Education Under Attack? The Impact of a Localized War on Schooling Achievements [*]

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Abstract

How does exposure to a war outside the immediate conflict area influence the educational performance of pupils, and how does this collective impact differ from that of direct family exposure? To address these questions, I link individual-level victim data from the 2020 Armenian-Azerbaijani war with individual school records from periods before and after the conflict. Capitalizing on the lottery-based draft system of Armenian Army and using constructed individual-level data, I find that exposure to war-related casualties at the school level (collective affectedness) prompts a shift in performance towards subjects that increase options for migration and safer living conditions. This results in decreased proficiency in native language and history studies. In contrast, family-level affectedness shapes patriotism and group identity, leading to improved performance in cultural and homeland-related subjects. These findings demonstrate how war affects schooling trajectories, potentially leading to long-term economic effects even decades later.

Keywords: Education, Schooling Performance, Localized War, Violent Conflict

JEL Codes: F51, I25, O12, O15

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1 Introduction

In 2022, an alarming 468 million children, accounting for more than one in six children, were reported to be residing in conflict-ridden countries but outside the immediate conflict zones (Østby et al., 2023). Despite this significant number, extensive research has predominantly focused on the social and economic consequences of wars within conflict epicenters (Brück et al., 2019; Fize & Louis-Sidois, 2020; Couttenier et al., 2019; Conzo & Salustri, 2019; Mironova & Whitt, 2021; Autor et al., 2011; Swee, 2015; Merrouche, 2011; Case & Paxson, 2010; Akbulut-Yuksel, 2014; De Groot & Göksel, 2011). This oversight fails to capture the broader impact of conflicts, including the psychological trauma experienced by children whose family members are serving in the military in war zones, confronting the genuine risk of death. Thus, the true costs of conflict, including the shadow costs of deterrence, are often underestimated (Rohner & Thoenig, 2021; Korovkin & Makarin, 2020).

To fill this gap, I utilized unique individual-level victim data on the Armenian-Azerbaijani (Nagorno-Karabakh) war of 2020, and integrated it with retrieved geocoded victim information, This dataset allowed me to connect war casualties to affected pupils' families and school districts. Subsequently, I explored the impact of war exposure, at varying degrees, on the educational performance of pupils. The study focuses on 112 schools in Syunik, the southern region of Armenia, comprising 15,920 unique pupils tracked throughout the study period. I employ an identification strategy that exploits the exogenous variation in conflict-related deaths across geographic areas through a difference-in-differences (DID) model.

To capture the impact of war-exposure, I utilize two treatment variables from unique individual-level datasets. One variable captures family-level affectedness, representing the direct impact of a localized war based on whether a pupil lost a brother during the conflict. I construct this measure by matching victims with pupils using family names, date of birth and residence district. The other, community-level affectedness, is an indicator variable, denoting war-related victims in the school district.

The identification strategy is capitalized on the lottery-based allocation of soldiers to the military units of the Armenian army. Importantly, the study finds that pupils who lost a family member during the 2020 war did not exhibit differences in school performance before the loss of their brother, but do so after. Similarly, schools with and without war-related victims in the neighborhood showed no significant differences before the war. Combined with the quasi-random assignment and the lack of significant correlation between soldiers' deaths and observational factors (such as voting participation and distance to the border), this set-up provides a robust basis for investigating the causal relationship between war exposure and educational performance.

By examining both family and community-level impacts, my findings highlight how pupils, though not directly exposed to bombings, experience significant effects due to the involvement of their family and community members in the conflict. Thus, this research goes beyond geographic limits, shedding light on the war effects that reach individuals beyond immediate war zones. This scenario is not unique to Armenia; it is also seen in other countries with conflicts that had localized wars. According to the International Institute for Strategic Studies in London (IISS), in 2023, there are 183 ongoing regional and local conflicts, which is the largest number of wars in 30 years. [1] By employing two treatment variables, this study reveals disparities in academic performance among students affected by the war to varying degrees—whether at the family or community level.

I find that family-level affectedness increases parochialism and group identity. This is reflected in improved performance in subjects related to the mother tongue, literature, and the history of the home country. This aligns with existing experimental and psychological literature, which suggests that experiences in intergroup conflicts enhance the sense of group identity (parochialism) (Bauer et al., 2014; Mironova & Whitt, 2021; Bellucci et al., 2020; Sherif, 2015; Reeve, 2020). My findings add empirical evidence to the literature. In contrast, community-level war exposure increases the consideration of alternative options, represented by better performance in the language associated with the most popular migration destination.

The study contributes to several strands of literature. First, it adds to the literature on the economics of conflict and education economics by providing an estimation of the impact of personal, family-level exposure to war-related death on education. A study by Brück et al. (2019) define pupils as treated at the school level based on the number of victims within a certain distance. Bellucci et al. (2020) define war exposure in a more granular way, considering individuals who experienced at least one month of conflict during infancy as exposed to war. The limitation in previous literature is data-driven, as information on both individual victims and pupils is limited. Thanks to the possibility to distinguish

[1] For example, the impact of the Donbas War (2014) on students in Western Ukraine or the consequences of the South Ossetia War (2008) on students in Georgia.

between pupils directly exposed to war (family member loss) and those experiencing community-level war exposure, I additionally add to the knowledge on the impact of conflict expectation (high risk of conflict) on social outcomes. Witnessing the aftermath of conflict within one's neighborhood may heighten the perceived risk of personal exposure to war or conscription. Consequently, community-level exposure becomes associated with higher expected risk of conflict. Existing literature extensively explores the implications of war expectations on diverse socio-economic outcomes. Zussman et al. (2008) and Willard et al. (1995) explore how conflict events impact asset prices, emphasizing the role of expectations. Besley & Mueller (2012) demonstrate how expectations of peace influence regional housing market dynamics. Tapsoba (2023) investigates how cohorts of children exposed to a high risk of violence suffer significant health setbacks, even in the absence of actual violent events. Leveraging a unique dataset, I contribute to this literature by exploring the impact of higher risk affectedness (proxied by community level exposure) on the education of pupils potentially leading to long-term economic effects (Hanushek et al., 2015).

Second, the individual-level data limitation extends to the outcome variable, posing challenges to assess the impact of war exposure on the quality of schooling. Many studies primarily utilize quantitative measures of education, such as attendance rates and enrollment (extensive margin), rather than qualitative measures (Justino et al., 2014; Swee, 2015; Shemyakina, 2011) [2]. The use of these outcome

[2] Justino et al. (2014) examine the short and long-term impact of violence in Timor Leste in 1999-2002 on school attendance and primary school completion. They find a mixed impact on school attendance but a significant effect of not completing primary school. Another study by Swee (2015) analyzes the effects of the Bosnian War on schooling attainment. He finds that affected cohorts of the Bosnian War were less likely to complete secondary school.

variables limits our understanding of how wars and armed conflicts affect the quality of schooling, which can be better measured by pupils' grades in individual subjects and exams. To bridge this gap, I use a unique individual-level dataset from the National Center of Educational Technologies of Armenia, enabling an exploration of the spillover effect of war on the intensive margin of learning.

Third, by analyzing localized wars, my findings provide novel understanding of the consequences of conflict, as it allows eliminating some of the primary mechanisms proposed in the existing literature. This includes factors like infrastructure destruction, school closures, and the fear of exposure to conflict during the journey to school (Brück et al., 2019; Dabalen & Paul, 2014).

Fourth, I add to the literature on development economics by exploring gender differences in the impact of war on schooling outcomes. Existing literature shows mixed findings across different conflict settings. For instance, in the Bosnian War, Swee (2015) suggests a stronger impact on males, while in Tajikistan, Shemyakina (2011) finds that girls are more affected. Another study by Valente (2014) claims that the impact on gender differences depends on the conflict type. Intense conflicts, measured by casualties, tend to increase female educational attainment, while conflicts directly targeting schools boost male schooling. My study extends these findings by demonstrating that, among other factors, the gender disparities in the impact of war exposure also depend on the level of affectedness. Specifically, while direct family affectedness further boosts the academic performance of girls, particularly in homeland-related subjects, community-level affectedness significantly impacts boys, increasing their performance in certain foreign languages.

Finally, the Nagorno-Karabakh war provides a unique case for analysis as it was not only localized but also short and intensive, addressing a limitation in existing literature concentrated on developing countries with prolonged 'non-intensive' conflicts, such as Pakistan, Nigeria, and Syria. Brück et al. (2019), for example, study the effect of "the Second Intifada (2000-2006) in the West Bank (Israeli–Palestinian conflict) on final exam scores exploiting within-school variation in the number of conflict-related Palestinian fatalities. They show that the conflict reduces both the probability of passing the final exam and the total test score. Another study by Poirier (2012) exploits the effect of armed conflict on school enrollment rates in Sub-Saharan Africa from 1950 to 2010 and finds a strong negative effect. These studies are limited in understanding the impact of non-continuous, short wars in the sense that students living in countries with long-term conflicts may become used to it or update their beliefs on the education outcome. Thus, the impact of conflict fatalities may be underestimated.

The remainder of this paper is as follows. Section 2 introduces the historical background of the conflict and provides an overview in the education system of Armenia. Section 3 introduces the data and construction of the treatment variable. Section 4 introduces empirical strategy and the assumptions behind it. Section 5 shows the results on community and family levels. Section 6 adds robustness exercises. Section 7 discusses the mechanism behind the observed effects. Section 8 provides concluding remarks.

2 Background

2.1 Nagorno-Karabakh Conflict

The Nagorno-Karabakh conflict [3] has a complex history, starting in the 1920s and ending in 2023. During this conflict, there were several periods of hot and frozen wars and ceasefire violations.

The conflict started in the 1920s, when the Nagorno-Karabakh Autonomous Region, where 95% of the population was ethnically Armenian, was established within Azerbaijan. In the late 1980s Nagorno-Karabakh legislature passed a resolution to join Armenia. After the Soviet Union dissolved in 1991, Nagorno-Karabakh declared independence, sparking a war between Armenia and Azerbaijan. The war caused roughly thirty-thousand deaths, hundreds of thousands of refugees and ended in 1993 with a victory for Armenia, with the country controlling Nagorno-Karabakh and occupying 20 percent of the surrounding Azerbaijani territory. Between 1994 and 2020, Nagorno-Karabakh remained in a frozen conflict with occasional ceasefires [4].

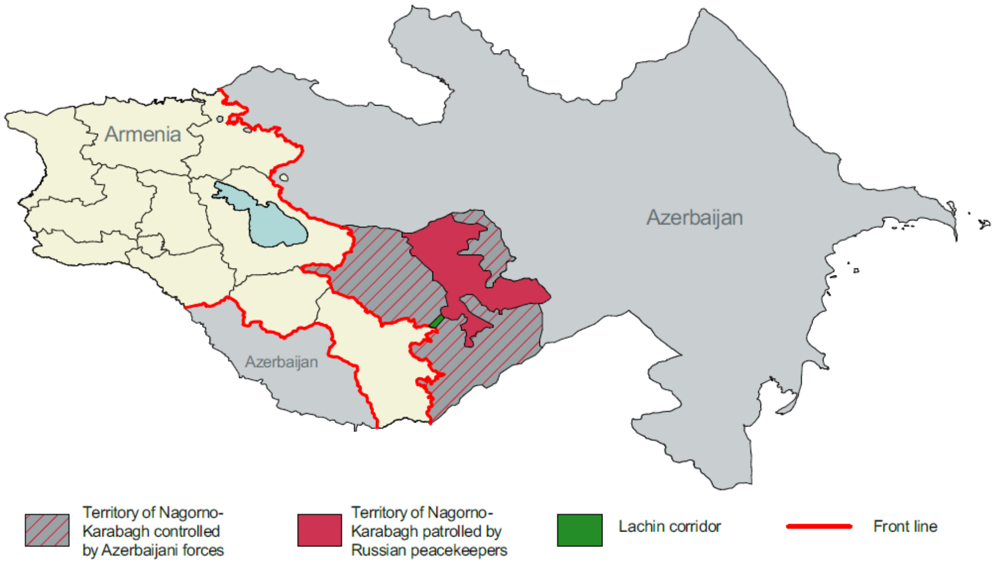
I focus on a major outbreak of the conflict in late September of 2020, which lasted 44 days and took around four-thousand Armenian lives. This was the most intensive and severe war since 1991. As an outcome of the war, a significant part of Nagorno-Karabakh fell under the control of Azerbaijan as shown in Figure 1. Since then, the conflict was frozen for a short time with about two thousand Russian

[3] Source: Center for Preventive Action, Nagorno-Karabakh Conflict: https://www.cfr.org/global-conflict-tracker/conflict/nagorno-karabakh-conflict

[4] For example, in 2016, heavy fighting broke out along the border, which lasted for four days.

peacekeeping forces along the Lachin corridor between Armenia and Nagorno-Karabakh[5] In 2023, the entire region came under Azerbaijani control.

Figure 1: Nagorno-Karabakh Conflict.



Notes: The map depicts the location of Nagorno-Karabakh (the striped and red shaded zones) between Armenia and Azerbaijan. The striped area indicates the part of Nagorno-Karabakh that came under Azerbaijani control as a result of the 2020 war. The red shaded area remained under Armenian control and was patrolled by Russian peacekeepers. [6]The green corridor, known as the Lachin corridor, served as the sole connection between Nagorno-Karabakh and Armenia following the war, and it was also patrolled by Russian peacekeepers. The red line denotes the frontline along Armenian borders.

To investigate the impact of war exposure on education outcomes and parochialism in this setting, it is essential to understand the role of Nagorno-Karabakh in Armenian society. The region, located between Armenia and Azerbaijan, while internationally being recognized as part of Azerbaijan, it was de facto part of

[5]The peace achieved in 2020 was fragile. In September 2023, after enduring a nine-month blockade without access to essential supplies such as food, medicine, and fuel, facing ethnic cleansing and a new war attempt by Azerbaijan, 100,400 ethnic Armenians, representing 99% of the remaining population of Nagorno-Karabakh, fled to Armenia, leaving several dozen people within the region. It is worth noting that the data for this study predates these recent developments, and thus the influence of the latter will not be discussed in the subsequent chapters.

[6]More information is available at https://www.crisisgroup.org/content/nagorno-karabakh-conflict-visual-explainer

Armenia until 2020, enabling unrestricted movement similar to any other region within Armenia. This meant that, both for pupils and soldiers, the conflict in Nagorno-Karabakh carried the same psychological weight and level of involvement (directly/family level, or indirectly/community level) as if it would carry for the conflicts in any other region of the country.

2.2 Education System in Armenia

The Armenian education system consists of 12 years of general secondary education divided into three stages. The first two stages, primary school and middle school, are mandatory. Primary education begins at age six and lasts for four years, followed by middle school, which serves students up to the tenth grade. Upon completion of middle school, students are transited to high school based on their professional interests. Grading follows a scale from one to ten, with ten denoting the highest level of performance. Additionally, at the end of each academic year, students undergo "control tests" administered by school authorities to assess their progress.

Allocation of students to schools is organized through an online platform, where parents have equal opportunity to queue up their children in preferred schools regardless of any family characteristics. The preferred school can be both inside or outside the district of residency. However, Caucasus Research Resource Center (CRRC) suggests that a significant majority of students, 92% (CRRC, 2012) attend schools close to their residences, typically within a maximum walking distance of 20 minutes . This observation is also supported by data collected and analyzed within the context of this study.

3 Data

My dataset comprises individual-level data on victims of the2020 Nagorno-Karabakh War, individual-level daily grades for all pupils from the included schools and voting registry lists. I obtained these rich datasets from three different sources, which allows me to undertake a comprehensive examination at different levels of exposure.

3.1 Soldier Casualties

The primary dataset, documenting all victims of the 2020 Armenian-Azerbaijani War from the Armenian side, originates from provincial administrations. This dataset provides comprehensive information, including victims' full names, towns or villages of residency, date of birth, and date of death. However, it lacks the precise address of each soldier, which is crucial for an accurate definition of war exposure.

To address this limitation and enhance the accuracy of victims' residency, I utilized data from the Central Election Commission of Armenia. This publicly accessible source, available through the voter registration platform, contains individual-level data on all citizens of voting age. This dataset includes details such as full name, patronymic, date of birth, address, all residents from the same address, and the polling station for voting.

Using this resource, I retrieved precise addresses of victims based on an individual's full name and date of birth. I was able to uniquely identify a victim's address in 87.6% of cases. Next, I matched these exact addresses with the victims' data, allowing for a more refined definition of treatment. Appendix A contains further information regarding this integration.

3.2 Grading Records

The second dataset, provided by the National Center of Educational Technologies (NCET), a non-profit organization operating under the Ministry of Education of Armenia, contains individual-level data on pupils. This dataset includes academic details such as grades and attendance, demographic information, such as gender and age, alongside insights into school dynamics, including instances of school changes. Additionally, the dataset contains individual-level information about teachers, covering essential aspects such as age, gender, years of teaching experience, and the courses they instruct. Spanning from 2019 onwards, this comprehensive dataset is collected on a daily basis, offering a detailed foundation for novel analysis.

Beyond individual-level insights, the dataset also provides information on school-level characteristics, including classroom size, school locality, and overall school size. The study focuses on 112 schools in Syunik, the southern region, comprising around 15,920 unique pupils tracked throughout the study period.

3.3 Treatment

Leveraging this granular-level data, I define treatment at two levels: family (personal) and community (school-district). First, to define family level exposure, I conduct a unique 1-to-1 matching process, directly pairing victims with pupils. Specifically, by aligning pupils' surnames and patronymics with victims' surname and patronymics, while controlling for age, date of birth, and locality, I identify all pupils who lost their brothers during the war. Similarly, by matching pupils' surnames and patronymics with victims' surname and name, I identify all pupils who lost their fathers[7]. Overall, I was able to uniquely identify 87% of soldiers.

The construction of this unique micro-level dataset serves a dual purpose. Firstly, it facilitates the estimation of the impact of family exposure to war-related death on educational performance. Secondly, it enables the exploration of nuanced distinctions between community versus family exposure within the context of war-related events.

4 Empirical Strategy

The main proposed identification strategy exploits the spatial variation in the number of fatalities occurring during the 2020 war at the family and community levels and relies on the absence of pre-trends in the difference-in-difference (DID) methodology.

To understand the impact of war-related deaths on pupils' schooling outcome and changes in parochialism, I use a difference-in-difference framework with the following specification:

$$Y_{ist} = \beta_1(FamilyExp_i \times Post_t) + \beta_2(CommunityExp_s \times Post_t) + \\ \mathrm{X}_{it}\delta_1 + Z_{st}\delta_2 + \gamma_i + \lambda_t + \epsilon_{ist} (1)$$

[7]Refer to the A.2 for a detailed illustration of the data merging process.

where Y_{ist} is the outcome of interest, which is the GPA of the i_{th} student at s school at time t, $FamilyExp_i$ is a dummy treatment variable, which is equal to 1 if a student lost his brother during the war. I define this as family-level treatment. $CommunityExp_s$, indicates exposure to the war at the community-level, equaling to one if there was a victim of war in a 1 km buffer of a school. This step allows me to analyze the difference in community versus family impacts. The reference group are the pupils who were not exposed to the war in any ways defined above. Z_{it} is a set of school control variables including number of classes, number of teachers, school size. λ_t is a semester fixed effect, which captures temporal shocks, and $gamma_i$ includes individual-level fixed effects capturing factors such as the abilities of pupils, family-background, birth date, etc. $post_t$=1 indicates the period after the war. β_1 captures the impact of war exposure at the family-level, proxied by having a victim of the war inside the family. Similarly, β_2 explores the impact of war-related deaths on education at the community level.

To understand the mechanism and heterogeneity, I also take subject grades as the outcome Y_it in equation 1. Therefore, grades from homeland-related studies (Armenian language, literature and history) are a proxy for patriochalism, while performance in Russian is a proxy for "outside safe option". Thus, an increase in grades from, e.g., "History of Armenia" will signal a higher connection to the homeland and national identity. On the other hand, the increased performance in a foreign language might signal the mechanism of attempting to find alternative places to live or study to escape from potential future conflict.

The main assumption behind this strategy is the quasi-random allocation of soldiers to the military units of the Armenian army. Conscription is compulsory for all males aged 18 to 27, with assignments determined via a lottery-based draft system. Upon reaching eligibility, individuals participate in a lottery, drawing unit assignments from a box encompassing all military divisions. This method guarantees the random allocation of soldiers across divisions and specializations. Additionally, the lottery can be attended by family members and media, which ensures transparency, fairness, and randomness in the assignment process.

To demonstrate that, even when distributed randomly, individual characteristics of soldiers do not predict their combat effectiveness or the outcome of their fighting, I examine the correlation between patriotism and the probability of mortality, as well as the distance from their residence to the border and the probability of mortality. The findings depicted in Figure B1 indicate that there is no significant relationship between the probability of mortality and these characteristics.

These features constitute a foundation for exogeneity variation of war victims' locations during the war irrespective of their individual characteristics, and consequently, exogenous variation of war exposure across the villages and towns in the country. However, since the exogeneity works only in the case of ordinary soldiers, I have excluded volunteers and professionals from the analysis. The balance table below supports the exogeneity assumption, as the difference between treated and non-treated groups is not statistically significant.

Block A checks the difference in political activity as a proxy for patriotism, as well as the differences of vote share for republican [8], democrat and "historically

[8]The republican party was governing party almost for last three decades until 2018. The party is known for its pro-Russian stance. Democrats include the current governing party from 2018, and are known for pro-European views. The third party, with strong ties to the diaspora and a century of activism, is widely regarded as historically patriotic.

Table 1: Summary Statistics and Balancing

	Control Mean	SD	Treatment Mean	SD	Diff
Panel A: Political variables					
Republican	0.28	0.10	0.28	0.09	-0.005
Democrat	0.74	0.09	0.75	0.09	0.004
Historically patriotic	0.05	0.06	0.05	0.04	-0.002
Politically active	0.60	0.07	0.60	0.07	-0.000
Panel B: Geographical determinants					
Urban	0.70	0.46	0.72	0.45	0.026
Distance to border	15.56	11.17	15.41	11.79	-0.222
Panel C: Schooling variables					
School Size	327.61	188.03	332.26	186.99	6.842
Average Performance	7.36	1.49	7.37	1.45	0.011
Female	0.48	0.50	0.47	0.50	-0.004
GPA from Russian	7.20	1.81	7.12	1.87	-0.037
GPA from Armenian	6.55	1.79	6.57	1.77	0.093
GPA from $\text{Arm}_h ist$	6.57	1.87	6.57	1.93	0.022
GPA from English	6.96	1.87	6.94	1.88	-0.004
GPA from Math	6.21	1.86	6.21	1.74	0.022
GPA from IT	7.06	1.74	7.06	1.70	0.002

Notes: Panel A shows the balance of voting shares for various political parties(republican, democrat and "historically patriotic") between the districts with and without a victim of war. Politically active variable refers to the share of voters who participated in the last two elections before the war. Panel B shows the balance of geographical determinants. Panel C shows the balance of school characteristics and pupils' average performance. Columns (1) and (3) show the mean for localities with and without war-related casualties respectively. Column (5) reports mean difference tests between treatment and control groups where standard errors are clustered at the school (polling station) level. Significance levels: *** 0.01, ** 0.05, * 0.10.

patriotic" parties. These were main parties in the elections before the war. Block B includes geographic features, such as the distance from the war zone. In both cases there is no significant difference between treated and control groups. In block C the comparability of schools is shown, measured by features such as school size, class size, GPA and number of teachers. Further exogeneity checks are shown in the Appendix. Since the exogeneity assumption is based on the random allocation of young soldiers without contracts, I exclude victims that were professional soldiers or volunteers and respective schools.

5 Main Results

5.1 Parochialism vs Preference for Safer External Options

As we can observe in Table 2, students exposed to war at the family level—specifically, those who lost their brothers during the war—demonstrate a significant increase in performance in subjects related to their homeland, in our case study, Armenian language and history. These findings align with insights from psychological and experimental literature, which suggest that personal experiences of intergroup conflicts, for children having a family member as a prisoner of war or as a war victim, can increase individuals' sense of group identity, a phenomenon known as parochialism (Bauer et al., 2014; Bornstein, 2003; Gneezy & Fessler, 2012).

Conversely, we do not observe a similar increase in parochialism among students exposed to war at the community level. In contrast, while performance in homeland-related studies among community-level treated students is significantly lower, there is a significant positive change in Russian language performance. Notably, aside from Russian, there is no significant change in mean performance across other foreign languages, such as English, German, and French. This suggests an increase in migration-induced language proficiency, given Russia's status as the primary migration destination for Armenia.

Table 2: Family Loss and Increased Parochialism

	(1) GPA	(2) Russian	(3) Foreign	(4) Armenian	(5) IT	(6) Math
CommExp x post	0.0485	0.148***	-0.0414	-0.138**	0.238***	0.0628
	(0.0442)	(0.0554)	(0.0528)	(0.0658)	(0.0768)	(0.0952)
FamExp x post	0.0225	0.0340	0.0774	0.149**	-0.153	0.0290
	(0.0381)	(0.0566)	(0.0696)	(0.0722)	(0.101)	(0.133)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	47793	50085	57584

Notes: In columns (1) to (6), the dependent variables are, respectively, GPA, average performance in Russian language, average grade from Armenian literature, language and Armenian history (as a proxy for parochialism), foreign languages, logical studies (including chess and IT), and mathematics. All models include control variables such as school size, share of female pupils, ratio of teachers to pupils, as well as semester and student fixed effects. Standard errors, represented in parentheses, are clustered at the class level. Significance levels: *** 0.01, ** 0.05, * 0.10.

This outcome is explained through two primary channels: (1) elevated trust in Russia or a belief that Russia is the only entity capable of preventing future conflicts, possibly due to its heightened influence in the region[9], and prevailing mistrust in the Armenian government; and (2) the potential motivation for migration. Section 7.2 will explore the plausibility of these mechanisms further through heterogeneity analyses.

5.2 Event Study

To assess the persistence of the observed impact, I conducted an event-study version of the baseline model at both family and community levels. This analysis also serves as a simple test of the parallel trend assumption. The main models

[9] It is worth noting that the data and conclusion predate the February 2022 Russian invasion of Ukraine.

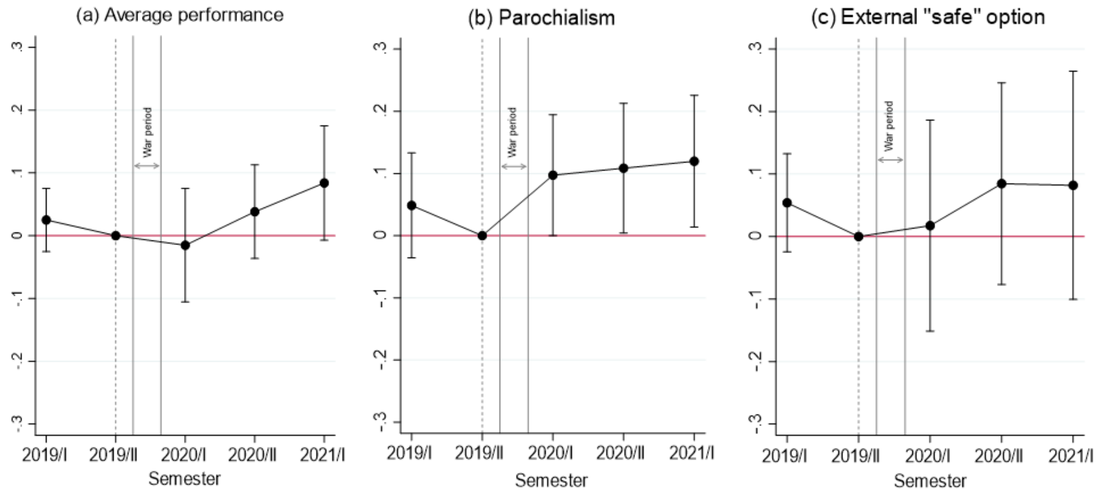
were augmented to include interactions of the semester variable and treatment. The difference was standardized to zero for the last pre-war semester, the 2019 second semester. Placebo effects before the war (interaction terms of a before semester variable and treatment) should not be statistically significant, indicating that pupils in treated and control schools were not initially different and were developing at similar rates and directions.

As observed in Figure 2, pre-war coefficients in all cases are not statistically different from zero, confirming the exogeneity of war-related death exposure. For pupils exposed to war at the family level, the average performance from all subjects initially shows no significant impact. However, the graph reveals evidence of a delayed increase in GPA. The second graph in the middle encompasses average performance in all subjects related to the homeland (Armenian language, literature, and history). While the impact is only slightly significant from the beginning, it is persistent over time. Thus, the event-study setup reveals strengthening of increased parochialism over time.

The second graph in the middle depicts the average performance in all subjects related to the homeland, including Armenian language, literature, and history. While the impact is initially only slightly significant, its significance persists over time. Consequently, the event-study setup reveals a gradual strengthening of increased parochialism as time progresses.

The coefficient plots for the impact of community-level treatment confirm the results of the main regression analysis.

Figure 2: Family-level affectedness: Persistent Shifts in Parochialism

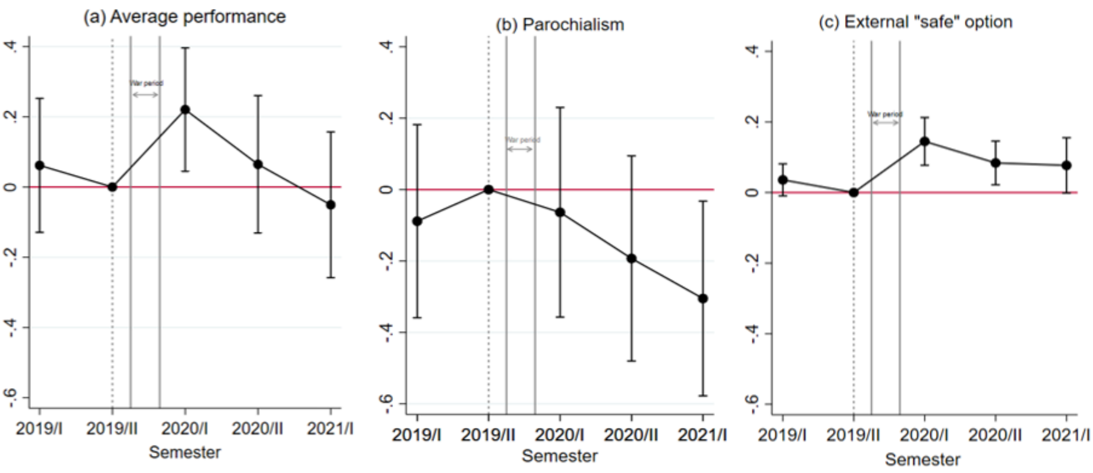


Notes: The figures show differences in performance among pupils with and without family losses. The coefficients are fixed-effects estimates. Performance differences are standardized for the semester before the war (2019, second semester). Gray lines indicate the period of war. Black lines around the coefficients represent 95% confidence intervals, which are based on standard errors clustered at the cohort level. Figure (a) displays the difference in average performance, while (b) focuses on parochialism, proxied by the average grade in Armenian literature, language, and history. Figure (c) illustrates the difference in Russian language performance.

The event study design also reveals that the adverse impact of war-related death exposure on performance in homeland related studies remains consistently and significantly negative throughout the observed period. Conversely, the impact on average performance and Russian language is not persistent, diminishing in significance over the last semesters.

In the context of the migration mechanism, this fading impact can be attributed to the fact that pupils only require basic proficiency in spoken Russian for migration. Thus, as soon as they attain the necessary level, the impact becomes statistically insignificant. Alternatively, if the second mechanism is at play (higher influence of Russia), pupils might adjust their beliefs over time based on the return of relative stability in the region (while not necessarily becoming part of Russia).

Figure 3: Community-level affectedness: Shifts in Parochialism and Preference for External Safe Options



Notes: : The figures show the coefficients of an event-study design of differences of various indicators of pupils' academic performance in the schools with and without war-related death exposure. Schooling performance differences are standardized to zero for the second semester of 2019, the last pre-war semester. Gray lines indicate the period of war. Black lines around the coefficients represent 95% confidence intervals, which are based on standard errors clustered at the cohort level. Figure (a) displays the difference in average performance, while (b) focuses on parochialism, proxied by the average grade in Armenian literature, language, and history. Figure (c) illustrates the difference in Russian language performance.

6 Robustness Checks

The findings thus far reveal significant distinctions between family and community-level exposure to war-related deaths. Specifically, The results show an increase in parochialism among pupils who lost their brothers during the war, while a rise in the study of foreign languages associated with potential migration directions is evident for students affected at the community level. In this section, I introduce several robustness checks designed to examine the main findings of the study.

Teachers' Effect

One concern of the study is that the change in grades may not necessarily reflect pupils' performance in a given subject but could indicate teachers' attitude toward a pupil who has lost a sibling.

Table 3: Do Teachers Matter? War Exposure Impact on Exam Scores

	(1) Russian	(2) Armenian	(3) Foreign	(4) Logical	(5) Math
CommExp x post	0.0682***	-0.0984***	-0.0194	0.0766***	-0.00913
	(0.0124)	(0.0181)	(0.0151)	(0.0163)	(0.0122)
FamExp x post	0.0139	0.0611*	0.0378	-0.0175	-0.00727
	(0.0335)	(0.0347)	(0.0370)	(0.0441)	(0.0331)
Controls	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes
Observations	57626	53731	47793	50112	57803

Notes: In columns (1) to (7), the dependent variables are exam scores, respectively, from Russian language, Armenian literature and language, foreign languages (English, German, French), logic studies (chess and IT), and mathematics. All models include control variables such as school size, share of female pupils, ratio of teachers to pupils, as well as semester and student fixed effects. Standard errors, represented in parentheses, are clustered at the class level. Significance levels: *** 0.01, ** 0.05, * 0.10.

To investigate this potential channel, instead of average grade I use test scores, which are held at the end of each semester by the school directorate and are not checked by the same teachers. I conduct the same analyses with exam scores as with the semester GPA. [10].

The outcome for all subjects is the same as for the baseline model, meaning that the average grades during the semester are appropriate indicators for pupils' academic

[10] There are no tests from Armenian History, thus the subject is missing from the regression output of test scores.

performance. In addition, the correlation maps of semester GPA and exam scores can be found in the Appendix.

Intensity of Exposure to Death

Another concern arises regarding the definition of the treatment variable at the school level as a binary variable, as varying numbers of war-related deaths in school districts may influence outcomes differently. To address this, I calculated the intensity of community-level war exposure by dividing the number of victims in each school district by the number of registered voters in the same district. This approach leverages voter registration data as a proxy for resident population, as schools typically serve as polling stations during elections. Subsequently, I conducted baseline regressions using this new treatment variable. Notably, the signs and significance of the coefficients remained unchanged, indicating robustness of the results.

Table 4: Intensity of War Exposure

	(1) Avr perf.	(2) Russian	(3) Armenian	(4) Arm History	(5) Logical	(6) Math
Intensity Of Exp $\times post$	0.0640**	0.0466**	-0.0251*	-0.0268*	0.0975**	0.0799**
	(0.00420)	(0.00681)	(0.0102)	(0.0116)	(0.0124)	(0.00939)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	28870	23184	45795

Notes: In columns (1) the dependent variable is the average performance for the semester. In columns (2) to (7), the dependent variables are semester GPAs, respectively, from Russian language, Armenian literature and language, Armenian History, chess and IT. The independent variable is the intensity of exposure to war-related deaths. It is calculated as the ration between the number of victims and the number of residents in the area of a particular school. All models include control variables such as school size, share of female pupils, ratio of teachers to pupils, as well as semester and student fixed effects. Standard errors, represented in parentheses, are clustered at the class level. Significance levels: *** 0.01, ** 0.05, * 0.10.

Placebo Estimates

Another concern in our study relates to the limited number of treated units and clusters, which can lead to over-rejection of the null hypothesis (Cameron et al., 2008; Ferman & Pinto, 2019; MacKinnon & Webb, 2017).

To address this issue, I adopt the approach outlined by Chetty et al. (2009) and conduct a non-parametric placebo test to examine the effect of war-related loss on academic performance. Initially, I randomly select pupils from the control group who have not been exposed to war at either the community or family levels. Subsequently, I assign placebo indicators for both family and community loss. Following this randomization, I estimate various versions of the model where the $community_exposed$ and $family_exposed$ indicator variables are replaced with the respective placebo indicators. This process is repeated 1,000 times, resulting in a distribution of placebo estimates.

In Figure B2, the empirical cumulative distribution function of placebo estimates is depicted, emphasizing that the actual estimate of war-related loss on schooling (both the impact on alternative safe option and parochialism) significantly differs from the placebo estimates and remains statistically significant. The p-value, calculated as the percentile of the actual estimate within the distribution of placebo estimates, further reinforces the robustness of our findings. A low p-value, such as 0.001, indicates that the observed effect is highly unlikely to occur by random chance alone if there was truly no effect of war-exposure on education. Overall, these results provide strong evidence that the main conclusions of my analysis are robust to alternative methods of inference.

To ensure the reliability of my results, I also examined various clustering approaches: (i) at the school level, (ii) at the cohort level, and (iii) based on distances. Table B1a and B1b displays the resulting p-values, indicating that the observed impact remains consistent in significance and magnitude across these different clustering methods.

Adjusting for Multiple Hypotheses Testing

The next potential challenge is related to the multiple hypothesis problem. This issue emerges when conducting numerous statistical tests on the same dataset, potentially inflating the Type I error rate and leading to false positive findings. I address this concern by employing a methodology rooted in the step-down resampling technique developed by Westfall and Young (1993). Table B2 not only presents adjusted values by Wyong but also provides Bonferroni-Holm and Sidak-Holm adjustments. The findings remain significant under adjusted p-values.

Non-linear Estimation

Another methodological challenge arises because schooling performance is measured by ordinal variable, which might lead to biased estimates and inaccurate inferences when estimated with a traditional linear model. To ensure the reliability and robustness of my findings, I estimate the impact of war on schooling performance by a non-linear mixed-effect logistic regression, where the dependent variable is the probability of a grade to be in different categories (e.g. 4-5, 7-8, etc). Moreover, school data might have a hierarchical structure, with pupils nested within schools and inside the school within classes, as pupils from the same school and same class might share a common characteristic or experience. The results in Table B3 confirm the robustness of the main findings.

7 Mechanisms

The analysis reveals a significant impact of war exposure, at both the community and family levels, on educational outcomes, uncovering subtle variations in their effects based on the level of exposure. In this section, I delve into the underlying mechanisms behind these findings, specifically examining the significantly higher performance in homeland-related subjects observed within treated families, as well as the improved proficiency in the language of the most migrated country among community-level exposed pupils.

7.1 Family-level Loss and Heightened Parochialism

The findings indicate that experiencing war-related loss within the family context leads to improved performance in subjects related to the homeland. Experimental literature suggests that such outcomes can be indicative of heightened parochialism. Studies by (Bauer et al., 2014; Bornstein, 2003; Gneezy & Fessler, 2012) propose that personal experiences of intergroup conflicts, such as having a family member as a prisoner of war or as a war victim, may increase individuals' sense of group identity, a phenomenon known as parochialism.

7.2 External Safe Option

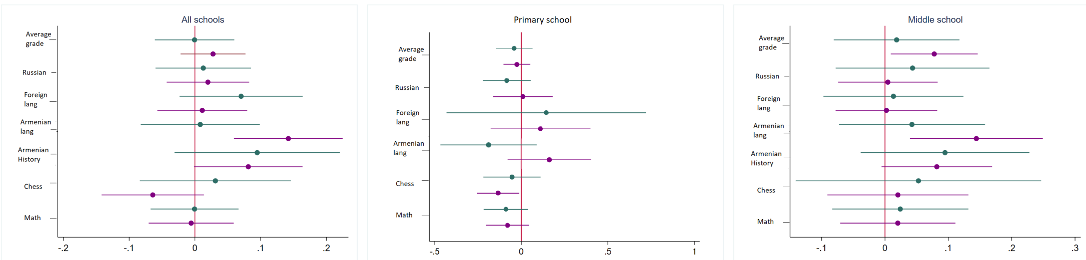
At the community level, unlike family-level loss, I find a diminished interest in homeland-related studies, with a greater inclination towards external "safe" options. This was indicated by higher performance in the language of the most popular migration destination, namely Russia, where a substantial proportion of migrants, particularly males, tend to migrate (ARMSTAT, 2020). Notably, the majority of recent migrants to Russia lack higher education (ARMSTAT, 2020), suggesting a potential impact on language proficiency, particularly among lower-performing students. Thus, if migration is the main mechanism, one would expect (i) to get a lower or less significant impact on the performance in Russian for females compared to males and an insignificant difference in the impact on other foreign languages, (ii) the impact should be present only for middle school pupils, as they are at the age of potential migration, and (iii) to observe significant impact only for the lower tail of the GPA distribution, as most migrants to Russia are not highly qualified, and usually do not have high education, The analyses below confirm all three assumptions.

7.3 Heterogeneity of effects

To understand the channels better, I conduct a gender analysis separately for primary and middle schools, which reveals notable differences. The purple and green colors in Figure 4 and Figure 5 represent treated females and males, respectively. At the family-level (Figure 4) I find no evidence of a significant impact of a localized war on boys who lost their brothers because of the war. In contrast, girls increase their performance in Armenia-related studies. As can be observed in Figure 5, the impact is coming from middle school pupils.

These results are partly in line with Valente (2014)'s study, according to which conflicts that do not directly target schools lead to increased female schooling.

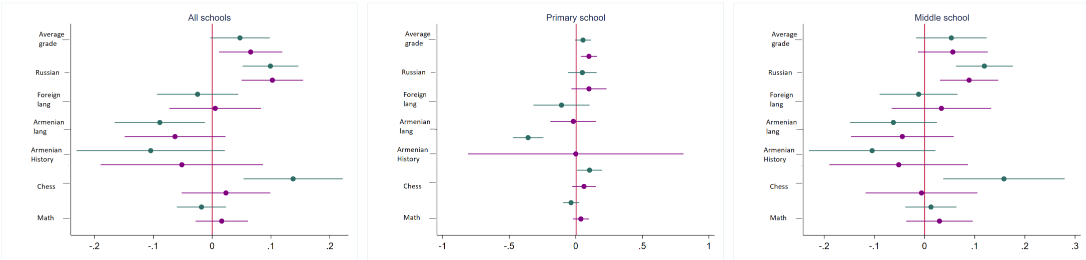
Figure 4: Heterogeneity of Family-Level Impact by Gender and School



Notes: The figures illustrate the gender-specific impact of war-exposure at the family level. Purple represents the impact for girls, while green represents the impact for males. The first figure encompasses all schools, while the second and third figures focus solely on primary and middle school pupils, respectively. Standard errors clustered at the cohort level for all models, consistent with the main analyses.

In the case of pupils experiencing war-related death in their neighborhood (community-level affectedness), the average impact on the intensive margin of education is positive. Notably, this impact is predominantly driven by male pupils studying in middle school. As hypothesized, while the significant increase in Russian language proficiency is more pronounced compared to females, there is no significant gender differences in the performance of other foreign languages.

Figure 5: Heterogeneity of Community-Level Impact by Gender and School



Notes: The figures illustrate the gender-specific impact of war-exposure at the community level. Purple represents the impact for girls, while green represents the impact for males. The first figure encompasses all schools, while the second and third figures focus solely on primary and middle school pupils, respectively. Standard errors clustered at the cohort level for all models, consistent with the main analyses.

Figure 4 shows no significant impact or gender differences on the performance in Russian language at primary school, which aligns with the logical inference that potential migrants are in middle school (second assumption). This result is consistent with an arguably related literature, according to which, in direct conflict areas, an increase in students' performance in foreign languages may signal their inclination to seek a future beyond their country (De Groot & Göksel, 2011). Tapsoba (2023) explains the behavioral change by the shift in war anticipation. Specifically, students experiencing community-level impact may develop a heightened fear of war, projecting scenarios of potential conscription or mortality, prompting them to consider alternative options, such as migrating to another country.

Quantile analysis

Table 5: Russian Proficiency: Impact on Lower GPA Quantiles

	(1) q10	(2) q25	(3) q50	(4) q75	(5) q90
CommExp $\times post$	0.145**	0.158*	0.0820	0.0708	0.113
	(0.0650)	(0.0882)	(0.347)	(0.394)	(0.189)
Controls	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes
Observations	57,477	57,477	57,477	57,477	57,477
Number of groups	15,290	15,290	15,290	15,290	15,290

Notes: The table shows the effects of community-level war exposure on average grades obtained in Russian language classes. Each column represents the coefficient from the same regression model, estimated for five distinct quantiles. All models include control variables, as well as student and semester fixed effects to account for potential confounding factors. Standard errors are clustered at the cohort level to address potential dependencies within the data. Significance levels: *** 0.01, ** 0.05, * 0.10.

To explain the improved proficiency in the language of the most popular migration destination, namely Russian, among affected pupils at the community level, I conducted quantile analyses. Given that many migrants to Russia are males without higher education, I anticipated observing a significant impact mainly in the lower tail of the GPA distribution.

The analysis in Table 5 confirmed this hypothesis, showing a notable increase in Russian language performance specifically in the two lowest tails of the performance distribution. Aligning with migration statistics, these findings strengthen the credibility of the proposed migration mechanism.

In addition to migration, another potential explanation is the increased influence of Russia in the region following the war. Specifically, after the 2020 war, with

Russian peacekeepers stationed in the remaining part of Nagorno-Karabakh, a significant number of Armenians may perceive this as the region becoming a de facto part of Russia. Others may view Russia as the sole guarantor of peace, thereby enhancing its influence in the area. As suggestive evidence, Russian became the second official language in Nagorno-Karabakh within six months of the end of the 2020 war.

8 Conclusion

Localized conflicts, despite their restricted geographic scope, exert significant social and economic repercussions that extend well beyond immediate conflict zones (Korovkin & Makarin, 2020). However, research on the spillover impact of such conflicts on education quality remains notably scarce. This paper addresses this gap by investigating how exposure to war outside immediate conflict areas influences pupils' educational performance, with a particular focus on understanding the differences between community and family-level exposure.

My findings show distinct patterns of academic achievement based on the level of exposure to war-related casualties. Family-level exposure to war-related casualties fostered parochialism and group identity among students. This was reflected in improved performance in subjects related to their national heritage and homeland. In contrast, community-level affectedness prompted students to consider alternative options, leading to increased proficiency in the language associated with a popular migration destination, and decreased proficiency in native language and homland studies.

This study contributes to the broader literature on the economics of conflict and education by highlighting alternative factors that shape educational outcomes in conflict-affected regions. By recognizing the varying levels of vulnerability among students, policymakers can can design targeted interventions to address the diverse needs of affected students and communities.

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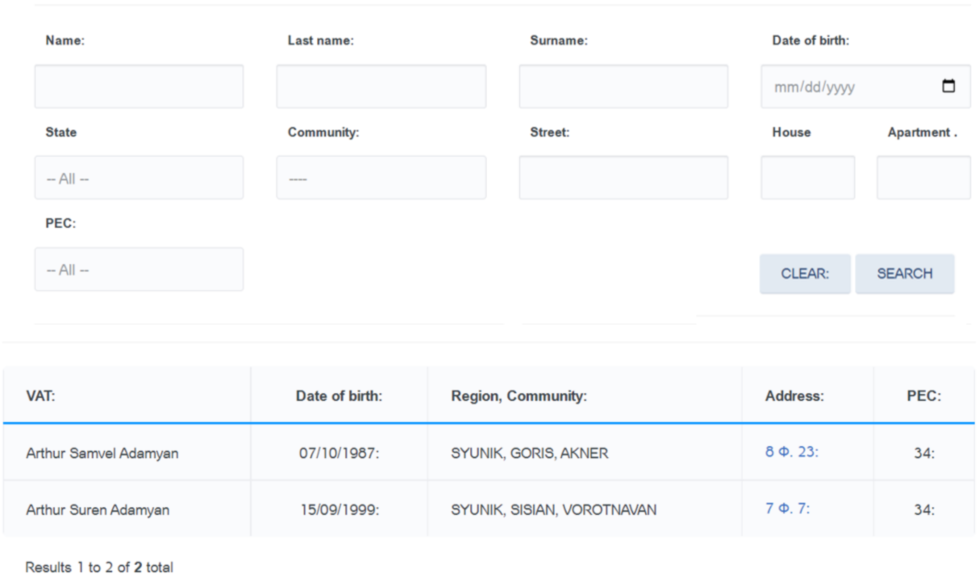
Appendix

A. Data Sources and Matching

Victims of the War

Individual-level data on victims is sourced from the provincial administration. The data includes victims' full names, year of birth, and year of death. The dataset is accessible upon request from the provincial administration of Syunik region. To geolocate victims, I retrieved their exact addresses from the online platform of Armenian Registrary [11].

Figure A.1: Armenian Registrary of Elections.



VAT:	Date of birth:	Region, Community:	Address:	PEC:
Arthur Samvel Adamyan	07/10/1987:	SYUNIK, GORIS, AKNER	8 Փ. 23:	34:
Arthur Suren Adamyan	15/09/1999:	SYUNIK, SISIAN, VOROTNAVAN	7 Փ. 7:	34:

Results 1 to 2 of 2 total

Notes: This figure presents the platform of the Armenian Registrary of Elections. The top picture shows the search field, where only one field is required to be filled, e.g. search can be done only based on a full name. The lower picture presents the results based on the search. The platform search is available only in Armenian. Source: https://www.elections.am/Register

[11] https://www.elections.am/Register

In particular, on this platform it is possible to extract the exact address and date of birth of any person by filling in their full name and district (see the example below). The data is open and publicly available.

Schooling performance

In the Appendix, the individual-level data on pupils' schooling performance is sourced from the National Center of Educational Technologies (NCET), a non-profit organization operating under the Ministry of Education of the Republic of Armenia. This dataset covers all schools in the region, comprising a total of 112 schools, and contains information on daily grades, absenteeism records of all pupils, as well as demographic details such as age, year of birth, and full name. Additionally, the dataset includes information on pupil cohorts, teacher names, and years of teaching experience. This data is bought under the condition of non-disclosure, and any acquisition inquiries should be discussed directly with the source.

Data Matching Process

To define the treatment variable, I first geocoded victims and schools based on the retrived data from Armenian Registrary described above.

I was able to uniquely identify a victim's exact address in 87.6% of cases. Next, I geocoded victims and schools, and conducted a buffer analysis and defined a school as treated if there was at least one victim in a school-district, and as control, otherwise.

Figure A.2: Data Matching Illustration

School Dataset									
Student id	Name	Surname	Father name	Date of birth	Sex	school id	semester	subject A grade	subject B grade
1	Alex	Adamyan	Davit						
2	Anna	Sargsyan	Sergey						

Victims Dataset				
Victim's Name	Victim's Surname	Father name	Date of birth	District
Davit	Adamyan	Arthur		
George	Sargsyan	Sergey		

Registrary Dataset				
Victim's surname	**Victim's father name**	**District**	**"-->**	**Exact address**
Adamyan	Arthur			
Sargsyan	Sergey			

Father victim

Brother victim

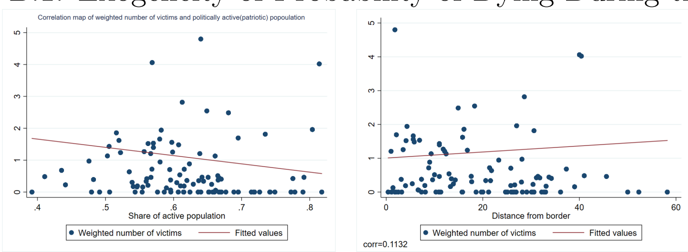
Source: Author's own illustration

Finally, to define the individual-level treatment, I identified pupils who have lost their fathers or brothers during the war. In particular, by matching pupils' surnames and patronymics with victims' surname and patronymics (red cells), respectively, and controlling for their age, date of birth and locality, I detect all pupils who lost their brothers during the war. Similarly, by matching pupils' surnames and patronymics with victims' surname and name (gray cells), I was able to define all the pupils who lost their fathers.

B: Exogeneity Checks

To mitigate potential identification threats, it is crucial to address the possibility that even if soldiers are randomly allocated, their individual characteristics might influence their fighting behavior and thus the outcome of their combat engagement. If such a correlation exists, districts with higher levels of patriotism might exhibit a greater number of casualties due to a positive association between patriotism and combat engagement. To investigate this, I adopted a proxy for patriotism drawn from the political economics literature. Studies such as Huddy & Khatib (2007) and Dalton (2008) suggest that voting behavior reflects patriotism rather than purely political affiliations. Additionally, a meta-analysis conducted by Bauer et al. (2016) based on ten studies found suggestive evidence of a positive relationship (albeit not necessarily causal) between voting and exposure to war. Since each school is a polling station, I defined the patriotic population as the share of participating voters from the particular school-polling station.

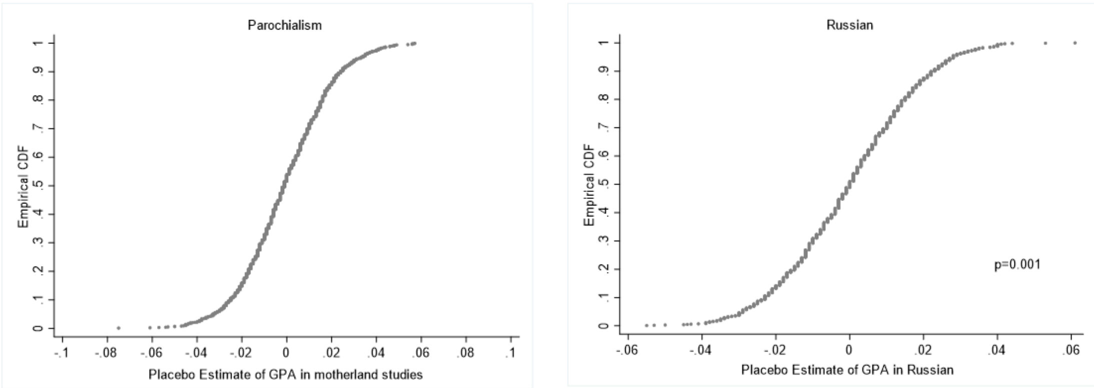
Figure B.1: Exogeneity of Probability of Dying During the War



Source: Author's own illustration

Further, it may be the case that soldiers who have a family not far from the conflict area might fight harder, since they are "protecting" their families. Another possible relation is between education and fighting. The correlation maps below show no relationship between any of the proposed channels and weighted number of victims.

Figure B.2: Placebo Estimates and Robustness of the Community-level Impact



Notes: The figures depict cumulative distribution of placebo estimates from Eq. 1. Placebo estimates are obtained by randomly selecting pupils from the control group, assigning treatment at the community level, and estimating the placebo equation 1000 times. In the left figure, the dependent variable is the combination of homeland-related subjects (a proxy for parochialism), while in the right, the dependent variable is the alternative external safe option, (proxied by Russian as the language for migration). For both dependent variables, the actual coefficient is significantly larger in absolute value, and thus not likely to be random.

Table B.1a: Clustering at School Level

	(1) GPA	(2) Russian	(3) Foreign	(4) Armenian	(5) IT	(6) Math
CommExp $\times post$	0.00746	0.148**	-0.0405	-0.138**	0.239***	0.0623
	(0.878)	(0.022)	(0.589)	(0.024)	(0.007)	(0.437)
FamExp $\times post$	0.0230	0.0332	0.0702	0.149**	-0.149*	0.0286
	(0.530)	(0.617)	(0.312)	(0.032)	(0.096)	(0.828)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	47793	50085	57584

Notes: This figure shows the estimates from equation 1 with standard errors clustered at the school level. The dependent variables are average performance from different subjects presented as columns. All models include control variables, as well as semester and student fixed effects.The results are robust to clustering at the cohort or school level. Significance levels: *** 0.01, ** 0.05, * 0.10.

Table B.1b: Clustering at Distance from the Border

	(1) GPA	(2) Russian	(3) Foreign	(4) Armenian	(5) IT	(6) Math
CommExp $\times post$	0.0523	0.148**	-0.0375	-0.138**	0.242***	0.0602
	(0.317)	(0.023)	(0.631)	(0.018)	(0.007)	(0.469)
FamExp $\times post$	0.0220	0.0332	0.0704	0.149**	-0.149	0.0285
	(0.562)	(0.606)	(0.302)	(0.027)	(0.105)	(0.832)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	47793	50085	57584

Notes: This figure shows the estimates from equation 1 with standard errors clustered at the distance from the border. The dependent variables are average performance from different subjects presented as columns. All models include control variables, as well as semester and student fixed effects.The results are robust to clustering at the cohort or school level. Significance levels: *** 0.01, ** 0.05, * 0.10.

Table B.2: Multiple Hypothesis Testing

	(1) GPA	(2) Russian	(3) Armenian	(4) Foreign	(5) Logical	(6) Math
CommExp x post	0.0527***	0.0820***	-0.0587***	-0.0194	0.0628***	-0.00984
	(0.00648)	(0.0110)	(0.0226)	(0.0151)	(0.0156)	(0.0108)
FamExp x post	0.0132	0.0150	0.0828**	0.0378	-0.0175	-0.00187
	(0.0258)	(0.0311)	(0.0393)	(0.0370)	(0.0428)	(0.0312)
Bonferroni adj P values	.0188	3.232e-06	.0008	.79499	.0490	.5996
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	47793	50085	50085

Notes: This table shows the robustness of my findings through the application of alternative inference techniques. Specifically, Bonferroni-Holm adjusted p-values are computed for each column, providing a more conservative approach to hypothesis testing. This adjustment method, rooted in the step-down resampling technique pioneered by Westfall & Young (1993), helps control the family-wise error rate across multiple tests and decrease the risk of Type I errors associated with multiple comparisons. The estimates are obtained from the estimation of Eq. 1. Significance levels: *** 0.01, ** 0.05, * 0.10.

Table B.3: Consistency of Results Under Mixed Effect Logistic Regression

	(1) Russian	(2) Armenian	(3) Foreign	(4) Logical	(5) Math
CommExp $\times post$	0.194***	-0.135*	0.0337	0.144***	0.00627
	(0.0437)	(0.0798)	(0.0492)	(0.0512)	(0.0439)
FamExp $\times post$	0.0799	0.185***	0.0364	0.0125	0.0639
	(0.0574)	(0.0694)	(0.0610)	(0.0632)	(0.0564)
Controls	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes
Observations	57447	53731	47793	50085	57584

Notes: This table presents estimates from an alternative non-linear mixed effect logistic regression model accounting for the ordinal structure of the dependent variable. The model assesses the probability of outcomes falling into ordered categories, with each column representing a distinct subject as the outcome variable. Standard errors are clustered in two stages: first by school and then by cohort. Significance levels: *** 0.01, ** 0.05, * 0.10

Table B.4: Standardized Grades

	(1) GPA	(2) Russian	(3) Armenian	(4) Foreign	(5) Logical	(6) Math
CommExp $\times post$	0.0527***	0.0820***	-0.0587***	-0.0194	0.0628***	-0.00984
	(0.00648)	(0.0110)	(0.0226)	(0.0151)	(0.0156)	(0.0108)
FamExp $\times post$	0.0132	0.0150	0.0828**	0.0378	-0.0175	-0.00187
	(0.0258)	(0.0311)	(0.0393)	(0.0370)	(0.0428)	(0.0312)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Semester FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57865	57447	53731	47793	50085	57584

Notes: In columns (1) to (6), the dependent variables are, respectively, GPA, average performance in Russian language, Armenian literature and language, foreign languages, logic studies (including chess and IT), and mathematics. All models include control variables such as school size, share of female pupils, ratio of teachers to pupils, as well as semester and student fixed effects. Standard errors, represented in parentheses, are clustered at the class level. Significance levels: *** 0.01, ** 0.05, * 0.10.