The Effects of Refugee Camps on Children of Host Communities: Evidence from Ethiopia *

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Abstract

Over three-quarters of refugees in the world are hosted in low and middle income countries with limited resources and infrastructure to support the refugees. We study the effects of hosting refugees on the host communities in Ethiopia, which is one of the poorest countries and the second largest host of refugees in Africa. We find that under-5 children with higher exposure to refugee camps have lower weight-to-age and weight-to-height z-scores. However, higher refugee exposure is also associated with increased school enrollment and higher grade-to-age ratio for school-age cohorts. The negative health effect is attributed to higher likelihood of contacting infectious diseases such as diarrhea and lower probability of receiving vaccinations whereas the positive effect on education is attributed to children in host community benefiting from increased school supply by NGOs for the refugee children. Our results are remarkably robust across a series of identification and measurement approaches.
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1 Introduction

According to UNHCR (2023) the number of forcibly displaced people worldwide nearly trebled from 41.1 million in 2010 to 117 million in 2023, and refugees constitute more than a third of these population. Such massive and forced movement of people has several consequences including immediate humanitarian crisis and loss of livelihoods in the short and long term for the displaced. According to 2021 data from UNHCR, low and middle income countries host 83% of the global forcefully displaced people (UNHCR, 2021a). The responsibility of hosting refugees also disproportionately falls on developing countries. Hosting refugees with limited amount of resource and infrastructure is likely to be a heavy burden to poor countries, but it may also bring economic opportunities and improved access to services such as education and health services, which are increasingly shared between the host and refugee communities (UNHCR, 2017; Anti and Salemi, 2021). For instance, UNHCR (2017) report shows that, in Ethiopia, nearly 13% of recipients of primary health care in health facilities in refugee camps are local host population while for access to secondary health care, refugees are referred to health facilities outside the camps.

In this paper, we study the effects of a protracted refugee crisis on host communities in Ethiopia, which is one of the poorest countries in the world and the second largest refugee host in Africa (following Uganda) due to its location as the neighbor to multiple war-torn countries. Close to 95% of these refugees are hosted in refugee camps and settlements. Even though they are meant to be temporary when they are opened, many of these camps last decades and some eventually morph into small towns.

Our estimation results show that proximity to refugee camps has a significant negative effect on the Weight-for-Age Z-score (WAZ) and Weight-for-Height Z-score (WHZ) of children, the two most widely used measures of child malnutrition and health. In our preferred specification, for a child in a community with the highest exposure to refugee camps (roughly 3 standard deviation higher exposure relative to the mean) WAZ is lower by about 0.13 (equivalent to 10% of the standard deviation of WAZ), and WHZ is lower by about 0.12 (about 10% of the standard deviation of WHZ). The effects are likely partially mediated via increased prevalence of infectious diseases and limited access to preventive health care in areas more exposed to refugee camps. In particular, we find that children in communities with high exposure to refugee camps are more likely to have contracted contagious infectious diseases, such as diarrhea. This could be attributed to the overly crowded settlements and lack of clean water and sanitation in refugee camps. We also find that these children are less likely to have received some crucial vaccinations such as polio and DPTs.

However, the negative health effect does not tell the full story on the effect of hosting refugees. We find that higher proximity to camps is associated with higher school enrollment of children aged 6-14, with little or no effect on school enrollment of children in the 15-19 age range. We find similar effect on grade-to-age ratio, an alternative measure of education outcome. Such positive effect of education is similar across boys and girls of the same age brackets. This positive effect is attributed to the host children obtaining access to schools constructed by NGOs to serve refugee children (Vemuru et al., 2020). Kreibaum (2016) finds closely related result in the context of Uganda: host communities consumption and access to education services improves but access to health services deteriorates following influx of refugees.

Several studies have looked at the effects of refugee camps on the host communities. We address some of the main identification issues in the literature including endogeneity of camp locations, cross-border conflict spillovers and selection issues due to migration of households in the host community. First, location of camps is unlikely to be exogenous. Governments make deliberate decisions on where to locate the camps in such a way to minimize negative externalities to the host community. Ethiopia provides us with a unique setting to construct exogenous source of variation to location of refugee camps. Because Ethiopia is located between multiple crisis-stricken countries, refugees flow into the country from many different directions: from Eritrea in the north and northeast, from Somalia in the east and south east, from South Sudan and Sudan in the west. As a result, refugee settlements in Ethiopia are spatially dispersed (see figure 3). This pattern, together with spatial settlement patterns of ethnicities in Ethiopia, allows us to construct an IV for location of refugee camps across districts of the country.

Second, conflicts in neighboring countries may affect the host community via other channels than hosting the refugees, such as direct spillover of the security crisis across borders or interruption of cross-border (informal) trade. We address this issue by looking into host communities that live farther from borders. Third, selection due to migration of households in the host community might confound identification. Households may migrate towards camps looking for better employment or business opportunities or migrate away from camps if they feel the economic opportunity or security situation is deteriorating. We address the issue of migration of households towards camps by looking at households who stayed at least 10 years at their location during the survey period.[1]

This paper is related to a growing literature on the effects of the presence of refugees on the host communities. These studies show mixed evidences on the effects of refugees on the wellbeing of the host community (see Verme and Schuettler, 2021 for a comprehensive literature review). Some of these studies find a negative

[1]Unfortunately our data does not allow us to address the issue of households migrating away from camps.

effect on the child health within and across generations. Baez (2011) finds that the influx of refugees from Burundi and Rwanda into Tanzania during the 1993/94 conflicts negatively affected child health among the Tanzanian hosts, using both child anthropometric measures and morbidity indicators as measure of child health. More recently, Sonne and Verme (2019) show negative inter-generational effects of the same refugee crisis – children born to parents who lived close to the refugee camps during their childhood have lower height for age z-score and are more likely to be stunted. Both these studies stipulate that increased impoverishment and malnourishment is the key channel through which the refugee crisis affects child health in the host community. Our results complement this literature in that we find negative effect on child health in a different context.

This paper's key contribution is that we document a significant positive effect of refugee camps on school enrollment of host children. This result is corroborated by qualitative studies that undertake an in-depth focused group discussion with the host communities (Vemuru et al., 2020), and it reinforces recent papers that argue that forced migrants are more likely to bring development opportunities rather than security risks to the host communities (Zhou and Shaver, 2021), or increase social conflict in the short term but eventually promote local economic development (Coniglio et al., 2021). Even in contexts such as Jordan where local infrastructure are expected to be highly crowded from massive refugee influx, a recent study (Assaad et al., 2020) finds almost no impact of the refugee camps on children's education outcomes and attribute this to the government's response to putting more resources into the education system.

Another distinguishing feature of this study from a policy point of view is that it estimates the effect of hosting refugees in the context where refugee camps are geographically scattered. Previous studies are typically based on contexts where refugee settlement is geographically concentrated in few locations (e.g. northwestern regions of Kigoma and Kagera in Tanzania, and the Kakuma in the northwest and Daadab in the eastern Kenya). One may wonder if dispersion of refugee camps across geographic regions might help to alleviate the negative externality. The fact that we find a smaller negative externality in Ethiopian context compared to, e.g. Baez (2011) for Tanzania, might be attributed to the scattered settlement of refugees in Ethiopia.

This paper is also related to a growing literature that documents the adverse effects of civil conflicts on child health and mortality in Sub-Saharan Africa including: Dagnelie et al. (2018) in DR Congo, Domingues and Barre (2013) in Mozambique, Minoiu and Shemyakina (2012) in Côte d'Ivoire, Akresh et al. (2011) in Rwanda, Akresh et al. (2012a) in Nigeria, and Akresh et al. (2012b) for Ethio-Eritrean border war. These papers document that cohorts of children that are more exposed to conflict in utero/during their early childhood have significantly poorer health than cohorts who are less exposed to conflicts. We contribute to this literature by showing that these adverse effects of civil conflicts also spillover to neighboring communities that host refugees from the conflict stricken regions/countries.

Finally, this paper is related recent studies on inclusion and integration of refugees with the local host communities, particularly in public goods provision. For instance, UNHCR (2017) documents that the Ethiopian government actively follows such inclusion and integration policies in the provision of health and education services to the refugees and the host communities. Similarly, Zhou et al. (2023) and Kreibaum (2016) find that presence of refugees improves delivery of public goods to the host communities.[2] Some of the results in this paper echoe similar findings.

The rest of this paper is organised as follows. Section 2 briefly discusses our data while Section 3 discusses the evolution of Ethiopia's refugee policy. Section 4 discusses the empirical strategy. Section 5 presents the main results while section 6 discusses robustness of our results to several identification concerns and alternative approaches to measurement of exposure. In Section 7 we discuss the potential mechanisms through which hosting refugees negatively affects child health in the host community and Section 8 concludes the paper.

2 Data and historical background

We use three main datasets in this study. The first is a georeferenced dataset on refugee camps in Ethiopia, which comes from UNHCR. This data includes several variables including the precise coordinates of all refugee camps, the number of refugees in each camp, and information on the aid received by the refugees. We also collected data on the opening year of refugee camps. During the early 1990's, Ethiopia hosted over 800,000 refugees fleeing civil wars in Sudan and Somalia[3]. The number of refugees decreased steadily over time, mainly due to return of refugees to both origin countries and was around 100,000 in 2007. Then, the number of refugees entering Ethiopia started to increase again, until 2018 as a result of the conflict, repression, and severe droughts in neighboring countries. Currently Ethiopia is the second largest destination country in Africa after Uganda, hosting nearly 800,000 refugees as of October 2020 (UNHCR). Almost all of these refugees originate from neighboring countries of South Sudan (45.6%), Somalia (25.3%), Eritrea (22.4%) and Sudan (5.5%).

The recent wave of refugee inflow started in 2007 from Somalia following con-

[2] See also Jahre et al. (2018).

[3] Refugee flows from Somalia started during late 1980's conflicts and early 1990s following the collapse in Siad Barre's government and the ensuing statelessness of Somalia.

flicts between Islamic insurgents and government forces backed by Ethiopian and African Union troops. Three camps were built in the Somali region of Ethiopia to accommodate about 50,000 refugees. This was followed by a large refugee influx following the 2010/11 drought and famine, the worst one that hit Somalia in 60 years. About 170,000 refugees fled to Ethiopia between 2011-2013. By 2018, the number of refugees from Somalia reached about 257,000 and four more refugee camps were opened in the Somali region of Ethiopia to host them.

Parallel to refugee inflow from Somalia, there has been a steady increase in the flow of refugees from Eritrea since 2003, when the Eritrean government started to coerce the youth into national service, including military training.[4] The refugee inflow from Eritrea peaked in 2014 when a record 40,000 new refugees fled to Ethiopia.[5] These refugees settled in six new refugee camps opened in Tigray and Afar regions.

The largest and most recent wave of refugee influx was instigated by the conflict in South Sudan following President Salva Kiir's accusation of his deputy Riek Machar for a coup attempt in December 2013. About 420,000 South Sudanese refugees have crossed across the border to Ethiopia since then. Most of these refugees were settled in six new refugee camps opened in Gambella region of Ethiopia. Figure 1 shows trends in number of refugee population by country of origin and figure 2 shows trends in the number of camps.

Refugees in Ethiopia are distributed unevenly across districts and states. Some regions bear disproportionate burden due to their geographic and cultural (common ethnicity and language) proximity to the regions from where the refugees are coming. Refugees account for 40% of total population in Gambella region, 9% in Benishangul Gumuz, 3% in Afar, 2.6% in Somali, 2.5% in Addis Ababa, 1.3% in Tigray, and less than 1% in the Oromia, Amhara and Southern regions.

The second dataset is the Ethiopian Demographic and Health Survey (EDHS). DHS is the most widely used dataset to analyse child and maternal health in Sub-Saharan African countries. We use two rounds of geocoded survey (2010 and 2016) that overlap with the period of rapid refugee influx. The DHS randomly alters the geolocations of respondents to protect their identity by 0-2km for urban locations and by 0-5km for most rural locations.[6] The DHS data provides as with anthropometric measures of children aged between 6-59 months and school enrollment information for children aged 6-19 years. The anthropometric and school enrollment information are measured during the survey time. Because children's health and education outcomes measured at the time of survey could be influenced by exposure to refugee camps

[4]See https://www.hrw.org/report/2019/08/08/they-are-making-us-slaves-not-educating-us/how-indefinite-conscription-restricts

[5]See https://www.hrw.org/world-report/2018/country-chapters/eritrea#

[6]Discussions about the potential biases due to such alterations can be found in Warren (2016), Grace et al. (2019),Wilson and Wakefield (2021), and Karra et al. (2020).

throughout their lifetime, we assess robustness of our estimation results by measuring exposure to camps at the time of birth, at the time of survey and cumulative lifetime exposure. Table 1 shows descriptive statistics for child anthropometric measures for each DHS survey rounds. The table shows that these child anthropometric measures moderately improved between the two survey rounds.

The third dataset includes administrative data on the entire road network in the country obtained from Ethiopian Roads Authority. This dataset has been used in few recent studies and detailed discussions about the dataset are provided (Kebede, 2022, 2024; Gebresilasse, 2023). We use the road data as of 2011 to calculate the travel cost between the refugee camps and host community villages. We use road distance, instead of straight line distance, because the externalities from refugee camps to the local communities are likely to be influenced by the extent of social and economic interactions. In areas where road infrastructure connecting the refugee camps to the local community is poor, such interactions are likely to be minimal, and impacting the magnitude of the resulting externalities. Our road data includes information about the road quality, i.e., whether road surfaces are asphalt, gravel, or dirt road, as well as the precise location to calculate travel distances. We use average cost of transporting a ton of weight on roads of different surface quality (i.e., asphalt, gravel, or dirt road) obtained from Ministry of Transport and Logistic to estimate travel cost between DHS sample locations and the refugee camps/district centeroids.

3 Ethiopia's refugee policy and refugee livelihood

The Ethiopian government follows a policy of encampment, which was formalized in 2004 Refugee Proclamation, that requires refugees to reside in camps, with some exceptions. These exceptions include refugees with serious security concerns or serious health issues. In 2010 the government adopted Out-of-Camp Policy (OCP) for Eritrean refugees (UNHCR, 2017). The OCP grants Eritrean refugees with no criminal records and with the financial capability to support themselves to live out of camp location of their choice. In 2016, the Ethiopian government pledged to expand the OCP policy to benefit 10% of the refugee population (regardless of their origin)[7]. However, legal proclamations to implement this plan was not drafted until February 2019 (Vemuru et al., 2020) and over 93% of UNHCR registered (as of September 2020) refugees still live in camps. Two-thirds of non-camp residents reside in Addis Ababa while majority of the remaining live in towns across the Tigray region.

Due to encampment policy and limited economic opportunities, refugees have low employment rate (only 22% of working age population work) and as a result, are heavily dependent on aid. About 83% of refugees derive their livelihood from

[7] See https://reliefweb.int/sites/reliefweb.int/files/resources/65916.pdf

aid (Pape et al., 2018). The remaining rely on labor income and self employment in non-farm businesses. Refugees participation in agriculture is very limited, only 7% (Pape et al., 2018). The sources of aid is over 50 NGOs (both local and international) and the Ethiopian government. The aid includes cash transfers, in-kind rationing of essential products, and services such as education and health.

The encampment policy has key implications for the effects of refugees on host communities (see Alix-Garcia et al. 2017 for detailed analysis). In particular, because encampment mainly restricts the refugees' participation in the production, rather than consumption, activities, their effect on local economy is likely channeled through changes in local demand for goods and services. In other words, while refugees reside in the camps, they are allowed to travel outside camps typically for shopping and social activities. Their economic participation outside the camps is minimal due to limited employment opportunities. However, they contribute significantly to the local demand for goods and services because in most cases they constitute a significant proportion of the population.

4 Empirical strategy

4.1 Baseline specification

The DHS data record anthropometric outcomes of the children at the time of survey. This poses a question of at what point we should measure a child's exposure, an issue that the previous literature overlooked. For example, living near a camp during infancy might have an impact that lasts years even after the camp is closed. In order to account for this possibility, we propose two measures: exposure at the year of birth of the child, and cumulative exposure between the year of birth and the time when his/her health/nutrition outcome is measured in the survey.

In our main specification for child health/nutrition analysis, we use exposure at the child's year of birth as the measure of exposure. Our estimation equation is given by

$$H_{ilts} = \alpha + \beta \text{RefugeeExposure}_{lt} + \delta X_{lt} + \mu Z_i + \gamma_z + \gamma_t + \varepsilon_{ilts} \tag{1}$$

where H_{ilts} is the standardized health outcome of child i in DHS sample location l born in year t and measured in year s (for example, s is 2016 for DHS round 2016). Location is generally a village and is identified quite precisely in the survey with its coordinates. X and Z are vector of variables that capture village and child characteristics, respectively; γ_z and γ_t are zone and cohort fixed effects, respectively.[8]

[8]There are about 72 administrative zone, 397 woredas (districts) and 1239 DHS sample locations in the pooled DHS2016 and DHS2011. We think that including the district fixed effects are

Observations are weighted by sampling weights. $\text{RefugeeExposure}_{lt}$ measures location l's exposure in year t and is given by the following:

$$\text{RefugeeExposure}_{lt} = \sum_m \frac{1}{d_{lm}} * I_{mt} * \frac{\text{RefugeePopulation}_{mt}}{\text{Population}_m} \tag{2}$$

where d_{lm} is travel cost (across the shortest route) between DHS sample location l and a refugee camp in district m. For our analysis on child education, we find it reasonable to consider exposure at the time of survey as the appropriate measure (i.e., the explanatory variable is $\text{RefugeeExposure}_{ls}$).

We use administrative data on the entire road network together with data on per-kilometer costs of transporting a ton of weight on roads of different surface type to calculate d_{lm}.[9] I_{mt} is indicator variable if there is a refugee camp in district m in year t. Finally $\frac{\text{RefugeePopulation}_{mt}}{\text{Population}_m}$ is a district-specific weight, which is given by the number of refugees relative to the size of the local population in district m. This weight aims to control for the size of the camp relative to the native population (the intensity of *treatment*).[10] Figure 6 present the spatial variation in refugee exposure measures corresponding to equation 2 across the DHS2016 sample locations for the year 2016. As clearly seen, locations near refugee camps have higher exposure measures.

4.2 Endogeneity in camp location

One important concern in identifying the causal effects of the presence of refugee camps on host communities is that the host governments consider a number of factors when choosing the camp locations. In the context of Ethiopia, camp locations are determined by UNHCR and Administration for Refugee and Returnee Affairs (ARRA) in consultation with local governments and communities hosting the refugees and camps are usually built in locations with the following features: less densely populated, ethnically similar to the refugees (to minimize conflicts), not too close the border (security reason), minimize future repatriation costs, and logistically convenient ((UNHCR, 2021b). Salemi (2021) discusses location of refugee camps are based on similar set of variables in Kenya, Rwanda, Uganda, and Tanzania while

demanding because in many cases we have only one DHS location per district. In those cases, including district fixed effects would leave us with only within- DHS location variation. This variation is limited particularly for the health-related outcomes where our unit of analysis is children aged between 6-59 months and the number of children in this age bracket with complete data is small.

[9] However, our results remain strongly robust if we use road distance, without accounting for road surface quality.

[10] We use population data from the 2007 census to avoid any concern of endogeneity of population size to camp openings. We show that an alternative measure that drops this weight gives similar results.

Maystadt and Verwimp (2014) argue that proximity to borders was a critical factor in choice of camp locations in Tanzania.

Governments' choices of camp locations may take into account the potential externalities on the host community. Ignoring this motivation would lead to underestimation of the true causal effect of the refugee camps. Table A.1 reports summary statistics of child health and education outcomes for districts with and without camps. The table shows that districts with refugee camps have poorer health and education measures compared to those without camps based on DHS2010/11 round. However, the education gap decreases (in most cases even reverses) in DHS2016 while the health gap remains more or less similar. While some of these changes could be attributed to changes in the composition (such as rural/urban composition) of DHS sample location across survey rounds, it is suggestive of potential endogeneity in camp location (camps tend to be built in less developed areas). While our zone and rural/urban dummies may address some of this concern, they do not fully address the problem.

To address the endogeneity problem, we use Instrument Variable (IV) estimation strategy. Our IV is based on predicted probability of camp location across Ethiopian districts based on a number of exogenous variables. The first variable is the ethnic similarity of the district's population with the refugees. The second variable is the district's distance from border to the region from where the refugees originate in the neighboring country. The third variable is the time of onset of conflict at the origin country of the refugees. In order to prevent cultural and political conflicts between refugees and hosts, refugees are often settled in districts where the local population shares a common ethnic and linguistic background with the refugees. For example, refugees from Somalia are mostly settled in Somali speaking districts in Ethiopia. Similarly, Ethiopian districts that are closer to the home regions of the refugees are more likely to host the camps since it would facilitate return in the future.

We predict the probability that a woreda/district m in Ethiopia has a refugee camp using the following regression:

$$I_{mt} = \alpha_0 + \alpha_1(\text{CommonEthnicity}_m \times \text{OriginConflict}_{mt}) + \alpha_2 \ln(\text{Distance})_m + \varepsilon_{mt} \tag{3}$$

where I_{mt} equals one if district m has a refugee camp in year t. CommonEthnicity_m is time-invariant and equal to one if district m shares a common ethnicity with the origin of the potential refugees. For districts in a given Regional State in Ethiopia, the origins of potential refugees are the country/countries that share a common border with that Regional State. $\text{OriginConfict}_{mt}$ equals one for the years since conflict broke-out in origin region/country of potential refugees for district m. $\ln(\text{Distance})_m$

is log distance between district m and the border of the potential refugee origin. We call this the *zero-stage* regression and we use probit to estimate the coefficients which, we, then, use to calculate the predicted probability of having a camp in a given district in a given year. We estimate probit regression for the periods 2011-2016 and 2006-2010 separately corresponding to the DHS rounds 2016 and 2010, respectively.[11] Table A.2 report these results. For both rounds of the DHS survey, both the Common Ethnicity×Origin Conflict and Log Distance to Border variables have statistically significant effect on the probability of camp opening in a district. Ethiopian districts that share the same ethno-linguistic identity with the refugee origin "conflict" regions in neighboring countries and districts that are geographically closer to the same source regions have higher probability of having a camp located within their borders.

Our IV is obtained by replacing I_{mt} in equation 2 with the predicted probability of having a refugee camp in district m based on equation 3, $\hat{I}_{mt}$:

$$\text{IV}_{lt} = \sum_{m} \frac{1}{d_{lm}} * \hat{I}_{mt} * \frac{\text{RefugeePopulation}_{mt}}{\text{Population}_{m}} \tag{4}$$

where $\hat{I}_{mt}$ denotes the predicted probability that district m has a refugee camp in year t, and d_{lm} denotes travel cost between DHS location l and district m centeroid.[12]

Our identification strategy is related to the shift-share research design (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020). In the shift-share research design, Borusyak et al. (2021) show that exogeneity of the "shifts" alone yield identification, regardless of whether or not the "shares" are exogenous while Goldsmith-Pinkham et al. (2020) argue that exogeneity of "shares" ensures identification regardless of exogeneity of the shifts. In our setting, the "shares" represent ethnic similarity and geographic proximity of districts in Ethiopia to refugee source countries and the "shifts" represent the period since onset of conflict and refugee inflow. Exogeneity of both the shifts and the shares are likely satisfied with respect to the outcome variables we study. The onset of civil-conflict and size of refugee flows in neighboring countries is likely influenced by factors in those countries. Moreover, settlement patterns of ethnicity were determined centuries ago and are exogenous to current child health and nutrition. However, our identification assumption is more likely to satisfy the assumptions in Goldsmith-Pinkham et al. (2020) than those in Borusyak et al. (2021) because consistency of estimates in the latter requires "many" independent shocks. While conflicts are frequent in East African countries and conflicts in different

[11] Pooling the two sample periods together gives very similar results.

[12] Note that our IV addresses only endogeneity of camp locations. We assume that conditional on camp opening in a district, the size of the camp (or the number of refugee population in the district) is exogenously determined by the severity of the conflict and the mass of potential refugees in the origin country.

countries can mostly be considered independent, this may not ensure the "many" independent shock assumption required for consistency in Borusyak et al. (2021).

4.3 Outcome variables

We consider a number of outcome variables on child health/nutrition including anthropometric (weight and height) measures, anemia status, and mortality. We also consider morbidity and access to health services including basic vaccinations. Table 1 reports descriptive statistics of main dependent variables – WAZ (weight-for-age z-score), WHZ (weight-for-height z-score) and HAZ (height-for-age z-score). Following the literature on health and nutrition we construct WAZ, WHZ, HAZ variables by using the 2006 World Health Organization's child growth standards as the reference points for each age-gender group. Figures 4 and 5 show the spatial variation in the average values of weight-to-age and weight-to-height z-scores together with the location of refugee camps.

For analysis of the effect of exposure to camps on education of school-aged children in the host community, we consider two commonly used outcome measures. The first is enrolment status of children aged 6-19 years. The second is grade-for-age (GFA) ratio calculated as GFA = grade completed/age. Also, we measure exposure to refugees at the time of survey (instead of exposure in the child's year of birth) because we found it more appropriate for the child's school enrollment.[13]

5 Main results

5.1 The effect on child health/nutrition

OLS results: We first present OLS estimation of equation 1 in Panel A of Table 2. To ease the interpretation and to facilitate comparison of results across different measures, we standardize all of our exposure measures. Thus, all of our results are interpreted as the effect of one standard deviation higher exposure relative to the average.

We present the effect of exposure to refugee camps *at year of birth* for host children as our main result. This is in line with the literature on child malnutrition which emphasizes the importance of adverse conditions, nutrition and healthcare during infancy. Our estimation sample is children aged 6-59 months in DHS rounds 2016 and 2010, for whom anthropometric data is available. Panel A of Table 2 report the OLS results. The results show negative and statistically significant effect of exposure to refugee camps on children's weight-for-age z-score (WAZ) and weight-for-height

[13] However, all our results are very similar if we use cumulative exposure.

z-score (WHZ), which are the most widely used measures of child malnutrition and health. However, we do not find any statistically significant effect on children's height-for-age z-score (HAZ), anemia status and mortality.

IV estimation results: Panel B of Table 2 reports the IV estimation results for child health. The first-stage statistics are reported in Table A.3 and the first-stage F-stats is above 10 (the rule of thumb for weak instrument). Comparing the point estimates on WAZ and WHZ against the baseline OLS estimates in Panel A of Table 2, we see that OLS estimation tends to underestimate the effect of refugee exposure on child health outcomes suggesting that the government's choice of location of the refugee camps may have taken into account the potential negative effects of camps on the host community.

It is important to shade light on the magnitude of the estimated effects. One way to interpret the magnitudes is to compare the effect in the *highest exposed community* against the *average exposed community*. We use the results in Table 2 to discuss the interpretation of the coefficients. The results in other tables can be interpreted in a similar manner. Using our IV estimation results in Columns 1 and 2 of Table 2 show that one standard deviation higher exposure to a refugee camp, relative to the mean exposure, is associated with 0.044 lower child WAZ and 0.041 lower child WHZ. For a child in the highest exposed community (roughly 3 standard deviations higher exposure relative to the mean), child WAZ is lower 0.132 and WHZ is lower by about 0.123. These are roughly equivalent to 10% of the standard deviations of WAZ and WHZ for the children in the pooled DHS round 2016 and 2010 (see Table 1). Hence, the magnitude of the estimated effects is modest.

Next, we explore heterogeneity in the effect of exposure to camps across children of different age groups in Table 3, where we report the IV estimation results by age groups.[14] The estimated effects are stronger for children between ages 13-36 months. The effect on WAZ is strongest for children aged 13-24 months while the effect on WHZ is strongest for children aged 25-36 months. Importantly, exposure to refugee camps does not have significant effect on the health of children between age 36-59 months. Also, children younger than 12 months are less affected than those between 13-36 months, which could perhaps be attributed to the protective effect of breastfeeding for younger children. The results in Table 3 indicate that the overall effect of exposure to refugee camps on child health is driven by its effect on children below 3 years of age.

In the next section, we conduct a series of robustness exercises to check sensitivity of these results to several identification and measurement issues and show that these results are remarkably robust.

[14]We do not find any heterogeneity across gender.

5.2 The effect on school enrolment

The analysis in the previous section shows that exposure to camps has a significant negative effect on certain health outcomes of children in the host communities, particularly among children aged below 36 months.

We now turn to the effect on educational outcomes. The Ethiopian government follows an active policy of increased integration of refugee with the local host communities for provision of services such as health and education. This might lead to overcrowding of local health and education facilities. On the contrary, local host communities might as well benefit from new school facilities built by donors primarily to serve the refugees. In the absence of the camps the facilities might not have been built. Anecdotal stories and evidence from qualitative studies suggest that host communities in Ethiopia are benefiting from schools built for the refugees by NGOs and international aid agencies. Vemuru et al. (2020, Page: II-146) quote the following statement from a respondent in the host community: "*Before refugees came, there was only a primary school; the locals used to send their children to Jigjiga and elsewhere to pursue secondary education. Now there are two primary schools and one secondary school. They are also lobbying to get a college or technical school providing technical skills. Therefore, I can say locals have benefited a lot from refugees.*"

In this section, we explore whether hosting refugee camps has a significant effect on school enrollment of children in the host communities. Our estimation sample is now school-aged children (aged 6-19 years) in DHS 2016 and 2010 rounds. We report the estimation results in Table 4. The dependent variable in columns 1-4 is an indicator variable defining whether a child is in school during the DHS survey year. In columns 5-8 the dependent variable is grade-for-age (GFA) ratio.

Panel A of Table 4 reports OLS estimation results. Focusing on enrolment status column 1 shows that higher exposure to camps is associated with significantly higher school enrollment of children between the ages of 6-19. Columns 2-4 report separate estimation results for children between the ages of 6-11, 12-14, and 15-19. The results show that children in the age range of 6-11 (primary school-age) benefit the most while children between ages 15-19 do not benefit significantly. Columns 5-8 replicate similar results using grade-for-age ratio as an outcome variable. Panel B of Table 4 reports the IV estimation results. These results are relatively stronger than the OLS results reported in Panel A for all age groups and regardless of the measure of education outcome considered.

To benchmark the magnitude of these estimates, we once again compare a DHS location with an average exposure against the most exposed DHS location (a location with three standard deviations above the average exposure). We base our interpretation on our IV estimation results in Panel B. Column 1 shows that the likelihood of school enrollment is higher by 0.22 for children between ages 6-19 in the most exposed communities, compared to similar aged children in communities with average exposure. This effect is economically significant given 63% school enrollment rate of children in the age range of 6-19 years old. Column 2 of Panel B shows that for children between 6-11 in the most exposed community, the likelihood of enrollment is higher by 0.29 while column 3 shows that the likelihood of enrollment for children between 12-14 in the most exposed communities is higher by nearly 0.20. These point estimates are large, particularly when compared to the average enrollment rates of school-age children (see the last row of Panel B of Table 4). Similarly, the grade-for-age ratio is higher by 0.072 among children aged 6-19 in the most exposed community relative to same age children in communities with average exposure. This is about 33% increase relative to average grade-for-age ratio of 6-19 age group. The gain in grade-for-age ratio (in percentage terms relative to the average) similar across different age groups. Overall, host communities near the refugee camps gain significantly in education outcomes, both in terms of enrollment as well as grade-for-age outcomes. Below, we explore the sensitivity of these results to several identification concerns.

Next, we explore potential gender heterogeneity in the school enrollment and grade-for-age gains in Panel C of Table 4. The estimated effects are broadly comparable across boys and girls of similar age groups. An exception is high-school age girls (age 15-19) who do not gain significantly both in terms of enrollment as well as grade-for-age ratio while boys in similar age group gain in grade-for-age ratio.

6 Robustness checks

6.1 Cross-border conflict spillover

One of the critical assumption in our OLS/IV estimations is that conflicts in neighboring countries affect communities in Ethiopia only through externalities from camps hosting refugees. However, conflicts in neighboring countries might affect health and education outcomes in Ethiopian communities closer to the border through conflict spillovers (e.g., disruption in cross-border trade or interruption of services due to the risk of conflict expansion). Such spillovers would lead to overestimation of the negative externalities in health/nutrition outcomes and underestimation of the positive externalities in education outcomes we document above. Any such cross-border conflict spillover would affect Ethiopian communities near the border. To address this issue, we restrict our estimation sample to DHS locations that are at least 20km away from borders as sensitivity check.

Panel A of Table 5 reports the results for child health. These results are very similar to the baseline IV estimation results in Panel B of Table 2. Note that the drop in the number of observations due to restriction of estimation sample to households which are at least 20km away from borders is modest (about 7% of the baseline observations in Table 2).

In Panel A of Table 6, we conduct similar robustness exercises for education outcomes. The results are similar to the IV estimation results in Panel B of Table 4 regardless of genders, age groups, and the measure of education outcome considered.

Overall, both our results for the education and health/nutrition outcomes remain remarkably robust to restricting estimation to communities at least 20kms away from the nearest border. We obtain similar result if we increase the distance threshold to 30km or 40km (results not reported). These results suggest that our findings about the effect of exposure to refugee camps are not spuriously driven by cross-border conflict spillover or disruption of economic activities due to conflict in neighboring countries.

6.2 Selection due to migration of hosts

Another identification concern is that households in the host communities may react to opening of camps by relocating closer to or away from the camps. Households may migrate closer to camps looking for better employment or business opportunities created by large markets due to arrival of refugees. They may also migrate away from camps if they find the economic opportunities, service qualities and/or security conditions deteriorating. Our DHS 2016 data includes information on how long the household stayed at their current location at the time of survey, though this information is missing in our DHS 2010 data. Nevertheless, we try to address the issue of households migrating closer to camps by restricting our estimation to households that lived at their current location for at least 10 years (80% of the households in DHS 2016 meet this condition and nearly 90% lived at their current location for at least five years). However, this robustness exercise should be cautiously interpreted in that it is based on only DHS round 2016.[15]

Panel B of Table 5 reports the result for the effect of refugee exposure on child health/nutrition by restricting the estimation sample to households that stayed at their current location for at least 10 years. The results are similar to the IV results in Table 2, despite significant drop in the number of observations partly due to dropping observations in DHS 2010.

In Panel B of Table 6, we report similar robustness exercises for education

[15]It is difficult to address the issue of household migrating away from camps because these households are not in the data. However, while out migration is theoretically a possibility, in practice most rural households (where most camps are located) are immobile because their livelihood is tied to their farmland (which cannot be legally bought or sold).

outcomes. While the signs of the estimated coefficients are generally consistent with those in the main result, the results are generally weaker in comparison with the main results in Table 4 both in terms of magnitude as well as precision. However, this is not surprising given the significant drop in the sample size and hence statistical power due to exclusion of DHS round 2010.

To sum up, these results suggest that our main results are not driven by households migrating closer to camps after arrival of refugees.

6.3 Cumulative exposure

One can argue that measuring exposure to refugee camps at the child's year of birth may not capture the child's total exposure to refugee camps. The *duration* of the exposure might matter, particularly for child health/nutrition outcomes. Consider two three-year old children A and B in 2016 living in similar but different villages. Child A is born near a refugee camp whereas a camp of the same size opens near child B when she is two-years old. That is, child A is exposed to refugee crisis since birth but child B is exposed only in her third year. Measuring *exposure at the year of birth* implies no refugee exposure for child B and would lead to underestimation of the effect of exposure on child health. To address this, we calculate a measure of cumulative exposure (measure of exposure from birth to the survey-year, i.e., when the child's health was measured), given by $\sum_{year=t}^{s} \text{RefugeeExposure}_{lts}$, where t is birth year of the child and s is survey year. We then standardize this measure to facilitate comparison with the results based on exposure measure at the child's year of birth.

Panel C of Table 5 reports results when we use cumulative exposure as our main explanatory variable. The estimated effects for WAZ and WHZ are similar to the baseline results in Table 2, suggesting that our results are not sensitive whether we consider exposure at year birth vs cumulative exposure since the child's year of birth.

7 Potential mechanisms: diseases and vaccination

There are several potential mechanisms through which exposure to refugee crisis would lead to negative health externalities for children in the host community. The first is outbreak of infectious diseases due to crowded settlements and lack of clean water and sanitation. According to Altare et al. (2019), 90% of refugee camps across the globe experienced one or two infectious disease outbreaks per year, spilling over to local community. Another potential mechanism is related to crowding out of local health facilities, which are in most cases in short supply to the host communities in the first place. UNHCR (2017) show that supply and administration of preventive health cares, such as vaccines, to refugees is often mandated to local health bureaus and such integration of refugees health care with that of local host communities has been actively advanced. Below we explore the empirical relevance of theses hypotheses.

We first explore if the negative impact of the presence of refugee camps on children's weight and height outcomes is mediated through child morbidity and healthcare. We estimate the same regression as in equation 1, replacing the dependent variable with an indicator variable measuring whether the child had (i) diarrhea, (ii)cough, (iii) diarrhea treatment, conditional on having diarrhea, (iv) heath card or (v) heath card, conditional on being sick.

Table 7 reports the IV estimation of Linear Probability Model (LPM). The results show that higher exposure is associated with higher likelihood of a child contracting diarrhea. A child in the highest exposed community (three standard deviations above the mean) has about 0.9 percentage points higher infection rate or around 7% higher probability of getting diarrhea compared to the average infection rate of 13%. Moreover, the likelihood of receiving treatment conditional on the child having diarrhea is higher for children near the refugee camps (column 3 of Table 7). On the other hand, exposure to refugee camps does not seem to be related to having coughs.

Column 4 of Table 7 shows that children with higher exposure to refugee camp are more likely to have *health card* from the health facility which indicates that the child has been admitted to receive healthcare or vaccination services. A child in the highest exposed community is 2.4 percentage points more likely to have visited the health station compared to a child with average exposure. While the straightforward implication of this is that children near refugee camps are more likely to have been admitted to health facilities, it might as well be interpreted as better health access for children in the most exposed community. If we condition on the child being sick with diarrhea or cough in the two weeks before survey, the effect of exposure on having card is stronger (see the last column of 7).

Our next set of results are on preventive healthcare access – more specifically vaccinations. The dependent variables of the Linear Probability model is an indicator variable on whether the child had one of the following vaccinations: (i) BCG, (ii), DPT-1, (iii) DPT-2, (iv) DPT-3, (v) Polio-0, (vi) Polio-1, (vii) Polio-2, (viii) Polio-3 and (ix) Measles. The vaccination information records vaccination history of children between 12-24 months of age. Table 8 reports that higher exposure negatively affects the likelihood that a child has received some crucial vaccinations such as DPT and Polio. A child in the highest exposed community (three standard deviations above mean) is less likely to have received vaccinations for DPT-1, DPT-3, Polio-0, Polio-2 and Polio-3, compared to a child in the community with average exposure. Compared to the coverage rates of these vaccines (the last row of table 8), these effects are modest.

Overall, the effects on illness and preventive healthcare are suggestive of the underlying the mechanism through which exposure to camps negatively affects health of the host children. This is consistent with reports showing that refugees generally rely on health facilities outside the camps for services beyond primary health care, which may create a burden on local health facilities (UNHCR, 2017). However, the same report also shows that local communities also benefit from health facilities built in camps for refugees: about 13% of primary care recipients at health facilities in refugee camps are local host communities.

8 Discussion and policy implications

The paper's main objective was to inform government, NGOs and policy makers by identifying and quantifying the positive and negative externalities of hosting refugees. We find robust evidence that hosting refugees has a negative effect on some aspects of the health of children aged 0-5 years, and a positive effect on education of children aged 6-19 years in the host community.

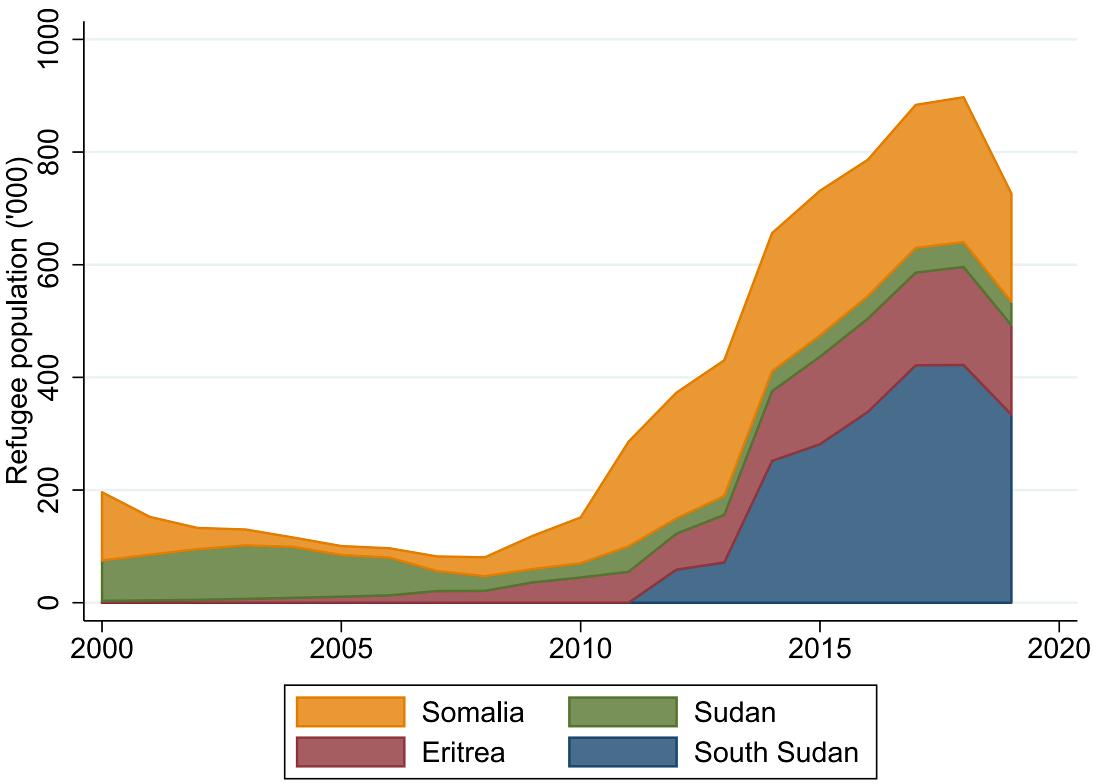
We find suggestive evidence that the negative health externality are mediated through higher incidence of infectious diseases such as diarrhea, and lower access to essential health services such as child vaccination.

While our data do not allow us to explore the mechanisms for the positive effects on education of school-age children, corroboration with past focused-group studies suggests that the result is driven by improved access to education via access to schools built to serve the refugee children by NGOs.

These results should be cautiously interpreted and do not imply isolation of refugees. Instead, the main target of the governments and NGOs should be how to minimize the negative spillovers while maintaining the positive spillovers and the integration of refugees. This could be done by investing more in health of the refugees. Any investment in refugees' wellbeing (such as sanitation, vaccination, and education) should take into account the spillover benefit to the host community.

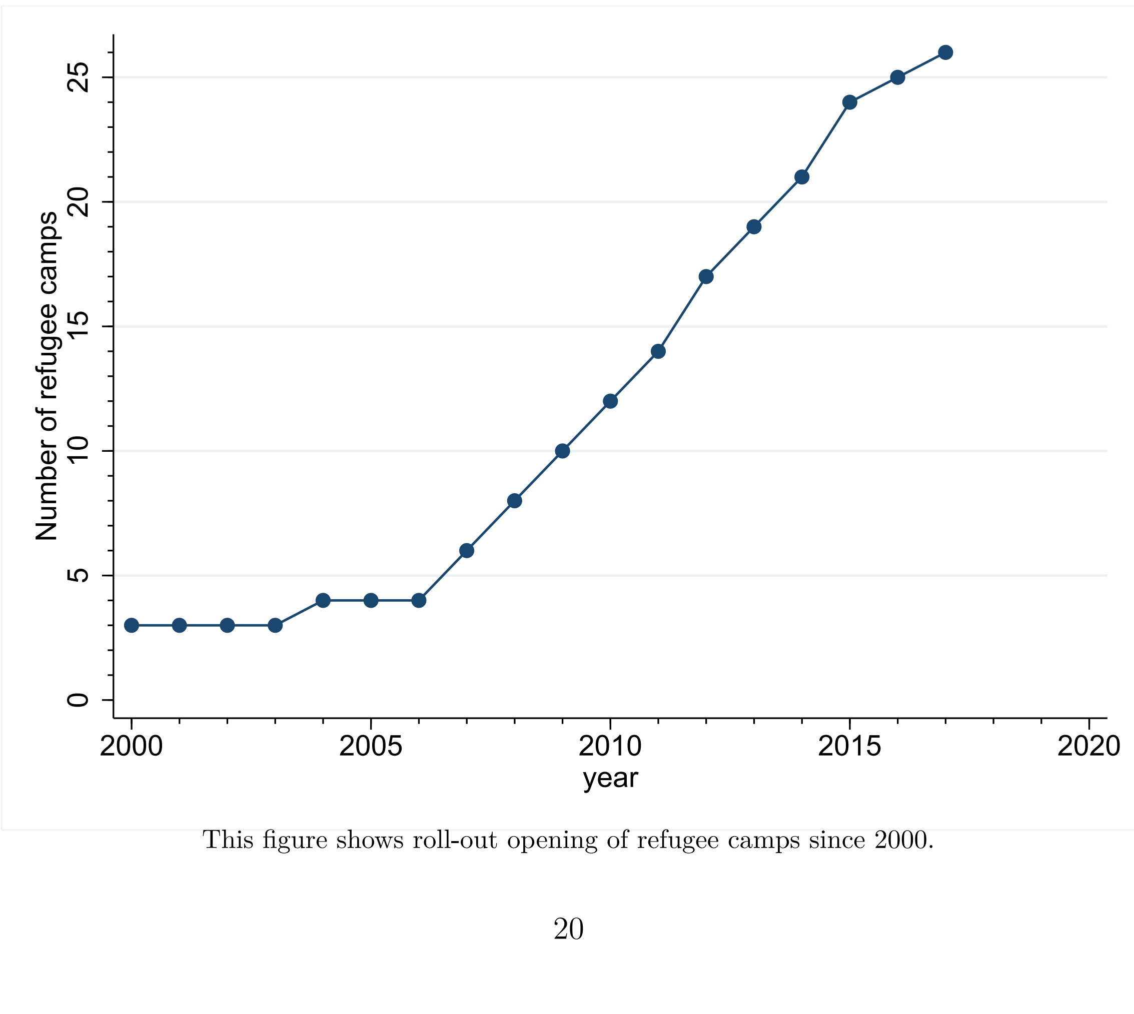
While the results in this paper provide some insights on the consequences of hosting refugees, it is far from being exhaustive or conclusive. In particular, future research should look into the effects of hosting refugees on informal labor (wages and employment), agricultural productivity and other economic outcomes. Refugees present large local market for services and agricultural outputs which might spur productivity in these sectors. They also present local labor market with cheap informal labor, which might affect local wages and productivity.

Figure 1: Trends in refugee population by origin country.



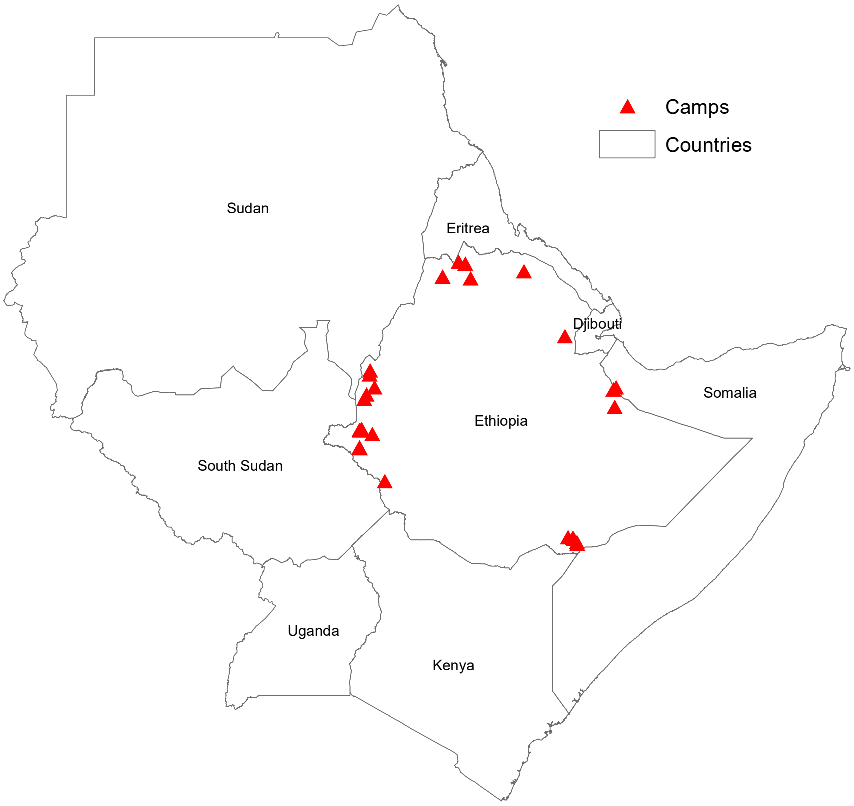
Source: Author calculation based on UNHCR data.

Figure 2: Trends in number of refugee camps.



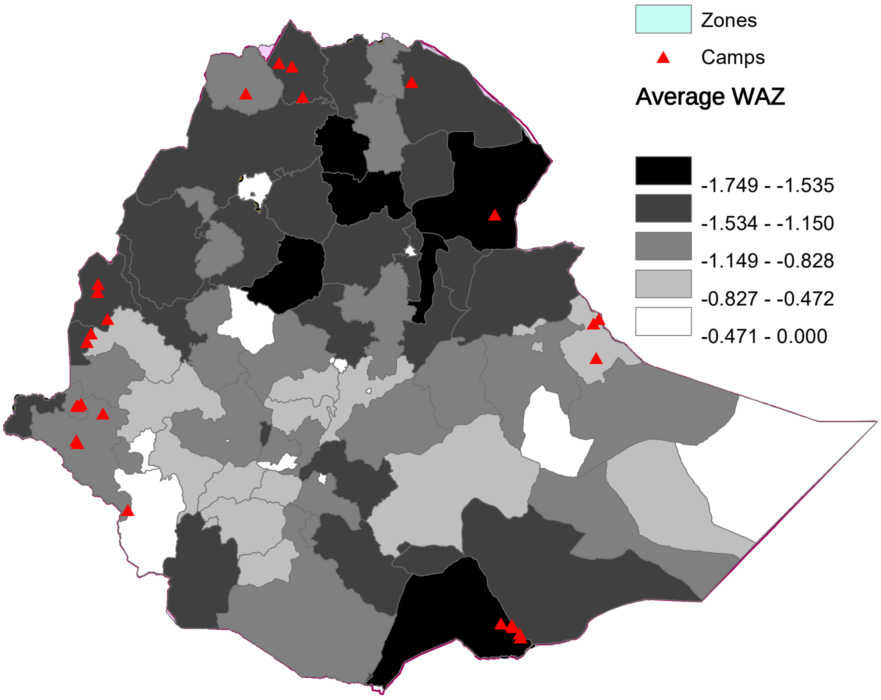
This figure shows roll-out opening of refugee camps since 2000.

Figure 3: Location of Refugee Camps in Ethiopia.



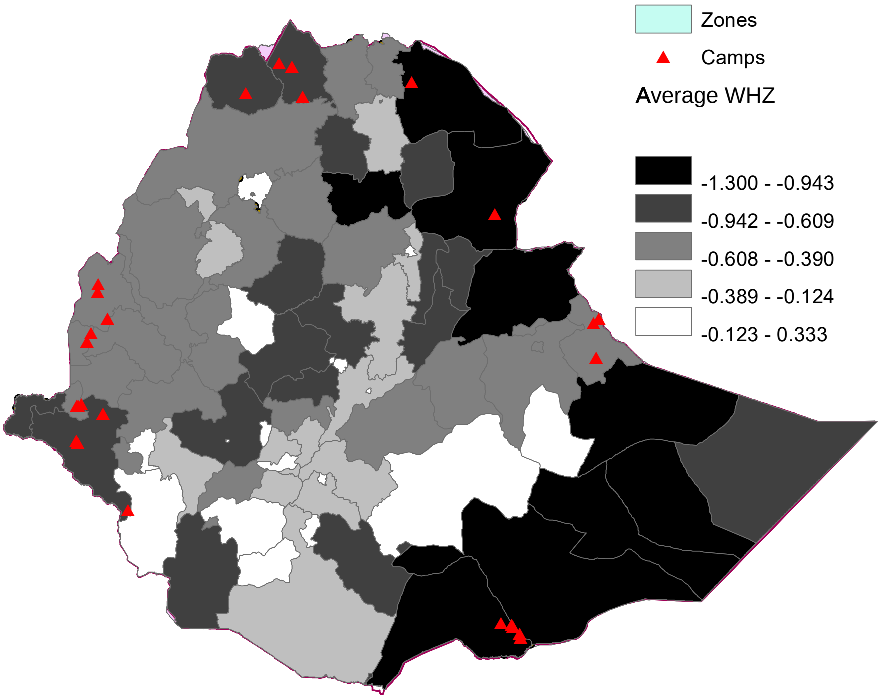
This figure shows location of refugee settlements in Ethiopia.

Figure 4: Average WAZ across DHS2016 sample locations within administrative zones.



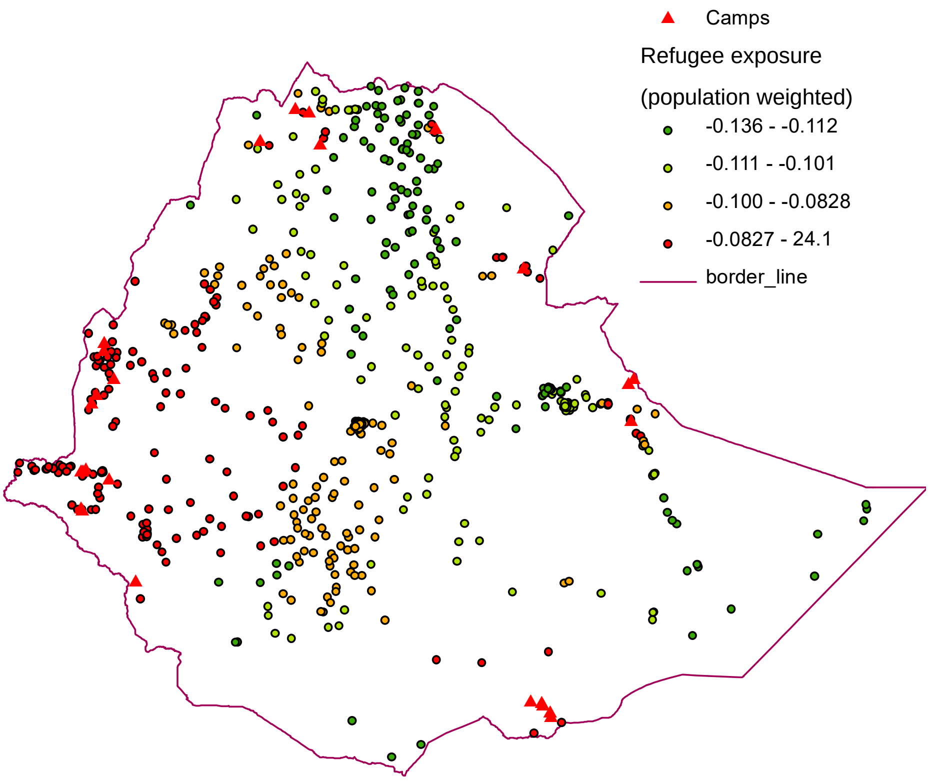
Notes: This figure shows the average WAZ across DHS2016 sample locations within administrative zones. Darker shades represent lower average WAZ.

Figure 5: Average WHZ across DHS2016 sample locations within administrative zones.



Notes: This figure shows the average WHZ across DHS2016 sample locations within administrative zones. Darker shades represent lower average WHZ.

Figure 6: Refugee exposure (population weighted) of DHS2016 sample locations.



Notes: This figure shows refugee exposure across DHS2016 sample locations as measured in 2016. This measure is weighted by camp population size relative to woreda population.The measure is standardized.

Table 1: Descriptive statistics

	DHS round 2016		DHS round 2010	
	Mean	S.d	Mean	S.d
WAZ	-1.097	1.317	-1.351	1.298
WHZ	-0.590	1.284	-0.638	1.235
HAZ	-1.180	1.736	-1.514	1.682
Boys	0.512	0.5	0.514	0.500
Age (months)	29	17.38	29.127	17.432
Rural	0.814	0.389	0.830	0.376
Mother education	0.361	0.665	0.368	0.632
Wealth group	2.729	1.515	2.730	1.503
Piped water	0.23	0.42	0.255	0.436
Household size (de jure)	4.438	2.347	4.53	2.42

Notes: This descriptive statistics excludes observations with biologically implausible WAZ, WHZ, or HAZ values. That is, observations with WAZ, WHZ, and HAZ below -5 or above 5 are dropped. We drop these observations in all our regression analysis as well. Mother education takes the following values: no education=0, primary=1, secondary=2, higher=3. Household wealth index takes the following values: poorest=1, poorer=2, middle=3, richer=4, richest=5. Child age ranges from 0-59 months.

Table 2: The effect of refugee exposure on child health: main results

	(1) WAZ	(2) WHZ	(3) HAZ	(4) Not anemic	(5) Alive
	Panel A: OLS estimation				
Refugee exposure (standardized)	-0.030**	-0.030**	-0.003	-0.002	-0.004
	(0.012)	(0.012)	(0.020)	(0.005)	(0.002)
N	15860	15610	15271	13798	18577
R^2	0.153	0.055	0.188	0.138	0.017
	Panel B: IV estimation				
Refugee exposure (standardized)	-0.044***	-0.041***	-0.015	0.000	0.005
	(0.015)	(0.014)	(0.022)	(0.006)	(0.004)
N	15860	15610	15271	13798	18577
R^2	0.123	0.029	0.161	0.081	0.010

Notes: All regressions include Zone FE, five wealth group dummy, mother's education, succeeding birth interval, age (except the last column), gender and month of interview dummy. SE are clustered at DHS sample locations. SE are clustered at zone level. This table is based on pooled data from DHS round 2016 and DHS round 2010, which includes children born between 2005 and 2016. Refugee exposure is measured at the year of birth of the child. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The effect of refugee exposure on child health: heterogeneous effect by age group (IV estimation)

	(1) WAZ	(2) WHZ	(3) HAZ	(4) Not anemic
	Age $\leq$ 12 months			
Refugee exposure	-0.054**	-0.021	-0.049	0.019*
	(0.023)	(0.036)	(0.042)	(0.010)
N	3457	3297	3286	1740
R^2	0.133	0.058	0.095	0.035
	Age 13-24 months			
Refugee exposure	-0.055***	-0.040**	-0.010	-0.002
	(0.019)	(0.018)	(0.020)	(0.004)
N	2812	2795	2726	2727
R^2	0.060	0.044	0.051	0.042
	Age 25-36 months			
Refugee exposure	-0.037***	-0.077**	0.028	0.005
	(0.012)	(0.032)	(0.045)	(0.007)
N	3080	3050	2935	3001
R^2	0.054	0.014	0.036	0.027
	Age 37-48 months			
Refugee exposure	0.060	-0.020	0.067	-0.001
	(0.051)	(0.032)	(0.043)	(0.015)
N	3374	3356	3261	3282
R^2	0.052	0.038	0.037	0.031
	Age 49-59 months			
Refugee exposure	-0.223	0.007	-0.330	-0.094*
	(0.198)	(0.081)	(0.276)	(0.049)
N	3131	3105	3055	3040
R^2	0.062	0.018	0.055	0.026

Notes: All regressions include Zone FE, five wealth group dummy, mother's education, succeeding birth interval, gender and month of interview dummy. SE are clustered at DHS sample locations. SE are clustered at zone level. This table is based on pooled data from DHS round 2016 and DHS round 2010, which includes children born between 2005 and 2016. Refugee exposure is measured at the year of birth of the child. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Refugee exposure and school enrollment for children between ages 6-19.

	Enrollment				Grade-for-age ratio			
	(1) Age 6-19	(2) Age 6-11	(3) Age 12-14	(4) Age 15-19	(5) Age 6-19	(6) Age 6-11	(7) Age 12-14	(8) Age 15-19
	Panel A: OLS							
Refugee exposure	0.050***	0.064***	0.043***	0.007	0.016***	0.013***	0.019***	0.013**
	(0.014)	(0.017)	(0.015)	(0.011)	(0.004)	(0.004)	(0.006)	(0.006)
N	54730	27949	12782	13999	54667	27934	12764	13969
R^2	0.072	0.216	0.091	0.114	0.203	0.285	0.205	0.210
Mean of dep var	0.63	0.60	0.77	0.58	0.21	0.15	0.28	0.26
	Panel B: IV							
Refugee exposure	0.074***	0.096***	0.065**	-0.007	0.024***	0.017***	0.034**	0.018*
	(0.023)	(0.030)	(0.025)	(0.022)	(0.008)	(0.006)	(0.014)	(0.011)
N	54730	27949	12782	13999	54667	27934	12764	13969
R^2	0.041	0.174	0.045	0.077	0.152	0.235	0.120	0.148
Mean of dep var	0.63	0.60	0.77	0.58	0.21	0.15	0.28	0.26
	Panel C: Gender heterogeneity							
	Boys							
Refugee exposure	0.084***	0.099***	0.077**	0.003	0.026***	0.002	0.034**	0.027**
	(0.027)	(0.032)	(0.035)	(0.024)	(0.009)	(0.003)	(0.016)	(0.013)
N	27183	14238	6685	6260	27149	14232	6677	6240
R^2	0.043	0.173	0.049	0.042	0.164	0.218	0.131	0.127
Mean of dep var	0.65	0.61	0.76	0.64	0.21	0.15	0.28	0.28
	Girls							
Refugee exposure	0.065***	0.095***	0.050**	-0.014	0.022***	0.019***	0.031**	0.011
	(0.021)	(0.031)	(0.022)	(0.028)	(0.008)	(0.007)	(0.014)	(0.015)
N	27547	13711	6097	7739	27518	13702	6087	7729
R^2	0.042	0.178	0.039	0.119	0.145	0.248	0.117	0.169
Mean of dep var	0.62	0.60	0.77	0.54	0.20	0.15	0.28	0.24

Notes: All regressions include five wealth group dummy, rural/urban dummy, household head's education l gender (in specifications that pool both genders) and zone fixed effects. SE are clustered at DHS sampl This table is based on pooled data from DHS rounds 2010 and 2016. * $p < 0.10$, ** $p < 0.05$, *** $p <$ 0

Table 5: The effect of refugee exposure on child health (Robustness exercises)

	(1) WAZ	(2) WHZ	(3) HAZ	(4) Not anemic	(5) Alive
	Panel A: Restricting to hosts ≥20km from border				
Refugee exposure (standardized)	-0.042***	-0.037***	-0.018	-0.001	-0.002
	(0.014)	(0.011)	(0.023)	(0.006)	(0.003)
N	14777	14536	14218	12871	17255
R^2	0.123	0.030	0.161	0.080	0.012
	Panel B: Restricting to hosts who stayed ≥10 years at current location				
Refugee exposure (standardized)	-0.040***	-0.042**	0.005	0.005	-0.000
	(0.012)	(0.017)	(0.026)	(0.005)	(0.002)
N	6436	6332	6219	5588	7492
R^2	0.122	0.033	0.149	0.089	0.013
	Panel C: Cumulative (life-time) exposure				
Refugee exposure (standardized)	-0.032*	-0.037*	-0.004	-0.005	-0.003
	(0.018)	(0.022)	(0.026)	(0.008)	(0.003)
N	15860	15610	15271	13798	18577
R^2	0.123	0.029	0.161	0.081	0.010

Notes: Notes: All regressions include Zone FE, five wealth group dummy, mother's education, succeeding birth interval, age (except the last column), gender and month of interview dummy. SE are clustered at DHS sample locations. This table is based on pooled data from DHS round 2016 and DHS round 2010, which includes children born between 2005 and 2016. Refugee exposure is measured at the year of birth of the child. Panel A addresses cross-border conflict spillover by restricting estimation to DHS sample locations 20KMs away from borders. Panel B addresses selection due to migration of households towards refugee camps by restricting estimation to households with a tenure of at least 10 years at their location during the survey. Results in this panel are based on DHS 2016 round only because information on duration of stay at current location is not available in DHS 2010. In Panel C refugee exposure is measured as cumulative between the child's year of birth to the year of survey. All regressions are based on IV estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Refugee exposure and primary school enrollment for children between ages 6-19 (Robustness exercises)

	Enrollment				Grade-for-age ratio			
	(1) Age 6-19	(2) Age 6-11	(3) Age 12-14	(4) Age 15-19	(5) Age 6-19	(6) Age 6-11	(7) Age 12-14	(8) Age 15-19
	Panel A: Restricting to hosts $\geq$20km from border							
Refugee exposure	0.074***	0.099***	0.061**	-0.009	0.025***	0.018***	0.034**	0.018
	(0.023)	(0.031)	(0.024)	(0.022)	(0.008)	(0.006)	(0.014)	(0.011)
N	51335	25997	11997	13341	51275	25983	11979	13313
R^2	0.042	0.175	0.045	0.077	0.153	0.234	0.120	0.148
	Panel B: Restricting to hosts that stayed $\geq$ 10 years at current location							
Refugee exposure	0.015	0.020	0.022	-0.009	0.006*	0.007*	0.012	-0.006
	(0.012)	(0.016)	(0.016)	(0.019)	(0.004)	(0.004)	(0.010)	(0.009)
N	11346	6115	2678	2552	11332	6113	2673	2545
R^2	0.049	0.168	0.063	0.104	0.165	0.238	0.132	0.150

Notes: All regressions include five wealth group dummy, rural/urban dummy, household head's education level, child gender (in specifications that pool both genders) and zone fixed effects. SE are clustered at DHS sample location. This table is based on pooled data from DHS rounds 2010 and 2016. Panel A addresses selection due to migration of households towards refugee camps. Panel B addresses selection due to migration of households towards refugee camps by restricting estimation to households with a tenure of at least 10 years at their location during the survey. Results in this panel are based on DHS 2016 round only because information on duration of stay at current location is not available in DHS 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Refugee exposure and Illness

	(1) Had Diarrhea	(2) Had Cough	(3) Had Diarrhea treatment	(4) Has Card	(5) Has card/sick
Refugee exposure	0.003***	0.000	0.006***	0.011***	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
N	16820	16811	2185	13403	3717
R^2	0.023	0.008	0.040	0.089	0.076
Mean dep var	0.13	0.18	0.44	0.62	0.64

Notes: All regressions include year and Zone FEs, five wealth group dummy, mother's education, age, gender, succeeding birth interval, and rural/urban dummy. SE are clustered at DHS sample location. This table is based on DHS round 2016 and 2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Refugee exposure and Vaccination rate

	(1) BCG	(2) DPT-1	(3) DPT-2	(4) DPT-3	(5) Polio-0	(6) Polio-1	(7) Polio-2	(8) Polio-3	(9) Measles-1
Refugee exposure	0.005	-0.011**	-0.006	-0.017***	-0.005*	-0.005	-0.010**	-0.009**	-0.007
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)
N	2984	2984	2984	2984	2984	2984	2984	2984	2984
R^2	0.066	0.076	0.098	0.114	0.105	0.036	0.050	0.073	0.068
Vaccination rate	0.700	0.70	0.61	0.49	0.30	0.81	0.72	0.55	0.58

Notes: All regressions include year and Zone FEs , five wealth group dummy, mother's education, age, gender, succeeding birth interval and rural/urban dummy. SE are clustered at zone level because clustering at DHS sample locations would cause too many clusters relative to the sample size. This table is based on DHS round 2016 and 2010. The vaccination records report the vaccination history of children aged 12-24 months. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendices

A Appendix tables

Table A.1: Summary statistics of variables in districts with and without refugee camps

	Districts without camp	Districts with camp	Difference	St Err	p value
Panel A: DHS2010/11					
Enrollment status					
Boys aged 6-11	0.566	0.526	0.039	0.033	0.234
Boys aged 12-14	0.752	0.639	0.113	0.05	0.022
Boys aged 15-19	0.637	0.657	-0.021	0.077	0.789
Girls aged 6-11	0.55	0.513	0.037	0.04	0.352
Girls aged 12-14	0.765	0.531	0.234	0.051	0
Girls aged 15-19	0.547	0.361	0.186	0.059	0.002
WAZ	-1.306	-1.492	0.186	0.08	0.019
WHZ	-0.626	-0.872	0.246	0.079	0.002
HAZ	-1.516	-1.536	0.021	0.108	0.848
Anemic	0.236	0.399	-0.164	0.028	0
Panel B: DHS2016					
Enrollment status					
Boys aged 6-11	0.651	0.651	0	0.021	1
Boys aged 12-14	0.777	0.793	-0.017	0.026	0.542
Boys aged 15-19	0.636	0.711	-0.074	0.033	0.022
Girls aged 6-11	0.642	0.686	-0.044	0.021	0.036
Girls aged 12-14	0.785	0.818	-0.032	0.028	0.255
Girls aged 15-19	0.531	0.531	0	0.03	0.996
WAZ	-1.074	-1.135	0.06	0.049	0.214
WHZ	-0.571	-0.841	0.27	0.049	0
HAZ	-1.196	-0.993	-0.203	0.067	0.003
Anemic	0.354	0.432	-0.078	0.02	0

Notes: This table provides descriptive statistics of key outcome variables based on DHS round 2010 and 2016. The sample is divided into districts with refugee camps and those without camps. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Zero-stage regression (panel): the dependent variable is whether there is a refugee camp in a district

	DHS 2016 round		DHS 2010 round	
	Probit	Marginal Effects	Probit	Marginal Effects
Common Ethnicity*Origin Conflict	0.998***	0.033***	1.165***	0.024***
	(0.155)	(0.006)	(0.258)	(0.006)
Log Distance to Border	-0.289***	-0.009***	-0.298***	-0.006***
	(0.025)	(0.001)	(0.031)	(0.001)
N	4098	4098	4098	4098
pseudo R^2	0.374		0.386	

Notes: Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: First-stage statistics for IV estimation

	Test statistic	P-values
	Weak identification test	
(Kleibergen-Paap rk Wald F statistic)	12.341	
	Weak instrument robust inference	
Anderson-Rubin Wald test	F(1,1188)= 12.27	0.0005
Anderson-Rubin Wald test	Chi-sq(1)= 12.30	0.0005
Stock-Wright LM S statistic	Chi-sq(1)= 16.90	0.0000

Notes: This table reports the first-stage summary results for the IV estimation of the effect of refugee exposure on school enrollment. The first-stage result for other health indicators and education outcome is very similar because the endogenous variable and the control variables similar across the regressions.

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