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 in Uganda during the civil war. 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 and harmonizing satellite data with novel administrative data, I document that the forced displacement episode led to an occupational shift towards services and an increase in overall education levels. Yet the effects were not distributed equally: while camps experienced population growth, it is the neighboring now-emptier localities experiencing higher increases in services employment. When delving into mechanisms, I find that increased market access due to infrastructure reconstruction played an important role. I show that the long-term effects of forced displacement are stronger in places where camps lasted longer, and had higher population size. I develop a general equilibrium model that rationalizes these results.

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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). In particular, the number of people displaced within their countries has been steadily increasing, from 26 million in 2012 to 83.4 million in 2024 [1]. Given the large- and growing scale nature of displacement and its profound consequences on the well-being of affected people, understanding the mechanisms through which it reshapes local economies 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).

In this paper, I ask: *how does forced displacement reshape the spatial and sectoral structure of the economy?* I argue that large-scale displacement can be conceptualized as a sudden increase in population density, 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 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. 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. An estimated 90% of the population in these affected locations was displaced into camps at different points in time. The setting presents a quasi-natural experiment with a forced urbanization shock that led to the reshuffling of the majority of the population across locations within that region: I argue and

[1] Of which 73.5 million were displaced due to conflict and violence, according to the *2025 Global Report on Internal Displacement*. In 2023, 46% of all IDPs were located in Sub-Saharan Africa.

provide evidence that parishes (localities one administrative unit above the village level) across North and East Uganda that experienced LRA-related conflict were equally likely to receive camps, and whether or not they were directly next to a camp was also random.

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 parishes), 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, without which it would not be possible to answer the research question. 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 was 15% higher in Camp parishes compared to those with no displacement, and remained lower in the bordering (neighboring) parishes up to 20 years after the initial displacement.

Next, using the census microdata I study how forced displacement affected the composition of people across locations. Specifically, I focus on sectoral occupation shifts and changes in educational attainment. I find that displacement led to an increase in the share of people working in services in both the camp and bordering parishes compared to those in no displacement parishes, with this increase being disproportionately higher in the bordering parishes (between 7.5 and 10.8 percentage points higher). Moreover, 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 and the camps remained populated with lower-educated people. However, this result is nuanced because we see that it's driven by lower-educated older adults staying in camps, and younger children becoming more educated *in* camps. 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 in the short run.

After that, I provide evidence for what I argue is a main channel that explains the results, first empirically and then through the lens of a structural model. In the aftermath of the displacement policy, several initiatives to construct infrastructure by international organizations were implemented, and this new road construction improved market access not only in camp-parishes, but also in the bordering parishes at direct proximity from the former. Only three years after free mobility was reinstated, roads had increased by 33% in camp-parishes, whereas those bordering did not experience any change in road infrastructure compared to the no displacement parishes. Although bordering parishes saw limited direct road construction, using a network-based approach, I find that the displacement policy led to a relatively higher increase market access in the bordering parishes compared to both camp-parishes and no displacement parishes.

I develop a static general equilibrium quantitative spatial model with multiple locations and two sectors, where conflict acts as a negative productivity shifter and a forced displacement shock affects the location-sector choice of a location through a change in the migration elasticity. The framework serves two purposes. First, it provides a structure to rationalize the empirical patterns documented above: following displacement, agricultural employment falls in bordering locations while non-agricultural activity expands, and population concentrates within camps. Second, it allows for counterfactual analysis of policies or conditions that affect post-conflict and displacement recovery, such as the scale of camps or the reconstruction of transport infrastructure after the war. In the model, increased market access boosts the productivity of the services sector and non-homothetic preferences translate into higher demand for services for individuals earning more. I calibrate the model using pre-displacement data and run counterfactuals that change this market access and population distribution. I find that had forced displacement taken place *without* an ensuing reconstruction of infrastructure, the distribution of income and sector would have been much less equally distributed across Northern Uganda, with a few locations benefitting at the cost of many. I also estimate that forced displacement led to long-run frictions to mobility, implied by a 57% decrease in the migration elasticity with preliminary calibrations of the model parameters.

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.

In this paper I make three main contributions. First, I assemble a new spatial dataset that links detailed information on the location, duration, and population of internally displaced persons (IDP) camps with recovered parish-level census microdata, providing spatially exhaustive coverage of both camp and host communities over two decades. Second, I integrate the study of forced displacement into the framework of economic geography by conceptualizing displacement as a spatial shock that redistributes population and economic activity. Third, I develop and estimate a spatial general-equilibrium model to quantify how displacement and post-war reconstruction shape labor allocation across space and sectors, and I simulate counterfactual scenarios such as the absence of infrastructure investments.

The rest of the paper proceeds as follows. In the remaining part of this section, I review related work and outline my contribution. Section 2 provides historical context, and Section 3 describes the data sources and construction process. Section 4 presents the empirical framework, and Section 5 reports the reduced-form effects of forced displacement on population distribution. In Section 6, I examine how displacement reshaped sectoral and educational composition across space. Section 7 explores potential mechanisms—market access and land conflict—that help explain these patterns. Section 8 develops and estimates a quantitative spatial model to study how displacement and post-war road construction affected the allocation of people across space and sectors. Section 9 analyzes how camp characteristics—size, duration, and conflict exposure—shaped these outcomes. Section 10 concludes.

Related Literature

This paper brings together two strands of literature: the economics of forced migration, and the literature on urbanization and structural transformation. A large literature examines the economic impact of forced displacement, yet few papers that investigate the impact of displaced populations in low-income economies (Becker and Ferrara, 2019, Verme and Schuettler, 2021). Even fewer papers study the effects of forced displacement into camps. Alix-Garcia et al., 2018 study the effect of a long-term refugee camp in Kenya on host populations. Also, Taylor et al., 2016 show positive net impact of refugee camps on local wages in a calibrated simulation of Congolese refugee camps in Rwanda, and find that cash-based aid has a more positive impact than food-based aid. They also find that the presence of refugee camps increases local trade. In Mozambique, Chiovelli et al. (2021) find that displacement raised schooling and shifted employment out of agriculture among children displaced during the civil war. I add to this literature by analyzing the impact of having multiple camps and being able to distinguish how camp characteristics, such as size, duration, and connectedness, shape local development.

There have also been studies that exploit the unique set up of the civil war in Northern Uganda to assess the impacts of the displacement policy implemented there. Lehrer (2009) show that prolonged displacement within camps reduced male labor participation, while Fiala (2009) document heterogeneous effects on household assets. Rohner, Thoenig, and Zilibotti (2013) link local violence to declines in social trust and slower recovery in ethnically fractionalized areas. These studies provide important micro evidence but are typically cross-sectional or confined to individual camps. By contrast, this paper uses spatially exhaustive data covering all conflict-affected parishes, thus permitting the analysis of both inflows (camp parishes) and outflows (bordering parishes) of displaced people.

I contribute by integrating the framework of forced displacement with that of economic geography and by showing that since forced displacement changes where people choose to live and work, it alters the spatial allocation of economic activity, I estimate a general equilibrium model that allows me to study how the displacement and following reconstruction efforts impact this allocation.

The paper also contributes to the literature on geography, structural transformation and cities in lower-income countries. Recent research distinguishes between productive and consumption-driven forms of urbanization in the developing world. Gollin, Jedwab, and Vollrath (2016) show that much of sub-Saharan Africa's urban growth has taken place without industrialization, generating "consumption cities" sustained by resource rents rather than manufacturing. Similarly, Huang, Xie, and You (2023) show that income shocks due to changes in mineral prices can accelerate structural transformation and relate the evidence to the non-homothetic preferences-strand of the structural transformation literature: higher incomes raise demand for services and shift labor out of agriculture even without productivity gains. Jedwab, Ianchovichina, and Haslop (2025) document that many cities in low-income countries are dominated by non-tradable services and public employment, features typical of consumption-led urbanization. Hsu, 2025 shows that agglomeration benefits due to displacement are ethnicity-specific dependent on compositional differences in income and sector across groups. Moreover, Duranton, 2015 points to the challenges faced by the literature in pinning down causal estimates linking city scale and productivity, citing biases arising from the sorting of people across cities by quality of labor. This paper adds to the literature on agglomeration and productivity and addresses these concerns by focusing on agglomeration that is accelerated due to a quasi-natural experiment (forced displacement) in Uganda.

Finally, my analysis connects to the literature linking transport infrastructure to spatial economic outcomes. Redding and Turner (2015) survey evidence that market access drives spatial concentration of activity. The seminal work by Donaldson and Hornbeck (2016) shows that U.S. counties with greater rail access experienced higher agricultural land values, while Fajgelbaum and Redding (2022) quantify how trade integration reshaped Argentina's spatial distribution of employment and population. This paper differs by studying an endogenous infrastructure shock triggered by conflict: international organizations financed road reconstruction precisely in the areas most affected by displacement. I document that market access increased disproportionately around former camps, amplifying regional inequality but also facilitating structural transformation.

I contribute to these studies by understanding the role of frictions placed by forced displacement and conflict in a developing economy, in the framework of urbanization, structural transformation, and growth.

2 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).

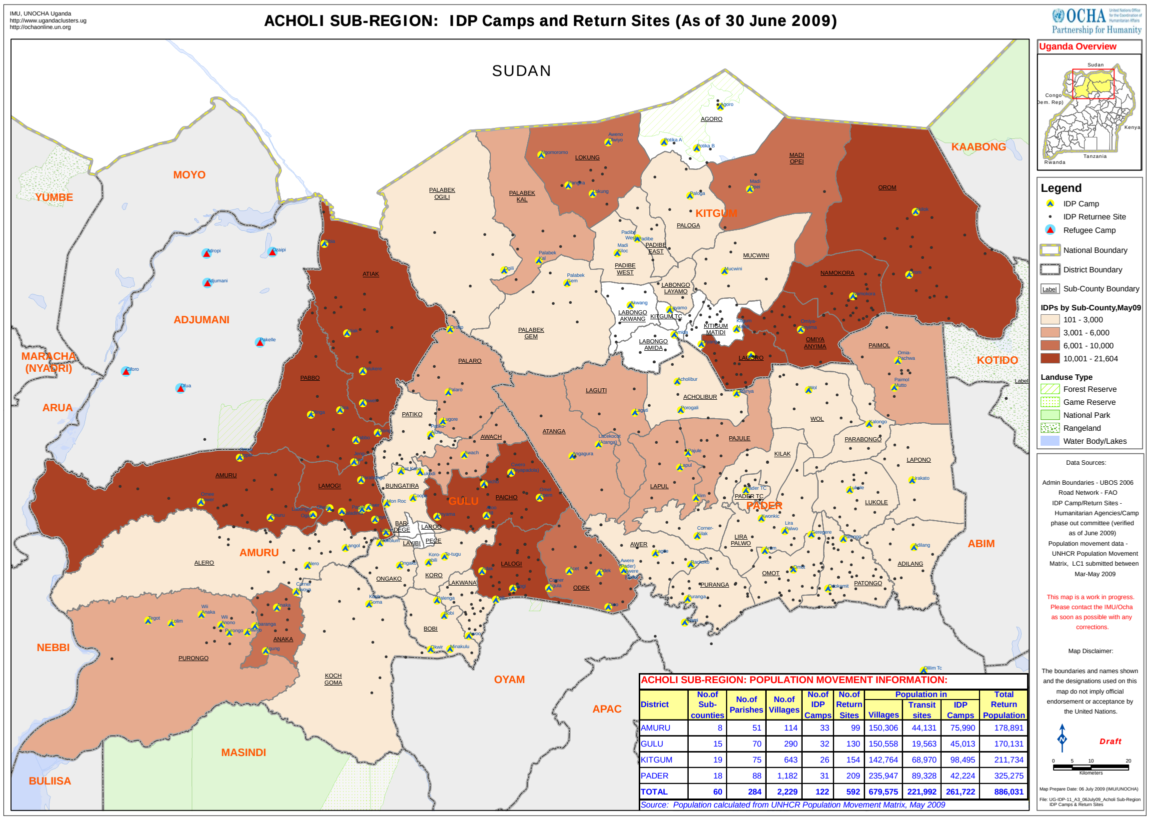
Life in camps starkly contrasted with life pre-displacement. Whereas before the displacement policy, people were mainly subsistence farmers and pastoralists, living in dispersed villages across the bushland, camps constrained entire villages to small spaces and military forces restricted the mobility of IDPs. A curfew was implemented and people could not move further than a few kilometres from a camp. Throughout the displacement and return period, humanitarian interventions were conducted by NGOs and international organizations, particularly the UN Development Program and World Food Program. Many IDPs unable to farm their land became unemployed, others, mostly women, engaged in petty manufacturing and trade. Village and loan associations were encouraged.

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]. 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). 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, between 70-90% 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 (IDMC, 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.

[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



District	No.of Sub-counties	No.of Parishes	No.of Villages	No.of IDP Camps	No.of Return Sites	Population in Villages	Population in Transit sites	Population in IDP Camps	Total Return Population
AMURU	8	51	114	33	99	150,306	44,131	75,990	178,891
GULU	15	70	290	32	130	150,558	19,563	45,013	170,131
KITGUM	19	75	643	26	154	142,764	68,970	98,495	211,734
PADER	18	88	1,182	31	209	235,947	89,328	42,224	325,275
TOTAL	60	284	2,229	122	592	679,575	221,992	261,722	886,031

Figure 1. Map of North Uganda's Acholiland Camp Depopulation
Source: UN OCHA

3 Data and Descriptive Statistics

3.1 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, 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 reached an appropriate state for data analysis. Moreover, the data had to be linked with the rest of the data in this project. In this section I explain the methodologies I

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

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.

3.1.1 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 had 38 districts in 1991, 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 all 4003[4]. 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, 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 2 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 be differential attrition due to parishes being split

[4]Excluding Mbarara district, which includes 125 parishes and for which essential documents were not recovered.

for administrative reasons purposefully because of population size changes. Since we are using the boundaries from 2002 which are prior to free mobility (although not prior to forced displacement in many locations), I argue that this diminishes these concerns regarding causal inference. In an ideal setup, we should be using 1991 borders, but this data doesn't exist. To understand the extent of the attrition bias in the data, I calculate the probability of a missing parish by whether or not a parish has been classified in our treatment (whether there is a camp, bordering a camp, 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. This means that Camp parishes are overrepresented in the census panel.

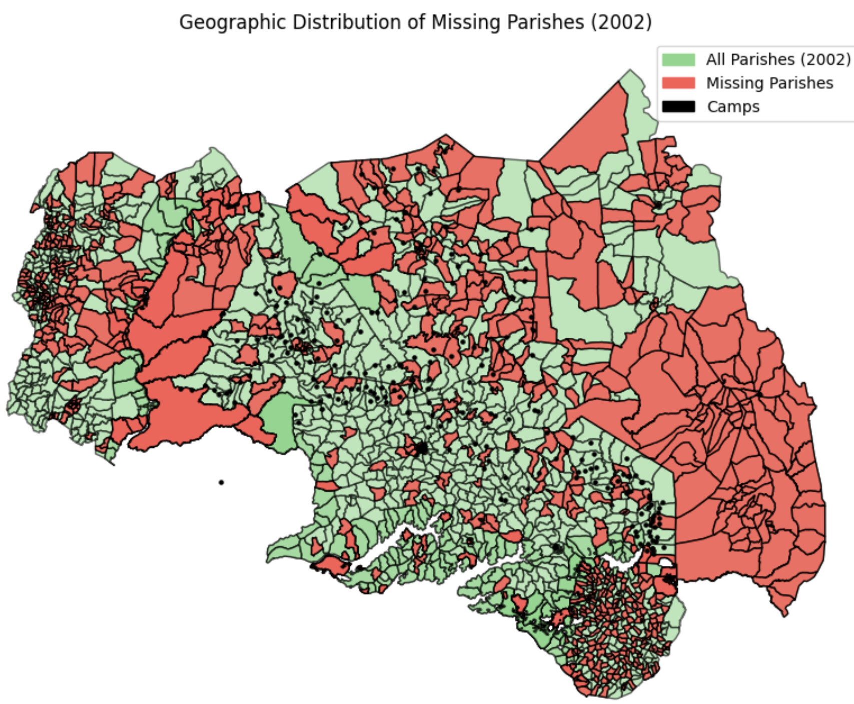


Figure 2. Matched Parishes

For matching parishes across 2002 and 2014, I use the cross-walks developed by Zhou, Grossman, and Ge, 2023. They provide a mapping between parish names in 2002 and 2014.

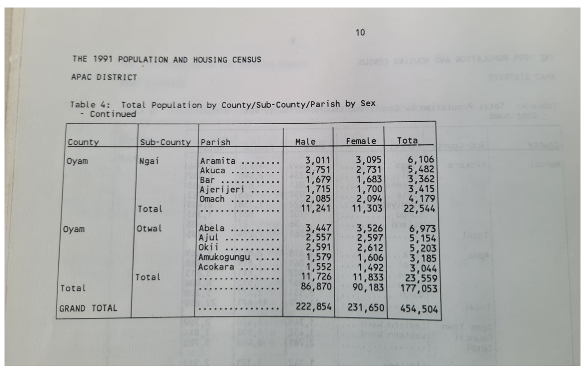
Table 1. Matching parishes over time- Differential Attrition Test

$Class_1$	$Count_1$	$\mathbb{P}(Match = 0 \vert Class_1)$	$Class_2$	$Count_2$	$\mathbb{P}(Match = 0 \vert Class_2)$	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.

3.1.2 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 3). I then matched parish IDs to names by population ranks, successfully recovering 3,997 out of 4,003 parishes .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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 3. 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.

3.2 Data Sources

Conflict Data

To measure exposure to conflict, I employ data from the Uppsala Conflict Data Program Geo-Referenced Events Dataset (UCDP GED). The dataset provides comprehensive spatial and temporal information on violent events from 1989 onwards, and includes information on the location, date, type, and the number of fatalities of each conflict event. 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 largely from WFP (World Food Programme) reports (WFP Uganda, 2005) and supplemented by reports from other humanitarian organizations. Data on camp duration periods was collected manually using Google Earth and Google Timelapse by identifying visually when a camp appears on the map.

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.

3.3 Sample Description

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. This leaves us with 1,056 parishes.

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

Table 2. Sample of Camps and Parishes

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

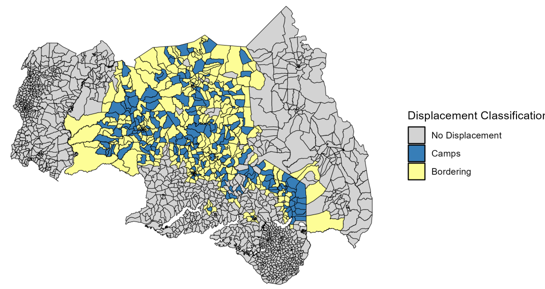


Figure 4. Displacement Classification

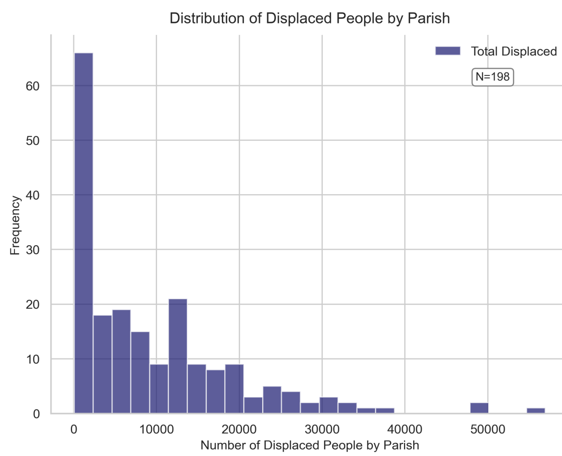


Figure 5. Distribution of camp population in parishes

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.

Regarding the characteristics of camps and their hosting localities, Figure 5 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 6 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 20 times the original population.

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	
Population Density 1990	567	1.485	175	1.293	314	1.468	742	0.192	881	0.016	489	-0.176
	567	(0.077)	175	(0.179)	314	(0.160)	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	
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	
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	

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.

4 Empirical Strategy

To identify the impact of forced displacement on economic outcomes, I distinguish between parishes were allocated camps, those that were just bordering these camp-parishes and whose populations therefore were forced to relocate into camps, and those who were neither camp parishes nor bordering parishes, which I call the “No Displacement” parishes. The sample of No Displacement parishes, which I use as my control units, is restricted to the subregions that were involved in the war (Acholi, Lango, Teso, Karamoja, and West Nile). I further restrict my sample to those that are located within a 10km boundary of a recorded conflict event within the years 1989[5] and 2006. Whereas it is not possible to identify with a 100% accuracy that there was truly no displacement in the chosen control units, an accounting exercise suggests that any forced displacement that took place outside the bordering and camp parishes was significantly lower: Camp population in 2005 makes up 100.4% of the populations of camp and bordering parishes in 1995. If we discount by the average growth rate of each district between 1991 and 2002, we get that the discounted 2005 camp population made up 72% of the total population of camp and bordering parishes in 1995 [6]. In other words, an estimated 30% of the total population of the “No Displacement” parishes that I use as a control was displaced, compared to 100% of the Camp and Bordering parishes. This means that while we can say that the camp population most surely comes from the parishes hosting the camps, as well as the direct neighbouring parishes, my control group

[5] The earliest year in the conflict UCDP dataset.

[6] This estimate would vary based on the assumed growth rate. In most humanitarian reports, this number was estimated between 80 and 90%

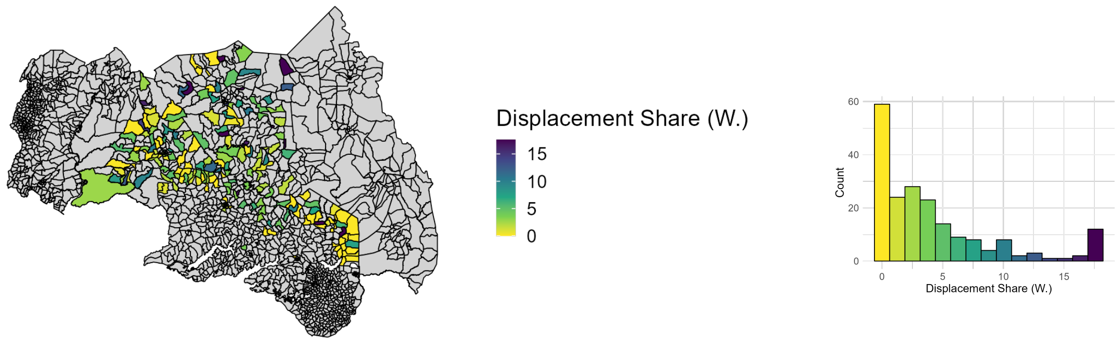


Figure 6. Share of Camp Population/ Parish Population

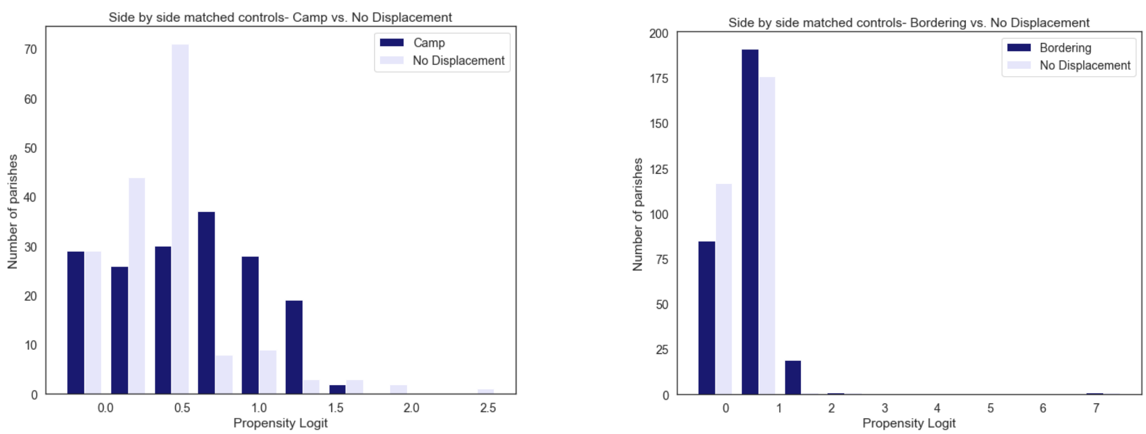
has experienced displacement to a lesser degree, which is also natural since these parishes have experienced conflict.

Given that the setting allows for a quasi-natural experiment, I assume that the assignment mechanism is such that once the government forces arrive at a location whether or not they set up a camp in that parish is random, and so whether a parish becomes bordering one with a camp or not, and therefore whether its population gets emptied out, is also random. To assess whether or not this assumption is plausible, I do two sets of tests: first, by plotting the propensity logit distributions to verify if there is an overlap in the covariate distribution. Figure 7 shows that there is indeed significant overlap for both treatments and the control. Second, I use machine learning techniques to predict whether a parish has a camp. I employ two models: the Random Forest model (RF) and the Histogram Gradient Boosting model (HGB). Both fail to predict treatment into camps at high rates: the HGB model can predict camps 45% of the time, whereas the Random Forest model can only do so with a 28% success rate. The results are displayed in Appendix B.1.

Nevertheless, while there is no direct evidence on why certain places were used to host camps, I conducted interviews in Northern Uganda with people who had been displaced and key figures of the peace process to understand the assignment of camps to locations. An employee at Caritas NGO in Gulu stated that “People knew where to go” when the army arrived to evacuate civilians from their villages.

That meant they went to the nearest schools, churches and town centres, where they knew other people would be gathering.

The balance Table 3 shows that there were indeed some disparities across locations based on parish characteristics that support this anecdotal evidence. Thus, this alludes to potential selection issues. To attenuate selection concerns, then, I will be using an approach of selection on observables: meaning that I assume that conditional on attributes that I can observe and measure, the assignment of parishes to camp or bordering status is random.



(a) Logit Score Distribution: Camp vs. No Displacement

(b) Logit Score Distribution: Border vs. No Displacement

Figure 7. Comparison of Logit Score Distributions for Treatments and Control

I start by employing the following specification to identify the effect of displacement on the distribution of population and on nighttime lights:

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

where $Y_{p,t}$ represents the logarithm 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. δ represents district fixed effects to absorb 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 and agricultural land use. I use Conley (1999) standard errors to take into account the spatial correlation

I am interested in the coefficients β_1 and β_2, which measure the difference in post-displacement outcome levels between Camp and Bordering parishes and the other conflict-affected parishes with similar initial population and baseline characteristics.

Identifying assumption

The identifying assumption in my analysis 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 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 since parishes within district were probably treated at the same time, were more similar in terms of ethnic composition, and experienced conflict progression differently over the 10 years of displacement. I cluster standard errors at the district level account for the spatial correlation of the outcome variable using Conley (1999) standard errors. In subsection 5.2 I complement this analysis with different identification strategies, and in section 9 I study different definitions of forced displacement based on camp population size and camp presence duration.

5 Results: Population Changes

5.1 Population Changes

First, I establish that if a parish had a camp assigned to it between the years 1996 and 2005, this led to a permanent increase in population in the camp parishes 8 years after people were free (and pushed even) to move back to their home villages, and a permanent decrease in population in the bordering parishes. The annual population growth rate in camp parishes increased by 0.568% compared to that of No Displacement. Given that average annual growth rate for the region between 1991 and 2014 was estimated to be 3.9%, this amounts to an estimated 14.5% increase in the annual population growth rate (this is a rough estimate since it assumes that the annual growth rate remained constant throughout the years 1991-2014 for the

Table 4. Population Growth

	Log Population (1)
Camp	0.152**
	(0.069)
Bordering	-0.069
	(0.065)
Camp = Bordering (p-value)	0.000
Pre-mean (No Disp.)	8.452
R^2	0.551
N	1056

Notes: Conley standard errors (20km) in parentheses. Controlling for: pre-war conflict, mean elevation, standard deviation of elevation, area, roads, shares of land use used in agriculture and urban settlement.
Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006. Growth is annual and in %. ***p<0.01, **p<0.05, *p<0.1.

region as a whole)[7]. On the other hand, being a bordering parish led to a population rate decrease of about 0.4% annually compared to No Displacement parishes, and if we compare both treatments, we find that camps experienced almost a 1% higher annual growth rate. Although β_2 is not significant in Table 4, the sign is robust (and otherwise significant) in various alterations of the specification and across different samples, and is consistently significantly lower than β_1.

GDP Growth After showing that the forced displacement policy changed population growth patterns across the region, I study how GDP growth, as proxied by nighttime lights, is affected by forced displacement. The results are displayed in Table 5. I find that *both* camp and bordering parishes experienced an increase in the annual growth rate of GDP, which indicates that there was an increase in economic development in those locations. However, perhaps surprisingly, the increase in GDP per capita is much more pronounced in the bordering parishes compared to the camp parishes, despite the fact that the bordering parishes have become emptier.

[7] If we estimate population growth starting 1995 instead of 1991, we obtain a camp effect of a 20% higher annual growth rate.

Table 5. Nighttime Lights Growth

	GDP Growth (1)	GDP per Capita Growth (2)
Camps	1.196***	0.558
	(0.342)	(0.456)
Bordering	0.895***	1.260***
	(0.297)	(0.404)
Log Population 1990	0.473***	3.366***
	(0.144)	(0.214)
Camp = Bordering	0.221	0.025
Mean (No Displacement)	2.938	-1.891
N	1056	1056

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.

5.2 Alternative Specifications

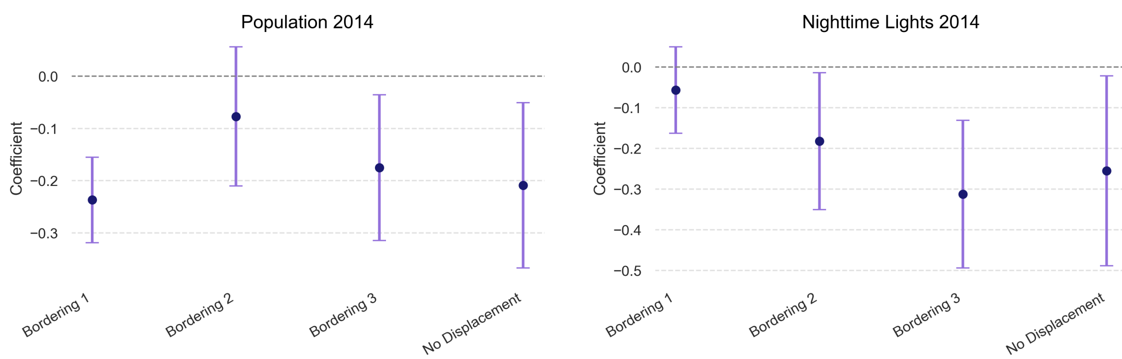
To move towards a more causal interpretation of the results in Section 5, I explore different identification strategies and specifications that show that the main results are robust. I take a different approach: rather than assuming that the No Displacement parishes were not affected, I consider that they were also treated. In Section B.3, I compare Camp parishes to all other parishes. In the strategy in Section 5.2.1, I test whether the effect of being a parish without a camp is diminishing in the distance from a camp. In Appendix B.4 I also repeat the analysis excluding a ring of second-degree bordering parishes to reduce SUTVA concerns. Results are robust and show that camps experienced higher population growth, more road infrastructure being built, experienced higher levels of nighttime light growth, but no significant increase in GDP per capita, mainly because in is the directly bordering parishes that experience an increase in GDP per capita higher than that of the camp parishes.

5.2.1 Border Decay

Next, I test for whether distance to a camp mattered for growth patterns across North and Eastern Uganda. The empirical specification is as follows:

$$Y_{p,t} = \beta_0 + \beta_1 \times Bordering1_p + \beta_2 \times Bordering2_p \\ + \beta_3 \times Bordering3_p + \beta_4 Y_{p,t-1} + \delta + C_{p,t} + X_{p,1992} + \epsilon_p \quad (2)$$

where $Camp_p$, the dummy for whether the parish p has a camp, is now the omitted category, and $BorderingI_p$ is a set of dummy variables for whether p is first-order, second-order, or third-order bordering a parish with a camp. "No Displacement" pools together all the parishes that are even further from camps. Standard errors are clustered at the parish level.



(a) Population change relative to camps (b) Nightlight change relative to camps

Figure 8. Effects of displacement on bordering parishes: population and nightlights relative to camps.
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.

5.2.2 Dynamic Population Changes

To examine the dynamic effects of displacement on population, I exploit variation in the timing of camp openings across locations and estimate an event-study specification following Callaway and Sant'Anna, 2021. This approach accommodates staggered treatment adoption and allows the treatment effects to vary across cohorts of parishes that were exposed to displacement at different points in time. The intuition is that by comparing parishes treated in a given year with those not yet treated or never treated, I can trace the evolution of population before and after displacement.

Formally, I estimate

$$\ln(\text{Population}_{pt}) = \alpha_p + \lambda_t + \sum_{g \neq 0} \sum_{\ell \in \mathcal{L}} \beta_{g,\ell} \mathbf{1}\{G_p = g\} \mathbf{1}\{t - g = \ell\} + \varepsilon_{pt}, \quad (3)$$

where α_p and λ_t are parish and year fixed effects, respectively. The coefficients $\beta_{g,\ell}$ capture deviations in log population ℓ years from camp opening for cohort g, relative to the year before treatment.

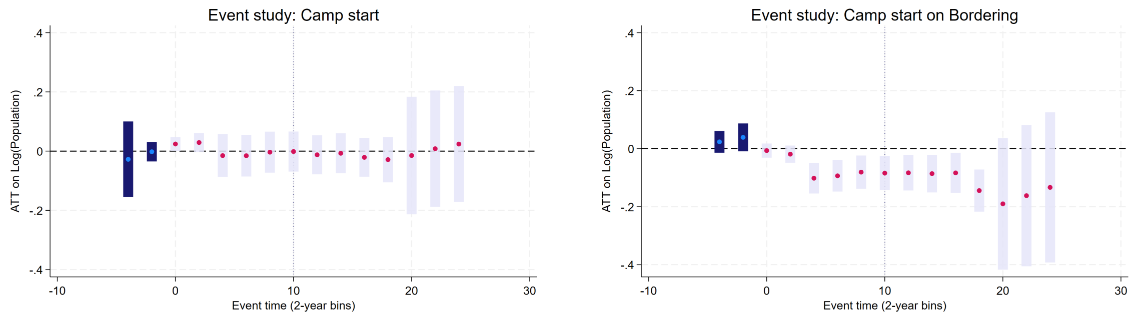
The identification then in this specification relies on the assumptions that parallel trends hold, that there were no anticipation effects, and that the stable unit treatment value assumption (SUTVA) holds. The parallel trends assumption for population holds visually in the results displayed in Figure 9. In addition, I match on pre-treatment covariates using inverse-probability weighting. Although anticipation cannot be tested formally, the abrupt and localized nature of conflict and the government's reaction (documented in Blattman and Annan, 2010 and Bozzoli, Brück, and Muhumuza, 2011) makes it less likely[8]. Since conflict shocks and camp opening timing decisions across the region happened contemporaneously, and conflict was mainly composed of random attacks, this makes anticipation effects and SUTVA less likely to bias the estimates.

The results displayed in 9 confirm that bordering parishes experienced lower population growth growth after people were free to move back to their villages of origin.

6 Micro- Evidence: Occupational Shifts and Human Capital Accumulation

In this section, I ask how did forced displacement shift the composition of people across parishes in North and East Uganda? First, I test whether the displacement

[8]In Subsection 9.1 I study in detail the role of camp duration length on economic activity and I show in Figure 16 that camp opening timing was co-moving with conflict and in Table B11 that the timing was balanced against most parish characteristics with the exception of road length and elevation.



(a) Camp Population

(b) Bordering Population

Figure 9. Displacement and Population Distribution

policy led to a change in the sectoral of people across parishes, and I find that it lead to an increase in the share of workers in the services sector. Second, I examine how the level of education of people changes across camp and bordering parishes and find an increase in the share of higher educated people in bordering parishes, with the caveat that there is heterogeneity in these changes by age group.

6.1 Occupational Shifts and Sorting

Is the increase in population density due to camps accompanied by a transition from agriculture to services? 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 find that conflict-induced higher population density is consistent with occupational shifts out of agriculture, with significant spillover effects. To do so, I make use of occupation and education data from the census of Uganda, with which I can run the following difference-in-difference regressions at the individual level:

$$\begin{aligned}\mathbb{P}(Y_i = 1) = \alpha + \beta_1 \text{Camp}_p + \beta_2 \text{Bordering}_p + \beta_3 \text{Post} \\ + \beta_4 (\text{Camp}_p \times \text{Post}) + \beta_5 (\text{Bordering}_p \times \text{Post}) + \mathbf{X_i fl} + \epsilon_i \end{aligned} \quad (4)$$

Where $P(Y_i = 1)$ denotes the probability that individual i is in a category of occupation. $\beta_4(\text{Camp}_p \times \text{Post}_t)$ and $\beta_5(\text{Bordering}_p \times \text{Post}_t)$ capture post-displacement changes in Camp and Bordering parishes, respectively. $\mathbf{X_i}\gamma$ is a vector of control variables for individual-level characteristics (age and gender), 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. I introduce parish fixed effects in the second and third columns to control for all unobserved, time-invariant characteristics that are shared by individuals within the same parish.

Table 6. Probability of Working in Agriculture

	Agriculture	Agriculture	Agriculture
Post	-0.099***	-0.048	-0.042
	(0.007)	(0.031)	(0.031)
Camps×Post	0.048***	-0.005	-0.008
	(0.012)	(0.051)	(0.051)
Bordering×Post	-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 and age. Sample includes all parishes that experienced conflict within 10km during the war. ***p<0.01, **p<0.05, *p<0.1.

Table 7. Parish-level Occupation Shifts

	Agri. Share (1)	Non-agri Share (2)	Services Share (3)
Post × Camp	-0.074**	0.049***	0.018
	(0.029)	(0.013)	(0.013)
Post × Bordering	-0.117***	0.095***	0.075***
	(0.026)	(0.012)	(0.010)
Camp = Bordering (p-value)	0.098	0.006	0.002
Pre-mean (No Disp.)	0.220	0.084	0.058
N	197	198	198

Notes: Conley standard errors in parentheses (20km). Sample includes all parishes that experienced conflict within 10km during the war that are observed in both years 1991 and 2014. ***p<0.01, **p<0.05, *p<0.1.

Table 8. Agriculture: Subsistence vs. Market

	Market Agriculture	Market Agriculture	Market Agriculture
Post	-0.016***	-0.030***	-0.030**
	(0.004)	(0.012)	(0.012)
Camps×Post	0.013***	0.036**	0.037**
	(0.005)	(0.016)	(0.016)
Bordering×Post	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 experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

The results from Table 6 show that the probability of being employed in agriculture after displacement is statistically indistinguishable from zero in camps compared to No Displacement parishes, but that it is *decreasing* in the Bordering parishes, such that relative to a mean of 82.5% share in agricultural workers, the probability of working in agriculture fell by around 10.8% in Bordering parishes and is statistically significantly different from the change in the Camp parishes. This decrease in agriculture in bordering regions is mirrored by an increase in the share of services workers of 11.1%, as shown in Table B1. Furthermore, to evaluate how occupational compositions are changing at the parish level, I aggregate the data and account for the spatial correlation in the outcome variable using Conley standard errors, as displayed in Table 7. In doing so, I find that the share of agricultural workers decreases significantly in both Camps and Bordering parishes. Specifically, Camp parishes saw a 7.4 percentage point decrease in the share of people working in agriculture, Bordering parishes saw an 11.7% decrease. Also, I find that that of non-agriculture increases in both, by 4.9 and 9.5 percentage points, respectively. As in Table B1, the increase in the share of service workers in Bordering parishes is significantly higher than that of both, Camp and No Displacement parishes.

To assess how the composition of workers is changing across occupations, I test whether there is any change in agricultural practices.

First, I distinguish between subsistence farming and market agriculture, and use as an outcome variable the probability of working in market agriculture. The results are displayed in Table 8. I find that being in a camp parish increased the probability of working in market agriculture relative to subsistence agriculture by 3.7%. This suggests that more market agriculture was adopted to meet the demands for agricultural produce in the camps, and that this adoption was done within the Camp parishes, and not further out. This narrative is in line with the findings of Alix-Garcia et al., 2018, who find that in Kakuma refugee camp in Kenya, agricultural activity increases in the proximity of the camp. Thus, while the share of people in Camps transitioning from agriculture to services is not consistently robust across specifications, and is consistently lower than the relative switch in the Bordering parishes, there is indeed a shift from subsistence agriculture to more market-based agriculture activity, which is still consistent with the literature on urbanization, market access and structural transformation.

Moreover, I examine whether there were observable changes in wealth, or capital accumulation, by studying how the share of people working in livestock compares to the overall share of agriculture workers. I find no such effect, as is shown in Table B2.

Evidence on selection.

Is there sorting across parishes as a response to forced displacement? To answer the question, I study the change in the probability of being an employee versus one's own employer for each of the agriculture and non-agriculture sectors. The intuition is that since primarily agricultural workers were displaced, and agricultural land in Camp parishes became scarce, then there was limited land available for people to be self-employed farmers. Therefore, people who stayed in camps and were not able to move back to the Bordering parishes and unable to switch to services employment had to work as employees on land owned by other people. This is in line with reports citing poverty and lack of opportunity for work in the camps, and also points towards increased inequality in the camps where few people benefited at the expense of the many displaced people who had lost their land and their assets.

Table 9 shows the probability of being employed in the agriculture sector (i.e, not an employer nor self-employed. 0 refers to being an employer). The results show that the probability of being an employee in agriculture increases by 10% in camp parishes, and decreases (although not consistently significant) in bordering parishes.

On the other hand, when inspecting the employment status in the non-agriculture sector I find that camps experience an increase in the share of people that report being their own employer in the services sector. The results are displayed in Panel B of Table 9. To provide further evidence on sorting, I classify services workers into high-skilled and low-skilled services and examine the probability of working in a higher-skilled job. The results are displayed in Panel C of Table 9. In contrast to Huang, Xie, and You (2023), where income shocks primarily expand low-skill services, I find evidence of higher skilled workers in the bordering areas, consistent with selective migration and sorting.

Table 9. Employment and Skill Decomposition

	(1)	(2)	(3)
Panel A: Agricultural Employee			
Post	-0.511***	-0.524***	-0.530***
	(0.011)	(0.031)	(0.028)
Camps×Post	0.016	0.100**	0.095**
	(0.019)	(0.049)	(0.047)
Bordering×Post	-0.062***	-0.074	-0.067
	(0.016)	(0.068)	(0.063)
N	1.89e+05	1.89e+05	1.89e+05
Mean Dependent Variable	0.524	0.524	0.524
Camps = Bordering (p-val.)	0.000	0.016	0.016
Panel B: Non-Agricultural Employee			
Post	0.252***	0.249***	0.227***
	(0.021)	(0.048)	(0.047)
Camps×Post	-0.231***	-0.331***	-0.309***
	(0.035)	(0.098)	(0.098)
Bordering×Post	-0.067	-0.121	-0.105
	(0.041)	(0.120)	(0.116)
N	6.78e+04	6.78e+04	6.78e+04
Mean Dependent Variable	0.471	0.471	0.471
Camps = Bordering (p-val.)	0.000	0.133	0.134
Panel C: Skilled vs. Unskilled Services			
Post	-0.277***	-0.328***	-0.275***
	(0.024)	(0.056)	(0.053)
Camps×Post	-0.156***	-0.044	-0.065
	(0.040)	(0.110)	(0.106)
Bordering×Post	-0.075	0.170*	0.149*
	(0.051)	(0.095)	(0.088)
N	4.51e+04	4.51e+04	4.51e+04
Mean Dependent Variable	0.411	0.411	0.411
Camps = Bordering (p-val.)	0.141	0.079	0.065
Controls	No	No	Yes
FE	No	Parish	Parish

Notes: The dependent variable in the regressions in Panels A & B is the probability of being an employee, as opposed to being an employer. The dependent variable in Panel C is the probability of working in a high-skilled job in services (clerk, professional, legislator) as opposed to lower-skilled job in services (elementary occupations, shop and market sales...). Standard errors clustered at the parish level in parentheses. Controls include sex and age. Sample includes all parishes that experienced conflict within 10km during the war.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

6.2 Effects on Educational Attainment

The impact of forced displacement on human capital has been widely studied in the economics literature. Since educational attainment has been linked to improved lifetime outcomes and increased long-run development, understanding the role of forced displacement in shaping educational uptake decisions in Sub-Saharan Africa is increasingly important. Whereas conflict and insecurity prevents many children from attending school and may lead to traumatic responses that hinder educational attainment (Shemyakina, 2011, Blattman and Annan, 2010[9]), provision of better education services in the destination location relative to the origin could lead to better schooling for children. Chiovelli et al., 2021 show that there are overall gains in human capital accumulation due to displacement, partly due to the relocation of migrants to districts with better provision of education and more urban locations. In addition, the composition of the people migrating can change the average levels of education, and effects may vary by gender and age. To study the impact of forced displacement on human capital, I focus on three key outcome variables: the probability of having above primary education, the probability of having above secondary education, and the number of years of schooling. I find that parishes that were *bordering* the Camp parishes experienced an increase in the probability of having acquired above primary education by 2.3 percentage points compared to the less affected parishes (Table 10). Given a baseline share of 8.5% in the No Displacement parishes, this represents an increase of roughly 27%. These results are robust to averaging at the parish level and using Conley standard errors (see Table B6). Furthermore, I find a similar increase in the years of schooling by 0.17 for Bordering parishes, which translates roughly to around two additional months of schooling. The corresponding results displayed in Table B5.

The aggregate results, however, mask underlying heterogeneity across age groups. Specifically, we expect that the impact of displacement would depend on whether someone displaced was already of working age, or school-aged. It is important to note that during the displacement period, camps not only received food aid, but also had schools built. However, these schools were reportedly congested and offered lower-quality education. In 2005, it was estimated that over 250,000 children were not attending school in the war-affected zones. Moreover,

[9] In fact, Blattman and Annan, 2010 show that the recruitment of child soldiers in Northern Uganda, which was highly prevalent during the conflict in that region, lead to a decrease in schooling and skilled employment. Their data was collected in 2005, before the official end of the conflict when children had been already abducted between 1 day and 10 years.

Table 10. Share of Above Primary Education

	Above Primary	Above Primary	Above Primary
Post	0.222^{***}	0.259^{***}	0.277^{***}
	(0.001)	(0.008)	(0.005)
Camps×Post	0.057^{***}	0.008	-0.001
	(0.003)	(0.014)	(0.011)
Bordering×Post	0.100^{***}	0.033^{***}	0.023^{**}
	(0.003)	(0.012)	(0.011)
N	6.88e+05	6.88e+05	6.88e+05
Mean Dependent Variable	0.057	0.055	0.057
Camps = Bordering	0.000	0.093	0.085
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 experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

we would expect some variation based on whether those children born in camp parishes during versus after the war.

To test the hypothesis whether camp schooling services may have aided the overall education levels in camps, I first divide people in 2014 into those who were already of working age in 1996 (above 35 years old), those who were displaced as children (18-35 years old), those who were born during the FD period (8-18), and those who were born after (8 and under). Then, I run the regression specified in Equation 4 separately for each age group and compare the coefficients. I am interested in where the discrepancy between Camps and Bordering comes from. The coefficients are plotted in Figure 10. They indicate that there is a change in the composition of the population after displacement across Camp and Bordering parishes. More specifically, the higher average educational attainment in the Bordering parishes compared to Camp parishes are driven mainly by a dip in the share of above-primary adults who are more than 35 years old in Camp parishes, who were already of working age when they were forcibly displaced. This pattern does not hold when studying the relationship between years of education and displacement for those below 35, and is even reversed for children born after displacement: those born in what were the previous Camp parishes have higher levels of education compared to the children in Bordering parishes($p - value = 0.101$). These findings suggest higher educational attainment among children born after displacement in former camp areas and a compositional shift among adults, where displaced working-age individuals were predominantly of lower education.

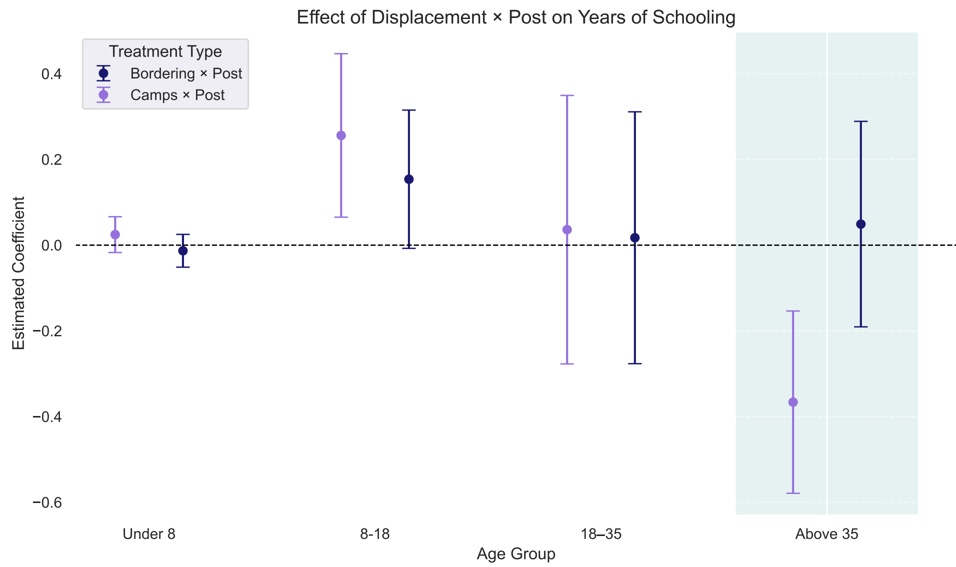


Figure 10. Effect of Displacement on Educational Outcomes by Age Group.
Note: Controls include age and sex. Shaded region corresponds to a significant ($p - value < 0.1$) difference between the $Camp \times Post$ and $Bordering \times Post$

7 Mechanisms

In this section, I explore two potential mechanisms that could explain the results observed above. First, I show that due to investment in reconstruction of infrastructure after the war, parishes that experienced forced displacement also received more roads and thus had improved market access. Second, I test whether the change in displacement led to changes in land use, since conflict and displacement may have altered patterns of land ownership. Specifically, anecdotal evidence and reports discuss that several villagers were unable to return to farming their land because it was unclear which land belonged to who, land grabbing was prevalent, and families involved in land disputes did not manage to farm their lands.

7.1 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), I 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 version of this network, where each edge (the connection between two parishes) is weighted by the product of the populations in both locations, to move towards a more market access interpretation of results. The outcome variables of interest are the log change in the centrality, meaning the level of connectedness, of a parish. I run the regression specified in Equation 1. The results are displayed in Table 11. 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:

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

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

Table 11 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.

Table 11. Camps and Evolution of Parish Network Centrality

	Log Road Length (1)	Degree Centrality (2)	Betweenness Centrality (3)	Closeness Centrality (4)
Camp	0.336***	0.184	0.561***	0.430***
	(0.073)	(0.185)	(0.128)	(0.109)
Bordering	0.020	0.322**	0.333***	0.192*
	(0.050)	(0.160)	(0.120)	(0.100)
Camp = Bordering (p-value)	0.000	0.177	0.000	0.000
Pre-mean (No Disp.)	10.359	-0.123	-0.297	-0.389
R^2	0.759	0.119	0.282	0.396
N	1056	1056	1056	1056

Notes: Conley standard errors (20km) are in parentheses. Controlling for: mean elevation, standard deviation of elevation, area, pre-war conflict, initial share of agricultural land and share of urban settlement land.
Sample includes all parishes that have experienced conflict within 10km between 1991 and 2006.
***p<0.01, **p<0.05, *p<0.1.

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- the most direct indicator for market access- 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. Bordering parishes experienced larger increases in market access after forced displacement.

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.

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, bordering parishes experienced higher gains in terms of market access compared to both, the No Displacement parishes, and the camp parishes.

7.2 Land Use

Next, I study whether there were changes to land use. Using an adjusted Land Use dataset of FAO by Mwanjalolo et al., 2018 that classify different categories of land use, I group these categories into land used for agricultural activities, livestock activities, urban settlement, protected land, and unused land, which I use to refer to land that is in neither of the previously listed categories. Using the same specification as Equation 1, I study whether forced displacement affected the shares of land used in each category. The results are displayed in Table 12. A shortcoming of the data is that it has little variation in land use across locations, and using district fixed effects becomes very restrictive. I find with parish fixed effects that locations with camps or were bordering the camps both had significant decreases in the share of land that is used, with this share coming from more land being used in agriculture for the bordering locations and (although not significant) in urban areas in the camp parishes. Both the camps and bordering locations have an increase in the share of land being used for livestock activity, which is in line with the results on the increases in nightlights for both camps and bordering locations.

Table 12. Changes in Land Use

	(1) Livestock Activity	(2) Agricultural Activity	(3) Unused Land	(4) Urban - settlement	(5) Protected Land
Camps	0.305***	0.0844	-0.199***	0.0190	-0.315***
	(0.0469)	(0.0754)	(0.0714)	(0.0443)	(0.0909)
Bordering	0.279***	0.147**	-0.260***	-0.00837	-0.183**
	(0.0402)	(0.0602)	(0.0591)	(0.0352)	(0.0793)
Observations	1056	1056	1056	1056	1056
Adjusted R^2	0.844	0.328	0.706	0.435	0.272

Notes: Standard errors clustered at the parish level in parentheses. Controlling for: mean elevation, standard deviation of elevation, initial population, road length, nighttime lights. Sample includes all parishes that experienced conflict within 10km. ***p<0.01, **p<0.05, *p<0.1.

Table 12 shows that both bordering and camp parishes experienced increases in land used for livestock. Although the microdata does not show that there was an increase in the number of people working in livestock as a result of forced displacement, the results could still suggest that there was a higher share of wealthier people in camps and bordering areas that owned cattle. Perhaps more importantly, we see that the share of land that is not used for production, is not an urban settlement, and is not a protected area- which can be thought of as a sign of misallocation of production, is decreasing, perhaps as a direct result of the increase in livestock activities, in the bordering parishes.

The results in Column (3) allow us to reject the hypothesis that the conflict, which restricted how much villagers could return to their own lands to farm, restricted production and economic activity in these lands.

8 Model

To interpret the spatial and sectoral reallocations induced by forced displacement, I develop a static general equilibrium model with multiple locations and two sectors—agriculture and non-agriculture. The model highlights how differences in local fundamentals such as land availability, market access, and conflict exposure shape the distribution of population and production across space. It also features non-homothetic preferences in which the demand for non-agricultural goods is increasing with income.

The framework serves two purposes. First, it provides a structure to rationalize the empirical patterns documented above: following displacement, agricultural employment falls in bordering locations while non-agricultural activity expands, and population concentrates within camps. Second, it allows for counterfactual analysis of policies or conditions that affect post-conflict and displacement recovery, such as the scale of camps or the reconstruction of transport infrastructure after the war.

8.1 Environment

We start with an economy of $\mathbf{I} = \{1, ..., \bar{\mathbf{I}}\}$ locations and two sectors $k \in \{A, S\}$ that represent the agriculture and non-agriculture sectors respectively. There is a measure Ω continuum of households that are distributed across locations and sectors. Households are endowed with an initial location $i \in \mathbf{I}$, and choose simultaneously which sector to work in, and which location to live in. They choose where to live and work after receiving an idiosyncratic location-sector taste shock, and migration is costless.

Population. We consider a unit measure of agents $\omega \in \Omega$, such that:

$$\sum_{i \in \mathbb{I}} \sum_{k \in \{A,S\}} N_{ik} = 1$$

where N_{ik} is the population in location i and sector k,

Preferences. An individual ω in a location i working in sector j consumes an agriculture and non-agriculture good subject to the income they earn in their sector:

$$U(C) = (C_A - \bar{C})^{\alpha} C_S^{1-\alpha} \cdot \epsilon_{ik}$$

subject to:

$$C_{iA} p_{iA} + C_{iS} p_{iS} = w_{ik}$$

and

$$C_A \geq \bar{C}$$

where the price of the agricultural good is the numeraire, and ϵ_{is} is a location-sector taste shock described below.

Location-Sector Taste Shocks. Let $\varepsilon_{is}(\omega)$ [10] be an idiosyncratic location-sector taste shock for option (i, s), such that:

$$\varepsilon_{ik} \sim \text{Fréchet}(T_{ik}, \theta), \quad \text{with } \mathbb{E}[\varepsilon] = \Gamma\left(1 - \tfrac{1}{\theta}\right)$$

θ captures how concentrated location-sector preferences are, and the scale parameter T_{ik} represents exogenous amenities in location i and sector s. Individuals first choose where to locate, and then which sector to work in.

Production. *Agriculture.* The representative firm in agriculture produces with Cobb-Douglas technology using land and labor as inputs:

$$Y_{iA} = Z_{iA} N_{iA}^{\mu} L_{iA}^{1-\mu} \tilde{X}_i$$

[10] such that $\omega \in \Omega$

Z_i represents agricultural productivity that allows for differences in comparative advantage in production in that sector.

Non-Agriculture.

First, let's define the market access of a location i using the concept of weighted closeness centrality, defined as follows:

$$ClosenessCentrality_i = \sum_{j \neq i} \frac{N_j}{d(i,j)}$$

$d(i,j)$ is the shortest-path distance between i and j.

The non-agriculture sector's representative firm produces its final good using labor as its only input, and it's productivity features an agglomeration externality term $\left(N_i^{\gamma}\right)$, and a market access externality term, represented in the expression $\left(\sum_{j\neq i} \frac{N_j}{d(i,j)}\right)^{\kappa}$, where the expression in the parentheses is the closeness centrality weighted by population[11] .

$$Y_{iS} = N_{iS}\left(N_i^{\gamma}\right)\left(\sum_{j\neq i}\frac{N_j}{d(i,j)}\right)^{\kappa}\tilde{X}_i$$

Firms in both sectors only choose labor, and take the land available for agriculture as given. Land is divided equally and freely across the workers in the agriculture sector[12]. Then the income of an individual in location i, sector s is the marginal product of labor:

$$w_{ik} = \begin{cases} p_{iA}\mu Z_{iA}\left(\frac{L_i}{N_{iA}}\right)^{1-\mu}\tilde{X}_i & \text{if } k = A \\ p_{iS}\left(N_i^{\gamma}\right)\left(\sum_{j\neq i}\frac{N_j}{d(i,j)}\right)^{\kappa}\tilde{X}_i & \text{if } k = S \end{cases}$$

where L_i is land in location i, $\tilde{X}_i$ is the location-specific productivity term (e.g., conflict-adjusted shock to productivity), and γ represents the agglomeration externality. A higher κ means that services income is more sensitive to centrality: being closer to larger populations increases productivity spillovers and wages.

[11]Note that this expression is a reduced form method of accounting for the importance of market access in the production of the services sector. It is currently a placeholder for the more microfounded version of the model that explicitly accounts for trade in the services sector, detailed in Appendix D.

[12]Since land distribution in Uganda is majorly customary and Northern Uganda in particular faced much uncertainty over land allocation post-conflict (Amone and Lakwo, 2014; Rugadya, Nsamba-Gayiiya, and Kamusiime, 2008; Hetz, Myers, and Giovarelli, 2007).

I assume that there are no trade costs, therefore

$$p_{jik} = p_{iik} = p_{ik}$$

Sectoral Labor Supply. Individuals supply their labor inelastically and earn income w_{ik} such that (for now), all individuals are equally productive and perfect substitutes across sectors.

Conflict. Define the conflict index in location i as an exponentially weighted sum of conflict deaths over years $t \in \mathbb{T}$:

$$X_i = \sum_{t \in \mathbb{T}} \delta^{\bar{t}-t} \cdot \text{Deaths}_{i,t}$$

where:

- $\delta \in (0, 1]$ is the decay parameter,
- $\bar{t} = \max(\mathbb{T})$,
- $\text{Deaths}_{i,t}$ is the number of conflict deaths in location i in year t.

I invert and normalize the conflict measure to lie in the interval $[b, 1]$, where $b \in (0, 1)$ is a lower bound to the damage that conflict can inflict on production quantity: Let $\bar{X} = \max_j X_j$, and

$$\text{range}(X) = \max_i(\bar{X} - X_i) - \min_i(\bar{X} - X_i).$$

The bounded transformation is then given by

$$\tilde{X}_i = b + (1 - b) \cdot \frac{(\bar{X} - X_i) - \min_k(\bar{X} - X_k)}{\text{range}(X)}.$$

Thus, going back to our production functions for both sectors, an increase in conflict would reduce $\tilde{X}_i$ and thus reduce the quantity produced in both sectors by an equal amount.

Equilibrium. The static equilibrium is characterized by a set of allocations $\{(N_{is}, C_{is})|i \in \mathbf{I}, k \in \{A, S\}\}$ and a set of prices $\{(p_{iS}, w_{ik})|i \in \mathbf{I}, k \in \{A, S\}\}$ such that,

$$\sum_{i \in \mathbf{I}} \sum_{k \in \{A,S\}} N_{ik} = \bar{N} = 1 \tag{5}$$

Consumption for given idiosyncratic preferences:

$$C_{iA} = \frac{\alpha w_i}{p_{iA}} + (1-\alpha)\bar{C} \tag{6}$$

$$C_S = \frac{(1-\alpha)}{p_{iS}} w_i - \frac{(1-\alpha) p_{iA}}{p_{iS}} \bar{C} \tag{7}$$

Location choice of consumers: The share of individuals who choose to be in location-sector pair (i,s) is given by

$$\pi_{ik} = N_{ik} = \frac{T_{ik} V_{ik}^{\theta}}{\sum_{i'} \sum_{k'} T_{i'k'} V_{i'k'}^{\theta}} \tag{8}$$

Profit maximization in the services sector implies:

$$w_{is} * \pi_{is} = p_{is} Y_{is} \tag{9}$$

whereas in the agriculture sector, free land implies positive profits for the agriculture workers:

$$\pi_{iA} = (1-\mu) Y_{iA} \tag{10}$$

which I assume are accrued equally by all the agriculture workers in i such that the income in the A sector is given by the marginal product of labor plus this quantity, which amounts to the average product of labor:

$$w_{iA} = Z_{iA} \left(\frac{L_i}{N_{iA}} \right)^{1-\mu} \tilde{X}_i \tag{11}$$

The goods market clearing conditions are for agriculture:

$$X_{iA} = Z_{iA} N_{iA}^{\mu} L_{iA}^{1-\mu} \tilde{X}_i \tag{12}$$

For services,

$$C_{iS} = N_{iS} \left(N_i^{\gamma} \right) \left(\sum_{j \neq i} \frac{N_j}{d(i,j)} \right)^{\kappa} \tilde{X}_i \tag{13}$$

Prices of services in each location are pinned down from equating the aggregate supply of services to the aggregate demand for each location:

The labor market clearing condition is

$$\sum_{k\in\{A,S\}} N_{ik} = N_i \tag{14}$$

We can also write down the expression of welfare(total utility) as follows:

$$\mathcal{W} = \Gamma\left(1-\frac{1}{\theta}\right)\left(\sum_i\sum_k T_{ik}\,V_{ik}^{\theta}\right)^{\frac{1}{\theta}}. \tag{15}$$

Key Mechanisms *Characterizing Forced Displacement in the Model*

In the empirical section of the paper, I classify forced displacement as two types of treatment affecting parishes: Camp parishes, and Bordering parishes. Not only did these locations experience a redistribution of the population, but also received an increase in roads being built as a part of the recovery and reconstruction directly after the war. I use places where people most likely did not get displaced ("No Displacement" parishes) as the control. These places also did not get allocated new roads after the war. Furthermore, the relative position (by definition) of the treatment assignment means that in general equilibrium, we expect displacement to affect the whole region due to externalities and spillover effects, which are assumed to be unimportant in the empirical section.

Suppose that we have the 3 types of parishes: $\{\text{Camp}, \text{Bordering}, \text{ND}\}$. Furthermore, for simplicity let's define the In the model, this translates to the following changes in fundamentals:

Assume forced displacement (FD) causes:

$$N_{\text{Camp}}\uparrow,\quad N_{\text{Bordering}}\downarrow,\quad N_{\text{ND}}\text{ unchanged},$$

and that building infrastructure to camps causes $d(i,j)$ to decrease for Bordering parishes.

Then we can decompose $\frac{\partial w_{iS}}{\partial \text{FD}}$ into

$$\frac{\partial w_{iS}}{\partial \text{FD}} = \underbrace{\frac{\partial w_{iS}}{\partial N_i}}_{\text{local agglomeration}} + \underbrace{\sum_{j\neq i}\frac{\partial w_{iS}}{\partial N_j}}_{\text{market access spillovers}} + \underbrace{\sum_{j\neq i}\frac{\partial w_{iS}}{\partial d(i,j)}}_{\text{network structure effects}} + \underbrace{\frac{\partial w_{iS}}{\partial \tilde{X}_i}}_{\text{conflict}}$$

8.2 Model Solution

To solve for the spatial equilibrium means solving for the set of population shares $\{N_{iA}, N_{iS}\}_{i\in\mathbf{I}}$ and prices p_{iS} such that the labor and the goods markets clear.

I implement a fixed-point iteration algorithm to obtain the solution. In each iteration, utility levels are updated based on current population shares, and new sector- location shares are computed as the probabilistic choice over all location-sector pairs. The algorithm continues until convergence– when the distribution of agents across locations and sectors is stable across iterations. Section C.2 includes a description of the iterative procedure to solve the model and internally calibrate the market access elasticity κ.

8.3 Inverting the Model

Rearranging the expression in 8, the implied T_{ik} consistent with observed shares is:

$$T_{ik} = \pi_{ik} \cdot \left(\sum_{i'} \sum_{k'} T_{i'k'} W_{i'k'}^{\theta} \right) \cdot W_{ik}^{-\theta}$$

Therefore we can calculate the implied average productivity T_{ik} and then ΔT_{ik}. Let's normalize $T_{1A} \equiv 1$, then we can write

$$T_{ik} = \frac{\pi_{ik}}{\pi_{1A}} \left(\frac{W_{1A}}{W_{ik}} \right)^{\theta}$$

What can we learn about the effect of camps on the overall predicted amenity changes? To answer this question, I run the regressions:

$$\Delta T_{is} = \beta_0 + \beta_1 Camp + \beta_2 Bordering + D_i + \epsilon_{is} \tag{16}$$

As well as:

$$\Delta T_{is} = \beta_0 + \beta_1 Displacement + D_i + \epsilon_{is}$$

where D_i represents district fixed effects and standard errors are clustered at the district level. The results for the non-agriculture sector are displayed in Figure 11 and those for agriculture are in Figure B1. They show that in general the change in non-agriculture and agricultural amenities cannot be explained by forced displacement per se, which indicates that forced displacement is already explained through changes in the fundamentals in the model.

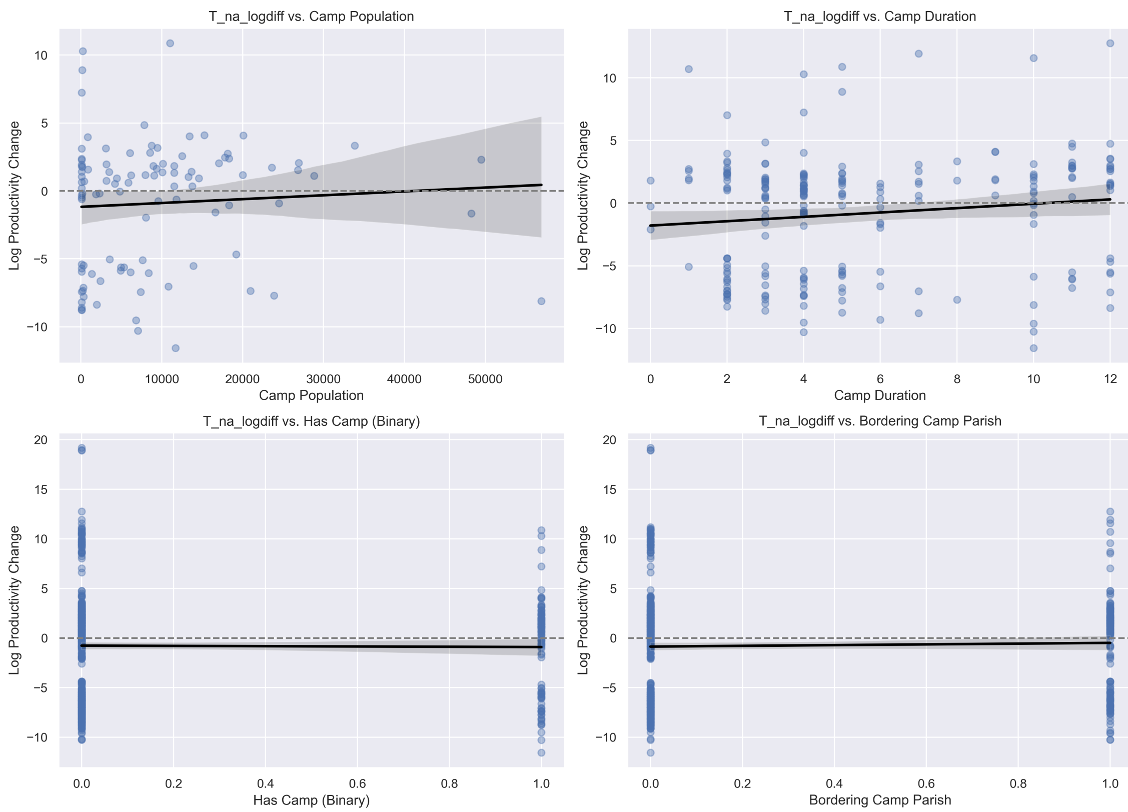


Figure 11. Model-Predicted Non-Agri Log Differences and Treatment

8.4 Counterfactual Analysis I: The Role of Road Reconstruction

To understand the role of reconstruction efforts after the war on the occupational shifts, I simulate the model in 2014 in a world where roads are the same as they were before the war, and compare the population-sector distributions π_{ik} in both scenarios.

Figure 12 shows $\Delta\pi_{ik} = \pi_{ik} - \hat{\pi}_{ik}$ shows that there is substantial heterogeneity in the spatial distribution of the sectoral changes due to infrastructure changes. Figure 13 decomposes the changes in the sectoral composition by treatment, and shows that on average both Bordering and No Displacement would have actually maintained *more* non-agriculture workers had there been no roads. This is not an obvious effect and is showing up because of the general equilibrium effects because of the change in the prices in services due to the change in the roads. In Figure 14 we can see that parishes are not affected equally by the reconstruction of roads. Table 13 shows that the reconstruction of roads actually led to a higher share of people in camps working in agriculture, because camps no longer had to specialize in non-agriculture occupations as they did when they were parishes that had disproportionately more roads. Note that these results do not hold fixed forced displacement and migration is costless.

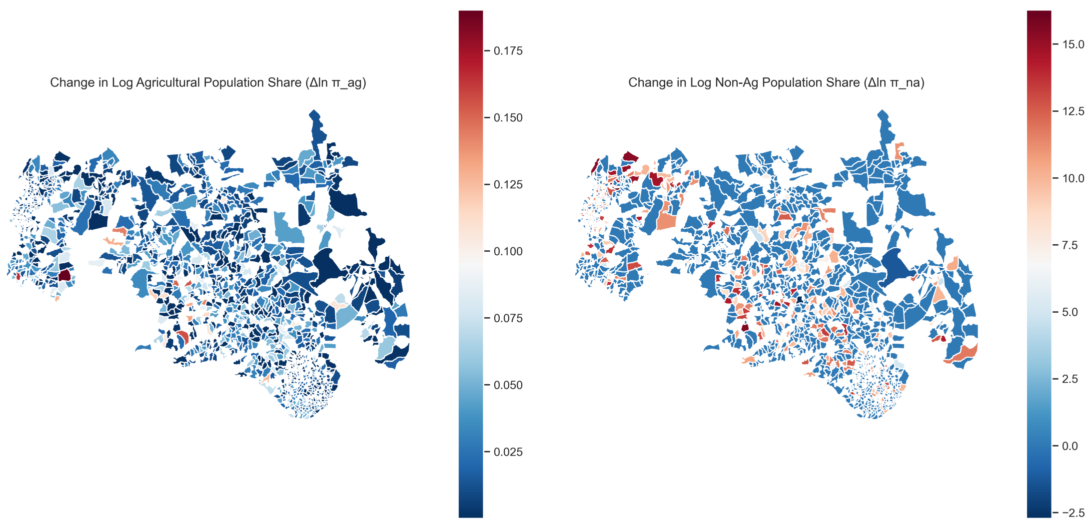


Figure 12. Model-Predicted Population Differences

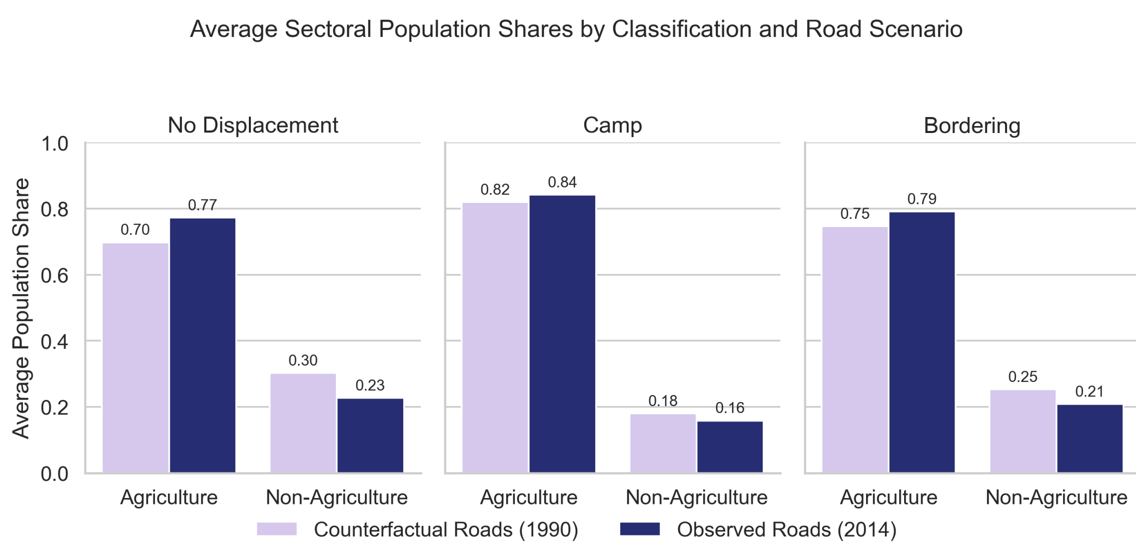


Figure 13. Counterfactual Sectoral Composition

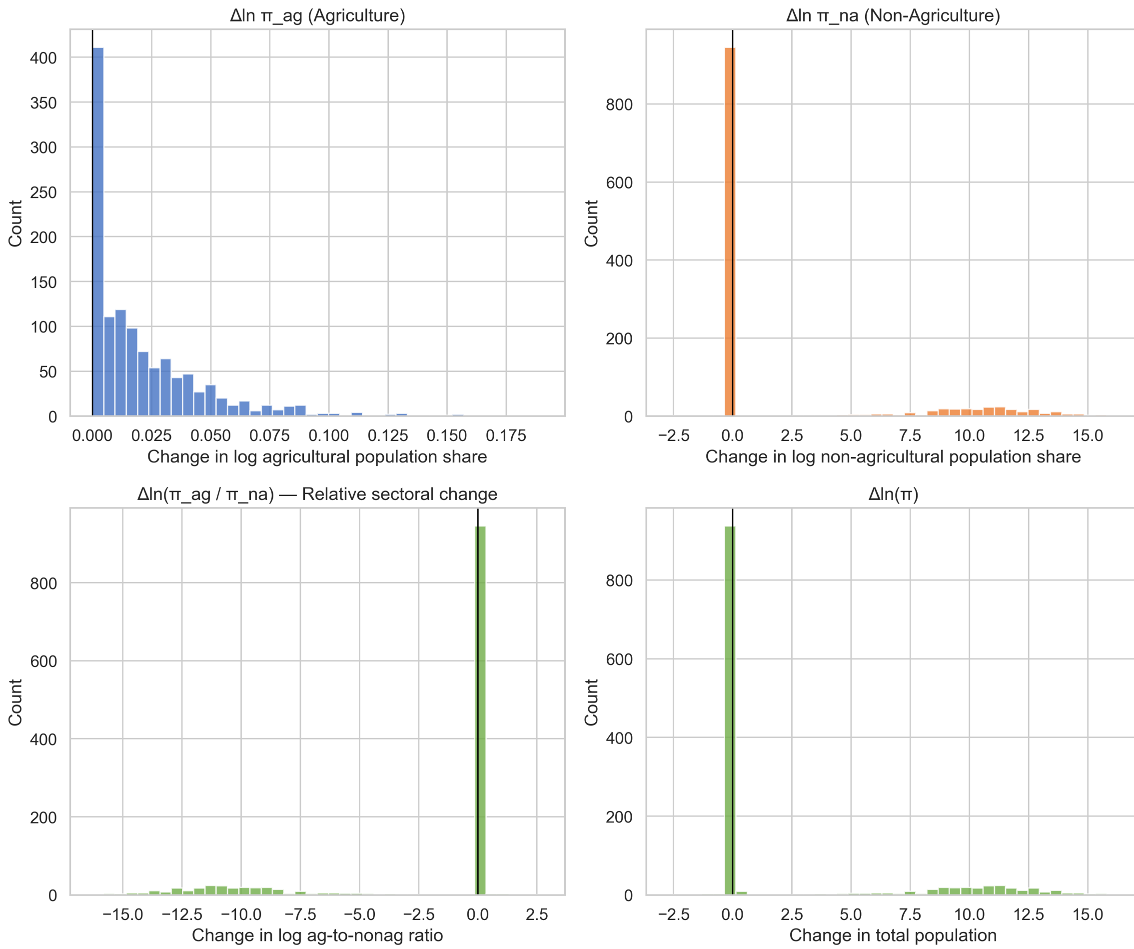


Figure 14. Changes in Sectoral Population Distribution

8.5 Counterfactual Analysis II: Measuring the FD Shock

To assess how forced displacement altered the spatial distribution of economic activity, I exploit the model to estimate the displacement shock, defined as the change in the migration elasticity θ under different regimes. By comparing model solutions under alternative values of θ, I measure the effect of forced displacement on both sectoral employment and welfare.

Methodologically, my approach parallels that of Caliendo, Dvorkin, and Parro (2019), who invert a structural spatial model to recover the productivity shocks from the China trade shock consistent with observed reallocations of trade volumes and then use these shocks to conduct counterfactual simulations. The key difference is in the choice of the parameter that embodies the displacement shock. Whereas their analysis interprets shifts in productivity as the primitive disturbances driving

	Agriculture	Non-Agriculture
	(0.001)	(0.226)
Camp	0.004*	-0.649
	(0.003)	(0.410)
Bordering	0.003	-0.192
	(0.002)	(0.363)
R-squared	0.005	0.003
R-squared Adj.	0.002	0.000
N	753	753

Table 13. $\Delta ln \pi_{ik}$

reallocation, I instead treat changes in the migration elasticity θ as the relevant shock. In doing so, I capture how forced displacement altered the responsiveness of households to spatial and sectoral differences in economic opportunities, and I use the model to quantify the implications of this shift for employment and welfare outcomes.

Of course, there are several inefficiencies that limit the accuracy of such an approach, mainly concerning how forced displacement interacts with conflict. The results below are under the assumption that conflict would have operated under the same process with or without forced displacement. This is also true about the counterfactual change in land use that could have taken place without conflict.

The logic for estimating the change in migration elasticity θ is detailed in Appendix C.4.

I find that forced displacement led to long-run frictions to mobility, implied by a 57% decrease in the migration elasticity with preliminary calibrations of the model parameters.

9 Heterogeneity Analysis

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 length of the period when people are forced to live in camps affect regional development and thus the welfare of the communities that live there. In this subsection I try to understand which characteristics of camps mattered more for development outcomes of parishes.

9.1 The Role of Camp Duration

In this section, I present a novel identification strategy to understand the impact of the duration of a forced displacement episode in economic development. In this approach, the effect of forced displacement can be thought of as the effect of concentrating a dispersed population for an amount X of years. So camp, or displacement duration, is the independent variable.

9.1.1 Descriptive Statistics

Taking advantage of the fact that the conflict and displacement timing across North and Eastern Uganda was as good as random, I construct clusters of parishes such that a cluster consists of a camp parish, and all the parishes that intersect within a 5km radius around the camp. Using data that I collected on the moment when a camp first becomes visible through satellite data, I assign to each cluster the earliest camp "birth" date. The clusters and camps are represented in Figure 15, with the start date of camps. We can see that there is variation across space in the timing of a camp opening. In Figure 16, I show that if I classify displacement clusters into Early and Late cluster based on whether the first camp in a cluster was established before or after 2001, both groups actually experienced similar conflict paths even though camps were created at different times. This means that we can interpret the results as the effect of displacement duration only, and not as a result of variation in the intensity of conflict at different times. Tables B11 and B12 show that Early and Late clusters are balanced on covariates pre-treatment . Earlier clusters had slightly more roads and were on lower levels of elevation compared to later clusters, and earlier clusters had on average older populations, but otherwise the two groups are very similar. In my empirical strategy, I will not divide clusters into early and late, but rather make use of the full variation of camp timing by having it as a continuous independent variable in my regressions.

9.1.2 Empirical Specification

To analyze the role of camp duration on economic development, I estimate the following regression at the parish level:

$$\Delta Y_c = \beta_0 + \beta_1 \times CampDuration_c + \beta_3 Y_{c,t-1} + \delta + C_{c,t-1} + X_{p,1992} + \epsilon_c \tag{17}$$

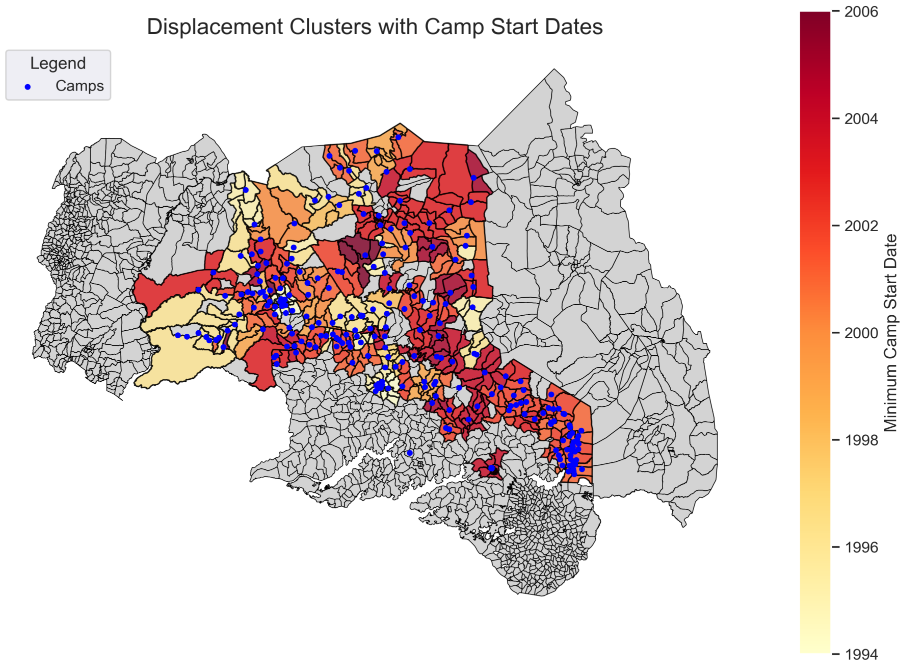


Figure 15. Camp Creation in North and East Uganda

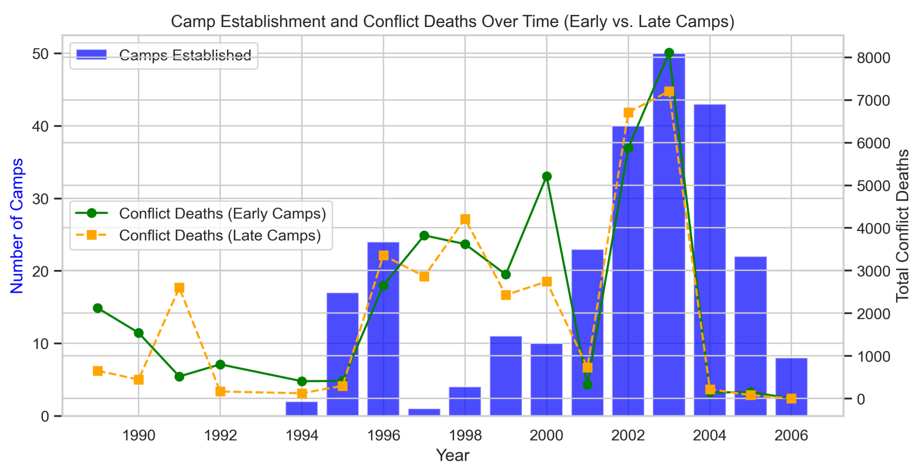


Figure 16. Camp Creation and Conflict Timing

At the individual level, I estimate the following regression:

$$\mathbb{P}(Y_i = 1) = \alpha + \beta_1 CampDuration_p + \beta_2 \text{Post}_t + \beta_3(CampDuration_c \times \text{Post}_t) + \mathbf{X_i}\gamma + \epsilon_i \tag{18}$$

The coefficient of interest, β_3, reports the effect of one more year of a population living in forced displacement on the outcome variable after free mobility.

9.1.3 Results

Growth at the parish level

First, I study whether camp duration had an effect on economic development in parishes. Table 14 illustrates through which mechanism Camp Duration most likely would affect outcomes: it affects the probability that a displaced person would choose to stay in a camp. The sample this time includes only parishes within a displacement cluster, i.e including both the camps and the parishes surrounding them. Column (1) shows that at the parish level, a parish grew 1.778% more for each additional year where there is a camp in its cluster (regardless for whether that parish has a camp or not). To understand whether this elasticity is the same whether a location is a camp or not, I run the regression in Equation 19, and in column (5) get that the effect is heterogeneous and is coming from Camp parishes. Camp duration does not seem to have a significant effect on roads or growth.

$$\begin{aligned} \Delta Y_i = \quad & \beta_0 + \beta_1 \text{CampDuration}_i \times \text{NoCamp}_i \\ & + \beta_2 \text{CampDuration}_i \times \text{Camp}_i + \mathbf{X}_i' \gamma + \delta_{d(i)} + \varepsilon_i \end{aligned} \tag{19}$$

Table 14. Parish-level Growth

	(1) Population Growth	(2) Road Length Growth	(3) Nighttime Light Growth	(4) GDP PC Growth	(5) Population Growth
Camp Duration	1.778**	-1.740	1.120	-0.658	
	(0.814)	(1.253)	(1.590)	(1.717)	
No Camp×Camp Duration					0.379
					(0.881)
Camp×Camp Duration					3.251***
					(0.884)
Observations	426	426	426	426	426
Controls	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
R^2 (adj.)	0.510	0.309	0.523	0.519	0.531

Notes: Standard errors clustered at the district-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Growth at the cluster level I find no effects, partially due to a significant decrease in the sample size since it is restricted to parishes in displacement clusters. The results are inconclusive, but suggest that whether the population of parishes in a cluster was displaced early or late did not have a significant effect on growth.

Individual-level results: Occupational shifts

I move on to study the effect of camp duration on occupational shifts. The results for Agriculture are displayed in Table 15. I find that an additional year of a people being forcibly displaced in a camp led to a 3.7% decrease in the probability of working in agriculture. Furthermore, Table B3 shows that this is accompanied by an increase in the probability of working in services by 2.8% for each additional year of displacement, and Table B4 shows that there is also a significant but very small increase in the probability of working in manufacturing. Therefore, the existence of a camp and the forced displacement of people into camps for longer periods of time led to a significant occupational shifts in North and Eastern Uganda. This could be largely due to longer presence of NGOs in these locations, or also due to agglomeration forces requiring time to lead to more structural change.

Table 15. Agriculture

	(1) Agriculture	(2) Agriculture	(3) Agriculture
Post Displacement	-0.0160	0.0977	0.106*
	(0.0548)	(0.0592)	(0.0580)
Post Displacement×Camp Duration	-0.0190*	-0.0369***	-0.0378***
	(0.00995)	(0.0104)	(0.0102)
N	125249	125249	125249
depvar_mean	0.854	0.854	0.854
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the Displacement Cluster-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Furthermore, I decompose the effect of camp duration within cluster depending on whether a parish is a camp parish or not (bordering, within 5km of a camp) by running the regression 20. The results are displayed in Table B14. They show that the occupational shifts experienced due to camp duration in a displacement cluster are coming not from the camp, but the bordering parishes.

$$\begin{aligned}\mathbb{P}(Y_i = 1) = \alpha + \beta_1 CampDuration_p + \beta_2 Camp_p + \beta_3 \text{Post}_t \\ + \beta_4(CampDuration_c \times \text{Post}_t) + \beta_5(CampDuration_c \times Camp_p \times \text{Post}_t) + \mathbf{X_i}\gamma + \epsilon_i\end{aligned} \tag{20}$$

Education and human capital

Next, I study the effects of camp duration on education levels. I find that longer displacement periods lead to an increase in education levels. Specifically, Table 16 shows that an additional year of forced displacement led to a 1.8% increase in the average education level. This could be due to the prolonged presence of schools provided by NGOs in the locations where displacement took place earlier.

Table 16. Education Level

	(1) Education	(2) Education	(3) Education
Post Displacement	0.407***	0.342***	0.348***
	(0.0616)	(0.0456)	(0.0462)
Post Displacement×Camp Duration	0.0103	0.0180**	0.0187*
	(0.00990)	(0.00906)	(0.00944)
N	295863	295863	295863
depvar_mean	1.643	1.643	1.643
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the Displacement Cluster-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

9.2 Camp Size

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 start by running the following specification:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p + \delta + C_{p,t-1} + X_{p,1992} + \epsilon_{p,t} \tag{21}$$

where $CampPop_p$ is the camp population in 2005, which is when the numbers of people in internal displacement camps was at its highest.

The results, in Table 17, 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.

This regression might suffer from endogeneity issues since camp parishes that received more people may have been already set on a different growth path compared to those that received less people. To mitigate these selection concerns, I

Table 17. 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)
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.

instrument camp population with the road length in a parish in 1992. The specification is displayed in Equation 23. The identifying assumption is that the road infrastructure in 1992 only affects the outcome variables of occupation composition and education composition through the variation in camp population. This is a plausible assumption since we expect camps that were more connected to also be ones where the government found it easier to move more people.

First Stage:

$$\text{CampPop}_{p,2005} = \alpha_0 + \alpha_1 \log(\text{RoadLength}_{p,1992}) \times \text{Post}_t + \gamma_p + \varepsilon_{pt} \tag{22}$$

Second Stage:

$$Y_{ipt} = \beta_0 + \beta_1 \widehat{\text{CampPop}}_{p,2005} \times \text{Post}_t + X'_{it}\delta + \gamma_p + \epsilon_{ipt} \tag{23}$$

The results show that camp population did not have a significant effect on the share of people working in services, but that it did have an effect increasing the level of education in bigger camps, by 2.3 percentage points for each 1000 additional people in a camp.

Table 18. Probability of Working in Services

	(1) OLS	(2) First stage	(3) 2SLS (IV)
Camp Size (per 1000)	0.002		0.003
	(0.001)		(0.004)
Age	-0.002***	0.000	-0.002***
	(0.000)	(0.000)	(0.000)
Female	-0.018***	-0.018	-0.018***
	(0.004)	(0.015)	(0.004)
Log Road Distance		1.072***	
		(0.130)	
Observations	61868	302298	61868

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

Table 19. Probability of Above Primary Education

	(1) OLS	(2) First stage	(3) 2SLS (IV)
Camp Size (per 1000)	0.010***		0.023***
	(0.002)		(0.003)
Age	0.002***	0.000	0.002***
	(0.000)	(0.000)	(0.000)
Female	-0.102***	-0.018	-0.102***
	(0.003)	(0.015)	(0.003)
Log Road Distance		1.072***	
		(0.130)	
Observations	203112	302298	203112

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

9.3 Conflict

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 24:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p \times Conflict_p + \beta_2 \times CampPop_p + \beta_3 \times Conflict_p + \delta + X_{p,1992} + \epsilon_{p,t} \tag{24}$$

The coefficient of interest, β_1, is reported in Table 20, 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.

Table 20. 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.

10 Conclusion

Forced displacement unfolds under extreme urgency, leaving little time for policy responses that shape the long-term trajectories of displaced populations and host communities. Still, despite its scale and persistence, research on the impacts of forced migration on development in Sub-Saharan Africa remains limited.

I make three main contributions: First, I assemble a new spatial dataset that links detailed information on the location, duration, and population of internally displaced persons (IDP) camps to recovered micro-census data at the parish level, allowing spatially exhaustive and precise measurement of population and occupational changes over two decades. Second, I integrate the study of forced displacement into the framework of economic geography by conceptualizing displacement as a spatial shock that redistributes population and economic activity. Third, I develop and estimate a quantitative spatial model that quantifies how displacement and post-war reconstruction affect the allocation of labor across locations and sectors, and enables counterfactual analysis of policies such as smaller camps or the absence of infrastructure recovery.

Forced displacement in Northern Uganda set in motion a process of unequal, consumption-led urbanization. Economic activity expanded in and around camps, but this growth was driven mainly by changes in who lived and worked where, rather than by broader industrial transformation. In other words, displacement reshaped the composition of people and sectors more than it transformed production itself—consistent with recent evidence on urban growth in developing economies. Post-war reconstruction and road investments reinforced these patterns by acting as local income shocks, increasing demand and connectivity, but given the new population allocation, narrowed spatial disparities through general equilibrium effects. Overall, the results highlight that camp characteristics: size, duration, and geographic connectedness, fundamentally shape who benefits and who loses from displacement-induced urbanization.

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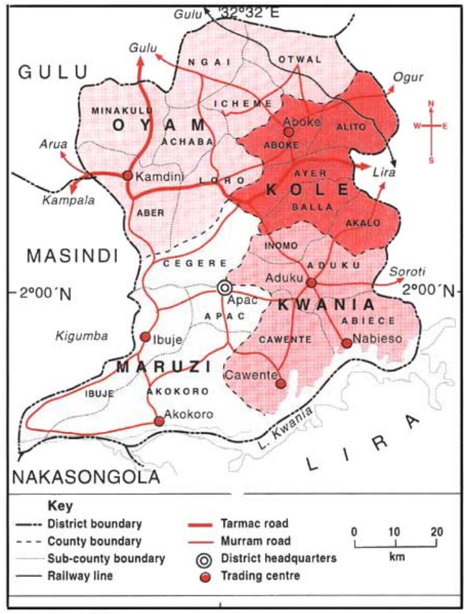
A Data Appendix

A.1 Linking Census Data

A.2 Digitizing 1991 Maps



Appendix Figure A1. 1992 Road Map

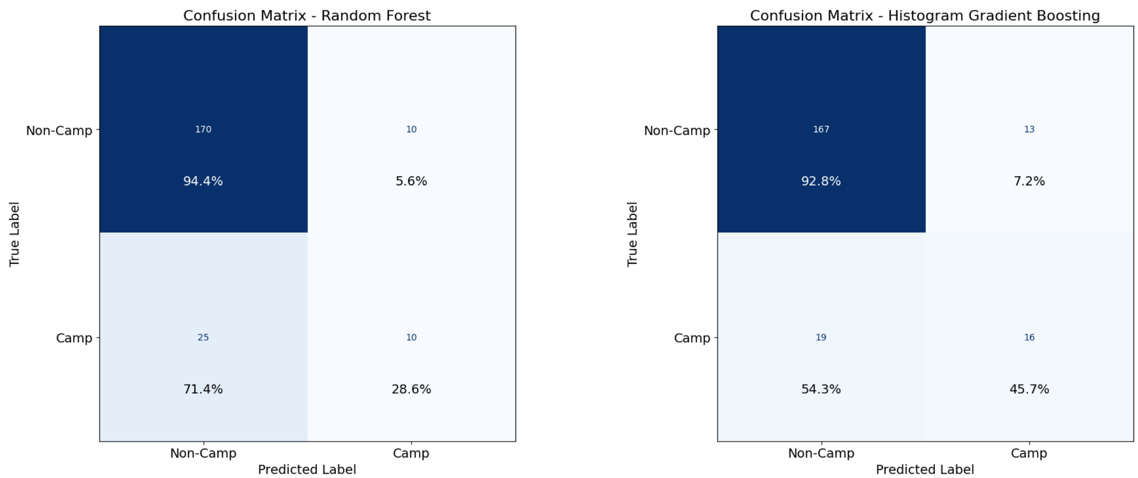
B Data Analysis Appendix

B.1 Assignment Mechanism: Prediction of Treatment using ML

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 45.7% of the camp parishes as camps, and misclassifies 7.2% of non-camp parishes as camp-parishes. A Random Forest model can only correctly assign camp treatment at 28.6% , and misclassifies only 5.6% of non-camp parishes as camps. This shows that the models are unable to distinguish between camp and noncamp parishes using the 93 covariates.

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

(b) HGB Model

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

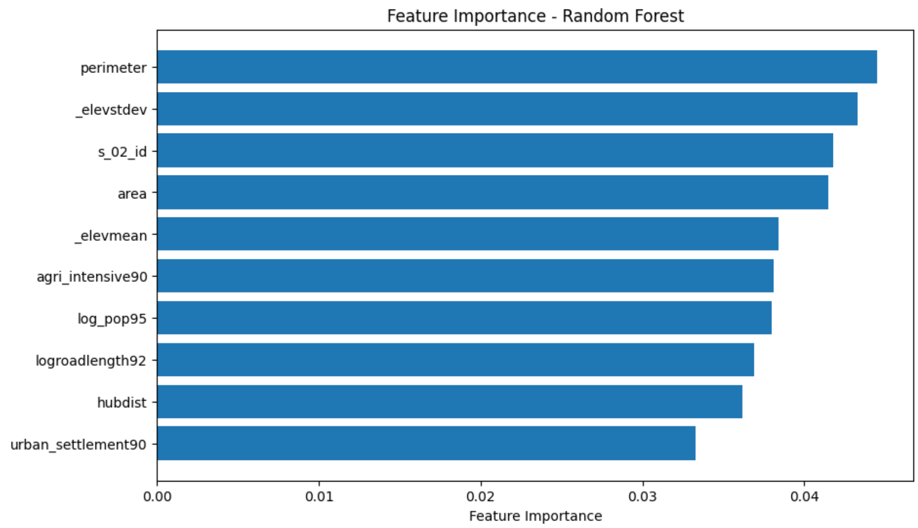
B.2 Additional Results

Education Outcomes

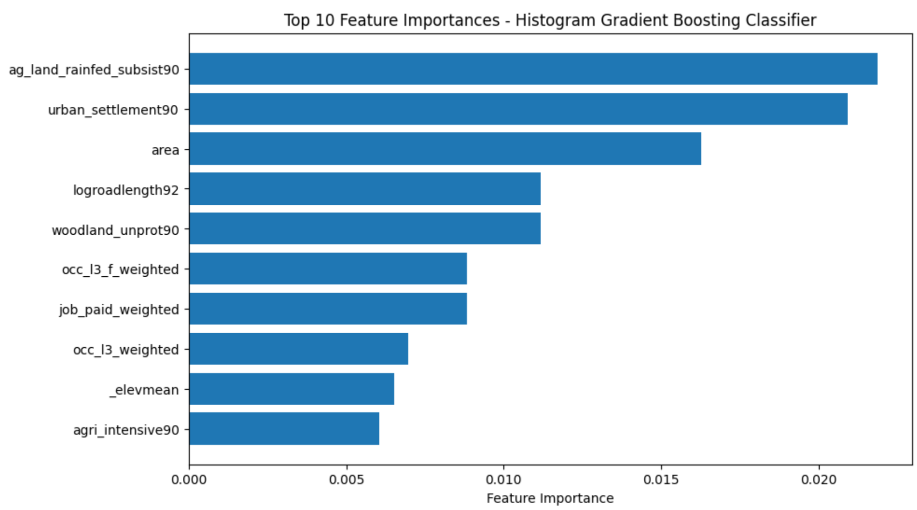
B.3 Camp vs. Non-Camp

I test whether a parish that had a camp experienced different patterns of growth compared to all other parishes in North and Eastern Uganda using the following specification:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times Camp_p + \beta_2 Y_{p,t-1} + \delta + C_{p,t} + X_{p,1992} + \epsilon_p \quad (25)$$



(a) Random Forest Model



(b) HGB Model

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

Results are displayed in Table B7.

B.4 Removing a ring of parishes between Bordering and No Displacement

To reduce concerns that the treatment status of No Displacement parishes is in violation of SUTVA, I run the main specifications as described in 5 excluding the ring of parishes that is just neighboring the Bordering parishes (but not Camp parishes). The results still hold:

Appendix Table B1. Services Linear Probability Model

	Services	Services	Services
Post	0.111***	0.064**	0.056**
	(0.006)	(0.029)	(0.029)
Camps×Post	-0.051***	-0.019	-0.018
	(0.010)	(0.049)	(0.049)
Bordering×Post	0.077***	0.105	0.111*
	(0.006)	(0.065)	(0.065)
N	3.07e+05	3.07e+05	3.07e+05
Mean Dependent Variable	0.116	0.116	0.116
Camps = Bordering	0.000	0.081	0.067
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 experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

Appendix Table B2. Agriculture: Farming vs. Livestock

	(1) Livestock Activities	(2) Livestock Activities	(3) 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 liestock, as opposed to subsistence agriculture. Standard errors clustered at the parish level in parentheses. Controls include sex and age. Sample includes all parishes that experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

B.5 Camp Duration Tables

Appendix Table B3. Services

	(1) Services	(2) Services	(3) Services
Post Displacement	0.0568	-0.0317	-0.0394
	(0.0414)	(0.0514)	(0.0504)
Post Displacement×Camp Duration	0.0139*	0.0276***	0.0283***
	(0.00813)	(0.00966)	(0.00953)
N	125249	125249	125249
depvar_mean	0.0928	0.0928	0.0928
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the Displacement Cluster-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B4. Manufacturing

	(1) Manufacturing	(2) Manufacturing	(3) Manufacturing
Post Displacement	-0.0408	-0.0660***	-0.0665***
	(0.0278)	(0.0247)	(0.0246)
Post Displacement×Camp Duration	0.00504	0.00935***	0.00957***
	(0.00336)	(0.00274)	(0.00271)
N	125249	125249	125249
depvar_mean	0.0530	0.0928	0.0530
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the Displacement Cluster-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B5. Years of Schooling

	Years of Schooling	Years of Schooling	Years of Schooling
Post	1.069***	1.231***	1.376***
	(0.015)	(0.041)	(0.032)
Camps×Post	0.186***	0.064	0.092
	(0.039)	(0.107)	(0.070)
Bordering×Post	0.706***	0.232***	0.172**
	(0.030)	(0.076)	(0.075)
N	1.15e+06	1.15e+06	1.15e+06
Mean Dependent Variable	2.623	2.543	2.623
Camps = Bordering	0.000	0.154	0.387
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 experienced conflict within 10km during the war.
***p<0.01, **p<0.05, *p<0.1.

Appendix Table B6. Education

	Above Primary Education Share (1)	Above Secondary Education Share (2)	Years Schooling (3)
Post × Camp	0.009	0.009	0.061
	(0.007)	(0.007)	(0.088)
Post × Bordering	0.015**	0.015**	0.168*
	(0.007)	(0.007)	(0.093)
Camp = Bordering (p-value)	0.174	0.129	0.061
Pre-mean (No Disp.)	0.041	0.036	2.600
N	1079	1079	1079

Notes: Conley standard errors in parentheses (20km).
Sample includes all parishes matched over the census years that experienced conflict within 10km during the war. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B7. Camp vs. Non-Camp

	Population Growth (1)	Road Length Growth (2)	Light Growth (3)	GDP per Capita Growth (4)
Camp	20.542***	31.989***	10.378*	-10.164
	(3.986)	(6.092)	(5.292)	(6.814)
Log Population 1990	-63.913***	12.706***	11.082***	74.995***
	(3.197)	(2.821)	(3.169)	(4.744)
Mean (No Camp)	94.294	34.510	82.709	-11.585
N	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, 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.

Appendix Table B8. Results with Excluded Parishes

	Population Growth (1)	Road Length Growth (2)	Light Growth (3)	GDP per Capita Growth (4)
Camps	24.444***	32.533***	34.744***	10.301
	(7.668)	(9.111)	(9.359)	(13.600)
Bordering	1.976	0.554	28.096***	26.121**
	(7.218)	(7.479)	(8.469)	(12.560)
lnpop90	-61.398***	12.136***	10.882***	72.280***
	(3.343)	(3.117)	(3.357)	(4.996)
Camp = Bordering	0.000	0.000	0.223	0.023
Mean (No Displacement)	105.145	17.928	62.861	-42.284
N	958	958	958	958

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, excluding the ring of second-degree bordering parishes. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B9. Results with Excluded Parishes- Centrality

	Degree Centrality (1)	W. Betweeness Centrality (2)	W. Closeness Centrality (3)	W. Page Rank Centrality (4)
Camps	0.072***	0.904	109.932	0.015**
	(0.016)	(0.653)	(86.727)	(0.006)
Bordering	0.051***	1.650***	124.349	0.010*
	(0.015)	(0.598)	(81.808)	(0.006)
Camp = Bordering	0.014	0.036	0.728	0.073
Mean (No Displacement)	0.062	0.566	434.448	0.003
N	958	958	958	958

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, excluding the ring of second-degree bordering parishes. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B10. Results with Excluded Parishes- Land Use

	Livestock Activity (1)	Agricultural Activity (2)	Urban - settlement (3)	Unused Land (4)
Camps	0.283***	-0.094	0.023	-0.295***
	(0.046)	(0.069)	(0.040)	(0.071)
Bordering	0.275***	-0.017	-0.009	-0.363***
	(0.042)	(0.056)	(0.033)	(0.061)
Camp = Bordering	0.783	0.227	0.412	0.350
Mean (No Displacement)	-1.112	0.267	-0.016	-0.956
N	958	958	958	958

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, excluding the ring of second-degree bordering parishes. Growth in %. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B11. Parish- Cluster Timing Characteristics

	(1) Later Clusters		(2) Earlier Clusters		(1)-(2) Pairwise t-test	
Variable	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference
Log Population 1990	84	8.699	58	8.936	142	-0.236
	84	(0.109)	58	(0.103)	142	
Log Nighttime Lights 1992	84	0.017	58	0.000	142	0.017
	84	(0.013)	58	(0.000)	142	
Road Length 1992	84	1.54e+05	58	1.91e+05	142	-3.75e+04*
	84	(12082.422)	58	(14979.472)	142	
Area	84	2.05e+08	58	2.54e+08	142	-4.85e+07
	84	(1.83e+07)	58	(2.57e+07)	142	
Mean Elevation	84	1029.319	58	1051.535	142	-22.215*
	84	(9.750)	58	(6.289)	142	
Distance to Border	41	320.705	35	301.444	76	19.262
	41	(17.173)	35	(17.807)	76	
Pre-war Conflict	84	80.238	58	57.345	142	22.893
	84	(31.061)	58	(18.789)	142	
During war Conflict	84	465.488	58	418.397	142	47.092
	84	(127.049)	58	(70.394)	142	
Livestock Activity 1990	84	0.188	58	0.247	142	-0.059
	84	(0.162)	58	(0.142)	142	
Agricultural Activity 1990	84	60.906	58	67.231	142	-6.325
	84	(3.315)	58	(3.627)	142	
Urban - settlement 1990	84	0.078	58	0.373	142	-0.295
	84	(0.054)	58	(0.359)	142	
Unused Land 1990	84	12.129	58	16.313	142	-4.184
	84	(2.240)	58	(2.912)	142	
Protected Land 1990	84	0.800	58	0.368	142	0.432
	84	(0.400)	58	(0.169)	142	

Notes: Standard errors clustered at the district level. Sample includes all clusters of parishes with 5km of a camp. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B12. Parish- Cluster Characteristics

	(1) Later Clusters		(2) Earlier Clusters		(1)-(2) Pairwise t-test	
Variable	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference
Agriculture	2713	0.868	2112	0.879	4825	-0.010
	16	(0.037)	13	(0.049)	29	
Manufacturing	2713	0.042	2112	0.057	4825	-0.015
	16	(0.015)	13	(0.023)	29	
Services	2713	0.089	2112	0.064	4825	0.026
	16	(0.028)	13	(0.035)	29	
Above Primary	7876	0.651	7309	0.608	15185	0.042
	16	(0.020)	13	(0.038)	29	
Age	7876	21.399	7309	20.525	15185	0.874*
	16	(0.378)	13	(0.323)	29	

Notes: Standard errors clustered at the district level. Sample includes all clusters of parishes with 5km of a camp. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B13. Cluster-level Growth

	(1) Population Growth	(2) Road Length Growth	(3) Nighttime Light Growth	(4) GDP PC Growth
Camp Duration (St)	1.538	-3.768	-2.757	-4.295
	(2.192)	(4.860)	(7.436)	(7.284)
Log Population 1990	-25.56**	41.50**	14.21	39.77**
	(7.703)	(12.59)	(12.80)	(13.24)
N	110	110	110	110

Notes: Standard errors clustered at the district-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B14. Agriculture- Parish Decomposition

	(1) Agriculture	(2) Agriculture	(3) Agriculture
Post Displacement	0.0501	0.199***	0.207***
	(0.0789)	(0.0657)	(0.0647)
Post Displacement×Camp Duration	-0.0385***	-0.0547***	-0.0556***
	(0.00931)	(0.00941)	(0.00944)
Post Displacement×Camp=1×Camp Duration	0.0390***	0.0315*	0.0314*
	(0.0114)	(0.0171)	(0.0171)
N	125249	125249	125249
depvar_mean	0.854	0.854	0.854
Controls	No	No	Yes
FE	No	Yes	Yes

Notes: Standard errors clustered at the Displacement Cluster-level in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix Table B15. Years of Education- IV

	(1) OLS	(2) First stage	(3) 2SLS (IV)
Camp Size (per 1000)	0.054***		0.121***
	(0.009)		(0.017)
age	0.025***	0.000	0.025***
	(0.001)	(0.000)	(0.001)
sex=2	-1.776***	-0.018	-1.773***
	(0.022)	(0.015)	(0.022)
Log Road Distance		1.072***	
		(0.130)	
Observations	255155	302298	255155

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

C Model Appendix

C.1 Price Data

To compute relative sectoral prices, I use national accounts data on the GDP by sector from different macroeconomic country-level reports. Since the reports include both nominal and real GDP values, I calculate an implicit price deflator $P_k(t) = \frac{NominalGDP_k(t)}{RealGDP_k(t)}$. Then I calulate the relative price of non-agricultural prices to agriculture.

Appendix Table C1. Implicit Deflators and Relative Prices, Uganda

Year	P_{Ag}	P_{NA}	$RP_{NA/Ag}$	$P_{NA\backslash M}$	$RP_{NA\backslash M/Ag}$
1990/91	0.85	0.85	1.01	0.85	1.00
1991/92	1.26	1.24	0.98	1.24	0.98
1993/94	1.72	1.71	1.00	1.72	1.00
2012/13	1.30	1.65	1.27	1.65	1.27
2013/14	1.36	1.67	1.23	1.66	1.22
2014/15	1.40	1.69	1.20	1.67	1.19

C.2 Equilibrium Solution and Calibration Algorithm

Algorithm 1 Calibration of the Market Access Externality (κ)

Inputs: 1990 shares $\pi_{ia}^{data}, \pi_{is}^{data}$; fundamentals $(Z_{ia}, L_i, X_i, D_{ij})$; parameters $(\mu, \beta, \gamma, \alpha, \bar{C}, \theta)$
Initialize: grid $\mathcal{K} \subset [0, 1.5]$
for $\kappa \in \mathcal{K}$ **do**
    (1) Inversion (recover $T_{ik}(\kappa)$)
    Compute market access MA_i^{1990} from the 1990 network
    Solve for wages (w_{ia}, w_{is}) and prices $p_{i,S}$ using the inner loop (Alg. 2), holding $\pi_{ik} = \pi_{ik}^{data}$
    Compute deterministic utilities V_{ia}, V_{is} and recover

$$T_{ik}(\kappa) = \frac{\pi_{ik}^{data}}{\pi_{\text{ref},k}^{data}} \left(\frac{V_{\text{ref},a}}{V_{ik}} \right)^{\theta}.$$

    (2) Forward equilibrium (given $T_{ik}(\kappa)$)
    Initialize $\pi_{ik} = \pi_{ik}^{data}$
    repeat
        Recompute market access: $\text{MA}_i = \text{MA}(\pi_{ia} + \pi_{is})$
        Solve for $(w_{ia}, w_{is}, p_{s,i})$ using Alg. 2
        Compute utilities V_{ik}
        Update shares:

$$\pi_{ik}^{new} = \frac{T_{ik}(\kappa)\, V_{ik}^{\theta}}{\sum_{i'} \sum_{k'} T_{i'k'}(\kappa)\, V_{i'k'}^{\theta}}$$

        Apply damping and renormalize to preserve total population by sector
    until $\max_i |\pi_{ik}^{new} - \pi_{ik}| < 10^{-8}$

    (3) Loss:

$$\text{MSE}(\kappa) = \frac{1}{2N} \sum_i \left[(\hat{\pi}_{ia} - \pi_{ia}^{data})^2 + (\hat{\pi}_{is} - \pi_{is}^{data})^2 \right]$$

end for
Select: $\kappa^* = \arg\min_{\kappa \in \mathcal{K}} \text{MSE}(\kappa)$
Recompute $T_{ik}(\kappa^*)$ via inversion to obtain the baseline fundamentals

$$AS_i = (1 - \alpha) \Big[\pi_{ia}\, (w_{ia} - \bar{C}) + \pi_{is}\, (w_{is} - \bar{C}) \Big] \tag{26}$$

$$AD_{s,i} = (\pi_{ia} + \pi_{is})^{\gamma}\, \text{MA}_i^{\kappa}\, X_i^{\beta} \tag{27}$$

$$p_{s,i} = \frac{1 - \alpha}{\alpha} \frac{AD_{is}}{AS_{is}} \tag{28}$$

Algorithm 2 Inner Wage–Price Loop

1: Initialize $p_{s,i} = 1$ for all i

2: **repeat**

3: Update agricultural wages:

$$w_{ia} = Z_{ia} \left(\frac{L_i}{\pi_{ia}} \right)^{1-\mu} \tilde{X}_i^{\beta}$$

4: Update service wages:

$$w_{is} = p_{s,i} \, (\pi_{ia} + \pi_{is})^{\gamma} \, \mathrm{MA}_i^{\kappa} \, \tilde{X}_i^{\beta}$$

5: Update service prices from market clearing:

$$p_{s,i}^{new} = \frac{1-\alpha}{\alpha} \frac{AD_{is}}{AS_{is}}, \quad p_{s,i} = (1-\lambda) p_{is} + \lambda p_{is}^{new}$$

6: **until** $\max_i |p_{is}^{new} - p_{is}| < 10^{-10}$

C.3 Model Inversion

To interpret T_{ik} , we can rewrite it as follows for each sector:

Agriculture:

$$T_{iA} = \left(\frac{\pi_{iA}}{\pi_{1A}} \right) \times \left(\frac{W_{1A}}{W_{iA}} \right)^{\theta} = \left(\frac{\pi_{iA}}{\pi_{1A}} \right) \left(\frac{L_1}{L_i} \right)^{\alpha\theta} \left(\frac{\tilde{X}_1}{\tilde{X}_i} \right)^{\theta}$$

NA Sector:

$$T_{iNA} = \left(\frac{\pi_{iNA}}{\pi_{1A}} \right) \left(\frac{L_1}{\pi_{1A}} \right)^{\alpha\theta} \left(\frac{\tilde{X}_1}{\tilde{X}_i} \right)^{\theta} \left[\sum_{j \in \mathcal{N}(i)} \pi_{jNA} \right]^{-\gamma\theta}$$

C.4 Schematic Algorithm for estimating the FD shock

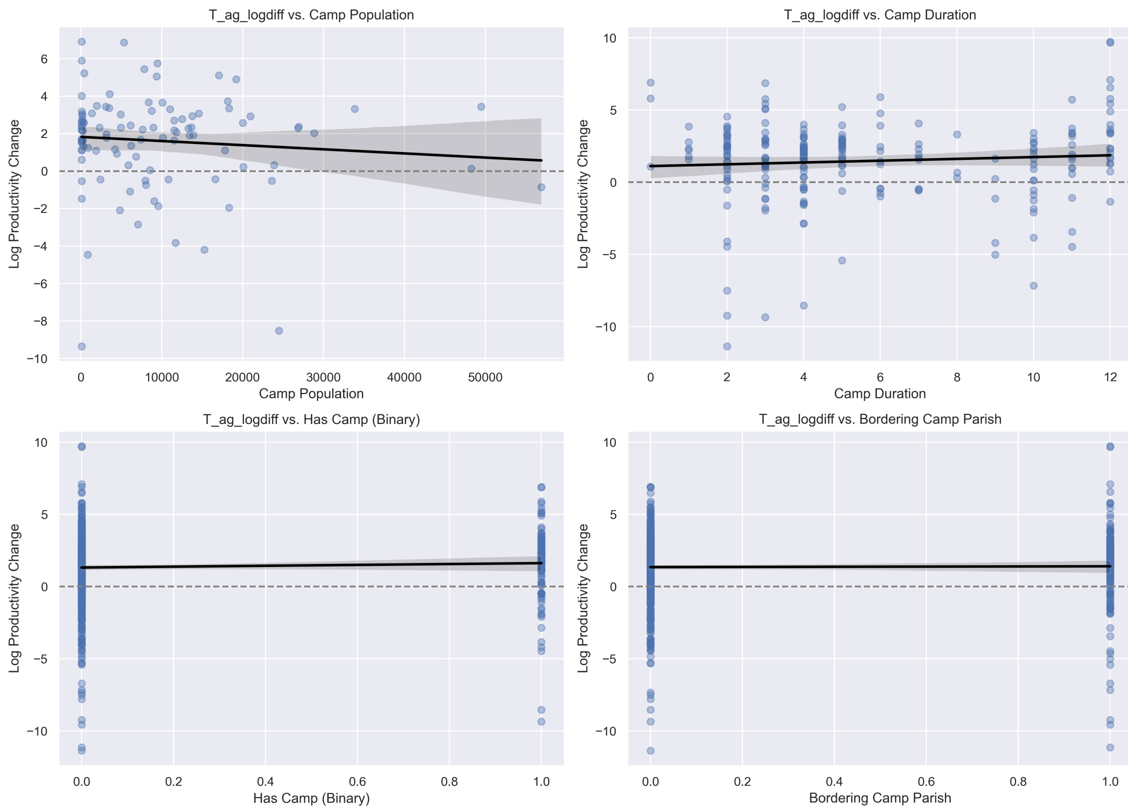
Fundamentals:

$$\{T_{ik}, Z_{iA}, \tilde{X}\}_{k \in \{A,S\}}$$

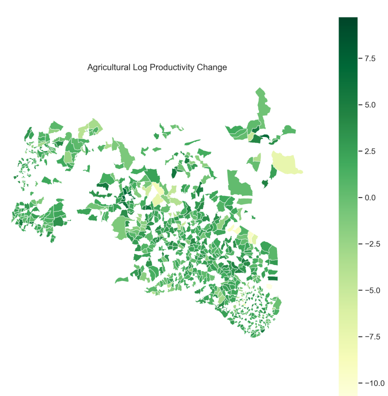
Parameters:

$$\{\theta, \gamma, \kappa, \alpha, \mu, b, \delta, \bar{C}\}$$

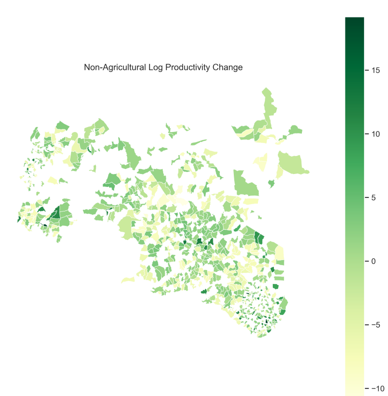
Algorithm:



Appendix Figure B1. Model-Predicted Agri Log Differences and Treatment



(a) Model-Predicted Agri Log Differences



(b) Model-Predicted Non-Agri Log Differences

Appendix Figure B2. Changes in Amenities

1. **Invert the model with real-world data.** Use observed $\{\pi_{ik}, p_{iS}, w_{ik}\}_{k\in\{A,S\}}$ to solve for baseline amenities T_{ik}^{1990} in the years before and after displacement.

2. **Establish the counterfactual no-FD world.** For any variable x, denote by $\hat{x}$ its predicted value, representing the counterfactual value it would take, for example, in a world with no forced displacement.

   (a) Assume $T_{ik}^{1990} = \hat{T}_{ik}^{2014}$.

   (b) Calculate the predicted population-sector distributions from the reduced form empirical specifications:
   To obtain the $\hat{\pi}_{ik}^{2014}$, I run the regression from the main analysis to obtain the predicted population distribution:

$$\hat{Y}_{it} = \hat{\beta}_1 \, \text{Camp}_i \times \text{Post}_t + \hat{\beta}_2 \, \text{Bordering}_i \times \text{Post}_t + \hat{\gamma}' X_i \times \text{Post}_t + \hat{\delta}_{d(i)} + \hat{\lambda}_t \tag{29}$$

$$\hat{Y}_{it}^{cf} = \hat{Y}_{it} - \hat{\beta}_1 \left(\text{Camp}_i \times \text{Post}_t\right) - \hat{\beta}_2 \left(\text{Bordering}_i \times \text{Post}_t\right). \tag{30}$$

   (c) Using $\{\hat{\pi}_{ik}^{2014}, p_{iS}, \hat{w}_{ik}^{2014}\}_{k\in\{A,S\}}$, compute the implied $\theta^{2\hat{0}14}$.

3. **Identify the displacement-induced shock.**

$$\Delta\theta = \hat{\theta}^{2014} - \theta^{2014}$$

4. **Re-simulate equilibrium outcomes.**

   (a) Feed counterfactual fundamentals $\{\hat{T}_{ik}^{2014}, Z_{iA}, \dots\}$ into the original model.

   (b) Solve for equilibrium outcomes $\{\pi_{iK}, P_{iS}, w_{iK}\}$ under both $\hat{\theta}^{2014}$ and θ^{2014}.

5. **Compare results.**

   (a) Evaluate how sectoral employment changes due to forced displacement.

   (b) Measure welfare differences across the two scenarios.

D A Static GE Model with Trade

We start with an economy of $\mathbf{I} = \{1, ..., \bar{\mathbf{I}}\}$ locations and two sectors $k \in \{A, S\}$ that represent the agriculture and non-agriculture sectors respectively. There is a measure Ω continuum of households that are distributed across locations and sectors. Households are endowed with an initial location $i \in \mathbf{I}$, and choose first which location to live in, and then which sector to work in. Migration is costless.

Population. We consider a unit measure of agents $\omega \in \Omega$, such that:

$$\sum_{i \in \mathbb{I}} \sum_{k \in \{A,S\}} N_{ik} = 1$$

where N_{ik} is the population in location i and sector k,

Preferences. An individual ω in a location j working in sector k consumes an agriculture and non-agriculture good subject to the income they earn in their sector. Individuals have nested preferences and consume a bundle of homogeneous crops C_{jA} and differentiated services C_{jS}.

$$U_j(\omega) = \left(C_{jA} - \bar{c}\right)^{\alpha} C_{jS}^{1-\alpha} \cdot \epsilon_{jk}, \qquad \alpha \in (0,1), \quad \bar{c} > 0 \tag{31}$$

where $\varepsilon_{jk}(\omega)$ [13] is an idiosyncratic location-sector taste shock for option (j,k), such that:

$$\varepsilon_{jk} \sim \text{Fréchet}(T_{jk}, \theta), \quad \text{with } \mathbb{E}[\varepsilon] = \Gamma\left(1 - \tfrac{1}{\theta}\right)$$

θ captures how concentrated location-sector preferences are, and the scale parameter T_{jk} represents exogenous amenities in location j and sector k. Individuals first choose where to locate, and then which sector to work in.

At the lower nest, both the agriculture and the non-agriculture bnudles are CES-aggregates with elasticities of substitution σ:

$$C_{jk} = \left[\sum_i c_{ijk}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad P_{jk} = \left[\sum_i p_{ijk}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \qquad \sigma > 1 \tag{32}$$

where p_{ijk} is the price in location j of a good of sector k from location i.

[13] such that $\omega \in \Omega$

Sectoral expenditures are thus given by:

$$E_{jA} = P_{jA}C_{jA} = P_{jA}\bar{C} + \alpha\big(E_j - P_{jA}\bar{C}\big), \tag{33}$$

$$E_{jS} = P_{jS}C_{jS} = \begin{cases} (1-\alpha)\big(E_j - P_{jA}\bar{C}\big), & \text{if } E_j \geq P_{jA}\bar{C}, \\ 0, & \text{if } E_j < P_{jA}\bar{C} \end{cases} \tag{34}$$

At the lower nest, the CES expenditure share can be written as:

Thus, the expenditure share in location j on a variety from location i of sector k can be written as:

$$X_{ijk} = \phi_{ijk}E_{jk} = E_{jk}\left(\frac{\tau_{ijk}p_{ik}}{P_{jk}}\right)^{1-\sigma} \tag{35}$$

with

$$\phi_{ijk} = \left(\frac{p_{ijk}}{P_{jk}}\right)^{1-\sigma} \tag{36}$$

For simplicity, I assume that the prices in the agriculture sector are the same across locations, and that trade in agriculture is free, such that $P_{jA} = 1; \forall_j$. Therefore, we can rewrite the demand functions as:

$$E_{jA} = C_{jA} = \bar{C} + \alpha\big(E_j - \bar{C}\big), \tag{37}$$

$$E_{jS} = P_{jS}C_{jS} = \begin{cases} (1-\alpha)\big(E_j - \bar{C}\big), & \text{if } E_j \geq \bar{C}, \\ 0, & \text{if } E_j < \bar{C} \end{cases} \tag{38}$$

The value of location j's imports from location i in sector S can be expressed as

$$X_{ijS} = \phi_{ijS}E_{jS} = E_{jS}\left(\frac{\tau_{ijk}p_{iS}}{P_{jS}}\right)^{1-\sigma} \tag{39}$$

$$X_{ijA} = E_{jA} \tag{40}$$

Production. *Agriculture.* The representative firm in agriculture produces with Cobb-Douglas technology using land and labor as inputs:

$$Y_{iA} = Z_{iA} N_{iA}^{\mu} L_{iA}^{1-\mu} \tilde{X}_i$$

Z_i represents agricultural productivity that allows for differences in comparative advantage in production in that sector.

Services (without agglomeration externality): The non-agriculture sector S produces goods using only labor, and is negatively affected by conflict.

$$Y_{jS} = N_{jS}\,\tilde{X}_{jS}, \tag{41}$$

Wages:

$$w_{jk} = \begin{cases} p_{jA} Z_{jA} \left(\dfrac{L_{jA}}{N_{jA}}\right)^{1-\mu} \tilde{X}_j = Z_{jA} \left(\dfrac{L_{jA}}{N_{jA}}\right)^{1-\mu} \tilde{X}_j, & \text{if } k = A, \\ p_{jS} \tilde{X}_j, & \text{if } k = S \end{cases} \tag{42}$$

The price of services produced in i and consumed in j:

$$p_{ijS} = \tau_{ijS}\, p_{iS} = \tau_{ijS} \frac{w_{iS}}{\tilde{X}_i}, \tag{43}$$

$$P_{jS}^{1-\sigma} = \sum_i \tau_{ijS}^{1-\sigma} \left(\frac{w_{iS}}{\tilde{X}_i}\right)^{1-\sigma} \tag{44}$$

Total bilateral trade:

$$X_{ij} = \sum_{k \in \{A,S\}} X_{ijk}. \tag{45}$$

Equilibrium. The static equilibrium is characterized by a set of allocations $\{(\pi_{ik}, C_{ik}) | i \in \mathbf{I}, k \in \{A, S\}\}$ and a set of prices $\{(p_{ijs}, w_{ik}) | i \in \mathbf{I}, k \in \{A, S\}\}$ such that,

Goods market clearing: income in a sector is equal to the value of goods sold in all locations.

In the agriculture sector:

$$\sum_{j}^{I} Y_{jA} = \sum_{i}^{I} X_{ijA} = \sum_{i}^{I} E_{iA} \tag{46}$$

In the services sector:

$$Y_{jS} = \sum_{i}^{I} X_{ijS} = \sum_{i}^{I} E_{iS} \frac{\tau_{ijS}^{1-\sigma} \left(\frac{w_{iS}}{\tilde{X}_i}\right)^{1-\sigma}}{\sum_{l}^{I} \tau_{ljS}^{1-\sigma} \left(\frac{w_{lS}}{\tilde{X}_l}\right)^{1-\sigma}} \tag{47}$$

Income consistency:

$$E_i = w_{iA}\pi_{iA} + w_{iS}\pi_{iS} = \sum_{k}\sum_{j} X_{ijk}. \tag{48}$$

Labor market clearing condition is: The share of individuals who choose to be in location-sector pair (i, k) is given by

$$\pi_{ik} = N_{ik} = \frac{T_{ik} V_{ik}^{\theta}}{\sum_{i'} \sum_{k'} T_{i'k'} V_{i'k'}^{\theta}} \tag{49}$$