DEPARTMENT
OF ECONOMICS

Essays on Education and Migration

Betül Türküm

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Economics
of the European University Institute

Florence, 08 September 2023

European University Institute
Department of Economics

Essays on Education and Migration

Betül Türküm

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Economics
of the European University Institute

Examining Board

Prof. Sule Alan, EUI, Supervisor
Prof. Andrea Ichino, EUI, Co-Supervisor
Prof. Stefania Bortolotti, University of Bologna
Prof. Marco Manacorda, Queen Mary University of London

Researcher declaration to accompany the submission of written work Department Economics - Doctoral Programme

I , Betül Türküm, certify that I am the author of the work Essays on Education and Migration I have presented for examination for the Ph.D. at the European University Institute. I also certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, that it is the work of others.

I warrant that I have obtained all the permissions required for using any material from other copyrighted publications.

I certify that this work complies with the Code of Ethics in Academic Research issued by the European University Institute (IUE 332/2/10 (CA 297).

The copyright of this work rests with its author. Quotation from it is permitted, provided that full acknowledgement is made. This work may not be reproduced without my prior written consent. This authorisation does not, to the best of my knowledge, infringe the rights of any third party.

I declare that this work consists of 51205 words.

Statement of inclusion of previous work

I confirm that chapter 1 was jointly co-authored with Yusuf Agus and I contributed 50% of the work.

I confirm that chapter 2 was jointly co-authored with Sule Alan and I contributed 50% of the work.

I confirm that chapter 4 was jointly co-authored with Murat Kirdar, Ivan Lopez Cruz and I contributed 33% of the work.

I confirm that chapter 4 draws upon an earlier article I published in the Journal of Economic Behavior and Organization (194 (2022) 568–582).

Signature and date:

30/05/2023

Betul Turkum

Abstract

This thesis in four chapters focuses on education and migration.

The first chapter, joint with Yusuf Agus, studies the impact of the COVID-19 outbreak on classroom peer relationships. We use a unique field dataset from 3rd and 4th-grade primary school children in Turkey, including pre-pandemic and pandemic cohorts for this investigation. Our findings show that the pandemic cohort experienced significant changes in their classroom social interactions following an extended school closure. We observe a deterioration in classroom cohesiveness, with a drastic increase in the probability of isolation, a decline in reciprocal relationships among classmates, and an increase in segregation within the classroom. We also highlight notable variations in the effects of the pandemic, with males and refugees experiencing more pronounced impacts.

The second chapter, joint with Sule Alan, examines the impact of extended school closures during the Covid-19 pandemic on children's development of abstract reasoning and cognitive empathy. We find that children who experienced prolonged school closures had significantly lower scores in these areas compared to pre-pandemic cohorts, with underprivileged children experiencing more pronounced delays. We also reveal disruptions in socioemotional skills, such as lower grit, emotional empathy, curiosity, and higher impulsivity. Although there was some recovery in abstract reasoning and theory of mind after approximately eight months of school exposure, the measured levels still indicated significant delays. Socioemotional skills, except for curiosity, did not show notable improvements. These findings emphasize the wide-ranging impact of school closures on children's cognitive and socioemotional development, highlighting the importance of the school environment in fostering these crucial skills.

The third chapter studies the impact of the Syrian refugee crisis on economic development measured by GDP per capita. The study examines variations in the proportion of refugees across different Turkish provinces after the Syrian Civil War and uses a difference-in-differences methodology to estimate the refugees' impact on economic development. To address potential selection bias, a two-stage least squares (2SLS) method is employed. The results provide suggestive evidence of a positive medium-term effect and a negative long-term effect of refugee arrivals on economic development, while the short-term effect remains uncertain. However, none of the observed impacts are statistically significant.

The fourth chapter, joint with Murat Kirdar and Ivan Lopez Cruz, exploits the impact of Syrian refugees in Turkey, the largest refugee group in any country, on crime rates. While most studies focus on economic migrants in developed countries, this study examines the crime impact of refugees in low-

and middle-income countries. Despite the economic challenges faced by Syrian refugees, including poverty, limited job opportunities, and mobility restrictions, the study finds that the total crime per person decreases with the arrival of refugees. This decline applies to various types of crime, except for smuggling, which increases due to the population influx. Additionally, the study shows that the decrease in crime is not attributed to increased security measures, as there is no evidence of changes in the number of armed forces in the regions hosting the refugees.

Acknowledgements

I would like to express my deepest gratitude to all those who have contributed to the completion of this Ph.D. thesis.

First and foremost, I am immensely grateful to my advisors, Sule Alan, and Andrea Ichino. Their guidance, expertise, and unwavering support throughout this journey have been invaluable. Their dedication to my intellectual growth and their commitment to excellence have shaped not only this thesis but also my overall development as a researcher. I also would like to express my gratitude to Marco Manacorda and Stefania Bortolotti for their generous acceptance to serve as members of my thesis committee.

Finally, I would also like to acknowledge the support and encouragement I received from my husband, friends, and parents. Completing this Ph.D. thesis has been a challenging yet rewarding endeavor, and I am privileged to have had the support and guidance of so many exceptional individuals along the way. Their contributions have shaped my academic growth and have undoubtedly left a lasting impact on my personal and professional journey.

Contents

1

Lost Connections: Examining the Impact of COVID-19 on Peer Relationships

Abstract In the spring of 2020, as the COVID-19 pandemic swept across the globe, governments took drastic measures to curb the virus spread, including shutting down educational institutions. This sudden and unexpected closure of schools not only disrupted the education of millions of students but also deprived them of their primary social environment—the classroom. In this study, we analyze the impact of the COVID-19 outbreak on classroom peer relationships using a unique field dataset collected from 3rd and 4th-grade primary school children in Turkey that includes both pre-pandemic and pandemic cohorts. Our findings reveal that the pandemic cohort undergoes significant changes in their classroom social interactions after an extended school closure, compared to the pre-pandemic cohort. We observe deteriorations in classroom cohesiveness, with an extreme increase in the probability of isolation, a decline in reciprocal relationships among classmates, and an increase in segregation within the classroom. Our research also uncovers significant heterogeneities in the effects of the pandemic, with impacts being more pronounced for males and refugees.

1.1 Introduction

The father of the French school of sociology, Durkheim (2005), states that in a socially cohesive society, there should be a lack of social conflicts and strong social bonds among the members. Such societies are characterized by reciprocal social relationships and a sense of belonging among members. The foundations of such a society can be laid out by public education as it has a significant socializing force that facilitates social cohesion (Gradstein and Justman, 2002). Schools with a good social climate provide an excellent platform for social cohesion to appear (Alan et al., 2021a; Maszk et al., 1999) as schools are one of the first places where individuals form and maintain their peer groups.

Peers are perhaps one of the most essential parts of an individual's education journey, as they contribute not only to academic achievements (Berthelon et al., 2019; Calvó-Armengol et al., 2009; Duflo et al., 2011; Feld and Zölitz, 2017; Hahn et al., 2015; Lavy and Sand, 2019; Sacerdote, 2001; Wang and Eccles, 2013; Wentzel, 2017) but also to various other outcomes, including emotional, social, and mental health(Bietenbeck, 2020; Kiessling and Norris, 2020; Kochenderfer-Ladd and Ladd, 2019; Wentzel, 2017). As such, peer relationships play a fundamental role in child development and schools have a crucial responsibility in fostering social cohesion through peer interactions.

Nonetheless, the “platform" that plays a crucial role in promoting social cohesion by facilitating peer relationships witnessed a large disruption during the COVID-19 Pandemic. In response to the global spread of COVID-19 in the spring of 2020, governments worldwide implemented various measures to control the transmission of the virus, including the widespread closure of educational institutions. These closures impacted over 90 percent of the world's student population, roughly 1.5 billion students in more than 190 countries [1]. As students spend a substantial amount of time in school with their peers, these closures deprived them of their primary social environment. In addition, other safety measures such as lockdowns and social distancing further reduced social interaction among peers[2]. All of these attributes together bring about the concern that the lack of social interaction during the COVID-19 pandemic may have continuing effects on students even after the pandemic restrictions are relaxed and they return to school.

In this paper, we look at how COVID-19 has impacted peer relationships in the classroom. As the pandemic is likely to impact each student differently, we further examine heterogeneities in the impact based on socioeconomic status (SES), gender and refugee status [3]. We explore the innate complexity of social interactions using insights from social network theory (Jackson, 2011). To answer our research questions, we employ a cross-cohort comparison strategy which allows us to uncover causal estimates

[1] Source: https://en.unesco.org/covid19/educationresponse#schoolclosures

[2] Survey evidence indicates that during the severe periods of the COVID-19 pandemic, students were meeting with their friends significantly less frequently (Werner and Woessmann, 2021).

[3] The province from which we collected data is located close to the Syrian border, resulting in many Syrians fleeing the war to settle in this Turkish province. As a result, around 14 percent of the sample we use comprises Syrian refugee children. This piques our interest in understanding whether natives and refugees are affected differently by the COVID-19 shock.

based on the comparability assumption of our cohorts. This assumption implies that the pandemic cohort's potential outcomes would be the same as those of the pre-pandemic cohort in the absence of the pandemic[4].

We address our research questions by utilizing unique and rich data collected in Turkey as part of a large-scale study on early childhood educational interventions. Our data encompasses two cohorts of primary school students, with the first wave collected in 2018, serving as the pre-pandemic cohort for our analysis. The second wave of data was gathered in 2021 after schools reopened, and we refer to this cohort as the pandemic cohort. The data includes students' self-reported network nominations based on friendship, academic support, and emotional support, as well as numerous controls.

Our empirical analysis provides strong evidence that the COVID-19 pandemic causes various changes in peer relationships within the classroom. Specifically, social exclusion within the classroom increases, with the probability of being an isolated student skyrocketing by over 100% for all types of social networks[5]. Furthermore, there is a notable decline in the reciprocity of ties in the classroom, ranging from 1.79 to 3.28 SD for given network types. For both outcomes, the effects are more pronounced for males and refugees. The decrease in reciprocity is accompanied by an increase in betweenness scores, especially for academic and emotional support networks, meaning that some students become more central in their classroom networks. As a result, clusters in academic and emotional support networks strengthen, while friendship clusters weaken.

In addition to our primary research focus, we investigate the association between peer interaction and academic performance. We collect additional data on the academic outcomes of the pandemic cohort at the end of the 2021-2022 academic year to track their progress over time and compare the academic scores of isolated and non-isolated students at the beginning and end of the academic year. Our findings suggest that after roughly a year of attending school, there is an overall improvement in academic outcomes, measured by math and verbal test scores. However, non-isolated students show more significant recovery than their isolated peers. This indicates that peer interaction plays a crucial role in academic success, and socially isolated students may not benefit as much from the stimulating classroom environment.

Our paper makes a twofold contribution. Firstly, while the short-run negative impact of the COVID-19 pandemic on students' various outcomes, particularly academic performance, has been shown in numerous studies (Ardington et al., 2021; Betthäuser et al., 2023; Engzell et al., 2021; Grewenig et al., 2021; Hanushek, 2020; Hevia et al., 2022; Kogan and Lavertu, 2021; Kuhfeld et al., 2020; Lichand

[4]The details and the justifications of this identification assumption are discussed in Section 1.4.

[5]Friendship, academic, and emotional supports. See Section 1.3 for details.

et al., 2022; Maldonado and De Witte, 2021; Vegas, 2022), none have investigated how the pandemic influenced peer interaction in the classroom. Therefore, we provide the first study to examine how peer relationships in the classroom change in response to the significant shock of COVID-19. Our empirical evidence on this relationship contributes to the literature on the impact of COVID-19 on children and social networks. Besides our main contribution, we highlight the importance of onsite education and peer interaction in fostering children's skill development, contributing to the empirical literature on children's skill formation. Through our research, we hope to raise policymakers' awareness of the need to consider social skill development while designing educational programs to prevent the effects of the COVID-19 pandemic to be long-lasting for the students in affected cohorts.

The rest of the paper proceeds as follows: In section 1.2, we briefly provide the background. In Section 1.3, we describe the data set and the outcomes that we investigate, then in Section 1.4, we lay out the empirical strategy, and explain the empirical results in Section 1.5. Finally, in section 1.6 we discuss the potential mechanism and we conclude in Section 1.7.

1.2 Background

The Turkish government implemented strict measures in response to the first cases of Covid-19 detected on March 11, 2020. As one of these measures, schools closed for two weeks, starting on March 13, 2020. However, due to recommendations from the Scientific Committee, the closure was extended until April 30, 2020, and ultimately until May 31, 2020, the end of the academic year. Despite multiple attempts to reopen schools, Turkey experienced one of the most prolonged school closures worldwide, lasting a total of 49 weeks from March 2020 to September 2021. This duration far exceeded both the world and OECD averages of 37.85 and 35.42 weeks, respectively[6]. To clarify, the duration of the closure in Turkey was longer than a typical academic year, which lasts for around 36-37 weeks.

Throughout the school closures, all actors in education, including the Ministry of Education, school authorities, teachers, parents, and students, made efforts to establish remote learning methods. The Ministry of Education began broadcasting lectures that follow the original curriculum, and teachers attempted to deliver lectures over Zoom and exchange materials and assignments via WhatsApp. However, unfortunately, these new methods were inadequate in compensating for or replacing the value of in-person education. The effectiveness of these methods relied heavily on the economic resources of students' parents and their level of attention to their children's educational well-being. According to the 2019 Household Information Technologies Usage Survey by TURKSTAT (Turkey Statistical

[6]Source:https://en.unesco.org/covid19/educationresponse#schoolclosures

Institute)[7], only 48.7% of households had portable computers such as laptops, tablets, and netbooks. This number was even lower among low-income households, and given that these technological tools are typically shared among siblings, it's clear that students from these households faced significant physical difficulties with online education, leading to a disconnection from their peers.

In addition to closure and certain restrictions in educational institutions, various curfews, and social distancing measures were implemented in Turkey in response to the COVID-19 pandemic. Curfews were imposed for citizens under the age of 20 and over 65, which later extended to everyone during certain hours of the day. Measures were put in place to limit public gatherings and transportation. The government adjusted these measures according to the pandemic situation. Unfortunately, these measures significantly reduced the opportunities for social interaction, exacerbating the already limited possibilities for peer interaction caused by school closures.

1.3 Data

1.3.1 Data Description

Our data set consists of two waves of data collected from two different cohorts, pre-pandemic and pandemic, from the same schools and grade levels, 3rd and 4th graders[8]. Since the pre-pandemic (2018) and pandemic (2021) cohorts are from the same schools, they show almost identical characteristics. The pre-COVID data set is a subset of large-scale RCTs focused on early childhood interventions on skill formation in Turkey. These RCTs aim to evaluate the effectiveness of skill-based programs in enhancing academic performance. This subset was collected in Mersin, Turkey, during September and October of 2018, and includes 4,928 students from 71 primary schools and 185 classes, with 1,104 3rd-grade students and 3,824 4th-grade students.

We visited the schools where pre-pandemic data was collected right after in-person education resumed in September 2021 to gather data on the pandemic cohort. The data of this cohort includes 4,400 3rd and 4th-grade students from 70 primary schools and 181 classes. Of these students, 925 are 3rd-graders, and 3,475 are 4th-graders. The research team and trained field assistants helped to carry out both data collection processes. During data collection, teachers were occupied with their surveys in isolated rooms, ensuring that all students' data collection occurred in the absence of teachers. The collected data set is extensive and covers a large sample of students. It contains information on

[7] Data source is https://data.tuik.gov.tr/Bulten/Index?p=Hanehalki-Bilisim-Teknolojileri-(BT)-Kullanim-Arastirmasi-2020-33679

[8] See Figure A1 for the timeline of data collection.

various aspects of the students, including their characteristics, classroom social networks, teachers, and classroom characteristics.

In addition, we collected the academic outcomes of the pandemic cohort in May 2022, which enables us to investigate the differential recovery (or deepening) of academic losses between isolated and non-isolated students using a panel comparison. This supplementary dataset includes 4,327 students, all of whom overlap with the students in the 2021 dataset[9].

1.3.2 Variables

The focus of our study is to evaluate the impact of the COVID-19 shock on students' peer relationships using social network theory. For this purpose, during data collection, we asked students to nominate up to three classmates for three categories of social ties - friendship, emotional support, and academic support - with overlaps allowed [10]. Based on these survey answers, we construct several social network measures. The descriptive statistics of these outcomes can be found in Table 1.2. These measures include the following network outcomes:

- *Isolate:* This is a binary variable taking 0 if the student received any nominations while taking 1 if the student did not receive any nominations. Not receiving any nominations means the student is isolated (Alan et al., 2021b).
- *In-degree ties:* This variable presents the number of nominations a student received from her classmates.
- *Reciprocity:* This variable measures the fraction of reciprocated (mutual) ties to all ties in a given classroom and is calculated at the classroom level.
- *Betweenness:* This variable measures the ability of a student to connect two students who are not directly connected. Formally, betweenness centrality is defined as the number of shortest paths among all other students that pass through the student herself. The higher the student's betweenness score, the more significant her role is in bridging other students who are not directly linked.
- *Clustering Coefficient:* The clustering coefficient is a metric that measures the extent to which a student's connections with others are interconnected. It calculates the ratio of observed links between a student's nominations to the total number of possible links between them (Watts and Strogatz, 1998). The clustering coefficient is relevant to the concepts of homophily and

[9]The sample excludes newly enrolled students and includes only those whose data is available at the beginning of the 2021/22 academic year.

[10]Survey questions for eliciting social network outcomes are given in appendix A.2.

segregation, which refer to the tendency of people with similar attributes to form connections with each other. This phenomenon results in higher clustering coefficients within groups of students who share common characteristics such as gender or ethnicity.

Table 1.1 Covariates

	(1) Mean of 2018	(2) Mean of 2021	(3) Difference	(4) p-value
Student characteristics:				
Male	0.514	0.508	0.006	0.522
Refugee	0.141	0.132	0.009	0.468
Age in months	97.145	97.161	-0.016	0.960
Classroom characteristics:				
Share of males	0.511	0.516	-0.006	0.455
Share of refugees	0.160	0.182	-0.022	0.069
Teacher characteristics:				
Male	0.335	0.375	-0.040	0.441
Age	42.757	43.673	-0.916	0.231
Experience in Years	18.821	19.742	-0.921	0.241
Number of Children	1.620	1.743	-0.124	0.130
Married	0.827	0.829	-0.002	0.948

Note: All variables are coming from students' survey answers. Differences are obtained by subtracting the mean of 2018 from the mean of 2021. P-values are obtained by regressing the variable on COVID variable controlling for districts.

Besides social network outcomes, this study utilizes math and verbal test scores to investigate how academic achievement is related to peer interaction. These tests are designed in accordance with the national curricula of the respective grades since there is no centralized test for the grade levels in the dataset. Lastly, control variables used in the regression analysis fall into three categories: student, teacher, and classroom characteristics. Student characteristics include gender, age in months, and dummy variable for refugee status. Teacher characteristics comprise gender, age, years of experience, number of children, and marital status. Classroom characteristics involve the share of males and refugees in the classroom. The descriptive statistics of these control variables are presented in Table 1.1.

Table 1.2 Outcomes: Network measures

	(1) Mean of 2018	(2) Mean of 2021	(3) Difference	(4) p-value
Friendship:				
Isolates	0.078	0.191	-0.113	0.000
In-degree ties	-0.000	-0.247	0.247	0.000
Betweenness	-0.000	-0.018	0.018	0.628
Clustering coef.	-0.000	-0.161	0.161	0.000
Reciprocity	0.000	-2.140	2.140	0.000
Academic support (provided):				
Isolates	0.055	0.258	-0.203	0.000
In-degree ties	0.000	-0.273	0.273	0.000
Betweenness	0.000	0.468	-0.468	0.000
Clustering coef.	0.000	0.549	-0.549	0.000
Reciprocity	0.000	-3.120	3.120	0.000
Academic support (received):				
Isolates	0.062	0.314	-0.252	0.000
In-degree ties	0.000	-0.255	0.255	0.000
Betweenness	-0.000	0.506	-0.506	0.000
Clustering coef.	0.000	0.425	-0.425	0.000
Reciprocity	0.000	-3.380	3.380	0.000
Emotional support (provided):				
Isolates	0.059	0.233	-0.174	0.000
In-degree ties	0.000	-0.227	0.227	0.000
Betweenness	0.000	0.235	-0.235	0.000
Clustering coef.	-0.000	0.265	-0.265	0.000
Reciprocity	0.000	-2.862	2.862	0.000
Emotional support (received):				
Isolates	0.060	0.261	-0.201	0.000
In-degree ties	-0.000	-0.298	0.298	0.000
Betweenness	0.000	0.139	-0.139	0.002
Clustering coef.	-0.000	0.161	-0.161	0.000
Reciprocity	0.000	-3.105	3.105	0.000

Note: All variables are constructed based on students' nominations for specific network types and standardized to have a mean of 0 and a standard deviation of 1 for the 2018 cohort. Differences between the cohorts are calculated by subtracting the mean of 2018 from the mean of 2021. Except for reciprocity, the outcomes are at the individual level, and the p-values are obtained by regressing the variable on the COVID dummy variable while controlling for schools. The reciprocity outcome is at the classroom level, and the p-values for it are obtained by regressing the variable on the COVID variable while controlling for districts. For reciprocity, the number of observations is 185 in 2018 and 181 in 2021; for the other network measures, it is 4927 in 2018 and 4340 in 2021.

1.4 Empirical analysis

1.4.1 Identification

The empirical analysis we undertake for this paper evaluates the impact of the COVID-19 pandemic on students' classroom social network outcomes by a cross-cohort comparison between pre-pandemic and pandemic cohorts. Specifically, we investigate how the pandemic cohort differs from the pre-pandemic cohort of the same grade levels from the same schools conditional on the individual, teacher, and classroom characteristics and school-fixed effects.

The identification of this study relies on the comparability of the pre-pandemic and pandemic cohorts. For a valid cross-cohort comparison, it is crucial that both groups must have the same potential outcomes. We have considered this requirement while selecting our sample. This condition is likely satisfied as both cohorts are sourced from the same schools and classrooms, with only a two-year gap between them. In Turkey, public schools only admit students who reside within their designated catchment areas. This policy significantly reduces the likelihood of substantial socio-demographic changes occurring over only a two-year period. Moreover, the characteristics of teachers in public schools are also similar for these cohorts since public school teachers are appointed centrally, and the Covid pandemic did not cause any changes in the number or composition of teachers. Lastly, in Turkey, the Ministry of Education mandates that students must be randomly assigned to their classes in their first year and remain with the same group until the end of fourth grade. This consistent allocation mechanism across cohorts minimizes potential confounding variables. Statistical evidence in Table 1.1 supports our claims, demonstrating no significant differences between these cohorts regarding student, teacher, and classroom characteristics. Therefore, any differences in observed outcomes can be attributed to the effects of COVID-19.

1.4.2 Estimation strategy

To examine the differences between the pre-pandemic and pandemic cohort in the outcomes of interest through a conditional mean analysis, we use the following empirical specification,

$$y_{ist} = \alpha + \beta COVID19 + X_{ist}\Gamma + \theta_{st} + \epsilon_{ist}$$

where y_{ist} is the outcome of interest for child i in school s in period t, which regressed on the COVID19, which is a dummy variable for the pandemic cohort (2021), as well as other covariates that are likely to be predictive of the outcome y. The vector of student, teacher, and classroom characteristics, which can be found in Table 1.1, is denoted as X_{ist}. θ_{st} is the school fixed effect which enables us to discard all variation between schools which can potentially bias our findings. Standard errors, ϵ_{ist}, are clustered at the school level.

The variable of interest in this study is COVID19, with the coefficient of interest being $\hat{\beta}$. It represents the impact of the COVID-19 pandemic on the outcome variables—the measures of social networks. In this context, the effect of the pandemic is largely attributed to school closures and curfews, which significantly limited students' opportunities for social interactions with their peers. It is worth mentioning that the COVID-19 pandemic may have affected a wide range of parameters that can influence a student's social relationship formation. As a result, we acknowledge that there is a possibility of confounding variables that could impact our findings. Thus, we remain cautious about interpreting the results as causal.

1.5 Results

This section presents the results of the empirical analysis. First, subsection 1.5.1 presents the main results derived from the above estimation equation. Then in subsection 1.5.2, we assess the heterogeneity of the results based on SES, gender, and refugee status. Finally, subsection 1.5.3 provides evidence on the relationships between peers and academic outcomes. Before proceeding, we need to explain a few points for the rest of this section. Firstly, to ease interpretation, all outcome variables, except the binary ones, are standardized such that the mean of the 2018 cohort is 0 and the standard deviation is 1. Secondly, due to the richness of the outcome variables, we only present the treatment effect from the fully specified estimations, which control for school-fixed effects, student, teacher, and classroom characteristics. The unconditional treatment effects and their associated p-values can be found in columns 3 and 4 of Table 1.2.

1.5.1 Main Results: Social Network Outcomes

The main objective of this paper is to demonstrate how the COVID-19 outbreak affects peer relationships, with a particular focus on social network outcomes presented in Table 1.3. Panel 1 of the table shows the impact of the pandemic on the likelihood of being an isolated student for different network types (friendship, academic, and emotional support), with significant results. The probability of isolation substantially increases for all network types, ranging from two to five times. Notably, academic support is the network type with the most significant rise in the likelihood of isolation, indicating that more students feel academically isolated in 2021 (pandemic cohort) than in 2018 (pre-pandemic cohort).

Panel 2 provides the estimation results using the outcome of the in-degree tie, revealing that the pandemic cohort received fewer nominations from their classmates across all network types (indicated by negative coefficients of up to 0.33 SD) than the pre-pandemic cohort. Overall, the combined results of Panel 1 and Panel 2 imply a deterioration in the classroom climate as a result of the COVID-19 pandemic.

Panel 3 presents the results of the betweenness outcome, which measures the ability of a student to serve as a bridge along the shortest path between two other students, only exhibiting a statistically significant treatment effect for three network types: academic support (both provided and received) and emotional support provision. COVID-19 is associated with a 0.41 SD (0.22 SD) increase in students' betweenness scores for academic (emotional) support provision and a 0.49 SD increase in academic support receiving. Overall, for these network types, the pandemic causes an increase in the number of students who function as intermediaries between their peers. These findings show that students are more strategic in their network formation, favoring direct ties with centrally located students (with high betweenness scores) who provide easier access to other classmates with whom they do not have direct connections.

Panel 4 reveals the results of the clustering coefficient, which show a statistically significant increase in clustering for academic and emotional support of the pandemic cohort compared to the pre-pandemic cohort. It suggests that some students' relationships in these networks tend to be highly connected to one another, forming tightly connected clusters in the pandemic cohort. However, if specific characteristics such as ethnicity or gender form the basis for these clusters, high clustering coefficients can contribute to social segregation. Using heterogeneity analysis as a tool, we demonstrate that this is the case in our sample. In contrast, the clustering coefficient for the friendship network decreases by 0.22 SD, indicating that students are less likely to form direct connections with their peers who are directly connected to each other. These results suggest that the pandemic leads to changes in the way students form social connections, with a greater emphasis on seeking support from peers with similar characteristics in academic and emotional support networks.

Panel 5 shows the impact of COVID-19 on the reciprocity measure, which is a social network measure at the classroom level[11]. This measure is the fraction of mutual nominations in all nominations of students in a given class. Our findings indicate a striking reduction in the reciprocity measure due to the pandemic. The treatment effect ranges from 1.97 to 3.2 SD, indicating a substantial decrease (up to

[11]The other social network variables are at the individual level.

Table 1.3 Results for Social Network Outcomes

	Friendship	Academic support		Emotional support	
		Out	In	Out	In
Panel 1: Isolates					
COVID	0.097***	0.195***	0.253***	0.167***	0.202***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control Mean	.078	.055	.062	.059	.06
Romano-Wolf p	.002	.002	.002	.002	.002
N	7441	7441	7441	7441	7441
R-Squared	0.049	0.096	0.126	0.077	0.098
Panel 2: In-degree ties					
COVID	-0.251***	-0.333***	-0.318***	-0.255***	-0.333***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Romano-Wolf p	.002	.002	.002	.002	.002
N	7441	7441	7441	7441	7441
R-Squared	0.045	0.054	0.060	0.050	0.059
Panel 3: Betweenness					
COVID	-0.065	0.415***	0.497***	0.229***	0.053
	(0.06)	(0.10)	(0.10)	(0.07)	(0.06)
Romano-Wolf p	.439	.004	.002	.016	.445
N	7441	7441	7441	7441	7441
R-Squared	0.065	0.125	0.126	0.094	0.084
Panel 4: Clustering coef.					
COVID	-0.228***	0.464***	0.337***	0.206***	0.120**
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
Romano-Wolf p	.002	.002	.002	.002	.09
N	7441	7441	7441	7441	7441
R-Squared	0.058	0.094	0.070	0.043	0.038
Panel 5: Reciprocity					
COVID	-1.972***	-3.010***	-3.204***	-2.730***	-3.022***
	(0.14)	(0.15)	(0.16)	(0.12)	(0.18)
N	326	326	326	326	326
R-Squared	0.732	0.883	0.890	0.834	0.862

Note: Each cell shows the OLS estimates of the treatment effect, i.e. COVID-19, on the respective dependent variable at the beginning of the row and for the network type specified on top of columns. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. The dependent variable in Panel 1, isolates, is binary, while the rest of the dependent variables are standardized to have mean 0 and standard deviation 1 for the baseline group, the cohort of 2018. Standard errors, given in parentheses, are clustered at the school level (except reciprocity since it is a classroom-level outcome, we clustered its standard errors at the district level). *, **, or *** indicates significance at the 10%, 5%, and 1% levels, respectively.

$\sim$50%) in mutual nominations among students in the classroom. Since reciprocal relationships are an essential indicator of a cohesive environment (Durkheim, 2005), this decline suggests that the pandemic has severely disrupted the social fabric of the classroom, leading to an erosion of social cohesion within the classroom.

1.5.2 Heterogeneities

In this subsection, we briefly discuss heterogeneities in the treatment effect based on gender, refugee status, and SES, which are very prominent in some cases. Before discussing the results in detail, notice that the heterogeneities presented here should not be interpreted as causal effects as they may be correlated with some characteristics that influence students' social networks.

Figure A3 clearly shows that male students become more likely to be isolated in the classroom across all network types, which is supported by Figure A4. This figure demonstrates that male students receive significantly fewer nominations in 2021 than in 2018. Furthermore, Figure A5 shows us that female students become much more central, particularly in the academic network of their classrooms, following the pandemic. Results on the differences in clustering coefficient in Figure A6 provide further evidence that female students also become more prominent in their classmates' clusters for academic and emotional support networks. The p-values associated with these findings indicate that almost all the differences between male and female students are statistically significant.

COVID-19 was harmful to refugee students as well. In Figure A7, we see that the probability of being isolated in classroom social networks is much higher for refugee students compared to the case in 2018. Similar to male students, but on a much larger scale, refugee students are nominated drastically less than their host student counterparts after the COVID-19 pandemic, as Figure A8 presents. Moreover, Figure A9 provides that the betweenness score of refugees decreased after the COVID shock, which means that host students became much more central in the classroom. P-values indicate that all these disparities between the host and refugee students are statistically significant at the conventional levels. The only outcome variable we do not observe such statistically significant differentiations is the clustering coefficient shown in Figure A10. We witness an overall increase in the clustering coefficient for refugee and host students across all network types, except for the friendship network, consistent with the main results in Table 1.3.

Lastly, to analyze SES heterogeneity, we utilize district-level variation in our sample, which includes five districts. Specifically, we compare the lowest and highest socio-economic development index districts in our sample using the calculation of the Turkish Ministry of Industry and Technology (Acar et al., 2019). Figures A11-A14 present these SES heterogeneity results. Unlike the differences in the impact of the pandemic based on gender and refugee status, we do not observe any SES heterogeneities in the effect of the pandemic. Figures illustrate an overall deterioration in peer relationships in classrooms, which aligns with the main results shown in Table 1.3; however, it seems that the pandemic has similarly affected the social networks of students from low-SES and high-SES regions.

1.5.3 Peer Relationships and Academic Outcomes

This subsection examines the association between peer interaction and academic outcomes, specifically math and verbal scores. While we cannot establish a causal link between the two due to data limitations, we can offer suggestive evidence. To accomplish this, we compare the academic outcomes of isolated and non-isolated pupils after eight months of schooling. For this analysis, we only utilize the longitudinal part of our data, which tracks the same students from the beginning to the end of the 2021-2022 academic year.

Table 1.4 shows that the academic losses due to COVID-19[12] are partly recovered after approximately one (academic) year of schooling. Specifically, there is a 0.45 SD increase in math scores and a 0.41 SD increase in verbal scores from the beginning to the end of the 2021-2022 academic year. However, the recovery in academic achievement is significantly less pronounced for students who were isolated in their friendship networks at the beginning of the 2021-2022 academic year. Isolated students show a 0.09 SD lower recovery in math scores and a 0.14 SD lower recovery in verbal scores compared to their non-isolated counterparts.

These findings underscore the critical role of healthy peer relationships in academic achievement. In line with the previous research (Berthelon et al., 2019; Juvonen et al., 2012; Kindermann, 2016; Ladd et al., 2009; Wentzel, 2017), our findings suggest that children who have more social interactions with their peers tend to perform better academically. One potential explanation could be that social engagement enables them to work with their peers, share ideas, and learn from one another. Additionally, social connection can foster crucial social abilities like communication, problem-solving, and teamwork, all of which are beneficial for academic performance. Last but not least, pupils who are in good relationships with their classmates may be more likely to have a favorable attitude about learning and school, which can make these students more motivated and successful.

[12]To see academic losses incurred by the pandemic, see (Alan and Turkum, 2023).

Table 1.4 Heterogeneity in Academic Scores Based on Isolation

	All	Non-Isolated	Isolated	Difference
Panel 1: Math scores				
Recovery	0.452***	0.467***	0.374***	-0.093**
	(0.02)	(0.03)	(0.04)	(0.04)
N	6150	5170	980	6150
R-Squared	0.268	0.265	0.348	0.286
Panel 2: Verbal scores				
Recovery	0.417***	0.439***	0.297***	-0.143***
	(0.02)	(0.02)	(0.04)	(0.04)
N	6150	5170	980	6150
R-Squared	0.228	0.228	0.255	0.244

Note: Reported results are from OLS estimations. Each cell shows the estimates for the degree of academic recovery on the respective academic score. Outcome variables are standardized to have a mean of 0 and a standard deviation of 1 for 2021. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics, and the test score in the previous term. Standard errors, given in parentheses, are clustered at the school level. *, **, or *** indicates significance at the 10%, 5%, and 1% levels, respectively.

1.6 Discussion of Mechanisms

One mechanism for the results could be that the pandemic deteriorated children's sociocognitive and socioemotional skills, and some of the decline in peer relationships we observe may be due to this deterioration. Several studies document a strong association between social skills and positive peer relationships. Peterson et al. (2016), Hughes and Leekam (2004), and Caputi et al. (2012) highlight the relationship between cognitive empathy (Theory of mind), as measured by the Reading the Mind in the Eyes test (RMET) (Baron-Cohen et al., 2001), and peer relationships. They demonstrate that higher levels of cognitive empathy are associated with greater social competence and improved friendship quality. Studies by Portt et al. (2020), Van der Graaff et al. (2014), and Van der Graaff et al. (2018) provide empirical support for the association between emotional empathy (empathetic concern) and peer relationship. Their findings emphasize the importance of emotional empathy in fostering positive connections with peers. A study by Bagwell et al. (2001), which explores the role of impulsivity in peer interaction, reveals that children with higher levels of impulsivity are more likely to experience rejection by their peers. Similarly, Parker et al. (2015) shows that patience, a component of self-regulation, can contribute to more positive peer relationships.

Our data is rich enough to test these associations in our context. Consistent with the literature, we find cognitive empathy and empathetic concern are negatively correlated with social isolation and positively correlated with the number of in-degree ties. We also document that impulsivity is associated with an increase in isolation and a decrease in in-degree ties, see Table A.2. Consistent with these findings, Table A.1 gives evidence of the erosion of these skills due to the pandemic in our data. We document 0.09 sd lower cognitive empathy, 0.42 sd lower emotional empathy, and 0.28 sd higher impulsivity[13]. These results, combined with the existing literature on the role of social skills in shaping social relationships, suggest that the deterioration in peer relationships we document may be partially driven by the decline in sociocognitive and socioemotional skills.

In terms of the heterogeneous effects of the pandemic, we do not know enough to pin down the underlying mechanism, however, we can offer some potential explanations. The gender differences in the pandemic's effects may be explained by existing survey evidence that provides boys spent more time on detrimental activities such as playing computer games or watching TV than girls during the pandemic (Grewenig et al., 2021). This excessive exposure to these activities may have limited their engagement in social life, leading to a further decline in their social skills. Additionally, traditional gender norms may discourage boys from expressing their emotions and dealing with stress related to the pandemic. These might lead them to become more isolated. These setbacks in social skill development can make it harder for them to form healthy peer relationships once in-person education resumes, given the cumulative nature of social skill development.

For the observed refugee status heterogeneity in the results, one possible explanation could be that the disruptions to normal patterns of interaction and relationship-building caused by the COVID-19 pandemic may have made it harder for students to form relationships with classmates from different backgrounds. It may be due to a lack of opportunities for students to interact with each other as they would do in a traditional classroom setting. While the data does not provide a clear understanding of the underlying mechanism, it underscores the need to support and facilitate the integration of refugee students into the classroom and provide them with opportunities to form healthy relationships with their peers.

1.7 Conclusion

School closures and other COVID-19 measures like lockdowns and social distancing measures decreased the possibility of peer interaction during the pandemic. This reduction in peer interaction may have

[13]These findings align with the study conducted by Alan and Turkum (2023).

lasting effects on social bonds and classroom cohesion even after schools reopen and social distancing measures are relaxed. To investigate this relationship, we use a unique data set collected from public schools in a southeast province of Turkey. The empirical analysis reveals a significant impact of COVID-19 on classroom cohesion indicators, with increased probabilities of social exclusion, decreased reciprocity amongst classmates, and greater segregation within the classroom. Furthermore, our findings demonstrate that the peer relationships of males and refugees are disproportionately affected by the pandemic; however, the impact is uniform across different SES regions.

One of the motivations of our study is the crucial role that peer relationships play in academic success. We find suggestive evidence that the COVID-19 pandemic has worsened social isolation among students, impacting their academic journey. Our research provide an association that students who experienced social isolation faced more challenges in achieving academic recovery compared to their non-isolated peers. These findings underscore the crucial importance of peer relationships in shaping students' educational outcomes.

All in all, we find these results concerning. We aim to demonstrate the short-term impact of the COVID-19 shock on children, but we also have concerns that the effects may persist over the long term and affect individual outcomes in later life stages, such as in the labor market (Lleras-Muney et al., 2020). Social skills are critical for success in the professional realm, as they can increase workplace success and career advancement. Furthermore, strong social skills are associated with better communication and collaboration, which can lead to higher productivity and job satisfaction. Therefore, the development of social skills is essential not only for childhood but also for adulthood success and well-being. Lastly, it is important to note that weaker social skills also have significant results at the aggregate level. It leads to lower human capital and national income (Barro, 1991). Considering these potential consequences, our findings have important policy implications. Policymakers and education professionals must better assess their strategies for enhancing students' social skills in their attempts to return them to pre-pandemic levels. In this regard, schools play a crucial role in building the social capital of children and should be effectively utilized to this end.

2

Disruption to Schooling Impedes the Development of Abstract Reasoning and Theory of Mind in Children

Abstract We show that the development of abstract reasoning and cognitive empathy (theory of mind) is severely hindered when children are deprived of the stimulation of a school environment. We document significantly lower abstract reasoning and cognitive empathy scores in elementary school children who returned from an extended school closure caused by the Covid-19 pandemic relative to proximate pre-pandemic cohorts. This developmental delay has a significant socioeconomic gradient, with underprivileged children experiencing more substantial delays. We also document a significant disruption in the development of socioemotional skills: 0.24 sd lower grit, 0.43 sd lower emotional empathy, 0.06 sd lower epistemic curiosity, and 0.24 sd higher impulsivity. About eight months of school exposure results in a remarkable recovery in abstract reasoning and theory of mind for all socioeconomic groups. However, the measured levels still indicate significant delays relative to the expected developmental trajectories. No notable improvements are observed in socioemotional skills except for curiosity. These findings reveal that the damage school closures inflicted on children goes beyond well-documented academic losses and highlight the crucial role of the school environment in fostering fundamental cognition and socioemotional development in children.

2.1 Introduction

It has been shown that early life stimulation is crucial for children's cognitive and socioemotional development (Almlund et al., 2011; Black et al., 2017; Cunha and Heckman, 2007; Cunha et al., 2010; Doyle et al., 2009; Heckman et al., 2006; Manning and Patterson, 2006). However, the role of formal education in shaping fundamental cognition and socioemotional skills is not well understood. Formal education, or schooling, is commonly viewed as a means to transmit knowledge and enhance academic abilities. However, while achieving this, schooling likely reinforces the development of fundamental cognition and shapes essential character skills in children. The formal educational process shapes children's cognitive function and socioemotional skills through multiple channels, but two stand out as the most prominent. First, there is an apparent direct channel where students learn abstract reasoning via curricular tasks, such as working on math and science problems and doing reading comprehension.[1] Social and emotional development is likely to benefit from direct teaching as children are taught good behavior in schools, typically with the guidance of a set curriculum and through pedagogical practices. The second channel relates to the learning externalities schools create whereby knowledge is disseminated, and behavioral norms are reinforced through peer interactions.[2] In this paper, we show that depriving children of school-related stimuli impedes the growth of their abstract reasoning, cognitive empathy (theory of mind), and socioemotional skills in a lasting manner. We also show that developmental delays are much more pronounced for socioeconomically underprivileged children.

Abstract reasoning is a human ability to reason through complex and abstract ideas and find solutions to unfamiliar problems, and as such, it is closely related to fluid intelligence. We measure abstract reasoning using Raven's Progressive Matrices (RPM) (Raven et al., 2000). RPM is a non-verbal test to measure general fluid intelligence and abstract reasoning as early as age five. Theory of mind is a sociocognitive ability, also known as cognitive empathy. It refers to the ability to recognize and understand the mental states of others and use this understanding to predict human behavior. We use the Reading the Mind in the Eyes test (RME-T) to measure the theory of mind performance (Baron-Cohen et al., 2001). In addition to these two cognitive skills, we also consider several socioemotional (character) skills that are shown to be instrumental for children's learning processes and well-being. Specifically, we consider grit, the ability to persevere through challenging tasks and setbacks (Alan

[1] For example, the role of formal education in the development of abstract thinking was put forward by Flynn (2000) and then Daley et al. (2003), Must et al. (2009), Rönnlund and Nilsson (2009), Flynn (2012), Liu et al. (2012), and Baker et al. (2015) as one of the explanations of the secular increase in fluid intelligence over time.

[2] A recent study by Alan and Mumcu (2022) shows peer learning constitutes a substantial part of learning in schools.

et al., 2019; Duckworth et al., 2016), emotional empathy (ability to respond to others' emotional state) (Alan et al., 2021a), epistemic curiosity (urge to know and explore novel phenomena) (Alan and Mumcu, 2022; Kashdan et al., 2020) and impulsivity/patience (lack of emotional control and acting without thinking of consequences) (Alan and Ertac, 2018; Dohmen et al., 2010; Perez-Arce, 2017; Sleddens et al., 2013).

To document the developmental delays caused by the lack of school exposure, we leverage a setting where rich data from several cohorts of primary school students were collected as part of a large education project in Turkey. The project's objective was to measure a wide range of cognitive and noncognitive skills and evaluate interventions to improve some of these skills in the school environment. In addition to several randomized evaluations of various educational programs, this project resulted in a comprehensive database covering three cohorts of children aged 9-11 (grades 3 and 4) before the Covid-19 pandemic. These pre-pandemic data allow us to establish a benchmark, the expected cohort-to-cohort variation, for our outcomes of interest. To gauge the developmental delays in these outcomes, we collected another round of data from a new cohort of students when Turkish schools opened in September 2021 after about 1.5 academic years of closure. We augmented our pre-pandemic data with this new cohort, which we refer to as the "pandemic cohort". We then tracked these children and conducted one more round of data collection in May 2022 (at the end of the academic year) to assess the extent of recovery after about an 8-months of school exposure.

Children in our augmented sample have similar socio-demographic characteristics and are exposed to similar school and teacher characteristics across cohorts. Moreover, we show that in the pre-pandemic years, our outcomes of interest do not exhibit any significant cohort-to-cohort variation. We then show that our pandemic cohort lags severely behind previous cohorts in almost all skills we consider. The children of this cohort scored 0.51 sd lower in Raven's test (abstract reasoning test) and 0.28 sd lower in the RME test (cognitive empathy-theory of mind test) relative to the base pre-pandemic cohort. They also exhibited significantly lower grit (0.24 sd), lower emotional empathy (0.43 sd), lower epistemic curiosity (0.06 sd), and higher impulsivity (0.24 sd) relative to pre-pandemic cohorts. Tracking our pandemic cohort and measuring these skills again at the end of the 2021-2022 academic year, we observe significant improvements in abstract reasoning and cognitive empathy scores. However, the observed levels are still short of what is expected from the respective developmental stage. While we see promising improvements in abstract reasoning and cognitive empathy, we see no evidence of recovery in socioemotional skills. The pandemic cohort remains 0.34 sd and 0.23 sd behind in emotional empathy and grit, respectively, and becomes even more impulsive after eight months of schooling. Interestingly, they also become more curious than previous cohorts.

The documented cognitive delays have a significant socioeconomic gradient, with children of lower socioeconomic status (SES) exhibiting more substantial delays in abstract reasoning and cognitive empathy. For abstract reasoning, we record a 0.22 sd delay at the highest SES and 0.48 sd for the lowest SES relative to the most proximate cohort for grade 4 students. For cognitive empathy, we find no significant delay in the highest SES children but a significant delay (0.16 sd) for the lowest SES. While both 3rd and 4th graders remained behind what is expected from their developmental stage at the end of the academic year, high SES children recovered better in abstract reasoning. The damage on socioemotional development exhibits a similar socioeconomic pattern for emotional empathy and impulsivity, with low SES children lagging further behind high SES children. The striking finding is that the follow-up data show no evidence of recovery in socioemotional skills. Given the existing socioeconomic gaps we document in pre-pandemic cohorts, the lack of recovery implies further widened socioeconomic gaps in socioemotional skills.

Our paper makes two key contributions. First, we show that the development of basic cognition requires school-related stimuli, and disruptions to schooling severely disturb the developmental trajectory of abstract reasoning and theory of mind in children. There is now voluminous research on the impact of school closures on learning outcomes. Combining 42 studies across 15 countries, a recent meta-analysis by Betthäuser et al. (2023) documents large and persistent learning losses worth roughly one-third of a school year. The studies show that losses are much more pronounced for socioeconomically disadvantaged children and larger in math than reading in middle-income countries. Besides confirming these learning losses, our study reveals much deeper damage inflicted on children due to school closures. Second, we show that formal education plays an essential role in character building, particularly for socioeconomically disadvantaged children (Alan et al., 2019; Alan and Kubilay, 2023; Cappelen et al., 2020). By showing the lack of recovery in cognitive and emotional empathy and a further increase in impulsive behavior in children of underprivileged backgrounds, our results underscore the possible social consequences of disruptions to formal education in years to come (Alan and Kubilay, 2023).

2.2 Context and Data

Academic years run from September to June in Turkey. The first COVID-19 cases were recorded on March 11, 2020, and all schools were closed on March 13, 2020, until the end of the 2019-2020 academic year. The 2020-2021 academic year started on September 18, 2020, and after two weeks of face-to-face teaching, schools were closed again due to an alarming increase in cases, and this closure lasted until September 2021. In May and June 2021, only preschoolers, students with special needs, and 8th and 12th-grade students were allowed to receive face-to-face teaching. Therefore, from March 2020 until September 2021, Turkey experienced about 50 weeks of country-wide school closure, one of the highest among the OECD countries.[3] Given that the number of weeks within one academic year in Turkey is around 36 weeks, the length of disruption to schooling was about 1.5 academic years.

Throughout the closure period, the Turkish national TV broadcasted primary, secondary, and high school lecture videos through the Education Information Network (EBA). In addition to EBA, schools were encouraged to use various digital platforms to reach students, such as zoom. However, students from disadvantaged households had little or no capacity to access these digital platforms due to the lack of equipment and internet access. More importantly, while EBA was easy to access, the proper use of it required significant parental input, especially at the primary school level. It required monitoring lecture times, helping the child to follow the correct lectures, and handling homework assignments unmarked by a teacher. Therefore, as in most countries, school closures not only generated inequality in access to education across cohorts but also across socio-economic groups within cohorts (Agostinelli et al., 2022; Bacher-Hicks et al., 2021; Bailey et al., 2021; Betthäuser et al., 2023; Chetty and Hendren, 2020; Engzell et al., 2021; Hanushek and Woessmann, 2020; Kogan and Lavertu, 2021; Maldonado and De Witte, 2021; Parolin and Lee, 2021).

Our data come from a large field project launched in the Fall of 2015. The project involved three randomized controlled trials (RCTs) aiming at improving social and emotional skills in primary and post-primary school children. A large number of state schools located in Turkey's most ethnically diverse and economically active provinces were enlisted to be part of the project. Each RCT included randomly selected schools within this pool and involved at least two data collection rounds, baseline and endline. By 2019, these data collection efforts resulted in rich data on three cohorts of 3rd and 4th graders and a cohort of 5th and 6th graders. Unfortunately, the project was halted in the spring of 2020 due to the pandemic, preventing us from doing fieldwork to collect data.

Our pre-pandemic database contains three cohorts of more than 15,000 3rd 4th-grade students and a single cohort of 5th and 6th-grade students from 165 primary and 77 post-primary schools in the provinces of Mersin, Sanliurfa, Istanbul, and Sakarya.[4] Schools for the educational project were chosen based on their infrastructural and socio-demographic characteristics to ensure that they are homogeneous within districts and socio-demographic characteristics of districts are similar across provinces. Because the project only included state schools and Turkey's higher-income families tend to send their children to private schools, our sample represents Turkey's middle, lower-middle, and

[3]Source: https://en.unesco.org/covid19/educationresponse#schoolclosures

[4]The planned RCT for grades 5 and 6 was launched in the Fall of 2019 by collecting baseline data but interrupted by the pandemic.

low-income households. Our first pre-pandemic cohort (2015), which we take as the base cohort for cognitive outcomes, refers to the 3rd and 4th graders of the 2015-2016 academic year. The second cohort (2018) is the same graders of the 2018-2019 academic year, and the third cohort (2019) is the same graders of the 2019-2020 academic year. These pre-pandemic data were collected at the beginning of each academic year as baseline data for the RCTs mentioned above, therefore free from the effect of any intervention. These data allow us to establish expected cohort-to-cohort variation (our benchmark) in the skills we study. Furthermore, because we measured these skills at grades 3, 4, 5, and 6 at baseline, the pre-pandemic data also provided us with the expected developmental trajectory (age profile) of these skills.

We complemented our rich pre-pandemic database with the data we collected in September 2021 from the new cohort of 3rd and 4th graders in schools in our database in the province of Mersin. We refer to this fourth cohort (the academic year of 2021-2022) as the “pandemic cohort". We collected data from this cohort by following the protocol we used to build the pre-pandemic database. Specifically, we visited the schools in person and spent around two-three lecture hours collecting data in every classroom with the help of trained field assistants. Our combined data allow us to assess the extent of developmental delays relative to our pre-pandemic benchmark. We then followed our new cohort and collected the same data just before the end of the academic year (May 2022) to assess the degree of recovery against our benchmark developmental trajectory.

To measure abstract reasoning, we implemented a sub-scale of the Raven's Progressive Matrices (Raven et al., 2000). The test is progressive in the sense that it gets harder within sub-scales. Raven's test is thought to reflect one's fluid (general) intelligence, and since it is a non-verbal test, considered to be free from language bias. To measure cognitive empathy (theory of mind), we implemented a sub-scale of the Reading the Mind in the Eyes test developed by (Baron-Cohen et al., 2001). The test aims to measure the ability to recognize mental states expressed by human eyes. It involves presenting a photograph of the eye region of an actual human showing a particular emotional state and asking participants to choose one from four mental state options. Both fluid intelligence and cognitive empathy are often misquoted as “innate" abilities and thought to be formed and set very early in life (3 for fluid intelligence, 4-5 for the theory of mind behavior). However, research shows an age-dependent positive developmental trajectory for both, and our data corroborates this. We provide example questions for each test in the appendix (see Figure B4 and B5).

Tangential to the paper's primary focus, we also measure learning losses concerning math and verbal skills. We present these results in the appendix only to show that academic losses recorded in Turkey, a middle-income country, are similar to those documented in previous studies such as those discussed in Betthäuser et al. (2023). Because there are no centralized objective tests in the grade levels we consider in this study, we designed math and Turkish tests based on the requirements of the national curricula for each grade level in the education projects. To measure the learning losses of the pandemic cohort, we use the same tests we used for the previous cohorts, both at the beginning and the end of the academic year. As in abstract reasoning and cognitive empathy, we measure the losses by comparing the test scores of the pandemic cohort with previous cohorts' scores on the same tests.

The primary objective of the education project that led to the collection of these data was to identify ways to enhance achievement-related socioemotional skills. We collected data on these skills using item response questionnaires and constructed measures of epistemic curiosity (Kashdan et al., 2009), grit (Duckworth and Quinn, 2009), impulsivity (Sleddens et al., 2013) and emotional empathy. For character skills data, we only have two pre-covid cohorts (2018-2019 and 2019-2020 academic years), so our base pre-pandemic cohort refers to students in the 3rd and 4th grades in the 2018-2019 academic year. To measure the effect of school closures on these skills, we implemented the same survey items for the pandemic cohort in September 2021 and again in May 2022, just before the summer holiday began. We provide all our survey items in the appendix (see Table B1).

2.3 Internal Validity

The key assumption behind attributing the differences between the pandemic cohort and pre-pandemic cohorts to the lack of school exposure is that the pandemic cohort has the same potential outcomes as the pre-pandemic cohorts. This assumption is likely to be valid in our context for a number of reasons. First, cohorts in our data are close to each other, and the pandemic cohort is only two years apart from the last pre-pandemic cohort. Second, as mentioned above, schools in our database are all chosen for a particular education project and share almost identical infrastructural features. Third, all public schools take students only from their catchment areas in Turkey, and catchment area socio-demographic characteristics are unlikely to change over a few years. Finally, teacher characteristics are similar across state schools as public school teachers are centrally appointed, and the pandemic had no effect on the number and the composition of teachers. In fact, over 80% of the teachers of the original project were still working in the same schools at our final measurement phase.

Table 2.1 Panel 1 provides the statistical evidence of the validity of our assumption. It shows the balance across cohorts with respect to student demographics and classroom/teacher characteristics, taking the 2015 cohort as the reference for abstract reasoning and academic skills and 2018 for other skills. As can be seen from the joint F-test results on pre-covid cohorts (column 5), students are statistically similar in demographics, classroom, and teacher characteristics. Column 6 includes the pandemic cohort in the tests. As expected, this addition does not affect the balance regarding demographics and school/teacher characteristics.

Panel 2 presents the balance tests for our outcomes of interest. The test results in column 5 confirm that there is no significant cohort-to-cohort variation in the outcomes we consider in pre-pandemic data. Pre-pandemic cohorts were similar in terms of fundamental cognitive and sociocognitive skills (abstract reasoning and cognitive empathy), academic achievement (math and verbal abilities), and socioemotional skills. However, we see a very different picture when we include the pandemic cohort in this analysis. All cognitive and socioemotional outcomes rejected the F-test of equality except for curiosity. In what follows, we detail cohort differences in outcomes of interest using a conditional mean analysis. First, we assess how the pandemic cohort of 3rd and 4th graders differs from previous cohorts conditional on demographics, teacher and classroom characteristics, and school fixed effects (cohort comparisons). We then assess the extent to which the pandemic cohort recovered after eight months of school exposure (panel comparisons). Note that the covariate adjustment is only to gain additional precision. The fact that all our results hold without covariate adjustments is another assurance of the internal validity of our results.

Table 2.1 Balance Across Cohorts

	(1)	(2)	(3)	(4)	(5)	(6)
	2015	2018	2019	2021	Prob >F*	Prob >F
Panel 1						
Student Demographics						
Male	0.515	0.514	0.512	0.509	0.731	0.849
Age in month	109.345	109.143	109.950	109.129	0.507	0.498
Number of Sibling	2.870	2.864	2.864	2.999	0.918	0.135
Working Mother	0.311	0.288	0.288	0.316	0.436	0.187
Teacher/Classroom Characteristics						
Female	0.777	0.679	0.692	0.625	0.162	0.093
Year of Experience	18.766	19.094	19.068	19.860	0.969	0.726
Age	43.926	42.971	42.956	43.801	0.779	0.701
Class Size	35.328	31.307	31.998	31.827	0.217	0.295
Share of Male in the Class	0.515	0.514	0.512	0.509	0.730	0.852
Panel 2						
Cognitive Skills						
Abstract Reasoning	0.000	-0.059	-0.055	-0.527	0.902	0.000
Cognitive Empathy (ToM)		0.000	-0.047	-0.268	0.619	0.000
Mathematics Score	0.000	-0.039	-0.033	-0.559	0.994	0.000
Verbal Score	0.000	-0.045	-0.009	-0.350	0.877	0.000
Socioemotional Skills						
Emotional Empathy		0.000	0.024	-0.427	0.459	0.000
Grit		0.000	-0.046	-0.242	0.173	0.000
Impulsivity		0.000	0.016	0.239	0.817	0.000
Curiosity		0.000	0.023	-0.064	0.524	0.123

Note: The table presents balance across cohorts. Columns 1-4 Panel present the means of the respective variable. Columns 5 and 6 present the p-values obtained via joint F-test from the regressions of the respective variable on cohort dummies by taking either 2015 or 2018 as the reference cohort, depending on the data availability. Column 5 excludes the pandemic cohort, and Column 6 includes it. Variables in Panel 2 are standardized to have a mean 0 for the years 2015 and 2018, based on the available data. Total sample size 21,155 (n=1,157 in 2015, n=4,928 in 2018, n=10,690 in 2019, and n=4,400 in 2021).

Remeasuring our pandemic cohort in May 2022, we can document the extent of recoveries. However, the skills we consider are likely to keep developing for our age groups. Therefore, we need another cohort comparison to assess whether the pandemic cohort's recovery was sufficient, i.e., whether children caught up with what was expected from their grade levels at the end of the academic year. Figure 2.1 Panel 1 shows the developmental trajectory of our outcomes of interest. For this, we take the 2018-2019 cohort and plot the skill levels for grades 3,4,5, and 6, representing the developmental trajectory of these skills within a limited age range. Panel 2 presents the age profile of skill gains in standard deviation terms, taking grade 3 as the reference. As seen in Panel 1, abstract reasoning and cognitive empathy are increasing with age, with substantial heterogeneity within each age range. Depicted age profiles of Raven's and RME-T scores are consistent with the existing studies.[5]

The positive age trajectories we document also imply possible high malleability of these cognitive skills, including their vulnerability to negative shocks in early developmental stages. Unfortunately, we cannot plot an age profile for socioemotional skills as we measured these skills only for grades 3 and 4. Absent any established age profile for these skills in the literature, it is hard to infer a developmental trajectory as a benchmark. Nevertheless, our data suggests some emotional maturity is expected going from grade 3 to 4: a decline in impulsivity and an increase in grit, emotional empathy, and curiosity (see Figure B1 in the appendix).

[5] Pind et al. (2003) documents the age profile of Raven's test, increasing until the mid-twenties. Dorris et al. (2022) show a hump-shaped developmental trajectory for cognitive empathy, using RME-T, increasing between the ages 6 and 12, then forming a dip during adolescence, followed by another hump-shaped trajectory, with a peak around the mid-30s. The age profile we document for RME-T is consistent with this study.

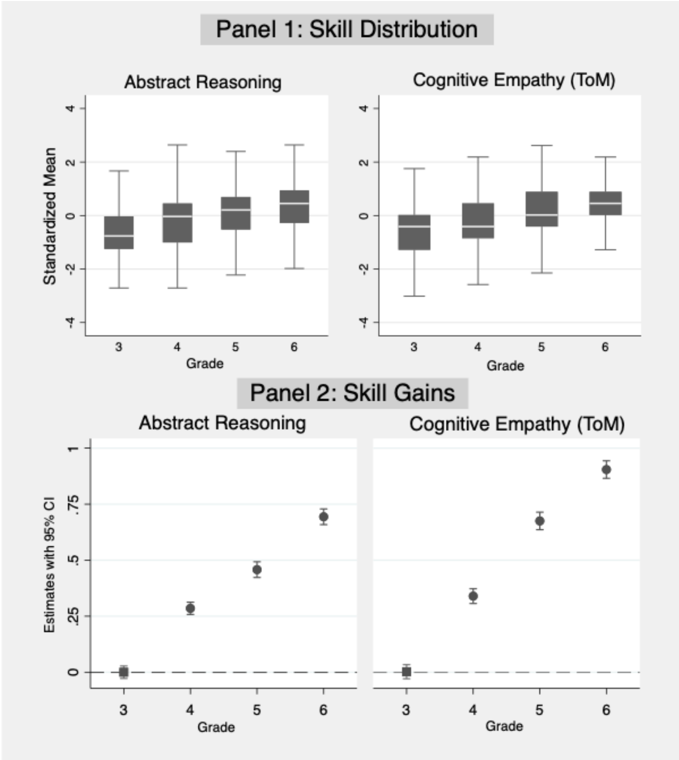


Figure 2.1 Age Profile of Cognitive Outcomes

Note: Panel 1 shows the developmental trajectory of abstract reasoning and cognitive empathy (ToM) using the 2018-2019 cohort for grades 3,4,5, and 6. Panel 2 presents the age profile of skill gains in terms of standard deviations, with grade 3 as the reference point. Total sample size is 19,544 for abstract reasoning and 17,382 cognitive empathy (ToM). All statistical tests are two-tailed.

2.4 Results

We first document the effect of disruption to schooling on our cognitive outcomes of interest, abstract reasoning, and cognitive empathy. To do this, we compare cohort means of respective outcomes controlling for student demographics, classroom and teacher characteristics, and school fixed effects. We take those in grade 3 or 4 in the 2015-2016 academic year as the reference category for abstract reasoning and those in grade 3 or 4 in the 2018-2019 academic year for cognitive empathy. Figure 2.2 depicts the estimated mean differences relative to the 2015 cohort in abstract reasoning and relative to the 2018 cohort in cognitive empathy.

First, note that consistent with the unconditional means shown in Table 2.1, there is no significant cohort-to-cohort variation in these two outcomes for pre-pandemic cohorts. The estimated developmental delay for the pandemic cohort in abstract reasoning and cognitive empathy is 0.51 and 0.28 standard deviations, respectively. These estimates indicate a substantial disturbance to fundamental cognitive and sociocognitive development. Fortunately, our panel analysis, comparing the September 2021 test results

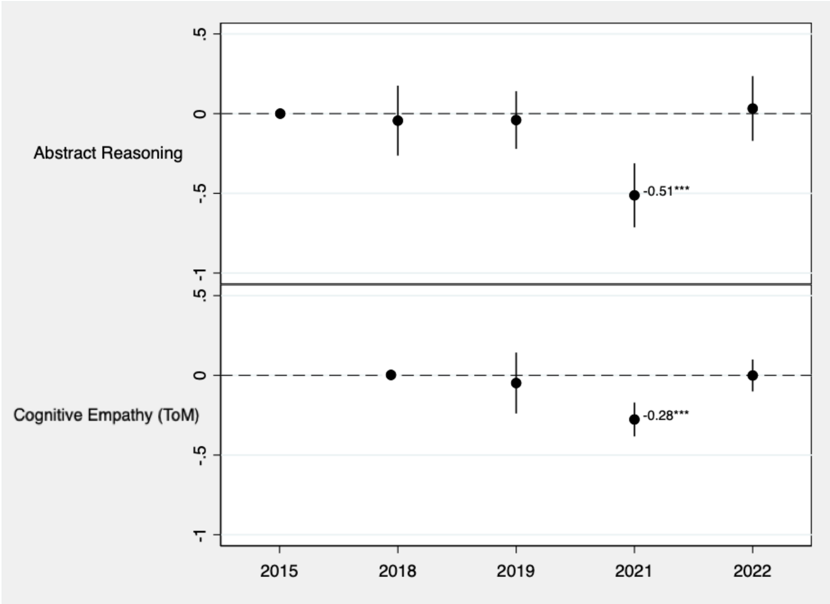


Figure 2.2 Cohort Profiles of Abstract Reasoning and Cognitive Empathy

Note: The figure illustrates the estimated coefficients and 95% confidence intervals obtained from regressing the standardized outcomes on year dummies. The base year is 2015 for abstract reasoning and 2018 for cognitive empathy (ToM). Data on the latter are not available for 2015. This figure uses the test results from the start of each academic year for all years except 2022 to illustrate the recovery of the pandemic cohort. The full set of covariates of student demographics and classroom/teacher characteristics given in Table 2.1 is used in the regression analysis. Student demographics includes gender, age in months, number of siblings, and a dummy variable for students whose mother is working. The classroom/teacher characteristics consist of gender, years of teaching experience, age of the teacher, class size, and the share of male students in the class. Standard errors are clustered at the school level. Asterisks indicate that the estimated coefficient is statistically significant at 1% ***, 5% **, and 10% * levels. The sample size is 15,217 for abstract reasoning and 14,386 for cognitive empathy. All statistical tests are two-tailed.

with those of May 2022, reveals a remarkable recovery in both these skills. We observe that in May 2022, after about eight months of exposure to the school environment, the pandemic cohort reached the level expected from their grade levels at the beginning of the academic year. Note that our findings for the academic skills (math and verbal) show the same pattern (see Figure B2 in the appendix). Recorded losses (0.54 sd in math, 0.35 sd in verbal ability) imply one school year's worth of loss in crystallized intelligence consistent with the losses documented for countries with similar lengths of school closures (Ardington et al., 2021; Hevia et al., 2022; Kogan and Lavertu, 2021; Lichand et al., 2022; Vegas, 2022).

However, as we document in Figure 2.1, abstract reasoning and cognitive empathy are still on a positive developmental trajectory for the age range we consider. Depicted level differences in Figure 2.2 use the test results taken at the beginning of respective academic years, except for the estimates for 2022. The estimates of 2022 indicate recovery, but this recovery should be assessed against what is expected at the end of an academic year since 2022 test results were taken at the end of the 2021-2022 academic year. Figure 2.3 depicts this cohort comparison. It compares the achieved levels in May 2022 with what was expected from grade 3 and grade 4 at the end of the 2021-2022 academic year.

Expected levels are calculated using the respective grades of the 2018 cohort (2018-2019 academic year). Comparing the recovered levels against what is expected based on the developmental profile, we find that the pandemic cohort of grade 3 students remains 0.27sd (10%) and 0.48 sd (17%) behind the expected level of abstract reasoning and cognitive empathy, respectively. The picture is similar for the grade 4 students. The pandemic cohort of grade 4 students remains 0.21 sd (7%) and 0.69 sd (21%) behind the expected level of abstract reasoning and cognitive empathy, respectively.

We next repeat our analysis for socioemotional skills. There is now a large and growing literature showing how the school environment helps socioemotional development in children. Alan and Ertac (2018) show how impulsive behavior can be reduced using a combination of pedagogical and curricular interventions. Alan et al. (2019) show that grit can be developed in the classroom, and doing so leads to increased and persistent math achievement. In a recent paper, Alan and Mumcu (2022) show that a particular pedagogical training of teachers can stimulate children's curiosity and, in turn, improve achievement scores. Recently, several papers highlighted the importance of social skills, such as perspective-taking (Alan et al., 2021a), cooperation, and altruism (Cappelen et al., 2020), and show that these skills respond to school stimuli. The question is, then, what happens to socioemotional development when students are deprived of their teachers and peers for an extended period?

Figure 2.4 presents the same analysis we conducted for cognitive outcomes for emotional empathy, grit, impulsivity, and curiosity. Note that the 2018 cohort is the based cohort in this analysis as we do not have data on these skills for the 2015 cohort. Consistent with Table 2.1 results, while we see no difference across pre-covid cohorts in these socioemotional skills, we record a significant decline in emotional empathy and grit for the pandemic cohort. The loss is 0.43 sd for the former and 0.24 sd for the latter. We observe a weakly significant decline in curiosity but a large and significant increase (0.24 sd) in impulsivity. Unlike the recoveries we observe in all cognitive outcomes, we record no notable recovery in socioemotional skills after eight months of school exposure. We estimate even further deterioration (increase) in impulsivity but a significant increase in epistemic curiosity in children.

Recent evidence documenting learning losses due to school closures highlight that losses exhibit a significant socioeconomic gradient, with children from lower socioeconomic segment suffering deeper and more persistent losses (Agostinelli et al., 2022; Chetty and Hendren, 2020; Dorn et al., 2020; Kogan and Lavertu, 2021; Maldonado and De Witte, 2021).

Although our sample provides a much more limited socioeconomic gradient than these studies, there is some variation we can exploit to complement them. For this, we leverage the fact that there are significant socioeconomic differences across districts within provinces of Turkey. We can capture this variation using the socioeconomic development index calculated by the Turkish Ministry of Industry and

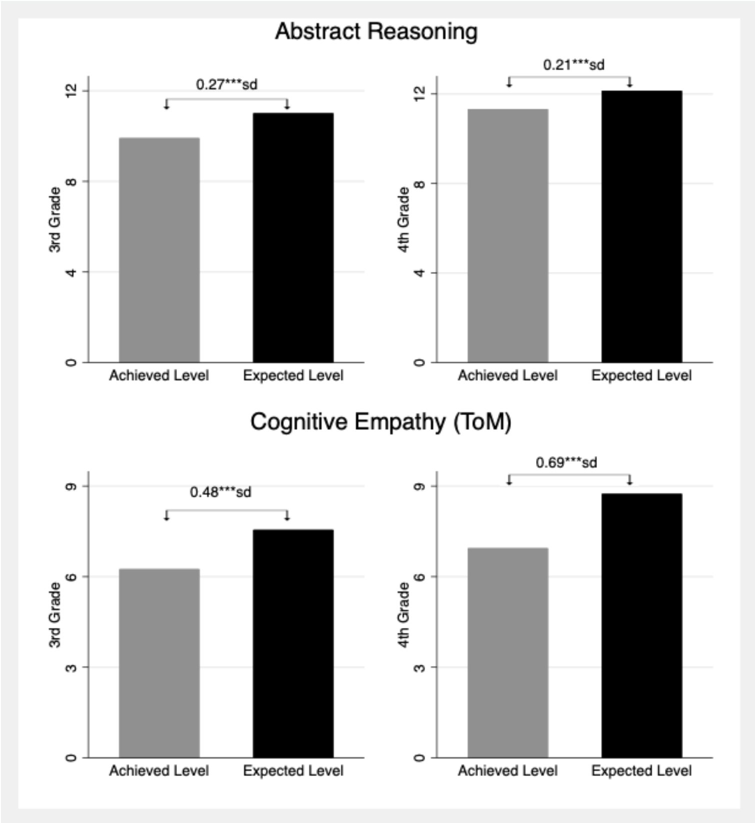


Figure 2.3 Recovery of Abstract Reasoning and Cognitive Empathy

Note: The figure compares the pandemic cohort's achieved levels of abstract reasoning and cognitive empathy at the end of the academic year (May 2022) with the 2018 cohort's achieved levels measured at the end of the 2018-2019 academic year. The figure also provides estimated differences in standard deviation units. Asterisks indicate that the estimated coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels. All statistical tests are two-tailed.

Technology (Acar et al., 2019), covering about 1000 districts. According to this index, our highest SES district corresponds to the 70th from the top and our lowest to the 188th from the top. Therefore, neither high nor low SES status in our data represents Turkey's high and low SES. Nevertheless, observing any SES differences in developmental delays in our data would be informative of the severity of damage inflicted on underprivileged children due to school closures.

Figure 2.5 depicts the socioeconomic differences in abstract reasoning and cognitive empathy using our highest and lowest SES levels for a sharp comparison.

Each figure panel presents four bars. The difference between the first two bars depicts the developmental delay in the respective skill by comparing the 2018 cohort with the pandemic cohort. The difference between the second and third bars shows the extent of recovery the pandemic cohort achieved (panel comparison). Finally, by comparing the third and the last bar, the latter being the level expected for the respective age group, we assess the extent of persistence in delays (cohort comparison). First, note the existing SES differences in these skills in pre-pandemic times. High SES children

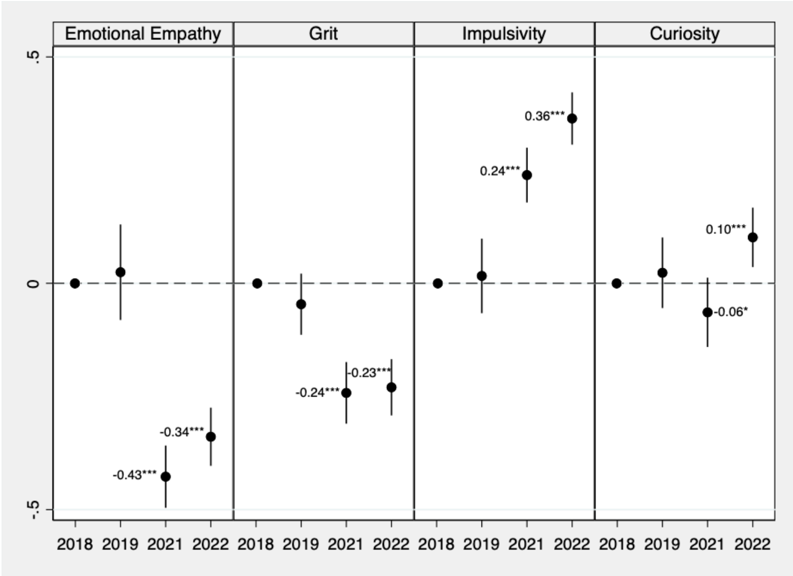


Figure 2.4 Cohort Profiles of Socio-Emotional Outcomes

Note: The figure illustrates the estimated coefficients and 95% confidence intervals obtained from regressing the standardized outcomes on year dummies. The base year is 2018 for all outcomes. The results refer to the start of the respective academic year for all years except 2022 to illustrate the recovery of the pandemic cohort. The full set of covariates of student demographics and classroom/teacher characteristics given in Table 2.1 is used in the regression analysis. Student demographics includes gender, age in months, number of siblings, and a dummy variable for students whose mother is working. The classroom/teacher characteristics consist of gender, years of teaching experience, age of the teacher, class size, and the share of male students in the class. Standard errors are clustered at the school level. Asterisks indicate that the estimated coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels. The sample size is 15,217 for abstract reasoning and 14,386 for cognitive empathy. The sample size is 15,253 for curiosity, 15,126 for emotional empathy, 13,363 for grit, and 13,389 for impulsivity. All statistical tests are two-tailed.

have higher abstract reasoning and cognitive empathy than low SES noting the 2018 cohort, and this pattern continues as they age, noting the expected levels. For abstract reasoning, we observe significant developmental delays in both low and high SES groups, especially older children (grade 4). However, while high SES children seem to have recovered entirely, low SES children still lag behind what was expected from their developmental trajectory. The results are somewhat different for cognitive empathy. We observe that much of the delays come from low SES fourth graders. What is striking here is the lack of recovery in both SES levels and both age groups. All pandemic children lag significantly behind in their development of cognitive empathy.

Figure 2.6 presents the socioeconomic gradient for socioemotional skills.

As mentioned above, we do not have an expected age profile for these skills, so we only look at the losses (cohort comparisons) and recoveries (panel comparisons), corresponding to the first 3 bars of Figure 2.5. Figure panels clearly show that there are significant SES differences in socioemotional skills even in normal times (2018 cohort). Low SES children are significantly less empathetic, less gritty, less curious, and more impulsive. The lack of school stimuli adversely affected both groups, but the higher damage inflicted on the low SES group is evident in these figures. Documented disruptions

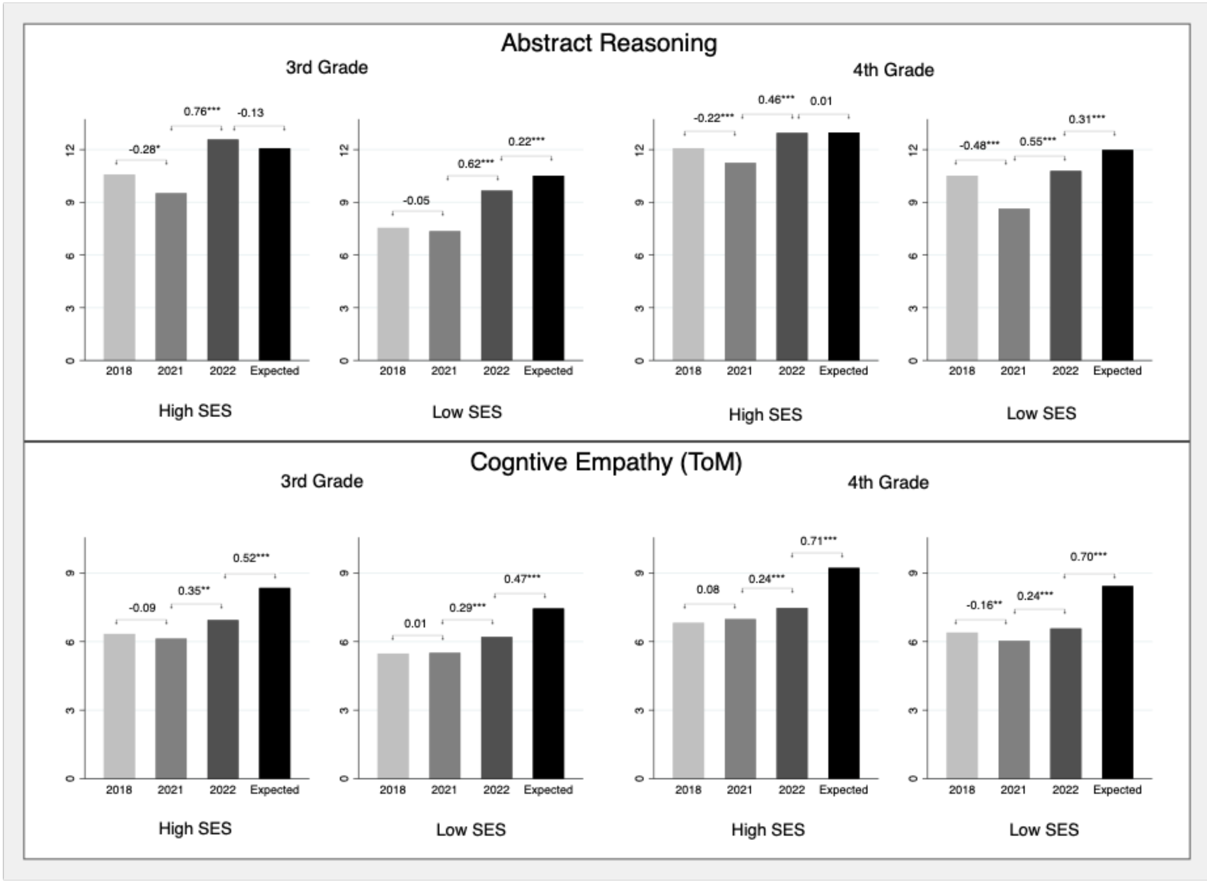


Figure 2.5 SES Differences in Cognitive Delays

Note: This figure shows the socioeconomic differences in abstract reasoning and cognitive empathy (ToM) for the highest and lowest SES levels. The difference between the first two bars illustrates the developmental delay in the corresponding skill by comparing the 2018 cohort with the pandemic cohort (cohort comparison). The difference between the second and third bars indicates the degree of recovery achieved by the pandemic cohort (panel comparison). Finally, the difference between the third and last bar indicates the extent of persistence in delays (cohort comparison). Values give estimated differences in standard deviation units. Standard errors are clustered at the school level. Asterisks indicate that the estimated coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels. All statistical tests are two-tailed.

exhibit a significant socioeconomic gradient for all socioemotional skills considered. We observe larger impacts on low SES children's curiosity, emotional empathy, and grit. Similarly, we observe increased impulsivity in both SES, but much more significantly for the low SES group. Except for epistemic curiosity, none of the socioeconomic skills recovered, suggesting widened socioeconomic gaps in these vital skills.

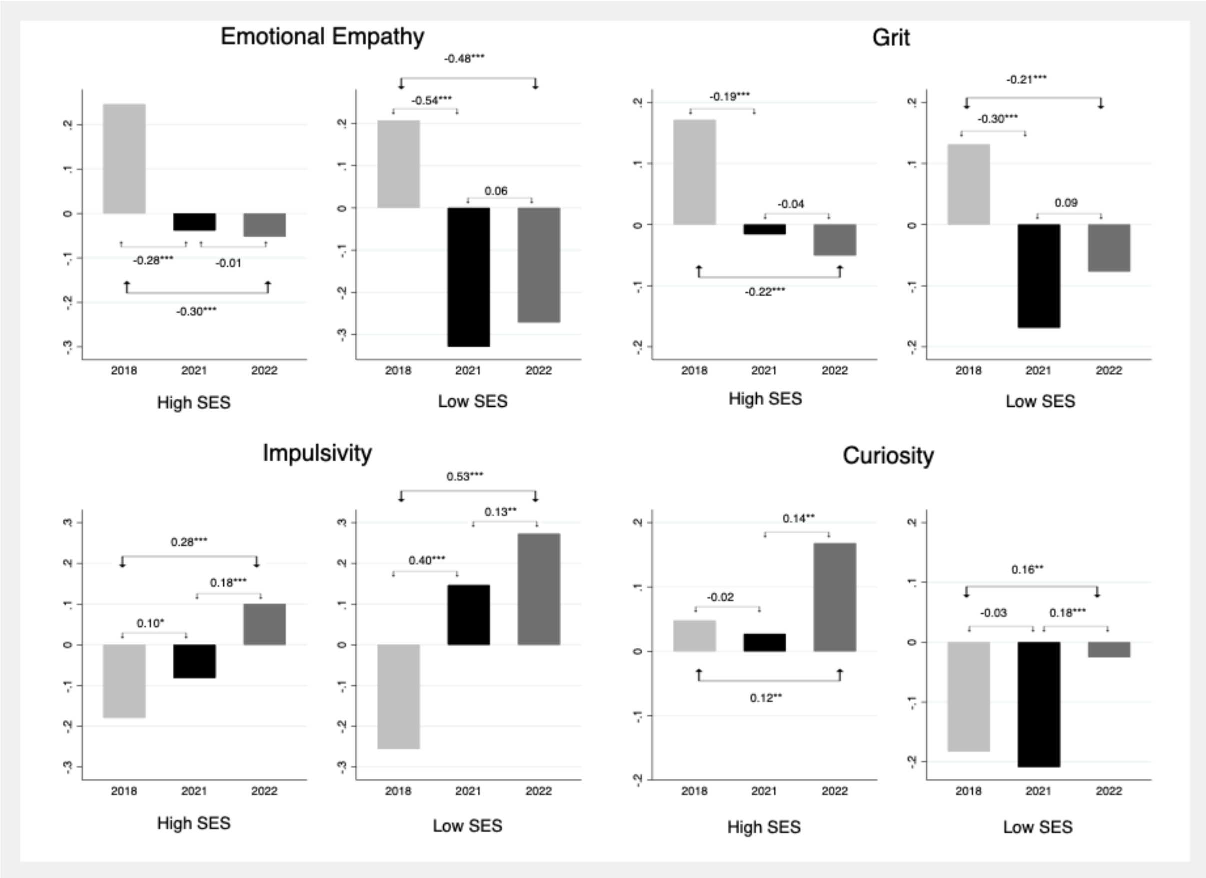


Figure 2.6 SES Differences in Socioemotional Skill Development

Note: This figure shows the socioeconomic differences in socioemotional skills for the highest and lowest SES levels. The difference between the first two bars illustrates the difference in the respective skill comparing the 2018 cohort with the pandemic cohort (cohort comparison). The difference between the second and third bars indicates the degree of recovery achieved by the pandemic cohort at the end of academic year (panel comparison). The figure also provide the coefficients of regressing the standardized outcomes on year dummies for each pair of years are on the figure. Values give estimated differences in standard deviation units. Standard errors are clustered at the school level. Asterisks indicate that the estimated coefficient is statistically significant at the 1% ***, 5% **, and 10% * levels. All statistical tests are two-tailed.

2.5 Discussion of Mechanisms

It is clear that the school closures severely hindered the cognitive and socioemotional development of the pandemic cohort. While we observe a remarkable recovery for cognitive skills, the delays persist, and we observe no notable recovery for socioemotional skills. We attribute these effects to not being exposed to school-related stimuli for an extended period. The lack of school-related stimuli can generate these delays through different mechanisms for different skills. For abstract reasoning, an obvious direct effect would be through the lack of exposure to complex and abstract tasks that primary school curricula offer (Baker et al., 2015; Bratsberg and Rogeberg, 2018; Daley et al., 2003; Flynn, 2012; Liu et al., 2012; Must et al., 2009; Rönnlund and Nilsson, 2009; Teasdale and Owen, 2000). For sociocognitive and socioemotional skills, the social environment the school offers (peer interactions and student-teacher interactions) may be more relevant.

The deprivation of school stimuli came with over-exposure to parental inputs during the pandemic. The effect of this substitution on the development of skills depends on the quality of parental inputs. Differential parental ability to support virtual learning has been shown to be the primary driver of the socioeconomic gradient observed in learning losses (Agostinelli et al., 2022; Contini et al., 2021; Dorn et al., 2020). High-SES parents have more resources to reduce the adverse effects of the lack of school inputs. On the other hand, low-SES parents lack these resources and may even reinforce the delays through low-quality (harmful) input.

Starting from the 2018 cohort, we collected information on parenting styles from the children themselves. For this, we gave students item response questions and constructed four parenting styles: obedience-demanding parenting, warm (permissive) parenting, punishment-oriented parenting, and reasoning-oriented (responsive) parenting.[6] Figure B3 in the appendix shows the difference between the 2018 cohort and the pandemic cohort in their perception of their parents' parenting styles. Note first the existing SES differences for each parenting style. Low SES parents are more obedience-demanding and tend to use harsh punishment tools more than high SES parents. High SES parents seem to be warmer (more permissive) toward their children and tend to reason with them more. Therefore even if there was no change in parenting styles, to the extent that parenting styles affect child development, extended exposure to parental input might have had different effects on high and low-SES children.

Nevertheless, we do observe a general deterioration in parent-child interactions as reported by children for both high and low SES. The observed changes are consistent with the findings we discuss in Figure 2.5 and Figure 2.6: School closures adversely affected the development of both high and low SES children, but the latter experienced more damage. Consistent with this, Figure B3 shows that the low SES pandemic cohort reported that their parents were more obedience demanding and less willing to reason than the low SES of the 2018 cohort. The reported parental tendency of punishment is higher for the pandemic cohort for both SES levels. Moreover, high SES parents seemed to have abandoned the habit of reasoning with their children during the lockdown. Unfortunately, the evidence on the causal link between parenting styles and the developmental trajectory of cognitive and socioemotional skills is weak. Several studies document a strong association between responsive, authoritative parenting and positive cognitive and socioemotional outcomes (Carlo et al., 2018; Kaufmann et al., 2000; Kong and

[6]Literature highlights three broad parenting styles based on the level of parental control and warmth. These are authoritarian (corresponding to obedience demanding and harsh punishment tendency), permissive (warmth), and authoritarian (reasoning tendency with elements of soft punishment) (Baumrind, 1966; Dornbusch et al., 1987; Paulson, 1994; Steinberg et al., 1990).

Yasmin, 2022; Radziszewska et al., 1996; Steinberg et al., 1992). Our results on the SES differences in cognitive delays and parenting styles are consistent with our claim that substituting school inputs with low-quality parent-child interactions is likely to be an important driver of our results.[7]

Another mechanism, especially for the cognitive outcomes, could be that children's test-taking abilities eroded during the pandemic, and part of the delays we measure may reflect this erosion. There could be two reasons for this erosion. First, if children are regularly exposed to tests, they get better at them controlling for the content knowledge. The lack of schooling (lack of test taking in particular) may have led to some erosion in test-taking ability. Second, the erosion may be related to the loss of socioemotional skills. Test-taking requires the ability to concentrate for an extended period, i.e., it requires patience, perseverance, and motivation, which were adversely affected by the lack of schooling. The first reason remains valid in our context. However, given that we observe recovery in cognitive skills despite high impulsivity and low grit, the most important channel that explains the delays seems to be the lack of school inputs (exposure to peers and teachers) combined with low-quality parental input.

2.6 Conclusion

We show that the development of abstract reasoning and cognitive empathy requires school-related stimuli, and the cohort deprived of the school environment experienced severe delays in the development of these skills. Furthermore, we document that their socioemotional development was also significantly disrupted. The documented delays and disruptions exhibit a socioeconomic gradient, with underprivileged children experiencing more severe delays and disruptions. Despite some recovery in abstract reasoning and cognitive empathy after an 8-month school exposure, the achieved levels indicate persistent delays.

Our findings show that the damage the school closures inflicted on children goes beyond academic losses, as widely documented in the literature. We show that school inputs are crucial to encourage the development of cognition and sociocognition and are vital for socioemotional development. The fact that we find no evidence of recoveries in socioemotional skills is of particular concern. The disruption to the development of cognitive and emotional empathy and heightened impulsivity may have significant societal consequences in years to come. This paper shows that the pandemic-related school closures revealed the broader purpose of fair access to public schooling, which goes beyond

[7] Another channel could be sources that are not directly related to school closures, such as the loss of family members or family economic hardship imposed by the pandemic. While we acknowledged the role of this particular channel, given the documented recoveries upon 8-month school exposure, we believe that the lack of school stimuli is the primary driving force of the effects we document.

building human capital. Schooling is instrumental in building fundamental cognitive and socioemotional skills, especially for the underprivileged segment of society, and, as such, it has a significant role in building social cohesion between socioeconomic segments and ensuring social mobility. Therefore our study underscores the importance of maintaining access to education during crises, especially for underprivileged children.

3

The Effect of Mass Migration on Economic Development

Abstract The Syrian refugee crisis is one of the significant humanitarian challenges of the 21st century, and Turkey is among the countries significantly impacted. This study analyzes the impact of the approximately 3.65 million Syrian refugees residing in Turkey, the largest concentration of refugees in a single country, on economic development proxied by GDP per capita. Since Turkish provinces faced distinctive rises in refugee numbers after the Syrian Civil War, I exploit the differences in the proportion of refugees across different Turkish provinces to estimate refugees' impact on economic development using a difference-in-differences methodology. To address the potential selection bias arising from the refugees' settlement patterns, I employ a two-stage least squares (2SLS) method. Results offer suggestive evidence of a positive medium-term effect and a negative long-term effect of the arrival of refugees on economic development, while the short-term effect is unclear. However, none of the impacts are statistically significant.

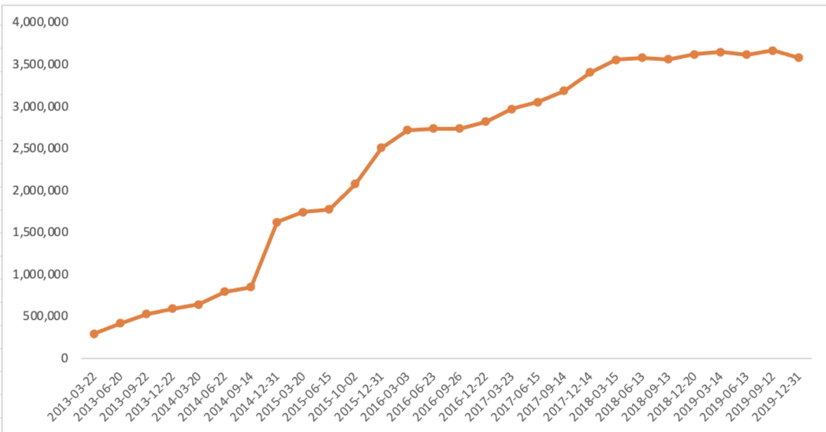
3.1 Introduction

The worldwide refugee number reached 26 million at the end of 2019 (UNHCR, 2020)[1]. The Syrian Civil War, which occurred on the southern border of Turkey, is one of the major conflicts contributing to

[1] See https://www.unhcr.org/data.html

the boost in the refugee population. As of June 2020, there were 5,543,746 registered Syrian refugees in nearby countries such as Turkey, Egypt, Iraq, Jordan, and Lebanon[2]. Of these, 3.65 million were registered by the Turkish Government, making Turkey the nation hosting the largest number of refugees globally[3]. Figure 3.1 illustrates the rise in the registered Syrian refugees in Turkey from 2013 to 2019. This extreme refugee flow to Turkey has brought about concerns, including their impact on the economy. This paper specifically focuses on the effect of immigration on per capita GDP, which is used as a proxy for economic development similar to Elgin and Oztunali (2014). Existing studies investigating this relationship yield mixed results (Felbermayr et al., 2010; Jeffrey and Romer, 1999; Kane and Rutledge, 2018; Morley, 2006), with most studies focusing on developed countries. Little is known about the impact of migrants on per capita GDP in developing countries, and even less is known about the impact of refugees compared to labor migrants. However, it is crucial to evaluate the economic effect of refugees separately from that of labor migration due to the unique circumstances of forced migration. This paper aims to address this research gap.

Figure 3.1 Syrian Refugee Numbers by Year



Note: The information is sourced from the UNHCR.

This study examines the impact of refugees on per capita GDP in Turkey using provincial-level data on GDP per capita and refugee numbers from 2006 to 2019, along with multiple complementary datasets. To measure this impact, a difference-in-differences (DID) framework is employed, which

[2]While Syrians in Turkey are referred to as "refugees" or "asylum-seekers", they can be divided into 4 categories. The first and largest group has "temporary protection" status, and the second group is Syrians with a "residence permit." The third group is those who have not been registered yet. And the last group is the Syrians who have become citizens of Turkey. The Syrian refugees referred to in this paper are those under temporary protection, as this group constitutes the majority of Syrians in Turkey, and publicly available data for other groups are not available. Although the Syrians in Turkey, who are the focus of this article, do not have official refugee status, I use the term "refugee" (or migrant) for these Syrians throughout the article for ease of use.

[3]See https://data.unhcr.org/en/situations/syria

takes into account variation in per capita GDP and refugee proportions among Turkish provinces over time. In the empirical investigation of this relationship, two key issues need to be addressed. The first is to meet the main identification assumption of the DID methodology, which requires that in the absence of the treatment, the treatment and control groups (provinces affected by the refugee influx and non-affected provinces) would have followed the same trend over time. Another critical concern that could undermine the validity of the empirical analysis is the endogeneity issue. It is possible that the provinces where Syrian refugees reside were chosen by the refugees based on economic opportunities. This could lead to biased estimation results. To address these potential issues, this study includes 5 region[4] and NUTS1-year interaction terms in the estimations to relax the common/parallel trend assumption, and employs an instrumental variable that relies on an exogenous distance variable[5].

OLS estimation[6] reveals that the effect of the refugee shock is positive in the short, medium, and long run, however, the effect is statistically significant only for the the medium term. 2SLS estimations using the same specification exhibit different results, with the estimates being unclear in the short term, positive in the medium term, and negative in the long term. Notably, none of the 2SLS estimates are statistically significant. The variation between the estimates produced by OLS and 2SLS gives evidence of the endogeneity in the refugees' settlement patterns. One potential explanation for the negative estimates can be the demographics of the Syrians. In Turkey, on average they are less educated than the natives[7]. Hence their contribution to the GDP may be less than that of natives. Furthermore, Syrian refugees have a high proportion (70.9%)[8] of women and children, who are largely dependent and unable to participate in the workforce. These factors may result in a drop in the GDP-per-capita level in the provinces where refugees settle more. However, there are also factors that could explain the positive estimates. For instance, refugees can stimulate trade and investment by creating new business opportunities and increasing demand for goods and services. Additionally, refugees can contribute to the labor force and attract humanitarian aid and investments that can provide funding for essential services and infrastructure development in the host country. Overall, despite the challenges of accommodating refugees, they can have positive impacts on Turkey's economy.

[4]I borrow this 5 region argument from Aygün et al. (2020) and these 5 regions are namely Central (comprising of NUTS-1 regions 5 and 7), East (comprising of NUTS-1 regions 10 to 12), West (consisting of NUTS-1 regions 1 to 4), North (made up of NUTS-1 regions 8 and 9), and South (which includes NUTS-1 region 6).

[5]Detailed explanations on the potential issues related the empirical analysis and how I address these are given in Section 3.3.

[6]I refer to the OLS estimations with preferred specification, i.e., the results in Column 3 of Table 3.2, which controls for the year, province fixed effects, province-specific controls, and 5 region-year interaction term.

[7]More detailed information regarding the demographics of Syrians in Turkey is given in Section **??**.

[8]See https://multeciler.org.tr/turkiyedeki-suriyeli-sayisi/

This study contributes to the increasing body of literature on the impacts of massive refugee shocks on host economies. To the best of my knowledge, this study is one of the first to explore the short-, medium-, and long-term impact of refugees on per-capita GDP using a difference-in-differences IV methodology. Although the impact of refugees on a host country's GDP per capita is viewed as a macro issue, this study takes a novel approach by examining the impact from a micro perspective. Exploring this relationship is particularly important now since refugee crisis is a global issue and an ongoing phenomenon[9], concerning not only neighboring countries but also other countries, especially those in Europe since better labor market opportunities and higher living standards make Europe more attractive for refugees. Therefore, a better understanding of the effect of refugees on the host country would help to initiate better solutions regarding their integration and settlement.

This study complements several bodies of literature. First, this study adds to the growing body of literature examining the impact of migrants on the GDP per capita of the host country. While some studies find a positive relationship between immigration and economic growth, others find no causal effect or negative effect. For example, Morley (2006) utilizes data from the United States, Canada, and Australia from 1930 to 2002 to examine this relationship and finds that while there is a causal relationship running from per capita GDP to immigration, the reverse is not true. Similarly, Boubtane et al. (2013) conduct a study on 22 OECD countries using annual data from 1980 to 2005 and reveal that immigration does not cause growth, rather growth has a positive influence on immigration. On the other hand, several empirical studies find evidence of the positive impact of immigration on GDP per capita. Kane and Rutledge (2018), for instance, use the fifty US states with similar institutional frameworks that experienced different rises in immigration since 1980 to evaluate the effect of immigration on per capita GDP and find a positive relationship between immigration and economic growth. Likewise, Feridun et al. (2005) employ the Granger causality test to explore the causal link between economic development and immigration in Norway. The study concludes that there is a positive effect of immigration on per capita GDP. Felbermayr et al. (2010) also utilize the IV approach of Jeffrey and Romer (1999) on a sample of countries to demonstrate a non-negative causal effect of immigration on per capita GDP in the host nation. Despite these studies conducted in developed economies, limited research is available on the effect of refugees on per capita GDP in developing economies. This study aims to fill this gap and complement previous literature by providing additional insights into the potential effects of refugees on economic development.

[9] After the Syrian refugee crisis, with Russia's invasion of Ukraine a new refugee crisis has emerged, which gives us the signals that the refugee crisis will continue in the future.

This paper also adds to the existing literature on the economic effects of Syrian refugees in neighboring countries. One of the studies in this literature examines the effect of Syrian refugees on Jordan and finds a negative effect on the country's economic growth (Alshoubaki, 2017). Another study investigating the effect of refugees on the overall economy in Lebanon shows that the large influx of Syrian refugees has a negative impact (ILO, 2014). In Turkey, although some studies look at the impact of Syrian refugee shocks on the labor market, there is little research on the effect of refugees on per capita GDP. Only one study by (Uslu, 2021)[10] has explores this relationship, but he uses an entirely different methodology and data than the present study[11]. As a result, this study serves to fill the gap in the existing literature on the economic impact of Syrian refugees in neighboring countries and complement existing literature.

The rest of the paper's structure is organized as follows: Section 3.2 provides contextual information, Section 3.3 describes the data and presents the identification and estimation methods. Section 3.4 presents the primary results and sensitivity analyses, and Section 3.5 provides discussion and conclusion.

3.2 Contextual Information

The Syrian uprising in 2011 began as a protest against Bashar al-Assad's regime but quickly escalated into a devastating civil war. The conflict caused immense destruction throughout the country and forced millions of Syrians to flee their homes. As a result, more than 6.1 million Syrians were internally displaced, while an additional 5.6 million sought refuge in other countries, making it one of the most significant refugee crises in recent history[12]. According to the United Nations, Syria's neighboring countries were hosting 5,600,039 registered Syrian refugees in April 2021, with Turkey serving as the top hosting country with over 3.65 million Syrians[13].

In April 2011, the initial wave of Syrian refugees began to arrive in Turkey, when the Turkish government still maintained diplomatic ties with the Syrian government. However, when the Syrian government began committing atrocities against Syrian civilians, the relationship between the two governments quickly deteriorated. From the outset of the Syrian war, Turkey has implemented an "open door" policy, allowing Syrians fleeing from the violence to seek refuge in Turkey. However, due to the geographical limitations of the 1951 Geneva Convention, which serves as the foundation for

[10] See https://sites.duke.edu/farukuslu/2021/12/09/333/

[11] He uses annual time series data for Turkey from 1991 to 2020 and estimates a VAR model to show this relationship with Impulse Response Functions and displays that the refugee inflow causes a decrease in GDP per capita in short term, but it has no direct impact in the long term.

[12] Syria had a population of 22 million before the war.

[13] See https://data.unhcr.org/en/situations/syria

refugee laws in Turkey, Syrian refugees who first arrived in Turkey were referred to as “guests" rather than refugees. This classification has two noteworthy consequences: firstly, guests are not eligible to seek asylum in another country, limiting their migration prospects, and secondly, guest status allows the Turkish authorities to relocate them without following constitutional procedures, unlike refugee status (Akgündüz et al., 2018)[14]. Despite not being legally recognized as refugees in Turkey, the Syrian community is commonly referred to as such in everyday use. In October 2014, the Turkish government provided temporary protection status to Syrians in Turkey, providing them with a clearer legal status[15]. This legal framework grants them with the opportunity to utilize public health services, educational facilities, and social protection.

When Syrians began arriving in Turkey, the Turkish government initially assigned the Turkish Disaster and Emergency Management Presidency (TDEMA) with the responsibility of delivering urgent humanitarian assistance and establishing refugee camps. As a result, 21 camps were set up in 10 provinces. However, the number of refugees grew, as depicted in Figure 4.1, causing them to move from camps to cities[16]. As they move out of camps, finding work becomes crucial for sustaining their lives. This has led to a significant number of Syrians seeking work opportunities in the informal sector. In response to this trend, the Turkish government passed the enactment of Law 8375 on January 15, 2016, granting Syrians under Temporary Protection the right to work [17]. Although this was a significant attempt at integrating Syrians into the Turkish labor market and providing formal employment opportunities, it did not produce the expected results, and refugees who were officially employed remained low. As reported Caro (2020), out of 813,000 Syrian refugees who were employed in 2017, 97 percent worked informally[18]. Since the majority of Syrian refugees work informally as cheap labor, on average they are poorer than natives. Moreover, their demographic characteristics are

[14] Although Syrians in Turkey are not refugees in the legal framework, in daily use we call them refugees, therefore, I use the refugee, migrant and Syrian interchangeably throughout the article for ease of use.

[15] Temporary protection is a response by governments to address the influx of people seeking protection in a country. This measure is used when it becomes challenging to review each individual’s situation during high volumes of arrivals. To meet the standards of temporary protection, there are three things that governments should do. Firstly, they should adopt an open-door policy, which means they should let people in who are seeking protection. Secondly, they should not send these people back to where they came from, a principle known as non-return. Lastly, they should make sure that people are provided with fundamental necessities such as housing, nourishment, and medical assistance. This ensures that people are protected, and their basic human rights are respected.

[16] In 2013, recognizing that TDEMA would be unable to handle the growing influx of refugees, the Turkish government founded the General Directorate of Migration Management (TDGMM) which is responsible for registering and coordinating activities related to refugees.

[17] Accordingly this law, Syrians who have been registered in Turkey for at least 6 months can work in a workplace at a ratio of one Syrian to ten Turkish employees, depending on the employer’s request, and provided that the Syrians earn at least the minimum wage (Erdogan, 2014).

[18] Despite these refugees are making contributions to the economy through informal work, these contributions may not be accurately captured through standard GDP measurement.

also different than natives in several ways. Firstly, Syrians are younger with a lower median age of 21 years old, in comparison to natives who have a median age of 31 years old (Eryurt, 2017). Secondly, on average, Syrians are less educated than natives. Less than primary school education is observed in 29.2% of Syrians compared to 10.9% of natives, while university graduates constitute only 9.9% of Syrians compared to 16.5% of natives [19]. Finally, Syrian families are larger, with an average family size of 5.8 whereas natives have an average family size of 3.35 in 2019 [20]. Taken together, these demographic differences between Syrian refugees and native populations may affect GDP per capita, as they can impact economic productivity and growth.

Turkey became a refuge for many Syrians fleeing the civil war, with the convenient transportation links making it an attractive transit point. For many, Turkey was just a temporary stop, and they hoped to move on to Europe for better living conditions and employment prospects. Some achieved this goal through irregular migration. To address the challenges posed by irregular migration to Europe and assist Turkey in dealing with the refugee crisis, the European Union (EU) agreed with Turkey to provide financial aid to refugees. The agreement was summarized by the Commissioner for Neighbourhood Policy and Enlargement Negotiation, Johannes Hahn, as "Turkey now hosts one of the world's largest refugee communities and has committed to significantly reducing the numbers of migrants crossing into the EU. The facility for refugees in Turkey will go straight to the refugees, providing them with education, health, and food. The improvement of living conditions and the offering of a positive perspective will allow refugees to stay closer to their homes" (European Commission, 2016)[21]. As a result of this agreement, the Emergency Social Safety Net (ESSN) was founded, which is regarded as one of the EU's most significant humanitarian initiatives. The program is run in collaboration with the Turkish Red Crescent Society and the International Federation of Red Cross and Red Crescent Societies (IFRC), with the aim of providing financial aid to more than 1.5 million refugees residing in Turkey. This is one of the most significant humanitarian aid attracted to Turkey by the influx of Syrian refugees. However, Syrians' presence in Turkey has not been without its challenges, as it has also resulted in significant costs for the Turkish government. President Erdogan reported that the Turkish government spent $37 billion on Syrian refugees until 2019[22]. These together highlight the multifaceted impact of

[19] The data about Turkish natives was derived from the 2015 Turkish Household Labor Force Survey, whereas the details about Syrians were gathered from a survey that was conducted in December 2015 by the Disaster and Management Authority of Turkey and the World Health Organization (WHO).

[20] It is widely acknowledged that large family size, high fertility, and poverty are interlinked. The data for the natives come from the TURKSTAT (2019). The data for Syrians is taken from the Turkish Red Crescent and World Food Programme (2019)

[21] See https://ec.europa.eu/commission/presscorner/detail/it/IP_16_225

[22] See http://www.kamubulteni.com/turkiye/cumhurbaskani-erdogan-suriyeliler-icin-37-milyar.html

the refugees on the country's economy. Thus, it is clear that a detailed empirical analysis is needed to fully understand the effects of refugees on the Turkish economy.

3.3 Data and Empirical Method

3.3.1 Data

This study uses provincial GDP per capita data in 2009 prices sourced from the Turkish Statistical Institute (TurkStat), which calculates GDP using the "production approach[23]". The dataset is a province-level panel design, spanning from 2006 to 2019, except for the year 2012[24]. In total, the dataset comprises 1053 observations across 81 provinces for a period of 13 years. The data on Syrian refugees comes from multiple sources. The Disaster and Emergency Management Presidency of Turkey (AFAD) provides statistics on the number of refugees for 2013, while Erdogan (2014) is the source of numbers for 2014. The Directorate General of Migration Management, operating under the Ministry of Interior, releases details on the count of Syrian refugees between 2015 and 2019. To calculate the proportion of Syrian refugees in each province across time, I use these refugee numbers along with provincial citizen numbers obtained from TurkStat.

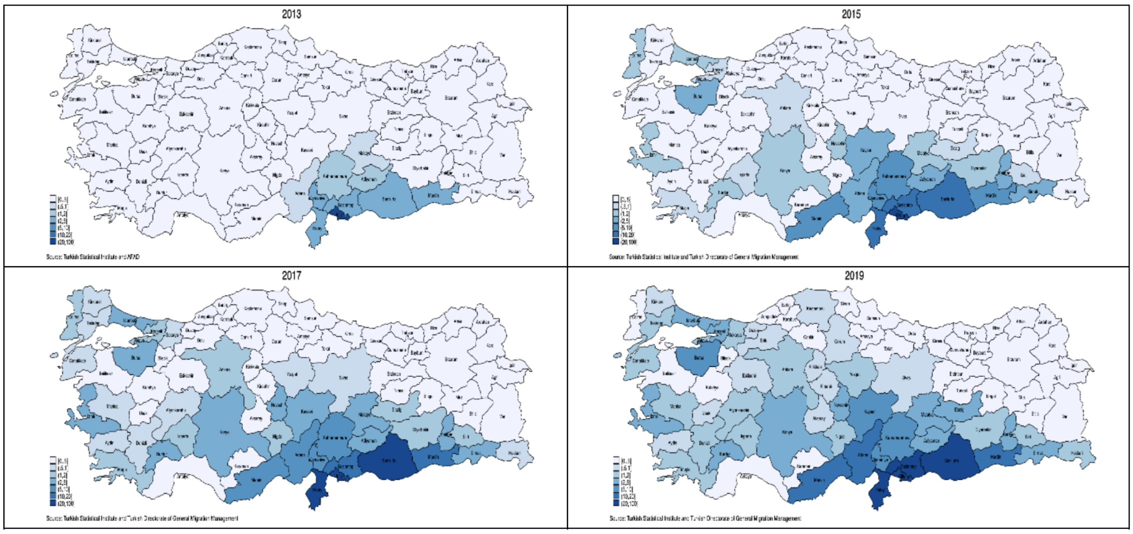
I also utilize supplementary datasets at the province level to create control variables for the period spanning from 2008 to 2019[25]. TurkStat (2021a) provides data on the population categorized by age, which I use to create five age groups, namely 15-24, 25-34, 35-44, 46-54, and 55-64. To construct education categories, I rely on data from TurkStat (2021b) that pertains to the education levels attained by individuals who are 15 years old or older. These education categories include (i) individuals who cannot read or write, (ii) those who can read and write but do not hold a diploma, (iii) graduates of primary school or equivalent, (iv) graduates of junior high school, vocational school, or equivalent, (v) graduates of high school or equivalent vocational schools, and (vi) graduates of university or higher education institutions. Another dataset that I use provides information on the age dependency ratio (TurkStat, 2021c), which is calculated by dividing the number of individuals in the "0-14" and "65 and over" age groups by the number of individuals in the "15-65" age group (the working age group), and average household size (TurkStat, 2021d) at the provincial level. Lastly, I obtain data on the share of the three GDP sectors: services, industry, and agriculture, from TurkStat (2021e), which represent the distribution of these sectors in the economy.

[23] Appendix C explains the production approach used by TurkStat.
[24] The year 2012 is omitted from the analysis as provincial data on the Syrian refugee number is not available for 2012.
[25] Data on control variables is unavailable for 2006 and 2007.

The descriptive statistics for the dependent and control variables are presented in Table 3.1. The average GDP per capita across provinces and years is approximately 20 thousand, but there is significant variation in this variable, ranging from 3,406 to 86,723[26]. The control variables also display substantial differentiation among provinces, suggesting that there exist socioeconomic disparities throughout the provinces of Turkey. Hence, accounting for these variables in the regression analysis is important.

Figure 3.2 displays the density of Syrian refugees in provinces of Turkey from 2013 to 2019. The darkness of the shade increases as the refugee concentration goes up. Initially, Syrian refugees were mainly located near the Syrian border as the government set up camps there. Later, they spread out to other provinces, especially industrialized ones such as Istanbul, Bursa, Izmir, and Kocaeli. However, even in 2019, the concentration of refugees is highest in regions near the Syrian border. This may be because they prefer to stay close to their family members who still reside in those areas [27].

Figure 3.2 Syrian Refugee Densities in Turkey across Provinces by Year



Note: The data for the number of Syrians in 2013 is obtained from the Disaster and Emergency Management Presidency of Turkey (AFAD), whereas the data for 2015 to 2019 are provided by the Ministry of Interior Directorate General of Migration Management. The percentage of Syrian refugees in each province over time is calculated using the number of Syrians at the provincial level and the provincial population obtained from TurkStat.

[26]In addition to the default GDP per capita, I also provide another measure called GDP per capita*. The difference between the two is that the GDP per capita* additionally takes into account the population of refugees registered in each province. To calculate this measure, I divide the GDP of a province by the total population, including both refugees and citizens. On average, this measure is around 19 thousand across provinces and years, with significant variation between 2,900 and 82,632. The estimation results using this outcome variable are given in Appendix D.

[27]Additionally, Table C1 provides the refugee shares, which represent the proportion of refugees to the total population (refugees + citizens), for the provinces where the share is greater than 5%.

Table 3.1 Descriptive Statistics

	Mean	SD	Min.	Max.	No Obs.
Dependent Variables					
GDP percapita	19725	12414	3406	86723	1053
GDP percapita*	19326	12150	2900	82633	1053
Control Variables					
Age Dependenty Ratio*100	51.69	10.37	35.93	93.69	972
Average Household Size	3.85	1.07	2.60	8.40	891
Shares of Sectors in GDP					
Agriculture	0.17	0.09	0.00	0.47	972
Industry	0.27	0.11	0.05	0.62	972
Services	0.56	0.09	0.34	0.81	972
Shares of Education Groups					
Illiterate	0.07	0.05	0.01	0.31	891
No degree	0.07	0.04	0.02	0.24	891
Primary School	0.44	0.08	0.14	0.61	891
Middle School	0.09	0.05	0.01	0.34	891
High School	0.21	0.04	0.11	0.32	891
University	0.11	0.04	0.02	0.28	891
Shares of Age Groups					
Age: 15-24	0.26	0.05	0.18	0.44	891
Age: 25-34	0.23	0.03	0.18	0.30	891
Age: 35-44	0.20	0.02	0.13	0.25	891
Age: 45-54	0.17	0.03	0.08	0.22	891
Age: 55-64	0.13	0.04	0.05	0.22	891

Note: The dataset comprises data on dependent variables for 81 Turkish provinces from 2006 to 2019, except for 2012. In addition, it includes information on control variables for the years 2008 to 2019, excluding 2012. GDP percapita* is the constructed variable by adding the province level Syrian refugee numbers to the denomitanor. The data of control variables come from the Turkish Household Labor Force Surveys(THLFS). The target population of THLFS is the registered residents of Turkey.

3.3.2 Empirical Method

To evaluate the effect of Syrian refugees on per-capita GDP in Turkey, this study employs a difference-in-differences (DID) approach. Specifically, the comparison is made between provinces with the high concentration of refugees and those with the low concentration of refugees prior to and following the refugees' arrival. The estimating equation utilized in this study is as follows:

$$\mathrm{GDPpercapita}_{p,t} = \alpha + \beta \mathrm{R}_{\mathrm{p,t}} + X' \theta_{p,t} + \mu_p + \tau_t + \gamma_{p,t} + \epsilon_{p,t} \tag{3.1}$$

where $\mathrm{GDPpercapita}_{\mathrm{p,t}}$ denotes the per-capita GDP in province p during year t. $\mathrm{R}_{\mathrm{p,t}}$ represents the proportion of refugees relative to the overall population (refugees + citizens) in province p at time t.

Additional province level characteristics at time t are denoted by X, which are presented in Table 3.1. μ_p and τ_t are the fixed effects for province and year, respectively. To address the potential variations in pre-existing trends across regions, I introduce fixed effects for region-year interactions $\gamma_{p,t}$, which allow for time effects to differ across regions. These fixed effects for interactions comprise of (i) five regions with years and (ii) NUTS1(12) regions with years. Finally, the error term is represented by $\epsilon_{p,t}$, and the constant term is denoted by α. The primary focus of this equation is the parameter β, which quantifies the change in per-capita GDP resulting from variation in the percentage of Syrian refugees in province p during year t [28].

This analysis derives identification from the variation in refugee shares across 81 Turkish provinces. The key identifying assumption for the internal validity of the DID (Difference-in-Differences) method to estimate the causal effect of refugee density on per capita GDP is the parallel/common trend assumption. This assumption necessitates that in the absence of treatment, the distinction between the treatment and control groups remains constant over time. Specifically, for this study, it needs to be ensured that similar trends in per capita GDP are shown in the treatment group (provinces with high refugee intensity) and the control group (provinces with low refugee intensity) before the arrival of refugees. However, meeting this assumption can be quite challenging (Angrist and Pischke, 2014). To relax this assumption, I incorporate year-region interaction terms to the model, as suggested by Stephens Jr and Yang (2014) and Aksu et al. (2022), to account for potential variations in per-capita GDP trends among different regions.

The validity of this empirical strategy is also threatened by the self-selection issue. This problem arises because refugees might choose their settlement locations based on economic factors, which may be related to the per capita GDP of the provinces. Consequently, the estimates could be biased. Tumen (2016) identifies the influx of Syrian refugees to Turkey as a natural experiment, as their movement was sudden and mainly driven by the conflicts in Syria, which were beyond their control. This method was applicable for the short-term impact analysis of the inflow of Syrian refugees since at the outset of their arrival, the Turkish government placed them in camps, making their initial settlement mainly exogenous. However, since refugees have been in Turkey for a considerable amount of time, they have had the opportunity to move to other regions. However, despite they are dispersing across the country over time, a greater concentration still exists in the border regions, indicating that distance is the primary factor

[28]The primary variable of interest in this study is $\mathrm{R_{p,t}}$. Its value is null before 2013 because of the unavailability of provincial data concerning the number of Syrians in 2012, and the figures before that year are insignificant. Consequently, the years preceding 2012 are categorized as pre-treatment years, while the years 2013 to 2019 are regarded as treatment years.

influencing their settlement patterns, as evidenced by Figure 3.2[29]. Therefore, I employ an instrumental variable that relies on an exogenous distance factor to address the potential self-selection issue. The instrument for the refugee number in province p and year t is defined as follows:

$$I_{p,t} = \sum_{s=1}^{13} \frac{(\frac{1}{d_{s,T}})\pi_s}{(\frac{1}{d_{s,T}} + \frac{1}{d_{s,L}} + \frac{1}{d_{s,J}} + \frac{1}{d_{s,I}})} \frac{T_t}{d_{p,s}}, \tag{3.2}$$

where $I_{p,t}$ is the instrumental variable representing the expected refugee numbers at time t in province p. The distance between Syrian provinces and the nearest border crossing points in Turkey, Iraq, Jordan, and Lebanon are denoted by $d_{s,T}$, $d_{s,L}$, $d_{s,J}$, and $d_{s,I}$, respectively. π_s refers to the proportion of the population residing in Syrian province s before the war, whereas $d_{p,s}$ represents the distance between Turkish province p and Syrian province s. Additionally, T_t denotes the total Syrian refugee number in the four neighboring countries.

Many other studies, such as (Kırdar et al., 2022), have utilized this distance-based instrument[30], which is an updated version of the instrument developed by (Del Carpio and Wagner, 2015). The del Carpio-Wagner instrument distributes the Syrian refugee population in Turkey to Turkish provinces based on the distance between Turkish and Syrian provinces, as well as the population proportions of Syrian provinces before the war[31]. The instrument I employ in this study additionally takes into account the distance between Syrian provinces and neighboring countries of Syria, including Iraq, Lebanon,and Jordan, as Syrians also fled to these countries[32].

The validity of this instrument depends on the assumption that the trends in GDP per capita, are independent of the distance-based instrument, after accounting for the province and year-fixed effects and province-specific controls, in the absence of refugees' arrival. If there is a relationship between the instrument and the unobserved fluctuations in economic conditions, then this assumption cannot hold. However, the instrument depends on a less stringent independence assumption when I include time-region interaction to the regression analysis. Through these interactions, it is assumed that the

[29]This is because the border area serves as the entry point for refugees, where they are immediately set up in camps upon arrival. As the government perceived their stay as temporary, the camps were located near the border. Despite their departure from these camps, a significant number of refugees decided to remain in the provinces that were in close proximity to their original place of residence, possibly because they still have family members residing in those areas in Syria or because the Turkish government requires that Syrian refugees utilize education and health services in the province where they are officially registered.

[30]This instrument has also been applied in Aksu et al. (2022), Akgündüz et al. (2018), and Aygün et al. (2020).

[31]For more information on this instrument, see Del Carpio and Wagner (2015).

[32]For more information on this instrument, see Kırdar et al. (2022), Aksu et al. (2022), Akgündüz et al. (2018), or Aygün et al. (2020).

distance is uncorrelated with the unobserved variations in GDP per capita within the given region of the country, which is a less strong and more feasible assumption.

3.4 Results

This section conveys the findings of the empirical investigation of the impact of the refugee shock on GDP per capita. Subsection 3.4.1 provides the findings of the OLS and 2SLS estimations in Table 3.2 and Table 3.3, respectively. Subsection 3.4.2 reports the results of placebo tests. Subsection 3.4.3 presents a variety of robustness checks. Firstly, I replicate the main results using the del Carpio and Wagner instrument. Next, I use alternative specifications for the key variable of interest, namely the lagged values, and the dummy treatment. Lastly, I evaluate the robustness of the results by examining their sensitivity to different regional constraints.

3.4.1 Main Results

This section provides estimates of the effect of Syrian refugee inflow on the level of economic development, proxied by GDP per capita. Tables 3.2 and 3.3 show the findings of the OLS and 2SLS estimations, respectively, with three panels in each table. Panels A, B, and C present the short-term, medium-term, and long-term effects of the shock on GDP per capita from 2006 to 2015, 2006 to 2017, and 2006 to 2019 (excluding 2012), respectively[33]. The tables exhibit four distinct specifications, with column 1 accounting for the province and year-fixed effects and column 2 incorporating further controls for province-specific variables, including age categories, education categories, household size, and GDP sector shares. In column 3, fixed effects for 5 region-year interactions are added, while column 4 includes fixed effects for NUTS1-year interactions.

The OLS findings are displayed in Table 3.2, and Panel A presents mixed short-term (S-T) estimates, with negative estimates in the first column and positive estimates in the other specifications. For instance, column 3, which is one of the preferred specifications[34] and controls fixed effects for the province and year, province-specific controls, and 5 region-year fixed effects, indicates that a 10-point increase in the proportion of refugees in the population increases the GDP per capita by 3,957 from a baseline level of 14,171, but it is not statistically significant. Panel B presents the medium-term (M-T) results,

[33]The threshold for the short-term impact is set at 2015 because Turkey witnessed a 33 percent nominal rise in the minimum wage in 2016, which made it challenging to establish new firms and sustain existing ones, resulting in a reduction in the number of registered firms in the economy (Bossavie et al., 2019). For the medium term, the threshold is set at 2017 due to the increasing currency fluctuations that began in 2018.

[34]It is one of the preferred specifications since it passes the placebo tests along with the specification in column 4. See the subsection 3.4.2 for detail.

Table 3.2 Refugee Shock on GDP per Capita, OLS

Panel A: The Short-Term Effect of the Migrant Shock on GDP per Capita (Until 2015), OLS					
Dependent Variable	(1)	(2)	(3)	(4)	Mean
GDP percapita	-9,977.38*	2,048.46	3,956.71	7,025.52**	14,171.14
	(5,592.27)	(1,950.64)	(3,332.78)	(2,690.62)	
Observations	729	567	567	567	
Panel B: The Medium-Term Effect (Until 2017)					
GDP percapita	-9,648.46*	3,199.48	6,431.03**	7,645.26***	16,557.91
	(5,023.62)	(2,662.97)	(3,176.90)	(2,682.83)	
Observations	891	729	729	729	
Panel C: The Long-Term Effect (Until 2019)					
GDP percapita	-11,846.56*	-5,254.70	6,421.27	5,874.26	19,724.78
	(6,253.06)	(4,821.39)	(5,323.99)	(3,768.09)	
Observations	1,053	891	891	891	
Controls					
Year Fixed Effects	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	
Province-specific Controls	No	Yes	Yes	Yes	
5 Region-Year Fixed Effects	No	No	Yes	No	
NUTS1-Year Fixed Effects	No	No	No	Yes	

Note: The dataset consists of 81 Turkish provinces from 2006 to 2015 (except 2012) in Panel A, 2006 to 2017 (except 2012) in Panel B, and 2006 to 2019 (except 2012) in Panel C. Each cell presents the OLS regression estimates for the proportion of refugees to the population with different specifications. The first column provides the results of the regressions controlling for year and province-fixed effects. The second column additionally controls for province-specific variables, which are age and education groups, age dependency ratio, average household size, and GDP sector shares (services, industry, and agriculture). Due to the unavailability of data for the years 2006 and 2007, the inclusion of province-specific controls results in a reduced number of observations. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

and the coefficients of the GDP per capita with all specifications are almost identical to those in Panel A. The only difference is in column 3, which shows positive and statistically significant estimates. The long-term (L-T) estimates in Panel C also exhibit mixed results, but the preferred specifications' estimates are positive but not statistically significant. The OLS estimations overall imply a positive effect of the refugee shock with the preferred specifications, but the impact is only statistically significant in the medium term.

Table 3.3 offers the 2SLS counterpart of the OLS results, which display noteworthy differences from the corresponding OLS findings. For example, column 3 gives that the 2SLS coefficient for GDP per capita is negative but not statistically significant at conventional levels in the S-T and L-T. Quantitatively, the GDP per capita coefficient shows that a 10-point increase in the percentage of refugees in the population reduces GDP per capita by 714 from a baseline level of 14,171 in the S-T, indicating a 5.04 percent drop. Similarly, in the L-T, the GDP per capita falls by 6,713 from a baseline level of 19,725, implying a 34.03 percent decline. In the M-T, column 3 provides positive, but not

Table 3.3 Refugee Shock on GDP per Capita, 2SLS

Panel A: The Short-Term Effect of the Migrant Shock on GDP per Capita (Until 2015), 2SLS					
Dependent Variable	(1)	(2)	(3)	(4)	Mean
GDP percapita	-24,460.562*	-6,738.095	-713.887	2,067.712	14,171.14
	(12,835.134)	(6,343.547)	(5,416.576)	(5,209.866)	
First-stage regression	3.015***	3.121***	3.059***	3.232***	
	(0.795)	(0.856)	(0.915)	(0.888)	
Partial R-squared	0.697	0.662	0.626	0.683	
Observations	729	567	567	567	
Panel B: The Medium-Term Effect(Until 2017)					
GDP percapita	-25,007.266**	-7,905.702	1,790.686	1,911.696	16,557.91
	(11,995.852)	(7,470.039)	(4,522.318)	(4,625.292)	
First-stage regression	3.006***	3.112***	3.063***	3.269***	
	(0.946)	(0.984)	(1.023)	(1.002)	
Partial R-squared	0.733	0.685	0.648	0.698	
Observations	891	729	729	729	
Panel C: The Long-Term Effect(Until 2019)					
GDP percapita	-33,969.080**	-26,998.077*	-6,712.651	-6,958.304	19,724.78
	(15,049.297)	(14,235.890)	(8,543.619)	(8,203.186)	
First-stage regression	2.898***	2.908***	2.867***	3.032***	
	(0.670)	(0.687)	(0.764)	(0.733)	
Partial R-squared	0.747	0.704	0.646	0.700	
Observations	1,053	891	891	891	
Controls					
Year Fixed Effects	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	
Province-specific Controls	No	Yes	Yes	Yes	
5 Region-Year Fixed Effects	No	No	Yes	No	
NUTS1-Year Fixed Effects	No	No	No	Yes	

Notes: The dataset includes 81 Turkish provinces from 2006 to 2015 (except 2012) in Panel A, 2006 to 2017 (except 2012) in Panel B, and 2006 to 2019 (except 2012) in Panel C. Each cell presents the 2SLS regression estimates for the proportion of refugees to population with different specifications. The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables, which are age and education groups, age dependency ratio, average household size, and GDP sector shares (services, industry, and agriculture). Due to the unavailability of data for the years 2006 and 2007, the inclusion of province-specific controls results in a reduced number of observations. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

statistically significant estimates. Column 4, which also passes the placebo tests, supports the findings in column 3 for M-T and L-T, but gives different results for S-T, with positive estimates in contrast to column 3. In conclusion, using the preferred specifications, 2SLS estimates indicate that the refugee shock has an unclear impact in S-T, a positive impact in the M-T, and a negative impact in L-T. However, these estimates lack statistical significance[35].

[35]It is also worth mentioning that examining the results of the first-stage regression is crucial for the 2SLS. In each panel's bottom section, the coefficients of the instrument in the first stage are statistically significant at the 1% level in all specifications, with each of them showing a quite high partial R-squared of around 0.7. These results provide evidence supporting the validity of the instrument used for the 2SLS estimations.

3.4.2 Placebo Results

This subsection presents the findings of placebo regressions in Table 3.4. Panel A provides estimates based on the assumption that Syrians in 2019 came in 2011. In particular, I restrict the sample to 2006-2011 and run 2SLS, after assigning 2019 values of the instrumental variable and the refugee share to corresponding values in 2011. Since there are no statistically significant coefficients in columns 3 and 4, these specifications support the main identification assumption of this study—the instrument is uncorrelated with unobserved shocks in GDP per capita. In other words, with placebo regressions, I measure the effect of refugee shock at a time when there should be no effect. Indeed, I observe no effect of refugees on economic development with two specifications: (1) controlling for year, province fixed effect, province-specific controls, and 5-region-year fixed effect; (2) controlling for year, province fixed effect, province-specific controls, and NUTS1-year fixed effect. To check the sensitivity of the results, I also assume that the refugees in 2017 and 2015 arrived in 2011, in panels B and C of Table 3.4, respectively. Columns 3 and 4 do not exhibit any unobserved pre-shock trends in economic development in any of the IV estimates. Hence, the preferred specifications for all results are columns 3 and 4 across all tables.

Table 3.4 Placebo Regressions on Refugee Impact on Economic Development, 2SLS Estimates

Panel A: Instrument of 2019 are Assigned to 2011				
	(1)	(2)	(3)	(4)
GDP percapita	-8,776.85***	-4,952.03**	-1,969.40	-1,846.26
	(2,431.81)	(2,116.81)	(1,740.75)	(1,547.40)
Panel B: Instrument of 2017 are Assigned to 2011				
GDP percapita	-8,970.55***	-5,059.33**	-1,984.60	-1,864.88
	(2,718.88)	(2,282.52)	(1,780.32)	(1,594.10)
Panel C: Instrument of 2015 are Assigned to 2011				
GDP percapita	-10,757.94***	-6,099.70**	-2,358.49	-2,201.00
	(3,607.18)	(2,935.14)	(2,174.01)	(1,931.35)
Observations	486	324	324	324
Controls				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
NUTS1-Year Fixed Effects	No	No	No	Yes

Note: The dataset consists of 81 Turkish provinces from 2006 to 2011(before the arrival of Syrians) for dependent variable, and from 2008 to 2011 for control variables. For the placebo analysis, the key variable of interest, which is the proportion of refugees to the overall population (refugees+citizens), and instrumental variable values for 2019, 2017, and 2015 are assigned to the related values for 2011 in Panel A, Panel B, and Panel C, respectively. The instrumental variable and the key variable of interest are valued at zero for the duration of 2006-2010. Each cell presents the 2SLS regression estimates for the proportion of refugees to population, with different specifications. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year fixed effects and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

3.4.3 Robustness Checks

Alternative Instrument

To test the robustness of my findings, I employed an alternative instrument –Del Carpio and Wagner (2015)'s instrument. The instrument used in this study differs from that of del Carpio and Wagner in two distinct aspects. Firstly, I adjust the pre-war population distribution of Syrian provinces based on their proximity to the four neighboring countries. Secondly, rather than assigning the refugee numbers to Turkey alone, I distribute the overall refugee population among the four neighboring nations, like several other studies (Akgündüz et al., 2018; Aksu et al., 2022; Aygün et al., 2020; Kırdar et al., 2022). Consequently, this methodology acknowledges the possibility of endogeneity in the timing and extent of Syrian refugee inflows into Turkey, given that potential refugees have various country options to choose from. As noted by Aksu et al. (2022), if Syrian refugees were only able to flee to Turkey, the population distribution of Syrian provinces prior to the war and their proximity to the Turkish border would determine the distribution of refugee shares in Turkish provinces. But given that other neighboring countries such as Iraq, Lebanon, and Jordan also received large numbers of Syrian refugees, it is crucial to account for these potential destinations.

Table 3.5 The Impact of Refugees on the Economic Development with an Alternative Instrument

	(1)	(2)	(3)	(4)
GDP percapita	-19,927.41**	-4,466.42	5,244.57	4,372.53
	(9,483.90)	(6,143.83)	(3,985.70)	(3,986.81)
First-stage regression	1.07***	1.04***	1.00***	1.06***
	(0.24)	(0.23)	(0.25)	(0.24)
Partial R-squared	0.751	0.695	0.659	0.694
Observations	891	729	729	729
Controls				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
NUTS1-Year Fixed Effects	No	No	No	Yes

Note: The dataset cover 81 provinces of Turkey over the years 2006 to 2017 (except 2012) for dependent variable; the years 2008 to 2017 (except 2012) for control variables. Each cell shows the estimates for the share of refugees. The 2SLS regression instruments the key variable of interest using the del Carpio-Wagner distance-based instrument. The regressions controls for year, province fixed effects, province specific variables, 5-Region linear time trend and NUTS1-year fixed effects in different columns as shown above. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

To assess the robustness of my findings using the alternative instrument, I compare the results obtained using the del Carpio-Wagner instrument in Table 3.5 to the results presented in Panel B Table

3.3. The results show that using the del Carpio-Wagner instrument does not significantly impact the main findings of the study. Hence, the conclusions drawn from the different instruments are consistent[36].

Alternative Specifications

Lagged Value of the Key Variable of Interest

It is reasonable to expect that the effect of the refugee shock on economic development may take some time to appear, and expecting an immediate and simultaneous relationship between the two may not be realistic. To address this, I utilize lagged values of the key variable of interest in 2SLS regressions as an alternative approach that allows for an examination of the sensitivity of the main findings. Table 3.6 replicates the analysis carried out in Panel C Table 3.3, but this time using the one-year and two-year lagged values of the main variable of interest in Panel A and B, correspondingly.

The findings suggest that the effects are similar in Panel A and B, hence utilizing either one-lagged or two-lagged value of refugee share yields comparable results. Moreover, these estimates are highly similar (with only slight variations in absolute value) to those presented in Panel C Table 3.3, which confirms the main empirical approach.

Table 3.6 The Impact of Refugees on the Economic Development with Lagged Value of Refugee Ratio: 2SLS Estimates

Panel A: With One-Period Lagged Value of Refugee Share				
	(1)	(2)	(3)	(4)
GDP percapita	-36,468.70**	-29,960.21*	-8,015.78	-8,695.15
	(16,474.72)	(15,627.47)	(9,423.62)	(9,089.54)
Observations	891	810	810	810
Panel B: With Two-Period Lagged Value of Refugee Share				
GDP percapita	-38,732.90**	-33,068.58**	-9,725.87	-11,178.87
	(17,761.71)	(16,738.00)	(10,043.57)	(9,811.09)
Observations	810	810	810	810
Controls				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
NUTS1-Year Fixed Effects	No	No	No	Yes

Note: The dataset covers 81 Turkish provinces from 2006 to 2015 (except 2012) for dependent variable, and from 2008 to 2019 (except 2012) for control variables. Each cell presents the 2SLS regression estimates of the lagged values of the key variable of interest, the proportion of refugees to population with different specifications. The regressions use one-period lagged values and two-period lagged values, and the estimates are presented in Panel A and Panel B, respectively. The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

[36]The analysis covers the years 2006 to 2017 (excluding 2012), therefore, the results are compared with those presented in Panel B Table 3.3.

Dummy Treatment for the Key Variable of Interest

Rather than relying on the differences in refugee intensity between provinces, I also use a dummy treatment status to examine the sensitivity of the results to this alternative definition of the key variable of interest [37]. The rationale behind using this alternative approach is the possibility of measurement issues associated with refugees not residing in the provinces where they are registered, resulting in measurement error in the main variable of interest—the share of refugees. To mitigate the likely impact of such measurement error, I generate a binary variable for the treatment condition that is assigned the value of one if the proportion of refugees exceeds a certain threshold, namely 0.03, 0.05, or 0.08. The estimates of these regressions are presented in Table 3.7, which replicates the analysis in panel C Table 3.3 on the long-term effects of the migrant shock on economic development. Although the magnitudes are smaller in absolute terms than those in Table 3.3, the main findings remain consistent, showing an adverse effect of the migrant shock on GDP per capita that is not statistically significant.

Table 3.7 The Impact of Refugees on the Economic Development with Dummy Treatment Variable: 2SLS Estimates

Panel A: For the Treatment Dummy, Threshold= 0.03				
	(1)	(2)	(3)	(4)
GDP percapita	-7,612.756***	-7,381.495***	-2,994.349	-2,325.300
	(2,199.048)	(2,179.038)	(3,128.593)	(2,324.990)
First-stage regression	12.93***	10.64***	6.43**	9.07***
	(2.19)	(2.00)	(2.50)	(2.23)
Panel B: For the Treatment Dummy, Threshold= 0.05				
GDP percapita	-7,430.208***	-6,520.451***	-1,966.705	-1,972.700
	(2,277.460)	(2,068.926)	(2,212.334)	(2,028.062)
First-stage regression	13.25***	12.04***	9.79***	10.69***
	(1.91)	(1.79	(2.75)	(2.17)
Panel C: For the Treatment Dummy, Threshold= 0.08				
GDP percapita	-9,025.567***	-7,491.206**	-2,200.558	-2,107.670
	(3,270.292)	(3,013.859)	(2,580.319)	(2,253.861)
First-stage regression	10.91***	10.48***	8.75***	10.01***
	(1.17)	(1.22)	(1.86)	(1.33)
Observations	1,053	891	891	891
Controls				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
NUTS1-Year Fixed Effects	No	No	No	Yes

Note: The dataset consists of 81 Turkish provinces from 2006 to 2019 (except 2012) for dependent variable, and from 2008 to 2019 (except 2012) for control variables. Each cell demonstrates the 2SLS regression estimates of the key variable of interest, a treatment dummy taking the value of one when the share of refugees exceeds 0.03 in Panel A (0.05 in Panel B, and 0.08 in Panel C) and zero otherwise) with different specifications. The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

[37] Similar dummy treatment variables are used by Ceritoglu et al. (2017), and Aksu et al. (2022) to evaluate the impacts of migrants on the labor market.

Alternative Regions

Like Aygün et al. (2020), I assess the impact of varying regional restrictions on my results. I implement four distinct constraints: (1) excluding Istanbul (NUTS-1 region 1), the most populous region, (2) excluding the more developed regions (NUTS-1 regions 1-4), (3) only including regions with higher refugee percentages (NUTS-1 regions 6, 10, 11, and 12), and (4) only including the regions with the highest Syrian proportions, namely the Mediterranean and Southeastern regions (NUTS-1 regions 6 and 12)[38]. Table 3.8 reports the results of these regional restrictions. The findings align with the previous results that demonstrate a negative but not statistically significant effect of the refugee shock on GDP per capita in the L-T, as seen in Panel C Table 3.3.

Table 3.8 The Impact of Refugees on the Economic Development with Alternative Subsamples, 2SLS Estimates

	A:Excludes Istanbul Region			B: Exclude Western Turkey		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP percapita	-23,369.92*	-6,712.65	-6,526.32	-6,663.93	-2,525.50	-3,388.77
	(12,303.45)	(8,543.62)	(7,643.65)	(5,065.86)	(6,577.87)	(6,436.96)
First-stage regression	2.93***	2.87***	3.03***	3.14***	2.89***	3.07***
	(0.69)	(0.76)	(0.73)	(0.72)	(0.75)	(0.73)
Observations	880	880	880	649	649	649
	C:Includes nuts1= 6,10,11, and 12			D:Includes nuts1= 6 and 12		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP percapita	-1,588.40	-1,310.33	-2,106.85	-6,876.31	-7,018.87	-7,018.87
	(5,785.60)	(6,485.27)	(6,585.01)	(5,142.37)	(6,163.97)	(6,163.97)
First-stage regression	3.00***	2.90***	2.99***	2.81***	2.70***	2.70***
	(0.62)	(0.66)	(0.63)	(0.51)	(0.47)	(0.47)
Observations	352	352	352	187	187	187
Controls						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	Yes	Yes	No	Yes	Yes
NUTS1-Year Fixed Effects	No	No	Yes	No	No	Yes

Note: Each cell in the table presents the 2SLS regression estimates of the proportion of refugees to population with different specifications. The first (fourth) column provides the results of the regressions controlling for year and province fixed effects, and province-specific variables. The second (fifth) and third (sixth) columns control for 5-Region-year and NUTS1-year fixed effects, respectively. The results are presented in separate panels, each with distinct regional restrictions. In Panel (A), Istanbul (NUTS1 region 1) is excluded, while in Panel (B), western Turkey (NUTS1 regions 1-4) is excluded. On the other hand, Panel (C) involves NUTS1 region 6 (the Mediterranean Region) and NUTS1 regions 10-12 (eastern Turkey), whereas Panel (D) only includes NUTS1 region 6 and NUTS1 region 12.

3.5 Discussion and Conclusion

The influx of millions of Syrian refugees to Turkey has sparked a heated debate on their impact on the economy. This study investigates the causal relationship between refugee inflow and economic

[38]Information about the share of refugees is presented in Figure 3.2. I adapted the majority of these regional constraints from Aygün et al. (2020).

development in Turkey. Using the spatial distribution of Syrians across Turkish provinces within a difference-in-differences (DID) approach, I estimate the impact of the migrant shock on GDP per capita. The parallel trend assumption is crucial to ensure the internal validity of DID estimation, but it is challenging to meet. Therefore, I include the year-region interaction in the regression analysis, along with province-fixed effect, year-fixed effect, and province-specific controls, to capture the distinct trends in per-capita GDP across regions. This allows me to assume a more moderate assumption, where there is no correlation between the instrument (distance) and the unobserved trends in GDP per capita across five regions and NUTS1(12) regions of the country. Another potential challenge to the validity of the empirical strategy is the self-selection issue, wherein the distribution of refugees across provinces may be related to the economic development of those provinces, leading to biased estimates. To address this issue, I employ 2SLS methods (in addition to OLS) with the instrumental variable based on an exogenous distance factor.

The empirical analysis, using 2SLS, provides suggestive evidence that the migrant shock decreases GDP per capita in the L-T, increases it in the M-T, and has an unclear influence in the S-T. However, none of these effects are statistically significant. In addition to 2SLS, I conduct OLS regressions, which generate positive estimates but are only statistically significant in the M-T. Because the discrepancy between the 2SLS and OLS estimates is evidence of endogeneity in the geographic distribution of refugees across provinces, the preferred results are those obtained from 2SLS.

The unclear impact of refugee shock in the S-R results from the conflicting channels. On the one hand, Turkey was unprepared for such a massive influx of Syrian refugees, and hosting them came at a significant cost to Turkey. In general, because they were the victims of forced migration and the Turkish government was taking care of their necessities, they were unable to contribute to the economy immediately. However, their legal framework gives them the right to access public education, healthcare, and social protection. Hence, they may lead to negative economic impacts. But they also draw humanitarian aid and often enter Turkey with some financial resources, which stimulate consumption and trigger a supply response. These channels can be the driving forces behind their effect on the economy, but it is uncertain which channels are more potent in the short term. Therefore, we observe a complex situation where risks and opportunities are intertwined.

One of the potential mechanisms to explain the positive effect of refugee shock in the M-T (until the end of 2017) is humanitarian aid, particularly the ESSN. This program, funded by the European Union (EU), provides cash assistance to over 1.5 million refugees residing in Turkey, making it one of the largest humanitarian initiatives in history. Besides the cash support provided by the EU, according to Oytun and Gündoğar (2015), the majority of humanitarian aid provided by Turkey to Syrian refugees in camps and inside Syria is sourced from local Turkish companies, particularly in the textile and food industries. Additionally, companies in border provinces handle the delivery of aid materials sent to Syria from around the world. As a result, this situation has created opportunities for businesses in these sectors. Syrian refugees also contribute to production and trade through enterprises. Yet, most of these businesses operate illegally, which makes them unaccountable via standard GDP measures.

Several explanations can be offered for the Syrian's negative effects on the Turkish economic development in the L-T. One of the potential factors contributing to the negative impact is the decline in humanitarian aid in the region, particularly in the L-T in comparison to the earlier stages of the conflict. Additionally, the increase in the minimum wage, a 33 percent nominal rise, in 2016 made it challenging for businesses to launch or maintain operations, resulting in fewer firms being registered in the economy. With many Syrians still seeking employment opportunities in Turkey, the minimum wage increase may have deterred potential employers from hiring refugees, at least formally leading to a further decline in accountable economic activity. Another channel to explain the negative impact of the refugee shock on the per capita GDP is the educational and demographic characteristics of refugees[39]. Syrians are, on average, less educated than natives, limiting their ability to contribute to GDP. Furthermore, a significant portion of the refugees is women and children who are more likely to be dependent on others, further hindering economic growth. Although the contribution of Syrians to the Turkish economy is not insignificant, the negative impact of the migrant shock appears to outweigh their contribution in the long run.

This study provides some insights into the impacts of refugees on a host country's economy, but further research is necessary for several reasons. First, Syrian refugees mostly work in the informal sector, therefore, how much the GDP per capita variable obtained from TurkStat captures their contribution is ambiguous. Additionally, the GDP per capita variable obtained from TurkStat only accounts for the citizens of Turkey, not the refugees under temporary protection[40]. To address this, I create a new GDP per capita* variable that includes both citizens and Syrian refugees in each province[41] and I run all regressions using this version of GDP per capita, as well. The results using this variable can be found in Appendix D. The findings reveal that the effect of refugee shock on GDP per capita is negative and statistically significant for S-T, M-T, and L-R. These results are not surprising since the new calculation

[39]This is also explained in Appendix A using the standard augmented neoclassical Solow-Swan model.
[40]In other words, only citizens are included in the GDP per capita variable's denominator.
[41]This variable is created by dividing the GDP by total population (migrants+citizens) for each province.

of the independent variable (GDP per capita) increases only its denominator, causing a decrease in GDP per capita, particularly in the provinces with a high Syrian refugee population[42].

This study contributes to a new field of research on the influence of refugees on economic development in developing nations by using Syrian refugees in Turkey as a case study. The significance of this study extends beyond Turkey's borders, as the refugee crisis is a global issue and an ongoing phenomenon, concerning many countries, particularly those in Europe. Since better labor market opportunities and higher living standards make Europe more appealing to refugees [43]. Therefore, gaining a better understanding of the impact of refugees on the host country's economy is crucial in developing effective solutions for their integration and settlement.

[42]It is uncertain which of the GDP per capita variables is more accurate to employ for this analysis. However, since the first results (with the ones using the default GDP per capita) imply the second results, I find it more appropriate to present the results of the default GDP per capita variable as the main ones.

[43]Many refugees have passed or trying to pass to Europe for these opportunities.

4

The Effect of 3.6 Million Refugees on Crime

Abstract Most studies examining the impact of migrants on crime rates in hosting populations are in the context of economic migrants in developed countries. However, we know much less about the crime impact of refugees in low- and middle-income countries—whose numbers are increasing worldwide. This study examines this issue in the context of the largest refugee group in any country—Syrian refugees in Turkey. Although these refugees are much poorer than the local population, have limited access to formal employment, and face partial mobility restrictions, we find that total crime per person (including natives and refugees) falls due to the arrival of the refugees. This finding also applies to several types of crime; the only exception is smuggling, which increases due to the population influx. We also show that the fall in crime does not result from tighter security; we find no evidence of a change in the number of armed forces (military and civil personnel) in the migrant-hosting regions.

4.1 Introduction

Due to the advent of the so-called "European migrant crisis," which saw the number of asylum seekers in Europe reach its highest mark since World War II (Dumont and Scarpetta, 2015), the effort to understand the impacts of migration on the host societies have gained much prominence. Traditionally, economists have focused on the effects of immigration on the labor market; however, the analysis of the immigration-crime nexus has increasingly gained prominence. This paper contributes to this literature by exploiting the population influx that Turkey experienced after the Syrian Civil War onset in 2011. More specifically, our work aims at quantifying the causal impact on the commission of crimes in Turkey stemming from the arrival of more than 3.6 million Syrian refugees, a development that adds to an increasing worldwide flow of forcibly displaced populations. Indeed, the UNHCR (2021) estimates that natural disasters and conflicts have forced approximately 1 percent of the world's population to leave their places of residence, a fact that highlights the importance of assessing the socioeconomic impacts that involuntary migration brings on.

In many countries, citizens are much concerned about the migrants' impact on crime rates (see, e.g., Simon and Sikich (2007)), and Turkey is no exception. Indeed, the public opinion about the effects of Syrian refugees on crime is severely unfavorable. Such a situation often emerges in surveys. For instance, a study conducted by Hacettepe University showed that 62.2 percent of the participants agree with the proposition that "Syrian refugees disturb the peace and cause depravity of public morals by being involved in crimes, such as violence, theft, smuggling, and prostitution." In comparison, those who disagree account for 23.1 percent (Erdogan, 2014). Thus, our work helps to elucidate the underpinnings of a heated debate on an issue of global relevance, which, at least in public opinion, criminalizes refugees.

This study combines administrative data on provincial-level crime rates for the 2008-19 period with several complementary datasets. For the identification of the refugee effect, we employ variations in the number of incarcerated criminals per 100k inhabitants and refugee stocks across Turkish provinces and over time within a difference-in-difference framework. We address the potential endogeneity in the spatial distribution of refugees using an instrumental variable, which depends on the distance of Syrian provinces to Turkish provinces, the distance of Syrian provinces to other neighboring countries, pre-war population shares of Syrian provinces, and the total number of Syrian refugees in all neighboring countries over time.

Our instrumental variable estimates show that a ten-point increase in the percentage of refugees in the provinces' population results in a statistically significant 8.1 percent drop in crime rates. Furthermore, when we distinguish between crime types, we primarily observe a negative refugee effect across them, albeit except for smuggling, a finding that concurs with numerous journalistic reports and official records[1]. Also, to strengthen our results' credibility, we conducted a battery of robustness checks, including placebo regressions based on pretreatment data and estimations of the relationship between

[1]The Appendix explores the triggers of smuggling, and clarifies the non-predatory nature of this crime. It also discusses the non-significant refugee effect on drug-related crimes.

refugee shares and variations in the presence of armed forces (military and civil personnel). Indeed, violence erupting across the border could have codetermined the spatial distribution of refugees and Turkish armed forces in the same provinces, thereby reducing crimes. Nevertheless, we find no evidence that variations in the refugee share affected armed forces' geographic allocation.

Our work contributes to the scholarship on the immigration-crime nexus by advancing an intriguing result: a negative immigration-crime relationship in a scenario remarkably adverse to the emergence of immigrants' law-abiding behaviors. Indeed, refugees had no access to the formal labor market and experienced partial mobility restrictions that likely subjected them to skill mismatch issues[2]. Furthermore, they did not self-select into migration pursuing superior legal earnings, and, being relatively less educated and younger than natives, the Syrian refugees displayed a socioeconomic composition typically paired with a higher crime-proneness[3]. On the natives' side, there are also reasons to think that the refugees' arrival may have pushed individuals towards criminal activities. More pointedly, some studies (Aksu et al., 2022; Ceritoglu et al., 2017; Del Carpio and Wagner, 2015) show that while refugees were legally impeded to work in the formal sector, many of them took up jobs in the informal economy and ended up displacing low-skilled natives.

Also, by taking Turkey and Syria as a case study, our paper expands an essentially new line of research, namely the impact of refugees influxes on crime in developing economies. Moreover, besides palliating potential confounding pitfalls, the massive nature of the developments at issue is also novel in the academic exploration of the crime-immigration linkage.

This paper belongs to a body of research that, concerning its results, one can divide into two main categories. First, a significant majority of papers studies the relationship between the two variables under discussion in the context of economic migrants and systematically conclude that either a null or a negative link exists between crime and immigration[4]. The second category, much sparser than the first one, comprises papers that use non-economic migrants (e.g., refugees) as their raw material and often find a positive link between immigration and crime[5].

[2] See the European Council on Refugees and Exiles (2020) report on Turkey for a comprehensive explanation of the Syrian refugees' mobility and employment restrictions.

[3] Our data from 2021 shows that the average age among Syrian refugees is 22 years, while that of locals is 32.4 years. Moreover, the 15-24 age group represents 20.9% for Syrians, while it amounts to 15.5 for Turks. The former group comprises around 28 percent of illiterates; while for the latter group, illiterates represent 11 percent. See Loeber et al. (2014) for a discussion on the age-crime curve.

[4] MacDonald et al. (2013), Stowell et al. (2009), and Sampson (2008) argue that the fact that economic immigrants are likely to positively self-select along the honest-vs.-criminal dichotomy may underlie this regularity. For their part, Powell et al. (2017) and Nowrasteh et al. (2020) show that mass immigration improves the host countries' institutions, which may constitute another mechanism explaining a negative migration effect on crime.

[5] Borjas et al. (2010) offer an interesting example that lies amid these two categories for they find a positive effect of (economic) immigration on crime rooted on increased offenses committed by locals.

A clear illustration of the first category is the work by Ozden et al. (2018), who study the impact on crime rates from the arrival of on-work visa immigrants to Malaysia, concluding that immigration decreases property and violent crimes, even when no prospects of enjoying permanent residency or citizenship existed. Likewise, Maghularia and Ubelmesser (2019), Machin and Bell (2013), and Jaitman and Machin (2013) arrive at similar results for developed economies. In a related vein, Forrester et al. (2019) demonstrate that immigrants departing from either Muslim majority or conflict-afflicted countries do not increase terrorist attacks in the areas receiving them.

Regarding the second category, which encompasses our paper, Bell et al. (2013) found that non-economic migrants in the UK, specifically asylum seekers whom the government prevented from seeking legal employment, were more crime-prone. Similarly, Mastrobuoni and Pinotti (2015) show that recidivism rates among amnestied foreign-born criminals in Italy were much higher for individuals facing a prohibition to work versus unrestricted ones[6]. Also, Piopiunik and Ruhose (2017) quantify a sizeable positive effect from immigration on crime associated with the arrival in Germany of a wave of ethnic German immigrants. The authors' chief explanation is that the newcomers exhibited several crime-conducive socioeconomic traits and experienced a policy environment that failed to encourage law-abiding behaviors[7]. In particular, the imposition of binding mobility restrictions on immigrants and granting them immediate citizenship were counterproductive[8]. All these papers differ from ours in crucial aspects. First, none of them focuses on developing countries. Second, the magnitude of the population influxes they exploit is much lower. Third, and more importantly, their conclusions are at variance with ours.

In light of this paper's results that contradict the expectation of higher crime rates, our work calls for a more refined characterization of the immigration-crime nexus. Unfortunately, data limitations impede us from empirically investigating the mechanisms underlying our findings. However, regarding refugees' incentives, we advance a twofold hypothesis congruent with existing theoretical work[9]. First, on the expected punishment side, the reported refoulement of refugees, alongside the strengthening of the

[6]At the same time, Mastrobuoni and Pinotti (2015), and Baker (2015) found that immigrant legalization has a considerable negative effect on property crime.

[7]These socioeconomic traits are a disproportionately large share of males exhibiting low education levels and, as the authors label it, at a "criminal risk" age (15-25). See Loeber et al. (2014) for a discussion on the age-crime curve.

[8]The authors argue that receiving instantaneous citizenship lowered the immigrants' expected cost of committing crimes for the deportation threat vanished.

[9]Mariani and Mercier (2021) expand Becker (1968)'s model to analyze how self-selection shapes immigrants' incentives to engage in crime. As to economic immigrants, their pursuit of higher legal wages may suffice to keep them away from illegality. At the other end, when subject to policies that hamper their labor market integration, or when non-economic reasons drive their decision to migrate, immigrants' inclination to commit crimes may increase.

local immigration authorities' detention capacity, may have constituted a significant crime-determent device for refugees[10]. Second, regarding the availability of non-criminal rents to refugees, employment opportunities in the sizeable Turkish informal sector as well as cash transfers from humanitarian aid programs, most notably the Emergency Social Safety Net (ESSN) program[11], may have provided enough resources to keep them away from participating in predatory activities. As to potential increases in crime commission associated with natives, evidence shows (see Aksu et al. (2022)) that an expansion of the formal sector, for its most part, countered the documented displacement of the latter from the informal sector[12].

All in all, our research sheds new light on the responsiveness of the immigrant's crime proneness to distinct balances between the severity and certainty of punishment and labor market integration. In particular, we offer evidence that even when facing those conditions that the literature has labeled as the most criminogenic, the negative relationship between crime and immigration may persist.

In the next section, we provide contextual information. Then, Section 4.3 presents the data used in the analysis, while Section 4.4 discusses the identification method and estimation. Section 4.5 gives the results, and Section 4.6 concludes.

4.2 Background Information

Displacement of Syrians started after the civil Arab Spring uprisings, and Turkey received its first Syrian refugees in April 2011. Initially, the government tasked the Turkish Disaster and Emergency Management Authority (TDEMA) with humanitarian aid and emergency response, including setting up camps for the refugees. Figure 3.2 shows the time evolution of the number of Syrian refugees in Turkey, thereby demonstrating that the speed of the refugees' arrival reached its high point in 2014 and 2015 and that the total number of them continued increasing until 2018.

As the number of refugees swelled, they started moving out of camps and into urban areas. In October 2014, the Turkish government established the Turkish Directorate General for Migration Management (TDGMM), responsible for registering refugees and coordinating policies regarding

[10] See Üstübici (2019) for a detailed description of Turkish Immigration policies. As to refoulement records, see Simpson (2019) and Dalhuisen(2016).

[11] The ESSN program is an unconditional cash transfer scheme providing monthly assistance to refugees in Turkey. It was implemented nationwide in November 2016 and has become the world's largest cash transfer program that targets refugees. In fact, over 1.8 million refugees in Turkey were covered as of February 2021 (IFRC, 2021). It is funded by the European Union.

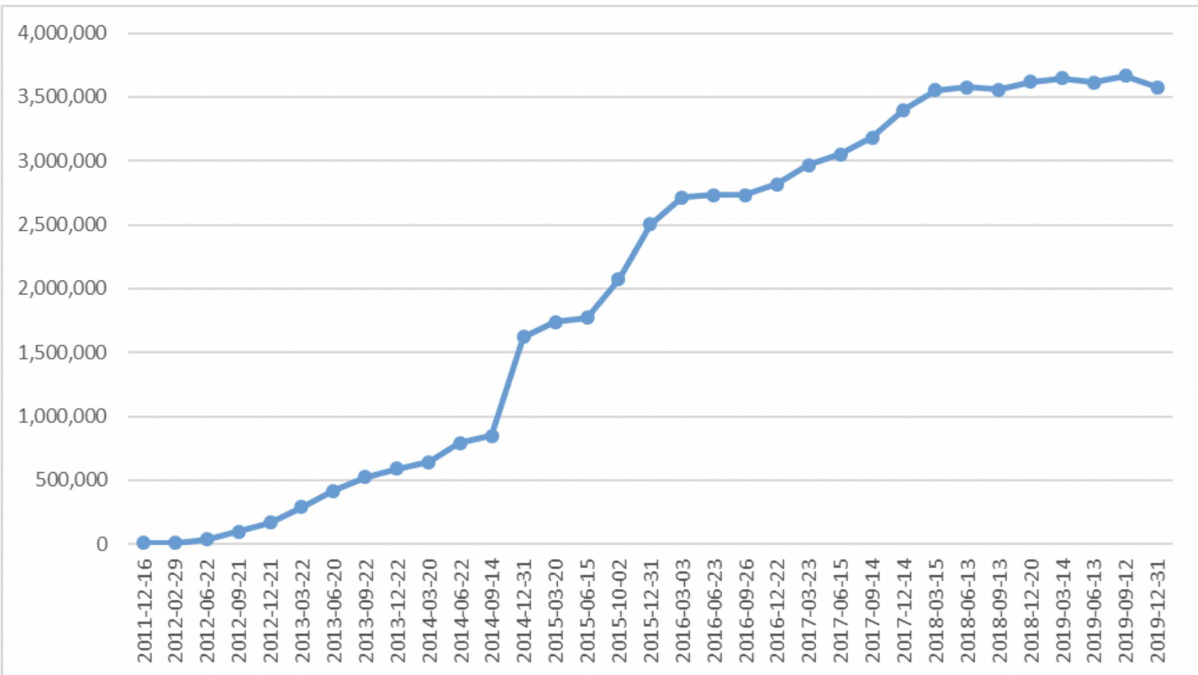
[12] Aksu et al. (2022) find that in terms of replacement of natives, the informal workers took the brunt of the Syrians' arrival. However, the authors show that via the opening of formal jobs, overall employment of native males did not change—although that of native women fell.

them. Simultaneously, the Turkish government passed the Temporary Protection Regime for the Syrian refugees, which defined their rights to access public health, public education, and social protection. According to this, Syrians have free access to public health and education services.

As refugees started marching towards Europe in large numbers in 2015, Turkey and the EU signed an agreement on the funding and the handling of the refugee crisis, which led to the establishment of the Emergency Social Safety Net (ESSN), a program targeting refugees with funding from the EU (WFP, 2018)—discussed in more detail below. This program coped with an impressive population inflow. Indeed, the number of refugees reached 2.5 million by the end of 2015, and only 10% lived in refugee camps at this time. In the following years, refugees' arrival continued, and their number reached 3.6 million at the end of 2020, out of which only 1.6 percent of them lived in refugee camps. In fact, of the 5.5 million Syrian refugees who left their country since the onset of the civil war, 65 percent lived in Turkey at this date (UNHCR, 2020).

Syrians are, on average, younger and less educated than the local population in Turkey. Their median age is 21, compared to 31 for natives (Eryurt, 2017). The median years of education are 4.5 years for Syrian women and 5.1 years for their male counterparts, whereas they amount to 4.8 years and 7.1 years for Turkish women and men, respectively (Hacettepe University Insititute of Population Studies, 2019a, 2019b).

Figure 4.1 Number of Syrian refugees in Turkey over time



Notes: Data source is UNHCR.

Syrian refugees could not get official work permits before Law 8375's enactment in January 2016 (with few exceptions, primarily those who started a business). However, even after this law, the number of formally employed refugees remained low. The number of work permits issued to Syrians was 34,573 in 2018 (MoFLSS, 2019). As a result, most Syrian refugees worked in the informal sector to sustain their lives. Caro (2020) estimates that 813,000 Syrians were employed in 2017, and 97 percent worked informally. The Syrian module of the 2018-Turkish Demographic and Health Survey (TDHS-S) shows that among 18- to 64-year-old individuals, 60.1% of Syrian men were in paid jobs compared to 65.9% of Turkish men. Among women, the gap in paid employment is wider; only 5.8% of Syrian women were in paid jobs compared to 20.9% of Turkish women. Child labor among Syrian refugees is also high; based on the same dataset, Dayioglu et al. (2021) report that 48% of 15- to 17-year-old refugee boys worked in paid employment.

Refugees are also much poorer. Pooling the Syrian and Turkish samples of the 2018 TDHS, Dayioglu et al. (2021) report that 79 percent of Syrian households lie in the bottom quintile of the wealth index they generate using 21 different household assets. WFP (2016) reports, based on the Pre-Assistance Baseline (PAB) survey conducted before the launch of ESSN, that 28.6 percent of Syrian refugees that resided outside camps were food insecure, and 93 percent were below the national poverty line. In part, their poverty is due to the lower employment among refugees, but refugees also work in worse jobs that pay less. As reported above, they are much more likely to work informally. In addition, Caro (2020) reports that although the majority of Syrian men work long hours (76 percent of Syrians worked more than 45 hours per week, the maximum legal number of working hours in Turkey), they earned 1,300 TL per month on average in 2017, which was 7 percent below the minimum wage in that year.

It is also important to note that several aid programs have targeted Syrian refugees in Turkey. The most salient one has been the Emergency Social Safety Net (ESSN) program, first implemented in November 2016, which reached 1.8 million refugees as of February 2021 (IFRC, 2021). The amount of pay in this unconditional cash transfer program is sizeable. For the average Syrian household with six members (based on the 2018-Demographic and Health Survey of Turkey), the monthly payment is 720 TL (around USD 105)—which is roughly equal to 55% of the average monthly labor earnings of Syrian men in Turkey (as estimated by ILO). Furthermore, Aygün et al. (2021) estimate that the monthly payment is about 36% of the average monthly consumption value of the refugee households in the nationally representative micro-level dataset used in this study and that these cash transfers substantially alleviate extreme poverty and reduce a family's need to resort to harmful coping strategies.

4.3 Data

The data we use on crime rates come from the Turkish Statistical Institute (TURKSTAT). This dataset enumerates convicts received into prison by type of crime and the province where the crime occurred. We use the data on overall crime and ten different categories of offenses: assault, crimes involving firearms and knives, homicide, robbery, smuggling, theft, sexual crimes, kidnapping, defamation, use and purchase of drugs, and production and commerce of drugs[13]. Our outcome variables are crime rates per 100K inhabitants (including natives and refugees) of each province in the corresponding year. The crime data include both convicted Turkish citizens and foreigners[14].

We use several supplementary province-level datasets to generate our control variables for the 2008-19 period. First, we employ data on exports and imports (in USD; TurkStat, 2021a). Second, we use gross domestic product per capita data in USD (TurkStat, 2021b). Third, we use the gross domestic product at current prices by economic activity branches (TurkStat, 2021c) to generate the shares of different sectors in GDP (agriculture, industry, and services). Fourth, we use province-level data on the age dependency ratio provided by TurkStat (2018d), on the average size of households (TurkStat, 2021e), and population by age categories (TurkStat, 2018f) to create our age groups. Finally, we use data on attained education levels for the population over 15 years of age provided by TurkStat (2018g) to construct education categories. In addition, we use one dataset that provides information at the NUTS-2 region level; the number of armed forces (military and civil personnel) comes from Turkey's Household Labor Force Surveys.

The control variables include the logarithm of trade volume, the logarithm of GDP per capita, the shares of different sectors in GDP (agriculture, industry, and services), age dependency ratio, average household size, shares of five age brackets, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv)

[13]The total crime rate that we use includes – in addition to these nine categories of crime – swindling, forgery, bad treatment, embezzlement, bribery, traffic crimes, forestry crimes, opposition to the bankruptcy and enforcement law, opposition to the military criminal law, threat, damage to property, prevention of performance, contrary to the measures for family protection and other crimes.

[14]It is worth emphasizing that all our crime measures use the number of convicted criminal for various offenses to construct crime rates. One concern could be that the judicial system get to process a fixed number of cases per year, and that the population influx, therefore, trivially dilutes our crime rates variables. However, the data shows the opposite. Indeed, there is significant variation in the aggregate level of convicted criminals across years. For instance, while the aggregate crime rate was 224 per 100K population in 2013, it was 205 in 2015, 247 in 2017, and 319 in 2019.

junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) graduates from university and higher education institutions. Each sub-group in the age category indicates the group's share within the population aged 15-64. Similarly, each sub-group in the education category shows the share of the specific group over "15 years of age and over".

The number of Syrian refugees used for this study comes from different sources. The figure for 2013 comes from the Disaster and Emergency Management Presidency of Turkey (AFAD). Erdogan (2014) provides the refugee numbers for 2014, and the Ministry of Interior Directorate General of Migration Management provides information on the number of Syrian refugees for 2015 to 2019. The number of refugees in this analysis starts from 2013 since the number of Syrian refugees in Turkey for 2012 is unavailable at the province level. Using these numbers and the province populations obtained from TurkStat, we generate the percentage of Syrian refugees in each province over time.

Although the data on crime rates covers the years 2006-19, GDP per capita and trade volume are the only control variables available for this period. Hence, we restrict our analysis to the years 2008-19 – although we check the robustness of our findings using the crime data for the more extended period of 2006-19 but with a much shorter list of control variables. In addition, our analysis excludes the data for 2012 because the data on the distribution across provinces of refugees is not available for this year. Hence, we have 11 years of data over 81 provinces, resulting in 891 observations.

Table 4.1 provides descriptive statistics. The average number of crimes per 100,000 people is about 196 across provinces and years. The variation in this variable is also significant, ranging between 17 and 531. Of the ten subcategories of crime that we focus on, the most frequent are assault and theft. Smuggling and the use and purchase of drugs display more variation across province-year observations; their standard errors are larger than their means, unlike for all other variables. Many control variables also show significant variation across geography, indicating large socioeconomic differences between Turkish provinces and the importance of accounting for these measures.

Table 4.1 Descriptive Statistics

	Mean	St. Dev.	Min.	Max.	No Obs.
Dependent Variables (Rate per 100,000 people)					
All Crimes	195.918	104.460	16.944	530.835	891
Assault	28.307	18.319	0.398	111.887	891
Crimes related with firearms and knifes	5.496	3.560	0.000	23.931	891
Homicide	8.058	4.522	0.000	28.504	891
Robbery	6.625	5.997	0.000	32.116	891
Smuggling	5.311	8.696	0.000	133.113	891
Theft	25.342	19.214	0.000	102.206	891
Sexualcrimes	5.021	4.078	0.000	18.607	891
Kidnapping	3.009	2.659	0.000	16.028	891
Defamation	4.094	3.000	0.000	19.459	891
Use and Purchase of Drugs	3.400	4.766	0.000	36.788	891
Production and Commerce of Drugs	9.993	9.788	0.000	60.426	891
Control Variables					
Log GDP per capita	8.935	0.353	7.911	9.939	891
Average Household Size	3.853	1.068	2.600	8.400	891
Average Dependency Ratio $*100$	51.376	10.038	35.930	91.650	891
Log Trade Volume	19.427	2.476	0.000	26.215	891
Shares of Education Groups					
Illiterate	0.072	0.049	0.012	0.310	891
No Degree	0.070	0.038	0.019	0.242	891
Primary School	0.438	0.082	0.141	0.609	891
Middle School	0.093	0.052	0.014	0.343	891
High School	0.212	0.040	0.105	0.316	891
University	0.115	0.042	0.024	0.281	891
Shares of Age Groups					
Age: $15-24$	0.264	0.054	0.181	0.444	891
Age: $25-34$	0.231	0.025	0.182	0.299	891
Age: $35-44$	0.203	0.018	0.133	0.247	891
Age: $45-54$	0.170	0.029	0.083	0.216	891
Age: 55-64	0.131	0.035	0.048	0.218	891
Shares of Sectors in GDP					
Agriculture	0.169	0.085	0.001	0.469	891
Industry	0.268	0.111	0.052	0.615	891
Services	0.563	0.085	0.343	0.812	891

Notes: The data cover 81 provinces of Turkey over the years 2008 to 2019 (except 2012). The rates of the 11 sub-categories of crime do not add up to the overall crime rate because some crime types are not included. This is because either these crimes were not reported consistently over the years or they were rare.

4.4 Identification Method and Estimation

To estimate the impact of the refugee inflow on crime rates, we use a difference-in-differences methodology to compare the provinces with high refugee intensity with those with low refugee intensity before and after the arrival of refugees. In particular, we use the following equation,

$$c_{pt} = \alpha + \beta R_{pt} + X_{pt}\Gamma + \delta_p + \theta_t + \mu_{p't} + \varepsilon_{pt} \tag{4.1}$$

where c_{pt} denotes the crime rate in province p at time t, R_{pt} is the percentage of refugees in the total population (natives and refugees) of province p at time t, and X_{pt} stands for other province-time level characteristics at time t (presented in Table 4.1 and explained in the previous section). Province fixed effects and time fixed effects are shown by δ_p and θ_t, respectively. To account for potential differences in pre-existing trends across regions, we allow the time effects to vary across them using various region-year interactions ($\mu_{p't}$): (i) five region-specific time trends, (ii) twelve NUTS-1 region-specific time trends, (iii) fixed effects for interactions of five regions with years, (iv) fixed effects for interactions of twelve regions with years. Finally, α stands for the constant term and ε_{pt} represents the error term.

A potential identification problem is that refugees' settlement patterns could correlate with the crime rates across provinces. Refugees might not choose their location of residence based on the crime rates; however, if they choose them based on economic and employment conditions, we might still expect their settlement patterns to be associated with crime rates. Therefore, we use an instrumental variable approach to generate an exogenous variation in the settlement patterns of refugees.

We employ the distance-based instrument used by Aksu et al. (2022)[15], an extension of the instrumental variable used by Del Carpio and Wagner (2015). The del Carpio-Wagner instrument distributes the yearly number of Syrian refugees in Turkey across Turkish provinces according to the distance of each Turkish province from each Syrian province and the pre-war population shares of Syrian provinces. Noting that many Syrian refugees left for other bordering countries of Syria—Lebanon, Jordan, and Iraq—Aksu et al. (2022) also accounts for the distance of each Syrian province to these countries. The instrument is defined as follows,

$$I_{p,t} = \sum_{s=1}^{13} \frac{\left(\frac{1}{d_{s,T}}\right)\pi_s}{\left(\frac{1}{d_{s,T}} + \frac{1}{d_{s,L}} + \frac{1}{d_{s,J}} + \frac{1}{d_{s,I}}\right)} \frac{T_t}{d_{p,s}} \tag{4.2}$$

where $I_{p,t}$ stands for the expected number of refugees in province p at time t (the instrument) and $d_{s,T}, d_{s,L}, d_{s,J}$, and $d_{s,I}$ stand respectively for the distance of Syrian provinces to the closest border entry in Turkey, Lebanon, Jordan, and Iraq. In equation (2), π_s is the pre-war population share of Syrian

[15]This instrument has also been used in Akgündüz et al. (2022) and Aygün et al. (2021).

province $\mathrm{s}, d_{p,s}$ is the distance of Turkish province p to Syrian province s, and T_t stands for the total number of Syrian refugees in the bordering four countries.

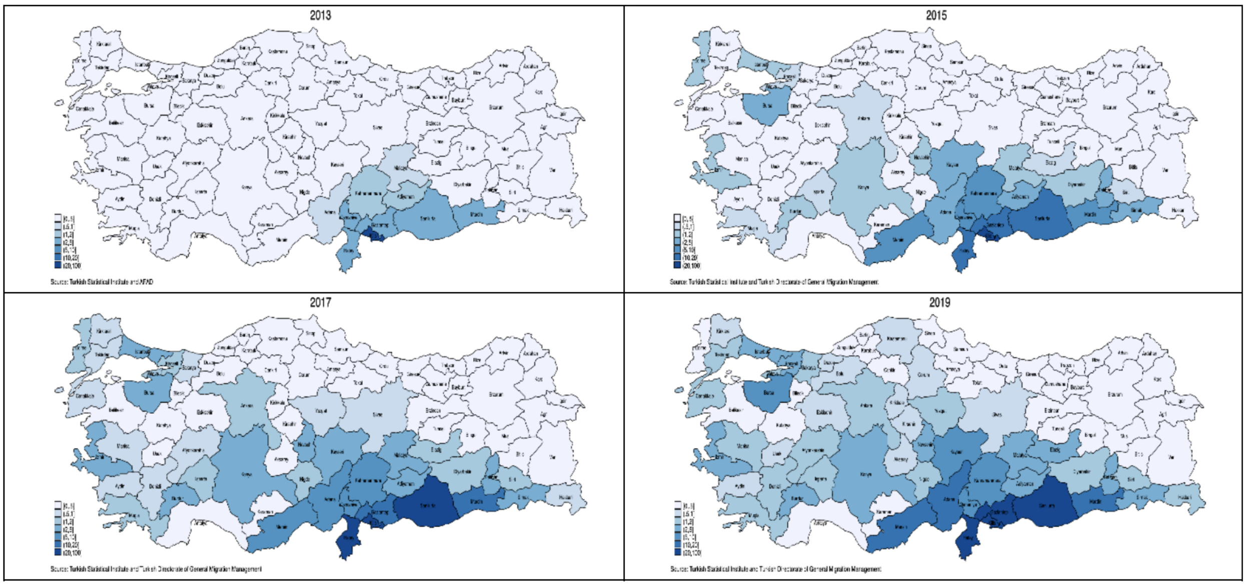
This instrument is different from that of del Carpio and Wagner in two ways. First, we reweight the pre-war population shares of Syrian provinces according to their distance from the four countries. For instance, while the pre-war population share of Aleppo is 0.21, with the scaling in equation (2), its pre-war population share (for Turkey) increases to 0.45. Second, instead of allocating the number of refugees in Turkey, it assigns the total number of refugees in the four neighboring countries. Hence, this instrument accounts for the potential endogeneity of the level and timing of Syrian refugees entering Turkey, as there are different countries to choose from for the potential refugees. In addition, this extension makes the first-stage regression stronger because a disproportionate amount of refugees in Turkey originate from Syrian provinces that border Turkey, such as Aleppo and Idlib, than provinces that border the other three neighboring countries.

Regarding the instrument, finally, we discuss why distance matters. As shown in Figure 2, even in 2019, refugees are still concentrated in the regions bordering Syria—although, over time, their presence in the industrialized cities in western Turkey increased. The primary reason is that the border region is the entry point of the refugees, where camps were established immediately after their arrival. Since the government initially conceived them as temporary, it mounted the camps in areas close to the border. Moreover, even after leaving these shelters for urban areas, many refugees preferred to stay in provinces closest to their original residence in Syria, where many family members still resided[16]. Finally, Syrian refugees in Turkey are supposed to use the health and educational facilities in the province they are registered. Although the local authorities do not strictly enforce this, it might have created some inertia against further movement.

The assumption for the validity of our instrument is that the trends in crime outcomes in the absence of the refugee shock, conditional on region and time fixed effects and a set of covariates, are uncorrelated with our distance-based instrument. This assumption could fail, for instance, if our instrument is correlated with the unobserved trends in economic and employment conditions, hence with the unobserved trends in crime outcomes. When we use time-region interactions $(\mu_{p't})$, our instrument relies on a weaker independence assumption. For instance, when we use region-year fixed effects, we assume that distance does not correlate with unobserved trends in crime outcomes—within the country's five regions—a more plausible assumption. We leave the presentation of support for this identification assumption to the Robustness Check subsection (as its interpretation requires a comparison with the main results, given in the next section).

[16]In fact, they can visit their family members on certain occasions like religious holidays.

Figure 4.2 Density of Syrian Refugees in Turkey across Provinces: 2013, 2015, 2017, and 2019



Note: The provincial data on the number of Syrians for 2013 comes from the Disaster and Emergency Management Presidency of Turkey (AFAD). The Ministry of Interior Directorate General of Migration Management provides information on the number of Syrian refugees across provinces for 2015 to 2019. Using these numbers and the province populations obtained from TurkStat, we generate the percentage of Syrian refugees in each province over time.

4.5 Results

We provide our estimates of the refugee impact on crime in Table 4.2 for the OLS estimates and Table 4.3 for the 2SLS estimates. In each table, five different specifications are used that differ according to how we account for pre-existing trends. Column (1) provides the estimates for the baseline specification with no controls for potential pre-existing trends (only province and time fixed effects are used). On the other hand, potential pre-existing trends are accounted for via 5 region-specific linear time trends in column (2), 12 NUTS-1 regions specific linear time trends in column (3), fixed effects for 5 region-year interactions in column (4), and fixed effects for 12 region-year interactions in column (5).

Before we start presenting our results, we will discuss the first-stage regression results in our 2SLS estimation. As shown in the bottom part of Table 4.3, the first stage coefficients of the instrument are statistically significant at the 1 percent level for all five specifications. In addition, the partial R-squared is quite high at about 0.7, and the F-statistics are above the suggested levels in the literature for all five specifications.

The OLS results in Table 4.2 show that while the coefficients of refugee effect on all crimes (given in the first row) are negative across all specifications, they are not statistically significant at the conventional

Table 4.2 Refugee effect on various types of crime, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-84.883	-75.279	-27.085	-93.779	-36.512	195.918
	(61.452)	(75.689)	(80.349)	(81.466)	(95.619)	
Assault	-41.853***	-46.364***	-32.578**	-49.041***	-33.806*	28.307
	(14.208)	(15.731)	(14.605)	(16.367)	(17.070)	
Crimes related with firearms and knifes	2.516	3.260	4.444	3.335	4.255	5.496
	(3.921)	(3.053)	(3.386)	(3.349)	(4.085)	
Homicide	-13.424***	-15.468***	-10.294***	-15.095***	-10.170**	8.058
	(3.541)	(3.746)	(3.574)	(4.151)	(4.308)	
Robbery	0.026	2.044	2.629	1.914	2.777	6.625
	(5.615)	(5.843)	(6.833)	(6.446)	(8.234)	
Smuggling	16.837*	17.062	15.776	14.964	17.582	5.310
	(9.778)	(10.833)	(14.678)	(11.908)	(17.187)	
Theft	-20.181*	-24.017	-32.598*	-26.749	-33.007	25.342
	(11.131)	(16.555)	(19.126)	(18.099)	(22.134)	
Sexual Crimes	-11.320***	-10.066***	-7.795**	-10.309***	-8.238**	5.021
	(2.669)	(2.827)	(3.088)	(3.168)	(3.475)	
Kidnapping	-7785***	-7.937***	-4.278**	-8.734***	-4.779**	3.009
	(1.931)	(2.511)	(1.890)	(2.879)	(2.399)	
Defamation	-5997***	-5.117**	-4.258	-6.631**	-5.721*	4.094
	(1.921)	(2.546)	(2.639)	(2.888)	(3.155)	
Use and Purchase of Drugs	6.102	8.946	4.954	8.511	4.701	3.400
	(5.239)	(5.774)	(7.924)	(5.859)	(8.893)	
Production and Commerce of Drugs	4.021	-0.852	-12.587	-3.096	-15.326	9.993
	(12.170)	(9.569)	(13.072)	(10.373)	(15.462)	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891 . The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest - the ratio of migrants to population (migrants+natives) - in a separate OLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. Province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24,25-34,35-44,4654, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the province level. *, **, *** indicates significance at the 10 %, 5 % and 1%, respectively.

levels. The 2SLS coefficients on the refugee impact on all types of crimes are larger in absolute value than the corresponding OLS estimates. Moreover, the negative 2SLS coefficient in column (1) with the baseline specification is statistically significant at the 10 percent level. While the coefficients with other specifications are similar in magnitude, they are not statistically significant due to larger standard errors. Quantitatively, the coefficient in the first column indicates that a 10-point increase in the percentage of refugees in the population decreases the crime rate by 16 from a baseline level of 196—implying an 8.1 percent drop. The fact that the 2SLS estimates are more negative than the OLS estimates suggests that the provinces that the refugees settle in would have more positive time trends in the absence of the refugee shock—controlling for the covariates.

When we examine the migrant effect by the type of crime, we find evidence of a conclusive negative effect (that holds across all specifications) on assaults, sexual crimes, kidnapping, and defamation. Quantitatively, a 10-point increase in the percentage of refugees in the population decreases assaults by about 4 to 6 (about 15-20 percent), sexual crimes by about 1.1 to 1.4 (about 22-30 percent), kidnapping by about 0.6 to 1.2 (20-40 percent), and defamation by about 0.9 to 1.1 (about 25 percent).

For homicide, the specifications in columns (1), (2), and (4) provide evidence of a negative refugee impact, whereas the other two do not. Since all specifications pass the placebo test in Table 4.2, no reason exists to prefer any specification to the others, and we conclude that suggestive evidence of a negative impact of the refugee shock on homicides exists. For thefts, the specifications in columns (1), (3), and (5) present evidence of a negative effect. Moreover, the negative effects in the two other specifications are just marginally statistically insignificant and similar in absolute magnitude. Hence, overall, the results suggest a negative refugee impact on thefts. Quantitatively, a 10-percent rise in the percentage of refugees decreases homicides by about 0.8-1.5 (by 10-20 percent) and thefts by about 4 to 6 (by 15-25 percent).

For one crime type, the refugee impact is positive. Specifications (1) to (3) show evidence that smuggling increases with the arrival of refugees. The coefficients in specifications (4) and (5) are marginally statistically insignificant and slightly lower. Overall, the results suggest that a 10-percent rise in the refugee percentage increases smuggling crimes per 1000 people by about two units (close to 40 percent). In other words, this effect is also quantitatively large.

Nevertheless, as we elaborate in the Appendix, one can hardly regard increased smuggling as reflective of aggravated predation. For one thing, smuggling itself seems to be a victimless crime. Secondly, as Karaçay (2017) and Yildiz (2017) document, what triggered the increase in the variable at issue could have very well been the provision of an illegal service whose users greatly valued. More specifically, an upsurge of illegal crossings into Turkey and from Turkey into the EU, a phenomenon that,

Table 4.3 Refugee Effect on Various Types of Crime, 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-157.282*	-147.620	-114.552	-175.252	-140.377	195.918
	(89.023)	(113.301)	(128.815)	(119.168)	(138.970)	
Assault	-45.920***	-54.363***	-40.617**	-59.091***	-43.956**	28.307
	(15.977)	(18.722)	(19.714)	(19.046)	(19.601)	
Crimes related with	0.486	2.451	3.586	3.229	3.522	5.496
firearms and knifes	(5.317)	(3.586)	(5.211)	(4.079)	(5.158)	
Homicide	-12.622***	-14.732***	-7.559	-14.871***	-7.539	8.058
	(3.918)	(4.266)	(5.940)	(4.853)	(6.196)	
Robbery	-7.820	-4.765	-4.102	-5.507	-4.785	6.625
	(9.105)	(10.439)	(11.529)	(11.132)	(12.464)	
Smuggling	20.524**	21.732**	23.043*	17.081	21.701	5.310
	(8.101)	(9.593)	(13.726)	(10.896)	(16.390)	
Theft	-36.520**	-40.660	-55.126*	-46.601	-60.569*	25.342
	(17.233)	(26.999)	(30.421)	(29.089)	(33.007)	
Sexual Crimes	-14.575***	-13.147***	-11.358**	-13.890***	-12.218***	5.021
	(3.266)	(3.739)	(4.464)	(4.000)	(4.439)	
Kidnapping	-9372***	-10.165***	-6.388**	-11744***	-7.788**	3.009
	(2.715)	(3.562)	(3.029)	(3.947)	(3.365)	
Defamation	-9.057***	-9.275**	-9.445**	-10.823***	-10.954**	4.094
	(2.671)	(4.064)	(4.464)	(4.141)	(4.393)	
Use and Purchase	-4.379	0.191	-6.157	-0.148	-7.155	3.400
of Drugs	(8.842)	(10.052)	(12.140)	(10.354)	(13.016)	
Production and Commerce	4.037	-7.073	-23.835	-10.154	-28.352	9.993
of Drugs	(14.330)	(16.181)	(19.579)	(17.711)	(22.155)	
First-stage regression	2.880***	2.996***	2.837***	2.981***	2.806***	
	(0.668)	(0.701)	(0.701)	(0.719)	(0.751)	
Partial R-squared	0.703	0.700	0.646	0.691	0.634	
F-Stat	18.570	18.271	16.394	17.173	13.977	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891 . The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest- the ratio of migrants to population (migrants+natives) - in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people inthe "0-14" and "65 and over" age groups per 100 people inthe "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, *** indicates significance at the 10 %, 5 % and 1%, respectively.

in turn, was fueled by the Syrian conflict, required the intervention of human smugglers[17]. Interestingly, the refugees systematically report that they do not think of the former as criminals, for they do not defraud them. Indeed, they conceive them as facilitators of an essential service[18].

4.5.1 Placebo Regressions

This subsection presents the results of placebo regressions that support the identification assumption by measuring the impact of refugees when no effect is supposed to come about. For this purpose, we act as if the refugees in 2019 arrived in 2011. More specifically, we restrict our data to the pre-shock period 2008–2011. Then we assign the 2019 distribution of our instrument and the refugee-to-native ratio across provinces to 2011 and run a 2SLS regression. If the instrument were correlated with unobserved pre-shock trends in crime outcomes—contrary to the identification assumption—this regression would yield a statistically significant coefficient for the refugee intensity which is instrumented.

Table 4.4 presents the results of this placebo regression. We find no evidence of a correlation between the instrument and the pre-existing time trends (after accounting covariates) for any specification for the overall crime rate. Moreover, the magnitudes of the coefficients are much smaller than the coefficients we estimate in Tables 2 and 3. For some subcategories of crime that we report a refugee impact, statistical evidence of a correlation emerges. However, in these cases, the placebo coefficients are much smaller than the actual coefficients in Table 4.3 (sexual crimes, defamation) or have the opposite sign (theft). Hence, Table 4.4 provides strong support for our identification assumption.

4.5.2 Potential Channel via Armed Forces

An increase in the number of armed forces (military and civil personnel) in the migrant-receiving locations could in part explain our findings that the arrival of migrants did not increase crime. To examine this issue, we first check whether the government increased the number of armed forces in the migrant-dense regions. Since we do not have data on the number of police officers and gendarmerie, we use data on the number of all armed forces (including the military personnel) from the Household Labor Force Surveys of Turkey, as explained in the Data Section.

Panel (A) of Table 5 shows the results of regressing the logarithm of the number of armed forces on the migrant ratio and the list of control variables, which now also includes the logarithm of the

[17]For reasons we flesh out in the Appendix, Turkey has long hosted a loose network of human smugglers who have served the logistic needs of illegal migrants from various origins.

[18]In a related vein, we fail to find statistical evidence of a refugee effect on drug-related crimes. As the Appendix explains, this fact could be due to a common cause structure. Specifically, Cengiz (2017) documents that the Syrian war unleashed a shift in the the drug trafficking networks traversing Turkey. However, no direct causal link can be weaved between the spatial allocation of refugees and increased drug trafficking.

Table 4.4 Placebo Regressions on Refugee Effect on Various Types of Crime, 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	Mean
All	-12.045	4.373	-11.688	11.102	-40.999	104.490
	(22.871)	(31.378)	(35.763)	(32.738)	(42.627)	
Assault	-0.058	1.107	-3.420	2.656	-1.811	11.754
	(4.566)	(5.207)	(4.836)	(5.978)	(5.727)	
Crimes related with firearms and knifes	-3.376	-2.980	-2.021	-2.740	-2.221	3.413
	(2.208)	(2.079)	(2.052)	(1.956)	(2.099)	
Homicide	-2.074	-2.831	-3.408	-2.410	-4.686	4.030
	(2.225)	(2.252)	(2.380)	(2.803)	(3.523)	
Robbery	1.771	4.052*	3.277	4.621**	4.175**	1.654
	(2.669)	(2.155)	(2.048)	(2.056)	(2.001)	
Smuggling	0.193	1.079	0.542	1.120	-0.577	1.416
	(3.598)	(3.468)	(3.678)	(3.839)	(3.933)	
Theft	4.315**	3.517*	1.197	2.036	-0.052	6.796
	(2.138)	(2.079)	(2.162)	(3.089)	(3.720)	
Sexual Crimes	-2.852	-3.685**	-4.011**	-3.583**	-4.324**	1.224
	(1.814)	(1.591)	(1.682)	(1.612)	(1.790)	
Kidnapping	-0.771	0.973	0.603	0.367	-0.310	0.742
	(0.710)	(1.050)	(1.123)	(0.983)	(1.085)	
Defamation	-0.126	-0.589	-2.932**	0.628	-3.220**	1.939
	(1.339)	(1.401)	(1.286)	(1.637)	(1.289)	
Use and Purchase of Drugs	4.026***	3.303***	2.246	3.501***	2.650**	0.738
	(1.442)	(1.267)	(1.423)	(1.013)	(1.185)	
Production and Commerce of Drugs	0.534	-2.183	-2.484	-2.544	-2.135	2.412
	(3.043)	(4.817)	(5.548)	(4.102)	(4.738)	
Observations	324	324	324	324	324	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2011 (pre-shock period), therefore the number of observations is 324 . The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. For this placebo analysis, the values of the key variable of interest and instrument for 2019 are assigned to the corresponding values for 2011. The key variable of interest and the instrument take the value of zero for 2006-2010. Each cell shows the estimates for the key variable of interest - the ratio of migrants to population (migrants+natives) - in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control variables, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume and the logarithm of GDP per capita. Standard errors, given in parentheses, are clustered at the province level. *, **, *** indicates significance at the 10 %, 5 % and 1%, respectively.

Table 4.5 Investment in Armed Forces and Change in per-capita Armed Forces in Migrant Receiving Regions

	(1)	(2)	(3)	(4)	(5)	Mean
A) Effect of the Migrant Shock on the Number of Security Personnel (Controlling for the Native Population)						
A1) OLS Results	0.099	0.141	-1.870	0.234	-1.639	10.756
	(0.921)	(0.858)	(1.512)	(1.375)	(1.931)	
A2) 2SLS Results	0.470	0.698	-0.720	0.808	-0.703	10.756
	(0.825)	(0.797)	(1.316)	(1.157)	(1.336)	
First-stage regression	1857***	1.946***	1724***	1.883***	1.660***	
	(0.123)	(0.199)	(0.118)	(0.246)	(0.190)	
Partial R-squared	0.717	0.731	0.720	0.719	0.749	
F-Stat	229.509	95.710	211.798	58.846	76.604	
Observations	286	286	286	286	286	
B) Effect of the Migrant Shock on the Number of Security Personnel per Person (Native and Refugee)						
B1) OLS Results	-0.145	-0.152	-0.221**	-0.154	-0.186*	0.029
	(0.089)	(0.090)	(0.099)	(0.095)	(0.105)	
B2) 2SLS Results	-0.062	-0.105	-0.192*	-0.107	-0.108	0.029
	(0.058)	(0.086)	(0.116)	(0.081)	(0.070)	
First-stage regression	1.853***	1.945***	1.716***	1.878***	1.574***	
	(0.125)	(0.197)	(0.144)	(0.242)	(0.247)	
Partial R-squared	0.715	0.731	0.695	0.719	0.694	
F-Stat	221.396	97.229	141.929	60.247	40.464	
Observations	286	286	286	286	286	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
NUTS2 Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 26 NUTS-2 level regions for each year from 2008 to 2019 (except 2012). Therefore, the number of observations is 286 . The dependent variable in panel (A) is the logarithm of the number of security personnel (working in the field of defense and compulsory social security), whereas it is the number of security personnel per capita (natives+migrants) in panel (B). The regression in panel (A) controls for the logarithm of native population. Each cell shows the estimates for the key variable of interest - the ratio of migrants to population (migrants+natives) - in a regression of the dependent variable on the key variable of interest, a set of NUTS2-region specific control variables, a set of geographical-area and year specific control variables as indicated above. In the 2SLS regresssions, the instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The Nuts2-specific control variables include the logarithm of trade volume, the logarithm ofGDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people inthe "0-14" and "65 and over" age groups per 100 people inthe "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, *** indicates significance at the 10 %, 5 % and 1%, respectively.

native population as a control variable because the dependent variable is in levels. From these results, it follows that no evidence exists of an increase in the number of armed forces. In other words, it does not seem like the government responded to the refugee shock by adjusting the allocation of armed forces across regions.

Second, we examine how the refugee shock altered the number of armed forces per capita (including natives and refugees). Panel (B) of Table 5 shows suggestive evidence of a decline in the dependent variable due to the migrant shock. All the coefficients are negative and similar in magnitude, and they are either marginally statistically significant or significant at the 10 percent level. In essence, these findings imply that a rise in the number of armed forces is not the underlying reason for the absence of a rise in crime rates in refugee-receiving regions.

Finally, we introduce the number of armed forces per capita to our main regression equation as a control variable. Table D1 in the Appendix provides the results. We leave this as a robustness check because the data on the per capita armed forces is available at the NUTS-2 region level—which requires clustering of the standard errors at this level, decreasing the precision of our estimates. In fact, with this additional control, the coefficient estimates change very little; however, as expected, the standard errors are larger.

4.5.3 Robustness Checks

Our crime measures use the number of convicted criminals for various offenses to construct crime rates. One concern could be that much time may elapse between a crime commission, say at year t-1 or earlier, and the time the perpetrator gets convicted, say at year t. To deal with this potential issue, in an alternative specification, we use the lagged values of our key variable of interest in our 2SLS regressions. Tables A2 and A3 in the Appendix replicate the analysis in Table 4.3 using one-year and two-year lagged values of the key variable of interest, respectively. In support of our empirical strategy validity, the estimated refugee effects are similar in magnitude; in fact, the estimate in column (1) is slightly higher in Table D2 and about 17 percent higher in Table D3. However, the precision is lower; it becomes marginally statistically insignificant. (It was statistically significant at the 10 percent level in Table 4.3.)

We construct the key variable of interest using the total populations of refugees and natives. However, the fraction of children in the population is higher among refugees than natives. Therefore, in another robustness check, we use the population aged 18 or above in generating the key variable of interest. While we use the province-level population that is 18 or above for natives, we know only the refugee population that is 18 or above at the country level. Hence, we assume that the fraction of the adult population among refugees is the same across provinces. Table D4 in the Appendix gives the results. The estimated coefficients in Table D4 are only slightly lower than the main results in Table 4.3.

4.6 Conclusion

In this paper, we examine the causal link between immigration and crime in the context of the arrival in Turkey of 3.6 million Syrian refugees. For this purpose, we combine administrative data on crime rates for the 2008-19 period with several complementary datasets and use the spatial distribution of refugees across provinces within an IV difference-in-differences methodology to estimate the effect of interest.

We find suggestive statistical evidence that the refugee shock reduced the aggregate crime rate. Quantitatively, the estimated effect is large: a 10-point increase in the percentage of refugees in the population decreases our measure of crime rate by 8.1 percent. When we examine the effects by crime type, we find conclusive statistical evidence of a negative effect of the refugee shock on assaults, sexual crimes, kidnapping, and defamation. Our analysis also points to a negative impact of the refugee shock on homicides and thefts. On the other hand, in line with anecdotal information, we find a positive impact of the refugees' arrival for one crime type: smuggling. However, this last finding also calls for a careful interpretation. As we already explained in the Results Section, our smuggling variable may be encoding a higher incidence of human smuggling into Turkey and from there into the EU, executed by individuals whom Syrian refugees and other migrants regard as simple service providers. In short, the Syrians arrival did not increase the incidence of predatory activities.

We also find that the reduction in crime rates with the arrival of refugees does not result from an increased presence of armed forces (civilian and military personnel) in the refugee-hosting regions. On the contrary, we find suggestive evidence of a decrease in the per capita number of armed forces when the resident population includes native and refugee populations.

Our case study comprises a series of features that render our results intriguing. Indeed, the empirical research that finds a positive immigration-crime nexus conceives the imposition of partial mobility impediments and restrictions to accessing the legal labor market on the newcomers as the driving force behind their results. In light of this observation, the Turkish scenario poses a breeding ground for increases in crime derived from the Syrian's arrival. As a potential explanation, we hypothesize that the existence of a significant local informal sector, humanitarian aid programs targeting refugees via cash transfers (in particular, the ESSN program), plus a palpable threat of refoulement shied refugees away from illegal behaviors.

On the other hand, as Borjas et al. (2010) demonstrate, population influxes may propel natives into criminal activities via worsening overall conditions in the host economy's labor market. Given that Syrians ended up displacing a significant number of native informal workers(see Ceritoglu et al. (2017), Del Carpio and Wagner (2015), and Aksu et al. (2022)), the refugees, in principle, could have sparked an indirect crime increase. However, as Aksu et al. (2022) demonstrate, employment and wages of natives in the formal sector increased with the arrival of Syrian refugees, leaving overall native male employment conditions primarily intact. Such a fact likely suppressed the potential rise in crime among natives.

In this manner, and given the impressive scale and abrupt nature of the phenomenon we study, our results serve to characterize further a regularity found in papers focusing on either more sluggish or less dramatic immigration episodes, namely a negative immigration-crime relationship. More precisely, we conclude that even when it comes to non-economic migrants, the proper balance between expected punishments and job opportunities may serve to curb their incentives to carry out crimes.

Due to data limitations, we cannot empirically test the above hypothesis, let alone provide an estimation of what elements counted the most to produce a negative immigration-crime link. Thus, as more data becomes available, future research may pin down the sensitivity of crime committed by refugees to policy changes. Also importantly, as the Syrian refugee crisis drags on, it will be possible to test whether second-generation immigrants are more crime-prone than the original ones, a result introduced by Morenoff and Astor (2006), Hagan et al. (2008), and Bucerius (2011). Likewise, it will be possible to contribute to a series of papers showing that individuals exposed to extreme violence or criminal cultures are more prone to commit violent crimes themselves (Aliprantis, 2017; Carvalho and Soares, 2016; Couttenier et al., 2019; Damm and Dustmann, 2014; Sviatschi, 2022). Finally, if distinguishing detained criminals' nationality becomes eventually viable, one could test whether the Syrians arrival affected the number of crimes committed by locals, which lies at the center of other papers' analyses (Borjas et al., 2010).

References

Acar, Salih, Levetcan Gultekin, Mustafa Isik, Leyla Kazancik, Mustafa Meydan, Ozsan Mehment, and Feyzettin Yilmaz (2019) "Socio-Economic Development Ranking Research of Districts Sege-2017," The Turkish Ministry of Industry and Technology, https://www.bebka.org.tr/admin/datas/sayfas/89/lce-sege-2017_1598265107.pdf.

Agostinelli, Francesco, Matthias Doepke, Giuseppe Sorrenti, and Fabrizio Zilibotti (2022) "When the great equalizer shuts down: Schools, peers, and parents in pandemic times," *Journal of Public Economics*, 206, 104574, 10.1016/j.jpubeco.2021.104574.

Akgündüz, Yusuf Emre, Marcel van den Berg, and Wolter Hassink (2018) "The impact of the Syrian refugee crisis on firm entry and performance in Turkey," *The World Bank Economic Review*, 32 (1), 19–40.

Akgündüz, Yusuf Emre, Yusuf Kenan Bağır, Seyit Mümin Cılasun, and Murat Güray Kırdar (2022) "Consequences of a Massive Refugee Influx on Firm Performance and Market Structure," IZA Discussion Paper 13953.

Aksu, Ege, Refik Erzan, and Murat Güray Kırdar (2022) "The impact of mass migration of Syrians on the Turkish labor market," *Labour Economics*, 102183.

Alan, Sule, Ceren Baysan, Mert Gumren, and Elif Kubilay (2021a) "Building social cohesion in ethnically mixed schools: An intervention on perspective taking," *The Quarterly Journal of Economics*, 136 (4), 2147–2194.

Alan, Sule, Teodora Boneva, and Seda Ertac (2019) "Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit*," *The Quarterly Journal of Economics*, OCLC: 8005404627.

Alan, Sule and Seda Ertac (2018) "Fostering patience in the classroom: Results from randomized educational intervention," *Journal of Political Economy*, 126 (5), 1865–1911.

Alan, Sule and Elif Kubilay (2023) "Impersonal trust in a Just and Unjust world: Evidence from an educational intervention," *Journal of Development Economics*, 103044.

Alan, Sule, Elif Kubilay, Elif Bodur, and Ipek Mumcu (2021b) "Social Status in Student Networks and Implications for Perceived Social Climate in Schools," 10.2139/ssrn.3855974.

Alan, Sule and Ipek Mumcu (2022) "Nurturing Childhood Curiosity to Enhance Learning: Evidence from a randomized pedagogical intervention," CEPR Discussion Paper no. 17601, 2022, https://cepr.org/publications/dp17601.

Alan, Sule and Betul Turkum (2023) "Disruption to Schooling Impedes the Development of Abstract Reasoning and Theory of Mind in Children,"Technical report, CEPR Discussion Papers.

Aliprantis, Dionissi (2017) "Human capital in the inner city," *Empirical economics*, 53 (3), 1125–1169.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz (2011) "Personality psychology and economics," in *Handbook of the Economics of Education*, 4, 1–181: Elsevier.

Alshoubaki, Wa'ed (2017) *The impact of Syrian refugees on Jordan: A framework for analysis* Ph.D. dissertation, Tennessee State University.

Angrist, Joshua D and Jörn-Steffen Pischke (2014) *Mastering'metrics: The path from cause to effect*: Princeton university press.

Ardington, Cally, Gabrielle Wills, and Janeli Kotze (2021) "COVID-19 learning losses: Early grade reading in South Africa," *International Journal of Educational Development*, 86, 102480.

Aygün, Aysun Hızıroğlu, Murat G Kirdar, Murat Koyuncu, and Quentin Stoeffler (2021) "Keeping Refugee Children in School and Out of Work: Evidence from the World's Largest Humanitarian Cash Transfer Program," IZA Discussion Papers 14513.

Aygün, Aysun, Murat G Kirdar, and Berna Tuncay (2020) "The Effect of Hosting 3.4 Million Refugees on the Health System in Turkey and Infant, Child, and Elderly Mortality among Natives."

Bacher-Hicks, Andrew, Joshua Goodman, and Christine Mulhern (2021) "Inequality in household adaptation to schooling shocks: Covid-induced online learning engagement in real time," *Journal of public economics*, 193, OCLC: 9056383600.

Bagwell, Catherine L, Brooke SG Molina, William E Pelham Jr, and Betsy Hoza (2001) "Attention-deficit hyperactivity disorder and problems in peer relations: Predictions from childhood to adolescence," *Journal of the American Academy of Child & Adolescent Psychiatry*, 40 (11), 1285–1292.

Bailey, Drew H, Greg J Duncan, Richard J Murnane, and Natalie Au Yeung (2021) "Achievement gaps in the wake of COVID-19," *Educational Researcher*, 50 (5), 266–275.

Baker, David P, Paul J Eslinger, Martin Benavides, Ellen Peters, Nathan F Dieckmann, and Juan Leon (2015) "The cognitive impact of the education revolution: A possible cause of the Flynn Effect on population IQ," *Intelligence*, 49, 144–158.

Baker, Scott R (2015) "Effects of immigrant legalization on crime," *American Economic Review*, 105 (5), 210–213.

Baron-Cohen, Simon, Sally Wheelwright, Jacqueline Hill, Yogini Raste, and Ian Plumb (2001) "The "Reading the Mind in the Eyes" Test Revised Version: A Study with Normal Adults, and Adults with Asperger Syndrome or High-functioning Autism," *The Journal of Child Psychology and Psychiatry and Allied Disciplines*, 42 (2), 241–251, 10.1017/S0021963001006643, Publisher: Cambridge University Press.

Barro, Robert J (1991) "Economic growth in a cross section of countries," *The quarterly journal of economics*, 106 (2), 407–443.

Baumrind, Diana (1966) "Effects of authoritative parental control on child behavior," *Child development*, 887–907.

Becker, Gary S (1968) "Crime and punishment: An economic approach," *Journal of political economy*, 76 (2), 169–217.

Bell, Brian, Francesco Fasani, and Stephen Machin (2013) "Crime and immigration: Evidence from large immigrant waves," *Review of Economics and statistics*, 95 (4), 1278–1290.

Berthelon, Matias, Eric Bettinger, Diana I Kruger, and Alejandro Montecinos-Pearce (2019) "The structure of peers: The impact of peer networks on academic achievement," *Research in Higher Education*, 60 (7), 931–959.

Betthäuser, Bastian A, Anders M Bach-Mortensen, and Per Engzell (2023) "A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic," *Nature Human Behaviour*, 1–11.

Bietenbeck, Jan (2020) "The long-term impacts of low-achieving childhood peers: evidence from Project STAR," *Journal of the European Economic Association*, 18 (1), 392–426.

Black, Maureen M, Susan P Walker, Lia CH Fernald et al. (2017) "Early childhood development coming of age: science through the life course," *The Lancet*, 389 (10064), 77–90.

Borjas, George J, Jeffrey Grogger, and Gordon H Hanson (2010) "Immigration and the economic status of African-American men," *Economica*, 77 (306), 255–282.

Bossavie, Laurent, Ayşenur Acar Erdoğan, and Mattia Makovec (2019) "The Impact of the Minimum Wage on Firm Destruction, Employment and Informality."

Boubtane, Ekrame, Dramane Coulibaly, and Christophe Rault (2013) "Immigration, growth, and unemployment: Panel VAR evidence from OECD countries," *Labour*, 27 (4), 399–420.

Bratsberg, Bernt and Ole Rogeberg (2018) "Flynn effect and its reversal are both environmentally caused," *Proceedings of the National Academy of Sciences*, 115 (26), 6674–6678.

Bucerius, Sandra M (2011) "Immigrants and crime," *The Oxford handbook of crime and criminal justice*, 385–419.

Calvó-Armengol, Antoni, Eleonora Patacchini, and Yves Zenou (2009) "Peer effects and social networks in education," *The review of economic studies*, 76 (4), 1239–1267.

Cappelen, Alexander, John List, Anya Samek, and Bertil Tungodden (2020) "The effect of early-childhood education on social preferences," *Journal of Political Economy*, 128 (7), 2739–2758.

Caputi, Marcella, Serena Lecce, Adriano Pagnin, and Robin Banerjee (2012) "Longitudinal effects of theory of mind on later peer relations: the role of prosocial behavior.," *Developmental psychology*, 48 (1), 257.

Carlo, Gustavo, Rebecca MB White, Cara Streit, George P Knight, and Katharine H Zeiders (2018) "Longitudinal relations among parenting styles, prosocial behaviors, and academic outcomes in US Mexican adolescents," *Child development*, 89 (2), 577–592.

Caro, Luis Pinedo (2020) "Syrian Refugees in the Turkish Labour Market: A Socio-Economic Analysis," *Sosyoekonomi*, 28 (46), 51–74.

Carvalho, Leandro S and Rodrigo R Soares (2016) "Living on the edge: Youth entry, career and exit in drug-selling gangs," *Journal of Economic Behavior & Organization*, 121, 77–98.

Cengiz, Mahmut (2017) "Amped in Ankara: Drug trade and drug policy in Turkey from the 1950s through today," Brookings Institute.

Ceritoglu, Evren, H Yunculer, Huzeyfe Torun, and Semih Tumen (2017) "The impact of Syrian refugees on natives' labor market outcomes in Turkey: evidence from a quasi-experimental design," *IZA Journal of Labor Policy*, 6 (1), 1–28.

Chetty, John N Raj, Friedman and Michael Team The Opportunity Insights National Bureau of Economic Research Nathaniel Hendren, Stepner (2020) *How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data*, Cambridge, Mass.: National Bureau of Economic Research, http://papers.nber.org/papers/w27431, OCLC: 1178732151.

Contini, Dalit, Maria L Di Tommaso, Caterina Muratori, Daniela Piazzalunga, and Lucia Schiavon (2021) "The COVID-19 pandemic and school closure: learning loss in mathematics in primary education."

Couttenier, Mathieu, Veronica Petrencu, Dominic Rohner, and Mathias Thoenig (2019) "The violent legacy of conflict: evidence on asylum seekers, crime, and public policy in Switzerland," *American Economic Review*, 109 (12), 4378–4425.

Cunha, Flavio and James Heckman (2007) "The technology of skill formation," *American economic review*, 97 (2), 31–47.

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach (2010) "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 78 (3), 883–931, 10.3982/ECTA6551, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA6551.

Daley, Tamara C, Shannon E Whaley, Marian D Sigman, Michael P Espinosa, and Charlotte Neumann (2003) "IQ on the rise: The Flynn effect in rural Kenyan children," *Psychological science*, 14 (3), 215–219.

Damm, Anna Piil and Christian Dustmann (2014) "Does growing up in a high crime neighborhood affect youth criminal behavior?" *American Economic Review*, 104 (6), 1806–1832.

Dayioglu, Meltem, Murat G Kirdar, and Īsmet Koç (2021) "The Making of a Lost Generation: Child Labor among Syrian Refugees in Turkey," IZA Discussion Paper 14466.

Del Carpio, Ximena V and Mathis C Wagner (2015) "The impact of Syrian refugees on the Turkish labor market," *World Bank policy research working paper* (7402).

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde (2010) "Are risk aversion and impatience related to cognitive ability?" *American Economic Review*, 100 (3), 1238–1260.

Dorn, Emma, Bryan Hancock, Jimmy Sarakatsannis, and Ellen Viruleg (2020) "COVID-19 and learning loss—disparities grow and students need help," *McKinsey & Company, December*, 8, 6–7.

Dornbusch, Sanford M, Philip L Ritter, P Herbert Leiderman, Donald F Roberts, and Michael J Fraleigh (1987) "The relation of parenting style to adolescent school performance," *Child development*, 1244–1257.

Dorris, Liam, David Young, Jill Barlow, Karl Byrne, and Robin Hoyle (2022) "Cognitive empathy across the lifespan," *Developmental Medicine & Child Neurology*, 64 (12), 1524–1531.

Doyle, Orla, Colm P Harmon, James J Heckman, and Richard E Tremblay (2009) "Investing in early human development: timing and economic efficiency," *Economics & Human Biology*, 7 (1), 1–6.

Duckworth, Angela et al. (2016) *Grit: The power of passion and perseverance*, 234: Scribner New York, NY.

Duckworth, Angela Lee and Patrick D Quinn (2009) "Development and validation of the Short Grit Scale (GRIT–S)," *Journal of personality assessment*, 91 (2), 166–174.

Duflo, Esther, Pascaline Dupas, and Michael Kremer (2011) "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya," *American Economic Review*, 101 (5), 1739–1774, 10.1257/aer.101.5.1739.

Dumont, Jean-Christophe and Stefano Scarpetta (2015) "Is this humanitarian migration crisis different," *Migration Policy Debates*, 9, 1–15.

Durkheim, Emile (2005) *Suicide: A study in sociology*: Routledge.

Elgin, Ceyhun and Oguz Oztunali (2014) "Institutions, informal economy, and economic development," *Emerging Markets Finance and Trade*, 50 (4), 145–162.

Engzell, Per, Arun Frey, and Mark D. Verhagen (2021) "Learning loss due to school closures during the COVID-19 pandemic," *PNAS*, 118 (17), 10.1073/pnas.2022376118, Publisher: National Academy of Sciences Section: Social Sciences.

Erdogan, M Murat (2014) "Perceptions of Syrians in Turkey.," *Insight Turkey*, 16 (4).

Erdogan, Murat (2014) "Syrians in Turkey: Social acceptance and integration research," *Migration and Politics Research Centre, Hacettepe University*.

Errighi, L and J Griesse (2016) “The Syrian refugee crisis: Labour market implications in Jordan and Lebanon (No. 029),” *Directorate General Economic and Financial Affairs (DG ECFIN), European Commission*.

Eryurt, MA (2017) “Türkiye’ye Göç: Demografik Durum ve Etkiler,” *Hacettepe University, Institute of Population Studies, PowerPoint Slides*.

Felbermayr, Gabriel J, Sanne Hiller, and Davide Sala (2010) “Does immigration boost per capita income?” *Economics Letters*, 107 (2), 177–179.

Feld, Jan and Ulf Zölitz (2017) “Understanding peer effects: On the nature, estimation, and channels of peer effects,” *Journal of Labor Economics*, 35 (2), 387–428.

Feridun, Mete et al. (2005) “Investigating the economic impact of immigration on the host country: the case of Norway,” *Prague Economic Papers*, 4, 350–362.

Flynn, James (2012) *Are we getting smarter?: Rising IQ in the twenty-first century*: Cambridge University Press.

Flynn, James R (2000) “IQ gains, WISC subtests and£ uid g: g theory and the relevance of Spearman’s hypothesis to race,” *The nature of intelligence*, 202.

Forrester, Andrew C, Benjamin Powell, Alex Nowrasteh, and Michelangelo Landgrave (2019) “Do immigrants import terrorism?” *Journal of Economic Behavior & Organization*, 166, 529–543.

Van der Graaff, Jolien, Susan Branje, Minet De Wied, Skyler Hawk, Pol Van Lier, and Wim Meeus (2014) “Perspective taking and empathic concern in adolescence: gender differences in developmental changes.,” *Developmental psychology*, 50 (3), 881.

Van der Graaff, Jolien, Gustavo Carlo, Elisabetta Crocetti, Hans M Koot, and Susan Branje (2018) “Prosocial behavior in adolescence: Gender differences in development and links with empathy,” *Journal of youth and adolescence*, 47 (5), 1086–1099.

Gradstein, Mark and Moshe Justman (2002) “Education, social cohesion, and economic growth,” *American Economic Review*, 92 (4), 1192–1204.

Grewenig, Elisabeth, Philipp Lergetporer, Katharina Werner, Ludger Woessmann, and Larissa Zierow (2021) “COVID-19 and educational inequality: How school closures affect low-and high-achieving students,” *European economic review*, 140, 103920.

Hagan, John, Ron Levi, and Ronit Dinovitzer (2008) “The symbolic violence of the crime-immigration nexus: Migrant mythologies in the Americas,” *Criminology & Public Policy*, 7(1), 95–112.

Hahn, Youjin, Asad Islam, Eleonora Patacchini, and Yves Zenou (2015) “Teams, Organization and Education Outcomes: Evidence from a field experiment in Bangladesh,” *Organization and Education Outcomes: Evidence from a Field Experiment in Bangladesh (May 2015)*.

Hanushek, Eric A. (2020) “Chapter 13 - Education production functions,” in Bradley, Steve and Colin Green eds. *The Economics of Education (Second Edition)*, 161–170: Academic Press, 10.1016/B978-0-12-815391-8.00013-6.

Hanushek, Eric A.. and Ludger Woessmann (2020) *The economic impacts of learning losses*, https://doi.org/10.1787/21908d74-en, OCLC: 1236209205.

Heckman, James J, Jora Stixrud, and Sergio Urzua (2006) “The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior,” *Journal of Labor economics*, 24 (3), 411–482.

Hevia, Felipe J, Samana Vergara-Lope, Anabel Velásquez-Durán, and David Calderón (2022) “Estimation of the fundamental learning loss and learning poverty related to COVID-19 pandemic in Mexico,” *International Journal of Educational Development*, 88, 102515.

Hughes, Claire and Sue Leekam (2004) "What are the links between theory of mind and social relations? Review, reflections and new directions for studies of typical and atypical development," *Social development*, 13 (4), 590–619.

ILO (2014) "Assessment of the impact of Syrian refugees in Lebanon and their employment profile 2013."

Jackson, Matthew O. (2011) "Chapter 12 - An Overview of Social Networks and Economic Applications*," in Benhabib, Jess, Alberto Bisin, and Matthew O. Jackson eds. *Handbook of Social Economics*, 1, 511–585: North-Holland, 10.1016/B978-0-444-53187-2.00012-7.

Jaitman, Laura and Stephen Machin (2013) "Crime and immigration: new evidence from England and Wales," *IZA Journal of Migration*, 2, 1–23.

Jeffrey, Frankel and David Romer (1999) "Does trade cause growth?" *American Economic Review*, 83 (3), 379–99.

Juchem Neto, JP, JCR Claeyssen, Daniele Ritelli, and Giovanni Mingari Scarpello (2009) "Migration in a Solow Growth Model," *Available at SSRN 1578565*.

Juvonen, Jaana, Guadalupe Espinoza, and Casey Knifsend (2012) "The role of peer relationships in student academic and extracurricular engagement," *Handbook of research on student engagement*, 387–401.

Kane, Tim and Zach Rutledge (2018) "Immigration and economic performance across fifty US states from 1980-2015," *Hoover Institution. Economics Working Paper*, 18112.

Karaçay, Ayşem Biriz (2017) "Shifting human smuggling routes along Turkey's borders," *Turkish Policy Quarterly*, 15 (4), 97–108.

Kashdan, Todd B, David J Disabato, Fallon R Goodman, and Patrick E McKnight (2020) "The Five-Dimensional Curiosity Scale Revised (5DCR): Briefer subscales while separating overt and covert social curiosity," *Personality and Individual Differences*, 157, 109836.

Kashdan, Todd B, Matthew W Gallagher, Paul J Silvia, Beate P Winterstein, William E Breen, Daniel Terhar, and Michael F Steger (2009) "The curiosity and exploration inventory-II: Development, factor structure, and psychometrics," *Journal of research in personality*, 43 (6), 987–998.

Kaufmann, Dagmar, Ellis Gesten, Raymond C Santa Lucia, Octavio Salcedo, Gianna Rendina-Gobioff, and Ray Gadd (2000) "The relationship between parenting style and children's adjustment: The parents' perspective," *Journal of Child and family studies*, 9, 231–245.

Khoudour, David and Lisa Andersson (2017) "Assessing the contribution of refugees to the development of their host countries," *Organisation for Economic Co-operation and Development Development Center*.

Kiessling, Lukas and Jonathan Norris (2020) "The long-run effects of peers on mental health," *MPI Collective Goods Discussion Paper* (2020/12).

Kindermann, Thomas A (2016) "Peer group influences on students' academic motivation," in *Handbook of social influences in school contexts*, 31–47: Routledge.

Kırdar, Murat G, Ivan Lopez Cruz, and Betül Türküm (2022) "The effect of 3.6 million refugees on crime," *Journal of Economic Behavior & Organization*, 194, 568–582.

Kochenderfer-Ladd, Becky and Gary W Ladd (2019) "Peer relationships and social competence in early childhood," in *Handbook of research on the education of young children*, 32–42: Routledge.

Kogan, Vladimir and Stéphane Lavertu (2021) "How the covid-19 pandemic affected student learning in ohio: Analysis of spring 2021 ohio state tests," *Ohio State University, John Glenn College of Public Affairs*, 2021–10.

Kong, Chuibin and Fakhra Yasmin (2022) "Impact of Parenting Style on Early Childhood Learning: Mediating Role of Parental Self-Efficacy," *Frontiers in Psychology*, 13.

Kuhfeld, Megan, James Soland, Beth Tarasawa, Angela Johnson, Erik Ruzek, and Jing Liu (2020) "Projecting the Potential Impact of COVID-19 School Closures on Academic Achievement," *Educational Researcher*, 49 (8), 549–565, OCLC: 8892782277.

Ladd, Gary W, Sarah L Herald-Brown, and Karen P Kochel (2009) "Peers and motivation.."

Lavy, Victor and Edith Sand (2019) "The Effect of Social Networks on Students' Academic and Non-cognitive Behavioural Outcomes: Evidence from Conditional Random Assignment of Friends in School," *The Economic Journal*, 129 (617), 439–480, 10.1111/ecoj.12582.

Lichand, Guilherme, Carlos Alberto Doria, Onicio Leal-Neto, and João Paulo Cossi Fernandes (2022) "The impacts of remote learning in secondary education during the pandemic in Brazil," *Nature Human Behaviour*, 6 (8), 1079–1086.

Liu, Jianghong, Hua Yang, Linda Li, Tunong Chen, and Richard Lynn (2012) "An increase of intelligence measured by the WPPSI in China, 1984–2006," *Intelligence*, 40 (2), 139–144.

Lleras-Muney, Adriana, Matthew Miller, Shuyang Sheng, and Veronica T. Sovero (2020) "Party On: The Labor Market Returns to Social Networks and Socializing," Working Paper 27337, National Bureau of Economic Research, 10.3386/w27337, Series: Working Paper Series.

Loeber, R., Bruinsma Farrington, D., and D. G., Weisburd (2014) "Age-Crime Curve," *Encyclopedia of Criminology and Criminal Justice*.

MacDonald, John M, John R Hipp, and Charlotte Gill (2013) "The effects of immigrant concentration on changes in neighborhood crime rates," *Journal of Quantitative Criminology*, 29, 191–215.

Machin, Stephen J and Brian Bell (2013) "Immigrant Enclaves and Crime," *Journal of Regional Science*, 53 (1), 118–141.

Maghularia, Rita and Silke Ubelmesser (2019) "Do immigrants affect crime? Evidence from panel data for Germany," CESifo Working Paper 7696.

Maldonado, Joana Elisa and Kristof De Witte (2021) "The effect of school closures on standardised student test outcomes," *British Educational Research Journal*, OCLC: 9168223727.

Mankiw, N Gregory, David Romer, and David N Weil (1992) "A contribution to the empirics of economic growth," *The quarterly journal of economics*, 107 (2), 407–437.

Manning, Maryann and Janice Patterson (2006) "LIFETIME EFFECTS: The High/Scope Perry preschool study through age 40," *Childhood Education*, 83 (2), 121.

Mariani, Fabio and Marion Mercier (2021) "Immigration and crime: The role of self-selection and institutions," *Journal of Economic Behavior & Organization*, 185, 538–564.

Sala-i Martin, RJ Barro X (1995) "Economic Growth McGraw-Hill New York."

Mastrobuoni, Giovanni and Paolo Pinotti (2015) "Legal status and the criminal activity of immigrants," *American Economic Journal: Applied Economics*, 7 (2), 175–206.

Maszk, Patricia, Nancy Eisenberg, and Ivanna K Guthrie (1999) "Relations of children's social status to their emotionality and regulation: A short-term longitudinal study," *Merrill-Palmer Quarterly (1982-)*, 468–492.

Morenoff, Jeffrey D. and Avraham Astor (2006) *Chapter 3 Immigrant Assimilation and Crime: Generational Differences in Youth Violence in Chicago*, 36–63, New York, USA: New York University Press, doi:10.18574/nyu/9780814759530.003.0006.

Morley, Bruce (2006) "Causality between economic growth and immigration: An ARDL bounds testing approach," *Economics Letters*, 90 (1), 72–76.

Must, Olev, Jan te Nijenhuis, Aasa Must, and Annelies EM van Vianen (2009) "Comparability of IQ scores over time," *Intelligence*, 37 (1), 25–33.

Nowrasteh, Alex, Andrew C Forrester, and Cole Blondin (2020) "How mass immigration affects countries with weak economic institutions: A natural experiment in Jordan," *The World Bank Economic Review*, 34 (2), 533–549.

Oytun, Orhan and S Senyücel Gündoğar (2015) "Suriyeli sığınmacıların Türkiye'ye etkileri raporu," *Orsam-Tesev Rapor* (195), 1–40.

Ozden, Caglar, Mauro Testaverde, and Mathis Wagner (2018) "How and why does immigration affect crime? Evidence from Malaysia," *The World Bank Economic Review*, 32 (1), 183–202.

Parker, Jeffrey G, Kenneth H Rubin, Stephen A Erath, Julie C Wojslawowicz, and Allison A Buskirk (2015) "Peer relationships, child development, and adjustment: A developmental psychopathology perspective," *Developmental psychopathology: Volume One: Theory and method*, 419–493.

Parolin, Zachary and Emma K Lee (2021) "Large socio-economic, geographic and demographic disparities exist in exposure to school closures," *Nature human behaviour*, 5 (4), 522–528.

Paulson, Sharon E (1994) "Relations of parenting style and parental involvement with ninth-grade students' achievement," *The Journal of Early Adolescence*, 14 (2), 250–267.

Perez-Arce, Francisco (2017) "The effect of education on time preferences," *Economics of Education Review*, 56, 52–64.

Peterson, Candida, Virginia Slaughter, Chris Moore, and Henry M Wellman (2016) "Peer social skills and theory of mind in children with autism, deafness, or typical development.," *Developmental psychology*, 52 (1), 46.

Pind, Jörgen, Eyrún K Gunnarsdóttir, and Hinrik S Jóhannesson (2003) "Raven's Standard Progressive Matrices: new school age norms and a study of the test's validity," *Personality and Individual Differences*, 34 (3), 375–386.

Piopiunik, Marc and Jens Ruhose (2017) "Immigration, regional conditions, and crime: Evidence from an allocation policy in Germany," *European Economic Review*, 92, 258–282.

Portt, Erika, Staci Person, Brandi Person, Edward Rawana, and Keith Brownlee (2020) "Empathy and positive aspects of adolescent peer relationships: A scoping review," *Journal of Child and Family Studies*, 29, 2416–2433.

Powell, Benjamin, Jeff R Clark, and Alex Nowrasteh (2017) "Does mass immigration destroy institutions? 1990s Israel as a natural experiment," *Journal of Economic Behavior & Organization*, 141, 83–95.

Radziszewska, Barbara, Jean L Richardson, Clyde W Dent, and Brain R Flay (1996) "Parenting style and adolescent depressive symptoms, smoking, and academic achievement: Ethnic, gender, and SES differences," *Journal of behavioral medicine*, 19, 289–305.

Raven, John, J. C Raven, and John H Court (2000) *Manual for Raven's progressive matrices and vocabulary scales*, Oxford: OPP Ltd, OCLC: 1158423515.

Rönnlund, Michael and Lars-Göran Nilsson (2009) "Flynn effects on sub-factors of episodic and semantic memory: Parallel gains over time and the same set of determining factors," *Neuropsychologia*, 47 (11), 2174–2180.

Sacerdote, Bruce (2001) "Peer Effects with Random Assignment: Results for Dartmouth Roommates*," *The Quarterly Journal of Economics*, 116 (2), 681–704, 10.1162/00335530151144131.

Sampson, Robert J (2008) "Rethinking crime and immigration," *Contexts*, 7 (1), 28–33.

Simon, Rita J and Keri W Sikich (2007) "Public attitudes toward immigrants and immigration policies across seven nations," *International migration review*, 41 (4), 956–962.

Simpson, Gerry (2019) "Repatriation of Syrians in Turkey needs EU action," *Human Rights*.

Sleddens, Ester FC, Stef PJ Kremers, Nanne K De Vries, and Carel Thijs (2013) "Measuring child temperament: Validation of a 3-item Temperament Measure and 13-item Impulsivity Scale," *European Journal of Developmental Psychology*, 10 (3), 392–401.

Steinberg, Laurence et al. (1990) "Authoritative parenting and adolescent adjustment across varied ecological niches.."

Steinberg, Laurence, Susie D Lamborn, Sanford M Dornbusch, and Nancy Darling (1992) "Impact of parenting practices on adolescent achievement: Authoritative parenting, school involvement, and encouragement to succeed," *Child development*, 63 (5), 1266–1281.

Stephens Jr, Melvin and Dou-Yan Yang (2014) "Compulsory education and the benefits of schooling," *American Economic Review*, 104 (6), 1777–92.

Stowell, Jacob I, Steven F Messner, Kelly F McGeever, and Lawrence E Raffalovich (2009) "Immigration and the recent violent crime drop in the United States: A pooled, cross-sectional time-series analysis of metropolitan areas," *Criminology*, 47 (3), 889–928.

Sviatschi, Maria Micaela (2022) "Making a narco: Childhood exposure to illegal labor markets and criminal life paths," *Econometrica*, 90 (4), 1835–1878.

Teasdale, Thomas W and David R Owen (2000) "Forty-year secular trends in cognitive abilties," *Intelligence*, 28 (2), 115–120.

Tumen, Semih (2016) "The economic impact of Syrian refugees on host countries: Quasi-experimental evidence from Turkey," *American Economic Review*, 106 (5), 456–460.

Üstübici, Ayşen (2019) "The impact of externalized migration governance on Turkey: technocratic migration governance and the production of differentiated legal status," *Comparative Migration Studies*, 7 (1), 1–18.

Vegas, Emiliana (2022) "COVID-19's impact on learning losses and learning inequality in Colombia," *Center for Universal Ed-598 ucation at Brookings*, 599.

Wang, Ming-Te and Jacquelynne S Eccles (2013) "School context, achievement motivation, and academic engagement: A longitudinal study of school engagement using a multidimensional perspective," *Learning and Instruction*, 28, 12–23.

Watts, Duncan J. and Steven H. Strogatz (1998) "Collective dynamics of 'small-world' networks," *Nature*, 393 (6684), 440–442, 10.1038/30918, Number: 6684 Publisher: Nature Publishing Group.

Wentzel, Kathryn R (2017) "Peer relationships, motivation, and academic performance at school."

Werner, Katharina and Ludger Woessmann (2021) "The legacy of covid-19 in education."

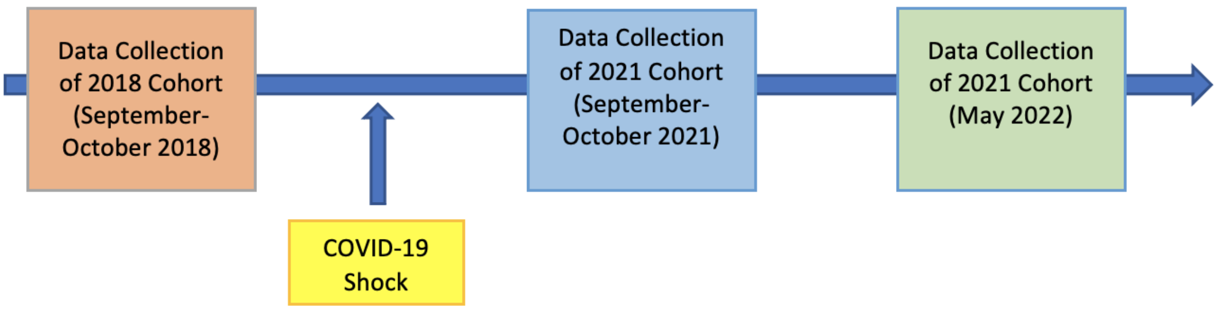
Yildiz, Ayselin (2017) "Perception of 'smuggling business' and decision making processes of migrants," *International Migration Organization*.

A

Appendix to Chapter 1

A.1 Timeline of Data Collection

Figure A1 Timeline



A.2 Survey Instrument for Eliciting Students' Social Networks

	1	2	3
My best friends in the class			
Classmates whom I academically support			
Classmates who support me academically			
Classmates whom I emotionally support			
Classmates who support me emotionally			

Figure A2 Network Elicitation Templates

A.3 Description of Social Network Measures

A network consists of nodes and links between these nodes. Such a network can be characterized by an adjacency matrix which will describe whether there is a link between any two node combinations.

Networks can be divided in two categories depending on the directionality of the links between nodes. If links in a network are always reciprocal, then we consider an *undirected network*. However, if links in a network are allowed to be non-reciprocal, we consider a *directed network*.

For the purposes of our study, each node will represent a student. Assume that we have n students. If student i nominates student j in their network, a link from student i to student j will be formed and the corresponding cell in the adjacency matrix A will be 1 (i.e., $A_{ij} = 1$). By the nature of our data, the networks that we construct are directed networks as we allow for student i to nominate student j without requiring student j to nominate student i. In other words, if $A_{ij} = 1$, A_{ji} does not need to be equal to 1.

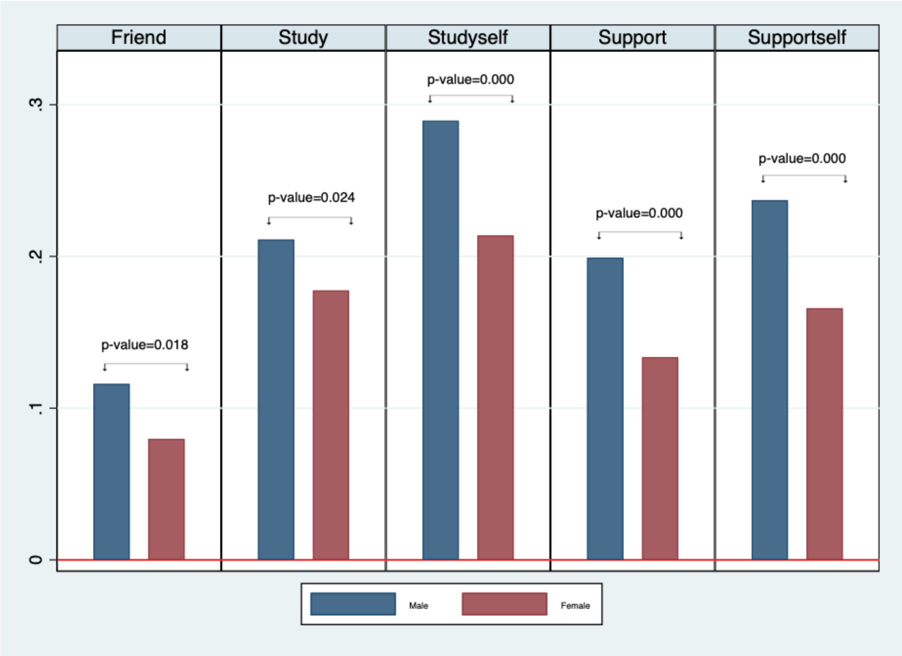
Finally, our surveys do not include any questions regarding the intensity of friendships between students, therefore the networks that we construct are *unweighted*, meaning that corresponding adjacency matrices only include zeros and ones.

- **Isolates**: This variable is based on the nominations that a student received for a given network type. It is a binary variable taking the value 0 if the student received any nominations, while taking value 1 if the student did not receive any nominations. This variable was defined this way in Alan et al. (2021b).

- **In-degree Centrality**: This variable measures how many nominations a student received from her classmates.
- **Betweenness**: It captures the idea that important nodes are important for connecting other nodes among each other. The betweenness centrality of a node is defined as the number of shortest paths among all other nodes that pass through this node. Nodes with high betweenness centrality are intermediaries who matter a lot for the connections between other nodes. (Grund, Thomas U. (2015))
- **Clustering**: The local clustering coefficient of node i is defined as the proportion of links between the vertices within its neighbourhood divided by the number of links that could possibly exist between them Watts and Strogatz (1998). Network-level measure for clustering coefficient is the overall clustering coefficient. It counts the number of closed triplets and divides it by the number of connected triplets. (Grund, Thomas U. (2015))
- **Reciprocity**: This is a classroom-level variable that measures the fraction of reciprocated (mutual) ties to all ties in a given classroom.

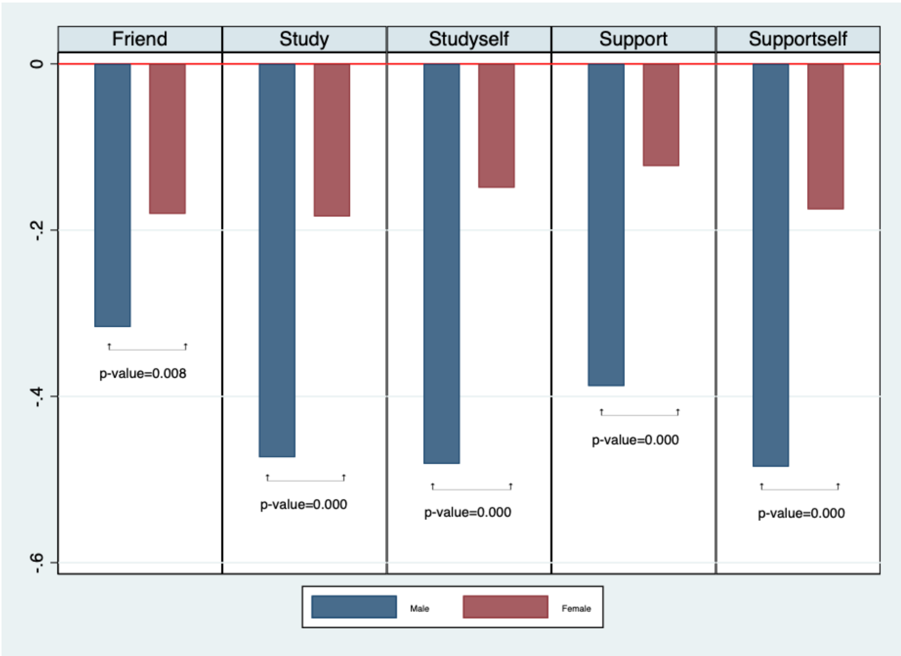
A.4 Heterogeneity Analysis

Figure A3 Heterogeneity of Gender in treatment effect: Isolate



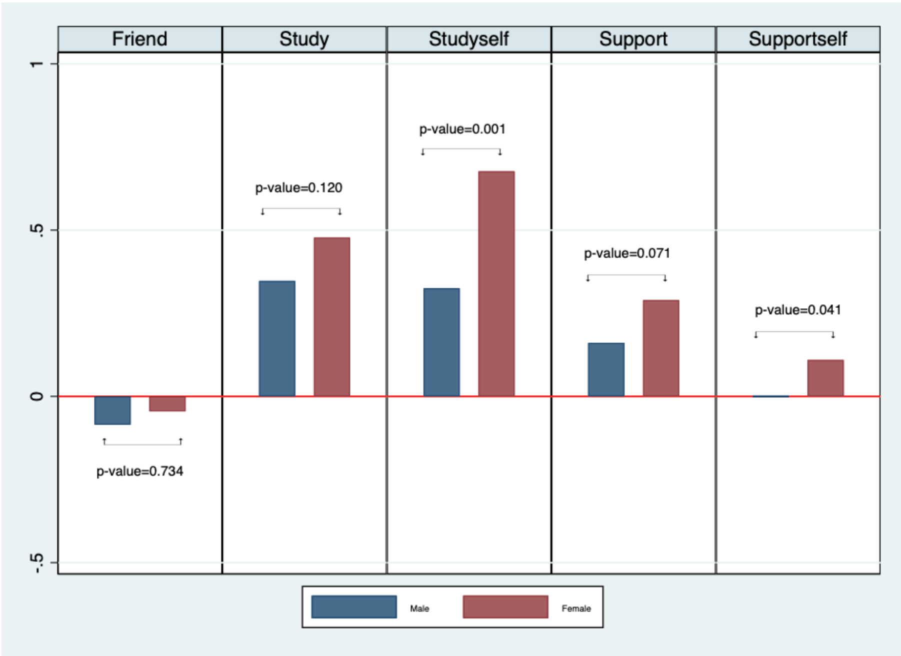
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for male and female students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A4 Heterogeneity of Gender in treatment effect: In-degree ties



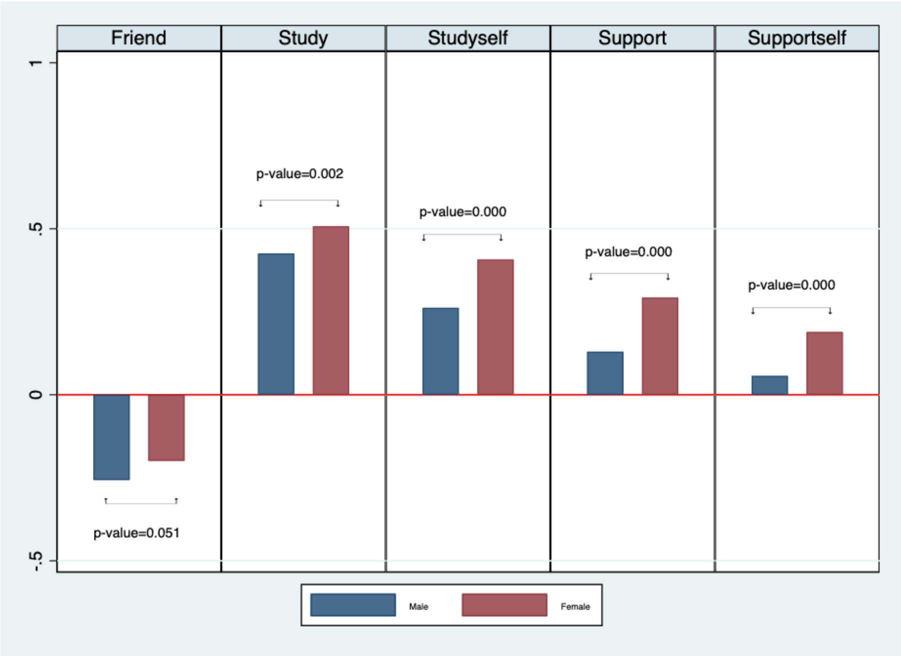
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for male and female students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A5 Heterogeneity of Gender in treatment effect: Betweenness



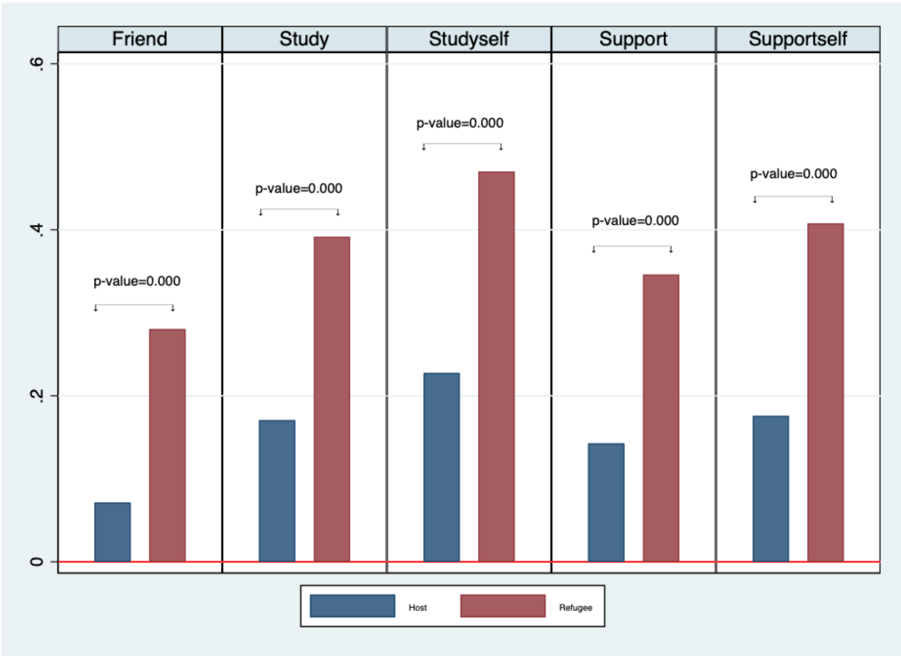
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for male and female students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A6 Heterogeneity of Gender in treatment effect: Clustering



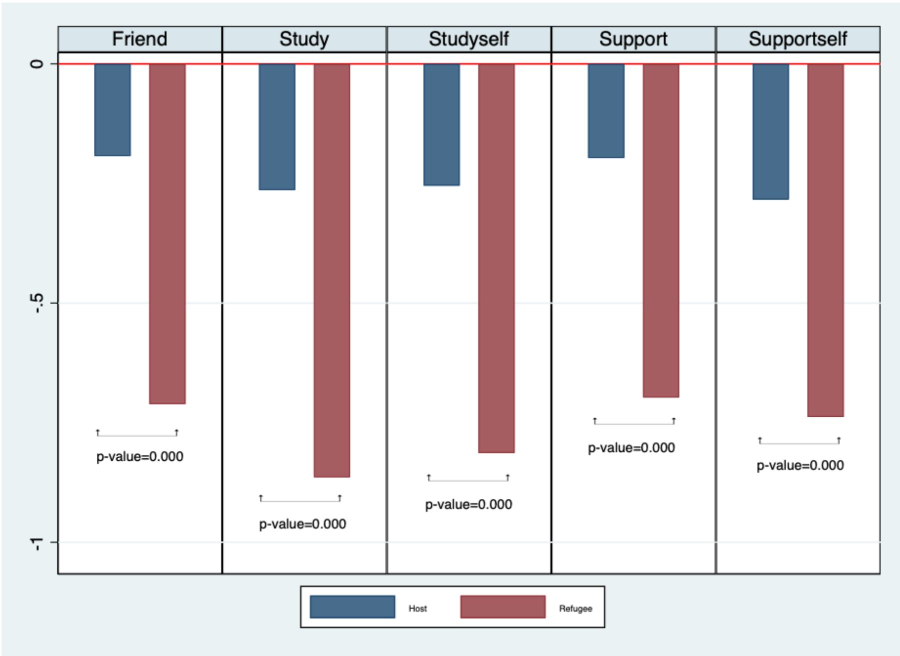
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for male and female students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A7 Heterogeneity of Refugee status in treatment effect: Isolate



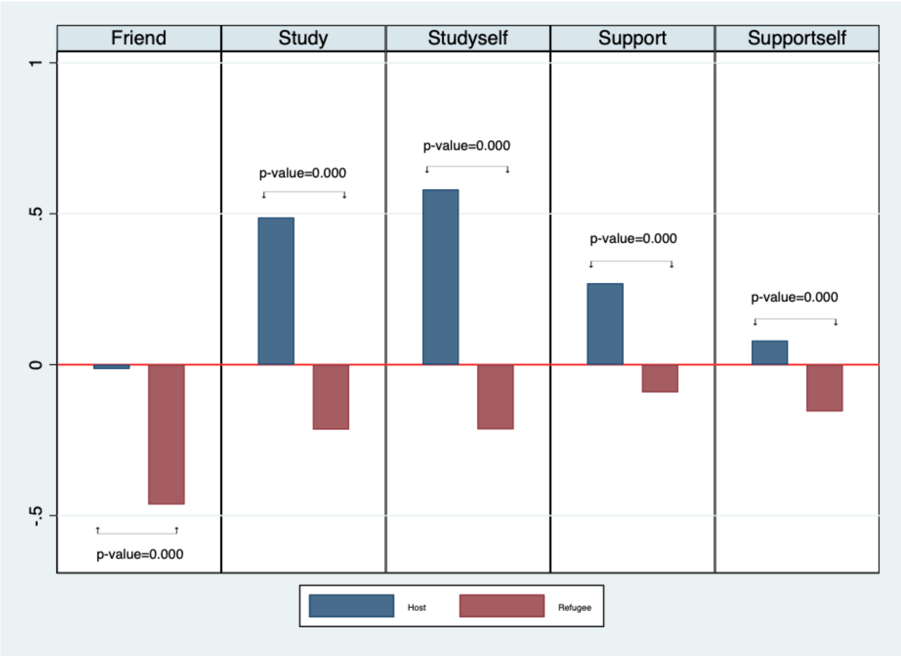
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for host and refugee students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A8 Heterogeneity of Refugee status in treatment effect: In-degree ties



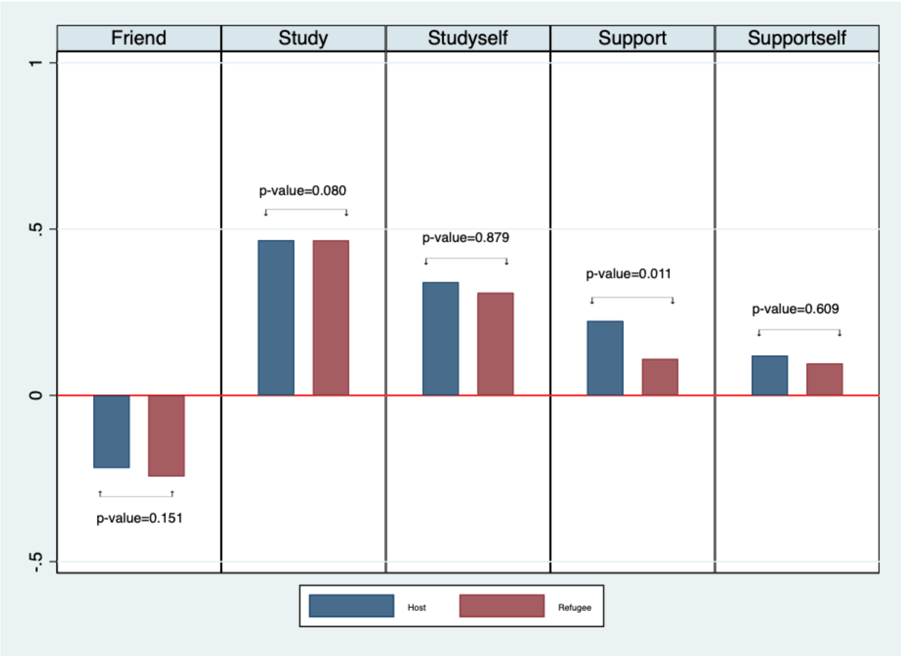
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for host and refugee students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A9 Heterogeneity of Refugee status in treatment effect: Betweenness



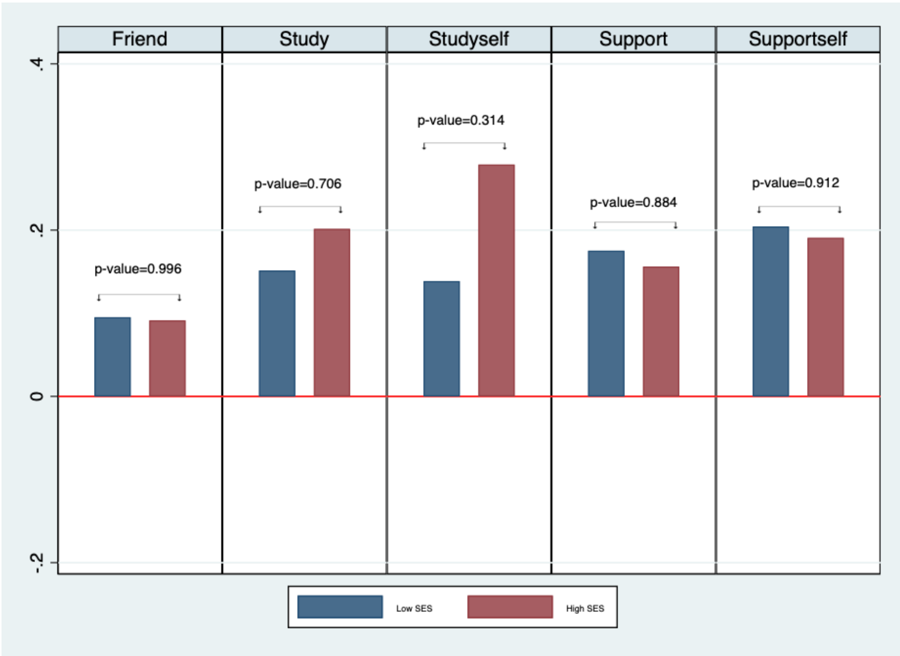
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for host and refugee students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A10 Heterogeneity of Refugee status in treatment effect: Clustering



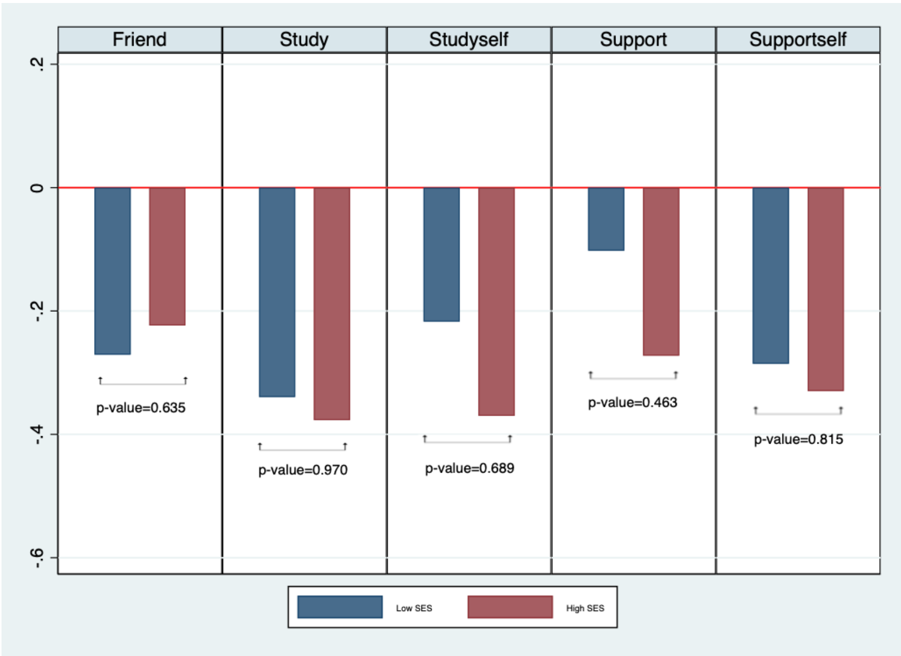
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from OLS estimations that are run separately for host and refugee students. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. P-values, given in each column for each network type, describe the significance of the difference in coefficients.

Figure A11 Heterogeneity of SES in treatment effect: Isolate



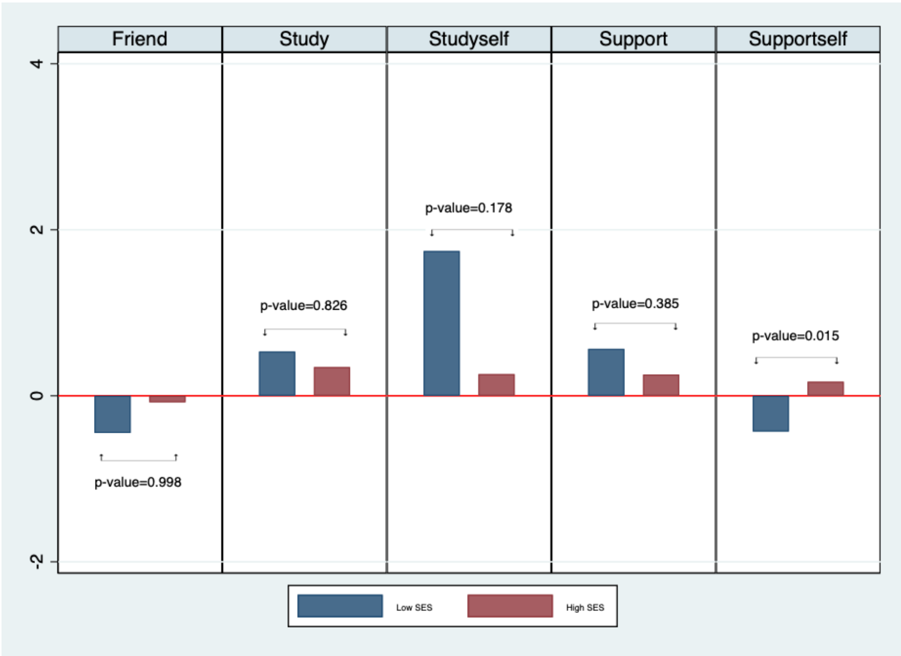
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from separate OLS estimations conducted for students from low SES and high SES. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. The p-values provided in each column for each network type indicate the significance of the difference in coefficients.

Figure A12 Heterogeneity of SES in treatment effect: In-degree ties



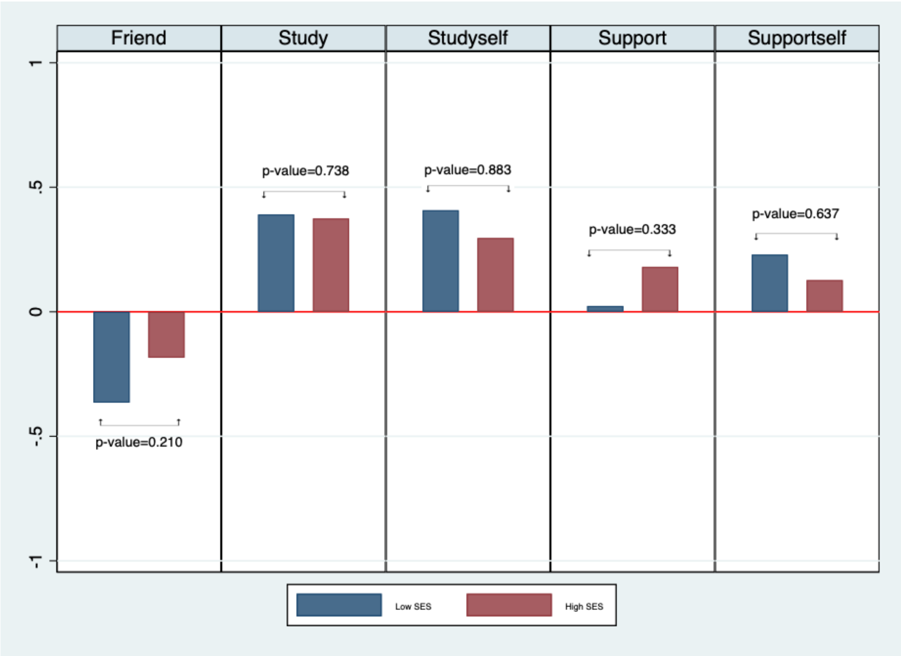
Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from separate OLS estimations conducted for students from low SES and high SES. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. The p-values provided in each column for each network type indicate the significance of the difference in coefficients.

Figure A13 Heterogeneity of SES in treatment effect: Betweenness



Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from separate OLS estimations conducted for students from low SES and high SES. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. The p-values provided in each column for each network type indicate the significance of the difference in coefficients.

Figure A14 Heterogeneity of SES in treatment effect: Clustering



Note: Each column represents a different network type for the outcome of interest as stated in the column title. Within each column, reported results are from separate OLS estimations conducted for students from low SES and high SES. All regressions use fully specified models which control for school-fixed effects, student, teacher, and classroom characteristics. The p-values provided in each column for each network type indicate the significance of the difference in coefficients.

A.5 Additional Tables on Mechanism

	Cognitive Empathy	Emotional Empathy	Impulsivity
COVID	-0.086***	-0.417***	0.278***
	(0.03)	(0.03)	(0.03)
N	9353	8688	8296
R-Squared	0.077	0.067	0.047

Table A.1 Effect of COVID-19 on Sociocognitive and Socioemotional Skills

Note: Reported results are from OLS estimations. Outcome variables are standardized to have a mean of 0 and a standard deviation of 1 for 2018. All regressions control for school-fixed effects. Standard errors, given in parentheses, are clustered at the school level. *, **, or *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Table A.2 Associations between Social Network Measures and Social Skills

	Friendship	Academic support		Emotional support	
		Out	In	Out	In
Panel 1: Isolates					
Cognitive Empathy	-0.024***	-0.016***	-0.028***	-0.014***	-0.023***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Empathetic Concern	-0.010**	-0.011**	-0.012**	-0.013***	-0.018***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Impulsivity	0.004	0.013***	0.021***	0.011***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	8122	8122	8122	8122	8122
R-Squared	0.042	0.093	0.128	0.076	0.094
Panel 2: In-degree ties					
Cognitive Empathy	0.166***	0.085***	0.125***	0.126***	0.111***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Empathetic Concern	0.130***	0.067***	0.076***	0.073***	0.110***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Impulsivity	-0.084***	-0.076***	-0.107***	-0.085***	-0.071***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	8086	8086	8086	8086	8086
R-Squared	0.047	0.048	0.060	0.044	0.055

Note: Reported results are from OLS estimations. All regressions control for school-fixed effects. Standard errors, given in parentheses, are clustered at the school level. *, **, or *** indicates significance at the 10%, 5%, and 1% levels, respectively.

B

Appendix to Chapter 2

B.1 Additional Figures

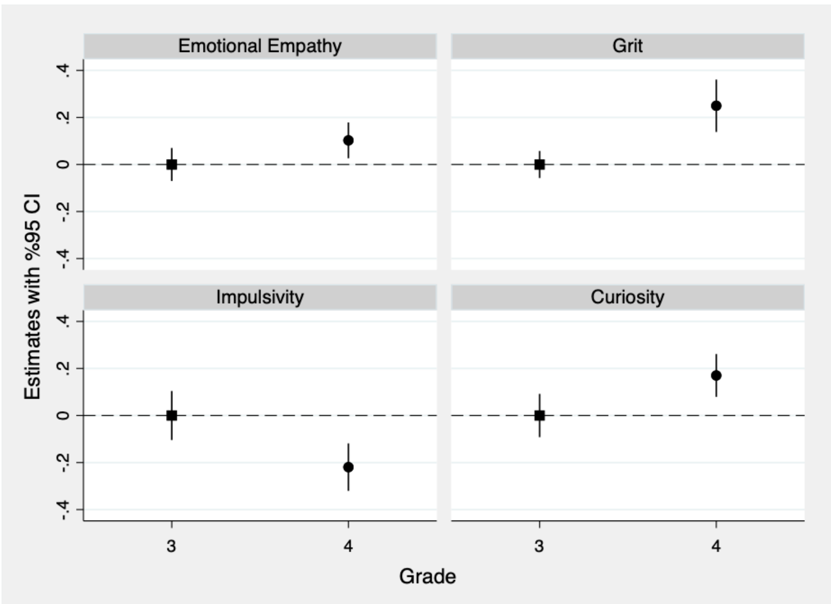


Figure B1 Change in Socioemotional Skills from Grade 3 to Grade 4

Note: The figure illustrates gains in socioemotional skills going from grade 3 to grade 4. The point estimates give OLS coefficients of the regression of socioemotional skills (impulsivity, grit, emotional empathy and curiosity) on grade dummy. All coefficient estimates indicate standard deviation effects with a 95% confidence interval, calculated by clustering at the school level. All statistical tests are two-tailed.

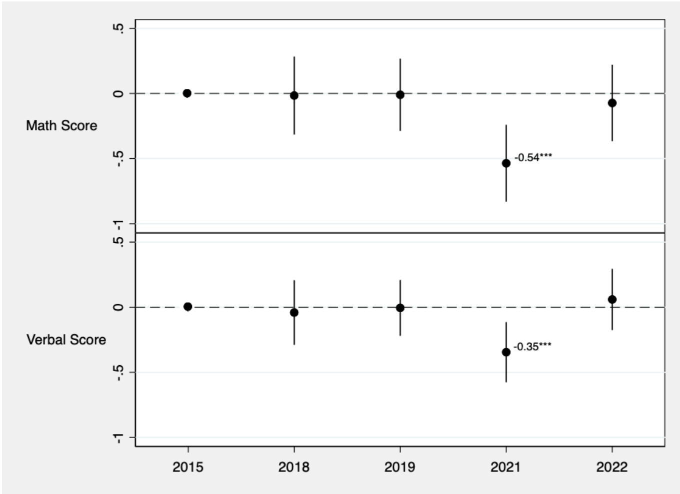


Figure B2 Cohort Profiles of Academic Outcomes (Math and Verbal Test Scores)

Note: The figure illustrates the estimated coefficients and 95% confidence intervals obtained from regressing the standardized outcomes on year dummies. The base year is 2015. This figure uses the test results from the start of each academic year for all years except 2022 to illustrate the recovery of the pandemic cohort. The full set of covariates of student demographics and classroom/teacher characteristics given in Table 2.1 is used in the regression analysis. Student demographics includes gender, age in months, number of siblings, and a dummy variable for students whose mother is working. The classroom/teacher characteristics consist of gender, years of teaching experience, age of the teacher, class size, and the share of male students in the class. Standard errors are clustered at the school level. Asterisks indicate that the estimated coefficient is statistically significant at 1% ***, 5% **, and 10% * levels. Sample size is 15,245 for math score and 15,247 for verbal score. All statistical tests are two-tailed.

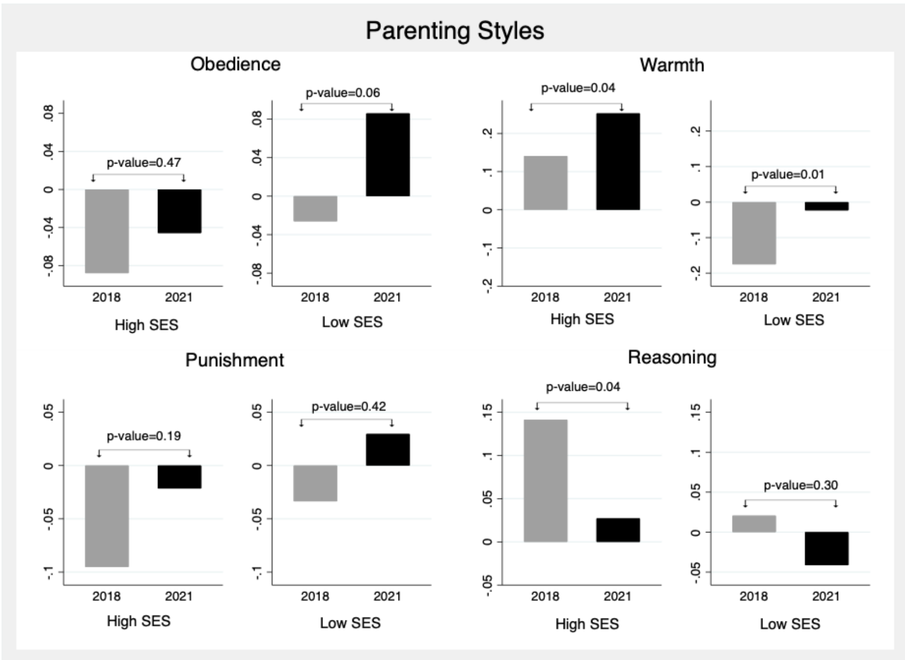


Figure B3 Parenting Styles: SES Gradient

Note: This figure shows the socioeconomic differences in parenting styles (obedience, warmth, punishment, and reasoning). The outcomes are standardized, so the y-axis shows values in standard deviation units. The difference between the two bars illustrates the change in the corresponding parenting styles when comparing the 2018 cohort with the pandemic cohort. The p-values of regressing the standardized outcomes on year dummies are given in the figure for each parenting style. All statistical tests are two-tailed.

B.2 Data Inventories

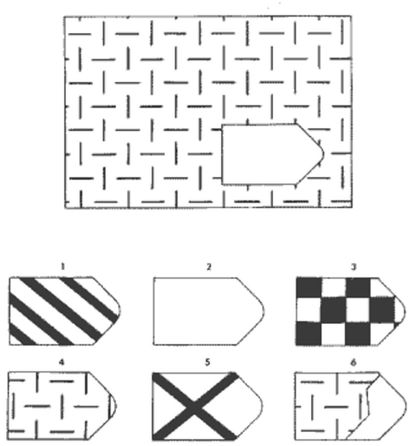


Figure B4 Sample Question: Raven's Progressive Matrices

Note: The questions ask what shape is needed to complete the pictures correctly. There are multiple options provided for each question, and the student is asked to select the correct one. In the sub-scale of the Raven's Progressive Matrices that we employ, there are 23 questions.

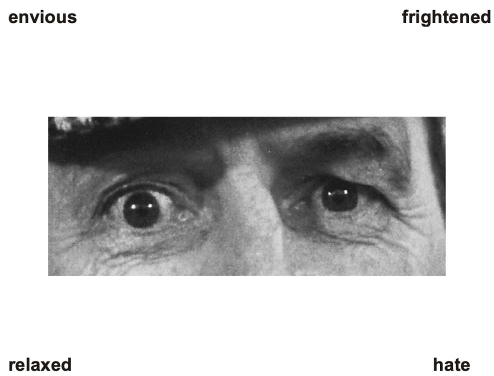


Figure B5 Sample Question: Reading the Mind in the Eyes

Note: The questions inquire about the emotion conveyed by the eyes. There are four options provided for each question, and the student is asked to select the correct one. The sub-scale of the Reading the Mind in the Eyes that we use contains 14 questions.

4-point likert scale: completely agree, agree, disagree, completely disagree	
Inventory	**Items**
Emotional Empathy	When I see someone being treated unfairly, I feel very much pity for them. I often have tender, concerned feelings for people less fortunate than me. When I see someone being taken advantage of, I feel protective towards them. I would describe myself as a pretty soft-hearted person. Sometimes I don't feel very sorry for other people when they are having problems.
Grit	I am diligent. Setbacks discourage me. I finish whatever I begin. I often set a goal but later choose to pursue a different one. I cannot focus on a subject long time. I easily lose interest.
Impulsivity	I get on nerves when close to solving but can't figure it out. I cannot focus on a subject long time. I easily lose interest . I decide what to do quickly and then go and do it right away. Waits turn when playing a game I get into trouble because I do things without thinking first. I tend to say the first thing that comes to mind, without stopping to think about. I cannot help it, but I touch things without getting permission. I call out answers in class before the teacher calls on me I interrupt people when they are talking. I decide what to do quickly and then go and do it right away. I control temper in conflict situations.
Curiosity	Mysteries make me curious. I have always questions in my mind. I look up meaning of a word if I do not know the word. I daydream and fantasize, with some regularity, about things that might happen. I get frustrated if I cannot figure out the solution. Therefore, I work even hard.

Table B1 Student Survey Inventory: Socioemotional Skills

4-point likert scale: completely agree, agree, disagree, completely disagree	
Inventory	**Items**
Obedience	My mom asks me to do something without explaining why. My dad asks me to do something without explaining why. My mom does not allow me to question her decisions. My dad does not allow me to question her decisions. My mom expects me obey her rules without any questions. My dad expects me obey her rules without any questions.
Warmth	When I am scared or sad, my mom hugs and comforts me. When I am scared or sad, my dad hugs and comforts me. My mom jokes and plays games with me. My dad jokes and plays games with me. My mom hugs and kisses me. My dad hugs and kisses me.
Punishment	My mom uses physical punishment when I do something wrong. My dad uses physical punishment when I do something wrong. My mom takes away a privilege when I go against a rule. My dad takes away a privilege when I go against a rule. My mom sometimes spansks me when I do not obey rules My mom sometimes spansks me when I do not obey rules
Reasoning	My mom gets angry with me when I do something wrong, but she never explains why. My dad gets angry with me when I do something wrong, but she never explains why. My mom tells me how people feel. My dad tells me how people feel.

Table B2 Student Survey Inventory: Parenting Styles

C

Appendix to Chapter 3

C.1 Conceptual Framework

A common apprehension is that refugees result in a net cost on the economy of the host country. In the short run, refugees might have adverse impacts since they may harm the local workers who are operating informally and competing in the same market (Aksu et al., 2022). However, refugees can also imply economic opportunities and economic growth. The inflow of refugees can contribute to receiving countries via attracting aid and humanitarian investment, stimulating trade and investment, and generating employment opportunities (Khoudour and Andersson, 2017).

According to the standard augmented neoclassical growth model developed by Mankiw et al. (1992), an increase in the permanent inflow of migrants can have a detrimental effect on economic growth in the long-run. However, this negative impact may be counteracted by the positive contribution of new migrants to the accumulation of human capital, as suggested by (Sala-i Martin, 1995). Therefore, the effect of migration on host countries depends on a variety of elements, including the features of the receiving country and the educational and demographic characteristics of immigrants. To evaluate the effect of refugees on economic development from a theoretical framework, this study introduces the refugee inflow in the standard augmented neoclassical Solow-Swan model.

Theoretical Model

In this part, I present a basic theoretical framework to examine the effect of refugees on economic growth. I introduce the refugee inflow in the standard augmented neoclassical Solow-Swan model. I follow the setting of Juchem Neto et al. (2009) with enhancing their production function with human capital. In this version of the Solow model, the output is produced by physical capital K, human capital H, labor force L, and constant factor A, denoting the technological level of the economy.

$$Y = f(H,K,L,A) \qquad \text{with } K,L,H,A > 0 \tag{C.1}$$

In the Solow model, the production function needs to satisfy the following conditions: i) f(.) is increasing function of human capital, physical capital and labor force, ii) f(.) needs to satisfy Inada condition, iii) f(.) needs to satisfy constant return to scale. Because Cobb-Douglas function satisfies all these conditions, I choose Cobb-Douglas production function following the literature.

$$Y = K^{\alpha} H^{\beta} (AL)^{1-\alpha-\beta} \tag{C.2}$$

where $\alpha + \beta < 1$ and A is labor-augmenting technological progress which raises at rate g. Labor force follows,

$$\dot{L} = nL + R \iff \frac{\dot{L}}{L} = n + r \tag{C.3}$$

where R is the net number of new refugees, $r = \frac{R}{L}$ is the net refugee inflow rate and $\frac{\dot{L}}{L}$ is the working population growth rate. Here I assume that the refugees of time t-1 is counted in the native population (more accurately, they seen as citizens) of time t. The physical capital grows as in the standard Solow model,

$$\dot{K} = \phi Y - \delta K \tag{C.4}$$

where ϕ is the proportion of output that is allocated to the accumulation of physical capital, while δ refers to the rate at which physical capital depreciates. The human capital grows as,

$$\dot{H} = \theta Y - \delta H + R h^{R} = \theta Y - (\delta - r\tilde{h})H \tag{C.5}$$

where θ is the proportion of output invested in human capital accumulation, δ is the depreciation rate of human capital and similar to Boubtane et al. (2013) $\tilde{h} = \frac{h^R}{\hat{h}}$ is the ratio of human capital of refugees to average human capital in the host country. For simplicity, as Mankiw et al. (1992), I equated the rate of human capital depreciation with that of physical capital depreciation.

Per effective labor unit, we can define the followings,

$$y = k^{\alpha} h^{\beta}; \quad y = \frac{Y}{AL} \quad k = \frac{K}{AL} \quad h = \frac{H}{AL} \tag{C.6}$$

By using equation 5,6 and 7;

$$\dot{h} = \theta y - (n + \delta + g - r\tilde{h})h \tag{C.7}$$

$$\dot{k} = \phi y - (n + \delta + g)k \tag{C.8}$$

The steady state of this economy;

$$h^* = \left(\frac{\theta}{n + \delta + g - \tilde{h}r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\phi}{n + \delta + g}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \tag{C.9}$$

$$k^* = \left(\frac{\theta}{n + \delta + g - \tilde{h}r}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\phi}{n + \delta + g}\right)^{\frac{\beta}{1-\alpha-\beta}} \tag{C.10}$$

By using equation 11 and 12 in the production function and using the fact that $\frac{\partial lny}{\partial t} = \frac{\dot{y}}{y}$,

$$\frac{\dot{y}}{y} = -(1 - \alpha - \beta(n + \delta + g))(lny(t) - lny^*) \tag{C.11}$$

where

$$\begin{aligned} \ln y^* = &\frac{\beta}{1-\alpha-\beta} \ln \phi + \frac{\alpha}{1-\alpha-\beta} \ln \theta - \frac{\beta}{1-\alpha-\beta} \ln \left(n + \delta + g - \tilde{h}\right) \\ &- \frac{\alpha}{1-\alpha-\beta} \ln (n + \delta + g) \end{aligned} \tag{C.12}$$

From equation 13 and 14, for a given constant parameters, the economic growth is positively related to $\tilde{h}$, which means if new refugees have higher human capital than the resident population on average, then they can contribute to the growth of the economy by compensated the negative effect of net refugee flows due to capital dilution (Boubtane et al., 2013; Sala-i Martin, 1995).

To be able to see the economic growth from provincial perspective, I simply take the log of equation

4 and differentiate the log of equation 4 with respect to time and redefine at province level,

$$\mathrm{logY} = \alpha + \beta \mathrm{logH} + (1-\alpha-\beta)\mathrm{logA} + (1-\alpha-\beta)\mathrm{logL} \tag{C.13}$$

$$(\frac{\dot{Y}}{Y})_p = \alpha(\frac{\dot{K}}{K})_p + \beta(\frac{\dot{H}}{H})_p + (1-\alpha-\beta)(\frac{\dot{L}}{L})_p + g_p \tag{C.14}$$

where p denotes province, g_p the annual rate of technical progress in province p. Equation 16 illustrates the elements of economic growth. These are growth in labor, growth in human capital, growth in physical capital and technological progress. By assuming that refugees do not bring significant amount of physical capital to the hosting country, the main source of refugee effect comes from the human capital of refugees.

Consequently, in this setting, whether or not refugees positively impact per-capita GDP significantly depend on the demographic and the educational characteristics of the refugees. The educational attainment of natives is higher than the Syrian refugees and more than 50% of the Syrian refugees are children under the age of 18 and women in Turkey.[1] Therefore, in this theoretical setting, the significant positive effect of Syrian refugees on per capita GDP is not much likely. However, this model leaves out some important components through which refugees may contribute to the economy. For instance, on the one hand, refugees can promote trade and investment, attract humanitarian aids, and generate job opportunities. On the other hand, they stimulate consumption and trigger a supply response, therefore, result in a boost in GDP (Errighi and Griesse, 2016). To be able to better understand the impact of Syrian refugees on per-capita GDP, we might need a more comprehensive theoretical model, however, with using the variation in the share of refugees across Turkish provinces in Turkey over time, we have power to evaluate the impact of Syrian refugees on per-capita GDP in Turkey empirically.

[1] Source: Ministry of Interior, Directorate General of Migration Management

C.2 GDP Calculation Method

This section simply gives how the GDP by provinces is calculated using the “production approach"[2].

Production – Intermediate consumption = Gross Value Added (GVA)

where production is the outcome of economic activities in the form of goods and services, while intermediate consumption is the goods and services used in the production process.

GVA + Net taxes = GDP

where net taxes are taxes on the product minus subsidies.

C.3 Additional Tables

Table C1 The Provinces that Hosted more Refugees Than 5% of their Population in 2019

Province	Population	Refugee Share (%)
Kayseri	1,407,409	5.248
Bursa	3,056,120	5.338
Kahramanmaras	1,154,102	7.369
Osmaniye	538,759	8.479
Mardin	838,778	9.562
Adana	2,237,940	9.727
Mersin	1,840,425	10.054
Sanliurfa	2,073,614	17.455
Gaziantep	2,069,364	17.660
Hatay	1,628,894	21.314
Kilis	142,490	44.892
Turkey	83,154,997	4.193

Note: The refugee shares, the proportion of migrants to the total population (refugees + natives), are shown in this table for the provinces where the share is greater than 5%, along with Turkey’s population.

[2] Source is TurkStat.

Table C2 Refugee Shock on GDP per Capita*, OLS

Panel A: The Short-Term Effect of the Migrant Shock on GDP per Capita (Until 2015), OLS					
Dependent Variable	(1)	(2)	(3)	(4)	Mean
GDP percapita*	-25,875.87***	-11,935.99***	-10,573.80***	-7,769.70**	14031.02
	(5,489.72)	(2,823.06)	(3,706.31)	(3,314.84)	
Observations	729	567	567	567	
Panel B: The Medium-Term Effect (Until 2017)					
GDP percapita*	-28,631.72***	-15,885.00***	-12,835.25***	-11,884.26***	16296.99
	(4,807.85)	(3,140.91)	(3,245.60)	(2,873.91)	
Observations	891	729	729	729	
Panel C: The Long-Term Effect (Until 2019)					
GDP percapita*	-34,963.89***	-27,577.79***	-17,124.14***	-17,403.20***	19326.44
	(5,900.04)	(5,472.88)	(5,547.21)	(4,082.76)	
Observations	1,053	891	891	891	
Controls for					
Year Fixed Effects	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	
Province-specific Controls	No	Yes	Yes	Yes	
5 Region-Year Fixed Effects	No	No	Yes	No	
Nuts1-Year Fixed Effects	No	No	No	Yes	

Note: The dataset consists of 81 Turkish provinces from 2006 to 2015 (except 2012) in Panel A, 2006 to 2017 (except 2012) in Panel B, and 2006 to 2019 (except 2012) in Panel C. Each cell presents the OLS regression estimates for the proportion of refugees to population with different specifications, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. Due to the unavailability of data for the years 2006 and 2007, the inclusion of province-specific controls results in a reduced number of observations. The third and fourth columns control for 5-Region-year fixed effects and NUTS1-year fixed effects, respectively.Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C3 Refugee Shock on GDP per Capita*, 2SLS

Panel A: The Short-Term Effect of the Migrant Shock on GDP per Capita (Until 2015), 2SLS					
Dependent Variable	(1)	(2)	(3)	(4)	Mean
GDP percapita*	-40,526.592***	-19,626.325***	-13,059.072**	-11,068.824**	14031.02
	(13,112.405)	(6,301.072)	(5,944.705)	(5,645.773)	
First-stage regression	3.015***	3.121***	3.059***	3.232***	
	(0.795)	(0.856)	(0.915)	(0.888)	
Partial R-squared	0.697	0.662	0.626	0.683	
Observations	729	567	567	567	
Panel B: The Medium-Term Effect(Until 2017)					
GDP percapita*	-44,119.788***	-26,869.824***	-16,824.298***	-17,185.104***	16296.99
	(11,934.993)	(7,469.661)	(4,422.178)	(4,565.750)	
First-stage regression	3.006***	3.112***	3.063***	3.269***	
	(0.946)	(0.984)	(1.023)	(1.002)	
Partial R-squared	0.733	0.685	0.648	0.698	
Observations	891	729	729	729	
Panel C: The Long-Term Effect(Until 2019)					
GDP percapita*	-57,328.499***	-49,294.562***	-30,395.045***	-30,549.808***	19326.44
	(14,852.358)	(13,874.908)	(8,343.210)	(8,055.224)	
First-stage regression	2.898***	2.908***	2.867***	3.032***	
	(0.670)	(0.687)	(0.764)	(0.733)	
Partial R-squared	0.747	0.704	0.646	0.700	
Observations	1,053	891	891	891	
Controls for					
Year Fixed Effects	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	
Province-specific Controls	No	Yes	Yes	Yes	
5 Region-Year Fixed Effects	No	No	Yes	No	
Nuts1-Year Fixed Effects	No	No	No	Yes	

Note: The dataset includes 81 Turkish provinces from 2006 to 2015 (except 2012) in Panel A, 2006 to 2017 (except 2012) in Panel B, and 2006 to 2019 (except 2012) in Panel C. Each cell presents the 2SLS regression estimates for the proportion of refugees to population with different specifications, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. Due to the unavailability of data for the years 2006 and 2007, the inclusion of province-specific controls results in a reduced number of observations. The third and fourth columns control for 5-Region-year fixed effects and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C4 Placebo Regressions on Refugee Impact on GDP per Capita*, 2SLS Estimates

	(1)	(2)	(3)	(4)
Panel A: Instrument for 2019 are Assigned to the Corresponding Values for 2011				
GDP percapita*	-8,928.58***	-5,210.88**	-2,371.94	-2,152.51
	(2,530.52)	(2,231.73)	(1,841.85)	(1,676.48)
Panel B: Instrument for 2017 are Assigned to the Corresponding Values for 2011				
GDP percapita*	-9,125.38***	-5,323.62**	-2,389.93	-2,174.05
	(2,825.31)	(2,417.51)	(1,896.39)	(1,738.63)
Panel C: Instrument for 2015 are Assigned to the Corresponding Values for 2011				
GDP percapita*	-10,943.89***	-6,418.58**	-2,840.56	-2,566.18
	(3,726.84)	(3,119.86)	(2,336.00)	(2,118.91)
Observations	486	324	324	324
Controls for				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
Nuts1-Year Fixed Effects	No	No	No	Yes

Note: The dataset consists of 81 Turkish provinces from 2006 to 2011(before the arrival of Syrians) for dependent variable, and from 2008 to 2011 for control variables. For the placebo analysis, the key variable of interest, which is the proportion of refugees to the overall population (refugees+natives), and instrumental variable values for 2019, 2017, and 2015 are assigned to the related values for 2011 in Panel A, Panel B, and Panel C, respectively. The instrumental variable and the key variable of interest are valued at zero for the duration of 2006-2010. Each cell presents the 2SLS regression estimates for the proportion of refugees to population with different specifications, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C5 The Impact of Refugees on GDP per Capita* with an Alternative Instrument

	(1)	(2)	(3)	(4)
GDP percapita*	-39,877.66***	-25,018.67***	-15,087.62***	-16,263.57***
	(9,430.80)	(6,278.10)	(3,905.68)	(3,939.55)
First-stage regression	1.07***	1.04***	1.00***	1.06***
	(0.24)	(0.23)	(0.25)	(0.24)
Partial R-squared	0.751	0.695	0.659	0.694
Observations	891	729	729	729
Controls for				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
Nuts1-Year Fixed Effects	No	No	No	Yes

Note: The dataset cover 81 provinces of Turkey over the years 2006 to 2017 (except 2012) for dependent variable; the years 2008 to 2017 (except 2012) for control variables. Each cell shows the estimates for the share of refugees, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The 2SLS regression instruments the key variable of interest using the del Carpio-Wagner distance-based instrument. The regressions controls for year, province fixed effects, province specific variables, 5-Region-year and NUTS1-year fixed effects in different columns as shown above. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C6 The Impact of Refugees on GDP per Capita* with Lagged Value of Refugee Ratio: 2SLS Estimates

Panel A: With One-Period Lagged Value of Refugee Share				
	(1)	(2)	(3)	(4)
GDP percapita*	-62,143.26***	-54,441.40***	-33,632.96***	-34,340.64***
	(16,584.07)	(15,719.98)	(9,512.67)	(9,169.49)
Observations	891	810	810	810
Panel B: With Two-Period Lagged Value of Refugee Share				
GDP percapita*	-65,873.25***	-58,810.60***	-36,036.10***	-37,805.02***
	(18,335.98)	(17,541.72)	(10,820.31)	(10,533.86)
Observations	810	810	810	810
Controls for				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
Nuts1-Year Fixed Effects	No	No	No	Yes

Note: The dataset covers 81 Turkish provinces from 2006 to 2015 (except 2012) for dependent variable, and from 2008 to 2019 (except 2012) for control variables. Each cell presents the 2SLS regression estimates of the lagged values of the key variable of interest, the proportion of refugees to population with different specifications, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The regressions use one-period lagged values and two-period lagged values, and the estimates are presented in Panel A and Panel B, respectively. The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C7 The Impact of Refugees on GDP per Capita* with Dummy Treatment Variable: 2SLS Estimates

	(1)	(2)	(3)	(4)
Panel A: For the Treatment Dummy, Threshold= 0.03				
GDP percapita*	-12,847.798***	-13,477.536***	-13,558.485***	-10,209.022***
	(2,499.661)	(1,935.013)	(4,013.312)	(2,187.451)
First-stage regression	12.93***	10.64***	6.43**	9.07***
	(2.19)	(2.00)	(2.50)	(2.23)
Panel B: For the Treatment Dummy, Threshold= 0.05				
GDP percapita*	-12,539.718***	-11,905.396***	-8,905.287***	-8,660.964***
	(2,537.592)	(1,928.474)	(2,559.780)	(2,090.754)
First-stage regression	13.25***	12.04***	9.79***	10.69***
	(1.91)	(1.79	(2.75)	(2.17)
Panel C: For the Treatment Dummy, Threshold= 0.08				
GDP percapita*	-15,232.152***	-13,677.853***	-9,964.181***	-9,253.536***
	(3,459.310)	(3,133.702)	(3,290.063)	(2,526.129)
First-stage regression	10.91***	10.48***	8.75***	10.01***
	(1.17)	(1.22)	(1.86)	(1.33)
Observations	1,053	891	891	891
Controls for				
Year Fixed Effects	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes
Province-specific Controls	No	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	No	Yes	No
Nuts1-Year Fixed Effects	No	No	No	Yes

Note: The dataset consists of 81 Turkish provinces from 2006 to 2019 (except 2012) for dependent variable, and from 2008 to 2019 (except 2012) for control variables. Each cell demonstrates the 2SLS regression estimates of the key variable of interest with different specification, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The key variable of interest is the treatment dummy taking the value of one where the share of refugees is greater than 0.03 in Panel A (0.05 in Panel B, and 0.08 in Panel C) and zero otherwise.The instrument relies on multiple factors, including the combined count of Syrian refugees in Turkey, Iraq, Jordan, and Lebanon in each year. Additionally, it considers the pre-war population distribution of Syrian provinces, the proximity of each province to the nearest border crossing of neighboring countries, and the distance between each Syrian province and each Turkish province. The first column provides the results of the regressions controlling for year and province fixed effects. The second column additionally controls for province-specific variables. The third and fourth columns control for 5-Region-year and NUTS1-year fixed effects, respectively. Standard errors are clustered at the province level and asterisks show that the estimate is statistically significant at 1% ***, 5% **, and 10% * levels.

Table C8 The Impact of Refugees on GDP per Capita* with Alternative Subsamples, 2SLS Estimates

	A:Excludes Istanbul Region			B: Exclude Western Turkey		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP percapita*	-45,938.27***	-30,395.04***	-30,165.60***	-30,302.19***	-27,540.27***	-27,985.84***
	(12,096.45)	(8,343.21)	(7,543.78)	(4,921.34)	(6,570.01)	(6,359.42)
First-stage regression	2.93***	2.87***	3.03***	3.14***	2.89***	3.07***
	(0.69)	(0.76)	(0.73)	(0.72)	(0.75)	(0.73)
Observations	880	880	880	649	649	649
	C:Includes nuts1= 6,10,11, and 12			D:Includes nuts1= 6 and 12		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP percapita*	-26,599.24***	-26,564.28***	-26,916.07***	-32,214.19***	-32,631.83***	-32,631.83***
	(5,593.39)	(6,271.21)	(6,347.08)	(5,004.50)	(5,827.66)	(5,827.66)
First-stage regression	3.00***	2.90***	2.99***	2.81***	2.70***	2.70***
	(0.62)	(0.66)	(0.63)	(0.51)	(0.47)	(0.47)
Observations	352	352	352	187	187	187
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
5 Region-Year Fixed Effects	No	Yes	Yes	No	Yes	Yes
Nuts1-Year Fixed Effects	No	No	Yes	No	No	Yes

Note: Each cell in the table presents the 2SLS regression estimates of the proportion of refugees to population, with different specifications, where dependent variable is GDP percapita* (TL) constructed by dividing the GDP by the total population of each province(refugees and citizens combined). The first (fourth) column provides the results of the regressions controlling for year and province fixed effects, and province-specific variables. The second (fifth) and third (sixth) columns control for 5-Region-year and NUTS1-year fixed effects, respectively. The results are presented in separate panels, each with distinct regional restrictions. In Panel (A), Istanbul (NUTS1 region 1) is excluded, while in Panel (B), western Turkey (NUTS1 regions 1-4) is excluded. On the other hand, Panel (C) involves NUTS1 region 6 (the Mediterranean Region) and NUTS1 regions 10-12 (eastern Turkey), whereas Panel (D) only includes NUTS1 region 6 and NUTS1 region 12.

D

Appendix to Chapter 4

D.1 A Note on Smuggling and Drug Trafficking in Turkey

This section provides more information that can help explain and better interpret the positive refugee effect on smuggling and its statistically non-significant influence on drug-related offenses.

The work by Karaçay (2017) and Yildiz (2017) document a number of developments that shed light on the facts that our smuggling variable encodes. First, these authors explain the type of wrongdoings nourishing our measure. More specifically, their analysis indicates that human smuggling routes have increasingly shifted towards Turkey even before the outbreak of the Syrian conflict:

1). The European Border Coast Guard Agency, Frontex, carried out several operations between 2000 and 2010 to stop illegal migration into the EU, which diverted illegal crossings towards the East Mediterranean and the Aegean Sea.

2). Developments of political, social, and economic nature, such as the demise of the Soviet Union, economic decay in Africa, and the onset of a myriad of conflicts in the Middle East, made Turkey a migration recipient country. As a result, migrant smugglers began weaving their routes into the EU long before the Syrian war.

3). Increased migration pressure stemming from the Arab Spring conflict propelled illegal crossings to the EU via Turkey.

Second, this illicit activity severely increased right after the outbreak of the civil war in Syria. Interestingly, although the notion of human smuggling may be despicable at face value, the above authors explain that migrants do not regard smugglers as criminals but as simple service providers. More pointedly, Karaçay (2017) states that human smuggling networks do not operate as criminal syndicates in Turkey. On the contrary, human smugglers seemed to provide a much-needed service that turned out to be illegal.

All in all, we conclude that the higher magnitude of smuggling does not necessarily reflect a higher incidence of predatory activities but the rational response to the imposition of a legal restriction to the free movement of people amid a violent conflict.

Regarding drug trafficking, as Cengiz (2017) points out, Turkey has been a long-lasting transshipment and destination country of Afghan heroin that typically entered through the easternmost Turkish provinces. Indeed, Cengiz (2017)'s work documents that the onset of the Syrian conflict entailed an extensive relocation of that country's armed forces towards the territories engulfed by the then ongoing rebellion, thereby leaving the borderline with Turkey unpoliced. This development arguably cheapened drug trafficking organizations' logistic costs in that area, which spurred a shift of the drug trafficking routes of Afghan heroin to the southeastern Turkish border. Predictably, Turkish law enforcement agencies strengthened their efforts to stop these illicit shipments resulting in the seizure of 10 tons of heroin in 2014 (KOM, 2014). In a related vein, the increase in drug shipments entering the country could also have prompted local consumption and associated detentions. Thus, the Syrians' arrival fails to affect drug-related crimes because the latter's only link to them is the war erupting in Syria. In other words, the ensuing violence is a common cause of increased drug trafficking activities and the settlement of Syrian refugees in Turkey.

D.2 Additional Tables

Table D1 Investment in Armed Forces and Change in per-capita Armed Forces in Migrant Receiving Regions

	(1)	(2)	(3)	(4)	(5)	Mean
All	-157.237*	-147.596	-115.089	-175.053	-140.343	195.918
	(87.194)	(120.948)	(145.566)	(128.352)	(156.880)	
Assault	-46.168**	-55.181**	-41.548**	-59.974**	-44.400*	28.307
	(15.977)	(18.722)	(19.714)	(19.046)	(19.601)	
Crimes related with firearms and knifes	0.484	2.459	3.617	3.221	3.533	5.496
	(6.175)	(4.456)	(5.814)	(4.579)	(6.015)	
Homicide	-12.545***	-14.514***	-7.377	-14.636**	-7.362	8.058
	(4.508)	(4.901)	(5.632)	(5.711)	(6.517)	
Robbery	-7.796	-4.704	-4.235	-5.416	-4.783	6.625
	(9.896)	(11.352)	(13.342)	(12.152)	(14.489)	
Smuggling	20.644***	22.128**	23.398	17.435	21.902	5.310
	(5.496)	(10.156)	(14.480)	(10.616)	(15.796)	
Theft	-36.566*	-40.875	-55.807	-46.703	-60.723	25.342
	(18.886)	(31.999)	(35.567)	(34.746)	(38.994)	
Sexual Crimes	-14.624***	-13.284***	-11.514**	-14.032***	-12.237**	5.021
	(2.578)	(3.569)	(4.601)	(4.101)	(4.827)	
Kidnapping	-9.386***	-10.216**	-6.406*	-11.801***	-7.747*	3.009
	(2.488)	(4.031)	(3.834)	(4.497)	(4.229)	
Defamation	-9.088***	-9.369*	-9.552*	-10.905**	-10.986**	4.094
	(2.810)	(4.939)	(5.596)	(4.997)	(5.351)	
Use and Purchase of Drugs	-4.333	0.344	-6.086	-0.026	-7.173	3.400
	(7.157)	(9.504)	(10.176)	(9.585)	(10.495)	
Production and Commerce of Drugs	4.139	-6.881	-23.637	-9.923	-28.100	9.993
	(15.171)	(18.601)	(22.283)	(20.352)	(25.080))	
First-stage regression	2.880***	2.996***	2.836***	2.980***	2.805***	
	(0.540)	(0.541)	(0.599)	(0.553)	(0.643)	
Partial R-squared	0.703	0.699	0.645	0.690	0.634	
F-Stat	28.420	30.69	22.394	29.066	19.025	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The sample includes 81 provinces for each year from 2008 to 2019 (except 2012), therefore the number of observations is 891. The dependent variable is the rate for various types of crimes given above, where the denominator includes both natives and refugees. Each cell shows the estimates for the key variable of interest – the ratio of migrants to population (migrants+natives) – in a separate 2SLS regression of the dependent variable on the key variable of interest, per capita number of individuals working in the field of defense and compulsory social security at the NUTS2-region level, a set of province-specific control variables, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the ”0-14” and ”65 and over” age groups per 100 people in the ”15-65” age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over “15 years of age and over”. Standard errors, given in parentheses, are clustered at the Nuts2- level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.

Table D2 Refugee Effect on Various Types of Crime, 2SLS Estimates – with One-Period Lagged Value of Refugee Ratio

	(1)	(2)	(3)	(4)	(5)	Mean
All	-160.701	-158.126	-124.799	-183.899	-165.315	205.237
	(98.443)	(126.166)	(141.366)	(132.859)	(153.125)	
Assault	-47.616***	-59.500***	-44.953**	-66.118***	-52.489**	29.869
	(17.780)	(21.367)	(21.155)	(23.209)	(22.824)	
Crimes related with firearms and knifes	3.125	4.936	6.150	5.885	5.656	5.625
	(5.545)	(4.488)	(5.714)	(4.554)	(5.735)	
Homicide	-12.557***	-14.364***	-6.633	-14.524***	-8.024	8.388
	(4.029)	(4.454)	(5.904)	(4.998)	(5.935)	
Robbery	-7.881	-4.474	-3.313	-6.183	-6.075	7.085
	(8.999)	(10.238)	(11.340)	(11.090)	(12.377)	
Smuggling	22.845**	23.302**	24.927	18.241	19.562	5.683
	(9.467)	(11.029)	(15.713)	(12.508)	(20.144)	
Theft	-33.383*	-36.997	-50.078	-46.703	-65.839*	27.125
	(18.467)	(28.958)	(32.823)	(31.372)	(35.402)	
Sexual Crimes	-14.712***	-13.430***	-11.845***	-15.298***	-14.410***	5.363
	(2.908)	(3.356)	(3.977)	(3.795)	(4.222)	
Kidnapping	-8.842***	-9.475**	-5.196	-11.249***	-7.808**	3.254
	(2.948)	(3.820)	(3.360)	(4.159)	(3.758)	
Defamation	-8.808***	-9.249**	-9.151*	-11.357**	-10.851**	4.266
	(2.998)	(4.430)	(4.781)	(4.724)	(4.841)	
Use and Purchase of Drugs	-6.218	-1.798	-8.578	-0.358	-8.125	3.738
	(10.218)	(11.426)	(13.477)	(11.550)	(14.408)	
Production and Commerce of Drugs	1.639	-10.028	-28.220	-13.216	-34.054	10.646
	(14.727)	(16.870)	(20.307)	(18.466)	(22.967)	
First-stage regression	2.942***	3.064***	2.915***	3.043***	2.885***	
	(0.708)	(0.729)	(0.721)	(0.752)	(0.788)	
Partial R-squared	0.703	0.702	0.653	0.691	0.637	
F-Stat	17.273	17.687	16.338	16.359	13.421	
Observations	810	810	810	810	810	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The data cover the years 2008 to 2018 (except 2012) for the key variable of interest, however, the data cover the years 2009 to 2019 (except 2012) for the dependent variable and control variables. The sample includes 81 provinces for each year, therefore, the number of observations is 810. Each cell shows the estimates for one-period lagged value of the key variable of interest – the ratio of migrants to population (migrants+natives) – in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control variables, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the province level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.

Table D3 Refugee Effect on Various Types of Crime, 2SLS Estimates – with Two-Period Lagged Value of Refugee Ratio

	(1)	(2)	(3)	(4)	(5)	Mean
All	-183.567	-169.165	-136.373	-190.722	-191.273	205.237
	(116.295)	(140.397)	(154.126)	(147.762)	(167.854)	
Assault	-42.763**	-50.432**	-34.027*	-58.592***	-50.719**	29.869
	(17.365)	(19.664)	(20.143)	(21.629)	(21.942)	
Crimes related with	2.814	4.922	6.656	6.449	4.755	5.625
firearms and knifes	(5.937)	(4.726)	(5.651)	(4.945)	(5.601)	
Homicide	-12.294***	-13.902***	-5.707	-15.331***	-8.476	8.388
	(4.560)	(4.724)	(5.969)	(5.672)	(6.514)	
Robbery	-6.180	-2.365	-0.647	-4.567	-4.320	7.085
	(9.220)	(10.254)	(11.233)	(11.614)	(12.934)	
Smuggling	17.195	18.404	17.938	13.118	9.820	5.683
	(12.003)	(14.406)	(17.999)	(15.153)	(24.163)	
Theft	-35.890*	-36.631	-46.505	-48.671	-66.788*	27.125
	(20.118)	(29.978)	(34.399)	(33.581)	(38.154)	
Sexual Crimes	-14.520***	-12.649***	-10.139***	-14.831***	-13.096***	5.363
	(3.231)	(3.367)	(3.870)	(3.915)	(4.052)	
Kidnapping	-8.735***	-9.167**	-5.012	-10.716**	-7.408**	3.254
	(3.156)	(3.914)	(3.302)	(4.336)	(3.487)	
Defamation	-8.436***	-8.365**	-7.695*	-11.659**	-12.551**	4.266
	(2.689)	(3.950)	(4.230)	(4.783)	(5.114)	
Use and Purchase	-10.824	-6.182	-13.849	-2.856	-10.947	3.738
of Drugs	(11.028)	(12.120)	(13.659)	(12.026)	(14.848)	
Production and Commerce	1.532	-9.490	-25.733	-12.469	-32.747	10.646
of Drugs	(14.522)	(17.206)	(20.638)	(18.988)	(23.428)	
First-stage regression	2.995***	3.118***	3.004***	3.129***	2.995***	
	(0.767)	(0.774)	(0.770)	(0.809)	(0.854)	
Partial R-squared	0.697	0.701	0.662	0.693	0.646	
F-Stat	15.256	16.233	15.240	14.971	12.302	
Observations	810	810	810	810	810	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The data cover the years 2008 to 2018 (except 2012) for the key variable of interest, however, the data cover the years 2009 to 2019 (except 2012) for the dependent variable and control variables. The sample includes 81 provinces for each year, therefore, the number of observations is 810. Each cell shows the estimates for two-period lagged value of the key variable of interest – the ratio of migrants to population (migrants+natives) – in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control variables, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the province level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.

Table D4 Refugee Effect on Various Types of Crime, 2SLS Estimates – Ratio of Migrants Defined across Individuals Aged 18 or above

	(1)	(2)	(3)	(4)	(5)	Mean
All	-141.668	-139.512	-88.775	-188.969	-134.025	280.154
	(135.293)	(188.931)	(225.867)	(199.711)	(245.372)	
Assault	-68.382***	-88.214***	-62.496*	-95.439***	-66.464**	40.143
	(25.285)	(29.096)	(32.092)	(30.036)	(32.568)	
Crimes related with firearms and knifes	4.969	8.121	11.093	10.474	12.107	8.049
	(10.412)	(8.305)	(10.591)	(8.326)	(10.758)	
Homicide	-19.057**	-24.274***	-9.860	-24.184***	-9.649	11.633
	(7.655)	(8.028)	(12.423)	(9.116)	(12.686)	
Robbery	-1.691	2.080	3.140	-0.091	0.924	9.480
	(17.029)	(20.194)	(22.981)	(21.494)	(24.735)	
Smuggling	50.409***	55.854***	58.991*	44.969*	56.478	8.231
	(18.719)	(21.158)	(33.114)	(24.158)	(39.067)	
Theft	-33.275	-46.066	-83.714	-58.245	-95.509*	36.268
	(28.556)	(46.871)	(51.444)	(50.742)	(56.787)	
Sexual Crimes	-24.382***	-22.775***	-19.419***	-24.037***	-21.034***	7.041
	(4.604)	(5.738)	(7.454)	(6.302)	(7.501)	
Kidnapping	-16.004***	-18.137***	-10.398**	-21.323***	-13.258**	4.246
	(4.364)	(5.928)	(4.957)	(6.619)	(5.515)	
Defamation	-15.109***	-16.061**	-16.274**	-18.894***	-18.925**	5.726
	(4.117)	(6.721)	(7.361)	(6.924)	(7.360)	
Use and Purchase of Drugs	-1.983	5.802	-7.686	5.090	-9.520	4.868
	(16.873)	(19.429)	(23.672)	(19.918)	(25.271)	
Production and Commerce of Drugs	23.852	0.608	-38.842	-6.359	-49.180	14.824
	(31.005)	(32.726)	(38.623)	(35.213)	(43.266)	
First-stage regression	2.128***	2.200***	2.033***	2.192***	2.023***	
	(0.441)	(0.448)	(0.438)	(0.465)	(0.485)	
Partial R-squared	0.698	0.690	0.631	0.681	0.624	
F-Stat	23.241	24.156	21.581	22.220	17.397	
Observations	891	891	891	891	891	
Controls for						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	
5-Region Linear Time Trends	No	Yes	Yes	Yes	Yes	
NUTS1 Linear Time Trends	No	No	Yes	Yes	Yes	
5-Region-Year Fixed Effects	No	No	No	Yes	Yes	
NUTS1-Year Fixed Effects	No	No	No	No	Yes	

Notes: The data cover the years 2008 to 2019 (except 2012). The sample includes 81 provinces for each year, therefore, the number of observations is 891. Each cell shows the estimates for the key variable of interest – the ratio of migrants to population (migrants+natives) defined across individuals aged 18 or above – in a separate 2SLS regression of the dependent variable on the key variable of interest, a set of province-specific control varibles, a set of geographical-area and year specific control variables as indicated above. The instrument depends on the total number of Syrian refugees in four neighboring countries (Turkey, Lebanon, Jordan, and Iraq) in each year, pre-war population shares of Syrian provinces, the distance of each Syrian province to the closest border entry in each of the neighboring countries, and the distance of each Syrian province to each Turkish province. The province-specific control variables include the logarithm of trade volume, the logarithm of GDP per capita, GDP sector shares, age dependency ratio, average household size, shares of five age categories, and shares of six education categories. The age dependency ratio is the number of people in the "0-14" and "65 and over" age groups per 100 people in the "15-65" age group. GDP sector shares include the shares of agriculture, industry, and services. The age groups are 15-24, 25-34, 35-44, 46-54, and 55-64. The education categories are (i) illiterate, (ii) literate but no diploma, (iii) primary school or primary education graduates, (iv) junior high school and middle school equivalent vocational school graduates, (v) high school and high school equivalent vocational school graduates, and (vi) university and higher educational institution graduates. Each sub-group in the age category indicates the share of that group within the population aged 15-64. Similarly each sub-group in education category shows the share of the specific group over "15 years of age and over". Standard errors, given in parentheses, are clustered at the province level. *, **, or *** indicates significance at the 10%, 5% and 1%, respectively.