The Effects of Internally Displaced Peoples on Consumption and Inequality in Mali

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Abstract

A series of civil conflicts in Mali has generated more than 346,000 internally displaced people (UNHCR, 2020). This study estimates the effect of conflict-generated internal displacement on consumption, poverty, and inequality in host communities. Using comprehensive nationwide household survey data this study finds that wealth at the commune and household level is non-decreasing in IDP hosting communes relative to non-IDP host communes. This study also finds some partial evidence of increasing consumption at the household level although inequality and poverty at the commune level remain the same. The evidence suggests a fairly successful hosting and aid process in Mali for IDPs in terms of mitigating economic disruption for host communities.

Keywords: Internal displacement, Conflicts, Inequality, Poverty

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1 Introduction

Despite seemingly wider media coverage on international refugees, much of the world's forcibly displaced persons do not cross international borders. In fact, 58% of worldwide forced displacement in 2020 consists of internally displaced persons (IDP) who flee from violence, natural or human-made disasters and alike without crossing an internationally recognized border (UNHCR, 2021). While more studies on internationally displaced persons, particularly with regard to their effects on host communities, have appeared in recent years, those related to IDP are few. This paper, therefore, analyzes the effects of IDP presence on host communities in the Malian context.

In the last decade, Mali has become the epicenter of one of the world's worst civil conflicts (ACLED, 2020), generating more than 346,000 IDPs (UNHCR, 2020). Real and perceived inequalities between and within communities have helped fuel this conflict (Pezard & Shurkin, 2015). The plight of IDPs in Mali is severe, and they are actively aided by national and international organizations. At this moment it is unclear whether IDPs will remain for the long-term in their host communities or return to their homes. A recent study among the IDP population in Mali indicates that some but not all IDPs intend to return home (Hoogeveen, Rossi, & Sansone, 2019).

The short and long-term presence of IDPs in other Malian towns potentially affects the population of host communities by changing economic conditions including wealth, poverty, and inequality. Policymakers dealing with an internal displacement crisis are often challenged to mitigate shocks caused by a sudden inflow of people on host populations, while providing adequate support for incoming displaced peoples. If IDPs foster increased inequality or negatively affect local wealth, then they may affect the social and economic structures of host communities in ways that exacerbate the conflict. Therefore, the current paper tries to answer this research question: How does the arrival of IDPs in host communities in Mali affect wealth, consumption, poverty, and inequality?

To answer the above research question we analyze the effects of IDP presence and numbers on consumption, poverty, and inequality of host communities in Mali using a unique combination of secondary data sets on Mali. More specifically, we use comprehensive nationwide household survey data on over 36,000 households from 2013 - 2019 combined with data on IDP populations to estimate econometric models of the effects of IDP presence and numbers. Our empirical strategy uses multiple econometric methods, difference-in-difference, instrumental variable, and propensity score matching to provide the most robust results to concerns about the endogenous location choices of IDPs.

The results in this work show that, in the Malian context, IDP host communities and the households in them fare at least as well as other Malian communities and households that do not host IDPs. Our analysis shows the positive effects of IDP hosting on household consumption, under some modeling assumptions, and zero effects on poverty and inequality at the community level consistently across different estimation methods. These results are suggestive of the effects of IDP presence on hosting communities being fairly evenly distributed across all residents, and not different for households with farming as their major occupation. Our analysis provides important insights into under-researched questions about how the internal displacement caused by the Malian and broader Sahelian conflict has affected host communities. Understanding that, with proper support, IDP populations may not exacerbate inequality in host communities is an important piece for policymakers in deciding how to work with and create social cohesion in host communities.

This work contributes to a now burgeoning literature on the economic impact of displaced peoples on host communities first by focusing on inequality and poverty, and second by extending its scope to IDP. For instance, a systematic review by Verme and Schuettler (2020) finds a low probability of a decline in well-being for households in host communities. Furthermore, aid to displaced persons has generally been shown to produce positive externalities on host community incomes and consumption (see e.g. Taylor et al. (2016)); however, it may also change inequality, especially between ethnic groups. This effect on inequality is not yet well studied in part because of the need for larger and longer-term data sets, which we partially solve in this study. There is, moreover, little evidence on what hosting displaced peoples does to inequality. A positive effect of IDPs on inequality is potentially important, given that inequality between groups can lead to further conflicts (Østby, 2008). In addition, our study advances the forced displacement literature that largely focuses on middle-income countries by providing an analysis from the low-income county settings similar to some recent innovations by Hoogeveen et al. (2019) and Sedova, Ludolph, and Talevi (2021).

2 Context: Conflict and Internal Displacement in Mali

Since its independence in 1960, Mali has had a series of rebellions in the north, primarily led by northerners, primarily from parts of the Tuareg ethnic group, unhappy with the government rule led by mostly southern Malians. The first three of these rebellions happened in 1963–64; 1990 – 96; 2006 – '09; and were ended by peace accords and agreements, which were not effective at resolving the underlying problems and reducing the probability of future conflict (Nomikos, 2019; Pezard & Shurkin, 2015). The current civil conflict started in 2012 with a fourth northerner rebellion,[1] which took on a new character with the insertion of international violent extremists who both had a stronger ability to fight and control territory and had a wider appeal beyond the ethnically determined communities through their ability to weaponize local disputes. A military coup d'etat in 2012, in part due to the government's ineffective campaign against the northern rebellion, also exacerbated the conflict. This wider support for rebellion, rekindling of old rivalries, and dissatisfaction of the population with the status quo helped lead to the expansion of the conflict from northern to central Mali.

In 2013, after northern rebels and their international violent extremist allies had conquered much of northern Mali a French-led military intervention, Operation Barkhane, pushed them out of the area. Violent events spiked in 2013, especially in northern Mali

[1]While these rebellions take the form of northerners who oppose the central government and would like to secede from the country, they are by no means uniformly supported by all northerners. They are as much power struggles between the different groups and clans within the north of Mali as much as they are a conflict between north and south.

as the French fought with violent extremists and their local allies. That violence subsided somewhat after 2013 due to the deployment of French troops and a UN peacekeeping mission MINUSMA (ACLED, 2020; Nomikos, 2019). The early wave of fighting in 2012/13 produced a wave of displacement, but much of it was short-lived as the French intervention pushed the violent extremist connected groups out of the major population centers of the north, Gao and Timbuktu. Hoogeveen et al. (2019) show great heterogeneity in those who decided to return to their hometowns from this initial wave of displacement.

While the French-led intervention tamped down the immediate conflict, the violence started to spread to other countries (Niger and Burkina Faso) and other parts of Mali. We show in figure 1 the location of violent events in Mali as measured by ACLED for the period of this study. What is obvious is the spread of violence from being mostly in the north in 2014 to expanding into more parts of the country by 2017 and increasing in intensity (as seen by larger/darker circles on figure 1).

Starting in 2014 the violence that starts to pick up in central Mali becomes in part driven by long-simmering issues between ethnic groups where the spread of violence is pushed by discontent with the status quo, deficiencies in national security, and justice institutions. The violent extremist groups provide the promise of personal security and rudimentary justice for rural residents who do not see the government as able to provide that. In opposition to the violent extremist groups and their local allies, many villages developed their own self-defense or communal militias as their own response to the inadequacy of government justice and security institutions. These self-defense groups along with the violent extremists have raised levels of inter-communal violence and have been a major source of fatalities, especially in central Mali (Hoogeveen et al., 2019).

For example, in the Mopti region, there have been increasingly violent conflicts between livestock herders and sedentary agriculturalist groups. A number of observers have claimed that the violent extremist movements have forged alliances with Peulh pastoralist groups (Assanvo, Dakono, Théroux-Bénoni, & Maïga, 2019; Benjaminsen & Ba, 2019; Diallo Aly,

2017) and some have suggested that Peulh livestock sales partially finance these groups (Daniel, 2020). The central Mali conflict builds on long-standing conflicts between livestock herders and agriculturalists that in the past had been settled through customary means (Turner, 2004). Increases in the population, in the number of livestock, in the returns to agriculture, and the variability of the climate (Benjaminsen & Ba, 2019; Nomikos, 2019; Raleigh, 2010) as well as the ready availability of small and large arms in the area has meant that old disputes have led to increasing violence. By 2017, central Mali becomes the major locus of violence in Mali (ACLED, 2020). At the same time in the last few years, some conflict has spread into southern Mali including the northern parts of the Segou and Koulikoro regions, and the eastern Sikasso region, particularly areas close to the Burkina Faso border.

While the conflict in Mali may have started out, and is often seen from outside, as a bilateral conflict between northerners and the Malian government, it ensnares Malians of all ethnicities and backgrounds. The conflict, especially within central Mali, is much more complicated in its make-up and often pits neighbors against each other. Such a conflict produces a wide range of displaced persons both within the country and abroad.

As of the beginning of 2021, the conflict in Mali that started in 2012 has generated over 346,000 internally displaced peoples as well as well as more than 165,000 refugees, most of whom are in the countries immediately neighboring Mali: Mauritania, Burkina Faso, and Niger (UNHCR, 2021). The displacement of peoples in Mali has grown from 62,000 IDPs in 2015, dropping to 37,000 in 2016, before starting to rise exponentially from 2018 onwards, to its current level of more than a quarter of a million people. Figure 1 shows the evolution of the location of IDPs in Mali from 2014 to 2019, the period of our study.

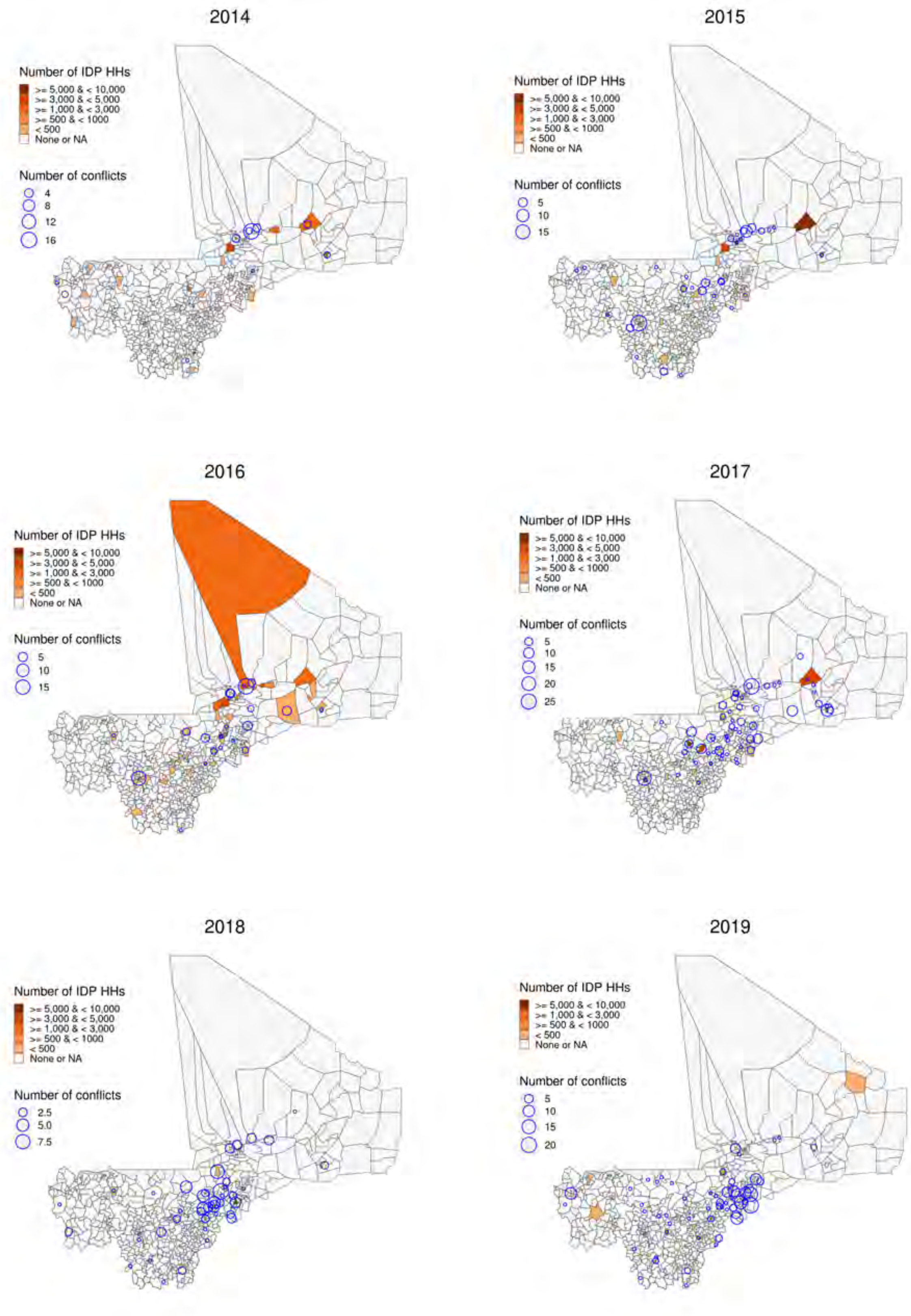
The IDP situation in Mali appears to be fairly typical of IDPs throughout the world. The IDPs come from across all parts of the conflict zone and some areas near the conflict. From discussions with in-country workers, it appears that IDPs come from all different ethnic groups, rather than being concentrated in a single ethnic group. In many cases, IDPs from multiple ethnic groups will move to the same commune, sometimes because the fighting targeted multiple ethnic groups and other times because they are non-adherents to the conflict by their co-ethnics.

IDP's in Mali can be individuals or families: that are fleeing the fighting, that has had their crops or livestock or access to land taken away, that are ethnic minorities in their particular village, that are minorities in their region, or that have beliefs and ways of living different from the local governing polity, which may be led by violent extremists, local self-defense groups or the local government. Where violent extremists predominate they often chase out government functionaries such as school teachers. Such government functionaries may make some IDPs in Mali wealthier and better connected than might be typical elsewhere.

The available evidence suggests that IDPs in Mali are well received within their host communities. A number of communities in the north (e.g. Sofara and Konna) that host IDPs have held successful financing appeals to the diasporas from their community in the capital, Bamako, and abroad to help house, feed, and clothe IDPs. We are unaware of any incidents in which IDPs themselves have become a source of conflict, but that always remains a possibility. In some central Malian areas, people have concentrated in villages of the same ethnicity for safety, especially where there are ethnically based self-defense groups, while in other areas IDPs of all ethnicities have moved to single locations, usually larger towns with more diverse populations.

The international community has come together to provide large amounts of aid to Mali to alleviate this conflict-induced crisis and the plight of IDPs in the country. The overall budget for the humanitarian situation in Mali was $354 million in 2016 (UNOCHA-Mali, 2016) and $262 million in 2018 (UNOCHA-Mali, 2018). This humanitarian operation has typically been funded by 40 - 50 different international humanitarian organizations and implemented by 150+ humanitarian organizations on the ground in Mali (UNOCHA-Mali, 2017). It has provided protection services, housing, nutrition, health, cash transfers, education, and other resources to IDPs as well as others within the conflict zone. At least a portion of the support provided to IDPs appears to be in the form of direct cash grants to recipients, which is likely to create positive economic spillover effects on local communities in the form of increased local purchases of goods and services.

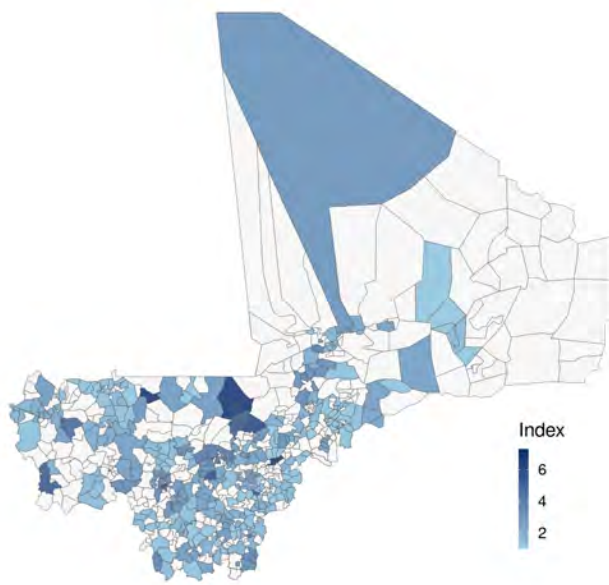
Figure 1: The Number of Conflicts and IDP HHs per Commune



Source: ACLED

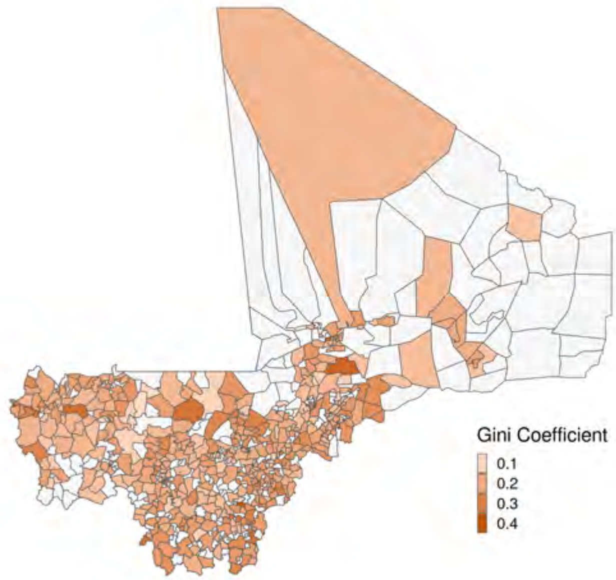
Notes: The large area with IDPs between 3000 to 5000 in 2016 is the commune of Tombouctou. Northern Mali is largely uninhabitable due to its acrid climate; thus, IDP are likely concentrated in the south of the commune.

Figure 2: Ethnic Diversity in 2006



Source: The Demographic and Health Surveys, 2006
Notes: The geographical unit is commune. Light gray indicates NA. Ethnic diversity is shown as an inverted Herfindahl-Hirshmann index, where a larger value indicates a greater diversity. The large area in the north of the country is the commune of Tombouctou. Northern Mali is largely uninhabitable due to its acrid climate; thus, its population is concentrated in the south of the commune.

Figure 3: Inequality in Mali



Notes: The total household consumption-based Gini coefficients are commune mean values over 2014-2019, and calculated using the EMOP data. Light gray indicates NA. A greater value indicates higher inequality. The large area in the north of the country is the commune of Tombouctou. Northern Mali is largely uninhabitable due to its acrid climate; thus, its population is concentrated in the south of the commune.

3 Theoretical Motivation

3.1 Literature Review

The literature investigating the effects of forced displacement has grown rapidly in recent years with many of the recent studies focused on understanding the effects of a large inflow of Syrian refugees crossing international borders on the economies of host countries. Much of the attention has been given to middle-income host counties which have the smaller fiscal capacity to accommodate large inflows of refugees compared to high-income host countries, but receive less international humanitarian aid relative to low-income host countries such as West African countries (Verme & Schuettler, 2020). Most existing studies have focused their efforts on the effects of displaced peoples, particularly refugees, on labor and real estate market outcomes. For example, Depetris-Chauvin and Santos (2018) analyzes how IDPs in

Colombia affect rental markets and crime and Rozo and Sviatschi (2021) shows how Syrian refugees spike rental housing market prices in Jordan. Few studies have focused on internally displaced people and their effects on economic welfare in a low-income country context.[2] We have identified several studies relevant to the effects of refugees on income, consumption, inequality, and poverty on host communities in a low-income country setting, but did not find many studies that investigate the effects of forced internal displacement on inequality and poverty.

While refugees and IDPs both fall under the category of displaced peoples, there are differences that might mean they have different effects on the local economy. First, IDPs are more likely to be ethnically similar to their hosts than refugees would be. Second, IDPs are still within their own country, they may receive more care from the central government because they are citizens of that country. [3] Third, the host population may be more willing to accept IDPs because they are citizens of the same country and potentially of similar ethnic groups.

Studies on the effects of forced displacement on household economic outcomes in the low-income country context tend to report positive effects of the influx of people on wealth outcomes for host communities. Most studies find a positive correlation between an inflow of refugees and host community household consumption and wealth. These studies typically attribute this positive correlation between displaced peoples and host community wealth to increased economic opportunities due to the inflow of new people including international aid workers and sometimes the creation of new infrastructure such as roads.

An example of this work, Taylor et al. (2016), conducts a Monte Carlo simulation to estimate the effects of cash transfer to Congolese refugees in Rwanda on the local economies

[2] Braun, Kramer, Kvasnicka, and Meier (2021) is the main economic paper we could find focused on economic welfare and community hosting of IDPs but its analysis of the effects of the post-WWII internal displacement of Germans from Eastern Europe to Western Germany is in an economic context that differs greatly from our context.

[3] Note that this effect really depends on the nature of the conflict and the relationship of the displaced persons to the government. In some cases, such displacement during the Rwandan conflict, displaced peoples may be better accepted in a neighboring country than their own.

within the 10 km radius from three refugee camps. Their results indicate that an additional cash transfer recipient can increase the annual income of a local household by USD 205 to 253. Their study provides clear short-term evidence of significant positive economic externalities of refugees on host communities. The effects they measure of forced displacement combine both population effects and potential spill-over effects of the cash transfer program in place in those particular refugee camps. Loschmann, Bilgili, and Siegel (2019) study the same context, and document a shift away from agricultural production to wage employment in the host communities, which may or may not be beneficial in the long-term for the farm population.

Other recent work investigates the effects of refugee presence on host community household consumption, which may provide a more consistent way of depicting the economic experience of local households in host communities. Maystadt and Duranton (2019) investigate the effects of the inflow of refugees from Burundi and Rwanda due to the civil wars in the 90s, and estimates the effects on household consumption and poverty. They find that a higher refugee index is associated with higher per adult consumption, and a lower poverty rate. It is not clear, however, how the results from refugees should be expected to translate to IDPs. In addition, some of their results come from decades of residence by refugees and major infrastructural investments by aid agencies and governments, which may also not be relevant for the rapidly changing IDP situation in the Sahel.

While there seems to be a general finding that the presence of displaced peoples (primarily refugees) has a positive effect on host community wealth, this effect is complicated by a potential increasing inflation on prices on food and housing, which may undermine some measures of wealth and consumption. For example, Alix-Garcia and Saah (2009) study the effects of the inflow of Brunudian and Rwandan refugees from 1993 to 1994 on western Tanzanian host communities. While they find positive effects on household wealth in rural areas, they find negative effects in urban areas. Combined with their presentation of evidence of increases in the prices of agricultural commodities consumed largely by local people, they argue that the refugee inflow might have benefited local farmers while it might have had adversely affected urban Tanzanians due to price effects. Similarly, Alix-Garcia, Bartlett, and Saah (2012) suggests a framework for analyzing the effects of forced displacement on host communities, and emphasizes the importance of price dynamics in order to obtain a full picture of how forced displacement affects households in host communities.

3.2 Hypotheses

The existing literature generally suggests that, if the effects of hosting IDPs follow the same pattern as those of refugee-hosting communities, one should expect to see positive relationships between an inflow of IDPs and the economic well-being of households in host communities. There are two channels through with an introduction of IDPs can affect host communities' economies, as suggested by Verme and Schuettler (2020). First, a sudden inflow of IDPs can directly affect host communities by increasing their population and labor force levels. This mechanical effect can lead to a second effect with fiscal implications, when, in the absence of outside or national level interventions, host communities may have to internalize fiscal burdens to accommodate IDPs by providing direct assistance and expanding public services. In the Malian context, a large-scale humanitarian assistance program came from various international organizations, along with the help from the diaspora and the central government in Bamako. All of this suggests that there would likely be some positive economic shock along with the introduction of IDPs.

This study asks: How does the influx of IDPs affect host commune consumption, poverty, and inequality over time and space in Mali? Based on the literature, we hypothesize that an increase in IDPs increases average host community incomes and consumption, but that this increase is not evenly distributed about the population. We further hypothesize that the heterogeneity in benefits from IDPs will favor certain types of households (male-headed households, farmers) and disfavor others. Finally, we hypothesize that these inequalities in consumption may widen as IDP numbers increase in a community.

4 Research Design

In order to test our hypotheses about the potential effects of IDPs on household and village level consumption and inequality we turn to an empirical estimation using data from 2011 - 2019, spanning the beginning, early, and middle periods of the current conflict in Mali. Our data provides fine-grained observations on households across more than three-quarters of the communes in Mali. In terms of methods, we take a broad-brush view of the appropriate methods, presenting different ways to measure the outcomes of interest-based on different assumptions. The point of this multi-method technique is to provide the most robust understanding of the outcomes across different issues of data quality and data generating processes. We first present the data, then the empirical strategy, the details of which are more fully outlined in the online appendix.

4.1 Data

This work merges three main data sources on household consumption and IDPs to capture their effects on household and village consumption, poverty, and inequality. These are: a comprehensive household income and consumption data set (EMOP) collected by the same unit responsible for Mali's Living Standard Measurement Survey (LSMS) data collection, data from the International Organization for Migration (IOM) on IDP movements, and data from the Demographic and Health Surveys (DHS). In addition, we access Malian census data and use conflict data from the Armed Conflict Location and Event Data Project (ACLED).

We use eight years (2011, 2013-2019) of Mali's Enquête Modulaire et Permanente auprès des Ménages (EMOP), a nationally representative household survey on employment, income, consumption, with indicators on demographics and well-being (Institut National de La Statistique, n.d.). This data set offers detailed documentation on household non-agricultural earnings and expenditures (consumption) which enable us to measure inequality and poverty. The EMOP data has 38,625 household observations in 607 of Mali's 703 communes, with coverage in 9 of Mali's 10 regions. The 10th region, Kidal, is not included due to insecurity in the zone. The sample size is large enough to estimate commune-level inequality and 90% of the communes in the data set are sampled more than twice, giving us a panel at the commune level over time. Within a commune, the choice of household is random, such that at the household level the data represents a repeated-cross section. Furthermore, the EMOP data are largely representative at the commune level.[4] Combined with the sampling strategy at the commune level, these data provide us with consistent data to estimate effects at the commune level including both urban and rural communes.[5]

The commune-level IDP data come from the Displacement Tracking Matrix (DTM) provided by the IOM (IOM, n.d.). These data derive from approximately monthly surveys on the number of IDPs in host communities from 2014 to the present. With this data set, we are able to calculate the total yearly number of IDPs and households in each host community identified by the IOM, and also construct an indicator variable of IDP presence. While the data collection involves multiple layers of data validation, this data set will mostly reflect the number of IDPs recognized by regional authorities, NGO representatives, civil society organizations, who are potentially beneficiaries of humanitarian assistance, as the IOM relies on such local actors as major informants. Therefore, IDP households who temporarily live with relatives to escape violence without seeking assistance are unlikely to be counted in the data.[6]

The ethnic diversity measure we use as an instrument in some specifications is calculated

[4]The average number of sampled households in the EMOP data is 15 households. There are, however, two communes out of the 370 communes surveyed in 2019 with only one household interviewed in each village. These villages are Didieni in the Djidieni arrondissement in the Koulikoro region, and Niantaga in the M'pessoba arrondissement in Sikasso region.

[5]We have tested aggregating the data to the arrondissement level and find similar effects as reported here, though they have less precision because our measures are necessarily less precise at a higher level of aggregation. The EMOP data we use show 46% of the households as urban, which almost exactly matches national statistics on urbanization rates, suggesting that our data are broadly representative of both urban and rural areas.

[6]This implies that our measure of IDP presence and population should be considered as a measure of formally recognized IDPs who are likely receiving services. To the extent that there might be large numbers of IDPs in communes who are not receiving services, our data do not measure them. The available evidence that we can glean from the EMOP survey suggests that the number of people who fit such a category is very small.

with the self-reported ethnicity data from the 2006 DHS (Samaké, Traoré, Ba, Dembélé, & Diop, 2006) as an inverted Herfindahl-Hirschman Index (HHI). The HHI, first developed to study levels of market competition, is commonly used in the literature to measure ethnic fractionalization indices. It is simply an inverse of the sum of the squares of the share of each ethnic group per population in each commune.[7] Figure 2 shows the distribution of the index across the country for communes where we have DHS survey data. In the figure a greater index value and darker color indicates a greater level of ethnic diversity. Additionally, we gather the 2009 commune population from the Malian census reported on the Wikipedia pages (Wikipedia, n.d.).[8] Lastly, all maps are made with the administrative geographical boundaries made available by the Database of Global Administrative Areas (University of California Berkely, n.d.).

For outcomes measures, we use per-capita household non-agricultural income and consumption from EMOP and then calculate commune-level poverty measures and the Gini coefficient as a measure of inequality from the consumption data. One important caveat on the EMOP income data is that it captures non-agricultural household income rather than total household income. The EMOP questionnaires are structured in a way that is more suitable to collect data on income with stable flows. We believe that this likely ignores most agricultural income. In fact, about a quarter of observations on household income is reported to be zero, while there is no report on zero consumption. Therefore, we interpret the EMOP income data to be reflective of non-agricultural household income, rather than total household income.

[7]Please refer to Equation 5 in the online appendix for details on the creation of the index.

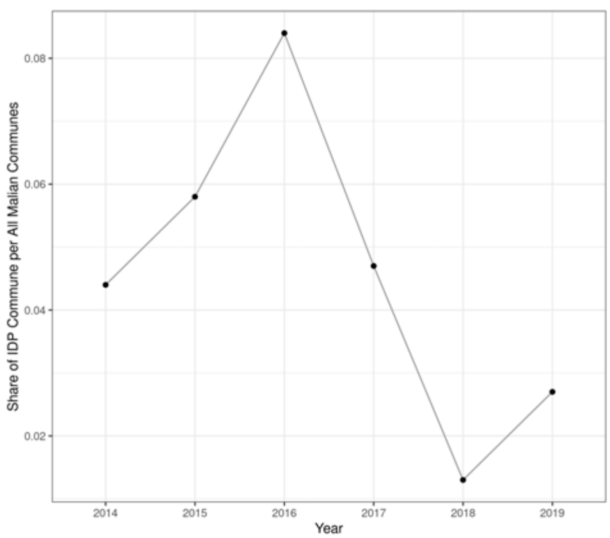
[8]The Wikipedia page offer both circle- and commune-level population counts. We checked its internal consistency by comparing each circle-level value to a sum of commune-level values for each circle. After we verified internal consistency, we took the sum of all the commune population values to obtain the country population value, and compared it to Mali's population count available on the World Bank's DataBank. The data aggregated up accurately and we concluded that the data posted on the Wikipedia page is the valid, true data.

4.2 Descriptive statistics

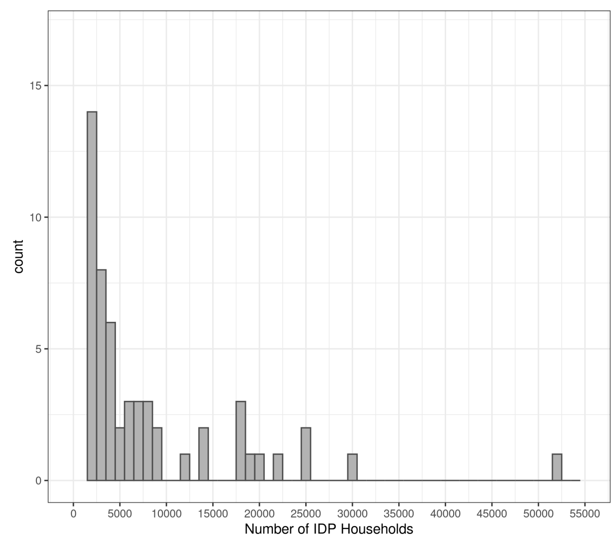
We now turn to descriptive statistics of IDPs and wealth levels in IDP and non-IDP communes. The number of IDP host communes fluctuates over time in our sample time period as shown in Figure 4a, which shows the share of IDP host communes to the total of 703 communes in Mali. We see a large spike in 2016, which corresponds to the increase in the number of IDP households shown in Figure 1. The IDP host communes in our analysis sample are also diverse in terms of the number of IDP households they host (Figure 4b).

Figure 4: Distribution of IDP Host Communes

(a) Share of IDP Host Communes in Mali



(b) Distribution of IDP Communes across IDP Population Levels

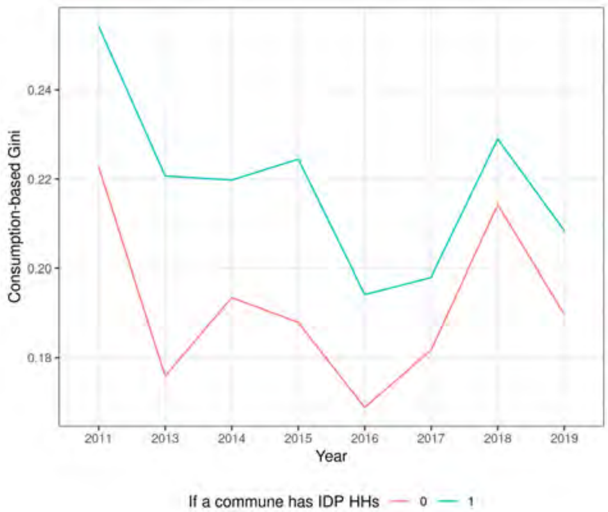


Notes: There are total 703 communes in Mali.

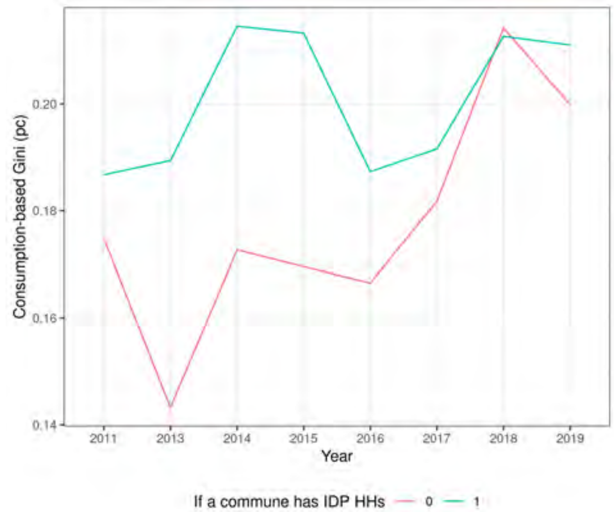
Figures 5 and 6 present yearly trends for our outcome variables: non-agricultural income, consumption, poverty, and inequality. On average across all communes, IDP communes have fewer poor people than non-IDP communes. In addition, inequality based on both household and per capita consumption is higher in IDP communes than in non-IDP communes. Households in the IDP and non-IDP communes seem to earn a similar level of non-agricultural income on average, except the non-IDP trend is a lot more volatile. Lastly, at least on the raw descriptive level, households in the IDP communes generally consume less on average than those in the non-IDP communes.

Figure 5: Trends of the Outcome Variables (Commune Level)

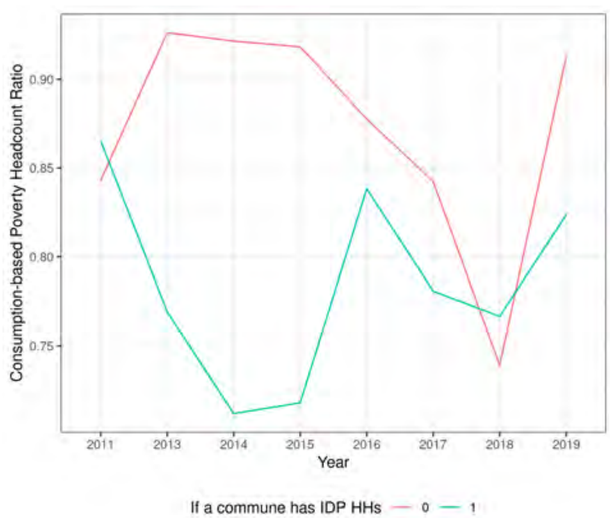
(a) Consumption-based Gini



(b) Per capita Consumption-based Gini



(c) Poverty Headcount Ratio



(d) Poverty Gap

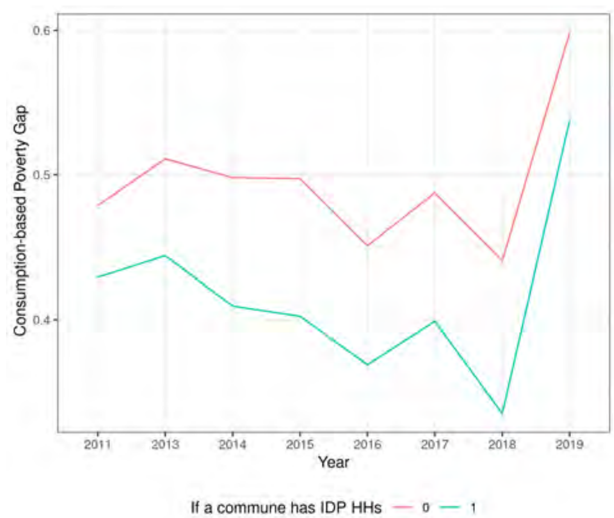
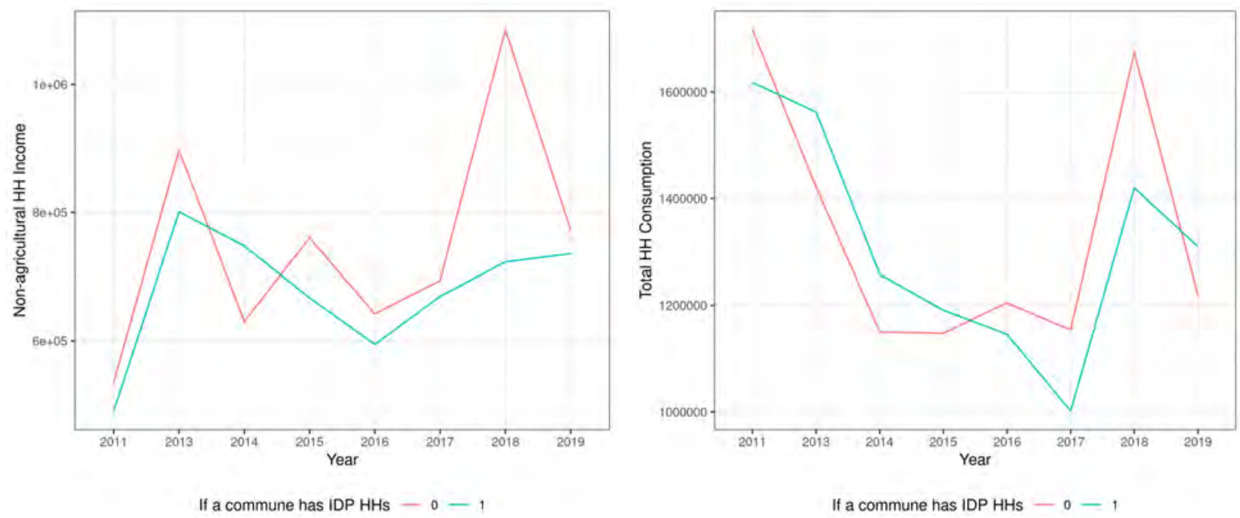


Figure 6: Trends of the Outcome Variables (HH Level)

(a) Non-agricultural HH Income (b) Total HH Consumption



Tables 1 and 2 in the online appendix describe other household and commune characteristics, which we use as control variables in our econometric analysis. In our analysis sample, 8% of the households have female household heads, 2% are Christian, 39% have literate household heads, and the mean age of households heads is 49 years old. Among households, they have an average of 6 members, 27% are polygamous, 47% have farming as a primary occupation, while only 0.4% are livestock herders. 46% of the sample households live in urban areas. Lastly, 78% of the sample households have total household consumption under the national poverty line (INS, 2017).

In terms of commune-level characteristics, the sample communes are, on average, fairly equal in terms of Gini coefficients for average household and per capita consumption: 0.22 and 0.2, respectively. Meanwhile, the average commune-level consumption-based poverty headcount ratio and gap index are 0.86 and 0.46. Our sample communes are broadly equally poor across households. The average commune population in 2009 was 25,259 with a standard deviation of 28,018, which says that communes vary greatly in population size. About 16% of the sample communes host IDPs. These host communes on average accommodate

170 IDP households and about 885 IDPs. However, as shown in Figure 4b the number of IDPs hosted varies greatly between host communes with a standard deviation of 1,765 for IDP households, and 8,438 individuals.

4.3 Empirical Strategy and Identification

Estimating the effects of IDP presence on host communes' economic outcomes is made difficult by the possibility that communes with and without IDPs may differ in fundamental and potentially unobservable ways.[9] This complicates our estimation because we want to attribute the observed differences in consumption, inequality, and poverty to the difference in IDP presence after controlling for observable characteristics. If communes with and without IDPs are different in ways that are unobservable in our data and uncorrelated with control variables, for example, the level of hospitality and tolerance toward outsiders, that complicates the estimation and potentially the validity of our inference from the results. In particular, we are concerned about being able to control for: unobservable differences in the initial conditions in IDP and non-IDP villages, IDPs choosing wealthier or more equal villages (endogenous selection), and other endogenous processes or reverse causality between IDP presents and household or village level wealth outcomes.

In order to be able to link the observed difference in the economic outcomes to IDP presence, we use three types of econometric tools: difference-in-difference (DID), instrumental variable (IV), and propensity score matching (PSM). Each of these common estimation techniques helps address a different potential type of bias in our estimate and each one comes with different sets of assumptions that might be more or less valid given the empirical setting in Mali and the data we can access. Taken together these estimates provide a broad picture of the relationship between IDPs and wealth in Mali. For policymakers, they provide estimates on all the key outcome variables of interest, although in some cases the estimates are weak or based on strong assumptions. The aim of this paper is to present a broad view

[9]For a technical discussion of our identification strategy, please refer to the online appendix.

of the relationship between these factors.[10]

The first econometric approach we use is the Difference in Differences (DID) estimation approach, which compares how households or communes with and without IDPs move from initial conditions before IDPs arrive to after their arrival. Like the matching methods, this method assumes that once one has controlled for observable differences, communes or households would have followed similar paths, typically called "parallel trends", had IDPs not arrived in their communes. This approach is particularly helpful in controlling for the initial differences between IDP and non-IDP communes before a sequence of conflicts had occurred in 2013 which have triggered the mass internal displacement we observe in Mali today. This method is only valid where we have strong evidence of parallel trends, and where we do not, such as for consumption levels, we do not report results. Additionally, given IDPs arrive in various years in host communes, we implement our DID estimation using the sequential treatment approach suggested by Callaway and Sant'Anna (2020), which accounts for staggered treatments as is the case here. In this analysis, we estimate the effect of IDP for groups of communes that have received IDPs for the first times in 2014 and 2016. In addition to estimating the IDP effect on each treatment group, we also present the overall effect.

The second approach is the instrumental variable (IV) approach. In this method, to control for potential endogeneity of the placement of IDPs in communes, we estimate a first stage that uses an instrument, correlated with IDP location but uncorrelated with our main outcomes of interest, to "clean" the IDP location variable of the endogeneity of location choice. We use ethnic diversity from the previous decade as the instrumental variable to help identify the variation in IDP presence.[11] This IV technique would be valid under the assumption that more diverse places would be more attractive and hospitable to IDPs,

[10]In the results and policy implications section, we base our analysis on the results we believe are most robust across models and assumptions.

[11]We also tested using conflict incidence within geographic bands of the communes in our data set as an instrument. These tests showed that conflict incidence did not pass the first stage tests and so are not presented here.

but that diversity itself a decade ago would not change current economic activity. This methodology is particularly useful in mitigating potential bias due to the possibility that the economic differences between IDP and non-IDP communes actually attract IDPs, rather than the differences being caused by IDP presence. This method is only valid where we have a strong first-stage relationship between ethnic diversity and IDP presence and numbers, and we only report it for those cases.

The third approach is Propensity Score Matching (PSM) estimation, which seeks to match communes or households between IDP hosting communes and non-hosting communes. This method allows us to construct counterfactuals of communes and households that are very similar in characteristics to the actual IDP communes. Rather than using the full analysis sample, we construct two groups of IDP and non-IDP communes whose only difference is in the presence of IDPs, and compare them. Given the panel nature of the commune-level data, we implement an approach suggested by Imai, Kim, and Wang (2020). The PSM technique works well for the commune level estimates where we have good successes matching observable household characteristics between IDP and non-IDP communes (Figure 14), but does not work well at the household level since the same households are not sampled every round of the survey. In this exercise, we identify commune observations similar in characteristics to the actual IDP communes in the year of the event and the year before.

5 Results

We now present the results from our regression analysis in three groups. First, we show the estimated results of IDP presence on economic outcomes in host communes using the binary indicator of IDP presence as the main explanatory variable. Second, we present the effects of IDPs at the intensive margin with the IDP population in communes as the main explanatory variable. Third, we investigate the possible existence of heterogeneous effects of IDP presence at the household level for different types of households. We use all three different estimation approaches for estimates of IDP presence, only IV for IDP population, and only DID for the heterogeneity estimates. The conventional propensity score matching does not achieve the covariates balance necessary in the household level analysis, so we do not include it.

5.1 Effects of IDP presence on host communes

We first discuss the estimation results from our analysis in which we represent the existence of IDP households with a simple binary variable. This section presents estimates from the DID, IV, and the PSM estimation approaches.

First, we present the DID results. We conduct the DID analysis on inequality, and poverty at the commune level, and on non-agricultural income, and total household consumption at the household level. Figure 12 and 13 in the online appendix show the parallel trend assumption holds in each of the timing groups.

The DID estimates show mixed effects on non-agricultural income and total household expenditures (consumption). We observe a statistically meaningful positive correlation between IDP presence and per capita consumption at the household level analysis (Figure 7). This indicates that households residing in the IDP communes have on average higher expenditures. We observe, however, no statistically significant relationship between IDP presence and either household consumption or non-agricultural income. In both cases, the estimates produce precisely estimated zeros. Figure 8 presents the DID estimation result of the effects of hosting IDPs on inequality and consumption.[12] The graphs show that at the commune level the existence of IDP households has no statistically meaningful effect on any of the measures of inequality and poverty.

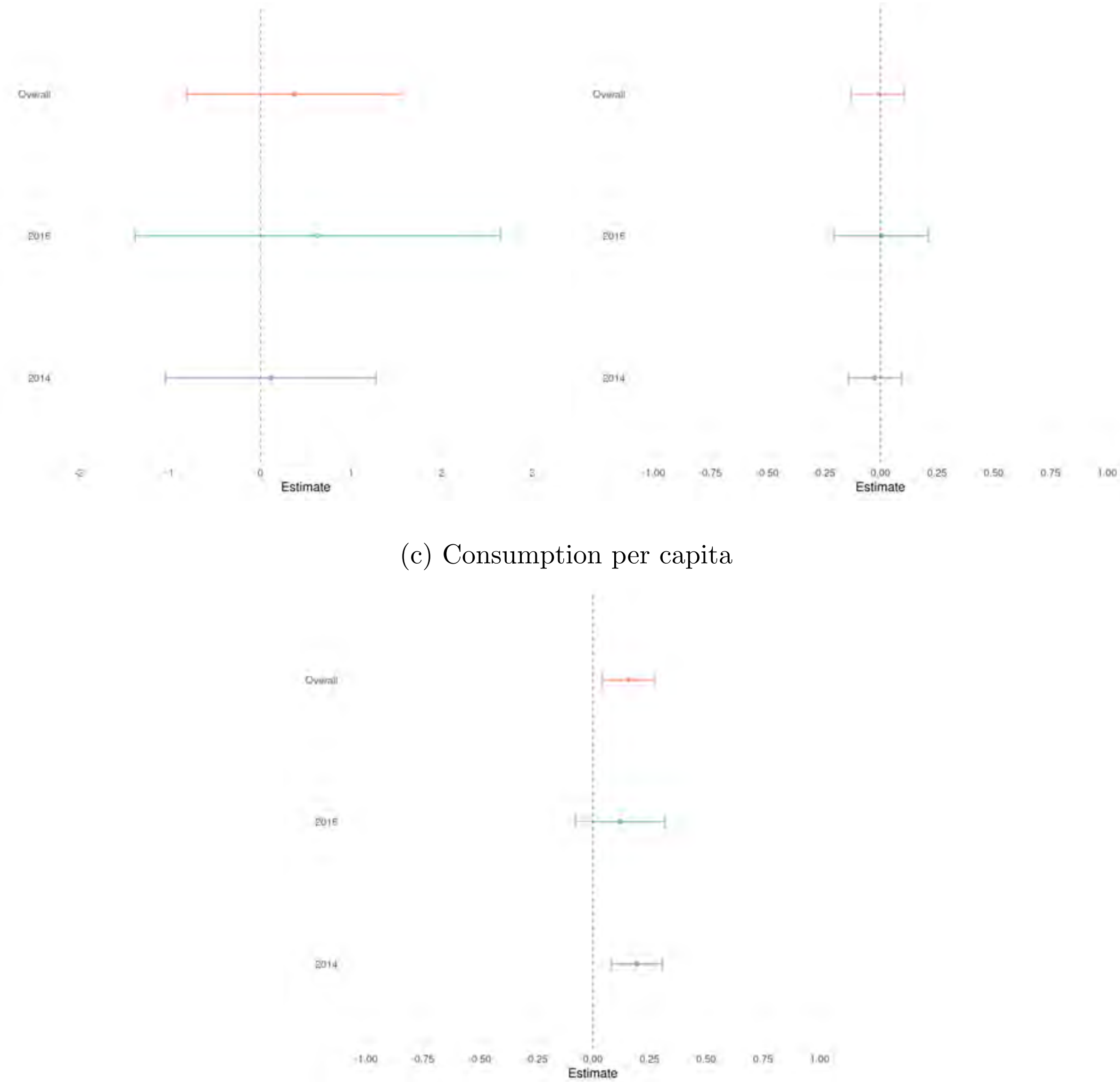
[12] See Table 4 in the online appendix for the regression coefficients and model statistics.

Figure 7: DID Estimates of The IDP Effects (Household Level)

(a) Non-ag. Income

(b) Consumption

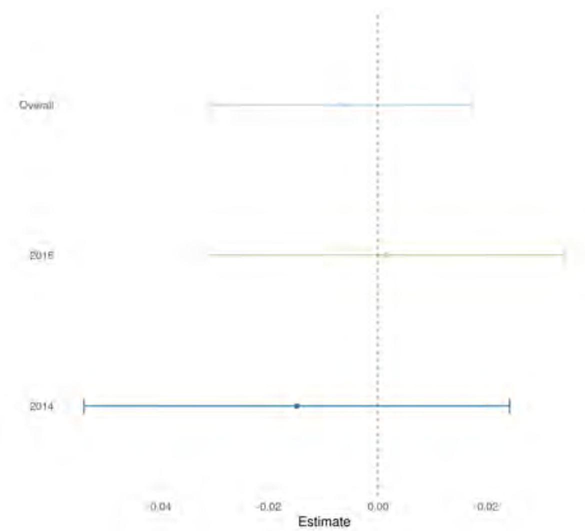
(c) Consumption per capita



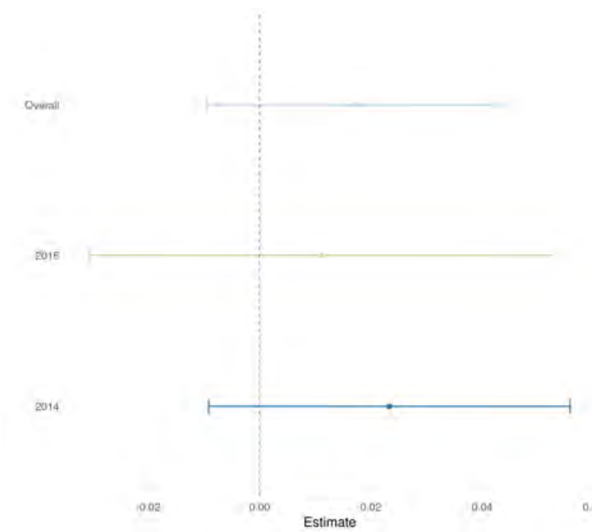
Notes: Estimates plotted above are from the DID estimation at the household levels based on Callaway and Sant'Anna (2020). The bars represent the 95% confidence intervals. The corresponding table 3 is presented in the appendix. Robust cluster SE at the household level.

Figure 8: DID Estimates of The IDP Effects (Commune Level)

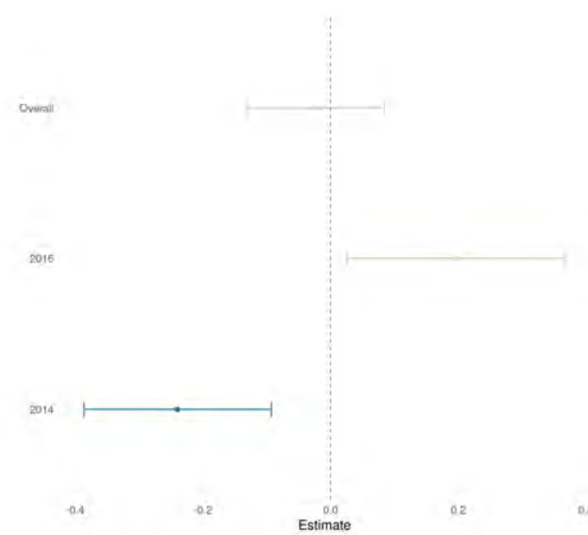
(a) Consumption Gini



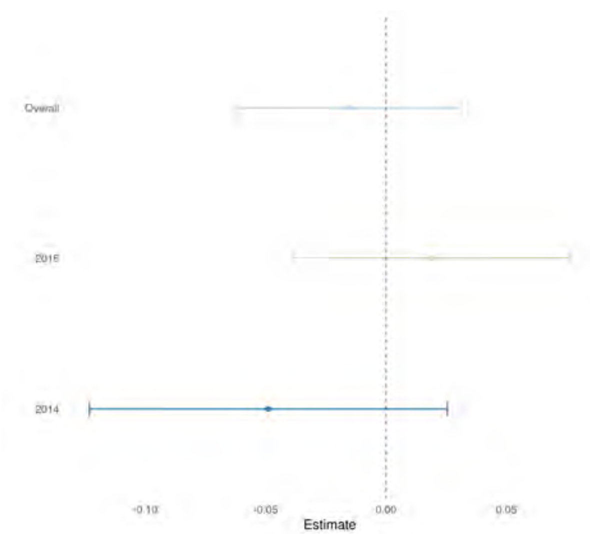
(b) Per Capital Consumption Gini



(c) Poverty Share



(d) Poverty Gap



Notes: Estimates plotted above are from the DID estimation at the communes levels based on Callaway and Sant'Anna (2020). The bars represent the 95% confidence intervals. The corresponding table 4 is presented in the appendix. Robust cluster SE at the commune level.

Next, we turn to our findings from the IV analysis, which allows us to estimate effects for more outcome variables than is possible with DID, and also better account for potential reverse causality. To estimate the effect of IDP presence using ethnic diversity in 2006 as an instrument, we must first verify that the instrumental variable has a sufficiently strong correlation with IDP presence.[13] The results shown in the online appendix of strong first stages leads us to conclude that 2006 ethnic diversity can be used as an instrument to the IDP presence indicator for the commune- and household-level estimation under the assumption that lagged ethnic diversity does not have a direct effect on wealth outcomes post-2014.

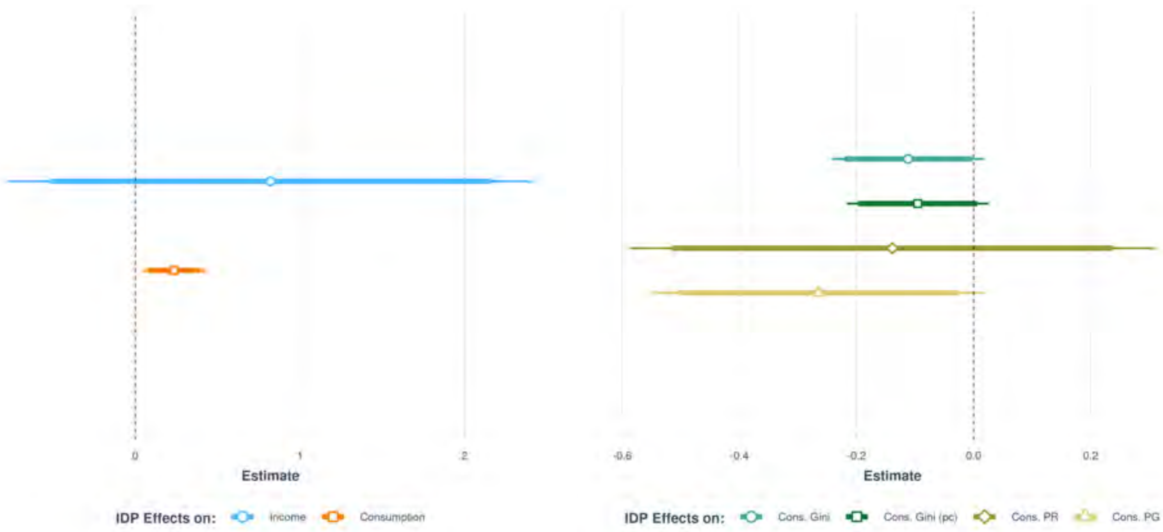
Figure 9a presents the results from the IV estimation of the household-level regressions of IDP presence on non-agricultural household income, and total household consumption. The results show a statistically significant positive relationship on household consumption. More specifically, they suggest that when a commune hosts IDP households, total household expenditures on average increases by 25.4%. Such a level of consumption change would be consistent with the scale of effects found for refugees by Taylor et al. (2016). There is, however, no statistically significant evidence in the IV regressions that IDP presence has an effect on non-agricultural household income.

Figure 9b presents the results from the IV estimation of commune-level regressions of IDP presence on inequality and poverty. The results show no statistically significant relationships between IDP presence, and host community inequality, and poverty. Note that the IDP coefficients on all the inequality and poverty measures are pretty close to 0 or negative with substantially larger imprecision. These results suggest that the true effect of IDP presence on poverty and inequality may be close to 0, consistent with our finding from the DID analysis.

[13]Columns 1 and 2 of Table 7 in the online appendix show the results from the OLS estimation of regressions of IDP presence on ethnic diversity. The column 1 estimate at the commune level indicates that ethnic diversity is not meaningfully correlated with the number of IDP households. However, The column 2 shows that it has a strong statistical association with IDP presence with a F-statistic of 61. Both of the endogenous variables are strongly correlated with 2006 ethnic diversity at the household level as Columns 3 and 4 show. We have also considered the number of conflicts and fatalities within 50km outside of each commune's boundary as an instrumental variable to IDP presence. As Table 8 in the online appendix shows no meaningful statistical relation between nearby conflicts and IDP presence. Thus, we only use the ethnic diversity index as an instrument in this section.

Figure 9: IV Estimates of The Effects of IDP Presence

(a) Household Level (b) Commune Level

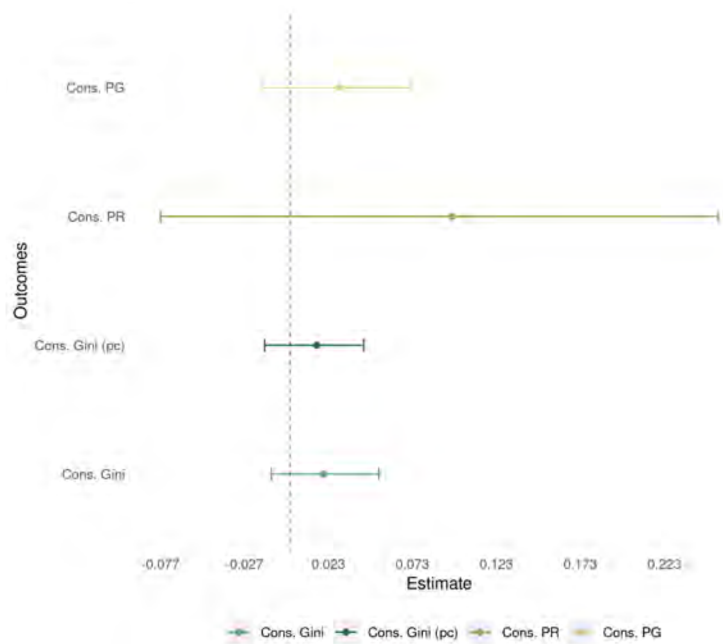


Notes: The IV estimates shown here have robust cluster standard errors at the commune level. Fixed effects included are region and year. The independent variable is a binary variable which is 1 if a commune has IDPs. The inner bar shows the 90% confidence interval, and the outer bar shows the 95% confidence interval. All models are instrumented with the ethnic diversity index which is an inverted Herfendalh-Hirshman index with greater values indicating greater diversity. The dependent variables are log total household consumption and income for the household-level analysis, and household and per capita consumption-based Gini; consumption-based poverty head count ratio; and consumption-based poverty gap index. PR stands for poverty headcount ratio, and PG for poverty gap index for the commune-level analysis. Covariates included are: if HHH female; if Christian; if HHH literate; HHH age; and HH size. A corresponding tables 9 and 10 are presented in the appendix.

Third, we now bring our attention to the Propensity Score Matching estimation. A proper estimation of the effects of IDP presence is possible only when we can establish a counterfactual to the group of IDP host communes from the non-IDP units in the year contemporaneous to the event year, as well as the year before the event. To verify this, we check if our matching is successful by making sure that these groups of communes have similar characteristics. Figure 14 in the online online appendix plots the difference in standard deviation between the IDP and non-IDP groups on commune characteristics: the share of female household heads; the share of Christian household heads; the share of literate household heads, the average age of households; the share of household heads whose primary occupation is a farmer; the share of households living in urban areas; the ethnic diversity index; and commune populations. The graph shows that the post-matching difference in most of the characteristics is close to zero in this time period, except for the share of female household heads. This result indicates that the counterfactual constructed through the matching procedure is reasonably similar to the IDP group, and can be used to conduct a proper comparison on the outcome variables.

Figure 10 shows the results of the PSM estimation of the effects of IDP presence on consumption-based Gini coefficients, per capita consumption-based Gini coefficients, poverty ratio, and poverty gap. The result indicates that there are no statistically significant relationships between hosting IDP households and changes in these outcome variables.

Figure 10: PSM Estimates of The IDP Effects (Commune Level)



Notes: Estimates plotted above are from the PSM estimation at commune level. The bars represent the 95% confidence intervals. The corresponding table 13 is presented in the appendix. Standard errors are bootstrapped.

5.2 Effects of the Number of IDP Households

Now, we investigate whether IDP presence can have effects on household-level economic outcomes at an extensive margin by using the number of IDP households as the treatment variable, rather than the binary indicator used above. For this estimation, we use an IV approach to test the effects of increasing numbers of IDPs on host community outcomes.[14] We again start by checking the strength of our instrumental variable, ethnic diversity in 2006, by estimating its effect on the number of IDP households.[15] We conclude that 2006 ethnic diversity can be used as an instrument for IDP populations at the household level, but not at the commune level.

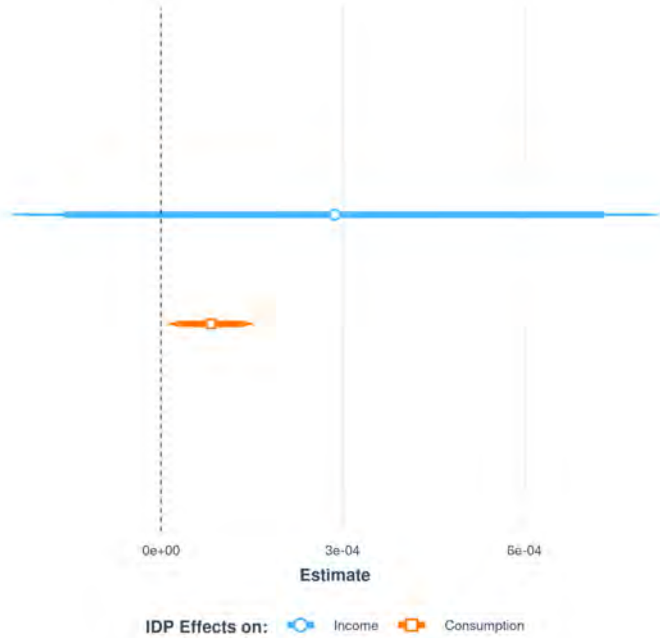
Figure 11 provides the results from the IV estimation of regressions of the household economic outcome on the IDP population with ethnic diversity in 2006 as the instrumental variable. The results demonstrate a positive and significant effect on total household consumption, while we observe a positive but insignificant result on non-agricultural income. The consumption result implies that an inflow of 1,000 new IDP households into a community would lead to a substantial 10% increase in total household consumption. The scale of the point estimate for non-agricultural income is even higher, but since it is insignificant we cannot conclude that the true value is different from zero.[16]

[14] The estimation with DID and PSM approaches requires the explanatory variable to be a binary variable.

[15] Columns 1 and 3 of Table 7 in the online appendix indicates that the correlation between ethnic diversity and IDP population is negative but insignificant at the commune level, while it is positive and significant at the 1% level at the household level with an F-statistic of 365.

[16] Additionally, we have considered the number of conflicts within 50km outside of each commune's boundary as an instrumental variable to the number of IDP households. As Table 8 in the online appendix again shows the statistical relation between nearby conflicts and the number of IDPs. Thus, we use these conflicts variables to instrument the number of IDPs in the commune-level estimation. The estimated results (Tables 11 and 12) shows generally null effects on inequality and poverty. While Columns 1 and 3 of Table 11 indicates statistical significance at the 10% level, the magnitudes of the effects are nearly zero. This further adds to our evidence that the influx of IDP may not necessarily impact the inequality and poverty of host communities.

Figure 11: IV Estimates of The Effects of IDP Population on Income and Consumption (HH Level)



Notes: The IV estimates shown here have robust cluster standard errors at the commune level. Fixed effects included are region and year. The independent variable is the number of IDPs. The inner bar shows the 90% confidence interval, and the outer bar shows the 95% confidence interval. All models are instrumented with the ethnic diversity index which is an inverted Herfendalh-Hirshman index with greater values indicating greater diversity.. The dependent variables are log total household consumption and income. Covariates included are: if HHH female; if Christian; if HHH literate; HHH age; and HH size. A corresponding table 9 is presented in the appendix.

5.3 Heterogeneity

We next explore the possible existence of heterogeneous effects of IDPs on the economic outcomes of different types of households within their host community using the DID estimation models. We test two types of heterogeneity, by gender of the household head and by principle occupation of the household head, in particular, whether they are farmers.[17]

Table 5 in the online appendix shows the results of the heterogeneity check by the gender

[17] For this exercise, we run regression on each of the following sub-sample groups: only female household heads, only male household head, only primary farming households, and only non-primary farming households, and compare the difference in the magnitudes of the coefficients with the Clogg test (Clogg, 1995).

of the household heads. We find that, the female coefficients are statistically significant on consumption and consumption per capita, the male coefficients are only significant for consumption per capita. When comparing these female and male coefficients, we learn that the gender difference is positive statistically significant for consumption (Column 2, Panel C). In other words, a female-headed household tends to consume more as a household than its male counterpart in an IDP host community. However, the statistical significance of this difference disappears in per capita consumption, potentially indicating that accounting for household size there may not be any difference between female- and male-headed household in IDP host communities. In our other heterogeneity analysis by household head job type, IDP presence has no statistically different affects on farming and non-farming households in either consumption or non-farm income as shows in Table 6 in the online appendix. Despite a literature that suggests there might be heterogeneity in effects of IDP presence between farmers and non-farm households, we do not find any meaningful differences across groups by job type in our sample.[18]

6 Policy and Program Implications

In this work, we have estimated the effects of IDP presence on consumption, inequality, and poverty in Mali, a country with a burgeoning IDP presence due to the ongoing conflict in the Sahel. In contrast to a literature that has sometimes found negative effects, we find evidence that IDP presence in Malian communes is either beneficial or at the very least not detrimental to economic outcomes for the local population across multiple different estimation techniques and modeling assumptions. Our results suggest that overall household consumption goes up on average and that poverty and inequality measures are stable. We do not find much of a differential effect of the scale of IDP populations, which is suggestive of the effects being driven by the UN or NGO presence in helping IDPs rather than the scale of the operation.

The results presented here suggest a number of implications for the current IDP crisis

[18]We were unable to test between agriculturalist and herder households due to small sample sizes.

in Mali. It appears overall that the UN, NGOs, and the Malian government working with IDPs in Mali have succeeded in providing resources to IDPs and IDP hosting villages in a way that modestly enhances average village level consumption as well as not exacerbating inequality or poverty within the hosting communes. The results generally do not suggest that IDPs would have a detrimental effect on social cohesion due to the economic effects from their presence. But one should be cautious since we are observing the effects of IDP presence when there is a large humanitarian operation to help them, and acknowledge that results might differ where humanitarian operations are of a smaller scale or unable to reach IDP populations due to the conflict.

There are some limitations that are worth highlighting before we turn to policy and program implications. First, our measure of IDP presence comes from the UN and NGOs that work with IDPs and may miss IDPs who are not known of or registered with the UN or NGOs in the area. Our EMOP data do suggest that there are small numbers of people who might fit this category, but not of a scale likely to significantly bias our results. Nonetheless, the effects reported here should be considered effects of officially registered IDPs. If there are large numbers of unregistered IDPs in communes without official IDPs, then our control commune measures will be contaminated, biasing our results toward zero.

Second, this work only measures the effects of IDP presence on non-IDP households, such that our measures of poverty and inequality are only within the host community estimate and do not measure inequality between host community and IDP wealth. It is along this dimension that some of the potential effects of inequality on social cohesion might be most felt.

Third, it is possible that our empirical strategy fails to sufficiently address the endogeneity of IDP presence discussed in 4.3. Since none of the estimation strategies is perfect, our conclusion relies on the consistency of the results across various estimations. It is possible that bias in all the different estimations in this study is equally strong and contaminates the estimates in the same direction. We think this unlikely, but acknowledge it is possible.

Fourth, the results presented here are specific to the Malian cultural context, a country that has a long-standing cultural history of accepting and housing outsiders. Called *"Diatiguiya"* in the local language, Bambara, which translates as the keeper of hospitality, this feature of Malian society means that all members of a community are expected to provide hospitality to strangers (Cross, 2022; Faye, 2020; Hill, 1966; Launay, 1979; Ratnagar, 1990; Skinner, 2020). Such an institution, which automatically confers social capital and networks on strangers has the potential to mitigate the effects of IDPs on host communities. While we lack data to analyze the role of social capital and networks in this context, previous studies suggest that displaced persons cope with the shock using such social mechanisms (Allen, 2009; Beaman, 2012; Lamba & Krahn, 2003). Other places without a tradition of *Diatiguiya* may not see the same non-effects of IDP presence.

Lastly, due to the inability to measure prices at a fine enough scale, the current analysis does not account for potential localized inflation in communes with IDPs that might bias our consumption and wealth findings.

The results we present here should be taken as one piece of information on the effects of IDP presence in Mali, rather than thorough evidence on the economic effects of IDPs on host communities in all places. Given these limitations, we recommend that policy-makers and program-implementers allocate more resources toward collecting comprehensive data on IDPs, as well as on economic indicators, in Mali and other countries with IDPs. Doing so can 1) further our collective understanding of the relationships between IDPs and their host communities; and 2) provide knowledge to inform policy making for both IDPs and their host communities. We specifically recommend improving on the types of data collected.

First, finding ways of quantifying and obtaining data on those IDPs who are not served by aid organizations as they, for instance, temporarily live with relatives or in slums in urban areas would provide a more comprehensive view of what happens to host communities' economies when IDPs arrive in a large numbers. Second, following up on the pioneering work by Hoogeveen et al. (2019), tracking individual IDP households over time, for example every month for a year or over multiple years, to generate data on how they cope with displacement, and interact with their host communities. Such data can shed light both on the results presented here and on general social cohesion in the host communities. Third, providing support to the Malian statistical authority to collect more frequent price data at a granular geographical level will help researchers understand the macroeconomic effects of IDPs. An effort to collect these types of data ultimately will help policy-makers and program-implementers design better projects that support both IDPs and host communities.

References

ACLED. (2020). Ten Conflicts to Worry about in 2020. (January). Retrieved from www.crisisgroup.org/connect%0Ahttps://foreignpolicy.com/2018/01/02/10-conflicts-to-watch-in-2018/

Alix-Garcia, J., Bartlett, A., & Saah, D. (2012). Displaced Populations, Humanitarian Assistance and Hosts: A Framework for Analyzing Impacts on Semi-urban Households. *World Development*, *40*(2), 373–386. Retrieved from http://dx.doi.org/10.1016/j.worlddev.2011.06.002 doi: 10.1016/j.worlddev.2011.06.002

Alix-Garcia, J., & Saah, D. (2009). The effect of refugee inflows on host communities: Evidence from Tanzania. *World Bank Economic Review*, *24*(1), 148–170. Retrieved from https://academic.oup.com/wber/article/24/1/148/1734945?login=true doi: 10.1093/wber/lhp014

Allen, R. (2009). Benefit or burden? social capital, gender, and the economic adaptation of refugees. *International Migration Review*, *43*(2), 332–365.

Assanvo, W., Dakono, B., Théroux-Bénoni, L.-A., & Maïga, I. (2019). *Violent extremism, organised crime and local conflicts in Liptako-Gourma* (Vol. 2019; Tech. Rep. No. 26). Retrieved from https://issafrica.org/research/west-africa-report/violent-extremism-organised-crime-and-local-conflicts-in-liptako-gourma

Beaman, L. A. (2012). Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the us. *The Review of Economic Studies*, *79*(1), 128–161.

Benjaminsen, T. A., & Ba, B. (2019). Why do pastoralists in Mali join jihadist groups? A political ecological explanation. *Journal of Peasant Studies*, *46*(1), 1–20. Retrieved from https://doi.org/10.1080/03066150.2018.1474457 doi: 10.1080/03066150.2018.1474457

Braun, S. T., Kramer, A., Kvasnicka, M., & Meier, P. (2021). Local labor markets and the persistence of population shocks: Evidence from West Germany, 1939-1970. *Journal of Economic Geography*, *21*(2), 231–260. doi: 10.1093/jeg/lbaa013

Callaway, B., & Sant'Anna, P. H. (2020). Difference-in-Differences with multiple time periods. *Journal of Econometrics*(xxxx), 1–31. Retrieved from https://doi.org/10.1016/j.jeconom.2020.12.001 doi: 10.1016/j.jeconom.2020.12.001

Clogg, C. C. (1995). Statistical Methods for Comparing Regression Coefficients Between Models Author (s): Clifford C . Clogg , Eva Petkova and Adamantios Haritou Published by : The University of Chicago Press Stable URL : http://www.jstor.com/stable/2782277 Statistical Meth. , *100*(5), 1261–1293.

Cross, B. E. (2022). *Long-Distance nationalism in the global city: A cultural history of the malian diaspora in lagos.* Lexington Books.

Daniel, S. (2020, oct). *Dans le centre du Mali, les combats entre groupes armés s'intensifient.* Retrieved from https://www.rfi.fr/fr/afrique/20200410-mali-centre-pays-les-combats-entre-groupes-arm{\unhbox\voidb@x\bgroup\let\unhbox\voidb@x\setbox\@tempboxa\hbox{e\global\mathchardef\accent@spacefactor\spacefactor}\let\begingroup\let\typeout\protect\begingroup\def\MessageBreak{Ω(Font)}\let\protect\immediate\write\m@ne{LaTeXFontInfo:\def{}oninputline349.}\endgroup\endgroup\relax\let\ignorespaces\relax\accent19e\egroup\spacefactor\accent@spacefactor}s-sintensifient

Depetris-Chauvin, E., & Santos, R. J. (2018). Unexpected guests: The impact of internal displacement inflows on rental prices in Colombian host cities. *Journal of Development Economics*, *134*(April), 289–309. Retrieved from https://doi.org/10.1016/j.jdeveco.2018.05.006 doi: 10.1016/j.jdeveco.2018.05.006

Diallo Aly, O. (2017). Ethnic Clashes, Jihad, and Insecurity in Central Mali. *Peace Review: A Journal of Social Justice*, *29*, 299–306. Retrieved from https://doi.org/10.1080/10402659.2017.1344529

Faye, A. (2020). Refonder L'Hospitalité du migrant sur les trois pierres D'Assise du foyer africain: L'Accueil, la famille et la solidarité. *Sci. esprit*, *72*(3), 325–336.

Hill, P. (1966). Landlords and brokers: a west african trading system (with a note on kumasi butchers). *Cahiers d'études africaines*, *6*(Cahier 23), 349–366.

Hoogeveen, J. G., Rossi, M., & Sansone, D. (2019). Leaving, Staying or Coming Back? Migration Decisions During the Northern Mali Conflict. *Journal of Development Studies*, *55*(10). Retrieved from http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2013/12/18/000442464_20131218151209/Rendered/PDF/793790JRN0Natu00Box0379850B00OUO090.pdf

Imai, K., Kim, S. I., & Wang, E. (2020). *Matching methods for causal inference.* Retrieved from https://imai.fas.harvard.edu/research/files/tscs.pdf

INS. (2017). *EMOP 2017* (Tech. Rep.). Institut National de La Statistique. Retrieved from http://www.instat-mali.org/contenu/eq/ranuel17_eq.pdf

Institut National de La Statistique. (n.d.). *Enquête Modulaire et Permanente auprès des Ménages (EMOP).*

IOM. (n.d.). *Displacement Tracking Matrix.* International Organization for Migration. Retrieved from https://displacement.iom.int/mali

Lamba, N. K., & Krahn, H. (2003). Social capital and refugee resettlement: The social networks of refugees in canada. *Journal of International Migration and Integration/Revue* *de l'integration et de la migration internationale*, *4*(3), 335–360.

Launay, R. (1979). Landlords, hosts, and strangers among the dyula. *Ethnology*, *18*(1), 71–83.

Loschmann, C., Bilgili, Ö., & Siegel, M. (2019). Considering the benefits of hosting refugees: evidence of refugee camps influencing local labour market activity and economic welfare in Rwanda. *IZA Journal of Development and Migration*, *9*(1). Retrieved from https://izajodm.springeropen.com/articles/10.1186/s40176-018-0138-2 doi: 10.1186/s40176-018-0138-2

Maystadt, J. F., & Duranton, G. (2019). The development push of refugees: Evidence from Tanzania. *Journal of Economic Geography*, *19*(2), 299–334. doi: 10.1093/jeg/lby020

Nomikos, W. G. (2019). *Mali Country Report. Risks from the EU's Southern Border* (Vol. 5; Tech. Rep. No. 769886). Retrieved from https://www.cidob.org/en/publications/publication_series/project_papers/eu_listco/mali_country_report_risks_from_the_eu_s_southern_border

Østby, G. (2008). Polarization, horizontal inequalities and violent civil conflict. *Journal of Peace Research*, *45*(2), 143–162. doi: 10.1177/0022343307087169

Pezard, S., & Shurkin, M. (2015). *Achieving Peace in Northern Mali: Past Agreements, Local Conflicts, and the Prospects for a Durable Settlement.* doi: 10.7249/rr892

Raleigh, C. (2010). Political Marginalization, Climate Change, and Conflict in African Sahel States. *International Studies Review*, *12*(1), 69–86. Retrieved from https://www.jstor.org/stable/40730710?seq=1#metadata_info_tab_contents doi: 10.1111/j.1468-2486.2009.00913.x

Ratnagar, S. (1990). Dealings with strangers. *Bulletin of the Deccan College Research Institute*, 347–356.

Rozo, S. V., & Sviatschi, M. (2021). Is a refugee crisis a housing crisis? Only if housing supply is unresponsive. *Journal of Development Economics*, *148*. doi: 10.1016/j.jdeveco.2020.102563

Samaké, S., Traoré, S. M., Ba, S., Dembélé, É., & Diop, M. (2006). *Enquête Démographique et de Santé du Mali 2006* (Tech. Rep.). Calverton, Maryland, USA: Cellule de Planification et de Statistique du Ministère de la Santé - CPS/MS/Mali, Direction Nationale de la Statistique et de l'Informatique du Ministère de l'Économie, de l'Industrie et du Commerce - DNSI/MEIC/Mali and Macro International. Retrieved from http://dhsprogram.com/pubs/pdf/FR199/FR199.pdf

Sedova, B., Ludolph, L., & Talevi, M. (2021). Inequality and Security in the Aftermath of Internal Population Displacement Shocks : Evidence from Nigeria. *Unpublished Working Paper. Commissioned as part of the "Preventing Social Conflict and Promot-*

ing Social Cohesion in Forced Displacement Contexts" Series. Washington, DC: World Bank Group., 1–53.

Skinner, R. T. (2020). *The hospitality of a mentor: A tribute to chérif keïta* (Vol. 22) (No. 5).

Taylor, J. E., Filipski, M. J., Alloush, M., Gupta, A., Valdes, R. I. R., & Gonzalez-Estrada, E. (2016). Economic impact of refugees. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(27), 7449–7453. doi: 10.1073/pnas.1604566113

Turner, M. D. (2004). Political ecology and the moral dimensions of "resource conflicts": The case of farmer-herder conflicts in the Sahel. *Political Geography*, *23*(7 SPEC.ISS.), 863–889. Retrieved from https://www.sciencedirect.com/science/article/pii/S0962629804000654?casa_token=cbRIVO0lxFoAAAAA:CRZd3AfCq3N2xXip8kmTvy0Cn_bzFLHrYkfphridaPilCslfTLo2Gk30ivcLyE88qfhc9x0u doi: 10.1016/j.polgeo.2004.05.009

UNHCR. (2020). External Operational Update UNHCR Sahel Crisis Response. (June), 1–12.

UNHCR. (2021). *Refugee statistics.* Retrieved from https://www.unhcr.org/refugee-statistics/

UNHCR. (2021, May). *UNHCR global trends - forced displacement in 2020* (Tech. Rep.). United Nations High Commissioner for REfugees.

University of California Berkely. (n.d.). *Global Administrative Areas.* Retrieved 2020-06-22, from https://gadm.org/download_country_v3.html

UNOCHA-Mali. (2016). *Plan de Réponse Humanitaire-2016* (Tech. Rep.). Bamako. Retrieved from www.humanitarianresponse.info/en/operations/mali

UNOCHA-Mali. (2017). *Plan de Réponse Humanitaire-2017* (Tech. Rep.). Bamako. Retrieved from www.humanitarianresponse.info/en/operations/mali

UNOCHA-Mali. (2018). *Plan de Réponse Humanitaire-2018* (Tech. Rep.). Bamako.

Verme, P., & Schuettler, K. (2020). The Impact of Forced Displacement on Host Communities. A Review of the Empirical Literature in Economics.

Wikipedia. (n.d.). *Communes of Mali.* Retrieved 2021-02-01, from https://en.wikipedia.org/wiki/Communes_of_Mali

7 Online Appendix

7.1 Empirical Strategy

In this analysis, we employ three types of estimation tools: difference-in-differences (DID), instrumental variable (IV), and propensity score matching (PSM). While the overview of our estimation approach is explained in the main body of this paper, we would like to further elaborate on these methods, and better elucidate the logic of our empirical strategy.

The effects of hosting IDPs on the economic outcomes of individual households can be calculated by estimating equation 1 where $HHOutcome_{it}$ is the natural log of non-agricultural household income or consumption for household i residing in commune j in region k at year t; IDP_{jkt} is either the number of IDP households or a binary indicator variable with 1 being a commune has IDP households; X_{it} a vector of household and commune characteristics; and ρ_k and τ_t are region and time fixed effects.

$$HHOutcome_{ijkt} = \alpha_0 + \alpha_1 IDP_{jkt} + X_{ijkt}\alpha_2 + \rho_k + \tau_t + \epsilon_{ijkt} \tag{1}$$

Additionally, the effects of hosting IDPs on commune-level inequality and poverty can be captured by estimating equation 2 below where $CommuneOutcome_{jkt}$ is either poverty headcount ratio, poverty gap index, income-based or consumption-based Gini coefficients; and W_{jkt} is a vector of commune level characteristics.

$$CommuneOutcome_{jkt} = \beta_0 + \beta_1 IDP_{jkt} + W_{jkt}\beta_2 + \rho_k + \tau_t + e_{jkt} \tag{2}$$

A major challenge in accurately computing the IDP effects on the economic outcomes is that either measure of the existence of IDPs is that it is highly likely correlated with unobserved household and/or commune characteristics which is captured by error terms ϵ_{ijkt} in the case of equation 1, and e_{jkt} in the case of equation 2. This lack of independence between the explanatory variables of our interests and errors terms introduces bias in the estimation of the parameters α_1 and β_1.

While commune level controls and fixed effects will help with identification, our key independent variable, IDP presence and population, may still suffer from endogeneity issues because of a potential correlation with unobservable characteristics of the communes.

In addition, there is a possibility that communes with better economic conditions attract IDPs escaping insecurity. If this is the case, it becomes difficult to know whether any differences in economic outcomes between communes with or without IDPs are due to their presence, or because they attracted the inflow of IDPs.

Therefore, we use three different strategies to mitigate these identification problems. None of these strategies alone is perfect. We are limited to account for all factors that possibly causes variations in economic outcomes and IDP presence by the availability of data which dictates what we as researchers can and cannot observe. We attempt estimating the effects of IDPs with three approaches largely to see if there is a consistent story across different estimations.

The first strategy we use is the difference-in-differences approach. The DID estimation is particularly helpful in minimizing potential bias attributed to selection. For instance, it is possible that there are certain characteristics of communes that attract IDPs such as social networks and hospitality to outsiders. If communes with and without IDPs are different in characteristics other than their IDP presence, attributing their difference in the economic outcomes to their IDP presence cannot be justified because they are likely fundamentally different in other characteristics. In this paper, we rely on the DID approach proposed by Callaway and Sant'Anna (2020), given that Malian communes received refugees at different timings. Namely, we estimate the effect of IDP presence for groups of communes which received IDPs in 2014, and 2016, as well as the overall effects. Although there are communes which started to host IDPs in 2015, 2017, and 2018, there are unfortunately not enough observations before the introduction of IDPs for these treatment groups, which is because some communes are not surveyed every year.

The DID approach ensures a comparison between IDP hosting communes, and communes that have never hosted IDPs (never-hosted communes) by presuming that these two groups of communes have parallel trends before they have received IDPs. We check for a potential violation of this assumption in Figures 13 and 12. In all figures, red indicates pre-IDP differences on the dependent variables of our interest between IDP communes and never-hosted communes. That all the estimates in red cross the zero line implies the mostly small observed differences in the outcome variables in the post-IDP periods are statistically irrelevant. With these results, we can plausibly assume that IDP host communities, and never-hosted communities are reasonably similar for comparison.

In order to estimate the effects of IDP on these outcome variables, we estimate Equation 3 and 4 with ordinary least squares (OLS). Since we are interested in estimating the IDP effects for two groups of communes who started to host IDPs in 2014 and 2016, we first construct dummy variables, $FirstTreat$ that indicate which commune received IDPs at which year. We consider 2011 to be a "true" pre-treatment period in which no commune has had IDPs, since a sequence of conflicts has been initiated in 2013, which has been the major cause of internal displacement. We drop the data from 2013, as we cannot be sure which communes have hosted IDPs in that year due to the lack of data. As mentioned earlier, the counterfactual for either of the IDP host groups is communes which never receive IDPs in the analysis periods. Therefore, the estimates ofγ_1, γ_2, δ_1, and δ_2 reflect the IDP effects on the economic outcomes relative to never-hosted communes.

$$\begin{aligned} HHOutcome_{ijkt} =& \gamma_0 + \gamma_1 FirstTreat_{jk(t=2014)} \\ &+ \gamma_2 FirstTreat_{jk(t=2016)} \\ &+ \phi_i + \rho_k + \tau_t + w_{ijkt} \end{aligned} \tag{3}$$

$$\begin{aligned} CommuneOutcome_{jkt} =& \delta_0 + \delta_1 FirstTreat_{jk(t=2014)} \\ &+ \delta_2 FirstTreat_{jk(t=2016)} \\ &+ \rho_k + \tau_t + \omega_{jkt} \end{aligned} \tag{4}$$

The second strategy is the IV approach. We belief a measure of ethnic diversity can be an instrument to mitigate the endogeneity issue of the IDP explanatory variables given the nature of Mali's internal displacement. When Malians fleeing from conflicts decide on destinations, they may consider the level of ethnic diversity, since they may believe it is easier for them to assimilate or be welcomed in a more ethnically diverse commune. In general much of the movement of people post-2013 has been from rural areas, which are less diverse to urban areas with higher levels of diversity. Ethnic diversity is calculated using the 2006 data from the Demographic and Health Survey (DHS) (Samaké et al., 2006). We use diversity data from nearly a decade before to capture historic diversity as opposed to current diversity, which might be affected by the conflict. The diversity measure is calculated as an inverse of Herfindahl-Hirschman Index described below:

$$EthnicDiversity_{jk2006} = \left[\sum_{g=1}^{G} s_g^2 \right]^{-1} \tag{5}$$

where s_g is a share of people who have reported to be of an ethnic group $g \in \{1, ..., G\}$ in commune j in region k in the 2006 DHS data. Since the index is inverted, a greater value corresponds to greater ethnic diversity.

We first estimate the relationship between ethnic diversity and IDP presence with Equations 7 and 9, and use the predicted IDP presence to estimate its effect on the economic outcomes with Equation 6 and 8. The resulting estimates of ζ_1 and κ_1 provides the local average effects of IDP for communes which is affected by their ethnic diversity.

$$HHOutcome_{ijkt} = \zeta_0 + \zeta_1 \widehat{IDP}_{jkt} + \zeta_2 X_{ijkt} + \rho_k + \tau_t + \nu_{ijkt} \tag{6}$$

where

$$\widehat{IDP}_{jkt} = z_0 + z_1 EthnicDiversity_{jk2006} + z_2 X_{ijkt} + \rho_k + \tau_t + \upsilon_{jkt} \tag{7}$$

$$CommuneOutcome_{jkt} = \kappa_0 + \kappa_1 \widehat{IDP}_{jkt} + \kappa_2 W_{jkt} + \rho_k + \tau_t + \eta_{jkt} \tag{8}$$

where

$$\widehat{IDP}_{jkt} = k_0 + k_1 EthnicDiversity_{jk2006} + k_2 W_{ijkt} + \rho_k + \tau_t + n_{jkt} \tag{9}$$

For this instrument to be valid, two assumptions must be satisfied. First, the instrument has to have a strong correlation with the endogenous variable. We test this assumption by estimating Equations 7 and 9 with OLS, and check the resulting F-statistics. Second, the exclusion restriction, the instrument can affect the outcome variables only through the endogenous variable, IDPs, and nothing else. In other words, our lagged measure of ethnic diversity cannot affect the economic outcomes directly or via factors other than the presence or number of IDPs. This would be the case if IDPs moved to places based on historical ethnic diversity and affinities, but that same historic ethnic diversity did not have a contemporary effect on economic outcomes once we had controlled for community or household differences. If these conditions are satisfied the IV approach can provide a clearly identified estimates of the local average effects of IDP on the economic outcomes by mitigating the omitted variable biases and potential reverse causality.

The third strategy is the Propensity Score Matching (PSM) approach. Since the assignment of IDP presence may be non-random, another way to construct a counterfactual is to find non-IDP communes which are similar in observable control variables to actual IDP communes. More specifically, we match IDP communes to non-IDP units in the year of the IDP introduction as well as the year before based on commune-level characteristics including the shares of female, christian, farmer populations, commune population, and ethnic diversity. We then construct a sample consisting of predicted IDP and non-IDP communes, and use this matched sample to estimate Equation 10 to estimate θ_1, which provides the effects of residing in an IDP commune on household income and consumption.

$$CommuneOutcome_{jkt} = \theta_0 + \theta_1 IDP_{jkt} + \theta_2 X_{jkt} + \lambda_{jkt} \tag{10}$$

The main identification assumption in this approach is that the data we use in this project are fully capable of characterizing the IDP and non-IDP communes. One needs to consider whether unobserved characteristics not included in our data sets might bias our results. We consider a range of both commune-level characteristics which affect both their IDP status, and economic outcomes, but there remain unobservable characteristics about these communes. To test this assumption, we conduct tests of means on the commune-characteristics mentioned above, and check if the differences on these characteristics are close to zero in a statistical sense between the actual IDP and predicted non-IDP communes. The results (Figure 14) are generally confirmatory that we have a reasonably good match between the IDP hosting and never-hosted communes.

7.2 Tables

7.2.1 Descriptive Statistics

Table 1: Descriptive Statistics of Household Characteristics

Statistic	N	Mean	Median	St. Dev.	Min	Max
Non-ag. HH income	34,160	574,591.10	600,000	592,319.30	0	13,440,000
Total HH consumption	34,160	1,009,465.00	823,878.20	785,073.80	20,880.55	24,522,538.00
Total p.c. consumption	34,160	148,628.90	121,404.90	122,575.70	6,960.18	4,866,031.00
Female HHH	34,160	0.08	0	0.28	0	1
Christian HHH	34,160	0.02	0	0.15	0	1
Literate HHH	28,825	0.39	0.00	0.49	0.00	1.00
HHH age	34,160	49.48	48	14.09	15	98
Polygamous HHH	34,160	0.27	0	0.44	0	1
HHH farmer	28,487	0.47	0.00	0.50	0.00	1.00
HHH herder	28,487	0.004	0.00	0.06	0.00	1.00
Live in urban area	34,160	0.46	0	0.50	0	1
HH size	34,160	5.96	5	5.51	1	78
If HH poor (cons.)	34,160	0.78	1	0.42	0	1

Notes: The currency unit is CFA. If HH is poor with determined with the national extreme povery lines. The third column is the per capital consumption.

Table 2: Descriptive Statistics of Commune Characteristics

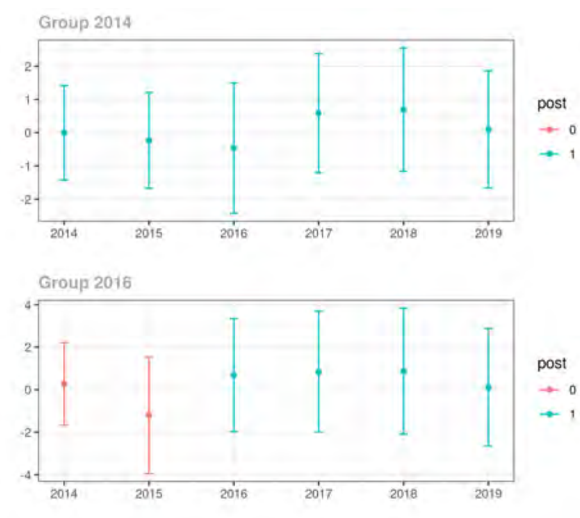
Statistic	N	Mean	Median	St. Dev.	Min	Max
HH consumption Gini	2,719	0.22	0.20	0.08	0.00	0.74
Per capita consumption Gini	2,719	0.20	0.18	0.09	0.00	0.74
Poverty ratio (cons.)	2,719	0.86	1	0.34	0	1
Poverty gap (cons.)	2,719	0.46	0.46	0.15	0.00	0.88
Population 2009	2,719	23,259.59	17,932	28,018.15	1,718	469,662
Share of IDP communes	2,719	0.16	0	0.37	0	1
Mean # of IDP HHs	2,719	181.74	0	1,765.90	0	52,233
Mean # of IDP persons	2,719	885.62	0	8,438.53	0	221,298
Ethnic diversity 2006	2,001	0.62	0.62	0.23	0.14	1.00
Inverted ethnic diversity	2,001	2.11	1.77	1.14	1.00	7.29

Notes: The currency unit is CFA. The poverty indices are estimated with the national povery lines.

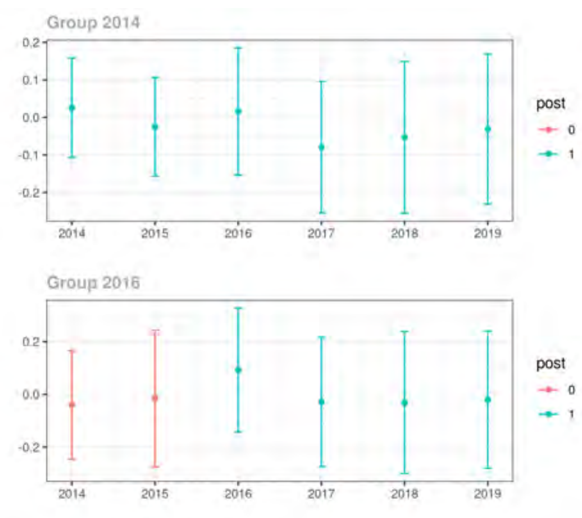
7.2.2 DID Results

Figure 12: Pre- and Post-Trends of the IDP Effects (Household Level)

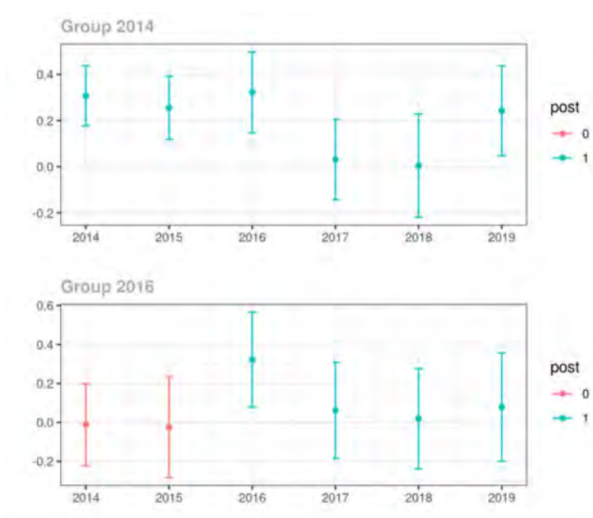
(a) Non-ag. Income



(b) Consumption



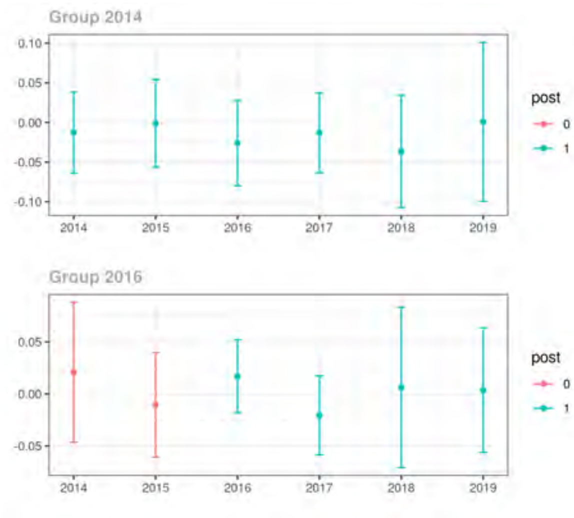
(c) Consumption



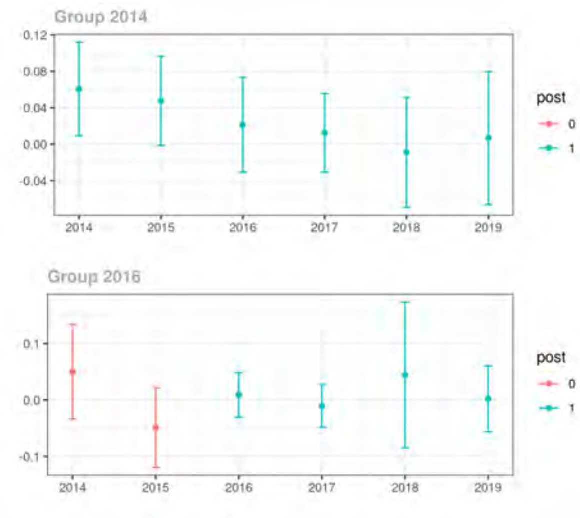
Notes: Callaway and Sant'Anna (2020)

Figure 13: Pre- and Post-Trends of the IDP Effects (Commune Level)

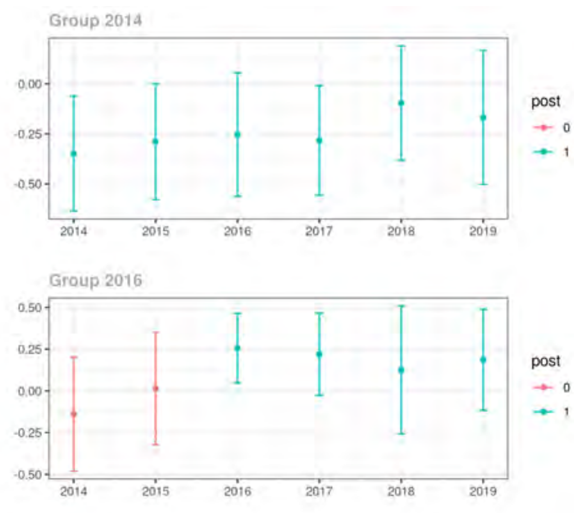
(a) Consumption Gini



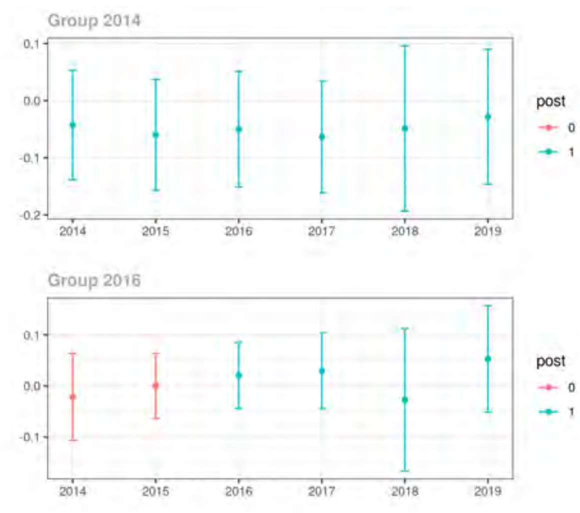
(b) PC Consumption Gini



(c) Poverty Ratio



(d) Poverty Gap



Notes: Callaway and Sant'Anna (2020)

Table 3: DID Estimates of the IDP Effects (Household Level)

	Non-ag. Income	Consumption	Consumption pc
Overall	0.375	-0.011	0.157*
	(0.558)	(0.053)	(0.052)
2014	0.115	-0.025	0.194*
	(0.544)	(0.052)	(0.051)
2016	0.63	0.003	0.121
	(0.943)	(0.094)	(0.09)
Observations	36046	36046	36046

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust cluster SE at the household level in parenthesis.

Table 4: DID Estimates of the IDP Effects (Commune Level)

	Cons. Gini	Cons. pc Gini	Poverty Ratio	Poverty Gap
Overall	-0.007	0.017	-0.023	-0.015
	(0.011)	(0.011)	(0.055)	(0.024)
2014	-0.015	0.023	-0.24	-0.049
	(0.018)	(0.015)	(0.071)	(0.033)
2016	0.002	0.011	0.197	0.019
	(0.014)	(0.017)	(0.074)	(0.03)
Obervations	2310	2310	2310	2310

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust cluster SE at the commune level in parenthesis.

Table 5: DID Estimates of the Heterogeneous IDP Effects by Gender (HH Level)

	Non-ag. Income	Consumption	Consumption pc
Panel A: All female HHH sample			
Overall	0.542	0.633***	0.236**
	(2.102)	(0.244)	(0.105)
2014	-2.99	0.408*	0.406**
	(1.521)	(0.2)	(0.188)
2016	4.296	0.872***	0.056
	(4.048)	(0.338)	(0.136)
Observations	2945	2945	2945
Panel B: All male HHH sample			
Overall	0.486	-0.05	0.144*
	(0.566)	(0.054)	(0.057)
2014	0.483	-0.06	0.161***
	(0.552)	(0.052)	(0.055)
2016	0.49	-0.041	0.126
	(0.935)	(0.091)	(0.097)
Observations	33101	33101	33101
Panel C: Z scores			
Overall	0.025	2.732***	0.776
2014	-2.146**	2.27**	1.249
2016	0.916	2.605**	-0.424

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust cluster SE at the household level in parenthesis.

Table 6: DID Estimates of the Heterogeneous IDP Effects by Farmer/Non-farmer (HH Level)

	Non-ag. Income	Consumption	Consumption pc
Panel A: All farmer sample			
Overall	0.581	-0.037	0.091
	(1.113)	(0.105)	(0.121)
Observations	12102	12102	12102
Panel B: All non-farmer sample			
Overall	-1.27	-0.072	-0.034
	(1.857)	(0.302)	(0.179)
Observations	17391	17391	17391
Panel C: Z scores			
Overall	0.855	0.109	0.581

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust cluster SE at the household level in parenthesis. Estimation for the farmer only sample is possible only for the 2016 treatment group, because of the lack of enough observations in the pre-treatment period for the 2014 treatment group. Thus, we only compare the 2016 effects.

7.2.3 First Stage Results

Table 7: Correlation between IDP and Ethnic Diversity

	N. IDPs	If IDP	N. IDPs	If IDP
	(1)	(2)	(3)	(4)
Ethnic diversity	-31.27	0.04^{***}	492.10^{**}	0.17^{***}
	(51.31)	(0.02)	(218.09)	(0.02)
Observations	1,300	1,300	23,917	23,917
F statistics	13.65	61.81	364.94	995.61
Unit	Commune	Commune	HH	HH

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Robust cluster SE at the commune level. Fixed effects included are region and year. The 2006 ethnic index is an inverted Herfindalh-Hirshmann index with greater values indicating greater diversity.

Table 8: Correlation between IDP and Conflicts

	N. IDPs	If IDP	N. IDPs	If IDP
	(1)	(2)	(3)	(4)
N. conflicts w/i 50km	20.12^{*}	0.001		
	(11.59)	(0.001)		
N. fatalities w/i 50km			16.36^{**}	0.0002
			(7.53)	(0.0002)
Observations	1,743	1,743	1,743	1,743
F statistics	16.54	63.63	20.97	63.42
Unit	Commune	Commune	Commune	Commune

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Robust cluster SE at the commune level.
Fixed effects included are region and year.
The 2006 ethnic index is an inverted Herfindalh-Hirshmann index with greater values indicating greater diversity.

7.2.4 IV Results

Table 9: IV Estimations (Household Level)

	Income	Income	Consumption	Consumption
	(1)	(2)	(3)	(4)
N of IDP HHs	0.0003		0.0001**	
	(0.0003)		(0.00003)	
If a IDP commune		0.820		0.236**
		(0.814)		(0.096)
Observations	23,917	23,917	23,917	23,917
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	574591	574591	1009465	1009465

Notes: Robust cluster SE at the HH level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
The dependent variables are log total HH income, and total HH consumption.
Fixed effects included are region and year. Covariates included are: if HHH female; if Christian; if HHH literate; HHH age; and HH size.
All models are instrumented with the 2006 ethnic diversity index which is an inverted Herfindalh-Hirshman index. Fixed effects included are region and year.

Table 10: IV Estimations (Commune Level)

	Gini	Gini (per capita)	Poverty Ratio	Povety Gap
	(1)	(2)	(3)	(4)
If a IDP commune	-0.112^{*}	-0.100	-0.114	-0.307^{*}
	(0.066)	(0.066)	(0.232)	(0.165)
Observations	1,300	1,300	1,300	1,300
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.208	0.199	0.857	0.455

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10. Region and year fixed effect. Robust cluster SE at the commune level. The dependent variables are household and per capita consumption-based Gini, consumption-based poverty head count ratio, and consumption-based poverty gap index. Covraiates included are: share of female HHH; share of Christian HH; share of literate HHH; mean HHH age; share of HH in an urban commune; and commune population. All models are instrumented with the 2006 ethnic diversity index which is an inverted Herfendalh-Hirshman index with greater values indicating greater diversity.

Table 11: IV Estimations with the Conflict Instrument (Commune Level)

	Gini	Gini (per capita)	Poverty Ratio	Povety Gap
	(1)	(2)	(3)	(4)
Number of IDPs	0.00002	0.00001	-0.00003	-0.00001
	(0.00001)	(0.00001)	(0.00003)	(0.00001)
Observations	1,743	1,743	1,743	1,743
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.208	0.199	0.857	0.455

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10. Region and year fixed effect. Robust cluster SE at the commune level. The dependent variables are household and per capita consumption-based Gini, consumption-based poverty head count ratio, and consumption-based poverty gap index. Covraiates included are: share of female HHH; share of Christian HH; share of literate HHH; mean HHH age; share of HH in an urban commune; and commune population. All models are instrumented with the number of conflicts in the 50km range from the commune border.

Table 12: IV Estimations with the Fatality Instrument (Commune Level)

	Gini	Gini (per capita)	Poverty Ratio	Povety Gap
	(1)	(2)	(3)	(4)
Number of IDPs	0.00001*	−0.00000	−0.00004*	−0.00001
	(0.00000)	(0.00000)	(0.00002)	(0.00001)
Observations	1,743	1,743	1,743	1,743
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.208	0.199	0.857	0.455

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Region and year fixed effect. Robust cluster SE at the commune level. The dependent variables are household and per capita consumption-based Gini, consumption-based poverty head count ratio, and consumption-based poverty gap index. Covraiates included are: share of female HHH; share of Christian HH; share of literate HHH; mean HHH age; share of HH in an urban commune; and commune population. All models are instrumented with the number of fatalities in the 50km range from the commune border.

7.2.5 PSM Results

Figure 14: Post-matching Covariate Balance (Commune Level)

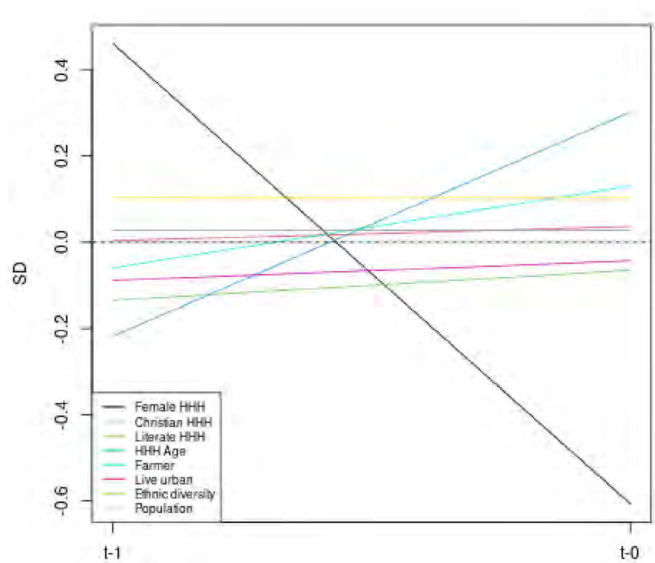


Table 13: Propensity Score Matching Estimates (Commune Level)

	Cons. Gini	Cons. pc Gini	Povery Ratio	Poverty Gap
Estimates	0.02	0.015	-0.074	0.03
	(0.017)	(0.015)	(0.086)	(0.022)
N. Treated	34	34	34	34
N. Matched	7538	7538	7538	7538
Dep. Var. Mean	0.208	0.199	0.772	0.45

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