Conflict, Forced Displacement, and Growth: Evidence from Uganda *

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Abstract

I study the long run economic impact of a large-scale forced displacement policy adopted by the government of Uganda during the civil war against the Lord's Resistance Army. This policy forcibly relocated approximately 90% of the affected districts' population into Internal Displacement Camps for up to ten years. The mass displacement led to a lasting increase in population density in the localities hosting camps, which persisted for nearly a decade after people were free to return to their villages of origin. Consequently, the spatial distribution of the population in Northern Uganda was shifted, altering the economic geography and growth in the region. Combining satellite data with novel administrative data, I document that forced displacement led to increases in nighttime light growth, market access, structural transformation and human capital, yet the effects were not distributed equally: while camps experienced population growth, it is the neighboring now-emptier localities experiencing increases in employment in services. These effects are primarily driven by selection and occupational sorting: educated individuals and those employed in services were more likely to return to neighboring non-camp localities once mobility restrictions were lifted. I find that the effects of forced displacement are stronger in cases where camps lasted longer, had higher population size, and experienced lower levels of conflict intensity.

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1 Introduction

Each year, millions of people are forcibly displaced from their homes as a result of conflict, repression, and other crises (UNHCR, IOM). Moreover, the number of people displaced within their countries has been steadily increasing, from 26 million in 2012 to 75.9 million in 2023 [1]. Given the large- and growing scale nature of displacement and its profound social and economic consequences, understanding the mechanisms through which it reshapes local economies and alters economic development across space is critical for designing effective policy interventions. Despite the prevalence of forced displacement, research on its impact on economic growth remains limited, particularly in agrarian and developing economies, where data constraints that hinder empirical analysis (Verme and Schuettler, 2021, Alix-Garcia et al., 2018). While conflict's effects on economic growth are well-documented, much less attention has been given to the economic consequences of displacement itself, especially in lower-income countries.

In this paper, I argue that large-scale displacement can be conceptualized as a sudden increase in urbanization, with potentially transformative effects on economic geography and regional development paths, particularly in low-income economies. If large-scale displacement functions as a sudden urbanization shock, it raises a fundamental question: can displacement-induced urbanization generate positive spillovers that partially offset the economic devastation of conflict? Moreover, under what conditions do these effects emerge, and how do they shape long-run development trajectories?

To answer these questions, I study an episode of mass internal displacement that took place in Northern Uganda during the civil war between the Ugandan government and the Lord's Resistance Army (LRA). The setting presents a quasi-natural experiment with a forced urbanization shock that led to the reshuffling of the majority of the population across space within that region: By the end of the war, almost 2 million residents had been evacuated by the Ugandan military forces into approximately 250 camps, where mobility was heavily restricted. This led to variation in the location, size, and timing of the camps being built. Parishes (one administrative unit above the village level) with camps hosted an average of 2.5 internally displaced persons (IDPs) in camps for every local resident. Locals of a parish were also displaced into camps. Thus, the scale and the nature of the shock make it ideal for causally identifying the

[1] Of which 68.3 million were displaced due to conflict and violence, according to the *2024 Global Report on Internal Displacement*

effect of forced urbanization in developing economies on economic development across space.

I find that forced displacement had persistent effects on spatial development and economic growth. First, displaced populations remained concentrated in camp-parishes nearly a decade after mobility restrictions were lifted, while neighboring (bordering) parishes experienced a population decline. Second, GDP as proxied by nighttime lights increased in *both* origin and destination locations. Also, GDP per capita was significantly lower in camp-parishes compared to the ones that lost population.Third, forced displacement led to changes in occupational composition, as bordering parishes saw a higher share of workers in services and a greater presence of educated individuals, which suggests sorting and positive spillover effects. I show that the positive effects of displacement are strongest when camps lasted longer, had larger populations, and experienced lower levels of conflict intensity. These findings contribute to the literature on forced migration, urbanization, and economic geography, providing new evidence on how large-scale displacement reshapes economic trajectories.

Understanding how displacement policies impact economic development and welfare is critical. Forced displacement is not only large in scale but also unfolds under extreme urgency, leaving little time for policy responses that shape the long-term trajectories of displaced populations and host communities. Furthermore, there does not seem to be a slow down in the number and intensity of conflicts worldwide, least of all in low-income countries. In fact, 46% of all IDPs in 2023 were located in Sub-Saharan Africa. Still, research on the impacts of forced migration on development in Sub-Saharan Africa is limited, partly due to the unavailability of microdata that covers internally displaced people over long periods of time (UNDP, 2022). A key component in the context of forced migration is, where should/do displaced people go? And how does the location where people have to stay, in a protracted state, affect how that region is developed? At the same time, little is also know about the locations that people flee from- how much do the displacement patterns play a role in their long-run economic growth? And what happens in general equilibrium? While much of the literature focuses on the effects of displacement on arrival locations, far less is known about what happens in places that experience mass outflows of people. The case of North Uganda provides a unique opportunity to study both: how host locations adapt to an influx of displaced populations and how origin locations evolve when they lose large portions of their residents.

To answer the question of how forced displacement affects economic development in the long-run across space, I focus on a specific episode of massive forced displacement that took place in Northern and Eastern Uganda between 1996 and 2005. During the civil war between the UPDF (Uganda People's Defense Force) and the LRA (Lord's Resistance Army), the government led by President Yoweri Museveni decreed that all residents of a locality at risk of being attacked (or recruited) by the LRA were forced to move into "protected villages" or Internal Displacement Camps. Civilians were only given between 24 and 48 hours to move to the nearest camp once the army reached their village. Moreover, not all people were displaced simultaneously: the timing of displacement depended mainly on factors related to the political environment and intensity of the conflict. Therefore, whereas many localities in the Acholi region were subject to the displacement policy starting 1996, others in different subregions only had IDP camps starting 2003. At the height of the displacement policy in 2005, there were 1,800,000 recorded IDPs living in 247 IDP camps. 93% of the population in these affected locations were displaced into camps.

I analyze the impact of forced displacement by distinguishing between inflows (parishes that hosted IDP camps) and outflows (parishes in direct proximity to camps). Using a Difference-in-Differences strategy, I compare parishes that directly experienced displacement (destinations and origins, i.e. camps and neighboring), to those that were further away from camps and had substantially lower displacement. The objective is to identify whether inflows and outflows of displacement have similar effects on the local economies in the long run- most papers studying the impacts of forced displacement can only investigate one or the other- and whether a different population distribution across space will lead to differences in economic outcomes, and whether there is a role for spillover effects.

A key contribution of this paper is the construction of a novel historical dataset. I compile data on camp locations and populations from WFP and UNOCHA reports, digitize road maps from 1992, and recover previously unused 1991 census data from the Uganda Bureau of Statistics, which is representative at the village-level. This allows me to construct a parish-level panel dataset across multiple censuses, enabling a more granular analysis of displacement's effects on economic development.

Using this novel dataset, I proceed to establish a set of facts that show the effect of forced displacement on economic outcomes across the region.

I begin by verifying that forced displacement led to a persistent shift in population distribution, not only increasing camp-parish populations during the war years but also nearly a decade after mobility restrictions were lifted. Population growth was 12% higher in camp-parishes compared to those with no displacement, and 9% lower in the bordering (neighboring) parishes. In the aftermath of the displacement policy, the World Bank and several other NGOs aiding the government of Uganda became involved in the reconstruction of affected regions and built road infrastructure. Only three years after free mobility was reinstated, roads increased by 30% in camp-parishes, whereas those bordering did not experience any change in road infrastructure compared to the no displacement parishes. We can conclude thus that market access increased in the camp-parish locations compared to everywhere else in the region.

Second, I analyze the effects of displacement on GDP as proxied by nighttime lights. I find that an inflow of people leads to an increase in GDP growth in the long run, which indicates that there was an increase in economic activity in camp-parishes. Whereas this may be intuitive and reassuringly in line with predictions of models of urban economics (Quigley, 2009, Duranton and Puga, 2023), I find that an outflow of people *also* led to an increase in GDP. Not only that, but also the increase in GDP per capita is higher in bordering parishes. This result seems puzzling at first glance.

To determine why GDP increased despite population decline in bordering parishes, I explore three potential mechanisms. First, the displacement policy may have improved market access not only in camp-parishes, but also in the bordering parishes at direct proximity from the former. Second, population composition may have changed after mobility restrictions were lifted, with individuals who chose to return contributing more to economic activity in their origin parishes. In other words, sorting across locations—whether by occupation, skill level, or other characteristics—may have played a role in driving economic growth. The nature of this sorting is also important to understand what specifically is driving this growth, i.e whether this sorting is based on occupation, skill, or other factors. Finally, land tenure conflicts may have introduced frictions that hindered land use and agricultural productivity. Individuals displaced for up to a decade may have returned to find their land occupied by others, leading to disputes that could result in land remaining unclaimed, underutilized, or even abandoned altogether, further disrupting agricultural and economic activity in affected areas.

Although bordering parishes saw limited direct road construction, using a network-based market access approach, I find that the displacement policy led to a relatively higher increase in how connected these parishes were compared to camp-parishes and no displacement parishes. Specifically, these bordering parishes became more strategically positioned *in between* other locations. This means that it is likely that the bordering parishes experienced positive spillover effects from increased market activity in the camps.

Moreover, I find that displacement led to an increase in the share of people working in services in the bordering parishes compared to those in no displacement parishes. Unexpectedly, and contrary to standard urban economics predictions, a similar relative increase is not detected in the camp parishes despite the increase in population and in GDP growth. Likewise, the share of people with higher levels of education increased in bordering parishes, providing further evidence for the sorting hypothesis, as more educated individuals appear to choose to live there. These findings imply that while displacement may have increased economic activity, the structure of employment and human capital accumulation across space were altered by it. This suggests that bordering parishes benefited from spillovers and selection effects, whereas camp-parishes—despite population growth—did not experience the same relative gains in service employment or education levels. This divergence may be driven by relative changes in market access, mobility costs characterized by conflicts related to land tenure, etc...

Finally, while conflict related to land tenure may have played a role in the decisions of IDPs to return to their home villages, I do not find empirical evidence to establish a direct causal link between forced displacement and changes in land use from satellite data.

To identify under which conditions camps may serve as a driver of economic growth, I conduct a heterogeneity analysis, focusing on how conflict intensity, camp size, and camp duration shape development outcomes. I find the effect of forced displacement on development outcomes to be stronger in the cases where camps (i) lasted longer, (ii) had higher population size, and (iii) experienced lower levels of conflict intensity. These results suggest that security, scale, and time horizon play crucial roles in determining the long-run economic impact of forced displacement. Understanding these dynamics is essential for designing policies that mitigate the costs of forced migration while harnessing its potential to reshape economic geography in conflict-affected regions.

2 Related Literature

3 Historical Background

Uganda's post-independence period was marked by prolonged violence and political instability. While the country achieved relative stability after the National Resistance Army seized power in 1986, Northern Uganda remained a hotspot for rebel movements. The most prominent among them was the Lord's Resistance Army (LRA), led by Joseph Kony. The LRA engaged in a violent guerrilla war against the Ugandan government, primarily targeting civilians in the Acholi region.

They employed tactics such as surprise attacks, abductions, and the use of child soldiers to terrorize Acholi civilians and undermine the central government. These tactics served both to weaken local support for the government and to sustain the rebel movement through coerced recruitment. As LRA abductions escalated in the late 1990s, the Ugandan government implemented a mass displacement strategy, relocating civilians into so-called "protected villages" or Internal Displacement Camps. Beginning in 1996, residents in conflict-affected areas were given between 24 and 48 hours to vacate their homes and report to designated camps. Those who failed to comply risked being classified as rebels and shot by government forces. Unlike other conflicts where displacement is often influenced by economic or geographic factors, in Northern Uganda, most displacement resulted from random attacks or government mandates (Blattman and Annan, 2010; Bozzoli, Brück, and Muhumuza, 2011).

The majority of violence and displacement occurred in the Acholiland region, expanding to the Lango and Teso regions in 2003. By the end of 2005, the number of displaced persons peaked, affecting over 1,800,000 Ugandans (UNHCR, 2011). In 2006, the LRA signed a Cessation of Hostilities Agreement with the Ugandan government, initiating the return from displacement. Despite challenges and Joseph Kony's withdrawal from peace talks in 2008, the population in IDP camps decreased significantly by the end of 2009, and camps were disbanded (UNHCR, 2009, 2011).

Throughout the displacement and return period, humanitarian interventions were conducted by NGOs and international organizations, particularly the UN Development Program and World Food Program.

In 2004, the Ugandan government published, and officially launched in February 2005, the National Policy for Internally Displaced Persons, which implied that once conflict ceased in the area of origin, camp residents would be free to return (voluntarily). Peace talks were held in 2006, and camp closures began swiftly in the areas where the conflict had ceased[2].

In the years following the cessation of hostilities, the Ugandan government actively encouraged the return of displaced persons, providing returnees with tools, seeds, and building materials to facilitate reintegration into their home communities. By 2010, more than 90% of displaced individuals had returned to their original villages or had resettled somewhere different, while approximately 182,000 people remained in camps or transit sites (Internal Displacement Monitoring Centre, 2010). Although formal camp closures accelerated, the return process varied significantly across regions, influenced by security concerns, land disputes, and access to basic services.

What happened to camps after the war ended? The return process varied widely, with household decisions influenced by factors such as prior exposure to violence, family composition, and access to services in camps. While many displaced individuals eventually returned to their villages, others remained in the former camps, contributing to the emergence of semi-urban settlements. Whyte et al., 2014 describes how some camps evolved into permanent trading centres: "As peace returns to northern Uganda, a unique arithmetic of development is evident in the former Internally Displaced Persons camps. Small trading centres whose populations multiplied as they became camps now envision futures as Town Boards." New roads were constructed, and schools and hospitals built to support the camps remained in use after displacement ended. However, the time in displacement introduced complex land tenure disputes. Many returnees struggled to reclaim their ancestral land, as property boundaries had eroded over time, and younger generations lacked formal documentation. The absence of clear land demarcation led to ownership disputes, which further complicated recovery in the region.

4 Data and Descriptive Statistics

4.1 Data Collection

A major contribution of this paper is accessing and recovering Uganda's 1991 Census from the Uganda Bureau of Statistics, which was previously deemed corrupted. Although 10% sample with sub-county information is publicly available in IPUMS,

[2] "Identification of camps selected for phase-out and closure: A threshold of a 50% of population departure was used to raise the discussion on camp phase-out and closure. A mixed committee of national officials and humanitarian actors determined whether a camp should be officially closed and if phase-out activities should be initiated".
Source: https://reliefweb.int/report/uganda/uganda-camp-closure

the original data with detailed geographic information was said to be irretrievable when this author inquired. With the help of the UBoS IT department [3], we managed to recover the back up files and sample 10% of the data as per the bureau's policy. The sample census is representative at the village level. However, since the recovered data is a back up of the original dataset, it required heavy processing until it arrived at an appropriate state for data analysis. Moreover, the data had to be linked joint with the rest of the data in this project. In this section I explain the methodologies I used to link parishes across census years, and how I recovered the labels of parish identifiers in 1991, which were not available in the data.

4.1.1 Linking Locations over Time

To the best of my knowledge, no prior effort has been done to link parishes across census years, including year 1991. The main concern is that as administrative boundaries have changed over time (Uganda went from having 38 districts to 135 today), without any geographic references (and there are none at the parish level prior to 2002) it would be impossible to match parishes over time. As it turns out, even though higher level administrative units have changed (districts, counties, and subcounties), the smallest units have to the most part remained unchanged: in Northern Uganda, the number of parishes changed from 959 in 1991 to 1,194 in 2002. The first step therefore is to match all the parishes from 1991 to those in 2002. In order to do so, I use the `fuzzywuzzy` package in python to do within-district matching of parishes by name. I do so for all of Uganda using a list of all parish names and populations from booklets in the UBoS library that I digitized using an OCR (Optical Character Recognition) program.

This does not result in a perfect mapping, because even within the same district, there are parishes with the same name, resulting with duplicate false matches.

To clean up the duplicates, I filter the data into sure and problematic matches by using information on the counties and subcounties across the years (which is not enough to get perfect matches for the full sample because of the changing administrative boundaries). I am able to match 3707 parishes in 1991 out of 4003. In the region affected by the war (Northern Uganda plus the Teso subregion), 1,246 parishes out of 1,320 in 1991 were matched to a parish in 2002. (94.39% success rate). Unfortunately, the number of parishes in this region increased to 1,734 in 2002. Which means that with the matches we're covering 70% of the 2002 parishes. In terms of population,

[3] A very special thanks to Allan Agaba and Akbar Kanyesigye.

we're covering 67% of the 1991 population in the 2002 parishes.

To understand how severe this issue is, I plot the matched and unmatched parishes on a map. The map in Figure 1 shows that although there is some cause for concern, most of the unmatched parishes lie on the borders and the periphery of the region, probably since these regions were mostly uninhabited natural reserves. A cause for concern is that there is differential attrition due to parishes being split for administrative reasons purposefully because of population size. Since we are using the boundaries from 2002 which are prior to free mobility, some these concerns are not as harmful. Ideally we should be using 1991 borders, but this data doesn't exist. To understand the extent of attrition bias, I calculate the probability of a missing parish by whether of not a parish has been classified in our treatment (whether there is a camp, bordering, or neither). i.e $\mathbb{P}(Match = 0|Class)$, and find that there is indeed some attrition such that we were able to match significantly less Bordering parishes and No Displacement parishes in 2002 than camp parishes.

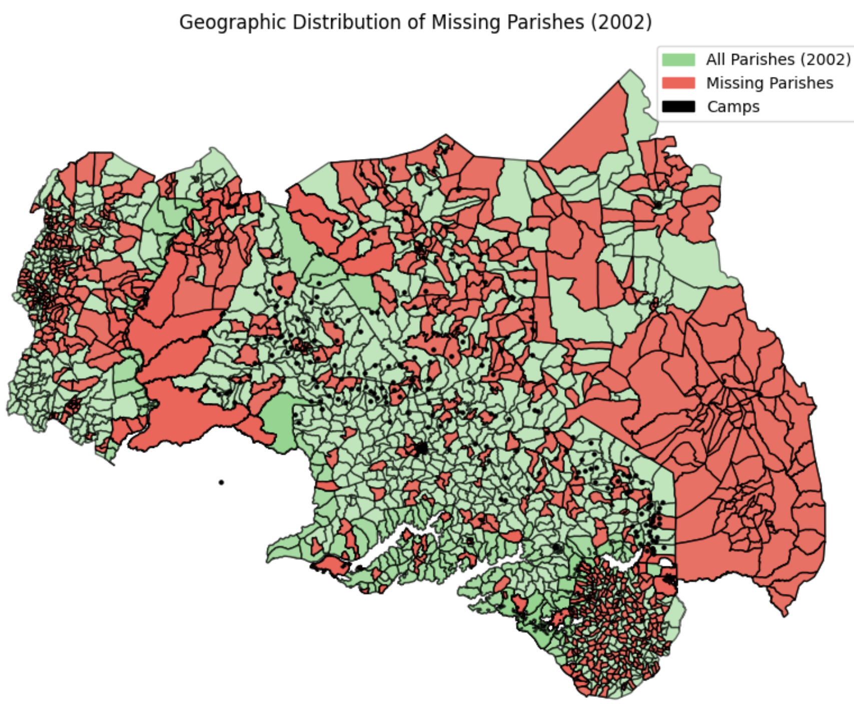


Figure 1. Matched Parishes

For matching parishes across 2002 and 2014, I use the cross-walks developed by Zhou, Grossman, and Ge, 2023.

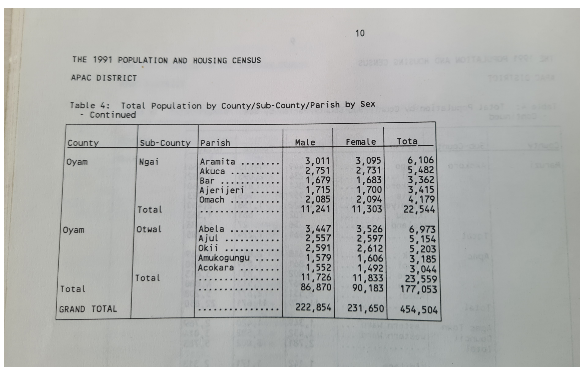
Table 1. Matching parishes over time- Differential Attrition Test

$Class_1$	$Count_1$	$\mathbb{P}(Match = 0 \mid Class_1)$	$Class_2$	$Count_2$	$\mathbb{P}(Match = 0 \mid Class_2)$	t-Statistic	p-Value
Bordering	307	0.407	Camp	176	0.278	2.926	0.004
Bordering	307	0.407	No Displacement	612	0.493	-2.493	0.013
Camp	176	0.278	No Displacement	612	0.493	-5.450	0.000

Notes: Sample includes all parishes that experienced conflict. Mean values represent the probability of a parish in 2002 not having a match (by name) in 1991.

4.1.2 Recovering Parish Identifiers

A big impediment in linking parishes across time was that the recovered 1991 Census data contained only parish IDs, not names. To resolve this, I used the digitized historical census reports from the UBoS library, which listed both parish names and populations (see Figure 2). I then matched parish IDs to names using population ranks, successfully recovering 3,997 out of 4,003 parishes [4].



10

THE 1991 POPULATION AND HOUSING CENSUS

APAC DISTRICT

Table 4: Total Population by County/Sub-County/Parish by Sex
- Continued

County	Sub-County	Parish	Male	Female	Tota
Oyam	Ngai	Aramita	3,011	3,095	6,106
		Akuca	2,751	2,731	5,482
		Bar	1,679	1,683	3,362
		Ajerijeri	1,715	1,700	3,415
		Omach	2,085	2,094	4,179
	Total	....	11,241	11,303	22,544
Oyam	Otwal	Abela	3,447	3,526	6,973
		Ajul	2,557	2,597	5,154
		Okii	2,591	2,612	5,203
		Amukogungu	1,579	1,606	3,185
		Acokara	1,552	1,492	3,044
	Total	....	11,726	11,833	23,559
Total		....	86,870	90,183	177,053
GRAND TOTAL		....	222,854	231,650	454,504

Figure 2. 1991 Parishes from Census Report

Once the censuses of 1991, 2002, and 2014 are merged, I can study changes in outcomes related to education, occupation, housing quality, and other demographics.

4.2 Data Sources

Conflict Data

To measure exposure to conflict, I employ data from the Uppsala Conflict Data Program Geo-Referenced Events Dataset (UCDP GED). Developed with the objective of providing the academic community with comprehensive spatial and temporal information on violent events from 1989 onwards, this dataset encompasses crucial

[4]I am missing the Mbarara district which has 125 parishes, for which I could not find the 1991 report

details for each event, including location, date, type, and the number of fatalities. An event is defined as an occurrence where armed force is used by an organized actor against another organized actor or civilians, resulting in at least one direct death at a specific location and date (Sundberg and Melander, 2013).

Camp Data

Camp location data was taken from maps produced by the UN Office for the Coordination of Humanitarian Affairs (UNOCHA) (Coordination of Humanitarian Affairs, 2009), and camp population data was taken from WFP (World Food Programme) reports (WFP Uganda, 2005).

Infrastructure and Geospatial Data

I obtain historical road data by digitizing maps from the *Uganda Districts Information Handbook 1992* (Rwabwogo, 1992). Figure A1 demonstrates a sample of the maps, which includes not only the roads and their classification (murram, tarmac, or railway lines), but also the locations of trading centres and district headquarters. In addition, I use 2009 road data extracted from OpenStreetMap. From OpenStreetMap I also export data on waterway locations in Uganda.

To proxy for GDP, I use a harmonized timeseries of nighttime light data spanning the years 1992-2018 from Li et al., 2020.

4.3 Descriptive Statistics

Table 2 shows the number of camps in the sample and the number of parishes with camps, as well as how many parishes are classified as "Bordering Parishes", which refers to the parishes from which people were most likely displaced (or in other words, the origin). The main sample of our analysis restricts the 1,734 parishes in North-East Uganda to only those that are within 10km of a conflict event that took place since 1989, to ensure a more balanced sample and such that the interpretation of results is always conditional on the occurrence of conflict.

Table 2. Sample of Camps and Parishes

	N
Camps	247
Parishes with Camps	175
Bordering Parishes	314
No Displacement	567

In Table 3, I compare the characteristics across parishes in Northern Uganda that have camps, those that are bordering, and those that do not fall in either category, which I consider did not experience any displacement of the population.

It shows that parishes with camps, and those bordering, had higher population in 1990 than those that experienced no displacement, but that the former two are not statistically different in that aspect. In terms of nighttime light intensity, which I use as a proxy for GDP, I find no difference between parishes with camps and others, but parishes with camps do have higher road length within their area than the other two categories, which speaks to the fact that camps were initially constructed where trading centres were located.

Table 3. Parish Characteristics

	(1) No Displacement		(2) Camps		(3) Bordering		(1)-(2)		(1)-(3) Pairwise t-test		(2)-(3)	
Variable	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference	N/Clusters	Mean difference	N/Clusters	Mean difference
Log Population 1990	567	7.389	175	7.828	314	7.725	742	-0.438***	881	-0.335***	489	0.103
	567	(0.036)	175	(0.055)	314	(0.043)	742		881		489	
Log Nighttime Lights 1992	567	0.003	175	0.020	314	0.045	742	-0.017	881	-0.041***	489	-0.024
	567	(0.002)	175	(0.011)	314	(0.015)	742		881		489	
Road Length 1992	567	38619.997	175	52858.595	314	48612.005	742	-1.42e+04***	881	-9992.008***	489	4246.591
	567	(2212.588)	175	(2537.213)	314	(2403.124)	742		881		489	
Area	567	4.46e+07	175	6.75e+07	314	7.06e+07	742	-2.29e+07***	881	-2.60e+07***	489	-3.09e+06
	567	(3.63e+06)	175	(3.84e+06)	314	(5.18e+06)	742		881		489	
Mean Elevation	567	1125.692	175	1046.971	314	1047.926	742	78.721***	881	77.767***	489	-0.955
	567	(7.059)	175	(5.319)	314	(4.710)	742		881		489	
Distance to Border	400	339.721	71	330.110	167	336.817	471	9.611	567	2.904	238	-6.707
	400	(5.216)	71	(14.327)	167	(8.622)	471		567		238	
Pre-war Conflict	567	7.640	175	25.097	314	18.497	742	-17.457***	881	-10.857***	489	6.600
	567	(0.675)	175	(3.361)	314	(2.299)	742		881		489	
During war Conflict	567	19.300	175	144.046	314	117.873	742	-124.746***	881	-98.573***	489	26.173*
	567	(1.732)	175	(11.255)	314	(7.716)	742		881		489	
Livestock Activity 1990	567	15.261	175	0.212	314	1.238	742	15.049***	881	14.023***	489	-1.026**
	567	(1.221)	175	(0.084)	314	(0.391)	742		881		489	
Agricultural Activity 1990	567	66.623	175	70.289	314	67.145	742	-3.666	881	-0.522	489	3.144
	567	(1.462)	175	(2.194)	314	(1.822)	742		881		489	
Urban - settlement 1990	567	0.617	175	0.097	314	0.443	742	0.520*	881	0.174	489	-0.346***
	567	(0.275)	175	(0.035)	314	(0.127)	742		881		489	
Unused Land 1990	567	8.787	175	11.532	314	12.242	742	-2.745	881	-3.455**	489	-0.710
	567	(0.732)	175	(1.508)	314	(1.133)	742		881		489	
Protected Land 1990	567	7.279	175	0.203	314	0.565	742	7.076***	881	6.713***	489	-0.362**
	567	(0.771)	175	(0.072)	314	(0.162)	742		881		489	

Notes: Standard errors clustered at the parish level. Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006. ***p<0.01, **p<0.05, *p<0.1.

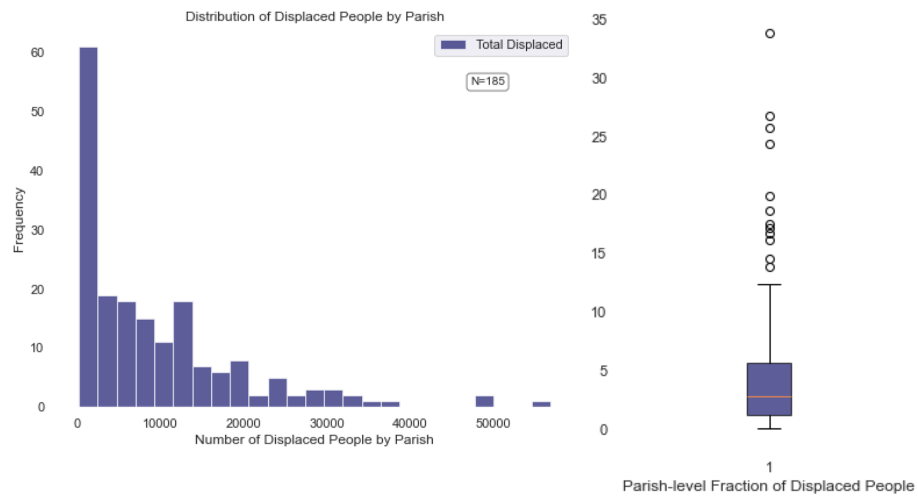
Regarding the characteristics of camps and their hosting localities, Figure 3a shows that there is much variation in the number of displaced people in camps in different parishes: camps hosted between 1,500 and 57,000 people, and Figure 3b demonstrates that across camps, there is a lot of variation in camp population: on average, a parish that hosted displaced people had on average 2.5 times its original population in camps, but the ratio of IDPs to original population is skewed to the right such that it could reach 25.

With regards to conflict experienced by parishes across the different parishes in our sample, there is also variation in both the intensity and timing of the conflict, and thus the durations of displacement. Figure **??** decomposes the conflict timeline across different affected subregions in Northern and Eastern Uganda.

Figure 3

(a) Camp Population Distribution

(b) Camp Population Distribution



5 Empirical Analysis

In this section, I document empirically how parishes with camps grew compared to those without camps- whether they are bordering parishes with camps, and thus were the origins of the increased camp population, or if they were further away such that displacement is unlikely.

5.1 Extensive margin: Camp existence

I start by employing the following specification to identify the effect of displacement on urbanization and growth:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times Camp_p + \beta_2 \times Bordering_p + \beta_3 C_{p,t} + \beta_4 Y_{p,1992} + \delta + X_{p,1992} + \epsilon_{p,t} \quad (1)$$

where $\Delta Y_{p,t}$ represents the change in logs of the outcome of interest (population, road length, or nightlight intensity), $Camp_p$ and $Bordering_p$ are indicators for whether the parish p has a camp or if it borders one with a camp, respectively. $C_{p,t}$ indicates the intensity of conflict in the years leading up to time t, $Y_{p,1992}$ is the initial value of Y before displacement to control for baseline differences that have permanent influence on the evolution of the outcome [5], δ represents district fixed effects to absorb the

[5]Since Table 3 indicates, that the sample remains unbalanced, it's important to control for the baseline characteristics that have permanent influence on the outcome variables. Since the

effects that stem from different conflict and displacement timings at the district level, and $X_{p,1992}$ indicates controls for parish characteristics before the start of the IDP policy, such as how isolated the parish was, population and area, urban population. Standard errors are clustered at the parish level.

The identification assumption required is that conditional on locations experiencing conflict, and with similar geographic and socioeconomic characteristics, then the parishes at close proximity of a camp (the bordering) were just as likely to have a camp assigned to them as the parishes that actually received the camp. I make sure to condition on initial economic conditions that may affect the growth path of parishes, since I don't have observations to control or observe trends in outcomes before treatment. In addition, I add district fixed effects and cluster standard errors at the district level because this is the most accurate notion I would have for a temporal indicator of displacement, since parishes within district were probably treated at the same time, and the conflict progressed differently across 10 years and across space. To ensure parishes in the analysis are statistically similar prior to treatment, I restrict my sample to parishes within 30km of a camp that have experienced conflict within 10km[6]. A detailed description of the methodology used in the sample selection is in the Appendix B.1. Furthermore, to ensure that the allocation of *Camp* as a treatment is random, I perform a prediction exercise using Machine Learning methods (Random Forest and Histogram Gradient Boosting models). Both models are unable to predict camp allocation to a parish (reaching only between 33% and 46% precision scores at best). The results and methods used for treatment prediction allocation are in Appendix B.2.

Results

Table 4 shows that with respect to parishes that had no displacement, parishes with camps grew by 10.23% in terms of population whereas bordering parishes experienced 16.6% less growth in terms of population. In terms of infrastructure, results show that parishes with camps had 22.8% higher road length growth, and when it

displacement policy allocated people to different parishes without regard to the original population size, and there is much variation in the latter, the question is how displacement lead to a persistent or transitory change in the growth path of locations. I focus on this question later on in the paper.

[6]In the World Bank report (Utz Johann Pape and Sharma, 2019), the authors use microdata to describe internal displacement patterns in 4 countries in Sub-Saharan Africa. They conclude that most IDPs stay near their places of origin- "In both South Sudan and Somalia, most IDPs (about 70 percent) report being displaced in the same district where they originally lived. In Nigeria, 95 percent of IDPs are displaced within the same state, regardless of whether they are in camps or living among host communities. Similarly, in Sudan, most IDPs did not travel far: 97 percent lived in the same state, North Darfur, before displacement as they do now."

Table 4. Population Growth, Infrastructure, and GDP Growth

	Population Growth (1)	Road Length Growth (2)	Light Growth (3)	GDP per Capita Growth (4)
Camps	12.487**	33.645***	30.780***	18.292*
	(6.088)	(7.464)	(7.641)	(10.155)
Bordering	-9.052	2.968	22.699***	31.751***
	(5.508)	(5.735)	(6.705)	(8.995)
lnpop90	-56.828***	11.028***	8.785***	65.613***
	(2.736)	(2.117)	(2.570)	(3.910)
Camp = Bordering	0.000	0.000	0.142	0.056
Mean (No Displacement)	88.404	19.726	78.400	-10.004
N	1773	1773	1773	1773

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, nighttime light, shares of land use used in agriculture, urban settlement, and abandoned land.
Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

comes to GDP, places with camps and bordering parishes experienced around 18% more GDP growth than parishes that had no displacement, but that there is no statistical significance in terms of differences in GDP per capita growth across origin parishes and camp parishes. The sample is composed of all parishes that have experienced conflict.

Given that the conflict did not progress homogeneously across the region (neither with timing nor intensity) as shown in **??**, meaning that the duration of displacement also varied spatially, we can leverage this variation to study how the duration of displacement plays a role in the development of a parish. Therefore, I run the same regression as in 1 but this time also including an interaction term between each district and the $Camp_p$ variable. I find that the results in Table 4 mask wide heterogeneous effects by district.

Population Persistence

Moreover, the change in population was not temporary, rather persistent. To show this, I perform an event study on population.

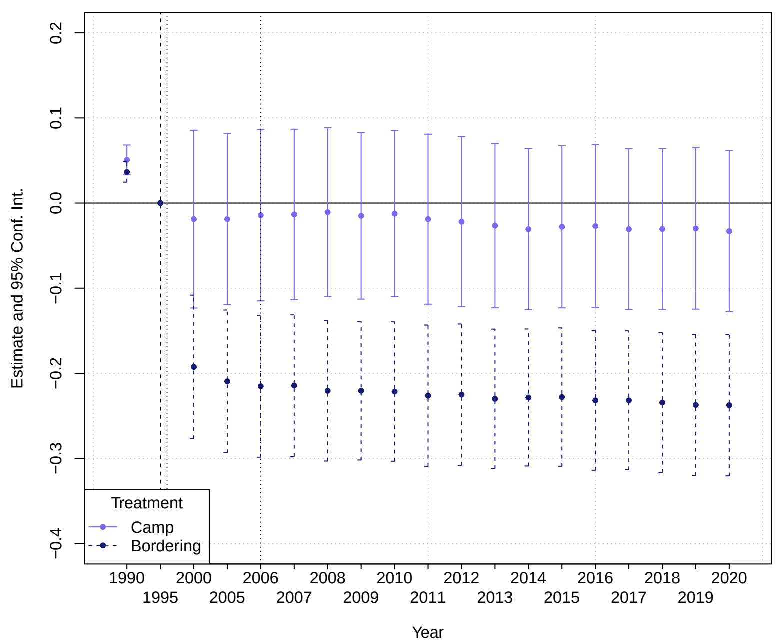
Although several parishes received significantly high numbers of displaced people compared to their original population (see Figure 3b), it's not clear whether an initial shock is transitory or permanent, and thus whether it is sufficient to give rise to urbanisation. Therefore, it's important to understand under which conditions people could choose to stay or go back to their rural homes.

I run the following two-way fixed effects regression:

$$Population_{p,t} = \beta_0 + \sum_{\tau=0}^{T} \beta_\tau Camp \times \tau_t + \sum_{\tau=0}^{T} \gamma_\tau Bordering \times \tau_t + \delta X'_{p,t} + \lambda_p + \epsilon_{p,t} \quad (2)$$

with the displacement event taking place at $\tau = 0$, corresponding to the year 1996. The corresponding coefficients are plotted in Figure 4.

Figure 4. Event Study of Log Population



Notes: Standard errors clustered at the parish level. Period of displacement, indicated between the dotted vertical lines, is in the interval (1996, 2006).

5.2 Land use and land access

To gain a deeper understanding on what could be causing a change in the level of growth upon displacement, it's important to investigate how land, the most valuable asset in rural areas, is being used.

Using data from Mwanjalolo et al., 2018 that classifies land in Uganda into 29 different land use categories. I study how subsistence agriculture, commercial agriculture, grassland and bushland, and urban settlement land shares changed over time across parishes with camps, bordering parishes, and those with no displacement within 30km of the camps.

Although there is little variation in the land shares across parishes in our sample, we can still make inference on how land use is changing over time for some of the land categories. The regression results in Table B3 following the specification 1 (not including district fixed effects because it washes out variation in land shares by category) show that the share of land used for subsistence agriculture decreased by 14.6% in parishes with camps compared to No Displacement parishes. Although there is an increase in land being used for urban settlements in camps by 7.2%, this is only significant at the 13% level and bordering regions, confirming previous results that there is an increase in population in parishes with camps, and also an increase in roads passing through bordering parishes. There is a 12% increase in livestock activity in parishes with camps, in comparison with both, No Displacement and Bordering parishes. This could indicate an increase in assets

Importantly, there is an increase in the share of unused land by 41% in camps and 32% in bordering parishes compared to parishes with no displacement. This land is composed of unprotected bushlands and grasslands- lands where there is no agriculture, pasture activities, and are not protected for conservation reasons. This indicates there is more land being abandoned and left behind in parishes that had camps and were bordering camps. Whereas this is accompanied with an increase in land being used for livestock, and urban settlements in places with camps, and a decrease in the share of agricultural activity, which consisted of around 50% of the share of land in 1990 (the category with the highest land shares).

5.3 Forced Displacement and Market access

Market access and infrastructure are key drivers of long-term economic growth. To understand how internal displacement could affect development in the medium-long run, therefore, we need to investigate how market access developed in the wake of displacement. In Table 4 column (2), we find that road length grew significantly more in parishes that had IDP camps. This suggests that there were changes in the road network as a response to the construction of camps and the movement of people.

To verify this, I define a network of parishes P, where any two parishes are connected if there is a road that passes through both of them. I also define a weighted

Table 5. Changes in Land Use

	Livestock Activity (1)	Agricultural Activity (2)	Urban - settlement (3)	Unused Land (4)
Camps	0.397***	0.089	-0.050	-0.150**
	(0.042)	(0.073)	(0.056)	(0.067)
Bordering	0.356***	0.152**	-0.090*	-0.247***
	(0.036)	(0.059)	(0.053)	(0.055)
Camp = Bordering	0.155	0.353	0.417	0.185
Mean (No Displacement)	-1.009	0.063	0.005	-0.728
N	1773	1773	1773	1773

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, initial population, road length, nighttime lights, shares of land being used for agriculture, unused land, urban settlements.
Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006. ***p<0.01, **p<0.05, *p<0.1.

version of this network, where each edge (the connection between two parishes) is weighted by the product of the populations in both locations, to give a better sense of market access. Table 6 shows regression results where the outcome variables are the log change in the centrality level of a parish. Column (1) demonstrates the growth in degree centrality, defined as the number of nodes that each parish is connected to directly, as a fraction of all the nodes in the graph.

$$DC(p) = \frac{d_i(p)}{n-1}$$

Betweenness centrality measures how well located a parish is, in terms of the paths it lies upon. A ratio close to 1 indicates that a parish lies on most of the shortest paths connecting any other 2 parishes:

$$c_B(p) = \sum_{s,t \in P} \frac{\sigma(s,t|p)}{\sigma(s,t)}$$

where P is the set of parishes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|v)$ is the number of those paths passing through some node v other than s,t. If $s = t$, $\sigma(s,t) = 1$, and if $v \in s,t$, $\sigma(s,t|v) = 0$

Another measure of centrality is closeness, which expresses how close a parish is to any other parish in the network:

$$C(p) = \frac{1}{\sum_{u \in P} l_{p,u}} \tag{3}$$

where $l(p, u)$ indicates the shortest path distance between u, p nodes.

Table 6. Camps and Evolution of Parish Network Centrality

	Degree Centrality (1)	Betweeness Centrality (2)	W. Betweeness Centrality (3)	Closeness Centrality (4)	W. Closeness Centrality (5)	Page Rank Centrality (6)	W. Page Rank Centrality (7)
Camps	0.058***	0.893***	0.187	0.407***	102.900	0.011***	0.014***
	(0.012)	(0.327)	(0.522)	(0.123)	(62.649)	(0.003)	(0.004)
Bordering	0.038***	0.798***	0.937**	0.326***	118.355**	0.008***	0.009**
	(0.011)	(0.281)	(0.476)	(0.117)	(59.011)	(0.003)	(0.004)
Camp = Bordering	0.019	0.747	0.035	0.295	0.708	0.240	0.086
Mean (No Displacement)	0.059	0.517	0.666	1.141	405.254	0.000	0.000
N	1056	1056	1056	1056	1056	1056	1056

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, nighttime lights, initial share of agricultural land and unused land.
Sample includes all parishes within 30km of a camp that have experienced conflict within 10km between 1991 and 2006.
***p<0.01, **p<0.05, *p<0.1.

Table 6 presents the regression results for the log change in centrality measures between 1992 and 2009. Parishes hosting camps experienced significant increases in degree centrality (column 1), with a 3.5% growth, indicating that they became more directly connected in the road network compared to non-displaced areas. This suggests that camps acted as hubs, facilitating greater connectivity through expanded infrastructure.

The significant positive result for unweighted betweenness centrality in bordering parishes suggests that these areas became more strategically located in the road network, acting as critical intermediaries between other parishes. This means that in terms of physical location and road connections, both camp parishes and bordering parishes became more central in facilitating movement. However, the fact that weighted betweenness centrality is not significant in the case of camps suggests that although camps were located in physically strategic areas (captured by the unweighted version), the population-weighted significance of these paths was not as high relative to the No Displacement and Bordering parishes.

Closeness centrality (column 4) shows significant increases for camp parishes. The log change in closeness centrality when accounting for population suggests that these parishes became more central in terms of accessibility, but the result is not significant.

Finally, both weighted and unweighted Page Rank centrality (columns 6 and 7) grew significantly for camp parishes, reinforcing the idea that camps became central nodes in the overall network.

To conclude, the disparity between the unweighted and weighted centrality measures reflects the distinction between physical connectivity and economic significance. While camps and bordering parishes became important physical connectors in the network, the linkages they facilitated were not necessarily economically dominant when population size is considered. This suggests that while infrastructure expanded, it may not have been accompanied by substantial population growth in the parishes connected by these roads.

5.4 Individual-level Results: Structural Change and Human Capital

We have already shown that parishes with camps experienced higher urbanization rates and received more roads than places with no displacement and those bordering. Furthermore, parishes with camps experienced slower growth in agricultural activity, and higher growth in livestock activities, accompanied with an increase in unused-unprotected land.

One might ask, is the increase in urbanization due to camps accompanied by different structural transformation patterns? Michaels, Rauch, and Redding, 2012 find empirical evidence that urbanization and structural transformation are highly correlated, arguing that urbanization plays a critical role in whether structural transformation occurs, and emphasizing that it's the initial population that matters for whether structural transformation and growth take place.

In this section I try to go one step further to study whether we can identify a causal link such that urbanization leads to structural transformation, in the context of forced displacement.

To do so, I make use of occupation and education data across the census years.

Using the census data, I can run the following logistic difference-in-difference regression:

$$\log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \alpha + \beta_1 \text{Camp}_p + \beta_2 \text{Bordering}_p + \beta_3 \text{Post}_t + \beta_4(\text{Camp}_p \times \text{Post}_t) + \beta_5(\text{Bordering}_p \times \text{Post}_t) + \mathbf{X_i}\gamma + \epsilon_i \tag{4}$$

Where:

- $P(Y_i = 1)$ is the probability that individual i is in an agricultural occupation
- $\log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right)$ is the log-odds of the outcome, which is the logarithm of the ratio between the probability of being in the occupation category (agriculture) and the probability of not being in that category (non-agriculture).
- $\beta_4(\text{Camp}_p \times \text{Post}_t)$ captures how the effect of being in a camp parish changes after displacement.
- $\beta_5(\text{Bordering}_p \times \text{Post}_t)$ captures how the effect of being in a bordering parish changes after displacement.
- $\mathbf{X_i}\gamma$ is a vector of control variables for individual-level characteristics (age, gender, education), with γ representing the associated coefficients.
- ϵ_i is the error term, capturing the unexplained variation in the model for individual i. Standard errors are clustered at the parish level.

Table 7. Agriculture Linear Probability Model

	Agriculture	Agriculture	Agriculture
Post Displacement	-0.099***	-0.048	-0.042
	(0.007)	(0.031)	(0.031)
Camps×Post Displacement	0.048***	-0.005	-0.008
	(0.012)	(0.051)	(0.051)
Bordering×Post Displacement	-0.088***	-0.103	-0.108*
	(0.009)	(0.065)	(0.065)
N	3.07e+05	3.07e+05	3.07e+05
Mean Dependent Variable	0.825	0.825	0.825
Camps = Bordering	0.000	0.164	0.155
Controls	No	No	Yes
FE	No	Parish	Parish

Notes: Standard errors clustered at the parish level in parentheses. Controls include sex, age, education level, and marital status.
Sample includes all parishes that experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

The results from Table 7 show that the probability of being employed in agriculture after displacement does not change in camps compared to No Displacement parishes, but that it is *decreasing* in the Bordering parishes, also relative to camps. This suggests that individuals in Bordering regions are more likely to be working in services

Table 8. Agriculture: Subsistence vs. Market

	Market Agriculture	Market Agriculture	Market Agriculture
Post Displacement	-0.016***	-0.030***	-0.030**
	(0.004)	(0.012)	(0.012)
Camps×Post Displacement	0.013***	0.036**	0.037**
	(0.005)	(0.016)	(0.016)
Bordering×Post Displacement	0.010**	0.019	0.019
	(0.004)	(0.015)	(0.015)
N	2.23e+05	2.23e+05	2.23e+05
Mean Dependent Variable	0.031	0.031	0.031
Camps = Bordering	0.488	0.238	0.228
Controls	No	No	Yes
FE	No	Parish	Parish

Notes: The dependent variable in the regressions is the probability of working in market agriculture, as opposed to subsistence. Standard errors clustered at the parish level in parentheses. Controls include sex and age.
Sample includes all parishes that were within 30km of a camp and experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

Table 9. Agriculture: Farming vs. Livestock

	(1)	(2)	(3)
	Livestock Activities	Livestock Activities	Livestock Activities
Post Displacement	0.00893**	-0.00736	0.00925
	(0.00384)	(0.0186)	(0.0110)
Camps×Post Displacement	0.00125	0.0234	0.00654
	(0.00436)	(0.0198)	(0.0132)
Bordering×Post Displacement	0.00580	0.0285	0.0121
	(0.00409)	(0.0209)	(0.0143)
N	226474	226472	156335
depvar_mean	0.0380	0.0380	0.0380
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: The dependent variable in the regressions is the probability of working in market agriculture, as opposed to subsistence. Standard errors clustered at the parish level in parentheses. Controls include sex and age.
Sample includes all parishes that were within 30km of a camp and experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

after displacement. Table 9 shows that this change in occupation is not coming from changes in the livestock activities (there is no differential change in the share of market agriculture in any region, and the share of market agriculture is also marginal to start with). If anything, livestock activities are decreasing in Camps, which goes against the lack of change in the non-services sector in camp parishes. However,

Table 8 indicates that there is a small but significant increase in market agriculture activities in camp-parishes due to displacement, which means that part of the relative sustenance of agriculture levels in camps are different from those in no displacement parishes, because they consist of higher market agriculture.

Education

Table 10. Primary Education Linear Probability Model

	Education	Education	Education
Post Displacement	0.296***	0.389***	0.400***
	(0.005)	(0.018)	(0.019)
Camps×Post Displacement	0.070***	-0.027	-0.029
	(0.010)	(0.029)	(0.030)
Bordering×Post Displacement	0.193***	0.024	0.020
	(0.008)	(0.024)	(0.025)
N	7.20e+05	7.20e+05	7.20e+05
Mean Dependent Variable	1.626	1.626	1.626
Camps = Bordering	0.000	0.070	0.082
Controls	No	No	Yes
FE	No	Parish	Parish

Notes: Standard errors clustered at the parish level in parentheses. Controls include sex and age.
Sample includes all parishes that were within 30km of a camp and experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

Results from Table 10 show that Bordering parishes experienced an increase in the share of people who have more than primary education compared to camp parishes.

This indicates that there is a significant change in the composition of the population after displacement. It points towards a theory of positive selection into Bordering parishes, and compositional changes in camps that affect the overall outlook on structural transformation in these parishes.

5.5 Heterogeneity within Camps

One aim of this project is to understand how policy decisions surrounding forced displacement, such as the location of IDPs, the number of people in a camp, and the typography of the region affect regional development and thus the welfare of the communities that live there, whether they be initially hosts, or those who decide to stay. In this subsection I try to understand which characteristics of parishes that received camps mattered more for development outcomes.

By using the data on camp population, I look at the intensive margin of displacement, to see whether parishes with camps that received more people were affected differently than those with smaller displaced populations. I run the following specification:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p + \delta + C_{p,t-1} + X_{p,1992} + \epsilon_{p,t} \quad (5)$$

Table 11. Population Growth, Infrastructure, and GDP Growth

	(1) Population Growth	(2) Road Length Growth	(3) Nighttime Light Growth	(4) GDP PC Growth
Log Camp Population	13.67***	15.09***	6.799	-0.0152**
	(3.263)	(4.493)	(5.419)	(0.00654)
Log Population	-64.54***	-1.608	-19.14**	-0.0543***
	(6.036)	(7.458)	(8.124)	(0.0136)
Road Length 1992	0.0000756	-0.000574***	-0.000342**	-0.000000120
	(0.0000986)	(0.000175)	(0.000168)	(0.000000188)
Pre-war Conflict 20km	-0.0881	0.301***	0.336***	0.000331***
	(0.0562)	(0.0967)	(0.0808)	(0.000122)
N	185	185	185	185
Mean(Dep. Variable)	92.21	99.56	99.56	126.3
Adjusted R^2	0.478	0.349	0.299	0.329

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, nighttime light intensity, shares of land use used in agriculture, urban settlement, and abandoned land.
Sample includes all parishes that had camps between 1991 and 2006. Growth in %.
***p<0.01, **p<0.05, *p<0.1.

The results, in Table 11, are consistent with what we would expect: higher camp population is positively correlated with higher population growth road length growth, and GDP (but again, not per capita). The results are consistent when we also add controls for subregion fixed effects, which experienced displacement at different timing and rates.

Next, I explore how regions that had displacement at different timings could have experienced different levels of growth. The time that people spend in camps can significantly affect their decision to stay or return, and the civil war in Uganda did not advance uniformly geographically, so some parishes experienced conflict much later, and displacement much later, than others. Thus, I use subregions as proxies for displacement and conflict timings[7], focusing on the three main subregions that experienced displacement: Acholiland, Lango and Teso. The results are displayed in

[7] see Figure **??** for how conflict evolved differently across locations

Table 12.

A closer investigation shows that within parishes with camps, there is much heterogeneity in how development evolved based on region. For example, the increase in road infrastructures built that we see in the main results is coming mostly from the Acholi subregion, whereas the Lango region experienced no increase in infrastructure being built. However, a marginal increase in camp population in the Lango subregion did lead to an increase in the growth of roads being built by 22%, significantly more than that in bothe Acholi and Teso subregions. Similarly, the change in GDP per capita is significantly lower for the Lango and Teso subregions, but a marginal log point increase in camp population is associated with a higher GDP per capita there than in the Acholi region. This suggests that in the Lango and Teso region, where displacement was for a shorter period, there were no reached "gains" from displacement compared to Acholiland.

Table 12. Growth Heterogeneity by Subregion

	Population Growth (1)	Road Length Growth (2)	Light Growth (3)	GDP per Capita Growth (4)
Log Camp Population	8.104***	-1.160	0.515	-7.590*
	(2.322)	(3.039)	(2.837)	(4.017)
Lango Subregion=1	55.193	-208.864***	-110.238**	-165.431**
	(37.129)	(50.803)	(48.984)	(71.712)
Lango Subregion=1 × Log Camp Population	-4.619	17.520***	0.716	5.336
	(3.964)	(5.616)	(5.341)	(7.712)
Teso Subregion=1 × Log Camp Population	4.503	8.663	0.205	-4.298
	(4.047)	(5.345)	(6.209)	(7.862)
Teso Subregion	-20.822	-155.439***	-87.838*	-67.016
	(34.472)	(41.482)	(44.722)	(62.287)
Lango = Teso	0.051	0.261	0.664	0.200
Lango × Log Camp Pop = Teso × Log Camp Pop	0.046	0.173	0.942	0.309
Mean (Acholiland)	89.879	127.863	164.979	75.100
N	197	197	197	197

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, nighttime light intensity, shares of land use used in agriculture, urban settlement, and abandoned land.
Sample includes all parishes that had camps between 1991 and 2006. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

5.5.1 The role of conflict and camps in parish development

How does conflict affect peoples' decision to stay in camps, or move back?

Joireman, Sawyer, and Wilhoit, 2012 find by comparing two IDP settlements with satellite images, that the location that experienced more conflict and for longer time saw displaced people resettling near roads and urban areas, whereas those living in the camp with less conflict and more temporary displacement tended to return to their previous rural homes and villages (return instead of resettlement).

Furthermore, dynamics could be different based on initial differences in displacement. To test how conflict interacts with return migration decisions, I run the regression described in Equation 6. The coefficient of interest, β_1, is reported in Table 13, along with β_2 and β_3. The results show that while conflict is positively correlated with the increase in roads built, more intense conflict experienced during displacement actually lead to less roads being built the higher the number of displaced people there are.

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p \times Conflict_p + \beta_2 \times CampPop_p + \beta_3 \times Conflict_p + \delta + X_{p,1992} + \epsilon_{p,t} \tag{6}$$

Table 13. Camp Population, Conflict and Growth

	(1) Road Length Growth	(2) Nighttime Light Growth	(3) GDP PC Growth	(4) Unused Land
Log Camp Population	24.05***	19.26*	0.0124	-0.260**
	(7.616)	(10.58)	(0.00991)	(0.107)
High Conflict	125.8	171.7*	0.315***	-3.072***
	(84.16)	(103.4)	(0.116)	(1.014)
High Conflict×Log Camp Population	-12.53	-15.44	-0.0354***	0.340***
	(9.279)	(12.26)	(0.0133)	(0.117)
N	185	185	185	185
Mean(Dep. Var)	99.56	126.3	0.0781	-1.493
Adjusted R^2	0.343	0.348	0.349	0.740

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, nighttime light intensity, shares of land use used in agriculture, urban settlement, and abandoned land.
Sample includes all parishes that had camps between 1991 and 2006. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

5.6 Discussion: External Validity

One question that arises from the results above is that of external validity: to what extend can we extrapolate our results to other instances of internal displacement and conflict around the world today? I argue that the IDP policy of 1995 resembles instances of displacement today in the following way: First, on the dimension of urbanization: the *UNHCR Global Trends 2023* states that the data reports 58% of IDPs globally are displaced to urban areas, with this number likely being an underestimate since urban IDPs are harder to track formally(UNHCR, 2024).

Second, in terms of the distance displaced: Cantor and Woolley, 2020 explain that most internal displacement takes place in relatively short distances. U. Pape et al., 2019 study the characteristics of IDPs in Somalia, Nigeria, South Sudan and Sudan and find that the majority of IDPs remain in the same district (70% in South Sudan and Somalia) or state (95% and 97% in Nigeria and Sudan respectively).

6 Conclusion

To conclude, this project investigates the impact of forced displacement on economic growth and development, by focusing on the case of Northern Uganda during the civil war between the government and the Lord's Resistance Army. I use historical data on conflict, displacement, and transportation infrastructure to shed light on the role of urbanisation as a key player in how forced displacement affects development.

My findings suggest that the presence of IDP camps within parishes had varied effects on population growth, infrastructure development, and GDP growth. Parishes with camps experienced higher population growth compared to those that did not face displacement, and bordering parishes experienced spillover effects from the receiving parishes. Moreover, the duration and size of displacement camps were significant factors that influenced local development.

The results contribute to the literature on forced displacement, urbanization and geography, and economic growth, providing insights into the process of post-conflict recovery. Understanding the regional variations in the impact of displacement can inform policymakers and aid organizations in designing targeted interventions to foster sustainable development in conflict-affected areas.

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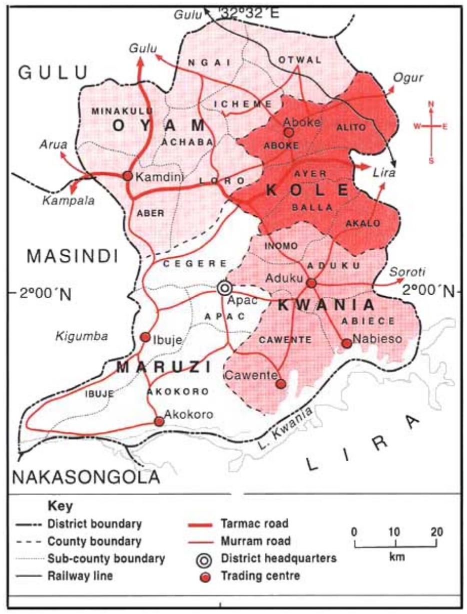
A Data Appendix

A.1 Linking Census Data

A.2 Digitizing 1991 Maps



Appendix Figure A1. 1992 Road Map

B Data Analysis Appendix

B.1 Selection of Sample

The research question posed is *what is the effect of forced displacement on economic activity and the economic geography of a location*? To answer this question precisely and methodologically, this requires a rethinking of the selection of the relevant population as well as the definition of treatment and control groups. There are several factors to consider that increase the complexity and restrict the choices that can be made for this decision. First: whether to consider the existence and evolution of conflict as part of the treatment. Given that conflict and displacement come hand in hand, if we compare places that had conflict and displacement to places that didn't have conflict because they were distant from the reach of the war, then it would not be clear whether we are capturing the effects of conflict or those of displacement. Furthermore, since a larger radius might misclassify areas with indirect exposure as directly impacted, I choose a 10km radius.

Therefore, it's important to consider a sample that includes only parishes that are located within 10km of an event of conflict[8], and thus have experienced the consequences of war, such as the destruction of assets, and individual trauma.

Second, the radius of displacement. Since there is no direct information on the migration flows, and I am using an extensive measure describing whether displacement took place from one parish (Origins), or towards another (Destinations). To ensure accuracy, and given that we expect effects to be local yet still want to take into account spillover effects, I set a radius of 30km from a camp for a parish to be included in the analysis[9].

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[8] As recorded in the UCDP Sundberg and Melander, 2013.

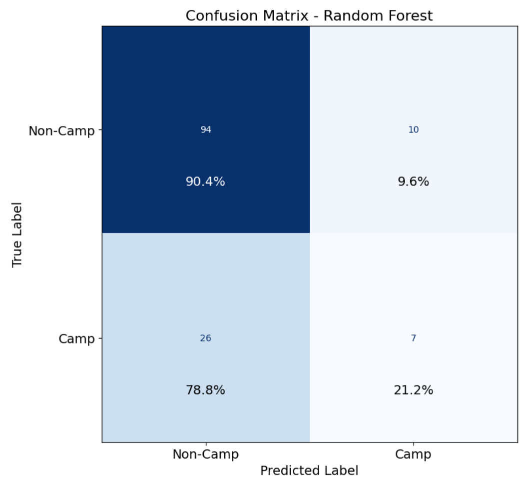
[9] In the World Bank report (Utz Johann Pape and Sharma, 2019), the authors use microdata to describe internal displacement patterns in 4 countries in Sub-Saharan Africa. They conclude that most IDPs stay near their places of origin- "In both South Sudan and Somalia, most IDPs (about 70 percent) report being displaced in the same district where they originally lived. In Nigeria, 95 percent of IDPs are displaced within the same state, regardless of whether they are in camps or living among host communities. Similarly, in Sudan, most IDPs did not travel far: 97 percent lived in the same state, North Darfur, before displacement as they do now. The short distance between the place of original residence and the current location is an important dimension for durable solutions. Being close to the original residence may increase the chances for return or family reunification if transit routes are safe, for example."

B.2 Prediction of Treatment

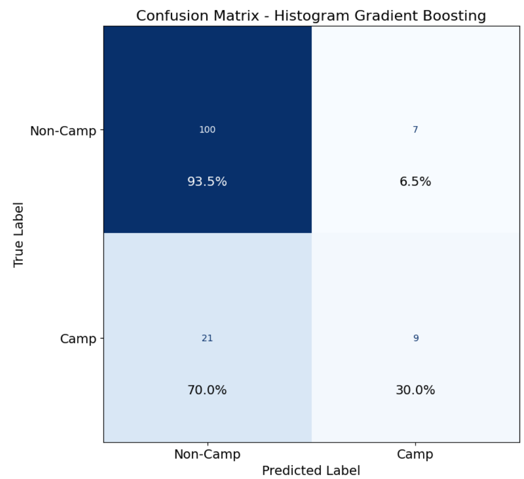
An integral argument for the causal identification of the effect of displacement into camps is that the historical event provide a quasi-natural experiment *because* camps are randomly allocated in parishes in the affected regions, and that the allocation is not correlated with economic outcomes. Of course, sample selection is an important concern in this context. Therefore my identification assumption is that conditional on locations experiencing conflict, and within a 30km radius of camps, then the parishes at close proximity of a camp (the bordering) were just as likely to have a camp assigned to them as the parishes that actually received the camp. In the main regressions in the text, I make sure to condition on initial economic conditions that may affect the growth path of parishes, since I don't have observations to control or observe trends in outcomes before treatment. In addition, I add district fixed effects and cluster standard errors at the district level because this is the most accurate notion I would have for a temporal indicator of displacement, since parishes within district were probably treated at the same time, and the conflict progressed differently across 10 years and across space.

As an additional robustness check to support this argument, I employ machine learning methods to see if using observable variables in the dataset that I constructed at the parish level, I would be able to predict assignment to treatment. Specifically, I use both Random Forest and Histogram Gradient Boosting models for the prediction exercise. Figure B1 illustrates the ability of the Random Forest and Histogram Gradient Boosting methods for predicting whether a parish is a camp or non-camp location. I use, as is standard, 80% of the sample to train the models, including 93 covariates that feature geographic, economic, and demographic variables (pre-treatment) at the parish level. It shows that at best, the HGB model can correctly classify 23.3% of the camp parishes as camps, and misclassifies 6.5% of non-camp parishes as camp-parishes.

Furthermore, by looking at the features (covariates) that the models use to predict the outcome, and ranking them by their importance (how much the model relied on the covariate compared to other, the total importance sums up to 100), we see that the most predictive variables for camp location include geographic variables (area, elevation, standard deviation of elevation, distance from the border, subcounty and county) and land usage (land share of urban settlement, agriculture, woodlands). Other important covariates that show up are population and roads built. Interestingly, in the HGB model, an important feature that appears is the share of services occupations in a parish (the variable occ_l3_weighted). It is reassuring to a sense that the models' reliance on these features for predictions are in agreement with what our history and theory would tell us about matters for camp location, but what these models show is that it is still not enough to be able to correctly distinguish at least 75% of the camps' locations.



(a) Random Forest Model



(b) HGB Model

Appendix Figure B1. Confusion Matrices and Performance of ML Models.

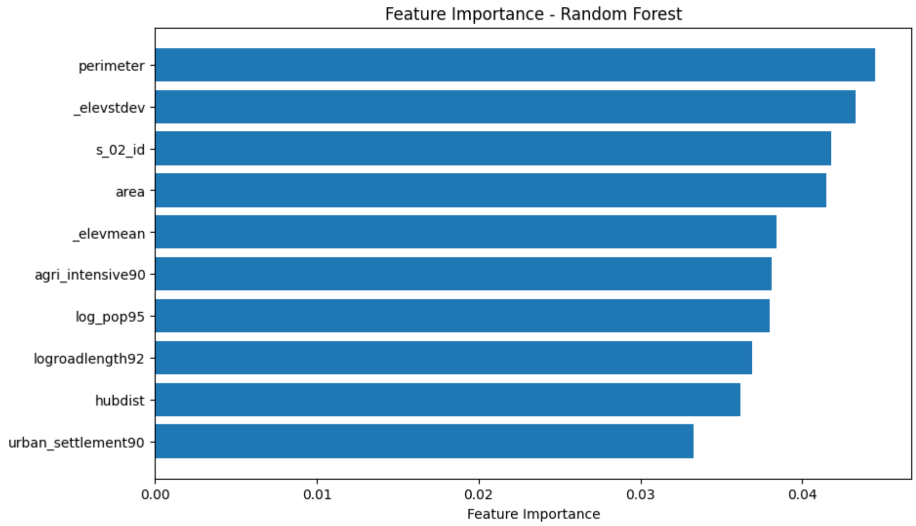
B.3 Parish-Level Results

Appendix Table B1. Growth in North-East Uganda

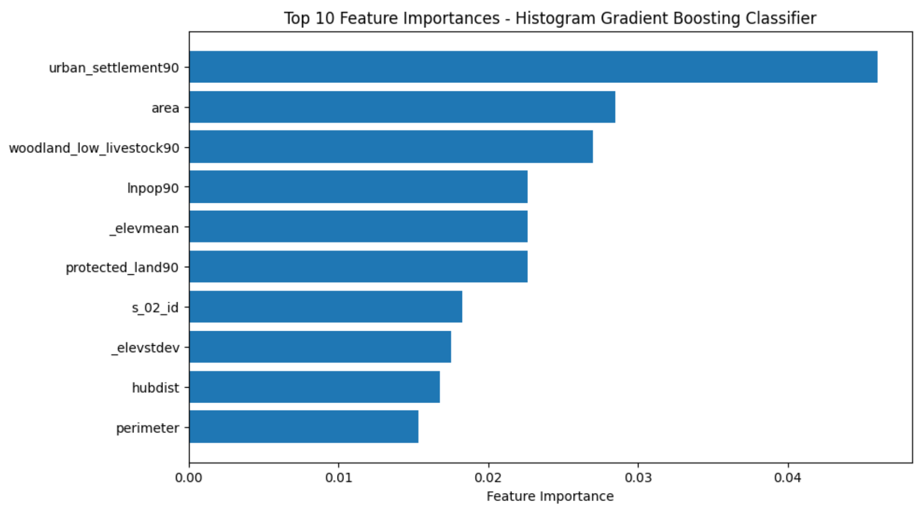
	(1) Population Growth	(2) Road Length Growth	(3) Nighttime Light Growth	(4) GDP PC Growth
Camps	14.89**	23.60***	18.20**	0.00584
	(5.978)	(7.658)	(8.170)	(0.0144)
Bordering	-11.89**	-5.007	19.55***	0.0417
	(5.647)	(5.992)	(7.424)	(0.0254)
Observations	1071	1071	1071	1071
Adjusted R^2	0.730	0.325	0.399	0.081

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, and nighttime lights when not the outcome variable.
Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006. Growth in %.
***p<0.01, **p<0.05, *p<0.1.

Alternative Identification Strategy: a measure of decay in displacement to



(a) Random Forest Model



(b) HGB Model

Appendix Figure B2. Confusion Matrices and Performance of ML Models.

camps

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times Bordering1_p + \beta_2 \times Bordering2_p + \beta_3 \times Bordering3_p + \beta_4 Y_{p,t-1} + \delta + C_{p,t} + X_{p,1992} + \epsilon_p$$

where

- $\Delta Y_p = Y_{p,t} - Y_{p,t-1}$

Appendix Table B2. Border Decay Specification

	(1) Population Growth	(2) Road Length Growth	(3) Nighttime Light Growth	(4) GDP PC Growth
Bordering 1	-24.02***	-30.52***	-6.215	15.37**
	(4.317)	(6.394)	(5.534)	(7.249)
Bordering 2	-6.878	-29.57***	-23.28***	-17.38
	(7.454)	(8.114)	(8.681)	(11.66)
Bordering 3	-19.87***	-29.10***	-35.90***	-16.28
	(7.281)	(9.008)	(9.340)	(12.46)
No Displacement	-7.398	-22.84**	-28.04**	-17.78
	(8.251)	(9.544)	(12.00)	(15.44)
Observations	1791	1791	1791	1791
Adjusted R^2	0.607	0.310	0.367	0.541

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, water sources nearby, and initial population, road length, and nighttime lights when not the outcome variable. Sample includes all parishes that have experienced conflict within 20km between 1991 and 2006. Growth in %.
***p<0.01, **p<0.05, *p<0.1.

- $Camp_p$: dummy for whether the parish p has a camp
- $BorderingI_p$: dummy for whether p has is first-order, second-order, or third-order bordering a parish with a camp
- δ: district fixed effects
- $C_{p,t}$ indicates the intensity of conflict in the years leading up to time t.
- $X_{p,1992}$ indicates controls for parish characteristics before the start of the IDP policy, such as how isolated the parish was, population and area, urban population ...

Table B4 presents results of changes in the occupation shares at the parish level.

In addition, using the census data, I can study changes in the level of education of the population in parishes that had camps versus those bordering, and those that did not experience displacement. Results are displayed in Table B5.

B.4 Individual-Level Results

C Estimating Migration Flows

To understand how the intensity of displacement matters for economic development, I develop an estimate of migration flows and use it as my treatment variable. To do that, I start with some simple accounting relations:

Appendix Table B3. Changes in Land Use

	Livestock Activity (1)	Agricultural Activity (2)	Urban - settlement (3)	Unused Land (4)
Camps	0.090***	-0.055	0.089**	0.336***
	(0.034)	(0.076)	(0.044)	(0.081)
Bordering	0.016	0.027	0.057	0.258***
	(0.038)	(0.060)	(0.036)	(0.071)
Camp = Bordering	0.000	0.211	0.443	0.291
Mean (No Displacement)	-0.433	0.442	-0.174	-2.200
N	679	679	679	679

Notes: Standard errors clustered at the district level in parentheses. Controlling for: mean elevation, standard deviation of elevation, initial population, road length, nighttime lights, shares of land being used for agriculture, unused land, urban settlements.
Sample includes all parishes within 30km of a camp that experienced some conflict before displacement. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B4. Displacement & Occupation Shares

	(1) Subsistence	(2) Crafts	(3) Elementary	(4) Market agriculture	(5) Factory	(6) Professional	(7) Services	(8) Admin
Camps	-0.00191	-0.00352	-0.0583**	-0.00663	-0.00242	-0.0160*	-0.0220*	0.00331
	(0.0939)	(0.00529)	(0.0255)	(0.00562)	(0.00166)	(0.00961)	(0.0127)	(0.00218)
Bordering	-0.0282	-0.0101	-0.0538**	-0.00995**	-0.00245	-0.00211	-0.00860	-0.00231
	(0.0742)	(0.00796)	(0.0206)	(0.00448)	(0.00169)	(0.00980)	(0.00861)	(0.00391)
Observations	106	106	106	106	106	106	106	106
Adjusted R^2	0.133	0.151	0.113	0.020	0.270	0.051	0.391	0.255

Notes: Standard errors clustered at the parish level in parentheses. Controlling for: mean elevation, standard deviation of elevation, initial population, road length, and nighttime lights.
Sample includes all matched parishes within 30km of a camp that experienced some conflict before displacement.

***p<0.01, **p<0.05, *p<0.1.

let g_p be the predicted population growth rate in a parish p. The estimates of g_p are taken as the district-level growth rates between 1992 and 2002. Then we can define:

$$\Delta_{2005,1995} Pop_p = Inflows_p(1 + g_p) + LocalPop_{p,1995}(1 + g_p) \tag{7}$$

$$Inflows_p = \frac{1}{1 + g_p} \Delta_{2005,1995} Pop_p - LocalPop_{p,1995} \tag{8}$$

In addition, let $B(p)$ denote the neighbouring parishes to p from which any positive inflows to p would be coming, and from there, we can make the assumption that there is an inflow $inflow_{p'p}$ from p' to p only if there is a decrease in the expected population

Appendix Table B5. Displacement & Changes in Education

	(1) Education- Primary	(2) Above primary
Camps	-0.0427*	0.0412
	(0.0241)	(0.0258)
Bordering	-0.00845	0.0111
	(0.0239)	(0.0238)
Observations	106	106
Adjusted R^2	0.063	0.098

Notes: Standard errors clustered at the parish level in parentheses. Controlling for: mean elevation, standard deviation of elevation, initial population, road length, and nighttime lights.
Sample includes all matched parishes within 30km of a camp that experienced some conflict before displacement.

***p<0.01, **p<0.05, *p<0.1.

Appendix Table B6. Agriculture Logit Model

	(1) Agriculture	(2) Agriculture	(3) Agriculture
Agriculture			
Post Displacement	-0.595***	-0.582***	-0.288
	(0.170)	(0.197)	(0.194)
Camps×Post Displacement	0.178	0.0223	-0.0206
	(0.332)	(0.332)	(0.318)
Bordering×Post Displacement	-0.872**	-0.904**	-0.819**
	(0.342)	(0.366)	(0.366)
N	308431	308431	308407
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the parish level in parentheses. Controls include sex and age.
Sample includes all parishes that were within 30km of a camp and experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

of p':

$$Inflows_p = \sum_{p' \in B(p)} inflow_{p'p} \tag{9}$$

$$= \sum_{p' \in B(p)} \frac{1}{1+g'_p} \Delta_{2005,1995} Pop_{p'} \times \mathbb{I}_{\{\Delta_{2005,1995} Pop_p - LocalPop_{p,1995}(1+g'_p)<0\}} \times \mathbb{I}_{\{camp_{p'}=0 \wedge camp_p=1\}} \tag{10}$$

where $camp_p = 1$

This rule would allow us to identify which parishes experienced an outflow, (de-

	(1)		(2)		(3)		(1)-(2)		(1)-(3)		(2)-(3)	
	No Displacement		Camps		Bordering				Pairwise t-test			
Variable	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference	N/Clusters	Mean difference	N/Clusters	Mean differe
Agriculture	3918	0.825	2080	0.818	2613	0.920	5998	0.007	6531	-0.095***	4693	-0.102**
	64	(0.024)	19	(0.039)	31	(0.021)	83		95		50	
Manufacturing	3918	0.058	2080	0.049	2613	0.048	5998	0.009	6531	0.011	4693	0.002
	64	(0.012)	19	(0.013)	31	(0.018)	83		95		50	
Services	3918	0.116	2080	0.133	2613	0.032	5998	-0.016	6531	0.084***	4693	0.100***
	64	(0.018)	19	(0.032)	31	(0.007)	83		95		50	
Market Agriculture	2589	0.031	1218	0.011	2037	0.015	3807	0.019	4626	0.016	3255	-0.003
	64	(0.012)	19	(0.004)	31	(0.006)	83		95		50	
Above Primary	93639	0.613	41710	0.643	61307	0.614	135349	-0.030	154946	-0.001	103017	0.029*
	287	(0.017)	127	(0.012)	198	(0.012)	414		485		325	
age	93639	20.927	41710	21.192	61307	20.775	135349	-0.265	154946	0.152	103017	0.417
	287	(0.179)	127	(0.193)	198	(0.169)	414		485		325	

noted by $inflow_{p'p}$ here) , and also to quantify this outflow by simply looking at the decrease in the population in each location. Some cases will arise where it's possible that the people of one parish got displaced to several other neighbouring parishes with camps. In that case, we need to make assumptions about how the outflow was distributed among these neighbouring parishes with camps. A simple start would be to simply divide the outflow by the number of neighbouring parishes with camps and distribute people equally among camps. A more accurate measure would take into consideration the existence of roads and distances between the origin and destinations.