Hometown Conflict and Refugees' Integration Efforts*

Cevat Giray Aksoy[†]
EBRD, King's College London, and CEPR

Gaurav Khanna[‡]
University of California, San Diego

Victoria Marino[§]
EBRD

Semih Tumen[¶]
Amazon and TED University

November 18, 2025

Abstract

How does violence in origin areas affect the educational outcomes of refugees in their destinations? Using administrative panel data, we find that heightened violence in the hometowns of Syrian students leads to improvements in their school outcomes in Türkiye. Turkish language and Math scores of refugees improve, with larger impacts on Turkish language scores. Naturalized Syrian students, however, exhibit negligible effects. Syrians' increased effort after home violence partially offset classroom congestion effects, and has positive spillovers on Turkish classmates. Our findings suggest that ongoing violence in refugee-origin areas reduces the perceived likelihood of returning home and motivates students to increase integration efforts by investing in education.

JEL codes: J15, I21, I25, F51, O15
Keywords: Conflict, refugees, integration, return migration

*We thank Ralph De Haas, David McKenzie, Katrin Millock, Giovanni Peri, Hillel Rapoport, seminar participants at Bocconi, IFS-UCL-LSE-STICERD Development Seminar, King's College London, London School of Economics, OECD, Paris School of Economics, as well as those at the CEPR Development Economics Annual Symposium, 14th Annual Conference on Immigration in OECD Countries, 17th AFD-World Bank Migration and Development Conference, 1st Istanbul Applied Micro Workshop, VII Workshop on Immigration, Health, and Wellbeing, and 8th InsTED Workshop on Advances in Institutions, Trade, and Economic Development for their valuable comments. Views presented are those of the authors and not necessarily of the European Bank for Reconstruction and Development or Amazon. The usual disclaimer holds.

[†]EBRD, London, UK. Email: aksoyc@ebrd.com.
[‡]UCSD, School of Global Policy and Strategy, San Diego CA, US. Email: gakhanna@ucsd.edu.
[§]EBRD, London, UK. Email: marinov@ebrd.com.
[¶]TED University, Department of Economics, Ankara, Türkiye. Email: semih.tumen@tedu.edu.tr.

1 Introduction

Amidst an unprecedented global displacement crisis, where 1.4 percent of the world's population was forcibly displaced by 2022—more than tripling the 0.4 percent recorded in 1990 (United Nations High Commissioner for Refugees, 2022)—the humanitarian challenges are profound and extensive. Notably, developing countries shoulder most of the burden, hosting approximately 75 percent of the world's refugees, with nearly half being children. Persistent crises in countries like Syria, Afghanistan, Ukraine, Venezuela, Libya, Palestine, and Yemen indicate that achieving political stability remains elusive in the foreseeable future.

The conflict in Syria began in 2011 and rapidly escalated into a full-scale civil war, triggering a mass exodus and leading to one of today's most significant refugee and displacement crises (World Bank, 2023). Millions sought refuge in neighboring Türkiye, Lebanon, and Jordan. Türkiye hosted the largest population of Syrian refugees, reaching approximately 3.8 million by June 2022.[1] By about 2023, the likelihood of return to Syria had diminished significantly due to ongoing political instability, persistent conflict, proxy wars, and the emergence of extremist groups.

Syrian children have borne a disproportionate burden of the adverse effects stemming from violent conflict, forced displacement, and persistent instability. At the beginning of the 2022-23 school year, approximately 1.4 million school-age (5-17) refugee children were present in Türkiye, exhibiting lower test scores, reduced enrollment, and higher absenteeism compared to their native peers (Tumen et al., 2023). These disparities are frequently attributed to language barriers, identified as a primary challenge for the educational integration of refugee children (UNHCR, 2019; Tumen, S. and Vlassopoulos, M. and Wahba, J., 2025). In addition to language barriers and other integration challenges arising from forced displacement, Syrian children in Türkiye are consistently exposed to news concerning ongoing violence and casualties in their hometowns. By 2022, an estimated 306,887 civilians (about 84 civilians a day) had lost their lives since the conflict's onset, underscoring the brutal impact on civilian lives (SNHR, 2023). As discussed later in the paper, violence and casualties in Syria exhibit significant variation across time and space.

Against this backdrop, we focus on a previously under-explored dimension: how contemporaneous violence in the district of origin affects refugee integration.[2] The unresolved conflicts, particularly in Syria, cast a long shadow on the prospects of return, prompting a closer examination of how this protracted instability affects human capital investment decisions—serving as a proxy for integration efforts, aspirations, and return expectations—among refugee children in Türkiye.

We estimate the causal effect of ongoing violence in Syria on the educational outcomes

[1] See https://data.unhcr.org/en/situations/syria/location/113 for data and the latest trends.

[2] In the context of this paper, "hometown" refers to the district of birth of Syrian students. The district (mintaqah) is the level of observation available in our data and serves as the primary geographical reference for analysis. The 14 governorates of Syria, or muhafazat, are divided into 65 districts, or manatiq, including the city of Damascus. Each district comprises multiple subdistricts (nahiya). Given data availability at the district level, we use "district" to define students' hometowns throughout the paper.

of refugee children in Türkiye. The heightened levels of concurrent violence may influence educational attainment through two opposing mechanisms. On the one hand, the trauma experienced may worsen schooling outcomes. On the other, the continued violence may alter expectations, prompting refugee children to reassess their beliefs about the likelihood of returning to Syria. This despair, in turn, may lead to more investments in their educational development, as an effort to integrate more effectively into their host communities.

To unravel this puzzle, we obtain individual-level administrative panel data that comprehensively document the academic performance of Syrian and Turkish students, and merge it with detailed information regarding the timing, location, and intensity of violence in their hometowns in Syria. Since we observe Syrian students' districts of birth, our identification strategy exploits variation in conflict intensity across origin districts and academic semesters.

Controlling for individual, years since arrival, and the unique combination of high-dimensional teacher-classroom-grade-academic year fixed effects, we find an improvement in both Turkish language and Math scores of refugee students in response to heightened violence in their Syrian hometowns. Notably, the increase in Turkish language scores is larger than that observed in Math, supporting the interpretation that these children are intensifying their efforts to integrate into their host communities. Conversely, naturalized Syrian students show a much smaller, or no response to hometown violence in terms of changes in academic performance, and absenteeism remains unaffected.

Additionally, there is no evidence suggesting that ongoing violence leads to differential attrition among Syrian students. Importantly, the impact of violence on Math scores is primarily driven by female students. We also document that the effects of hometown violence on education are compounding, as cumulative exposure—whether since migration or the start of the conflict—has a larger impact on Turkish language and Math scores than contemporaneous violence, suggesting that students respond to sustained violence by increasing their effort to integrate. Finally, Syrian students' increased academic effort in response to violence in their home districts creates positive spillover effects for Turkish students. Specifically, while a larger share of Syrian classmates is negatively associated with Turkish students' academic performance—likely due to congestion effects—this impact is partially offset by the increased academic effort of Syrian students exposed to home district violence.

Our estimates remain robust across various specifications and sensitivity checks. The results are consistent when using alternative measures of conflict intensity (violent events and fatalities), and when applying alternative transformations of our outcomes including the inverse hyperbolic sine (IHS) transformation and standardization by grade. We employ the "clean control" analysis to address potential biases in two-way fixed effects estimations (de Chaisemartin et al., 2022). The robustness of our results is further confirmed by excluding one Turkish province at a time and one semester at a time, ruling out the influence of any single geographic area or time period. Additionally, we find null effects for treatment leads, supporting the validity of our identification strategy. Since we include the unique combination of teacher-classroom-grade-academic year fixed effects throughout, our results

cannot be explained by teacher characteristics such as teaching style, experience, assessment practices, or potential grading biases — including any tendency to grade refugee students more favorably during periods of heightened conflict in their home countries.

Our estimates suggest that increased violence in Syrian children's hometowns leads to improved academic outcomes in Türkiye, likely because the violence-driven changes in expectations and increased despair about returning home generate greater integration efforts, which outweigh the potential negative effects of trauma.

These findings contribute to two distinct strands of the migration and conflict literature. First, we are the first to document the impact of ongoing violence in refugees' hometowns on the academic performance of immigrant students in the host country. While previous research has predominantly focused on the effects of past cumulative *direct* exposure to violence—highlighting its adverse impacts on various life outcomes (Verwimp and Van Bavel, 2014; Akbulut-Yuksel, 2014; Bertoni et al., 2019)[3]—our study shifts the focus to contemporaneous knowledge of violence while abroad, which can alter expectations and investments in human capital in unique ways. This complements the literature exploring how local exposure to crime and police activity around schools negatively affects educational outcomes (Brown and Velasquez, 2017; Ang, 2021; Bharadwaj et al., 2021; Koppensteiner and Menezes, 2021; Chang and Padilla-Romo, 2023; Cabral et al., 2024).[4] However, we examine the effect of large-scale violence occurring simultaneously in the hometowns of refugee students, albeit from a *distant* country. While this violence does not directly endanger refugee students' physical safety, it functions as a mechanism that reduces their perceived probability of returning home. Our findings reveal that exposure to ongoing violence in the hometown increases human capital accumulation by diminishing the expected likelihood of return.[5]

Second, we contribute to the refugee integration literature by offering causal evidence that worsening conditions in the home country increases refugees' integration efforts. We provide empirical support for theoretical notions suggesting that human capital investment abroad rises with the expected duration of migrant stay. Existing evidence indicates that refugees are less likely to return compared to economic (or voluntary) immigrants (Cortes, 2004). Generally, the longer immigrants envision staying, the more they invest in their human capital (Dustmann, 1996; Khan, 1997; Adda et al., 2022) and local language acquisition (Abramitzky et al., 2023), while saving less and sending fewer remittances to their home country (Galor and Stark, 1990; Merkle and Zimmermann, 1992).

Finally, our results inform the ongoing debate around refugee return in light of recent political developments in Syria. The overthrow of President Bashar al-Assad's regime by rebel forces has created new uncertainties for Syrian refugees. While this change may present opportunities for return, important obstacles persist. The prolonged conflict has severely dam-

[3]See also, Angrist and Kugler (2008), Chamarbagwala and Moran (2011), Shemyakina (2011), Leon (2012), Rodriguez and Sanchez (2012), Justino et al. (2014), and Bruck et al. (2019)

[4]See also Monteiro and Rocha (2017), Casey et al. (2018), and Michaelsen and Salardi (2020).

[5]In related work, Alfano and Görlach (2024) causally identify how terrorist attacks reduce school participation, with fears and safety concerns. Alfano and Görlach (2023) examine how media coverage amplifies the negative effects of terrorism on schooling by increasing perceived risks.

aged Syria's infrastructure, compromising access to essential services like housing, water, and electricity. Questions about the stability and governance capacity of the new ruling coalition raise concerns about sustainable resettlement. Meanwhile, policy shifts in host countries, including suspended asylum applications and planned deportations, are pressuring refugees to consider returning. Our findings suggest that such political and policy uncertainties will continue to shape Syrian refugee children's integration and human capital accumulation in host countries.

The plan of the paper is as follows. In Section 2, we provide an overview of the background. Section 3 delves into the specifics of our data, while Section 4 outlines our empirical strategy. Our findings are discussed in Section 5, and Section 6 concludes.

2 Background and Institutional Setting

2.1 Armed conflict and violence in Syria

The Syrian conflict began in early 2011 as a peaceful protest triggered by discontent with the government. However, it swiftly escalated, encompassing a vast geographical area and evolving into a full-scale civil war. This conflict gave rise to one of the largest refugee waves in human history. The origins of the crisis are rooted in a complex array of political, historical, religious, and economic factors.[6]

Here, we discuss three prominent features of the violence, crucial for understanding the context and research design. First, the conflict displayed significant temporal variation, as illustrated in Figure A1. It began escalating in early 2012, peaking by the end of 2014. Although it gradually subsided thereafter, intermittent spikes persisted. In December 2024, President Assad was overthrown, and rebel groups claimed to take control of the capital. A key factor contributing to this temporal variation was the direct involvement of foreign countries, such as Russia, the US, and Iran.[7] Additionally, the timing of Syrian refugee flows into Türkiye aligns with the pattern of violent events in Syria (Figure A2).

Second, the conflict and its temporal variation exhibit significant regional disparities, based on the presence of various rebel groups and Kurdish forces. Figure A3 illustrates cumulative violence across regions, showcasing considerable regional variation. Meanwhile, Figures A4 and A5 reveal significant variation in the patterns of violence across regions, with conflict events igniting and dissipating at different times in different areas. The ethnic and religious diversity of Syria's demographic structure plays a pivotal role in creating these regional differences.[8] Figure A6 displays the distribution of Syrian students in our data set based on their district of birth.

Finally, the temporal and regional variation in violence exhibit similar patterns across

[6]For further reading, see Phillips (2015), Van Dam (2017), Abel et al. (2019), Daoudy (2020), and Tumen (2023).

[7]Russia increased its military presence in Northern Syria in late 2014 and conducted a series of air strikes and ground operations throughout 2015, leading to an upsurge in violent events in 2014 and 2015.

[8]For information about the pre-war heterogeneity in population, see Khalifa (2013).

different violence measures. We employ two distinct measures of violence in this paper: the number of violent events and the number of conflict-related fatalities. The first measure can be viewed as the extensive margin of violence, relying solely on event counts. In contrast, the second measure represents the intensive aspect, quantifying the intensity of each event.[9]

2.2 School integration of refugee children

The integration of refugee children into schools has proven challenging, primarily due to language barriers. Syrians speak Arabic, and there are significant differences between Arabic and Turkish, notably in their alphabets. This distinction makes it particularly difficult for Syrian children to learn Turkish. Typically, Syrian children are exposed early to the Arabic alphabet at home or through preschool attendance in local Quran courses (Boucher et al., 2021; Tumen, S. and Vlassopoulos, M. and Wahba, J., 2025).

The number of Syrian refugees in Türkiye was relatively small during the initial stages of the conflict (Figure A2). The Turkish government constructed refugee accommodation camps near the Syrian border, primarily to provide emergency humanitarian assistance, with the initial expectation that refugees would eventually return to Syria.

By mid-2014, the Syrian conflict had intensified significantly, leading to a more than threefold increase in refugees by early 2016. Initially, educational services for Syrian refugee children were limited to small-scale, project-specific initiatives by non-governmental organizations within camps, supervised by the Ministry of National Education of the Republic of Türkiye (MoNE). However, recognizing the urgent need for educational integration as the crisis deepened, the Turkish government overhauled its policies to fully integrate Syrian children into the public education system, implementing nationwide programs funded by the EU Facility for Refugees in Türkiye (FRIT). A crucial aspect of this policy change was ensuring free access to education for all Syrian refugee children, granting them the same rights as Turkish citizens to attend public schools without paying tuition fees.

3 Data

Administrative data on educational outcomes. The primary data source for refugee and native students' academic performance is the administrative data obtained from MoNE, for the academic years between 2011-12 and 2018-19. In our main analysis, we focus on refugee students; but for analyzing spillovers, we also use data on Turkish students.

Our outcomes include the end-of-semester scores from all courses taken by all registered students, and their absenteeism records. The end-of-semester score is derived from a weighted average of exam results, quizzes, homework assignments, and other graded activities for each course. Absenteeism is quantified in terms of days missed per academic year for each student.

[9] While "extensive margin" often refers to binary treatment variables (exposure vs. non-exposure), we adopt a broader interpretation here. The number of events reflects conflict exposure across locations, akin to an extensive margin, while fatalities capture violence severity within exposed areas, aligning with an intensive margin. This distinction allows us to separately analyze the effects of conflict incidence and severity.

Additionally, the dataset contains school names, unique teacher ID numbers, classroom and grade-year information, and key individual-level characteristics, including gender, date of birth, and place of birth (governorate and district). While data on parental characteristics is available, it has several missing entries.

Our data set includes all refugee and native students registered in Turkish schools across four provinces: Ankara, Bursa, Gaziantep, and Şanlıurfa. Ankara, Türkiye's capital, is the second-largest city, with a population exceeding 5.7 million. Bursa, situated in the northwestern region of Türkiye, ranks as the fourth-largest city, with a population of over 3.1 million. It is an appealing destination for refugees due to the presence of large manufacturing companies, which provide employment opportunities. Gaziantep and Şanlıurfa, neighboring provinces to Syria, are known for hosting significant refugee populations, with some schools in these areas experiencing substantial refugee enrollments. Initially, during the early stages of the Syrian crisis, these provinces housed large refugee camps. Following the closure of these camps, a significant number of refugees remained in Gaziantep and Şanlıurfa due to geographical and cultural proximity to Syria.

We focus on grade levels 4 through 10. In grade levels 1 to 3, grading is rather informal and employs a three-category scale (good, intermediate, should be improved) primarily intended for guidance rather than evaluation. Conversely, for grade levels 4 to 10, a formal grading scale ranging from 0 to 100 is used.

Our empirical analysis focuses on mandatory courses (Turkish language and Math) taken by all students in grades 4 to 10, along with absenteeism, as key variables. Turkish language scores measure communication skills in the local language, also making them a valuable indicator of social integration. Additionally, language proficiency serves as a proxy for non-cognitive skills and enhances learning efficiency across other subjects. Math scores, on the other hand, assess students' cognitive and analytical capabilities. In combination, Math and Turkish language scores provide a comprehensive measure of the core components of refugee students' academic capacity, school performance, and human capital. Absenteeism serves as an indicator of school attachment or school integration for refugee students.

Conflict data. The conflict data is from the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset, which collects information on state-based armed conflicts, non-state conflicts, and one-sided violence. This data set specifically includes conflicts that have exceeded the threshold of 25 battle-related deaths in a single calendar year.[10] We concentrate on violent incidents and related fatalities that occurred during the Syrian civil war between 2011 and 2019, specifically at the district level, covering 44 Syrian refugee hometown districts.

Constructing the study sample. We merge administrative education data with the conflict data, using the district of birth information. While Math and Turkish language scores are recorded for each semester, absenteeism provides the school days missed in an academic year. We create two data sets: one at the semester level and the other at the year

[10] If a conflict exceeded the 25-death threshold in a single year, but produced events in either preceding or subsequent years, all events associated with that conflict are considered, even if the threshold was not surpassed in those years.

level. At the semester level, we aggregate conflict-related events and fatalities occurring in each Syrian district during semester s. The fall semester spans September to January, while the spring semester is from February to May. In the final semester sample, we only include students for which both Math and Turkish language scores were recorded in semester s. At the year level, we aggregate conflict-related events and fatalities occurring in each Syrian district during academic year y. We exclude events or fatalities that took place during the summer holidays, from June to August, from both of our data sets.

Descriptive statistics. Figure A7 shows the distribution of Math and Turkish scores among Syrian students. The red vertical dashed line illustrates the average scores achieved by native students, while the vertical blue solid line represents the corresponding scores for Syrian students. On average, Syrian students achieve a Math score of 57.8, whereas Turkish students score 64.9. Notably, the difference in Turkish language scores is more substantial, exceeding 10 points, with Syrian students averaging 58.3 and Turkish students 69.9.[11]

Figure A8 shows the distribution of the number of school days missed per school year for the full sample (Panel A) and observations below the 95th percentile (Panel B).[12] The red vertical dashed line represents the average number of school days missed per school year by native students, and the vertical blue solid line represents the mean for Syrian students. Both panels show that Syrian students are absent more frequently than their Turkish classmates. On average, Syrian students miss 10 days of school per year (Panel B), while their Turkish classmates miss 7.6 days (statistically significant at the 1% level).

We measure concurrent ongoing violence in the Syrian students' district of birth during each semester by the number of events, and separately the number of conflict fatalities. On average, Syrian students in Türkiye are exposed to 81 attacks, with 346 corresponding deaths in their hometowns during a semester.

4 Empirical Strategy

To investigate the impact of ongoing violence in the Syrian students' district of birth on their outcomes in Türkiye, we estimate the following specification with individual fixed effects:

$$\ln Y_{idaygstc} = \beta \ln V_{dys} + f_i + f_a + f_{ygtc} + \epsilon_{idaygstc}, \tag{1}$$

where i, d, a, y, g, s, t and c index individuals, districts of birth in Syria, years since arrival, academic years, grade, semesters, teacher and classrooms, respectively. Y is the end-of-semester Math or Turkish language score, V is a violence measure, and ϵ an error term.

The treatment variable, V, is defined in two ways to capture both the intensive and extensive margins: (i) the number of violent events in the district of birth d, during semester

[11] Differences in Math and Turkish language scores between refugee and native students are statistically significant by t-test at the 1% level.

[12] Panel A in Figure A8 illustrates the distribution of the number of school days missed in a year among Syrian students. On the right tail of the distribution, it is evident that some students missed more than 150 days of school, suggesting they were enrolled but did not attend. Panel B in Figure A8 removes these points.

s, and year y; and (ii) the number of conflict fatalities in the district of birth d, during semester s, and year y.[13] Figure 1 shows a timeline for variable construction.

Our administrative data uniquely positions us in including a rich set of fixed effects that may account for confounding factors. Individual fixed effects (f_i) capture the effect of time-invariant student characteristics on outcomes (such as innate ability or motivation, past conflict exposure, and parental background). Overall, it controls for the possibility that differences between students drive the observed outcomes. The years since arrival fixed effects f_a account for the influence of time-related factors (such as acculturation, language proficiency, education system familiarity, social integration) associated with a student's duration of residence in the host country on their academic outcomes.

Finally, we include a fixed effect for each unique combination of teacher, classroom, grade, and academic year f_{ygtc}, capturing a variety of characteristics. At the classroom level, these fixed effects account for environmental factors such as room layout, lighting, technology, class size, and time-of-day effects. Grade factors encompass availability of resources due to grade and the importance of each grade for progression while academic year factors encompass curriculum changes, policy updates, administrative shifts (such as test schedules), and cohort effects. Beyond these independent dimensions, the fixed effects capture teacher characteristics including teaching style, experience, assessment practices, and potential grading biases, such as whether teachers grade refugee students more favorably during periods of heightened conflict in their home countries. These fixed effects also account for how these elements interact — for instance, how teachers adapt their methods across different rooms or grades, how classroom dynamics and teaching effectiveness vary with available resources.

High-dimensional fixed effects of this approach account for any unobserved variation at the classroom or academic year level. Consequently, including separate fixed effects for classrooms, or academic years would be redundant and lead to perfect collinearity in the estimation model. To provide assurance that there is variation to estimate the main effects, Appendix Figure A9 shows that students from one and the same hometown do not tend to attend the same school. That is, there is a wide distribution of Turkish schools that students from the very same hometown attend.

Standard errors are clustered at the district of birth for refugee students in Syria. Additionally, we provide bootstrapped standard errors and explore alternative clustering levels in the Appendix Table A2, demonstrating that our results remain robust.

Our identification assumption is that the timing, occurrence, and magnitude of violence in a refugee student's hometown in Syria are independent of factors influencing their concurrent school performance in Türkiye, conditional on high-dimensional fixed effects. Given the set of fixed effects, we are comparing refugee students with the same teacher, classroom, grade, and academic year combination, with varying degrees of exposure to hometown violence after netting out any individual specific factors and the number of years since their arrival.

[13] We apply a logarithmic transformation to the values, adding 1 to avoid issues related to missing data. In the Appendix Table A1, we demonstrate that our findings are robust to the inverse hyperbolic sine (IHS) transformation.

5 Results and Discussion

5.1 Main estimates

In Table 1, we present the results based on Equation 1. Our analysis focuses on two key performance indicators that capture the academic achievements of Syrian children: (log) Turkish language scores and (log) Math scores. These scores represent overall outcomes at the end of the semester and encompass a composite evaluation of exams, assignments, class participation, and other graded components.

In columns 1, 3, 5, and 7, our estimates incorporate fixed effects for individuals, time since arrival, and grade level. For columns 2, 4, 6, and 8, we use a more detailed fixed effects specification that combines teacher-classroom-grade-academic year instead of grade-level effects. Throughout our tables, we refer to this comprehensive combination simply as "teacher fixed effects" for brevity. This latter specification is more stringent since it captures all unobserved characteristics at the teacher-classroom level, including teaching style, peer effects, and any temporal factors specific to that learning environment. Our analysis uses two different measures of the treatment: the logarithm of the number of violent events and the logarithm of the number of fatalities. The former represents the extensive margin of the treatment, while the latter captures the intensive margin.

Across all columns, for both measures of violence, we consistently find that the Turkish language and Math scores of Syrian students improve in response to heightened levels of violence in their place of origin.[14] Column 2 indicates that for a shift from the 50th to 75th percentile of violent events, we would expect Turkish language scores among Syrian students to increase by 2.7 percent. At the mean, this is an increase of around 2 points or equivalently closing the gaps between Syrian and Turkish students by 16 percent.[15]

The shift from the 50th to the 75th percentile in the casualties treatment, leads to an average 1.8 percent increase in Turkish language scores. Although this effect is economically smaller than effects at the extensive margin, it is meaningful. It is comparable to a 1 point improvement at the mean or equivalently would close the gap between the average Syrian and Turkish student by 8 percent.

While the effect of violence on Math scores is positive and statistically significant, it is somewhat less sizable. If the number of violent events shifts from the 25th to the 75th

[14] In Appendix Table A3, we report results from models without individual fixed effects. Unlike our main specifications with individual fixed effects, these models show no significant relationship between origin conflict and academic performance. This difference highlights the importance of accounting for individual heterogeneity in several ways. First, students from conflict-afflicted regions might differ systematically in unobserved characteristics such as resilience or family support, which could confound the conflict-academic achievement relationship. Second, the timing of conflict might correlate with broader economic or political changes that affect different students differently, making individual fixed effects crucial for isolating the conflict effect. Third, measurement error in conflict exposure might correlate with student characteristics, leading to attenuation bias in models that don't account for individual heterogeneity.

[15] The percent change in the outcome due to a shift from the 50th to 75th percentile of violent events, that is an increase from 33 to 96 violent events per semester, is equal to $(96/35)^{0.0261} = 1.027$, therefore a 2.7 percent increase. The mean Turkish language score among Syrian and Turkish students is 58 and 70 points, respectively. A 2.7 percent increase at the mean among Syrian students is approximately 2 points or 17 percent of the gap between Syrian and Turkish students $2/(70-58) = 0.17$.

percentile, Math scores increase by a little under 1 percent, on average. This corresponds to an approximately half point increase for Syrian students who score around the mean. While this is economically small, the gap between Syrian and Turkish students is only around 7 points when it comes to Math scores therefore a half point increase corresponds to closing the gap by around 7 percent. Similarly, if the number of fatalities rises from the 25th to the 75th percentile, Math scores are likely to increase by less than 1 percent, on average.

Our results suggest that heightened violence in hometowns is associated with a larger improvement in Turkish language scores compared to Math scores among Syrian refugees. This may reflect the fact that children put considerable effort to integrate into their new society. As violence intensifies in their hometowns, Syrian students proactively invest in Turkish language skills, a crucial step in achieving effective integration, which enhances their communication and participation in educational and social activities. We also find a modest increase in Math scores, which may reflect the increased academic effort stemming from the reduced likelihood of return, or reflect improved language skills needed for Math.

Do higher levels of violence affect absenteeism among Syrian students?

In Figure 2, we analyze the number of school absences per semester, serving as an indicator of school attachment among Syrian students. While school attachment does not directly reflect academic achievement, it captures the students' willingness to attend school and engage in educational activities, including exams.

Across both treatment variables, we consistently find null results for the outcomes, except at the intensive margin, where in one specification we find a negative effect suggesting fewer missed school days. These findings indicate that school attachment does not change meaningfully in response to heightened violence in students' hometowns.

Differential treatment effects by sub-samples

Table 2 examines whether the treatment effects differ between two groups of Syrian students: those who remain in school throughout our observation period and those who eventually drop out. This analysis is crucial since focusing only on average effects might mask important differences, particularly if violence disproportionately affects students at risk of dropping out. Our results show that the positive effects we document are driven by students who continue their education. Importantly, we find no evidence that hometown violence either reduces academic performance or increases risk of dropout among Syrian students.

To further investigate this pattern, we examine chronic absenteeism and probability of dropout. Chronic absenteeism is defined as missing at least 10 percent of the academic year, an established early warning sign of academic risk and subsequent dropout (Bruner et al., 2011; Tumen et al., 2023). Figure 2 confirms that exposure to violence in students' hometowns does not increase their likelihood of being chronically absent, whether measured at the extensive or intensive margin. In addition, Figure A10 also shows that treatment itself is not related to the probability of students dropping out.

Does naturalization status matter for the response to hometown violence?

Table 3 focuses on the outcomes for Syrian students who have received Turkish citizenship through naturalization. Some Syrian families obtain Turkish citizenship through avenues such as marriage or continued employment. As we observe information regarding their district of origin in Syria, we apply the same regression analyses to naturalized students.

Our findings show that the impact of violence on naturalized students is much smaller compared to their non-naturalized counterparts. This difference may be attributed to the fact that naturalized status already offers a permanent option to stay in Türkiye. Consistent with our main results, these students appear to be less likely to change their integration effort in the face of ongoing violence in their hometowns.

We find that for Turkish language scores, the overall effect for naturalized students is approximately half of that observed for Syrian students who have not yet naturalized. To illustrate, if we take the same example as our baseline and consider a shift from the 50th to the 75th percentile of violent events, this results in a 1.7 percent change in Turkish language scores for naturalized students and a 3.0 percent change for those not yet naturalized. Importantly, there is no statistically significant difference in Math scores between these two groups.

Heterogeneity by gender, father's education, time of arrival, perpetrators of violence, and past exposure to violence

Table 4 shows the effects of violence by gender. When we consider a shift from the 50th to 75th percentile of violent events, we observe a 2.5 percent change in Turkish language scores for male students, whereas for female students, this change is slightly higher at 3.1 percent. However, it's worth noting that the difference in the extensive margin is not statistically significant. What is particularly noteworthy is that the effect on Math scores appears to be primarily driven by female students.

We also examine whether the effect varies based on the father's education. Due to limited data availability, we focus on whether the student's father has formal education or not. Table 5 shows there is no evidence of heterogeneity along this dimension.

Table 6 examines the impact of violence on students based on their arrival time in Türkiye. We focus on 2017, five years into the conflict, when the likelihood of short-term return had significantly declined due to ongoing violence and large-scale destruction in Syria. By this point, prolonged conflict and infrastructure devastation had reinforced refugees' expectations that returning soon was improbable. Consistent with this, we find that students who arrived in 2017 exhibit larger treatment effects in Turkish language scores than those who arrived earlier, suggesting that lower return expectations strengthened their motivation to integrate. In contrast, we find no significant differences in Math scores across arrival cohorts.

Panels A and B of Figure 3 investigate whether reactions to violence vary depending on the actors involved. We classify violent events and resulting fatalities according to whether they are caused by state, non-state, or civilian actors. We reapply our baseline model from

Equation 1 with a treatment specific to each actor. We find no statistically significant difference between the treatments specific to each actor, nor compared to the baseline.

Lastly, we examine whether prior exposure to violence in Syria influences how students respond to ongoing violence. Understanding this heterogeneity is important, as students from areas with high levels of past violence may have already adjusted their behavior—such as increasing their academic effort as a coping mechanism—which could affect their response to new conflict exposure. Table 7 shows that refugee students from districts with below-median past violence exhibit a weaker response to current violence compared to their peers from high-violence districts. Specifically, the interaction terms indicate that the positive effect of violence on academic effort is significantly lower for students from less-violent origins, suggesting that those who previously endured high-intensity conflict may have been more motivated to invest in their studies upon displacement. These findings support the idea that prior exposure to extreme violence fosters an increased drive for educational integration in the host country.

Similarly, we find evidence of the effects of violence on education outcomes being compounding. Table 8 shows estimations from Equation 1 where contemporaneous violence is replaced with (i) cumulative exposure to hometown violence since migrating and (ii) cumulative exposure to hometown violence since the start of the conflict. As compared to the contemporaneous effect of hometown violence, cumulative effects are larger in magnitude for Turkish language and Math scores. This suggests that, with every new instance of violence, students exert greater effort to integrate into their new home.

Are there spillover effects to Turkish students?

To explore possible spillover effects on Turkish students, we collapse our semester-level data to the level of the school-academic year-grade-semester-classroom. At this level, we calculate two key measures: (1) the average Turkish language and Math scores for Turkish students, and (2) the share of Syrian students.

As detailed below, our analysis follows three steps. First, we construct a *weighted violence index* that captures the intensity of violence in the home districts of Syrian students within each classroom. This measure accounts for the variation in conflict exposure among refugee classmates and its potential indirect effects on Turkish students. Second, we estimate the direct impact of the share of Syrian students on the academic performance of Turkish students, isolating the congestion effect that may arise from larger class sizes or resource constraints. Third, we interact the weighted violence index with the share of Syrian students to examine whether the presence of Syrian classmates exposed to higher levels of violence influences Turkish students' outcomes, potentially through peer effects stemming from increased academic effort among refugee students.

We construct the weighted violence index as the sum of the shares of Syrian students from each district, weighted by the level of violence in their respective home districts. In particular, for each cell, we calculate the sum of the share of Syrian students born in each

district ($Share_{ysgcjdp}$) multiplied by the contemporaneous violence in the respective Syrian origin-district d ($Violence_{dys}$):

$$WeightedIndex_{ysgcjp} = \sum_{d=1}^{n} Share_{ysgcjdp} \times Violence_{dys}, \tag{2}$$

where the index is computed at the academic year y, semester s, grade g, classroom c, school j, Syrian origin-district d and Turkish destination-province p level.

To estimate spillover effects at the level of the school grade-semester, we estimate:

$$\begin{aligned} Score_{ysgcjp} =& \beta_1 \cdot Share_{ysgcjp} + \beta_2 \cdot WeightedIndex_{ysgcjp} \\ &+ \beta_3 \cdot WeightedIndex_{ysgcjp} \times Share_{ysgcjp} \\ &+ \Gamma_y + \gamma_s + \theta_g + \lambda_j + \alpha_{yp} + u_{ysgcjp}, \end{aligned} \tag{3}$$

where $Score_{ysgcjp}$ represents the (log) Turkish language scores and (log) Math scores of native students in academic year y, semester s, grade g, classroom c, attending school j, and located in province p.

The coefficient β_1 captures the baseline impact of having Syrian classmates regardless of their exposure to violence (including congestion effects). The coefficient β_2 measures the direct effect of violence exposure through Syrian classmates on Turkish students' academic performance, while β_3 captures spillover effects on Turkish students by interacting the weighted violence index with the share of Syrian students in the classroom. Together, β_2 and β_3 allow us to understand how exposure to violence affects Turkish students' academic performance both through the presence of Syrian students who experienced violence and through its interaction with classroom composition.

Our specification includes a rich set of fixed effects to account for various potential confounders: academic year fixed effects (Γ_y) control for common shocks affecting all students in a given year, a summer-semester indicator (γ_s) accounts for systematic differences between semesters, grade fixed effects (θ_g) control for grade-specific factors affecting student performance, school fixed effects (λ_j) absorb time-invariant school characteristics, and academic year-by-province fixed effects (α_{yp}) control for province-specific yearly shocks that might affect student outcomes. The error term is denoted by u_{ysgcjp}, and we cluster standard errors at the school level to account for potential correlation in outcomes within schools.

The spillover estimates are presented in Table 9, broken down across three panels. In Panel A, we present the results for the entire sample, offering a comprehensive view of the spillover effects. Panel B narrows the focus to schools with an above-median number of Syrian refugees during the school year, aiming to highlight instances with a substantial concentration of Syrian students. In contrast, Panel C concentrates on schools with a below-median number of Syrian refugees during the school year.

This partitioning serves a dual purpose. First, it allows us to conduct a validation test, ensuring the presence of spillover effects primarily in schools with a high concentration of

Syrian students, as one would expect. Secondly, it enables a more granular examination of how these effects may vary across schools with different levels of Syrian student enrollment, shedding light on the nuanced dynamics of refugee integration within the educational system.

The presence of Syrian students in the classroom, captured by the coefficient β_1, has a negative and statistically significant effect on the academic performance of Turkish students.This aligns with the well-documented mechanical congestion effect in the literature, which attributes such outcomes to reductions in teaching standards and diminished educational resources per student in classrooms with a higher number of refugee students (Betts and Fairlie, 2003; Tumen, 2019; Tumen et al., 2023). However, this relationship becomes more nuanced when considering the exposure to violence among Syrian students in their origin districts. The positive coefficient on the interaction term suggests that as the proportion of Syrian students in the classroom who were exposed to violence increases, the academic performance of Turkish students improves. This positive spillover effect likely stems from our earlier finding that Syrian students exposed to violence tend to perform better academically. Their improved performance appears to generate beneficial peer effects for Turkish students, possibly through enhanced classroom interactions and learning complementarities.

In terms of magnitudes, a one-unit increase in the share of Syrian students (about 12 students), is associated with an 18 percent decrease in the Turkish language score—as shown in Table 9, Column 1. This decrease represents 13.2 points as a percentage share of the mean. The impact of the intensity of violence is comparatively smaller than that of the share of Syrian students (the base effect) in the classroom, but remains meaningful.

All else being equal, a one-unit increase in the weighted index of violent events results in a 3.7 percent increase in the Turkish language score and a 4.5 percent increase in the Math score. To provide some context, the mean scores for Turkish language and Math are 73.7 and 68.9, respectively. The analogous effect of the intensity dimension is statistically significant, though the effect sizes are smaller.

Exploring these findings in more detail, our split-sample regressions reveal that the spillover effects are stronger in school-years with a substantial concentration of refugee students (Panel B). Specifically, all else being equal, a one-unit increase in the weighted index of violent events results in a 5.3 percent increase in the Turkish language score and a 6.4 percent increase in the Math score. These effect sizes are 1.4 and 1.9 percentage points higher than those observed in the full sample for Turkish and Math scores, respectively.

5.2 Robustness checks

In this section, we conduct a series of robustness checks to validate the reliability and stability of our main findings.

Clean control analysis

Recent work on difference-in-differences shows that standard two-way fixed effects estima-

tions may be prone to biases when confronted with treatment heterogeneity and differential treatment timing. These biases arise from units being concurrently considered as controls, even though they had undergone treatment in previous time periods. The literature suggests several difference-in-differences estimators that are resilient; however, their applicability is limited to specific settings. For example, Sun and Abraham (2021) and Callaway and Sant'Anna (2021) only apply to treatments that follow a staggered design (that is, once a unit is treated, the treatment cannot switch off) while de Chaisemartin et al. (2022) allow the treatment to be continuously distributed at every point in time under certain conditions.

We adopt the approach suggested by de Chaisemartin et al. (2022), employing "movers" as treated observations and "quasi-stayers" as control observations. To distinguish between these groups, we generate dummy treatment variables. In our context, movers are observations with a significant treatment intensity, defined as a treatment intensity ranking in the 25th percentile or higher within the distribution of the treatment.

A quasi-stayer is defined as an observation with a small and irrelevant treatment intensity, falling below the 25th percentile in the distribution of treatment intensity. As illustrated in Figure A1, there is significant variation in treatment over time, necessitating additional simplifications for a refined set of controls. Specifically, we (i) exclude units whose treatment switches on in time period t and then off in $t+n$, where n ranges from 1 to 16, and (ii) exclude units that consistently receive treatment. Consequently, our sample of interest comprises units that are never treated and units initially untreated in the first period, subsequently receiving treatment in a later period and remaining treated.

Table A4 shows that our findings remain robust in the clean controls analysis, suggesting that the effects we identify are not simply an artifact of the heterogeneous treatment effects in our empirical setting.

Ruling out influential observations

We rule out the importance of influential observations by plotting the coefficients of our preferred specifications as each province is omitted at a time. Figure A11 shows that our coefficient estimates are quite stable as a specific province is eliminated from our main sample in each iteration. We repeat a similar analysis with Figure A12 in which we drop one semester-year at a time and again find that our estimates are not driven by any single semester-year.

Placebo tests: Leads of exposure to violence

Figure A13 demonstrates that there are null effects of leads of violence on Turkish language and Math scores. Specifically, within the subset of students observed for at least three academic years, we demonstrate that the impact of contemporaneous violence continues to be positive and significant both at the extensive and intensive margins. Reassuringly, the effect of violence predicted one year in advance is nearly zero and not statistically significant at the 90% confidence level.

Alternative clustering of standard errors

Table A2 demonstrates the robustness of the main findings using three different approaches to clustering standard errors: district-level bootstrapping, district and academic year level clustering, and a district and academic year level bootstrapping. Across all specifications, the effects remain statistically significant.

Alternative parametrization of outcomes and treatment

We test the robustness of our results using alternative measures. Table A5 presents three transformations of academic performance: inverse hyperbolic sine (IHS), grade-standardized scores, and raw scores (0–100). Table A6 uses a binary indicator for passing (score ≥ 45). Table A1 replaces log-transformed violence measures with IHS transformations. Our findings remain robust across all specifications.

6 Conclusion

We investigate the relationship between ongoing violence in the hometowns of Syrian refugee students and its impact on their educational performance in Türkiye. Using an administrative panel dataset, we document several key findings. First, we find that heightened levels of violence in a refugee's hometown lead to improved academic outcomes in Türkiye. This improvement is observed in their scores for both Turkish language and Math classes, with Turkish language scores being larger in magnitude. Importantly, we do not observe a corresponding improvement among naturalized Syrian students. These findings suggest that increased violence levels may lead to greater efforts toward integration into the host country, driven by a recognition of the limited prospects for returning home. Furthermore, we identify a small yet statistically significant positive effect of the violence on the academic performance of Turkish students. This spillover indicates that the enhanced integration efforts of their Syrian peers have a beneficial impact on native students.

Our findings have important implications. Given the evident improvement in Turkish language scores among refugee students and related positive spillover effects to natives, there is a case for prioritizing language support measures. This may involve allocating additional resources to develop targeted courses and specialized tutoring programs. Such initiatives can effectively expedite the language acquisition and educational progress of refugees while also fostering interaction and mutual understanding with their Turkish peers. Tailored academic and social support should be a focus, such as academic assistance and counseling, alongside programs designed to facilitate their integration into the host country.

To sum up, our research highlights the influence of events in the refugees' home countries on the integration of refugee children into the education system and, consequently, into the host society. As a result, it becomes crucial for authorities to formulate educational policies that prioritize inclusiveness, nurturing academic achievement, and fostering mutual understanding among students from different backgrounds.

References

Abel, G. J., M. Brottrager, J. C. Cuaresma, and R. Muttarak (2019): "Climate, conflict and forced migration," *Global Environmental Change*, 54, 239–249.

Abramitzky, R., L. Boustan, P. Catron, D. Connor, and R. Voigt (2023): "The refugee advantage: English-language attainment in the early twentieth century," *Sociological Science*, 10, 769–805.

Adda, J., C. Dustmann, and J.-S. Gorlach (2022): "The dynamics of return migration, human capital accumulation, and wage assimilation," *Review of Economic Studies*, 89, 2841–2871.

Akbulut-Yuksel, M. (2014): "Children of war: The long-run effects of large-scale physical destruction and warfare on children," *Journal of Human Resources*, 49, 634–662.

Alfano, M. and J.-S. Görlach (2023): "Terrorism, media coverage, and education: Evidence from al-Shabaab attacks in Kenya," *Journal of the European Economic Association*, 21, 727–763.

——— (2024): "Terrorism and Education: Evidence from Instrumental-Variables Estimators," *Journal of Applied Econometrics*, 39, 906–925.

Ang, D. (2021): "The effects of police violence on inner-city students," *Quarterly Journal of Economics*, 136, 115–168.

Angrist, J. D. and A. D. Kugler (2008): "Rural windfall or a new resource curse? Coca, income, and civil conflict in Colombia," *Review of Economics and Statistics*, 90, 191–215.

Bertoni, E., M. Di Maio, V. Molini, and R. Nistico (2019): "Education is forbidden: The effect of the Boko Haram conflict on education in North-East Nigeria," *Journal of Development Economics*, 141, 102249.

Betts, J. R. and R. W. Fairlie (2003): "Does immigration induce 'native flight' from public schools into private schools?" *Journal of Public Economics*, 87, 987–1012.

Bharadwaj, P., M. Bhuller, K. V. Løken, and M. Wentzel (2021): "Surviving a Mass Shooting," *Journal of Public Economics*, 201, 104469.

Boucher, V., S. Tumen, M. Vlassopoulos, J. Wahba, and Y. Zenou (2021): "Ethnic mixing in early childhood: Evidence from a randomized field experiment and a structural model," CEPR Discussion Paper #15528.

Brown, R. and A. Velasquez (2017): "The effect of violent crime on the human capital accumulation of young adults," *Journal of Development Economics*, 127, 1–12.

Bruck, T., M. Di Maio, and S. H. Miaari (2019): "Learning the hard way: The effect of violent conflict on student academic achievement," *Journal of the European Economic Association*, 17, 1502–1537.

Bruner, C., A. Discher, and H. Chang (2011): "Chronic elementary absenteeism: A problem hidden in plain sight," Research Brief: Attendance Works and Child & Family Policy Center.

Cabral, M., B. Kim, M. Rossin-Slater, M. Schnell, and H. Schwandt (2024): "Trauma at school: The impacts of shootings on students' human capital and economic outcomes," *Review of Economic Studies*, forthcoming.

Callaway, B. and P. H. C. Sant'Anna (2021): "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 225, 200–230.

Casey, M., J. C. Schiman, and M. Wachala (2018): "Local violence, academic performance, and school accountability," *American Economic Association Papers and Proceedings*, 108, 213–216.

Chamarbagwala, R. and H. E. Moran (2011): "The human capital consequences of civil war: Evidence from Guatemala," *Journal of Development Economics*, 94, 41–61.

Chang, E. and M. Padilla-Romo (2023): "When crime comes to the neighborhood: Short-term shocks to student cognition and secondary consequences," *Journal of Labor Economics*, forthcoming.

Cortes, K. E. (2004): "Are refugees different from economic immigrants? Some empirical evidence on the heterogeneity of immigrant groups in the United States," *Review of Economics and Statistics*, 86, 465–480.

Daoudy, M. (2020): *The origins of Syrian conflict: Climate change and human security*, Cambridge, UK: Cambridge University Press.

de Chaisemartin, C., X. d'Haultfoeuille, F. Pasquier, and G. Vazquez-Bare (2022): "Difference-in-differences estimators for treatments continuously distributed at every period," *arXiv preprint arXiv:2201.06898*.

Dustmann, C. (1996): "Return migration: The European experience," *Economic Policy*, 11, 213–250.

Galor, O. and O. Stark (1990): "Migrants' savings, the probability of return migration and migrants' performance," *International Economic Review*, 31, 463–467.

Justino, P., M. Leone, and P. Salardi (2014): "Short- and long-term impact of violence on education: The case of Timor Leste," *World Bank Economic Review*, 28, 320–353.

Khalifa, M. (2013): "The impossible partition of Syria," Arab Reform Initiative, Thematic Studies.

Khan, A. H. (1997): "Post-migration investment in education by immigrants in the United States," *Quarterly Review of Economics and Finance*, 37, 285–313.

Koppensteiner, M. F. and L. Menezes (2021): "Violence and human capital investments," *Journal of Labor Economics*, 39, 787–823.

Leon, G. (2012): "Civil conflict and human capital accumulation: The long-term effects of political violence in Peru," *Journal of Human Resources*, 47, 991–1022.

Merkle, L. and K. F. Zimmermann (1992): "Savings, remittances, and return migration," *Economics Letters*, 38, 77–81.

Michaelsen, M. and P. Salardi (2020): "Violence, psychological stress and educational performance during the "war on drugs" in Mexico," *Journal of Development Economics*, 143, 102387.

Monteiro, J. and R. Rocha (2017): "Drug battles and school achievement: Evidence from Rio de Janeiro's favelas," *Review of Economics and Statistics*, 99, 213–228.

Phillips, C. (2015): "Sectarianism and conflict in Syria," *Third World Quarterly*, 36, 357–376.

Rodriguez, C. and F. Sanchez (2012): "Armed conflict exposure, human capital investments, and child labor: Evidence from Colombia," *Defence and Peace Economics*, 23, 161–184.

Shemyakina, O. (2011): "The effect of armed conflict on accumulation of schooling: Results from Tajikistan," *Journal of Development Economics*, 95, 186–200.

SNHR (2023): "On the 12th anniversary of the popular uprising," The Syrian Network for Human Rights.

Sun, L. and S. Abraham (2021): "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 225, 175–199.

Tumen, S. (2019): "Refugees and 'native flight' from public to private schools," *Economics Letters*, 181, 154–159.

——— (2023): "The case of Syrian refugees in Türkiye: Successes, challenges, and lessons learned," Background Paper for the *World Development Report 2023: Migrants, Refugees, and Societies*. The World Bank.

Tumen, S., M. Vlassopoulos, and J. Wahba (2023): "Training teacher for diversity awareness: Impact on school outcomes of refugee children," *Journal of Human Resources*, forthcoming.

Tumen, S. and Vlassopoulos, M. and Wahba, J. (2025): "The Power of Language: Educational and Mental Health Impacts of Language Training for Refugee Children," IZA Discussion Paper #17593.

UNHCR (2019): "Stepping up: Refugee education in crisis," The UN Refugee Agency.

United Nations High Commissioner for Refugees (2022): "Global Trends: Forced Displacement in 2022," .

Van Dam, N. (2017): *Destroying a nation: The civil war in Syria*, London, UK: I. B. Tauris & Co Ltd.

Verwimp, P. and J. Van Bavel (2014): "Schooling, violent conflict, and gender in Burundi," *World Bank Economic Review*, 28, 384–411.

World Bank (2023): "World Development Report 2023: Migrants, Refugees, and Societies," The World Bank. Washington, DC.

Table 1: Turkish language and Math scores improve in response to heightened violence

	Log Turkish score				Log Math score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log. # of violent events	0.0155***	0.0261***			0.0037**	0.0075**		
	(0.0022)	(0.0046)			(0.0014)	(0.0029)		
Log. # of fatalities			0.0108***	0.0137***			0.0034***	0.0041**
			(0.0020)	(0.0038)			(0.0009)	(0.0018)
R-squared	0.744	0.839	0.744	0.838	0.754	0.839	0.754	0.839
# of observations	53,973	53,973	53,973	53,973	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	60.49	60.49	58.33	58.33	58.33	58.33
Mean sample	58.31	58.31	58.31	58.31	57.77	57.77	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grade FE	Yes	No	Yes	No	Yes	No	Yes	No
Teacher FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(4) and *Log Math score* in Columns (5)-(8). Columns (1), (3), (5) and (7) incorporate fixed effects for individuals, time since arrival and grade level while Columns (2), (4), (6) and (8) include *Teacher FE* instead of *Grade FE*. *Teacher FE* captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 2: Improvements in education outcomes are driven by students continuing their education

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log # of violent events	-0.0082		-0.0128	
	(0.0088)		(0.0106)	
Continuing × Log # of violent events	0.0377***		0.0224*	
	(0.0117)		(0.0116)	
Log # of fatalities		-0.0073		-0.0077
		(0.0087)		(0.0064)
Continuing × Log # of fatalities		0.0228*		0.0128+
		(0.0128)		(0.0083)
R-squared	0.839	0.839	0.840	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(2) and *Log Math score* in Columns (3)-(4). *Continuing* refers a dummy variable equal to 1 if a student is continuing their education (outcome of final compulsory education unknown) and zero if the student dropped out of schooling before the end of their compulsory education. Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester-level data. In each regression individual, years since arrival and teacher fixed effects are included. Standard errors are clustered at the district level. ***, **, *, and + denote significance levels at the 1%, 5%, 10%, and 15% respectively.

Table 3: Heterogeneous effects – smaller impacts for naturalized students

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0273***		0.0075**	
	(0.0045)		(0.0033)	
Naturalised × Log. # of violent events	-0.0119**		0.0001	
	(0.0055)		(0.0061)	
Log. # of fatalities		0.0144***		0.0044**
		(0.0038)		(0.0020)
Naturalised × Log. # of fatalities		-0.0072**		-0.0031
		(0.0034)		(0.0032)
Total effect	0.0154	0.0072	0.0075	0.0013
p-value	0.0073	0.0102	0.0922	0.5413
R-squared	0.839	0.839	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	60.49	60.49
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(2) and *Log Math score* in Columns (3)-(4). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester-level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 4: Heterogeneous effects – female students drive the treatment effects for Math score

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0233***		-0.0004	
	(0.0040)		(0.0025)	
Female × Log. # of violent events	0.0053**		0.0153***	
	(0.0025)		(0.0023)	
Log. # of fatalities		0.0127***		-0.0003
		(0.0030)		(0.0009)
Female × Log. # of fatalities		0.0020		0.0085***
		(0.0021)		(0.0022)
Total effect	0.0286	0.0146	0.0149	0.0082
p-value	0.0000	0.0029	0.0001	0.0049
R-squared	0.839	0.838	0.840	0.840
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	60.49	60.49
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1), (2), (5) and (6), and *Log Math score* in columns (3), (4), (7) and (8). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester-level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 5: No heterogeneous effects by father's education

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0324***		0.0132***	
	(0.0028)		(0.0030)	
Log. # of violent events	-0.0094		-0.0086	
× Father has no formal education	(0.0057)		(0.0053)	
Log. # of fatalities		0.0166***		0.0064***
		(0.0035)		(0.0023)
Log. # of fatalities		-0.0043		-0.0034
× Father has no formal education		(0.0027)		(0.0028)
R-squared	0.839	0.839	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(4) and *Log Math score* in Columns (5)-(8). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 6: Heterogeneous effects – students who arrived later exhibit larger treatment effects in Turkish scores

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0148***		0.0065***	
	(0.0029)		(0.0018)	
Arrival: September 2017 onwards	0.0202**		0.0018	
× Log. # of violent events	(0.0098)		(0.0067)	
Log. # of fatalities		0.0060***		0.0026**
		(0.0017)		(0.0010)
Arrival: September 2017 onwards		0.0142*		0.0027
× Log. # of fatalities		(0.0080)		(0.0035)
R-squared	0.839	0.839	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester-level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 7: Heterogeneous effects – treatment effects are concentrated in students from high violence origins

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0350***		0.0119***	
	(0.0006)		(0.0006)	
Below median: past violence in Syria	-0.0185***		-0.0091**	
× Log. # of violent events	(0.0050)		(0.0034)	
Log. # of fatalities		0.0215***		0.0078***
		(0.0004)		(0.0003)
Below median: past violence in Syria		-0.0150***		-0.0071***
× Log. # of fatalities		(0.0037)		(0.0012)
R-squared	0.839	0.839	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester-level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 8: Effects of exposure to violence are compounding

	Log Turkish score				Log Math score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log. cumulative # of violent events since mig.	0.0406***				0.0131***			
	(0.0051)				(0.0029)			
Log. cumulative # of violent events		0.3133*				0.1749*		
		(0.1804)				(0.1012)		
Log. cumulative # of fatalities since mig.			0.0306***				0.0105***	
			(0.0038)				(0.0012)	
Log. cumulative # of fatalities				0.1441*				0.0732
				(0.0772)				(0.0462)
R-squared	0.840	0.838	0.839	0.838	0.840	0.839	0.840	0.840
# of observations	53,973	53,973	53,973	53,973	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44	44	44	44	44
Mean sample	58.31	58.31	58.31	58.31	57.77	57.77	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

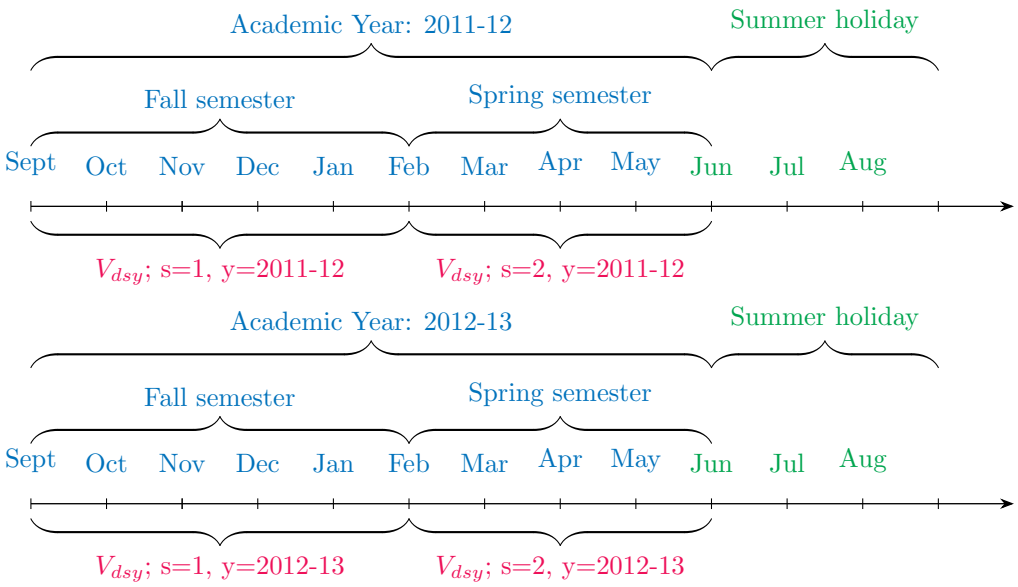
Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1) - (4) and *Log Math score* in Columns (5) - (8). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table 9: Spillovers to Turkish students

Panel A: All				
	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Share of Syrian students	-0.1791**	-0.1395**	-0.2293**	-0.1993**
	(0.0801)	(0.0670)	(0.1092)	(0.0913)
Weighted index: violent events	-0.0034**		-0.0014	
	(0.0015)		(0.0017)	
Share of Syrian students × Weighted index: violent events	0.0406**		0.0462*	
	(0.0195)		(0.0268)	
Weighted index: fatalities		-0.0027***		-0.0009
		(0.0010)		(0.0012)
Share of Syrian students × Weighted index: fatalities		0.0239*		0.0305*
		(0.0127)		(0.0173)
R-squared	0.624	0.624	0.614	0.614
# of observations	25,946	25,946	25,946	25,946
# of clusters	1,903	1,903	1,903	1,903
Mean sample	73.20	73.20	68.17	68.17
Panel B: At least median number of Syrian refugees in the school-year				
	Log Turkish score		Log Math score	
	(5)	(6)	(7)	(8)
Share of Syrian students	-0.2756***	-0.2246***	-0.3417***	-0.2904***
	(0.0931)	(0.0790)	(0.1250)	(0.1065)
Weighted index: violent events	-0.0049**		-0.0010	
	(0.0021)		(0.0026)	
Share of Syrian students × Weighted index: violent events	0.0579**		0.0652**	
	(0.0228)		(0.0309)	
Weighted index: fatalities		-0.0035**		-0.0002
		(0.0015)		(0.0018)
Share of Syrian students × Weighted index: fatalities		0.0353**		0.0411**
		(0.0151)		(0.0203)
R-squared	0.569	0.569	0.558	0.558
# of observations	13,463	13,463	13,463	13,463
# of clusters	550	550	550	550
Mean sample	72.81	72.81	67.54	67.54
Panel C: Below median number of Syrian refugees in the school-year				
	Log Turkish score		Log Math score	
	(9)	(10)	(11)	(12)
Share of Syrian students	0.2535	0.2677	-0.1221	-0.0405
	(0.3688)	(0.3636)	(0.4681)	(0.4653)
Weighted index: violent events	-0.0075***		-0.0070***	
	(0.0020)		(0.0025)	
Share of Syrian students × Weighted index: violent events	0.0212		0.0938**	
	(0.0305)		(0.0383)	
Weighted index: fatalities		-0.0048***		-0.0042***
		(0.0011)		(0.0014)
Share of Syrian students × Weighted index: fatalities		0.0136		0.0556***
		(0.0157)		(0.0211)
R-squared	0.927	0.927	0.921	0.921
# of observations	12,370	12,370	12,370	12,370
# of clusters	1,819	1,819	1,819	1,819
Mean sample	73.65	73.65	68.89	68.89
School FE	Yes	Yes	Yes	Yes
Grade FE	Yes	Yes	Yes	Yes
Academic year FE	Yes	Yes	Yes	Yes
Summer semester FE	Yes	Yes	Yes	Yes
Province × academic year FE	Yes	Yes	Yes	Yes

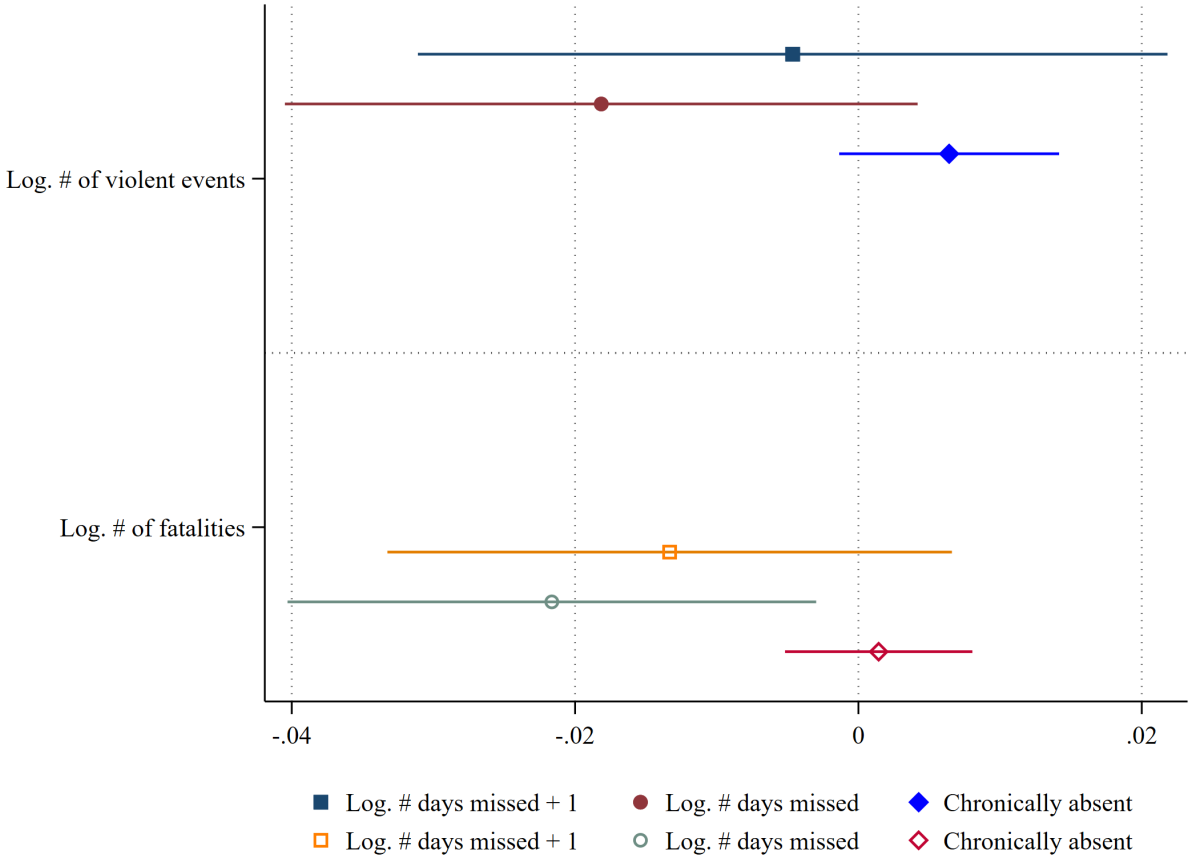
Notes: This table reports estimates from classroom level linear regressions. The dependent variable is *Log Turkish score* in Columns (1), (2), (5), (6), (9) and (10), and *Log Math score* in Columns (3), (4), (7), (8), (11) and (12). Panel A is the sample of Turkish students assigned to classrooms with at least 1 Syrian student, Panel B is the sub-sample of classrooms with at least the median number of Syrian students and Panel C is the sub-sample of of classrooms with below median number (and at least 1) of Syrian students. Standard errors are clustered at the school level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Figure 1: Treatment timing example



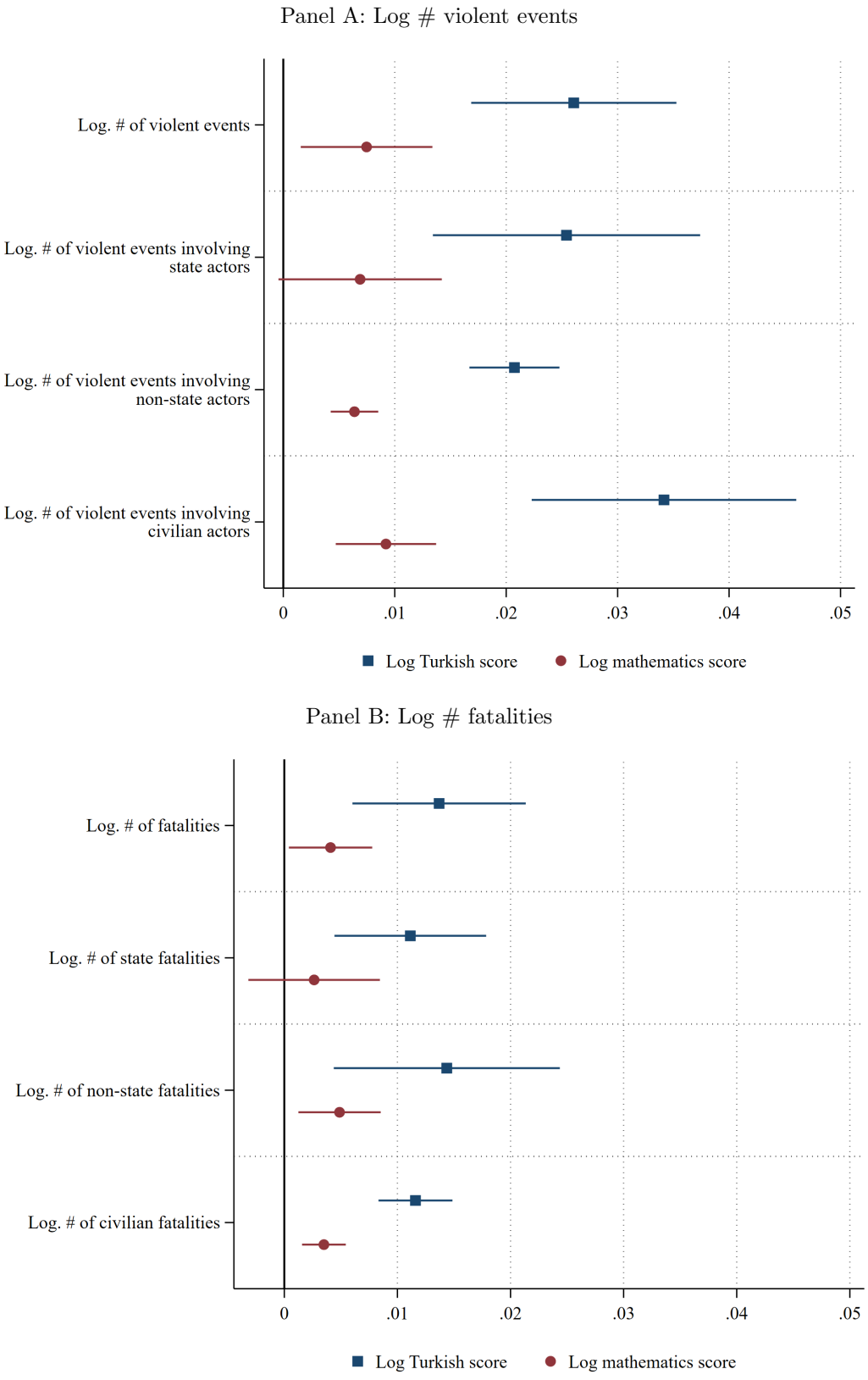
Notes: Visualization of how the treatment is calculated at the semester level, focusing on just two of the academic-years covered. s index semesters, and y, the academic year.

Figure 2: Exposure to violence does not increases school absences



Notes: This figure reports estimates from six individual fixed effect regressions. The dependent variable is *Log # of school days missed + 1*, *Log # of school days missed* and *Chronically absent* depicted by the square, circular and diamond markers. The sample is the academic year level data and students who have missed more than 115 school days in a year (95th percentile) are excluded from the sample. Standard errors are clustered at the district level. Whiskers correspondent to confidence intervals at the 90% level.

Figure 3: No heterogeneous effects – state, non-state, and civilian actors



Notes: This figure reports estimates from the baseline individual fixed effects regressions. The treatment variables in Panel A and Panel B are indicated on the vertical axis. Each point corresponds to a separate regression. Standard errors are clustered at the district level and whiskers show 95% confidence intervals.

A Appendix

Table A1: Robustness – Alternative parametrization of violence

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
IHS number of violent events	0.0245***		0.0070**	
	(0.0049)		(0.0029)	
IHS number of fatalities		0.0130***		0.0038**
		(0.0038)		(0.0019)
R-squared	0.839	0.838	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	58.33	58.33
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(4) and *Log Math score* in Columns (5)-(8). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table A2: Robustness – Alternative clustering of standard errors

Panel A: District level bootstrapping				
	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0261***		0.0075**	
	(0.0062)		(0.0031)	
Log. # of fatalities		0.0137***		0.0041**
		(0.0048)		(0.0018)
R-squared	0.839	0.838	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Panel B: District and academic year level clustering				
	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log # of violent events	0.0261***		0.0075*	
	-0.0079		-0.0041	
Log # of fatalities		0.0137*		0.0041*
		-0.0072		-0.0023
R-squared	0.839	0.838	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	219	219	219	219
Panel C: District and academic year level bootstrapping				
	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0261***		0.0075*	
	(0.0079)		(0.0039)	
Log. # of fatalities		0.0137**		0.0041**
		(0.0065)		(0.0020)
R-squared	0.839	0.838	0.839	0.839
# of observations	53,973	53,973	53,973	53,973
# of clusters	219	219	219	219
Mean baseline (2011-2014)	60.49	60.49	58.33	58.33
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(2) and *Log Math score* in Columns (3)-(4). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors bootstrapped with 100 replications and clustered at the district level in Panel A, clustered at the district-academic year level in Panel B and are bootstrapped with 100 replications and clustered at the district-academic year level in Panel C. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table A3: Robustness – Estimating effects of violence without individual fixed effects

	Log Turkish score		Log Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0087		-0.0018	
	(0.0070)		(0.0049)	
Log. # of fatalities		0.0064		-0.0003
		(0.0046)		(0.0029)
R-squared	0.589	0.589	0.572	0.572
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	58.33	58.33
Mean sample	58.31	58.31	57.77	57.77
Individual FE	No	No	No	No
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates from linear regressions. The dependent variable is *Log Turkish score* in Columns (1)-(4) and *Log Math score* in Columns (5)-(8). Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table A4: Robustness – clean controls analysis

	Log Turkish score				Log Math score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# of violent events ≥ 25th percentile	0.0314***	0.0583***			0.0043	0.0325***		
	(0.0057)	(0.0032)			(0.0035)	(0.0021)		
# of violent events ≥ 50th percentile			0.0355***	0.0527***			0.0093***	0.0253***
			(0.0025)	(0.0018)			(0.0018)	(0.0023)
R-squared	0.838	0.826	0.839	0.840	0.839	0.832	0.839	0.840
# of observations	53,973	23,207	53,973	23,243	53,973	23,207	53,973	23,243
# of clusters	44	39	44	39	44	39	44	39
Mean sample	54.63	53.47	54.63	53.94	53.59	52.20	53.59	52.83
Number of students	17,857	7,384	17,857	10,858	17,857	7,384	17,857	10,858
Number of treated students	4,838	4,838	8,299	8,299	4,838	4,838	8,299	8,299
Number of control students	2,546	2,546	2,560	2,559	2,546	2,546	2,560	2,559
	Log Turkish score				Log Math score			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
# of fatalities ≥ 25th percentile	0.0349***	0.0570***			0.0104***	0.0326***		
	(0.0040)	(0.0017)			(0.0024)	(0.0039)		
# of fatalities ≥ 50th percentile			0.0348***	0.0533***			0.0103***	0.0267***
			(0.0030)	(0.0020)			(0.0010)	(0.0046)
R-squared	0.839	0.842	0.839	0.839	0.839	0.845	0.839	0.840
# of observations	53,973	21,136	53,973	22,659	53,973	21,136	53,973	22,659
# of clusters	44	39	44	40	44	39	44	40
Mean sample	54.63	53.99	54.63	53.88	53.59	53.06	53.59	52.83
Number of students	17,857	10,060	17,857	10,685	17,857	10,060	17,857	10,685
Number of treated students	7,892	7,892	8,331	8,331	7,892	7,892	8,331	8,331
Number of control students	2,168	2,168	2,355	2,354	2,168	2,168	2,355	2,354
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates from individual fixed effect regressions. The dependent variable is *Log Turkish score* in Columns (1)-(4) and (9)-(12), and *Log Math score* in Columns (5)-(8) and (13)-(16). Teacher FE captures teacher-classroom-grade-academic year effects. Odd columns are the full semester level sample, while even columns are the sub-sample corresponding to the "clean control" analysis. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table A5: Robustness – Alternative parametrization of outcomes

Panel A: IHS outcomes				
	Turkish score		Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0260***		0.0075**	
	(0.0046)		(0.0029)	
Log. # of fatalities		0.0137***		0.0041**
		(0.0038)		(0.0018)
R-squared	0.840	0.839	0.841	0.841
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Panel B: Standardized outcomes				
	Turkish score		Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0665***		0.0165***	
	(0.0123)		(0.0051)	
Log. # of fatalities		0.0344***		0.0076*
		(0.0104)		(0.0041)
R-squared	0.888	0.888	0.891	0.891
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Panel C: Point scale outcomes (0-100)				
	Turkish score		Math score	
	(1)	(2)	(3)	(4)
Log. # of violent events	1.3343***		0.3458***	
	(0.2446)		(0.1069)	
Log. # of fatalities		0.6900***		0.1593*
		(0.2076)		(0.0854)
R-squared	0.890	0.889	0.894	0.894
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	58.33	58.33
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

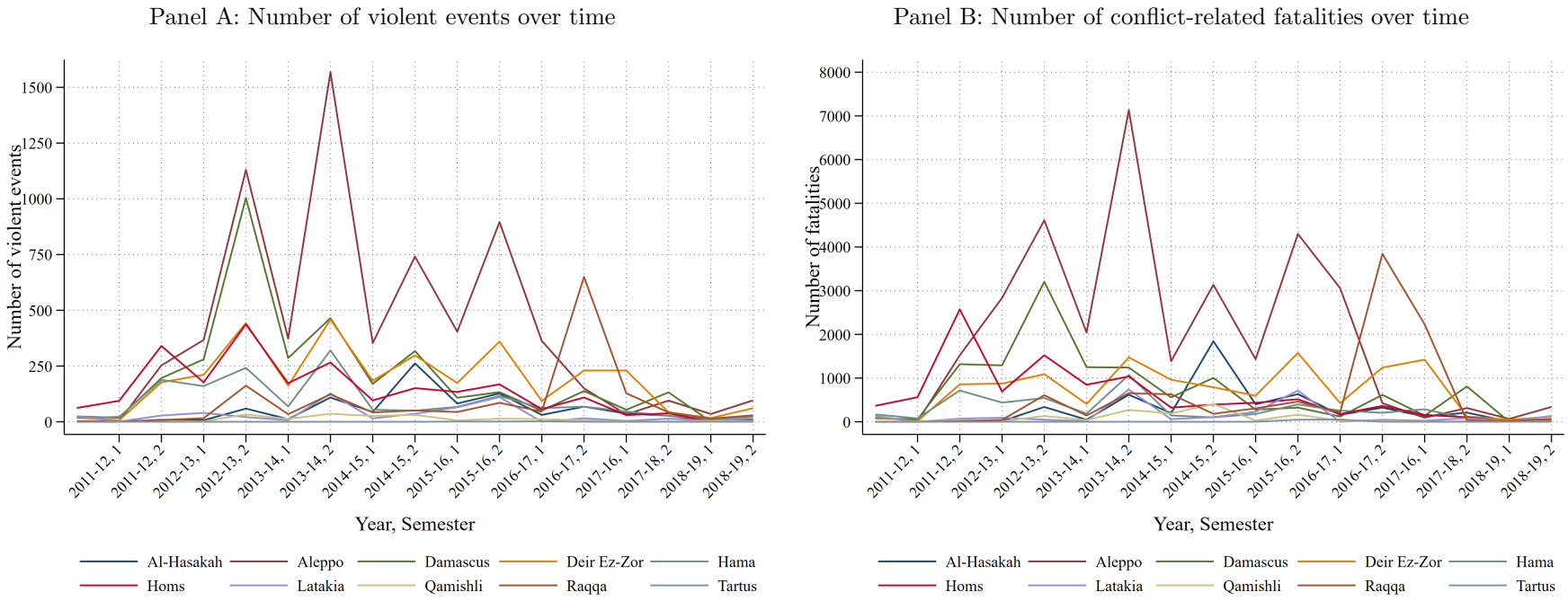
Notes: This table reports estimates from individual fixed effect regressions. The dependent variables are *Turkish score* and *Math score*. These outcomes are inverse hyperbolic sine transformation, standardized by grade, and in points from 1 to 100 in Panel A, B, and C, respectively. Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable in points calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Table A6: Robustness – Alternative parametrization of outcomes

	Turkish pass grade		Math pass grade	
	(1)	(2)	(3)	(4)
Log. # of violent events	0.0501***		0.0410***	
	(0.0075)		(0.0094)	
Log. # of fatalities		0.0275***		0.0238***
		(0.0066)		(0.0068)
R-squared	0.726	0.725	0.732	0.731
# of observations	53,973	53,973	53,973	53,973
# of clusters	44	44	44	44
Mean baseline (2011-2014)	60.49	60.49	58.33	58.33
Mean sample	58.31	58.31	57.77	57.77
Individual FE	Yes	Yes	Yes	Yes
Years since arrival FE	Yes	Yes	Yes	Yes
Teacher FE	Yes	Yes	Yes	Yes

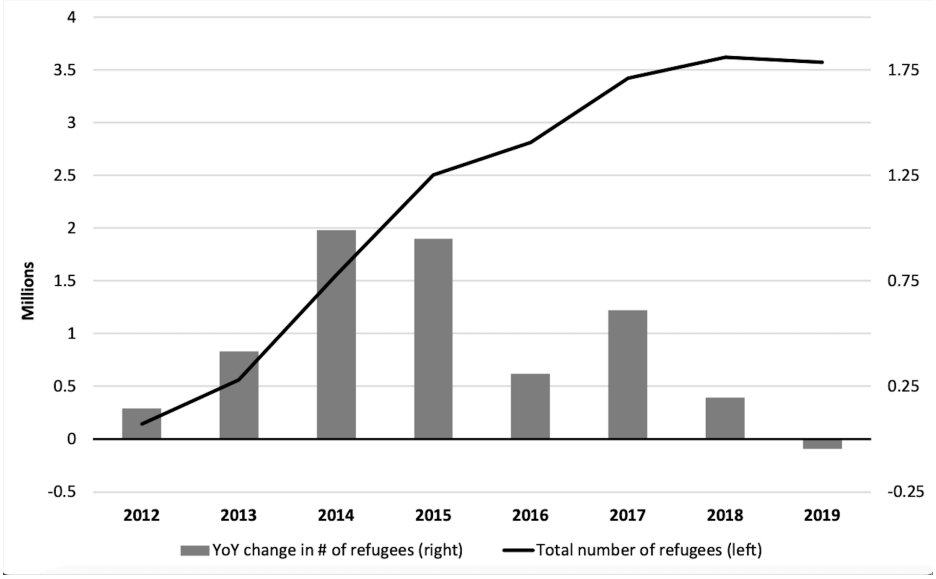
Notes: This table reports estimates from linear regressions. The dependent variable is *Turkish pass grade* in Columns (1)-(2) and *Math pass grade* in Columns (3)-(4). *Turkish (Math) pass grade* is a dummy variable equal to 1 if the students scores 45 points or above in their Turkish language (Math) course and therefore 'passes' the course and zero otherwise. Teacher FE captures teacher-classroom-grade-academic year effects. *Mean baseline* and *Mean sample* refer to the mean of the dependent variable calculated over the academic years from 2011-2012 to 2013-2014 and for the regression sample, respectively. The sample is the semester level data. Standard errors are clustered at the district level. ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

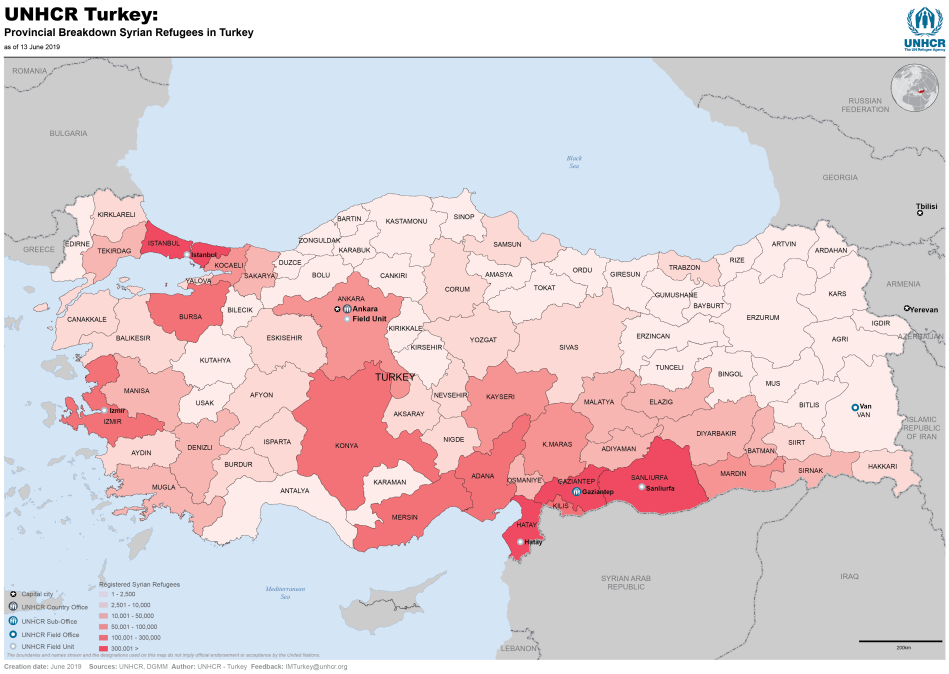
Figure A1: Temporal variation of violence



Notes: Panel A shows the number of violent events that occurred over time at the district level for our sample period. Panel B shows the number of conflict-related fatalities over time at the district level for our sample period. On the x-axis, the academic year is followed by the semester; "2011-12, 1" and "2011-12, 2" indicate the fall and spring semesters, respectively. For visual clarity, we focus on the most populated origin distracts based on population figures from the 2004 official census.

Figure A2: Syrian refugees in Türkiye

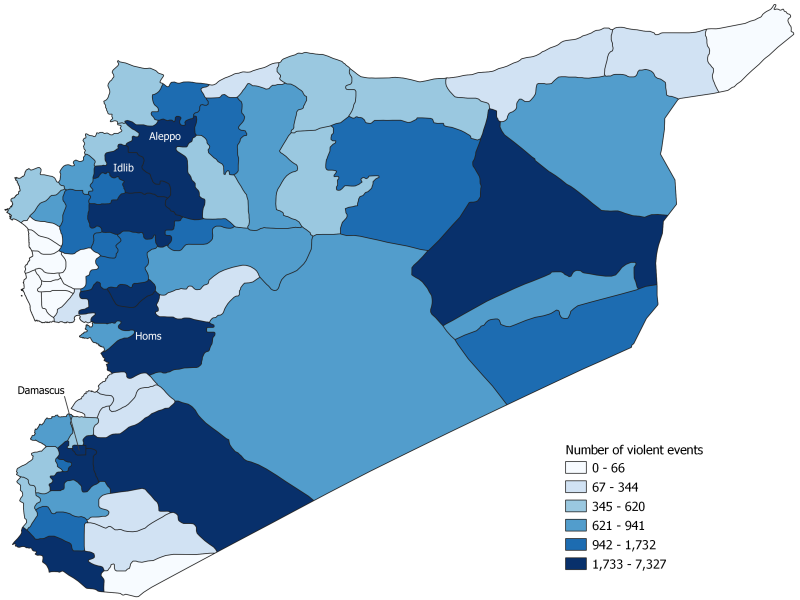




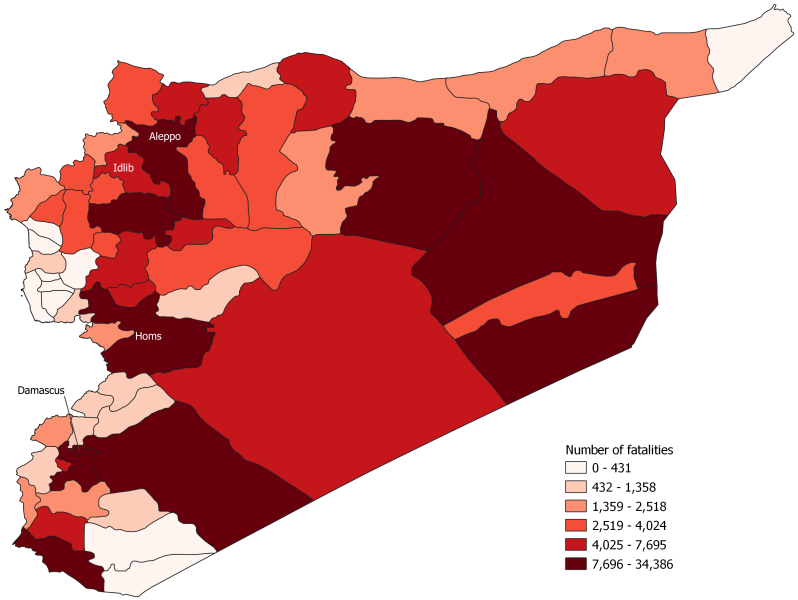
Notes: The upper panel shows the time variation in the number of Syrian refugees in Türkiye, while the lower panel shows the regional distribution as of 2019.

Figure A3: Considerable regional variation in cumulative violence

Panel A: Cumulative number of violent events

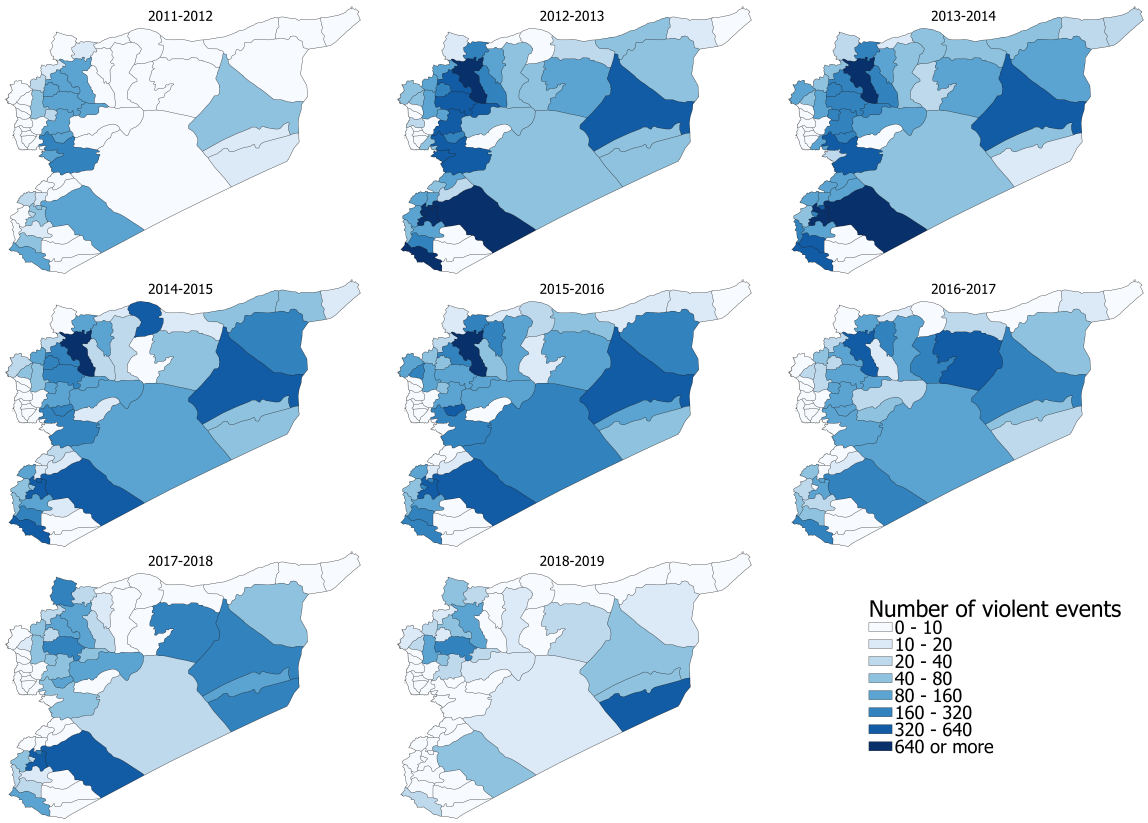


Panel B: Cumulative number of fatalities



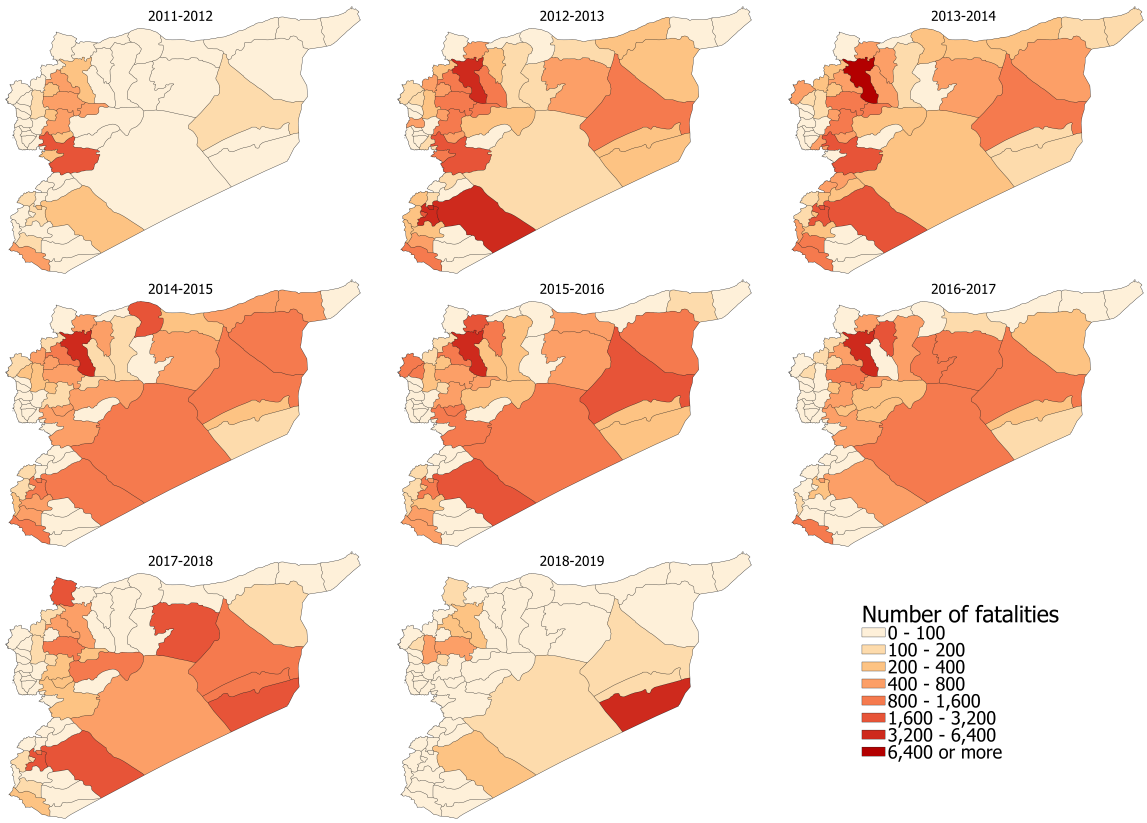
Notes: This figure shows cumulative violence during the academic years from 2011-2012 to 2018-2019. Panel A and Panel B correspond to the number of violent events and fatalities, respectively.

Figure A4: Significant variation in violent events across regions and over time



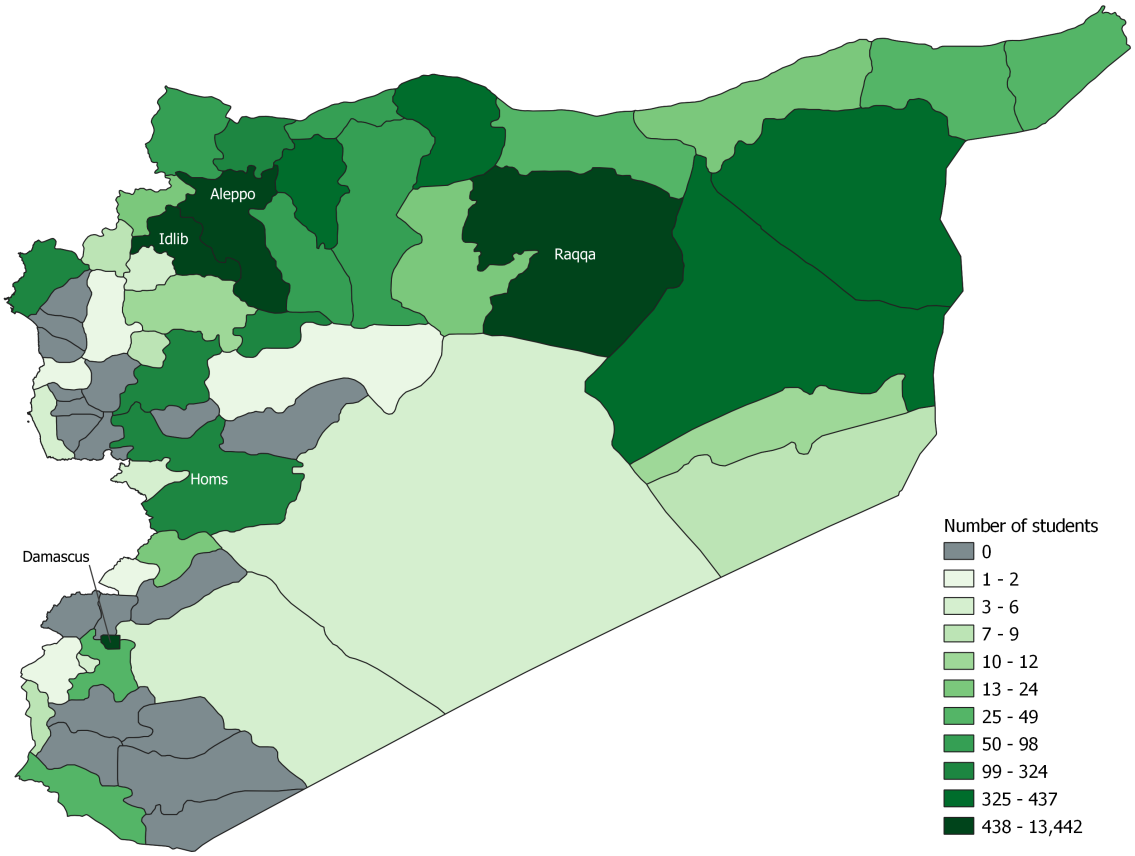
Notes: These maps show the number of violent events at the district level for the academic years from 2011-2012 to 2018-2019.

Figure A5: Significant variation in fatalities across regions and over time



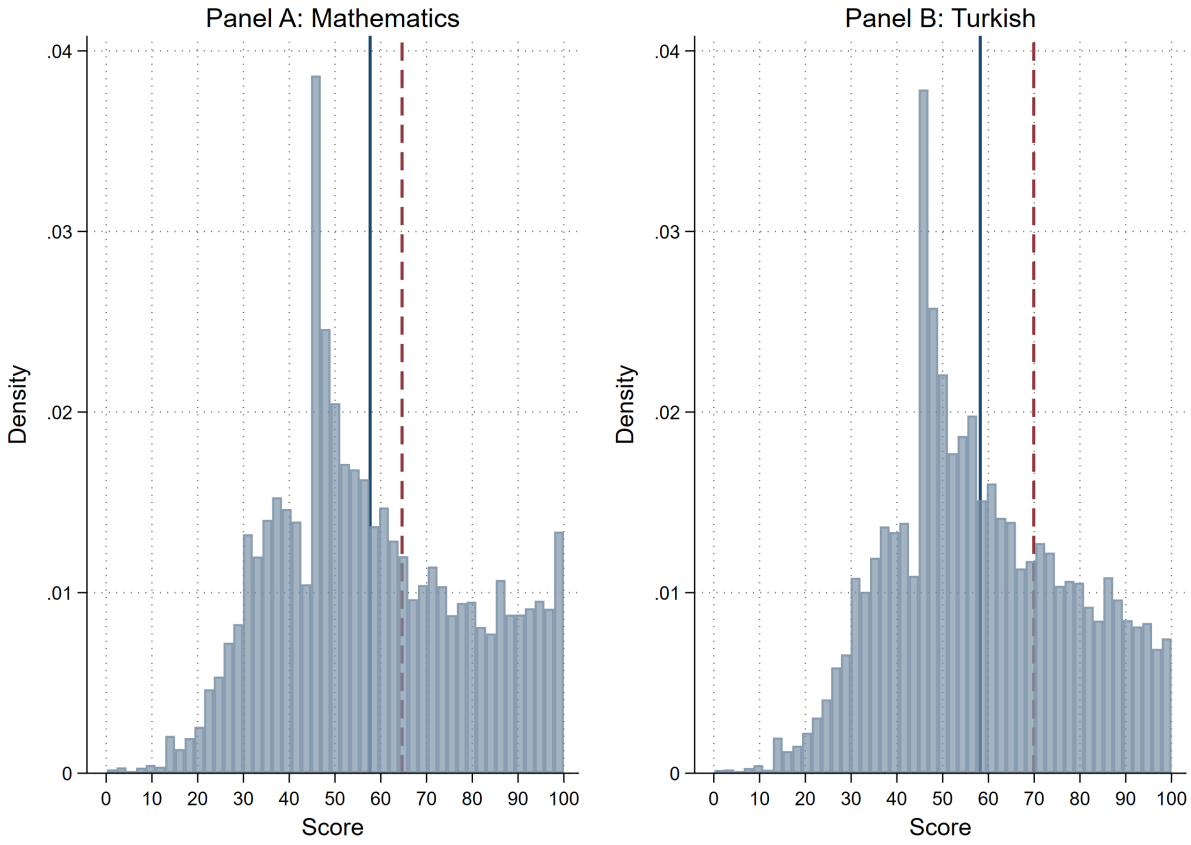
Notes: These maps show the number of conflict-related fatalities at the district level for the academic years from 2011-2012 to 2018-2019.

Figure A6: Distribution of students based on district of birth



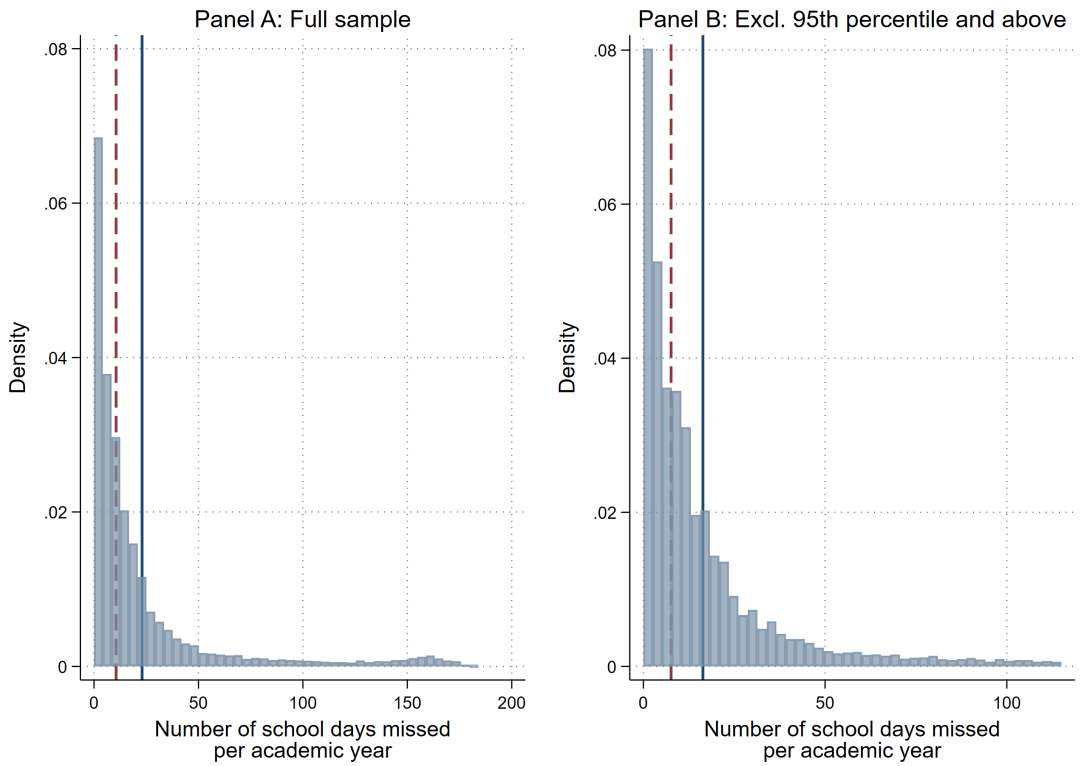
Notes: Figure shows the distribution of Syrian students according to their district of birth. District boundaries are indicated using thin black lines.

Figure A7: Turkish language and Math scores among Syrian students



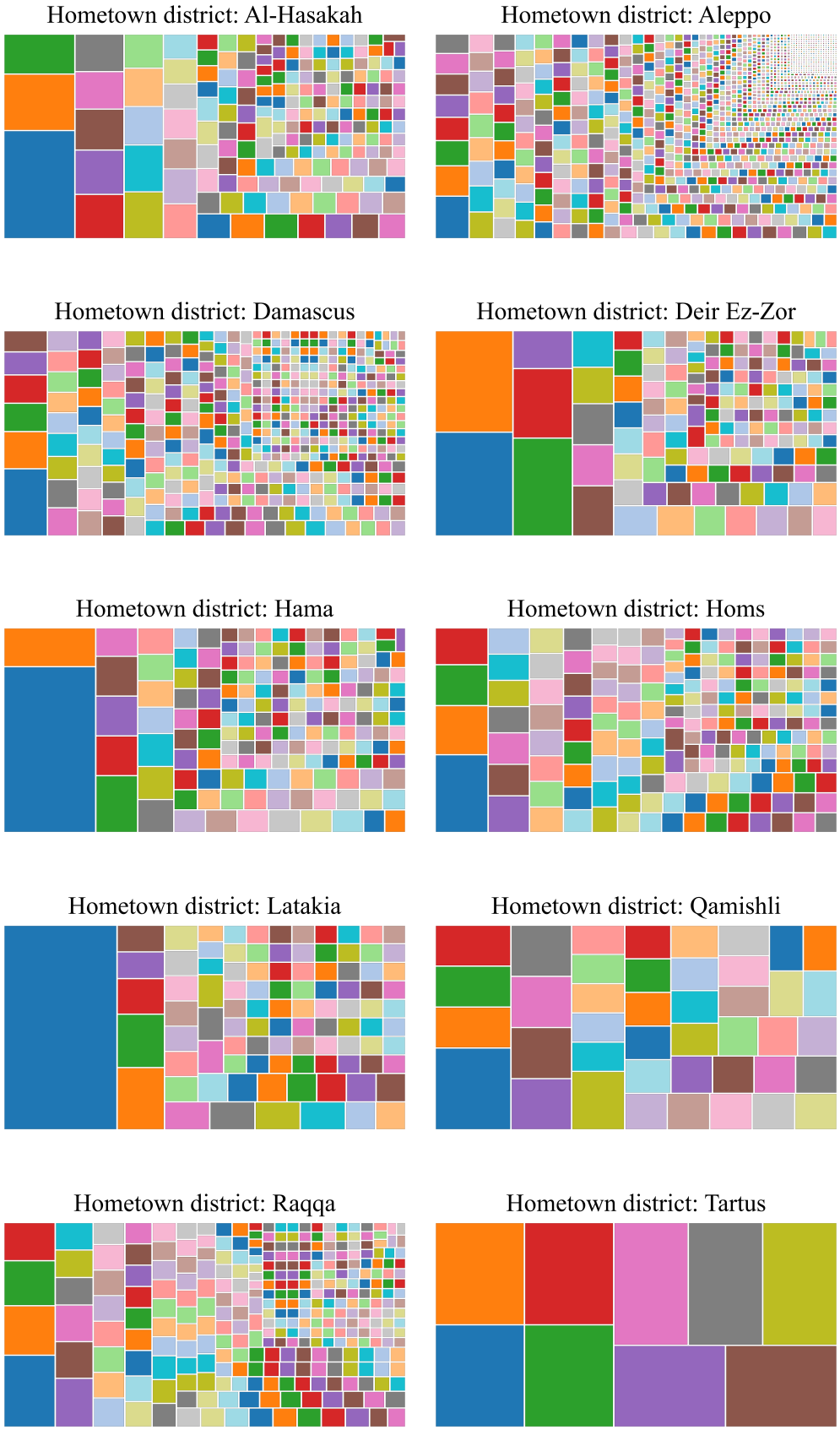
Notes: This figure shows the distribution of Math and Turkish language scores in Panel A and Panel B, respectively. Sample means are indicated by the blue solid lines and red dashed lines for Syrian and Turkish students, respectively. The sample is the semester-level data and corresponds to academic years between 2011-2012 and 2018-2019.

Figure A8: The number of school days missed among Syrian students



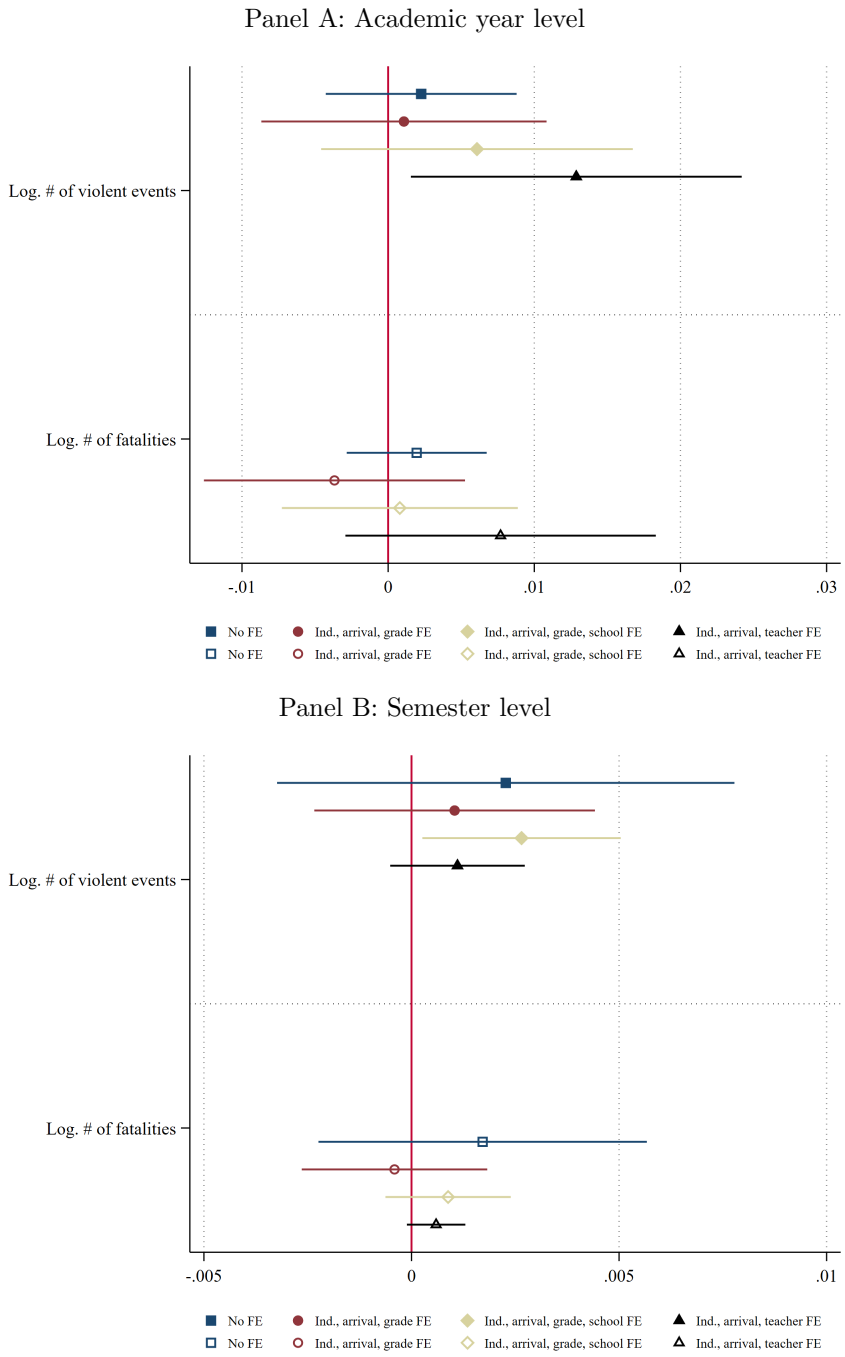
Notes: This figure shows the distribution of the number of school days missed per school year. Panel A is the full sample, while Panel B shows observations below the 95th percentile. ample means are indicated by the blue solid lines and red dashed lines for Syrian and Turkish students, respectively. The sample is the year-level data and corresponds to academic years between 2011-2012 and 2018-2019.

Figure A9: Students from the same hometown tend to disperse into different schools



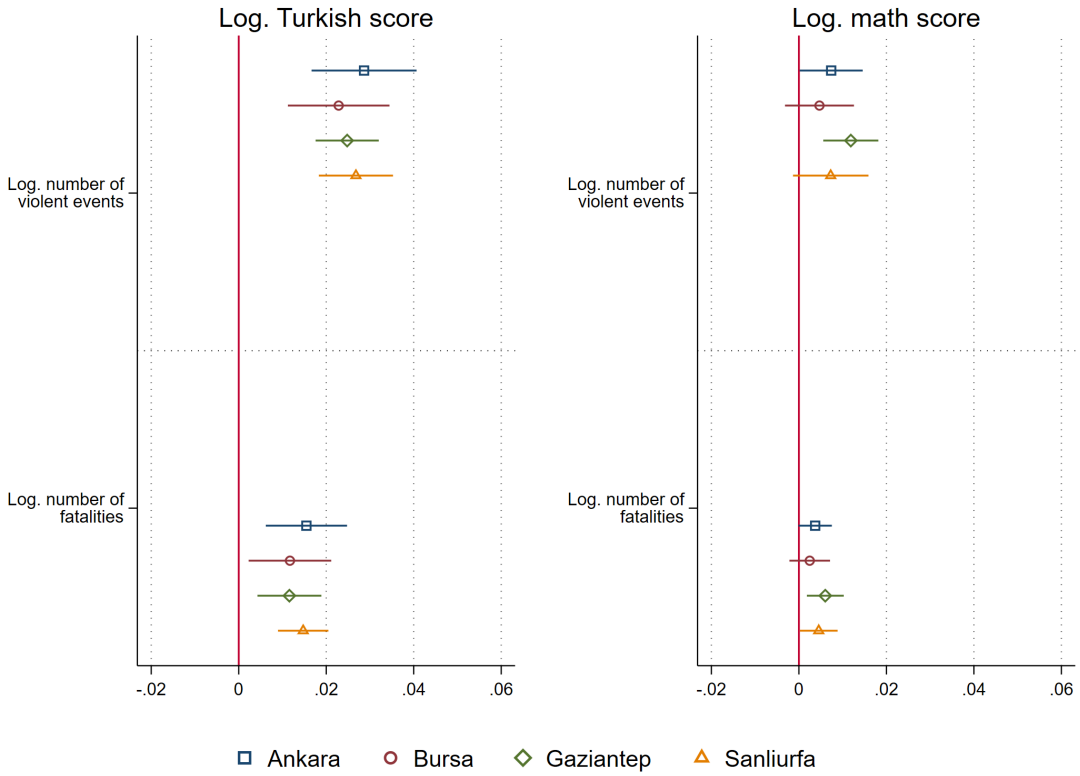
Notes: This figure shows the extent to which students from the same hometown disperse into different schools. Each plot focuses on students from one and the same hometown, within each plot, cells represent a distinct school and cell sizes are proportional to the number of students that attend the same school out of all students from the same hometown. For visual clarity, we focus on the most populated origin distracts based on population figures from the 2004 official census.

Figure A10: Violence in hometown is not meaningfully related to dropout



Notes: This figure reports estimates from linear regressions and each marker corresponds to a separate regression. The outcome is a *Dropout* dummy and marker plots the coefficient as indicated on the vertical axis. Fixed effects included in the estimation are indicated in the legend. Teacher FE captures teacher-classroom-grade-academic year effects. *Dropout* is equal to 1 if either mathematics or Turkish scores are missing and the grade is less than or equal to grade 10 and zero otherwise. Panel A and B use the academic-year and semester level data, respectively. Standard errors are clustered at the district level, and whiskers show 95% confidence intervals.

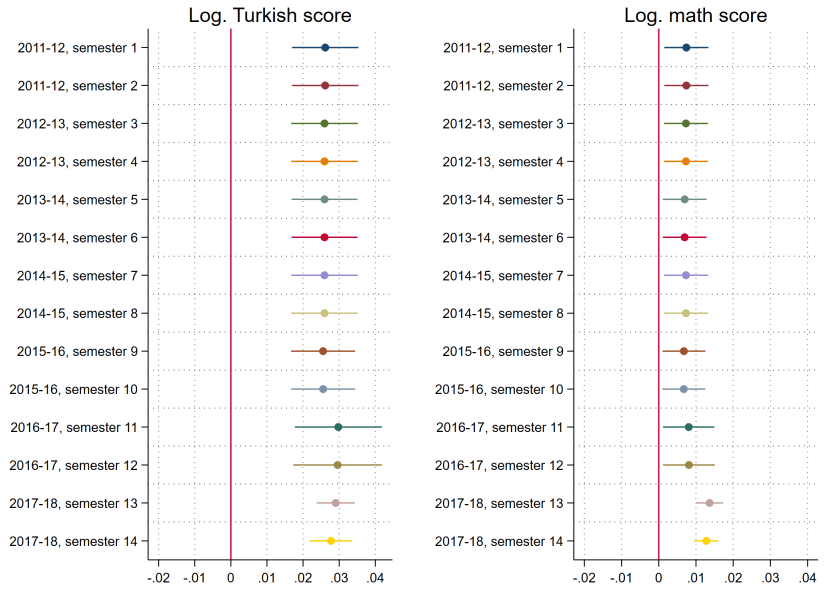
Figure A11: Robustness – Leaving out one (Turkish) province at a time



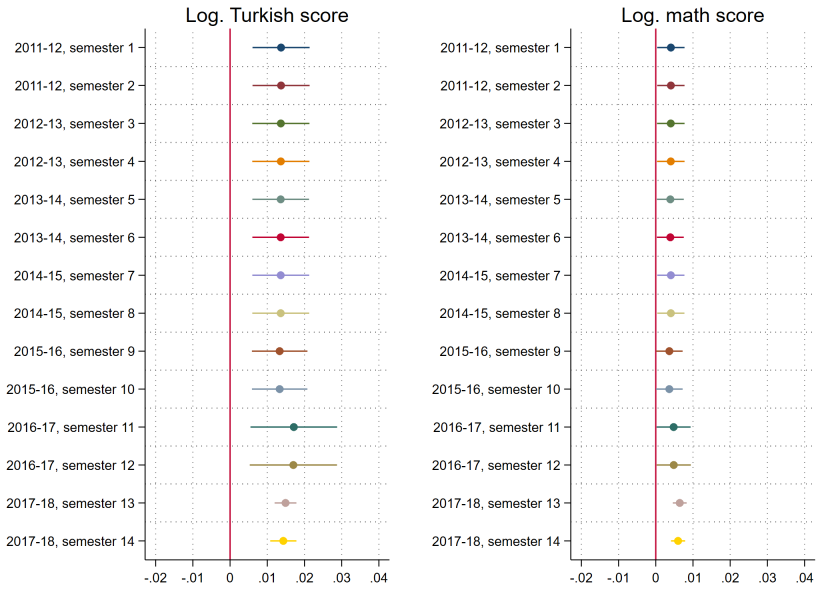
Notes: This figure reports estimates from the baseline individual fixed effects regressions. Each point corresponds to a sub-sample of the data where one of the four provinces, namely, Ankara (N = 47,927), Bursa (N = 38,618), Gaziantep (N = 28,049), and Şanlıurfa (N = 47,697) have been dropped from the data. Standard errors are clustered at the district level, and whiskers show 95% confidence intervals.

Figure A12: Robustness – Leaving one semester out at a time

Panel A: Log # violent events

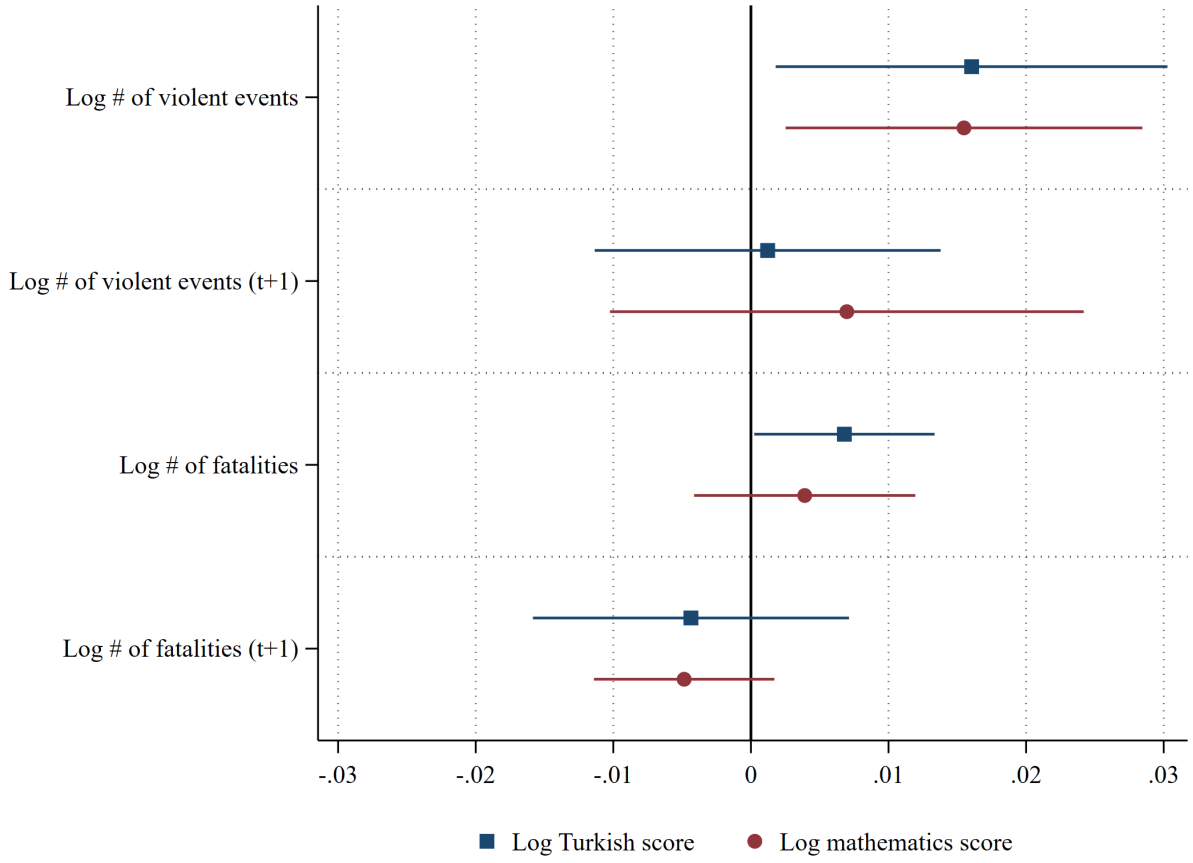


Panel B: Log # fatalities



Notes: This figure reports estimates from the baseline individual fixed effects regressions. The treatment variables in Panel A and Panel B are *Log # violent events* and *Log # number of fatalities*, respectively. Each point corresponds to a sub-sample of the data where the semester indicated on the vertical axis has been dropped. Standard errors are clustered at the district level and whiskers show 95% confidence intervals.

Figure A13: Null effects of treatment leads



Notes: This figure reports estimates from the baseline individual fixed effects regressions. Each marker corresponds to a separate regression. The sample is the sub-sample of students observed for at least seven semesters. Leads of the treatment in t+1 is the treatment in the spring or fall semester, one academic-year ahead. Standard errors are clustered at the district level, and whiskers show 90% confidence intervals.