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 that took place between 1996 and 2006 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. Harmonizing novel administrative data, I document that the forced displacement episode led to a permanent reallocation of labor across space and sectors, increasing schooling among younger generations and triggering a shift from agriculture to non-agriculture employment. 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 findings and use it to quantify the contribution of post-conflict infrastructure reconstruction to regional recovery.

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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. 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 (Internal Displacement Monitoring Centre, 2025)[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 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 "agglomeration" shock, it raises a fundamental question: can displacement-induced agglomeration generate positive spillovers despite 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 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

[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.

locations within that region: I argue and 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. Then I ask whether a different population distribution across space will lead to differences in economic outcomes, and whether there is a role for spillover effects.

A key contribution of this paper is the construction of a novel historical dataset.I compile data on camp locations and populations from the World Food Program (WFP) and United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) reports, digitize road maps from 1992, and recover previously inaccessible 1991 census data from the Uganda Bureau of Statistics, which is representative at the village-level[2]. 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 13% higher in Camp parishes compared to those with no displacement, and remained lower in the neighboring parishes that bordered the Camp 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

[2]The data was previously only available at the subcounty level through IPUMS, and the original census data had been deemed corrupted until as part of this project, the original dataset was recovered and adjusted for analysis.

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, I find that the share of people with higher levels of education increased in bordering parishes, with no effect on education in camps. However, this result is nuanced because it is driven by lower-educated older adults staying in camps, and younger children becoming more educated *in* camps, whereas this is not the case for the bordering locations. This provides evidence of positive selection, as more educated individuals appear to choose to live outside camps and the camps remained populated with lower-educated people. Taken together, the results suggests that bordering parishes benefited from spillover and selection effects, whereas camp-parishes—despite population growth—did not experience the same relative gains in service employment or education levels in the eight years after the displacement episode ended. These results also suggest that the more educated youth in the camps may in the longer run have better opportunities.

After that, I provide evidence, both empirically and through the lens of a structural model, for post-displacement infrastructure reconstruction as a principal driver of the new observed population and sectoral distribution of individuals after the war. 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 in 2006, 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 both the bordering parishes and camp parishes compared to 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 is modelled as a frictionless reallocation of the population across locations. Central for understanding how displacement reshapes sectoral allocation and spatial inequality are the following key elements. First, households face a subsistence requirement in agriculture, as in standard spatial

transformation frameworks. Second, locations differ in land availability. Together, these imply that when displacement pushes people into bounded areas, land per capita falls, agricultural incomes decline, and households reallocate away from agriculture toward non-agricultural activities. Third, mobility across locations is costly, so spatial adjustment is incomplete and the post-displacement distribution of people and activity remains highly uneven.

These mechanisms generate two key predictions. Forced agglomeration on limited land depresses agricultural incomes and crowds workers out of agriculture. At the same time, displacement increases spatial inequality: because migration remains costly, depopulated locations attract fewer workers and become relatively high-income, while congested former camp locations remain low-income.

In counterfactuals, forced displacement reduces welfare in both camp and bordering locations (by about 13% and 11%, respectively, relative to a no-displacement benchmark). Post-conflict road reconstruction raises welfare in camp locations, but can lower welfare in bordering areas because improved connectivity reshapes relative market access and draws activity toward better-connected nodes, altering the spatial distribution of gains.

To identify under which conditions camps may serve as a driver of economic growth, I conduct a heterogeneity analysis, focusing on how camp size, camp duration, and conflict intensity 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 time horizon, scale, and security 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 bring forth new evidence on how conflict-induced displacement into camps shapes migration and human capital accumulation decisions, therefore altering the economic geography of a region. Third, I document how camp design affects the spatial distribution of economic activity.

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 7.3 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 8 analyzes how camp characteristics—size, duration, and conflict exposure—shaped these outcomes. Section 9 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. Maystadt and Duranton (2019) study the long run impact of temporary refugee settlements in Tanzania and show that decreasing transport costs may have contributed to the positive impact on welfare of the local communities. 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) also document that many cities in low-income countries are dominated by non-tradable services and public employment. 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).

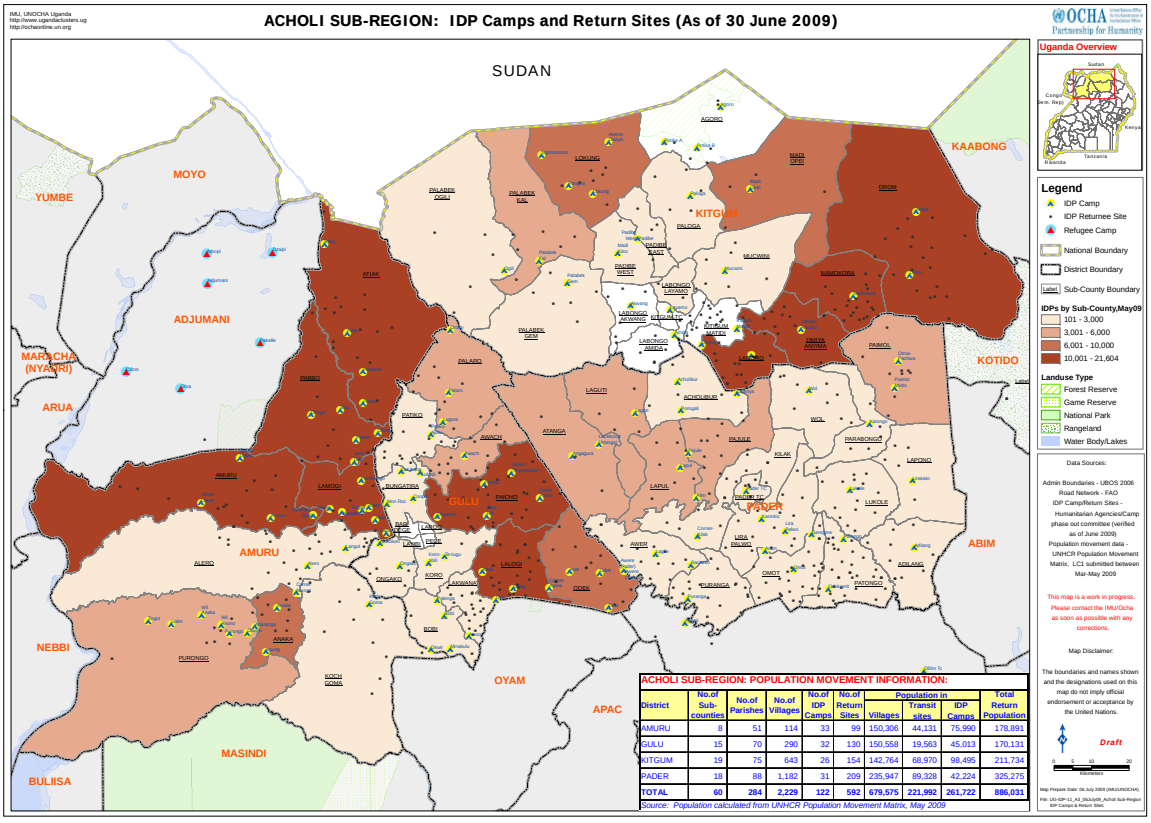
Life in camps starkly contrasted with life pre-displacement. Whereas before

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[3]. 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

[3]"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			Total Return Population
						Villages	Transit sites	IDP Camps	
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

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.

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 [4], 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 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[5]. I am able to match 3707 parishes in 1991 out of all 4003[6]. In the region affected by

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

[5] 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).

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

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 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 does not 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 $\mathbb{P}(Match = 0|Class)$. The numbers are displayed in Table 1. I 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.

Table 1. Matching Parishes Over Time — Differential Attrition Test

Comparison	Pr(No Match|$Class_1$)	Pr(No Match|$Class_2$)	t-Statistic	p-Value
Bordering vs Camp	0.407	0.278	2.926	0.004
Bordering vs No Displacement	0.407	0.493	-2.493	0.013
Camp vs No Displacement	0.278	0.493	-5.450	0.000

Notes: Sample includes all parishes that experienced conflict. Values show the probability that a parish in 2002 has no name match in 1991.

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.

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

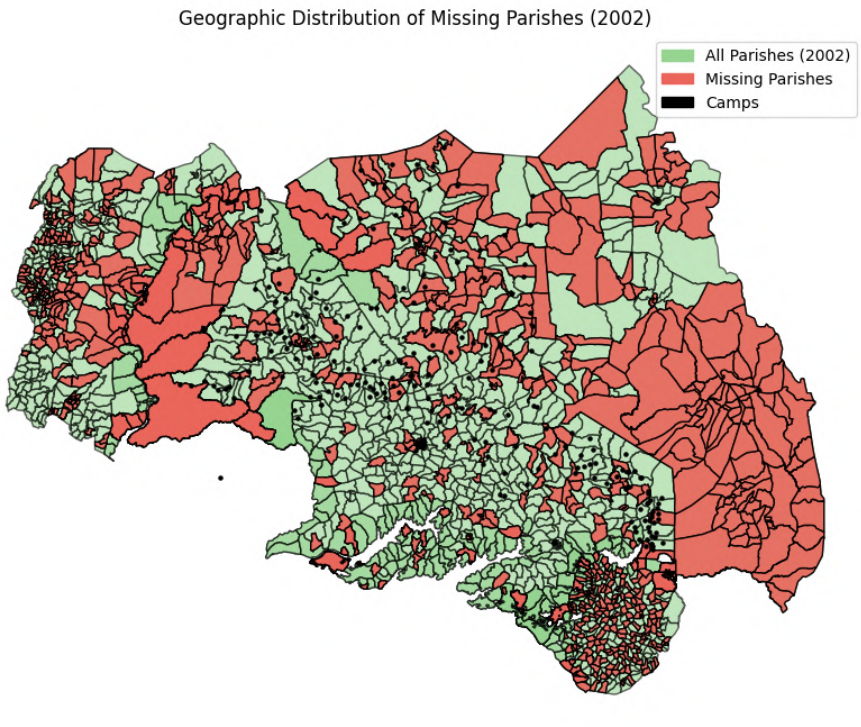


Figure 2. Matched Parishes

names and populations (see Figure A1). I then matched parish IDs to names by population ranks, successfully recovering 3,997 out of 4,003 parishes .

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 A2 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 economic activity, I use a harmonized timeseries of nighttime light data spanning the years 1992-2018 from Li et al., 2020.

3.3 Sample Description

The empirical analysis focuses on parishes in Northern and Eastern Uganda that were affected by the civil conflict between 1989 and 2006[7]. To ensure comparability and a consistent conflict exposure across units, I restrict the sample to parishes located within 10 km of at least one recorded conflict event since 1989. This restriction yields 1,056 parishes out of the 1,734 total in the region, ensuring that the interpretation of all results is conditional on exposure to conflict.

Within this conflict-affected sample, I classify parishes into three groups according to their experience with displacement:

1. **Camp parishes**, which hosted internally displaced persons (IDPs);
2. **Bordering parishes**, which share a boundary with a camp parish and from which most displaced populations are presumed to have originated;
3. **No-displacement parishes**, which neither hosted nor bordered a camp and are used as the comparison group.

[7]The sample is restricted to the subregions that were involved in the war: Acholi, Lango, Teso, Karamoja, and West Nile

Because no migration-flow matrix exists linking origins and destinations, I use geographical contiguity as a proxy for displacement outflows. The key assumption is that the majority of individuals displaced into camps originated from the camp parish itself or from its immediate neighbors. While this assumption is not innocuous, a population accounting exercise supports its plausibility: the total camp population in 2005 represents approximately 100% of the combined 1995 population of camp and bordering parishes. When adjusting for average district-level population growth between 1991 and 2002, this share becomes roughly 72%, which aligns with humanitarian estimates ranging between 80–90%.[8] This suggests that while some displacement occurred beyond these parishes, it was substantially smaller in magnitude. In other words, camp and bordering parishes capture the bulk of the displaced population, while the control group experienced conflict but limited forced displacement.

Table 2 reports the distribution of parishes by displacement status. Figure 3 illustrates the spatial classification.

Table 2. Sample of Camps and Parishes

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

In Table 3, I compare the characteristics across parishes in Northern Uganda by classification. 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, I find no difference between parishes with camps and others, but parishes with camps do have more roads within their area than the other two categories, which speaks to the fact that camps were initially constructed where trading centres were located.

There is also substantial heterogeneity in camp characteristics. Figure 5 shows that camps hosted between 1,500 and 57,000 people, and Figure 4 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

[8] Estimates vary depending on the assumed growth rate and population base.

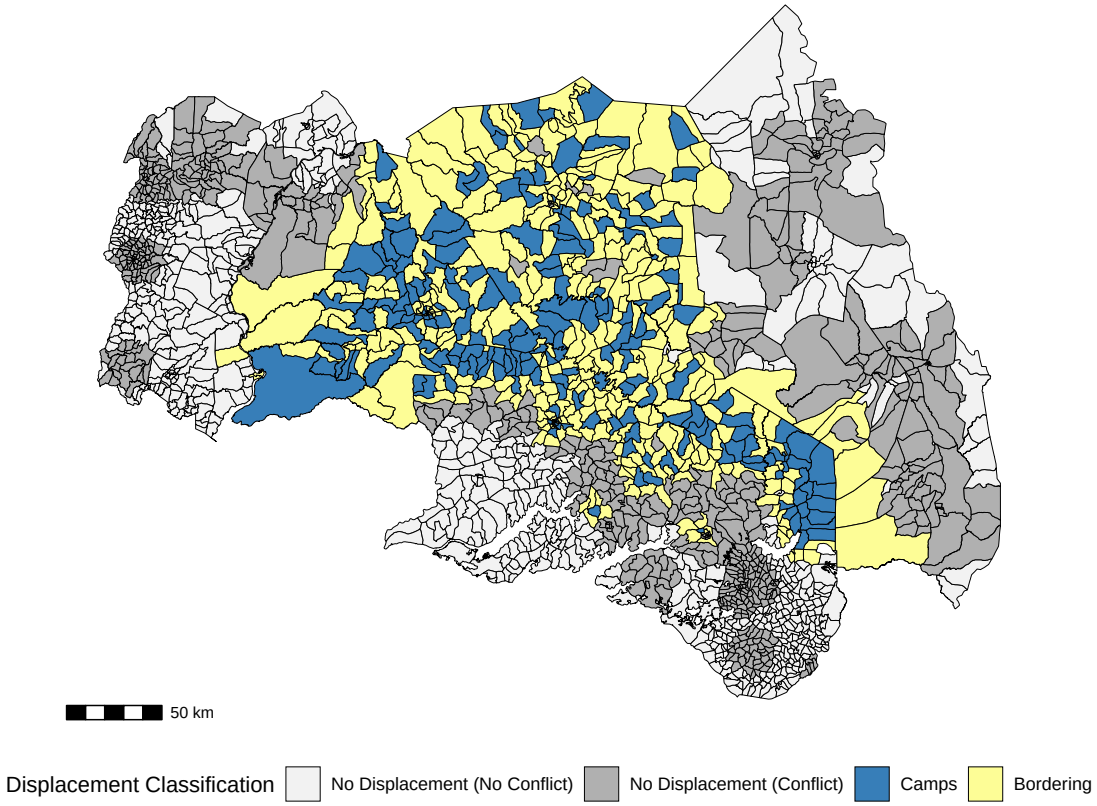


Figure 3. Displacement Classification

camps, but the ratio of IDPs to original population is skewed to the right such that it could reach 20 times the original population.

4 Empirical Strategy

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 6 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

Table 3. Parish Characteristics

Variable	(1) No Displacement Mean/(SE)	(2) Camps Mean/(SE)	(3) Bordering Mean/(SE)	(1)-(2) Mean difference	(1)-(3) Pairwise t-test Mean difference	(2)-(3) Mean difference
Population Density 1990	1.485	1.293	1.468	0.192	0.016	-0.176
	(0.077)	(0.179)	(0.160)			
Log Nighttime Lights 1992	0.003	0.020	0.045	-0.017	-0.041***	-0.024
	(0.002)	(0.011)	(0.015)			
Road Length 1992	38619.997	52858.595	48612.005	-1.42e+04***	-9992.008***	4246.591
	(2212.588)	(2537.213)	(2403.124)			
Mean Elevation	1125.692	1046.971	1047.926	78.721***	77.767***	-0.955
	(7.059)	(5.319)	(4.710)			
Pre-war Conflict	7.640	25.097	18.497	-17.457***	-10.857***	6.600
	(0.675)	(3.361)	(2.299)			
Agricultural Activity 1990	66.623	70.289	67.145	-3.666	-0.522	3.144
	(1.462)	(2.194)	(1.822)			
Number of observations	567	175	314	742	881	489
Number of clusters	567	175	314	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.

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.

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

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

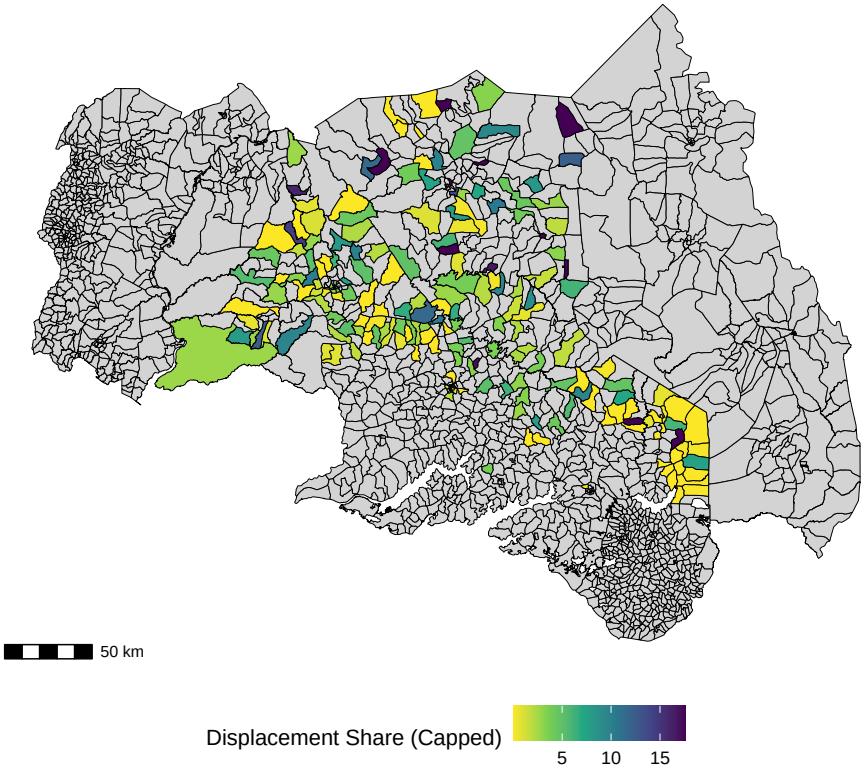


Figure 4. Share of Camp Population/ Parish Population

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 in the treatment.

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.

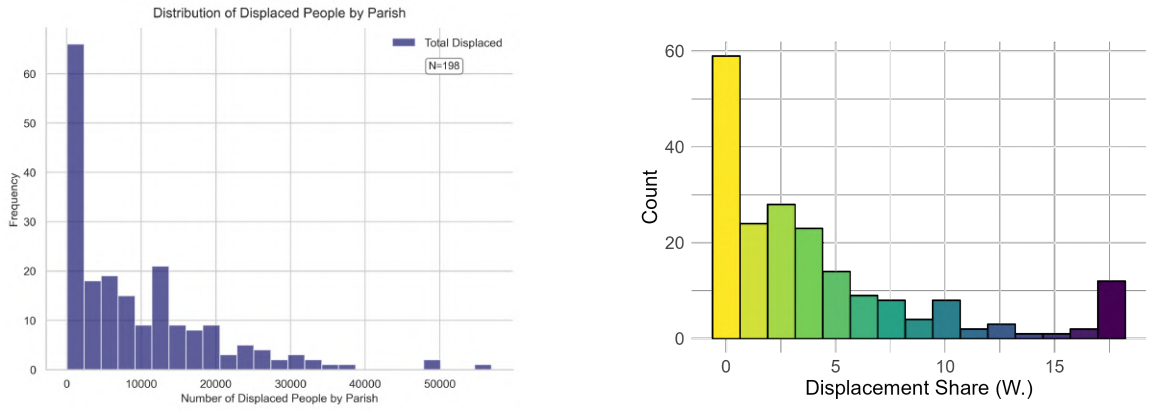
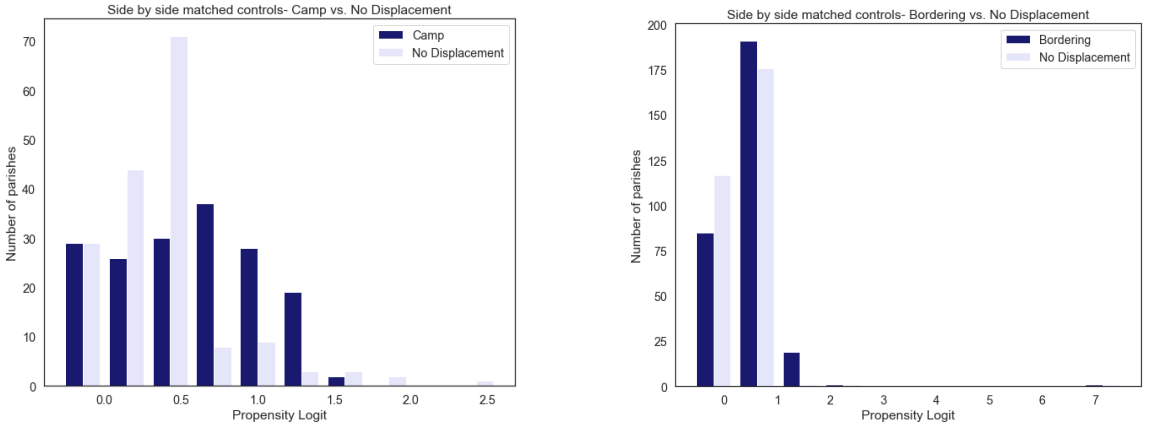


Figure 5. Distribution of camp population in parishes



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

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

Figure 6. Comparison of Logit Score Distributions for Treatments and Control

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 B.3 I complement this analysis with different identification strategies, and in section 8 I study different definitions of forced displacement based on camp population size and camp presence duration.

5 Results: Parish-level

Population Patterns

Table 4. Population Growth

	Log Population (1)
Camp	0.134**
	(0.068)
Bordering	-0.093
	(0.066)
Camp = Bordering (p-value)	0.000
Pre-mean (No Disp.)	8.451
Pre-mean (Camp)	8.732
Pre-mean (Bordering)	8.446
R^2	0.557
N	1035

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.

First, I establish that if a parish had a camp assigned to it between the years 1996 and 2006, 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 population in 2014 in Camp parishes became 13.4% higher compared to the No Displacement parishes. On the other hand, in Bordering parishes the population relatively decreased by 9.3% compared to the control parishes (p-value = 0.159). 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. Thus, camps left a persistent mark on

the population distribution in Northern Uganda years after conflict subsided and people were free to move.

Nighttime Light Growth

After showing that the forced displacement policy changed population growth patterns across the region, I study how the intensity of economic activity, 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 nighttime lights, which indicates that there was an increase in economic development in those locations. However, perhaps surprisingly, the increase in night lights 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.

Table 5. Nighttime Lights Growth

	Log Nighttime Lights (1)	Log NTL PC (2)
Camp	0.305**	0.153
	(0.123)	(0.141)
Bordering	0.236**	0.304**
	(0.107)	(0.120)
Camp = Bordering (p-value)	0.132	0.023
Pre-mean (No Disp.)	0.003	-7.365
Pre-mean (Camp)	0.020	-7.780
Pre-mean (Bordering)	0.045	-7.632
R^2	0.431	0.512
N	1056	1056

Notes: Conley standard errors (20km) 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.

Alternative Identification Strategies

To move towards a more causal interpretation of the results in 5, I explore different identification strategies and specifications that show that the main results are robust in Appendix B.3. I take several approaches: first, by considering that all parishes were treated. In the strategy in Section B.3.1, I test whether the effect of being a

parish without a camp is diminishing in the distance from a camp. In Section B.3.3, I compare Camp parishes to all other parishes. Moreover, to study the dynamic effects of displacement on population, I exploit variation in the timing of camp establishment across locations and estimate an event-study specification following Callaway and Sant'Anna, 2021 in Appendix B.3.2. In Appendix B.3.4 I also repeat the analysis excluding a ring of second-degree bordering parishes to reduce SUTVA concerns.

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? The forced displacement policy of the Ugandan government indiscriminately moved entire villages into IDP camps, and in the previous section I showed that it permanently changed the population distribution across locations. However, once people were free to choose where to live, what work to do, and whether or not they and their children should pursue more educational attainment, incentives differed for people in different locations and with different characteristics. For instance, Figure 7 shows the change in the age distribution for each treatment group[9].

First, I test whether the displacement policy led to a change in the sector 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

[9]Using the raw data.

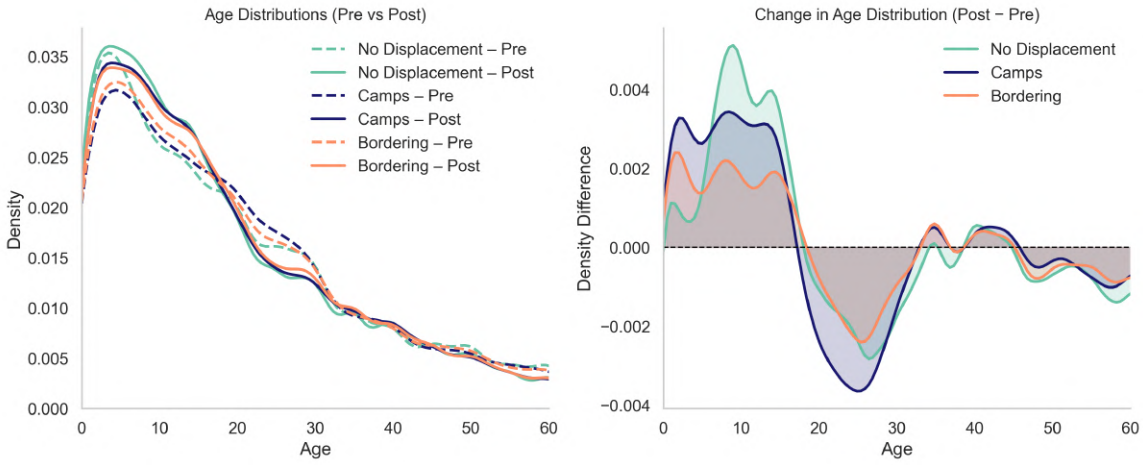


Figure 7. Age Distribution of Parishes

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:

$$\begin{aligned}\mathbb{P}(Y_i = 1) = \alpha + \beta_1 \text{Camp}_p + \beta_2 \text{Bordering}_p + \beta_3 \text{Post} \\ + \beta_4(\text{Camp}_p \times \text{Post}) + \beta_5(\text{Bordering}_p \times \text{Post}) + \mathbf{X_i}\gamma + \epsilon_i \end{aligned} \quad (2)$$

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.

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

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	-0.068**	0.050***	0.022
	(0.033)	(0.015)	(0.014)
Post × Bordering	-0.121***	0.095***	0.077***
	(0.029)	(0.013)	(0.012)
Camp = Bordering (p-value)	0.043	0.012	0.005
Pre-mean (No Disp.)	0.253	0.093	0.065
Pre-mean (Camp)	0.221	0.101	0.077
Pre-mean (Bordering)	0.249	0.095	0.060
N	195	196	196

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.

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 B5. 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

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.

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 B5, 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 B6.

6.2 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. A value of zero 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.

6.3 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[10]), 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 B10). 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 B9.

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,

[10]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 2 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 8. 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.

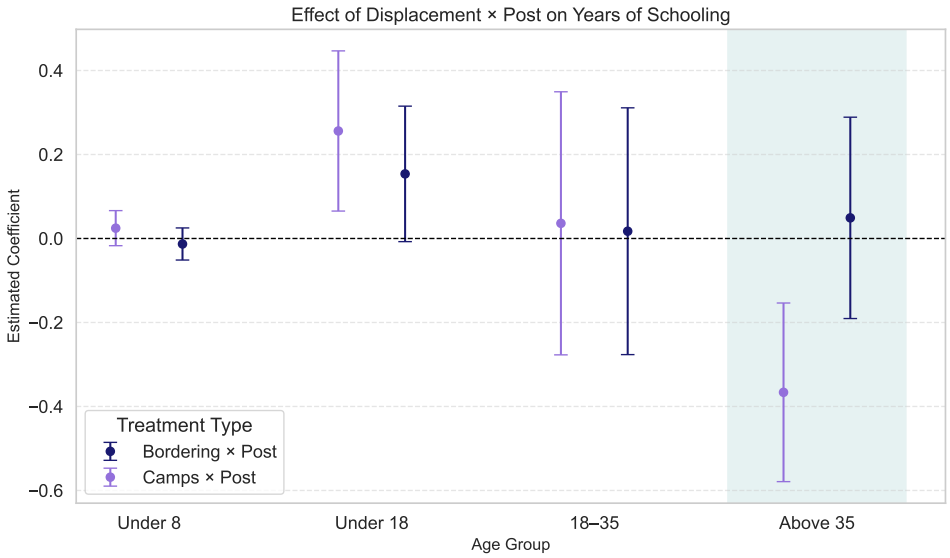


Figure 8. Effect of Displacement on Educational Outcomes by Age Group.
Note: Controls include age and sex. Shaded region corresponds to a significant ($p - value <$ 0.1) difference between the $Camp \times Post$ and $Bordering \times Post$

7 Mechanisms and Model

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.

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. This suggests that camps acted as hubs, facilitating greater connectivity through expanded infrastructure.

Table 11. Camps and Evolution of Parish Network Centrality

	Log Road Length (1)	Degree Centrality (2)	Betweenness Centrality (3)	Closeness Centrality (4)
Camp	0.334***	0.227	0.564***	0.421***
	(0.074)	(0.189)	(0.131)	(0.112)
Bordering	0.016	0.373**	0.332***	0.174*
	(0.052)	(0.166)	(0.125)	(0.103)
Camp = Bordering (p-value)	0.000	0.160	0.000	0.000
Pre-mean (No Disp.)	10.347	-0.133	-0.298	-0.393
Pre-mean (Camp)	11.673	0.040	0.540	0.657
Pre-mean (Bordering)	11.126	0.213	0.224	0.326
R^2	0.758	0.125	0.277	0.396
N	1035	1035	1035	1035

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.

The significant positive result for 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. 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.

To further explore the role of market access in reshaping the composition of post-displacement economic activity, I run the regression interacting the treatment variable with whether or not a location experienced an increase in road infrastructure after the war. I find that lack of market access explains the majority of the population decline in Bordering locations. The results are displayed in Table B12.

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.

In the Appendix B.6 I provide additional evidence from a different dataset that shows how being internally displaced led to households losing their land stock where the scale of displacement was larger.

7.3 Model

In order to assess the role of forced displacement on economic development, I develop a static spatial equilibrium model in which households choose both where to live and in which sector to work. The model provides a framework to evaluate how alternative forms of displacement and post-conflict reconstruction policies influence the spatial distribution of population and economic activity in Northern Uganda.

Locations differ in land availability, agricultural productivity, exposure to conflict, and residual amenities that affect location–sector attractiveness. Households sort across space and sectors in response to wages, consumption opportunities, and idiosyncratic taste shocks. These choices generate an equilibrium allocation of the population across locations and sectors, which in turn determines local production and incomes. I use the model to quantify how changes in fundamentals, specifically forced displacement and infrastructure reconstruction, reshape structural transformation and welfare.

Environment

The economy consists of a finite set of locations $\mathbf{I} = \{1, \ldots, \bar{\mathbf{I}}\}$, indexed by i, and two sectors $k \in \{A, S\}$, corresponding to agriculture and non-agriculture. A unit measure Ω continuum of atomistic households is initially distributed across locations according to an exogenous vector of shares π_0. Let π_{jk} denote the measure of households choosing location i and sector k. Total population is normalized to one:

$$\sum_{j \in \mathbf{I}} \sum_{k \in \{A,S\}} \pi_{jk} = 1 \tag{3}$$

Each household is born in some origin location i and, after observing idiosyncratic location–sector taste shocks, chooses a destination j and a sector k.

Preferences and Budget Constraints

A household ω choosing destination j and sector k consumes agricultural and non-agricultural goods. Preferences over consumption bundles ij a location j are non-homothetic and given by

$$U_j(C_A, C_S) = \begin{cases} (C_A - \bar{C})^{\alpha} C_S^{1-\alpha} \cdot m_{ij} \cdot \epsilon_{jk}(\omega), & \text{if } C_A \geq \bar{C}, \\ 0, & \text{if } C_A < \bar{C} \end{cases} \tag{4}$$

where C_{jA}, C_{jS} represent the quantity consumed from the agriculture and the services good in location j, respectively. $\bar{C}$ is a subsistence requirement for agricultural goods, $\alpha \in (0,1)$ governs expenditure shares, m_{ij} captures migration frictions, and $\epsilon_{jk}(\omega)$ is an idiosyncratic taste draw. Household within a location-sector pair are identical in the income that they earn and their consumption choices, and only differ in terms of their origin locations and the taste shock (hence they are indexed by ω).

The household faces the budget constraint:

$$C_{iA} p_{iA} + C_{iS} p_{iS} = w_{ik}, \qquad C_A \geq \bar{C}, \tag{5}$$

The non-homothetic Stone-Geary preferences imply that households require a minimum level of agricultural consumption before consuming services, making the relative attractiveness of sectors income-dependent. If a household earns below what is required to for subsustence ($C_{iA} < \bar{C}$), it obtains zero utility. I assume that the prices in the services sector are determined through market clearing in each location, and allow the agricultural good to be the numeraire and to be freely tradeable across all locations, such that $p_{iA} = p_A = 1$.

Migration Costs

Households face bilateral migration frictions represented as iceberg costs. Moving from origin i to destination j requires sacrificing a fraction of utility:

$$m_{ij} = d(i,j)^{-\eta}, \tag{6}$$

where $d(i,j)$ is a bilateral distance measure and $\eta \geq 0$ governs the elasticity of migration costs with respect to distance. Staying in one's origin involves no

migration cost:

$$d(i,i) = 1 \quad \Rightarrow \quad m_{ii} = 1. \tag{7}$$

Location–Sector Taste Shocks

Households draw an idiosyncratic taste term ε_{ik} for each location–sector pair. These taste shocks follow a Fréchet distribution:

$$\varepsilon_{ik} \sim \text{Fréchet}(T_{ik}, \theta), \qquad \mathbb{E}[\varepsilon] = \Gamma\left(1 - \frac{1}{\theta}\right), \tag{8}$$

where T_{ik} is a location–sector amenity parameter and θ is the dispersion parameter. Higher T_{ik} makes location–sector pair (i,k) more attractive, while higher θ reduces the influence of taste shocks. Amenities T_{ik} capture differences in local attractiveness not explained by wages or consumption opportunities.

Location Choice

Maximizing utility over consumption subject to the budget constraint yields indirect utility from choosing (j,k):

$$V_{jk} = \lambda \, p_{jS}^{\alpha-1}(w_{jk} - \bar{C}), \tag{9}$$

where $\lambda = \alpha^{\alpha}(1-\alpha)^{1-\alpha}$. Combining indirect utility, migration frictions, and taste shocks, the probability that a household born in i chooses (j,k) is

$$\pi_{jk|i} = \frac{T_{jk}(\omega) \cdot V_{jk}^{\theta}(\omega) \cdot m_{ij}^{\theta}}{\sum_{\ell,k'} T_{\ell k'}(\omega) \cdot V_{\ell k'}^{\theta}(\omega) \cdot m_{i\ell}^{\theta}}. \tag{10}$$

Aggregating over origins yields the unconditional population shares:

$$\pi_{jk} = \sum_{i \in \mathbf{I}} \pi_{jk|i} \cdot \pi_i^0. \tag{11}$$

Production

Each location produces agricultural and non-agricultural output using local labor and fundamental characteristics. Conflict affects productivity through a multiplicative shock described below.

Agriculture. Output in agriculture follows:

$$Q_{iA} = Z_{iA} N_{iA}^{\mu} L_i^{1-\mu} \tilde{X}_i, \tag{12}$$

where Z_{iA} is agricultural productivity, L_i is land, $\mu \in (0,1)$ governs congestion in agriculture, and $\tilde{X}_i$ is a conflict-adjusted productivity shifter. Higher conflict reduces $\tilde{X}_i$, lowering agricultural output and wages.

Non-Agriculture. Output in services scales with local agglomeration:

$$Q_{iS} = N_{iS} \left(N_i^{\gamma}\right) \tilde{X}_i, \tag{13}$$

where $\gamma \geq 0$ captures agglomeration effects, and $N_i = N_{iA} + N_{iS}$.

Wages

Wages are given by the average product of labor:

$$w_{ik} = \begin{cases} p_{iA} Z_{iA} \left(\dfrac{L_i}{N_{iA}}\right)^{1-\mu} \tilde{X}_i, & k = A, \\ p_{iS} N_i^{\gamma} \tilde{X}_i, & k = S, \end{cases} \tag{14}$$

which reflect congestion in agriculture and agglomeration in services. Note that $p_{iA} = 1$ since the price of the agricultural good is taken as the numeraire.

Conflict Conflict accumulates according to

$$X_{it} = \delta X_{i,t-1} + \text{Deaths}_{i,t}, \tag{15}$$

decaying in peaceful periods as

$$X_{i,t+\tau} = \delta^{\tau} X_{i,t}, \tag{16}$$

[11] To incorporate conflict into productivity, I transform the conflict index to

$$\tilde{X}_i = b + (1-b)\exp(-X_i), \tag{17}$$

The accumulated conflict index X_i reduces local productivity through a smooth exponential transformation. The term $\tilde{X}_i$ is a conflict-adjusted productivity shifter that maps conflict exposure into the interval $[b,1]$, where $b \in (0,1)$ is a lower bound ensuring that locations with very high conflict still retain positive productive capacity. The exponential form ensures that increases in conflict reduce $\tilde{X}_i$ at a diminishing rate and that $\tilde{X}_i$ remains strictly decreasing in X_i without requiring sample-dependent normalization. Conflict therefore affects production and wages

[11] with half-life $h = \frac{\ln(0.5)}{\ln(\delta)}$

through $\tilde{X}_i$, with the assumption that such that this productivity shifter enters the same way in both sectors.

Equilibrium

Given exogenous parameters $\{\epsilon, \theta, \alpha, \eta\}$, initial population distribution π_0, agricultural productivity $\{Z_{iA}\}$, and the road network M, a spatial equilibrium is a set of allocations and amenities $\{C_{ik}, \pi_{ik}, T_{ik}\}$ and prices $\{w_{ik}, p_{iS}\}$ such that:

Population.

$$\sum_{i \in \mathbf{I}} \sum_{k \in \{A,S\}} \pi_{ik} = 1 \tag{18}$$

Consumption.

Agriculture:

$$C_{iA} = \frac{\alpha w_i}{p_{iA}} + (1-\alpha)\bar{C}. \tag{19}$$

Services:

$$C_{iS} = \frac{(1-\alpha) w_i}{p_{iS}} - \frac{(1-\alpha) p_{iA}}{p_{iS}} \bar{C}. \tag{20}$$

Goods Market Clearing.

Agriculture:

$$X_{iA} = C_{iA}, \tag{21}$$

$$\sum_{i \in \mathbf{I}} Q_{iA} = \sum_{i \in \mathbf{I}} X_{iA}. \tag{22}$$

Services:

$$C_{iS} = \begin{cases} \pi_{iS}\, \pi_i^{\gamma}\, \tilde{X}_i, & \text{if } C_{iS} > \bar{C}, \\ 0, & \text{if } C_{iS} \leq \bar{C}. \end{cases} \tag{23}$$

Assume $\gamma = 0$.

$$w_{iS} = \frac{1-\alpha}{\alpha \pi_{iS}} \left(\pi_{iA} w_{iA} - \bar{C}(\pi_{iA} + \pi_{iS}) \right). \tag{24}$$

Labor Market Clearing.

$$\pi_i = \pi_{iA} + \pi_{iS}. \tag{25}$$

Welfare.

$$\mathcal{W} = \Gamma\left(1 - \frac{1}{\theta}\right)\left(\sum_i \sum_k T_{ik} V_{ik}^{\theta}\right)^{1/\theta}. \tag{26}$$

Mechanisms

The model highlights three main mechanisms through which forced displacement and post-conflict reconstruction affect the spatial distribution of population, sectoral employment, and welfare.

(1) Forced displacement and the population distribution. The introduction of IDP camps constitutes a large, localized population shock. In the model, this corresponds to a shift in the initial population distribution π_i^0, which increases the mass of households residing in camp locations. Because households face migration costs m_{ij}, this inflow makes these locations effectively "stickier," increasing the share of individuals who remain in or near camp locations even after displacement pressures subside.

This shift in population has direct implications for local factor ratios. In camp locations, the larger population reduces land per capita, tightening the agricultural congestion term

$$\left(\frac{L_i}{N_{iA}}\right)^{1-\mu}$$

in the agricultural wage (eq. 14). As N_{iA} rises, the average product of labor in agriculture falls, making agricultural work less attractive relative to services. This mechanism generates a reallocation of workers from agriculture into services. Thus, forced displacement induces structural transformation in locations that hosted camps, even in the absence of changes to fundamental productivity.

(2) Conflict and effective productivity. Conflict affects local productive capacity through the conflict-adjusted shifter $\tilde{X}_i$, which enters both agricultural and non-agricultural production (eqs. 12–13). Higher accumulated conflict reduces $\tilde{X}_i$, lowering output and thus wages in both sectors.

(3) Road reconstruction and migration costs. The post-war reconstruction of road infrastructure reduces migration frictions by lowering effective bilateral distances in

the migration cost function $m_{ij} = d(i,j)^{-\eta}$. Improved market access expands households' choice sets and weakens the spatial persistence induced by displacement. In particular, in locations where conflict lowered effective productivity, improved connectivity increases the return to out-migration, allowing households to relocate to higher-productivity or higher-amenity regions.

All in all, forced displacement generates a large distortion in the spatial allocation of population that, through decreasing returns to land, pushes households out of agriculture and into services. Conflict depresses local productivity, further shaping incentives to migrate or switch sectors. Reconstruction policies that lower migration costs partially offset the persistence of displacement by allowing households to re-optimize their location and sector choices. The equilibrium outcomes of the model reflect the interaction of these forces.

Calibration and Inversion Strategy

Calibration. Table 13 reports the structural parameters used in the model. Where possible, I adopt values from the existing literature: the agricultural expenditure share $\mu = 0.39$ from Fajgelbaum and Redding (2022) (which was estimated for 19th century Argentina, and has been used for Sub-Saharan African contexts such as in Conte, 2025), the preference parameter $\alpha = 0.31$ from Hsu (2025), and the Fréchet dispersion $\theta = 3.65$ together with the migration elasticity $\eta = 0.45$ from Conte (2025). The conflict-decay factor $\delta = 0.90$ and the lower bound $b = 0.10$ of the conflict-adjusted productivity shifter are calibrated using empirical evidence on the persistence and macroeconomic effects of conflict documented in the International Monetary Fund's analysis of fragile and conflict-affected states (IMF, 2017).

Inversion strategy. To recover the residual amenities in the base year, I invert the model by feeding in observed 1992 population and sectoral employment data together with measured fundamentals (land, conflict-adjusted productivity $\tilde{X}_i$, agricultural productivity Z_{iA}, and infrastructure). Holding all structural parameters fixed, I solve for the vector of amenities $\{T_{ik}^{1990}\}$ that rationalizes the observed spatial–sectoral allocation as an equilibrium of the model. These inferred amenities capture all unobserved determinants of location–sector attractiveness in 1990. I perform the same inversion in 2014, thus allowing for amenities to be altered because of the war period.

Table 13. Model Parameters and Calibration

Parameter	Value	Source / Calibration	Description
μ	0.39	Fajgelbaum & Redding (2022)	Share of expenditure on non-agricultural goods
δ	0.9	IMF (2017)	Conflict persistence (decay factor)
b	0.10	IMF (2017)	Maximum conflict damage to productivity
α	0.31	Hsu (2023)	Agricultural share in production
θ	3.65	Conte (2025)	Fréchet dispersion parameter (idiosyncratic productivity)
η	0.45	Conte (2025)	Migration cost distance elasticity

Notes: Parameters are taken from existing literature where available.

Validating the Model Before turning to the counterfactual analysis, I assess the empirical performance of the quantified model along several dimensions. The objective is to evaluate whether the calibrated fundamentals and the implied spatial equilibrium reproduce salient features of the Ugandan economy in 2014.

Fit to the Cross-Section of Population

To evaluate how well the model replicates the spatial distribution of population, Figure 9 plots model-predicted total population against actual 2014 values. The model predicts well the population distribution for low and moderate levels in the population distribution, but undershoots when it comes to the higher end of the population distribution, likely due to the absence of agglomeration externalities in the current calibration of the model.

Distribution of Sectoral Employment

Figure 10 shows the equilibrium distribution of agricultural and non–agricultural employment shares across parishes under the baseline calibration. These distributions reflect the expected features of Northern Uganda: agricultural employment is widespread and highly skewed, while non–agricultural employment is extremely concentrated, consistent with the model's strong diminishing returns in agriculture and the limited number of viable service-sector locations.

To inspect spatial patterns in the remaining discrepancies, Figure **??** displays the geographic distribution of residuals. Residuals are not random: the model slightly overpredicts population in historically secure areas and underpredicts population in former camp-hosting parishes. This is consistent with persistent post-conflict clustering that cannot be fully explained by fundamentals alone.

Sectoral Adjustments and Wage Differences

Figure 11 shows that declines in agricultural employment induced by displacement are negatively correlated with changes in agricultural wages. Locations experiencing stronger crowding due to displacement (less land per capita) exhibit



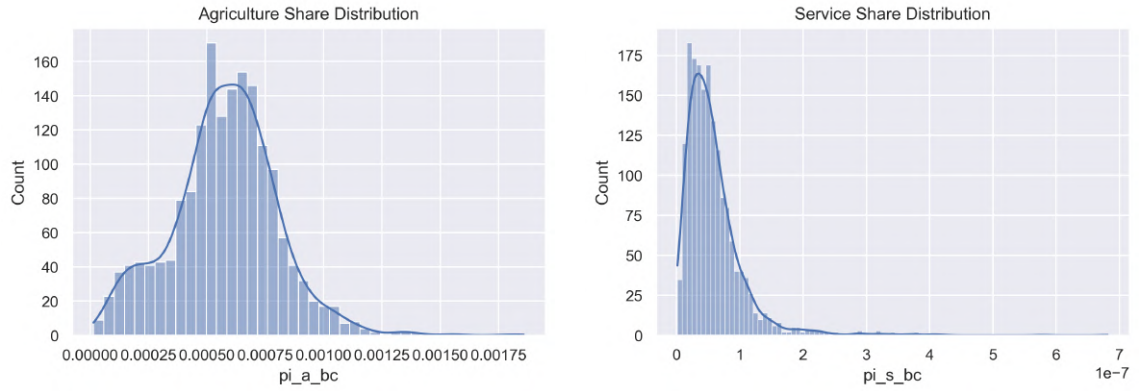
Figure 9. Fit of Population Distribution

larger reductions in agricultural employment, which is consistent with the model's main mechanisms.

Counterfactual Analysis: Occupational Shifts and Displacement Exposure

Tables 14 and 15 summarize how agricultural and non-agricultural employment shares changed between 1990 and 2014 across locations differentially exposed to forced displacement under different scenarios. Three patterns emerge that are highly consistent with the mechanisms embedded in the model.

(1) Forced displacement induces exits from agriculture in camp locations. Camp parishes exhibit declines in agricultural employment shares. Even though the



(a) Agricultural employment share distribution (b) Service employment share distribution

Figure 10. Distribution of equilibrium sectoral employment shares

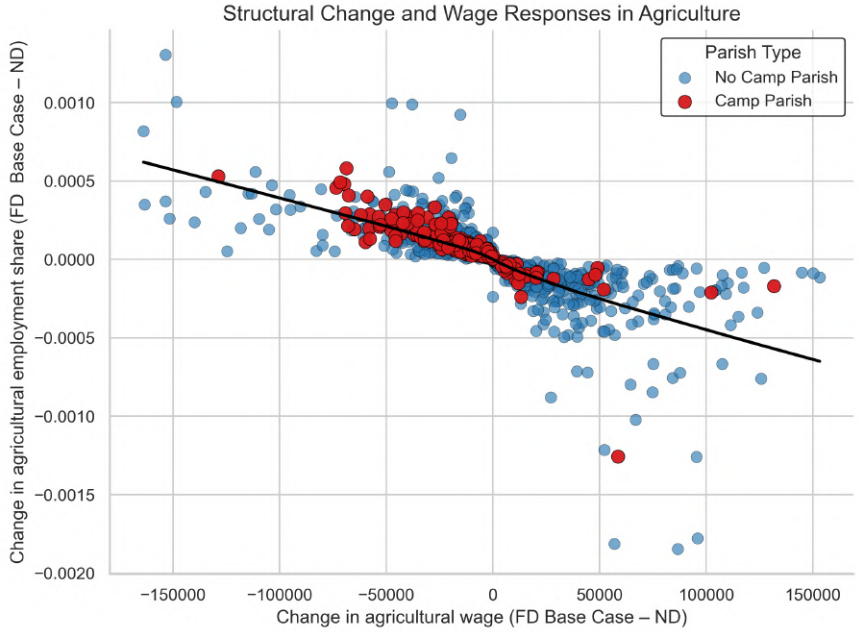


Figure 11. Change in agricultural wages and agricultural employment

mean percentage changes appear modest, the distribution displays pronounced negative tails, indicating that a subset of camp locations experienced significant reallocations out of agriculture. This pattern is directly implied by the model: the sudden inflow of internally displaced persons reduces land per capita, lowering agricultural returns and pushing workers toward alternative occupations.

Bordering parishes exhibit intermediate adjustments, suggesting that displacement generated localized congestion effects extending beyond camp boundaries,

Table 14. Agricultural Share Change (% Relative to 1990), by Displacement Exposure

Exposure Category	Mean	Std. Dev.	Min	Median	Max
(A) Base Case vs. 1990					
Border	-0.000	0.009	-0.105	-0.000	0.050
Camp	-0.011	0.078	-1.094	-0.003	0.018
No Disp.	0.169	4.132	-0.074	-0.002	99.983
(B) No Displacement vs. 1990					
Border	0.002	0.005	-0.034	0.002	0.061
Camp	0.001	0.005	-0.061	0.001	0.007
No Disp.	0.173	4.133	-0.050	0.002	100.000
(C) No Reconstruction vs. 1990					
Border	-0.001	0.005	-0.011	-0.002	0.049
Camp	-0.009	0.068	-0.945	-0.002	0.019
No Disp.	0.169	4.132	-0.055	-0.002	99.980

Table 15. Service Share Change (% Relative to 1990), by Displacement Exposure

Exposure Category	Mean	Std. Dev.	Min	Median	Max
(A) Base Case vs. 1990					
Border	18.415	122.373	-95.160	5.558	1269.585
Camp	218.384	1704.448	-76.318	47.222	23790.393
No Disp.	109.765	957.066	-99.983	24.893	16952.594
(B) No Displacement vs. 1990					
Border	-15.099	42.479	-93.210	-19.912	419.718
Camp	-12.710	100.023	-82.733	-19.364	1337.886
No Disp.	-19.616	44.267	-100.000	-19.954	648.854
(C) No Reconstruction vs. 1990					
Border	20.282	74.288	-93.245	24.910	1046.462
Camp	176.035	1473.528	-69.844	25.063	20565.732
No Disp.	101.328	813.746	-99.980	24.986	14507.126

i.e people remained close to the camps and so some of the bordering parishes may have also experienced some congestion effects. In contrast, parishes without displacement exposure display almost no change in agricultural employment across scenarios, which suggests that occupational patterns would have remained largely stable in the absence of population shocks.

(2) Service employment rises sharply in displaced areas, particularly under the baseline scenario. The non-agricultural employment results display much larger magnitudes in changes, with camp locations showing dramatic increases in service employment in the Baseline FD scenario. These increases reflect the effect of reduced agricultural returns.

Importantly, when displacement is removed in the counterfactual (No Displacement), service shares decline substantially across all classifications. Interestingly, the declines in the No Displacement parishes are also very high, which points to spillover effects from the initial displacement leading to also these parishes being emptier after the displacement policy.

(3) Higher incomes in less congested areas further stimulate service demand. In the bordering parishes that experienced outflows rather than inflows of population, land per capita increased relative to 1990, raising agricultural returns and local incomes. Because preferences in the model are non-homothetic, higher income raises the consumption share devoted to non-agricultural goods. This can be seen by comparing the scenarios (A) of baseline FD and (B) of No Displacement. Even without large inflows of workers, these bordering locations exhibit modest increases in service employment driven by income effects rather than congestion.

This income-driven channel complements the displacement-induced channel: whereas camp locations exhibit occupational shifts away from agriculture due to declining returns, some bordering locations exhibit shifts toward services due to rising purchasing power.

(4) Reconstruction slows down non-agricultural expansion. Comparing the No Reconstruction scenario with the Base Case reveals the tension between migration costs and congestion effects on sectoral transitions. Under No Reconstruction, service expansion in camp parishes remains positive but is substantially smaller than in the baseline. This indicates that in camps that are less connected after the war, migration frictions trap people, and although there is a crowding out of people from agriculture into services, wages in both sectors will be low enough to depress demand for services.

Improved road connectivity lowers migration costs, increasing the payoff to leaving congested camps, leading to higher per capita income in agriculture in camps and thus an increase in demand for services there.

In the bordering-origin parishes, however, the no reconstruction scenario leads to even higher increases in the share of services workers.

Taken together, the results reveal a coherent mechanism that is consistent with the empirical results: forced displacement generates sharp occupational shifts by lowering agricultural productivity in crowded destinations, while reconstruction and income effects shape the spatial heterogeneity of service-sector expansion. The combination of these forces produces distinct adjustment patterns across camp, border, and non-displaced areas.

Local Welfare Effects

Finally, I compare spatial welfare under the baseline with the no–displacement and no–reconstruction counterfactuals. The results are displayed in Table 16. I find by comparing the Base Case to No Displacement scenario that forced displacement led to a a decrease in welfare for both, bordering and camp locations. Specifically, camp parishes had 13% lower welfare in the Base Case, and bordering had 11% lower welfare. When evaluating the road of post-conflict road reconstruction on welfare, we can see that roads had a positive effect on welfare in camps(had there been no roads, welfare would have been 9% lower compared to the baseline FD scenario), and actually led to lower welfare in the bordering region compared to the base case with displacement.

Table 16. Welfare Change (% Relative to 1990), by Displacement Exposure

Exposure Category	Mean	Std. Dev.	Min	Median	Max
(A) Base Case vs. 1990					
Border	36	173	-86	0	1613
Camp	7	86	-82	-6	881
No Disp.	13	62	-100	6	918
(B) No Displacement vs. 1990					
Border	47	259	-83	4	2240
Camp	20	173	-77	3	2303
No Disp.	8	58	-100	2	1345
(C) No Reconstruction vs. 1990					
Border	48	196	-99	-7	1789
Camp	-2	91	-88	-19	881
No Disp.	10	60	-100	1	918

8 Camp Characteristics and Design

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.

8.1 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.

8.1.1 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 12, with the start date of camps. We can see that there is variation across space in the timing of a camp opening. In Figure 13, 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 B13 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.

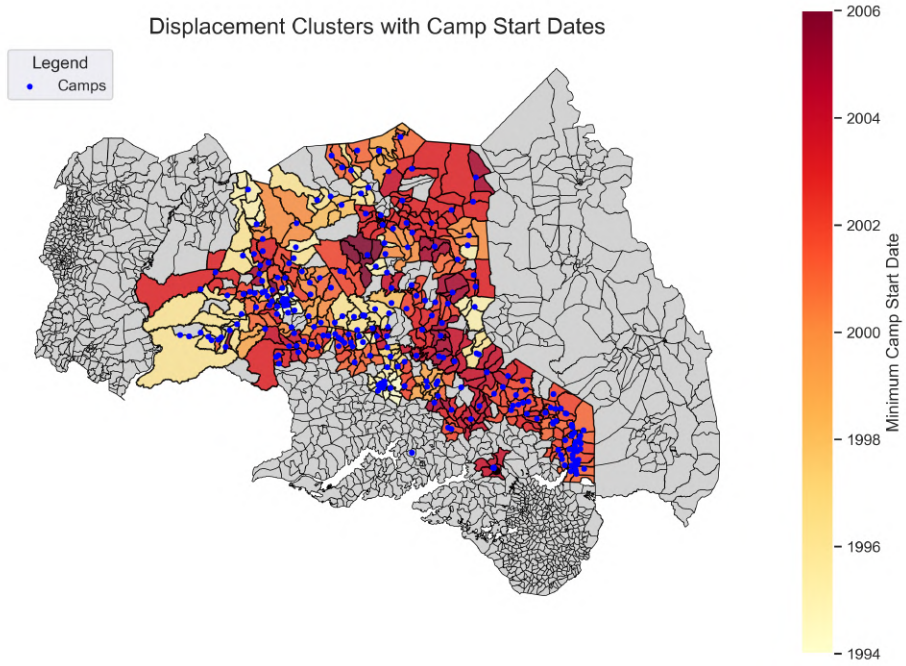


Figure 12. Camp Creation in North and East Uganda

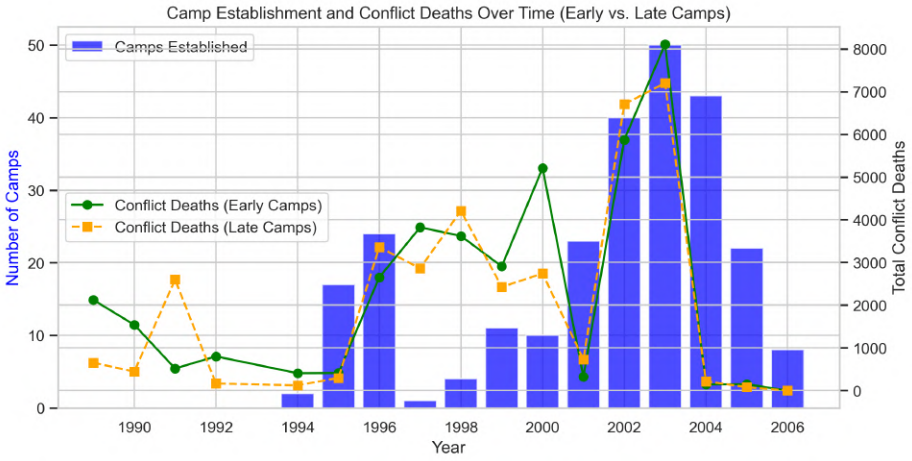


Figure 13. Camp Creation and Conflict Timing

8.1.2 Empirical Specification

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

$$\Delta Y_c = \beta_0 + \beta_1 \times CampDuration_c + \beta_3 Y_{c,t-1} + \delta + C_{c,t-1} + X_{p,1992} + \epsilon_c \tag{27}$$

At the individual level, I estimate the following regression:

$$\begin{aligned}\mathbb{P}(Y_i = 1) = \alpha + \beta_1 CampDuration_p + \beta_2 \text{Post}_t \\ + \beta_3 (CampDuration_c \times \text{Post}_t) + \mathbf{X_i}\gamma + \epsilon_i\end{aligned} \tag{28}$$

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.

8.1.3 Results

Growth at the parish level

First, I study whether camp duration had an effect on economic development in parishes. Table 17 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 29, 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.

$$\begin{aligned}\Delta Y_i = \quad & \beta_0 + \beta_1 \text{CampDuration}_i \times \text{NoCamp}_i \\ + & \beta_2 \text{CampDuration}_i \times \text{Camp}_i + \mathbf{X}_i'\gamma + \delta_{d(i)} + \varepsilon_i\end{aligned} \tag{29}$$

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.

Table 17. 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.

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 18. 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 B7 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 B8 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 18. 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 30. The results are displayed in Table B15. 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.

$$\begin{aligned}\mathbb{P}(Y_i = 1) = \alpha + \beta_1 CampDuration_p + \beta_2 Camp_p + \beta_3 \text{Post}_t \\ + \beta_4 (CampDuration_c \times \text{Post}_t) + \beta_5 (CampDuration_c \times Camp_p \times \text{Post}_t) + \mathbf{X_i}\gamma + \epsilon_i\end{aligned} \tag{30}$$

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 19 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 19. 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.

8.2 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:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p + \delta + C_{p,t-1} + X_{p,1992} + \epsilon_{p,t} \tag{31}$$

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

Table 20. 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.

The results, in Table 20, 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 instrument camp population with the road length in a parish in 1992. The specification is displayed in Equation 33. 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:

$$\text{CampPop}_{p,2005} = \alpha_0 + \alpha_1 \log(\text{RoadLength}_{p,1992}) \times \text{Post}_t + \gamma_p + \varepsilon_{pt} \tag{32}$$

Second Stage:

$$Y_{ipt} = \beta_0 + \beta_1 \widehat{\text{CampPop}}_{p,2005} \times \text{Post}_t + X'_{it}\delta + \gamma_p + \epsilon_{ipt} \tag{33}$$

Table 21. 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.

The results show that camp population size does not have a statistically significant effect on the share of people working in services. However, it does increase educational attainment: each additional 1,000 people hosted in a camp is associated with a 2.3 percentage point rise in the share of individuals with above-primary education.

In Appendix Table C3, I estimate a similar specification using camp population relative to the 1990 baseline population as the independent variable, and nighttime lights as the outcome. The coefficient is negative and statistically significant (-0.346), which indicates decreasing returns to scale in output at higher population densities. This is consistent with a largely agricultural economy, where limited land per worker implies Malthusian dynamics.

Table 22. 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.

8.3 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 34:

$$\begin{aligned} \Delta Y_{p,t} = \beta_0 + \beta_1 \times CampPop_p \times Conflict_p + \beta_2 \times CampPop_p \\ + \beta_3 \times Conflict_p + \delta + X_{p,1992} + \epsilon_{p,t} \end{aligned} \tag{34}$$

The coefficient of interest, β_1, is reported in Table 23, 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 23. 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.

9 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 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. Second, I study the effect of camps as a forced urbanization shock on the spatial distribution of economic activity. I show how population growth patterns change across locations, and using census data I document how transition from agriculture into services takes place due to displacement and how changes in the overall level of education are telling of a positive selection of people who live outside camps. I focus on market access from post-war road reconstruction as a main channel that explains this population reallocation, and using a simple quantitative spatial model I quantify the effect of these roads on the compositional change of people across the geography of North Uganda. Third, I study the determinants of camp "success" by focusing on the role of camp characteristics such as how long they lasted, how many people they hosted, and how close they were to conflict.

Forced displacement in Northern Uganda set in motion a process unprecedented 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. Post-war reconstruction and road investments reinforced these patterns by acting as local income shocks, increasing connectivity and demand, but these benefits were not reaped by locations that were further from camps.

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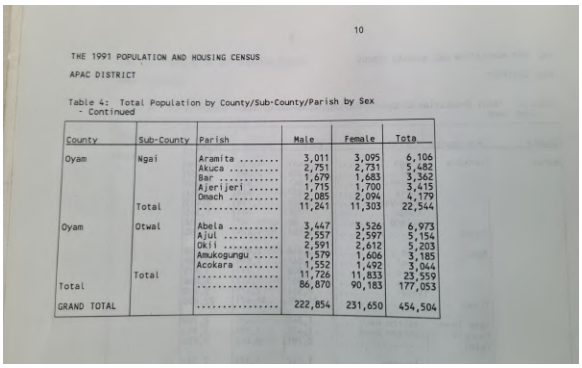
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A Data Appendix

A.1 Linking Census Data



10

THE 1991 POPULATION AND HOUSING CENSUS

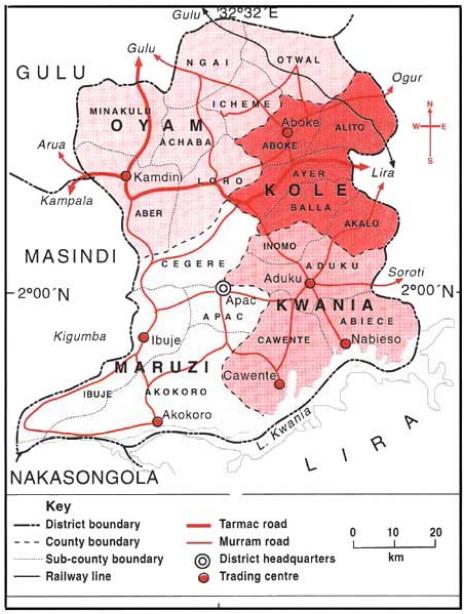
APAC DISTRICT

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

County	Sub-County	Parish	Male	Female	Tota
Oyam	Ngai	Aramita	3,011	3,095	6,106
		Akuca	2,751	2,731	5,482
		Bar	1,679	1,683	3,362
		Ajerijeri	1,715	1,700	3,415
		Omach	2,085	2,094	4,179
	Total	.....	11,241	11,303	22,544
Oyam	Otwal	Abela	3,447	3,526	6,973
		Ajul	2,557	2,597	5,154
		Okii	2,591	2,612	5,203
		Amukopungu	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

Appendix Figure A1. 1991 Parishes from Census Report

A.2 Digitizing 1991 Maps



Appendix Figure A2. 1992 Road Map

B Data Analysis Appendix

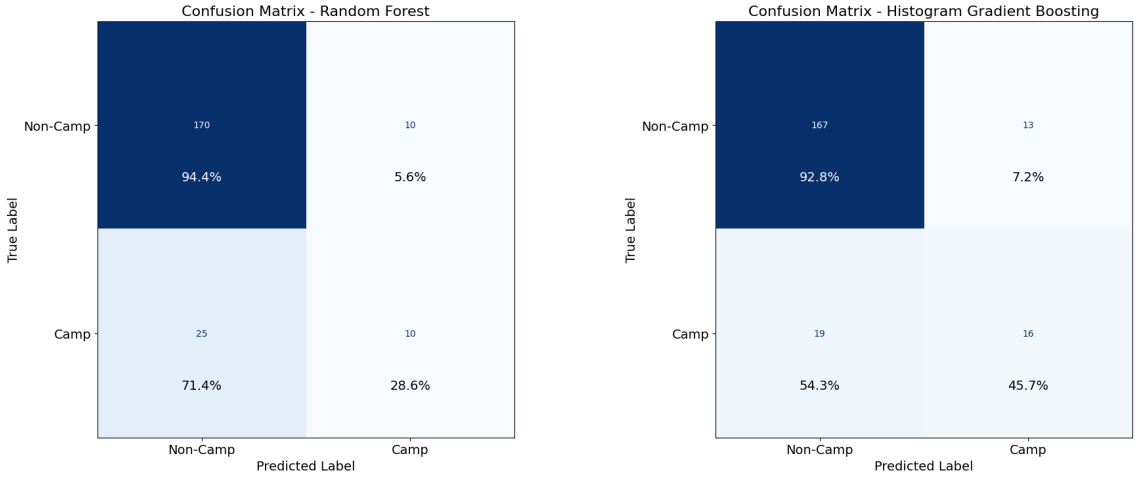
B.1 Assignment Mechanism: Prediction of Treatment using ML

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.



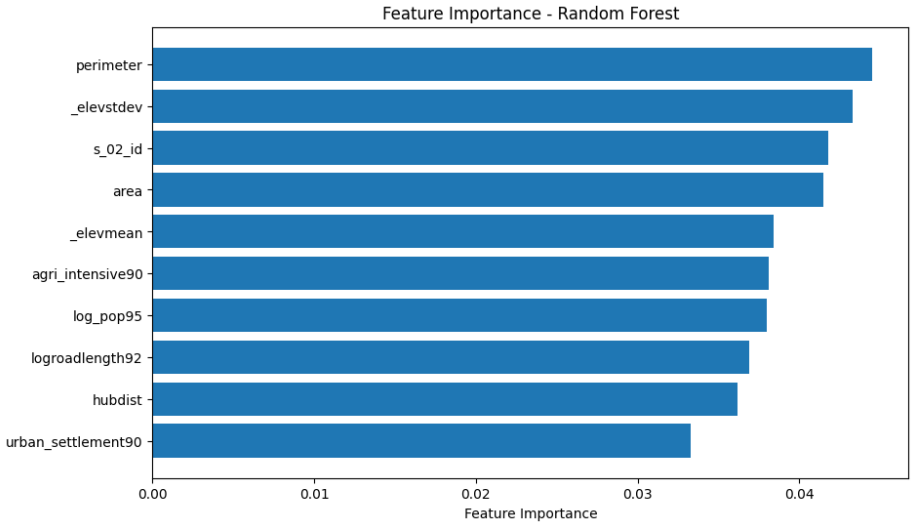
(a) Random Forest (b) HGB Model

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

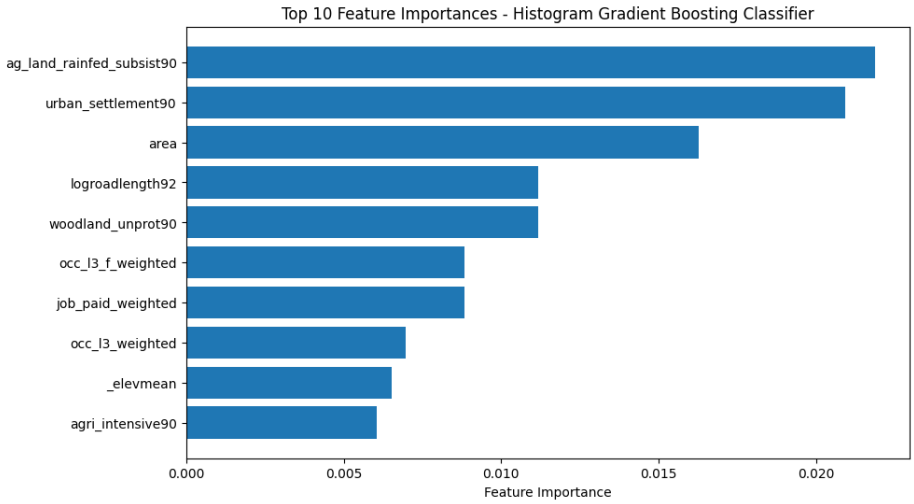
B.2 Additional Results

B.3 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.3.3, I compare Camp parishes to all other parishes. In the strategy in Section B.3.1, I test whether the effect of being a parish without a camp is diminishing in the distance from a camp. In Appendix B.3.4 I also repeat the analysis excluding a ring



(a) Random Forest Model



(b) HGB Model

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

of second-degree bordering parishes to reduce SUTVA concerns.

Moreover, to study the dynamic effects of displacement on population, I exploit variation in the timing of camp establishment across locations and estimate an event-study specification following Callaway and Sant'Anna, 2021 in Appendix B.3.2. 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

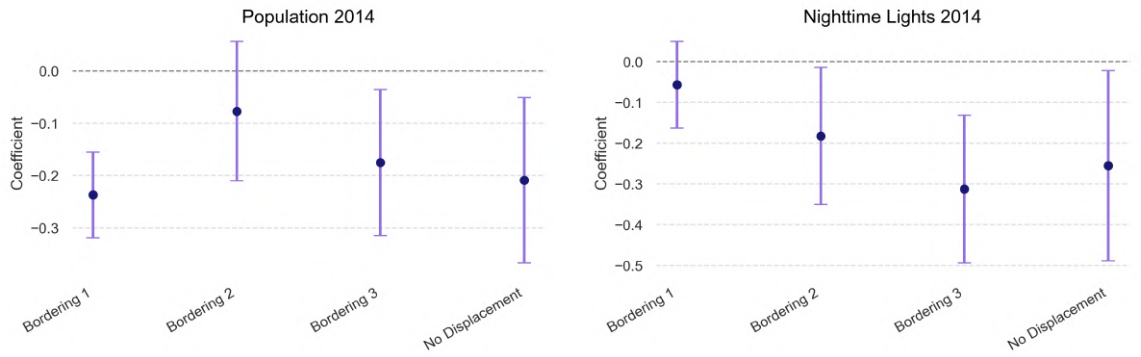
than that of the camp parishes.

B.3.1 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:

$$Y_{p,t} = \beta_0 + \beta_1 \times Bordering1_p + \beta_2 \times Bordering2_p + \beta_3 \times Bordering3_p + \beta_4 Y_{p,t-1} + \delta + C_{p,t} + X_{p,1992} + \epsilon_p \quad (35)$$

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

Appendix Figure B3. 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.

B.3.2 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

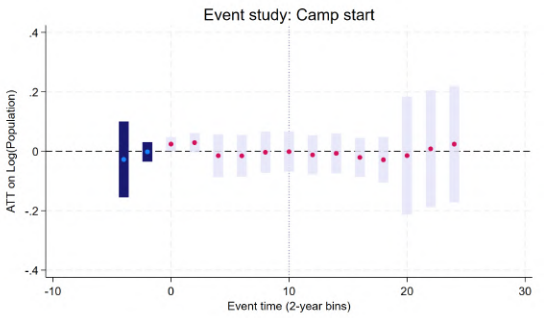
$$\ln(\text{Population}_{pt}) = \alpha_p + \lambda_t + \sum_{g \neq 0} \sum_{\ell \in \mathcal{L}} \beta_{g,\ell} \, \mathbf{1}\{G_p = g\} \mathbf{1}\{t - g = \ell\} + \varepsilon_{pt}, \qquad (36)$$

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.

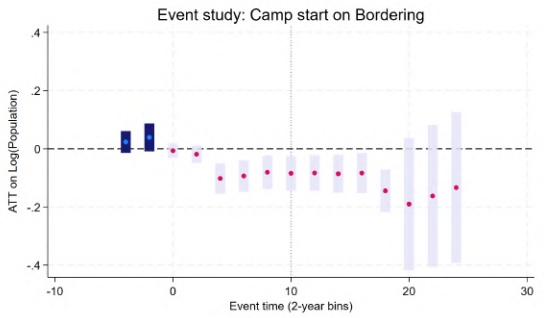
The identification then in this specification relies on the assumptions that parallel trends hold, that there were no anticipation effects, and that the stable unit treatment value assumption (SUTVA) holds. The parallel trends assumption for population holds visually in the results displayed in Figure B4. 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[12]. 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 B4 confirm that bordering parishes experienced lower population growth growth after people were free to move back to their villages of origin.

[12] In Subsection 8.1 I study in detail the role of camp duration length on economic activity and I show in Figure 13 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

Appendix Figure B4. Displacement and Population Distribution

B.3.3 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:

$$\Delta Y_{p,t} = \beta_0 + \beta_1 \times Camp_p + \beta_2 Y_{p,t-1} + \delta + C_{p,t} + X_{p,1992} + \epsilon_p \quad (37)$$

Results are displayed in Table B1.

Appendix Table B1. 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.

B.3.4 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 B2. 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.

Micro- Data

Education Outcomes

B.4 Camp Duration Tables

B.5 Estimating population retention rates

$$\text{First Stage:} \quad \Delta\text{CampPop}_p = \alpha_0 + \alpha_1 \,\text{RoadLength}_{p,1992} + X_p'\gamma + \nu_p, \tag{38}$$

$$\text{Second Stage:} \quad \ln(\text{Pop}_{p,2014}) = \beta + \eta \,\widehat{\Delta\text{CampPop}}_p + X_p'\gamma + \varepsilon_p, \tag{39}$$

The coefficient η measures the retention rate from a forced displacement shock.—the responsiveness of post-war population in 2014 to displacement-induced changes

Appendix Table B3. 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 B4. 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.

in local population during the conflict period. A value of $\eta = 0.14$ implies that a 1% increase in population inflows associated with internally displaced persons (IDP) camps led to a 0.14% increase in local population nearly a decade later. The estimate reflects long-run population persistence in the aftermath of forced displacement,

Appendix Table B5. 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 B6. 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.

where return migration, conflict, and land reallocation may all dampen the population response. Standard errors are clustered at the parish level, and estimation uses the limited-information maximum likelihood (LIML) estimator to reduce bias under weak instrument conditions. The results are displayed in

We can also use $Y_p = lnGDP_{2014}$ to measure the agglomeration elasticity of

Appendix Table B7. 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 B8. 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.

output. The results are displayed in Table C3. They show that once we partial out the endogenous component from the location of a camp, there are decreasing returns on output to having more population.

B.6 Displacement and Loss of Land

To understand how forced displacement affects the dynamics of land property rights, I employ information from the dataset of Northern Uganda Survey(NUS) which was conducted in 2004 and surveys both displaced and non-displaced households over the region. In the cross-sectional survey, respondents fill in information on how their land holdings have changed between 1992 and 2004, the latter being a year where there were not-yet displaced individuals.

In this section I show that the effect of displacement on household landownership varies systematically across districts with different levels of displacement

Appendix Table B9. 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 B10. Education

	Above Primary Education Share (1)	Above Secondary Education Share (2)	Years Schooling (3)
Post × Camp	0.009	0.009	0.059
	(0.006)	(0.006)	(0.085)
Post × Bordering	0.015**	0.015**	0.165*
	(0.007)	(0.007)	(0.088)
Camp = Bordering (p-value)	0.153	0.111	0.046
Pre-mean (No Disp.)	0.042	0.037	2.588
Pre-mean (Camp)	0.039	0.034	2.603
Pre-mean (Bordering)	0.047	0.041	2.675
N	1073	1073	1073

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.

intensity. First, I group districts into bins according to their displacement intensity. Let s_d denote the share of surveyed households in district d that report having been displaced at some point during the conflict. I classify these districts into three groups based on the observed distribution of s_d:

- **Low displacement**: $0 \leq s_d < 0.3$. These districts experienced relatively limited displacement, with fewer than 30% of households reporting displacement.

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.

- **High displacement**: $0.6 \leq s_d < 0.8$. These districts experienced large-scale displacement, typically between 60–80% of households.

- **Extreme displacement**: $0.8 \leq s_d \leq 1.0$. These districts experienced near-universal displacement, with more than 80% of households displaced.

The intermediate range ($0.3 \leq s_d < 0.6$) does not contain any districts in the sample, and therefore no "medium" category is defined. The three bins used in the analysis therefore correspond directly to the mass points in the empirical distribution of displacement intensity.

Within each displacement-intensity group, we estimate the following specification:

$$\log(\text{land}_{i,2004}) = \beta_g \, \text{IDP}_i + \gamma \log(\text{land}_{i,1992}) + \delta' X_i + \mu_{d(i)} + \varepsilon_i, \tag{40}$$

where $g \in \{\text{Low}, \text{High}, \text{Extreme}\}$ indexes the displacement-intensity group. The dependent variable is the logarithm of household landownership in 2004. The coefficient β_g captures the effect of displacement within group g. The vector X_i includes household-level controls (urban status and agricultural occupation), and

Appendix Table B12. Impact of New Roads on Population Growth Characteristics

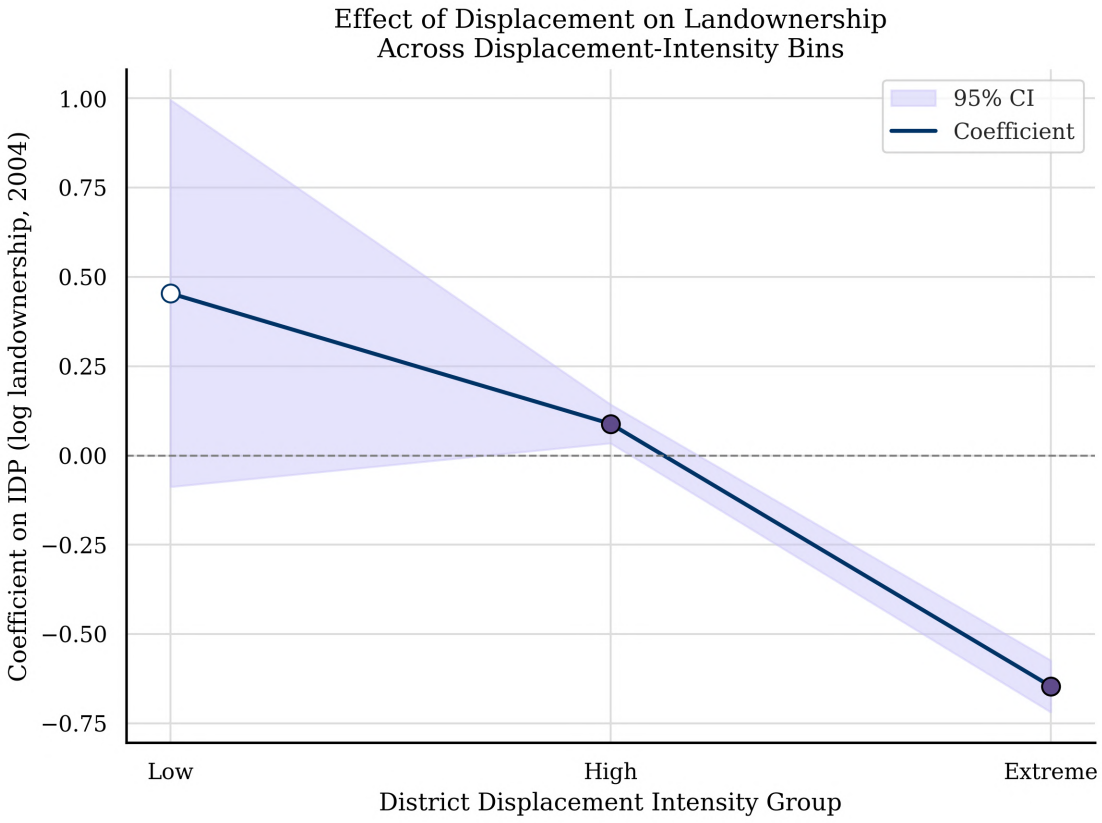
	Log Population (1)
Camp	0.031
	(0.111)
Bordering	-0.177**
	(0.075)
Camp × New roads	0.182*
	(0.096)
Border × New roads	0.187***
	(0.052)
No displacement × New roads	0.040
	(0.039)
Camp = Bordering (p-value)	
Pre-mean (No Disp.)	
R^2	0.557
N	1056

Notes: Conley standard errors (20km) in parentheses. ***p<0.01, **p<0.05, *p<0.1.

$\mu_{d(i)}$ are district fixed effects. All regressions are weighted using household survey weights, and standard errors are clustered at the district level.

Figure B5 demonstrates the coefficients β_g and their 95% confidence intervals. The results show that the effect of displacement on landownership is positive yet very noisy in districts with low displacement intensity. The effect shrinks significantly in high-displacement districts and becomes negative in extreme-displacement districts. In particular, in the extreme displacement districts, the coefficient implies that on average, being displaced there was correlated with losing approximately 50% of land holdings. Given that in 2004 displacement was not at its peak, it is not possible to interpret these estimates causally. Nonetheless, this pattern is consistent with the interpretation that substantial land loss occurred due to displacement, and primarily in districts where displacement was widespread or nearly universal, plausibly due to large-scale land abandonment, boundary degradation, encroachment, or conflict-related property destruction. Given that displacement became much more extreme in 2005, we can expect that the later-treated people and districts will have also suffered through the same mechanism.

Appendix Figure B5. Effect of Displacement on Landownership Across Displacement Intensity Thresholds



Appendix Table B13. 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 B14. 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 B15. 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 B16. 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.

Appendix Table B17. Instrumental Variables Estimates of FD Population Elasticity

	(1) Ln(Population) 2014
Displacement Share	0.140
	(0.092)
Observations	175

Estimator: LIML. Instrument: Road length (1992). Standard errors clustered at the parish level.

Appendix Table B18. Instrumental Variables Estimates of Population Density Elasticity

	(1) Log Nighttime Lights 2014
Displacement Share	-0.346*
	(0.180)
Observations	175

Estimator: LIML. Instrument: Road length (1992). Standard errors clustered at the parish level.

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}	$RP_{NA/Ag}$	$P_{NA\setminus M}$	$RP_{NA\setminus M/Ag}$
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

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

    (2) Forward equilibrium (given $T_{ik}(\kappa)$)
    Initialize $\pi_{ik} = \pi_{ik}^{data}$
    repeat
        Recompute market access: $\mathrm{MA}_i = \mathrm{MA}(\pi_{ia} + \pi_{is})$
        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:

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

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

$$AS_i = (1 - \alpha) \Big[\pi_{ia} \, (w_{ia} - \bar{C}) + \pi_{is} \, (w_{is} - \bar{C}) \Big] \tag{41}$$

$$AD_{s,i} = (\pi_{ia} + \pi_{is})^{\gamma} \, \mathrm{MA}_i^{\kappa} \, X_i^{\beta} \tag{42}$$

$$p_{s,i} = \frac{1 - \alpha}{\alpha} \, \frac{AD_{is}}{AS_{is}} \tag{43}$$

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:

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

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 Estimating population retention rates

$$\text{First Stage:} \quad \Delta \text{CampPop}_p = \alpha_0 + \alpha_1 \, \text{RoadLength}_{p,1992} + X_p' \gamma + \nu_p, \tag{44}$$

$$\text{Second Stage:} \quad \ln(\text{Pop}_{p,2014}) = \beta + \eta \, \widehat{\Delta \text{CampPop}}_p + X_p' \gamma + \varepsilon_p, \tag{45}$$

The coefficient η measures the retention rate from a forced displacement shock.—the responsiveness of post-war population in 2014 to displacement-induced changes in local population during the conflict period. A value of $\eta = 0.14$ implies that a 1% increase in population inflows associated with internally displaced persons (IDP) camps led to a 0.14% increase in local population nearly a decade later. The estimate reflects long-run population persistence in the aftermath of forced displacement, where return migration, conflict, and land reallocation may all dampen the population response. Standard errors are clustered at the parish level, and estimation uses the limited-information maximum likelihood (LIML) estimator to reduce bias under weak instrument conditions. The results are displayed in

We can also use $Y_p = lnGDP_{2014}$ to measure the agglomeration elasticity of output. The results are displayed in

Appendix Table C2. Instrumental Variables Estimates of FD Population Elasticity

	(1) Ln(Population) 2014
Displacement Share	0.140
	(0.092)
Observations	175

Estimator: LIML. Instrument: Road length (1992). Standard errors clustered at the parish level.

Appendix Table C3. Instrumental Variables Estimates of Agglomeration Elasticity

	(1) Log Nighttime Lights 2014
Displacement Share	-0.346*
	(0.180)
Observations	175

Estimator: LIML. Instrument: Road length (1992). Standard errors clustered at the parish level.

C.4 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.5 Schematic Algorithm for estimating the FD shock

Fundamentals:

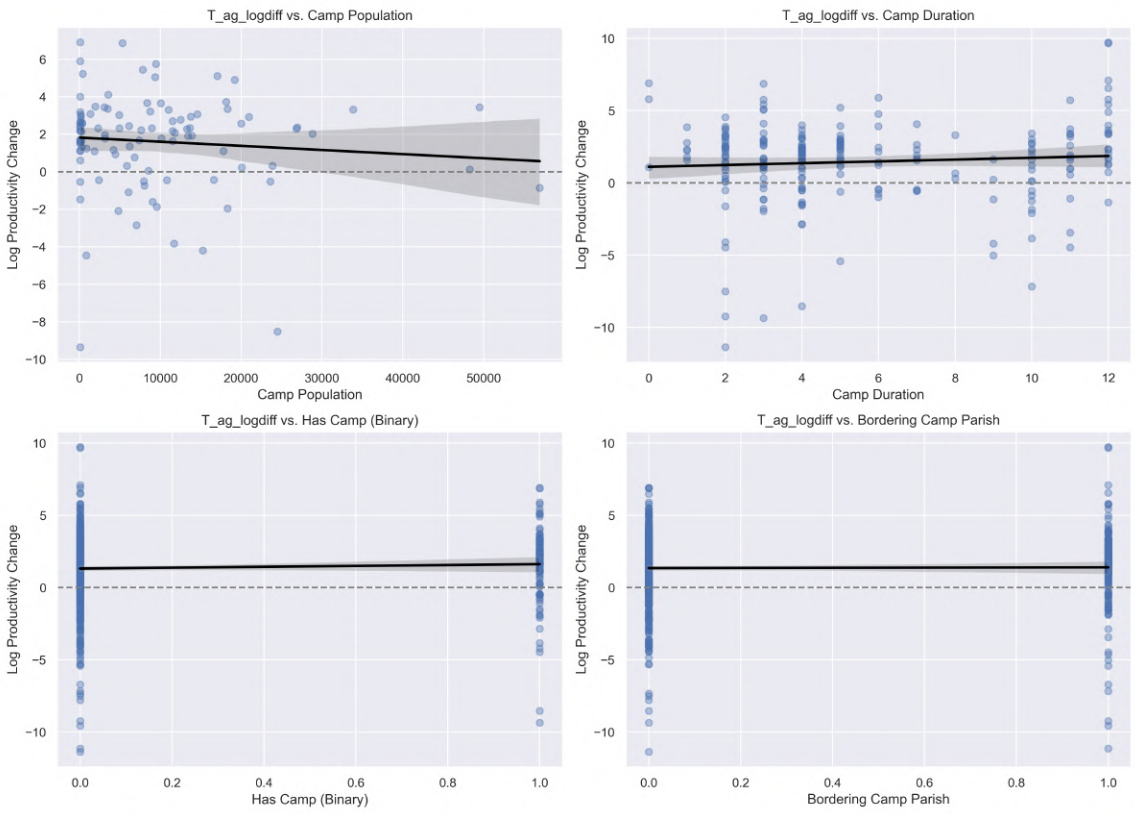
$$\{T_{ik}, Z_{iA}, \tilde{X}\}_{k \in \{A,S\}}$$

Parameters:

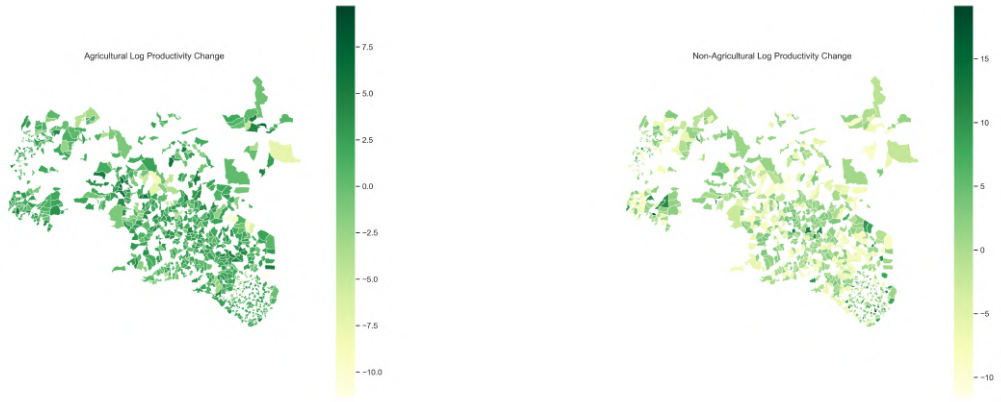
$$\{\theta, \gamma, \kappa, \alpha, \mu, b, \delta, \bar{C}\}$$

Algorithm:

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.



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

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:

$$\hat{Y}_{it} = \hat{\beta}_1 \,\text{Camp}_i \times \text{Post}_t + \hat{\beta}_2 \,\text{Bordering}_i \times \text{Post}_t + \hat{\gamma}' X_i \times \text{Post}_t + \hat{\delta}_{d(i)} + \hat{\lambda}_t \tag{46}$$

$$\hat{Y}_{it}^{cf} = \hat{Y}_{it} - \hat{\beta}_1 \,(\text{Camp}_i \times \text{Post}_t) - \hat{\beta}_2 \,(\text{Bordering}_i \times \text{Post}_t). \tag{47}$$

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

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}.

$$U_j(\omega) = \left(C_{jA} - \bar{c}\right)^{\alpha} C_{jS}^{1-\alpha} \cdot \epsilon_{jk}, \qquad \alpha \in (0,1), \quad \bar{c} > 0 \tag{48}$$

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:

$$C_{jk} = \left[\sum_i c_{ijk}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad P_{jk} = \left[\sum_i p_{ijk}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \qquad \sigma > 1 \tag{49}$$

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:

$$E_{jA} = P_{jA}C_{jA} = P_{jA}\bar{C} + \alpha\big(E_j - P_{jA}\bar{C}\big), \tag{50}$$

$$E_{jS} = P_{jS}C_{jS} = \begin{cases} (1-\alpha)\big(E_j - P_{jA}\bar{C}\big), & \text{if } E_j \geq P_{jA}\bar{C}, \\ 0, & \text{if } E_j < P_{jA}\bar{C} \end{cases} \tag{51}$$

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:

$$X_{ijk} = \phi_{ijk}E_{jk} = E_{jk}\left(\frac{\tau_{ijk}p_{ik}}{P_{jk}}\right)^{1-\sigma} \tag{52}$$

with

$$\phi_{ijk} = \left(\frac{p_{ijk}}{P_{jk}}\right)^{1-\sigma} \tag{53}$$

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:

$$E_{jA} = C_{jA} = \bar{C} + \alpha\big(E_j - \bar{C}\big), \tag{54}$$

$$E_{jS} = P_{jS}C_{jS} = \begin{cases} (1-\alpha)\big(E_j - \bar{C}\big), & \text{if } E_j \geq \bar{C}, \\ 0, & \text{if } E_j < \bar{C} \end{cases} \tag{55}$$

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

$$X_{ijS} = \phi_{ijS}E_{jS} = E_{jS}\left(\frac{\tau_{ijk}p_{iS}}{P_{jS}}\right)^{1-\sigma} \tag{56}$$

$$X_{ijA} = E_{jA} \tag{57}$$

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.

$$Y_{jS} = N_{jS}\, \tilde{X}_{jS}, \tag{58}$$

Wages:

$$w_{jk} = \begin{cases} p_{jA} Z_{jA} \left(\dfrac{L_{jA}}{N_{jA}} \right)^{1-\mu} \tilde{X}_j = Z_{jA} \left(\dfrac{L_{jA}}{N_{jA}} \right)^{1-\mu} \tilde{X}_j, & \text{if } k = A, \\ p_{jS} \tilde{X}_j, & \text{if } k = S \end{cases} \tag{59}$$

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

$$p_{ijS} = \tau_{ijS}\, p_{iS} = \tau_{ijS}\, \frac{w_{iS}}{\tilde{X}_i}, \tag{60}$$

$$P_{jS}^{1-\sigma} = \sum_i \tau_{ijS}^{1-\sigma} \left(\frac{w_{iS}}{\tilde{X}_i} \right)^{1-\sigma} \tag{61}$$

Total bilateral trade:

$$X_{ij} = \sum_{k \in \{A,S\}} X_{ijk}. \tag{62}$$

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:

$$\sum_{j}^{I} Y_{jA} = \sum_{i}^{I} X_{ijA} = \sum_{i}^{I} E_{iA} \tag{63}$$

In the services sector:

$$Y_{jS} = \sum_{i}^{I} X_{ijS} = \sum_{i}^{I} E_{iS} \frac{\tau_{ijS}^{1-\sigma} \left(\frac{w_{iS}}{\tilde{X}_i}\right)^{1-\sigma}}{\sum_{l}^{I} \tau_{ljS}^{1-\sigma} \left(\frac{w_{lS}}{\tilde{X}_l}\right)^{1-\sigma}} \tag{64}$$

Income consistency:

$$E_i = w_{iA}\pi_{iA} + w_{iS}\pi_{iS} = \sum_{k} \sum_{j} X_{ijk}. \tag{65}$$

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

$$\pi_{ik} = N_{ik} = \frac{T_{ik} V_{ik}^{\theta}}{\sum_{i'} \sum_{k'} T_{i'k'} V_{i'k'}^{\theta}} \tag{66}$$