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Ethnic Mixing in Early Childhood: Evidence from a Randomized Field Experiment and a Structural Mode

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ABSTRACT

We study the social integration of ethnic minority children in the context of an early childhood program conducted in Turkey aimed at preparing 5-year-old native and Syrian refugee children for primary school. We randomly assign children to groups with varying ethnic composition and find that exposure to children of the other ethnicity leads to an increase in the formation of interethnic friendships, especially for Turkish children. We also find that the Turkish language skills of Syrian children are better developed in classes with a larger presence of Turkish children. We then develop a model of friendship formation with two key mechanisms: preference bias and congestion in the friendship formation process. Structural estimation of the model suggests that interethnic exposure reduces the share of own-ethnicity friends (homophily) and has a non-monotonic effect on the propensity to form own-ethnicity friendships beyond what would be expected given the size of the group (inbreeding homophily). Counterfactual analysis indicates that improvement in the language skills of Syrian children can offset more than half of the effect that ethnic bias has on friendship formation patterns. Finally, we find that for Syrian children exposure to Turkish children in the pre-school program has a long-term effect on primary school absenteeism.

JEL Classification: J15, J18, Z13.

Keywords: Refugees, early childhood, randomized field experiment, structural estimation, network formation, non-cognitive skills.

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1 Introduction

Issues concerning the relations between majority and minority groups—both existing ones and those formed through migration—are important topics of policy debate in many countries. In particular, the social integration of minority groups is increasingly recognized as a critical factor for promoting social cohesion and closing gaps in economic prosperity between groups.[1] Can social integration be promoted by providing opportunities for diverse groups to interact in educational settings? Most of the existing evidence—discussed in more detail below—is based on high school or college students, and mostly in Western countries. There is a dearth of causal evidence on the effectiveness of mixing groups for integration when the interaction occurs in earlier years, as well as on the underlying mechanisms at play. This is important for the design of educational policies, as recent studies underline that interventions in early childhood can not only have lasting effects on the formation of human capital, particularly for disadvantaged children, but can also shape the development of preferences and personality more broadly (Heckman, 2000, 2006; Duncan and Magnuson, 2013).[2]

In this paper, we advance the literature on the social integration of minority groups in four main ways. First, we provide causal experimental evidence on the impact of mixing 5-year-old children of different ethnic backgrounds on the formation of friendship networks in a preschool education setting. Our context is unique, as it involves both native and refugee children in the country (Turkey) hosting the world's largest population of refugees (40% of all forcibly displaced persons).[3] Second, we develop a new model of friendship formation that embeds two main features that shape network formation: preference for forming friendships with members of one's own group (homophily) and congestion in the friendship formation process. The model is tractable and generates comparative statics predictions on how the friendship network structure varies with the composition of the group that are consistent with the patterns observed in the data. Third, we structurally estimate the model and use the resulting estimates to assess the quantitative relevance of the mechanisms identified by our theory and to perform counterfactual policy experiments. Fourth, we examine the long-term effects of out-group exposure in the preschool setting on children's school absenteeism in primary school.

Our data collection takes place in Turkey, a country that in recent years has been the largest host of refugees, mostly from neighboring Syria. As of the beginning of the 2019/20 academic year, there were approximately 1.1 million school-age (5-17) refugee children in Turkey.[4] Turkey has been systematically implementing programs, both to close the education gaps opened during

[1] Indeed, a large literature on the economic consequences of social network structure provides ample evidence that group segregation has implications on a wide range of important socioeconomic outcomes, such as educational achievement, employment, health, social mobility, and marriage patterns—see Jackson et al. (2017) for an overview of this literature.

[2] See Raabe and Beelmann (2011) for meta-analytic evidence that prejudiced attitudes toward outgroups develop early in life.

[3] See https://www.unhcr.org/data.html for more detailed data on forced displacement. Figure A1 in Appendix B shows the number of refugee flows into Turkey by years.

[4] See https://piktes.gov.tr/Home/IndexENG for statistics and documentation.

the transition from Syria to Turkey and to integrate the refugee children into the education system. The main lesson learned throughout this process is that these programs are more effective the earlier they are implemented. It has also become clear that differences between educational institutions in Syria and Turkey, and, in particular, the difficulty of transitioning from education in Arabic to education in Turkish—which have substantially different linguistic structures, and even alphabets—necessitates focusing additional effort at the early childhood level to facilitate social integration. Hence, the focus of integration programs has recently shifted toward the early childhood age group. As part of this shift in focus, a two-month early childhood program (Summer Camp) was implemented during July-August 2019 in 26 provinces. The Summer Camp program was developed for the purposes of (i) bringing 5-year-old refugee and native children together to begin early socio-cultural integration, (ii) familiarizing the preschool refugee children with the Turkish education system, and (iii) improving the Turkish language skills of refugee children— an essential element of a successful integration programs. The program specifically targets disadvantaged 5-year-old refugee and native children with no earlier access to any form of formal early childhood education.

We embed a randomized field experiment into the design of the Summer Camp program. The randomized field experiment is implemented in Gaziantep—one of the largest host provinces located near the Syrian border—in 11 randomly selected schools. Specifically, we randomly assign refugee children to classrooms with differing ethnic composition to estimate the causal effect of refugee share in a classroom on two main outcome variables: friendship formation of both refugees and natives and language skills of refugees. In addition, we elicit prosocial behavior of both refugees and natives measured by means of a simple dictator game, which we call the Sticker Game.[5] We collected these outcomes in two points: in the beginning of the program and two months later, as the program was coming to an end. In this setting, our intervention initiates a "randomized contact" between 5-year-old refugee and native children; then, we estimate the impact of random contact on the main outcomes of interest.

We find that higher exposure to children of the other ethnicity leads to an increase in the formation of interethnic friendships for Turkish children. In particular, a Turkish child in a class with a low share of refugee children (up to 36%) has a significantly larger share of own-ethnicity friends (85%) than one in a high refugee share group (more than 70%) in which the share of own-ethnicity friends is 38%. The effect is smaller for Syrian children: the fraction of own-ethnicity friends in groups with a high share of refugees is 85%, while in low refugee share groups it is 54%. These patterns are confirmed by reduced-form regression analysis that controls for various characteristics of the children and their parents, and also includes school fixed effects and measures of friendship links obtained at the start of the program. We also observe

[5] The dictator game is a frequently used vehicle to elicit social preferences of children—see, e.g., Sutter, Zoller, and Glatzle-Rutzler (2019) for a survey on economic experiments with children.

a significant improvement in Turkish language skills for Syrian children, with the improvement being less pronounced in groups with a higher concentration of Syrian children. With regards to prosocial behavior (i.e., the Sticker Game), we find that Turkish and Syrian children on average share the same fraction of their endowment of stickers with a random classmate (about 40%). However, for Turkish children, sharing decreases with in-class refugee concentration. In other words, they share less when the recipient is more likely to be a Syrian refugee, suggesting that they exhibit in-group favoritism in prosocial behavior. On the other hand, Syrian children do not significantly vary their sharing according to the ethnic composition of their group. This suggests that Syrian children do not discriminate on the basis of ethnicity—if anything, there is weak evidence of favoring the outgroup.

We then develop a new model of network formation to facilitate the interpretation of the empirical results and derive further predictions. In the model, children choose a level of socialization effort, which then determines the probability of forming links with other children.[6] The choice is influenced by a desire to conform to the average socialization behavior of the class (social norm)[7] without strategically anticipating the impact of socialization on the formation of the friendship network. This simplifying assumption is made for analytical convenience but is also conceptually plausible, as that high a level of strategic sophistication cannot be expected of children of that age. Two main forces determine friendship formation in our model: (i) preference for forming friendships with children of one's own ethnicity and (ii) type-specific congestion, which implies that—consistent with the data—one's number of friends does not mechanically increase with the size of one's ethnic group. The model predicts that the probability that a coethnic pair is linked decreases with the share of that ethnic group in the class, which is consistent with the patterns observed in our data.

The model is analytically tractable and sufficiently parsimonious to be identifiable with our data. We structurally estimate the key parameters of the model and show that it is a good fit for the data. In particular, we find that children have a strong preference to conform to the average socialization effort in their class, with Syrian children displaying a stronger such tendency than Turkish children.[8] We also find that interethnic links are less likely to be formed than intraethnic ones, and that the language skills of Syrian children play an important role.

We then simulate the model at the estimated parameters to investigate how a change in the ethnic composition of a group affects network formation. The key insight that emerges is that mixing majority and minority children has a nuanced effect on two widely used measures of the structure of friendship networks: homophily and inbreeding homophily. Homophily captures the extent to which children make friends with coethnics, and inbreeding homophily the extent to

[6] This approach is similar to Cabrales et al. (2011), Canen et al. (2020), and Banerjee et al. (2020).

[7] See Walker and Andrade (1996), Hanayama and Mori (2011), Haun and Tomasello (2011), Haun et al. (2014), and Sun and Yu (2016) for evidence that preschool children conform to their peers and the discussion after equation (4) in Section 5.1.

[8] We use sharing in the Sticker Game as an imperfect proxy for children's socialization effort.

which they do so compared to the opportunities available. As an example, consider two children who each have 90% of their friends being coethnic. These two children have the same homophily. However, suppose that one child is in a class with 90% coethnic children, whereas the other is in a class with 10% coethnic children. It is evident that the second child displays a stronger propensity to form friendships with own-ethnicity children. Inbreeding homophily would capture this. We find that exposure to non-coethnic children: (i) reduces homophily (share of own-group friends) and (ii) has a non-monotonic effect on inbreeding homophily (share of own-group friends relative to the size of own group). In particular, we find that inbreeding homophily of Syrian children is maximized for a moderate relative size of the refugee group (about 30%), while it is lower when the two groups are roughly equal. This suggests that if a policymaker's aim is to achieve better integration of Syrian children, then mixing them with Turkish children in classes with ethnic shares that are proportional to the population at large would not be optimal.

These homophily patterns arise due to the interplay between the opposing forces of preference biases and the congestion embedded in our theoretical framework. To shed some light on the quantitative importance of the two mechanisms, we then perform counterfactual simulations. What we find is that, if we remove the influence of congestion on friendship formation, the exposure to non-coethnic children has a monotonic negative effect on inbreeding homophily—which underlines that congestion effects are key for the non-monotonic patterns outlined above. We also observe that ethnic bias has a significant impact on homophily: in the baseline scenario that we simulate, the share of own-ethnicity friends is 8 percentage points (or 17%) higher than a counterfactual scenario with no preference biases.

Our next aim is to use the estimated model to assess the impact of language skills on the friendship network. To this end, we perform a counterfactual experiment in which we let all Syrian children be fluent in Turkish. This counterfactual analysis indicates that language skills explain a significant part of the influence that ethnic biases exert on homophily. That is, if all Syrian children were fluent in the Turkish language, this alone would offset more than half of the impact of ethnic bias on homophily. These results are informative for policymakers, as they indicate that policies that encourage the early acquisition of language skills by refugee children will foster their social integration in host countries.

Finally, we study the *long-term* effects of exposure to non-coethnic children during the Summer Camp on the development of non-cognitive skills, measured by school absenteeism during the academic year following the Summer Camp. We find that Syrian children are positively affected by exposure to Turkish children; the higher was the share of Turkish children in their Summer Camp group, the fewer days they were absent from school in the following academic year. Interestingly, there is no significant effect of Syrian exposure on the absenteeism of Turkish kids.

Our paper contributes to several strands of the literature. First, we contribute to the fast-growing empirical and theoretical literature on the formation of networks.[9] In line with the literature in sociology (McPherson et al., 2011), most papers find strong evidence of homophily: the salient feature of social networks that, regardless of the context, individuals who have similar characteristics (e.g., ethnicity, race) are more likely to be linked (Currarini et al., 2009, 2010; Boucher, 2015; Mele, 2020; Badev, 2021). Explanations for homophily are based on either preference or meeting biases (Bramoullé et al., 2012; Currarini et al., 2009). We build a model of network formation in which homophily originates from preference biases. This is well suited to our context, in which children socialize within small populations (i.e., classrooms). We introduce congestion, which interacts with preference biases and implies that the probability of a link decreases with the number of similar pairs. Children's involvement in the network formation process is endogenous and is chosen as a function of the classroom norm. Our network formation model is empirically tractable, fits the data well, and can be used to study the impact of random intergroup exposure on integration in the friendship network and to perform counterfactual policy experiments. In this regard, the closest papers to ours are Currarini et al. (2009, 2010), who document a non-monotonic pattern for inbreeding homophily using data on high-school teenagers in the U.S., and Mele (2017, 2020), who estimates a structural network formation model and finds that increasing exposure has a non-linear impact on measures of segregation using the same data. However, compared to these papers, the context and age group studied in our paper are different, the model is new, and ethnic mixing is random on account of the field experiment that we carry out.

Second, we add to the growing literature estimating the effects of various inputs on the development of non-cognitive skills. See, for example, Heckman et al. (2006), Cunha and Heckman (2007), Cunha et al. (2010), Attanasio et al. (2020), and List et al. (2020). Indeed, in our model, the child's socialization efforts are mainly "social" or *non-cognitive* and we focus on the impact of exposure on inter-ethnic friendships, language acquisition, and non-cognitive skills (absenteeism). Our study also connects with a growing body of evidence that childhood is a formative period for the development of social preferences (see Sutter et al. (2019) for a survey of this literature) and that educational interventions in this period can help shape them (Cappelen et al., 2020; Kosse et al., 2020). A few papers examine in-group favoritism among children and find more generous behavior within the same social group, which is defined as someone from the decision maker's class in school, from the same school, or someone speaking the same language (Fehr et al., 2008, 2013; Angerer et al., 2016). We contribute to this literature by studying the formation of social preferences along ethnicity lines in a unique context where one's majority/minority status is natural and salient, and documenting that in-group favoritism is displayed

[9] See Chandrasekhar (2016), De Paula (2020) and De Paula and Graham (2020) for reviews of the empirical and econometric literature on network formation and Pin and Rogers (2016) and Vannetelbosch and Mauleon (2016) for reviews of the theoretical literature.

only by children of the majority group.

Third, our analysis is related to the literature that studies the effects of intergroup contact in educational settings (Boisjoly et al., 2006; Carrell et al., 2019; Merlino et al., 2019; Rao, 2019; Corno et al., 2019). This line of work draws on the contact hypothesis, which is fundamentally a theory about contact reducing prejudice or bias against a minority group.[10] Compared to this literature, we do not directly examine whether contact is changing attitudes towards out-groups. Instead, we focus on how randomized exposure to non-coethnics affects key outcomes directly relevant for socio-cultural integration—such as, interethnic friendship formation and language acquisition—in a mixed educational environment. The fact that contact happens between refugee and native children of age 5 is interesting in its own right given the large wave of forced displacement experienced worldwide in recent years.[11] Beyond the reduced-form evidence, we also examine the impact of contact on the structure of the friendship networks through the lens of a theoretical model, and with the aid of structural estimation and counterfactual experiments. Consequently, we view our analysis as complementary to that of the literature on the contact hypothesis.

Finally, our paper contributes to the literature on the assimilation of refugees. Alan et al. (2021) and Alan et al. (2020) are earlier studies that examine the issue of ethnic segregation of Syrian refugee children in educational settings in Turkey. Specifically, Alan et al. (2021) implement and evaluate an educational/curriculum intervention aimed at enhancing the social integration of refugee children in a sample of elementary schools in Turkey. They collect a rich set of outcomes measuring interethnic segregation issues in educational settings. They find significant impacts on a number of dimensions: a reduction in peer violence and victimization on school grounds; an increase in interethnic friendships and prosocial behavior; and an improvement in refugee children's ability in the Turkish language. Alan et al. (2020) exploit random exposure of children to teachers with varying ethnic prejudice and find that teachers' ethnic prejudice negatively affects social integration outcomes. Although we share a similar setting with these two papers, namely studying the issue of social integration of refugee children in Turkey, our focus is different, albeit complementary. Alan et al. (2021) show the value of a particular curriculum intervention and Alan et al. (2020) the role of teachers' attitudes on social integration. Here, we assess the role of *random ethnic mixing* on similar outcomes and, contrary to these two studies, we run some counterfactual policies based on a network formation model. Furthermore, several studies have focused on the role played by ethnic networks in the economic integration

[10] The contact hypothesis originates from the seminal work of Allport (1954), who argues that intergroup contact is an effective way to eliminate prejudice under certain conditions (contact theory). The idea has generated a very large literature aiming to test its empirical relevance in various contexts (Pettigrew and Tropp, 2006; Paluck et al., 2019). Contact theory maintains that intergroup contact improves relationships between groups under certain circumstances—i.e., when both groups are of equal status or when they have common goals (Lowe, 2021; Mousa, 2020).

[11] Several recent papers examine the broader impact of exposure to refugee migration on the attitudes and preferences of natives, including preferences for redistribution (Dahlberg et al., 2012), political preferences (Dustmann et al., 2019; Steinmayr, 2020), and attitudes toward refugees (Hangartner et al., 2019).

of refugees (e.g., Edin et al. (2003); Martén et al. (2019)), while others have highlighted the key role played by language in the assimilation and integration of immigrants (Chiswick and Miller, 1995; Arendt et al., 2020) and refugees (Fasani et al., 2018). Brell et al. (2020) provide a recent survey on the factors affecting the success of refugees' economic integration. Yet, to our knowledge, there has been no comprehensive quantitative study of the causal effect of ethnic mixing in early childhood on assimilation, measured by interethnic friendship relationships.

The paper is organized as follows. Section 2 provides some background information on the case of Syrian refugees in Turkey and their educational integration. Section 3 describes the institutional setting, the experimental design, and the data. Section 4 presents our reduced-form results. Section 5 develops the model and discusses the main theoretical results. Section 6 explains our structural estimation, estimates the main parameters, and performs some counterfactual policies. Section 7 studies the long-term effects of the pre-school Summer Camp program on the students' school attendance/absenteeism patterns (which proxy non-cognitive skills) after they start primary school. Finally, Section 8 concludes.

2 Background: Educational Integration of Syrian Refugees in Turkey

This section begins with some background information on Syrian refugees in Turkey and the education services provided to refugee children. Early childhood education has evolved into a priority topic over time as the Turkish government and its international partners in refugee integration have realized that integration efforts are less costly early in life than later. The Summer Camp program, details of which are introduced in the next section, is designed with this consideration in mind.

Forced displacement has become one of the most important policy challenges around the world. As of the end of 2019, the number of forcibly displaced individuals exceeds 70 million worldwide, including about 26 million refugees. Forced displacement has always been a topic of debate globally; however, the Syrian crisis, which generated a refugee wave of around 7 million individuals and threatened stability in a wide range of hosting regions/countries, brought the forced displacement issue into the spotlight. Two distinctive characteristics of the Syrian refugee crisis are that it has generated one of the largest refugee waves in human history and that this huge refugee wave has been hosted almost exclusively by a small number of neighboring countries—namely, Turkey, Lebanon, and Jordan. The immediate humanitarian assistance phase was successfully addressed jointly by the hosting governments and the international community. That said, extensive refugee presence is expected to pose prolonged challenges on key policy areas such as labor markets, education, health, and other public services.[12] Hosting the largest

[12] A growing literature studies the impact of Syrian refugees on host-country outcomes, centered on the impact of refugees on the labor market outcomes of natives—e.g., Tumen (2016); Fallah et al. (2019). See Becker and Ferrara (2019) and Verme and Schuettler (2019) for very detailed literature surveys.

number (nearly 4 million) of Syrian refugees (see Figure A1 in Appendix B), Turkey has already begun tackling the social integration issues along various directions. Education of refugees is among the issues with highest priority, as gaps in human capital, which may persist into future generations, represent a socioeconomic threat to the society as a whole. There are more than 1.1 million refugee children of school age in Turkey, based on the latest Ministry of National Education figures.

Turkey and Syria are neighboring countries located around the northeastern part of the Middle East and North Africa (MENA) region. Muslims comprise a great majority of the population in both countries. The two countries also shared a common history for quite a long time—between the 16th and 20th centuries—under the rule of the Ottoman Empire. The bordering regions exhibit cultural similarities, and even kinship ties exist between Turkish and Syrian villages located near the border. Strong commercial ties in the region provide major sources of income for people living on both sides of the border. Despite these similarities, there are broad differences between the Turkish and Arabic cultures—which are distinct dominant cultures—that inhibit a smooth refugee integration process. Differences in educational institutions, languages, and alphabets (Latin versus Arabic) make linguistic and educational integration particularly challenging for children. There are also some ethnic and religious nuances. While these may seem trivial, they may, in fact, be sources of deeper conflict and controversies between Turkish and Syrian people.

The approach toward delivering of education services to refugee children in Turkey reached a turning point at the beginning of 2016. Up to that point, both the authorities and the refugees expected that the political turmoil in Syria was temporary and that the crisis would end soon, so there was no systematic attempt to integrate refugee children into the Turkish education system. By 2016, it was understood that the Syrian refugees would stay longer in Turkey than expected initially. Full integration into the society became a policy priority. In line with this priority, the education policy shifted again and the entire setup was redesigned so as to fully integrate Syrian children into the Turkish public education system. The integration program contained three major elements: language training, integration into the Turkish education system, and social integration. All three of these elements required substantial investment into educational resources. In line with the principle of international burden sharing, the EU Facility for Refugees in Turkey (FRIT) provided financial support in two tranches to support the undertaking of vital investments. Other international organizations provided project-specific financing. Various programs have been implemented to facilitate integration along several dimensions.

Integrating refugee children into the Turkish education system has been a challenging task, especially in terms of the language training and social integration aspects. School attachment levels of adolescent refugees have been very low, and policies to bring the dropouts back to school have had only limited effects.[13] This suggests that the interventions aimed at closing achievement gaps at the adolescent level are neither efficient nor cost effective. Accordingly, the Ministry of National Education launched a program, financially supported by FRIT, to close the gaps at the early childhood level. The preschool enrollment rate of Syrian children in Turkey has been around 35% percent, which means that additional effort is needed to increase the treatment intensity. In recognition of these needs, the Ministry of National Education designed an early childhood Summer Camp program in 2019. The aims, coverage, and content of this program are explained in the next section.

3 The Preschool Summer Camp, Experimental Design, and Data

Section 3.1 presents a description of the Summer Camp program during which our randomized field experiment was implemented. Section 3.2 presents the details of our experiment design and its implementation. Section 3.3 describes the data used in the empirical analysis.

3.1 The Preschool Summer Camp

The Ministry of National Education (MoNE) implemented a two-month Early Childhood Summer Camp Program in 2019, beginning on July 1 and ending on August 31. The target group was 5-year-old Turkish and Syrian children, who were to start elementary school in the Fall semester of the 2019-20 academic year. The program was implemented across Turkey in the 26 provinces with the highest concentrations of refugees.[14] More than 40,000 children were enrolled in the Summer Camp; of these, slightly fewer than 20,000 were refugees.[15]

The main goals of the program were (i) to provide an accelerated early childhood education for disadvantaged native and refugee children, (ii) to socially integrate native and refugee children, (iii) to formally introduce Turkish language to refugee preschoolers, (iv) to introduce the norms and informal rules of Turkish society to refugee children, and (v) to familiarize refugee children with the Turkish education system. A nutritious lunch and other afternoon snacks—which matter for low-income parents—were also provided during the program to encourage the enrollment of disadvantaged children.

The program relied on buildings, teachers, and other facilities of public schools located in the 26 provinces. Since it was implemented during the summer months, there were no physical

[13] See Tumen et al. (2019) for detailed impact assessment of those policies and programs. The report is available from the Ministry of National Education of the Republic of Turkey upon request at their own discretion.

[14] It should be noted that those 26 provinces were selected in collaboration with the EU and the FRIT funds have been primarily channeled into these provinces. A specific project, called the "Project on Promoting Integration of Syrian Kids into the Turkish Education (PIKTES)," was launched and administered by the MoNE. PIKTES has carried out a wide range of activities and the Summer Camp is part of those activities.

[15] The program was not designed specifically for Syrian refugees. Based on the inclusiveness principle, refugees from other nationalities—such as Afghanistan, Iran, Iraq, Somalia, and others—were also allowed to enroll; but, as expected, Syrians were the majority, i.e., more than 97%.

capacity concerns. The MoNE preschool teachers were assigned to the program on a voluntary basis, and they received extra payment for their service. The teachers and school administrators also received a short training during the last week of June about the program's content, goals, and curriculum.

A specific curriculum was designed by the Ministry—not within the context of our experiment—in collaboration with UNICEF and in line with the program's objectives. The curriculum clearly outlines the activities to be performed on a week-by-week basis. They include regular preschool skill acquisition activities that improve linguistic, manual, cognitive, and socio-emotional skills of participating children; group activities (such as teamwork and playgroups) to mix children of different genders and ethnicities; activities to teach them the formal rules they should follow in elementary school; and activities to familiarize the refugee children with the informal rules/norms of the Turkish society. Formal Turkish language training is jointly provided to both Syrian and Turkish children.

3.2 Experimental Design

We perform a medium-scale randomized field experiment, which is implemented as part of the Summer Camp program. The main goal of the experimental design is to randomly allocate refugees to classrooms to obtain a balanced mix of classrooms with high, medium, and low refugee concentration. In the absence of a random allocation, classroom formation would likely be endogenous and estimating the impact of refugee concentration on outcomes of interest would be a complicated issue.

The randomized experiment is implemented in Gaziantep, a large city close to the Syrian border with a population of around 2 million. Based on official figures of the Directorate General of Migration Management, the ratio of refugees to native population in Gaziantep varied between 0.16 and 0.19 during the 2016-2019 period. Gaziantep is an attractive refugee destination not only because it is close to the Syrian border, but because it has a vibrant economy and there are some cultural and socio-economic similarities between Gaziantep and major source provinces in Northern Syria—such as Aleppo. We focus on Gaziantep because it has a large refugee population and is a major implementation hub for the Summer Camp program.

After MoNE announced the program, which was advertised in refugee-intensive areas through the outreach activities of MoNE and its partners in the field, refugee and Turkish parents registered their 5-year-old children to designated schools based on their home address. In other words, parents did not directly choose the school, and school selection was made based on catchment area. A total of 4,634 5-year-old children (2,188 refugees and 2,446 natives) were registered to the program in Gaziantep in 121 schools. MoNE shared with us the lists of children registered to the program in each school before the children were assigned into groups. We initially identified

46 schools with around 50% refugee concentration. Then, we randomly selected 11 schools in which we implement our experiment—5 are located in Sehitkamil, 5 in Sahinbey, and 1 in Nizip. Figure A2 in Appendix B displays the locations of these schools on the map.

In these 11 schools, children were randomly assigned to 36 groups before the program began. To generate variation in the share of refugees across the groups, we first fixed the share of refugees in each group within each school in agreement with the school administration. Then we randomly assigned the kids into the groups.[16] The resulting groups vary in size from 10 to 24, with an average size of 16.9. Note that forming Syrian-only or Turkish-only groups was not allowed because the purpose of the program was to mix the two groups. Figure A3 in Appendix B shows the distribution of refugee share across these 36 groups, which suggests a balanced mix of groups with high, medium, and low share of refugees. Switching between the assigned classes and/or schools was not allowed in our sample.

The main goal of the empirical analysis—see Section 4—is to analyze how refugee intensity in a group affects various outcomes of participating children. One challenge against this goal was that a three-day Eid (Qurban) holiday occurred during the week before the program ended, and this posed a risk of losing students after Eid and, thus, not being able to measure their end-of-program outcomes. To avoid this risk, we collected data three times during the program. The pre-program baseline was collected at the beginning of the program. The end-of-program endline was collected twice: before Eid and after Eid. If the student showed up only after Eid or both before and after Eid, then we use data from the third wave as the end-of-program data for the corresponding student. If the student showed up only before Eid, then we use the second wave as the end-of-program data for the corresponding student.

3.3 Data Description

A total of 638 children were in the initial allocation list. Of those, 12 children (5 refugees, 7 natives) did not attend the program, which means that pre-program data collection was performed for 626 children. An additional 4 children dropped out (3 refugees, 1 native) after the second week, and 18 children (8 refugees, 10 natives) did not take the end-of-program assessment—i.e., they were able to take neither the second nor the third assessment wave. Overall, 604 children completed the program—328 refugees and 276 natives, 310 males and 294 females. The attrition rate is only 5%.[17]

We consider two main outcome variables: (1) friendship network and (2) Turkish language

[16] If, for example, there were 51 children, 25 Syrians and 26 Turkish, in a certain school who would be split into three groups of size 17 each (the average group size in our dataset), then we would determine the numbers of Syrian kids in each group (say 5, 8, and 12) in agreement with the school administration and then randomly assign the children into the groups. So the refugee shares would be $5/17 = 0.29$, $8/17 = 0.47$, and $12/17 = 0.71$, respectively, in the three groups of this school.

[17] Although attrition is very small, we still check whether non-attendees selectively dropped out. We find that the characteristics of the non-attendees are not meaningfully different from those of participating children. Basic summary statistics about the characteristics of dropouts are provided below in Table A2 in Appendix A.

skills (Syrian children). We elicited the friendship network of the children twice: in the pre- and end-of-program assessment exercises conducted by the teachers. Children were asked to report their best friends (up to 5) in the classroom[18] and rank them, and teachers recorded the names. In our analysis, we construct various outcome variables using the friendship network details. During the Summer Camp, Turkish language training was provided to both Turkish and refugee children. In addition to the language training, the refugee kids were exposed to Turkish students in the classroom. The Turkish language skills of the refugee children were assessed by the teachers at the beginning and end of the program. The language ability of refugee kids was reported on a six-category scale—1-none, 2-can only recognize letters, 3-can identify some words, 4-can bring together a few words to communicate, 5-can form sentences, and 6-can speak fluently.

In addition, we elicited *prosocial behavior* of the children through a version of the dictator game, which we call the Sticker Game. The Sticker Game was carried out by the teacher as follows. The teacher and the child sat at a table facing each other. The teacher gave 10 stickers to the child and clearly explained that all the stickers belonged to the child. Then the teacher put two envelopes on the table: one for the child and the other for another random child in the classroom. There was no hint regarding the ethnicity or gender of the other child, so the recipient could be interpreted as an average kid in the class.[19] Then the teacher closed his/her own eyes, asked the child to put the stickers that the child wanted to share into the other child's envelope, and put the rest into his/her own envelope. Next, the teacher asked the child to take his/her own envelope and leave the table. After the student left, the teacher counted and recorded the stickers in the envelope.

Table 1 presents summary statistics for the main outcomes of interest: friendship formation, language skills (only Syrian children), and sharing in the Sticker Game. In terms of friendship, a few interesting patterns in Table 1 are worth highlighting. First, both Turkish and Syrian children make more friends during the course of the Summer Camp. Second, Syrian children report a slightly greater total number of friends (2.8 vs 2.6; t-test, p=0.033) and have a slightly higher share of friends who are their own ethnicity (80% vs 74%; t-test, p=0.046) than Turkish children.[20] In reference to language skills, there is a significant improvement (72%) during the course of the Summer Camp. In terms of sharing, we observe an increase for both Syrian and Turkish children, with evidence of a stronger increase for the Syrian children (t-test; p=0.026).

We also collected a number of other variables through a survey of the parents. Number

[18] Observe that the maximum number of friends is not binding, since very few students report 5 friends and the average number of friends is 2.40. See Table 1.

[19] Note that, given the sensitive context and the young age of participating children, we refrained from asking them to share with a target recipient of a specific ethnicity in mind, but left the ethnicity and gender of the recipient undefined. This implies that, for a given child, we could not observe whether their preferences for sharing varied by the ethnicity of the recipient, but we can still draw inferences on whether at a group level there is an ethnic bias in preferences for sharing.

[20] A fraction of children report not to have any friends in the baseline (14.3% of Syrian and 13.8% of Turkish). Throughout our analysis, we set the value of the variable capturing "% of own ethnicity friends" for these children to zero.

of siblings, parental education, and parental employment information were collected for both native and refugee students. Moreover, we collected information on whether the parents reside close to refugees and whether parents' friends include any refugees. For Syrian parents only, we collected information on their region of origin in Syria, the year of arrival in Turkey, and their Turkish language skill level. Summary statistics for these variables are reported in Tables A2-A5 in Appendix A.

Table 1: Summary statistics: Outcome variables (means)

	All sample			**Syrian**			**Turkish**		
	[1]	**[2]**	**[Diff]**	**[1]**	**[2]**	**[Diff]**	**[1]**	**[2]**	**[Diff]**
ALL									
Turkish language skills	-	-	-	2.33	4.02	1.69	-	-	-
Stickers given	3.84	4.18	0.33	3.65	4.17	0.52	4.07	4.19	0.11
# of friends	2.40	2.72	0.32	2.51	2.82	0.31	2.27	2.59	0.32
# of Syrian friends	1.42	1.56	0.15	2.02	2.21	0.19	0.70	0.79	0.09
# of Turkish friends	0.98	1.15	0.17	0.49	0.61	0.12	1.58	1.80	0.23
% of own ethnicity friends				0.71	0.80	0.09	0.65	0.74	0.09
Number of obs.	604			328			276		

Notes: [1] indicates baseline; [2] indicates endline; [Diff] indicates the difference between the two. There are 604 children in the sample (328 Syrian, 276 Turkish; 310 male, 294 female).

4 Reduced-form Analysis and Results

4.1 Empirical Strategy

The main regression equation that we estimate is specified as follows:

$$y_{ig}^2 = \alpha_s + \beta q_g + \gamma y_{ig}^1 + \boldsymbol{\lambda_1'} \boldsymbol{x}_{ig} + \boldsymbol{\lambda_2'} \boldsymbol{z}_{ig}^p + \epsilon_{ig}, \tag{1}$$

where y_{ig}^2 is the outcome of child i in group g measured in the endline, and y_{ig}^1 is the same outcome measured at baseline. q_g is the share of refugees in group g. The vectors of controls $\boldsymbol{x}_{ig}$ and $\boldsymbol{z}_{ig}^p$ are sets of control variables specific to the children (gender, ethnicity, number of siblings) and their parents (education, employment status, ethnic composition of friends and neighborhood; for Syrian parents, we also control for region of origin in Syria, year of arrival in Turkey, and Turkish language skills), respectively, while α_s is a school fixed effect. Throughout the analysis, we cluster standard errors at the classroom level.

In a standard school setting, the refugee share will likely be correlated with the outcome variable, as students in classrooms with high refugee intensity would be of lower socioeconomic background due to the address-based enrollment system—i.e., neighborhoods with high refugee concentration would mostly consist of residents from lower socioeconomic backgrounds. Moreover, there may be a tendency—due either to the choices of school administrators or pressure from influential parents in the region—to selectively form classrooms. As a result, q_g might be correlated with unobserved determinants, ϵ_{ig}, of the outcome variable. In our setting, (1) both the Syrian and Turkish children in the 11 schools are randomly assigned to 36 classrooms, (2) the randomization is performed so that the refugee intensity also randomly varies across classrooms, and (3) the children in those classrooms are not allowed to change classrooms during the Summer Camp. Our main parameter of interest is β. This measures the change in y_{ig} in response to a one-percentage-point randomized change in q_g.

To examine possible nonlinear effects of the refugee share on the outcomes of interest, we also estimate a specification of the following form:

$$y_{ig}^2 = \alpha_s + \sum_{q=2}^{3} \beta_q t_{qg} + \gamma y_{ig}^1 + \boldsymbol{\lambda_1'} \boldsymbol{x}_{ig} + \boldsymbol{\lambda_2'} \boldsymbol{z}_{ig}^p + \epsilon_{ig}, \tag{2}$$

where t_{qg} are indicator variables that denote the tercile of the refugee share distribution.[21]

In Table A6 of Appendix A, we report a "balancing test" to check whether the share of refugees in one's class is related to a number of predetermined student characteristics: gender, mother's and father's education, number of siblings, mother's and father's employment status, ethnic composition of parents' friends and of neighborhood, and for Syrians, if Aleppo is the region of origin, arrival year, and Turkish language skills of parents. We do so by regressing the characteristics on refugee share, controlling for nationality and school fixed effects. As can be seen in the table, only for mother's employment is the estimated coefficient marginally statistically significant (p=0.099); note though that there is little variation in mother's employment as 95.7% of mothers in the sample are not employed (see Table A2). Overall, this analysis indicates that, as we might expect due to the randomized formation of classes, student observable characteristics are not systematically related to the ethnic composition of the class.

4.2 Friendship Network

In this section, we examine whether refugee exposure had any impact on friendship formation, focusing on the ethnic identity of the links. We present results for two outcomes: (i) number of own-ethnicity friends and (ii) share of own-ethnicity friends. In Table A7 of Appendix A we also present results for some additional outcomes: total number of friends, number of non-coethnic friends, and share of non-coethnic friends.

Table 2 presents regression results on the sample of Turkish children, while Table 3 presents

[21] The cutoffs are 38.5% for the first tercile and 70% for the second tercile. See Table A1 in Appendix A for summary statistics of the outcome variables by tercile.

results for Syrian children. In these tables, the first column includes only school fixed effects, in the second column we add a control for the outcome measured in the baseline, and in a third specification we include additional controls such as gender and family characteristics.

We present two specifications: one in which the refugee share enters linearly, and a second where we explore a nonlinear effect by including indicators for belonging to a group with a medium or high share of refugees (the omitted category is low share).

Starting with the evidence for Turkish children, what we see in the linear specification is a negative effect of exposure to refugee children, on both outcomes. In terms of size, the coefficient in column (3) of Table 2 implies that a one standard deviation increase in refugee share leads to a 0.24 decrease in the number of Turkish friends (the mean number of Turkish friends for Turkish children is 1.8), while in column (6) we find that it leads to a 0.14 decrease in the share of Turkish friends (the mean share of Turkish friends for Turkish children is 0.70). The tercile specification suggests decreasing returns to the impact of contact on friendship formation, as we cannot reject equality of the coefficients of the medium and the high refugee share (p=0.86; in column 6).

For Syrian children, the results indicate that the share of refugees in the group exerts a positive but weaker effect on the number and share of own-ethnicity friends. This is clear in the linear specification in which we find no statistically significant effect for either outcome. In the tercile specification, we find some evidence of a statistically significant difference for both outcomes comparing the medium to the low refugee share groups. The coefficient in column (3) in Panel B of Table 3 indicates that being in the medium refugee share group is associated with an increase in the number of Syrian friends of 0.4, when on average Syrian children report 2.2 Syrian friends. The coefficient in column (6) similarly indicates a difference of about 15pp, when the baseline share of Syrian friends is almost 80%. High refugee share groups also tend to have higher shares of Syrian friends compared to the low refugee groups, but the difference is not statistically significant when we add controls (see columns (5) and (6)). For the share of Syrian friends outcome (columns (4)-(6)), we fail to reject equality of the coefficients on the high and the medium groups indicating, again, decreasing returns of the effect of exposure to refugees on friendship formation.

Overall, the analysis of friendship networks indicates that the ethnic composition of the children's Summer Camp group does influence the ethnic composition of their friendship network. This can also be seen graphically in Figures 1 and 2, which plot the homophily index (share of friends that are coethnic) against the relative size of the refugee group in the class, for Syrian and Turkish children, respectively. Each dot in the figure represents one of the 36 groups in our data, and the line is a quadratic fit. These figures illustrate the presence of a negative relationship for both ethnic groups between exposure to members of the other group and homophily. We will

Table 2: Friends regressions (Turkish children)

	# of Turkish Friends			Share of Turkish Friends		
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Panel A - Linear Specification						
Refugee share	-0.014**	-0.011**	-0.012**	-0.731***	-0.626***	-0.669***
	(0.006)	(0.005)	(0.005)	(0.205)	(0.177)	(0.193)
Turkish friends Baseline		0.216***	0.215***			
		(0.059)	(0.062)			
Share of Turkish friends Baseline					0.189***	0.196***
					(0.054)	(0.060)
Panel B - Tercile Specification						
Refugee share (Med)	-0.487**	-0.452**	-0.442**	-19.240***	-17.111***	-20.725***
	(0.189)	(0.171)	(0.167)	(6.533)	(5.405)	(5.938)
Refugee share (High)	-0.864*	-0.692	-0.629	-24.767*	-19.436	-22.872*
	(0.489)	(0.417)	(0.400)	(14.256)	(12.289)	(11.343)
Turkish friends Baseline		0.218***	0.220***			
		(0.055)	(0.060)			
Share of Turkish friends Baseline					0.210***	0.212***
					(0.054)	(0.060)
School fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
# of obs.	276	276	276	276	276	276

Notes: The sample consists of Turkish children. The dependent variable is the number of Turkish children (col 1-3) and the share of Turkish children (col 4-6) in the student's friendship network in the endline of the Summer Camp. Controls include gender, number of siblings, education of parents, employment status of parents, ethnic composition of parents' friends and neighborhood. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 3: Friends regressions (Syrian children)

	# of Syrian Friends			Share of Syrian Friends		
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Panel A - Linear Specification						
Refugee share	0.022**	0.012	0.011	0.448*	0.310	0.332
	(0.009)	(0.008)	(0.008)	(0.225)	(0.207)	(0.207)
Syrian friends Baseline		0.320***	0.312**			
		(0.068)	(0.073)			
Share of Syrian friends Baseline					0.214***	0.212***
					(0.051)	(0.057)
Panel B - Tercile Specification						
Refugee share (Med)	0.714**	0.510**	0.420**	19.643**	15.484*	14.668**
	(0.295)	(0.215)	(0.204)	(8.762)	(7.757)	(6.471)
Refugee share (High)	0.578	0.058	-0.014	21.624**	13.637	13.202
	(0.423)	(0.289)	(0.300)	(10.544)	(10.169)	(9.356)
Syrian friends Baseline		0.346***	0.332***			
		(0.066)	(0.071)			
Share of Syrian friends Baseline					0.218***	0.220***
					(0.050)	(0.057)
School fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
# of obs.	328	328	328	328	328	328

Notes: The sample consists of Syrian children. The dependent variable is the number of Syrian children (col 1-3) and the share of Syrian children (col 4-6) in the student's friendship network in the endline of the Summer Camp. Controls include, in addition to those in Table 2, region of origin in Syria, year of arrival in Turkey, and Turkish language skills of parents. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

return to discussing what drives these patterns of homophily in Section 6.

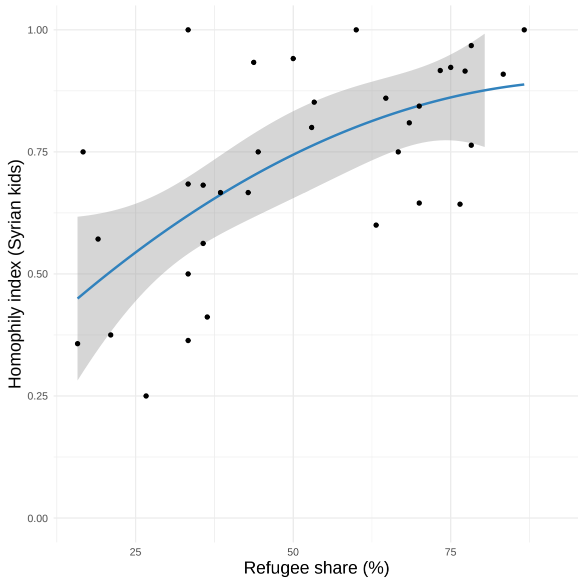

Figure 1: Homophily index by refugee share (Syrian kids).

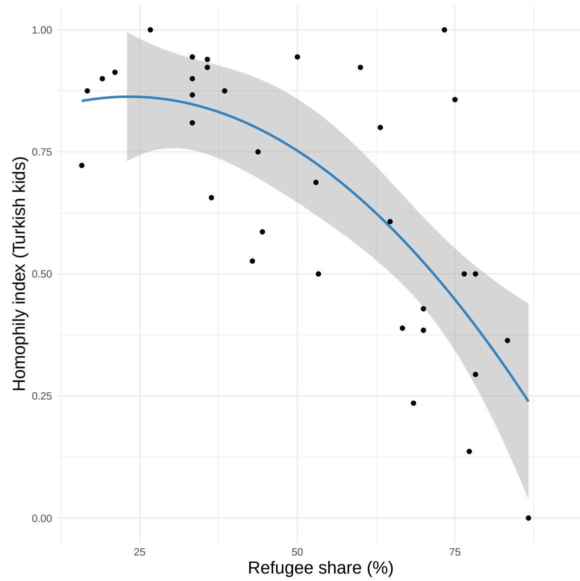

Figure 2: Homophily index by refugee share (Turkish kids).

4.3 Language Skills

We next investigate whether there are differences in language skill acquisition for Syrian children, depending on the share of refugees in their group. Table 4 presents regression results of our baseline linear and the tercile specifications where the outcome is a binary variable defined on whether the child has high or low skills. Recall that language skills are assessed by the teacher and are reported on a scale from 1 to 6. We define as high skill those children who are assessed to be 4 or higher (about 60% of the sample in the endline, and 25% in the baseline).

The first thing to note across the columns of the table is a positive and robust association between level of language skills at baseline and endline. With regards to the treatment effect of interest, the effect of refugee share is negative and statistically significant. The tercile specification indicates that the effect is non-linear, as there is a difference in language skills for children in high refugee share relative to those with medium or low shares (the p-value for comparison of high to medium is 0.003). In particular, the high share group is 30 percentage points less likely to be high skill than those in the low share group, which indicates a significant reduction over the baseline of 60%.

Overall, the above findings suggest that the classroom's ethnic composition has a significant bearing on the development of Turkish language skills among the refugee children.

Table 4: Language (Syrian kids)

	[1]	[2]	[3]
Panel A - Linear Specification			
Refugee share	-0.005***	-0.005***	-0.004**
	(0.001)	(0.001)	(0.002)
Language Baseline		0.420***	0.392***
		(0.053)	(0.051)
Panel B - Tercile Specification			
Refugee share (Medium)	-0.114	-0.126*	-0.146
	(0.086)	(0.072)	(0.095)
Refugee share (High)	-0.352***	-0.367***	-0.299***
	(0.084)	(0.067)	(0.092)
Language Baseline		0.420***	0.395***
		(0.054)	(0.052)
School fixed effects	Yes	Yes	Yes
Controls	No	No	Yes
# of obs.	328	328	328

Notes: The sample consists of Syrian kids. The dependent variable measures the Turkish language skills (0/1) of Syrian kids in the endline. Controls included are the same as in Table 3. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.4 Prosocial Behavior

We next focus on our measure of prosocial behavior: sharing in the Sticker Game. Recall that in the Sticker Game we elicited the willingness to share anonymously with a random classmate. Because the ethnic composition varies across groups, so does the expected identity of the recipient. This means that our setting allows us to examine whether children's willingness to share is affected by whether they are more likely to share with a coethnic or a non-coethnic child.

Table 5 presents regression results on prosocial behavior for the whole sample, while Table 6 and Table 7 present separate results for Turkish and Syrian children, respectively.

Starting with the results in Panel A of Table 5, we find a negative effect of the share of refugees on the sharing that is statistically significant, even after controlling for various characteristics of the children and their parents. The results in Panel B further indicate that the effect is mildly nonlinear, as the negative effect of being in a high refugee share group (relative to being in a small refugee share group) is larger (in absolute value), albeit statistically indistinguishable, from that of the medium share group (p-value of test for equality of coefficients in our preferred specification in column (3) is 0.105).

When examining the subgroups, what emerges is that this negative effect is driven mainly by

Table 5: Stickers given to random classmate (All sample)

	[1]	**[2]**	**[3]**
		Panel A - Linear Specification	
Refugee share	-0.022***	-0.019***	-0.024***
	(0.006)	(0.006)	(0.005)
Sticker Baseline		0.223***	0.226***
		(0.037)	(0.036)
		Panel B - Tercile Specification	
Refugee share (Med)	-0.889***	-0.798***	-0.872***
	(0.285)	(0.233)	(0.228)
Refugee share (High)	-1.209***	-1.020***	-1.360***
	(0.384)	(0.336)	(0.323)
Sticker Baseline		0.224***	0.227***
		(0.036)	(0.035)
School fixed effects	Yes	Yes	Yes
Controls	No	No	Yes
# of obs.	604	604	604

Notes: The dependent variable is the number of stickers given to a random classmate in the endline of the Summer Camp. Sticker Baseline denotes the number of stickers given in the baseline. Controls include gender, ethnicity, number of siblings, parents' education, employment status, ethnic composition of friends and neighborhood. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Turkish children. Both the linear and the tercile specifications in Table 6 suggest a negative and statistically significant effect of refugee share on the sharing of Turkish children. The coefficient of the high refugee share is more negative than that of the medium share group, though the difference is not statistically significant (p-value = 0.105). In terms of the magnitude of the effect, taking the estimates of our preferred specification (column (3)), a Turkish child in a high refugee share group gives 1.9 fewer stickers than a child in a low refugee share group, which is 45% of what Turkish children give on average. Thus, the effect is quite sizeable.

Table 6: Stickers given to random classmate (Turkish kids)

	[1]	[2]	[3]
Panel A - Linear Specification			
Refugee share	-0.035***	-0.030***	-0.030***
	(0.007)	(0.006)	(0.007)
Sticker Baseline		0.209**	0.190**
		(0.079)	(0.085)
Panel B - Tercile Specification			
Refugee share (Med)	-0.958***	-0.865***	-0.936***
	(0.302)	(0.267)	(0.251)
Refugee share (High)	-2.124***	-1.845***	-1.896***
	(0.555)	(0.512)	(0.595)
Sticker Baseline		0.214***	0.194**
		(0.078)	(0.084)
School fixed effects	Yes	Yes	Yes
Controls	No	No	Yes
# of obs.	276	276	276

Notes: The dependent variable is the number of stickers given to a random classmate in the endline of the Summer Camp. Controls included are the same as in Table 2. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

On the other hand, for the Syrian children the coefficients on the share of refugees presented in Table 7 are—perhaps surprisingly— also negative but are smaller numerically and not robust in terms of statistical significance. This indicates that Syrian children do not discriminate ethnically when sharing. If anything, there is some evidence in panel B of Table 7 that they share less in groups in which the recipient is more likely to be a coethnic, though these differences are not robust.

The finding that Turkish children share less in high refugee groups where the expected recipient is a Syrian child than they do in low refugee groups where the expected recipient is a Turkish child, is indicative of a tendency for in-group favoritism. That Syrian children display a weaker tendency for in-group favoritism (or even a tendency for outgroup favoritism) is perhaps not too

Table 7: Stickers given to random classmate (Syrian kids)

	[1]	[2]	[3]
Panel A - Linear Specification			
Refugee share	-0.012	-0.013	-0.018*
	(0.009)	(0.007)	(0.010)
Sticker Baseline		0.240***	0.235***
		(0.046)	(0.045)
Panel B - Tercile Specification			
Refugee share (Med)	-0.821**	-0.793**	-0.531
	(0.390)	(0.321)	(0.376)
Refugee share (High)	-0.760	-0.723	-0.884*
	(0.494)	(0.428)	(0.517)
Sticker Baseline		0.238***	0.232***
		(0.045)	(0.043)
School fixed effects	Yes	Yes	Yes
Controls	No	No	Yes
# of obs.	328	328	328

Notes: The dependent variable is the number of stickers given to a random classmate during the Summer Camp. Controls included are the same as in Table 3. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

surprising in light of previous evidence that this behavior is more prevalent among members of "high-status" groups (e.g., Sachdev and Bourhis (1991)).

5 Theory

In this section, we introduce a simple model that will allow us to gain additional insights regarding the integration of Syrian children. We discuss the model using a set of simplifying assumptions. A more general treatment is provided in Appendices D.1 and D.2.

5.1 Model

Consider a population of n students in a classroom, among whom n^T are Turkish and n^S are Syrian, i.e., $n^T + n^S = n$. For a student i, we denote by $e(i) = S, T$ the ethnicity of i. We denote the share of Syrian children in the classroom by $q = n^S/n$, so $1-q$ is the share of Turkish children.

We consider a simple network formation model featuring two key driving forces: *preference biases* and *congestion*. Preference biases reflect the fact that children may, everything else equal, prefer to interact with other children who have specific characteristics. A main example is *ho-*

mophily, i.e., the fact that children prefer to befriend children similar to themselves (McPherson et al., 2011).

Congestion interacts with homophily in a manner that prevents the number of friends a child has from mechanically increasing with the share of the child's ethnic group. Consider a classroom with only two Syrian kids. Because of homophily, they are highly likely to be friends. Now, consider another classroom of the same size, but in which there is a majority of Syrian kids. In this case, the probability that two randomly selected Syrian kids are friends is smaller. This is because, from the point of view of a given Syrian kid, there are many other Syrian kids to "choose" from. We call this effect congestion.

Finally, homophily and congestion are weighted by letting children choose an aggregate *socialization* level.[22] For example, some kids might be more shy than others, which may explain why they have a smaller number of friends. Formally, we assume that the probability p^{ij} that child i befriends child j is given by:

$$p^{ij} = \frac{\delta^{ij} s^i s^j}{\sum_{k \in C^i(j)} s^k}. \tag{3}$$

Here, δ^{ij} is the preference bias of i regarding j (homophily). The set $C^i(j)$ reflects congestion. It is defined as the set of children (excluding i but including j) that are comparable with j from i's point of view (e.g., children of the same ethnicity or gender as j). Finally, $s^i \in [0, 1]$ is the socialization level for any child i.[23]

In (3), the higher is i's socialization effort s^i, the more likely a link p^{ij} will be formed between i and j. Importantly, from the congestion effect $\sum_{k \in C^i(j)} s^k$, we can easily see that the impact of j's socialization effort is reduced when the socialization efforts of children comparable to j (from the point of view of i) increases.

As discussed above, a child's socialization level is a choice. As in Cabrales et al. (2011), each child i decides upon an aggregate level of socialization effort s^i but does not direct it toward a specific kid in the classroom. This socialization choice is made by each child, but we assume that they do not anticipate the impact of their socialization efforts on link formation. This assumption is made for both simplicity and credibility reasons. These are 5-year-old kids. It is therefore reasonable to assume they only care about "fitting in"; i.e., they want to conform to the classroom socialization behavior (social norm) and do not strategically anticipate the impact of socialization on the formation of the friendship network. Of course, this is not the only possible

[22] The idea that the formation of links is not pairwise, i.e., the exact identity of the interacting partner is not an object of choice, and that each child i chooses an aggregate level of socialization effort s^i, which is then distributed across each and every possible bilateral interaction, was introduced by Cabrales et al. (2011) and has been adopted by Albornoz-Crespo et al. (2019), Banerjee et al. (2020), Boucher et al. (2020), and Canen et al. (2020).

[23] Cabrales et al. (2011) provide a microfoundation of (3) by giving the properties on the links between agents needed to obtain it.

modeling approach, but the current one is empirically tractable—an important consideration in structural analysis (DellaVigna, 2018)—and fits the data well, as we show in the next section.

Formally, we assume that the utility of child i choosing socialization effort s^i is a function of both a private and a social component. It is given by:[24]

$$u^i = \underbrace{b^i s^i - \frac{1}{2}\left(s^i\right)^2}_{\text{Private}} - \underbrace{\frac{\kappa^i}{2}\left(s^i - \overline{s}^{-i}\right)^2}_{\text{Social}}, \tag{4}$$

where $\overline{s}^{-i}$ is the average socialization effort in the classroom *leaving out* i, $\kappa^i > 0$ and where b^i is i's marginal private benefit of socialization. In particular, b^i reflects the *ex ante* heterogeneity (observable characteristics such as gender, ethnicity, parents' characteristics, fluency in Turkish for Syrian kids, etc.) of individual i. We allow the taste for conformity κ^i to be ethnic specific and thus assume that it takes two values: $\kappa^i = \kappa^T$ for the Turkish students and $\kappa^i = \kappa^S$ for the Syrian students.

The utility function (4) has two terms. The first term, $b^i s^i - \frac{1}{2}\left(s^i\right)^2$, corresponds to the utility of exerting s^i units of effort when there is *no interaction* with other children. The second term, $-\frac{\kappa^i}{2}\left(s^i - \overline{s}^{-i}\right)^2$, captures the peer-group pressure faced by child i, who seeks to minimize his or her social distance from the average socialization effort in the classroom, and suffers a utility reduction equal to $\frac{\kappa^i}{2}\left(s^i - \overline{s}^{-i}\right)^2$ from failing to conform to others.[25] Indeed, there is strong evidence from the psychology literature that preschool children conform to their peers (Haun and Tomasello, 2011; Haun et al., 2014; Sun and Yu, 2016) and that conformity decreases with age (Walker and Andrade, 1996).[26] In particular, Haun and Tomasello (2011) demonstrate that children as young as 4 years of age are subject to peer pressure, indicating sensitivity to peers as a primary social reference group already during the preschool years, and Walker and Andrade (1996) found that 85 percent of 3– to 5–year-old children conform to their peers. Moreover, the findings of Sun and Yu (2016) suggest that 6-year-old children spontaneously change their private opinions under implicit social influence from peers. More importantly, Hanayama and Mori (2011) show that young boys aged 6–7 tended to conform more often than older men did.

The first-order conditions are given by: $s^i = b^i - \kappa^i\left(s^i - \overline{s}^{-i}\right)$, which we can rewrite as:

$$s^i = (1 - \phi^i) b^i + \phi^i \overline{s}^{-i}, \tag{5}$$

where $\phi^i := \kappa^i / (1 + \kappa^i)$.

[24] Instead of having a social norm $\overline{s}^{-i}$, which is the average socialization effort in the classroom, we could have assumed a social norm that is given by the average socialization effort of the *same ethnicity* in the classroom. The analysis would have been similar but less interesting and also less realistic.

[25] This is the standard way economists have modeled conformity in the utility function. See, e.g., Akerlof (1997); Patacchini and Zenou (2012); Ushchev and Zenou (2020).

[26] Observe that our utility function (4) is different from that of Cabrales et al. (2011) and the papers cited in footnote 22 because we consider very young children, especially Syrians who are refugees and want to fit in their new country, and, thus, include conformism as the main social aspect of their utility function.

5.2 Equilibrium

In order to gain additional intuition from the model and derive closed-form solutions to the equilibrium of this game, we assume that all Turkish students have the same characteristics and all Syrian students have the same characteristics, i.e., and $b^i = b^S$ for all Syrian children and $b^i = b^T$ for all Turkish children.[27] Under this assumption, there are only two socialization effort levels: one for each of the n^T Turkish kids, denoted by s^{T*}

$$\overline{s}^e = \overline{s} - \frac{s^e}{n}.$$

where

$$\overline{s} = qs^S + (1-q)s^T.$$

The first-order condition (5) can then be written as:

$$s^e = (1-\phi^e)b^e + \phi^e \left(qs^S + (1-q)s^T - \frac{s^e}{n} \right), \tag{6}$$

for $e = S, T$. When n is large, we can easily compute the unique equilibrium quantities of socialization efforts s^{S*} and s^{T*}, and social norm $\overline{s}^*$ as follows:[28,29]

$$s^{S*} = \frac{\left[1-\phi^T(1-q)\right]\left(1-\phi^S\right)}{1-\phi^T-q\left(\phi^S-\phi^T\right)}b^S + \frac{\phi^S(1-q)\left(1-\phi^T\right)}{1-\phi^T-q\left(\phi^S-\phi^T\right)}b^T, \tag{7}$$

$$s^{T*} = \frac{\left(1-\phi^S q\right)\left(1-\phi^T\right)}{1-\phi^T-q\left(\phi^S-\phi^T\right)}b^T + \frac{\phi^T q\left(1-\phi^S\right)}{1-\phi^T-q\left(\phi^S-\phi^T\right)}b^S, \tag{8}$$

$$\overline{s}^* = \frac{q\left(1-\phi^S\right)b^S + (1-q)\left(1-\phi^T\right)b^T}{1-\phi^T-q\left(\phi^S-\phi^T\right)}. \tag{9}$$

Observe that, when $\phi^S = 1$, the socialization effort of the Syrian kids is: $s^{S*} = \overline{s}^* = b^T$, which is independent of q. As a result, when $\phi^S = 1$, q has no impact on s^{S*}. Similarly, when $\phi^T = 1$, the socialization effort of the Turkish kids is: $s^{T*} = \overline{s}^* = b^S$, which is also independent of q. When $\phi^S = 0$, the socialization effort of the Syrian kids is: $s^{S*} = b^S$, which is independent of q; the social norm does not matter. Similarly, for Turkish kids, when $\phi^T = 0$, $s^{T*} = b^T$, which is also independent of q.

Using (3), we can now determine the different probabilities of *link formation*. Again, in order to gain additional insight from the model, we assume that $C^i(j)$ includes all children with the same ethnicity as j (except i) and that δ^{ij} only depends on the children's ethnicity.[30] We

[27] This assumption is relaxed in the empirical section and discussed in Appendix D.1 and Appendix D.2.
[28] Uniqueness of the equilibrium holds generally; see Appendix D.1.
[29] See Appendix C.1 for the calculation of s^{S*} and s^{T*} for finite n and for large n.
[30] This assumption is relaxed in Section 6.

therefore end up with four probabilities: p^{SS}, p^{ST}, p^{TT}, and p^{TS}. Simple algebra leads to:

$$p^{TT*} = \frac{\delta^{TT} s^{T*}}{n(1-q-1/n)}; \tag{10}$$

$$p^{TS*} = \frac{\delta^{TS} s^{T*}}{nq}; \tag{11}$$

$$p^{SS*} = \frac{\delta^{SS} s^{S*}}{n(q-1/n)}; \tag{12}$$

$$p^{ST*} = \frac{\delta^{ST} s^{S*}}{n(1-q)}. \tag{13}$$

Consider, for example, the probability of friendship between two Turkish kids, i.e., p^{TT}. When a Turkish kid wants to form links with other Turkish kids, there are exactly $n(1-q)-1$ other Turkish kids in the classroom and, therefore, the congestion for this link formation is equal to $[n(1-q)-1]\, s^T$.

5.3 Comparative Statics Results

Importantly, we can predict how the equilibrium quantities of the model (i.e., s^{S*}, s^{T*}, p^{SS*}, p^{ST*}, p^{TT*}, and p^{TS*}) vary with the share of refugees.

In order to lighten the text, formal results are presented in Appendix C.2. The following proposition summarizes the results of Proposition C1 and Proposition C2.

Proposition 1 (Comparative Statics)**.**

1. *When n is large, s^{S*} and s^{T*} decrease with q iff $b^S \leq b^T$;*
2. *If $b^S \leq b^T$, then p^{SS*} and p^{TS*} decrease with q;*
3. *If $b^S \geq b^T$, then p^{TT*} and p^{ST*} increase with q.*

The intuition behind Result 1 of Proposition 1 is the following. Recall that b^i is the marginal private benefit of socialization for i. When the fraction of Syrian children in the classroom q increases, Turkish children do not necessarily socialize more. However, if b^T is higher than b^S, then the effect of q on s^{T*} is negative. Indeed, s^{T*}, the equilibrium socialization effort of Turkish children, is a weighted average of the private benefits of socialization in Turkish and Syrian children, where the weights depend on ϕ^S, ϕ^T and q. So, when q increases, the first weight increases while the second one decreases. The same reasoning applies for the socialization effort of Syrian children.

Recall that the previous section showed that the number of stickers given to a random classmate decreases in the share of Syrian children (particularly for Turkish children), and suppose that the number of stickers given to a random classmate is a good proxy for the socialization level. Then, the interpretation of the model is that this is due to b^S being strictly smaller than b^T. Syrian children are, everything else equal, less prone to socializing. Classrooms with a higher share of Syrian children thus have smaller socialization norms, which in turns implies a smaller equilibrium socialization for everyone.

We explore this mechanism in more detail when we structurally estimate the model in the next section. In particular, under the assumption that $b^S < b^T$, Result 2 in Proposition 1) implies that p^{SS*} and p^{TS*} are decreasing with q. We show that these predictions are supported by the data and that the model is able to explain most of the empirical findings.

5.4 Homophily

So far, we have focused on socialization effort and the probability of forming links. Another measure commonly used in the literature (e.g., Currarini et al. (2009)) is the share of own ethnicity links for each ethnic group. This is called the *homophily index*, denoted as H^e for ethnicity $e = S, T$, and defined as:

$$H^e = \frac{\sum_{ij:e(i),e(j)=e} g_{ij}}{\sum_{ij:e(i)=e} g_{ij}}, \tag{14}$$

where $g_{ij} = 1$ if i and j are friends and zero otherwise. For example, for Syrian kids, this is the number of Syrian-Syrian friendship relations divided by the number of Syrian-Syrian and Syrian-Turkish friendships.

Because link formation is random, *ex-ante* homophily indices H^S and H^T are random variables for which it is hard to describe the behavior as q changes. To obtain some intuition, we can derive analytical approximations of the expected values $\mathbb{E}\left[H^S\right]$ and $\mathbb{E}\left[H^T\right]$.[31]

Proposition 2 (Homophily)**.** *For any $q \in \left(\frac{2}{n}, \frac{n-2}{n}\right)$, using a second order Taylor expansion, $\mathbb{E}\left[H^S\right]$ and $\mathbb{E}\left[H^S\right]$ are given by (C.12) and (C.13) in Appendix C and we have:*

$$\frac{\partial \mathbb{E}\left[H^S\right]}{\partial q} > 0 \Leftrightarrow \frac{\delta^{SS}}{\delta^{ST}} < \frac{(1-2q)\,(q-1/n)^2}{(1-q)^2\,(2q-1/n)} \tag{15}$$

$$\frac{\partial \mathbb{E}\left[H^T\right]}{\partial q} < 0 \Leftrightarrow \frac{\delta^{TT}}{\delta^{TS}} < \frac{(2q-1)\,(1-q-1/n)^2}{q^2(2(1-q)-1/n)} \tag{16}$$

It is worth noting that, in large populations, $\mathbb{E}\left[H^S\right]$ and $\mathbb{E}\left[H^T\right]$ converge respectively to $\frac{\delta^{SS}}{\delta^{SS}+\delta^{ST}}$ and $\frac{\delta^{TT}}{\delta^{TT}+\delta^{TS}}$ while the right-hand side of (15) and (16) to $\frac{(1-2q)}{2(1-q)^2}$ and $\frac{(2q-1)}{2q^2}$, respectively. The restriction that $q \in \left(\frac{2}{n}, \frac{n-2}{n}\right)$ imposes that the classroom has at least two children of each ethnicity so that all types of friendship are possible.

[31] The proof of Proposition 2 can be found in Appendix C.3.

Interestingly, although we would expect that homophily should increase with the share of own-ethnicity kids in the classroom, Proposition 2 shows that this is not necessarily the case. For $q > 1/2$, the model predicts that increasing q decreases the expected homophily index for Syrians. This effect comes from changes in the variance of the number of Syrian-Syrian and of the number of Syrian-Turkish friendships, and disappears in large populations.

Importantly, Propositions 1 and 2 rely on an important homogeneity assumption: the only source of heterogeneity is the children's ethnicity. In the next section, we therefore proceed to structurally estimate a more flexible version of the model developed in this section. We show that the results of Proposition 1 carry through, but that homophily indices are always increasing in the share of own-ethnicity kids in the classroom.

6 Structural Estimation

6.1 Empirical Strategy

We now proceed to structurally estimate an extended version of the model presented in the previous section, in which we introduce additional degrees of heterogeneity in b^i, δ^{ij}, and C^i. The model has two main components: the children's socialization choices and the network formation technology. Importantly, socialization choices are made *before* the network is realized. We therefore adopt the following estimation strategy.

First, we estimate a model of socialization choices using the share of stickers given in the *baseline* as a proxy for the socialization choices. Importantly, we make no parametric assumption on the approximation error. Second, we estimate the network formation model using the realized network in the *endline*, controlling for the network in the baseline.[32] To ensure that the inference of the resulting two-stage estimator is valid, the estimations are performed jointly, following Arellano and Meghir (1992).

Consider first the children's socialization choices. Denote by r the classroom with $r = 1, ..., \bar{r}$, where $\bar{r} = 36$ is the number of classrooms in our dataset. From the theoretical model developed in the previous section, the socialization choices for all i and r are given by:

$$s_r^i = b_r^i[d_r^i(1-\phi^S) + (1-d_r^i)(1-\phi^T)] + d_r^i \frac{\phi^S}{n_r - 1}\sum_{j\neq i} s_r^j + (1-d_r^i)\frac{\phi^T}{n_r - 1}\sum_{j \neq i} s_r^j, \tag{17}$$

where d_r^i is a binary variable equal to 1 if i is Syrian and 0 otherwise.

Equation (17) is the equivalent of the first-order condition in the model (6), without the additional simplifying assumptions made there for analytical tractability. Indeed, instead of limiting

[32] Note that the Sticker Game in the endline is not a good proxy for socialization since it is likely to be affected by the realized friendship relations that are developed during the Summer Camp.

b^i to only two values, we assume that $b_r^i = \mathbf{x}_r^i \boldsymbol{\beta} + \epsilon_r^i$, where $\mathbf{x}_r^i$ is a vector of characteristics of child i in classroom r (e.g., gender, school dummy, fluency in Turkish for Syrian kids, etc.),[33] and where $\epsilon_r^i \sim N(0, \sigma^2)$. With this additional heterogeneity, the vector of equilibrium socialization levels (c.f., equations (7) and (8)) cannot be derived analytically. However, it can be found as the limit of an iterative process described in Appendix D.1.

Since we do not observe the children's socialization effort s_r^i, we assume that $s_r^i = \tilde{s}_r^i + \eta_r^i$, where $\tilde{s}_r^i$ is the fraction of stickers that i gave to a random child in class r in the baseline, and where η_r^i is the approximation error. Importantly, we make no parametric assumption on η_r^i and only assume that it is exogenous, i.e., $\mathbb{E}[\eta_r^i|\mathbf{X}] = 0$ for all i. We show in Appendix D.2 that under this conditional mean independence assumption, the moment conditions in Lee (2007) and Bramoullé et al. (2009) remain valid, and allow to identify $\boldsymbol{\beta}$, ϕ^S and ϕ^T. Intuitively, the idea is to instrument the endogenous variable $\frac{1}{n_r-1}\sum_{j\neq i} s_r^j$ (the average socialization levels of the $n_r - 1$ other children in the classroom) using $\frac{1}{n_r-1}\sum_{j\neq i} \mathbf{x}_r^j$ (the average characteristics of the $n_r - 1$ other children in the classroom).

Consider now the formation of the friendship network. As described in the theoretical model, children's socialization choices affect their probability of creating friendship relations. Specifically, for any $j \neq i$ and r, we assume that the probability that i and j are friends during the endline is given by:

$$p_r^{ij} = \frac{\delta_r^{ij} s_r^i s_r^j}{\sum_{k \in C_r^i(j)} s_r^k}. \tag{18}$$

We assume that $\delta_r^{ij} = \Phi(\mathbf{z}_r^{ij}\boldsymbol{\gamma})$, where Φ is the standard normal distribution, $\mathbf{z}_r^{ij}$ is a vector of characteristics of the pair ij (e.g., if i and j are of the same ethnicity, or if they were friends during the baseline),[34] and $\boldsymbol{\gamma}$ is a vector of unknown parameters. Coherently with the theoretical model, we assume that $C_r^i(j)$ is the set of all children (except i) who have the same ethnicity, gender, and link status in the baseline as j, in classroom r.[35]

An important challenge for the estimation of $\boldsymbol{\gamma}$ comes from the fact that the true socialization levels s_r^i are observed with noise. Our estimation strategy relies on integrating over the socialization levels in the moment conditions implied by the network formation model. This numerical integration is possible due to our parametric assumption on ε_r^i, which allows us to simulate the equilibrium socialization levels for a given value of $\boldsymbol{\beta}$, ϕ^S, ϕ^T, and σ.[36] Details

[33] See Table A8 (Panel A) of the Appendix A for the entire set of covariates. Lee (2007) shows that it is possible to estimate the model in deviation with the classroom average and thus to control for classroom-level fixed effects. However, this approach is not applicable to our data. This is due to the fact that we have a small number of relatively large classrooms and the fact that almost all of our explanatory variables are binary. See Boucher et al. (2014) for a discussion of the identification of this type of model in practice.

[34] See Table A8 (Panel B) of the Appendix A for the entire set of covariates.

[35] Namely, the set of all children k that are linked to i in the baseline if j was linked to i in the baseline, or not linked to i in the baseline if j was not linked to i in the baseline.

[36] Note that $\boldsymbol{\beta}$, ϕ^S, and ϕ^T are identified from the estimation of (17).

and explicit moment conditions are provided in Appendix D.2. The resulting simulated moment conditions (Gourieroux and Monfort, 1996) allow us to identify $\boldsymbol{\gamma}$ and σ, conditional on $\boldsymbol{\beta}$, ϕ^S and ϕ^T. Here, the instruments are simply given by $\mathbf{z}_r^{ij}$, as for standard discrete choice models (see, e.g., Train (2009); Chapter 10).

Then, all of the model's parameters are identified from two sets of moment conditions. However, notice that the moment conditions for $(\boldsymbol{\beta}, \phi^S, \phi^T)$ and those for $(\boldsymbol{\gamma}, \sigma)$, are not based on the same number of observations. Indeed, the first set of moments characterizes individuals ($N_1 = 604$), while the second set of moments characterizes *pairs* of individuals ($N_2 = 9940$). As such, we may consider the two sets of moments as coming from two different data sets (e.g., Angrist and Krueger (1992) or Arellano and Meghir (1992)). We then follow Arellano and Meghir (1992) and build our estimator as an observation-weighted average of the GMM objective functions for both sets of moments. See Appendix D.2 for details.

6.2 Results and Model Fit

We now present the estimation results for $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}, \phi^S, \phi^T, \sigma)$. Results for the main parameters of interest are presented in Table 8 (socialization effort in Panel A, and network formation in Panel B). The complete results are presented in Tables A8 and A9 of Appendix A.

Table 8: Structural Estimation

	Estimator	**Std. Err.**
Panel A: Socialization effort ($\boldsymbol{\beta}$,ϕ^S,ϕ^T)		
Syrian	-0.741	(0.065)
Fluent in Turkish in baseline (Syrians)	0.140	(0.084)
ϕ^S	0.955	(0.003)
ϕ^T	0.694	(0.001)
Panel B: Network formation (γ, marginal effects on δ_r^{ij})		
Syrian-Syrian pair	0.127	(0.017)
Syrian-Turkish pair	-0.212	(0.004)
Turkish-Syrian pair	-0.218	(0.013)
Fluent in Turkish in baseline (Syrians)	0.115	(0.013)
Linked in baseline	0.235	(0.102)

Notes: Socialization choices control for: gender, ethnic composition of the parents' friends and neighborhood, arrival year (Syrians), region in Syria (Syrians), Turkish skills in the baseline (Syrians), and school fixed effects. Network formation controls for gender, ethnic composition of the parents' neighborhood, and school fixed effects. The entire set of estimated coefficients can be found in Table A8 (point estimates) and A9 (marginal effects) of Appendix A. The estimates for the network formation panel correspond to the average marginal effects on δ^{ij}. That is, $(1/N_2)\sum_{i,j}[\Phi(\sum_{k'\neq k} z_{r,k'}^{ij}\gamma_{k'} + \gamma_k) - \Phi(\sum_{k'\neq k} z_{r,k'}^{ij}\gamma_{k'})]$ for the binary variable k. Standard errors are simulated using 500 draws of $\boldsymbol{\theta}$ using its estimated asymptotic distribution. This is done to account for the covariance between the estimated values for $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ and ϕ. The entire set of marginal effects can be found in Table A9 of Appendix A.

Table 8 (Panel A) shows that Syrian children socialize less than Turkish children. As such, the interpretation for the negative coefficient on refugee share found in the regressions reported in Tables 6 and 7 is as follows. Since Syrians socialize less, everything else equal, classrooms with higher shares of Syrians have lower socialization norms, which leads all children in those groups to socialize less.

We also see in Table 8 (Panel A) that Syrian children have a stronger taste for conformism than Turkish children. The fact that conformism is stronger for Syrians would imply that the equilibrium socialization choices of Syrians are less impacted by the share of Syrians in the classroom (see equations (C.5) and (C.7) in Appendix C.2), which is consistent with the results reported in Tables 6 and 7.[37]

Table 8 (Panel B) also shows the impact of the children's characteristics on the formation of the friendship network. We find that interethnic links, Syrian-Turkish and Turkish-Syrian, are less likely to be formed than intraethnic links (i.e., Syrian-Syrian or Turkish-Turkish links), while Syrian-Syrian links are more likely than Turkish-Turkish links. The network is also affected by the language skills of Syrian children and additionally shows persistence, as friendship in the baseline strongly predicts friendship in the endline. Note that the reported numbers are not the marginal effects on the probability of a link, but rather marginal effects on the preference bias δ_r^{ij}, which is the preference parameter of interest.[38] The interpretation of the coefficients is as follows: interethnic pairs have (everything else equal) a value of δ^{ij} that is roughly 22 percentage points lower than that of intraethnic pairs for Turkish children and roughly 34 pp lower than that of intraethnic pairs for Syrian children. We also observe that Syrian children who are fluent in Turkish have a value of δ^{ij} that is 11.5 pp higher than those who are not, and that pairs that were linked in the baseline have a 23.5 pp higher δ^{ij} than those that were not.

We next look at the fit of the model. Specifically, we examine the predictions of the model on outcomes that are not directly matched by the estimation procedure. In Table 9, we look at aggregate levels of the friendship network and socialization variables, while in Table 10, we look at how those variables vary with the ethnic composition of the classroom q.

In Table 9, we present the observed values of socialization and network links in the empirical data alongside those of data simulated by the model. Note that these quantities are not directly matched by the estimation procedure. Indeed, the simulation of the socialization choices is the outcome of the resolution of a non-linear fixed point problem (see Appendix D.1). As such, even with consistent estimates for $\boldsymbol{\beta}$ and ϕ^S and ϕ^T, there is no guarantee that the simulated

[37]While Table 8 (Panel A) implies that Syrian children have a stronger taste for conformism than Turkish children (i.e. $\phi^S > \phi^T$), one must be careful regarding the interpretation of the values of ϕ^S and ϕ^T. Indeed, as discussed in Bramoullé et al. (2020) [Section 3], even if classrooms are formed at random, estimates might not be immune to correlated effects. In our context, suppose that teachers react to the ethnic composition in the classroom by encouraging (or not) interactions between students. Then, this would be picked up by ϕ^S and ϕ^T. That being said, to the extent that such correlated effects are homogeneous among children (as usually assumed), they would not affect the ranking between ϕ^S and ϕ^T.

[38]Marginal effects are rarely computed for network formation models (see, e.g., Mele (2017); Badev (2021)). One reason is that they are often complex, or computationally intensive to produce. Here, in particular, the probability of a link depends not only on the preference bias, but also on the equilibrium socialization levels (which in turn depend on the preference biases). Another reason is that networks are sparse, leading to extremely small, and poorly informative, marginal effects.

Table 9: Model fit: Average outcomes

Outcome	Simulated Data		Empirical Data
	Mean	S.E.	Value
s^S	0.530	(0.061)	0.365
s^T	0.533	(0.034)	0.407
g^{SS}	0.131	(0.016)	0.211
g^{ST}	0.110	(0.013)	0.096
g^{TT}	0.121	(0.010)	0.209
g^{TS}	0.098	(0.007)	0.106

Notes: On simulated data, Column "Mean" represents the average of the simulated sample average among $s = 1, ..., 500$ simulations. The Column "S.E." represents the standard deviation of the simulated sample average among $s = 1, ..., 500$ simulations. For each simulation, a value of $\boldsymbol{\theta}$ is drawn from its asymptotic distribution and predicted values are computed for all ij.

socialization will be centered on the (proxied) levels of socialization. Similarly, while consistent estimates of $\boldsymbol{\gamma}$ provide a consistent estimate of the preference biases δ^{ij}, the probability of a link between i and j is a non-linear function of preference biases and socialization choices. Again, there is no guarantee that the simulated values are centered on the observed ones.

Table 9 shows that the model over-predicts the children's socialization choices. For the network formation, we see that the probabilities of interethnic links are correctly predicted, while the probabilities of intraethnic links are under-predicted. However, as we show in the next section, this does not diminish the predictive power of the model over homophily patterns, which is our main object of interest. Moreover, the outcomes in Table 9 are not of primary interest, since they are independent of the ethnic composition of the classrooms.

In Table 10, we explore the performance of the model in replicating the results found in Section 4. Specifically, the column *Empirical Data* presents a regression of each outcome on q (with controls) in the data. The corresponding row for the column *Simulated Data* represents the same regression, but performed on simulated data. Results generally have the same sign, and when they do not, the differences between the data and the model are not statistically significant. It is worth noting that the regressions on simulated socialization choices are too imprecise to provide any meaningful information. However, regressions on the simulated network formation variables are much more precise and are more consistent with the model. In the next section, we explore further the predictions of the model on homophily patterns in the friendship network.

Table 10 shows the impact of congestion on the formation of the network. In particular, the fact—which is strongly supported by the data—that the probability of same-ethnicity links decreases with the share of same-ethnicity children in the classroom (i.e., g^{SS} decreases and g^{TT} increases with q) is due to congestion. Consider the probability that a given pair of Syrian

Table 10: Model fit: Refugee share (values in percentages)

Outcome	Nobs	Simulated Data		Empirical Data	
		Refugee share	S.E.	Refugee share	S.E.
g^{SS}	3428	-0.286	(0.139)	-0.206	(0.110)
g^{ST}	2064	0.155	(0.092)	0.020	(0.089)
g^{TT}	2384	0.152	(0.102)	0.171	(0.047)
g^{TS}	2064	-0.170	(0.071)	0.012	(0.081)
s^{S}	328	-0.106	(0.304)	0.054	(0.104)
s^{T}	276	-0.035	(0.268)	-0.234	(0.072)

Notes: Each outcome corresponds to a separate linear regression. The unit of observation is a pair. Probability of links (in the endline) are regressed on the share of refugees, controlling for gender, composition of the parents' neighborhood, Turkish skill in baseline (Syrians), link status in the baseline, and school FE. For example, for p^{SS}, only pairs of Syrian kids are used. The regressions for socialization include controls for gender, ethnic composition of the parents' neighborhood and friends, arrival year, region in Syria, and Turkish language skills. For regressions (on data), standard errors are clustered at the class level. Regressions on simulated data are based on 500 simulations of the model. For each simulation, a value of $\boldsymbol{\theta}$ is drawn from its asymptotic distribution, and predicted values are computed for all ij. Then, the same regression as the one performed on data (column "Data") was performed. Reported numbers are the mean and standard deviation of the estimated effect of the refugee share among the simulations. All results are in percentages for clarity.

children are friends. If there are few other Syrian children in the classroom, the probability that they are friends is high. However, if there are many other Syrian children in the classroom, the probability that they are friends is much smaller, since both children could alternatively be friends with other Syrian children. A similar argument applies for Turkish children.

Note also that although the theoretical model in Section 5 makes strong homogeneity assumptions, the predictions of Proposition 1 appear to hold more generally. Specifically, since Syrian children socialize less (everything else equal) than Turkish children (see Table 8 (Panel A)), Proposition 1 implies that socialization decreases with q for Syrian and Turkish children and that the probability of a link between two Syrian children, or between a Turkish child and a Syrian child, decreases with q. This is reflected by the fact that the estimated coefficients for outcomes g^{SS}, g^{TS}, s^{S}, and s^{T}, on simulated data, are all negative.

6.3 Homophily

6.3.1 Baseline Simulations

We now turn to simulations of the estimated model to better understand the properties of the network structure, with an emphasis on homophily. In particular, we aim at exploring the impact of an exogenous change in the refugee share on the homophily index, as well as on *inbreeding homophily*, which accounts for the classroom ethnic composition (see below for a formal definition). These are properties of the network defined at the class level, of which we have only 36 in the data, so a major advantage of the structural estimation is that it allows us to simulate a much larger number of classes for the analysis of homophily to be more meaningful.

Specifically, we keep the size of the 36 classes and reshuffle children using the following procedure. We randomly select classes until their combined capacity reaches the number of Syrian children in our dataset (328) and designate these as "Syrian classes" and the remaining ones as "Turkish classes." We then randomly select children and assign them to classes, putting a weight of α on classes of their own ethnicity and a weight of $(1 - \alpha)$ on the other classes (subject to capacity constraints). Then, by varying α, we can exogenously change the expected share of refugee children in any given classroom, keeping everything else constant. We repeat the procedure 500 times for four different values of $\alpha = (0.2, 0.4, 0.6, 0.8)$. This gives us 72,000 simulated observations, treating a classroom as a unit of analysis. For each simulation, we then compute the equilibrium socialization level and resulting links for each child, and the homophily and inbreeding homophily indices, which are class-level objects.

Figures 3 and 4 plot the values of the simulated share of own-ethnicity friends in a class (i.e., the *homophily index*) as a function of the refugee share, and a quadratic fit for Syrian and Turkish children, respectively. The simulations replicate an important feature of the data—that is, the homophily index is large (above the 45 degree line) in classes with a low share of refugee children, and increases less rapidly than the classroom share; thus, beyond some point it lies below the 45 degree line in classes with a large share of refugees. Note that in the absence of preference biases and congestion, the homophily index would (in expectation) be equal to the own-ethnicity share in the classroom, implying that the points in the figure would be concentrated along the 45 degree line. As seen in Figures 5 and 6, this is not supported by the data, even if the measured effect in the data is much less precise. This is mostly a small sample issue: the homophily index is a classroom-level variable, and there are only 36 classrooms in our sample.

The concave shape of the homophily index in Figures 3–4 reflects the interplay between preference biases and congestion. Consider Figure 3. Since Syrian children are biased toward coethnic children, the share of own ethnicity friends (homophily index) is greater than the share of Syrian children in the class for low values of q. However, the rate at which homophily increases is less than one. This is due to congestion: the rate at which friendship opportunities open for Syrians is not as fast as the rate at which the share of Syrians increases in the classroom. This implies that homophily of Syrians is not increasing as fast as the share of Syrians in the classroom.

This, in turn, implies that *inbreeding homophily* (Coleman, 1958), which measures the amount of in-group bias with respect to baseline homophily, is non-monotonic. In particular, let q^e be the share of children of ethnicity $e = T, S$ in the classroom, inbreeding homophily is defined as:

$$IH^e = \frac{(H^e - q^e)}{(1 - q^e)}.$$

When $H^e > q^e$ ($H^e < q^e$), i.e., the fraction of same-ethnicity friends is higher (lower) than the

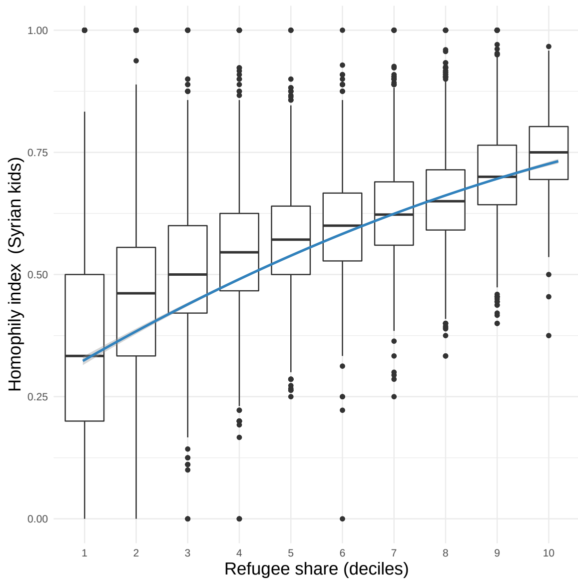

Figure 3: Simulated homophily index by refugee share (Syrian kids).

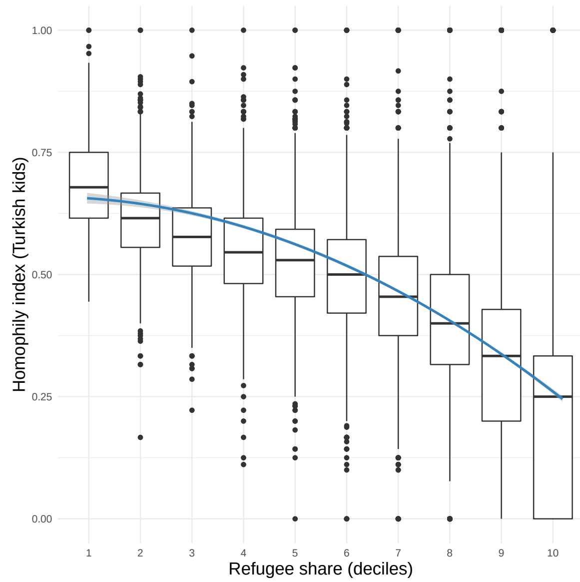

Figure 4: Simulated homophily index by refugee share (Turkish kids).

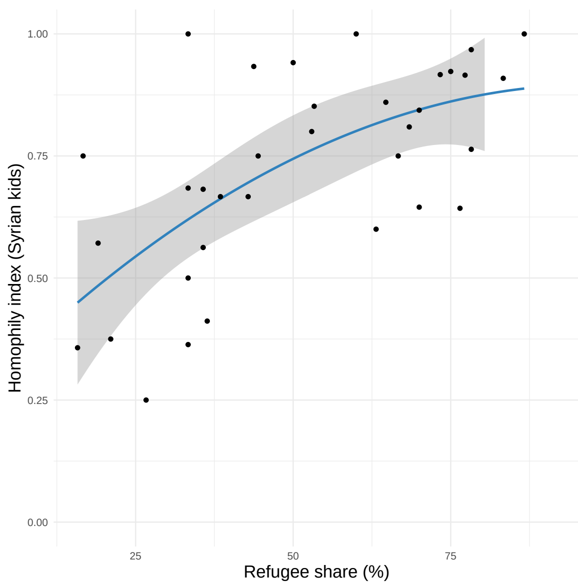

Figure 5: Homophily index by refugee share in the data (Syrian kids).

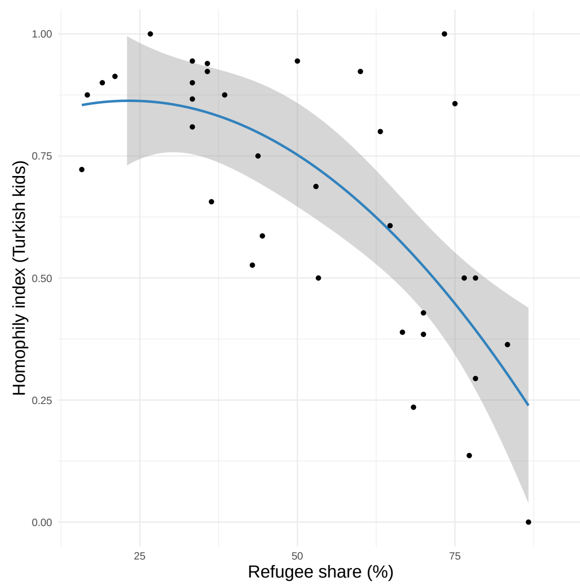

Figure 6: Homophily index by refugee share in the data (Turkish kids).

fraction of children of the same ethnicity in the class, then there is *inbreeding homophily*, i.e., $IH^e > 0$, (or *inbreeding heterophily*, i.e., $IH^e < 0$,). The index of inbreeding homophily IH^e is equal to 0 if there is pure baseline homophily, i.e., $H^e = q^e$, and 1 if a group completely inbreeds, i.e., $H^e = 1$. Clearly, if the aim of the government is to promote the *integration* of Syrian children, then it wants to reduce inbreeding homophily; a value of zero, i.e., $IH^e = 0$, should then be desirable.

Figures 7 and 8 illustrate inbreeding homophily for Syrian and Turkish children, respectively, using simulated data based on the structural model, while Figures 9 and 10 show the equivalent based on the empirical data. Again, the small number of classrooms implies that limited information can be obtained from the empirical data alone. In Figure 7, we see that inbreeding homophily for Syrians varies *non-monotonically* with the share of own-ethnicity children in the classroom. The intuition for this is as follows: consider a classroom with very few Syrian children. Congestion implies that each child has a certain number of friendship openings that they wish to fill. Since students are biased toward students of their own ethnicity (preference bias), Syrian-Syrian friendships are more likely to be formed than Syrian-Turkish ones. However, since there are not many Syrians in the classroom, we still observe a significant number of Syrian-Turkish friendships filling the remaining openings. When the number of Syrians increases, Syrians will trade their friendships with Turkish children for friendships with those additional Syrians, and this leads to an initial increase in inbreeding homophily. When the number of Syrians in the class is such that all the friendship capacity of Syrians can be filled with own-ethnicity friends, then inbreeding reaches its maximum. Beyond this point, increasing the number of Syrian children does not further increase the share of Syrian friends that a Syrian kid will have, so inbreeding homophily starts to decrease.[39]

Therefore, the interplay between preference biases and congestion leads to a non-monotonic impact of the refugee share on inbreeding homophily. Assuming a quadratic fit, we can compute that inbreeding homophily is maximal when $q = 36.2$ for Syrians. Past that point, inbreeding homophily is decreasing, since the congestion effect implies that the composition of the friendship network does not change as fast as the population share (i.e., the slopes in Figures 3 and 4 are less than 1 in absolute value) and is zero for $q = 60.7$. Similarly, for Turkish children, inbreeding homophily is maximal for $q = 71.6$ and crosses zero for $q = 46.7$.[40]

It is worth noting that a similar non-monotonic pattern for inbreeding homophily is found in Currarini et al. (2010), which looks at racial homophily across middle and high schools in the United States. However, the underlying source for this pattern is quite different. In their case, they find that, for average levels of exposure, homophily increases *faster* than the population share. Using the model in Currarini et al. (2009), they argue that this is due to a meeting bias: children meet friends of friends, which amplifies homophily. In our context, congestion implies that homophily increases *slower* than the population share. Our model disregards meeting biases. Indeed, in small classrooms in which kids interact daily, it is unlikely that children are not aware of one another.

[39]The intuition provided through this stylised example applies more generally, if Syrians have a weaker ethnic bias and therefore prefer having a mix of friends with the composition skewed toward their own ethnicity, or if friendship capacity is not fixed but varies more flexibly with the one's ethnic share.

[40]Note that these numbers may not exactly correspond to the Figures. This is because the horizontal axis in the Figures shows deciles, and not actual shares.

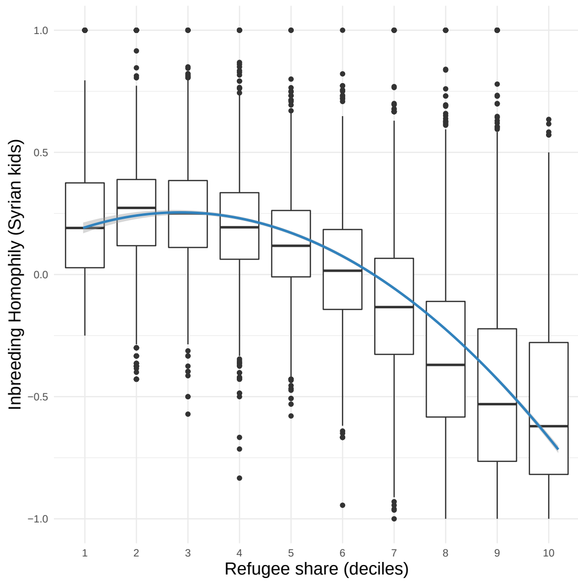

Figure 7: Simulated inbreeding homophily by refugee share (Syrian kids).

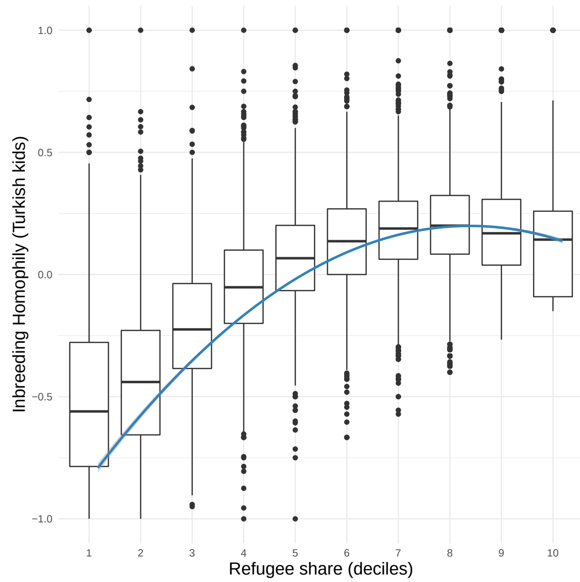

Figure 8: Simulated inbreeding homophily by refugee share (Turkish kids).

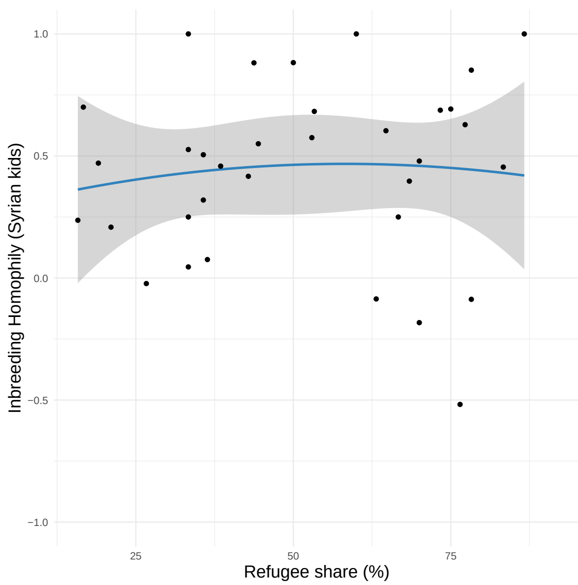

Figure 9: Inbreeding homophily by refugee share in the data (Syrian kids).

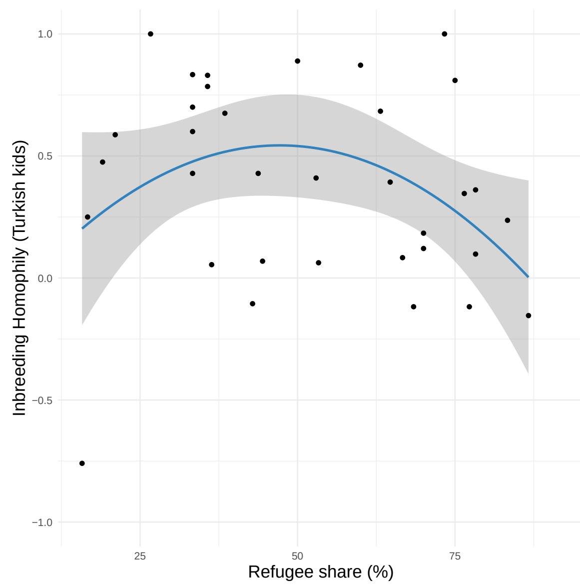

Figure 10: Inbreeding homophily by refugee share in the data (Turkish kids).

6.3.2 Counterfactual Simulations: Preference Bias and Congestion

We now study in more detail how the patterns of inbreeding homophily are affected by the interplay between preference biases and congestion. We perform two counterfactual simulation exercises.

First, we vary the strength of the ethnic-based preference bias. Specifically, we look at two alternative scenarios: one in which there is no ethnic bias and one in which the ethnic bias is double that of the baseline level. We do so by setting the values of $\boldsymbol{\gamma}$ associated with ethnic bias to either 0 (no ethnic bias) or double their estimated value (high ethnic bias) and compare the model predictions with those under the estimated values (baseline). Figures 11–12 illustrate the impact on inbreeding homophily (see Figures A4–A5 in Appendix B for the impact on the homophily index). As the preference biases increase, the impact of congestion in the network formation process (18) becomes relatively less important. As such, the equilibrium network exhibits very high levels of inbreeding homophily, even when the share of own-ethnicity children is high. In particular, we can see that for Syrian children, when preference bias is high, inbreeding homophily is maximal for $q = 37.6$ and zero for $q = 76.2$, while when there is no preference bias, it is maximal for $q = 35.4$ and zero for $q = 53.6$. To obtain a sense of the quantitative impact that preference bias has on homophily, at q=0.5 it is the case that the share of own-ethnicity friends is about 8 percentage points higher in the baseline scenario than in the no-bias scenario (see Figures A4–A5 in Appendix B).

Second, we remove the congestion effect. Figures 13–14 illustrate the impact on inbreeding homophily (see Figures A6–A7 in Appendix B for the impact on the homophily index). Without congestion, inbreeding homophily is monotonically increasing with the share of own-ethnicity children in the classroom. Consider, for example, Syrian kids (Figure 13). Because of preference biases, links with other Syrian kids are more likely. Thus, when the share of Syrian children increases, the (expected) number of friends Syrian children have also increases. Because these additional friendships are more likely to be with other Syrian children, this leads to a faster increase in homophily and gives rise to a monotonically increasing inbreeding homophily index (see Figures A6–A7 in Appendix B). Therefore, what this counterfactual illustrates clearly is that in the absence of congestion, interethnic contact would lead to a monotonic reduction in inbreeding homophily, which would be in line with the spirit of the contact hypothesis that interethnic exposure can foster integration.

6.3.3 Counterfactual Simulations: Language

As shown in Table 8, Turkish skills of Syrian children play an important role in the formation of interethnic friendships. In the next counterfactual experiment, we examine the impact on homophily of an intervention that would improve the Turkish language fluency of Syrian children.

Figures 15–16 illustrate the impact of this experiment on inbreeding homophily (see Figures A8–A9 in Appendix B for the impact on the homophily index). We compare the baseline specification with a situation without any preference bias, and a situation in which every Syrian child is fluent in Turkish. In practice, we create the latter scenario by setting the binary variable *Turkish skill* to 1 for all Syrian children. The resulting inbreeding homophily of making every Syrian kid fluent is roughly halfway between the baseline curve and the one with no ethnic bias.

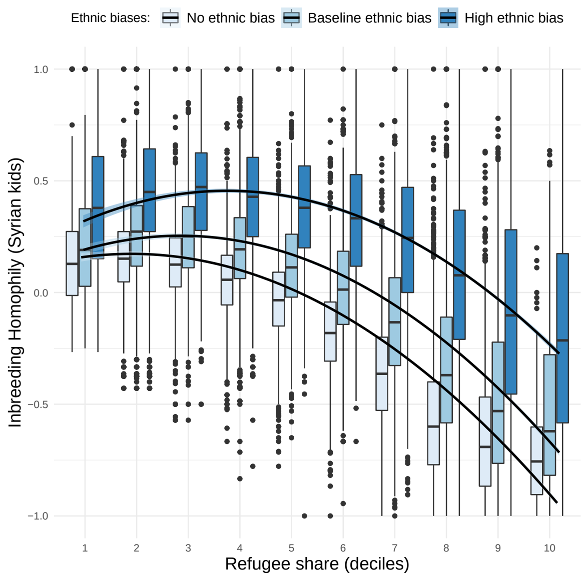

Figure 11: Simulated inbreeding homophily by refugee share (Syrian kids): Changes in preference biases.

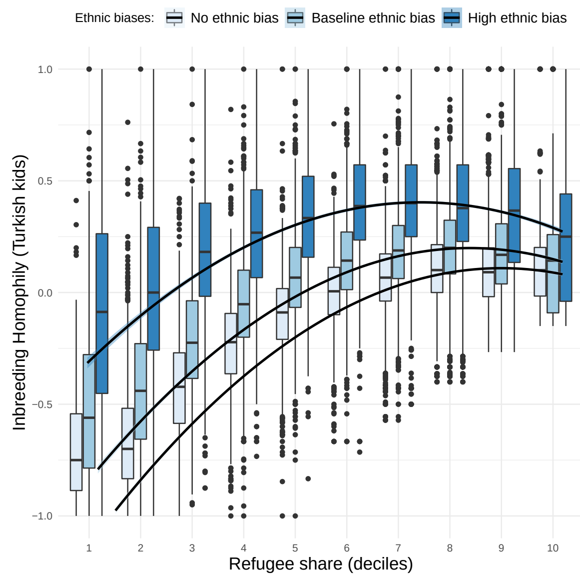

Figure 12: Simulated inbreeding homophily by refugee share (Turkish kids): Changes in preference biases.

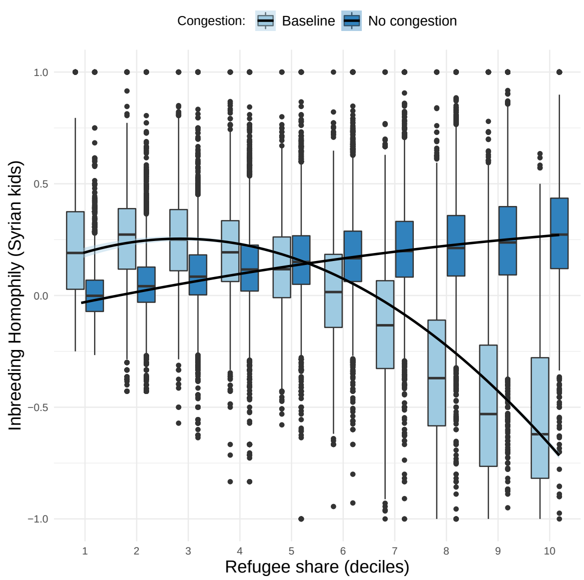

Figure 13: Simulated inbreeding homophily by refugee share (Syrian kids): Changes in congestion.

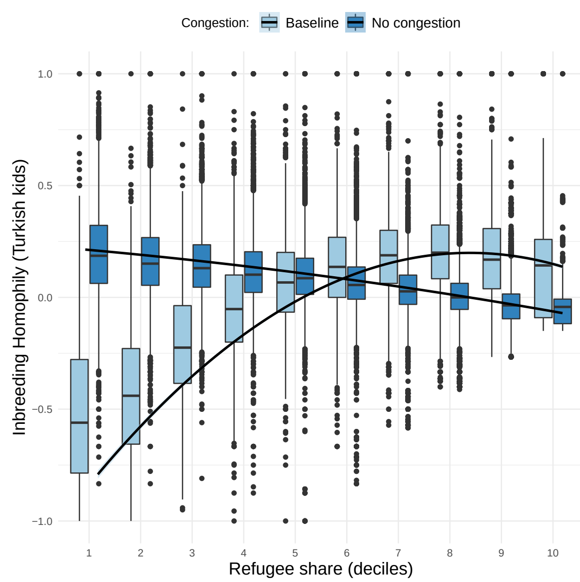

Figure 14: Simulated inbreeding homophily by refugee share (Turkish kids): Changes in congestion.

For instance, at $q = 0.5$, inbreeding homophily for Syrian children under the fluency scenario is 57% of the difference between the baseline and the no-bias case (the equivalent for Turkish children is 55%). This suggests that the policy would have the equivalent effect on inbreeding homophily as reducing ethnic biases by more than 50%. This confirms the strong impact of language and the importance of investing in language acquisition for the integration of young children.

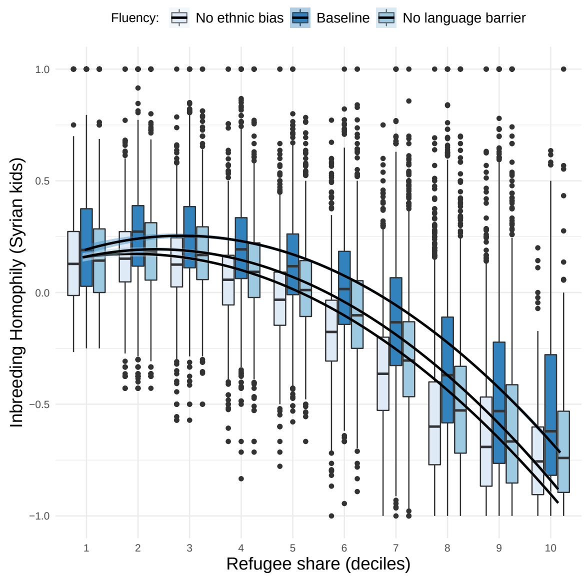

Figure 15: Simulated inbreeding homophily by refugee share (Syrian kids): Preference biases vs Syrian fluency.

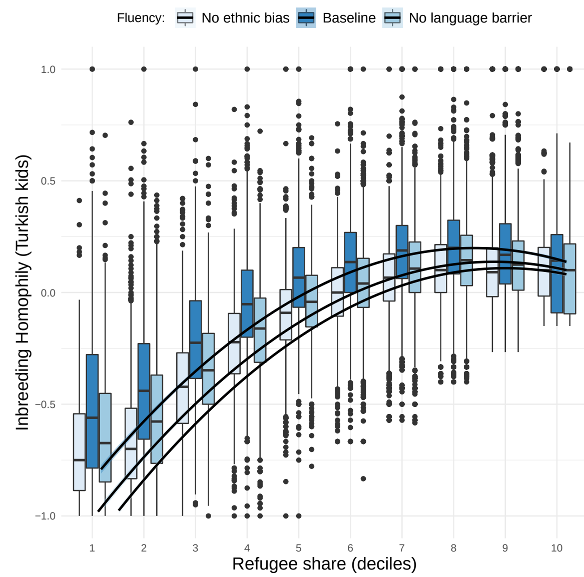

Figure 16: Simulated inbreeding homophily by refugee share (Turkish kids): Preference biases vs Syrian fluency.

7 Long-term Effects on School Absenteeism

In this section, we examine whether the Summer Camp program had an impact on children's long-term outcomes measured after the Summer Camp. Indeed, students who participated in the Summer Camp in July-August 2019 went on to start primary school in the following academic year (2019-20), starting in September 2019. Primary school attendance is free and compulsory for all children in Turkey. These children's first year of primary school was interrupted by school closures in March 2020 due to the Covid-19 pandemic. Remote education was provided for the remaining of the academic year.

We obtained school administrative data on the *absenteeism* of these students up to March 2020, that is, 9 months after children started the Summer Camp.[41] Absenteeism, which is measured by the total number of absent days from school, is a meaningful outcome as it captures the *attachment* and *integration* into the educational system but is also a measure of *noncognitive skills* (Jackson, 2018), and has been shown to impact academic achievement in early grade levels (Gottfried, 2010). Moreover, Lounsbury et al. (2004) show that absenteeism is strongly correlated (in the expected direction) with all Big Five personality traits—Agreeableness, Conscientiousness, Emotional Stability, Extroversion, and Openness—which strongly predict school and labor market success later in life (Heckman et al., 2006; Borghans et al., 2008).

Overall, the school records indicate that Syrian children were more absent from school than

[41] We were not able to match only three Syrian children in the school administrative data, quite possibly because their families moved.

Turkish children. The average days of absence was 5.8 among Syrian children and 4.3 among Turkish children. This difference is statistically significant according to a t-test and a Mann-Whitney test (p-values of 0.0013 and 0.0009, respectively).

Table 11: Long-term Effects of Summer Camp on Absenteeism

	Syrian children		**Turkish children**	
	[1]	**[2]**	**[3]**	**[4]**
Panel A - Linear Specification				
Refugee share	0.047*	0.048**	-0.008	-0.018
	(0.024)	(0.023)	(0.024)	(0.030)
Panel B - Tercile Specification				
Medium Share	0.802	1.108	-0.202	-0.369
	(1.197)	(1.240)	(0.714)	(0.913)
High Share	2.434*	1.490	0.073	-0.887
	(1.439)	(1.379)	(2.024)	(2.384)
School fixed effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
# of obs.	325	325	276	276

Notes: The dependent variable is the number of absent days from school in the academic year following the Summer Camp. Controls include, those in Table 2 and Table 3, for the Turkish and Syrian subsample, respectively. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

To assess whether exposure to non-coethnic children during the Summer Camp had an impact on children's school absenteeism, we estimate versions of equations (1) and (2) with days of absence from primary school acting as the outcome of interest. The results estimated by OLS are reported in Table 11—we obtain similar results estimating Poisson regressions. For Syrian children (columns 1 and 2), using the linear specification reported in Panel A, we find that being in a class with a larger share of refugee children during the Summer Camp led to more days of absence in the following academic year. The effect is not negligible: taking the coefficient estimated in column 2 that includes controls (0.048), we find that a one standard deviation increase in the share of refugee children in the class (22.7) leads to an increase in absenteeism by 1.09 days or a 18.8% increase over the average. The tercile specification reported in Panel B indicates positive effects of being in a medium or high share refugee groups on subsequent absenteeism (relative to being in a small refugee share group), although these estimates are not precisely estimated. On the other hand, for Turkish children (columns 3 and 4), the estimates are smaller and not statistically significant.

These results provide some evidence that, for Syrian children, exposure to Turkish children during the Summer Camp had a lasting positive impact on their integration into the education system that carried over to primary school.

8 Concluding Remarks

Integrating refugee children into the national education systems is a serious challenge for the host countries. In this paper, we evaluate the impact of an early childhood Summer Camp program organized in summer 2019 in Turkey targeting disadvantaged 5-year-old refugee and native kids with no earlier access to any form of formal early childhood education. During the Summer Camp, we implemented a randomized field experiment with the ultimate goal of examining the effect of random exposure to a different ethnicity on various outcomes, including friendship formation and language skills.

In reduced-form regression analysis, we find that increased exposure to children of the other ethnicity leads to some increase in the formation of interethnic friendships. We also find a significant improvement in Turkish language skills for Syrian children across all groups, and that this improvement is related to in-class refugee concentration. Finally, we find that Turkish children exhibit in-group favoritism in prosocial behavior, while Syrian kids do not discriminate on the basis of ethnicity.

We then develop and structurally estimate a model of friendship formation. Simulations of the estimated structural model suggest that exposure alone does not guarantee improved intergroup outcomes between refugees and natives in educational settings. In particular, we find that the impact of exposure on inbreeding homophily is non-monotonic, so more exposure can lead to less integration. We also find that improving the language skills of Syrian kids can offset the prejudice bias of Turkish children in interethnic friendship relations. Finally, we show that, for Syrian children only, exposure to Turkish children during the Summer Camp had a lasting positive impact on their non-cognitive skills, measured by their absenteeism at school.

Beyond Turkey, the non-monotonic effect of inbreeding homophily we identify contributes to the debate on social integration of minority groups. Indeed, our findings indicate that a large exposure of minority children to native children can backfire by increasing in-group bias on friendship formation. From a policy perspective, programs aiming to integrate refugee—or, more generally, immigrant—children into home country education systems should incorporate ingredients specifically and effectively designed to address social cohesion, prosociality, and interethnic exposure issues as early as the preschool level.

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Ethnic Mixing in Early Childhood: Evidence from a Randomized Field Experiment and a Structural Model

Online Appendix

By Vincent Boucher, Semih Tumen, Michael Vlassopoulos, Jackie Wahba and Yves Zenou

A Additional Tables

Summary statistics: Outcome variables (means), by group

	All sample			Syrian			Turkish		
	[1]	**[2]**	**[Diff]**	**[1]**	**[2]**	**[Diff]**	**[1]**	**[2]**	**[Diff]**
LOW SHARE									
Turkish language skills	-	-	-	2.89	4.23	1.34	-	-	-
Stickers given	3.98	4.40	0.42	3.83	4.53	0.70	4.04	4.36	0.32
# of friends	2.26	2.60	0.34	2.59	2.87	0.28	2.14	2.50	0.36
# of Syrian friends	0.65	0.69	0.04	1.53	1.57	0.04	0.32	0.36	0.04
# of Turkish friends	1.61	1.91	0.29	1.06	1.30	0.25	1.82	2.14	0.31
% of own ethnicity friends				0.59	0.55	-0.04	0.85	0.86	0.01
Number of obs.	194			53			141		
MEDIUM SHARE									
Turkish language skills	-	-	-	2.07	3.70	1.64	-	-	-
Stickers given	3.62	4.10	0.47	3.40	4.08	0.69	3.90	4.11	0.21
# of friends	2.35	2.65	0.30	2.22	2.70	0.48	2.51	2.58	0.08
# of Syrian friends	1.27	1.62	0.36	1.66	2.19	0.54	0.80	0.93	0.13
# of Turkish friends	1.08	1.03	-0.06	0.57	0.51	-0.06	1.71	1.65	-0.06
% of own ethnicity friends				0.75	0.81	0.06	0.68	0.64	-0.04
Number of obs.	197			108			89		
HIGH SHARE									
Turkish language skills	-	-	-	2.33	4.17	1.84	-	-	-
Stickers given	3.93	4.05	0.13	3.76	4.12	0.36	4.52	3.80	-0.72
# of friends	2.58	2.89	0.31	2.68	2.88	0.20	2.22	2.91	0.70
# of Syrian friends	2.25	2.30	0.05	2.41	2.43	0.02	1.65	1.83	0.17
# of Turkish friends	0.33	0.59	0.26	0.26	0.45	0.19	0.57	1.09	0.52
% of own ethnicity friends				0.90	0.84	-0.06	0.26	0.38	0.12
Number of obs.	213			167			46		

Table A1: Notes: [1] indicates the baseline; [2] indicates the endline; [Diff] indicates the between the two. The sample consists of children of age 5. The study includes 36 classrooms in 11 schools in the Gaziantep region. There are 604 children in the sample (328 Syrian, 276 Turkish; 310 male, 294 female).

Parental characteristics: Summary Statistics

	All sample		Syrian		Turkish	
	Mother	**Father**	**Mother**	**Father**	**Mother**	**Father**
Parental education						
No degree (illiterate)	11.6	7.5	18.6	11.9	3	2.2
No degree (literate)	21.2	9.6	35.4	16.2	4.4	1.8
Primary school	37.6	35.4	29.0	36.6	47.8	34.1
Secondary school	17.7	26.8	10.4	23.2	26.5	31.2
High school	8.1	13.6	3.1	6.4	14.1	22.1
College & above	3.8	7.1	3.7	5.8	4.0	8.7
Parental employment						
Non-employed	95.7	4.5	95.7	5.5	95.7	3.3
Employed	4.3	95.5	4.3	94.5	4.3	96.7
Composition of parents' friends						
All refugees	7.5		13.4		0.4	
Mostly refugees	26.0		45.4		2.9	
Balanced mix	25.2		39.0		8.7	
Mostly natives	8.8		1.2		17.8	
All natives	32.6		0.9		70.3	
Composition of neighbors						
All refugees	6.1		9.2		2.5	
Mostly refugees	32.6		45.4		17.4	
Balanced mix	26.0		39.0		10.5	
Mostly natives	8.4		2.1		15.9	
All natives	26.8		4.3		53.6	

Table A2: Summary statistics—parental characteristics: All entries are percentages. The sample consists of children of age 5. There are 604 children in the sample (328 Syrian, 276 Turkish). There were 638 children in the initial allocation list and 34 of them (16 refugees and 18 natives by ethnicity; 15 females and 19 males by gender) dropped out at various stages of the program. The attrition rate is approximately 5 percent. The parental characteristics of the dropouts are quite similar to those of the participated children. In particular, the employment rate among mothers and fathers of the dropouts are 8.8% and 94.1%, respectively. Similarly, the fractions of less than high school educated mothers and fathers of the dropouts are 85.3% and 79.4%, respectively. There are no statistically significant differences between the observable characteristics of participated children and dropouts.

Region of residence in Syria

Region	Number	Percent
Aleppo	308	93.9
Deir-ez-Zor	5	1.5
Idleb	5	1.5
Damascus	4	1.2
Hama	3	0.9
Homs	2	0.6
Ar-Raqqa	1	0.3
Total	328	100

Table A3: Summary statistics—region of residence in Syria prior to displacement: The sample consists of Syrian kids of age 5. The study includes 36 classrooms in 11 schools in the Gaziantep region. There are 333 kids in the Syrian sample.

Year of arrival to Turkey

Year	Number	Percent
2011	6	1.8
2012	26	7.9
2013	71	21.7
2014	88	26.8
2015	71	21.7
2016	42	12.8
2017	15	4.6
2018	9	2.7
Total	328	100

Table A4: Summary statistics—year of arrival to Turkey: The sample consists of Syrian kids of age 5. The study includes 36 classrooms in 11 schools in the Gaziantep region.

Syrian parents' Turkish language skills

Skill level	Number	Percent
None	64	19.5
Some understanding	115	35.1
Spoken	132	40.2
Spoken & written	17	5.2
Total	328	100

Table A5: Summary statistics—Turkish language skills of Syrian parents: The sample consists of the parents of Syrian kids of age 5. The study includes 36 classrooms in 11 schools in the Gaziantep region.

Balancing Tests for Ethnic Composition of Class

Dependent Variable	**Share of refugees**	**P-value**
	(1)	(2)
Gender	-.0007996	0.594
Mother's education	.0007678	0.626
Father's education	.0008279	0.596
Number of siblings	.007817	0.152
Mother employed	.0007834	0.099
Father employed	-.0002097	0.776
Ethnic Composition of Parents' Friends	-.0029229	0.241
Ethnic Composition of Neighborhood	-.0008215	0.690
Syrian only		
Region of origin Aleppo	-.0009912	0.274
Arrival year	.0110325	0.309
Turkish Language Skills of Parents	-.0032701	0.341

Table A6: Notes: Each entry of column (1) reports coefficients from a regression of the variable indicated in the first column on the share of refugees and also controls for nationality and school fixed effects. Column (2) reports the respective p-value of the estimated coefficient. Standard errors are clustered at classroom level. Mother's and Father's education is a binary variable that takes the value of 1 if the person has obtained primary education and above and 0 otherwise. Ethnic composition of Parents' Friends and Neighborhood is a binary variable that takes the value of 1 if all or the majority of friends or neighbors are co-ethnic and 0 otherwise. Region of origin is a binary variable that takes the value of 1 if it is Aleppo and 0 otherwise.

Table A7: Friends regressions: Other outcomes

	Turkish			Syrian		
Dependent variable	**Total # of Friends**	**# of Syrian Friends**	**Share of Syrian Friends**	**Total # of Friends**	**# of Turkish Friends**	**Share of Turkish Friends**
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Panel A - Linear Specification						
Refugee share	0.002	0.010*	0.528***	-0.001	-0.014**	-0.312
	(0.007)	(0.005)	(0.183)	(0.010)	(0.006)	(0.216)
Panel B - Tercile Specification						
Refugee share	-0.108	0.251	16.416***	-0.190	-0.667***	-13.558*
(Med)	(0.285)	(0.156)	(5.353)	(0.265)	(0.193)	(7.368)
Refugee share	-0.021	0.376	12.206	-0.646	-0.712**	-14.349
(High)	(0.568)	(0.347)	(10.963)	(0.459)	(0.287)	(9.360)
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline outcome	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	276	276	276	328	328	328

Notes: The sample consists of Turkish children in columns 1-3 and Syrian children in columns 4-6. The dependent variable in each column is indicated in the heading of the table. Controls are the same as in Table 2 for Turkish and Table 3 for Syrians. Standard errors are clustered at classroom level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A8: Detailed structural estimation results

Variable	Point estimate	Standard Error
Panel A: Socialization		
Syrian	-0.741	(0.065)
Male	0.093	(0.021)
Parents have diverse friends†	0.226	(0.079)
Parents live in diverse Neighborhood†	0.045	(0.033)
Arrived in 2012 (Syrians)	0.516	(0.834)
Arrived in 2013 (Syrians)	0.517	(0.510)
Arrived in 2014 (Syrians)	0.526	(0.830)
Arrived in 2015 (Syrians)	0.388	(0.537)
Arrived in 2016 (Syrians)	0.407	(1.251)
Arrived in 2017 (Syrians)	0.966	(3.325)
Arrived in 2018 (Syrians)	0.350	(1.216)
Syrian region 3 (Syrians)	-0.378	(3.150)
Syrian region 4 (Syrians)	0.252	(5.802)
Syrian region 5 (Syrians)	1.550	(41.654)
Syrian region 6 (Syrians)	-1.747	(19.395)
Syrian region 7 (Syrians)	-0.451	(8.522)
Syrian region 8 (Syrians)	1.151	(64.895)
Fluent in Turkish in baseline (Syrians)	0.140	(0.084)
School 1	0.698	(0.008)
School 2	0.544	(0.007)
School 3	0.642	(0.031)
School 4	0.559	(0.021)
School 5	0.593	(0.009)
School 6	0.247	(0.009)
School 7	0.590	(0.004)
School 8	0.577	(0.016)
School 9	0.562	(0.029)
School 10	0.854	(0.012)
School 11	0.646	(0.008)
ϕ^S	0.955	(0.003)
ϕ^T	0.694	(0.001)
Panel B: Network		
Syrian-Syrian pair	0.691	(0.098)
Syrian-Turkish pair	-1.076	(0.026)
Turkish-Syrian pair	-1.103	(0.062)
Same Gender	1.686	(0.056)
Parents live in diverse neighborhood†	1.661	(4.521)
Fluent in Turkish in baseline (Syrians)	0.700	(0.088)
Linked in baseline	1.791	(1.201)
School 1	0.615	(0.060)
School 2	0.180	(0.062)
School 3	1.031	(0.253)
School 4	-0.498	(0.042)
School 5	-0.375	(0.023)
School 7	-0.363	(0.024)
School 8	1.020	(0.195)
School 9	-0.170	(0.059)
School 10	1.162	(0.074)
School 11	-0.081	(0.031)
σ	2.853	(0.223)

Notes: The variables "Parents have diverse friends" and "Parents have diverse neighbors" are dummy variables taking a value of 1 if more than 50% the student's parents friends or neighbors are ethnically different to themselves. For the network, "Diverse neighbors" take a value of 1 if either kid's parents live in a diverse neighborhood.

Table A9: Structural Estimation: Marginal effects on the preference biases

Variable	Point estimate	Standard Error
Syrian-Syrian pair	0.127	(0.017)
Syrian-Turkish pair	-0.212	(0.004)
Turkish-Syrian pair	-0.218	(0.013)
Same Gender	0.329	(0.016)
Parents live in diverse neighborhood†	0.213	(0.361)
Fluent in Turkish in baseline (Syrians)	0.115	(0.013)
Linked in baseline	0.235	(0.102)
School 1	0.097	(0.009)
School 2	0.030	(0.010)
School 3	0.148	(0.029)
School 4	-0.090	(0.008)
School 5	-0.067	(0.005)
School 7	-0.064	(0.005)
School 8	0.149	(0.023)
School 9	-0.030	(0.011)
School 10	0.175	(0.009)
School 11	-0.014	(0.006)

Notes: The estimates correspond to average marginal effects on $\delta^{i(e)j(e)}$. That is, $(1/N_2)\sum_{i(e),j(e)}[\Phi(\sum_{k'\neq k} z_{r,k'}^{i(e)j(e)}\gamma_{k'} + \gamma_k) - \Phi(\sum_{k'\neq k} z_{r,k'}^{i(e)j(e)}\gamma_{k'})]$ for the binary variable k. Standard errors are simulated using 500 draws of $\boldsymbol{\theta}$ centered at its point estimate and using the estimated variance-covariance matrix. This is done in order to account for the covariance between the estimated values for $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ and ϕ.

† "Diverse neighbors" take a value of 1 is either kid's parents live in a diverse neighborhood.

B Additional Figures

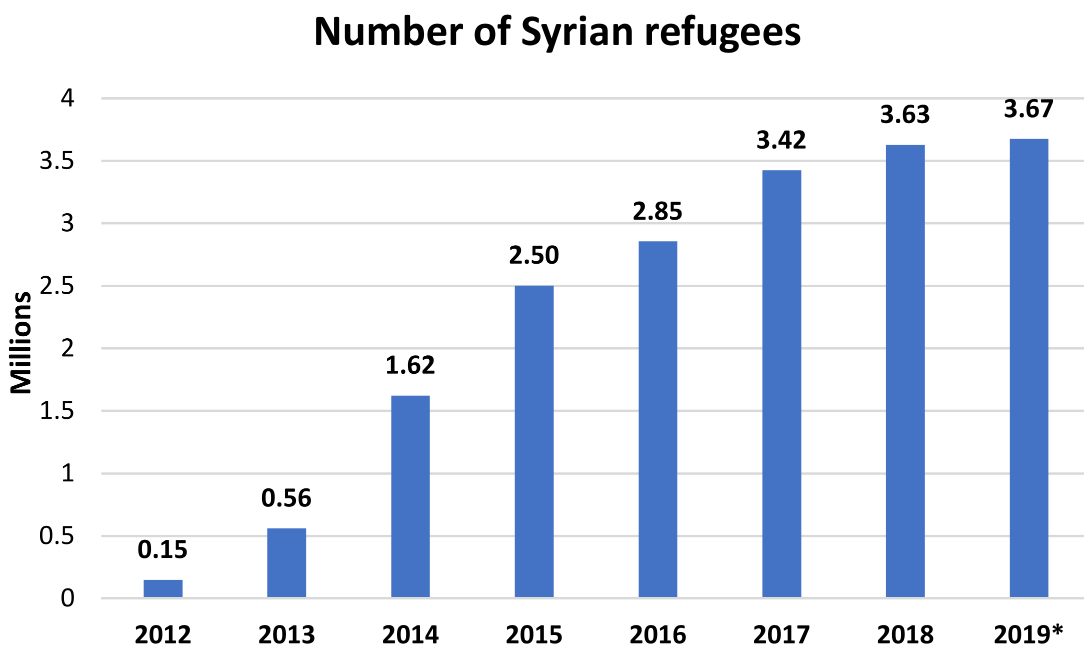

Figure A1: Number of Syrian refugees in Turkey over years. Data source is the UNHCR. The numbers correspond to registered Syrian refugees. The 2019 figure is as of October 10, 2019. There are approximately 370,000 registered refugees from other nationalities. The total number of registered refugees is above 4 millions.

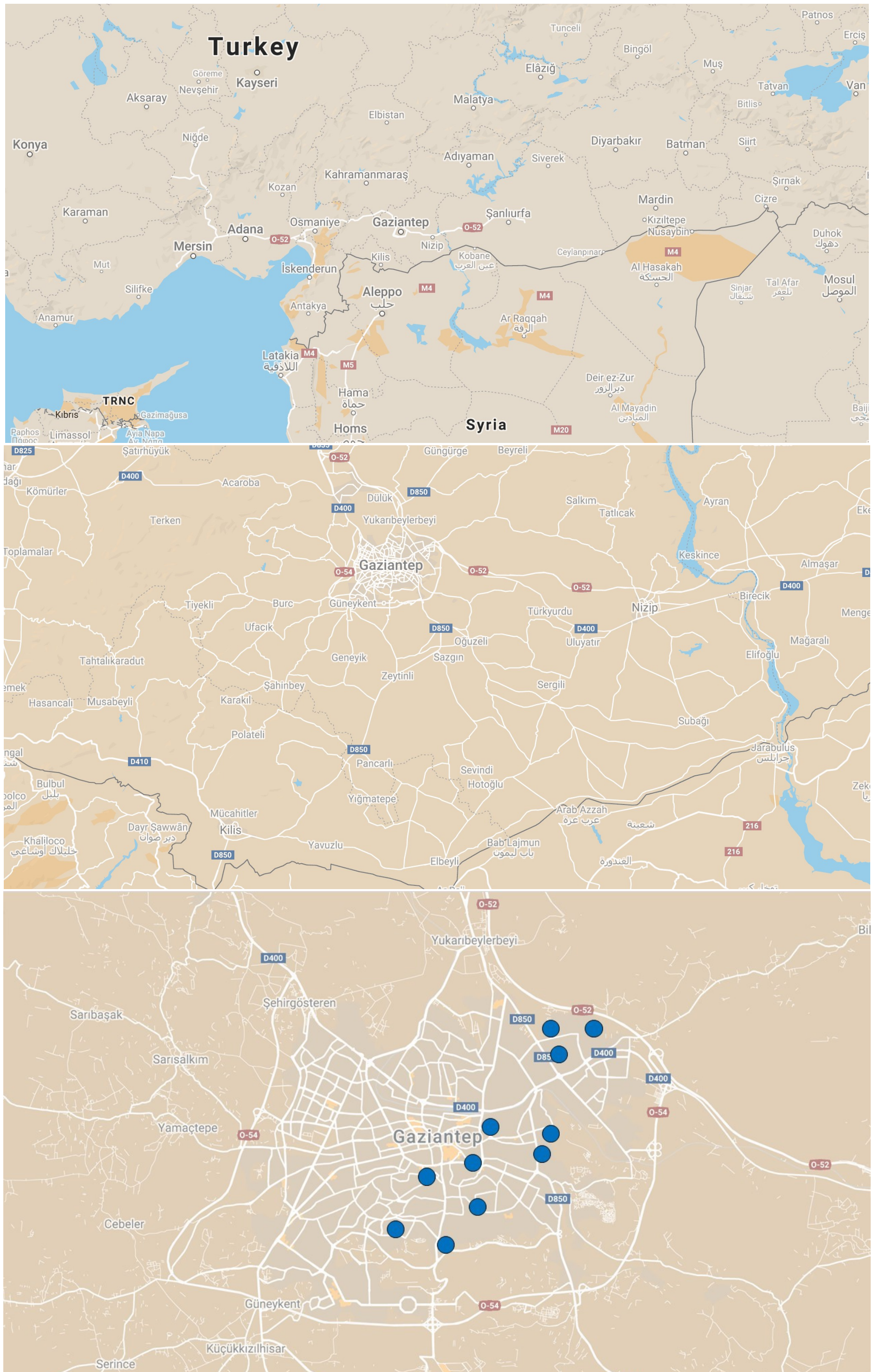

Figure A2: Locations of schools. The maps start from a general view of the Syrian border region of Turkey and zooms into inner-city Gaziantep. The map at the bottom marks the locations of the 11 schools in which our randomized field experiment is implemented. The names of those schools are as follows: Salih Ekmekci Ilkokulu, Alparslan Ilkokulu, Sehit Karayilan Ilkokulu, Ahmet Celebi Ilkokulu, Emrullah Sule Anaokulu, Gurteks Gulsen Ozkaya Anaokulu, Mehmet Erdemoglu Ilkokulu, Karagul Anaokulu, Hatice Karsligil Ilkokulu, Bahattin Teymur Ilkokulu, and Omer ve Sabriye Ersoy Ortaokulu.

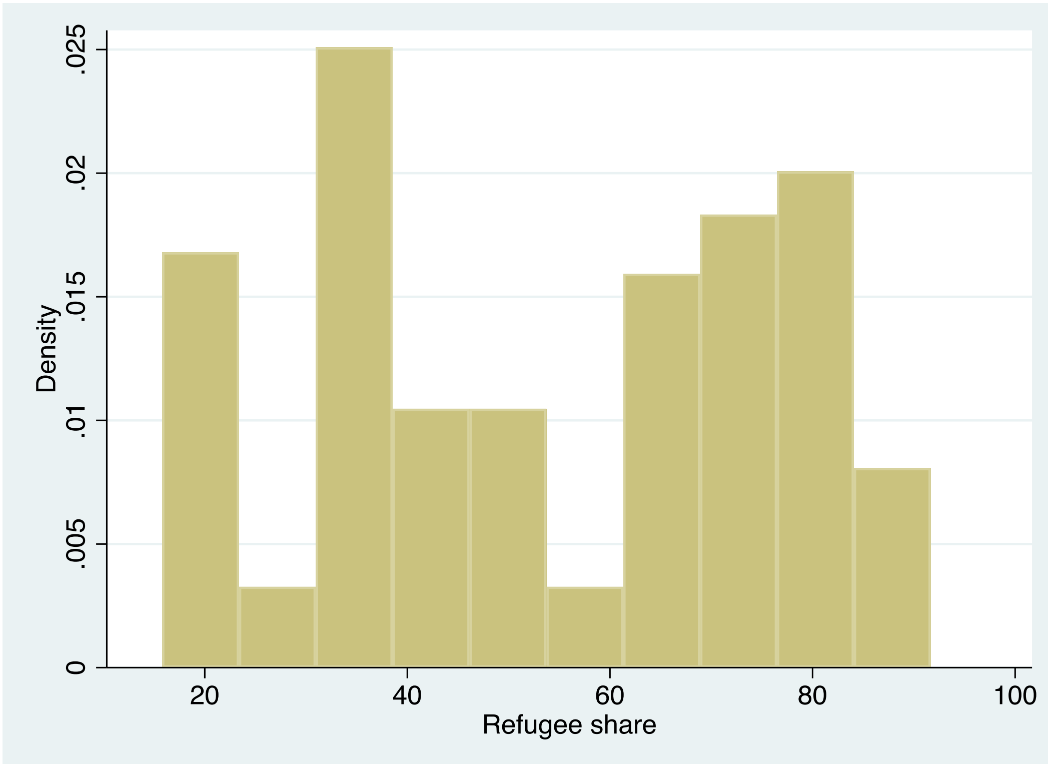

Figure A3: Distribution of refugee share across groups. The sample consists of Syrian kids of age 5. The study includes 36 classrooms in 11 schools in the Gaziantep region.

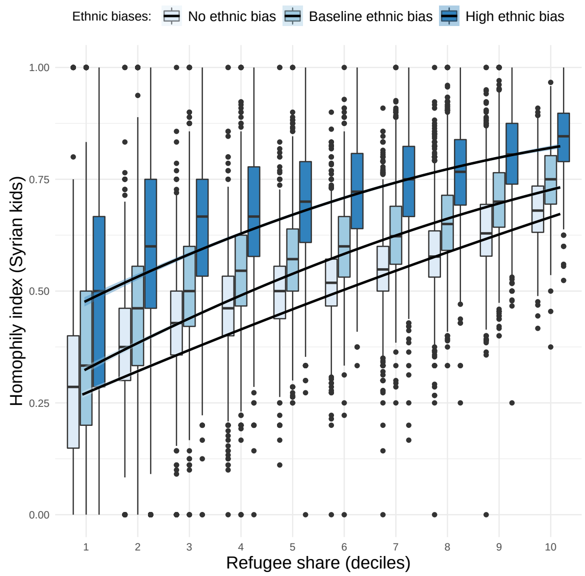

Figure A4: Simulated homophily index by refugee share (Syrian kids): Changes in preference biases.

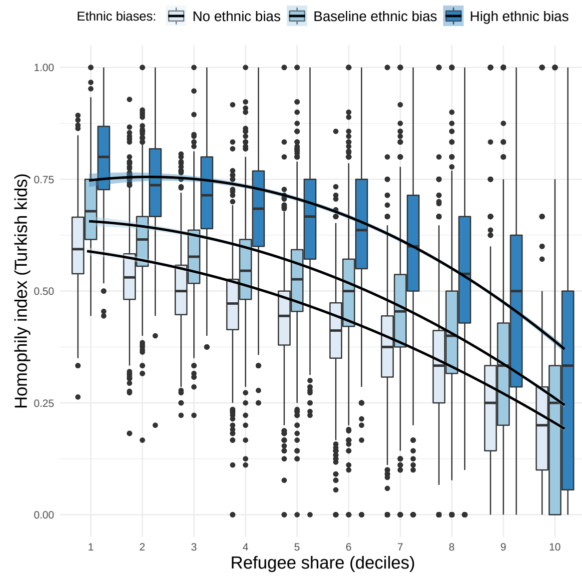

Figure A5: Simulated homophily index by refugee share (Turkish kids): Changes in preference biases.

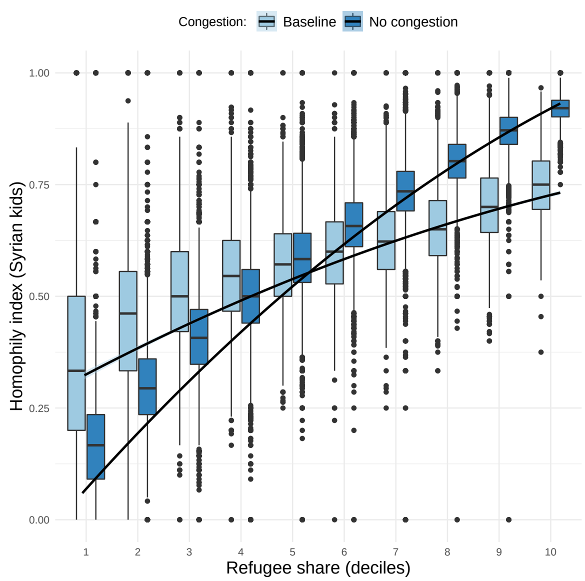

Figure A6: Simulated homophily index by refugee share (Syrian kids): Changes in congestion.

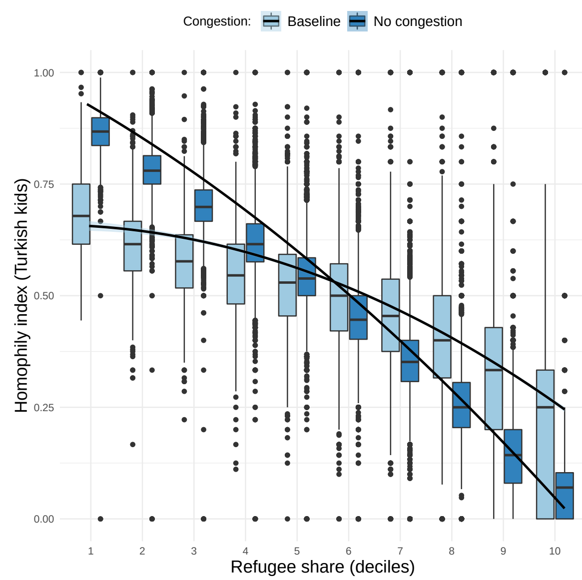

Figure A7: Simulated homophily index by refugee share (Turkish kids): Changes in congestion.

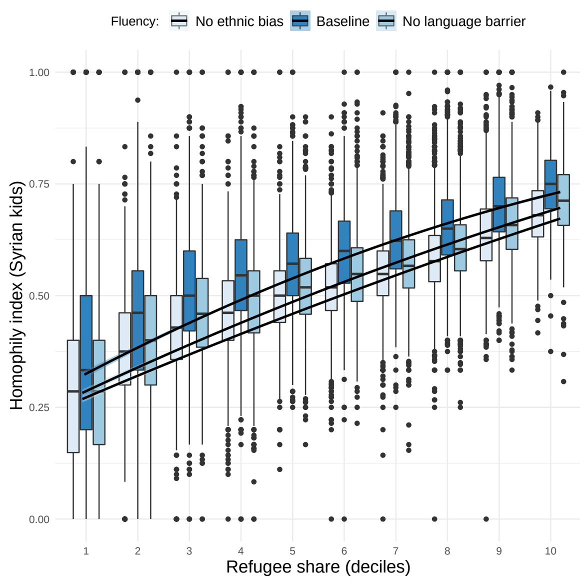

Figure A8: Simulated homophily index by refugee share (Syrian kids): Preference biases vs Syrian fluency.

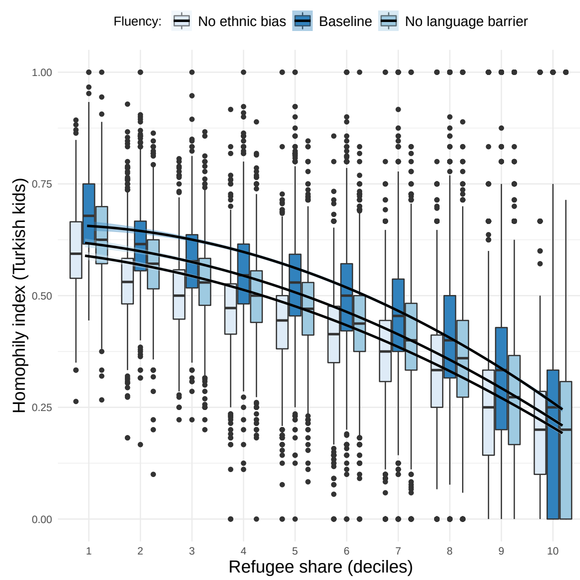

Figure A9: Simulated homophily index by refugee share (Turkish kids): Preference biases vs Syrian fluency.

C Additional aspects of the theory

C.1 Determination of the equilibrium socialization efforts

The first-order conditions (5) are given by:

$$s^i = (1-\phi^i)b^i + \phi^i \overline{s}^{-i}$$

The social norms in the classroom can be written as:

$$\overline{s}^{-i(S)} = \frac{\left(n^S - 1\right)}{n} s^S + \frac{n^T}{n} s^T = q s^S + (1-q) s^T - \frac{s^S}{n} = \overline{s} - \frac{s^S}{n}$$

and

$$\overline{s}^{-i(T)} = \frac{n^S}{n} s^S + \frac{\left(n^T - 1\right)}{n} s^T = q s^S + (1-q) s^T - \frac{s^S}{n} = \overline{s} - \frac{s^T}{n}$$

The first-order conditions (5) can then be written as:

$$s^{S*} = \frac{\left(1-\phi^S\right)}{\left(1-\phi^S q + \frac{\phi^S}{n}\right)} b^S + \frac{\phi^S (1-q)}{\left(1-\phi^S q + \frac{\phi^S}{n}\right)} s^{T*} \tag{C.1}$$

$$s^{T*} = \frac{\left(1-\phi^T\right)}{\left[1-\phi^T (1-q) + \frac{\phi^T}{n}\right]} b^T + \frac{\phi^T q}{\left[1-\phi^T (1-q) + \frac{\phi^T}{n}\right]} s^{S*} \tag{C.2}$$

By solving these equations, we obtain:

$$s^{S*} = \frac{\left[1-\phi^T (1-q) + \frac{\phi^T}{n}\right]\left(1-\phi^S\right) b^S + \phi^S (1-q)\left(1-\phi^T\right) b^T}{\left(1-\phi^S q + \frac{\phi^S}{n}\right)\left[1-\phi^T (1-q) + \frac{\phi^T}{n}\right] - \phi^S \phi^T q (1-q)}$$

$$s^{T*} = \frac{\left(1-\phi^S q + \frac{\phi^S}{n}\right)\left(1-\phi^T\right) b^T + \phi^T q \left(1-\phi^S\right) b^S}{\left(1-\phi^S q + \frac{\phi^S}{n}\right)\left[1-\phi^T (1-q) + \frac{\phi^T}{n}\right] - \phi^S \phi^T q (1-q)}$$

When n is large, these equations can be written as:

$$s^{S*} = \frac{\left[1-\phi^T (1-q)\right]\left(1-\phi^S\right)}{1-\phi^T - q\left(\phi^S - \phi^T\right)} b^S + \frac{\phi^S (1-q)\left(1-\phi^T\right)}{1-\phi^T - q\left(\phi^S - \phi^T\right)} b^T \tag{C.3}$$

$$s^{T*} = \frac{\left(1-\phi^S q\right)\left(1-\phi^T\right)}{1-\phi^T - q\left(\phi^S - \phi^T\right)} b^T + \frac{\phi^T q \left(1-\phi^S\right)}{1-\phi^T - q\left(\phi^S - \phi^T\right)} b^S \tag{C.4}$$

The equilibrium social norm in the classroom is then given by:

$$\overline{s}^* = q s^{S*} + (1-q)\, s^{T*} = \frac{q\left(1-\phi^S\right) b^S + (1-q)\left(1-\phi^T\right) b^T}{1-\phi^T - q\left(\phi^S - \phi^T\right)}$$

with

$$\frac{\partial \overline{s}^*}{\partial q} = \frac{\left(1-\phi^T\right)\left(1-\phi^S\right)\left(b^S-b^T\right)}{\left[1-\phi^T-q\left(\phi^S-\phi^T\right)\right]^2}$$

C.2 Comparative statics results

Using the expression of the equilibrium socialization levels in (7) and (8) and replacing in equations (10)–(13), we can compute the following results.

Proposition C1. *Assume that n is large. Then, in terms of socialization efforts, for Turkish kids, we have:*

$$\frac{\partial s^{T*}}{\partial q} = \frac{\phi^T\left(1-\phi^S\right)\left(1-\phi^T\right)\left(b^S-b^T\right)}{\left[1-\phi^T-q\left(\phi^S-\phi^T\right)\right]^2}. \tag{C.5}$$

which implies that

$$\frac{\partial s^{T*}}{\partial q} \gtreqless 0 \Longleftrightarrow b^S \gtreqless b^T, \tag{C.6}$$

For Syrian kids, we have:

$$\frac{\partial s^{S*}}{\partial q} = \frac{\phi^S\left(1-\phi^S\right)\left(1-\phi^T\right)\left(b^S-b^T\right)}{\left[1-\phi^T-q\left(\phi^S-\phi^T\right)\right]^2}, \tag{C.7}$$

which implies that

$$\frac{\partial s^{S*}}{\partial q} \gtreqless 0 \Longleftrightarrow b^S \gtreqless b^T. \tag{C.8}$$

Proposition C2. *In terms of probability of linking, we have the following:*

1. *Consider friendship links between Turkish kids. We have:*

$$\frac{\partial p^{TT*}}{\partial q} = \frac{\delta^{TT}}{n\left(1-q-1/n\right)^2}\left(\frac{\partial s^{T*}}{\partial q}\left(1-q-1/n\right)+s^{T*}\right). \tag{C.9}$$

2. *Consider friendship links between Syrian kids. We have:*

$$\frac{\partial p^{SS*}}{\partial q} = \frac{\delta^{SS}}{n\left(q-1/n\right)^2}\left(\frac{\partial s^{S*}}{\partial q}\left(q-1/n\right)-s^{S*}\right). \tag{C.10}$$

3. *Consider inter-ethnic friendship links. We have:*

$$\frac{\partial p^{TS*}}{\partial q} = \frac{\delta^{TS}}{nq^2}\left(\frac{\partial s^{T*}}{\partial q}q-s^{T*}\right) \text{ and } \frac{\partial p^{ST*}}{\partial q} = \frac{\delta^{ST}}{n(1-q)^2}\left(\frac{\partial s^{S*}}{\partial q}\left(1-q\right)+s^{S*}\right). \tag{C.11}$$

C.3 Homophily results

Proof of Proposition 2:

Let us start with the homophily index of the Syrian kids. First, note that H^S can be written as $H^S = \frac{A}{A+B}$, where A and B are independent binomial distributions with respective parameters $\left(n^S\left(n^S-1\right), p^{SS}\right)$ and $\left(n^S n^T, p^{ST}\right)$. Indeed, for A, $n^S\left(n^S-1\right)$ is the number of trials (maximum number of links) and p^{SS} is the success probability for each trial. The same interpretation applies for B. If we take a second-order Taylor expansion evaluated at $\frac{\mathbb{E}[A]}{\mathbb{E}[A]+\mathbb{E}[B]} = \frac{\delta^{SS}}{\delta^{SS}+\delta^{ST}}$, we obtain:[1]

$$\mathbb{E}\left[H^S\right] = \frac{\mathbb{E}\left[A\right]}{\mathbb{E}\left[A+B\right]} - \frac{cov\left[A, A+B\right]}{\left(\mathbb{E}\left[A+B\right]\right)^2} + \frac{V\left[A+B\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A+B\right]\right)^3}$$

Because of independence between A and B, we have:

$$V\left[A+B\right] = V\left[A\right] + V\left[B\right]$$

and

$$cov\left[A, A+B\right] = cov\left[A^2\right] + cov\left[A, B\right] = V\left[A\right]$$

since $cov\left[A, B\right] = 0$. Thus,

$$\begin{aligned}
\mathbb{E}\left[H^S\right] &= \frac{\mathbb{E}\left[A\right]}{\mathbb{E}\left[A+B\right]} - \frac{cov\left[A, A+B\right]}{\left(\mathbb{E}\left[A+B\right]\right)^2} + \frac{V\left[A+B\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A+B\right]\right)^3} \\
&= c - \frac{V\left[A\right]}{\left(\mathbb{E}\left[A\right]+\mathbb{E}\left[B\right]\right)^2} + \frac{V\left[A\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A\right]+\mathbb{E}\left[B\right]\right)^3} + \frac{V\left[B\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A+B\right]\right)^3} \\
&= c - \frac{\left(\mathbb{E}\left[A\right]\right)^2}{\left(\mathbb{E}\left[A\right]+\mathbb{E}\left[B\right]\right)^2}\left(\frac{V\left[A\right]}{\left(\mathbb{E}\left[A\right]\right)^2} - \frac{V\left[A\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A\right]\right)^2\left(\mathbb{E}\left[A\right]+\mathbb{E}\left[B\right]\right)} - \frac{V\left[B\right]\mathbb{E}\left[A\right]}{\left(\mathbb{E}\left[A\right]\right)^2\left(\mathbb{E}\left[A+B\right]\right)}\right) \\
&= c - c^2\left[\left(1-c\right)\frac{V\left[A\right]}{\left(\mathbb{E}\left[A\right]\right)^2} - c\frac{V\left[B\right]}{\left(\mathbb{E}\left[A\right]\right)^2}\right]
\end{aligned}$$

Since A follows a binomial distribution with parameter $\left(n^S\left(n^S-1\right), p^{SS}\right)$, we have:

$$\mathbb{E}\left[A\right] = n^S\left(n^S-1\right)p^{SS} \text{ and } V\left[A\right] = n^S\left(n^S-1\right)p^{SS}\left(1-p^{SS}\right)$$

Similarly, since B follows a binomial distribution with parameter $\left(n^S n^T, p^{ST}\right)$, we have:

$$\mathbb{E}\left[B\right] = n^S n^T p^{ST} \text{ and } V\left[B\right] = n^S n^T p^{ST}\left(1-p^{ST}\right)$$

[1] If we take a first-order Taylor expansion, we obtain:

$$\mathbb{E}\left[H^S\right] = \mathbb{E}\left[\frac{A}{A+B}\right] = \frac{\mathbb{E}\left[A\right]}{\mathbb{E}\left[A+B\right]} = \frac{\mathbb{E}\left[A\right]}{\mathbb{E}\left[A\right]+\mathbb{E}\left[B\right]} = \frac{\delta^{SS}}{\delta^{SS}+\delta^{ST}},$$

which is independent of q.

Recall also that $p^{SS} = \delta^{SS}s^S/(n^S-1)$ and $p^{ST} = \delta^{ST}s^S/n^T$. Using these values, we easily find:

$$\mathbb{E}[A] = n^S\delta^{SS}s^S$$

$$V[A] = \frac{n^S}{n^S-1}\delta^{SS}s^S(n^s - 1 - \delta^{SS}s^S)$$

and

$$V[B] = \frac{n^S}{n^T}\delta^{ST}s^S(n^T - \delta^{ST}s^S)$$

We can therefore compute:

$$\frac{V[A]}{(E[A])^2} = \frac{n^S - 1 - \delta^{SS}}{(n^S-1)n^S\delta^{SS}s^S}$$

and

$$\frac{V[B]}{(E[A])^2} = \frac{n^T - \delta^{ST}}{nTn^S(\delta^{SS})^2s^S}.$$

Then, we have:

$$\left[(1-c)\frac{V[A]}{(E[A])^2} - c\frac{V[B]}{(E[A])^2}\right] = \frac{\delta^{St}}{\delta^{SS}(\delta^{SS}+\delta^{ST})n^S}\left[\frac{\delta^{ST}}{n^T} - \frac{\delta^{SS}}{n^S-1}\right]$$

so

$$\mathbb{E}\left[H^S\right] = \frac{\delta^{SS}}{\delta^{SS}+\delta^{ST}} - \frac{\delta^{SS}\delta^{ST}}{(\delta^{SS}+\delta^{ST})^3n^S}\left[\frac{\delta^{ST}}{n^T} - \frac{\delta^{SS}}{n^S-1}\right].$$

Replacing $n^S = nq$ and $n^T = n(1-q)$, we finally obtain:

$$\mathbb{E}\left[H^S\right] = \frac{\delta^{SS}}{\delta^{SS}+\delta^{ST}} - \frac{\delta^{SS}\delta^{ST}}{(\delta^{SS}+\delta^{ST})^3n^2}\left[\frac{\delta^{ST}}{q(1-q)} - \frac{\delta^{SS}}{q(q-1/n)}\right]. \tag{C.12}$$

For n large enough, $\mathbb{E}\left[H^S\right] > 0$. Further,

$$\frac{\partial\mathbb{E}\left[H^S\right]}{\partial q} > 0 \Leftrightarrow \frac{\delta^{SS}}{\delta^{ST}} < \frac{(1-2q)\,(q-1/n)^2}{(1-q)^2\,(2q-1/n)}$$

Note that the right-hand side is approximately equal to $\frac{(1-2q)}{2(1-q)^2}$ when n is large.

Let us now consider the homophily index of the Turkish kids and calculate $\mathbb{E}\left[H^T\right]$. Proceeding exactly in the same way by taking a second-order Taylor expansion evaluated at $\frac{\delta^{TT}}{\delta^{TT}+\delta^{TS}}$, we obtain

$$\mathbb{E}\left[H^T\right] = \frac{\delta^{TT}}{\delta^{TT}+\delta^{TS}} - \frac{\delta^{TT}\delta^{TS}}{\left(\delta^{TT}+\delta^{TS}\right)^3n^2}\left[\frac{\delta^{TS}}{q(1-q)} - \frac{\delta^{TT}}{(1-q)(1-q-1/n)}\right]. \tag{C.13}$$

For n large enough, $\mathbb{E}\left[H^T\right] > 0$. Further,

$$\frac{\partial \mathbb{E}\left[H^T\right]}{\partial q} < 0 \Leftrightarrow \frac{\delta^{TT}}{\delta^{TS}} < \frac{(2q-1)\,(1-q-1/n)^2}{q^2(2(1-q)-1/n)}$$

Note that the right-hand side is approximately equal to $\frac{(2q-1)}{2q^2}$ when n is large. □

D Details on the structural estimation procedure

D.1 Uniqueness for generic b^i

Child i chooses $s^i \in [0,1]$ to maximize

$$u^i = b^i s^i - \frac{1}{2}\left(s^i\right)^2 - \frac{\kappa^i}{2}\left(s^i - \bar{s}_i\right)^2, \tag{D.1}$$

where $\bar{s}_i = \frac{1}{n-1}\sum_{j\neq i} s_j$. The first derivative is equal to:

$$b^i - s^i(1+\kappa^i) + \kappa^i \frac{\sum_{j\neq i} s_j}{n-1}$$

Since the utility is concave in s^i, the best response for i is given by:

$$s^i = h\left(\frac{b^i}{1+\kappa^i} + \frac{\kappa^i}{(n-1)(1+\kappa^i)}\sum_{j\neq i} s^j\right),$$

where $h(\cdot) = \max\{\min\{\cdot, 1\}, 0\}$. We can easily see that the best-response function is a contraction mapping over $[0,1]^n$ since $\frac{\kappa^i}{1+\kappa^i} < 1$ for all i. This implies that there exists a unique socialization level (i.e., a unique Nash equilibrium) and that it can be found using an iterative procedure.

D.2 Estimator

Recall that we observe socialization with errors: $s_r^i = \tilde{s}_r^i + \eta_r^i$. We can therefore rewrite:

$$\tilde{s}_r^i = [d_r^i(1-\phi^S) + (1-d_r^i)(1-\phi^T)]\mathbf{x}_r^i\boldsymbol{\beta} + d_r^i \frac{\phi^S}{n_r - 1}\sum_{j\neq i}\tilde{s}_r^j + (1-d_r^i)\frac{\phi^T}{n_r-1}\sum_{j\neq i}\tilde{s}_r^j + \nu_r^i, \tag{D.2}$$

where $\nu_r^i = [d_r^i(1-\phi^S)+(1-d_r^i)(1-\phi^T)]\varepsilon_r^{i(e)} - \eta_r^{i(e)} + d_r^i \frac{\phi^S}{n_r-1}\sum_{j\neq i}\eta_r^j + (1-d_r^i)\frac{\phi^T}{n_r-1}\sum_{j\neq i}\eta_r^j$. Importantly, since $\mathbb{E}[\eta_r^{i(e)}|\mathbf{X}] = 0$ for all i and given our assumption on $\varepsilon^{i(e)}$, this implies that we also have $\mathbb{E}[\nu_r^{i(e)}|\mathbf{X}] = 0$ for all i.

Then, under this conditional mean independence, the instrumental variable strategy proposed by Lee (2007) can be used in order to identify $\boldsymbol{\beta}$, ϕ^S and ϕ^T. Intuitively, the idea is to instrument the endogenous variable $\frac{1}{n_r-1}\sum_{j\neq i}\tilde{s}_r^j$, the average of the other students' (proxied) socialization choices, using the average of their characteristics, i.e. $\frac{1}{n_r-1}\sum_{j\neq i}\mathbf{x}_r^j$.

This leads to the following empirical moment conditions:

$$M_1(\tilde{\mathbf{s}}, \boldsymbol{\beta}, \phi^S, \phi^T, \mathbf{X}) = \frac{1}{N_1}\sum_r\sum_i \nu_r^i \left[\mathbf{x}_r^i, \frac{d_r^i}{n_r-1}\sum_{j\neq i}\mathbf{x}_r^j, \frac{1-d_r^i}{n_r-1}\sum_{j\neq i}\mathbf{x}_r^j\right] = 0, \tag{D.3}$$

where $N_1 = 604$ is the number of individuals in our sample. The term in brackets includes the included instruments $\mathbf{x}_r^i$ identifying $\boldsymbol{\beta}$ and the excluded instruments $\frac{1}{n_r-1}\sum_{j\neq i}\mathbf{x}_r^j$, identifying ϕ^S and ϕ^T.

We now turn to the observed network structure. Let $\boldsymbol{\theta} = [\boldsymbol{\beta}, \boldsymbol{\gamma}, \phi^S, \phi^T, \sigma]$. Recall that for all pairs of individuals i and j, the probability of a link is given by:

$$\mathbb{P}(g_r^{ij} = 1|\mathbf{X}, \mathbf{Z}, \boldsymbol{\varepsilon}) = \frac{\Phi(\mathbf{z}_r^{ij}\boldsymbol{\gamma})s_r^{*i}(\mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\varepsilon})s_r^{*j}(\mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\varepsilon})}{\sum_{k\in T_r^i(j)} s_r^{*k}(\mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\varepsilon})},$$

where $s_r^{*i}(\mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\varepsilon})$ is the equilibrium value of the socialization level of individual i.

If $\boldsymbol{\varepsilon}$ was observed, we could base the estimation on the following empirical moment conditions:

$$M_2(\mathbf{G}, \boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}, \boldsymbol{\varepsilon}) = \frac{1}{N_2}\sum_r\sum_{i\neq j}[g_r^{ij} - \mathbb{P}(g_r^{ij} = 1|\mathbf{X}, \mathbf{Z}, \boldsymbol{\varepsilon})]\mathbf{z}_r^{ij} = 0,$$

where $N_2 = 9,940$ is the number of pairs of individuals in our sample. Here, the term in brackets is the error of the model and $\mathbf{z}_r^{ij}$ are the (included) instruments, which are sufficient for the identification of $\boldsymbol{\gamma}$.

Obviously, the error terms ε_r^i are not observed, but since $\varepsilon_r^i \sim N(0, \sigma^2)$, we can integrate the previous moment condition (e.g. Chandrasekhar and Lewis (2011)) and obtain the unconditional moment conditions:

$$M_2(\mathbf{G}, \boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}) = \frac{1}{N_2}\sum_r\sum_{i\neq j}[g_r^{ij} - \mathbb{P}(g_r^{ij} = 1|\mathbf{X}, \mathbf{Z})]\mathbf{z}_r^{ij} = 0.$$

These last moment conditions cannot be written down in close form since $\mathbb{P}(g_r^{ij} = 1|\mathbf{X}, \mathbf{Z})$ cannot. However, $\mathbb{P}(g_r^{ij} = 1|\mathbf{X}, \mathbf{Z})$ can be easily simulated by 1) drawing a value for $\boldsymbol{\varepsilon}$ and 2) computing the unique equilibrium socialization level $s_r^{*i}(\mathbf{X}, \boldsymbol{\theta}, \boldsymbol{\varepsilon})$ for all i. The resulting simulated moment conditions are therefore:

$$M_2(\mathbf{G}, \boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}) = \frac{1}{N_2 L} \sum_{l=1}^{L} \sum_{r} \sum_{i \neq j} [g_r^{ij} - \mathbb{P}(g_r^{ij} = 1 | \mathbf{X}, \mathbf{Z}, \boldsymbol{\varepsilon}_l)] \mathbf{z}_r^{ij} = 0, \tag{D.4}$$

where L is the number of simulations. The estimation based on such simulated moments conditions leads to consistent and asymptotically normal estimators, even for a fixed number of simulations $L > 0$ (Gourieroux and Monfort, 1996).

To summarize, the identification of $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, ϕ and σ follows from the moment conditions $M_1(\tilde{\mathbf{s}}, \boldsymbol{\beta}, \phi^S, \phi^T, \mathbf{X})$ and $M_2(\mathbf{G}, \boldsymbol{\theta}, \mathbf{X}, \mathbf{Z})$. However, those two sets of moments are not based on the same number of observations.

We therefore follow Arellano and Meghir (1992) and base our estimator on the minimization of the following objective function:

$$\frac{1}{N} Q_N(\boldsymbol{\theta}) = \lambda \frac{1}{N_1} Q_{1,N_1}(\boldsymbol{\beta}, \phi^S, \phi^T) + (1 - \lambda) \frac{1}{N_2} Q_{2,N_2}(\boldsymbol{\theta}),$$

where $N = N_1 + N_2$, $\lambda = N_1/N$ and $Q_{1,N_1}(\boldsymbol{\beta}, \phi^S, \phi^T)$ and $Q_{2,N_2}(\boldsymbol{\theta})$ are objective functions based on the moment conditions M_1 and M_2.

Under the assumption that classrooms have bounded sizes, even as the sample size grows, we have $\lim_{N \to \infty} \lambda = \bar{\lambda} \in (0, 1)$ so both sets of moments are asymptotically informative. As such, under the usual regularity conditions, the estimator minimizing $Q_N(\theta)$ is asymptotically normal with an asymptotic variance-covariance matrix of the sandwich form, and based on the $\bar{\lambda}-$weighted Hessian and outer-product matrices of $Q_{1,N_1}(\boldsymbol{\beta}, \phi^S, \phi^T)$ and $Q_{2,N_2}(\boldsymbol{\theta})$. See Appendices B.1 and B.2 in Arellano and Meghir (1992) for details.

Finally, note that this is essentially a two-step estimator, estimated in a single step. Alternatively, one could first obtain estimators $\hat{\beta}$, $\hat{\phi}^S$ and $\hat{\phi}^T$ from moments $M_1(\tilde{\mathbf{s}}, \boldsymbol{\beta}, \phi^S, \phi^T, \mathbf{X})$, and then get estimators for $\boldsymbol{\gamma}$ and σ in a second step using $M_2(\mathbf{G}, \boldsymbol{\theta}, \mathbf{X}, \mathbf{Z})$ conditional on $\hat{\boldsymbol{\beta}}$, $\hat{\phi}^S$ and $\hat{\phi}^T$. If this would yield consistent estimators, the computation of the standard errors in the second step would be very challenging.