Vaccines on the Move and the War on Polio*

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Abstract

The rising number of refugees and internally displaced people (IDPs) in developing countries presents new challenges for vaccine distribution and the spread of diseases. How do IDP inflows affect polio incidence in host communities? Can a policy intervention that vaccinates IDP children during their migration mitigate the impacts? To answer these questions, we examine the Pakistani mass displacement from the conflict-affected Federally Administered Tribal Areas in 2008. Using a difference-in-differences approach, we compare new polio cases in districts near and far from the conflict zone before and after 2007. The spatial distribution of districts relative to the historical region of Pashtunistan allows us to design a sample of comparable units. We show that a standard deviation increase in predicted IDP inflow leads to a rise in the new polio cases per 100,000 inhabitants. Poorer vaccination levels among IDP compared to native children are one of the main mechanisms. Implementing a vaccination policy targeting IDP children during their migration journey helps bridge this gap.

Keywords: internal displacement, infectious diseases, vaccines, Pakistan

JEL Classification: D60, I15, O15.

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1 Introduction

The spread of infectious diseases can lock people into poverty and have devastating consequences for a country's human capital accumulation and social cohesion (Correia, Luck, and Verner 2022). Factors such as the increased movement of people and low vaccination rates facilitate the spread (Greenwood 2014). The growing number of refugees and internally displaced people (henceforth refer as IDPs), hence, poses new challenges in the spread of diseases. Refugees and IDPs present significant obstacles to vaccine delivery. Most of these individuals lack access to essential medical care because they live in areas where healthcare systems have collapsed due to conflict and mass migration. Refugees and IDPs also face numerous barriers to immunization services, such as literacy issues, lack of information in local languages, safety concerns, and mistrust of governments (UNHCR 2023). Yet, we know very little about which vaccination policies can effectively reach these hard-to-reach populations.

In this paper, we investigate whether the inflow of IDPs affects the incidence of polio in host communities. We also examine whether a policy that vaccinates IDP children during their migration can make a difference. To address these questions, we study the mass displacement of the population from the conflict-affected Federally Administered Tribal Areas (FATA) to other districts in Pakistan from 2008 onward. Using a difference-in-differences approach, we compare the new polio cases in districts closer and further away from the FATA border before and after the beginning of the IDP crisis in 2008.

We rely on districts closer to the FATA border receiving more IDPs when the total yearly inflows increase. More formally, as data on migration flows are unavailable at the district level, we construct a yearly district measure of predicted IDP inflows. The predicted IDPs measure is based on the interaction of the inverse distance to the FATA's border and the total yearly IDP flows (Rozo and Sviatschi 2021; Rozo and Vargas 2021). Additionally, due to cultural and linguistic barriers, most IDPs settled within the pre-colonial region of Pashtunistan. So, we restrict the sample to Pashtunistan districts. This approach allow us to compare districts with similar economic, political, and cultural characteristics.

We find that an increase of one standard deviation in predicted inflows results in 0.001538 additional polio cases per 100,000 inhabitants, corresponding to a 30% of the mean incidence. Why are the main effects meaningful? Polio has been eliminated in 193 countries. With the transmission of wild-type polio limited to Afghanistan and Pakistan, an official eradication declaration is in sight. In 2005, 28 cases were reported in Pakistan, compared to the 1,147 cases in 1997. Moreover, most host districts had zero or close to zero polio cases before 2008. Ultimately, the estimates we present in this paper capture the impacts of IDP inflows on the extensive rather than the intensive margin in new polio cases.

A lower vaccination rate among IDP children is one of the major underlying mechanisms behind the results. We use individual-level data from the Demographic and Health Survey (DHS) from 1990 to 2017 to generate supporting evidence. First, we show that children living in host districts born after December 2007 are more likely to be vaccinated compared to older children. Crucially for our setting, the opposite is true for IDP children, whose probability of being vaccinated is 17.5% than their native counterparts.

Can a policy intervention vaccinate the hard-to-reach IDP children? To this end, we discuss and evaluate an innovative program implemented in April 2012 in the adjacent districts to FATA. The Permanent Transit Point (PTP) program aims at vaccinating High-Risk Mobile Populations, including IDP children. We exploit a geographic subset of the Pashtunistan region that is close to the Southern FATA border to evaluate the program. We document that the program successfully targets IDP children and increases their probability of being vaccinated by about 12.6%.

We provide supporting evidence for two alternative mechanisms that complement the immunization mechanism. First, the arrival of IDPs in overcrowded households, where polio can quickly spread and undermine the children's health. Second, a sudden increase in the demand for health services causes congestion in the local healthcare system, with just a partial response in the supply.

To support the validity of our results, we show that districts closer and further away from the FATA border possess similar pre-treatment characteristics. Further, a dynamic difference-in-differences specification supports the validity of the parallel trend assumption. We also rule out the existence of confounders' effects deriving from the conflict, such as its direct effects, the arrival of Afghan refugees, international migration outflows, and mistrust towards vaccines. Lastly, we validate our estimates with a series of falsification tests, alternative sample definitions, outcomes, and sets of fixed effects.

This paper adds to the literature on the consequences of forcibly displaced populations in host communities' health outcomes. Much of this agenda has looked at mortality, children's anthropometrics, and utero conditions (Saarela and Finnäs 2009; Lavy, Schlosser, and Shany 2016; Haukka et al. 2017).[1] The literature on the impacts of hosting displaced people on the spread of diseases is still limited (Montalvo and Reynal-Querol 2007; Baez 2011; Ibáñez, Rozo, and Urbina 2021; Ibáñez, Moya, et al. 2023). We differ from previous literature by exploring polio,

[1] See Becker and Ferrara 2019 for an overall review on the forcibly displaced populations literature.

a disease close to being globally eradicated. Our study is also one of the few to examine the impact of hosting IDPs. IDPs do not cross an internationally recognised border, making monitoring their health and vaccination status much harder. As a result, the impact of IDP inflows may differ from refugee inflows. Understanding the role of IDPs in the transmission of infectious diseases is vital for formulating quick and cost-effective interventions in transit zones, and host communities.

The role of vaccines in explaining the increase in polio incidence in host communities relates this paper to the research agenda on the determinants of the transmission of infectious disease. Most of the existing literature has focused on studying the mistrust of vaccines (Martinez-Bravo and Stegmann 2022), the role of trade (Oster 2012), and public transportation closure (Adda 2016). Although there is a wide consensus on the importance of vaccines on the spread of infectious diseases. To the best of our knowledge, no study has documented the effects of a policy designed to vaccinate forcibly displaced children during their migration journey.

The rest of the paper is organized as follows. Section 2 provides background information on the conflict, mass migration, and polio in Pakistan. Sections 3 and 4 present the data and identification strategy. Section 5 presents the main results and robustness checks. Section 6 discusses the mechanisms, including the policy evaluation of the PTP program. Section 7 concludes.

2 Background

2.1 Conflict in FATA Region

Pakistan witnessed a vast surge in violence after the terrorist attack in September 2001 (9/11) in the United States (U.S.). The increase in violence manifested in waves of violent attacks against state institutions and civilians across Pakistan. Terrorists carried out around 1,600 attacks in the pre-9/11 era. However, a significant surge in the number of attacks was observed (around 12,000) in the aftermath of the 9/11 period (GTD 2021). The intensity of such violence was substantial in the Federally Administered Tribal Areas (FATA) when the Tehrik-e-Taliban militants began entering into the region (Malik, Mirza, and Rehman 2023).[2] Figure A1 plots the number of attacks in Pakistan and the FATA region.

FATA was an autonomous tribal region in north-western Pakistan that existed from 1947 until being merged with the neighbouring province of Khyber Pakhtunkhwa in 2018.[3] FATA

[2]The Pakistani Taliban, formally called the Tehreek-e-Taliban-e-Pakistan, is an umbrella organisation of various Islamist armed militant groups operating along the Afghan–Pakistani border (Abbas 2008)

[3]From 2018, the administrative units of Pakistan comprise four provinces, one federal territory, and two disputed

were bordered by: Afghanistan to the north and west, Khyber Pakhtunkhwa to the east, and Balochistan to the south. Figure 1 illustrates the three administrative levels of Pakistan.[4] FATA's population was estimated in 2000 to be about 3,341,080 people or roughly 2% of Pakistan's population. FATA is the most rural administrative unit in the country. FATA was located in Pashtunistan (*land of the Pashtuns* in Pashto), a historical pre-colonial region wherein Pashtun culture, the Pashto language, and Pashtun identity have been based.[5]

The acceleration of violence in the FATA led to a domestic and international military response. After 9/11, Pakistani and U.S. forces carried out military offensives against alleged sanctuaries of terrorist outfits. On June 19, 2004, the U.S. undertook its first drone strike in Pakistan. Since then, the U.S. has carried out more than 406 drone attacks against alleged Al-Qaeda-linked affiliates in Pakistan's North-West. These attacks increased from 2007 and peaked around 2010. 98% of the drone attacks across Pakistan were in the FATA Figure 2 shows the total number of drones from 2001 to 2022 (New-America 2021).

2.2 Forced Displacement within Pakistan

Since 2008, 13,289,880 million people have been displaced driven by the conflict. 98% of the forcibly displaced population migrated within Pakistan (UNHCR 2023). See Figure A2 for a visual representation of the Pakistani forcibly displaced population who migrated inside and outside the country from 2001 to 2022. A concern would be that the decision to migration could be affected by other factors beyond the conflict. In Figure 2, we plot the number of drones and yearly total IDPs from 2001 to 2022. The onset of the IDPs crisis was in 2008, corresponding with a big jump in drone strikes between 2007 and 2008. In 2009, the total IDPs reached more than 1.9 million individuals, corresponding to 57% of the FATA's population (UNHCR 2023).[6]

The IDPs came from different FATA districts, but especially from the most affected by the

territories: Punjab, Sindh, Khyber Pakhtunkhwa, and Balochistan; the Islamabad Capital Territory; and the administrative territories of Azad Jammu and Kashmir and Gilgit–Baltistan.

[4] A province (administrative level 1) has different divisions (administrative level 2), and a division is divided into other districts (administrative level 3).

[5] Pashtunistan is a historical region on the Iranian Plateau, inhabited by the indigenous Pashtun people of southern Afghanistan and north-western Pakistan. During British rule in India in 1893, Mortimer Durand drew the Durand Line, fixing the limits of the spheres of influence between the Emirate of Afghanistan and British India and dividing the historical Pashtunistan as a share of two different countries (Bezhan 2014).

[6] It exists a later peak in newly IDPs in 2014. Figure A1 shows how the number of terrorists attacks in FATA peaked also in 2014.

conflict (North Waziristan and South Waziristan, in southern FATA) (UNHCR 2023). In line with the hypothesis of conflict as the main migration-push factor, Figure 3 shows in panel b) the positive correlation between the number of drones and IDPs from a given district. We present the total number of IDPs by origin in Table A1.

Due to cultural and linguistic similarities, most IDPs migrated to relatively safe districts within the historical region of Pashtunistan. We list the total IDPs in host districts in 2008 in Table A2. Many arrived to host districts as cohesive groups (IDMC 2015). IDPs often struggle to integrate in host communities, and they often rely on social networks from their home areas. In specific locations, IDPs were discriminated against by the native population and political leaders whipping up xenophobia against the displaced (Din 2010; IDMC 2015). Most of the affected population has been displaced multiple times, and very few have returned to their places of origin.

IDPs usually reside in informal settlements within host communities. They avoid living in camps for multiple reasons, including the fear of attack by non-state armed groups, poor conditions and lack of private space. Usually, the informal settlements lack safe drinking water, sanitation, and health care (IDMC 2015).

2.3 Polio

Polio or Poliomyelitis is a highly infectious viral disease. The virus is transmitted by person-to-person contact. The virus can live in an infected person's intestines or throat for many weeks. It spreads through contact with an infected person's stool (poop) or, less frequently, droplets from a sneeze. An infected person may spread the virus to others immediately before and up to two weeks after developing symptoms. Infected children can contaminate food and water when they touch them with unwashed hands (CDC 2021).

There is no cure for polio, and it can only be prevented. Two polio vaccines are available: oral polio (OPV) and inactivated polio (IPV).[7] Children should usually get four doses of the polio vaccine at ages two months, four months, 6–18 months, and 4–6 years.

Although anyone not fully vaccinated against polio is at risk for polio, polio predominantly affects children under five. Most people who get infected with polio will not have any visible symptoms. About 1 out of 4 people with polio infection will have flu-like symptoms (fever, fatigue,

[7]OPV is administered orally and can be given by volunteers. OPV protects both the individual and the community because it induces gut immunity, which is essential to stopping poliovirus transmission. IPV is given by injection and needs to be administered by a trained health worker. IPV is highly effective in protecting individuals from severe diseases caused by poliovirus. However, it cannot stop the virus's spread in a community.

headache, vomiting, stiffness of the neck and pain in the limbs). These symptoms usually last 2 to 5 days. One in 200 infections leads to irreversible paralysis (usually in the legs). Among those paralysed, 5–10% die when their breathing muscles become immobilised (WHO 2022).

Cases of polio have fallen dramatically over time. In 1988, more than 350,000 polio cases were reported annually across 125 countries. In 2021, the number of cases was down to 649. The main reason was the increased number of children vaccinated. Globally in 1980, only 22% of one-year-olds were vaccinated against polio, which increased to coverage of 86% of the world's one-year-olds in 2015.[8] In 2001, 14 countries reported cases of wild polio. By 2021 there were only two countries where wild poliovirus cases were recorded: Afghanistan and Pakistan (WHO 2022).

Polio in Pakistan. Since 1994, the Pakistan Polio Eradication Programme (PPEP) has been fighting to end the crippling poliovirus in the country. In 1997, Pakistan reported 1,147 cases, constituting 22% of the cases reported worldwide. Pakistan reduced cases from 20,000 in 1990 to 28 in 2005. However, about 100 cases have been reported annually after 2007. Cases steadily rose from 32 in 2007 to 118 in 2008 to 198 in 2011 (WHO 2022).

The surge in violence in FATA could be one of the leading reasons of the increase in polio cases in Pakistan. Almost 70% of Pakistan's polio cases from 2004 to 2018 were reported in FATA. poor sanitary conditions with large families living in packed houses resulted in widespread polio transmission. Moreover, the militants carried out continuous propaganda against polio vaccination, translating into increased vaccine refusal. As the extremists banned polio vaccination, almost 400,000 children could not be vaccinated in the tribal north during 2010–2011. Even vaccination workers began to be attacked and killed (Mushtaq et al. 2015).

Immunization in Pakistan. Children receive three main vaccines through routine immunisation activities: the poliomyelitis, the DPT (against diphtheria, pertussis, and tetanus), and the measles vaccines. Pakistan follows the recommended vaccination calendar of the World Health Organization, and the first dose of most vaccines is distributed shortly after birth.

As part of the PPEP, Lady Health Workers are responsible for child immunisation. These workers are assigned to a local health facility, each responsible for approximately 1,000 people or 150 homes. In 2014, there were approximately 110,000 Lady Health Workers in Pakistan. They regularly visit households to provide family planning information and immunise children. However, vaccination drives is still the main vaccination strategy through which Pakistani children

[8]In 1988, the World Health Assembly created the Global Polio Eradication Initiative to eradicate polio by 2000.

get immunised. There are national and subnational immunisation days during which vaccinators (typically lady health workers joined by other volunteers) provide vaccines at households' doorstep. They typically last for three days and target all children up to age 5. Since 2010, the provision of public health goods is a provincial responsibility. All the vaccines provided during immunisation drives or at public health facilities are free of charge (Martinez-Bravo and Stegmann 2022).

***Permanent Transit Vaccination* program.** To minimize the risk of spread and provide additional vaccination opportunities, Pakistan launched the *Permanent Transit Vaccination* program in April 2012. The program targets the High-Risk Mobile Populations (e.g., nomads, IDPs, or refugees). The Polio Global Eradication Initiative designed the program. It has been only implemented in Nigeria and Pakistan.

The *Permanent Transit Vaccination* program sets up permanent local vaccination teams to reach the hard-to-reach population. The teams are deployed across all major population transit points. For instance, Permanent Transit Points (henceforth refer as PTPs) are located throughout the routes used by the population coming from or going to the conflict-affected region of FATA. The PTPs' location includes major roads, bridges, ferry crossing points, motorway rest stops, bus stops, Country/Province/District borders, main bus-train stations, major health facilities, religious shrines and other places of the congregation having the possibility of a large number of people gathering. There are around 500 PTPs nationwide.

Permanent Transit teams have at least two members who screen, vaccinate, and record the children vaccinated at the site. There are more than one team in places with high traffic load. Team members belong to the community, are adult males, familiar with the area and transit site, and respect the local customs. Each team is trained, and provide with vaccines, cold chain and logistics. In 2018, 1.7 million children have been vaccinated at PTPs (UNICEF 2019).

3 Data

We construct a panel dataset at the district-month level that combines data on conflict, the total forcibly displaced population, polio cases, and the supply-demand for vaccines.

3.1 Conflict data

We use two geo-referenced variables to measure conflict intensity in Pakistan—the number of drone strikes and terrorist attacks at district and monthly levels.

The conflict data on drone strikes comes from the World of Drones Database developed by New America (New-America 2021). New America gathers information on each drone strike's timing (day, month, year), location (latitude and longitude) and total deaths. The World of Drones database draws upon media reports and other open-source information to track which countries and non-state actors have armed drones or are developing them; and which actors have used them in combat and where.

The New America Database has reported 406 drone strikes in Pakistan from January 1, 2001, to December 31, 2022. The first drone was recorded on June 19, 2004, and the last on July 4, 2018. Only 10 of the 406 drones were located outside FATA. Figure A3 presents in panel a) the spatial distribution of drone strikes in Pakistan. We construct our primary measure of conflict by aggregating the drones that fall in a district monthly. Figure A4 presents the spatial distribution of total deaths by drone strikes in Pakistan.

The data on attacks against the state and civilians are extracted from the Global Terrorism Database - GTD (GTD 2021). The GTD provides details on more than 200,000 terrorist incidents worldwide since 1970. For each incident, information is provided on the timing (day, month, and year), location (latitude and longitude), fatalities (wounded and killed), type (assassination, explosion, suicide, hijacking, etc.), target (civilians, businesses, government officials, religious institutions, NGOs, etc.), the terrorist group which carried out the attack, and the motivation of the episode (political or religious).

The GTD reported 13,638 terrorist attacks from January 1, 2001, to December 31, 2020 in Pakistan. We construct a measure of terrorist attacks at the district-month level by aggregating the number of incidents that fall in a district.

3.2 Forced displacement data

United Nations High Commissioner for Refugees - UNHCR provides the data on forcibly displaced populations (UNHCR 2023). UNHCR 2023 contains information about the countries and provinces of destination and origin, total population, year of arrival, and demographic characteristics (age and gender). Therefore, this data allows us to quantify the yearly IDPs, Pakistani refugees outside Pakistan, and Afghan refugees in Pakistan. Figure A2 shows how a large share of the forcibly displaced population remained within Pakistan, refereed as IDPs.

Among the IDPs who fled from FATA, 54% of them are below 18 and 18% below 5. Figure A5 plots the total IDP distribution by age. Moreover, 47% of the IDPs were women or girls. The destination districts were concentrated in Khyber Pakhtunkhwa, as shown in Figure A6. UNHCR provides also data at the district level for 2008, the beginning of the IDP crisis (see Table A2 for the distribution across districts).

3.3 Polio data

We collect data on polio incidence in Pakistan from January 1, 2001, to December 31, 2022. The data comes from the Polio Eradication Program established by the World Health Organization (WHO). The Polio Eradication Program gathers information on the timing (year, month and year), location (district), and the type of virus of each polio case. We build our outcome measure on polio incidence by aggregating the number of new polio cases in a given district and month.

The Polio Eradication Program reported 2,080 new polio cases from 2001 to 2022 in Pakistan. As we can see in Figure A7, the cases in the entire country and FATA have followed a similar pattern. There are three critical years where the trend switched to positive: 2008, 2012 and 2018.

3.4 Vaccination supply and demand

For this project, we also collect data on Pakistan's polio vaccination campaigns between 2001 and 2022. We obtain this data from the Polio Eradication Program. These data contain district-month measures of whether a polio vaccination campaign was conducted, the type of campaign—case response, mop-ups, child health days, sub-national or national immunization days—, the age group targeted, and vaccine type.[9]

We obtain measures of polio immunization at the individual level from two the Pakistani Demographic Health Surveys (DHS). We use information on the demand for the polio vaccine from the 2012/13 and 2017/18 DHS surveys. We profit from the 2006/07 and 1990/91 DHS surveys to look at the the pre-treatment characteristics.

[9]Mop-ups are polio campaigns targeting areas where a large immunity gap persists. Mop-ups hold between larger-scale national Immunization Days or sub-national Immunization Days. Child Health Days are not specifically polio campaigns, but the polio vaccine is added to Child Health Days alongside other vaccines and health interventions. National Immunization Days are nationwide campaigns targeting all children aged 0-5. Sub-national Immunization Days are vaccination campaigns in key high-risk provinces.

3.5 Other data

The DHS asks each household member whether the individual was born in the current district of residence and the reason for the migration. We exploit this migration data to build a variable on whether an individual is IDP or native.

The DHS also gathers information on household (e.g., geo-referenced household location, sanitation, overcrowding, house conditions, and health provision) and individual levels (e.g., date of birth, health-seeking behaviour, labour, and education) characteristics.

For our empirical strategy, we obtain geo-referenced information on the historical pre-colonial region of Pashtunistan. The datasource is the Georeferencing Ethnic Power Relations - GeoEPR 2021 dataset (Vogt et al. 2015). GeoEPR geo-codes politically relevant ethnic groups from the Ethnic Power Relations-Core 2021 dataset.

We use a bunch of district-level covariates to test the validity of our identification strategy. The National Oceanic and Atmospheric Administration (NOAA) processes night light density data. We construct a variable on satellite night light density as a proxy of economic development.[10] We also use socio-demographic data from the 1998, 1981, and 1973 Population Census.[11]

4 Identification Strategy

This paper aims to study the impacts of internally displaced population (IDPs) inflow on the incidence of polio in host districts. For this purpose, we employ a difference-in-difference methodology comparing districts closer and further away from FATA, before and after the beginning of the IDP crises in 2008.

4.1 Sample: Pashtunistan historical region

The decision of where to migrate is a potential endogenous decision (Foged and Peri 2016; Morales 2018; Cengiz and Tekgüç 2022). Additionally, time-varying characteristics in host districts could affect the incidence of polio.[12] For example, if IDPs were to migrate to poor areas closer to

[10]NOAA uses satellite images collected by the U.S. Air Force Defense Meteorological Satellite Program.

[11]The 1998 Census sample covers a share of Khyber Pakhtunkhwa (23 out of the 31 districts) and Punjab (24 out of the 38 districts). The 1973 Census sample covers all Balochistan (28 districts) and Punjab (38 districts), a shared of Khyber Pakhtunkhwa (18 out of the 31 districts) and Sind (26 out of the 27 districts). The 1981 Census has information for 76 out of the 141 districts in Pakistan.

[12]See Verme and Schuettler 2021 for a review focused on IDP.

their original communities, and we compare poorer and richer districts, we would overestimate the effects. To overcome this challenge, we restrict our sample to a set of districts with similar economic, political, and cultural characteristics. To do so, we exploit the location of districts with respect to the Pashtunistan historical border.

Pashtunistan is a pre-colonial region covering a share of Afghanistan and Pakistan, including FATA (see section 1.1 for more details). Due to cultural and linguistic similarities, most of the IDP families from FATA migrated to other districts within Pashtunistan.[13] Even if Pashtunistan is split into different administrative units, Pashtun tribes tend to ignore the borders. For instance, many Pashtun tribes from the FATA area and the adjacent regions of Afghanistan used to cross back and forth with relative ease. After 2004, this cross-border movement is checked via the military and has become much less common compared to the past.

To identify the effects, we restrict our main sample to the districts which territory falls entirely or partially into Pashtunistan. Figure 1 shows the main sample. The central identifying assumption is that the IDP population mostly moved to Pashtu districts, and non-Pashtu districts had no or negligible presence of IDPs. Although FATA is part of Pashtunistan, we drop it from the sample to avoid potential confounding effects from the conflict.[14]

4.2 Main specification

We estimate the following specification in a panel dataset at Pashtunistan district-month level.

$$Y_{d,tm} = \beta_0 + \beta_1 IDPCrisis_t * PredictedInflow_{d,t} + \beta_2 X_{d,t} + \gamma_d + \delta_{tm} + \epsilon_{d,tm} \quad (1)$$

where d stands for district, t for year and m for month. $Y_{d,tm}$ represents the district outcome: the number of new polio cases per 100,000 inhabitants in the year and month tm. We use the population in 2017 to calculate the number of cases per 100,000 inhabitants.[15] $IDPCrisis_t$ is a dummy variable that takes the value of one after 2007. $X_{d,t}$ is a matrix of district-year controls. Namely, we control for district-level nightlight intensity as a proxy of economic development (Pérez-Sindín, Chen, and Prishchepov 2021) and the total number of polio vaccination campaigns in a given district month, which account for the vaccination supply. γ_d and δ_{tm} account for district

[13] The main language spoken in the delineated Pashtunistan region is Pashto. The Pashtuns practice Pashtunwali, the indigenous culture of the Pashtuns.

[14] We use an alternative sample definition in the robustness section.

[15] Azad Jammu and Kashmir and Gilgit-Baltistan provinces are not in the 2017 Population census. So, Kargil, Kupwara, Muzaffarabad and Neelum districts drop from the sample.

and year-month fixed effects. The year-month fixed effect accounts for seasonal shocks standard across all districts in Pakistan. District fixed effect controls for time-invariant characteristics within a district. Standard errors are clustered at the district level.

Based on empirical evidence, we rely on districts closer to the FATA border receiving more IDPs when the total yearly inflows of IDPs increase (Calderon-Mejia and Ibañez 2016).[16] Table A2 shows how most of the IDPs displaced in 2008 stayed in the surrounded districts. Figure A5 presents descriptive evidence on how this pattern also persisted after 2008. Data on the IDP inflow at the district-year level is not available. Therefore, we approximate district-year inflows of the IDP population using a predicted inflow measure:

$$PredictedInflow_{d,t} = IDPinflow_t * \frac{1}{DistFATA_d}$$

where $IDPinflow_t$ stands for the total IDPs registered in Pakistan in each year t. $\frac{1}{DistFATA_d}$ is the inverse Euclidean distance of each centroid district to the closest FATA border.[17] We standardized $PredictedInflow_{d,t}$ to ease the interpretation of our results. This is an accepted procedure in the related literature (Rozo and Sviatschi 2021; Rozo and Vargas 2021). The interaction $IDPCrisis_t * PredictedInflow_{d,t}$ implies that we formally estimate a 2x2 continuous difference-in-differences (DID). Hence, we compare the new polio cases in districts closer and further away from FATA's border, before and after the IDP crises in 2008.

5 Results

We show the main results in Table 1. Column (1) shows that an increase of one standard deviation in predicted inflows leads to 0.001541 additional polio cases per 100,000 inhabitants. Column (1) presents the estimates without fixed effects and controls. The magnitude of the effects does not substantially change when adding district and year-month fixed effects (column (2)). Column (3) shows that the results hold when controlling for nightlight intensity and total vaccination campaigns. We could be concerned that the difference in sanitation and overcrowding characteristics between closer and further districts could drive our results. In column (4), we also control for the average number of children under five, the average number of members in a household, and the total share of the literate population in a district before 2008. The data comes from the 1973,

[16](Calderon-Mejia and Ibañez 2016) instruments the IDPs inflow with the aggregate number of massacres in city c at time t, weighted by the inverse of the distance to city c.

[17]The results hold when I use distance to the border of each municipality.

1981 and 1998 Population Census at the division-level.[18] An increase of one standard deviation in predicted inflows leads to 0.00154 additional polio cases per 100,000 inhabitants. The average number of new polio cases in our sample from 2001 to 2022 equals 0.005. Therefore, the effects correspond to a 31% the mean incidence. In column (5), we control for contemporary characteristics in instead (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). The last set of covariates are at division-level and come from the 2017 Population Census. The coefficient remains statistically significant, with a slightly higher magnitude.

Why are the main effects meaningful? During the last decades, eradicating polio has been a worldwide effort. Polio has been eliminated in 193 countries, with the transmission of wild-type polio limited to Afghanistan and Pakistan. But, until polio is not worldwide eradicated, all countries remain at risk of imported wild polio. Identifying the determinants of new cases is critical to prevent additional ones. In 2005, 28 cases were reported in Pakistan, compared to the 1,147 cases in 1997. Moreover, most host districts had zero or close to zero polio cases before 2007. Ultimately, the estimates we present in this paper capture how unexpected events, such as wars, can disrupt the eradication efforts of a disease in a region or a country. We show this to take place via IDPs. Moreover, despite finding estimates with a magnitude quite substantial, a quite high risk of underreporting is present, as 75% of people infected with poliovirus are asymptomatic (WHO 2022). Ideally, we would look at the incidence of other diseases -measles, chickenpox, or malaria- to validate our findings. To bring credibility to main findings we should observe an increase in the incidence of those diseases. Unfortunately, data limitations prevent this important analysis, as we could not find comparable data for other diseases.[19]

5.1 Identification threats

Unbalanced pre-treatment characteristics. Table A3 presents summary statistics of key demographics and socioeconomic variables that compare districts with high IDP intensity (closer districts) and districts without or with negligible IDP population (further districts).[20] Closer districts are defined as those whose territory falls entirely in Pashtunistan. Further districts are

[18]None of the censuses covers the entire sample. So, we pull them together to increase the sample size. This approach implies that the covariates are measured at different points in time.

[19]The data available for the other diseases were insufficient to grant a meaningful regression analysis or were not available before 2008.

[20]It is worth mentioning that we still restrict the sample to Pashtunistan districts.

those with only a share within Pashtunistan. The balancing test in Table A3 does not reveal significant pre-shock differences.[21]

Pre-trends outcomes. The key identifying assumption on the validity of the main results is that treated and control units should evolve similarly regarding the outcome of interest, absent the treatment. To overcome the fact that formally our treatment variable is continuous, we still identify treatment exposure comparing districts with high IDP intensity (referred as closer districts), and districts without or with negligible IDP population (referred as further districts). Qualitatively, **??** plots the new polio cases from 2001 to 2022 in closer and furhter districts, suggesting that consistent differences in the pre-treatment period should be minimal. More rigorously, we estimate the following event-study specification,

$$Y_{d,t} = \beta_0 + \sum_{p=-5}^{8} \alpha_p IDPCrisis_{t+p} + \gamma_d + \delta_{tm} + \epsilon_{d,t} \tag{2}$$

where $\sum_{p=-5}^{8} \alpha_p IDPCrisis_{t+p}$ identifies year dummies relative to the start of the IDP crisis (2008) for closer districts. We investigate back to $p = -5$ and up to $p = +8$ years. The omitted year is 2007. Figure A11 reports the results of this exercise, and it is possible to see that in the pre-treatment period, closer and further districts do not exhibit statistical differences.

Conflict effect. Conflict can affect the health outcomes of children at an early age (Bundervoet, Verwimp, and Akresh 2009). The conflict is primarily concentrated in FATA, which is not in our baseline sample. Still, we want to purge our estimates of the direct effect of conflict on the incidence of polio cases. In Table A4, we report estimates when we control for, respectively, the number of terrorist attacks and the number of drone attacks. 43% of the districts of our sample experienced at least a terrorist attack during our period of analysis. And, 10 drones hit the host districts. Remarkably, when we control for either of the two, the results remain in line with those of Table Table 1.

Afghan refugees. Since the late 1970s, Pakistan has been a host country for millions of refugees and some 1.35 million still reside in the country. (UNHCR 2023). Figure A12 shows the evolution of total Afghan refugees in Pakistan from 2001 to 2022. Most refugees are in the Pashtun-dominated areas of Pakistan. This fact is a major problem for our identification, as their presence can bias

[21] The characteristics are time-invariant, taken in 1998 from teh Population Census.

our estimates. To upfront this empirical limitation, we conduct two different exercises in Table A5. First, we show that the results of Table 1 hold when we control for the total district-year Afghan refugees (panel A). As a second exercise, we also show evidence that the estimates do not change when we control for the number of refugee camps in a district.[22]

Migration outflows. Although very few Pakistanis migrated internationally, a big jump in the number of Pakistani refugees before and after 2007 could affect our results. Figure A2 helps to remove this concern. The number of Pakistani refugees has been relatively constant from 2000 to 2011, with an increase from 2012. However, the results remain unchanged when we restrict the time horizon of our analysis until 2011 (see Table A6).

Polio vaccine mistrust. After the conflict in FATA, the resistance to foreign interventions has considerably increased across the country. Additionally, the misinformation and vaccines mistrust have also been a barrier to stopping polio eradication in Pakistan. Misconceptions on vaccines' efficacy has been spread across local communities. As documented by Martinez-Bravo and Stegmann 2022, the disclosure of information on July 11th of 2011 describing a fake vaccination roll-out delivered by the Central Intelligence Agency (CIA) accentuated the mistrust on vaccines.[23] As a result, the Taliban initiated an anti-vaccine campaign aimed at discrediting vaccines and vaccination workers. This event is potentially problematic for us, as they may introduce potential bias to our estimates. Following Martinez-Bravo and Stegmann 2022, we retrieve the votes share of the Islamist coalition at the 2008 general elections. We use it as a proxy of ideological affinity to the Taliban.[24] We include this data in our estimating equations interacted with year fixed effects. Table A7 shows that accounting for the political support for Taliban our estimates unchanged.

[22] Only 3 out of the 296 camps had IDPs as the targeted population, implying that the refugees camps mainly were for foreign refugees, rather than IDPS.

[23] The CIA wanted to find out if Bin Laden was hiding in Abbottabad, Pakistan. To this end, the CIA organised a fake vaccination ruse. The objective was to obtain DNA samples of children living in the compound and compare them to the DNA of Bin Laden's sister, who had died in Boston in 2010. On July 11th of 2011, the British newspaper *The Guardian* published an article describing the vaccine ruse (Martinez-Bravo and Stegmann 2022)

[24] Districts with higher support for Islamist groups are likely to be more exposed to the antivaccine propaganda campaign, and grant more credibility to their anti-vaccine messages (Martinez-Bravo and Stegmann 2022).

5.2 Additional robustness tests

We present evidence of the validity of our results in three ways. First, three falsification tests rule out anticipatory effects, and the reverse causality, and validate the baseline sample. Second, we validate the treatment definition using alternative definitions. Third, we show that the results hold using additional sets of fixed effects.

Falsification Tests. In this project, we look at the impacts of hosting conflict-induced IDPs on polio incidence in host communities. A possible concern is that the effects of Table 1 could be driven by anticipatory effects of conflict. To address this concern, we should observe no effect on host districts before the treatment takes place. We use the one year lag prior the onset of the IDP crisis (2008) as a falsification test.[25] Table A8 shows that there is no effect on the number of polio cases before 2008.

The peculiarity of this paper's setting is that most IDPs moved to districts within historical Pashtunistan for socio-cultural reasons. If large IDP inflows are behind the main effects, we should not observe an effect when comparing districts without or with negligible IDP population (further districts) (light-red polygons in Figure A10) to other non-Pashtu districts (white polygons in Figure A10). The results of panel B of Table A9 align with this assumption.

Finally, it could be a concern that IDP families chose their host community based on previous or existing polio case numbers. Hence, a potential reverse causality could threaten our identification. Table A10 rules out this hypothesis using the aggregate district polio cases from 2001 to 2007.

Sample definition. The definition of sample relies on the historical border of Pashtunistan. As explained in subsection 4.1, the estimating sample includes the districts whose territory, either totally (closer districts) or partially (further districts), falls within Pashtunistan. As an alternative sample specification, we include the adjacent districts to the "further districts". They correspond to the most-light-red polygons in Figure A13. In Table A11 we show that, although the magnitude of the effects slightly decreases, the coefficients are remarkably in line with the main results.

Alternative outcomes. We investigate the sensitivity of our results to the use of two different outcomes. These are: the probability of observing in a district d at time tm a new polio case; the number of polio cases per 100,000 inhabitants in 1998, rather than in 2017. Table A12 shows

[25] The results do not change when using either six months or one year and a half before 2008.

that, despite with lower significance, the estimates of the two different outcomes are in line with our preferred outcome.[26]

Alternative specification with different sets of fixed effects. In our baseline specification (equation 1), we control for a year-month fixed effect and a district fixed effect. Polio cases have changed in the country over time, where the health response is the provincial government's responsibility. We show that our results are robust to alternative specifications. In Table A13 we further include either provincial (panel A), division (panel B) or district (panel C) linear trends to flexibly control for province, division or district evolution not captured by either the district or the year-month fixed effects.[27] Remarkably, the coefficients remain in line with the main results.[28]

6 Mechanisms

The main findings show that the arrival of a large IDP inflow increases polio incidence in host communities. What are the underlying mechanisms behind the increase in new polio cases? We hypothesise that low vaccination rates among IDP children is the main mechanism behind the results. We also study two alternative mechanisms that complement the immunization hypothesis. First, the arrival of IDPs in overcrowded households, where polio can quickly spread. Second, a sudden increase in the demand for health services causes congestion in the local healthcare system, with just a partial response in the supply. We use individual-level data from the DHS from 1990 to 2017 to test the mechanisms. In this section, we provide empirical evidence suggesting that the three proposed mechanisms could have a role in the increase in polio incidence in host districts.

6.1 Lower vaccination rates among IDP children

The conflict in FATA have affected routine immunisation, leading to less than 45% of children living in FATA being vaccinated against polio (Hussain et al. 2016). Moreover, the militants carried out continuous propaganda against polio vaccination, translating into increased vaccine refusal (Mushtaq et al. 2015; Rahim, Ahmad, and Abdul-Ghafar 2022). 70% of Pakistan's polio

[26]It is notable the drop in observation for the number of polio cases per 100,000 inhabitants in 1998 (panel B), that is due to the poor coverage of the 1998 census.

[27]It is worth mentioning that divisions are nested within provinces.

[28]The results are not affected by the inclusion of either province * year or division * year fixed effects, allowing to control non-linearities in the above-discussed evolution. Results are available upon request.

cases from 2004 to 2018 were reported from FATA. As a result, IDP children are more likely to be unvaccinated and, more likely to be infected or get infected in the host district.

Does the arrival of IDPs affect the inmunization in host districts? Are children born after 2007 less likely to be vaccinated? Are IDP children differently affected compared to natives? We address these questions by exploiting within-district cohort variation and estimating the following specification.

$$Y_{i,k,d} = \beta_0 + \beta_1 Cohort_k + \beta_2 X_{i,d} + \alpha_d + \epsilon_{i,d} \tag{3}$$

where $Y_{i,k,d}$ is equal to one if child i from the cohort k living in district d received at least one dose of the polio vaccine, zero otherwise.[29] The timing of the treatment is given by the year and month of birth: $Cohort_k$. $Cohort_k$ is one if child i was born after December 2007. We control for covariates $X_{i,d}$ at the district and individual levels. District-level covariates include nightlight intensity and the number of polio activities in the year of the interview. We include the work status of the head of household, urban location, and gender of the child as individual-level covariates. Additionally, we include district α_d fixed effect, which accounts for districts' changes in immunisation supply or social patterns. Standard errors are clustered at the district level.

We find that children in host communities born after the arrival of the IDP population are more likely to be vaccinated than those born before. Panel A of Table 2 shows the results. The IDP inflow seems to increase the probability of immunisation in the host districts roughly by 5.7 percentage points (pp) in Column (2), with the estimates being statistically significant at the one per cent level. The magnitude of the effects does not change with covariates. Column (3) shows that the point estimates increase to 6.7 pp when controlling for nightlight intensity and the total vaccination campaigns in a year (significant at the one per cent level). We could be concerned that the employment or socio-demographic characteristics could drive our results. In column (4), we control for the head of household's work status, urban location, and gender of the child. The results hold. The results also hold when we simultaneously control for the covariates of columns (3) and (4) (see column (5)). These findings suggest that the immunisation rates did not decrease after the arrival of IDP inflows, they actually increased. However, Panel B unveils a crucial heterogeneity between IDP and native children. IDP children are 17.5% less likely to be vaccinated compared to native ones, with the coefficients being stable across columns. This heterogeneity confirms our hypothesis outlined above.

[29] $Y_{i,k,d}$ is equal to one if the parents' child can show vaccination documents proving the vaccination date. The results also hold relaxing the definition (i.e., at least one dose of polio without vaccination documents).

Overall, the gap in immunisation against polio between IDPs and native children could be one of the channels explaining why an IDP inflow leads to new polio cases in host districts. Although there is an important vaccination gap between IDPs and native children in host districts, the nationwide immunisation rates are pretty low. In overpopulated communities, low immunisation rates can facilitate the spread of polio.

***Permanent Transit Point* program evaluation.** The previously discussed results show the importance of vaccinating hard-to-reach children. How a policy intervention can vaccinate IDP children before they arrive to host communities? As presented in the subsection 2.3, Pakistan is one of two countries implementing a Permanent Transit Point (PTP) program. The PTP program was implemented in April 2012 and aims at targeting high-risk mobile population such as IDP children. As part of this project, we evaluate the program.

Despite not having access to the whole country, we digitise **??** and retrieve the number of PTPs at the district level for a subset of the Pashtunistan historical region.[30] The fact that we focus on a subset of the Pashtu territory is a limit of this analysis. However, we argue that this area is the most salient in terms of IDP inflows, as argued in section 2. Then, we estimate the following estimating equation,

$$Y_{i,k,d} = \beta_0 + \beta_1 Cohort_k + \beta_2 N\,PTP_d + \beta_3 Cohort_k * N\,PTP_d + \beta_4 X_{i,d} + \alpha_d + \epsilon_{i,d}, \tag{4}$$

where $Y_{i,k,d}$ is still equal to one if child i from the cohort k living in district d received at least one dose of the polio vaccine, zero otherwise. $Cohort_k$ is equal to one if a child i was born after December 2007, that is after the onset of the IDP crisis. $N\,PTP_d$ is the number of PTPs in district d. In line with the previous evidence on children's vaccination, we further augment these interactions by including IDP_i that captures whether a child i is IDP or not. $X_{i,d}$ is still a vector of child i and district d controls. We conclude by including district fixed effects.

Table 3 shows the results on the policy evaluation. In Panel A, we replicate Panel B of Table 2 to show that, despite the different samples, we still find similar pattern. Although the interaction between the exposed cohort and the IDP variable is statistically insignificant, the signs of the coefficients are consistent across the two tables. The cohort of children exposed to the treatment are more likely to be vaccinated, while this is not the case for IDP children. It is worth mentioning that, while the un-interacted cohort coefficients show similar magnitude between the two tables,

[30]We still exclude FATA from the estimating sample.

the ones related to the interaction between the cohort and the IDP variable show quite a sizeable difference, with the ones from Table 3 being substantially smaller.

In Panel B of Table 3, we formally carry out the evaluation of the program. The triple interaction between the exposed cohort, the number of PTPs and the IDP variable yields coefficients that are positive, and remarkably stable across columns. The estimates are statistically significant at the 1% level. An additional PTP increases the likelihood of an exposed IDP child being vaccinated by 12.6% (column 2). Moreover, the fact that the interaction between exposed children and the number of PTPs does not show any statistical significance signals that the PTPs target specifically IDP children. Overall, this empirical exercise supports the effectiveness of the PTPs program in increasing vaccination against polio in areas subject to migration inflows. Unfortunately, we are limited by sample size to show if this translates into a district-level negative trend in polio cases per 100,000 or not. However, despite being limited by the geographical sample available, we argue that this empirical exercise is a valid evaluation of the program.

6.2 Other mechanisms

Household Conditions in Overcrowded Communities. Most IDP families migrated to informal settlements, Pashtun slums, or into squeezed houses of friends or relatives. Access to safe drinking water and hygiene was a major problem for them. Appropriate facilities for bathing, doing laundry or keeping personal hygiene were not always available, facilitating the transmission of polio (IDMC 2015).

One crucial question is whether IDPs settle in poorer locations or if the living conditions get worse with the sudden arrival of IDPs. The balancing exercise of Table A14 suggests that IDP population does not necessarily move to the poorest locations, but to more overcrowded settings. Table A14 also shows how the number of household members and children under five was higher in host districts closer to the FATA border before 2008. Moreover, Table A14 presents evidence that households in closer districts were also more likely to have toilet and television, and children are more likely to have a fever in the last week of the interview and less likely to be a girl. These pre-treatment characteristics may be a key channel behind the main results and, as well, a vital identification threat. Even if we control for local economic development, we cannot ensure that our estimates capture the actual impact of IDP inflows rather than the pre-treatment differences in disadvantages characteristics. Nonetheless, what is certain is that crowded households cannot respond efficiently to an IDP inflow. As a result, crowded families are systematically more affected by the waves of displaced persons. Keeping this limitation in mind, how does the arrival of IDPs affect socio-demographic health conditions? To shed light on this question, we estimate equation (3) on six outcomes related to household conditions in host communities (i.e. access to drinkable water, access to a toilet, floor quality, number of children under five, household members, and head of the household's working status).

$$Y_{i,h,d,t} = \beta_0 + \beta_1 IDPCrisis_t * PredictedInflow_{d,t} + \beta_2 X_{h,t} + \gamma_d + \delta_t + \epsilon_d \tag{5}$$

where $Y_{i,h,d,t}$ is equal to one if child i from household h living in district d has a given household characteristic at the time of the survey t. The timing of the treatment is given by the year of the survey. Specifically, $IDPCrisis_t$ is a variable equal to one if a household h was interviewed after December 2007. We control for nightlight intensity and urban location. Additionally, we include district γ_d and time of survey δ_t fixed effect, which accounts for time-invariant covariates across households in a district.

We find that an increase of one standard deviation in predicted inflows decreases the probability of having a piped water system and having an additional child under five (see Panel A of Table A15 for the results). We also look at diarrhoea and fever during the last week from the date of the interview. We do not observe an effect (see Table A16). In Panel B of Table A15, we look at the heterogeneity between IDP and native children. IDP households are more likely to have water piped in their household and additional members compared to native children. At the same time, the head of IDP households are less likely to have a job.

The above results suggest that the household conditions are not affected in average terms. However, IDPs are more likely to end up in overcrowded households where a new polio case can quickly multiply.

Congestion of Health Services. The sudden arrival of IDP families could create logistical hurdles in health service delivery. The increased demand for healthcare services could have caused additional strain on the local infrastructure, which was often hardly adequate even for the needs of the local population (Din 2010). Host districts with an unstable access to health services could affect the incidence of polio.

Having data on the aggregate demand for health services would enable us to shed some light on the potential changes created by IDP inflows. Unfortunately, this information is not available. We can only capture the individual demand by using individual-level data on prenatal and postnatal doctor assistance from the DHS. Figure A14 and Figure A15 illustrate an increase in the share of children with both prenatal and postnatal assistance after 2007 in closer districts relative to further ones. To complement the descriptive analysis, we repeat equation (5) with the prenatal and postnatal doctor assistance outcomes (columns (1) and (4)). We include province-fixed effects in columns (2), (3), (5), and (6). Results in Table A17 (panel A) point out that an increase in a standard deviation in the predicted inflow led to an increase in demand for health services (i.e., demand for pre-natal and post-natal assistance). There are no heterogeneous effects between IDP and native children (see columns (2) and (4)).

Did the healthcare supply equally respond to an increase in the demand for health services? Ideally, we would like to study this question using district-level data on health service delivery (health centres and workforce). Unfortunately, we could not get this data. To address this limitation, we proxy health services supply with district-level data on polio vaccination campaigns from the Polio Eradication Program. In Pakistan, health is primarily the responsibility of the provincial government. Therefore, the central assumption is that the supply of health services follows the same pattern as the polio vaccination campaigns. Figure A16 shows how the total vaccination activities per 100.000 inhabitants increased in 2008 in host districts with respect to 2007.[31] Results of Table A17, in Panel B, support the idea of a responsive supply. An increase of one standard deviation in predicted inflows results in a 0.06 additional vaccination campaign (see column (4)). However, we can not disentangle if the increase in the supply is high enough to meet the demand for formal health services.

7 Conclusion

This paper demonstrates that communities receiving internally displaced persons (IDPs) experienced a notable increase in new polio cases per 100,000 inhabitants. We analyzed the mass displacement of 57% of the population from the conflict-affected Federally Administered Tribal Areas (FATA) to other districts in Pakistan between 2008 and 2022. Using a difference-in-differences approach, we compared the incidence of new polio cases in districts closer to and farther from the FATA border before and after 2008.

Our findings indicate that the surge in polio cases in host communities was driven by the arrival of poorly immunized children, whose vaccination schedules were disrupted by the conflict. Refugees and IDPs face significant barriers to accessing immunization services, including overcrowded living

[31] We use the 2017 Population Census to construct Figure A16. We obtain a similar graph using the 1998 Population Census (see Figure A17).

conditions and overwhelmed healthcare facilities. However, our evidence also underscores the positive impact of targeted vaccination policies for IDP children during their migration. Specifically, the Permanent Transit Point program effectively reached IDP children affected by the post-2008 crisis, significantly increasing their likelihood of being vaccinated against polio.

The situation in Pakistan is not unique. Since 2022, polio outbreaks have resurfaced in regions such as Malawi, Mozambique, and Gaza—areas that had been polio-free for decades but are now grappling with new displacements due to ongoing conflicts. Prioritizing the immunization of hard-to-reach populations, such as IDP and refugee children, is essential for public health. Vaccinated children are more likely to thrive, succeed in education, and lead healthy lives (UNICEF 2023).

Finally, the low vaccination rates among IDP children may stem from various factors, such as inadequate vaccine delivery in conflict zones or low demand from IDP families. The success of the Permanent Transit Point program suggests that increasing vaccine supply enhances the likelihood of IDP children being vaccinated. However, our data does not allow us to assess the program's impact on institutional trust. Future research should explore whether vaccination programs discriminate against IDPs and how these experiences influence IDPs' national identity and trust in government, as well as the potential for rebuilding that trust.

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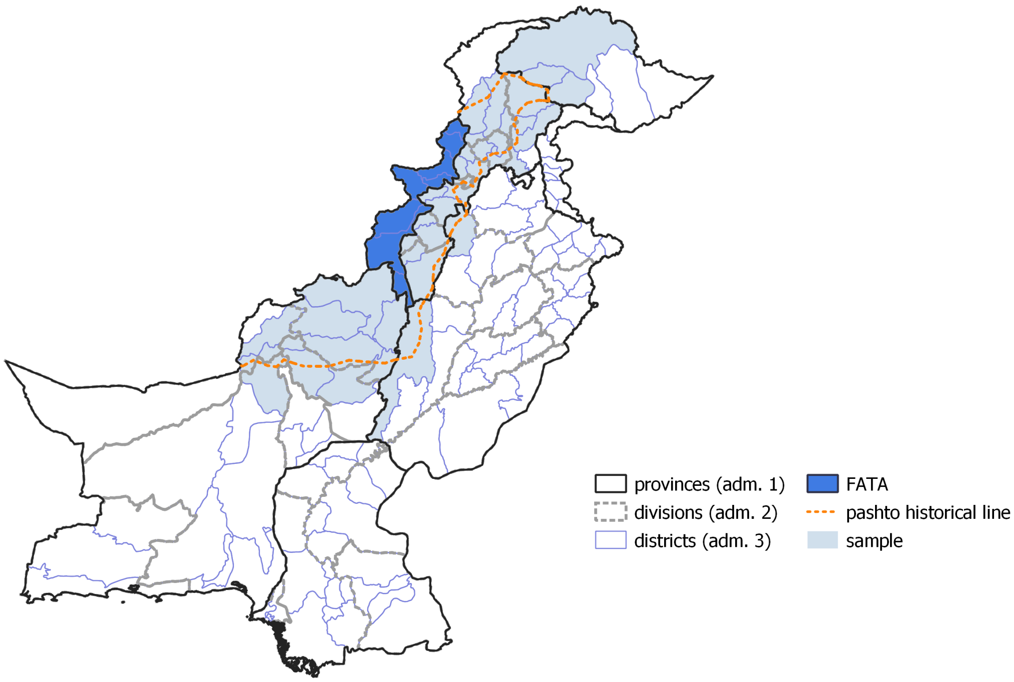
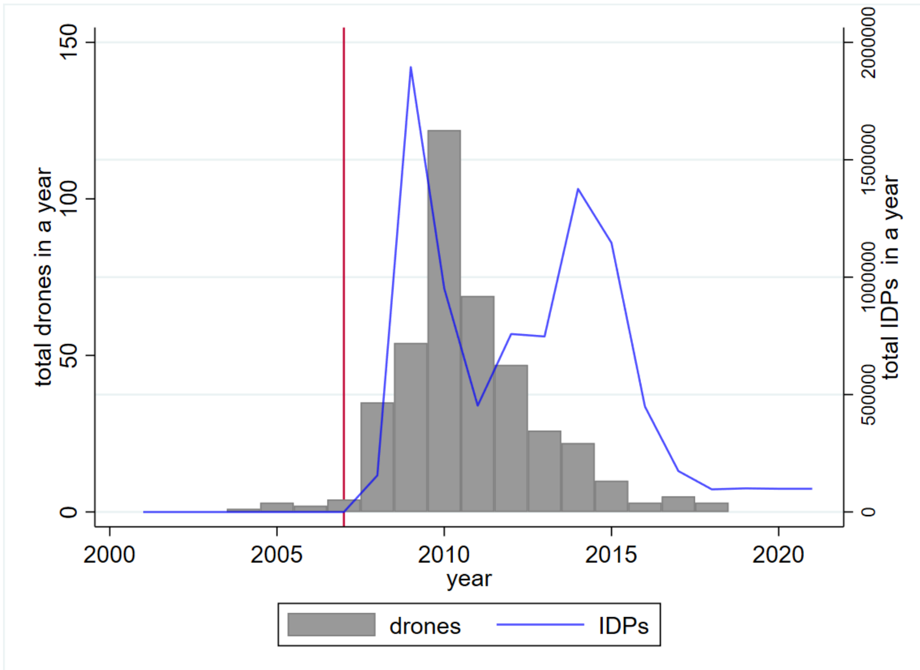
Figures and Tables

Figure 1: Sample districts



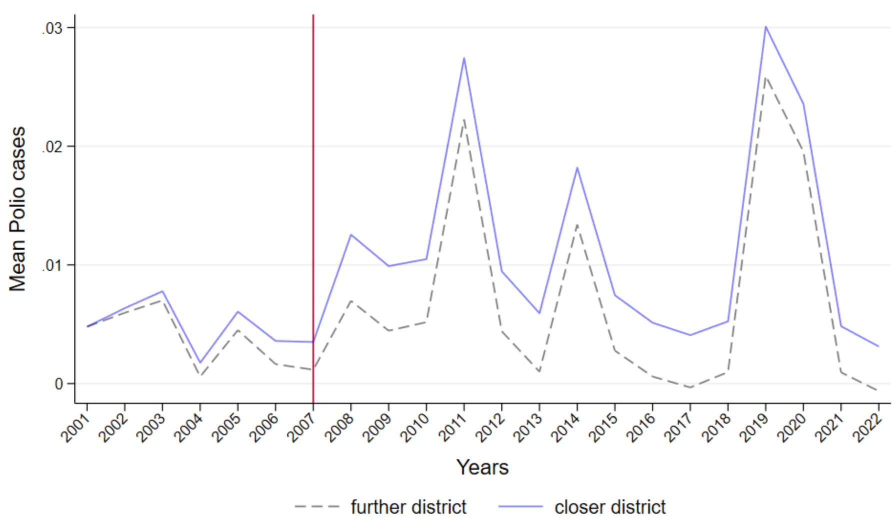
Note: This figure shows the spatial distribution of the main sample. In light blue, we show the districts within the baseline sample. The sample includes the districts that entirely or partially fall within Pashtunistan and that received the internally displaced population (IDPs) from the Federally Administered Tribal Areas (FATA). The region of FATA is in dark blue. The orange line illustrates the pre-colonial region of Pashtunistan. The black line corresponds to the provinces (the first administrative division in Pakistan). The grey line corresponds to division (the second administrative division). The white polygons with purple lines are the districts (the third administrative division).

Figure 2: Total drones strikes and IDP population (2001-2022)



Note: This figure shows the yearly number of drones and internally displaced persons (IDPs) from 2001 to 2022. The grey bars show the number of drones and the blue line to the number of IDPs. The vertical red line corresponds to 2007.

Figure 3: Polio cases (2001-2022)



Note: This figure plots the mean polio cases per 100,000 inhabitants in closer (i.e., districts with high IDP intensity) and further (i.e., districts without or with negligible IDP population) districts. Closer and further districts are part of the pre-colonial region of Pashtunistan. Therefore, they are part of the estimating sample of equation (1).

Figure 4: Permanent Transit Points (PTPs) to vaccinate children on the move

Number of Functional Transit Points bordering NWA

Province	District	Tehsil	Total
FATA	FR Bannu	FR Bannu	6
FATA	FR D I Khan	FR D.I Khan	2
FATA	FR Tank	FR Tank	2
FATA	Kurram Agency	Central Kurram	2
FATA	Kurram Agency	Lower Kurran	4
KP	Bannu	Bannu	14
KP	D I Khan	D I Khan	11
KP	D I Khan	Daraban	1
KP	D I Khan	Kulachi	1
KP	D I Khan	Paharpur	1
KP	D I Khan	Pariva	1
KP	Hangu	Hangu	6
KP	Hangu	Thall	10
KP	Karak	B D Shah	2
KP	Karak	Karak	5
KP	Karak	Takht e Nasrati	1
KP	Lakki Marwat	Lakki Marwat	6
KP	Lakki Marwat	Sarai Naurang	12
KP	Tank	Tank	9
Total			96

Note: This figure illustrates the functional Permanent Transit Vaccination Points in districts bordering the North Waziristan district. The Pakistan Polio Eradication Programme vaccinates children travelling or on the move at the Permanent Transit Points (PTPs). There are 500 PTPs across all major transit points nationwide. These PTPs are set up along country and district borders and other essential transit points such as railway stations, bus stops, and highways. Source. World Health Organization.

Table 1: Effect of IDP inflow on new polio cases per 100,000 inhabitants.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00139**	0.00156***	0.00154**	0.00154**	0.00154**
	(0.00061)	(0.00055)	(0.00058)	(0.00058)	(0.00064)
N	8713	8713	8713	8713	8713
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts. $IDPCrisis_t$ is a dummy variable that takes the value of one after 2007. $PredictedInflow_{d,t}$ stands for predicted IDP inflow. $PredictedInflow_{d,t}$ is the interaction of $IDPinflow_t$ and $\frac{1}{DistFATA_d}$. $IDPinflow_t$ stands for the total IDPs registered in Pakistan in each year t. $\frac{1}{DistFATA_d}$ is the inverse Euclidean distance of each centroid district to the closest FATA border. We standardized $PredictedInflow_{d,t}$ to ease the interpretation of our results. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Effect of IDP inflow on vaccination against polio

	(1)	(2)	(3)	(4)	(5)
			Panel A: Cohort specification		
Cohort$_{08}$	0.05028*	0.05668***	0.06659***	0.05376***	0.06179***
	(0.02534)	(0.01831)	(0.01730)	(0.01789)	(0.01674)
			Panel B: Cohort specification, IDP heterogeneity		
Cohort$_{08}$	0.05150*	0.05854***	0.06780***	0.05565***	0.06302***
	(0.02545)	(0.01834)	(0.01716)	(0.01792)	(0.01658)
*Cohort$_{08}$ * IDP*	-0.18126***	-0.17568***	-0.16955***	-0.17523***	-0.17063***
	(0.03580)	(0.03277)	(0.03306)	(0.03350)	(0.03317)
N	13504	13504	13504	13504	13504
District FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	38	38	38	38	38
Mean Y	0.219	0.219	0.219	0.219	0.219

Notes. This Table presents the impacts of the IDP inflows on vaccination behaviours at individual level. The dependent variable is a binary variable for being vaccinated, coded to one if the children is vaccinated. In Panel A, we use the date of birth from the Demographic and Health Survey (DHS) from 1998 to 2017 to define an alternative treatment. Children born from January 2008 are exposed to the treatment. Panel B investigates the heterogeneity between exposed cohorts and IDP children. The specification related to panel A and B is presented in equation 3. Column (1) presents the results without covariates and fixed effects; column (2) includes district fixed effects; column (3) controls for nightlight intensity and total vaccination campaigns; columns (4) controls for the head of household, urban location, and gender of the child; column (5) control for the full set of covariates included in columns (3) and (4). Robust standard errors are clustered at the district level. *** p. *** p¡0.01, ** p¡0.05, * p¡0.1

Table 3: Number of PTPs and polio vaccination

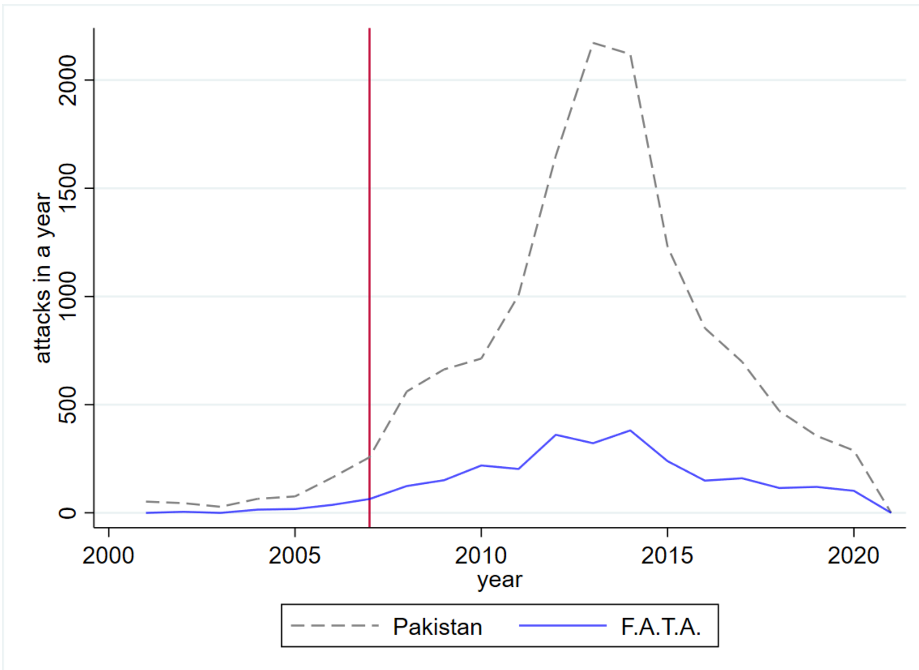
	(1)	(2)	(3)	(4)	(5)
	Panel A: Cohort specification, IDP heterogeneity				
$Cohort_{08}$	0.07465***	0.08357***	0.08218***	0.08321***	0.06712**
	(0.01701)	(0.01759)	(0.02867)	(0.01751)	(0.02818)
$Cohort_{08}$ * IDP_i	-0.00890	-0.02423	-0.02634	-0.01962	-0.02057
	(0.08347)	(0.08460)	(0.08446)	(0.08218)	(0.08209)
	Panel B: PTP and polio vaccination, IDP heterogeneity				
$Cohort_{08}$ * N. PTP_d	-0.00158	0.00262	0.00300	-0.00104	0.00092
	(0.00549)	(0.00573)	(0.00633)	(0.00587)	(0.00638)
$Cohort_{08}$ * N. PTP_d * IDP_i	0.12430***	0.12648***	0.12676***	0.12360***	0.12259***
	(0.03244)	(0.03315)	(0.03322)	(0.03170)	(0.03178)
N	1896	1896	1896	1895	1895
District FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	6	6	6	6	6
Mean Y	0.148	0.148	0.148	0.148	0.148

Notes. This Table presents the impacts of the number of PTPs on the probability of vaccinated with polio at individual level. The dependent variable is a binary variable for being vaccinated, coded to one if the child is vaccinated. In Panel A, we use the date of birth from the Demographic and Health Survey (DHS) from 1998 to 2017 to define exposure to treatment. Children born from January 2008 are exposed to the treatment. This exposure is interacted with a dummy that captures whether a child is IDP. Panel B investigates the heterogeneity between exposed cohorts and PTPs and IDP children. The specification related to panel A and B is presented in equation 4. Column (1) presents the results without covariates and fixed effects; column (2) includes district fixed effects; column (3) controls for nightlight intensity and total vaccination campaigns; columns (4) controls for the head of household, urban location, and gender of the child; column (5) control for the full set of covariates included in columns (3) and (4). Robust standard errors in parantheses. *** p. *** p¡0.01, ** p¡0.05, * p¡0.1

Appendices

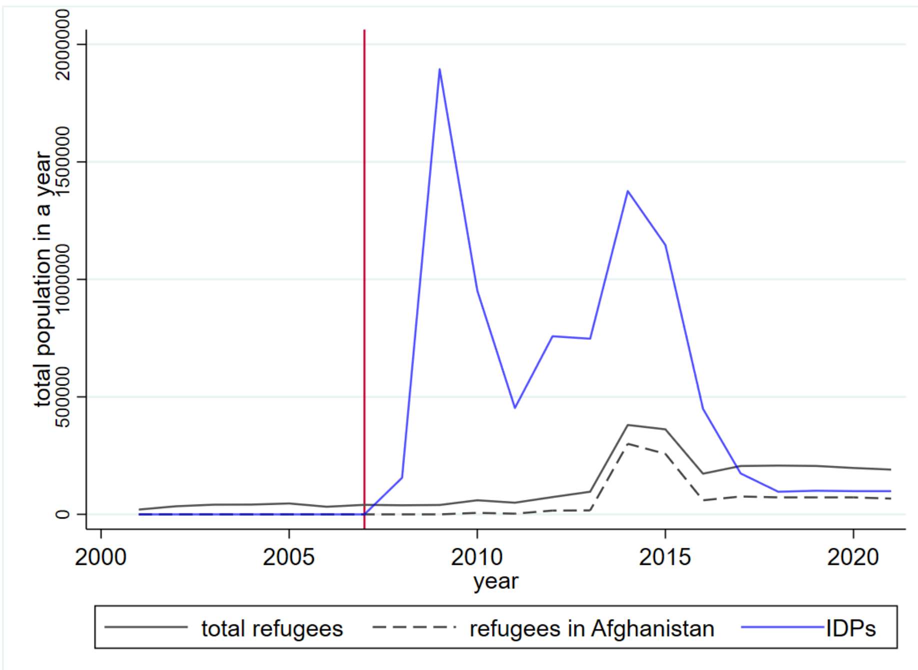
A Additional Figures

Figure A1: Terrorist attacks (2001-2022)



Note: This figure shows the yearly number of terrorist attacks from 2001 to 2022. The grey dashed line for Pakistan and the blue line for FATA The vertical red line corresponds to 2007. Source. The Global Terrorism Database - G.T.D. (GTD 2021).

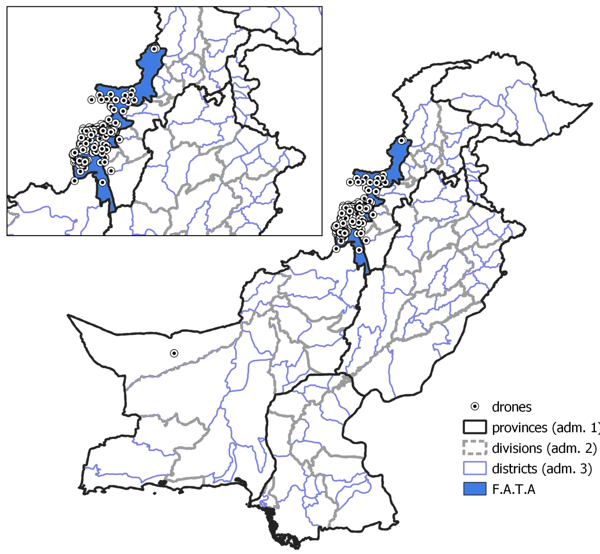
Figure A2: Forcibly displaced population within and outside Pakistan (2001-2022)



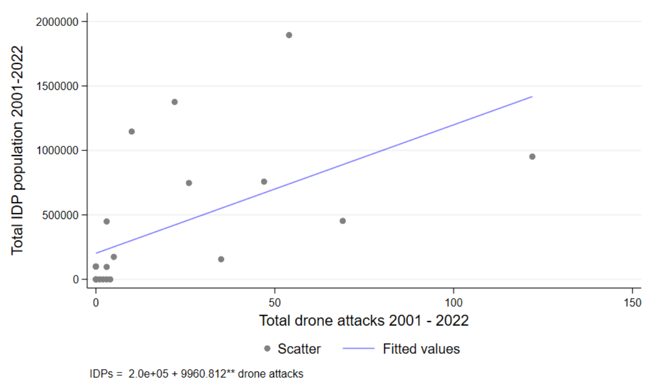
Note: This figure shows the yearly displaced population from Pakistan from 2001 to 2022. The blue line corresponds to the internally displaced persons (IDP). The black line shows the number of Pakistani refugees worldwide. And the black dashed line of the Pakistani refugees in Afghanistan. The vertical red line corresponds to 2007. Source. The United Nations High Commissioner for Refugees - U.N.H.C.R. (UNHCR 2023).

Figure A3: Drones as a migration push factor

a) Drone strikes locations

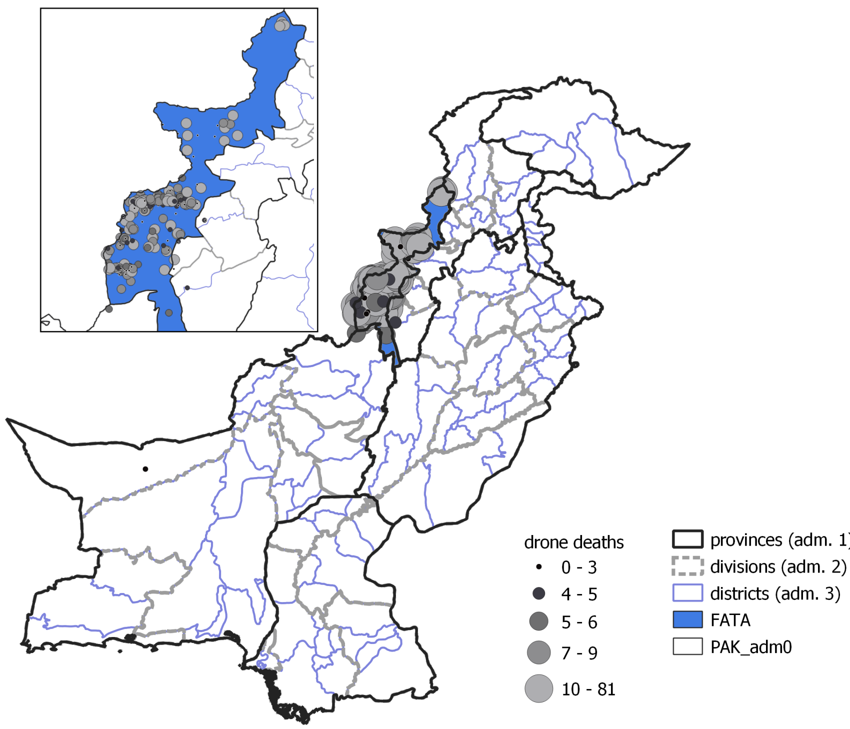


b) Correlation between the number of drones and IDPs



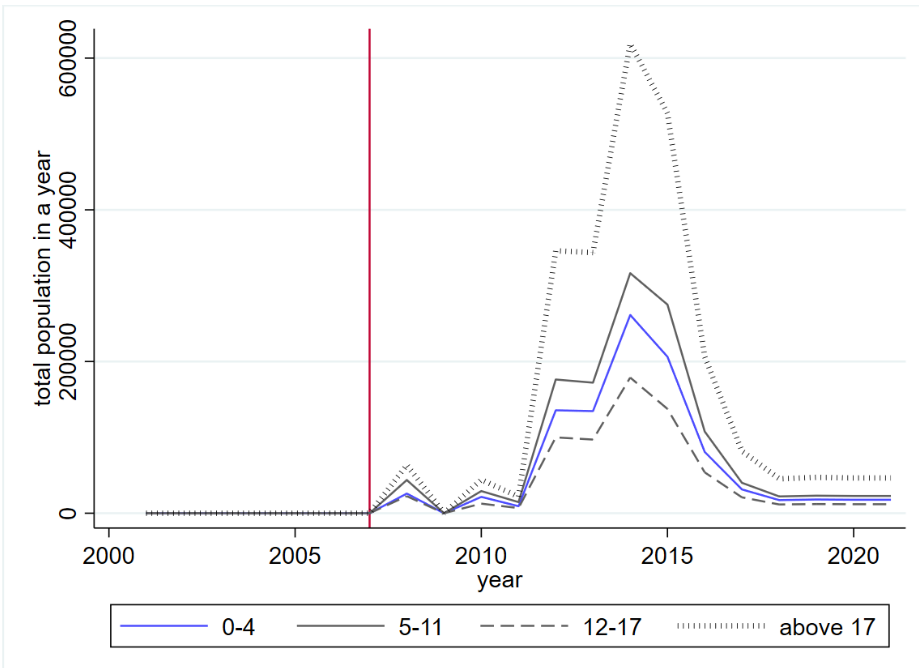
Note: This figure shows the relationship between the intensity of drone strikes and migration. Figure A illustrates the spatial distribution of drones from 2001 to 2022 in Pakistan. The blue polygons correspond to the Federally Administered Tribal Areas (FATA) region. Figure B plots the correlation between the district's number of drones and the aggregate IDPs from 2001 to 2022.

Figure A4: Total deaths by drones (2001-2022)



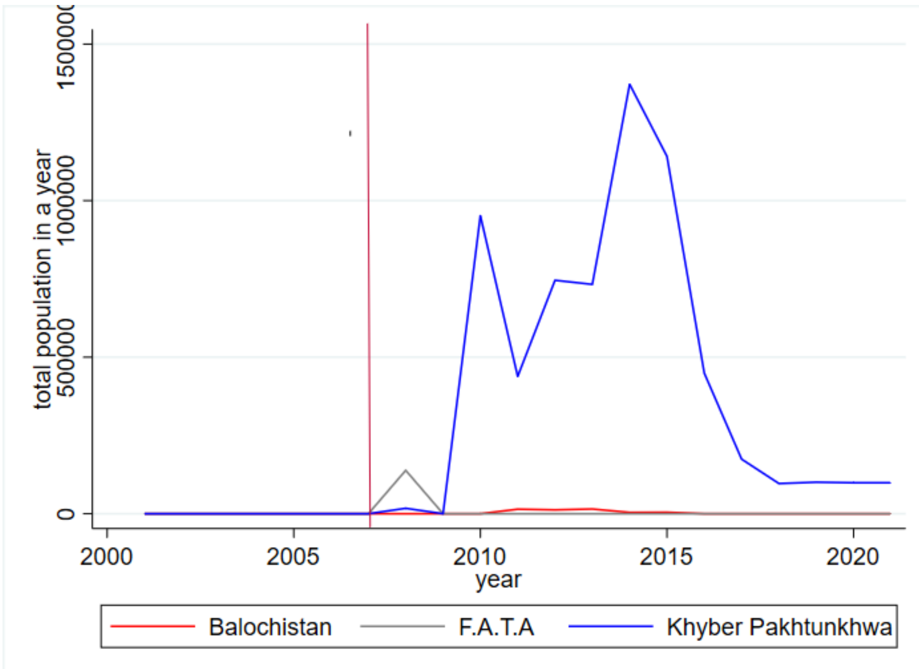
Note: This figure shows the spatial distribution of deaths associated with each drone strike from 2001 to 2022. The higher the dot higher is the total number of deaths. Source. The World of Drones Database developed by New America (New-America 2021).

Figure A5: Internally Displaced Persons by age (2001-2022)



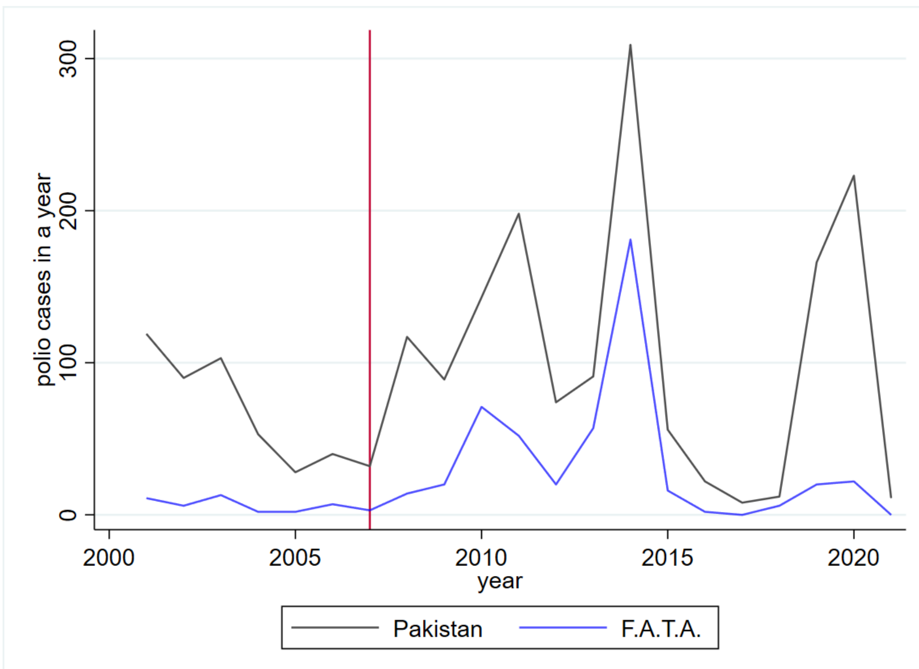
Note: This figure shows the yearly internally displaced population by age from 2001 to 2022. The blue line corresponds to the ages 0-4, the black line to the ages 5-11, the black dashed line to the ages 12-17 and the black pointed line to the ages above 17. The vertical red line corresponds to 2007. Source. The United Nations High Commissioner for Refugees - U.N.H.C.R. (UNHCR 2023).

Figure A6: Internally Displaced Population by province



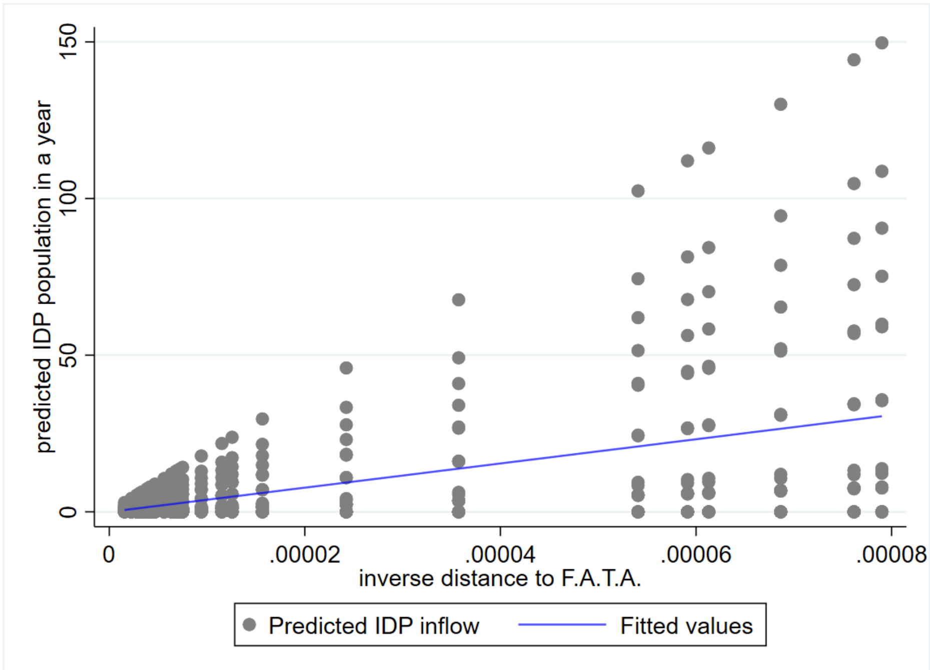
Note: This figure shows the yearly internally displaced population by province from 2001 to 2022. The red line corresponds to the province of Balochistan, border to Southern FATA. The grey line are the IDPs in FATA The blue line corresponds to Khyber Pakhtunkhwa province. Khyber Pakhtunkhwa is the border of the Eastern and Northern FATA The vertical red line corresponds to 2007. Source. The United Nations High Commissioner for Refugees - U.N.H.C.R. (UNHCR 2023).

Figure A7: Polio cases in Pakistan and FATA (2001-2022)



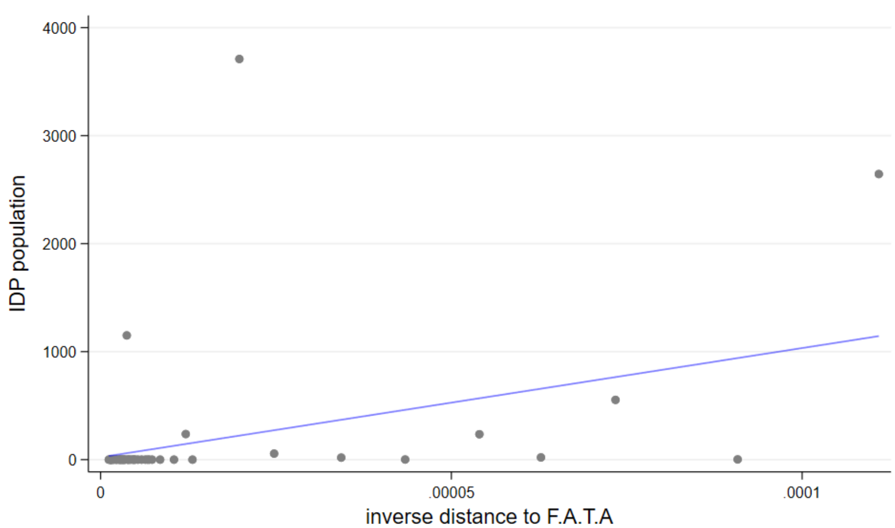
Note: This figure plots the yearly polio cases in Pakistan and FATA Treated districts are the host districts, and control districts are the non-host districts. Source. The Polio Eradication Program established by the World Health Organization (WHO).

Figure A8: Inverse distance and predicted inflow



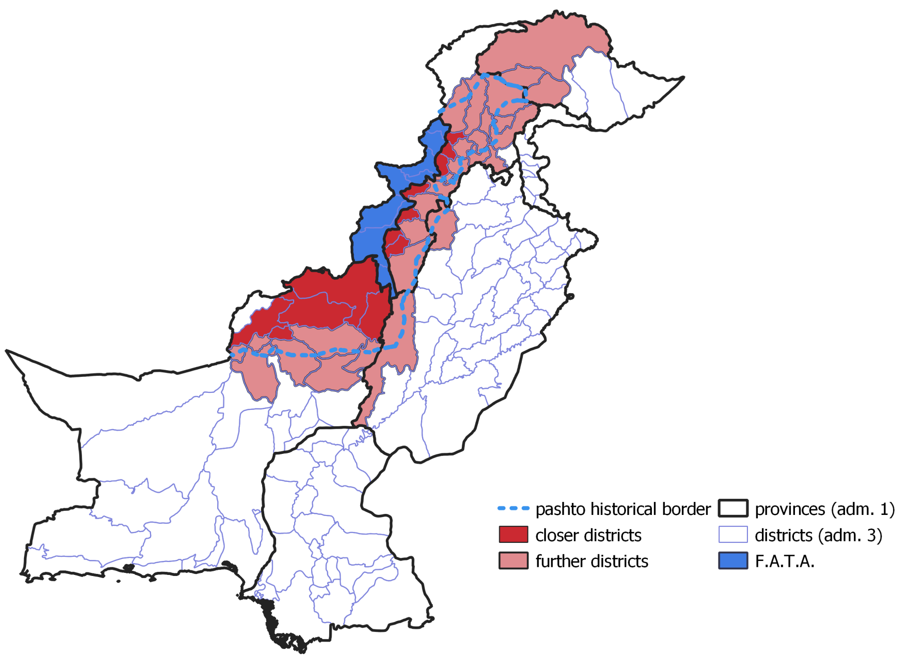
Note: This figure shows the correlation between the predicted inflow measure and the inverse distance to the closest FATA border. The predicted inflow measure is equal to the interaction of the inverse distance of each district to the nearest FATA border (district variation) and the total yearly number of IDP population (annual variation).

Figure A9: Inversed distance and reported IDPs



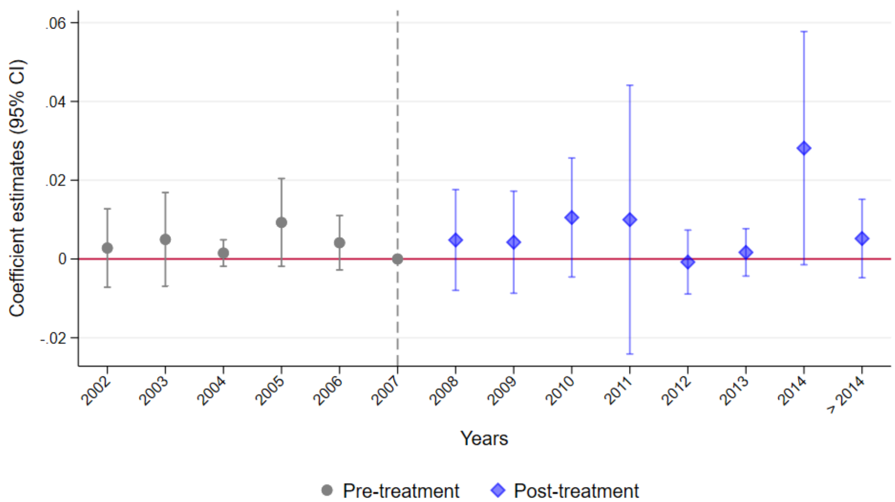
Note: This figure shows the correlation between the actual IDP inflow and the inverse distance to the closest FATA border. The IDP information comes from the United Nations High Commissioner for Refugees - UNHCR (UNHCR 2023).

Figure A10: Closer and Further districts



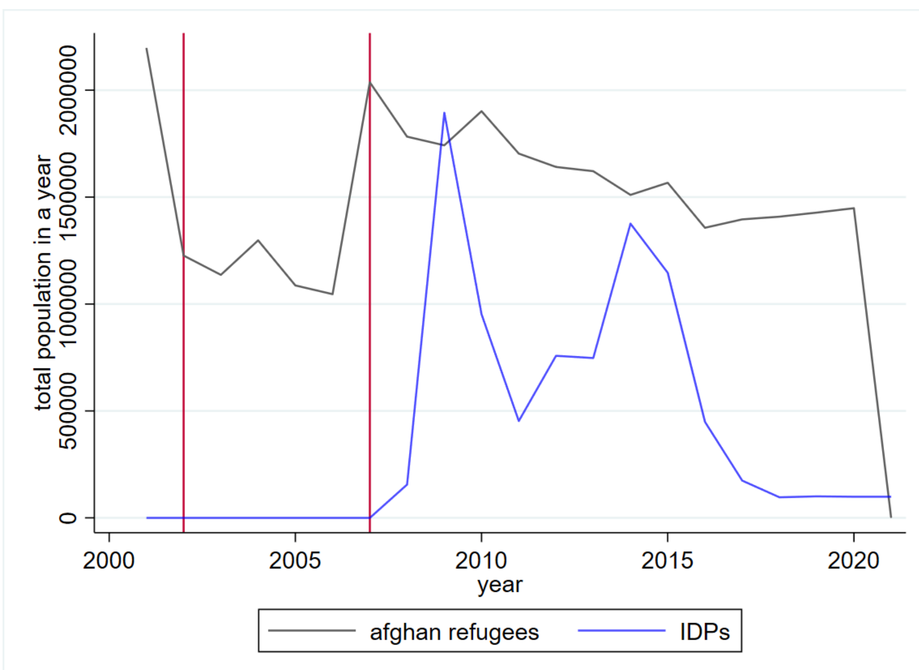
Note: This figure shows treated (host) and control (non-host) districts. To define them, we use the spatial distribution of districts relative to the pre-colonial region of Pashtunistan. The red line corresponds to the Pashtunistan's border. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose territory is outside Pashtunistan but adjacent to the historical border.

Figure A11: Event study



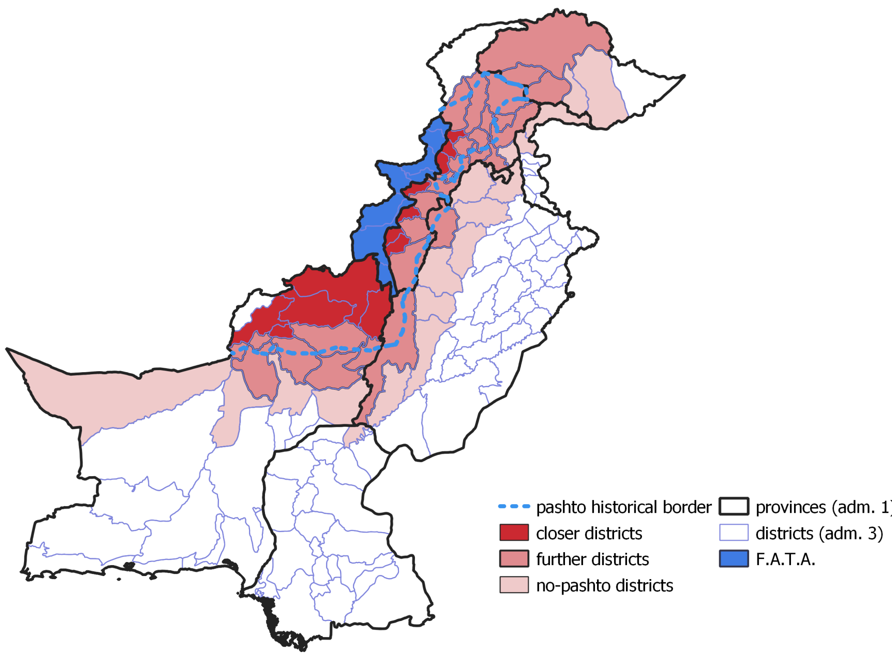
Note: the figure shows the coefficients estimates resulting from the event-study specification in Equation 2. The confidence intervals are 95%. The omitted year is 2007, that is a year before the beginning of the IDP crisis. The dataset is in a year-district panel format.

Figure A12: Afghan refugees (2001-2022)



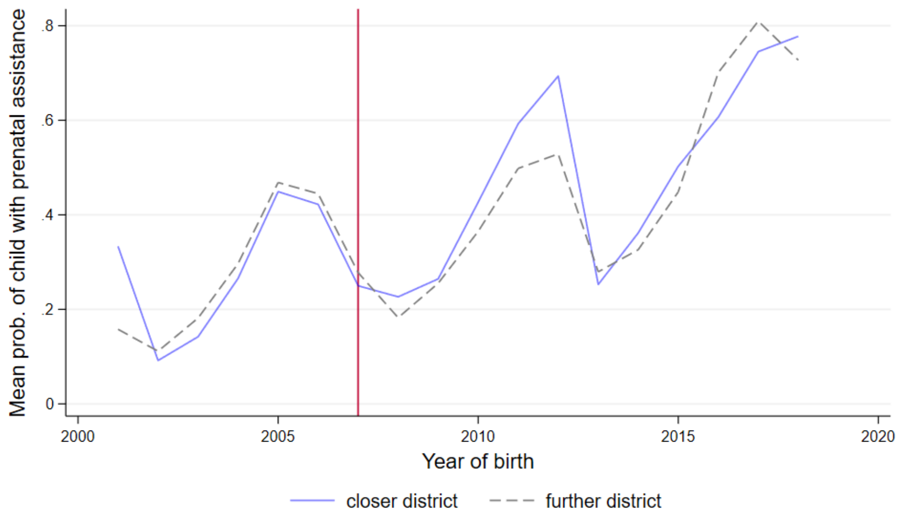
Note: This figure shows the yearly internally displaced population and Afghan refugees in Pakistan from 2001 to 2022. The blue line corresponds to the internally displaced persons (IDP). The black line indicates the number of Afghan refugees in Pakistan. The vertical red line corresponds to 2007. Source. The United Nations High Commissioner for Refugees - U.N.H.C.R. (UNHCR 2023).

Figure A13: Alternative treated and control districts



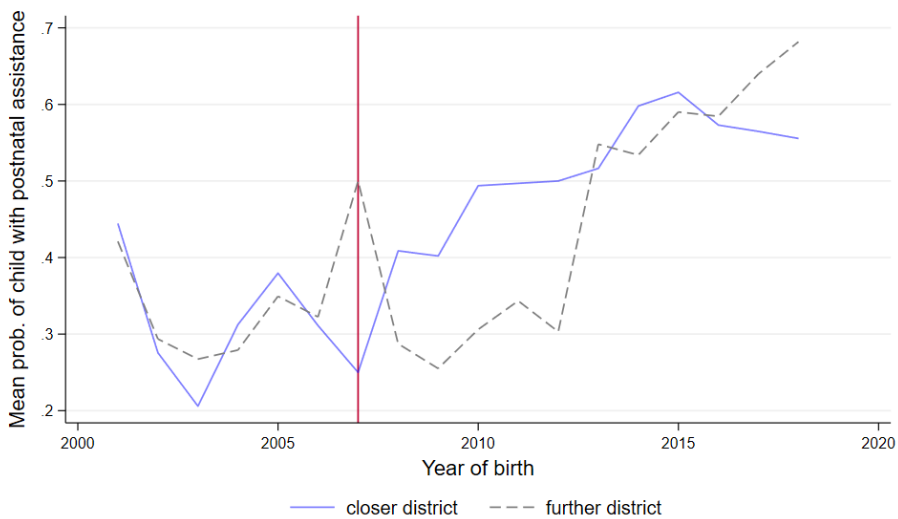
Note: This figure shows the districts partially within Pashtunistan. To define them, we use the spatial distribution of districts relative to the pre-colonial region of Pashtunistan. The red line corresponds to the Pashtunistan's border. The districts overlapping the border are the red dashed polygons, with only a share of the territory is in Pashtunistan. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose territory is outside Pashtunistan but adjacent to the historical border.

Figure A14: Probability of children with prenatal assistance



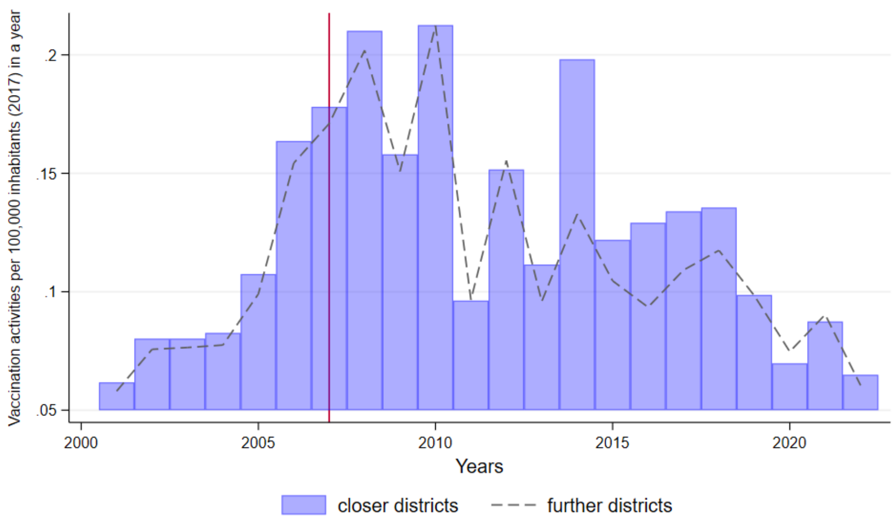
Note: This figure plots the mean probability of having a child with prenatal assistance in treated and control districts by the year of birth cohort. Treated districts are the host districts and control districts are the non-host districts. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose part is outside Pashtunistan but adjacent to the historical border. The vertical red line corresponds to 2007. Source. Demographic and Health Survey (DHS).

Figure A15: Probability of children with postnatal assistance



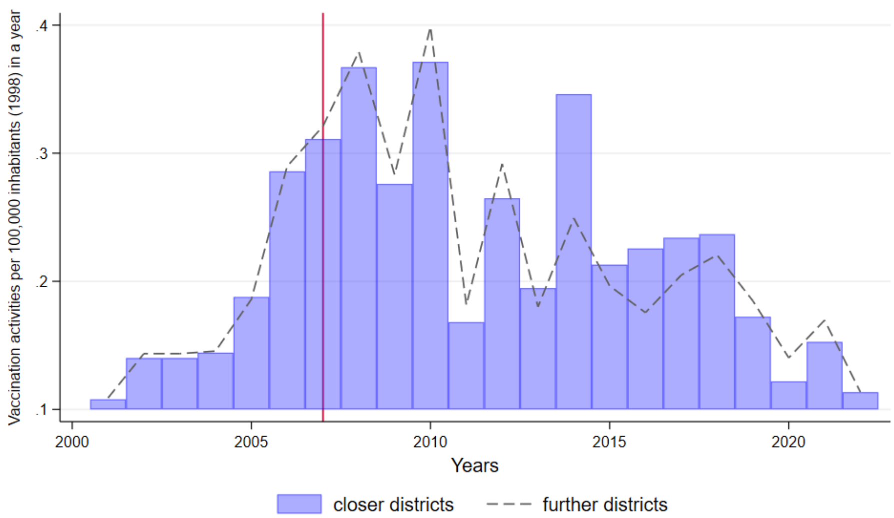
Note: This figure plots the mean probability of having a child with postnatal assistance in treated and control districts by the year of birth cohort. Treated districts are the host districts and control districts are the non-host districts. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose part is outside Pashtunistan but adjacent to the historical border. The vertical red line corresponds to December 2007. Source. Demographic and Health Survey (DHS).

Figure A16: Polio campaigns per 100,000 inhabitants



Note: This figure plots the number of vaccination campaigns against polio per 100,000 inhabitants in treated and control districts from 2001 to 2022. We calculate the campaigns per 100,000 inhabitants relative to the population in 2017 from the 2017 population census. The blue bars show the campaigns in treated districts, and the grey dashed line in control districts. Treated districts are the host districts and control districts are the non-host districts. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose part is outside Pashtunistan but adjacent to the historical border. The vertical red line corresponds to December 2007. Source. The Polio Eradication Program from the World Health Organization (WHO).

Figure A17: Polio campaigns per 100,000 inhabitants in 1998 (2001-2022)



Note: This figure plots the number of vaccination campaigns against polio per 100,000 inhabitants in treated and control districts from 2001 to 2022. We calculate the campaigns per 100,000 inhabitants relative to the population in 1998 from the 1998 population census. The blue bars show the campaigns in treated districts, and the grey dashed line in control districts. Treated districts are the host districts and control districts are the non-host districts. Districts whose territory falls within the pre-colonial region of Pashtunistan are host districts. Non-host districts are those whose part is outside Pashtunistan but adjacent to the historical border. The vertical red line corresponds to December 2007. Source. The Polio Eradication Program from the World Health Organization (WHO).

B Additional Tables

Table A1: Aggregate IDPs by district of origin (2001-2022)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Province and Division	Position	District	IDP families	IDP individuals	Drones	Total deaths
F.A.T.A	Southern	North Waziristan	108,149	648,894	291	2003
F.A.T.A	Southern	South Waziristan	71,124	426,744	84	678
F.A.T.A	Southern	Largha Shirani	0	0	1	6
F.A.T.A	Northern	Bajaur	72,895	437,370	4	128
F.A.T.A		Khyber	91,689	550,134	6	61
F.A.T.A		Kurram	33,024	198,144	9	83
F.A.T.A		Mohmand	36,759	220,554	0	0
F.A.T.A		Orakzai	35,823	214,938	1	13
N.W.F.P.	Southern	Tank	2,256	13,536	1	5
TOTAL			451,719	2,710,314	396	2,971

Note: This Table shows the aggregate number of internally displaced persons (IDP) from 2001 to 2022 by district of origin. The IDP data source is **UNHCR2022**. Columns (6) and (7) present the aggregate number of drones and the number of deaths created from 2001 to 2022 from New-America 2021.

Table A2: Total IDPs by district of destination in 2008

(1)	(2)	(3)	(4)
Province	District	2008	share
Khyber Pakhtunkhwa (NWFP)	Adam Khel	1168	0.007
Khyber Pakhtunkhwa (NWFP)	Charsadda	187	0.001
Khyber Pakhtunkhwa (NWFP)	Dir	190	0.001
Khyber Pakhtunkhwa (NWFP)	Hangu	63	0.000
Khyber Pakhtunkhwa (NWFP)	Kohat	1237	0.008
Khyber Pakhtunkhwa (NWFP)	Peshawar	21	0.000
Khyber Pakhtunkhwa (NWFP)	Swat	15639	0.100
Khyber Pakhtunkhwa (FATA)	Bajaur	114717	0.736
Khyber Pakhtunkhwa (FATA)	Khyber	110	0.001
Khyber Pakhtunkhwa (FATA)	Kurram	5275	0.034
Khyber Pakhtunkhwa (FATA)	Mohmand	15516	0.100
Khyber Pakhtunkhwa (FATA)	N. Waziristan	11	0.000
Khyber Pakhtunkhwa (FATA)	Orakzai	1632	0.010
Khyber Pakhtunkhwa (FATA)	S. Waziristan	43	0.000
TOTAL		155809	

Note: This Table shows the total number of internally displaced persons (IDP) from 2008 to 2015 by district of destination. The IDP data source is **UNHCR2022**. There are no data for 2009 and after 2015.

Table A3: Pre-treatment characteristics in 1998, closer vs further districts

	(1) Further	(2) Closer	(3) Diff
monthly new polio cases per 100,000 inhabitants	0.004	0.005	-0.001
	(0.029)	(0.035)	(0.001)
monthly polio campaigns	0.686	0.702	-0.000
	(0.464)	(0.457)	(0.000)
night light	6.233	7.831	0.430
	(2.957)	(5.841)	(0.992)
electricity share	0.714	0.838	0.000
	(0.155)	(0.126)	(0.000)
roof share	0.262	0.219	0.000
	(0.088)	(0.068)	(0.000)
wall share	0.575	0.470	-0.000
	(0.165)	(0.190)	(0.000)
water share	0.255	0.308	-0.000
	(0.083)	(0.078)	(0.000)
petrol cooker share	0.072	0.111	0.000
	(0.062)	(0.118)	(0.000)
own house share	0.821	0.807	0.000
	(0.062)	(0.086)	(0.000)
N. members in household	10.451	11.540	0.000
	(1.492)	(0.871)	(0.000)
N. children under 5	0.289	0.301	0.000
	(0.025)	(0.017)	(0.000)
literate share	0.283	0.270	-0.000
	(0.046)	(0.038)	(0.000)
primary education share	0.161	0.153	0.000
	(0.030)	(0.026)	(0.000)
Muslim share	0.995	0.993	0.000
	(0.002)	(0.003)	(0.000)
Pashto share	0.650	0.816	-0.000
	(0.362)	(0.207)	(0.000)
Observations	2,268	1,008	3,276

Note: This table reports a balancing test on a series of district characteristics of the sample considered in the main analysis. The balancing test covers 39 districts from 2001 to 2007 at the monthly level. Pre-treatment characteristics are from the 1998 Population Census and the polio cases and campaigns from the Polio Eradication Program from 2001 to 2007.

Table A4: Controlling for terrorist and drone attacks.

	(1)	(2)	(3)	(4)	(5)
	Panel A: controlling for terrorist attacks				
IDP $Crisis_t$ * *Predicted* $Inflow_{d,t}$	0.00095	0.00120**	0.00119**	0.00119**	0.00118**
	(0.00060)	(0.00049)	(0.00052)	(0.00052)	(0.00057)
	Panel B: controlling for drone attacks				
IDP $Crisis_t$ * *Predicted* $Inflow_{d,t}$	0.00139**	0.00157***	0.00155**	0.00155**	0.00155**
	(0.00061)	(0.00055)	(0.00057)	(0.00057)	(0.00063)
N	8713	8713	8713	8713	8713
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Panel A controls for the number of terrorist attacks, while Panel B controls for the number of drone attacks. Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Potential Afghan refugees effect.

	(1)	(2)	(3)	(4)	(5)
	Panel A: controlling for total afghan refugees				
$IDP\ Crisis_t$ * $Predicted\ Inflow_{d,t}$	0.00139*	0.00159***	0.00157**	0.00157**	0.00157**
	(0.00071)	(0.00056)	(0.00059)	(0.00059)	(0.00065)
	Panel B: number of refugee camps fixed effects				
$IDP\ Crisis_t$ * $Predicted\ Inflow_{d,t}$	0.00139**	0.00156***	0.00154**	0.00154**	0.00154**
	(0.00061)	(0.00055)	(0.00058)	(0.00058)	(0.00064)
N	8713	8713	8713	8713	8713
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Panel A controls for the number of total afghan refugees in a district year-month, while Panel B includes the number of refugees camps fixed effects. Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Potential international migration effects.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00114*	0.00156***	0.00154**	0.00154**	0.00154**
	(0.00059)	(0.00055)	(0.00058)	(0.00058)	(0.00064)
N	8713	8713	8713	8713	8713
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). All columns control for the total number of Pakisthani refugees abroad. Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Potential Taliban political support effects.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00278***	0.00163***	0.00162***	0.00162***	0.00153**
	(0.00088)	(0.00055)	(0.00058)	(0.00058)	(0.00063)
N	8185	8185	8185	8185	8185
District FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). All columns control for the votes share of the Islamist coalition in a district in the 2008 elections, interacted with year dummies. Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Falsification test: effects one year before treatment.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_{t,t0=2007}$ * *Host District*$_d$	0.00270	0.00268	0.00251	0.00251	0.00246
	(0.00329)	(0.00334)	(0.00338)	(0.00338)	(0.00344)
N	8713	8713	8713	8713	8713
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the effect of one year before the IDP crisis on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The placebo treatment timing starts in 2007. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in Equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Falsification test: non-pashtu districts counterfactual.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	-0.00157	0.00150	0.00162	0.00162	0.00164
	(0.00116)	(0.00157)	(0.00161)	(0.00161)	(0.00169)
N	19536	19536	19536	19536	19536
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	74	74	74	74	74
Mean Y	0.003	0.003	0.003	0.003	0.003

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. The falsification test consist in comparing districts whose territory do not fall within the pre-colonial region of *Pashtunistan* with the one over the border. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Potential reverse causality: post-crisis predicted inflow and pre-crisis yearly polio cases.

	(1)	(2)	(3)	(4)	(5)
$\textit{Polio Cases}_{d,tm\text{-}2001\text{-}2007}$	0.01166	0.01532	-0.02676	-0.02676	-0.02713
	(0.02591)	(0.02291)	(0.02415)	(0.02415)	(0.02483)
N	6480	6480	6480	6480	6480
Division FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of divisions	14	14	14	14	14
Mean Y	0.009	0.009	0.009	0.009	0.009

Notes. This Table presents the relationship between $\textit{IDP Crisis}_t$ * $\textit{Predicted Inflow}_{d,t}$ and the number of polio cases in district d and at year-month t,m, before the IDP crisis kicked in. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2008 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without division, year-month fixed effects and covariates. Column (2) includes division and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Alternative sample definition.

	(1)	(2)	(3)	(4)	(5)
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00173***	0.00146***	0.00146**	0.00146**	0.00132**
	(0.00061)	(0.00053)	(0.00056)	(0.00056)	(0.00059)
N	12409	12409	12409	12409	12409
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	48	48	48	48	48
Mean Y	0.006	0.006	0.006	0.006	0.006

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. The alternative sample definition consist in districts whose territory falls either within or just outside the pre-colonial region of *Pashtunistan*. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) adds controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) adds controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A12: Alternative outcomes.

	(1)	(2)	(3)	(4)	(5)
	Panel A: *Pr(new polio case) = 1*				
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.02199*	0.01599*	0.01641*	0.01641*	0.01626*
	(0.01092)	(0.00907)	(0.00947)	(0.00947)	(0.00935)
N	8713	8713	8713	8713	8713
	Panel B: polio cases per 100,000 inhabitants (1998)				
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00247*	0.00252*	0.00254	0.00254	0.00325*
	(0.00111)	(0.00130)	(0.00147)	(0.00147)	(0.00150)
N	2904	2904	2904	2904	2904
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.010	0.010	0.010	0.010	0.010

Notes. This table presents the impacts of the IDP inflows on: the probability of observing a new polio case in a district and year-month; the new polio cases per 100,000 inhabitants (in 1998); in host districts compared to non-host district. Districts whose polioitory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A13: Additional set of fixed effects.

	(1)	(2)	(3)	(4)	(5)
	Panel A: province linear trends				
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00139**	0.00150**	0.00150**	0.00150**	0.00136**
	(0.00061)	(0.00056)	(0.00059)	(0.00059)	(0.00061)
Prov. lin. trends FE	No	Yes	Yes	Yes	Yes
	Panel B: division linear trends				
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00139**	0.00137**	0.00137**	0.00137**	0.00128**
	(0.00061)	(0.00063)	(0.00064)	(0.00064)	(0.00062)
Div. lin. trends FE	No	Yes	Yes	Yes	Yes
	Panel C: district linear trends				
IDP Crisis$_t$ * *Predicted Inflow*$_{d,t}$	0.00139**	0.00137**	0.00137**	0.00137**	0.00128**
	(0.00061)	(0.00063)	(0.00064)	(0.00064)	(0.00062)
N	8713	8713	8713	8713	8713
Dist. lin. trends FE	No	Yes	Yes	Yes	Yes
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
N. of districts	34	34	34	34	34
Mean Y	0.007	0.007	0.007	0.007	0.007

Notes. This Table presents the impacts of the IDP inflows on new polio cases per 100,000 inhabitants (in 2017) in host districts compared to non-host district. Districts whose territory falls within the pre-colonial region of *Pashtunistan* are part of the sample. The treatment timing starts in 2008. Observations are at the district and month level from 2001 to 2022. The baseline specification is presented in equation (1). Column (1) presents the results without district, year-month fixed effects and covariates. Column (2) includes district and year-month fixed effects. Column (3) controls for nightlight intensity and total vaccination campaigns. Column (4) controls for pre-treatment district-covariates (the average number of children under five, the average number of members in a household, and the total share of the literate population from 1973, 1981 and 1998 Population Census). Column (5) controls instead for contemporary characteristics (the average number of children under five, the average number of members in a household, shared households with piped water, and shared households with a finished floor). Panel A includes province linear trends, Panel B includes division linear trends and Panel C includes district linear trends. Robust standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A14: Pre-treatment individual characteristics, closer vs further districts

	(1) Further	(2) Closer	(3) Diff
polio vaccine	0.182	0.210	0.011
	(0.386)	(0.407)	(0.044)
doctor prenatal	0.208	0.256	0.044
	(0.406)	(0.436)	(0.050)
doctor assistance	0.161	0.214	0.049
	(0.368)	(0.411)	(0.035)
diarrhea	0.137	0.146	0.017
	(0.344)	(0.353)	(0.021)
fever	0.219	0.252	0.034*
	(0.414)	(0.434)	(0.019)
water piped	0.522	0.615	0.094
	(0.500)	(0.487)	(0.067)
toilet	0.311	0.456	0.158**
	(0.463)	(0.498)	(0.064)
floor	0.313	0.390	0.079
	(0.464)	(0.488)	(0.073)
television	0.352	0.485	0.139**
	(0.478)	(0.500)	(0.066)
watch tv every week	0.261	0.425	0.181**
	(0.439)	(0.495)	(0.072)
radio	0.437	0.488	0.040
	(0.496)	(0.500)	(0.039)
n. number children under 5	2.597	3.073	0.467***
	(1.538)	(2.045)	(0.118)
n. number household members	9.890	11.309	1.493**
	(5.442)	(6.494)	(0.685)
mother education level	0.302	0.374	0.091
	(0.713)	(0.785)	(0.082)
head working	0.112	0.072	-0.010
	(0.315)	(0.258)	(0.018)
head women	0.076	0.033	-0.049***
	(0.265)	(0.178)	(0.017)
urban	0.382	0.544	0.161
	(0.486)	(0.498)	(0.149)
girl	0.493	0.471	-0.027**
	(0.500)	(0.499)	(0.013)
pashtu	0.677	0.886	0.147
	(0.468)	(0.318)	(0.103)
Observations	4,043	2,290	6,333

Note: This table reports descriptive statistics for the main variables and sample considered in the baseline analysis. The analysis covers 39 district from 2001 to 2007 at the monthly level. For the pre-treatment analysis I restrict my timeframe from 2001 to 2007. Pre-treatment characteristics are from the 1991-1992 and 2006-2007 Demographic and Health Survey (DHS).

Table A15: Effect of IDP inflow on households' conditions

	(1)	(2)	(3)	(4)	(5)	(6)
	water piped	toilet	floor	N. children	N. members	head working
	PANEL A: Average effect					
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$	-0.089***	0.019	0.052**	-0.127*	-0.365	0.007
	(0.023)	(0.017)	(0.019)	(0.069)	(0.291)	(0.011)
	PANEL B: Heterogeneity IDP vs native children					
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$	-0.091***	0.019	0.051**	-0.124*	-0.389	0.008
	(0.023)	(0.018)	(0.019)	(0.070)	(0.295)	(0.011)
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$ * IDP	0.057**	-0.016	0.007	-0.087	0.766*	-0.030***
	(0.024)	(0.035)	(0.040)	(0.073)	(0.409)	(0.010)
Observations	13,544	13,544	9,570	13,544	13,544	13,519
Number of districts	38	38	38	38	38	38

Note: This Table presents the impacts of the IDP inflows on household characteristics. There are six different dependent variables: access to drinkable water (column (1)), access to a toilet (column (2)), floor quality (column (3)), number of children under five (column (4)), households member (column (5)), and head of the household working (column (6)). The dependent variables are a binary, coded to one if the household has a certain characteristic. We use individual-level data on household characteristics and the date of the interview from the Demographic and Health Survey (DHS) from 1998 to 2017. Households interviewed from January 2008 are exposed to the treatment. The baseline specification is presented in Equation 5, where we rely on within-district household variation. Panel A presents the baseline results. Panel B adds an interaction if a child is IDP. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Table A16: Effect of IDP population on other diseases

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	diarrhea	diarrhea	diarrhea	fever	fever	fever
	PANEL A: District fixed-effects					
2007 x Host district	-0.016			-0.148***		
	(0.033)			(0.036)		
Predicted Inflow		-0.020**	-0.020**		-0.024	-0.022
		(0.009)	(0.009)		(0.019)	(0.019)
Predicted Inflow x IDP			-0.027			-0.048***
			(0.020)			(0.016)
Number of districts	31	31	31	31	31	31
	PANEL B: Province fixed-effects					
2007 x Host district	0.016			-0.067**		
	(0.013)			(0.021)		
Predicted Inflow		-0.007	-0.006		-0.009	-0.008
		(0.006)	(0.006)		(0.007)	(0.006)
Predicted Inflow x IDP			-0.028***			-0.048***
			(0.006)			(0.005)
Number of provinces	7	7	7	7	7	7
Observations	10,623	10,623	10,623	10,623	10,623	10,623
Province FE	No	No	No	No	No	No
Time FE	No	No	No	No	No	No
Controls	No	No	No	No	No	No

Note: This Table presents the impacts of the IDP inflows on diarrhea and fever. I use individual level data from the Demographic health surveys. The outcome on diarrhea is equal to one if the child had diarrhea recently, zero otherwise. Fever is 1 if the child had fever the last two weeks. The baseline specification is presented in equation (2). Panel A shows the results with district fixed effects as in equation (2). In panel B, I control for province fixed effects. Standard errors are clustered at the province level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A17: Effect of IDP inflow on the demand and supply of health services

	(1)	(2)	(3)	(4)	(5)
	PANEL A: Demand health services				
	doctor prenatal		doctor assistance		
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$	0.028*	0.028**	0.051***	0.051***	
	(0.014)	(0.014)	(0.018)	(0.019)	
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$ * IDP		-0.006		0.004	
Observations	13,544	13,544	13,544	13,544	
District FE	Yes	Yes	Yes	Yes	
Cohort FE	Yes	Yes	Yes	Yes	
Controls	Yes	Yes	Yes	Yes	
Number of districts	38	38	38	38	
	PANEL B: Supply health services - Polio vaccination campaigns				
	polio activities				
$IDP\,Crisis_t$ * $Predicted\,Inflow_{d,p,t}$	0.100725***	0.032068	0.031307	0.056293***	0.043116***
	(0.009504)	(0.025081)	(0.024317)	(0.014158)	(0.011795)
Observations	10,296	10,296	10,296	8,976	6,516
District FE	No	Yes	Yes	Yes	Yes
Year-month FE	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Number of districts		39	39	34	38

Note: This Table presents the impacts of the IDP inflows on the demand and supply of health services. In Panel A we exploit individual-level data and investigate prenatal (columns (1) and (2)) and postnatal doctor assistance (columns (4) and (5)). We exploit the within-district cohort variation to identify the effects. Panel B shows the estimates of the predicted IDP inflows on district-level data on polio vaccination campaigns from the Polio Eradication Program. Robust standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1