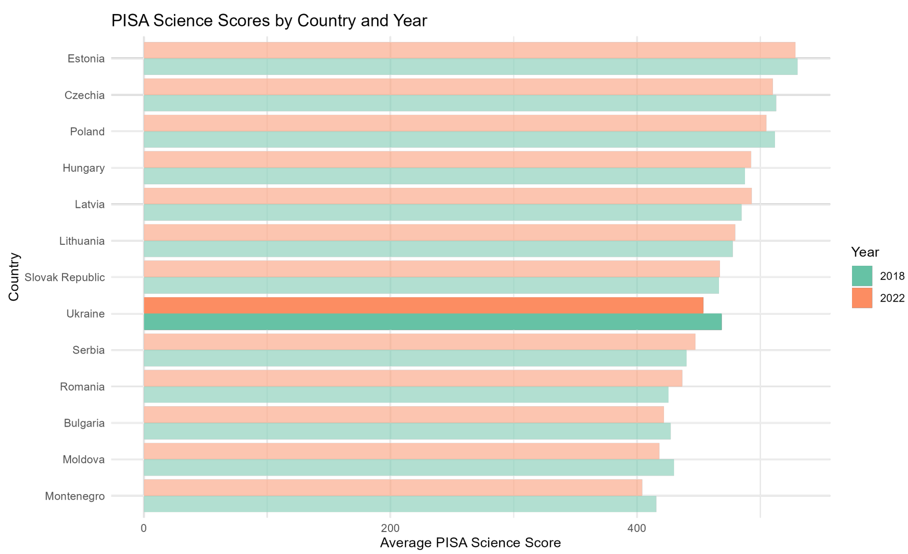


Figure 2: Average PISA scores in Science, by country and year



7 Results

Table 3 shows the result from the difference-in-difference cross-country regression in which "Ukraine" identifies whether the given student is from Ukraine (vs peer countries), "Year:2022" indicates whether the observation is from the year 2022 or 2018 and "Ukraine:2022" is an interaction variable between "Ukraine" and "Year:2022". Panel A presents results from the specification with no controls, Panel B includes only country-fixed effects, while Panel C includes a full set of controls. For the most part, unless stated otherwise, I will focus on discussing results from Panel C, as the specifications without controls or Country FE may lead to biased results.

Overall, in all countries, results declined both in Reading and, to a lesser extent in Science as indicated by the negative coefficient for "Year:2022". This drop may be attributed to the COVID-19 pandemic and the subsequent school closures.

The main variable of interest is the interaction between "Ukraine" and "Year:2022" as it indicates how the PISA results in Ukraine changed between 2018 and 2022 relative to the peer countries. The results suggest that the scores in Reading and Science have decreased in Ukraine more than in other countries: by 22.8 points in Reading and by 8.8 points in Science. To put these declines in perspective, the global average of Reading results in 2022 was 482 points, while in Science it was 491, with a standard deviation of 100. Thus the decrease in Reading represents 0.22 standard deviation and the reduction in Science equals 0.08 standard deviation.

Table 3: Difference-in-difference results

Panel A: No controls		
	Reading	Science
Ukraine	2.670	1.256
	(10.562)	(11.331)
Year:2022	-6.482^{***}	0.465
	(2.134)	(1.991)
Ukraine:2022	-29.080^{***}	-15.487^{***}
	(2.223)	(2.379)
Num. obs.	155794	155794
R squared	0.003	0.001
Controls	No	No
Country FE	No	No
Panel B: Only country FE		
	Reading	Science
Year:2022	-7.461^{***}	-0.535
	(2.258)	(2.184)
Ukraine:2022	-28.102^{***}	-14.488^{***}
	(2.341)	(2.548)
Num. obs.	155794	155794
R squared	0.117	0.141
Controls	No	No
Country FE	Yes	Yes
Panel C: With controls		
	Reading	Science
Year:2022	-12.220^{***}	-6.450^{*}
	(3.422)	(3.317)
Ukraine:2022	-22.780^{***}	-8.812^{***}
	(2.053)	(2.452)
Num. obs.	139148	139148
R squared	0.271	0.276
Controls	Yes	Yes
Country FE	Yes	Yes

Note: The regressions are first estimated for each of the plausible scores individually and then aggregated. The control variables include gender, region, an indicator of whether the student lives in an urban area, type of school, parents' education, COVID-19 school closures, economic and social status of the student's family, index of home possessions, and the number of teachers per student. The standard errors are clustered by country. The "Not Ukraine" category includes Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania. Panel A presents results from the specification with no controls, Panel B includes only country-fixed effects, while Panel C includes a full set of controls. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

7.1 Discussion and potential mechanisms

It is difficult to definitively say what mechanisms are the most responsible for driving these results, as the war has affected multiple dimensions of students' lives. Nevertheless, there is some suggestive evidence of which factors are more or less at play, which I will discuss in this section.

First of all, surprisingly, the prevalence of air alerts and missile attacks has no significant negative effects on the students' academic performance (the results are available upon request).[4] There are several possible explanations for that: students could have adapted to the constant air alerts at night and stopped reacting to air alerts by going to a shelter, thus by the time of the PISA exam air alerts could not have significantly affected their sleeping schedule. In fact, Van Dijcke et al. (2023) find that the average reaction to air alerts attenuates significantly by September 2022, suggesting that many Ukrainians stopped reacting to air alerts, thus it is plausible that it stopped affecting the students' sleep as much.

Instead, the data shows that school closures due to war seem to play a greater role. Since the Russian invasion of Ukraine in February 2022 the educational system has transferred to remote learning until the end of the 2021/22 academic year. While some schools reopened for in-person attendance in September 2022, others, which did not have a bomb shelter, continued remote learning. In fact, on average, controlling for the same control variables as in the original specification, I can observe that the average number of days a school was closed due to non-COVID reasons increased by 47 days more between 2018 and 2022 in Ukraine as compared to peer countries. It also seems that on average, the PISA results of students from schools that had more days in which the school was closed, had worse scores in PISA, regardless of whether these closures were due to COVID or not. Other research has also shown the important role school closures play in deteriorating student's learning outcomes during the COVID pandemic (König and Frey, 2022; Betthäuser et al., 2023).

Another possible mechanism that could impact the academic performance is the effect of the war on mental health of the Ukrainian students. While there is no detailed information on students' mental health, we can observe that the life satisfaction of Ukrainian students has decreased by 4.5 more points (on a 10 points scale) than that of students in the peer countries between 2018 and 2022 (controlling for the same factors).

Therefore, while it is difficult to make definitive conclusions regarding which mechanisms play the greatest role in the deterioration of academic performance, suggestive evidence points to the conclusion that school closures and mental health issues play the greatest role.

[4] As a reminder, the PISA examination did not take place in the frontline regions, that are most heavily affected by war. Therefore, the relationship between exposure to missile attacks and academic performance may be different there. Nevertheless, relatively safer regions still suffer both from air alerts and missile attacks. For instance, between February 24th, 2022, and April 2025 the relatively safer regions experienced between 637 and 4507 hours of air alerts (alerts.in.ua, 2025).

8 Robustness checks

8.1 Propensity score weights

To account for potential endogeneity and selection issues (e.g. the peer countries having different characteristics compared to Ukraine) I use propensity score weights.

I use the same set of controls used in the regression to estimate the propensity score (how likely a given individual is to be "treated"), where the treatment is being in Ukraine. The inverse probability weights are generated, so the covariates are balanced equally between the "treated" and "control" groups.

Table 4 displays the balance in the covariates between Ukraine and peer countries. The first column provides the name of the variable, the second column states its type, and the third column displays the difference in means for adjusted (weighted) treatment and control group (Ukraine and peer countries respectively).[5]

Table 4 results show that after the adjustment (weighting) the average values of all of the covariates become very close between the treated group (Ukraine) and the control group (peer countries).

[5]Due to the fact that recent literature is advising against relying on p-values or other significance tests when judging whether the covariates are well-balanced, as the p-values and hypothesis testing are misleading due to the fluctuating sample during the adjustment process (e.g. see Ho et al. (2007); Ali et al. (2014); Linden (2014); Imai et al. (2008) among others), I only report summary statistics here.

Table 4: Balance of the covariates

	Diff.Adj
Propensity score	0.128
COVID closures	0.448
COVID closures (NAs)	-0.025
Econ. soc. status	-0.306
Econ. soc status (NAs)	-0.002
Female	-0.082
Home possessions	-0.336
Home possessions (NAs)	-0.003
Mother high edu	0.012
Mother high edu (NAs)	-0.002
Father high edu	0.052
Father high edu (NAs)	0.012
Teachers per student	0.766
Teachers per student (NA)	-0.020
Urban	0.039
Private school	-0.010
Private school (NAs)	-0.016

Note: The second column shows the average difference between the values of variables in Ukraine and in peer countries after applying propensity score weights. For variables with the (NAs), the difference between the share of missing values in Ukrainian and peer countries subsample is shown.

Table 5 shows the results of the same regressions as in Table 3, but with propensity score weights. The results stay very similar to the original results, with Ukrainian results in Reading decreasing by 25.5 more points between 2018 and 2022 than in other countries and the Science scores decreased by 13.2 more points.

Table 5: Difference-in-difference results with propensity score weights

Panel A: No controls		
	Reading	Science
Ukraine	-35.309^{***}	-31.646^{***}
	(10.631)	(11.408)
Year:2022	-6.468^{***}	0.421
	(2.155)	(2.005)
Ukraine:2022	-51.524^{***}	-35.166^{***}
	(3.172)	(4.346)
Num. obs.	155794	155794
R squared	0.143	0.090
Controls	No	No
Country FE	No	No
Panel B: Only country FE		
	Reading	Science
Year:2022	-7.410^{***}	-0.539
	(2.257)	(2.180)
Ukraine:2022	-50.582^{***}	-34.205^{***}
	(3.242)	(4.425)
Num. obs.	155794	155794
R squared	0.196	0.163
Controls	No	No
Country FE	Yes	Yes
Panel C: With controls		
	Reading	Science
Year:2022	-7.394^{**}	-4.365
	(3.553)	(4.402)
Ukraine:2022	-25.502^{***}	-13.217^{*}
	(7.971)	(7.544)
Num. obs.	139148	139148
R squared	0.333	0.277
Controls	Yes	Yes
Country FE	Yes	Yes

Note: The regressions are first estimated for each plausible score individually and then aggregated. The control variables include gender, region, an indicator of whether the student lives in an urban area, type of school, parents' education, COVID-19 school closures, economic and social status of the student's family, index of home possessions, and the number of teachers per student. The standard errors are clustered by the country "Not Ukraine" category includes Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania. Panel A presents results from the specification with no controls, Panel B includes only country-fixed effects, while Panel C includes a full set of controls. Significance levels:$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

8.2 Cheating

One potential concern regarding the validity of the results is whether the students who took the exams had been cheating and if so, whether this cheating was significantly higher or lower in Ukraine than in the peer countries. To determine whether this is the case, I create a proxy for cheating and use it as the dependent variable in the same specifications as in equation 1 but at the school level.

As a proxy for cheating, I use the Jensen-Shannon Divergence (JSD) measure which represents the difference between each school's grade distribution for a specific subject and the overall distribution for that subject for a given year. Jensen-Shannon divergence has been widely used to detect fraud, dishonesty, and abnormalities in various contexts, such as credit card fraud (Toledo et al., 2022). While it is impossible to tell with certainty whether any individual student has cheated, if the distribution of scores within a school is narrow and skewed upwards compared to other schools, this could provide some suggestive evidence of academic dishonesty. This indicator takes values between 0 and 1, where 0 indicates that the grade distribution within a given school is identical to the overall distribution, while 1 indicates that the distribution is completely different from the general distribution.

The results (Table 6) suggest that cheating is not correlated with exposure to war, thus I can conclude that cheating does not affect the results.

Table 6: Cheating results

Panel A: No controls		
	Reading	Science
Ukraine	-0.005^{*}	-0.005^{**}
	(0.002)	(0.002)
Year:2022	0.002	0.002
	(0.002)	(0.001)
Ukraine:2022	0.001	0.000
	(0.002)	(0.002)
Num. obs.	6186	6186
R squared	0.046	0.047
Controls	No	No
Country FE	No	No
Panel B: Only country FE		
	Reading	Science
Year:2022	0.001	0.002
	(0.001)	(0.001)
Ukraine:2022	0.001	0.001
	(0.002)	(0.002)
Num. obs.	6186	6186
R squared	0.046	0.047
Controls	No	No
Country FE	Yes	Yes
Panel C: With controls		
	Reading	Science
Year:2022	-0.009^{***}	-0.008^{**}
	(0.003)	(0.003)
Ukraine:2022	-0.003	-0.003
	(0.003)	(0.003)
Num. obs.	5750	5750
R squared	0.119	0.119
Controls	Yes	Yes
Country FE	Yes	Yes

Note: The regressions are first estimated for each plausible score individually and then aggregated. The control variables include gender, region, an indicator of whether the student lives in an urban area, type of school, parents' education, COVID-19 school closures, economic and social status of the student's family, index of home possessions, and the number of teachers per student. The standard errors are clustered by country. The "Not Ukraine" category includes Moldova, Slovak Republic, Poland, Romania, Latvia, Serbia, Montenegro, Czechia, Hungary, Bulgaria, Estonia, and Lithuania. Panel A presents results from the specification with no controls, Panel B includes only country-fixed effects, while Panel C includes a full set of controls. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

9 Conclusion

In conclusion, this study provides compelling evidence that the Russian invasion of Ukraine in 2022 has significantly undermined Ukrainian students' short-run academic performance in Reading and Science, when compared to students in peer countries. By employing a difference-in-differences approach on PISA data from 2018 and 2022, the analysis demonstrates that the adverse effects of conflict—namely the disruption of in-person schooling, the frequency of air alerts, and the toll on mental well-being—collectively led to a substantial deterioration in test scores. Additionally, there is no indication that such an observed decline can be attributed to differential cheating practices across regions, reinforcing the robustness of the main findings.

These results suggest that even relatively short episodes of war, marked by displacement, nighttime missile attacks, and psychological stress, can carry measurable and immediate ramifications for students' academic outcomes. Notably, the drop in Reading scores appears more pronounced, indicating that literacy-related skills might be particularly sensitive to systemic shocks and learning interruptions—whether through remote schooling difficulties, interrupted lesson plans, or constrained access to learning materials. The findings contribute to a broader body of literature on how crises—ranging from natural disasters to pandemics—affect learning trajectories. Yet, unlike shorter-term disruptions such as school closures during COVID-19, a protracted conflict introduces a more complex set of stressors, exacerbating educational losses over time and potentially widening gaps relative to neighboring countries.

From a policy perspective, these results hold considerable relevance. First, policymakers in Ukraine and in the international community should prioritize the continuity of quality education, be it through consistent and better-structured remote platforms or by ensuring that physical school sites are outfitted with adequate bomb shelters and resources. Psychological and emotional support services for students need to be strengthened, as the war's mental health impact likely compounds academic difficulties. School administrators might also incorporate targeted interventions—such as additional reading-focused sessions and small-group tutoring—to address specific learning losses in Reading and to mitigate cumulative gaps in Science. Crucially, the experiences of countries and regions with successful post-disaster educational recovery offer models for Ukraine, underscoring the importance of flexible, context-specific policies that blend in-person instruction (when safe) with well-designed remote strategies.

Looking ahead, further research is warranted to track the long-term repercussions of these short-run academic setbacks. As this analysis focuses on only the initial months following the onset of war, subsequent data collection could reveal whether students manage to catch up over time or whether academic deficits persist and deepen. Future studies might also investigate the role of psychosocial factors in shaping academic outcomes, exploring, for instance, the protective influence of supportive family or community networks. By continuing to document and analyze educational disruptions in conflict zones, researchers and policymakers can develop informed strategies to safeguard children's learning amid even the most challenging circumstances.

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